Merging and calibration of radar rain products for quantification of input uncertainty in urban drainage modelling for the Haute-Sûre catchment in Luxembourg

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Abstract

Common practice in urban drainage modelling requires high temporal and spatial resolution of data inputs as land use, rainfall and runoff. In the case of rainfall input, the fast response to rainfall over small catchments has a direct effect on the temporal scale required to simulate with a good accuracy the hydrological and hydraulic dynamics processes. We present and illustrate a proposed work flow to build and calibrate a space-time geostatistical model of rain, using radar imagery as a covariate in regression-kriging based simulation. Then, a work flow for run-off and sewer system modelling is presented as well. These work flows are repeated as many times as the Monte Carlo simulation design requires to obtain an ensemble of rainfall input maps and time series of quantity variables (volume of the CSO tank, and CSO volume) and quality variables (loads and concentrations of COD and NH_4) are produced to analyze how input uncertainty propagates to output uncertainty. We expect that these work flows represent a more realistic simulated time series of rainfall originating run-off that enters the sewer system, and we can do the Monte Carlo input uncertainty propagation and compare with results obtained in previous studies we did. In the future, we expect that validation will show a better job done not only in terms of mean error and root mean squared error of tank volume and overflow, but also in quantifying the uncertainty in the sewer system model outputs.

1. Introduction

Common practice in urban drainage modelling requires, depending of the model in use, high temporal and spatial resolution of data inputs as land use, rainfall and runoff. In the case of rainfall input, the fast response to rainfall over small catchments (area about 20 hectares) has a direct effect on the temporal scale required to simulate with a good accuracy the hydrological and hydraulic dynamics processes. In this case, rain gauges represent an important source of information. However, with these point measurements a spatial distribution of the rainfall field is hardly taken into account if a dense rain gauge network is not available. A very helpful source of information to overcome this issue is weather radar data which provides suitable

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spatial estimates of rainfall fields. Nevertheless, the data provided by the network of rain gauges is required to calibrate the radar imagery for having accurate measurements of rainfall over the catchment surface. Thus, merging data from rain gauges and radar imagery is a key task in the calibration of such radar data.

In the framework of the PhD research project “Optimal complexity of urban drainage system models accounting for spatial uncertainty propagation across different scales” of the QUICS project (Quantifying Uncertainty in Integrated Catchment Studies), we used already a fairly simple characterisation of input uncertainty in an urban drainage modelling application. We learned that rainfall is the main source of uncertainty in the Haute-Sûre drainage system model. We basically ignored the spatial dimension and treated rainfall as a time series that had the same characteristics as times series of rainfall measured at a rainfall gauge station, but in fact the ‘rain’ that enters the system is the accumulation of rainfall and its run-off over the catchment. So it is an aggregate over space and time because rainfall that hits the surface and runs off needs time to flow to the inlet of the sewer system. In this current work we will go for a more realistic characterisation of modelling rainfall input to a simple urban drainage model, EmiStatR, and evaluate how this affects the results of the uncertainty analysis. The aim of this work is to build and calibrate a space-time geostatistical model of rain, using radar imagery as a covariate using regression-kriging based simulation. Once we have a realistic space-time statistical model of rainfall that can simulate it over space and time for our catchment of study and time period, while also conditioning the simulations to observed rainfall (rain gauges and also radar). Next, we need a routing run-off model which computes the run-off and provides this as input to EmiStatR. For this we use a GIS-based model or a two-dimensional hydrodynamic model as run-off model using a digital elevation model and catchment delineation techniques to derive the water entering the urban drainage network.

The present study comprises two main research questions: 1) What is the most appropriate workflow to calibrate five-minute rainfall radar imagery with ground rain gauges at one-minute resolution? 2) Is it possible to use this calibrated data for temporal and spatial up- and down-scaling with the purpose of modelling volume of combined sewer overflows (CSOs) and wastewater quality determinants as chemical oxygen demand (COD) and ammonium (NH_4) in CSOs?

The expected outcome is to present a more realistic simulated time series of rainfall originating run-off that enters the sewer system, do the Monte Carlo input uncertainty propagation and compare with results obtained in previous studies we did. We expect that validation will show a better performance (not only in terms of mean error and root mean squared error of tank volume and overflow, but also in quantifying the uncertainty in these model outputs).

2. Methods and Materials

In the following sub-sections, the radar imagery and rain gauge data are presented, and the merging and calibration procedure is introduced. Later the run-off and sewer modelling for the uncertainty propagation analysis are presented. We briefly introduce the simplified urban drainage model and the case study from the Haute-Sûre (Obersauer, in German language) catchment in Luxembourg (Figure 1) is introduced.

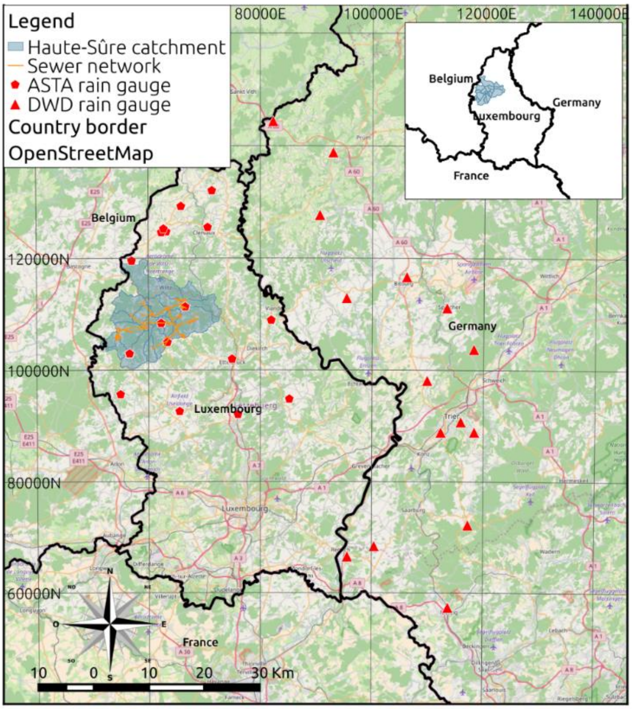

Fig. 1. Location of the case study, Haute-Sûre catchment, and the location of the ASTA rain gauge network, and the DWD rain gauge network. The radar imagery from the Neuheilenbach radar is not presented but it covers the whole extend of the map presented here.

2.1 Radar imagery and rain gauge data

Calibrated hourly rainfall radar imagery from the German Weather Service (DWD for the initials in German) is available at one-kilometer spatial resolution for the entire German territory including the Neuheilenbach radar station which covers the territory of Luxembourg and surroundings. Additionally, The DWD provides rainfall sub-products at five-minute temporal resolution, which have to be calibrated with ground rain gauges to have an accurate estimate of rainfall [1]. Rain gauge data are available also from the DWD at one-minute resolution (Figure 1). The 5 rain gauges from the DWD are based on a weighting system, and their data is in MR90-Format whereas the format of the five minute radar data is radolan binary format which can be extracted using the wradlib library in Python [2]. Besides the DWD data, there is available data from 17 tipping bucket rain gauges of the Luxemburgish *Administration des services techniques de l'agriculture* (ASTA) (Figure 1). These observations, available at 10-minute resolution, have been validated by the Observatory for Climate and Environment (OCE) of the Luxembourg Institute of Science and Technology (LIST).

The radar products delivered by the DWD are from the national composite RY (5 min) and RW (1 h). The hourly data is already calibrated but the five minute data is not yet calibrated against ground observations. Nevertheless, the five minute data is already converted to rainfall in millimeters.

We would like to use radar imagery as a covariate using regression-kriging based simulation, using both DWD and ASTA rain gauge datasets.

2.2 Merging of radar and rain gauge rainfall data

The radar calibration is often done by adjusting the bias between the average of all the rain gauges and the average of the radar at rain gauge locations. If merging is required, there is no need to do bias correction, because we use the radar only as a covariate, i.e. we use a linear function of the radar as an estimate of the process mean. However, we decided to use a kriging-based merging technique, which allows us to estimate the associated uncertainty thanks to the kriging variance estimation. Regression-kriging, also known as kriging with external drift or universal kriging, is not sensitive to spatially homogeneous biases in the radar, therefore a mean areal bias correction is not necessary. It is important to be sure that the rain gauges are correctly quality checked and that there are no outliers nor malfunctionings. First of all, before merging, radar data need the following passages:

1) Projection from polar to Cartesian coordinates
2) Correction of the following:
   2.1) Clutter
   2.2) Bright band
   2.3) Attenuation
   2.4) Beam blockage
3) Transformation from reflectivity Z to rainfall rate R

It is necessary to check if this has already been done, even on the 5-minute product, which can be confirmed directly with the DWD. After radar and rain gauge quality check, a radar - rain gauge merging will be performed.

Regression kriging is a geo-statistical technique that is used to merge radar and rain gauges. It interpolates the rain gauges, using a linear function of the radar as a drift. The estimation in any point is calculated as:

$$\hat{R}_{OK}(x_0) = \sum_{\alpha=1}^{n} w_\alpha \cdot R(x_\alpha) \tag{1}$$

where $\hat{R}_{OK}(x_0)$is the rainfall estimated in a generic point x_0, $R(x_\alpha)$ is the rainfall measured by the rain gauges at locations x_α, n is the number of available observations, and w_α are kriging weights, estimated minimizing the variance under unbiasedness conditions, which results in the following kriging system:

$$\begin{cases} \sum_{\alpha=1}^{n} w_\alpha(x_0) = 1 \\ \sum_{\alpha=1}^{n} w_\alpha(x_0) \cdot C(x_\beta - x_\alpha) + \mu_1 + \mu_2 \cdot r(x_\beta) = C(x_\beta - x_0) \beta = 1, \dots, n \\ \sum_{\alpha=1}^{n} w_\alpha(x_0) \cdot r(x_\alpha) = r(x_0) \end{cases} \tag{2}$$

Where $C(d)$ is a covariance function at distance d,$r(x)$ is the radar estimate at location x, x_α and x_β are rain gauge locations,μ_1 and $\mu_2$are Lagrange parameters [3]. After the optimization, the kriging variance associated to the rainfall estimate is calculated as follows:

$$\sigma^2(x_0) = c - \mu_1 - \mu_2 \cdot r_0 - \sum_{\alpha=1}^{n} w_\alpha \cdot C(x_\alpha - x_0) \tag{3}$$

where $\sigma^2(x_0)$is the kriging variance, and c is the sill parameter, an estimate of the variance at large distances obtained from the dataset.

The covariance function is derived from the rainfall residual variogram:

$$C(d) = c + c_0 - \gamma(d) \tag{42}$$

where $\gamma(d)$is the variogram and c_0 is the nugget, an estimate of the variance expected at infinitesimal distance. In this work the variogram will be estimated in four steps:

1. A variogram of the rainfall is derived from the radar imagery, using the Fast Fourier Transform (FFT) technique by [4].
2. The rainfall variogram is used to perform an ordinary kriging interpolation of rain gauges.
3. The residuals are calculated as the difference between the ordinary kriging of the rain gauges and a linear function of the radar.
4. The variogram of the residuals is estimated using the same FFT technique.

Regression-kriging is implemented in R, in the gstat package, and can easily be extended to block regression-kriging, which gives both the rainfall estimate and the kriging variance on an area, rather than on points. This will be useful to estimate the average rainfall on the Haute-Sûre catchment and the associated uncertainty.

We must be aware that we are going to use a space-time model which merges radar with different temporal resolutions of rain gauge observations. They might have also different measurement techniques for the rain gauges in Germany and Luxembourg. Therefore, we need to address it.

2.3 The run-off sub-model

The FLOW-R2D [5] is a numerical hydrodynamic two-dimensional model and is proposed for modelling the run-off in the case study. The model is based on the Finite Difference Method with a discretisation of 2D-Shallow Water Equations Equations made by the explicit McCormack numerical scheme [6] in a non-staggered cell-centred computational grid.

The input of the model consist of the rainfall maps and the Digital Elevation Model. The parameters which should be determined, are the required parameters for the infiltration process and the simulation of the bottom shear stresses (friction modelling). The output of the model is a final hydrograph at the outlet of each sub-catchment, i.e. at the entrance of the manholes of the sewer network.

2.4 The sewer system sub-model

After the definition of the output hydrograph at the entrance of the manholes of the sewer network, we use a simplified urban drainage model, EmiStatR, to simulate the volume in the CSO tank of each structure and to simulate the loads and concentrations of typical indicators of water pollution e.g. chemical oxygen demand (COD) and ammonium (NH_4). This model represents the current minimum level of complexity under study.

3. Results

As a result of the present work in progress we deliver as outcome the Figures 2 and 3, which illustrate the proposed work flow for rainfall estimation and uncertainty quantification where the red nodes are terminal nodes (start or end), the blue rectangular nodes indicate a process, the blue trapezoidal nodes indicate input data, and the green trapezoidal nodes indicate output. The work flow presented in Figure 2 is related to a new scenario to estimate rainfall on the catchment accounting for uncertainty quantification in the estimation. In this work flow the input data is presented in Level 2 (Figure 2). After a quality check of input data, the radar rainfall is used to calculate the variogram (Level 5, Figure 2). The resulting variogram together with the rain gauge measurements checked are the inputs for the Block Regression-kriging algorithm (Level 6, Figure 2). The output of the Block Regression-kriging are the estimated rainfall map on the catchment and the quantification of the estimation uncertainty by means of the calculation of the kriging variance on the catchment (Level 7, Figure 2). Finally the work flow is finished and a new scenario can be started again.

Figure 3, presents the proposed work flow for run-off and sewer system modelling. The work flow is concerned to one scenario of rainfall input map given a Digital Elevation Model (DEM) and a sewer network (Level 2, Figure 3), then the sub-catchments delineation is done (Level 3, Figure 3) and together with an input of the CORINE land use map, the friction zones for the 2D run-off model are defined (Level 4-5, Figure 3). The run-off sub-model comprises the Level 6 and Level 9 of Figure 3, with output the final hydrograph at the outlet of every sub-catchment or manhole of the sewer network. This is the input for the sewer system sub-model which is described in the Levels 10 to 14 of Figure 3. After one cycle is completed from Level 1 to Level 15 (Figure 3), the work flow is repeated for a different input rainfall map with the same DEM and sewer network. This process is repeated as many times as the Monte Carlo simulation design requires. At the end an ensemble of rainfall input maps and time series of quantity variables (volume of the CSO tank, and CSO volume) and quality variables (loads and concentrations of COD and NH_4) are produced to analyze how input uncertainty propagates to output uncertainty.

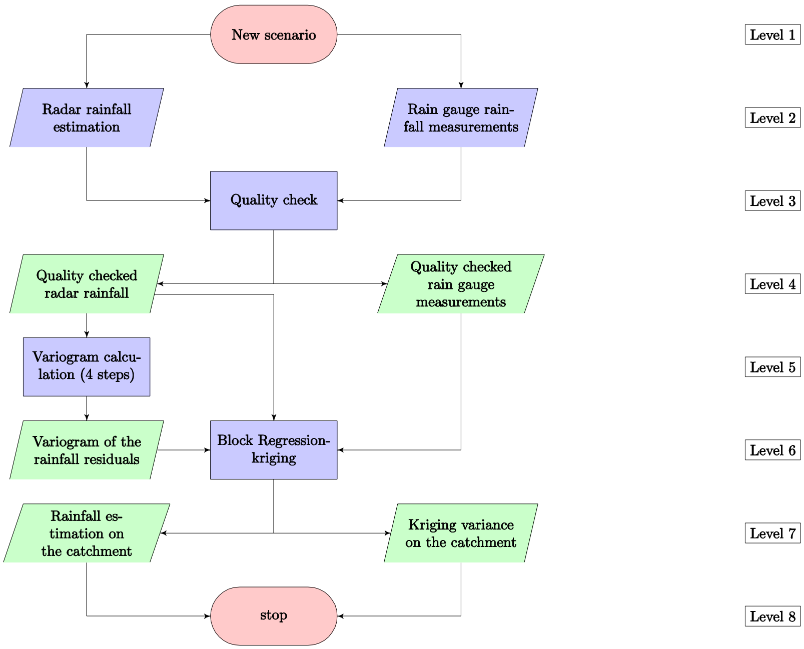

Fig. 2. Work flow for rainfall estimation and uncertainty quantification. Red node = terminal; blue rectangular node = process; blue trapezoidal node = input; green trapezoidal node = output.

4. Conclusions

We presented and illustrated a proposed work flow to build and calibrate a space-time geostatistical model of rain, using radar imagery as a covariate in regression-kriging based simulation. Then, a work flow for run-off and sewer system modelling was presented as well. These work flows are repeated as many times as the Monte Carlo simulation design requires to obtain an ensemble of rainfall input maps and time series of quantity variables (volume of the CSO tank, and CSO volume) and quality variables (loads and concentrations of COD and NH_4) are produced to analyze how input uncertainty propagates to output uncertainty. We expect that these work flows represent a more realistic simulated time series of rainfall originating run-off that enters the sewer system, and we can do the Monte Carlo input uncertainty propagation and compare with results obtained in previous studies we did. In the future, we expect that validation will show a better job done (not only in terms of mean error and root mean squared error of tank volume and overflow, but also in quantifying the uncertainty in the sewer system model outputs).

5. Acknowledgements

The work presented is part of the QUICS (Quantifying Uncertainty in Integrated Catchment Studies) project. This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement No. 607000, and the Luxembourg Institute of Science and Technology (LIST). The authors thank to the German Weather Service (DWD) for the rainfall time series and radar imagery provided, to the *Luxemburgish Administration des services techniques de l'agriculture* (ASTA) for the time series of rainfall provided, and to the Observatory for Climate and Environment (OCE) of the LIST for its technical support.

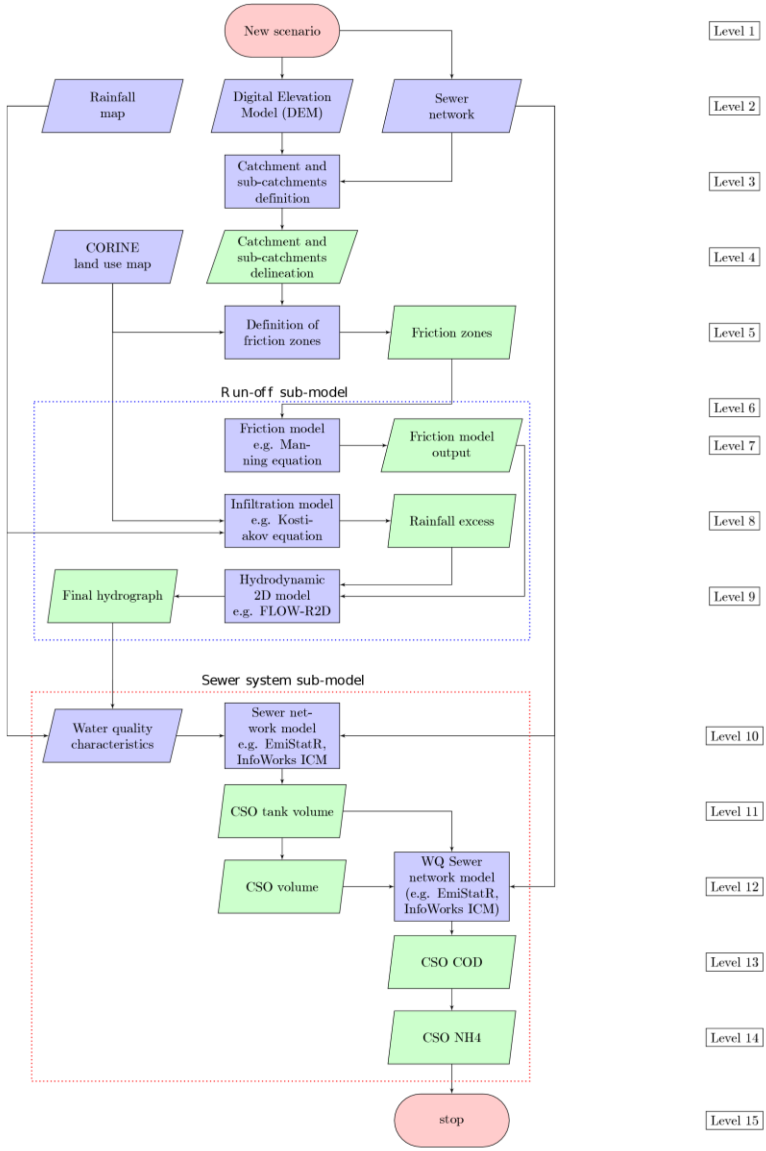

Fig. 3. Work flow for run-off and sewer system modelling. Red node = terminal; blue rectangular node = process; blue trapezoidal node = input; green trapezoidal node = output.

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