ASSESSING THE IMPACT OF THE ASSIMILATION OF SATELLITE-RETRIEVED PRECIPITATION AND HUMIDITY PRODUCTS INTO THE HYDROSTATIC BOLAM: TWO ITALIAN CASE STUDIES

Stefano Mariani[1], Oxana Drofa[2], Silvio Davolio[2], Antonio Speranza[3], Andrea Buzzi[2]

[1]Institute for Environmental Protection and Research (ISPRA), Via Curtatone 3, 00185 Rome, Italy, stefano.mariani@isprambiente.it

[2]Institute of Atmospheric Sciences and Climate-Italian National Research Council (ISAC-CNR), Via Gobetti 101, 40129 Bologna, Italy, o.drofa@isac.cnr.it, s.davolio@isac.cnr.it, a.buzzi@isac.cnr.it

3University of Camerino (UniCam), Via Madonna delle Carceri 9, 62032, Camerino (Macerata), Italy, antonio.speranza@unicam.it

(Dated: 26 August 2011)

I. INTRODUCTION

Satellite-borne instruments represent a useful data sources additional and, in some case alternative, especially in terms of coverage, to more traditional in-situ instruments. Satellite estimations can have indeed a high impact in operational flood forecasting and early warming systems.

This was the goal of a pilot research project funded by the Italian Space Agency (ASI), as part of its Earth Observation Program, dealing with the exploitation of satellite-based measurements for the flood risk management (Progetto Pilota "*Protezione Civile dalle Alluvioni: il Nowcasting*"). With reference to the numerical modelling activity, one of the main objectives of this pilot project was to assimilate satellite-retrieved precipitation and surface products into the hydrostatic BOLAM model (developed by ISAC-CNR; Buzzi et al., 1994; Buzzi and Foschini, 2000) and to evaluate its performance in terms of quantitative precipitation forecasts (QPFs). BOLAM QPFs obtained without any assimilation scheme were considered as control simulations.

In addition, the evaluation results obtained for BOLAM (with and without assimilation) were compared and contrasted against those related to the non-hydrostatic MOLOCH model (also developed by ISAC-CNR; Malguzzi et al. 2006).

Starting from the results obtained within the ASI-funded pilot project (see, e.g., Fig. 1), a multi-method verification approach, based on categorical skill scores and subjective and object-oriented techniques (Mariani et al., 2005, 2008; Lanciani et al., 2008), have been then applied for a more thorough investigation of the QPF assessment. Rainfall measurements from the Italian regional gauge networks – made available through the Italian National Department of Civil Protection – have been employed to produce the comparing observational gridded analyses for the two intense events (occurred in July and November 2009) chosen as case studies.

Brief overviews of the assimilation schemes used in the present work are described in Sects. II and III, whereas the multi-method approach is summarized in Sect. IV. An outlook of the work is provided in Sect. V.

II. RAINFALL ASSIMILATION SCHEME

A physical assimilation scheme was developed in order to assimilate satellite precipitation estimates into a mesoscale model, namely BOLAM. The 4D assimilation algorithm (Davolio and Buzzi, 2004), based on the nudging technique, modifies the specific humidity profile of the BOLAM model according to the difference between observed (1-h accumulated) and forecast rain rate. Moisture changes lead to changes of temperature and other dynamical variables through the forward atmospheric model evolution.

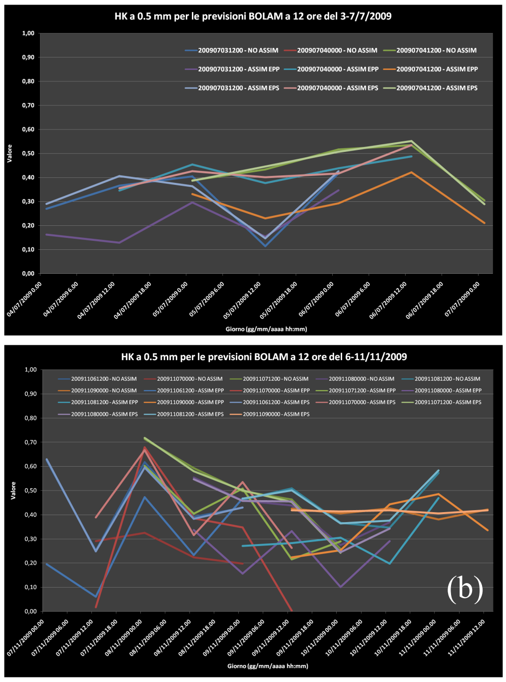

FIG. 2: The Hanssen and Kuipers (HK) skill score calculated (see Sect. IV) with respect to a 0.5-mm threshold for the BOLAM runs related to the July 2007 (a) and November 2007 (b) case studies.

The procedure compares forecast and observed precipitation at every convective time step (corresponding to about 15 minutes). Moisture profiles are nudged at grid points where the two values differ, according to the following equation:

$$\frac{\partial q(k)}{\partial t} = -\nu_{s,c}(k)\tau^{-1}\left\{q(k) - \varepsilon_{s,c}q^*(k)\right\},$$

where k is the model σ-level, $q(k)$ is the specific humidity profile prior to the nudging, $q^*(k)$ is the saturation humidity profile (obtained from the model), τ is a relaxation time, $\varepsilon_{s,c}$ is an over/under saturation coefficient and $\nu_{s,c}(k)$ is a vertical modulation profile, whose value varies in the interval [0-1].

Convective and stratiform precipitation are handled differently. Different vertical modulation profiles $v_{s,c}(k)$ and different coefficients $\varepsilon_{s,c}$ are used in the two cases in order to introduce/remove humidity only where it is needed to better fit model precipitation to observed precipitation. After a thorough testing phase, aimed at implementing and tuning the scheme on the most recent model version, the following values have been selected for the over/under saturation coefficient $\varepsilon_{s,c}$: 1.1-0.8 and 1.0-0.5 in case of stratiform or convective precipitation, respectively.

In the real-time application of this study, for each forecast starting time, two model forecasts are performed and compared. One is the standard (free) forecast initialized at the nominal starting time. The second is the forecast including the assimilation procedure, which is initialized 12-h before the nominal starting time and is composed by a 12-h period of assimilation of satellite precipitation data (only over the sea areas), followed by a free forecast. During the assimilation, boundary conditions are updated every 6 hours using the global analysis fields, while during the free forecast, 3-hourly global forecasts are provided as boundary conditions. Therefore, although the nominal initial time of the two predictions is the same, the initial analysis of the assimilation run is 12-h older than that of the standard forecast. This introduces an unavoidable (at least for real time applications) penalty to the forecast with assimilation, since an older analysis is expected to be affected by larger errors on the various atmospheric fields than a newer one.

III. SURFACE PARAMETERS ASSIMILATION SCHEME

The scheme of assimilation of surface parameters was developed to use data retrieved from satellite observations (below named "observation data"), namely surface soil water content and snow cover water content. The scheme was applied to the BOLAM model simulations (see an example in Fig. 1).

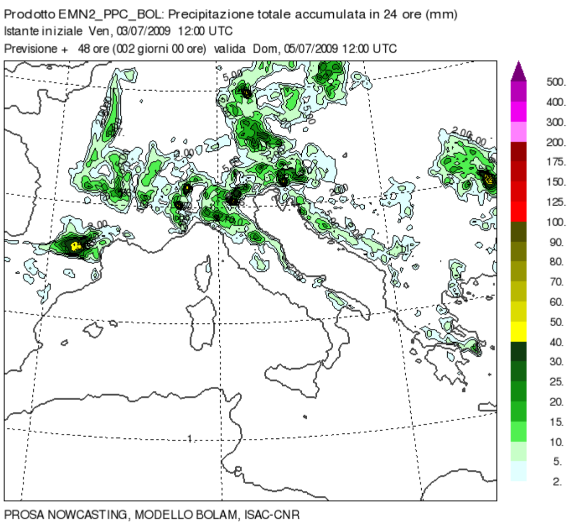

FIG. 1: Example of 24-h BOLAM forecast at 1200 UTC 5 July 2009 obtained by assimilating satellite-retrieved surface products.

Observation data were elaborated at IFAC-CNR (Italy), using data of the MicroWave AMSR-E sensor on board of AQUA polar satellite and of the SSM/I sensor on board of DMSP polar satellites. This dataset has a spatial resolution of about 10 km and are provided one time a day. Observation data are available on "bare surface" only. "Bare surface" means a land surface deprived of trees and can be represented by grassland, cropland, shrubs, true bare soil etc. Used observation data are available on a restricted area (with respect to the model domain) and are characterized by great spatial inhomogeneity. The developed assimilation scheme must therefore solve the above problems.

The algorithm defines an influence radius R_e that is a distance around a model grid point including some observation data pixels (if there are no surrounding observation data pixels, then model grid point gets a missing data value). An analytical weight factor is defined for grid points with observation data available. The definition is a Gaussian function of distance (S_i) between a model grid point and an observation pixel (number i):

$$W_i^{analit} = \exp\left[-\left(S_i \cdot f_S\right)^2\right],$$

where f_s is a scale factor, depending on an parameter A, function of observation data type: A = f_s/R_e. In the present study, the value R_e is defined equal to 16 km.

Once the analytical weight factors have been defined for observation data pixels contained in the circle of radius R_e, the effective weight factors are defined for all np observation points around each model grid point, including pixels with missing data values:

$$W_i = \frac{W_i^{analit}}{\sum_{i=1}^{np} W_i^{analit}} .$$

The final value (V) on a model grid point is calculated using increment values V_i^{increm} (difference between first guess approximation value and observation value), determined on grid points, and effective weight factors W:

$$V = \sum_{i=1}^{np}\left(V_i^{increm} \cdot W_i\right).$$

The model forecast nearest to the observation instant was used as first guess in the assimilation procedure. The assimilation is performed using the following expression:

$$F_{i,j} = F_{i,j}^0 \cdot W_{i,j}^{F^0} + \left(F_{i,j}^0 + H_{i,j}\right) \cdot W_{i,j}^{obs},$$

where $F_{i,j}$ is an assimilated value on the (i,j) grid point, $F^0_{i,j}$ is a first guess field value, $H_{i,j}$ is an increment value, $W^{F0}_{i,j}$ is a first guess weight factor, $W^{obs}_{i,j}$ is an observation weight factor. Weight factors of both first guess and observation should be defined for all grid points on the basis of information on respective error statistics. However, since in the present study such information is not available, the following hypotheses have been applied: weight factors of both first guess and observation weight are constant in space; the sum of them is 1. The final assimilation algorithm is:

$$F_{i,j} = F_{i,j}^0 + H_{i,j} \cdot W^{obs}.$$

In the present work assimilation was applied to the BOLAM daily forecast chain using GFS (NOAA, NCEP, USA) global model forecast data as initial and boundary conditions and IFAC-CNR observation data.

IV. THE MULTI-METHOD VERIFICATION APPROACH

Precipitation forecasts have been verified as categorical events by introducing a set of thresholds. Thus, verification is based on a categorical dichotomous "yes/no" statement by considering whether the precipitation forecast exceeded or not a pre-defined threshold. The same kind of statement is also true for the rainfall gridded analyses. The combination of the occurrence possibilities of observation and forecast gives origin to the 2×2 contingency table

(Wilks, 2006), in which are reported the number of occurrences with both observed and forecast precipitation at and above the defined threshold (*hits*); the number of occurrences with forecast precipitation at and above the defined threshold and observed forecast below (*false alarms*); the number of occurrences with forecast precipitation below the defined threshold and observed precipitation at and above (*misses*); and the number of occurrences with both observed and forecast precipitation below the defined threshold (*correct non-rain forecasts*).

The elements of the contingency tables have been then used to calculate several categorical scores and skill scores. Different scores evaluate indeed different aspects of the forecast performance. In the present work, some of the most used categorical scores have been applied (BIAS, ETS, HK, FAR, POD, etc.). In addition, it has been investigated how contingency table's hits, false alarms, and misses are spatially located over the verification.

To assess if the forecast and the observational fields being compared are defined on grids with the same resolution and if they have the same amount of small-scale detail, a power spectrum analysis has been considered, as well. In fact, being the scores based on point-to-point matches, they are sensitive to small displacement errors (the so-called "double penalty effect") and then they could worsen in inverse proportion to the increase of details present into the forecast analysed (Weygandt et al., 2004).

A contiguous rain area (CRA) analysis (Ebert and McBride, 2000, Mariani et al., 2008) has been then employed to provide a quantitative estimation of the most relevant qualitative features that characterize the difference between the forecast and observed precipitation patterns.

V. OUTLOOK

During the ASI-funded project, the QPF verification based only on categorical scores and skill scores was not sufficient to provide a clear picture of the performance the BOLAM model when satellite-based fields are assimilated. Given such results, authors have then decided to further investigate the performance of the BOLAM forecasts (and also of the corresponding MOLOCH forecasts) by means of a multi-method approach, which was able in previous research works to provide a more realistic and reliable QPF evaluation.

Since this work is still ongoing, it is not possible to provide in the present extended abstract a discussion of the verification results. Hence, attention is here fixed only on the methodologies used to assimilate the satellite-retrieved precipitation and surface fields into BOLAM and on the statistical methods employed to evaluate the forecast performance in terms of precipitation.

VI. ACKNOWLEDGMENTS

The authors would like to thank all the research partners of the Progetto Pilota "*Protezione Civile dalle Alluvioni: il Nowcasting*", and in particular those who provide in-situ and satellite data used in the present work.

VII. REFERENCES

Buzzi A., Foschini L., 2000: Mesoscale meteorological features associated with heavy precipitation in the southern Alpine region. *Meteor. Atmos. Phys.*, 72 131–146.

Buzzi A., Fantini M., Malguzzi P., Nerozzi F., 1994: Validation of a limited area model in cases of Mediterranean cyclogenesis: Surface fields and precipitation scores. *Meteor. Atmos. Phys.* 53 53–67.

Davolio S., Buzzi A., 2004: A nudging scheme for the assimilation of precipitation data into a mesoscale model. *Wea. Forecasting*, 19 855–871.

Ebert E., McBride J. L., 2000: Verification of precipitation in weather systems: Determination of systematic errors. *J. Hydrol.*, 239 179–202.

Lanciani A., Mariani S., Casaioli M., Accadia C., Tartaglione N., 2008: A multiscale approach for precipitation verification applied to the FORALPS case studies. *Adv. Geosci.*, 16 3–9.

Malguzzi P., Grossi G., Buzzi A., Ranzi R., Buizza R.: The 1996 "century" flood in Italy. A meteorological and hydrological revisitation, *J. Geophys. Res.*, 111 D24106. doi:10.129/2006JD007111, 2006.

Mariani S., Casaioli M., Accadia C., Llasat M. C., Pasi F., Davolio S., Elementi M., Ficca G., Romero R., 2005: A limited area model intercomparison on the "Montserrat-2000" flash-flood event using statistical and deterministic methods. *Nat. Hazards Earth Syst. Sci.*, 5 565–581.

Mariani S., Accadia C., Tartaglione N., Casaioli M., Gabella M., Michaelides S. Chr., Speranza A., 2008: Multisensor comparison and numerical modeling of atmospheric water fields: A VOLTAIRE case study over Cyprus. *Wea. Forecasting*, 23 674–701.

Weygandt S. S., Loughe A. F., Benjamin S. G., Mahoney J. L., 2004: Scale sensitivities in model precipitation skill scores during IHOP. In *Proc. 22nd Conference on Severe Local Storms*, Hyannis, MA, 4-8 Oct 2004. American Meteorological Society.

Wilks D. S., 2006: Statistical Methods in the Atmospheric Sciences, International Geophysics Series, Vol. 91. Academic Press, 649.