QUICS: Quantifying Uncertainty in Integrated Catchment Studies

4.3 Guidelines on rainfall resolution and associated uncertainty

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Author(s): Francesca Cecinati (FC) and Miguel A. Rico-Ramirez (MRR)

with contributions from Antonio Moreno Ródenas (ESR7) and Manoranjan Muthusamy (ESR11)

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Acronyms and Abbreviations

AR(1)	Autoregressive model with one-step dependency
AR(2)	Autoregressive model with two-step dependency
BK	Block Kriging
CM	Conditional Merging
CSO	Combined Sewer Overflow
DO	Dissolved Oxygen
KED	Kriging with External Drift
KNMI	Royal Netherlands Meteorological Institute
ICM	Integrated Catchment Models
NST	Normal Score Transformation
OK	Ordinary Kriging
QPE	Quantitative Precipitation Estimates
QUICS	Quantifying Uncertainty in Integrated Catchment Studies
SA	Singularity Analysis
TBR	Tipping Bucket Rain-gauges
WFD	Water Framework Directive

Executive Summary

Integrated catchment models are useful decision making tools that can couple urban and natural hydrology, modelling both water quality and quantity. Rainfall is one of the main inputs of integrated models, and its uncertainty affects the model output uncertainty. Not much is known on the optimal spatial and temporal resolution of rainfall, as input for an integrated catchment model.

The QUICS project has conducted research on rainfall uncertainty estimation and on rainfall optimal resolution for model application. The main research outcomes are illustrated in this document. The document is discursive and does not report mathematical derivations, technical details and case studies, but the appropriate references are reported, both in terms of QUICS publications and in terms of bibliography.

Since there is no unique answer to the question "*What are the optimal spatial and temporal resolutions for rainfall as an input to an integrated catchment model?*" the approach presented here is to provide the user with the tools to evaluate it for each case study. In particular, the document offers an overview of the constraints and factors that influence the selection of the optimal rainfall resolution and a list of tools that can be used to change the spatial and temporal resolutions, to estimate rainfall uncertainty, and to propagate rainfall uncertainty in a model.

Geo-statistical tools are suggested to accomplish these tasks. In particular the following instruments are recommended:

- *Ordinary Kriging* can be used to interpolate rain gauges when no radar rainfall estimate is available.
- *Kriging with External Drift* is recommended to optimally merge radar estimates and rain gauge measurements.
- *Block Kriging* is recommended to obtain rainfall estimates on areas, rather than on points.
- Accumulation and disaggregation techniques are illustrated to change the temporal resolution of the rainfall estimates, but also of the associated uncertainty.
- Kriging techniques have the advantage of estimating the interpolation uncertainty associated to the rainfall estimate and the use of a nugget effect or the use of *Kriging for Uncertain Data* can help to include the measurement uncertainty.
- A fourth root transformation is recommended to reduce the uncertainty due to the non-Gaussianity of rainfall probability distribution.
- An ensemble approach is suggested to propagate rainfall uncertainty in models.

Once the users are able to produce rainfall estimates at different spatial and temporal resolutions, to estimate the associated uncertainty, and to propagate it in the studied model, they can select the optimal product minimising the uncertainty in the model output.

CONTENTS

1 Introduction

1.1 Partners involved in deliverable

University of Bristol (UB): Francesca Cecinati (FC), Miguel Rico-Ramirez (MRR), Dawei Han (DH)

Delft University of Technology (TUD): Antonio Moreno Ródenas (AMR)

University of Sheffield (USFD): Manoranjan Muthusamy (MM)

1.2 Deliverable Objectives

The general objective of the deliverable is to provide practical advice on the optimum spatial and temporal resolutions of rainfall estimates for an integrated water quality model, in order to minimise uncertainty.

The deliverable addresses the following specific objectives:

A. Define and discuss the optimal spatial resolution for integrated catchment models (ICM)
B. Define and discuss the optimal temporal resolution for integrated catchment models (ICM)
C. Provide advice on techniques to produce probabilistic rainfall estimate at optimal spatial and temporal resolutions
D. Provide advice on techniques to estimate the uncertainty of rainfall estimates and the propagation of uncertainty in ICM

1.3 Related publications

The material in this deliverable is partially derived by journal papers and conference proceedings produced (or in phase of development) in the QUICS project framework. Technical details, mathematical formulations, and case studies are not reported in this work, but can be found in the related QUICS publications. In particular, the publications relevant for the deliverable are:

- Cecinati F., Rico-Ramirez M.A., Heuvelink G.B.M., and Han D. “Representing Radar Rainfall Uncertainty with Ensembles Based on a Time-Variant Geostatistical Error Modelling Approach.” Journal of Hydrology. Under review.
- Muthusamy M., Schellart A., Tait S., and Heuvelink G.B.M. “Geostatistical Upscaling of Rain Gauge Data to Support Uncertainty Analysis of Lumped Urban Hydrological Models.” Earth Syst. Sci. Discuss. Earth Syst. Sci. Under review.
- Moreno Ródenas, M. A., Cecinati F., ten Veldhuis M., and Langeveld J. 2016. “Effect of Spatiotemporal Variation of Rainfall on Dissolved Oxygen Depletion in Integrated Catchment Studies.” In 8th International Conference on Sewer Processes and Networks.
- Cecinati F., Moreno Ródenas A.M., Rico-Ramirez M.A., and Han D. 2016. “Integration of Rain Gauge Measurement Errors with the Overall Rainfall Uncertainty Estimation Using Kriging Methods.” In EGU General Assembly 2016.
- Cecinati F., Wani O., Rico-Ramirez M. A., “Dealing with non-Gaussianity of rainfall data in Kriging-based merging”, Water Resources Research. Under review.
- Cecinati F., Wani, O., Rico-Ramirez M.A. 2016, “Evaluation and correction of uncertainty due to Gaussian approximation in radar – rain gauge merging using kriging with external drift” In AGU Fall Meeting 2016.

- Cecinati F., de Niet A.C., Sawicka K., Rico-Ramirez M.A., "Optimal temporal resolution of rainfall for urban applications and uncertainty propagation". In preparation phase (expected in 2017).
- Cecinati, F., de Niet A. C., Sawicka K., and Rico-Ramirez M. A. 2017. "Optimal Temporal Resolution of Merged Radar – Gauge Rainfall for Urban Applications." In 2017 International Symposium Weather Radar and Hydrology.
- Sawicka K. and Heuvelink G.B.M. 2016, "Software tools for quantifying uncertainty across different scales". QUICS deliverable n. 2.1.
- Sawicka K. and Heuvelink G.B.M. 2016 "*spup – an R package for uncertainty propagation in spatial environmental modelling*". In 12th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences.

1.4 Background

The Water Framework Directive (WFD, 2000/60/EC 200) aims at reaching a good quality standard for inland and coastal water bodies under an ecological and a chemical point of view. Many European river systems are highly urbanised and struggle to meet the WFD targets. Complying with the environmental standards requires substantial investments and regulatory measures (Moreno Ródenas et al., 2016). Integrated catchment models (ICM) are powerful tools for decision support, modelling interactions between urban sewer networks, water treatment plants and receiving water bodies. ICM are designed to perform fast and being robust for long-term scenario studies and system optimization (Benedetti et al., 2013; Langeveld et al., 2013; Langeveld et al., 2013). However, not much is known about the rainfall input requirements and their impact on the model performance.

There are several factors affecting the optimization of the rainfall input for ICM, for example: data native resolution, data aggregation for uncertainty reduction, data disaggregation to improve process definition or to meet model requirements, rainfall process characteristics in space and time, model characteristics, model objectives, and computational limits.

The optimal spatial and temporal resolutions of rainfall in urban hydrological models has been widely investigated. For example, Schilling, (1991), studied the optimal spatio-temporal resolution of rainfall as a function of catchment hydrological parameters; Berne et al., (2004), proposed equations to find the optimal spatio-temporal resolution of rainfall, given the catchment area. However, models radically evolved in the last decades and the concept of optimal rainfall resolution with them. Thanks to the increasing computing power, model complexity increases and allows us to represent finer scale processes, typical of the urban environment (Einfalt et al., 2004). The trend to move towards ICM, builds on the recent years of technological development (Fletcher et al., 2013). At the same time, rainfall measurement techniques improved; weather radars achieved a finer spatial resolution and their accuracy improved thanks to technological developments like dual polarization and Doppler capabilities (Berne and Krajewski, 2013; Islam and Rico-Ramirez, 2013). Nowadays, operational weather radars typically provide rainfall estimates at 5 minutes/1 kilometre resolutions, although they still have a lower accuracy compared to rain gauges, due to the indirect nature of radar rainfall estimation (Villarini and Krajewski, 2010). Merging radar rainfall and rain gauge data improves the accuracy of the rainfall estimation, maintaining the radar rainfall spatial characteristics (Goudenhoofdt and Delobbe, 2008;

Haberlandt, 2007; Jewell and Gaussiat, 2015; Schuurmans et al., 2007; Wilson, 1970). Among the various developed techniques, Kriging with External Drift (KED) and Conditional Merging (CM) are often preferred thanks to their high performance and robustness (Goudenhoofdt and Delobbe, 2008; Jewell and Gaussiat, 2015; Li and Heap, 2011; Nanding et al., 2015). The performance of KED is often better than the performance of CM (Berndt et al., 2014). However, KED does not perform comparably well at short temporal resolutions, due to the sensitivity to low quality data, and some temporal accumulation is recommended (Berndt et al., 2014).

No unique answer exists to define the optimal spatio-temporal resolution for rainfall in ICM, but different techniques can be used to optimise the rainfall input according to the data, the model, and uncertainty needs. This document illustrates the available data and the spatio-temporal characteristics of commonly adopted models, as well as techniques that can be used to adapt the rainfall input to the required resolution, to estimate the associated uncertainty, and to assess its propagation in models. The suggested approach is based on the idea that optimisation can be reached producing different rainfall products at different resolutions, and selecting the one that minimises the ICM output uncertainty. The research developed in QUICS by early stage and experienced researchers is used as an example to illustrate the variety of available rainfall data as well as the variety of models, in terms of structure, data requirements, and objectives that one can potentially encounter when studying and working with ICM. Section 2 illustrates the typical spatial characteristics of rainfall data and model requirements; Section 3 2 discusses the typical temporal characteristics of rainfall data and model requirements; Section 4 illustrates techniques that can be used to adapt the data resolution to the desired one, in order to meet model requirements or to reduce uncertainty; Section 5 presents techniques that can be used to estimate the rainfall input associated uncertainty and to estimate its propagation in models. In Section 0conclusions and recommendations are drawn.

2 Optimal spatial resolution

Some studies tried to propose equations to derive the optimal rainfall resolution for model applications. Schilling, (1991) defines the optimal spatio-temporal resolution for urban applications as a function of catchment hydrologic parameters, and recommends a resolution of at least 1 minute and 1 kilometre. Berne et al., (2004), derived equations to assess the optimal spatio-temporal resolution as function of the catchment area, and recommends for example 5 minutes – 3 kilometres for a 1000 ha catchment and 3 minutes – 2 kilometres for a 100 ha catchments. However, in conditions of convective storms, a finer spatial resolution is necessary (e.g. 5 ha according to Faures et al., 1995). Rainfall is a highly variable process and its spatial characteristics are strongly variable. Rainfall processes are commonly more uniform and correlated in space during stratiform events, in Europe more common during winter in the form of frontal weather systems, and they are more spatially variable during convective events, commonly happening in the warmer summer conditions (Van De Beek et al., 2011). The Foundation for Water Research and the Wastewater Planning Users Group found that 5 ha and 2 minutes resolutions are necessary for modelling street and building scale processes (WaPUG, 2004). Despite rainfall variability can be relevant even at small sub-kilometre scales (Fiener and Auerswald, 2009; Peleg et al., 2013), its detailed spatial description may not be significant for every model application (Moreno Ródenas et al., 2016).

The optimal spatial resolution for a model's rainfall input is therefore influenced by the available data resolution, by the characteristics of the process to be represented, and by the characteristics of the model in use.

2.1 Overview of rainfall data resolution

Three main sources of rainfall data are commonly available: satellite estimates, weather radar estimates, and rain gauge measurements. Satellite data are characterised by a lower resolution and a lower accuracy, and are mainly used for global or continental scale applications or for data-scarce environments; therefore this source is not relevant for the aim of this deliverable, looking at smaller European basins with sufficient data coverage, and it is not discussed here.

Weather radars are ground-based systems that operate in the microwave frequency range (3-10GHz) and are capable to send high-power waves in a particular direction; if precipitation particles lie along the path of the waves then a small percentage of energy is reflected back to the radar antenna. The reflected power is related to the radar reflectivity and this in turn is used to retrieve Quantitative Precipitation Estimates (QPE) from precipitation targets. Although the indirect nature of radar QPE makes them typically less accurate than rain gauge measurements, weather radars are becoming increasingly popular thanks to new technologies that improve their accuracy (e.g. Doppler and dual-polarisation capabilities) and to their ability to produce areal estimates with a high spatio-temporal resolution (Berne and Krajewski, 2013). Typical European operational weather radars operate at C-band (5.5GHz) and produce rainfall estimates at 1-kilometre resolution. For urban applications, some X-band (10 GHz) radars are used and able to estimate rainfall at sub-kilometre resolution, but they are not usually available for operational use (ten Veldhuis and van Riemsdijk, 2013).

Rain gauges are the most traditional instruments for rainfall measurements, and technological advancements keep on improving their accuracy. Rain gauge measurements are more direct and are typically considered more accurate than radar QPE, but provide only point measurements that require interpolation. National and regional rain gauge networks usually have densities lower than 1 rain gauge per km^2.

In the QUICS project, several case studies are analysed by the researchers, using very different rainfall data. Radar data is provided for research purposes by the UK Met Office, by MeteoSwiss, and by the Royal Netherlands Meteorological Institute (KNMI), in all cases with a spatial resolution of 1-kilometer. Rain gauge networks used in the QUICS project have very diverse resolutions, spacing from a density of 1 rain gauge per 160 km^2 for larger scale applications, to sub-kilometer research networks with a density of 3.4 rain gauges per km^2.

Often radar and rain gauges are merged in order to obtain an areal rainfall estimate, with higher accuracy than radar QPE. Out of the several possible techniques that can be used to merge radar rainfall and rain gauge measurements, Kriging with External Drift (KED) is recognised as one of the best in terms of product quality, computational efficiency, robustness, and in terms of uncertainty estimation. Section 4 discusses how KED can be used to obtain rainfall estimates on a desired grid or on a desired area, while Section 5 illustrates how to estimate uncertainty with KED.

2.2 Model input requirements

If on the one hand available data are a constrain in the selection of the optimal rainfall resolution, on the other hand ICM and hydrological models have very different characteristics, both in terms of structure and in terms of objectives.

In terms of structure, many ICM (e.g. SWMM, WEST - MIKE) require lump rainfall information, i.e. time series of rainfall on a catchment or a sub-catchment (Muthusamy et al. - under review). Depending on the scale of the problem to address, the catchment or sub-catchment sizes are highly variable; in the QUICS project lumped models are used with sub-catchments ranging from 0.2 km^2 to 150 km^2. Other models instead accept time series of rainfall distributed on grids of arbitrary resolution (e.g. InfoWorks, MIKE SHE). Methodologies to derive rainfall data at a given catchment resolution or on a grid are presented in Sections 4 and techniques to estimate the associated uncertainty are presented in Section 5

In terms of objectives, ICM usually have the ability to model different water quality and quantity variables (e.g. river stage, flow, dissolved oxygen, various pollutant concentrations, etc.). Each of these variables can be more or less sensitive to the rainfall spatial resolution and requires a different input resolution optimisation. For example, Moreno Ródenas et al., (2016) found that the use of only one rain gauge in an area of 570 km^2 is not sufficient to correctly model the dissolved oxygen (DO) in an ICM, but in case of stratiform rainfall the use of only 13 rain gauges performs comparably to the use of distributed radar rainfall or merged rain gauge – radar products at 1 kilometre resolution. Ochoa-Rodriguez et al., (2015) observed that the ideal spatial resolution for urban drainage modelling is strongly correlated to the size of the catchment, but in general found that a typical rain gauge network density is not sufficient to correctly estimate the hydraulic behaviour of urban catchments.

3 Optimal temporal resolution

The optimal temporal resolution for rainfall applications in ICM is affected by several factors. Rainfall data are often available with high temporal resolution, but accumulation is advisable to reduce the impact of random errors in rainfall measurements and to reduce uncertainty. At the same time, some urban hydrological processes have short characteristic time, depending on the study area size and on the modelled phenomena, and rainfall input needs a sufficiently fine temporal resolution to capture the variability of the processes; for example, Schellart et al., (2012) found that using a coarse temporal resolution in the rainfall measurements results in the underestimation of peak flows and Combined Sewer Overflow (CSO) volumes in small urban catchments. Some other processes instead may be insensitive to a fine description of rainfall temporal variability. Moreno Ródenas et al., (2016) did not observe significant differences in Dissolved Oxygen (DO) modelling using rainfall information of 10 minutes, 30 minutes and 1 hour temporal resolution in urban ICM applications with a large WEST model. In addition, the optimal rainfall resolution may be affected also by the temporal resolution of other model input data, i.e. fine temporal resolution rainfall inputs may be beneficial only if the other model inputs have a fine temporal resolution as well.

3.1 Rainfall data temporal resolution

Radar QPE are usually available at 5-minute resolution, throughout most European radar networks. This is due to the time that radars require to scan 360° at different elevation angles.

Rain gauge data, instead, are very variable in terms of temporal resolution. A primary factor is the type of rain gauge to be used. The simplest rain gauges require a manual reading of the water level and this is typically done on a daily basis (e.g. KNMI manual network). Tipping bucket rain gauges (TBR) record a tip every time a fixed amount of rainfall is accumulated (usually 0.1 or 0.2 mm). This means that TBR can provide rainfall data with variable temporal resolution every time they record a tip, or can report the number of tips in a given temporal interval (e.g. 1, 10, or 15 minutes). Due to the underlying mechanism, TBR data are more accurate with longer accumulation intervals. Other more sophisticated rain gauges are able to provide more accurate estimates for short accumulation intervals (e.g. 1 minute) using weighting or floating devices. Rain gauge networks can be diversified, due to the fact that the most accurate rain gauges are usually also significantly more expensive. Some countries have invested considerable resources to substitute national networks with high-accuracy rain gauges, some other couple a limited number of accurate rain gauges with a larger number of less accurate ones, other prefer to have a denser network of tipping bucket rain gauges. In addition, local networks are often available, which can have highly variables accuracy characteristics, depending on their type, their purpose, and on the network and data management.

Merging radar and rain gauge measurements usually requires to meet the temporal resolution of the coarser data source or the minimum common multiple. Alternatively, downscaling techniques exist and are discussed in Section 4 , but would introduce additional uncertainty. A good practice for merging is to accumulate time series to a coarser temporal resolution in order to reduce uncertainty, perform the merging, and then downscale the merged results (Berg et al., 2016; Cecinati et al., 2017). The optimal accumulation and downscaling resolutions need to be investigated for each specific case. For example, Cecinati et al., (2017) estimated that the optimal accumulation and downscaling resolutions for an ICM in an area of approximately 20 km^2 were respectively 3 hours and 30 minutes, in terms of optimal water level estimation.

3.2 Model input requirements

In terms of structure, most models are very flexible in accepting rainfall inputs of different resolutions. The optimal temporal resolution, under a model point of view, is often driven by the process to be modelled. In QUICS, models are operated with temporal resolutions ranging from 1 minute to 1 day. Due to the small scale, urban applications often require higher temporal resolution than rural areas (Einfalt et al., 2004). Several studies have assessed the impact of the rainfall temporal resolution in the behaviour of urban drainage system, but the results are usually only relevant for the analysed case. Ochoa-Rodriguez et al., (2015), observed that a coarse temporal resolution in the rainfall measurements can result in significant peak discharge errors, especially in small catchments. Moreno Ródenas et al., (2016) instead, did not observe significant differences in DO estimation using rainfall products with different resolutions in a larger ICM.

4 Techniques to produce rainfall estimates at optimal spatial and temporal resolutions

Given the variability of factors affecting the optimal spatial and temporal resolutions, tools are needed to combine the different sources of rainfall data in a rainfall product at the desired resolution. Geo-statistics offers several tools that can be used to:

- Merge rain gauge and radar rainfall measurements
- Change the spatial support of rainfall data
- Change the temporal resolution by accumulating/downscaling time series
- Consider the uncertainty in the measurements
- Estimate the uncertainty at the desired spatio-temporal resolution
- Propagate the uncertainty in a model

4.1 Geo-statistical techniques for change of spatial support

Most of the geostatistical techniques presented here are based on Kriging, an interpolation method that allows to estimate the spatial distribution and the associated uncertainty of a given variable (e.g. rainfall) given a number of point measurements at specific locations. The principle is to estimate the process in a given point using a weighted average of the available rain gauge measurements, taking into consideration the distance from the measurement points and the process decorrelation in space to calculate the weights. Based on this principle, several variations of the basic (Ordinary) Kriging interpolation algorithms are available to estimate rainfall on areas rather than points, to include radar measurements, to consider rain gauge measurement uncertainty, and more. No technical detail is reported in this document and for rigorous formulations the reader is advised to refer to Cressie (1993), Wackernagel (2003), and Chiles and Delfiner (1999).

When a model requires a distributed input, Kriging can be used to estimate the rainfall at each grid node. If radar data is not available, Ordinary Kriging (OK) can be used to interpolate the rain gauge data. If instead radar data is available, Kriging with External Drift (KED) is a valid alternative to Ordinary Kriging. KED is a variation of OK that does not consider a spatially homogeneous mean for the process, but instead considers the mean as a linear function of an external variable (drift), in this case the radar data. The advantage of such an approach is that radar data, which have a lower accuracy, are not used directly to estimate the process values, but are used instead to reproduce the spatial features that the rain gauges are unable to capture. Figure 1 compares a radar QPE product that overestimates the rainfall intensities when compared to rain gauge measurements, an OK interpolation product that is consistent with rain gauge measurements but appears too smooth, and a radar - rain gauge KED merged rainfall product that has a better agreement with rain gauges and represents the rainfall spatial features derived from the radar QPE. Both OK and KED have the advantage of being able to estimate the rainfall and the associated uncertainty on any desired point, therefore grids of the preferred resolution can be derived.

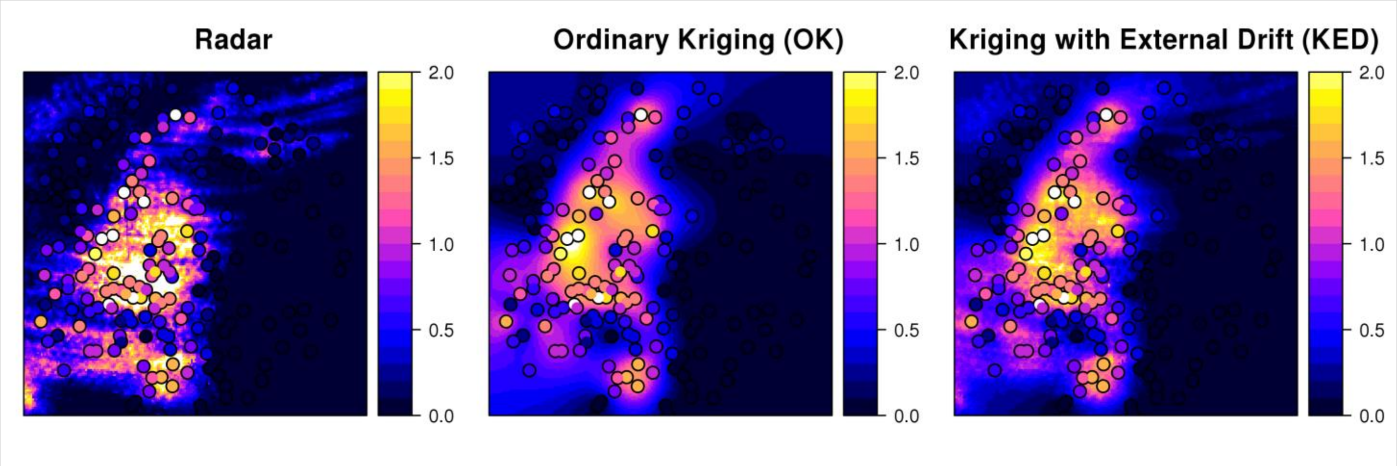

Figure 1 - Radar rainfall estimate, rain gauge interpolation with ordinary Kriging and merged radar - rain gauge rainfall estimate with KED for an example hourly window on 26th March 2009 at 9:00 in a 200 km x 200 km area in the North of England. Rain gauge measurements are super-imposed. The units are [mm/h].

A very useful variation of OK and KED is Block Kriging (BK) that can be used in both, the ordinary version, and the version with external drift. Block Kriging allows to obtain the estimation for an area of desired shape or size rather than for a point, and to calculate the associated uncertainty. It can be used in grid predictions, to acknowledge that we actually use the average rainfall on pixels rather than point estimates, or it can be used as rainfall input for lumped models, to estimate the average rainfall on a given catchment or sub-catchment.

4.2 Geo-statistical techniques to modify the temporal resolution

As mentioned before, accumulations are often used to reduce the impact of random measurement errors. Therefore a coarser temporal resolution tends to reduce the uncertainty in the rainfall estimate. However, rainfall temporal resolution needs to be fine enough to represent the modelled processes correctly. The optimal resolution is thus derived for a specific case study balancing the two needs.

In order to change the spatial resolution of a rainfall estimate, accumulation and disaggregation techniques exist. While accumulation is a very simple process, disaggregation is less straightforward. Most of the methodologies used in literature to temporally downscale time series are based on the use of statistical properties to reproduce the most probable pattern in the observed temporal interval (Ferraris et al., 2003; Liu et al., 2007). An alternative to stochastic approaches is the use of the pattern observed by one of the finer resolution rainfall data. For example, if a rain gauge measures only daily accumulations, each accumulation can be distributed in hourly intervals according to the pattern observed by the radar. This approach is particularly useful using the radar data to downscale coarser rain gauge data or KED merged rainfall products, since the radar estimates are distributed (Cecinati et al., 2017).

The uncertainty associated to a rainfall product can be upscaled and downscaled as well, using three principles (Cecinati et al., 2017):

1. The variance of a sum is the sum of the covariances between all summed elements.

2. The unknown covariances between rainfall estimates at a certain temporal lag can be approximated deriving an autocorrelation function from rainfall time series.
3. The standard deviation is proportional to the rainfall rate.

The correct equations for upscaling and downscaling can be derived combining the above mentioned principles.

5 Techniques to estimate and propagate rainfall uncertainty

To identify the optimal rainfall spatio-temporal resolution, the objective is to minimise the ICM output uncertainty. In order to estimate what is the rainfall input impact on the model output uncertainty, we need to estimate what is the rainfall uncertainty and how it propagates to the model output uncertainty.

5.1 Techniques to estimate rainfall uncertainty

One of the advantages in using kriging-based methods to estimate rainfall inputs, is that kriging allows to produce probabilistic rainfall estimates made of process mean and variance estimates. The kriging variance is the starting point to estimate rainfall uncertainty. The kriging variance mainly estimates the uncertainty due to the interpolation, but techniques exist to include the uncertainty in the measurements as well.

Rain gauge uncertainty needs to be modelled knowing the used device and its characteristics. The simplest method to consider rain gauge uncertainty in the kriging variance is to introduce a nugget effect in the geo-statistical model, i.e. to acknowledge that two measurements at an infinitesimal distance may not be perfectly identical due to the occurrence of random errors. The nugget effect is an estimation of how decorrelated two measurements at an infinitesimal distance are (Clark, 2010). Nevertheless, the use of a nugget implies an assumption of rain gauge error stationarity in space and often in time. The reality is that rain gauges errors are usually proportional to the rainfall rate, and therefore highly variable in space and time (Ciach, 2003; Habib et al., 2001). A technique called Kriging for Uncertain Data (KUD) helps in modelling a different uncertainty for each rain gauge at each time step. KUD modifies the kriging equations at each time step to introduce a different variance for each measuring point (Cecinati et al., 2016; Mazzetti and Todini, 2009). Although it proved to be a valuable technique when applied to KED, it is not always successful when applied to OK.

Another uncertainty source is due to the non-Gaussianity of rainfall. Kriging methods are based on the assumption of process Gaussianity. When applied to rainfall interpolation and radar-rain gauge merging, the process Gaussianity is an approximation that may introduce some additional uncertainty. Although this effect is usually not significant, Gaussianity of the process may be improved using transformations. Erdin et al., (2012) compared transformations in the Box-Cox family, while Cecinati et al., (under review) extended the comparison to the Normal Score Transformation (NST) and to a Singularity Analysis (SA) technique (Wang et al., 2015). NST and the Box-Cox transformations corresponding to a square root and a fourth root resulted optimal for KED applications. However, the square and fourth root transformations have the advantage of having an analytical transformation and back transformation both for the kriging estimate and for the kriging variance, which make the algorithm simpler and more efficient (Sideris et al., 2014).

5.2 Techniques to propagate rainfall uncertainty

The propagation of the input uncertainty in a model is a key element to evaluate how sensitive the model is to the rainfall uncertainty and to identify the optimal rainfall resolution. Analytical propagation methods are rarely applicable, both because most ICM have a complex structure, and because rainfall has a multivariate distribution with statistical characteristics varying in space and time.

The most popular and effective technique to evaluate rainfall input uncertainty propagation is to use an ensemble approach. Similarly to other Monte Carlo techniques, the idea underlying the use of ensembles is that we can sample the probability distribution of rainfall in order to generate a large number of possible alternative model inputs, use them one by one in the analysed model, and observe the distribution of the model outputs. As mentioned, rainfall has a multivariate distribution and its sampling and ensemble generation requires to respect the spatial and temporal characteristics of the process. A method to generate rainfall ensembles from a kriging product is to consider each ensemble member as the sum of the mean and of a variable error component. The mean is modelled as the kriging mean. The error components are derived multiplying the kriging standard deviation, i.e. the square root of the kriging variance, by a spatially correlated field with zero mean and unit variance. A large number of such fields can be generated with unconditional simulations, respecting the spatial characteristics of the observed rainfall (Sawicka and Heuvelink, 2016a, 2016b). Subsequently, autoregressive models with one-step dependency (AR(1)) or two-step dependency (AR(2)) can be used to reconstruct the temporal auto-correlation of the observed rainfall process. The auto-correlation and the parameters of the autoregressive models can be derived from the observed time series (Cecinati et al. - under review; Germann et al., 2009).

Once a large number of possible alternative rainfall time series are generated, they can be used as model input, obtaining a large number of outputs. The obtained outputs can be used to reconstruct the output probability distribution, and therefore evaluate the uncertainty in the output due to the input uncertainty.

6 Conclusions

Integrated Catchment Models (ICM) are precious tools for decision making, being able to represent the interaction between urban environments and natural river systems, and the feedback between water quality and quantity. Due to the complex structure, ICM are affected by a variety of uncertainty sources. Rainfall is one of the main ICM inputs and the uncertainty associated to the rainfall data is a function of the spatial and temporal resolution selected for its representation. Identifying the optimal rainfall spatio-temporal resolution helps in reducing the ICM output uncertainty.

There is no unique answer to what the optimal spatio-temporal resolution of rainfall is as an input for ICM. Among the most important factors:

- The native resolution of rainfall data, either from radar, rain gauges, or a radar-gauge merged rainfall product, set a constrain on rainfall spatio-temporal resolution.
- The reduction of the impact of the random error can be achieved through accumulation.
- To capture the characteristics of the modelled processes, spatial and temporal resolutions need to be sufficiently fine.

- Different ICM structures require different types of inputs.
- Different ICM objectives can be more or less sensitive to rainfall resolution.

The approach used in this document is to offer an overview of the tools that can be used to produce rainfall estimates at the desired spatial and temporal resolution with an associated uncertainty estimation, and to propagate the rainfall uncertainty to observe its effect on the model output uncertainty. Using the tools presented in this work, a user can compare rainfall products at different spatio-temporal resolutions and identify the optimal one for a specific case study minimising the ICM output uncertainty.

Geo-statistical approaches based on Kriging offer the possibility to obtain rainfall estimates at the desired resolution, with an associated uncertainty estimation. In such a framework, the use of Kriging with External Drift is recommended to optimally merge radar and rain gauge rainfall data, while the use of Ordinary Kriging is advisable if radar rainfall data is not available. The presented Kriging tools to obtain rainfall on the desired spatial support, to estimate uncertainty, to consider measurement uncertainty, or to correct Gaussianity can be flexibly combined to correctly reproduce the spatial rainfall distribution and its uncertainty for the study cases.

Temporal upscaling can be easily achieved with accumulations, while either a stochastic or a data-driven approach can be used for temporal downscaling. The principles to follow to upscale or downscale the uncertainty associated to the rainfall data were also illustrated.

In order to propagate the rainfall uncertainty in a model, an ensemble approach is recommended. Ensemble members can be derived from kriging products, combining the kriging mean with a zero-mean error component proportional to the kriging standard deviation, using unconditional simulations. Autoregressive models are suggested to reproduce the observed temporal auto-correlation of the rainfall process. Once an ensemble of numerous possible rainfall time series are produced, they can be used as input for the studied model to observe the impact of rainfall uncertainty on the model output uncertainty.

The optimal rainfall input can thus be identified comparing rainfall products at different spatio-temporal resolutions and minimising the ICM output uncertainty.

In this work, the description of the techniques is discursive and does not include mathematical formulations or case studies. The reader is encouraged to refer to the QUICS publications and the cited references to have a more technical insight of the specific techniques.

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