U.S.- Italy Research Workshop on the
Hydrometeorology, Impacts, and Management of Extreme Floods
Perugia (Italy), November 1995

ATMOSPHERE MODELING AND HYDROLOGIC-PREDICTION UNCERTAINTY

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Abstract. Some of the fundamental principles of Quantitative Precipitation Forecasts from operational numerical atmospheric models are briefly addressed. The attention is then focused on the relations among the QPF uncertainty, the sub-grid variability of the forecasted precipitation patterns and the uncertainty of the hydrologic prediction. Recognizing the fundamental deterministic nature of numerical models' outputs, a few kinds of probabilistic parametrization for the forecasted precipitation are analyzed with the use of a conceptual non-linear hydrologic model. The definition of the scores that commonly define the quality of the QPF products is also reviewed in the same probabilistic framework. Finally, some research topics to be developed in the field of QPF related to flood prediction are suggested.

1. INTRODUCTION: QPF IN OPERATIONAL ATMOSPHERIC MODELS

Quantitative Precipitation Forecasting (QPF) has been recognized to be a fundamental tool for the prediction of hazardous floods and the reduction of the related risk (Lanza and Siccardi, 1994). Accurate short-term (12-48 hours) rainfall forecasts are often the only means to increase the flood forecast lead time up to that minimum critical value that allows the activation of civil protection plans, especially when small and medium size watersheds, with characteristic response time of a few hours at most, are the concern (Siccardi and Adom, 1993).

Recent advances in numerical atmosphere modeling made it possible to introduce precipitation amounts as a standard forecasted variable in many operational numerical models used in weather prediction (ECMWF, 1993, Atger, 1994, Jacobs, 1994). This approach is progressively replacing or accompanying other techniques, based on the subjective (Doswell, 1986, Van den Dool, 1989) or statistical interpretation (Model Output Statistics, Carter *et al.*, 1989, Analogue Sorting, Guilbaud *et al.*, 1994) of other forecasted meteorological parameters (pressure, wind convergence, moist and dry static stability, ...).

The solutions to many problems, which remain unsolved in atmospheric modelling, are crucial to the improvement of the quality of forecasts and to bridge the present gap between the operational and theoretical limits of predictability of the weather system (Islam *et al.*, 1993). A common factor of these problems originates from scale issues; the limited spatial and temporal resolution of the meteorological data collection networks on one side and the heavy computational and data storage demands on the other, allow detail resolution of only synoptic-scale and large-meso-scale weather patterns.

The representation of important smaller scale phenomena, such as the cumulus convection and the turbulent surface fluxes, is necessarily left to parametrization schemes (Tiedtke, 1989, Miller et al., 1989, 1992). The forecasted precipitation amounts are then given as the combination of, ideally, two different processes: stratiform precipitation, due to large scale ascent of frontal or cyclonic origin, explicitly resolved, and convective precipitation, parametrized inside each grid pixel (Atger, 1994).

The continuous progress in computer sciences and technology is strongly reducing the computational burden, so much so that one could hope to run, in the near future, General Circulation Models at a grid resolution that is comparable to the characteristic size of single cumulus clouds. As an example, the operational model of the European Centre for Medium-Range Weather Forecasts has improved from the nominal 1.125° horizontal resolution over 19 pressure levels of 1987 to the 60km resolution over 31 levels as of 1991 (Figure 1). Such an improvement allowed a much better representation of the orography and of the related effects on the predicted weather. The availability of atmospheric data, which are necessary to initialize and update the models, and in particular, the sparse density of vertical soundings seem to remain as the main obstacles for the increasing of the grid resolution in operational models.

A further step in this direction has been done in recent years with the implementation of Limited Area Models (LAMs). These models are usually nested inside weather forecasting models of the whole globe, such as the ECMWF one, which provide the initial and the predicted boundary conditions for the LAM's (Black, 1988, Buzzi *et al.*, 1994, Paccagnella *et al.*, 1994). An example of a QPF output for a severe precipitation event is shown in Fig. 2; a recursive nested procedure was used in the case displayed in Fig. 2, with horizontal resolutions of 40km and 20km.

Such resolutions are, however, not yet close to those of the experimental cloud models (Johnson *et al.*, 1993) needed for a full 3-dimensional approach to flow dynamics. The hydrostatic approximation is still widely adopted in operational models, either global or area-limited, and convection is left to parametrization. A sensible advantage in the coupled use of global weather prediction and LAM models is the possibility, given the reduced computational demand, of including more sophisticated parametrization schemes for the sub-grid processes. Also, specific interpolation techniques are incorporated in order to optimize the use of the point meteorological data, whose sparseness may vary dramatically from one region to another (Buzzi *et al.*, 1991).

From the point of view of short-term QPF in severe weather conditions, particularly the parametrization of the cumulus convection (Buzzi *et al.*, 1994) and of the various microphysical processes appears to be particulary important (Sundqvist *et al.*, 1989, Ødegaard, 1994). When the parametrized convective precipitation is combined with the resolved stratiform precipitation, the resulting forecasted precipitation assumes an intrinsic sub-grid uncertainty that has a serious impact on its usefulness for flood prediction purposes. As specifically addressed in section 2, the characteristic scales of the hydrological processes may be much smaller than the ones resolved by the given QPF model. Both the QPF uncertainty at the resolved scales and the QPF sub-grid variability will affect the final uncertainty of the flood prediction (Lanza and Siccardi, 1994).

Advanced cumulus convection parametrization, such as the one proposed in Emanuel (1991), and adopted in several LAM models, are based on simple statistical assumptions about ensembles of cumulus clouds. Recognizing the relevant non-linearity of the moist convective process, the unstable profiles are adjusted to neutrality considering "episodic-mixing clouds" and averaging the subsequent mass and energy fluxes over the grid size rather than assuming an adjustment based on average buoyancy as in previous schemes (Kuo, 1974). Such an approach

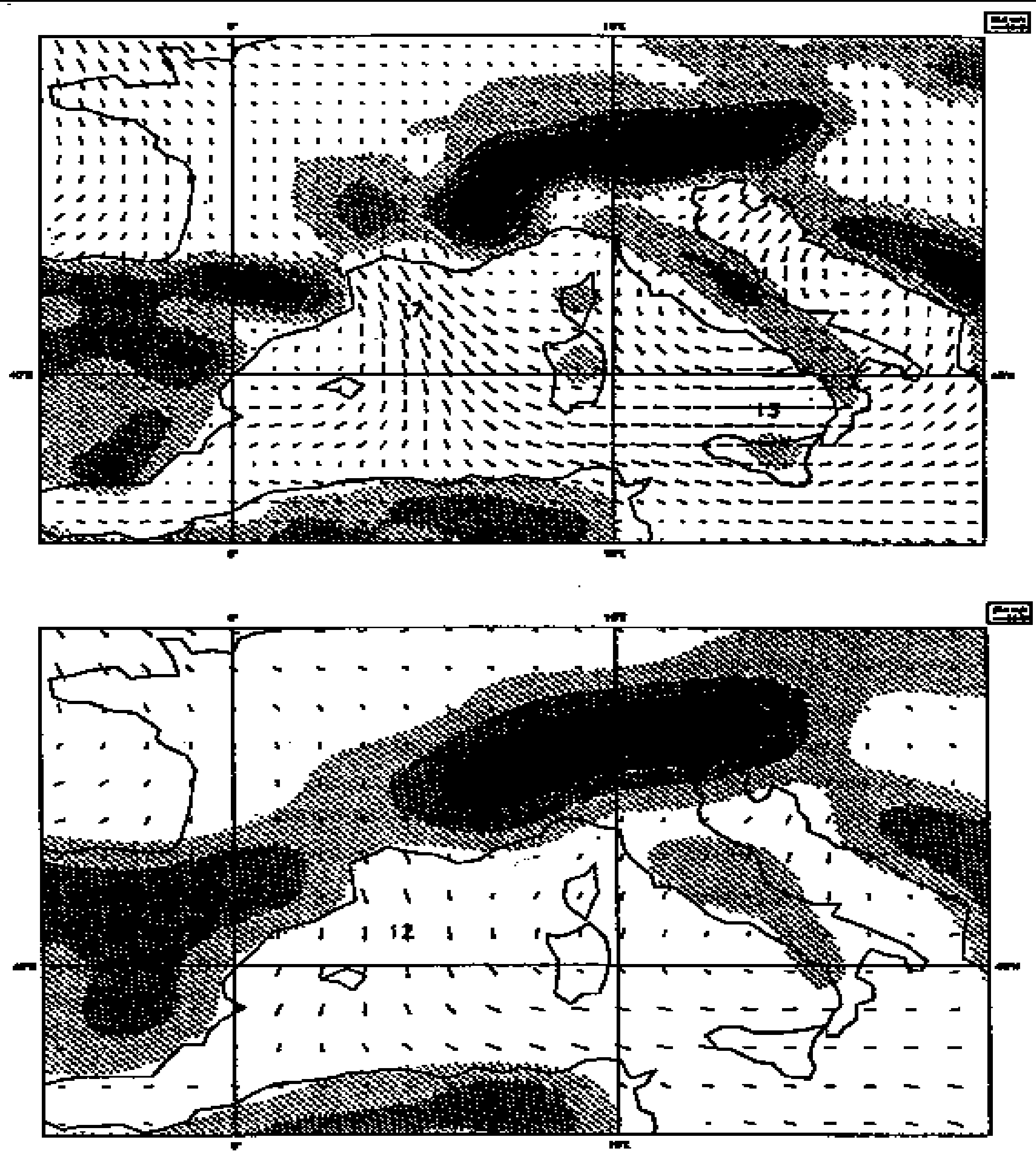

Fig. 1 – Model resolution improvemnets, as seen in Day-3 forecasts of 10m wind (m/s) from 12 UTC 15 April 1991 for T213/L31 (upper) and T106/L19 (lower). Model orographies are indicated by shading. (Adapted from ECMWF, 1993).

has the fractional areal coverage of the updraft velocity at each level as a fundamental parameter. The resulting vertical mass flux and subsequent precipitation reflects both the mean instability conditions and their sub-grid variability. This kind of approach may then give hints for addressing, on a probabilistic basis, the short-scale spatial structure of precipitation patterns inside numerical models. The definition of automated procedures for estimating the above parameter is, however, still under verification (Emanuel, 1994).

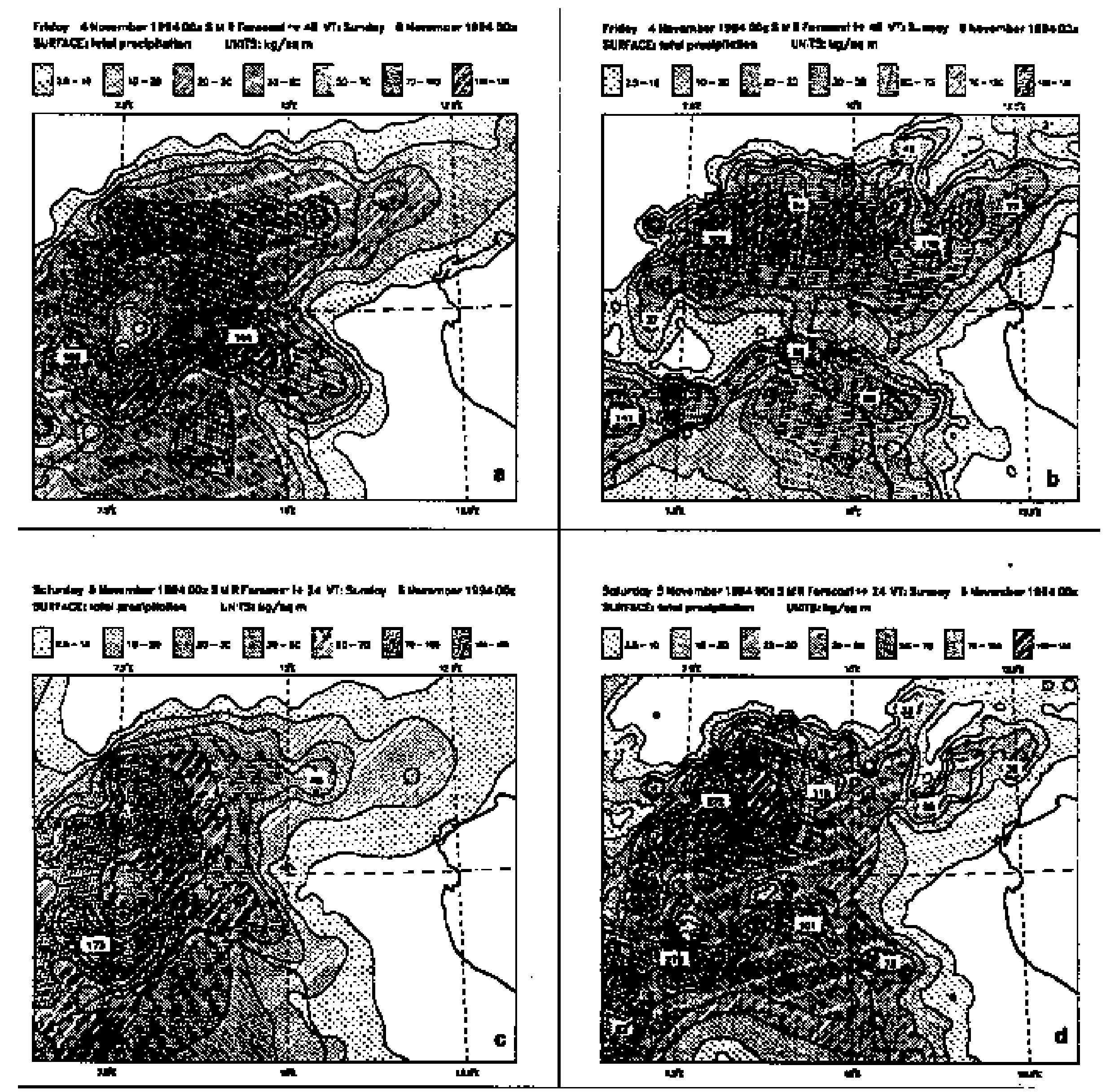

Fig. 2 - Forecasted precipitation cumulated in 24 hours for the 5th of November 1994. Panels a) and b) during the second 24 hours of integrations respectively by the lowest resolution run F4-48 and by the highest resolution run S4-48; Panels c) and d) during the first 24 hours of integrations respectively by the lowest resolution run F5-24 and by the highest resolution run S5-24. (Adapted from Paccagnella et al., 1994).

Also, it must be stressed that such parametrization schemes are designed to represent the effects of convective overturning on large-scale dynamics, rather than to explicitly quantify sub-grid fluctuations. The adjustment of unstable profiles to neutrality is usually performed "instantaneously" within each integration time step. Even if the calculation time step of numerical models is quite short (of the order of one or more minutes), the same time scale is used with the large (spatial) scale dynamics. Both for this reason and for the problems related to the storage and dissemination of data and results, the temporal resolution of operational QPF products and LAM's is still constrained to a minimum step of 6 hours.

In the reminder of this paper, attention is focused on the specific issue of the probabilistic interpretation of QPFs produced by deterministic numerical atmosphere models and on their impacts on the flood prediction uncertainty.

2 QPF UNCERTAINTY AND THE HYDROLOGIC RESPONSE

The hydrologic response to precipitation events, in terms of the surface runoff produced over a watershed, is characterized by a large variability of the land properties and states, both in time and space (Wood et al., 1988). The infiltration mechanism, which acts as a highly non-linear filter in the rainfall-runoff transformation, is usually modelled as an integrated process over Representative Elementary Areas (REA) and discrete time steps inside which the land characteristics and states may be described in a statistical framework (Rosso, 1994). The spatial resolution of the available precipitation inputs is, quite often, the main constraint in defining the spatial extent of the REA.

We may consider, as a reference example, the case where the extent of the REA coincides with the grid spacing of the produced QPF. Given the non-linearity of the runoff production mechanism, the prediction of the hydrologic response to a forecasted rainfall may be substantially biased, even in the hypothesis of accurate QPF, if the mean values of various quantities over the grid element are considered (Castelli, 1996). Furthermore, any prediction needs that are to have reasonable operational use must be accompanied by an estimate of its uncertainty (Murphy, 1993). The sub-grid variability of both the forecasted rainfall and the hydrologic response needs then to be simultaneously addressed.

We then raise the question of which are the more appropriate statistical indicators that, coupled with the usual mean rainfall forecasts from "deterministic" atmospheric models, may lead to a better estimate of the hydrologic response. In other words, we are asking whether it is possible, at least in a simplified framework, to guess a statistical description for the outputs of a deterministic approach to QPF.

Answers to a similar question have been addressed, in the framework of subjective precipitation forecasting based on weather prediction models, through the definition of a protocol for Probabilistic QPF (Krzysztofowicz *et al.*, 1993). A more rigorous probabilistic approach is implicit in the techniques based on Model Output Statistics (Carter *et al.*, 1989), which are still referring to the outputs of numerical weather prediction models that rely on running data records that are long enough to be statistically significative .

In the framework of advanced numerical atmospheric models, such as the ones addressed in the previous section, the issue of the probabilistic interpretation of the results at the operational level is still wide open. Recent experiments addressed the possibility of estimating the forecast variance through the use of Ensemble Forecast techniques (Pelosini *et al.*, 1994). In these experiments, a set of equally-likely perturbations were added to a reference initial condition in order to compute an ensemble of perturbed forecasts and to estimate the mean and variance of the various forecasted quantities (Murphy, 1988). However, computational demand of numerical models often prevents the generation of ernsembles large enough to support an operational basis. Also, the estimated forecast variance refers to grid-average quantities, whereas the estimation of the sub-grid variability (both in time and space) has not yet been addressed.

2.1 PRECIPITATION SUB-GRID VARIABILITY AND HYDROLOGIC PREDICTION

In order to address the posed question above, we consider a simple conceptual hydrologic model for the estimation of surface runoff inside a REA with known statistical properties. Let $R(t)$ be the average surface runoff, with units of depth over time, produced inside the area at time t since the beginning of rainfall, and let P be the time-average precipitation intensity at a point inside the area. The soil is modeled as a population of storages with initial random capacities whose distribution is characterized by a mean value (w_a) and a dispersion coefficient ($1/m$). Assuming that each storage fills linerarly till saturation, the effect of storage variability on the runoff may be modeled through the simple non-linear expression (Kitadinis and Bras, 1981, Becchi and Federici, 1987):

$$R(t;P)=\begin{cases} 0 & \text{if} \quad P \le E \\ (P-E)\left[\tan^{-1}\left(m\dfrac{(P-E)t-w_a}{w_a}\right)+\tan^{-1}m\right]\left(\dfrac{\pi}{2}+\tan^{-1}m\right)^{-1} & \text{if} \quad P > E \end{cases} \tag{1}$$

where E is the sum of evapotranspiration and percolation.

To take into account for subgrid variability of precipitation, we may consider P as a random variable with partial differential equation $(\ f_P(x)\ )_X$, and compute the runoff statistics as:

$$\mathbf{E}\left[R^n(t)\right]=\int_0^\infty R^n(t;x)f_P(x)dx \tag{2}$$

To proceed with the analysis, let us assume a simple log-normal pdf, as suggested by Gupta and Waymire (1991), to describe precipitation. We also want to take into consideration the evidence that, especially for areas of hundreds of square kilometres and for precipitation events with a relevant convective component, the precipitation field shows finite probability of null values (intermittency). Indicating with f_0 such a probability and with α and β the parameters of a log-normal distribution, we write:

$$f_P(x)=f_0\delta(x)+\frac{1-f_0}{x\alpha\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{\ln x-\beta}{\alpha}\right)^2\right] \tag{3}$$

$$\mathbf{E}[P]=(1-f_0)\exp\left(\beta+\alpha^2/2\right) \tag{4}$$

$$CV_P^2=\frac{\exp\left(\alpha^2\right)}{1-f_0}-1 \tag{5}$$

As a suitable time scale for the response, we take the time of concentration t_c of the watershed where floods need to be predicted. A natural depth scale is given by the average soil storage capacity w_a. The ratio between the two may be taken as a reference rainfall intensity scale for soil saturation. As an example of hydrologic response in the presence of rainfall variability, Fig. 3 shows the expected value of the non-dimensional runoff, and its coefficient of variation, as a function of the expected non-dimensional precipitation intensity. Three different values of f_0 have been considered, corresponding to a precipitation event with either prevalent stratiform component ($f_0 = 0.2$), prevalent convective component ($f_0 = 0.8$), or an intermediate case ($f_0 = 0.5$), while values of $CV_P = 1$ $m = 2$ have been chosen as representative of an "average" situation. From a severe flood point of view, it may be thought that cases with prevalent convection are more hazardous for small watersheds, while large basins are more prone to floods caused by large, long lasting but less intermittent, stratiform frontal precipitation.

From the first graph of Fig. 3, we observe that the expected runoff is quite sensitive to the value of f_0 till the rainfall intensity is a few times larger than the saturation scale w_a / t_c. Due to the threshold characteristics of the infiltration process, precipitation with higher intermittency is expected to produce more runoff. Also, as the rainfall intensity or the time response of the watershed decreases, the sensitivity to the intermittency parameter f_0 increases. Conversly, as the size of the watershed or rainfall intensity increases, the basin is likely to be completely saturated and the hydrologic response becomes linear.

Analysing the coefficient of variation, we observe higher values for lower precipitation, while for high precipitation a minimum is reached asymptotically as a function of the value of f_0. Note that, given the distribution (3), the coefficient of variation of precipitation remains constant for varying expected values.

2.2 PROBABILISTIC PARAMETRIZATION OF QPF

In order to test the possibility of defining simple probabilistic parametrization for the QPF outputs, we take the following simplifying assumptions as limit cases:

- the distribution $f_p(x)$ represents the p.d.f. of the "true" point precipitation intensity inside the reference REA, averaged over the time t_c;
- the QPF outputs have optimal forecast skills, in the sense that the value $\mathbf{E}[P]$ inside the reference REA is exactly guessed.

With these assumptions, four different configurations may be tested based on limited optimal forecast skill hypotheses, namely:

- A purely deterministic approach, in which the forecasted rainfall is assumed as constant over the REA;
- A first order probabilistic approach (hereafter denoted as I), in which only the exactly guessed mean value is provided in the forecast. In this case, the predicted point rainfall intensity, denoted S, is assumed as a random variable with exponential distribution (single parameter):

$$f_S(x) = \frac{1}{\lambda} e^{-x/\lambda} \quad (6)$$

$$\lambda = (1 - f_0)\exp(\beta + \alpha^2 / 2) \quad (7)$$

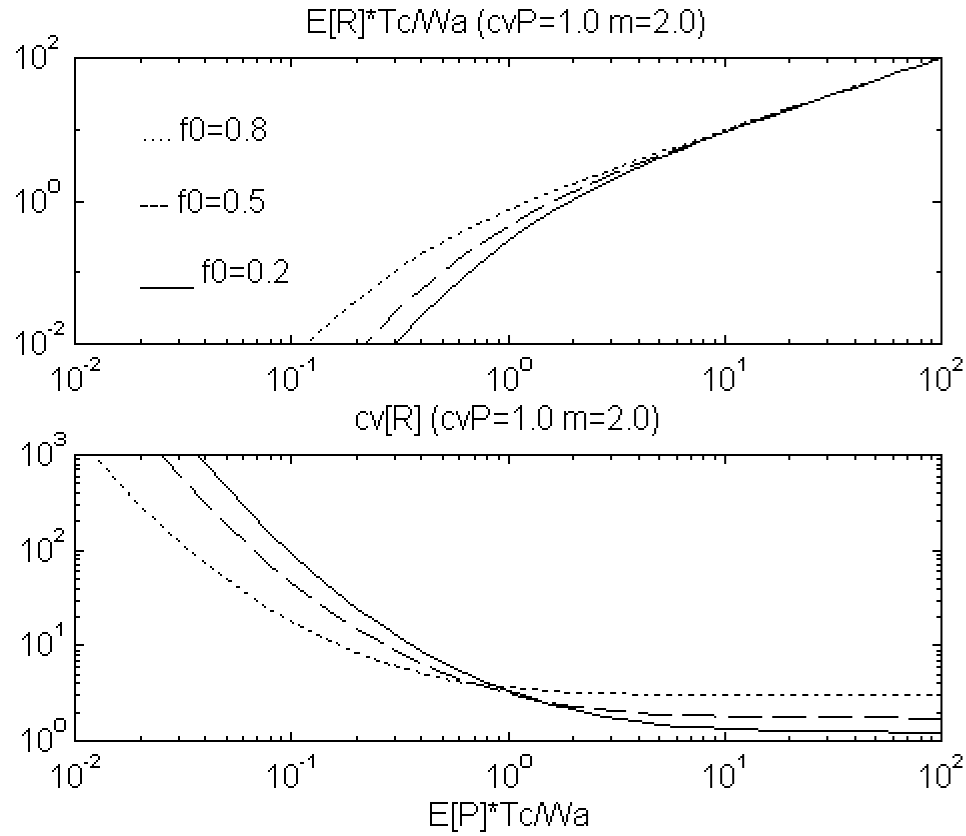

Fig. 3 - Expected non-dimensional runoff and its coefficient of variation as a function of the non-dimensional precipitation intensity

- A first order intermittent probabilistic approach (hereafter denoted as I0), in which both the mean and the probability of zero rainfall, both exactly guessed, are provided in the forecast:

$$f_S(x) = f_0\delta(x) + \frac{1 - f_0}{\lambda} e^{-x/\lambda} \tag{8}$$

$$\lambda = \exp\left(\beta + \alpha^2 / 2\right) \tag{9}$$

- A second order probabilistic approach (hereafter denoted as II), in which both the mean and variance of the rainfall intensity, both exactly guessed, are provided in the forecast:

$$f_S(x) = \frac{1}{x\gamma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{\ln x - \lambda}{\gamma}\right)^2\right] \tag{10}$$

$$\lambda = \beta + \frac{3}{2}\ln(1 - f_0) \tag{11}$$

$$\gamma^2 = \alpha^2 - \ln(1 - f_0) \tag{12}$$

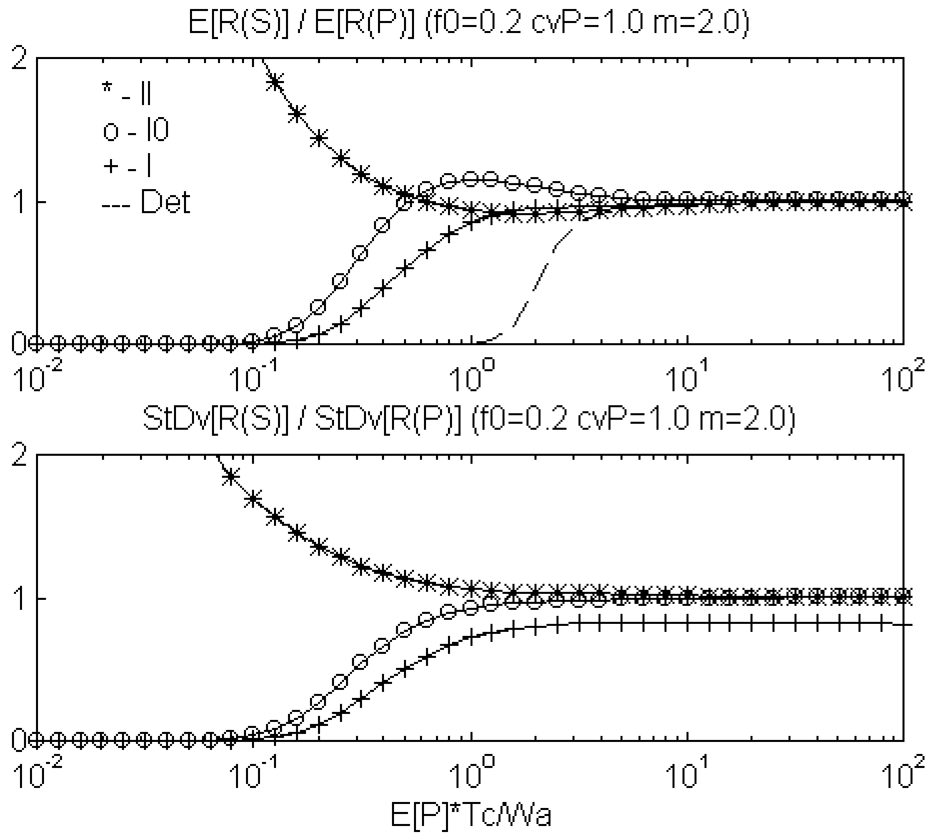

Fig. 4 - Ratios between the means and the standard deviations of the QPF-based and the "true" surface runoff, R(S) and R(P), for various probabilistic parametrization of the forecasted precipitation S, assuming a zero-rainfall probability f0=0.2.

The optimal case of a correct forecast of whole statistics is not considered because it would give, in the simplified analysis presented here, trivial results.

Figures 4, 5 and 6 show the computed runoff using the above described probabilistic approaches, for three different values of the "true" zero rainfall probability. In particular, ratios between the values of the mean and the standard deviation of the forecast-based runoff and of the one estimated using the "true" rainfall distribution (3) are shown. We recall that, in the present formulation, R is defined as the average runoff over the area of interest, so that its coefficient of variation may be interpreted as the relative confidence interval (+ or -), rather than as the variability of the point runoff.

It is evident from such graphs how a purely deterministic approach to QPF tends to dramatically under-estimate the produced runoff over a wide range, unless the rainfall intensity is exceptionally high or the time response of the basin very large. Also, no confidence interval can be defined with such a deterministic approach.

The first order I approach, based only on mean estimates, gives a moderate increase in the runoff estimate accuracy. This improvement is not significant around the reference saturation rainfall intensity. It is also larger for low values of f_0. The coefficient of variation graphs show how the runoff estimates tend to be systematically overestimated, the more so as the zero rainfall probability increases.

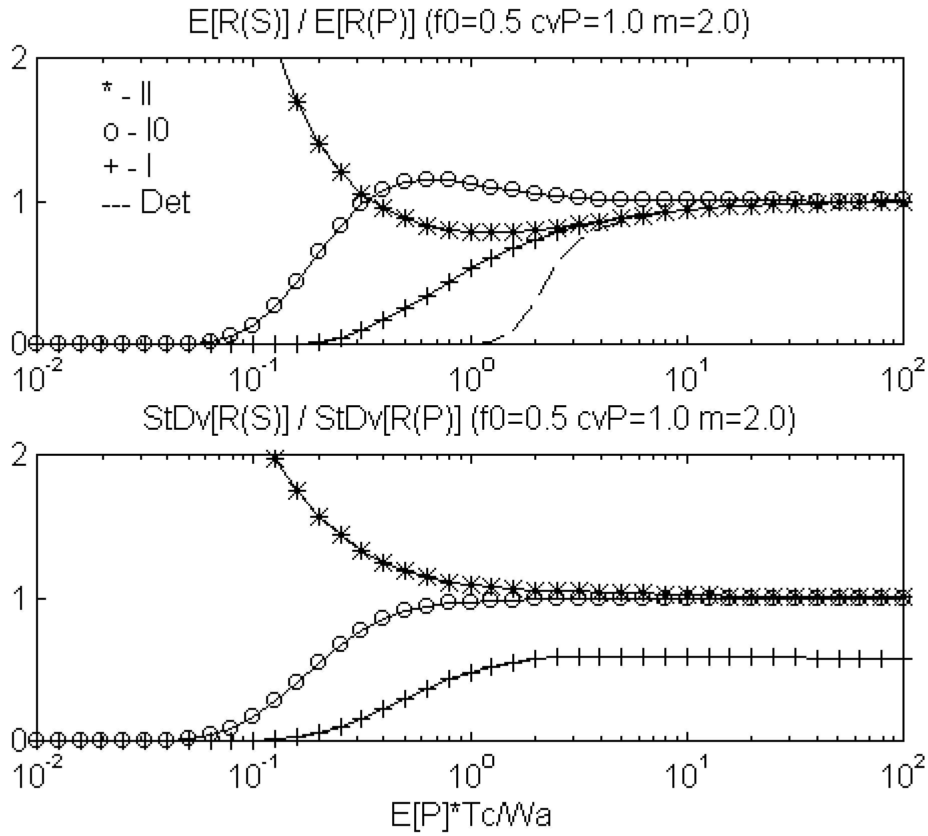

Fig. 5 - As in Figure 4, but for f0=0.5.

When either the zero rainfall probability or the rainfall variance are correctly guessed in the forecast (I0 and II approaches), reasonable estimates of the runoff are obtained for a much wider range. While the use of f_0 predicts too low a runoff rate for very small precipitation intensities, the use of the variance overpredicts in the same region, thereby artificially improving the forecast. Focusing attention in the range of rainfall intensities around the saturation value $\mathbf{E}\left[P\right] = w_a / t_c$, we observe a higher sensitivity to the zero probability of the "true" precipitation. As expected, the IO approach works better for high values of f_0. While for low values of the same parameter, consideration of the variance becomes more important.

Finally, we observe that the zero rainfall probability of the "true" rainfall has no significant effect on the estimated standard deviations. Correct estimates of the confidence interval in the runoff forecast are obtained, in both the I0 and II schemes, as the rainfall intensity approaches the saturation value.

3 PERFORMANCE MEASURES OF QPF

The analysis presented in the previous section has been derived in the optimistic framework of a perfectly skillful QPF model. As mentioned in the introduction, the utility of QPF outputs from present numerical atmospheric models is promising, but still quite far from such a goal, at least on the operational basis.

Some analysis may be proposed, on the basis of the described probabilistic approaches, to revisit the quantities commonly used to measure the forecasting performance of such models, and to better define, from a hydrologic point of view, what we may assume as an accurate forecast.

The measure of the QPF skill possessed by a numerical atmospheric model is commonly based on the definition of a number of scores (Buzzi et al., 1994). Let S_j represent the grid-average forecasted precipitation intensity (amount), at the grid pixel j, averaged over a time period h, and P_j the precipitation subsequently measured at a point inside the same pixel. The more commonly used scores - Bias $B_h(p)$, Threat $T_h(p)$ and False Alarm $A_h(p)$ - are defined as the following functions of the precipitation intensity (amount) p:

$$B_h(p) = \frac{G(p)}{O(p)} \tag{13}$$

$$T_h(p) = \frac{C(p)}{G(p) + O(p) - C(p)} \tag{14}$$

$$A_h(p) = \frac{G(p) - C(p)}{G(p)} \tag{15}$$

where:

$$G(p) = \frac{1}{N}\sum_j^N \left(S_j \geq p\right) \approx \mathbf{P}\left[S_j \geq p\right] \tag{16}$$

$$O(p) = \frac{1}{N}\sum_j^N \left(P_j \geq p\right) \approx \mathbf{P}\left[P_j \geq p\right] \tag{17}$$

$$C(p) = \frac{1}{N}\sum_j^N \left(S_j \geq p\right)\left(P_j \geq p\right) \approx \mathbf{P}\left[S_j \geq p, P_j \geq p\right] \tag{18}$$

Note that such scores are not mutually independent. It is easy to show that:

$$T_h = \frac{(1 - A_h)B_h}{1 + A_h B_h} \tag{19}$$

If rainfall was uniform inside each grid pixel, a perfect forecast would simply give $P_j = S_j$ and hence the "optimal forecast scores" would be $B_h(p) \equiv T_h(p) \equiv 1$ and $A_h(p) \equiv 0$.
In real cases, the sub-grid variability has to be taken into account, and the optimal scores need to be redefined. In order to do this, let us again assume the hypothesis of perfect forecast of the pixel-mean rainfall, $S_j = \mathbf{E}\left[P_j\right]$.

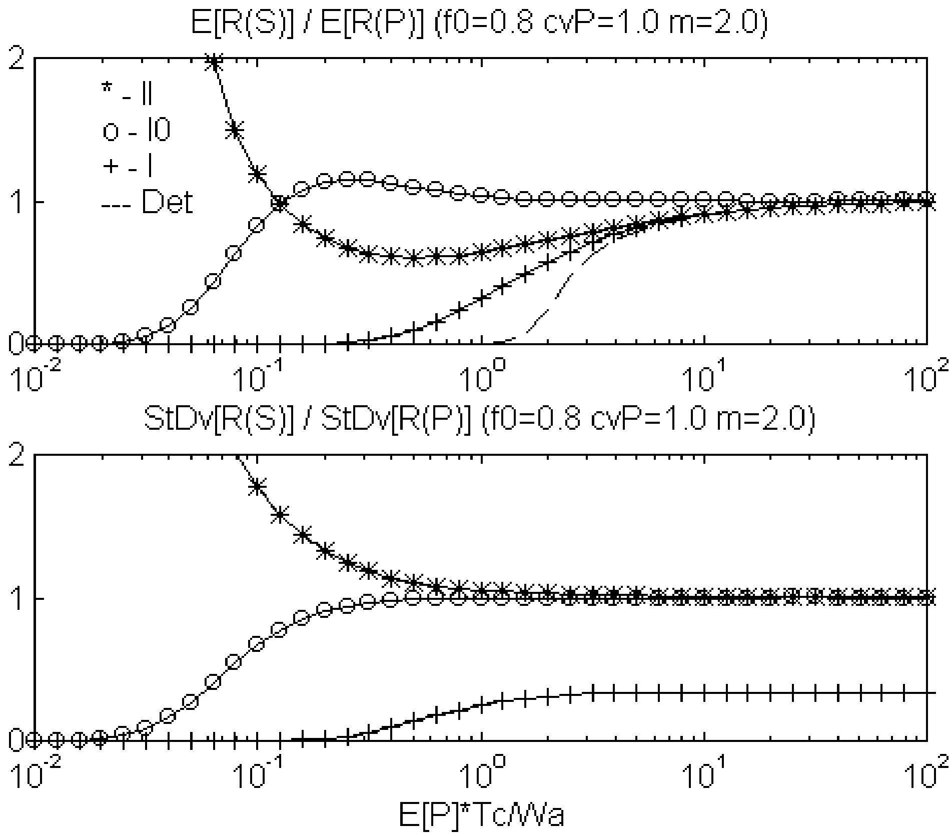

Fig. 6 - As in Figure 4, but for f0=0.8.

If one could assume spatial stationarity for the rainfall process over the whole region of N pixels where the scores are computed, such scores could easily be interpreted simply through the joint p.d.f. ($f_{S,P}(x,y)$) of S and P. Such a hypothesis is, however, very difficult to sustain when the region of interest is large enough to have statistically significant samples of the S and P populations.

We may instead assume, given the more common grid spacing used in the atmospheric models and the usually observed short correlation distances for the rainfall field (Islam *et al.*, 1988), that the observations P_j are single samples from statistically independent populations with a p.d.f. ($f_{Pj}(x)$) inside each pixel j, whose expected value is forecasted to be S_j.

As an illustrative example, let us assume that such independent distributions may be represented with the same probabilistic model, where all the parameters except the mean are constant in space:

$$f_{Pj}(x) = f_P(x;\mathbf{E}[P_j]) \tag{20}$$

In the log-normal intermittent model (3), this corresponds to the assumption of constant probability of zero rainfall and a constant coefficient of variation.

If we call $f_{ES}(x)$ the distribution function of S inside the region, we may write:

$$G(p) \approx 1 - F_{ES}(p) \tag{21}$$

And for the optimal scores:

$$O(p) \approx 1 - \int_0^\infty f_{ES}(x) F_p(p;x)\,dx \tag{22}$$

$$C(p) \approx G(p)^2 - G(p) \int_p^\infty f_{ES}(x) F_p(p;x)\,dx \tag{23}$$

Optimal forecast should be seen as upper limits to the forecasting performance of a model and are themselves dependent on the distribution properties of the forecasted rainfall field, especially with respect to sub-grid variability and intermittency. In genereal, such upper limits may rapidly diverge from the "deterministic" constant optimal values as the precipitation intensity increases. Figure 7 shows an example of the scores for a set of forecast experiments with a LAM (Buzzi *et al.*, 1994) with the optimal limits defined above. Such limits have been added here on the basis of heuristically guessed sub-grid variability parameters and must be considered qualitative.

4 CONCLUSIONS AND PROPOSED RESEARCH TOPICS

The use of numerical atmospheric models for operational Quantitative Precipitation Forecasting is becoming a central issue in flood risk mitigation policies. A very wide spectra of unsolved problems continuously challenge the scientific community, regarding the improvement of the quality of weather forecasts in general and precipitation forecasts in particular. Most of them are of a strict "meteorological" character, concerned mainly with the formulation and implementation of parametrization for unresolved cloud dynamics and microphysics. Some others may take advantage of cooperation among the meteorological and hydrological scientific communities, such as those related to the parametrization of surface fluxes and the better understanding of the active role of hydrology on the weather evolution (Entekhabi *et al.*, 1996).

All of them, however, may be thought to have originated from a common "father" problem, the sparseness of meteorological data collection stations as a constraint for the refinement of space-time models resolutions. Strictly connected to this main problem, is experimentation regarding the use of remote sensing as further support to the vertical soundings used for model initialization and to the ground stations used for verification.

More specific to the use of QPF for flood prediction purposes are the issues related to the uncertainty and to the space-time resolution of short-term precipitation predictions. It has been here shown how, even in the hypothesis of a perfectly skillful precipitation forecast over the atmospheric model grid spacing, the flood prediction requires quantification of the sub-grid structure of the rainfall field. To this purpose, simple probabilistic models have been discussed for the characterization of such sub-grid variability and the commonly used measures of the QPF "goodness" have been revisited.

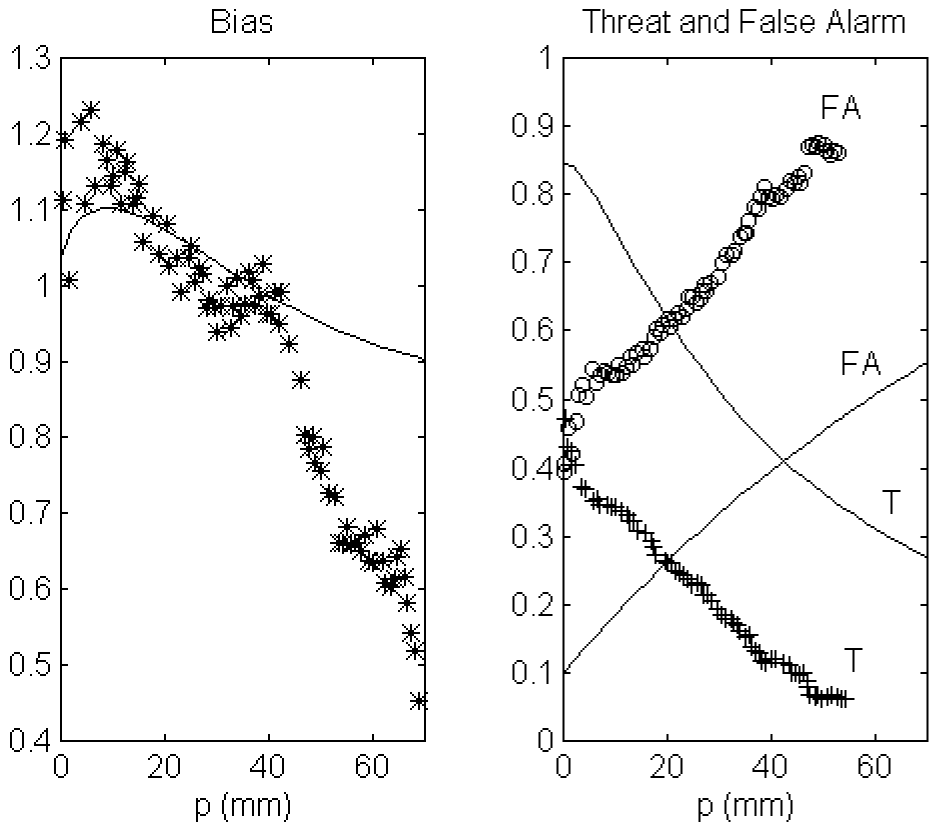

Fig. 7 - Forecast scores for an ensemble of QPF experiments with a LAM (+ o symbols, adapted from Buzzi et al., 1994), and theoretical optimal scores (solid lines).*

Starting from these considerations the following more specific research topics may be proposed, as of interest of both the hydrological and the meteorological communities:

- the inclusion of more robust estimate procedure of the forecast uncertainty into operational QPF atmospheric models by taking full advantage of approaches based on both Ensemble Forecast and Model Output Statistics and the redefinition of the performance scores on more rigorous statistical basis. This last issue is strictly connected, as suggested in the present work, to the next topic.
- the formulation of simple, scale oriented, probabilistic models of sub-grid rainfall variability to be used in the QPF production and interpretation processes. These models may be based, as suggested in the present work, on the determination of a limited set of "accompanying" statistical parameters, such as the variance and the probability of zero rainfall, to be related to both the scale of the grid and to the predicted rainfall activity. While a very wide literature exists on the issue of the scale properties of the rainfall field, operational use of such scaling and multi-scaling theories requires a deeper analysis that is oriented to severe cases, which detail the relations between the (multi) scaling parameters and the large-scale meteorological factors, including orography and surface conditions.
- Improvement of the actual parametrization schemes for the cumulus convection and microphysical processes to the extent that the sub-grid variability, in both the space and time domains, are explicitly considered as output variables. This process would ideally imply the inclusion of cloud-scaling theories into convective parametrization schemes.

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