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Quantification Of Rainfall Forecast Uncertainty And Its Impact On Flood Forecasting

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QUANTIFICATION OF RAINFALL FORECAST UNCERTAINTY AND ITS IMPACT ON FLOOD FORECASTING

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Rainfall forecast errors are considered to be the key source of uncertainty in flood forecasting. To quantify the rainfall forecast uncertainty itself and its impact on the total flood forecast uncertainty, a Monte-Carlo based statistical method has been developed. This method takes into account the dependency of the rainfall forecast error with the lead time and the rainfall amount. The forecasted rainfall errors are described by truncated normal distributions, allowing to quantify the full uncertainty distribution of the deterministic rainfall forecast. By means of Monte-Carlo sampling and taking the forecast error autocorrelation into account, the impact of the rainfall forecast uncertainty on a flood forecast was quantified. This was done for the Rivierbeek river in Belgium. In addition, comparison was made between the total flood forecast uncertainty and the uncertainty due to the forecasted rainfall. The total flood forecast uncertainty was quantified by a non-parametric data-based approach. It was concluded that the forecasted rainfall uncertainty contributes for about 30 percent to the total flood forecast uncertainty.

INTRODUCTION

For both fluvial and pluvial flood forecasts, rainfall forecasts are the main forcing. It is well known that the uncertainty in these rainfall forecasts affects the total flood forecast uncertainty significantly [1, 2, 3]. In addition to the uncertainty in the forcing data, the two other sources of uncertainty are uncertainty in the initial conditions and model uncertainty [1,4]. In this paper a methodology is presented to calculate the rainfall forecast uncertainty, based on historical rainfall forecasts, and its influence on the total flood forecast uncertainty. The analysis is based on the data for the Belgian catchment of the Rivierbeek and an operational flood forecasting system making use of the NAM hydrological model. This paper is a reduced version of a full paper where, in addition to the methodology to quantify the rainfall forecast uncertainty also a comparison is made with ensemble rainfall forecasts (see: Van Steenbergen & Willems [5]).

CASE STUDY

Catchment

The Rivierbeek is a strong meandering stream situated in the western part of Flanders, Belgium (Figure 1). It is a tributary of the Ghent-Ostend Canal, issuing into the Canal at Oostkamp, near the historical city of Bruges. The average flow is 0.6m³/s, but the flow can rise up to above 8m³/s during flood periods. The catchment of the Rivierbeek has an area of 64 km², a mean

slope of 0.4% and a mean elevation of 24m above the mean sea level. The main soil type is sand and loamy sand. About 77% of the land is used for agriculture, 18% of the area is urbanized and 5% is forest.
The average annual rainfall varies from 750mm to 850mm. Summer storms are characterized by intense but short convective rainfall periods, whereas the winter is characterized by longer less intense rainfall periods.

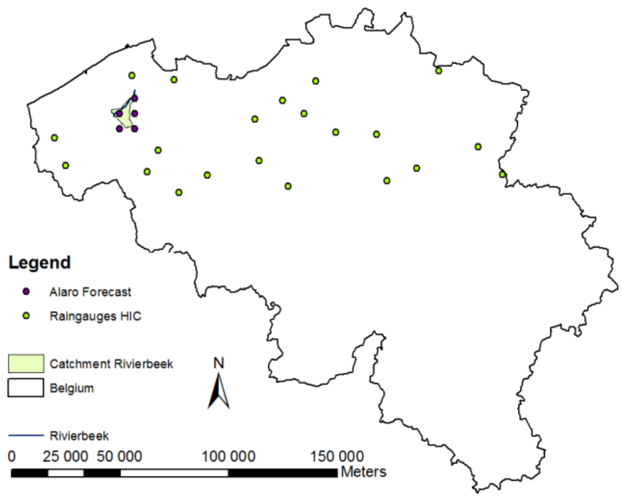

Figure 1: Rain gauge network of the Hydrological Information Centre (HIC) for the Flanders region of Belgium, Alaro forecast points and catchment of Rivierbeek in Belgium.

Flood forecasting system

The case study in this research is the operational flood forecasting system of Flanders Hydraulics Research. It covers most of the Flanders region in Belgium. The flood forecasting models consist of a combination of catchment hydrological and river hydrodynamic models. Here only the hydrological part of the flood forecasting system is considered.
The hydrological models are implemented in the NAM module of the Mike11 software of DHI Water & Environment [6]. NAM (*Nedbør-Afstrømnings Model)* is a lumped conceptual rainfall-runoff model [7,8]. NAM generates three components of the catchment runoff (overland flow, interflow, baseflow) by means of reservoir-based routing and storage components. The storage components describe the storage of catchment water at the surface (Umax), in the soil (subsurface) and in the groundwater. The distribution of the rainfall input depth over the different reservoirs and storages is described by means of model equations, which consider dependency on the soil water content.

Forecasted rainfall

The forecasted rainfall used, is generated by the numerical weather prediction model Alaro. Alaro is a version of the Action de Recherche Petite Echelle Grande Echelle-Aire Limitée Adaption Dynamique Développement International (ARPEGE-ALADIN) operational limited-area model with a revised and modular structure of the physical parameterizations and is operational at the Royal Meteorological Institute of Belgium [9]. The Alaro model generates three hourly cumulative rainfall on a 7x7 km grid for a lead time of 48h.

MATERIALS AND METHODS

Rainfall forecast uncertainty

Method to assess the rainfall forecast uncertainty

Raingauges of the Flanders Hydrological Information Centre (HIC) are used as observed rainfall source in this study. The raingauge network is shown in Figure 1. To allow a comparison between forecasted and observed rainfall, the observed rainfall is interpolated on the same grid as the Alaro rainfall output making use of simple kriging interpolation. Kriging interpolation is chosen because it allows to easily calculate the interpolation error. If this interpolation error is significant in comparison with the forecasted rainfall error, it has to be taken into account. From the grid rainfall, the catchment rainfall can be computed. The error between the observed catchment rainfall and the forecasted catchment rainfall is divided into categories based on the forecasted rainfall volume and the lead time for all 3-hour time steps in the period 2005-2010. The forecasted rainfall error is considered dependent on the amount of forecasted rainfall and on the lead time: the larger the forecasted rainfall and lead time, the higher the errors. Note that the methodology would also allow to make further classification based on e.g. atmospheric pressure, weather pattern, season, but this is currently not included in this study.

The observed and forecasted rainfall depths (R_{obs} and R_{for}) have a minimum value of 0mm and the errors are analysed for forecasted rainfall depth classes to take into account the heteroscedasticity of the forecast error. A truncated normal distribution (TND) is derived for each combination of lead time and rainfall depth class to represent the forecasted rainfall error. The use of TNDs was also suggested by Coccia and Todini [10] for representing the normal joint distributions of the forecast error of water levels in the 'Model Conditional Processor' framework. The probability density function (pdf) of a TND for $a \le x \le b$ is given by:

$$f(x;\mu,\sigma,a,b) = \frac{\frac{1}{\sigma}\phi\left(\frac{x-\mu}{\sigma}\right)}{\Phi\left(\frac{b-\mu}{\sigma}\right)-\Phi\left(\frac{a-\mu}{\sigma}\right)} \quad (1)$$

Where a and b represent the ranges of the distribution. In this case the forecasted rainfall error is calculated by $R_{for} - R_{obs}$, which lead to a value of $-\infty$ for the parameter a, and b is given by the upper limit of the forecasted rainfall class. Because a is equal to $-\infty$, the term $\Phi\left(\frac{a-\mu}{\sigma}\right)$ is set to zero. The following rainfall classes are considered: 0 mm, 0-2 mm, 2-5 mm, 5-10 mm, 10-20mm, >20mm. μ and σ are the mean and standard deviation, and are calculated for each combination of forecasted rainfall class and lead time class. $\phi()$represents the standard normal pdf and $\Phi()$ its cumulative.

Representation error

When analysing the rainfall forecast error, one has to consider the error made by interpolating the raingauge observations on the same grid as the rainfall forecast, in this case the Alaro grid of 7 x 7 km. This type of errors is hereafter called representation error. It typically occurs when measurements are available at different time and space scales as the model or forecast output [11]. Considering the concept of variance decomposition [12, 13], given that the forecast error (E_{for}) can be assumed independent from the representation error (E_{rep}), the variance of the forecast residuals ($s^2_{R_{for}-R_{obs}}$) subtracted by the variance of the representation error ($s^2_{E_{rep}}$) equals the variance of the forecast error ($s^2_{E_{for}}$) (Eq.2).

$$s^2_{R_{for}-R_{obs}} - s^2_{E_{rep}} = s^2_{E_{for}} \quad (2)$$

The standard deviation $s_{R_{for}-R_{obs}}$ is computed based the empirical forecast residuals for each combination of lead time and forecasted rainfall depth; and also used as a parameter of the TND. The representation errors' variance, $s^2_{E_{rep}}$, follows directly from the application of the (kriging) spatial interpolation method (see Goovaerts [14] for its mathematical derivation). $s_{E_{for}}$ is calculated for each combination of forecasted rainfall class and lead time and can directly be used as estimator for the standard deviation in the TND.

Autocorrelation

In addition to the dependence of the forecasted rainfall error on the lead time and forecasted rainfall depth, also the autocorrelation of the rainfall forecast error within the same forecast run might need to be taken into account. This is the case if one wants to sample the error in a Monte-Carlo analysis. The autocorrelation of the forecasted rainfall error therefore is considered in relation to the time lag. This is done similar to the model uncertainty propagation approach by Willems [12].

Monte Carlo sampling

To propagate the forecasted rainfall uncertainty to the flood forecasting results, Monte Carlo sampling of the forecasted rainfall error is performed in this study. The error, randomly sampled from the TND in relation to the lead time and rainfall depth class, and the error at the previous timestep, is superposed on the forecasted rainfall time series. In this study, 500 Monte-Carlo error time series have been generated, superimposed on the forecasted rainfall series and propagated through the hydrological model, generating a Monte Carlo ensemble of rainfall runoff discharge forecasts. This ensemble explains the part of the total uncertainty in the flood forecast due to the rainfall forecast uncertainty.

Method to assess the total flood forecast uncertainty

To quantify the total uncertainty in the forecasted discharges the non-parametric data-based approach (NDA) introduced by Van Steenbergen et al. [15] and optimized for discharge forecasts in Van Steenbergen & Willems [3] is used. The method calculates the relative flow residuals between the historical forecasts and observations at the location of flow gauging stations according to Eq. (3).

$$Residual = \frac{Q_{OBS} - Q_{FOR}}{Q_{FOR}} \quad (3)$$

Where Q_{OBS} is the observed discharge and Q_{FOR} the forecasted discharge.

These residuals are sorted in classes based on the forecasted discharge value and the lead time. For each combination of forecasted discharge class and lead time class, quantiles of the residuals are computed based on the empirical cumulative frequency distribution. These quantile values are stored in a three dimensional error matrix. The matrix describes the residual error as a function of forecasted discharge, lead time and percentile. By interpolation in the 3D error matrix, confidence intervals on any discharge forecast value can be calculated, representing the total forecasted discharge uncertainty.

RESULTS

Rainfall forecast uncertainty

Figure 2 shows the mean absolute forecasted rainfall error, calculated after comparison of observed and forecasted 3-hour rainfall depths for the period 2005-2010. The figure shows that the forecasted rainfall error increases with increasing lead time, here defined for different lead time classes. In Figure 3 the relation between the forecasted rainfall error and the forecasted rainfall depth is shown. Also here an increase of the error for higher forecasted rainfall depth is noticed.

The representation error $s^2_{E_{interp}}$ calculated by the kriging interpolation method varies between 0.191 mm² and 0.263 mm² for this case study.

Figure 4 shows the correlation coefficient of the forecasted rainfall error in function of the time lag. This coefficient is about 0.5 for rainfall errors with a time lag of one time step (= 3h). For higher time lags the correlation reduces significantly. This means that for this case study only the lag-1 autocorrelation has to be taken into account.

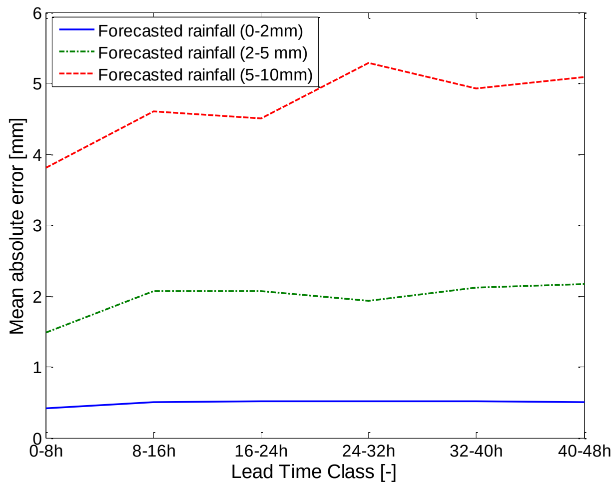

Figure 2: Mean absolute forecasted 3-hour rainfall error in function of lead time class and different forecasted rainfall depth classes.

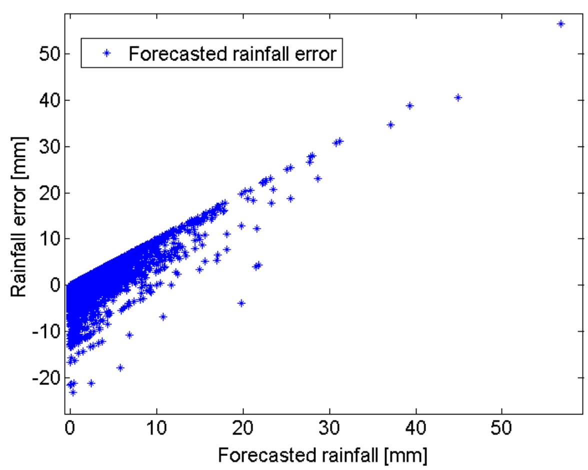

Figure 3: 3-hour forecasted rainfall error, defined as forecasted minus observed rainfall, in relation to the forecasted rainfall depth.

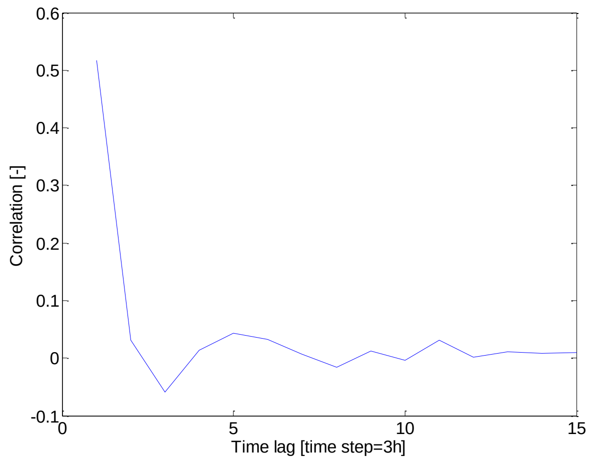

Figure 4: Correlation coefficients of the forecasted rainfall error in function of time lag.

In Figure 5, the deterministic Alaro forecast is shown together with the 500 generated Monte Carlo (MC) rainfall forecast members, making use of the TNDs and taking into account the lead time and forecasted rainfall value for the forecast on 10/11/2010 at 06:00h (local time). Obviously, the uncertainty in the forecasted rainfall is a lot larger for higher rainfall depths.

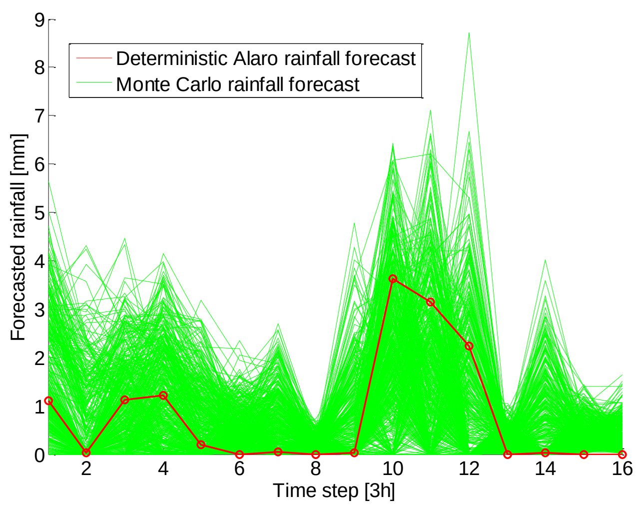

Figure 5: Deterministic Alaro forecast with 500 Monte Carlo rainfall forecast members. Time of forecast 10/11/2010 06:00h.

Flood discharge uncertainty

In addition one also has to consider that the forecasted rainfall uncertainty is not the only source of uncertainty. If the total river discharge forecast uncertainty for the event of 10 November 2010 is calculated, by the NDA methodology. It is seen in Figure 6 that the total discharge forecast uncertainty is much larger than what is computed after propagation of the forecasted rainfall uncertainty only. For this case study the rainfall uncertainty is only responsible for about 30% of the total forecast uncertainty, for the longer lead times. This confirms that it is not only important to know the total forecast uncertainty but also the relative importance of each component in the flood forecasting system [16, 17].

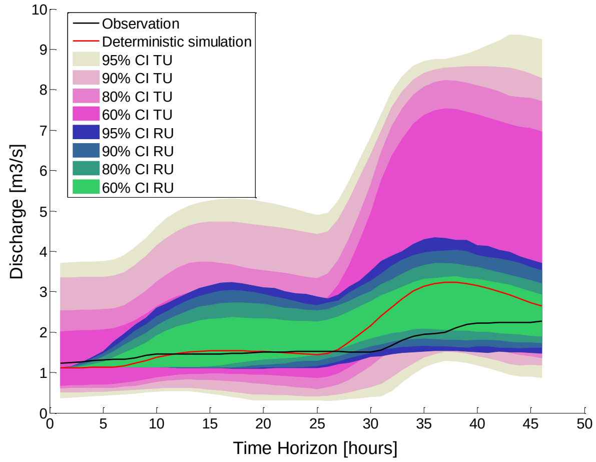

Figure 6: Forecasted discharge based on the deterministic Alaro rainfall forecast together with confidence intervals (CI) representing the contribution of the Monte-Carlo based forecasted rainfall uncertainty (RU) and total forecast uncertainty (TU), versus the observed discharge. Rivierbeek at Oostkamp. Time of forecast 10/11/2010 06:00h.

CONCLUSIONS

Uncertainty is undeniably linked with flood forecasting. Good practice of operational flood forecasting therefore should include assessment of the uncertainty in the forecast. This research has studied the total forecasted rainfall uncertainty after statistical analysis of all 3-hour rainfall forecasts in the period 2005-2010. Also the contribution of the forecasted rainfall uncertainty to the flood forecast uncertainty was analysed.

First the uncertainty in the forecasted rainfall was analysed by comparing the forecasted catchment rainfall with the observed catchment rainfall after interpolation of rain gauge data applying kriging interpolation. This analysis was performed taking into account the dependence of the forecast error with the lead time and the rainfall depth, as well as the representation error introduced by the interpolation method. As expected, the uncertainty increases with increasing lead times and rainfall depths. In addition a correlation coefficient of approximately 0.5 was observed for the lag-1 autocorrelation. The results of this analysis allowed to generate Monte Carlo rainfall forecasts by truncated normal distributions describing the full range of the forecasted rainfall error based on a deterministic rainfall forecast.

Statistical analysis also allows separation of the total forecast uncertainty in its different uncertainty sources, hence to provide insight in the relative importance of the different uncertainty sources.

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