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Evaluation of a conceptual rainfall forecasting model from observed and simulated rain events

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Abstract

Very short-term rainfall forecasting models designed for runoff analysis of catchments, particularly those subject to flash-floods, typically include one or more variables deduced from weather radars. Useful variables for defining the state and evolution of a rain system include rainfall rate, vertically integrated rainwater content and advection velocity. The forecast model proposed in this work complements recent dynamical formulations by focusing on a formulation incorporating these variables using volumetric radar data to define the model state variables, determining the rainfall source term directly from multi-scan radar data, explicitly accounting for orographic enhancement, and explicitly incorporating the dynamical model components in an advection-diffusion scheme. An evaluation of this model is presented for four rain events collected in the South of France and in the North-East of Italy. Model forecasts are compared with two simple methods: persistence and extrapolation. An additional analysis is performed using an existing monodimensional microphysical meteorological model to produce simulated rain events and provide initialization data. Forecasted rainfall produced by the proposed model and the extrapolation method are compared to the simulated events. The results show that the forecast model performance is influenced by rainfall temporal variability and performance is better for less variable rain events. The comparison with the extrapolation method shows that the proposed model performs better than extrapolation in the initial period of the forecast lead-time. It is shown that the performance of the proposed model over the extrapolation method depends essentially on the additional vertical information available from voluminal radar.

Introduction

Specific aspects of environmental water resources, such as evaluation of potential for flash flooding and real-time management of urban runoff systems, require very short-term rainfall forecasts. The spatial and temporal characteristics of a rainfall forecast depend on the hydrological requirements: lead times of interest range on the order of fifteen minutes for urban applications to one or two hours for flash-floods, so that the required spatial resolution of the rainfall forecasts varies from about one to a few hundred km^2 depending on the catchment geomorphology. These requirements are not satisfied by typical operational numerical weather prediction models, including mesoscale models (Collier, 1991). The ideal solution would involve the use of site-specific models, incorporating non-hydrostatic cloud physics, and designed to meet the spatial and temporal resolution needs of the hydrological application environment. A recent study (Thielen and Creutin, 1997) confirmed that the site-specific approach remains a long-term objective and depends on the successful completion of additional research and more practical issues such as: i) availability of on-site data necessary for model initialization, ii) methods for real-time assimilation of local data such as radar data into numerical weather prediction models (Collier, 1991), and iii) computational time consistent with hydrological applications. Considering these issues, a viable alternative consists of adapting suitable modelling methods to observational measurements that are routinely available. Knight (1987) suggested simplifying models the better to connect them to field data and applications; that work inspires this approach. Typical operational observations consist of ground meteorological data, volumetric radar data, and satellite data. Actually, methods addressing very short-term rainfall forecasting consider these data type simplicitly. For instance, most forecasting methods based on radar data extrapolate the displacement of rainfields recorded by low elevation radar images (Bremaud and Pointin, 1993; Bellon and Zawadzki, 1994). In order to address the practical issues mentioned earlier, these advection methods assume implicitly that: (i) rainfield evolution is governed by its velocity as deduced from previous observations, and

(ii) rainfall dynamics, which are difficult to characterize by low elevation radar data, are in a steady state. Incorporation of rainfall dynamics was addressed by Georgakakos and Bras (1984a and b) who proposed a simplified dynamical approach considering an atmospheric column as a reservoir of liquid water to describe the rainfall evolution at the catchment scale. The formulation required only ground meteorological observations and later, was extended to two dimensions (Lee and Georgakakos, 1991). Seo and Smith (1992) and French and Krajewski (1994) reformulated the model to benefit from volumetric radar observations that provide an estimate of the liquid water content. An enhanced form of this model was tested in an orographic region (Andrieu *et al.*, 1996). The more recent improvement (Lee and Georgakakos, 1996) introduces a parameter for characterizing the intensity of convection in the atmospheric column and proposes an equation for real-time updating of this parameter.

This work continues the effort to produce a rainfall forecasting model suited to routinely available data and useful for hydrologic applications. It extends the study of Andrieu *et al.* (1996) and differs in several aspects. In particular, the rainfall forecast model is modified to use only volumetric radar data. This change emphasizes the importance and dominant role of volumetric radar data for identification of the primary dynamics of rainfall systems at short time scales and is comparable to a simplified form of a detailed meteorological model. The modifications are possible by focusing on the evolution of rainwater content as observed from volumetric radar data. Comprehensive evaluation of any rainfall forecasting model requires long duration sets of quality controlled radar data. Unfortunately, due to the relatively recent archiving of volumetric weather radar data, such data sets are not readily available. In the present case, the model is tested using four rainfall events: two events recorded at a well controlled radar site, (Andrieu *et al.*, 1997); and two rain events recorded by the volumetric radar of Monte-Grande in Italy (Borga and Frank, 1998). An additional validation based on a microphysical model is used to complement the tests based on real-world data. The microphysical model produces realistic precipitation and related rainwater content states, and these variables can be considered as error-free measurements. The model evaluation is performed by sampling these simulated measurements, using the values to drive the forecast model, and validating the forecasted rainfield to the reference provided by the microphysical model. This type of simulation study is useful to gain insights into and to understand the behaviour and limitations of the proposed rainfall forecasting model.

The paper is organized in the following way. The model formulation focuses on the modifications introduced to make it fully consistent with volumetric radar data. The section on model evaluation introduces the observations data, describes the sensitivity analysis of the model to hydrometeorological variables and presents and discusses results of the case studies. The detailed model analysis conducted using the microphysical model follows.

Model formulation

This section summarizes the rainfall model dynamics. The precipitating cloud is conceptualized as an atmospheric column of rainwater; the influx of rainwater and the response time of the cloud are deduced from volumetric radar data. The advection and lateral mixing are explicitly incorporated and the rainwater influx evolution is explicitly defined. This type of formulation is well suited to be initialized and updated in real time from volumetric radar data. The multi-scan radar provides the means for evaluating the total rainwater content, the rain rate and the horizontal displacement vector of the atmospheric column. The model state incorporates only processes associated with the final stages of precipitation production, includes water vapour influx component, but does not explicitly address the spectrum of precipitation formation processes.

RAIN WATER CONTENT

The temporal evolution of the total rainwater content or vertically integrated liquid water content VIL (kg/m^2) for the atmospheric column is given by the difference between the influx of rainwater $S(t)$ and the rainfall rate at the column base $R(t)$:

$$\frac{dVIL(t)}{dt} = S(t) - \underbrace{h(t)VIL(t)}_{R(t)} \qquad (1)$$

where $h(t)$ is the inverse of the model response time. Equation (1) is similar to the model proposed by Georgakakos and Bras (1984a); however in this work, the VIL represents the rainwater category of atmospheric water and can be measured directly using weather radar.

The source term $S(t)$ is not directly measurable, but can be estimated using consecutive radar images and a form of Eqn. (1).

The term $R(t)$ is the output flux of moisture, i.e. the rainfall rate at the cloud column base, and is assumed to be equivalent to the rainfall rate at ground level. The coefficient $h(t)$ depends on the vertical profile of rainwater and is deduced from:

$$h(t) = \frac{R(t)}{VIL(t)} \qquad (2)$$

In order to move the atmospheric columns, an advective component is included in (1) and the final form of the conservation equation of rainwater content becomes:

$$\frac{\partial VIL(x,y,t)}{\partial t} = -u\frac{\partial VIL(x,y,t)}{\partial x} - v\frac{\partial VIL(x,y,t)}{\partial y} - h(x,y,t)VIL(x,y,t) + S(x,y,t) \qquad (3)$$

where u and v are vertically-averaged horizontal velocities.

The other aspect introduced into the model formulation concerns the estimation and evolution of the source term $S(t)$.

THE SOURCE TERM EVOLUTION

The initial condition for the source term is deduced from volumetric radar data and the advective dynamics over the radar domain defined by the following:

$$\frac{\partial S(x,y,t)}{\partial t} = -u\frac{\partial S(x,y,t)}{\partial x} - v\frac{\partial S(x,y,t)}{\partial y} + G_S(x,y,t) \quad (4)$$

where G_S represents the generation and decay rate of the influx of rainwater. In order to maintain the intent of this work, it is appealing to relate G_S to meteorological variables influencing rain cell evolution. In this formulation, G_S only accounts for orographic influences, and is parameterized as (Bell, 1978; Alpert and Shafir, 1989; Andrieu *et al.*, 1996):

$$G_s(x,y,t) = \alpha_m \; V_g(t) \; \nabla z_0(x,y) \quad (5)$$

where α_m is a calibration parameter representing a constant rainwater flux, $V_g(t)$ is an indicator of the horizontal wind vector and ∇z_o is the ground slope vector. The horizontal advection displacement vector (u,v) is taken as an indicator of the horizontal wind velocity.

MODEL OPERATION

Implementation of the model equations requires initial conditions for all variables: *VIL*, source term representing rainwater flux, response time and rainfield velocity components. One advantage of a model suited for use with radar includes the direct means available for initialization and updating model variables in real-time from observed radar data. The following section provides a description of the operational algorithms and procedures introduced to create an environment for model implementation. In some cases, such as in dealing with the presence of bright band, a direct and effective means of addressing the issues is described. In such conditions, the proposed approach is only one of several viable options for addressing operationally challenging issues. The remaining components of model initialization and operation are summarized in the following points:

- the *VIL* is estimated from volumetric radar observations of reflectivity, reflectivity being transformed into water content according to the relationship: $M = cZ^d$, where M is liquid water content, Z is reflectivity, c and d are two constants. The bright band, the peak of reflectivity due to the melting layer, is corrected by replacing the peak of reflectivity by a linear decrease in rainwater content.
- the components of the rainfield velocity are determined using a classical cross-correlation analysis of successive base-level radar reflectivity observations (Bellon and Austin, 1984).
- the rainfall rate is determined from the lowest elevation radar data according to the relationship $Z = 200R^{1.6}$.
- the initial value of the source term is developed from consecutive radar images by tracing the rainwater influx associated with an observed *VIL* variation. The source term is estimated at a 2 km × 2 km radar grid resolution, and averaged over the grid trace displacement within the rainfield.
- the response time is estimated at the beginning of each forecast lead-time using (2).

After initialization, the rainfall forecast is carried out according to the following assumptions:

- the vertical profile of rainwater, the response time and the horizontal velocity components remain constant during the forecast lead-time,
- the source term evolution is described by the evolution equation (Eqn. 4), i.e. the source term is advected explicitly and accounts directly for the orographic influence.
- the *VIL* evolution is driven by the integration of the rainwater content evolution equation (Eqn. 3). Integration is performed in conjunction with an advection component based on a finite difference, antidiffusive scheme (Smolarkiewicz, 1983).

Model evaluation

CASE STUDIES AND OBSERVATION DATA

Two case studies are used to illustrate the model implementation and provide an environment for model performance evaluation. In each case, the rainfall is forecasted for 4 catchments in the radar domain. The catchment averaged rainfall rates are compared to the model forecast of the same. The first case study is composed of two rain events recorded in the mountainous region of Cevennes in the South of France, and the second case study groups two rain events recorded by the radar of Monte Grande in North-Eastern Italy.

Two significant rain events were recorded during the Cevennes Radar Experiment: 13–15 November 1986 (denoted NOV86), and 4–6 October 1987 (denoted OCT87), respectively grouping 38 hours and 35 hours of data. Detailed characteristics of these data are described in (Andrieu *et al.*, 1996). The *VIL* and rainfall rate are estimated every 8 minutes on a 2 km × 2 km grid. The rainfall rate and rainwater content at the cloud column base are provided by the lowest angle radar scan. Multi-scan radar provides a means of estimating the *VIL* and in this case study, the radar recorded two elevation angles (1.1 deg and 3.1 deg). A specific procedure was designed to deduce the vertical profile of reflectivity (VPR) from the two PPI (plan position indicator) radar scans (see Andrieu and Creutin, 1995 and Andrieu *et al.*, 1995). This identification method assumes that the profile of reflectivity is homogeneous over the study area during a one hour time interval. The VPR is reinitialized each hour using the latest observations. The assumption of a homogenous and constant VPR is a minor limitation, and then principally in convective rainfall systems that vary rapidly in time and space. This is somewhat characteristic of the OCT87 event and will be discussed later. The indirect estimation of *VIL* is the primary control on model performance in this section on model evaluation.

Two rain events recorded by the Monte Grande radar constitute the second case study: the rain events were recorded during the period 14–18 October 1996 (denoted OCT96) and 13–17 November 1996 (denoted NOV96), respectively grouping 117 hours and 120 hours of data. During these two rain events, the observed rain rates are moderate and do not exceed 10 mm/h. The total volume of rainfall collected per catchment for these events is 60 mm. The Monte Grande radar is a multi-scan C-band radar operating at 5.5 cm and a volume scan consists of 10 PPI scans at elevation angles ranging from 0.5° to 15° (Borga and Frank, 1998). The radar domain covers a zone of 240 km × 240 km centred on the radar location. The *VIL* and rainfall rate are estimated every 15 minutes on a 2 km × 2 km grid using respectively the volume scan and the lowest elevation angle.

A digital terrain model is used to define the ground slope and the catchment area extent. Model calibration was performed using a simplex method and a simplified method of Rosenbrock's algorithm; both lead to a similar result.

The conceptual rainfall forecast model, denoted MODEL, is used to forecast spatially-averaged rainfall accumulation in the two case studies over four catchments, ranging from 300 to 600 km^2 (Fig. 1).

The performance criteria used to evaluate the model are the coefficient of efficiency (CE) or Nash criterion (Nash and Sutcliff, 1970), the root mean square error (RMSE) between the observed rainfall and the forecasted rainfall and the corresponding coefficient of correlation (CC). Model performance is best when CE approaches 100%, RMSE is low and CC approaches 1.

Additionally, model performance is compared with two simple rainfall forecasting methods: persistence (PERS) and advection (EXTRA). The persistence method implies that the rainfield is fixed in space, its dynamics are in a steady state and the rainfall rate remains constant over the forecast lead-time. The advection method is based on the assumption that the atmospheric column dynamics are in a steady-state, and the rainfall rate evolution at a given location is driven by the rainfield velocity.

SENSITIVITY ANALYSIS

This section addresses the influence of model variables, the advection procedure and *VIL* initialization on model performance for the first case study. The source term includes two components: an advective component and an orographic component representing the generation of rainwater influx due to the relief (Eqn. 4). The model sensitivity to the two components of the source term is shown by Fig. 2 which represents the variation of the coefficient of efficiency due to a variation of these components. The optimal value is defined by a CE of 85% prior to the introduction of any variation in the advective component or the optimal value of the parameter. The model presents a weak sensitivity to the orographic component of the source term and shows a high sensitivity to the advective component of the source term. The advective component of the source term influences both the coefficient of efficiency which measures deviation between modelled and observed rainfall rate, and the correlation coefficient (not shown) which depends on the temporal evolution of modelled and observed rainfall rate.

The advection of the atmospheric columns is performed by applying a uniform displacement vector over the entire radar domain. The role of the advection procedure on model performance is analyzed by using the model, alternatively, in a Lagrangian and an Eulerian system explicitly accounting for vertically-averaged lateral mixing. The variation observed in model performance is small for the NOV86 event; a weak improvement of the model performance using the Eulerian approach is observed for the OCT87 event. The coefficient of efficiency varies from 67% in the Lagrangian system to 71% in the Eulerian system for the one-hour lead-time forecast. In summary, implementation of an explicit advection algorithm using a uniform velocity improves model performance to a limited degree.

As observations of rain water content become available from the radar, the *VIL* term in Eqn. (3) is reinitialized. In Eqn. (3), rather than excluding the model estimate from reinitialization of the *VIL* state, the state can be updated as an optimal combination of observed and model forecasted *VIL* (Gelb, 1974) as:

$$VIL = K_x VIL_o + (1 - K) VIL_p \tag{6}$$

where VIL_o is the observed *VIL*, VIL_p the model forecasted *VIL* and K is the Kalman filter gain depending on both model and data variance. The influence of *VIL* initialization, in two different cases, is analyzed: in the first case, *VIL* is updated at the beginning of each forecast lead-time only from the observed *VIL* ($K = 1$); in the second case, the *VIL* is updated from model forecasted *VIL* i.e. only the source term is updated from observation data ($K = 0$). The model performance is similar for both cases; the coefficient of efficiency varies from 87.0% ($K = 1$) to 83.0% ($K = 0$) for NOV86 and from 71.2% ($K = 1$) to 69.0% ($K = 0$) for OCT87. An additional test shows that the model performance decreases regularly when the Kalman gain filter, K, varies from 1 to 0. The *VIL* initialization is important for model performance, but implementation of a Kalman filter

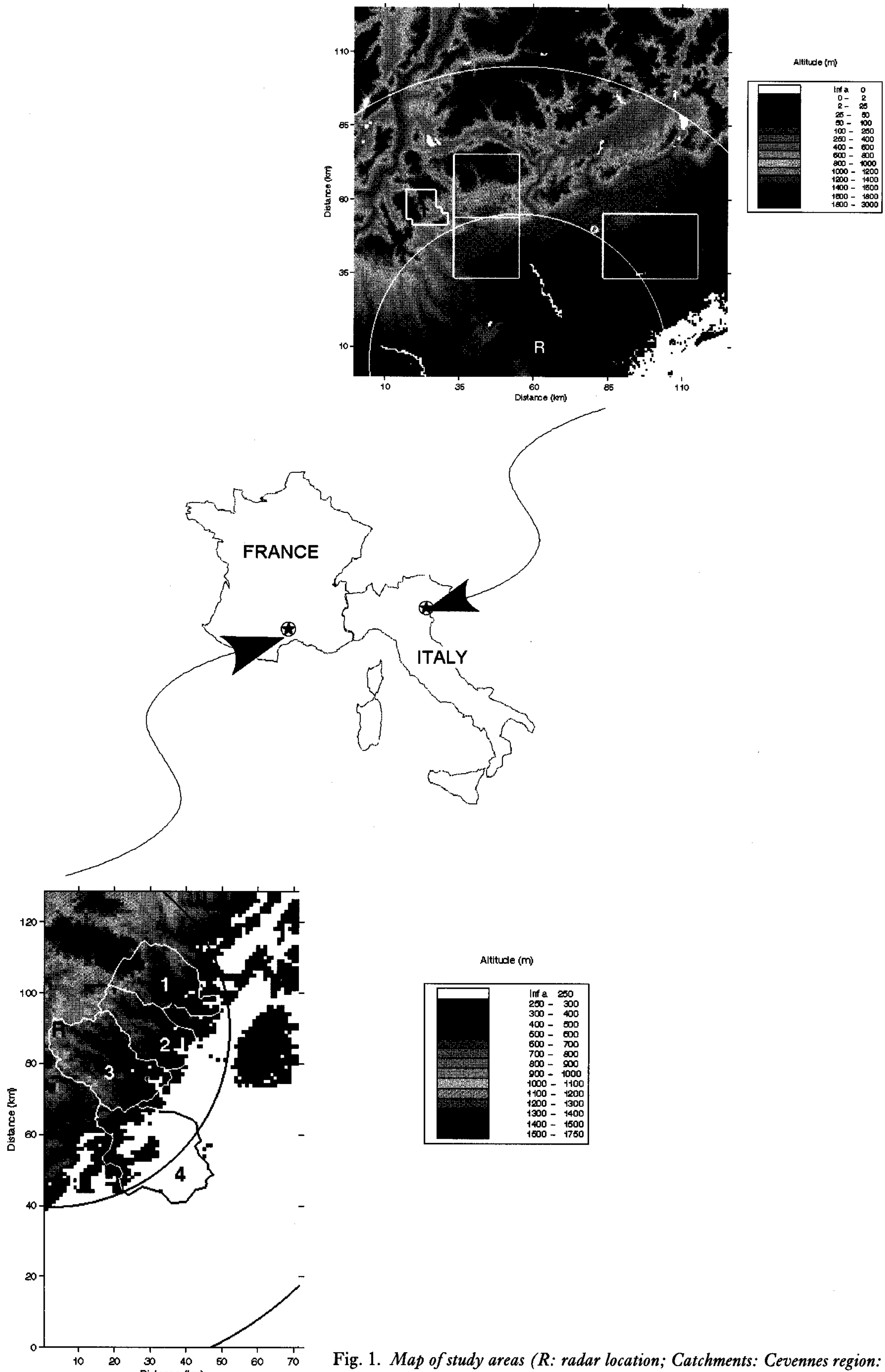

Fig. 1. *Map of study areas (R: radar location; Catchments: Cevennes region: 1- Ceze; 2- Ales; 3- Anduze; 4- Virdoule; Monte Grande region: 1- Posina and three fictitious catchments).*

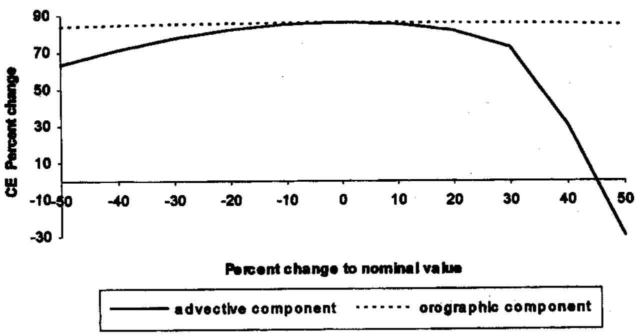

Fig. 2. *Sensitivity of the model to rainwater influx components.*

for updating the *VIL* improves model performance only to a limited degree. Consequently, the complete Kalman filter was not implemented in this work.

RESULTS AND DISCUSSION

The model calibration required the estimation of one parameter, α_m, associated with the orographic component of the source term. Calibration was performed using the first case study, and the parameter remained constant at this value for the four catchments in the study region. Under these conditions, the optimal value for the parameter is 1.6×10^{-4} for the NOV86 event, and 1.5×10^{-4} for the OCT87 event. For the second case study, the orographic enhancement of the rainfall is negligible which allows the model to be applied without calibration. The results are grouped in Tables 1 and 2 that compare the tested model to the persistence and extrapolation methods for the four catchments. For three of the four rain events, the model performs better than the two other methods: persistence (PERS) and extrapolation (EXTRA) (Tables 1 and 2). However, for the OCT87 event, model performance is similar to the EXTRA method and better than the PERS approach (Tables 1 and 2). Overall peaks of catchment-averaged rainfall rate are relatively well predicted by the model for the one-hour lead-time rainfall forecast (Fig. 3a, b, c and d). A study of a two-hour lead-time forecast showed that the f.recast model performance remains good. The performance decreases respectively from 87.0% and 71.2% to 62.0% and 47.0% for the two rain events of the first case study, and respectively from 87.2% and 87.0% to 68.0% and 63.0% for the two rain events of the second case study. The change in model performance for the two-hour lead-time forecast is essentially due to the changes in boundary conditions, and to rain development during the second-hour of the forecast period.

For the first case study, the orographic influence is more pronounced during the NOV86 event, explaining the poorer performance of the EXTRA method for this rain event. Performance of all methods is decreased for the OCT87 event, which consists of a convective rain system induced by a cold front. For the second case study, the performance of the EXTRA method is equally good for the one-hour forecast. The PERS method gives the poorest results by all the criteria.

Model validation is performed by inverting the model parameter for each event: the calibrated parameter value determined from the NOV86 rain event is used in forecasting the OCT87 rain event and *vice versa*. Results (Table 3) illustrate the overall stability of the model; in validation, model performance is similar to the calibration case. Figure 3 illustrates the spatially-averaged rainfall rate hyetographs of observed and one-hour lead-time forecasts for the Ceze catchment in the Cevennes region (Fig. 3 a and b) and the Posina catchment in the Monte Grande region Fig. 3 c and d). The convective nature of the OCT87 event and the homogeneous spatial characteristics associated with the estimated vertical profile of reflectivity are reasons for the deterioration of model performance in this case. One of the primary appealing features of the conceptual model lies in the direct use of three-dimensionally scanning radar data for improving short-range rainfall forecasting.

Table 1. *First case study. One-hour lead-time rainfall forecsat.*

Method	parameter α_m	CE(%)	Performance Criteria RMSE(mm/h)	CC
NOV86 rain event				
MODEL	1.6×10^{-4}	87.0	1.2	0.94
PERS		30.7	2.7	0.65
EXTRA		75.4	1.6	0.94
OCT87 rain event				
MODEL	1.5×10^{-4}	71.2	1.8	0.87
PERS		–4.2	3.5	0.48
EXTRA		73.3	1.8	0.90

Table 2. *Second case study. One-hour lead-time rainfall forecast.*

Method	Performance Criteria		
	CE(%)	RMSE(mm h^{-1})	CC
OCT96 rain event			
MODEL	87.2	0.3	0.94
PERS	17.0	0.8	0.58
EXTRA	82.5	0.4	0.92
NOV96 rain event			
MODEL	87.0	0.2	0.93
PERS	–50.0	0.6	0.25
EXTRA	84.5	0.2	0.92

Model analysis

The sensitivity analysis and application described in the previous section have shown the importance of the source term, the *VIL* update, and the influence of the rainfall variability on model performance. However, the limited number of rain events and the influence of the spatially-homogeneous vertical profile of reflectivity on one event in the first case study, to some degree limits the generalization of results. To supplement and refine the results, an additional evaluation of the model utilizing simulated rain events, created with a microphysical model was performed. The microphysical model is used to produce realistic precipitation and related rainwater contents that are free of measurement error. The analysis, based on simulated data, avoids the influence of measurement error and allows the application to account only for errors associated with model structure. The rain events are simulated by a mono-dimensional microphysical model, equivalent to a fixed atmospheric column or a column moving in a Lagrangian frame of reference. Moreover, this simple context allows the analysis to focus on the terms in (1) representing the *VIL* evolution.

The microphysical model describes the evolution of atmospheric water categories including water vapour, cloud water, rainwater and snow. The moisture input component of the microphysical model is controlled by the distribution of the vertical velocity and requires a definition of the vertical profiles of temperature, dewpoint and pressure profiles (Hales, 1989).

MODEL APPLICATION

The moisture input in the microphysical model, denoted MODM, is driven by the updraft velocity. However, the equation of vertical motion is not implemented explicitly. The vertical distribution of the updraft $w(z,t)$ is approximated by the following parabolic distribution (Kessler, 1969).

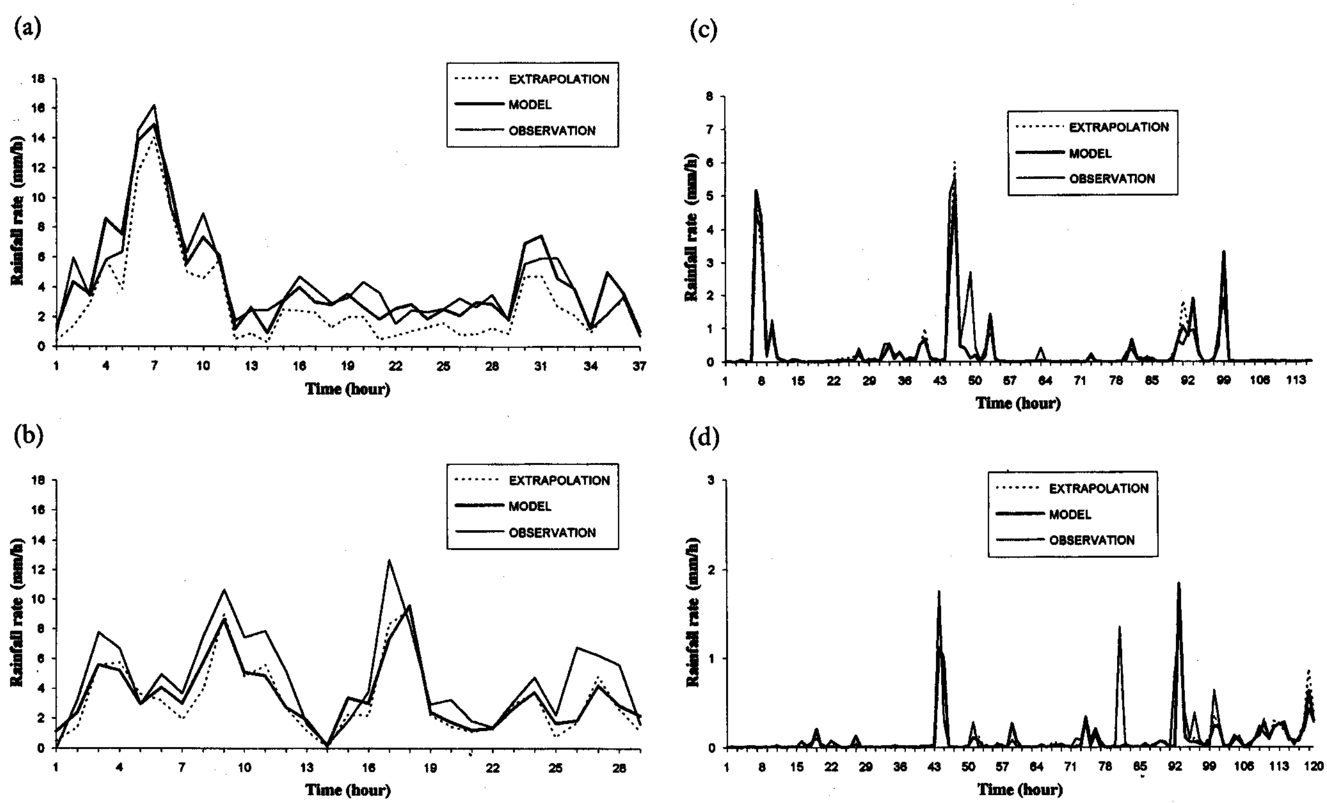

Fig. 3. *Forecasted and observed rainfall rate for an one-hour lead-time a) NOV86 rain event b) OCT87 rain event c) OCT96 rain event d) NOV96 rain event.*

Table 3. *Model validation. One-hour lead-time rainfall forecast.*

Rain events	parameter	Performance Criteria		
		CE(%)	RMSE(mm/h)	CC
NOV86	1.5×10^{-4}	85.1	1.2	0.94
OCT87	1.6×10^{-4}	71.1	1.8	0.87

$$w(z,t) = \frac{4w_{\max}(t)}{H_w}\left(z - \frac{z^2}{H_w}\right) \tag{7}$$

where H_w is the height of the updraft column, w_{max} is the maximum updraft and z the vertical direction. For the present simulation purpose, the temporal evolution of the updraft velocity is given by:

$$w_{\max}(t) = \frac{w_m}{\beta(a,b)}\left(\frac{t}{t_{\max}}\right)^{a-1}\left(1-\frac{t}{t_{\max}}\right)^{b-1} \tag{8}$$

where w_m is a magnitude constant of the updraft, t_{max} is the duration of the simulated rain event, $\beta(a,b)$ is the β-function, and a and b are shape parameters. Rainfall variability is produced by modulating the magnitude and shape function of the updraft velocity.

The microphysical model is initialized using an idealized and realistic vertical profile of temperature, dewpoint temperature and pressure profile as determined from ground-level pressure. The simulated rain events are produced by integrating the dynamic equations of the model over the duration of the rain events.

The evaluation of the forecast model is based on three simulated rain events of six hours duration, denoted EVT1, EVT2, EVT3. Figure 4 shows the rainfall rate over the duration of the event. As illustrated by Fig. 4, the events display an increasing temporal variability defined by the slope (dw/dt) of the vertical velocity temporal variation. The evaluation procedure for the forecast model is carried out in an identical manner as in the case of observed data. At the beginning of the forecast lead-time, the variables, rainwater content and rainfall rate, are initialized by assuming that they are measured, these measurements being generated by the microphysical model MODM. The rainwater content in the forecast model is assumed implicitly as the sum of both solid and liquid rainwater content. This initialization stage of the forecast model is repeated each thirty minutes. In particular, the source term $S(t)$ and the response time $h(t)$ are constant during the forecast lead-time.

MODEL RESULTS

The forecast model performance is evaluated by comparing the predicted rainfall rate to the rainfall rate generated by MODM using the same criteria as in the previous section. The forecast lead-time is equal to 30 minutes, and a forecast is generated every minute. The performance results for the three simulated rain events are presented in

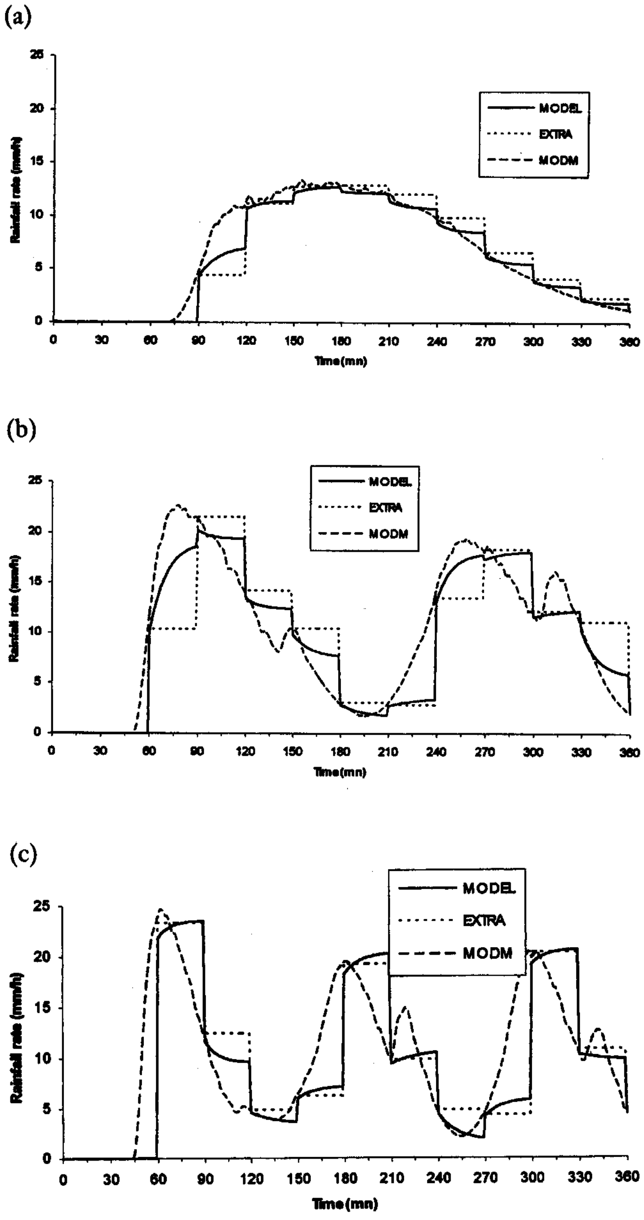

Fig. 4. *Comparison of the MODEL and EXTRA rainfall rates to the MODM rainfall rate for 30 minutes lead-time forecast a) EVT1 b) EVT2 c) EVT3.*

Fig. 4 and Table 4. For a short forecast lead-time, the forecast model performs better than the EXTRA method. As clearly illustrated by Fig. 4, the accuracy of the forecast model decreases when the forecast lead-time increases and reaches a steady-state characterized by a constant rainfall rate driven by the source term. At the beginning of the forecast lead-time, the forecasted rainfall is closer to the observed rainfall and deviates with the increasing of the forecast lead-time. Figure 4 shows the performance of both methods MODEL and EXTRA, decreases from EVT1 to EVT3, i.e. performance decreases with increasing temporal rainfall variability. However, under the performance criteria, the forecast model performs better than EXTRA in all the events. The best performance of the forecast model relative to EXTRA is obtained for the moderately variable event EVT2. The performance of both methods is relatively poor for the highly variable event EVT3, which shows the need for an improved model formulation addressing highly variable rainfalls, increasing the forecast lead-time and model response time.

These results are further explained by the fact that a conceptual model of the type developed here, can be posed in the context of a linear reservoir model. The forecasted rainwater content $VIL(t+\Delta t)$ for a lead-time Δt and response time $h(t)^{-1}$ is given by:

$$VIL(t + \Delta t) = e^{-h(t)\Delta t}\, VIL(t) + (1 - e^{-h(t)\Delta t})S(t) \quad (9)$$

The forecasted rainwater content $VIL(t+\Delta t)$ is a linear combination of the initial rainwater content $VIL(t)$ and the source term $S(t)$. The weighting is a function of the ratio of the lead-time Δt to the response time $h(t)^{-1}$. For a lead-time greater than the response time, the source term becomes predominant and the need for a better description of the source evolution and the rainfall dynamics arises. It is clear that the rainfall dynamics implemented in the present model is limited in this way because it deals only with the rainwater category and an indirect estimate of the source term. Additionally, the rainwater source term plays an important role in the model and its evolution might be described in order to improve the conceptual model performance.

Table 4. *Models results for simulated rain events.*

Method	Performance Criteria		
	CE(%)	RMSE(mm/h)	CC
Simulated rain event EVT1			
MODEL	94.5	1.1	0.97
EXTRA	87.0	1.8	0.94
Simulated rain event EVT2			
MODEL	84.0	2.9	0.92
EXTRA	54.2	4.8	0.76
Simulated rain event EVT3			
MODEL	34.0	5.5	0.71
EXTRA	25.8	5.9	0.66

By addressing only the evolution of rain water content and not explicitly accounting for the cloud water content, the conceptual forecast model partially represents the processes of rain generation. Due to this control, the response time of the modelled system can be shorter than the expected response time of the natural system for some cases. The result is that the source term is predominant for long lead-time forecasts. The response time of the modelled system is physically representative of the mean fall duration of drops between the cloud and the ground.

Other more general considerations in the development of operationally-oriented hydrologic rainfall models are briefly stated here as related to this work. Underestimation of the rainwater content can be a factor in decreased performance. A formulation that neglects solid precipitation content leads to a decrease in model performance by affecting both the initial rainwater content and the model response time. Additionally, an underestimation of the modelled vertical profile of reflectivity can affect the estimation of the total rainwater content of the atmospheric column. Finally, an evaluation of the influence of radar measurements errors on the model performance is an important issue that remains to be addressed.

Conclusion

An approach using volumetric radar data, explicit advection dynamics, and orographic rainfall enhancement into a short-term rainfall forecasting model was presented. An application to four observed rain events illustrated the performance of the model relative to persistence and advection forecast methods. A complementary evaluation of the conceptual forecast model performance from rain events simulated using a microphysical model confirmed the results and provided an insight into the limits of the current conceptual model formulation. The present model does not explicitly account for cloud water and details of microphysical processes; this implies a system response time shorter than the expected natural system response time. Additionally, the model source term is a key variable for forecast lead-times exceeding the model response time. The useful and realizable forecast lead-time is dependent on the radar domain size, and also on the type of rain system. For convective rain systems, where the rain system evolves rapidly, the potential lead-time is short and applications are best suited to management of urban hydrologic applications such as sewerage system control. The type of investigation addressed in this work focused on conceptual methods to both improve the description of microphysical processes incorporated in hydrologic models and increase rainfall forecast model response time as a component for extending the realizable forecast lead-time.

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References

Alpert, P. and Shafir, H., 1989. Meso-γ-scale distribution of orographic precipitation: numerical study and comparison with precipitation derived from radar measurements. *J. Appl. Meteorol.*, **28**(10), 1105–1117.

Andrieu, H. and Creutin, J.D., 1995. Identification of vertical profile of reflectivity for hydrological applications using an inverse method, 1-Formulation. *J. Appl. Meteorol.*, **34**(1), 225–239.

Andrieu H., Delrieu, G. and Creutin, J.D., 1995. Identification of vertical profile of reflectivity for hydrological applications using an inverse methods, 2-Sensitivity analysis and case study. *J. Appl. Meteorol.*, **34**(1), 240–259.

Andrieu H., French M.N., Thauvin V. and Krajewski, W.F.,1996. Adaptation and application of a quantitative rainfall forecasting model in a mountainous region. *J. Hydrol.*, **184**, 234–259.

Andrieu H., Creutin J.D., Delrieu G. and Faure D., 1997. Use of a weather radar for the hydrology of a mountainous area. Part I. Radar measurement interpretation. *J. Hydrol.*, **193**, 1–25.

Bell, R.S., 1978. The forecasting of orographically enhanced rainfall accumulations using 10-level model data. *Meteorol., Mag.*, **107**, 113–124.

Bellon, A. and Austin, G.L., 1984. The accuracy of short-term radar rainfall forecasts. *J. Hydrol.*, **70**, 35–49.

Borga, M. and Frank, E., 1998. Use of radar-rainfall estimates for flood simulation in mountainous basins, in Ribamod: Proceedings of the 2nd Expert Meeting: Integrated Systems for real-time flood forecasting and warning, 'Jino Tonini' International Center of Hydrology, Montelice, Padova, Italy, 25–26 Sept. 1997. European Commission, 12p. (in press).

Bremaud, P.J. and Pointin, Y.L., 1993. Forecasting heavy rainfall from rain cell motion using radar data. *J. Hydrol.*, **142**, 373–389.

Collier C.G., 1991. The combined use of weather radar and mesoscale numerical model data for short period rainfall forecasting, in *Hydrological applications of weather radar*, editors I.D. Cluckie, C.G. Collier, Ellis Horwood, 331–340.

French, M.N. and Krajewski, W.F., 1994. A model for real-time quantitative rainfall forecasting using remote sensing, 1-Formulation. *Wat. Resour. Res.*, **30**, 1075–1083.

Gelb, 1974. *Applied optimal estimation*, The MIT Press, Cambridge, Mass, 374 pp.

Georgakakos, K.P. and Bras R.L., 1984a. A hydrologically useful station precipitation model, 1-Formulation. *Wat. Resour. Res.*, **20** (11), 1585–1596.

Georgakakos, K.P. and Bras, R.L., 1984b. A hydrologically useful station precipitation model, 2-Case studies. *Water Resour. Res.*, **20**(11), 1597–1610.

Hales, J.M., 1989. A generalized multidimensional model for precipitation scavenging and atmospheric chemistry. *Atmos. Environ.*, **23**, 2017–2031.

Knight, C., 1987. Precipitation formation in a convective storm, *J. Atmos. Sci.*, **44**, 19, 2712–2726.

Kessler, E., 1969. On the distribution and continuity of water substance in atmospheric circulations. *Meteorol. Monographs*, AMS, **10**(32), 84 pp.

Lee, T.H. and Georgakakos K.P., 1991. A two-dimensional stochastic-dynamical quantitative precipitation forecasting model. *J. Geophys. Res.*, **95**(D3), 2113–2126.

Lee, T.H. and Georgakakos, K.P., 1996. Operational rainfall prediction on meso-g scales for hydrologic applications, *Wat. Resour. Res.*, **32**, 987–1003.

Nash, J.E. and Sutcliff, J.V.Z., 1970. River flow forecasting through conceptual models. Part 1. A discussion of principles. *J. Hydrol.* **10**, 282–290.

Seo, D.J. and Smith, J.A. 1992. Radar-based short term rainfall prediction, *J. Hydrol.*, **131**, 341–367.

Smolarkiewicz, P.K., 1983. A simple positive definite advection scheme with small implicit diffusion. *Mon. Wea. Rev*, **111**, 479–486.

Thielen, J. and Creutin, J.D., 1997. An urban hydrological model with high spatial resolution rainfall from a meteorological model. *J. Hydrol.* **200**, 58–83.