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EFFECTS OF RAINFALL AND CATCHMENT SCALES ON HYDROLOGICAL RESPONSE SENSITIVITY IN URBAN AREAS

Effects of rainfall and catchment scales on hydrological response sensitivity in urban areas

Dissertation

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Odi et amo.
Quare id faciam fortasse requiris.
Nescio, sed fieri sentio et excrucior.
“Carmina LXXXV”, **Catullus**

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SUMMARY

Spatial and temporal rainfall variability play an important role in generation of pluvial flooding. In urban areas, this phenomenon has increased in the last decades, due in particular to an intensification of urbanization and imperviousness degree. In fact, population is growing and moving from rural areas to cities, which are becoming more and more urbanized and densely populated. The increase of urbanization and related increase of imperviousness degree, combined with short and intense rainfall events, caused by climate changes, result in a fast hydrological response, with high probability of flooding. Hydrological models can represent the overall flow behaviour but they remain poorly capable of predicting flow peaks, especially in urban areas. In view of this, a better knowledge of the hydrological response of the urban catchment is needed to improve flood prediction and prevent damages caused by pluvial flooding.

Due to the high variability of catchment characteristics at small scale, urban runoff processes are particularly sensitive to spatial and temporal variability of rainfall. For this reason, high resolution data are required for accurate runoff estimation. Rainfall is generally measured with rain gauges, which provide accurate measurements in a specific point, but they are not able to fully describe rainfall variability in space. New technologies, such as weather radars, have been used in recent decades to estimate rainfall intensity. Although these instruments provide an indirect measurement of rainfall and require good calibration and error corrections, they can provide rainfall distribution in space and time, which is fundamental to investigate the hydrological response.

Rainfall characteristics, such as intensity, total depth, storm velocity and intermittency, strongly affect the hydrological response of the system and it is important to properly characterize them to estimate the runoff. Catchment characteristics, such as drainage area, drainage network, imperviousness degree and slope, and their representation in hydrological models also play an important role in the prediction of hydrological response. At present, combined effects of rainfall and catchment characteristics and scales on urban hydrological response needs further investigations.

The aim of this work is to address the following questions:

- What is the interaction between rainfall and catchment scale in generating the hydrological response?
- How does this interaction influence the sensitivity of model prediction to input rainfall resolution?

In order to answer these questions, two ranges of rainfall resolution are investigated. Rainfall observations, available for two different climatological regimes in Europe and US at 100 m - 1 min and 1000 m - 15 min respectively, are aggregated in space (up to 3000 m and 6000 m) and in time (up to 10 min and 60 min). Aggregation in space and time of rainfall radar observations allows to simulate different rainfall resolutions and evaluate hydrological response sensitivity to coarser rainfall resolutions.

A new rainfall classification, based on the identification rainfall cluster above a selected threshold, is introduced to describe rainfall variability in space and time. In particular, the new spatial classification allows to identify the core of the storm, that strongly determines the hydrological response of the system, in a fast and efficient way. Different thresholds are tested to properly characterize the core of the rainfall storm and the threshold corresponding to the 75 percentile of the rainfall events dataset have shown to be the most adequate for this purpose. This new rainfall classification gives a good representation of the rainfall spatial and temporal variability.

Catchments are characterized in space using the dimension of the drainage area, while the response time is described by the lag time. The new rainfall classification is then combined with the characterization of the catchment variability in space and time with the aim to develop dimensionless factors, that describe the complex interaction between rainfall and catchment scales and rainfall resolution. Three scale factors are introduced to predict model performance in relation to rainfall and catchment scales. These factors aim to be dimensionless in order to be generally applicable at different scales. Scale factors are computed for Cranbrook, a small highly urbanized catchment (8 km^2), close to London (UK). These factors are subsequently tested for catchments in Little Sugar Creek (111 km^2, Charlotte metropolitan area, USA), in order to investigate their applicability to different catchment scales and climatological condition.

Results show strong effects of aggregation in space and time on rainfall peak especially in the 100 m - 1 min to 3000 m - 10 min range, highlighting the need of using high rainfall resolution to avoid strong underestimation of concentrated rainfall peaks that are relevant for urban scale. A median reduction of 80% of the rainfall peak is observed when aggregating in space from 100 m to 3000 m at 1 min temporal resolution. This reduction can increase up to 90%, when the effects of time aggregation are included.

Results highlight how low model performance often depends on the interactions between small catchment scale and rainfall resolution. For Little Hope, the smallest subcatchment of Little Sugar Creek, rainfall resolutions is too coarse to properly represent the hydrological response of the catchment. Only 7% of the investigated cases for this small sub-catchment present a good model performance (coefficient of determination higher than 0.9) for the highest rainfall resolution used as model input and local flow measurements used as reference for the analysis.

The three new dimensionless scale factors (α_1, α_2 and α_3) are defined as combination of rainfall resolution and rainfall and/or catchment spatial and temporal scales. These factors are investigated in relation to the coefficient of determination, used in this work to represent the model performance. Scale factors allow to predict the level of model performance for the available rainfall resolution, given the geophysical and climatological characteristic of the catchment. Moreover, these scale factors could also be used to derive the required rainfall resolution, for given rainfall and catchment scales at a certain level of model performance. This aspect is very useful in practical applications, for example to select the required rainfall resolution in a specific area. Scale factor $\alpha-$thresholds are developed for Cranbrook in order to identify relationship between scale factors and model performance. In particular, two level of performance, corresponding to coefficient of determination equal to 0.9 and 0.8, are investigated. The scale factor thresholds for α_2 show to be applicable for Little Sugar for 60% of investigated scenarios for acceptable model performance (coefficient of determination higher than 0.8), when using as reference the output obtained with highest rainfall resolution used as input of the model. This percentage drops to 50% of cases that satisfy the α_2-thresholds for acceptable model performance, when considering flow observation as reference for the analysis. These results suggest the applicability of the presented scale factors and their thresholds to the Little Sugar study case.

However, for some specific events, model performance is particularly low for high scale factor values. Most of the low-performance data points that do not satisfy the proposed thresholds (73%) present low values of intermittency (between 4% and 20%), and 43% of these points also show high maximum rainfall intensity. Rainfall events characteristics, such as intermittency or maximum intensity, should be included in the definition of the scale factors. More rainfall events and study cases with different climatological characteristics and different scales should be investigated in order to validate the global applicability of the scale factors.

Samenvatting

In de afgelopen decennia zijn stroomgebieden verder verstedelijkt en is de bevolkingsdichtheid in stedelijke gebieden toegenomen. Tegelijkertijd zorgt klimaatverandering voor een toename in regenbuien, die worden gekenmerkt door een hogere intensiteit en een kortere duur dan voorheen. De toename van verstedelijking en de gerelateerde toename van verhard oppervlak, gecombineerd met kortere en meer intense regenbuien, resulteert in een versnelde afvoer, en verhoogt de kans op overstroming. Een toename in de mate van kennis over de afvoer is vereist voor het verbeteren van overstromingsvoorspellingen en het voorkomen van schade veroorzaakt door pluviale overstroming. Door de sterke variatie in kenmerken van stroomgebieden op kleine schaal zijn de stedelijke afstromingsprocessen met name gevoelig voor variatie van regenval in ruimte en tijd. Voor nauwkeurige schattingen van afstromingen is daarom data van hoge resolutie vereist. Regenval wordt over het algemeen gemeten met behulp van regenmeters die nauwkeurige metingen verstrekken op specifieke locaties, maar niet in staat zijn om de ruimtelijke variatie van regenval in kaart te brengen. Nieuwe technologieën, zoals weerradars, zijn de afgelopen decennia gebruikt om indirect schattingen te maken van de intensiteit van regenval. Deze instrumenten bieden een indirecte meting van regenval en vereisen goede kalibratie en correctie van fouten. Ze zijn in staat om de regenval verdeling te meten in ruimte en tijd, wat fundamenteel is voor het correct voorspellen van de afvoer. Regenvalkenmerken, zoals intensiteit, totaal volume, treksnelheid van buien en intermittency, hebben een sterke invloed op de afvoer. Voor het benaderen van de afstroming is het essentieel om deze kenmerken juist te benaderen. Kenmerken van stroomgebieden, zoals het rioleringsgebied, het rioleringsnetwerk, de mate van doorlaatbaarheid, helling en de representatie hiervan in hydrologische modellen spelen ook een belangrijke rol in de voorspellingen over de afvoer. Op het moment is nog weinig bekend over de gecombineerde effecten van regenval en de kenmerken van stroomgebieden en schaal op de stedelijke afvoer. Deze studie tracht de volgende verbanden beter te verklaren:

- Wat is de interactie tussen regenval en de schaal van stroomgebieden bij het genereren van afvoer?
- Hoe beïnvloedt deze interactie de gevoeligheid van de modelvoorspelling naar inputresolutie?

Om bovenstaande vragen beter te kunnen beantwoorden wordt een regenval classificatie gepresenteerd, gebaseerd op clusteridentificatie boven een bepaalde drempel. De classificatie zorgt ervoor dat regenbuien kunnen worden geclassificeerd in ruimte en tijd en dat de kern van de storm wordt geïdentificeerd, die directe invloed heeft op de afvoer. De nieuwe regenvalkarakterisering wordt gecombineerd met de stroomgebiedenkarakterisering in ruimte en tijd om zo dimensieloze parameters te ontwikkelen, die

de complexe interactie tussen regenval en de schaal van stroomgebieden en de regenvalresolutie beschrijven. Twee reeksen van regenval resolutie zijn onderzocht: 100 m – 1 min tot 3000 m – 10 min en 1000 m – 15 min tot 6000 m – 60 min, voor twee verschillende klimatologische regimes in Europa en de Verenigde Staten. Aggregatie maakt het mogelijk om verschillende regenvalresoluties te simuleren en de gevoeligheid van de afvoer in verhouding tot de ruwheid van de regenvalresolutie te evalueren. Drie dimensieloze schaalfactoren worden geïntroduceerd voor het voorspellen van de modelprestatie in relatie tot de regenval en de schalen van stroomgebieden. Deze factoren zijn dimensieloos zodat ze algemeen toepasbaar zijn op verschillende schalen. De schaalfactoren waren ontwikkeld voor Cranbrook, een klein en sterk verstedelijkte stroomgebieden (8 km^2), in de buurt van London (UK). Deze factoren worden vervolgens gebruikt voor stroomgebieden in Little Sugar Creek (111 km^2, Charlotte metropolitan area, USA), om zo meer duidelijkheid te krijgen over de toepasbaarheid op verschillende schalen van stroomgebieden en klimatologische omstandigheden. De resultaten laten zien dat er sterke effecten van aggregatie in ruimte en tijd ontstaan bij regenval pieken, vooral in de 100 m – 1 min tot 3000 m – 10 min reeks. Dit toont aan dat het gebruik van hoge regenval resolutie noodzakelijk is voor het voorkomen van zware onderschattingen van geconcentreerde regenval pieken, die relevant zijn voor een stedelijke schaal. De nieuwe regenvalclassificatie geeft een goed beeld van de variatie van regenval in ruimte en tijd. De nieuwe ruimtelijke classificatie zorgt in het bijzonder ervoor dat de kern van de storm, die een sterke invloed heeft op de afvoer van het systeem, op een snelle en efficiënte wijze kan worden geïdentificeerd. De resultaten lichten vooral uit hoe lage modelprestatie verband houdt met een kleine schaal van het stromingsgebied en dat deze afhankelijk is van de interactie tussen regenval en de schaal van het stromingsgebied. Voor Little Hope, het kleinste sub-stromingsgebied van Little Sugar Creek, is de regenvalresolutie te grof om adequaat een representatie te geven van de afvoer van het stromingsgebied. Slechts 7% van de onderzochte situaties voor dit kleine sub-stromingsgebied laten een goede modelprestatie zien (vaststellingscoëfficiënt hoger dan 0.9) wanneer de hoogste regenvalresolutie gebruikt wordt als invoer voor het model en lokale stromingsmetingen gebruikt worden als referentiepunt voor de analyse. Schaalfactoren kunnen, gegeven de geofysische en klimatologische karakteristieken van het stroomgebied, gebruikt worden om de modelprestatie te voorspellen voor de beschikbare regenvalresolutie. Voor een verwachte modelprestatie kan, gegeven de regenval en schaal van het stroomgebied, ook de vereiste regenvalresolutie afgeleid worden. Dit aspect is erg nuttig voor praktische applicaties, bijvoorbeeld om de vereiste regenvalresolutie in een specifiek gebied te bepalen. Schaalfactordrempelwaardes voor α_2, ontwikkeld voor Cranbrook, blijken toepasbaar te zijn voor Little Sugar voor 60% van de onderzochte scenario's voor een acceptabele modelprestatie (zijnde bij een vaststellingscoëfficiënt hoger dan 0.8), wanneer de uitkomst die verkregen is met de hoogste regenvalresolutie als invoer voor het model gebruikt wordt als referentiepunt. Dit percentage daalt naar 50% van de gevallen die aan de α_2 drempelwaardes voldoen voor een acceptabele modelprestatie, wanneer stroomobservering wordt geschouwd als referentiepunt voor de analyse. Echter voor enkele specifieke evenement is de modelprestatie in het bijzonder laag voor hoge waarden van de schaalfactoren. De meeste datapunten voor lage prestaties die niet voldoen aan de voorgestelde drempelwaarden (73%) laten lage waarden voor intermittency zien (tussen 4% en 20%) en 43% van deze punten hebben daarbij een hoge maximale regenintensiteit. Regenevenementkarakteristieken, zoals intermittency of maximale intensiteit, zouden door de schaalfactoren inbegrepen moeten worden.

Sommario

Negli ultimi decenni, i bacini idrografici sono diventati molto piu urbanizzati. Allo stesso tempo, i cambiamenti climatici hanno portato ad un aumento degli eventi di pioggia, che presentano un'intensità maggiore ed una durata più breve rispetto al passato. L'aumento di urbanizzazione e il relativo aumento del grado di impermeabilità del terreno, combinato con eventi di pioggia brevi e intensi, si traduce in una risposta idrologica intensità, che rende il rischio inondazione piú probabile. I modelli idrologici possono rapprentare i vari deflussi, ma spesso non sono in grado di fornire una stima precisa dei picchi, specialmente in area urbana. Una migliore conoscenza della risposta idrologica del sistema può aiutare a migliorare la previsione delle inondazioni e prevenire i danni causati da inondazioni pluviali.

A causa dell'alta variabilità delle caratteristiche del bacino a piccola scala, i processi di deflusso urbano sono particolarmente sensibili alla variabilità spaziale e temporale delle precipitazioni. Per questo motivo, sono richiesti dati ad alta risoluzione per una stima accurata del deflusso. Le precipitazioni sono generalmente misurate con pluviometri, che forniscono misure accurate in un punto specifico della superficie, ma non sono in grado di descrivere la variabilità spaziale delle precipitazioni. Nuove tecnologie, come i radar meteorologici, sono state recentemente utilizzate per stimare indirettamente l'intensità di pioggia. Questi strumenti forniscono una misura indiretta delle precipitazioni e richiedono una buona calibrazione e notevoli correzioni degli errori. I radar sono in grado di fornire una distribuzione delle precipitazioni nello spazio e nel tempo che è fondamentale per lo studio della risposta idrologica del sistema urbano.

Le caratteristiche di pioggia, come intensità, altezza totale, velocità dell'evento e intermittenza, influenzano fortemente la risposta idrologica ed è importante caratterizzarle correttamente per stimarne il deflusso corrispondente. Le caratteristiche del bacino, come l'area di drenaggio, la rete di drenaggio, il grado di impermeabilità del terreno e la pendenza e la loro rappresentazione attraverso modelli idrologici, giocano un ruolo particolarmente significativo nella stima della risposta idrologica. Allo stato attuale, gli effetti combinati delle scale di pioggia e delle caratteristiche del bacino idrico sulla risposta idrologica urbana rimangono scarsamente compresi. L'obiettivo di questo lavoro é dunque una migliore compresione di questi fenomeni attraverso l'analisi delle seguenti domande:

- Qualé l'interazione tra la grandezza dell'evento di pioggia e le dimesioni del bacino idrico nella generazione della risposta idrologica del sistema?
- In che modo questa interazione influenza la sensibilità della risposta idrologica alle diverse risoluzioni di pioggia richieste come input per il modello idrologico?

Per rispondere a queste domande, viene presentata una nuova classificazione delle precipitazioni, basata sull'identificazione di cluster al di sopra una certa sogli. Questa

classificazione consente di classificare nello spazio e nel tempo gli eventi piovosi e di identificare il nucleo principale, che influenza direttamente la risposta idrologica del sistema. La nuova caratterizzazione delle precipitazioni viene poi combinata con la caratterizzazione del bacino nello spazio e nel tempo, al fine di sviluppare parametri adimensionali, che descrivano la complessa interazione tra le caratteristiche di pioggia e di baciono e la risoluzione usata per le misure di pioggia. Vengono esaminati due range di risoluzione di pioggia: da 100 m - 1 min a 3000 m - 10 min e da 1000 m - 15 min a 6000 m - 60 min, per due diversi regimi climatologici, uno in Europa e uno negli Stati Uniti. L'aggregazione di pioggia consente di simulare diverse risoluzioni di precipitazioni e di valutare la sensibilità di risposta idrologica a risoluzioni di precipitazioni più grossolane.

Con l'obiettivo di comprendere le complesse interazioni tra scala di bacino e di precipitazione e di identificare la risoluzione minima richiesta per le precipitazioni in un'area specifica, in questo lavoro, vengono introdotti alcuni fattori di scala. Vengono presentati tre fattori di scala adimensionali per prevedere le prestazioni del modello in relazione alle scale di pioggia e di bacino. Questi fattori mirano ad essere adimensionali per essere generalmente applicabili a diverse scale. I fattori di scala sono calcolati per Cranbrook, un piccolo bacino altamente urbanizzato (8 km^2), vicino a Londra (Regno Unito). Questi fattori sono successivamente testati per i sottobacini di Little Sugar Creek (111 km^2, area metropolitana di Charlotte, USA), al fine di indagare la loro applicabilità per diversi bacini idrografici e per diverse condizioni climatiche.

I risultati mostrano forti effetti di aggregazione nello spazio e nel tempo sul picco delle precipitazioni, in particolare nell'intervallo da 100 m - 1 min a 3000 m - 10 min, evidenziando la necessità di utilizzare un'alta risoluzione delle misure di pioggia per evitare una forte sottostima dei picchi di precipitazioni concentrate, che puó essere particolarmente rilevante per a scala urbana. La nuova classificazione delle precipitazioni basata sull'identificazione dei cluster fornisce una buona rappresentazione della variabilità spaziale e temporale delle precipitazioni. In particolare, la nuova classificazione spaziale consente di identificare in modo rapido ed efficiente il nucleo dell'evanto di pioggia, che determina fortemente la risposta idrologica del sistema.

I risultati evidenziano come un basso livello di performance del modello sia associato ad una scala di bacino piccola e come dipenda dall'interazione tra la pioggia e la scala del bacino idrografico. Per Little Hope, il più piccolo sotto-bacino di Little Sugar Creek, le risoluzioni di pioggia disponibili sono troppo grossolane per rappresentare correttamente la risposta idrologica del bacino. Solo il 7% dei casi esaminati per questo piccolo sottogruppo presenta un buon rendimento del modello (coefficiente di determinazione superiore a 0,9), nel caso in cui la risoluzione di pioggia piú elevata sia utilizzata come input del modello e misure di flusso locale siano usate come riferimento per l'analisi.

I fattori di scala consentono di prevedere il livello di prestazione del modello in base alla risoluzione di pioggia disponibile, date le caratteristiche geofisiche e climatologiche del bacino. Selezionato il livello di performance del modello che ci aspettiamo e date le scale di pioggia e di bacino, i fattori di scala consentono anche di derivare la risoluzione di pioggia minima necessaria. Questo aspetto è molto utile nelle applicazioni pratiche, ad esempio per selezionare la risoluzione di pioggia necessaria in un'area specifica.

Le soglie del fattore di scala α_2, sviluppate per Cranbrook, sono applicabili a Little Sugar per il 60% degli scenari investigati, con prestazioni del modello accettabili (coefficiente di determinazione superiore a 0,8), quando si utilizza come riferimento l'output ottenuto da precipitazioni a risoluzione più elevata, utilizzate come input del modello. Questa percentuale scende al 50% dei casi in cui le soglie per α_2 soddisfano prestazioni del modello accettabili, avendo come riferimento per l'analisi l'osservazione del flusso. Tuttavia, per alcuni eventi specifici, le prestazioni del modello sono particolarmente basse per i valori dei fattori di scala elevati. La maggior parte dei punti presenti con bassa performance che non soddisfano le soglie proposte (73%) presentano bassi valori di intermittenza (tra 4% e 20%), e il 43% di questi punti mostra anche un'intensità massima di pioggia elevata. Le caratteristiche degli eventi piovosi, come l'intermittenza o l'intensità massima, dovrebbero essere quindi incluse nella definizione dei fattori di scala.

1

Introduction

1.1. RESEARCH CONTEXT

Pluvial flooding in urban areas is one of the main weather-related problems of the last decades. It is due in particular to increase of urbanization, with people moving from rural areas to big cities. This effect is combined with the impact of climate change that is expected to lead to more intense rainfall events than in the past. The runoff generated by intense rainfall events in a densely urbanized environment is typically fast and characterized by high spatial variability and short response times. This can lead to a high frequency of occurrence of urban floods, with high levels of risk, due to the high vulnerability of urban areas. For these reasons, it is important to have a good understanding of runoff generation in urban basins. Hydrological response of urban catchments is particularly sensitive to rainfall variability and catchment characteristics at high space-time resolutions (Faures et al. 1995, Berne et al. 2004, Smith et al. 2012, Ochoa Rodriguez et al. 2015). For this reason, high resolution rainfall observations are required for hydrological response predictions.

New technologies were developed in recent decades to measure rainfall with high resolution and to improve forecasting of storm events. Particular attention was dedicated to weather radars (Thorndahl et al. 2017), instruments that enables to measure rainfall with high resolution. Compared to rain gauges, that are traditionally used to measure rainfall, weather radars provide an indirect measurement, that requires calibration to obtain rainfall estimates. On the other hand, they allow to obtain spatially distributed rainfall data. With knowledge of spatial and temporal rainfall variability, it is possible to classify the rainfall event scale, identifying which rainfall characteristics or combination of characteristics affects hydrological response. Rainfall spatial and temporal scales have been characterized in different ways in the literature (Lobligeois et al. 2014, Ochoa Rodriguez et al. 2015). However, further improvements need to be made in order to obtain a rainfall classification able to properly describe spatial and temporal scales of rainfall events.

Thanks to the recent increase of available geographical and topographical data, it has been possible to increase model resolution and to incorporate more detailed hydrological processes. Many studies addressed the implementation of high resolution hydrological models for small urbanized catchments. Several types of models with different representations of surface and subsurface processes have been developed for urban areas (Gires et al. 2012, Pina et al. 2016). These models present different approaches to the interactions between rainfall and catchment spatial and temporal variability. Lumped models consider the whole catchment as one single element, they use spatially averaged catchment characteristics as model input and do not take into account the spatial variability of rainfall. Semi-distributed models divide the surface in small subcatchmetns, each one behaving as a lumped basin. In this case, rainfall resolution can be captured, depending on whether model resolution is high enough to incorporate rainfall resolution. The last type of commonly used models is the fully distributed model, that divided the surface with a rectangular or triangular mesh. The mesh resolution is an important aspect to evaluate: a fine grid could lead to very long computational times, while a coarse grid could not be able to properly highlight the advantage of having high rainfall resolutions as input (Pina et al. 2016). Choosing an appropriate model type and model resolution in relation with the available rainfall resolution is an important element that needs deeper investigation.

Effects of catchment size and characteristics on hydrological response in urban areas have been partially investigated in previous studies. Relations between catchment size and rainfall resolution required to properly estimate the hydrological response have been proposed in the literature (Berne et al. 2004, Notaro et al. 2013, Ochoa Rodriguez et al. 2015). For small urban catchments (3 ha), Berne et al. (2004) suggested a minimum rainfall resolution of 1.5 km - 1 min, which could decrease to 3 km - 5 min for larger catchments (500 ha). The work presented by Ochoa Rodriguez et al. (2015) highlighted how required rainfall resolution is higher for small urban catchments. For very small urban catchments (smaller than 1 ha), 100 m spatial resolution is required. Slightly coarser rainfall resolution (500 m) can be used for catchments between 1 ha and 100 ha and for areas larger than 100 ha, rainfall observations at 1 km seem to be sufficient, as long as the temporal resolution is high (below 5 min).

Only few investigations, however, analysed the interactions between rainfall and catchment scales and the influence that they have on the hydrological response sensitivity. Further research needs to be done in order to determinate the influence that rainfall and catchment scales have on the hydrological response. Moreover, it is important to investigate and identify critical temporal and spatial scales of rainfall and catchment in order to define the minimum required rainfall resolution for a specific area.

From now on, the terms *sensitivity of hydrological response* or *hydrological response sensitivity* to different rainfall resolutions are equally used to describe the variability of hydrological response, represented by the runoff flow at the outlet of the catchment, when different spatial and temporal rainfall resolutions are used as input for the model. Runoff estimations obtained with different rainfall input resolutions are compared with the runoff estimation obtained using the highest rainfall resolution available, in order to evaluate how the response of the system varies using different rainfall inputs.

1.2. RESEARCH QUESTIONS

In this work, we aim to better understand and explain the complex interactions between rainfall and catchment spatial and temporal scale and their combined effects on the sensitivity of hydrological response to different rainfall resolutions. In particular we want to answer the following questions:

- How does small scale rainfall variability affect hydrological response in a highly urbanized area?
- How does model complexity affect sensitivity of model outcomes to rainfall variability?
- Can critical levels of rainfall resolutions be defined in relation to given catchment and storm scales?

Answering these questions will allow to fill in some of the gaps present in the literature and it will increase the knowledge of the hydrological response. In particular, rainfall and catchment characteristics that have a strong relevance for the hydrological response will be investigated, with the aim to identify the response sensitivity to different rainfall resolutions in space and time.

1.3. THESIS OUTLINE

The overall structure of this thesis consists of six chapters, including this introduction and a final concluding chapter.

Chapter 2 presents the state of the art of aspects of catchment and rainfall scales in hydrology, focusing on urban areas, where the variability at smaller scale is particularly relevant. After a definition of spatial and temporal catchment scales in urban hydrology, rainfall measurement techniques and rainfall variability are described, with special attention to the potential of weather radars, which allow to capture spatial and temporal rainfall variability. Urban hydrological processes are presented focusing on their variability in space and time. Model types and classifications are presented, analysing the different possible ways to model the spatial variability of a catchment. The importance of interaction between spatial and temporal aspects and between rainfall and catchment characteristics is shown, highlighting the need of further studies in this direction.

A new way to classify the rainfall variability in space and time, based on the identification of high intensity rainfall clusters, is presented in Chapter 3. Here the case study of Cranbrook (London, UK) is presented, with an analysis of the influence of rainfall spatial and temporal variability, catchment characteristics and model complexity on the sensitivity of hydrological response to different input resolutions. The effects of aggregation on rainfall peaks and hydrological response are investigated.

In Chapter 4, three dimensionless scale factors are presented, based on the analysis of the elements that strongly characterize the sensitivity of hydrological response. The proposed factors allow to identify the required rainfall resolution for rainfall and catchment with specific spatial and temporal variability. Scale factors can also be used to predict the level of performance of a model, given the rainfall resolution used as input for the system.

The applicability of the proposed scale factors to a larger scale and with different climatological characteristics is presented in Chapter 5. A different study case, the watershed of Little Sugar (Charlotte metropolitan area, USA) is investigated. A model-based analysis and an observation-based analysis are developed in order to take into account model calibration errors in the sensitivity analysis. Rainfall characteristics that could explain low performance of the scaling factors are investigated.

The last section, Chapter 6, summarizes the main conclusions derived from this work and highlights practical recommendations and directions for future research.

2

STATE OF THE ART

...fatti non foste a viver come bruti,
ma per seguir virtute e canoscenza.

Dante Alighieri, **Inferno XXVI**

In urban areas, hydrological processes are characterised by high variability in space and time, making them sensitive to small-scale temporal and spatial rainfall variability. Despite these efforts, interactions between rainfall variability, catchment heterogeneity and hydrological response remain poorly understood. This chapter presents a review of our current understanding of hydrological processes in urban environments as reported in the literature, focusing on their spatial and temporal variability aspects. Recent findings on the effects of rainfall variability on hydrological response were reviewed and gaps where knowledge needs to be further developed to improve our capability to predict urban hydrological response were identified.

This chapter is based on:
E. Cristiano, ten Veldhuis M.-c. & van de Giesen, N., *Spatial and temporal variability of rainfall and their effects on hydrological response in urban areas - a review*, Hydrology and Earth System Sciences **21(7)**, 3859-3878 (2017).

2.1. INTRODUCTION

The lack of sufficient information about spatial distribution of short-term rainfall has always been one of the most important sources of errors in urban runoff estimation (Niemczynowicz 1988). In the last decades considerable advances in quantitative estimation of distributed rainfall have been made, thanks to new technologies, in particular weather radars (Leijnse et al. 2007, van de Beek et al. 2010, Otto & Russchenberg 2011). These developments have been applied in urban hydrology researches (see Einfalt et al. (2004), Thorndahl et al. (2017) for a review). The hydrological response is sensitive to small-scale rainfall variability in both space and time (Faures et al. 1995, Emmanuel et al. 2012, Smith et al. 2012, Ochoa Rodriguez et al. 2015), due to a typically high degree of imperviousness and to a high spatial variability of urban land use.

Progress in rainfall estimation is accompanied by increasing availability of high resolution topographical data, especially digital terrain models and land-use distribution maps (Mayer 1999, Fonstad et al. 2013, Tokarczyk et al. 2015). High resolution topographical datasets have promoted development of more detailed and more complex numerical models for predicting flows (Gironás et al. 2010, Smith et al. 2013). However, model complexity and resolution need to be balanced with the availability and quality of rainfall input data and datasets for catchment representation (Morin et al. 2001, Rafieeinasab et al. 2015, Rico-Ramirez et al. 2015, Pina et al. 2016). This is particularly critical in small catchments, where flows are sensitive to variations at small space and time scales as a result of the fast hydrological response and the high catchment variability (Fabry et al. 1994, Singh 1997). Alterations of natural flows introduced by human interventions, especially artificial drainage networks, sewer pipe networks, detention and control facilities, such as reservoirs, pumps and weirs are additional elements to take into account for flow predictions. Recently, various authors investigated the sensitivity of spatial and temporal rainfall variability on the hydrological response for urban areas (Bruni et al. 2015, Ochoa Rodriguez et al. 2015, Rafieeinasab et al. 2015). Despite these efforts, many aspects of hydrological processes in urban areas remain poorly understood, especially in the interaction between rainfall and runoff.

It is timely to review recent progress in understanding of interactions between rainfall spatial and temporal resolution, variability of catchment properties and their representation in hydrological models. Section 2.2 is dedicated to definitions of spatial and temporal scales and catchments in hydrology and methods to characterise them. Section 2.3 focuses on rainfall, analysing the most used rainfall measurement techniques, their capability to accurately measure small-scale spatial and temporal variability, with particular attention to applications in urban areas. Hydrological processes are described in Section 2.4, highlighting their variability and characteristics in urban areas. Thereafter, the state of the art of hydrological models, as well as their strengths and limitations to account for spatial and temporal variability, are discussed. Section 2.6 presents recent approaches to understand the effect of rainfall variability in space and time on hydrological response. In Section 2.7, main knowledge gaps are identified with respect to accurate prediction of urban hydrological response in relation to spatial and temporal variability of rainfall and catchment properties in urban areas.

2.2. SCALES IN URBAN HYDROLOGY

2.2.1. SPATIAL AND TEMPORAL SCALE DEFINITIONS

Hydrological processes occur over a wide range of scales in space and time, varying from 1 mm to 10000 km in space and from seconds up to 100 years in time. A scale is defined here as the characteristic region in space or period in time at which processes take place or the resolution in space or time at which processes are best measured (Salvadore et al. 2015).

Several authors have classified hydrological process scales and variability, focusing in particular on the interaction between rainfall and the other hydrological processes (Blöschl & Sivapalan 1995, Bergstrom & Graham 1998). Blöschl & Sivapalan (1995) presented a graphical representation of spatial and temporal variability of the main hydrological processes on a logarithmic plane. The plot has been updated by other authors, each focusing on Fispecific aspects. For example, Salvadore et al. (2015) analysed phenomena related to urban processes, focusing small spatial scale, while Van Loon (2015), added scales of some hydrological problems, such as flood and drought. Figure 2.1 presents an updated version of the plot that integrates the information contributed by Berndtsson & Niemczynowicz (1986), Blöschl & Sivapalan (1995), Stahl & Hisdal (2004) and Salvadore et al. (2015). Figure 2.1 shows that in urban hydrology attention is mainly focused on small scales. Characteristic processes, such as storm drainage, infiltration and evaporation vary at a small temporal and spatial scale, from seconds to hours and from centimetres to hundreds of meters. Many processes are driven by rainfall, that varies over a wide range of scales.

Blöschl & Sivapalan (1995) highlighted the importance of making a distinction between two types of scales: the "process scale", i.e. the proper scale of the considered phenomenon, and the "observation scale", related to the measurement and depending on techniques and instruments used. Under the best scenario, process and observation scale should match, but this is not always the case, and transformations based on downscaling and up-scaling techniques (Fig. 2.2) might be necessary to obtain the required match between scales. These techniques are discussed in section 2.2.2.

2.2.2. RAINFALL DOWNSCALING

The term downscaling usually refers to methods used to take information known at large scale and make predictions at small scale. There are two main downscaling approaches: dynamic or physically based and statistical methods (Xu 1999). Dynamic downscaling approaches solve the process-based physics dynamics of the system. In statistical downscaling, a statistical relationship is defined between local variables and large scale prediction and this relationship is applied to simulate local variables (Xu 1999). Dynamical downscaling is widely used in climate modelling and numerical weather prediction, while statistical models are often used in hydrometeorology, for example rainfall downscaling. Dynamic downscaling models have the advantage of being physically-based, but they require a lot of computational power compared to statistical downscaling models. Statistical approaches require historical data and knowledge of local conditions (Xu 1999).

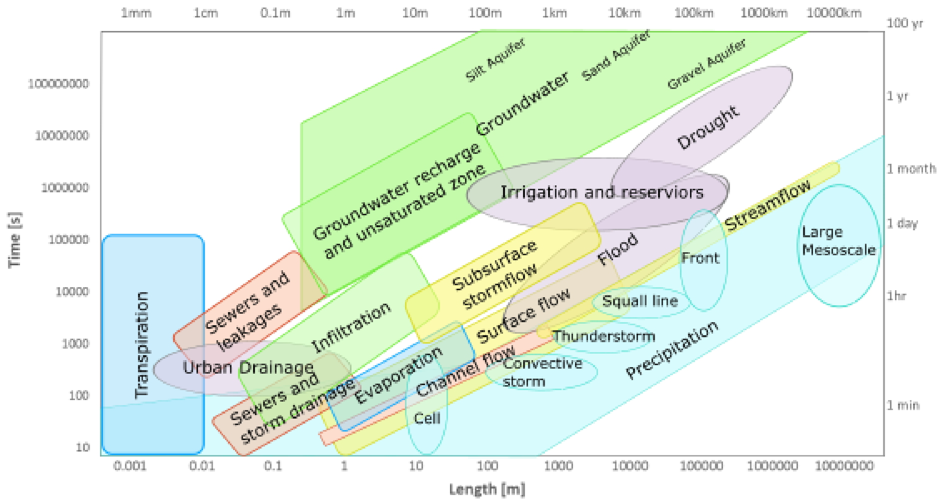


Figure 2.1: Spatial and temporal scale variability of hydrological processes. Figure adapted from Berndtsson & Niemczynowicz (1986), Blöschl & Sivapalan (1995), Stahl & Hisdal (2004) and Salvadore et al. (2015). Colours represent different groups of physical processes: blue for processes related to the atmosphere, yellow for surface processes, green for underground processes, red highlights typical urban processes and grey indicates problems hydrological processes can pose to society.

Ferraris et al. (2003) presented a review of three common stochastic downscaling models, mainly used for spatial rainfall downscaling: multifractal cascades, autoregressive processes and point process models based on the presence of individual cells. The first were introduced in the 1970s and are widely used to reproduce the spatial and temporal variability (see Schertzer & Lovejoy (2011) for a review). Autoregressive methods, also nowadays often referred to as "rainfall generator models", are used to generate multidimensional random fields while preserving the rainfall spatial autocorrelation, for natural (Paschalis et al. 2013, Peleg & Morin 2014, Niemi et al. 2016) and urban (Sørup et al. 2015) areas. Point-process models are used when the spatial structure of intense rainfall is defined by convective rainfall cells (see McRobie et al. (2013) for an example). They incorporate local information and require a more detailed storm cell identification.

Statistical downscaling and upscaling approaches are reported in the literature for a wide variety of variables (Rummukainen 1997, Deidda 2000, Ferraris et al. 2003, Gires et al. 2012, Wang et al. 2015, Muthusamy et al. 2017) and techniques such as regression methods, weather pattern-based approaches and stochastic rainfall generators (see Wilby & Wigley (1997), Wilks & Wilby (1999) for a review). Some recent studies about downscaling and upscaling focus mainly on urban areas (Gires et al. 2012, Wang et al. 2015,b, Muthusamy et al. 2017): Wang et al. (2015b), for example, presented a gauge-based radar rainfall adjustment methods sensitive to singularities, characteristic of small scale.

The importance of using downscaling methods was discussed by Fowler et al. (2007),

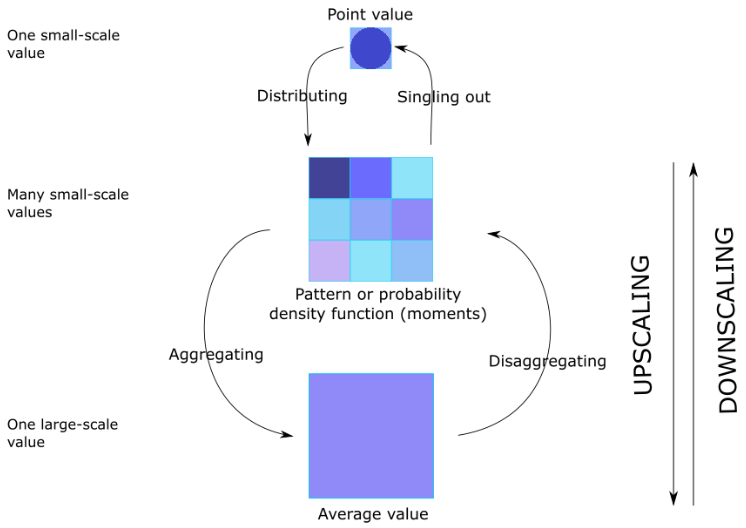


Figure 2.2: Downscaling and upscaling processes.Figure modified from Blöschl & Sivapalan (1995)

in a work where they investigated what can be learned from downscaling method comparison studies, what new methods can be used together with downscaling to assess uncertainties in hydrological response and how downscaling methods can be better utilized within the hydrological community. They highlighted that the importance given to the applied research is still too little, and manager and stakeholders should be more aware of uncertainties within the modelling system.

2.2.3. METHODS TO CHARACTERIZE HYDROLOGICAL PROCESS SCALES

SPATIAL VARIABILITY OF BASIN CHARACTERISTICS

Slope, degree of imperviousness, soil properties and many other catchment characteristics are variable in space and time and this variability affects the hydrological response (Singh 1997). This is especially the case of urban areas, where spatial variability and temporal changes in land-use are typically high.

Julien & Moglen (1990) gave a first definition of the catchment length scale L_s as part of a theoretical framework applied to a natural catchment, where they analysed 8400 dimensionless hydrographs obtained from one-dimensional finite element models under spatially varied input. Length scale was presented as function of rainfall duration d, spatially averaged rainfall intensity i, average slope s_0 and average roughness n:

$$L_s = \frac{d^{\frac{5}{6}} s_0^{\frac{1}{2}} i^{\frac{2}{3}}}{n} \tag{2.1}$$

Table 2.1: Time scale parameters

Characteristic	Reference	Description
Time of concentration t_c	Singh (1997) Gericke & Smithers (2014)	The time that a drop that falls on the most remote part of the basin needs to reach the outlet
Time of equilibrium t_e	Ogden & Julien (1995) Ogden & Dawdy (2003) van de Giesen et al. (2005)	Minimum time needed for a given stationary uniform rainfall to persist until equilibrium runoff flow is reached
Lag time t_{lag}	Berne et al. (2004) Marchi et al. (2010) Gericke & Smithers (2014)	The time difference between the gravity centre of the hyetograph of mean rainfall and the gravity centre of the generated hydrograph
Response time scale T_s	Morin et al. (2001) Morin et al. (2002) Morin et al. (2003) Shamir et al. (2005)	Time scale at which the pattern of time averaged radar hyetograph is most similar to the pattern of the measured hydrograph at the outlet of the basin

In urban catchments, the concept of catchment length, defined as the squared root of the (sub)catchment or runoff area, has been used (Bruni et al. 2015, Ochoa-Rodriguez et al. 2015b). Additionally, Bruni et al. (2015) introduced the sewer length or inter-pipes sewer distance, as the ratio between the catchment area and the total length of the sewer, to characterize the spatial scale of sewer networks. Ogden et al. (2011) used the width function, defined as the number of channel segments at a specific distance from the outlet, to represent the spatial variability of the drainage network. This parameter describes the network geomorphology by counting all stream links located at the same distance from the outlet, but it does not give an accurate description of the spatial variability of hydrodynamic parameters.

TIME SCALE CHARACTERISTICS

In this section, we present a brief overview of time scales reported in the literature and discuss approaches to estimate characteristic time scales that have been specifically developed for urban areas. A summary of time scale characteristics is presented in Table 2.1.

The first method to investigate the hydrological response is the rational method, presented more than a century ago by (Kuichling 1889) for urban areas. This method was later adapted for rural areas. The rational method requires the estimation of the time of concentration in order to define the runoff volume.

Time of concentration t_c is one of the most common hydrological characteristic time scales and it is defined as the time that a drop that falls on the most remote part of the basin needs to reach the basin outlet (Singh 1997, Musy & Higy 2010). Several equations to estimate this parameter are available in the literature for natural (Gericke & Smithers 2014) and urban (McCuen et al. 1984) catchments. The time of concentration is difficult to measure, because it assumes that initial losses are already satisfied and the rainfall event intensity is constant for a period at least as long as the time of concentration. Different theoretical definitions have been developed in order to estimate the time of concentration as function of basin length, slope and other characteristics (see for some examples Singh (1976), Morin et al. (2001), USDA (2010), Gericke & Smithers (2014)).

Due to difficulties related to the estimation of time of concentration, Larson (1965) introduced the time of virtual equilibrium t_{ve}, defined as the time until response is 97% of runoff supply.

When a given rainfall rate persists on a region for enough time to reach the equilibrium, this time is called time to equilibrium t_e (Ogden & Julien 1995, Ogden & Dawdy 2003, van de Giesen et al. 2005). Time of equilibrium for a turbulent flow on a rectangular runoff plane given rainfall intensity i, with given roughness n, length L_p and slope s_0 can be written as (Ogden & Julien 1995):

$$t_e = [\frac{nL_p}{s_0^{1/2} i^{2/3}}]^{3/5} \tag{2.2}$$

Another commonly used hydrological characteristic time scale or response time is the lag time t_{lag}. It represents the delay between rainfall and runoff generation. t_{lag} is defined as the distance between the hyetograph and hydrograph center of mass of (Berne et al. 2004), or between the time of rainfall peak and time of flow peak (Marchi et al. 2010, Yao et al. 2016). t_{lag} can be considered characteristic of a basin, and is dependent on drainage area, imperviousness and slope (Morin et al. 2001, Berne et al. 2004, Yao et al. 2016). Berne et al. (2004), including the results of Schaake & Knapp (1967) and Morin et al. (2001), defined a relation between the dimension of the catchment area A (in ha) and the lag time t_{lag} (in min): $t_{lag} = 3A^{0.3}$ for urban areas. Empirical relations between t_{lag} and t_c are presented in the literature (USDA 2010, Gericke & Smithers 2014).

Another characteristic time scale is the 'response time scale' T_s, presented for the first time by Morin et al. (2001). It is defined as the time scale at which the pattern of the time averaged and basin averaged radar rainfall hyetograph is most similar to the pattern of the measured hydrograph at the outlet of the basin. This definition was updated by Morin et al. (2002), that used an objective and automatic algorithm to analyse the smoothness of the hyetograph and hydrograph instead of the general behaviour, and by Shamir et al. (2005), who related the number of peaks with the total duration of the rising and declining limbs of hyetographs a and hydrographs.

In urban areas, where most of the surface is directly connected to the drainage system, concentration time is given by the time the rainfall needs to enter the sewer system and the travel time through the sewer system.

2.3. RAINFALL MEASUREMENT AND VARIABILITY IN URBAN REGIONS

Rainfall is an important driver for many hydrological processes and represents one of the main sources of uncertainty in studying hydrological response (Niemczynowicz 1988, Einfalt et al. 2004, Thorndahl et al. 2017, Rico-Ramirez et al. 2015).

Urban areas affect the local hydrological system, not only by increasing the imperviousness degree of the soil, but also by changing rainfall generation and intensity patterns. Several studies show that increase in heat and pollution produced by human activities and changes in surface roughness influence rainfall and wind generation (Huff & Changno 1973, Shepherd et al. 2002, Givati & Rosenfeld 2004, Shepherd 2006, Smith et al. 2012, Daniels et al. 2015, Salvadore et al. 2015). This phenomenon is not deeply investigated in this work, but it is an important aspect to consider.

In this section instruments and technologies for rainfall measurement are described, pointing out their opportunities and limitations for measuring spatial and temporal variability in urban environments. Subsequently, methods to characterise rainfall events according to their space and time variability are described.

2.3.1. RAINFALL ESTIMATION

Rain gauges were the first instrument used to measure rainfall and are still commonly used, because they are relatively low in cost and easy to install (WMO 2008).

Afterwards, weather radars were introduced to estimate the rainfall spatial distribution. These instruments allow to get measurements of rainfall spatially distributed over the area, instead of a point measurement as in the case of rain gauges. Rainfall data obtained from weather radars are used to study the hydrological response in natural watersheds and urban catchments (Einfalt et al. 2004, Berne et al. 2004, Sangati et al. 2009, Smith et al. 2013, Ochoa Rodriguez et al. 2015, Thorndahl et al. 2017) often combined with rainfall measurement from rain gauge networks (Winchell et al. 1998, Smith et al. 2005, Segond et al. 2007, Smith et al. 2012), as well as to improve short-term weather forecasting and nowcasting (Montanari & Grossi 2008, Liguori & Rico-Ramirez 2013, Dai et al. 2015, Foresti et al. 2016, Berenguer et al. 2005).

More recently, commercial microwave links have been used to estimate the spatial and temporal rainfall variability (Leijnse et al. 2007, Fencl et al. 2015, 2017). Rainfall estimates are obtained from the attenuation of the signal caused by rain along microwave link paths. This approach can be particularly useful in cities that are not well equipped with rain gauges or radars, but where the commercial cellular communication network is typically dense (Leijnse et al. 2007).

RAIN GAUGES NETWORKS

Several types of rain gauges have been developed, such as weighing gauges, tipping bucket gauges and pluviographs (Lanza & Stagi 2009, Lanza & Vuerich 2009). They are able to constantly register accumulation of rainfall volume over time, thus providing a measurement of temporal variability of rainfall intensity. Rain gauge measurements are sensitive to wind exposure and the error caused by wind field above the rain gauge is 2 – 10% for rainfall and up to 50% for solid precipitations (WMO 2008). Other errors can be due to tipping bucket losses during the rotation, to wetting losses on the internal walls of the collector, to evaporation (especially in hot climates) or water splashing into and out of the collector (WMO 2008). The main disadvantage of rain gauges is that the obtained data are point measurements and, due to the high spatial variability of rainfall events, measurements from a single rain gauges are often not representative of a larger area. Rainfall fields, however, present a spatial organization and, by interpolating data from a rain gauge networks, it is possible to obtain distributed rainfall fields (Villarini et al. 2008, Muthusamy et al. 2017). Uncertainty induced by interpolation strongly depends on the density of the rain gauge network and on homogeneity of the rainfall field (Wang et al. 2015).

In urban areas, rainfall measurements with rain gauges present specific challenges associated with microclimatic effects introduced by the building envelope and obstacles. WMO (2008) recommended minimum distances between rain gauges and obstacles of one to two times the height of the nearest obstacle, a condition that is hard to fulfil in densely built areas. A second problem is introduced by hard surfaces, that may cause water splashing into the gauges, if it is not placed at an elevation of at least 1.2 m (WMO 2008). Rain gauges in cities are often mounted on roofs for reasons of space availability and safety from vandalism. This means they are affected by the wind envelope of the building, unless they are elevated to a sufficient height above the building.

Rain gauge measurement error can be 30% or more depending on the type of instrument used for the measurement and local conditions (van de Ven 1990, WMO 2008).

WEATHER RADARS

In the last decades, weather radars have been increasingly used to measure rainfall (Niemczynowicz 1999, Krajewski & Smith 2005, Otto & Russchenberg 2011, Berne & Krajewski 2013)). Radars transmit pulses of microwave signals and measure the power of the signal reflected back by raindrops, snowflakes and hailstones (backscatter). Rainfall rate R [L T^{-1}] is estimated using the reflectivity Z [L^6 L^{-3}] measured from the radar through a power law:

$$R = aZ^b \tag{2.3}$$

where a and b depend on type of precipitation, raindrop distribution, climate characteristics and spatial and temporal scales considered (Marshall & Palmer 1948, van de Beek et al. 2010, Smith et al. 2013). Weather radars present different wavelengths λ, frequencies v and sizes of the antenna l. Characteristics of commonly used weather radars are reported in Table 2.2. X-band radars can be beneficial for urban areas: they are low cost and they can be mounted on existing buildings and measure rainfall closer to ground at higher resolution than national weather radar networks (Einfalt et al. 2004). Polarimetric weather radars transmit signals polarised in different directions (Otto & Russchenberg 2011), enabling it to distinguish between horizontal and vertical dimension, thus between rain drops and snowflakes as well as between smaller or larger oblate rain drops. A specific strength of polarimetric radars is the use of differential phase K_{dp}, which allows to correct signal attenuation thus solving an important problem generally associated with X-band radars (Otto & Russchenberg 2011, Ochoa Rodriguez et al. 2015, Thorndahl et al. 2017).

Table 2.2: Weather radar characteristics

	λ cm	ν GHz	l m
S-band	8-15	2-4	6-10
C-band	4-8	4-8	3-5
X-band	2.5-4	8-12	1-2

OPPORTUNITIES AND LIMITATIONS OF WEATHER RADARS

Berne & Krajewski (2013) presented a comprehensive analysis of the advantages, limitations and challenges in rainfall estimation using weather radars. One of the main problems is that an indirect relation is used (Eq. (2.3)) to estimate rainfall. Rainfall measurements have to be adjusted based on rain gauges and disdrometers. Various techniques have been studied to calibrate radars (Wood et al. 2000), to combine radar rainfall measurements with rain gauge data for ground truthing (Cole & Moore 2008, Smith et al. 2012, Wang et al. 2013, Gires et al. 2014, Nielsen et al. 2014, Wang et al. 2015) and to define the uncertainty related to radar-rainfall estimation (Ciach & Krajewski 1999, Quirmbach & Schultz 2016, Villarini et al. 2008, Mandapaka et al. 2009, Peleg et al. 2013, Villarini et al. 2014). These studies show that in most of the cases, radar measurements underestimate the rainfall compared to rain gauge measurements (Smith et al. 2012, Overeem et al. 2009a, Overeem & Buishand 2009b, van de Beek et al. 2010).

Another downsides of radars is their installation at high locations to have a clear view without obstacles, while rainfall intensities can change before reaching the ground (Smith et al. 2012). Moreover, radar measurements need to be combined with a rain drop size distribution to obtain an accurate rainfall estimation. Berne & Krajewski (2013) pointed out additional aspects that have to be taken into account like, e.g., management and storage of the high quantity of data that are measured, possibility to use the weather radars to estimate snowfall and the uncertainty related to it, and problems related to rainfall measurement in mountain areas.

Rain gauge measurements in urban areas tend to be prone to errors due to microclimatic effects introduced by the building envelope. In this context, the use of weather radar could represent a big improvement to obtain a more accurate rainfall information for studying hydrological response.

A promising application of radar is their combination with nowcasting models to obtain short-term rainfall forecasts. Liguori & Rico-Ramirez (2013) presented a review of different nowcasting models, that benefit from radar data. This work focused in particular on a hybrid model, able to merge the benefits of radar nowcasting and numerical weather prediction models. Radar data can provide an accurate short term forecast and recent studies have presented nowcasting systems able to reduce errors in rainfall estimation (e. g. Berenguer et al. (2005), Foresti et al. (2016)).

2.3.2. Characterising rainfall events according to their spatial and temporal scale

Rainfall events are characterized by several elements, such as duration, intensity, velocity and their spatial and temporal variability, and many possible classifications are presented in the literature. Some of the most used examples of rainfall classification considering the rainfall variability, are described in this section.

Characterizations and classifications of intense rainfall events have been proposed by various authors, combining rain gauges and radar rainfall data. In particular, weather radars are used as main tools to analyse rainfall spatial and temporal scale in urban areas. An example of characterisation of rainfall structure was given by Smith et al. (1994), who presented an empirical analysis of four extreme rainstorms in the Southern Plains (U.S.), using data from two networks of more than 200 rain gauges and from a weather radar. They defined *major rainfall event* as storms for which 25 mm of rain covered an area larger than 12500 km^2. Thorndahl et al. (2014) presented a storm catalogue of heavy rainfall, over a study area of 73500 km^2 in southern Wisconsin, and key elements of storm evolution that control the scale. The catalogue contains the 50 largest rainfall events recorded during a 16 year period by WSR-88D radar with spatial and temporal resolution of 1x1 km^2 and 15 min respectively. Over the 50 events, there is 0.60 probability that rainfall exceeds 25 mm of daily accumulation in a 1 km^2 pixel and 0.14 probability of exceeding 100 mm. Results showed that there is a clear relation between the characteristic length and time scale of the events. The length scale increased with time scale: a length scale of 35 ± 20 km was found for a time step of 15 minutes, up to 160 ± 25 km for a 12 hour aggregation time.

2.3.3. Rainfall variability at the urban scale

Rainfall events are often described and classified considering they variability in space and time. Spatial variability can be defined, following Peleg et al. (2017), as "the variability derived from having multiple spatially distributed rainfall fields for a given point in time". Peleg et al. (2017) introduced also the definition of climatological variability as the variability obtained from multiple climate trajectories that produce different storm distributions and rainfall intensities in time.

Studying rainfall variability at the urban scale, Emmanuel et al. (2012) classified 24 rain periods, recorded by the weather radar located in Treillieres (France), with a spatial and temporal resolution of $250X250$ m^2 and 5 min respectively. They classified the events into four groups, based on variogram analysis: light rain period, shower periods, storms organized into rain bands and unorganized storms. These groups are defined considering the decorrelation distance (and decorrelation time), defined as distance (and time) from which two points show uncorrelated statistical behaviour, and it is obtained as the range of the climatological variogram (Emmanuel et al. 2012). The first group, characterized by light rainfall events, presented very high decorrelation distance and time (17 km and 15 min) compared to the second group, with a decorrelation distance and time of 5 km and a decorrelation time of 5 min. The last two groups presented a double structure, where small and intense clusters, with low decorrelation distance and time (less than 5 km and 5 min) are located, in a random or organized way, inside areas with a lower variability (decorrelation of 15 km and 15 min).

Jensen & Pedersen (2005) presented a study about variability in accumulated rainfall within a single radar pixel of 500x500 m^2, comparing it with 9 rain gauges located in the same area. The results showed a variation of up to 100% at a maximum distance of about 150 m, due to the rainfall spatial variability. This study suggested that a huge quantity of rain gauges is needed to have a powerful rain gauge network capable of representing small scale variability. An alternative solution is to consider the variance reduction factor method, a numerical method to represent the uncertainty from averaging a number of rain gauges per pixel, taking into account their spatial distribution and the correlation between them. The variance reduction factor method was introduced for the first time by Rodriguez-Iturbe & Mejıa (1974) and lately applied in various studies (Krajewski et al. 2000, Villarini et al. 2008, Peleg et al. 2013).

Gires et al. (2014) focused on the gap between rain gauges and radar spatial scale, considering that a rain gauge usually collects rainfall over 20 cm of surface and the spatial resolution of most used radars is of 1x1 km^2. They evaluate the impact of small scale rainfall variability using a Universal Multifractal downscaling method. The downscaling process was validated with a dense rain gauge and disdrometer network, with 16 instruments located in 1x1 km^2. They showed two effects of small scale rainfall variability that are often not taken into account: high rainfall variability occurred below 1 km^2 spatial scale and the random position of the point measurement within a pixel influenced measured rainfall events. Similar results are confirmed by Peleg et al. (2016), who studied the spatial variability of extreme rainfall at radar subpixel scale. Comparing a radar pixel of 1 x 1 km^2 with high resolution rainfall data, obtained by applying the stochastic rainfall generator STREAP (Paschalis et al. 2013) to simulate rain fields, this study highlights that subpixel variability is high and increases with increasing of return period and with shorter duration.

In Table 2.3 four types of rainfall events are presented with their characterization and typical spatial and temporal decorrelation lengths, based on van de Beek et al. (2010), Emmanuel et al. (2012), Smith et al. (1994). Considering that the minimal rainfall measurement resolution required for urban hydrological modelling is 0.4 the decorrelation length (Julien & Moglen 1990, Berne et al. 2004, Ochoa Rodriguez et al. 2015), operational radars are not able to satisfy this requirement.

2.4. HYDROLOGICAL PROCESSES

In this section, general characteristics and parametrisations of hydrological processes are presented, highlighting their spatial and temporal variability and characteristics specific to urban environments.

2.4.1. PRECIPITATION LOSSES

INFILTRATION, INTERCEPTION AND STORAGE

The term infiltration is usually used to describe the physical processes by which rain enters the soil (Horton 1933). Different equations and models have been proposed to describe infiltration. The most commonly used is Richards equation (Richards 1931), which represents this phenomenon using a partial differential equation with nonlinear coefficients.

Table 2.3: Characterization of rainfall events. Spatial and temporal scales and rainfall uncertainty estimation are derived from van de Beek et al. (2010), Smith et al. (1994) and Emmanuel et al. (2012)

	Intensity	Spatial Range	Temporal Range	Radar Estimation
Light rainfall	$1mmh^{-1}$	$17km$	$15min$	Underestimation rainfall values often below the threshold ($0.17mmh^{-1}$)
Convective Cells	short and intense from $25mm$	$5km$	$5min$	Overestimation
Organized Stratiform	up to $17mmh^{-1}$	$< 5km$	$< 5min$	Underestimation, good representation of the hyetograph
Unorganized Stratiform	high intensity core + low intensity areas	$15km$	$15min$	Underestimation of the peaks, good representation of the hyetograph

Another possibility to estimate the infiltration capacity is given by the empirical equation presented by Horton (1939). In Horton's equation hydraulic conductivity and diffusivity are constant and do not depend on water content or on depth.

If water cannot infiltrate, as is the case in impervious areas, it can be stored in local depressions, where it does not contribute to runoff flow. This is the case of local depressions on streets or flat roofs, where water accumulates until the storage capacity is reached. Before reaching the ground, rainfall can be intercepted by vegetation cover or buildings. Interception can constitute up to 20% of rainfall at the start of a rainfall event (Mansell 2003), and decreases quickly to zero, once surfaces are wetted.

During the process of transformation of rainfall in runoff, part of the water is lost due to several phenomena, such as infiltration, storage or evaporation. Ragab et al. (2003) presented an experimental study of water fluxes in a residential area, in which they estimated infiltration and evaporation in urban areas, showing that the assumption that all rainfall becomes runoff is not correct and that it leads to an overestimation of runoff. Ramier et al. (2011) studied the hydrological behaviour of urban streets over a 38-month period to estimate runoff losses and to better define rainfall runoff transformations. They estimated losses due to evaporation and infiltration inside the road structure between 30 and 40% of the total rainfall.

Spatial scale of precipitation losses is strongly influenced by land cover variation. In urban areas, land cover variability typically occurs at a spatial scale of 100 m to 1000 m. Time scale is associated with local storage accumulation volume, sorptivity and hydraulic conductivity, which in turn depend on soil type and soil compaction.

GROUNDWATER RECHARGE AND SUBSURFACE PROCESSES IN URBAN AREAS

Groundwater recharge mechanisms change due to human activities and urbanization, both in terms of volume and quality of the water. The increase of imperviousness of land cover leads to a decrease in infiltration of rainfall into soil, reducing direct recharge to groundwater. The presence of leakage from drinking water and sewer networks can increase infiltration to groundwater and amount of contaminants that is spread from the sewer system into the soil (Salvadore et al. 2015).

Although it is well known that not all rainfall turns into runoff (Boogaard et al. 2013, Lucke et al. 2014), it is common to consider the losses from impervious areas so small that they can be assumed negligible compared to the total runoff volume (Ragab et al. 2003, Ramier et al. 2011). Ragab et al. (2003) tried to emphasise the importance of accounting for infiltration in the urban water balance, and found that infiltration through the road surface can constitute between 6 and 9% of annual rainfall. Due to high spatial variability of infiltration, representative measurements are difficult to obtain and require a large amount of point-scale measurements (Boogaard et al. 2013, Lucke et al. 2014).

Several types of pervious pavements are used in urban areas. They can generally be divided into monolithic and modular structures. Monolithic structures consist of a combination of impermeable blocks of concrete and open joints or apertures that allow water to infiltrate. In modular structures, gaps between two blocks are not filled with sand, as with conventional pavements, but with 2 – 5 mm of bedding aggregate, that facilitate infiltration (Boogaard et al. 2013). Following European standards, minimum infiltration capacity for permeable pavements is 270 $l\,s^{-1}\,ha^{-1}$, equal to 97.2 mm h^{-1} (OCW 2008).

Pervious areas in cities can effectively act as semi–impervious areas, because within the soil column there is a shallow layer that presents a low hydraulic conductivity at saturation, caused by soil compaction during the building process. Smith et al. (2015) studied the influence of this phenomenon on peak runoff flow by applying 21 storm events on a physically based, minimally calibrated model of the Dead Run urban area (U.S.) with and without the compacted soil layer. Results showed that the compacted soil layer reduced infiltration by 70 – 90% and increased peak discharge by 6.8%

2.4.2. SURFACE RUNOFF

When rainfall intensity exceeds infiltration capacity of the soil, water starts to accumulate on the surface and flows following the slope of the ground. This process is generally called Hortonian runoff (Horton 1933) or infiltration capacity excess flow. It is usually contrasted with saturation excess flow, or Dunne flow (Dunne 1978), that occurs when the soil is saturated and rainfall can no longer be stored (van de Giesen et al. 2011).

In urban areas, runoff is generated when the surface is impervious and water can not infiltrate, or when infiltration capacity is exceeded by rainfall intensity. Water flows over the surface and can reach natural drainage channels or be intercepted by the drainage network through gullies and manholes. If the drainage network capacity is exceeded, the system become pressurized, and water starts to flow out from gullies, increasing runoff on the street (Ochoa-Rodriguez et al. 2015b).

It is important to pay attention to some elements that characterize the runoff in urban environments: sharp corners or obstacles can, for example, deviate the flow and introduce additional hydraulic losses. Interactions between surface flow and subsurface sewer systems through sewer inlets and gully pots are hydraulically complex and their influence on overland and in-sewer flows remains poorly understood. Runoff flows are often characterised by very small water depths that are often alternated with dry surfaces, especially when rainfall intensities vary strongly in space and time.

2.4.3. IMPACT OF LAND COVER ON OVERLAND FLOW IN URBAN AREAS

In urban areas, the land cover, represented by an alternation of impervious surfaces, such as roads and roofs, and small pervious areas, such as gardens, vegetation and parks, shows a high variability in space.

The impact of increase of imperviousness on hydrological response was studied by Cheng (2002), who analysed the effects of urban development in Wu-Tu (Taiwan's catchment) considering 28 rainfall events (1966-1997). Results showed that response peak increased by 27% and the time to peak decreased from 9.8 to 5.9 hours, due to an increase of imperviousness from 4.78% to 11.03%.

In a similar study, Smith et al. (2002) analysed the effects of imperviousness on flood peak in the Charlotte metropolitan region (U.S.), analysing a 74 year discharge record. Results showed that different land covers were associated with large differences in timing and magnitude of flood peak, while there were not significant differences in the total runoff volume. Hortonian runoff was the dominant runoff mechanism. Antecedent soil moisture played an important role in this watershed, even in the most urbanized catchment.

The influence of antecedent soil moisture is, however, not always so evident. Smith et al. (2013) showed that in nine watersheds, located in the Baltimore metropolitan area, the antecedent soil moisture, defined as 5 day antecedent rainfall, seemed not to affect the hydrological response. Introduction of stormwater management infrastructure played an important role in reducing flood peaks and increasing runoff ratios. Results showed that rainfall variability may have important effects on spatial and temporal variation in flood hazard in this area.

Analysing the effects of a moderate extreme and an extreme rainstorm on the same area presented by Smith et al. (2013), Ogden et al. (2011) highlighted the importance of changes in imperviousness on flood peaks. They found that for extreme rainfall event, imperviousness had a small impact on runoff volume and runoff generation efficiency.

2.4.4. EVAPORATION

Evaporation plays an important role in the hydrological cycle: in forested catchment around 60 – 95% of total annual rainfall evaporates or is absorbed by the vegetation (Fletcher et al. 2013). In an urban catchment, evaporation is drastically reduced (Oke 2006, Fletcher et al. 2013, Salvadore et al. 2015). Evaporation is often neglected in analysis of fast and intense rainfall events (Cui & Li 2006): the order of magnitude of evaporation is very small compared to the total amount of rainfall. Some studies have shown that evaporation is not always negligible in urban areas and can constitute up to 40% of the annual total losses (Grimmond & Oke 1991, Salvadore et al. 2015).

In their experimental study, Ragab et al. (2003) showed that evaporation represents 21 – 24% of annual rainfall, with more evaporation taking place during summer than winter. It is particularly important to have measurements with high resolution because a coarse spatial description can hide heterogeneous land covers and consequently, heterogeneous evaporation losses (Salvadore et al. 2015).

Evaporation measurements in urban areas are one of the weak points of the water balance (van de Ven 1990) and they present many problems and challenges (Oke 2006). It is quite hard in fact to find a site, representative of the area, far enough from obstacles and not unduly shaded. Errors in estimation of annual evaporation in urban areas may still be higher than 20% (van de Ven 1990).

Different techniques and approaches have been developed to measure and estimate the impact of evaporation, from the standard lysimeter to the use of remote sensing (Nouri et al. 2013), to the combined used of remote sensing and ground measurements (Hart et al. 2009). Different models to estimate evaporation in urban areas have been proposed (Marasco et al. 2015, Litvak et al. 2017). Litvak et al. (2017) estimated evaporation in the urban area of Los Angeles, as combination of empirical models of turfgrass evaporation and tree transpiration derived from in situ measurements. Evaporation from non vegetated areas appears to be negligible compared with the vegetation, and turfgrass was responsible for 70% of evaporation from vegetated areas.

2.4.5. FLOW IN SEWER SYSTEMS

In urban areas, part of the surface runoff enters in the sewer system through gully inlets, depending on the capacity of these elements, on their maintenance (Leitão et al. 2016) and the sewer system itself.

Stormwater flow in sewer systems is highly non-uniform and unsteady, it can be considered as one dimensional, assuming that depth and velocity vary only in the longitudinal direction of the channel. Flow in sewer pipes is usually free-surface, but during intense rainfall events the system can become full and temporarily behave as a pressurised system, a phenomenon called surcharge. In particular conditions, as for example in flat catchments, inversion of the flow direction in pipes can occur during filling and emptying of the system. The most common form to model flow in sewer pipes is based on a one-dimensional form of the de Sain-Venant equations.

Sewer system density influences runoff generation (Ogden et al. 2011, Yang et al. 2016): a dense pipe network can, in fact, reduce the runoff generation, increasing the storage capacity of the system (Yang et al. 2016). Ogden et al. (2011)presented a study about the importance of drainage density on flood runoff in urban catchments. Defining the drainage density as channel length per total catchment area, they studied the hydrological response of the same basin modelled with drainage density that varied from 0.4 km km^{-2} and 3.9 km km^{-2}. Results showed a significant increase in peak discharge and runoff volume for drainage density between 0.4 km km^{-2} and 0.9 km km^{-2}, while for values higher than 0.9 km km^{-2}, effects were negligible. When the storage and transport capacity of a system is not sufficient to prevent flooding, detention basins are effective tools to reduce peak flows, and they can reduce the superficial runoff up to 11% (Smith et al. 2015).

Similarly, green roofs can significantly decrease and slow peak discharge and reduce runoff volume. Versini et al. (2014) presented a study on the impact of green roofs at urban scale using a distributed rainfall model. They showed that green roofs can reduce runoff generation in terms of peak discharge, depending on the rainfall event and initial conditions. The reduction can be up to 80% for small events, with an intensity lower than 6mm.

2.5. URBAN HYDROLOGICAL MODELS

Urban hydrological models were developed since the 1970s to better understand the behaviour of the components of the water cycle in urban areas (Zoppou 2000). Since then, many models, with different characteristics, principles and complexity have been built. These models are used for several purposes, such as to study and predict the effects of urbanization increase on the hydrological cycle, to support flood risk management, to ensure clean and fresh drinking water for the population, and to support improvement of waste water networks and treatments (see Zoppou (2000), Fletcher et al. (2013) for a review). A good summary of the most used urban hydrological models has been recently proposed by Salvadore et al. (2015), where a table with the most used hydrological models is presented and discussed.

Hydrological models have shown to be useful to compensate partially for the lack of measurements (Salvadore et al. 2015), but all models present errors and uncertainties of different nature and magnitude (Rafieeinasab et al. 2015). In this chapter, different classifications and characterizations of hydrological models are presented.

2.5.1. URBAN HYDROLOGICAL MODEL CHARACTERIZATION

Hydrological models can be characterized and classified in different ways. A first distinction can be made according to the representation of spatial variability of the catchment. A lumped model does not consider spatial variability of the input, and uses spatial averaging to represent catchment behaviour. In contrast, distributed models describe spatial variability, usually using a node-link structure to describe subcatchment components (Zoppou 2000, Fletcher et al. 2013). The choice of a suitable model depends on many factors and it is generally related to the applications and final objective. For example Berne et al. (2004) suggested a guideline for choosing between lumped and distributed modelling considering the representative surface associated to a single rain gauge A_r. This characteristic, defined in relation to the rainfall spatial resolution r as $A_r = \pi[r/2]^2$, is compared with the surface area of a catchment A. If $A_r > S$ or $A_r \sim S$ a lumped modelling approach is suggested, while for $A_r < S$, a distributed model is recommended, as well as collecting measurements at the subcatchment scale. Different sub-categories are presented to characterize model spatial variability. Distributed models can be divided into fully distributed and semi-distributed models. Fully distributed models present a detailed discretization of the surface, using a grid or a mesh of regular or irregular elements, and apply the rainfall input to each grid element, generating grid-point runoff. The flow can be estimated at any location within the basin and not only at the catchment outlet. This is, however possible only if the rainfall is provided with an appropriate spatial resolution. Semi-distributed models are based on subcatchment units, through which rainfall is applied. Each subcatchment is modelled in a lumped way, with uniform characteristics and a unique discharge point (Pina et al. 2014). Salvadore et al. (2015) proposed a model classification based on spatial variability with 5 categories: lumped, semi-distributed, Hydrological Response Unit based (semi-distributed with a specific way to define the subcatchment area), grid based spatially distributed and Urban Hydrological Element based (mainly focused on the urban fluxes).

Another distinction is between conceptual and physically based (or process based) models, depending on whether the model is based on physical laws or not. Recently, Fatichi et al. (2016) presented an overview of the advantages and limitations of physically based models in hydrology. They defined a physically based hydrological model as "a set of process descriptions that are defined depending on the objectives". The downsides of using a physically based model are related to over−complexity and over−parametrization: conceptual models are much easier to manage and they are usually less affected by numerical instability. Physically based models usually require high computational power and time and a large number of parameters, but there are situations in which it is important to keep the complexity to better understand system mechanisms. They are also necessary to deal with system variability and allow to include a stochastic component to represent uncertainty in parameter and input values (Del Giudice et al. 2015).

2.5.2. SPATIAL AND TEMPORAL VARIABILITY IN URBAN HYDROLOGICAL MODELS

Depending on their characteristics, models can be very sensitive to spatial and temporal rainfall variability or not be able to correctly reproduce effects of this variability. Spatial variability of land cover and soil characteristics is an important element in hydrological models. Choosing between a lumped, semi-distributed or fully distributed hydrological model leads to different representation of catchment characteristics and, consequently, to a different output (Meselhe et al. 2009, Salvadore et al. 2015, Pina et al. 2016).

A comparison between semi-distributed and fully distributed urban stormwater models was made by Pina et al. (2016). Two small urban catchments, Cranbrook (London, UK) and the centre of Coimbra (Portugal), were modelled with a semi- and a fully-distributed model. Flow and depth in the sewer system of the different models were compared with observations and, in general, semi-distributed models predicted sewer flow patterns and peak flows more accurately, while fully distributed models had a tendency to underestimate flows. This was mainly due to the presence of small−scale surface depressions, building singularities or lack of knowledge about private pipe connections. Although fully-distributed models are more realistic and able to better represent spatial variability of the land cover, they need a higher resolution and accuracy to define module connections. Calibration of detailed, distributed models remains a complex issue that is not yet well resolved. The authors suggested to use a semi-distributed model approach in cases of low data resolution and accuracy.

To study the hydrological response Aronica & Canarozzo (2000) presented the Urban Drainage Topological Model (UDTM), a model that represents sub-catchments of a semi−distributed model with two conceptual linear elements: a reservior and a channel. In a more recent study (Aronica et al. 2005), this model was compared to the Storm Water Management Model (EPA SWMM model, (Rossman 2010)), that allows the user to choose different conceptual models to simulate runoff and sewer flow. Results showed that model structure and sensitivity to parameters influence the sensitivity to the rainfall input resolution.

2.6. INTERACTION OF SPATIAL AND TEMPORAL RAINFALL VARIABILITY WITH HYDROLOGICAL RESPONSE IN URBAN BASINS

Storm structure and motion play an important role in the variability of the hydrological response (Smith et al. 1994, Bacchi & Kottegoda 1995, Ogden & Julien 1995, Singh 1997, Emmanuel et al. 2012, Nikolopoulos et al. 2014, Emmanuel et al. 2015), especially for small catchments (Faures et al. 1995, Fabry et al. 1994). The characterization and the influence of spatial and temporal rainfall variability on runoff response is still not well understood (Emmanuel et al. 2015).

Recent studies address the impact of rainfall variability, focusing on urban catchments (Berne et al. 2004, Ochoa Rodriguez et al. 2015, Rafieeinasab et al. 2015, Yang et al. 2016). The main results and conclusions are presented in the following sections. It is discussed how basin characteristics impact the sensitivity of hydrological response to rainfall variability and how the interaction between spatial and temporal rainfall variability influences hydrological response.

2.6.1. INTERACTION BETWEEN RAINFALL RESOLUTION AND URBAN HYDROLOGICAL PROCESSES

Many studies highlight the importance of high resolution rainfall data (Notaro et al. 2013, Emmanuel et al. 2012, Bruni et al. 2015) and how their use could improve runoff estimation, especially in an urban scenario, where drainage areas are small and spatial variability is high (Schilling 1991, Schellart et al. 2011, Smith et al. 2013). These studies have shown how catchments act as filters in space and time for hydrological response to rainfall, delaying peaks and smoothing the intensity. However, the influence of spatial variability of rainfall on catchment response in urban areas is complex and remains an open research subject.

A theoretical study, conducted by Schilling (1991), emphasised the necessity to use rainfall data with a higher resolution for urban catchments compared to rural areas, and suggested to choose a minimum temporal resolution of 1 – 5 min and a spatial resolution of 1 km. The effects of temporal and spatial rainfall variability below 5 min and 1 km scale were subsequently studied by Gires et al. (2012). They investigated the urban catchment of Cranbrook (London, UK), with the aim of quantifying uncertainty in urban runoff estimation associated with unmeasured small scale rainfall variability. Rainfall data were obtained from the national C-band radar with a resolution of 1 km^2 and 5 min and were downscaled with a multifractal process, to obtain a resolution 9 – 8 times higher in space and 4 – 1 in time. Uncertainty in simulated peak flow associated with small-scale rainfall variability was found to be significant, reaching 25% and 40% respectively for frontal and convective events.

To investigate the effects of spatial and climatological variability on urban hydrological response, Peleg et al. (2017) used a stochastic rainfall generator to obtain high resolution spatially variable rainfall as input for a calibrated hydrodynamic model. They compared the contributions of climatological rainfall variability and spatial rainfall variability on peak flow variability, over a period of 30 years. They found that peak flow variability is mainly influenced by climatological rainfall, while the effects of spatial rainfall variability increase for longer return periods.

Required rainfall resolution for urban hydrological modelling strongly depends on the characteristics of the catchment. Several researchers have studied the sensitivity of urban hydrological response to different rainfall resolutions, highlighting correlations between rainfall resolution and catchment dimensions, such as drained area (Berne et al. 2004, Ochoa Rodriguez et al. 2015) or catchment scale length (Ogden & Julien 1994, Chirico et al. 2001, Bruni et al. 2015).

2.6.2. INFLUENCE OF SPATIAL AND TEMPORAL RAINFALL VARIABILITY IN RELATION TO CATCHMENT DIMENSIONS

Drainage area dimensions influence hydrological response and their sensitivities to spatial and temporal rainfall resolution have recently been investigated.

Wright, Smith & Baeck (2014) presented a flood frequency analysis, based on stochastic storm transposition (Wright et al. 2013) coupled with high resolution radar rainfall measurements, with the aim to examine the effects of rainfall time and length scale on the flood response. Rainfall data were used as input for a physics-based hydrological model representative of 4 urbanized subcatchemnts. This study showed that there is an interaction between rainfall and basin characteristics, such as drainage area and drainage system location, that strongly affects the runoff.

Berne et al. (2004) studied the hydrological response of six urban catchments located in the south-east of the French Mediterranean coast. Rainfall data and runoff measurements were collected using two X-band weather radars, one vertically pointing radar and one radar performing vertical plane cuts of the atmosphere, with a spatial resolution of 7.5 m and 250 m and a temporal resolution of 4s and 1min respectively. The minimum temporal resolution required Δt was defined as $\Delta t = \frac{t_{ch}}{4}$, where t_{ch} is the characteristic time of a system and the value 4 depends on catchment properties (Schilling 1991). By considering lag time t_{lag} equal to the characteristic time t_{ch}, it was possible to write the minimum required temporal resolution as a function of surface area A, based on the relationship $t_{lag} = 3A^{0.3}$: $\Delta t = 0.75\ A^{0.3}$. Spatial resolution was studied considering rainfall data collected from the X-band weather radar performing vertical plane cuts of the atmosphere, combined with measurements of rain gauges. Two spatial climatological variograms were built with a time resolution of 1 min (from radar) and 6 min (from a network of 25 rain gauges). Based on variogram analysis, it was possible to define the relation between range r and time resolution Δ_t as: ($r = 4.5\sqrt{\Delta t}$). The minimum required spatial resolution Δs was defined by the authors as $\Delta s = \frac{r}{3}$, and it can also be expressed as a function of Δt:

$$\Delta s = 1.5\Delta t. \tag{2.4}$$

In this way, both spatial and temporal resolution requirements were defined as a function of surface dimensions of a catchment. Required resolutions for urban catchments of 100 ha are 3 min and 2 km, but common operational rain gauge networks are usually less dense, while radars seldom provide data at this temporal resolution. Results presented are valid for catchments with characteristics similar to the catchments studied, such as surface area (from 10 ha to 10000 ha), slope (1% to 10%), imperviousness degree (10% to 60%), and exposed to climatic conditions similar to those of Mediterranean area.

Ochoa Rodriguez et al. (2015) analysed the impact of spatial and temporal rainfall resolution on hydrological response in seven urban catchments, located in areas with different geomorphological characteristics. Using rainfall data measured by a dual polarimetric X-band weather radar with spatial resolution of 100x100 m^2 and temporal resolution of 1min, they investigated the effects of combinations of different resolutions, with the aim to identify critical rainfall resolutions. They investigated the impact of 16 combinations of 4 different spatial resolutions (100x100 m, 500x500 m, 1000x1000 m, and 3000x3000 m) combined with 4 different temporal resolutions (1, 3, 5 and 10 min). Resolution combinations were chosen considering different aspects, such as the operational resolution of radar and rain gauges networks, characteristics temporal and spatial scale. A strong relation between drainage area and critical rainfall resolution and between spatial and temporal resolutions was found. Sensitivity to different rainfall resolutions decreased when the size of the subcatchment considered increased, especially for catchment size above 1 km^2. This study highlighted the importance of high resolution rainfall data as input. Spatial resolution of 3x3 km^2 is not adequate for urban catchments and temporal resolution should be lower than 5 min. Most operational radars present a temporal resolution of 5 min, not sufficient to correctly represent the effects of temporal rainfall variability.

The sensitivity to rainfall variability on 5 urban catchments of different sizes, located in the City of Arlington and Grand Prairie (U.S.), was studied with a distributed hydrological model (HLRDHM, Hydrology Laboratory Research Distributed Hydrological Model) by Rafieeinasab et al. (2015). Rainfall data were provided by the Collaborative Adaptive Sensing Atmosphere (CASA) X-band radar with spatial resolution of 250x250 m^2 and temporal resolution of 1 minute and upscaled in various steps to 2x2 km^2 and 1 hour. Results showed peak intensity and time to peak error to be sensitive to spatial rainfall variability. The model was able to represent observed variability for all catchments except the smallest (3.4 km^2) at a temporal resolution of 15 minutes or lower, combined with spatial variability of 250x250 m^2 and capture variability in streamflow.

Resolution required to measure rainfall for small basins is usually high, as in the case of urban catchments. The influence of slope, imperviousness degree or soil type were not separately investigated, but the relationships between catchment area and rainfall resolution are expected to depend on these characteristics as well.

Sensitivity of hydrological response to different spatial and temporal rainfall resolutions have been investigated with dimensionless parameters to represent the length scales of storm events, catchments and of sewer networks.

Ogden & Julien (1994) identified dimensionless parameters to analyse correlations between catchment and storm characteristics and to study sensitivity of runoff models to radar rainfall resolution. Rainfall data of a convective storm event, measured by a polarimetric radar with a spatial resolution of 1x1 km^2, were applied on two basins. The storm smearing was defined as the ratio between rainfall data grid size and rainfall decorrelation length. Storm smearing occurs when rainfall data length is equal or longer than the rainfall decorrelation length. The watershed smearing was described as the ratio between rainfall data grid size and basin length scale. When infiltration is negligible, watershed smearing is an important source of hydrological modelling errors, if the watershed ratio (rainfall measurement length/basin length) is higher than 0.4.

A similar approach, with dimensionless parameters, was recently applied by Bruni et al. (2015) to urban catchments. Rainfall data from a X-band dual polarimetric weather radar were applied to an hydrodynamic model, to investigate sensitivity of urban model outputs to different rainfall resolutions. Runoff sampling number was defined as ratio between rainfall length and runoff area length. Results confirm what was found by Ogden & Julien (1994). A third dimensionless parameter, called runoff sampling number, was identified. Small-scale rainfall variability at the 100x100 m^2 affects hydrological response and the effect of spatial resolution coarsening on rainfall values strongly depends on the movement of storm cells relative to the catchment.

Using dimensionless parameters is a productive approach to study sensitivity of hydrological response to spatial and temporal rainfall variability. Effects of other catchment characteristics, such as slope or imperviousness, were so far neglected, but they need a deeper investigation.

2.6.3. SPATIAL VS TEMPORAL RESOLUTION

As it was already discussed in previous sections, there is a dependency between spatial and temporal rainfall required resolution and they affect in a different way the hydrological response (Marsan et al. 1996, Singh 1997, Berne et al. 2004, Gires et al. 2011, Ochoa Rodriguez et al. 2015).

A first interaction between spatial and temporal rainfall scale was defined based on the assumption that atmospheric properties are valid also for rainfall. Following this assumption, Kolgomorov's theory (Kolgomorov 1962) was combined with the scaling properties of the Navier-Stokes equation, in order to define a relation between space and time variability. For large Reynolds numbers, in fact, Navier-Stokes equation is invariant under scale transformations (Marsan et al. 1996, Deidda 2000, Gires et al. 2011), and in this way temporal and spatial "scale changing" operator can be defined by dividing space and time (s and t) by scaling factors λ_s and λ_t relatively: $s \mapsto s/\lambda_s$ and $t \mapsto t/\lambda_t$. For scaling processes, there is a relation between scaling factors in time and space to take into account, that is represented the anisotropy coefficient H_t: $\lambda_t = \lambda_s^{(1-H_t)}$. H_t is a priori unknown for rainfall, but it can be assumed equal to 1/3, a value that characterise atmospheric turbulence (Marsan et al. 1996, Gires et al. 2011, 2012). Lovejoy & Schertzer (1991) estimated $H_t = 0.5 \pm 0.3$ for raindrops. An example of application of this theory in a rainfall downscaling process is given by Gires et al. (2012): here, the rainfall is measured with a certain spatial resolution s and temporal resolution t. They hypothesised to downscale the radar pixels, dividing the length by a scaling factor $\lambda_s = 3$, to obtain 9 pixels out of one. In this case, to keep the relation between spatial and temporal resolution, the duration of the time step has to be divided by a scaling factor $\lambda_t = \lambda_s^{1-1/3} = 2^{2/3} \simeq 2$.

Studying the hydrological response of the south-east French Mediterranean coast, Berne et al. (2004) proposed another relationship between spatial Δ_s and temporal Δ_t resolution used to measure rainfall, as : $\Delta s = 1.5\sqrt{\Delta t}$ (see Section 2.6.2 for the formula derivation).

Ochoa Rodriguez et al. (2015) derived the theoretically required spatial rainfall resolution for urban hydrological modelling starting from a climatological variogram, that characterised average spatial structure of rainfall fields over the peak storm period, fitted with an exponential variogram model. They defined characteristic length scale r_c of a storm event as $r_c = (\frac{\sqrt{2\pi}}{3})r$, where r is the variogram range. The minimum required spatial resolution for adequate modelling of urban hydrological response was defined as half

Table 2.4: Critical Resolutions in relation with the drainage area

Drainage Area A_d (ha)	Critical spatial resolution (m x m)	Critical temporal resolution (min)
A_d<1	100	1
1<A_d<100	500	1
250<A_d<900	1000	<5

the characteristic length scale of the storm: $\Delta s = \frac{r_c}{2} \cong 0.418r$. The theoretically required temporal resolution Δt, was defined based on the time needed for a storm to move over distance equal to the characteristic length scale of the storm event r_c. It can be written as: $\Delta t = \frac{r_c}{v}$, where v is the magnitude of the mean storm velocity, obtained from the average of the velocity vectors (magnitude and direction) estimated at each time step. Ochoa Rodriguez et al. (2015)investigated also the impact of different combinations of spatial and temporal resolutions as described in Section 2.6.2. One of the criteria used to choose some of the resolution combination was the already discussed in the literature (Berne et al. 2004), and according to Kolgomorov's scaling theory (Kolgomorov 1962). Results showed that hydrodynamic models are more sensitive to the coarsening of temporal resolution of rainfall inputs than to the coarsening of spatial resolution, especially for fast moving storms.

In this work, the authors presented also a relation between spatial and temporal critical rainfall resolutions depending on drainage area(Table 2.4). For small catchments, with area smaller than 1 ha, was found to be equal to 100x100 m and 1 min, while for areas between 1 ha and 100 ha, a spatial resolution of 500x500 m can be sufficient to estimate the hydrological response. The critical spatial resolution found is lower than 5 min, for catchment size from about 250 to 900 ha. Results were confirmed by Yang et al. (2016), that presented an analysis of flash flooding in two small urban subcatchments of Harry's Brook (Princeton, New Jersey, US), focusing on the influence of rainfall variability of storm events on hydrological response.

Spatial variability seems to influence timing of runoff hydrograph, while temporal variability mainly influences peak value Singh (1997).

Ochoa Rodriguez et al. (2015) investigated the influence of spatial and temporal scaling factor introduced at the beginning of this section, on runoff estimation from different input, introducing also a combined spatio-temporal factor Θ_{st}. This factor was defined using the anisotropy coefficient as: $\Theta_{st} = (\frac{\Delta S_r}{\Delta S})(\frac{\Delta t}{\Delta t_r})^{(\frac{1}{1-H_t})}$, where ΔS and Δt_r are the required spatial and temporal resolutions, ΔS and Δt are the space and time resolutions used as input for model simulations and H_t is the scaling anisotropy factor. The stronger relation between drainage area and combined spatio-temporal factor Θ_{st} compared to the relation with singular spatial or temporal scaling factor suggests that the effects of space and time has to be considered together. However the combined effects of spatial and temporal resolution on the sensitivity to hydrological response requires future works and deeper investigations.

These studies highlighted the relatively more important role of temporal variability compared to spatial variability, for extreme rainfall events. The impact of the spatial variability, seemed to decrease with increase of total rainfall accumulation.

2.7. Conclusions

In this work, the state of the art of spatial and temporal variability impacts of rainfall and catchment characteristics on hydrological response in urban areas has been presented. The main key points and conclusion of this study are the following.

A first aspect that has been highlighted is the high variability in space and time of hydrological processes and phenomena in urban environments. Measuring, understanding and effectively characterising temporal and spatial variability at small-scales is therefore of utmost importance. High resolution data are essential given the high variability of catchment characteristics and hydrological processes, such as infiltration, evaporation and surface runoff. An important role in urban areas is played by drainage infrastructures that highly affect the hydrological response, while in some cases the effects of these structures are not perfectly understood. Current methods and instruments often have insufficient capability to measure the considered process at their relevant scales.

Several definitions to classify time scale characteristics are available in the literature, such as time of concentration, lag time, time of equilibrium and response time scale. However, measurement or estimation of those parameters is often ambiguous, which implies a high level of uncertainty. Thus so far, no common agreement has emerged on a unique set of parameters able to characterize small-scale variability of urban catchments in a way that enhances our understanding of urban hydrological response. Improved rainfall measurements have also allowed to investigate the relations between temporal and spatial rainfall scale. Relations have been presented, mostly adapting the Kolgomorov's theory to rainfall, to define the interaction between spatial and temporal scale in atmosphere. A unique relationship has not yet been found. This highlights the need for methods that can better characterise spatial and temporal scale parameters of rainfall and urban catchments in an effective way.

Uncertainty associated with rainfall spatial and temporal variability is one of the main sources of error in the estimation of hydrological response in urban areas. New technologies have been developed to measure rainfall spatial and temporal variability more accurately and at higher resolution. While rain gauges remain the most common used rainfall measurement instruments, weather radars are a promising example of recently developed instruments, able to estimate rainfall variability at high resolution. However, they still need to be combined with rain gauge networks in order to improve their accuracy. Rain gauges applied in urban areas present many limitations due to strong microclimatic variability, complicating identification of suitable locations for representative rainfall measurements. Polarimetric X-band radars combine high resolution and high accuracy measurement capability with the advantages of local installation thus avoiding overshooting and resolution loss with distance associated with large radar network. They constitute a promising direction for future urban hydrological research and rainfall and flood forecasting applications.

Many studies are reported in the literature using hydrological models with different characteristics and different representations of the catchment spatial variability. Different types of hydrological models have been developed in order to represent the spatial variability of catchment properties, such as land cover and imperviousness degree. Models can be classified based on their ability to represent the spatial variability of the catchment into lumped, semi-distributed and fully distributed models. These models have become more and more detailed, reaching high levels of spatial resolution. However, unless they are driven by similarly high resolution rainfall data, increasing model resolution cannot fundamentally improve understanding of hydrological processes or improve reliability of hydrological predictions. Infiltration, local storage, interception and evaporation are quite difficult to measure, especially in urban areas, because of the strong heterogeneity of urban land-use.

The impact of spatial and temporal rainfall variability on the hydrological response in urban areas and the role of drainage infrastructure and man-made control structures herein still remains poorly understood. It was found that sensitivity of hydrological response to spatial and temporal rainfall variability varies with catchment size, catchment shape, storm scale and storm velocity. So far, findings are mainly based on sensitivity studies using theoretical model scenarios. A wider range of conditions and scenarios based on observational datasets for urban hydrological basins need to be analysed in order to characterize better the hydrological response and its sensitivity to different spatial and temporal rainfall resolutions.

3

RAINFALL AND CATCHMENT SCALE

E piove su le tue ciglia,
Ermione.
Piove su le tue ciglia nere
sì che par tu pianga
ma di piacere

Grabriele D'Annunzio, **La pioggia nel pineto**

Rainfall variability in space and time, in relation to catchment characteristics and model complexity, plays an important role in explaining the sensitivity of hydrological response in urban areas. In this chapter, a new approach to classify rainfall variability in space and time is presented and used to investigate rainfall aggregation effects on urban hydrological response. The influence of rainfall spatial and temporal classification and the impact of model complexity is here investigated.

This chapter is based on:

E. Cristiano, ten Veldhuis M.-c., Gaitan, S., Ochoa-Rodriguez, S. & van de Giesen, N., *Critical scales to explain urban hydrological response: an application in Cranbrook, London*, Hydrology and Earth System Sciences **22(4)**, 2425-2447 (2018).

3.1. Introduction

Rainfall variability in space and time influences the hydrological response, especially in urban areas, where hydrological response is fast and flow peaks are high (Fabry et al. 1994, Faures et al. 1995, Smith et al. 2002, Emmanuel et al. 2012, Gires et al. 2012, Smith et al. 2012, Ochoa Rodriguez et al. 2015, Thorndahl et al. 2017). Finding a proper match between rainfall resolution and hydrological model structure and complexity is important for reliable flow prediction (Berne et al. 2004, Ochoa Rodriguez et al. 2015, Pina et al. 2016, Rafieeinasab et al. 2015, Yang et al. 2016). High resolution rainfall data are required to reduce errors in estimation of hydrological responses in small urban catchments (Niemczynowicz 1988, Schilling 1991, Berne et al. 2004, Bruni et al. 2015, Yang et al. 2016). New technologies and instruments have been developed in order to improve rainfall measurements and capture its spatial and temporal variability (Einfalt et al. 2004, Thorndahl et al. 2017). In particular, the development and use of weather radars for hydrological applications has increased in the last decades (Niemczynowicz 1999, Krajewski & Smith 2005, Leijnse et al. 2007, van de Beek et al. 2010, Otto & Russchenberg 2011, Berne & Krajewski 2013), improving the spatial resolution of rainfall data (Cristiano et al. 2017).

The increase of high-resolution topographical data availability led to a development of different types of hydrological models (Mayer 1999, Fonstad et al. 2013, Tokarczyk et al. 2015). These models represent spatial variability of catchments in several ways, varying from lumped systems, where spatial variability is averaged into sub-catchments, to distributed models, which evaluate the variability dividing the basin with a mesh of interconnected elements based on elevation (Zoppou 2000, Fletcher et al. 2013, Pina et al. 2014, Salvadore et al. 2015). Salvadore et al. (2015) analysed the most used hydrological models, comparing different model complexities and approaches. An investigation of the differences between high resolution semi and fully distributed models was proposed by Pina et al. (2016), where flow patterns generated with different model types were studied and compared to observations. This work suggested that although fully distributed models allow to represent catchment variability in space in a more realistic way, they did not lead to the best modelling results because the operation of this type of models requires very high quality and resolution data, including rainfall input.

Both rainfall and model resolution and scale are expected to have strong effects on hydrological response sensitivity. An increase of sensitivity is expected for small drainage areas and for rainfall events with high variability in space and time. Sensitivity to rainfall data resolution generally increases for smaller urban catchments. However, sensitivity of hydrological models at different rainfall and catchments scale and the interaction between rainfall and catchment variability need a deeper investigation (Ochoa Rodriguez et al. 2015, Pina et al. 2016, Cristiano et al. 2017). This work builds upon Ochoa Rodriguez et al. (2015), who showed that the influence of rainfall input resolution decreases with the increase catchment area and that the interaction between spatial and temporal rainfall resolution is quite strong. We investigate the sensitivity of urban hydrological response to different rainfall and catchment scales, with the aim of characterizing the effects of small scale rainfall variability and model complexity on the hydrological response sensitivity. A new rainfall classification is presented, in order to better characterize the spatial and temporal rainfall variability and its effects on the system response.

This Chapter is structured as follows. Section 3.2 presents the case study, describing study area, models and rainfall data used in this work. Methodology applied to identify variability in space and time of model and rainfall and hydrological analysis are explained in Section 3.3. Section 3.4 presents the results connected to the model and rainfall variability analysis and to the hydrological analysis respectively. In Section 3.5, results are discussed, by comparing the influence of rainfall and model characteristics on the hydrological response sensitivity. Conclusions and future steps are presented in the last section.

3.2. PILOT CATCHMENT AND DATASETS

3.2.1. STUDY AREA AND AVAILABLE MODELS

The city of London (UK) is exposed to high pluvial flood risk in the last years. The Cranbrook catchment, in the London Borough of Redbridge, is a densely urbanized residential area. For this reason, it has been chosen as study area. A total area of approximately 860 ha is connected to the drainage network, and rainfall is drained with a separate sewer system.

For this small catchment, several urban hydrodynamical models have been set up in InfoWorks ICM (Innovyze 2014). For a complete description of the hydrodynamical model see Appendix A Three models with different representations of surface spatial variability, are used in this study:

- **SD1**: Simplified semi-distributed low resolution,
- **SD2**: Semi-distributed high resolution
- **FD**: Fully distributed 2D high resolution.

Table 3.1 summarises the main characteristics of the three models: number of nodes, pipes and sub-catchments, dimensions of subacatchments, two dimensional surface elements and degree of imperviousness.

The first model, SD1, is a low resolution semi-distributed model, initially setup by the water utility (Thames Water) back in 2010 to gain a strategic understanding of the catchment. This model divides the area into 51 sub-catchments, connected with 242 nodes and 270 pipes, for a total drainage network length of just over 15 km. The other two models, SD2 and FD, have been developed at Imperial College London (Simões et al. 2015, Wang et al. 2015, Ochoa Rodriguez et al. 2015, Pina et al. 2016). SD2 and FD share the same sewer network design (6963 nodes and 6993 pipes), but use different surface representations. In SD2 the drainage area is divided into 4409 sub-catchments, where rainfall runoff processes are modelled in a lumped way and wherein rainfall is assumed to be uniform. In FD, instead, the surface is modelled with a dense triangular mesh (over 100’000 elements), based on a high resolution (1 m x 1 m) Digital Terrain Model (DTM). The rainfall - runoff transformation is different for the two types of models. For SD2, runoff volumes are estimated from rainfall depending on the land use type and routed, while for FD, runoff volumes are estimated and applied directly on the two-dimensional elements of the overland surface. Figure 3.1 illustrates how the surface area is modelled for each of the three models and sewer networks.

Table 3.1: Summary of the hydrological model characteristics of the 3 models.

	SD1	SD2	FD
# of sub-catchments	51	4409	4367
# of node	242	6963	6963
# of pipes	270	6993	6993
Catchment Area (ha)	846	851	851
Contributing % Impervious	43	40	15
Contributing % Pervious	56	60	0
Average area (ha)	16.6	0.2	0.006*
St. Dev (ha)	13.4	0.8	0.000*
Max (ha)	61.8	40.1	0.099*
Min (ha)	11.7	0.005	0.006*
Total length (km)	~ 16	~ 150	~ 150
N of manholes	236	6207	6207
N of 2D Elements	no	no	117712

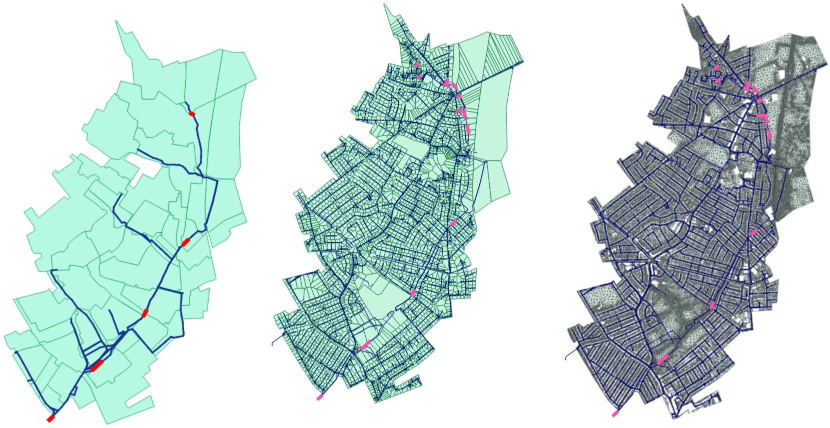
* Dimension of the 2D triangular mesh elements

3.2.2. RAINFALL DATA

Cranbrook was chosen for this study because of the availability of high quality models at different spatial resolutions. However, for this study area, only low-resolution rainfall data were available. For this reason, rainfall events measured at a different location, with similar climatological characteristics, were synthetically applied over the Cranbrook catchment. Rainfall events were selected from a dataset collected by a dual polarimetric X-Band weather radar located in Cabauw (CAESAR weather station, NL), considering that the Netherlands and United Kingdom are both in the European temperate oceanic climate (Cfb, following the Köppen classification (Kottek et al. 2006)). For technical specifications of the X-band radar device see Ochoa Rodriguez et al. (2015). The selected events were measured with a resolution of 100 m x 100 m in space and 1 min in time, much higher than what is obtained with conventional radar networks (1000 m x 1000 m and 5 min). Rainfall data where applied to the Cranbrook catchment, using sixteen combinations of space and time resolution aggregated from the 100 m - 1 min resolution: four spatial resolutions, Δs, (100 m, 500 m, 1000 m and 3000 m) with four temporal resolutions, Δt, (1 min, 3 min, 5 min and 10 min) (see Ochoa Rodriguez et al. (2015) for a motivation of the different resolution combinations). Nine rainfall events, measured between January 2011 and May 2014, were used as model input in this study. Storm characteristics are presented in Table 3.2.

3.3. METHODS

In this section, different ways of classifying spatial and temporal rainfall scale are described, as well as some possible classification of catchment characteristics. We propose a new characterization of spatial and temporal rainfall variability, based on percentage



(a) SD1 (b) SD2 (c) FD

Figure 3.1: Model schematization of the study area. Catchment area represented with the 3 different models: **(a)** SD1, **(b)** SD2 and **(c)** FD. The subdivision of the surface in sub-catchments or 2D elements is shown for each model, as well as the sewer network. The selected 13 locations/pipes are highlighted.

of coverage above selected thresholds.

3.3.1. CHARACTERIZING SPATIAL AND TEMPORAL RAINFALL SCALE

SPATIAL RAINFALL SCALE BASED ON CLIMATOLOGICAL VARIOGRAM

We computed characteristics spatial scale based on a climatological variogram, following the approach outlined by Ochoa Rodriguez et al. (2015). Ochoa Rodriguez et al. (2015) presented the theoretical spatial rainfall resolution required for an hydrological model in urban area, deriving it starting from a climatological (semi-) variogram. The (semi-) variogram γ was calculated at each time step as:

$$\gamma(h) = \frac{1}{2n}\sum_{t}^{n}(R(x) - R(x+h))^2, \quad (3.1)$$

where n is the numbers of radar pixel pairs located at a distance h, R is the rainfall rate and x is the center of the given pixel, normalized by the sample variance and averaged over the time period. The obtained variogram, characteristic of the averaged rainfall spatial structure during the peak period, was then fitted with an exponential variogram and the area A under the correlogram was calculated for the exponential variogram as: $A_r = \frac{2\pi r^2}{9}$. A_r can be considered as the average area of spatial rainfall structure estimated with radar measurements over the study area (Ochoa Rodriguez et al. 2015). Characteristic length scale r_c[L] of a rainfall event was defined as: $r_c = (\frac{\sqrt{2\pi}}{3})r$, where r [L] is the variogram range. Minimum required spatial resolution Δs_r was defined in this work as

Table 3.2: Rainfall events characteristics

Event ID	Date	Duration	Total depth (areal average / pixel min / pixel max) (mm)	Max intensity over 1 min (areal average / individual pixel) (mm/h)
E1	18/01/2011	05:10-08:00	31 / 18 / 46	32 / 1120
E2	18/01/2011	05:10-08:00	36 / 16 / 47	26 / 124
E3	28/06/2011	22:05-23:55	9 / 4 / 18	28 / 242
E4	18/06/2012	05:55-07:10	10 / 8 / 12	12 / 24
E5	29/10/2012	17:05-19:00	5 / 1 / 14	7 / 83
E6	02/12/2012	00:05-03:00	5 / 2 / 8	7 / 39
E7	23/06/2013	08:05-11:30	4 / 1 / 13	9 / 307
E8	09/05/2014	18:15-19:35	4 / 1 / 9	13 / 67
E9	11/05/2014	19:05-23:55	6 / 1 / 13	11 / 247

half of the storm characteristic length scale:

$$\Delta s_r = \frac{r_c}{2} \cong 0.418r. \quad (3.2)$$

This parameter describes the spatial variability of the rainfall event core.

RAINFALL SPATIAL VARIABILITY INDEX

Another parameter to quantify and compare the spatial variability of rainfall is the spatial rainfall variability index I_σ. This parameter was first proposed by Smith et al. (2004), who called it index of rainfall variability, and then recently redefined by Lobligeois et al. (2014). This index was estimated as:

$$I_\sigma = \frac{\sum_t \sigma_t R_t}{\sum_t R_t} \quad (3.3)$$

where σ_t is the standard deviation of spatially distributed hourly rainfall across all pixels in the basin, per time-step t, and R_t represents the spatially averaged rainfall intensity per time step. As can be seen, I_σ corresponds to a weighted average, based on instantaneous intensity, of the standard deviation of the rainfall field during a given storm event. Small values of I_σ indicate a low rainfall variability, typical of stratiform rainfall events. Large values of I_σ generally represent convective storms, characterized by high spatial variability. In the study presented by Lobligeois et al. (2014), I_σ was applied to rainfall data measured in the French region with a resolution of 1000 m - 5 min and it was varying between 0 and 5.

STORM MOTION VELOCITY AND TEMPORAL RAINFALL VARIABILITY BASED ON STORM CELL TRACKING

Ochoa Rodriguez et al. (2015) presented a characterization of storm motion and a definition of the minimum required temporal resolution. Storm motion was defined applying the TREC method (TRacking Radar Echoes by Correlation) proposed by Rinehart & Garvey (1978) This method allows to obtain at each time step a vector representing storm motion velocity magnitude and direction of the rainfall event. The minimum required temporal resolution Δt_r, was obtained considering the time that a storm needs to pass over the storm event characteristic length scale r_c. Δt_r can be written as:

$$\Delta t_r = \frac{r_c}{|\bar{v}|}, \qquad (3.4)$$

where $|\bar{v}|$ [L T^{-1}] correspond to the mean storm motion velocity magnitude. $|\bar{v}|$ is obtained from the average of the storm motion velocity vectors, estimated at each time step during the peak period.

RAINFALL SPATIAL SCALE BASED ON FRACTIONAL COVERAGE OF BASIN BY STORM CORE

In this work, a different approach to classify rainfall events is presented, considering storm spatial and temporal variability in combination with rainfall intensity thresholds. To select the thresholds Z for the 9 rainfall events over the radar grid (6 km x 6 km), percentiles at 25%, 50%, 75% and 95% of the entire 100 m - 1 min resolution rainfall dataset were calculated. In this way it was possible to calculate the different thresholds Z_{25}, Z_{50}, Z_{75} and Z_{95}, corresponding to the 25%-,50%-, 75%- and 95%-ile.

Fractional coverage was largely studied in the literature and it was shown that it has a strong influence on flood response (Syed et al. 2003, ten Veldhuis & Schleiss 2017). The percentage of coverage $\%cov$, used in this study, was defined as the sum of the number of pixel N_t above a threshold at each time step t divided over the total number of pixels of the catchment N_{tot} and over the total number of time steps d of the event:

$$\%cov = \frac{\sum_t N_t}{N_{tot} * d}. \qquad (3.5)$$

The percentage of coverage was calculated for each event, in order to give a first classification of the spatial rainfall variability.

RAINFALL CLUSTER CLASSIFICATION

Since variograms provide a strongly smoothed measure of rainfall field, we used alternative metrics to characterize space and time scale of storm events based on cluster identification. To analyse the spatial variability of the storm core, we identified, for each rainfall event, the main rainfall cluster dimension S_Z above the selected thresholds Z, as defined in Section 3.3.1.

For each time step, the area covered by rainfall above a certain threshold was considered. Main clusters were defined as the union of rainfall pixels above a given threshold. To identify the clusters, an algorithm based on Cristiano & Gaitan (2017), has been used. The algorithm executes the following rules:

- All pixels above a certain threshold are considered.
- A pixel is included in the cluster if at least one of its boundaries borders the cluster.
- Small clusters, with an area smaller than 9 ha (about 1% of catchment area) are ignored.

3

- In case of more than one cluster, the average of cluster areas is considered, in order to compare the cluster size at different time steps. This happens in only a few cases.

To obtain a characteristic number for each storm, cluster sizes per time step were averaged over the entire duration of rainfall event. Figure 3.2 presents an example of rainfall coverage at a time step t. Rainfall was divided considering different thresholds and the red line highlights the cluster for Z_{75} in Fig. 3.2 (a) and for Z_{95} in Fig. 3.2 (b). The clusters identified with yellow circles are ignored because they are too small to give a considerable contribution. In case there is more than one cluster, as for Fig. 3.2 (b), the average of the main clusters is considered.

MAXIMUM WETNESS PERIOD ABOVE RAINFALL THRESHOLD

To identify characteristic time scale of rainfall events, maximum wetness periods were defined as the number of time steps was estimated for which rainfall at a pixel is constantly above a given threshold. With this aim, every pixel in the catchment was analysed and maximum number of consecutive time steps above the chosen threshold was retrieved. Figure 3.2 (c) illustrates of the process followed to select the maximum duration Tw_{max} above the threshold Z. For each pixel, the value of the maximum duration above the threshold is identified. These values are averaged over the whole catchment to obtain a temporal length scale that characterizes rainfall event Tw_Z.

For each pixel n, the maximum wetness period Tw_Z above a selected threshold Z is defined as

$$Tw_Z = \frac{\sum_{n}^{N_{tot}} Tw_{max}}{\sum N_{tot}}, \tag{3.6}$$

where N_{tot} is the total number of pixels.

In order to characterize the intermittency of rainfall events, the maximum dry period Td_{max}, defined as the maximum number of time steps during which the threshold Z was not exceeded, was also identified. Figure 3.2 (c) shows how these lengths, Tw_Z and Td_Z, were selected. The combination of these two parameters gives an indication of how constant or intermittent the rainfall event is.

3.3.2. CHARACTERIZING HYDROLOGICAL MODELS' SPATIAL AND TEMPORAL SCALES

MODELS' SPATIAL SCALES

Several studies have shown that drainage area is one of the dominating factors affecting the variation in urban hydrological responses resulting from using rainfall at different spatial and temporal resolutions as input (Berne et al. 2004, Ochoa Rodriguez et al. 2015, Yang et al. 2016). Considering a larger drainage area implies aggregating and averaging rainfall and consequently smoothing rainfall peaks, with the result of having large areas that are less sensitive to high resolution measurements.

In order to compare spatial scale of models and rainfall spatial variability, the average dimension of subcatchments was analysed to characterize the model spatial scales. To investigate the effects of the drainage area A_d on hydrological response sensitivity,

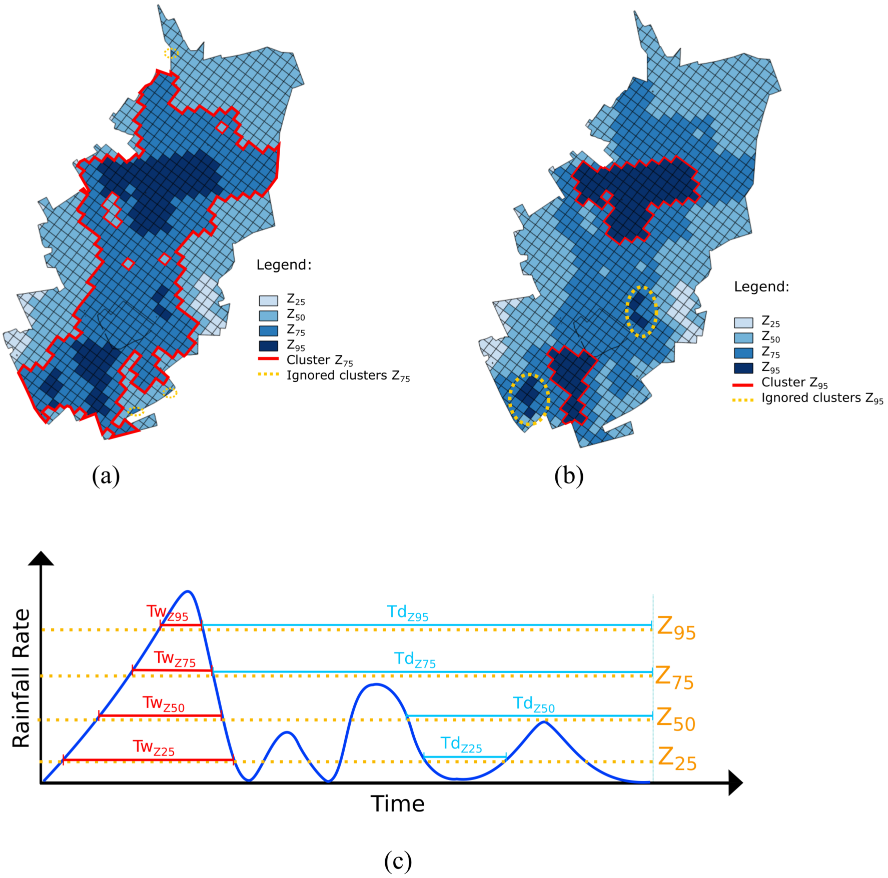


Figure 3.2: Rainfall cluster classification. Different colours represent different rainfall thresholds. The pixels above the same threshold are used to estimate the percentage of coverage above a certain threshold. The red line encloses the clusters above threshold Z_{25} and Z_{95} in **(a)** and **(b)** respectively. Single isolated pixels and small clusters (yellow dotted circles) are ignored. (c) Schematic representation of maximum wet period Tw_Z (red) and the maximum dry period Td_Z (light blue) for a pixel, for each threshold.

thirteen locations, with connected surface that varies from less than 1 ha to more than 600 ha, were considered. Given that the coarser resolution model (SD1) does not contain small drainage areas (<35ha), only eight of the thirteen selected locations were available for SD1. To compare FD with SD models, we assumed that FD sub-catchments have the same dimension of SD2 sub-catchments. Table 3.3 presents the drainage area A_d connected to each location, while in Figure 3.1 the location of the selected pipes is highlighted on the catchment, with a red thick line.

Dimensionless parameters as proposed by Bruni et al. (2015) and Ogden & Julien (1994) were determined to investigate the interaction and relation between rainfall resolution and different model properties and characteristic. The *catchment sampling num-*

Table 3.3: Drainage area connected to the investigated locations for each model

	SD1 (ha)	SD2 (ha)	FD (ha)
Loc1	-	0.9	0.9
Loc2	-	6.7	6.6
Loc3	-	9.5	9.5
Loc4	-	21.3	21.3
Loc5	-	24.6	24.6
Loc6	36	42.9	42.9
Loc7	80	43.7	43.7
Loc8	80	83.9	83.9
Loc9	137	129.2	129.2
Loc10	290	254.8	254.8
Loc11	484	448.3	448.3
Loc12	538	502.5	502.5
Loc13	846	626.6	626.6

ber $\frac{\Delta s}{L_C}$ was introduced as the ratio between the rainfall spatial resolution Δs and the characteristic length of the catchment L_C (square root of the total area). This parameter describes the interaction between rainfall resolution and study area. If the catchment sampling number is higher than 1, rainfall variability is insufficiently captured and for small rainfall events the position might not be properly represented. The *runoff sampling number* was defined as $\frac{\Delta s}{L_{RA}}$, where L_{RA} indicates the spatial resolution of the runoff model, defined as the square root of the averaged sub-catchment size (Bruni et al. 2015). Lower values of this ratio indicate that the model is unable to capture rainfall variability, while higher values indicate possible incorrect transformation of rainfall into runoff. The *sewer sampling number* $\frac{\Delta s}{L_S}$, describes the interaction between rainfall resolution and sewer length L_S, indicating higher sensitivity to rainfall variability with increasing values of this ratio.

MODELS' TEMPORAL SCALES

In the literature, there is no unique parameter to characterize the temporal variability of the model. Several authors have proposed different time scale characteristics (see Cristiano et al. (2017) for a review), but no unique formulation has been chosen yet, especially for urban areas. Time of concentration (McCuen et al. 1984, Singh 1997, Musy & Higy 2010) and lag time (Berne et al. 2004, Marchi et al. 2010) are the most commonly used temporal model scales, but other time length have been proposed in the literature (Ogden & Julien 1995, Morin et al. 2001). In this study, temporal variability of the three models was classified using lag time t_{lag}, which describes the runoff delay compared to rainfall input. t_{lag} can be defined in different ways: as difference between the centroid of hyetograph and the centroid of hydrograph (Berne et al. 2004), or as the distance between rainfall and flow peaks (Marchi et al. 2010, Yao et al. 2016). Hyetograph in a specific location was estimated as average of rainfall intensity that interests the considered sub-catchment, while the hydrograph was represented using the flow in selected pipes.

The lag time can be considered as a characteristic basin element. It depends on drainage area size, slope and imperviousness (Gericke & Smithers 2014, Morin et al. 2001, Berne et al. 2004, Yao et al. 2016), but it is also influenced by rainfall characteristics. For this reason, t_{lag} was calculated for the nine rainfall events and the average of these values was taken as representative number.

Lag time increases with drainage area, following a power law as proposed by Berne et al. (2004). For urban areas, an empirical relation between catchment area A (ha) and lag time t_{lag} (min) was presented:

$$t_{lag} = 3A^{0.3}. \tag{3.7}$$

This relation was confirmed, incorporating results obtained by Schaake & Knapp (1967) and Morin et al. (2001). t_{lag} was calculated for each selected sub-catchments, and then compared with the rainfall temporal scale, to investigate the interaction between model and rainfall scale. The relation between averaged lag time and connected drainage area was studied at each location.

3.3.3. STATISTICAL INDICATOR FOR ANALYSING RAINFALL SENSITIVITY

To investigate effects of rainfall aggregation on peak intensity, the peak attenuation ratio Re_R was calculated for rainfall. This parameter represents peak underestimation, when aggregating in space and time and it was defined as:

$$Re_R = \frac{P_{st} - P_{ref}}{P_{ref}} \tag{3.8}$$

where P_{ref} is the peak of the measured rainfall at 100 m - 1 min resolution and P_{st} is the rainfall peak at the aggregated resolution s in space and t in time. Re_R values vary from -1 to 0, condition for which there is no underestimation.

The coefficient of determination R_R^2 was used to describe rainfall intensity sensitivity to aggregation in space and time. R_R^2 represents the portion of variance of dependent variable that is predictable from the independent one. This parameter indicates how well regression approximates real data points. R_R^2 values can varies between 1 and 0, where 1 represents the perfect match between observed rainfall values R_{ref} and aggregated one R_{st} at spatial resolution s and temporal resolution t.

3.3.4. STATISTICAL INDICATORS FOR ANALYSING HYDROLOGICAL RESPONSE

Rainfall was synthetically applied over models and flow and depth were calculated in 13 selected locations, to study the hydrological response and to compare the three models. Following Ochoa Rodriguez et al. (2015), rainfall was applied in such way that the storm movement main direction was parallel to the main downstream direction of flow in pipes. The rainfall grid centroid coincided with the catchment centroid.

Using aggregated rainfall data as input and hydrodynamic simulation results derived from the highest-resolution rainfall (100 m and 1 min) as reference, the following two statistical indicators were calculated and analysed to quantify the influence of rainfall input resolution, at selected locations.

- Relative Error in peak flow Re_Q
  $Re_{Qst} = \frac{Qmax_{st} - Qmax_{ref}}{Qmax_{ref}}$ where Re_{st} is the relative error in peak ($Qmax_{st}$) corresponding to a rainfall input of spatial resolution s and temporal resolution t, in relation to the reference (100 m - 1 min) flow peak, $Qmax_{ref}$ (Ochoa Rodriguez et al. 2015). Re_{st} values bigger than zero indicate an overestimation of the peak associated to the rainfall input st, and vice versa, Re_{st} values smaller than zero indicate an underestimation.

- Coefficient of determination R^2_Q
  R^2_Q, as described in Section 3.3.3 for rainfall, was applied also to the flow, to investigate effects of rainfall aggregation on hydrological response.

3.4. RESULTS AND DISCUSSION

3.4.1. RAINFALL ANALYSIS

In this section, methods for quantifying rainfall space and time scales proposed in the literature (Ochoa Rodriguez et al. 2015, Lobligeois et al. 2014), are compared to the cluster classification we propose in this paper. Additionally, change in rainfall characteristics with spatial and temporal aggregation scale will be analysed.

SPATIAL AND TEMPORAL CLASSIFICATION RESULTS

Spatial variability index values for each of the 9 rainfall events are presented in Table 3.4 for the observed rainfall at 100 m - 1 min (I_σ) and at 1000 m - 5 min ($I_{\sigma 1000m}$). Last values were added to have a direct comparison with the values presented by Lobligeois et al. (2014), using the same resolution. I_σ values are generally high when compared to values found by Lobligeois et al. (2014) for all the investigated regions. This indicates that most events are characterised by high spatial variability.

Aggregation has a strong impact on this parameter, which becomes smaller with a coarser resolution, highlighting the fact that information about rainfall variability is lost during the coarsening process. $I_{\sigma 1000m}$ values are generally higher than values presented for the Northern region, where values are below 1, but are comparable to the Mediterranean area, where I_σ reaches values around 4.

Values obtained based on variogram analysis (spatial range) and storm tracking (temporal development) following Ochoa Rodriguez et al. (2015) are also presented in Table 3.4.

Results show that the spatial variability index tends to increase as well as the required spatial resolution for storms larger than 2500 m spatial range, while events with small spatial range (E5, E7 and E9, spatial range below 2500 m) are characterised by relatively high spatial variability indexes. Required temporal resolution Δt_r, obtained from the combination of storm motion velocity and required spatial resolution (see Section 3.3.1) varies between 1.7 and 5.9 minutes; lowest values of Δt_r are associated with fast storm events (e.g. E8 and E5) and small-scale events (e.g. E9 and E7).

THRESHOLDS AND PERCENTAGE OF COVERAGE

The first step in obtaining cluster dimensions is to identify rainfall thresholds (Z) characterising the rainfall values' distribution (see Section 3.3.1). Table 3.5 shows rainfall

Table 3.4: Rainfall spatial and temporal characterization proposed by Ochoa Rodriguez et al. (2015) and rainfall spatial variability index proposed by Lobligeois et al. (2014)

	Ochoa Rodriguez et al. (2015)				Lobligeois et al. (2014)	
ID	Spatial range (r) (m)	Mean storm velocity $(\lvert\bar{v}\rvert)$ (m/s)	Required spatial resolution Δs_r (m)	Required temporal resolution Δt_r (min)	Spatial Variability Index (100 m 1 min) I_σ (mm/h)	Spatial Variability Index (1000 m 5 min) $I_{\sigma 1000m}$ (mm/h)
E1	4057	9.8	1695	5.8	12.7	6.4
E2	3525	9.9	1473	5.0	7.4	5.2
E3	4655	14.0	1945	4.6	10.4	6.5
E4	3219	11.7	1345	3.8	2.6	1.5
E5	2062	14.1	861	2.0	7.7	4.2
E6	3738	11.7	1561	4.5	3.7	2.0
E7	1703	14.0	711	1.7	16.6	5.9
E8	3644	18.4	1523	2.8	7.9	4.2
E9	2355	17.0	984	1.9	15.3	6.5

Table 3.5: Thresholds values obtained for the 9 rainfall events considered.

Threshold	Z_{25}	Z_{50}	Z_{75}	Z_{95}
Percentile	25%	50%	75%	95%
Values	0 mm/h	0.5 mm/h	7 mm/h	22 mm/h

threshold values corresponding to the 25-, 50-, 75- and 90-%iles for the 9 rainfall events.

The 25%-ile of the rainfall values distribution is zero, indicative of strong intermittency and small areal coverage of some of the events (especially events E7 and E9). The 95%-ile is 22 mm/h (over a 1-minute time window), corresponding to a recurrence interval of less than a half year (KNMI 2011), indicating that the selected events are representative of frequently occurring events. For this region, rainfall intensities above 25 mm/h, over a 15-minute time window, correspond to a return period of once per year, indicating an intense rainfall event. For only few rainfall events, E1, E2, E3 and E7, the 25 mm/h threshold is exceeded over a 15-minute time window, for few time steps and, in particular, for E7 this happens only at the peak. This implies that rainfall events considered in this study are not classifiable as extreme.

The percentage of areal coverage, estimated for the catchment, is presented in Fig. 3.3(a, d, g, j). Areal coverage associated with 25%-ile values provides an indication of event scale intermittency. Events with 25%-iles close to 1 cover the entire catchment most of the time, while smaller and more intermittent events, especially E7 and E9, are characterised by lower 25%-ile values. Areal coverage for 95%-ile thresholds indicates the size of storm cell cores: E1 and E2 have storm cores covering up to 65-70% of the catchment; E4 and E6 have median coverage values close to zero, indicating that these are mild events without an intense storm core. Boxplots in Fig. 3.3 (b, e, h, k) show the number of time steps above selected thresholds as a percentage of total event duration, to enable comparison between events. Results confirm patterns identified based on areal coverage: events E7 and E9 are identified as high intermittency events (based on 25%-ile threshold). Maximum percentage of time steps above the highest threshold is 30% for events E1 and E2. Each boxplot represents the spatial variability of rainfall between pixels. Thresholds Z_{50} and Z_{75} present a high intra-event variability, highlighting the differences between rainfall events. For the other two thresholds, the intra-event variability is not high, suggesting that the rainfall event characteristics might not be well represented. For Z_{95}, all events present a coverage variability lower than 30%, and differences between events are not properly defined. Thresholds Z_{50} and Z_{75} present also a high inter-event variability, indicating that in these cases the spatial variability of the rainfall event above the catchment area is high.

RAINFALL CLUSTER CLASSIFICATION

Dimensions of the main cluster were determined for each of the four thresholds and for all time steps of the nine events. Results are presented in Fig. 3.3 (c, f, i, l), where the red line indicates the median and the blue dot the average.

The plots show that for Z_{25} only intermittent events, like E7 and E9, present a median below 861 ha (entire catchment area). The intra-event variability is generally quite high for most of the events, especially for the 50%-ile and 75%-ile, indicating that clusters change their dimension and shape during the event. Only few events, E4 and E2, do not show high variability above Z_{25} and Z_{50} threshold. For Z_{95}, the cluster dimension variability is relatively small, suggesting that the average or the median can be a good approximation of the storm core dimension. Values above Z_{50} present high inter-event variability. There is a clear distinction between constant events, such as E2 and E4, and intermittent events, E7 and E9, which show low median and average values.

Intense and constant rainfall events are also characterized by median values being generally higher than the mean. On the other hand, intermittent events, such as E9, have an average higher than the median, especially for the 50%- and 75%-ile. This results suggest that Z_{50} and Z_{75} are able to describe well rainfall spatial and temporal scale.

MAXIMUM WET AND DRY PERIOD

The maximum wet period Tw_Z and maximum dry period Td_Z were calculated for four rainfall intensity thresholds in order to represent temporal variability of a rainfall event. Table 3.6 presents maximum wetness period Tw_Z and maximum dry period Td_Z, normalized by total duration of the rainfall event, to enable comparison between events and to investigate how long the main core is in relation to the total duration of the event.

For some events Tw_Z decreases depending on the threshold, passing from values close to 1 for Z_{25} to values close to 0 for Z_{95}. The change between different thresholds can be gradual, as for example for E2, E8 or E5, or sharp, as is the case of E3 or E4. For intermittent events, on the other hand, the maximum wet period does not vary too much, and it is relatively short, like E7 or E9. This implies that there are probably multiple short periods above the threshold. When comparing Tw_Z and Td_Z, we can observe that some events show a symmetrical behaviour, when decrease in wet period coincides with

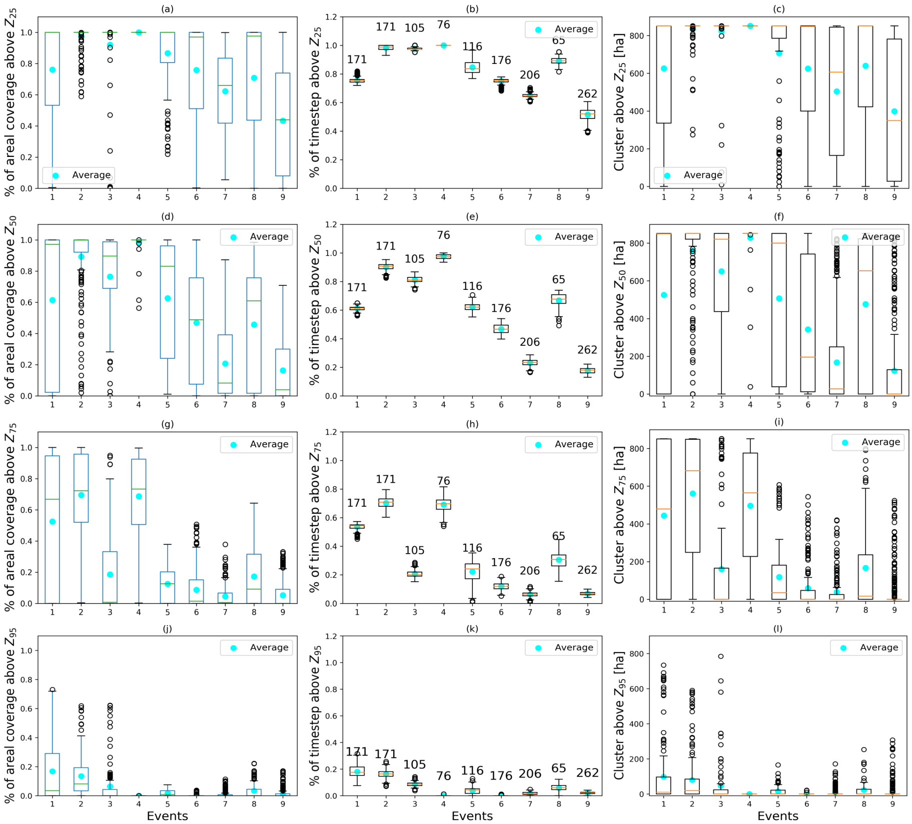


Figure 3.3: Boxplots characterizing the cluster classification variability. Percentage of areal coverage above selected threshold, calculated over all time steps and per rainfall event **(a, d, g, j)**. Temporal percentage of coverage above the selected threshold, defined as number of time steps above the threshold at each pixel, divided by the total duration of the event **(b, e, h, k)**. Temporal percentage is presented for each rainfall event and the number above each boxplot indicates the total duration of the rainfall event. Cluster dimensions across all time steps per event for the four selected thresholds **(c, f, i, l)**. Blue dots represent the average, green or red lines the median, boxes indicate the first to third quartile and whiskers extend 1.5 times the interquartile range below the first and above the third quartile.

Table 3.6: Maximum wetness periods above the threshold. These values were calculated for each pixel, averaged over the total catchment, and then divided by the total duration.

Event	Maximum wet period				Maximum dry period			
	Tw_{Z25} [-]	Tw_{Z50} [-]	Tw_{Z75} [-]	Tw_{Z95} [-]	Td_{Z25} [-]	Td_{Z50} ID [-]	Td_{Z75} [-]	Td_{Z95} [-]
E1	0.53	0.50	0.42	0.17	0.16	0.25	0.27	0.35
E2	0.98	0.74	0.30	0.06	0.02	0.07	0.13	0.30
E3	0.97	0.43	0.10	0.06	0.02	0.08	0.63	0.72
E4	1.00	0.98	0.32	0.01	0.01	0.02	0.11	1.00
E5	0.77	0.57	0.14	0.11	0.11	0.28	0.38	0.57
E6	0.52	0.24	0.13	0.12	0.12	0.29	0.52	0.99
E7	0.28	0.14	0.13	0.12	0.13	0.28	0.53	0.71
E8	0.83	0.43	0.14	0.07	0.07	0.22	0.34	0.53
E9	0.22	0.19	0.18	0.17	0.17	0.30	0.56	0.69

Table 3.7: Dimensionless parameters based on Bruni et al. (2015). These parameters were estimated for the three models presented in this study and used to describe the interaction between spatial rainfall resolution and model scale

Δs	Catchment sampling number			Runoff sampling number			Sewer sampling number		
(m)	SD1	SD2	FD	SD1	SD2	FD	SD1	SD2	FD
100	0.03	0.04	0.04	0.25	2.29	10	0.19	1.73	1.73
500	0.17	0.20	0.20	1.23	11.47	50	0.94	8.65	8.65
1000	0.34	0.40	0.40	2.45	22.94	100	1.87	17.30	17.30
3000	1.03	1.20	1.20	7.35	68.82	300	5.62	51.91	51.91

increase in dry period, with the increase of the threshold (E4, E3). E7 and E9 present a moderate decrease of Tw_Z while they have a steep increase of Td_Z, indicative of strong intermittency. For the other events, the behaviour is generally the opposite, indicative of a concentrate storm core.

3.4.2. HYDROLOGICAL MODELS, SPATIAL AND TEMPORAL SCALES

SPATIAL MODEL SCALE

Dimensionless sampling numbers, presented at first by Ogden & Julien (1994), and then re-proposed by Bruni et al. (2015), are presented in Table 3.7 for the three models (for underlying equations see Section 3.3.2).

SD2 and FD model have the same contributing area and network length, hence they show that values for the catchment sampling number and sewer sampling number are the same.

Catchment sampling numbers higher than 1 indicate that models can not properly represent rainfall variability (Bruni et al. 2015). In this study, for 3000 m spatial rainfall resolution values are bigger than 1, so poor model performance at this resolution is expected. The runoff sampling number suggests that SD1 will not be able to capture rainfall variability, because it presents low values for all spatial resolutions, while FD has high values of this parameter, which highlights some uncertainty in rainfall-runoff transformation. SD2, instead, presents runoff sampling numbers similar to the values found by Bruni et al. (2015), where this parameter varied between 2.6 for high resolution and 93 for lower resolution. The sewer sampling number applied to SD2 and FD, presents similar results to Bruni et al. (2015), where the values were varying between 2 for high resolution and 77 for low resolution. On the other hand, the sewer sampling number is pretty low for SD1, which indicates a low sensitivity of this model to rainfall variability. This parameter increases with coarsening of spatial resolution, suggesting a high sensitivity to coarser rainfall resolutions.

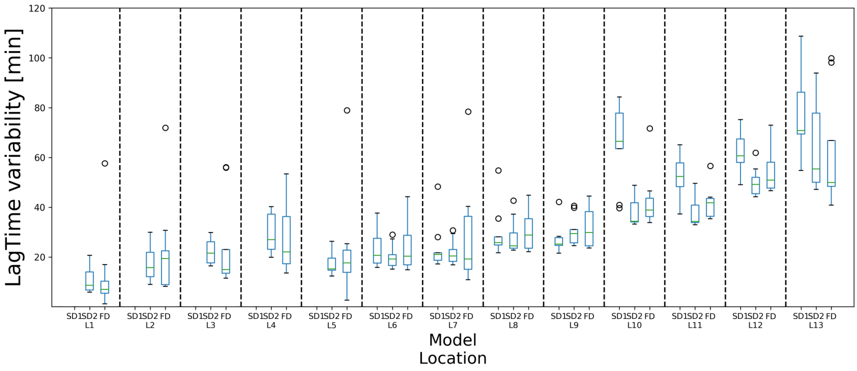
The catchment sampling number can be applied also to the selected sub-catchments, comparing spatial resolution with the sub-catchments dimension reported in Table 3.1(b). Also in this case, when the ratio is bigger than 1 the rainfall might not be well represented. This happens for sub-catchment L1, which is smaller than 100 m, and for all locations when they have to deal with 3000 m rainfall resolution. Locations from L2 to L5, presenting a drainage area between 100 m and 500 m, should show the effects of aggregation for spatial resolution of 500 m and 1000 m, when the catchment sampling coefficient is higher than 1, and the variability is not well captured. When the catchment sampling number is lower than 0.2, the catchment is too large to be compared to the rainfall input, and the effects of averaging over the area should be visible, as for example for L13 when considering a 100 m input resolution.

TEMPORAL MODEL SCALE

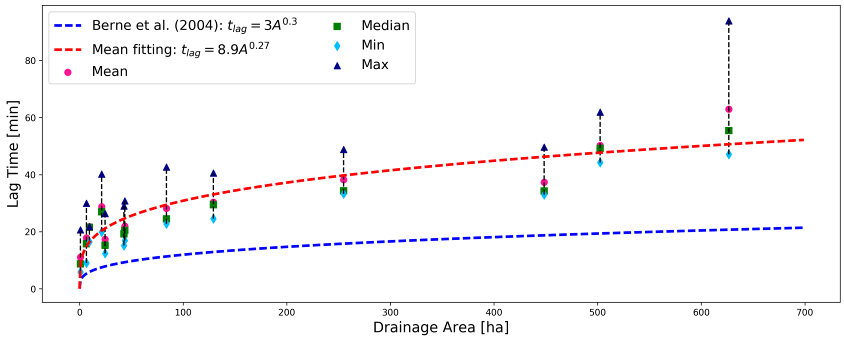
Lag time t_{lag} was computed for nine storms for each model at twelve sub-catchments and at the catchment outlet, as explained in Section 3.3.2. Results, presented in Fig. 3.4 (a), show that t_{lag} increases with drainage area and varies from just above 1 min for FD at L1 (upstream location with the smallest A_d) to over 100 min for the coarsest model and largest catchment scale.

Only for a few locations, t_{lag} is lower than 10 min and for this reason a low sensitivity to temporal variability of rainfall events is expected. On the other hand, lag times vary over a wide range between events and this highlights a strong influence of event characteristics. Model scale clearly influences computed lag times, which are generally larger for coarser model, where sub-catchments are bigger. However, for locations with smaller drainage area (< 245 ha), SD1 presents t_{lag} values comparable with the other models, but with a much lower variability compared to the finer scale models.

As discussed in Section 3.3.2, t_{lag} strongly depends on drainage area. Figure 3.4(b) shows how lag time varies, as a function of drainage area, for SD2, based on average, median, minimum and maximum values across rainfall events. Results confirm that t_{lag} increases with the drainage area, fitting a power law, similar to the one suggested by Berne et al. (2004) (eq. 3.7). In this case the power law that fits best the average of empirical data is $t_{lag} = 8.9 * A_d^{0.27}$ ($R^2 = 0.841$), equation that presents the same exponent of the one proposed by Berne et al. (2004) and slightly higher coefficient. The power law proposed by Berne et al. (2004) represents a wider range of surface areas wider than what is presented in this work, hence only a small part of it is considered.



(a)



(b)

Figure 3.4: Variability of the lag time, depending on the location, for each model **(a)**. The boxplots represent the median (red line), the upper (third quartile) and lower (first quartile) quartile (boxes boundaries), and 1.5 times the interquartile range below the first and above the third quartile (whiskers). Drainage areas corresponding to each location are presented in Table 3.1**(b)**. Average, median, minimum and maximum value of the lag time as function of A_d for SD2.(b) Fitting power law curves and the power law relation proposed by Berne et al. (2004) are plotted.

3.4.3. SENSITIVITY OF RAINFALL: EFFECTS OF SPATIAL AND TEMPORAL AGGREGATION ON RAINFALL PEAK AND DISTRIBUTION

EFFECTS OF AGGREGATING ON THE MAXIMUM RAINFALL INTENSITY AT CATCHMENT SCALE

Figure 3.5 presents rainfall peak attenuation ratios Re_R for the range of spatial and temporal aggregation levels investigated. The plot shows the median over the nine events (marker) and the variability of the data (from 25% to 75% solid lines and total range dotted lines).

Rainfall peaks are reduced up to 80% when aggregating in space or time and up to 88% when combining the spatial and temporal aggregation at the coarsest resolution.

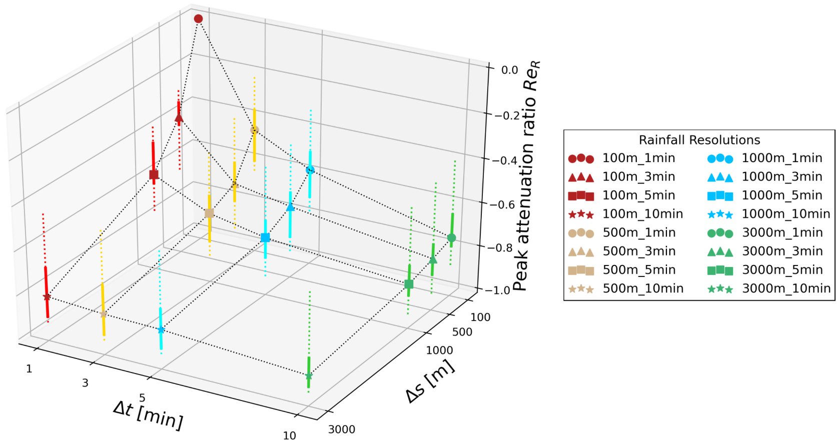


Figure 3.5: Peak attenuation ratio Re_R. The indicator is estimated for the 9 rainfall events, as a function of temporal and spatial rainfall resolution. Symbols indicate the median over the 9 events, solid lines represent the first to the third quartile, dotted lines vary from minimum to maximum. Colours represent different temporal resolutions and markers used for the median indicate different spatial resolutions.

For high resolution, aggregation over time seems to play a larger role then over space. Aggregating from 1 min to 3 min approximately half of the rainfall peak is lost, while from 100 m to 500 m peak attenuation is relatively smaller (40%). For lower resolutions, spatial aggregation has a slightly stronger attenuating effect than temporal aggregation. At 3000 m spatial resolution, rainfall peaks are strongly underestimated, independent of the temporal resolution.

RAINFALL AGGREGATION ANALYSIS AT SUB-CATCHMENT SCALE

In this sub-section, we compare effects of spatial and temporal aggregation on rainfall variability and peak intensity across sub-catchment scales. Figure 3.6 shows examples of rainfall aggregation effects, as a function of the drainage area. Results for two rainfall events are shown: E4 is a constant, low intensity event, which has a low variability in time and space, while E9 is an intermittent events, with multiple peaks. The plots clearly show that rainfall variability for the constant event is less sensitive to aggregation than for the intermittent event. Rainfall sensitivity to aggregation decreases for larger size. Re_R and R_R^2 results for all the 9 studied events are available in Appendix B.

3.4.4. RAINFALL AND MODEL INFLUENCE ON HYDROLOGICAL RESPONSE

SENSITIVITY OF THE HYDROLOGICAL RESPONSE TO RAINFALL INPUT RESOLUTION

Figure 3.7 shows results for statistical indicators Re_Q and R_Q^2 for sixteen combinations of rainfall resolution and in relation to catchment area. Results are shown for a stratiform low intensity rainfall event (E4) and a convective intermittent storm (E9) for increasing catchment. For both events, the sensitivity to rainfall input resolution generally decreases for increasing of catchment size. Variability of Re_Q and R_Q^2 is much stronger

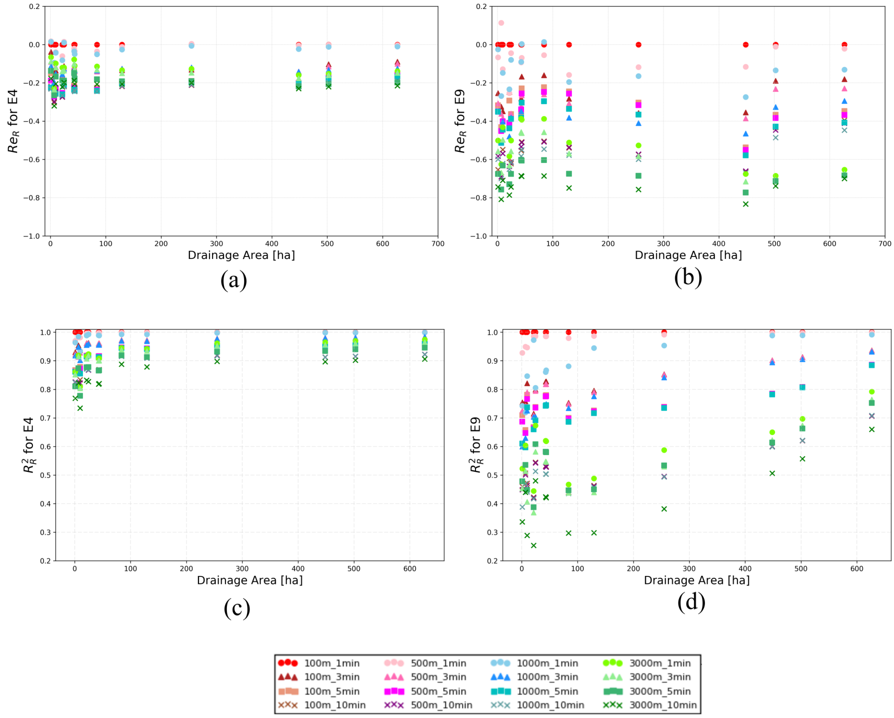


Figure 3.6: Impact of aggregation in space and time on rainfall peak (Re_R) and overall pattern (R_R^2) for two selected events, as function of sub-catchment size (A_d). E4 is a constant low intensity event with low spatial variability. E9 is an example of intermittent event, with a high storm motion velocity. Different colours and symbols indicates different rainfall resolutions used as input. Other events are presented in Appendix B

for E9 than E4, pointing out the important role of rain event characteristics.

Comparing Fig. 3.6 with Fig. 3.7, similar patterns are observed for rainfall and flow. In both cases, sensitivity to rainfall aggregation in space and time decreases with increase of the drainage area. Moreover, in both cases, the small and constant event (E4) is less sensitive to aggregation than the intermittent one (E9). Rainfall patterns are more sensitive to aggregation than flow, due to smoothing induced by rainfall runoff processes.

INFLUENCE OF THE MODEL COMPLEXITY ON HYDROLOGICAL RESPONSE SENSITIVITY

To investigate the influence that model complexity has on hydrological response sensitivity, results obtained with the three models are analysed. Figure 3.8 compares the influence of model complexity to the impact of spatial rainfall variability on the sensitivity of hydrological response. For each model, outputs at all locations are plotted for the 16 different rainfall input resolutions.

There is not a clear behaviour that characterizes differences between sensitivity of the three models. All models appear sensitive to 3000 m spatial resolution and 10 min temporal resolution: in these cases the performance is lower. For upstream location, SD1 seems to be slightly more sensitive than the other models to spatial coarsening for the

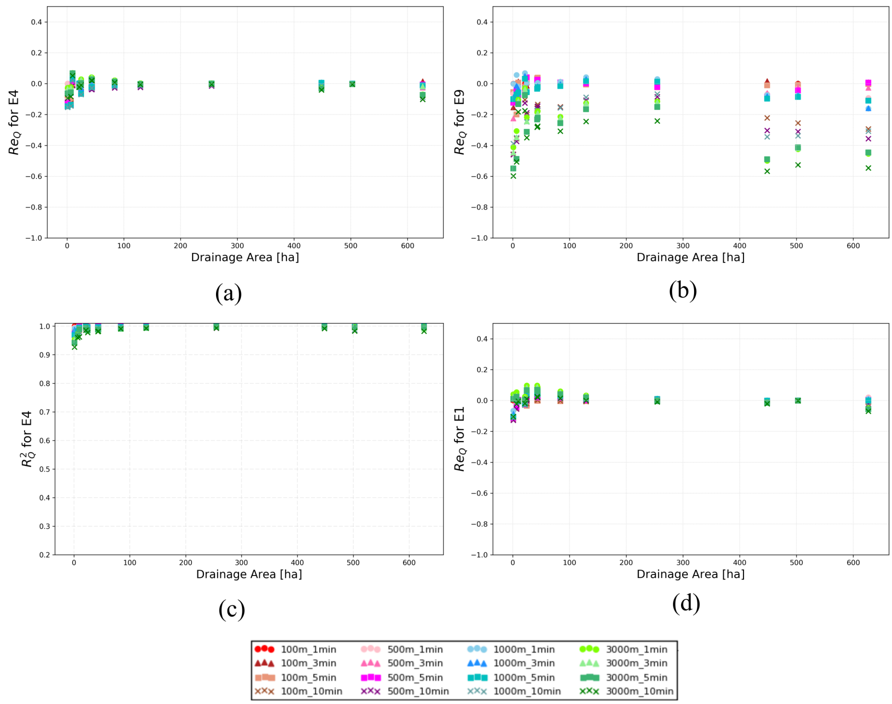


Figure 3.7: Relative error in peak Re_Q and coefficient of determination R_Q^2 for SD2, plotted as function of A_d, for the sixteen combinations of rainfall input resolutions. Two different events are presented: E4, a low-intensity constant event, and E9, a multiple peak event.

upstream location, while FD performs worse for L13. The plot shows that there are some minor differences between the outputs of the three models, but the strongest sensitivity is connected to the rainfall scale as characterized by the cluster dimension. All models show higher sensitivity to small clusters, especially for cluster sizes below 100 ha. For small clusters, SD1 presents a higher sensitivity for both statistical indicators, while it is less sensitive than SD2 and FD for large clusters.

Model complexity does not have a large influence on sensitivity to rainfall resolution coarsening, while other characteristics, such as rainfall parameters or catchment details, seem to have a higher impact.

INFLUENCE OF RAINFALL SCALE CLASSIFICATION ON HYDROLOGICAL RESPONSE

Several approaches to classify rainfall variability have been presented and discussed in Section 3.3.1 and in Section 3.4.1. In these sections, their influence on the hydrological response will be analysed.

Figure 3.9 compares the influence of spatial and temporal required resolutions (Δs_r and Δt_r), spatial variability index I_σ, cluster above Z_{75} and Z_{95} and the maximum wet period Tw_{Z75} to model performance for different resolutions. Sensitivity to rainfall input resolution generally increases for smaller required spatial and temporal resolution,

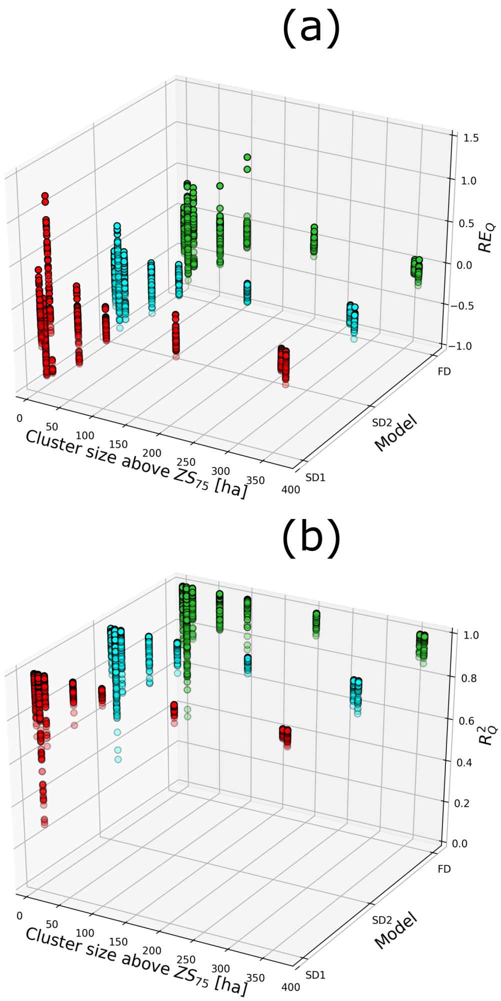


Figure 3.8: Influence of model complexity. Re_Q and R^2_Q variability, in relation to model type and rainfall characterized by cluster dimension S_{Z75}, for all locations and all combinations of rainfall input resolution. Colours identify the three different models.

for higher spatial variability index and for smaller cluster size. Clearest relationships are observed for required temporal resolution and cluster size above Z_{75}. This parameter seems to represent quite well the spatial scale of the rainfall events, and therefore is chosen in this work to characterize the spatial scale of rainfall events.

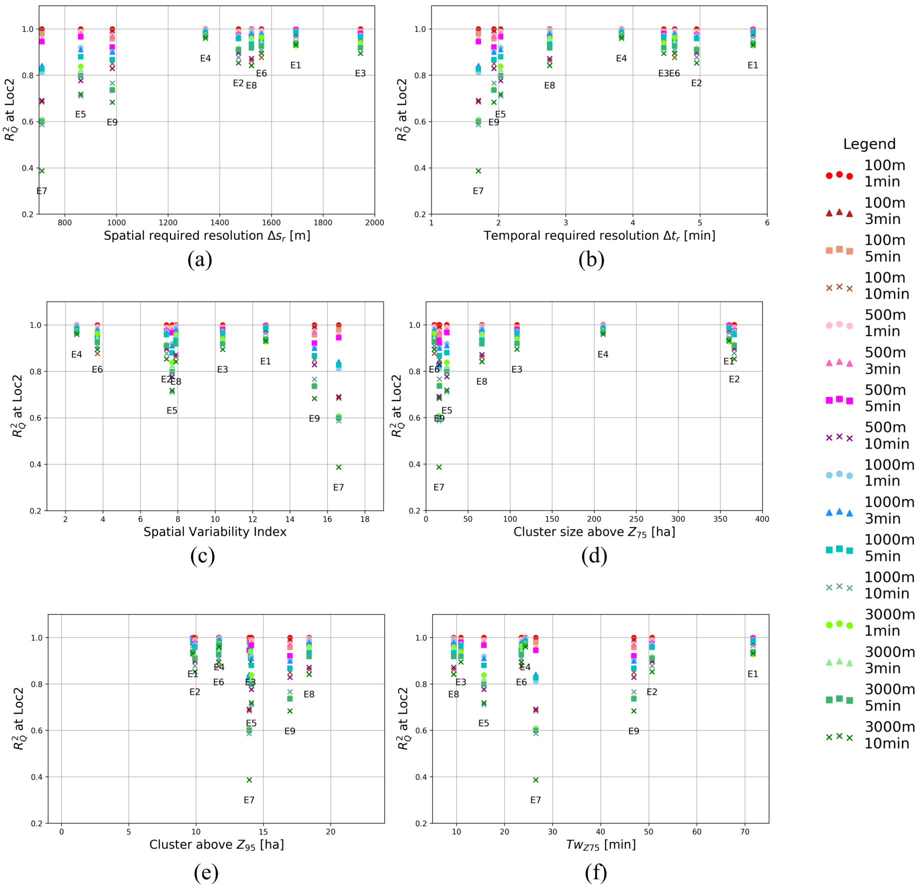


Figure 3.9: Influences of rainfall spatial and temporal characterization. R^2_Q at Loc2 for different rainfall resolution, plotted against different rainfall characterising scales: spatial **(a)** and temporal **(b)** required resolution, Spatial Variability Index **(c)**, dimension of cluster above Z_{75} **(d)** and Z_{95} **(e)** and maximum wet period above Z_{75} **(f)**.

Figure 3.10 compares the influence of rainfall spatial scale, based on cluster size above Z_{75}, with drainage area size. Variability of R^2_Q is higher for lower values of both rainfall scale and drainage area and decreases in a similar way with increase in both rainfall and catchment dimensions.

For this study case, we can conclude that sensitivity to rainfall resolution depends mainly on the scale of rainfall events and study catchment, and much less on complexity of models used. Choosing a complex model is useful only when studying small scale events and catchments only if high resolution rainfall data are available.

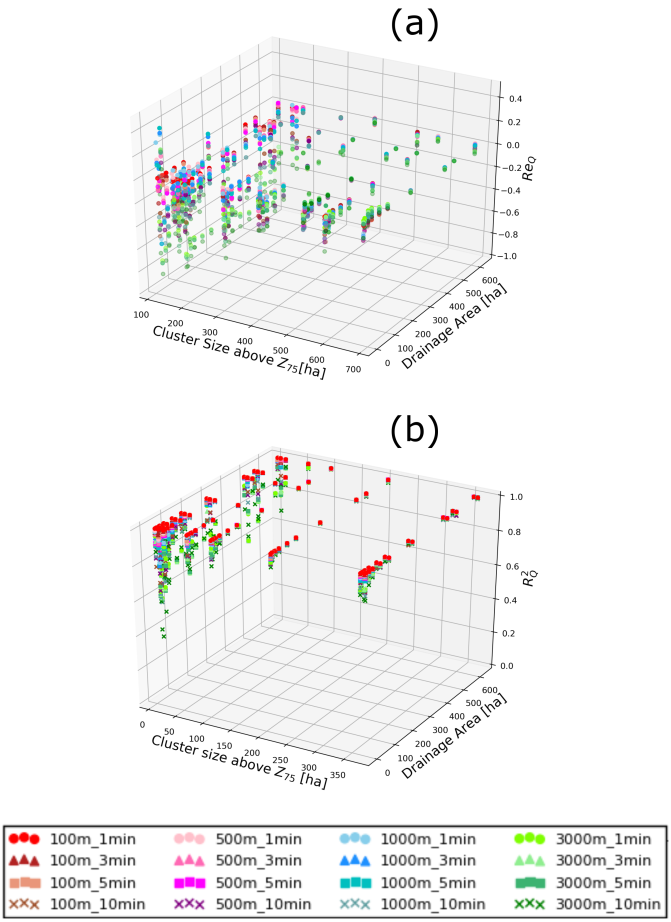


Figure 3.10: Sensitivity to cluster dimension and drainage area. Re_Q and R_Q^2 as function of cluster dimension above Z_{75} and A_d. Different colours and symbols indicates different rainfall resolution input.

3.5. CONCLUSIONS

In this study we investigated effects of rainfall and catchment scales on sensitivity of urban hydrological models to different rainfall input resolutions. The aim of this work was to evaluate the influence that rainfall spatial and temporal scale, catchment characteristics and model complexity have on the sensitivity of hydrological response. Cranbrook, a small urbanized area of 861 ha, was analysed with the help of two semi-distributed and a fully distributed models. Rainfall data measured at 100 m and 1 min resolution by a dual polarimetric X-band radar located in the Netherlands, were aggregated to obtain different rainfall resolutions and then used as input for the hydrological models. Storm events were assumed to be representative of the rainfall regime in the London area, as London and Cabauw are situated in the same temperate oceanic climatological region. Different rainfall classification methods were used to characterize storm event scales and a new rainfall classification method, based on cluster identification was presented in this work.

From this work we draw the following conclusions.

- Rainfall classification based on clustering is an easy and fast method to quantify spatial scale of rainfall events. In particular, rainfall clusters associated with the 75%-ile threshold turned out to give a realistic approximation of the spatial dimension of the storm core.

- Spatial and temporal aggregation of rainfall data can have a strong effect on rainfall peak and intensity. Rainfall peaks were reduced up to 80% when aggregating in space to 3000 m resolution or in time at 10 min resolution. Both space and time have a strong influence on peak attenuation. Temporal aggregation has a stronger influence at 1 - 5 min resolution, while aggregation in space has bigger impact at low (1000 - 3000 m) resolution.

- Lag time estimated for the investigated sub-catchments was used to represent the temporal characteristics of models. Lag time increased with the catchment area size, yet varied strongly between events (approx. by a factor of 2, 25-75%-ile range). Mean lag time fitted an empirical power law similar to the one proposed by Berne et al. (2004), yet with a higher intercept.

- Effects of rainfall aggregation in space and time on hydrological response depend on rainfall event characteristics. Rainfall events with constant intensity are less affected by aggregation than small scale intermittent events. However, results showed that aggregation effects are stronger for rainfall than flow. Results showed that smoothing of rainfall peak intensities by aggregation was much stronger than for flows. Rainfall aggregation effects on hydrological response are smoothed during the rainfall runoff transformation processes.

- For the case study under consideration, model spatial resolution does not appear to have a big impact on hydrological response sensitivity to rainfall input resolution. Three models of different complexity were all sensitive to rainfall resolution. Low resolution model was more sensitive to rainfall resolution for small scale storms, while the high resolution fully distributed model showed stronger sensitivity at larger catchment scale.

- Rainfall and catchment scales were shown to have a strong impact on hydrological response sensitivity. This indicates that the relation between rainfall and catchment scale needs to be taken into account when investigating the hydrological response sensitivity of a system.

Combinations of rainfall and catchment scale effects on the hydrological response sensitivity to different rainfall resolutions are deeper investigated in the next Chapter.

4

SCALE FACTORS

ὁ δὲ ἀνεξέταστος βίος οὐ βιωτὸς ἀνθρώπῳ
The unexamined life is not worth living

Plato, **Dialogues, Apology of Socrates, 38a**

Rainfall spatial and temporal scales, combined with catchment scales, play an important role on the sensitivity of hydrological response. With the aim to evaluate the combined effects of rainfall and catchment scales, three dimensionless scale factors are here introduced. Rainfall spatial and temporal scale definition, used to define scale factors, is based on the main cluster identification, proposed in Chapter 3. These factors enable to evaluate the interactions between rainfall and catchment scale and rainfall input resolution in relation to the performance of the model. Given specific catchment and rainfall scale, it is possible to identify the rainfall resolution needed to reach a defined level of performance. On the other hand, scale factors also enable to estimate model performance for the available rainfall resolution. The coefficient of determination is selected as statistical indicator to evaluate model performance. Performance thresholds connected to scale factors are defined for the Cranbrook study case.

This chapter is based on:

E. Cristiano, ten Veldhuis M.-c., Gaitan, S., Ochoa-Rodriguez, S. & van de Giesen, N., *Critical scales to explain urban hydrological response: an application in Cranbrook, London*, Hydrology and Earth System Sciences **22(4)**, 2425-2447 (2018).

E. Cristiano, ten Veldhuis M.-c., Wright D. B., Smith J. A., & van de Giesen, N., *The influence of rainfall and catchment critical scales on urban hydrological response sensitivity*, Water Resources Research , submitted.

4.1. INTRODUCTION

Rainfall and catchment characteristics have shown a strong impact on the sensitivity of hydrological response to different rainfall resolutions in urban areas. Sensitivity to different rainfall resolutions is high for small catchment and it decreases with the increase of the drainage area connected to the catchment (Ochoa Rodriguez et al. 2015, Yang et al. 2016, Cristiano et al. 2018). Rainfall spatial and temporal variability also have a strong influence on hydrological response sensitivity. Rainfall events with high spatial and temporal rainfall scale, such as stratiform events, present a lower sensitivity to rainfall resolutions input than convective events. This type of events is generally characterized by small spatial scale and high variability in time. For this reason, rainfall resolution coarsening can lead to a smoothing of rainfall peaks, with consequently errors in flow estimation.

4

Although, it is important to evaluate effects of both rainfall and catchment scale on the hydrological response, only few studies have considered their combined effects and further investigations need to be done. Ochoa Rodriguez et al. (2015) presented spatial, temporal and combined spatio-temporal rainfall scale factors to investigate the influence of rainfall scale on the hydrological response in relation to the spatial and temporal rainfall resolution. These scale factors analyse the effects of rainfall scale, focusing on spatial, temporal and combined spatio-temporal aspects. The proposed scale factors seem to be powerful tools to evaluate the influence of rainfall characteristics on the hydrological response sensitivity, although further developments are required to incorporate the influence of catchment spatial and temporal scales.

In this Chapter, a new methodology to combine rainfall and catchment scales into scale factors capable of describing the influence on the hydrological response sensitivity is described and applied to Cranbrook (see Chapter 3). In Section 4.2 scale factors derived from the work of Ochoa Rodriguez et al. (2015) are described and adapted to the Cranbrook study case. New dimensionless scale factors that account for both rainfall and catchment scales are also introduced in this Section. Results related to the Cranbrook study case are then presented and discussed in Section 4.3.

4.2. DEFINITION OF SCALE FACTORS

4.2.1. SCALE FACTORS PROPOSED BY OCHOA RODRIGUEZ ET AL. (2015)

To investigate the impact of spatial and temporal scales of rainfall events on the sensitivity of simulated runoff to different rainfall input resolutions, Ochoa Rodriguez et al. (2015) defined spatial and temporal scale factors, θ_S and θ_T. These factors were defined as the ratio between required spatial and temporal minimum resolutions, Δs_r and Δt_r, and spatial and temporal resolutions considered as input Δs and Δt:

$$\theta_S = \frac{\Delta s_r}{\Delta s} \tag{4.1}$$

$$\theta_T = \frac{\Delta t_r}{\Delta t} \tag{4.2}$$

The combined effects of spatial and temporal characteristics were evaluated defining a combined spatial–temporal factor which accounts for spatial–temporal scale anisotropy factor H_t (Ochoa Rodriguez et al. 2015). The anisotropy factor represents the relation between spatial and temporal scales, assuming that atmospheric properties and Kolgomorov's theory (Kolgomorov 1962) are valid also for rainfall (Marsan et al. 1996, Deidda 2000, Gires et al. 2011). Combined spatial-temporal factor is then defined as:

$$\theta_{ST} = \theta_S * \theta_T^{\frac{1}{1-H_t}}, \tag{4.3}$$

where H_t usually assumes the value of 1/3 (Marsan et al. 1996, Gires et al. 2011, 2012).

4.2.2. SCALE FACTORS CHARACTERISING RAINFALL AND MODEL SCALES

Building on the work of Ochoa Rodriguez et al. (2015), we proposed spatial and temporal scale rainfall factors, δ_S and δ_T. Rainfall cluster classification and maximum wetness period were used to describe the rainfall scale. The 75%-ile threshold was chosen as reference, accordingly to the results presented in Section 3.4.4. The rainfall factors are defined as ratio between cluster dimension S_{Z75} above Z_{75} and maximum wetness period Tw_{Z75} above Z_{75} and spatial and temporal rainfall resolutions:

$$\delta_S = \frac{\sqrt{S_{Z75}}}{\Delta s} \tag{4.4}$$

$$\delta_T = \frac{Tw_{Z75}}{\Delta t} \tag{4.5}$$

The characteristic spatial length of the main cluster, corresponding to the square root of the main cluster, was used to define the spatial rainfall scale factor. Combined effects of spatial and temporal rainfall scale were investigated defining δ_{ST} as a combination of δ_S and δ_T.

$$\delta_{ST} = \delta_S * \delta_T \tag{4.6}$$

The coefficient of anisotropy was not considered for the new parameters. The assumption that the anisotropy observed in the atmosphere is present also in the hydrological response is not always applicable. Results were however investigated with and without the anisotropy and no big differences were identified.

A similar concept was applied to model characteristics and spatial and temporal model scale factors were defined. These factors were obtained comparing model characteristic length (square root of drainage area A_d) and lag time t_{lag} with spatial and temporal resolution relatively.

$$\gamma_S = \frac{\sqrt{A_d}}{\Delta s} \tag{4.7}$$

$$\gamma_T = \frac{t_{lag}}{\Delta t} \tag{4.8}$$

The combined model scale factor was defined as:

$$\gamma_{ST} = \gamma_S * \gamma_T \tag{4.9}$$

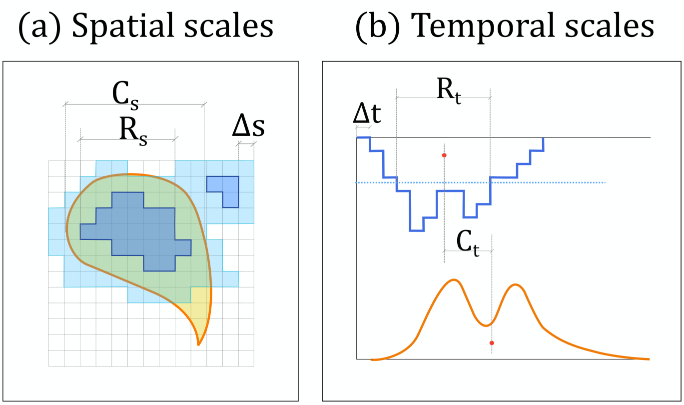


Figure 4.1: Schematization of spatial and temporal scales. **(a)** Spatial scale: schematic representation of a catchment and rainfall grid applied over it, at a fixed time step. Main cluster above the selected thresholds are represented. Rainfall spatial resolution Δs, rainfall spatial scale R_s and catchment spatial scale C_s are highlighted. **(b)** Temporal scale: schematization of a hietograph (blue line) and corresponding hydrograph (orange line) for a selected pixel. Light blue dotted line represent the selected threshold to determinate the maximum wet period. Red dots indicate centroids used to define the lag time. Rainfall temporal resolution Δt, rainfall temporal scale R_t and catchment temporal scale C_t are highlighted.

4.2.3. COMBINED SCALE FACTORS

In this work we wanted to identify dimensionless factors able to properly represent the behaviour of hydrological response sensitivity, in relation with rainfall and catchment scales. The purpose of these scale factors was to combine spatial and temporal rainfall and catchment scale and relate them to spatial and temporal rainfall resolutions (Δs and Δt) available to estimate rainfall. These elements were combined in order to determine three dimensionless scale factors. Rainfall spatial scale, R_s, was described in this study using the main cluster dimension above the 75 rainfall percentile (See Chapter 3 for the rainfall cluster classification). To obtain a dimensionless parameter, the corresponding main cluster length, defined as the square root of the main cluster dimension, was selected as rainfall spatial scale. Rainfall temporal scale R_t was represented using the maximum wet period, introduced in Chapter 3. To characterize the catchment scale C_s, the square root of the connected drainage area is chosen. This choice fits approximately circular catchments, while it could not be representative for elongated basins. Lag time centroid to centroid was selected to describe the catchment temporal scale C_t. Fig.4.1 gives a graphical representation of the different spatial (Fig.4.1a) and temporal (Fig.4.1b) scales involved in this study.

The three new dimensionless scale factors are here presented. The first factor, α_1, accounted only for the spatial aspects of model and rainfall variability and it was defined as:

$$\alpha_1 = \frac{R_s * C_s}{\Delta s^2} \tag{4.10}$$

A second possible way to combine rainfall and model characteristics was α_2:

$$\alpha_2 = \delta_S * \gamma_T = \frac{R_s}{\Delta s} * \frac{C_t}{\Delta t} \tag{4.11}$$

In this case, both spatial and temporal aspects were considered. The catchment temporal scale factor partially represents also spatial variability of catchment characteristics, because of the strong relationship between lag time and drainage area, described in Section 3.3.2.

The third scale factor, α_3, combined all spatial and temporal rainfall and model characteristics. α_3 was defined as:

$$\alpha_3 = \delta_{ST} * \gamma_{ST} = \frac{R_s * C_s}{\Delta s^2} * \frac{R_t * C_t}{\Delta t^2} \tag{4.12}$$

Scale factors enable to choose the minimum required rainfall resolution to use. Depending on the available data and on the level of performance that we want to achieve, it is possible to identify the required rainfall resolution. In this study, we investigated the level of performance using the coefficient of determination applied to the flow estimation as indicator. Two specific level of model performance have been highlighted in this study: $R^2 \geq 0.9$, which indicates a good model performance and $R^2 \geq 0.8$, that is representative of acceptable model performance conditions. Thresholds, identifying the scale factors α in correspondence of $R^2 = 0.9$ and $R^2 = 0.8$ were defined for the Cranbrook study case.

From a numerical point of view, rainfall resolution is represented by the two variables Δs and Δt, and consequently two equations are needed to identify a unique solution. For this reason, two α scale factors should be selected to identify the required rainfall resolution. On the other hand, some anisotropy relations, characterizing the interaction between spatial and temporal rainfall scales are available in the literature (Kolgomorov 1962, Gires et al. 2012, Ochoa Rodriguez et al. 2015), and they can be used in combination with the scale factors, to derive the minimum required rainfall resolution.

4.3. RESULTS

4.3.1. RAINFALL AND MODEL SCALE FACTORS

Spatial, temporal and combined scale factors proposed by Ochoa Rodriguez et al. (2015) and described in Section 4.2, were calculated for the Cranbrook study case and are presented in Fig. 4.2(a-c). Higher values of the scale factors θ_S (ratio between minimum required spatial resolution and rainfall spatial resolution), θ_T (ratio between minimum required temporal resolution and rainfall temporal resolution) and θ_{ST} (combination of spatial and temporal scale factors) are generally associated with higher modelling performance, expressed in terms of R^2. In particular, when θ_S and θ_T increase, the sensitivity of hydrological response to different input resolution decreases, and R^2 presents higher values. When combining θ_S and θ_T in θ_{ST}, it is possible to identify a θ-threshold: for values higher than the θ-threshold, model performance is quite high. In particular, the combined spatial-temporal scale factor, θ_{ST}, indicates good model performance ($R^2 > 0.9$) for $\theta_{ST} > 15$.

As described in Section 4.2.2, in this work we modified the rainfall scale factors proposed by Ochoa Rodriguez et al. (2015), using the rainfall characterization proposed in Chapter 3, to describe rainfall spatial and temporal scales. Results corresponding to the new rainfall scale factors δ_S, δ_T and δ_{ST} are plotted in Fig. 4.2(d-f). Plots show results similar to the one obtained for θ_S, θ_T and θ_{ST}: level of model performance is generally

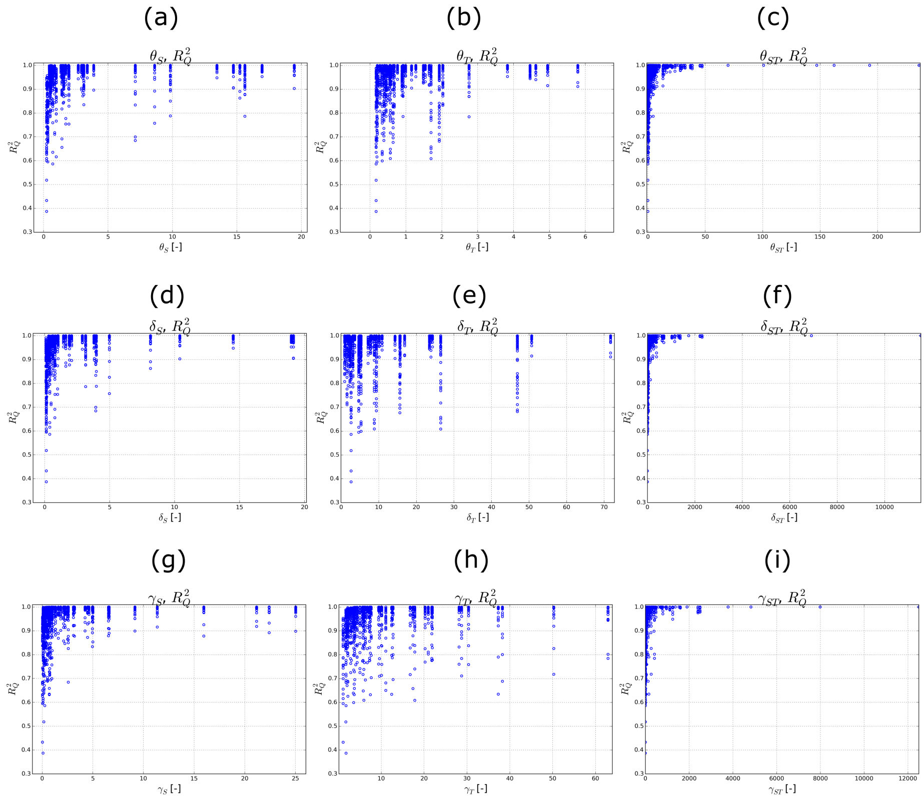


Figure 4.2: Spatial and temporal rainfall and catchment scale factors plotted in relation to the coefficient of determination R^2. **(a-c)** Rainfall spatial, temporal and combined spatio-temporal scale factors (θ_S, θ_T and θ_{ST}) proposed by Ochoa Rodriguez et al. (2015). **(d-f)** Rainfall spatial, temporal and combined spatio-temporal scale factors, obtained with the rainfall cluster characterization (δ_S, δ_T and δ_{ST}). **(g-i)** Catchment spatial, temporal and combined spatio-temporal scale factors (γ_S, γ_T and γ_{ST}).

high for high values of rainfall scale factors. This fact confirms that the new rainfall characterization based on cluster identification can be a good instrument to classify rainfall spatial and temporal variability.

Fig. 4.2(g-i) show results obtained when comparing catchment spatial γ_S, temporal γ_T and combined spatio-temporal γ_{ST} scale factors with the model performance output. When catchment spatial scale factor γ_S increases, the hydrological response sensitivity decreases, with a general increase of the coefficient of determination. This is generally true also the catchment temporal scale factor γ_T, although in this case the decrease of sensitivity is not particularly high, and some high values of γ_T correspond to low R^2 values. The combined spatio-temporal catchment scale factor γ_{ST} could be used to identify the rainfall resolution that should lead to a good model performance for specific catchment scales. For high values of γ_{ST}, a good level of model performance can be expected.

Table 4.1: Scale factor thresholds derived for the Cranbrook study case

Scale Factor	$R^2 > 0.9$	$R^2 > 0.8$
α_1	100	15
α_2	40	10
α_3	3000	450

4.3.2. SCALE FACTORS

As discussed in Section 3.4.4, both rainfall scale and catchment characteristics strongly affect the sensitivity of hydrological response to rainfall resolution. For this reason, the three new dimensionless factors combine rainfall and catchment properties. Scale factors are plotted against the coefficient of determination R^2. Fig.4.3 show the obtained results for the three dimensionless scale factors and highlights the opportunity to define α-thresholds to interpret the complex interactions between model performance, rainfall resolution and rainfall and catchment scales. Fig.4.4 plots the three dimensionless scale factors on a logarithmic scale, to better visualize all the values. In this figure, colours highlight different rainfall resolutions and dotted lines identify α-thresholds corresponding to a good ($R^2 > 0.9$) and acceptable ($R^2 > 0.8$) level of model performance.

From results shown in Fig. 4.2(a-c), spatial variability seems to have a better relation with the sensitivity variability than the temporal scale and, for this reason, the factor α_1 especially focuses on the spatial scale of model and rainfall variability. Figure 4.4(a) shows R^2 as a function of α_1. The plot presents a clear trend, indicating low model performance for low values of α_1 and high performance for values of α_1 larger than 100.

Figure 4.4(b) shows α_2 and response sensitivity. For values of $\alpha_2 > 40$, R^2 is higher than 0.95, indicating a very good performance. For values of $\alpha_2 < 10$, R^2 is lower than 0.8. Figure 4.4(b) shows the same plot on a logarithmic scale, which better visualises thresholds of performance. Different resolutions are highlighted in the plot. Low resolution in space generally lead to a lower α's values than low temporal resolution, and consequently to a lower performance of the model.

Figure 4.4(c) plots R^2 against α_3 and it indicates that, for values of α_3 higher than 3000, a high performance of R^2 is guaranteed ($R^2 > 0.90$). For $400 < \alpha_3 < 3000$ the performance of R^2 drops to 0.8. A summary of the identified values in presented in Table 4.1.

Comparing the scale factors, we observe that α_2 works better in distinguishing critical resolutions for a given model performance. Indeed, there are fewer points with high R_Q^2 below the identified thresholds. Moreover, α_2 should be preferred because it allows to use fewer parameters, without losing information about temporal characteristics, as it is for α_1.

4.4. CONCLUSIONS

In this Chapter new spatial, temporal and combined scale factors were introduced to analyse hydrological response sensitivity to rainfall resolution, in relation to rainfall and catchment scales. Three new dimensionless scale factors, that combine rainfall scale, model scale and rainfall input resolution and enable identification of critical rainfall res-

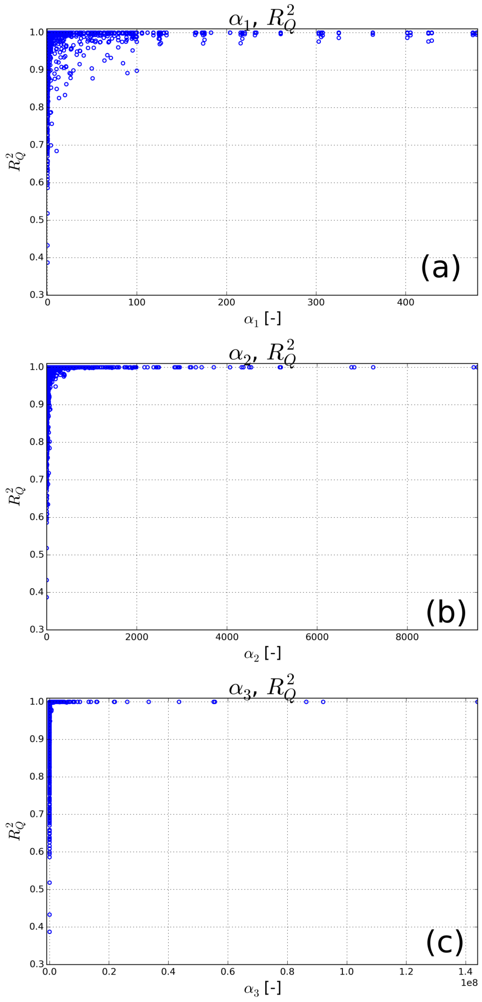


Figure 4.3: Dimensionless scale factors plotted in relation to the coefficient of determination R^2. **(a)** α_1, **(b)** α_2 and **(c)** α_3.

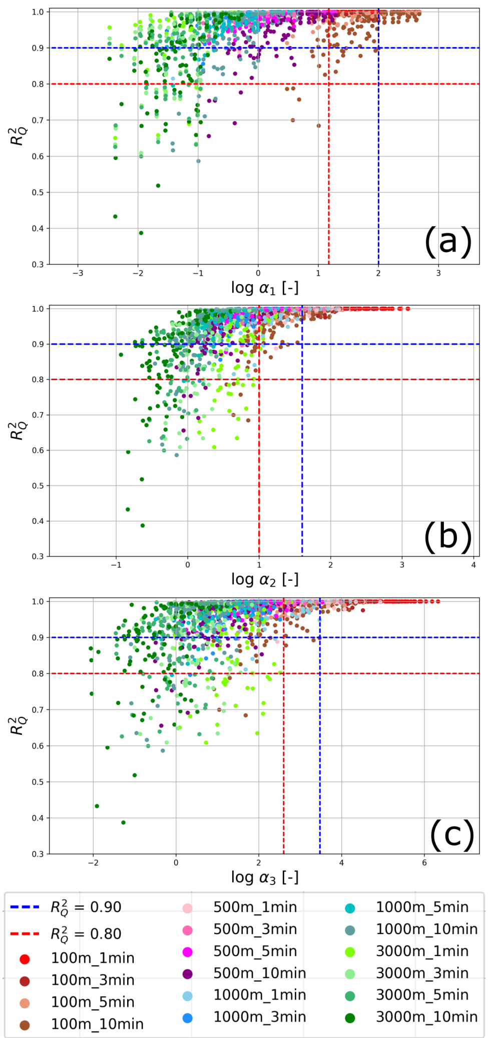


Figure 4.4: Results obtained combining scale factors and model performance. Colours indicate different rainfall resolutions and dotted lines highlight thresholds corresponding to model performance $R^2 = 0.9$ (blue line) and $R^2 = 0.8$ (red line). **(a)** α_1, **(b)** α_2 and **(c)** α_3.

olution thresholds to achieve a given level of accuracy, were presented in this Chapter. Scale factors are here presented as a powerful tool to support selection of adequate rainfall resolution to obtain a certain level of accuracy in the calculation of hydrological response.

These scale factors were derived for the specific study case of Cranbrook, for which it was possible to identify performance thresholds. In particular, for values of α_2 higher than 10, an acceptable model performance is expected, with a $R^2 > 0.8$. To achieve a good level of performance, where the coefficient of determination is higher than 0.9, values of α_2 larger than 40 are required. Knowing the values of α required to obtain a good model performance, it is possible to derive the rainfall resolution needed, given rainfall and catchment characteristics.

Although scale factors have shown to be powerful tools to estimate the required rainfall resolution, there are still some aspects that need further investigations. Rainfall events measured directly over the study area should be evaluated to allow a proper comparison between model results and observations. In particular, using local rainfall data as input for the model combined with local discharge measurements, would enable direct investigation the sensitivity of hydrological response with respective to an observed reference. Results presented in this work are, moreover, related to one specific study case and and different scenarios, in different climatological regions and with different hydrological characteristics, need to be investigated in order to test to what extent they can be generalised. More and different rainfall events and different catchments need to be investigated in order to test the applicability of the scale factors and thresholds identified for other geographical and climatological conditions. Additionally, a better definition of temporal rainfall scale needs to be developed, with a parameter able to represent rainfall variability, highlighting the constant or intermittent character of rainfall events.

In the next Chapter, cluster rainfall classification and dimensionless α parameters will be investigated based on field observations in combination with modelling. Different scales will be considered to investigate the range of applicability of the scale factors.

5

CHALOTTE STUDY CASE

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Leopardi, **Infinito**

Interactions between spatial and temporal variability of rainfall and catchment characteristics strongly influence hydrological response, especially in urban areas, where runoff generation is fast due to the high degree of imperviousness. The previous Chapter investigated the hydrological response in the urbanized catchment of Cranbrook (8 km^2, London, UK) and proposed three dimensionless scale factors to identify if the available rainfall resolution is sufficient to properly predict hydrological response given rainfall and catchment scales. With the aim to verify the applicability of the proposed scale factors to larger scales and distinct physiographic setting, Little Sugar Creek (Charlotte, USA) was chosen as new study case. Twenty-eight rainfall events were selected from a weather radar dataset from the National Weather Radar Next Generation Radar Network, with a resolution of 1 km^2 and 15 min. Rainfall data were aggregated to coarser resolutions and used as input for a distributed hydrological model. Results show strong effects of aggregation on rainfall and flow peaks. Scale factors and their thresholds are generally applicable at scales relevant in this study and cases where thresholds are not satisfied are discussed, evaluating rainfall characteristics that have strong impact on hydrological response sensitivity.

This chapter is based on: **E. Cristiano**, ten Veldhuis M.-c., Wright D. B., Smith J. A., & van de Giesen, N., *The influence of rainfall and catchment critical scales on urban hydrological response sensitivity*, Water Resources Research , submitted.

5.1. INTRODUCTION

Hydrological response is strongly influenced by interactions between rainfall variability in space and time and catchment characteristics. These interactions are particularly pronounced in urban areas, where the runoff generation is fast, due to the high degree of imperviousness and to the large heterogeneity of catchment characteristics. For these reasons, the use of high resolution rainfall data is necessary to investigate and predict hydrological response in urban systems (Faures et al. 1995, Sempere-Torres et al. 1999, Smith et al. 2012, Ochoa Rodriguez et al. 2015, Zhou et al. 2017). In recent decades, new technologies and instruments have been developed to measure rainfall variability in space and time at high resolution (Leijnse et al. 2007, 2010, van de Beek et al. 2010). Rainfall data derived from weather radar in particular are increasingly used for urban hydrological applications (Einfalt et al. 2004, Thorndahl et al. 2017). Although weather radars provide indirect rainfall measurements and require calibration with ground observations, they provide spatially distributed rainfall estimates, which are essential for understanding the effects of rainfall on hydrological response (Niemczynowicz 1988, Schilling 1991, Berne et al. 2004, Ochoa Rodriguez et al. 2015, Rafieeinasab et al. 2015, Yang et al. 2016).

Thanks to increasing computational power and the availability of high resolution geomorphological data (Tokarczyk et al. 2015), high resolution distributed models have been developed and implemented for urban areas, where detailed representation of surface and drainage network is especially important (Gironás et al. 2010, Smith et al. 2013, Pina et al. 2016). Poor model performance can arise from inadequate model structure and representation of catchment and network characteristics, in addition to rainfall errors and low resolution (Wright, Smith & Baeck 2014, Pina et al. 2016). Models can represent the surface in different ways, including lumped, semi-distributed using lumped sub-catchments and fully distributed schemes, in which the surface is represented with a regular or irregular mesh (Zoppou 2000, Salvadore et al. 2015). The choice of model type that is best suited for a given application can be strongly influenced by the resolution of available rainfall data (Pina et al. 2014, 2016).

With the emergence of high resolution models and rainfall observations, relationships between rainfall and catchment scales and their impact on hydrological response prediction can now be investigated in detail (Berne et al. 2004, Ochoa Rodriguez et al. 2015, Bruni et al. 2015, Cristiano et al. 2017, ten Veldhuis et al. 2018).

Ochoa Rodriguez et al. (2015), following the study presented by Berne et al. (2004), showed that there is a relation between increasing drainage area and decreasing runoff sensitivity to coarser rainfall resolutions. Their results, based on hydrological simulations of 7 different catchments, allowed to derive several scale factors, that combine rainfall scale with the minimum required rainfall resolution to investigate the influence of rainfall characteristics on the hydrological response, and they highlighted the importance of combining both spatial and temporal rainfall characteristics.

In a follow-up study by Cristiano et al. (2018), three dimensionless parameters were introduced to represent the interactions between rainfall and basin scale and their effects on hydrological response. These dimensionless factors combine spatial and temporal rainfall scales and spatial and temporal catchment characteristic scales in relation with the rainfall spatial resolution Δs and temporal resolution Δt. The performance

Table 5.1: Characteristics of the selected sub-catchments.

ID	Name	Connected Area (km^2)	Imperviousness (%)	Slope (%)
02146507	Little Sugar Creek at Archdale	111	32	2.4
02146470	Little Hope Creek	7	32.2	2.2
0214645022	Briar Creek	48.5	24.7	2.4
02146409	Little Sugar Creek at Med. Centre	31	48.2	2.2

of the hydrological model was evaluated in relation to a range of scale factor values, from which thresholds associated with certain minimum levels of model performance were derived. These scale factors and related thresholds were developed for the dense-urbanized small basin (9 km^2) of Cranbrook (London, United Kingdom). These factors and metrics are tested here for very different climatological and geomorphological catchment conditions and at a larger catchment scale. The aim of this study is to investigate the applicability of the scale factors and performance thresholds for catchments in the Charlotte metropolitan region (NC, US).

The Chapter is structured as follows. Rainfall data, catchment, and model description are presented in Section 2. Section 3 describes the methodology used in the current study to investigate the effects of rainfall aggregation, scale factors and their applicability. Section 4 shows the results obtained in the study. Section 5 summarizes the main findings of the research, focusing on the analysis of the rainfall event characteristics that affect hydrologic response sensitivity.

5.2. DATA

5.2.1. CATCHMENT AND MODEL DESCRIPTION

The Charlotte metropolitan region (North Carolina, US) is largely located within the watershed of Little Sugar Creek (111 km^2). As shown in Fig. 5.1, four sub-catchments of Little Sugar Creek, spanning a range of drainage areas and degrees of imperviousness (Table 1) were selected for this study to investigate relationships between rainfall resolutions and hydrological response across a range of catchment scales. Catchment dimensions vary form 7 km^2 to 100 km^2. Flow measurements at the outlet of each sub-catchment at 1 min resolution are used as reference when investigating hydrological response sensitivity, in the second part of the this study (Section 5.4.3). Flood response in Little Sugar Creek were at first investigated by Smith et al. (2002). In this work, additional information about catchment characteristics and rainfall variability in this area can be found.

The physically-based distributed Gridded Surface Subsurface Hydrologic Analysis (GSSHA, for a complete description see Downer & Ogden (2003, 2004)) model was used to estimate the hydrological response of the system. A GSSHA model including river network and major subsurface storm drain in the Little Sugar Creek catchment was developed and used in previous studies (Wright, Smith & Baeck 2014). The model represents

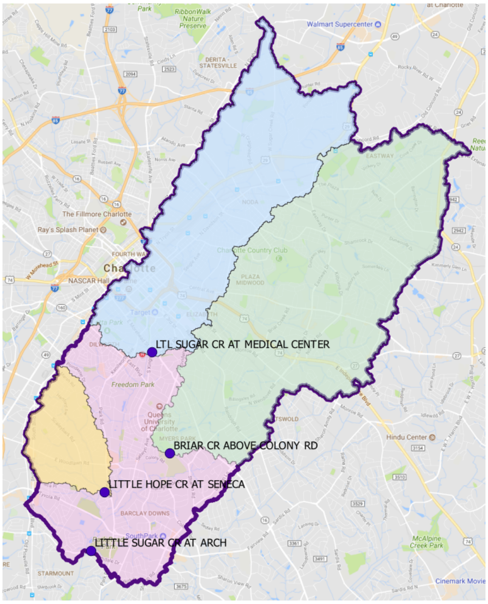

Figure 5.1: Map of the selected catchments and locations

the basin using a 90 x 90 m^2 grid and stream flow was simulated with a temporal resolution of 1 min. Model configuration and validation results can be found in Wright, Smith & Baeck (2014)

Rainfall Events

Twenty-eight storm events were selected from a 15-year (2001-2015) high-resolution (15 min, 1 km^2) radar data set (Wright, Smith, Villarini & Baeck 2014), developed from radar reflectivity observations from the National Weather Service (NWS) Next Generation Radar network (NEXRAD) processed using the Hydro-NEXRAD system (Krajewski et al. n.d., Seo et al. 2010). Table 5.2 summarizes rainfall event characteristics, presenting starting time, event duration, maximum intensity in a single pixel and total depth. Two events are assumed to be independent when there is at least a 6-hour dry period between them. Events present different characteristics, with durations varying between 3 and 38 h and rainfall peak intensities between 8 and 104 mm/h.

5.3. Method

5.3.1. Rainfall aggregation

To investigate hydrological response sensitivity to different spatial and temporal rainfall resolutions, radar rainfall fields were aggregated in space (to 3 x 3 km^2 and 6 x 6 km^2) and time (to 30 min and 60 min). Rainfall events at these different resolutions were used as input for the hydrological model to investigate the effects of aggregation on hydrological response. Simulated stream flows at sub-catchment outlets, generated using coarser rainfall resolutions, were first compared with the simulated streamflow obtained using

Table 5.2: Characteristics of the selected rainfall events. Total rainfall depth is accumulated over the whole drainage area of Little Sugar Creek.

ID	Starting Day UTC	Starting time UTC	Duration (h)	Maximum Intensity (mm/15min)	Total Depth (mm)
Ev2	2009-05-05	19:30	9.5	5.69	8.31
Ev3	2006-08-15	23:30	16.5	25.93	93.85
Ev4	2009-08-16	16:30	5.5	24.01	44.79
Ev5	2011-08-05	13:30	12.75	22.57	77.52
Ev6	2012-07-12	17:15	4.25	22.07	47.76
Ev7	2003-05-21	15:15	38.25	11.19	65.90
Ev8	2001-07-18	00:15	4.75	14.04	35.01
Ev9	2011-09-22	23:45	16.25	1.76	7.86
Ev11	2004-09-07	09:00	26.75	9.76	59.47
Ev12	2005-08-23	17:15	3	18.89	18.57
Ev13	2005-06-07	20:00	4.75	25.95	28.00
Ev14	2010-08-19	05:00	21.75	18.69	55.44
Ev15	2015-04-19	08:30	16.5	11.69	26.66
Ev16	2002-08-16	19:00	12.75	19.06	54.53
Ev17	2003-06-16	21:15	6	17.46	33.80
Ev18	2009-05-25	13:45	14.75	18.01	19.01
Ev19	2013-06-07	23:00	10.25	20.86	36.10
Ev20	2005-05-10	20:00	10.75	25.95	47.73
Ev21	2004-08-12	11:15	18.5	10.37	30.53
Ev22	2003-08-04	21:30	8.25	17.27	29.44
Ev23	2013-09-21	15:00	14.75	3.17	17.85
Ev24	2002-07-14	00:00	15.75	11.97	34.36
Ev25	2008-09-10	14:00	14.75	24.50	34.82
Ev26	2007-09-13	02:00	27.75	2.98	37.93
Ev27	2003-06-18	01:30	2.75	21.31	12.65
Ev28	2005-07-07	17:30	4.5	12.23	14.48
Ev29	2009-06-04	13:30	26.75	6.11	38.61
Ev30	2003-07-19	22:00	3.5	25.95	28.89

the original 15 min - 1 km^2 rainfall resolution as input of the model, and later with observed flows.

Effects of rainfall aggregation are investigated using the peak attenuation ratio P proposed Chapter and defined by Eq.3.8. In this case, P_{ref} corresponds to the rainfall peak rate of single pixel at 1 km^2 - 15 min and P_{st} is the rainfall peak at the spatial resolution Δs and temporal resolution Δt

The peak attenuation ratio indicates the percentage of peak intensity lost when aggregating to a coarser resolution. The rainfall aggregation analysis proposed in Chapter 3 highlighted that the effects of aggregation are substantial, up to -0.88 when aggregating from 100 m – 1 min to 3000 m − 10 min.

In this work, the peak attenuation ratio is applied to the selected 28 rainfall events, in order to evaluate aggregating effects at large catchment scale.

5

5.3.2. RAINFALL CLUSTER CLASSIFICATION

To classify the storm scale in space, the dimensions of the "cluster" of pixels above a selected threshold, as defined in Cristiano et al. (2018), is considered as the characteristic dimension of the rainfall event (Fig. 5.2a). The 75th percentile of the rain rate distribution of the selected events, was determined and used as the threshold for scale classification (Cristiano et al. 2018). The same threshold is applied to all 28 events. The cluster spatial dimension, defined as the cluster area, characterizes the main "core" of the storm event that leads to runoff generation.

For temporal classification, the rainfall time series for each pixel is analyzed. The "maximum wet period" for which the pixel exceeds the given threshold (defined as the 75-percentile of the total dataset) was selected and averaged over the total area. The estimated value was chosen as the characteristic temporal dimension of the main storm cell of the event (Fig. 5.2b).

The cluster dimension (R_s) and maximum period (R_t) above the selected threshold enable to describe the spatial and temporal variability of the storm events and were used to investigate the influence of this variability on the sensitivity of the hydrological response.

5.3.3. SCALE FACTORS AND THRESHOLDS: DEFINITION AND APPLICABILITY AT LARGE URBAN SCALE

Scale factors, introduced in Chapter 4 and described in Eq. 4.10, 4.11 and 4.12, combine spatial and temporal scales of rainfall (R_s and R_t) and catchment (C_s and C_t), with spatial and temporal rainfall resolution Δs and Δt, used to drive the hydrological model. In this work we consider the scale factors derived for the Cranbrook study case, and we apply them to the Little Sugar case, presented in this chapter. In this analysis, the characteristic rainfall spatial dimension R_s is represented by the rainfall cluster dimension above the 75-percentile threshold. The temporal rainfall scale R_t is characterized by the maximum period above the 75-percentile threshold. Drainage area and lag time are chosen in this study to represent the spatial and temporal catchment characteristic scales respectively (C_s and C_t).

Also in this study case, the coefficient of determination R^2 was chosen as statistical indicator, to represent the model performance. The coefficient of determination R^2 is

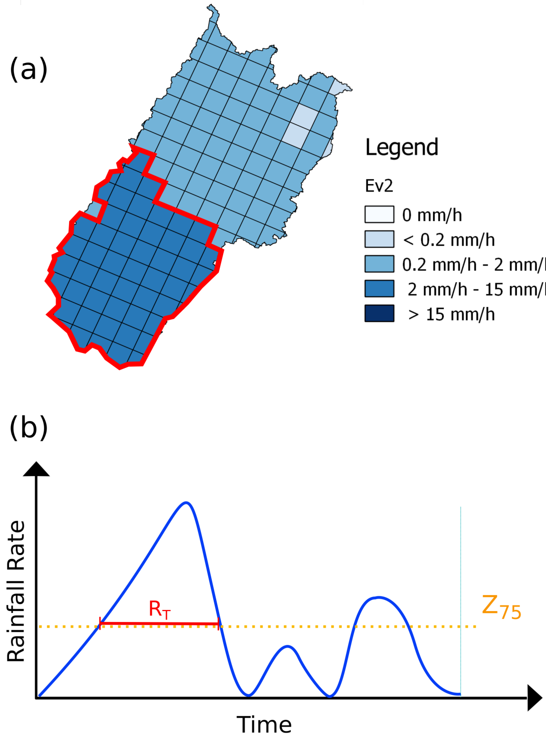

Figure 5.2: Schematic representation of the methodology used to classify rainfall characteristic dimensions in space **(a)** and time **(b)**.

defined as the square of the Pearson correlation coefficient, which represents the linear correlation between two variables, in this case, measured and simulated model results. R^2 can vary between 0 and 1, where 1 indicates a perfect overlap between observations and simulations.

Scale factors can be used to predict the level of performance, expressed in terms of coefficient of determination R^2, associated with a specific rainfall resolution, given rainfall event and catchment characteristic scales. Similarly, the scale factors can indicate the rainfall resolution, necessary to reach a certain level of performance given rainfall characteristics and basin dimensions. Scale factor thresholds, corresponding to model performance $R^2 > 0.9$ and $R^2 > 0.8$, were identified for Cranbrook. These thresholds are presented in Table 4.1.

5.3.4. EVALUATION OF THE SCALE FACTORS

When plotting scale factors α against the coefficient of determination R^2 and the performance thresholds, all the output scenarios are divided 4 groups, depending on their interaction with the scale factor thresholds:

- True Positive (T_+), where thresholds are satisfied with good model performance

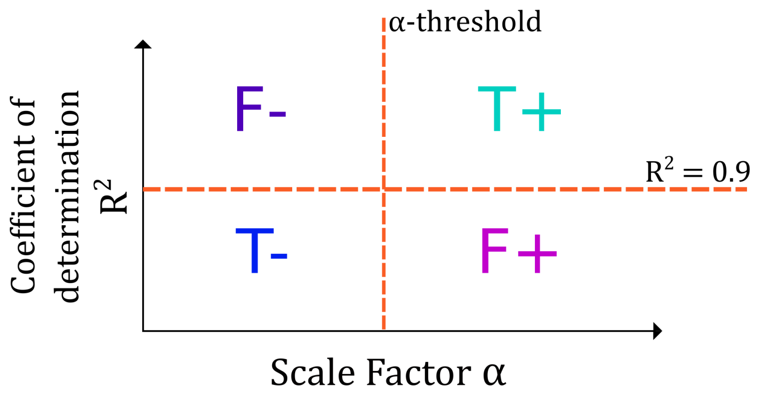

Figure 5.3: Schematization of the scale factor thresholds evaluation

and high α values;

- True Negative (T_-), which also satisfies the thresholds but with low level of performance and α values;
- False Positive (F_+), where thresholds are not satisfied because of the poor model performance in combination with high scale factor values;
- False Negative (F_-), where low α values are not able to characterize the good model performance.

Fig.5.3 gives a schematic representation of the four output scenario groups, obtained when scale factors are plotted in relation to R^2.

These indicators were combined in order to identify specificity, sensitivity, and positive and negative predictive values. The sensitivity S_e is defined as the ratio between True Positives and the total number of points that present good performance ($T_- + F_-$):

$$S_e = \frac{T_+}{T_+ + F_-} \tag{5.1}$$

Sensitivity represents cases that satisfy the thresholds with good model performance.

The specificity S_p, on the other hand, highlights the fraction of points that satisfy the scale factor threshold, among all scenarios with poor performance. Specificity is defined as:

$$S_p = \frac{T_-}{T_- + F_+} \tag{5.2}$$

High values of specificity suggest a good performance of the α scale factors, combined with a good performance of the model.

The Positive Predictive Value P_p is the fraction of values that present good performance among the values with high scale factor values:

$$P_p = \frac{T_+}{T_+ + F_+} \tag{5.3}$$

In the same way, the Negative Predictive Value P_n is described as the fraction of values that present poor performance among the values with low scale factor values:

$$P_n = \frac{T_-}{T_- + F_-} \tag{5.4}$$

High values of both positive and negative predictive value highlight a good applicability of the proposed thresholds for the α scale factors.

5.4. RESULTS

5.4.1. RAINFALL AGGREGATION EFFECT ACROSS RANGE OF SCALES

Fig. 5.4 shows the effect of aggregation in time and space on rainfall peaks. The peak attenuation ratio (Eq. 3.8) is plotted against rainfall spatial and temporal resolution. The figure shows results from Cristiano et al. (2018) for the 8 km^2 catchment of Cranbrook and results derived in this work for Little Sugar Creek (111 km^2 total area). In all plots, markers indicate the median peak attenuation ratio of the selected events, while solid lines highlight the interquartile (25 percentile to 75 percentile) range and dotted lines show the minimum to maximum range.

Fig. 5.4a presents results for Cranbrook, based on nine rain events and 16 resolution combinations from 1 to 10 min and from 100 m to 3000 m. In this case, the effects of aggregation on the rainfall peak are very strong, leading to up to −0.8 peak reduction when aggregating in space (from 100 m to 3000 m) or in time (from 1 min to 10 min). Peak reduction reaches −0.88 for spatial and temporal aggregation combined.

The effects of aggregation on the twenty-eight events selected for Little Sugar Creek (5.4b) confirm that aggregation results in strong peak attenuation, reaching a maximum peak reduction of −0.6 when aggregating in space and time, from 1 km - 15 min to 6 km - 60 min. Spatial aggregation shows a slightly stronger effect on peak attenuation, especially at the coarser resolutions, between 3 km and 6 km.

Stronger attenuation effects at smaller scale can be explained by the fact that the intermittency, defined as the alternation of dry and wet periods during the rainfall event, presents high variability at different scales. Rainfall intermittency is generally stronger for convective events (Gires et al. 2012) and it increases with finer resolution and spatial correlation increases at lower temporal resolution (Schleiss et al. 2011).

These results highlight the importance of using high-resolution spatially distributed rainfall data and suggest that using the 1 km - 15 min may not be enough to reach a reasonable level of accuracy in the flow estimation.

Effects of rainfall aggregation on stream flow are also quite strong. Applying the peak attenuation ratio on the simulated flow lead to a median loss of 0.15 for sub-catchment 507 and 45022, 0.28 for 490 and 0.38 for the smallest catchment 470, when using the coarser rainfall resolution (6000 m - 60 min). Losses are less than for the rainfall, but they are still quite high and they are higher for smaller catchment, suggesting higher sensitivity for smaller basins.

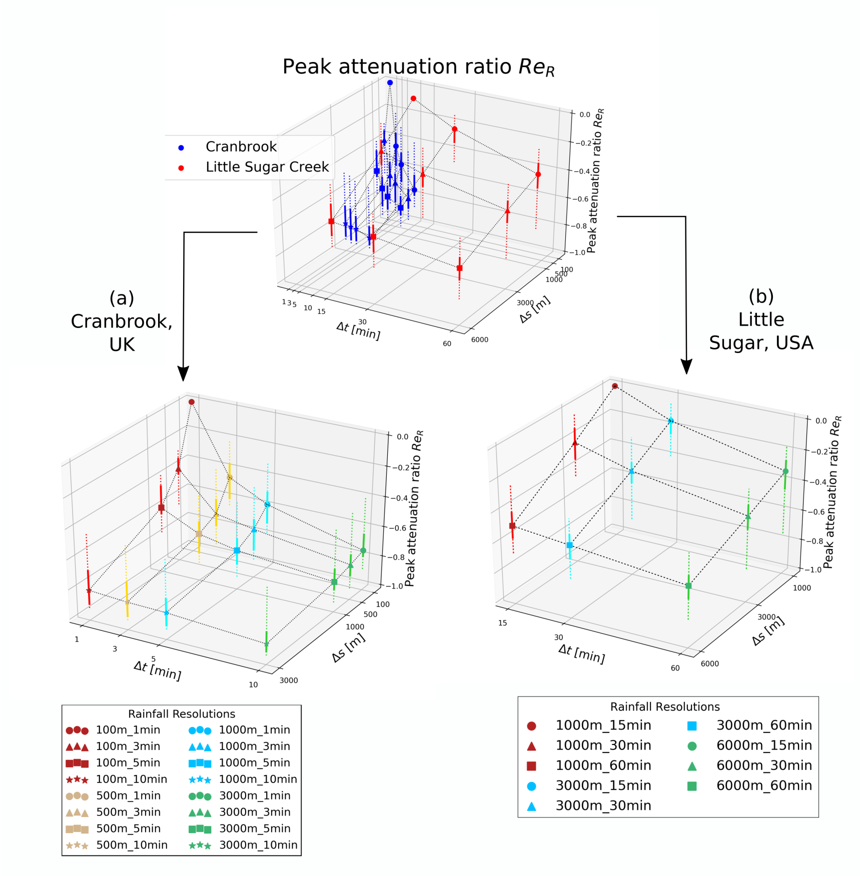

Figure 5.4: Peak attenuation ratios associated with rainfall aggregation. Comparison between the results presented in Cristiano et al. (2018) for Cranbrook **(a)** and the results obtained for Little Sugar Creek **(b)**. Markers indicate the median, solid lines the interquartile range and dotted lines the difference between minimum and maximum values.

5.4.2. RAINFALL CLUSTER CLASSIFICATION

The rainfall cluster classification approach described in Section 5.3.2 was applied to the selected twenty-eight rain events. The threshold used for cluster identification is 2 mm/h. Figure 5.5 shows the spatial and temporal scales obtained by applying the cluster classification. The main cluster dimension varies from 3 km^2 to 33 km^2. Events with a short maximum wet period present a high level of intermittency, while long maximum period indicates storms that are relatively homogeneous. For the selected events, spatial scale generally increases with temporal scale, but the relation is weakly linear (Pearson correlation coefficient of 0.45). A few events were characterized by small temporal scale yet large spatial scale, corresponding to fast-moving events with a large storm core.

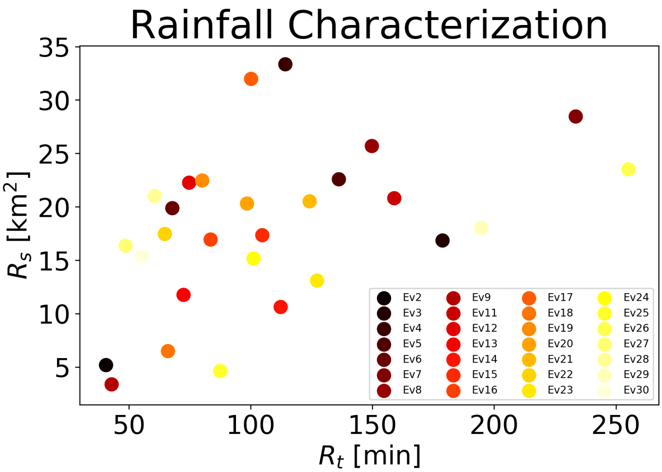

Figure 5.5: Spatial and temporal rainfall scales of the 28 selected events, based on cluster classification.

5.4.3. SCALE FACTORS

In this section we investigate the applicability of scale factors in relation to the performance thresholds described in Section 5.3.3, for two different situations. In the first case, the output obtained using the highest rainfall resolution, is used as a reference. This case, referred to as "Model-based analysis", characterizes the impact of rainfall input resolution on streamflow predictions. In the second case, referred as "Observation-based analysis", flow observations are used as a reference to assess model performance. This enables us to discriminate between the influence of rainfall resolution on model output versus the effect of model uncertainty on model performance. Table 5.3(a) summarizes the percentage of data points that present a good level of performance ($R^2 > 0.9$ and $R^2 > 0.8$) for both the analysis. This allows us to identify the decrease of performance due to model uncertainty. We can observe that the percentage of data points with $R^2 > 0.9$ drastically drop when we investigate the model based analysis. This loss of accuracy is also influenced by the sub-catchment characteristics and their representation in the model. Table 5.3(b) presents the loss of accuracy for the resolution 1000 m - 30 min as example to illustrate the influence of different sub-catchments. The model is able to represent better sub catchment 45022, which shows high level of performance, while the small basin of Little Hope (470) is not well represented in the model, as indicated by a low level of performance, for both model-based and observation-based analysis.

MODEL-BASED ANALYSIS

Figure 5.6 shows results for the model-based analysis, where model performance in terms of R^2 is plotted as a function of the three dimensionless scale factors. Blue and red dotted lines highlight the α thresholds described in Section 5.3.3 (corresponding respectively to $R^2 = 0.9$ and $R^2 = 0.8$), colors indicate different resolution combinations and markers represent different sub-catchments. Low α values are associated with low rainfall resolution relative to rainfall and catchment scale. As expected, model performance gen-

Table 5.3: Fraction of data points with high level of performance. **(a)** Aggregated results for the 4 sub-catchments. **(b)** The resolution 1000 m - 30 min is presented as example, to demonstrate differences between sub-catchments

(a)

Resolution	Model-based $R^2 > 0.9$	Model-based $R^2 > 0.8$	Observation-based $R^2 > 0.9$	Observation-based $R^2 > 0.8$
1000 m - 15 min	1.00	1.00	0.38	0.55
1000 m - 30 min	0.79	0.89	0.21	0.47
1000 m - 60 min	0.20	0.55	0.05	0.21
3000 m - 15 min	0.98	0.99	0.36	0.54
3000 m - 30 min	0.79	0.89	0.27	0.48
3000 m - 60 min	0.23	0.55	0.06	0.24
6000 m - 15 min	0.91	0.96	0.25	0.53
6000 m - 30 min	0.73	0.87	0.24	0.46
6000 m - 60 min	0.27	0.60	0.08	0.28

(b)

Resolution 1000 m - 30 min

Sub-catchment ID	Model-based $R^2 > 0.9$	Model-based $R^2 > 0.8$	Observation-based $R^2 > 0.9$	Observation-based $R^2 > 0.8$
409	0.89	1.00	0.29	0.64
45022	1.00	1.00	0.36	0.64
470	0.29	0.57	0.04	0.04
507	1.00	1.00	0.18	0.57

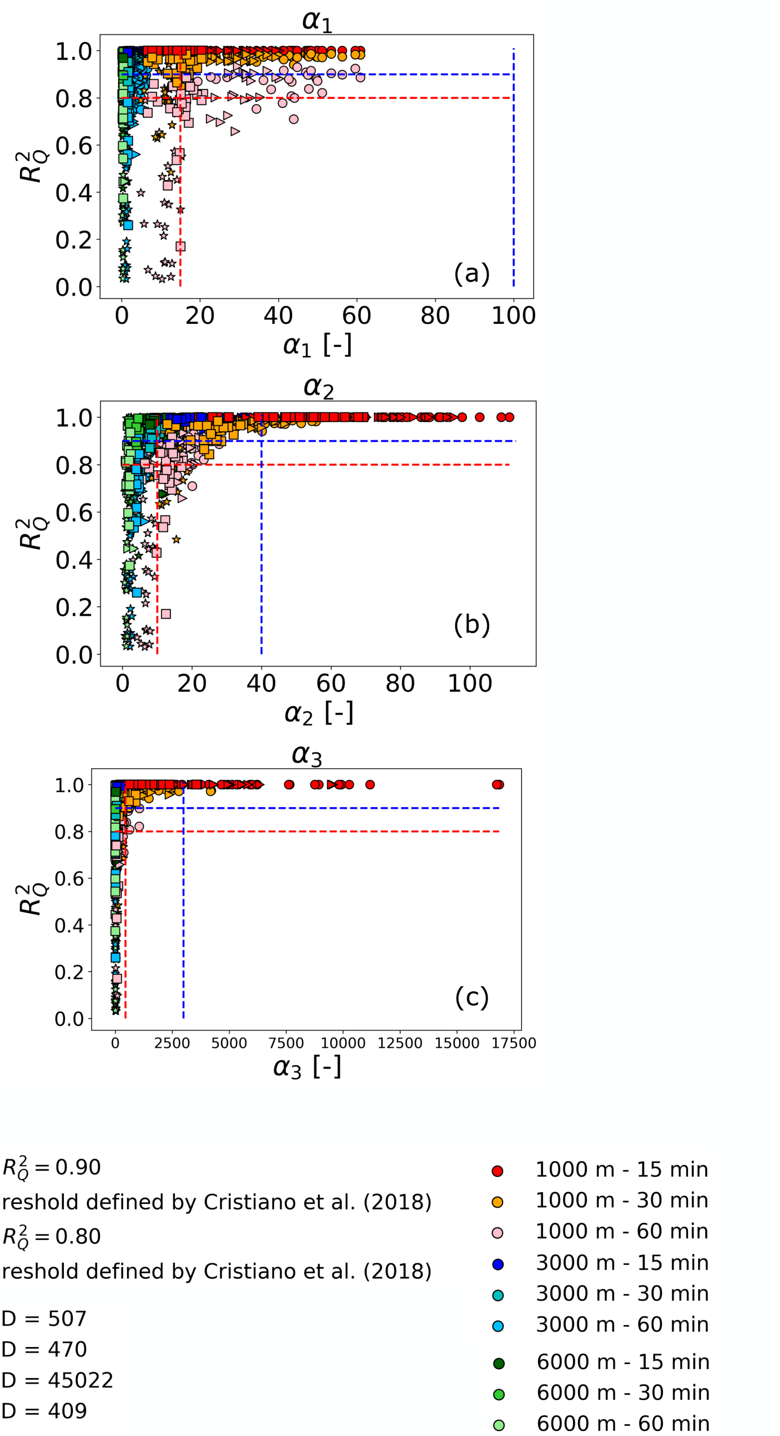

Figure 5.6: Coefficient of determination R^2 as function of scale factors. Colours indicate different rainfall resolutions and symbols represent different sub-catchments.

Table 5.4: Indicators estimated for **(a)** model-based analysis and **(b)** observation based analysis.

(a) **Indicators**	**Model-based analysis** $R^2 > 0.9$			$R^2 > 0.8$		
	α_1	α_2	α_3	α_1	α_2	α_3
Sensitivity S_e	0.00	0.00	0.00	0.00	0.16	0.01
Specificity S_p	1.00	1.00	1.00	1.00	1.00	1.00
Positive Predictive Value P_p	0	1.00	1.00	0.00	1.00	1.00
Negative Predictive Value P_n	0.50	0.50	0.50	0.29	0.33	0.30
(b) **Indicators**	**Observation-based analysis** $R^2 > 0.9$			$R^2 > 0.8$		
	α_1	α_2	α_3	α_1	α_2	α_3
Sensitivity S_e	0.00	0.13	0.07	0.21	0.53	0.25
Specificity S_p	1.00	0.92	0.96	0.76	0.55	0.82
Positive Predictive Value P_p	0	0.36	0.37	0.48	0.55	0.59
Negative Predictive Value P_n	0.73	0.74	0.74	0.48	0.52	0.51

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erally improves for higher α values. Still, a large number of results are concentrated in the upper left quadrant; for those events, model performance appears independent of rainfall input resolution.

The plots show that of the three scale factors, α_2 is best capable of separating good performance versus low performance events. The thresholds that were identified in the previous study, based on a range of higher rainfall input resolutions, seem to apply reasonably well for the case of Charlotte: especially for α_2 and α_3, the R^2=0.8 performance threshold correctly identifies events with performance above and below the α threshold value. The threshold value for R^2=0.9 performance seems too strict for the Charlotte case: it could be relaxed to lower values of 20 and 500 for α_2 and α_3 respectively. The performance indicators described in Section 5.3.3 are presented in Table 5.4a. Performance scores are generally better for α_2 than for α_1 and α_3, showing that α_2 is better able to predict good model performance. Negative predictive values generally indicates a good performance and it identifies low performance associated with insufficient rainfall resolution. The highest sensitivity of 0.16 is reached for α_2 at the R^2 >0.8 performance threshold, which implies that α thresholds are generally strict and reject many events with good performance. Performance for those events is relatively insensitive to rainfall input resolution. In Section 5.4.4, we will investigate in more detail what explains low sensitivity for these events.

OBSERVATION-BASED ANALYSIS

Figure 5.7(a-c) shows model performance comparing model results using the radar rainfall as input to flow observations. Model performance is generally good for catchment 45022 (21 out of 28 events present $R^2 > 0.8$) and generally poor for the smallest subcatchment (6 out of 28 events present $R^2 > 0.8$). Performance for the other sub-catchments falls within this range.

For the Little Hope (470) sub-catchment, low model performance is probably associated with the small scale of the catchment: model and rainfall resolutions are too low

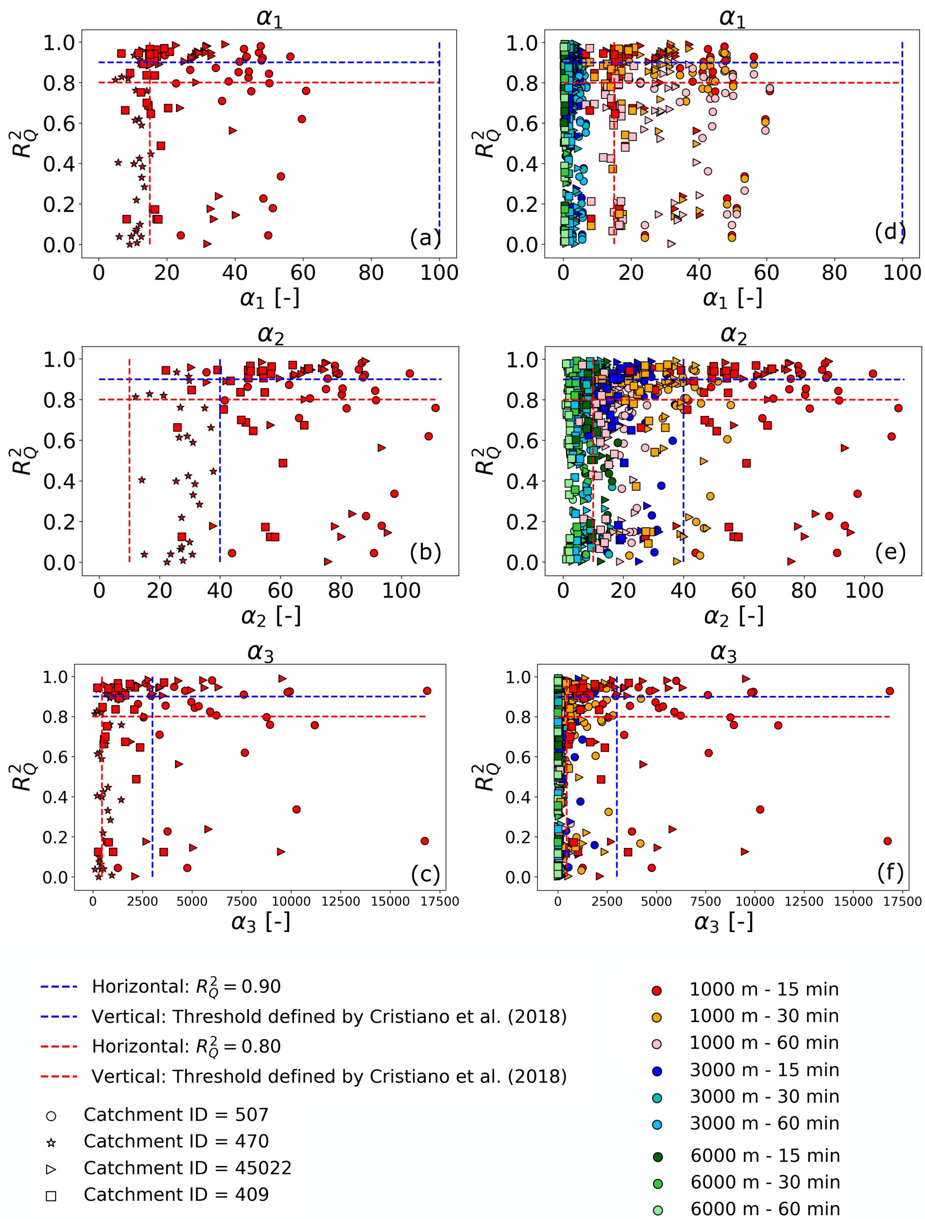

Figure 5.7: Coefficient of determination R^2 as function of scale factors. Colours indicate different rainfall resolutions and symbols represent different sub-catchments. **(a-c)** Observation-based analysis focusing on the highest rainfall resolution investigated and **(d-f)** observation-based analysis for all rainfall resolutions

to properly represent the catchment response. Moreover, the insufficient representation of storm drain for this sub-catchment leads to a poor model performance, as already highlighted in Wright, Smith & Baeck (2014). For this reason, Little Hope is excluded from the observation-based analysis. For α_2 and α_3 about 30% of the data points above the α thresholds show a low level of performance, mostly for catchments 509 and 409. This implies the model is unable to properly reproduce hydrological response for these events for reasons other than rainfall resolution. This will be investigated more in detail in Section 5.4.4.

In Fig. 5.7(d-f), R^2 values are plotted for all rainfall resolutions, in relation to the scale factors and their threshold values. Performance is generally poorer than in the model-based analysis, as would be expected, since model uncertainty is now added to the effect of varying rainfall input resolution. The number of events that do not reach indicated performance levels is higher. The plots show that α values are less capable of separating good and poor performance, with 9% and 13% of events above the threshold values for α_2 and α_3 respectively associated with R^2=0.8 not meeting the required performance. Comparing indicators of model- and measurement-based analysis (Table 5.4), we observe a general increase of sensitivity and of negative predictive value and a decrease of specificity and positive predictive value. This behavior can be explained by errors introduced by the model. The scale factor α_2 is still the one that better represents the influence of rainfall and catchment scale on the hydrological response. This is confirmed by the high values of sensitivity. The poor performance of α_1 to Little Sugar Creek study case highlights the importance of temporal dimensions, for both rainfall and catchment classification.

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5.4.4. ROLE OF RAINFALL CHARACTERISTICS

The decrease in model performance associated with rainfall resolution is relatively small compared to the difference in performance between events and catchments, presented in 5.6(g-i). Low model performance for catchment 407 is clearly associated with insufficient rainfall resolution for a basin of this small scale. For the other catchments, performance is good ($R^2 > 0.8$) for 70% of events, but falls as low as zero for some events.

In this section we investigate the properties of the rain events associated with low performance in order to identify which characteristics could explain this poor performance. In particular we focus on those events that present high values of α_2 and low values of R^2. Figure 5.8 shows α_2, which was previously shown to be the most reliable scale factor, in relation to the coefficient of determination. Different colors highlight the influence of different rainfall characteristics. On the left side (Fig. 5.8a-d) are plotted only the high rainfall resolution (1000 m -15 min) results for the three larger sub-catchments. On the right side (Fig. 5.8e-h) all the resolutions are presented. The following characteristics are investigated: maximum wet period above the 75th percentile threshold R_t (Fig. 5.8a and e), total rainfall depth in mm (Fig. 5.8b and f), ratio between the maximum wet period above the 75 percentile threshold and the total duration of the event $\%T$ (Fig. 5.8c and g) and the maximum 15-min intensity in a single pixel, expressed in mm/h (Fig. 5.8d and h).

Rainfall events with a short maximum wet period (darker color points in Fig. 5.8a and e) generally present lower performance, while lighter points (long maximum wet period)

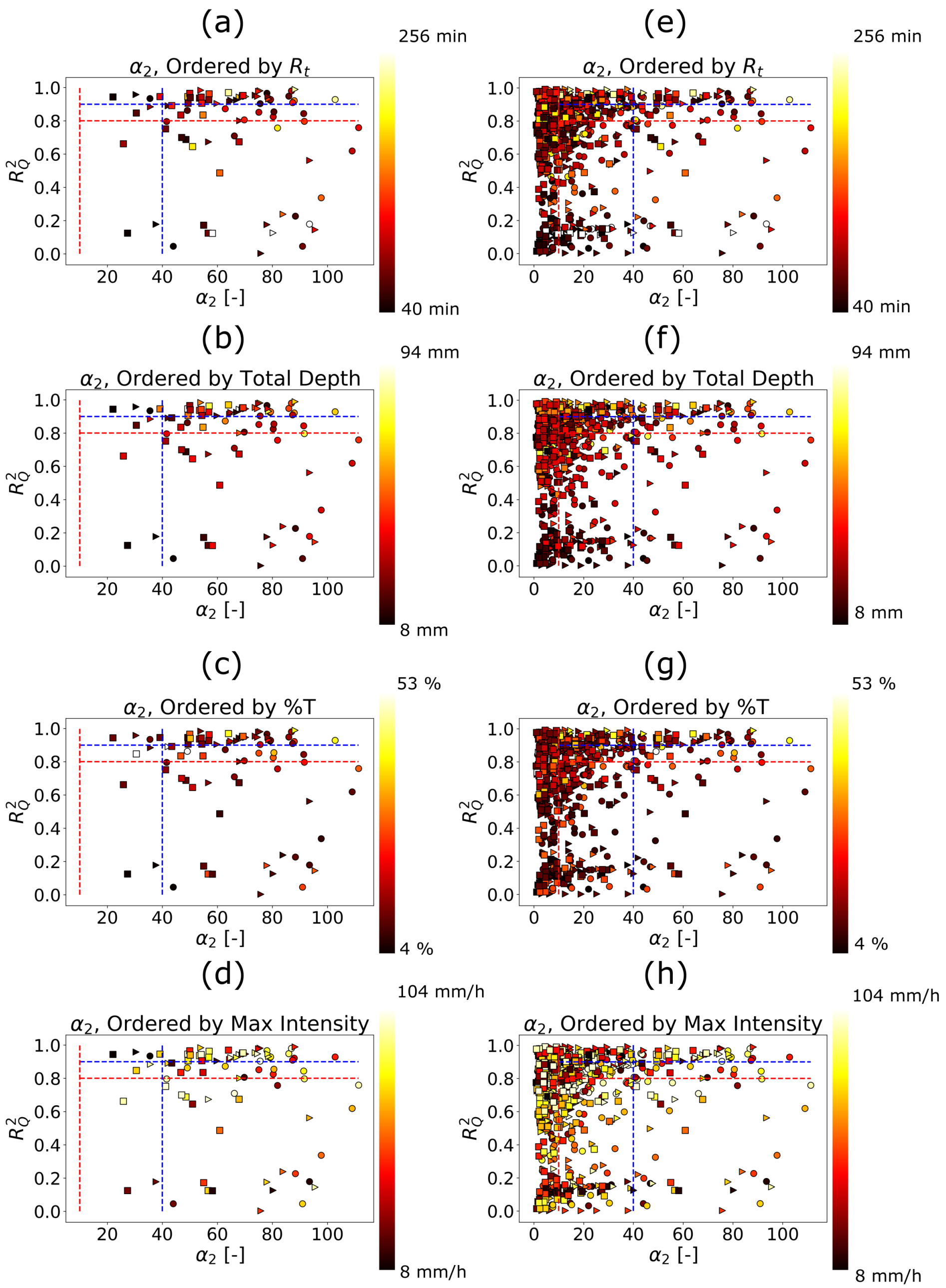

Figure 5.8: Influence of rainfall event characteristics on the hydrological response sensitivity. Different colors indicated different values maximum wet period above the 75 percentile, Total rainfall depth, Percentage of wet period over the total duration and maximum intensity for the highest resolution 1000 m - 15 min **(a-d)** and for all the resolution investigated **(e-h)**.

show a higher coefficient of determination. 63% of the data points with low performance present short maximum wet periods ranging between 40 min and 112 min.

Total rainfall depth can explain the low level of model performance for some rainfall events. Low values of total rainfall depth lead to a low level of performance: for the highest rainfall resolution, 80% of the rainfall events with a $R^2 < 0.8$ present a total rainfall depth between 8 mm and 37 mm. The percentage of data point drops to 72%, when considering all the rainfall resolutions. Total rainfall depth seems hence to have a relatively strong influence on the hydrological model performance.

Fig. 5.8c and g show that also $\%T$, the ratio between the maximum wet period and the total duration of the event, seems to affect the level of performance of the model. This parameter represents the intermittency of the rainfall event, estimating for how long the rainfall pixel is above the threshold, in relation to the total duration of the event. Most of the low-performance data points (73%) present low values of $\%T$ (in a range between 4% and 20%).

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The last rainfall characteristic investigated is the maximum pixel intensity. In this case, most of the data points with low model performance (43%) present high values of maximum rainfall intensity.

The rainfall characteristics investigated in this section, can partially describe the coexistence of poor model performance and high scale factor values. The combination of low intermittency, low total depth, short maximum wet period and high maximum intensity describe the rainfall events that lead to poor model performance.

5.5. SUMMARY AND CONCLUSIONS

In this study we investigate the relationships between rainfall and catchment spatial and temporal scales and the sensitivity of urban hydrological response to rainfall data resolution. The applicability of the cluster classification and the scale factors proposed by Cristiano et al. (2018) are here investigated for a different range of space and time scales. Little Sugar Creek, located in the Charlotte metropolitan area in the United States, was analyzed using a physically-based distributed hydrological model and 15 years of radar rainfall and streamflow data. Twenty-eight rainfall events were used as input for the model, with the aim to investigate the interactions between rainfall and catchment scales and analyze the applicability of scale factors at a larger scale and in a different physiographic and climatic setting.

The following conclusions were derived from the analyses:

- The effects of spatial and temporal aggregation on rainfall peak intensity are strong. For the selected events, a decrease of up to 60% of the rainfall peak is observed when aggregating from 1000 m - 15 min to 6000 m - 60 min. At these resolutions, aggregation in space has a slightly stronger influence than aggregation in time. If we compare the data with results at smaller scale (1-10 min, 100-3000 m) presented in Cristiano et al. (2018), however, aggregation effects are more pronounced, reaching a peak underestimation of 88%. This confirms strong sensitivity to aggregation at smaller catchment scales, associated with rainfall intermittency, as pointed out by previous studies.

- Cluster classification and maximum wet period above a selected threshold can be used to define characteristics rain event spatial and temporal scale.

- Scale factors, combining ratios of rainfall and catchment scales, enable identification of the critical rainfall resolution required to reproduce hydrological response. Scale factors showed good performance in identifying critical resolutions, beyond which model performance progressively deteriorates.

- The analysis highlights the contribution of model uncertainty compared to rainfall resolution to overall model performance. Storm events with strong rainfall intermittency were poorly represented by the model.

- The scale factors that combine spatial and temporal scales showed lower specificity than the scale factor based on the spatial scale only. This confirms the importance of temporal scale and the need of find a correct way to classify the temporal variability. The better performance of α_2 compared to α_3 suggests to improve the characterization of the temporal rainfall variability, including aspects like intermittency in the definition of rainfall temporal scale.

6

CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

In this thesis we aimed to investigate the influence of rainfall and catchment characteristics on sensitivity of hydrological response to rainfall model-input resolution. We refer to the sensitivity of hydrological response as the variability that the hydrological response, represented by the runoff estimated at the outlet of the sewer network, has when comparing the results obtained with different rainfall resolutions to the highest rainfall resolution available. Two urbanized catchments, Cranbrook (8 km^2, London, UK) and Little Sugar Creek (111 km^2, Charlotte, US), were chosen as case studies for the analysis. These catchments present different physiographies and climatological characteristics and allow to verify the developed methodology for different conditions and scales. The analysis focused on the combined effects of spatial and temporal rainfall and catchment scales. Hydrological response of the selected catchments, modelled for different rainfall model-input resolution combinations, was investigated with the aim to answer the following questions:

1. How does small scale rainfall variability affect hydrological response in a highly urbanized area?
2. How does model complexity affect sensitivity of hydrological response to rainfall variability?
3. Can critical levels of rainfall model-input resolutions be defined in relation to given catchment and storm scales?

6

Based on the obtained results, the following observations and conclusions can be highlighted.

6.1.1. Effects of small scale rainfall variability on hydrological response in a highly urbanized area

Characterization of rainfall spatial and temporal scales

Rainfall events present high variability in space and time, which strongly affects the hydrological response. In the literature, rainfall spatial and temporal scales are often derived using a semi-variogram (Ochoa Rodriguez et al. 2015). This approach, however, leads to a smoothing of rainfall scale, which is not always representative of the small scale variability. In this work we proposed a new method to characterize rainfall scales, based on identification of rainfall clusters above a selected threshold. Among the investigated thresholds most suitable to represent the storm core corresponds to the 75 percentile of the entire dataset. In this way, climatological characteristics of the storm are preserved and lower values, which do not lead to a relevant hydrological response, are neglected. This process allows to identify the storm core, that mostly affects the hydrological response. The proposed cluster classification provides a good representation of the spatial variability of rainfall events, and results presented in Chapter 3 clearly showed the benefits of using this characterization approach.

Temporal rainfall variability was represented in this study by the maximum wet period per storm event above a selected threshold, using the same thresholds used for the spatial rainfall characterization. This approach produces a good representation of the temporal scale of a storm, yet can not fully capture alternation of wet and dry periods within events (intermittency).

INFLUENCE OF RAINFALL SCALE AND RAINFALL CHARACTERISTICS ON HYDROLOGICAL RESPONSE SENSITIVITY TO DIFFERENT RAINFALL RESOLUTIONS

Results presented in Chapter 3 showed that rainfall spatial scale, characterized with cluster identification, strongly influences the sensitivity of hydrological response to rainfall model-input resolutions. Hydrological response simulated for rainfall events that present high spatial variability, with corresponding low values of spatial rainfall scale, is highly sensitive to the rainfall resolution that is used as model input. Sensitivity of hydrological response to rainfall model-input resolutions generally decreases for events characterized by large spatial scale.

Rainfall temporal characteristics also play a significant role in the runoff estimation. Intermittency and maximum wet period above selected thresholds (rainfall temporal scale) have a strong influence on the sensitivity of the hydrological response. Rainfall events that present strong temporal variability, such as convective events, are generally highly sensitive to different rainfall resolutions used as input for the model.

6.1.2. EFFECTS OF MODEL COMPLEXITY ON SENSITIVITY OF HYDROLOGICAL RESPONSE TO RAINFALL VARIABILITY

An important aspect in the investigation of the hydrological response in urban areas is the choice of the hydrological model used to represent the catchment. Two semi-distributed hydrological models (low resolution and high resolution models) and one fully distributed hydrological model were employed in order to estimate the hydrological response for Cranbrook. The three investigated models produced different output results, but the sensitivity of hydrological response was similar for all the models. When we consider as reference the output corresponding to the highest rainfall resolution input, the sensitivity to different rainfall model-input resolutions is not strongly affected by different model types. Low resolution semi-distributed model showed a slightly higher sensitivity to rainfall model-input resolutions than the other two models, presenting lower values of coefficient of determination for low rainfall resolutions used as input for the model. However, differences are negligible when considering the effects that rainfall or catchment scales have on sensitivity of hydrological response. In view of these results, we concluded that, model complexity and model resolution have only a small influence compared to rainfall and (sub)catchment scale.

6.1.3. INTERACTIONS BETWEEN RAINFALL AND CATCHMENT SCALES AND THEIR EFFECTS ON HYDROLOGICAL RESPONSE SENSITIVITY TO RAINFALL RESOLUTIONS

In this work, three dimensionless scale factors were derived in order to investigate the influence of combinations of catchment and rainfall spatial and temporal scale on the hydrological response. The three proposed scale factors focus on different rainfall and catchment scale combinations. These scale factors are used to investigate model performance (expressed with the coefficient of determination, R^2) as function of rainfall resolution, catchment and rainfall scales. The first scale factor, α_1 combines spatial rainfall and catchment scale. This parameter is not able to fully describe the complex interactions between rainfall and catchment scale, in relation with rainfall resolutions and it highlights the importance of considering also the influence temporal scales and temporal resolution.

The second factor, α_2, analyses the interactions between spatial rainfall scale and temporal catchment scale. This factor gives a good representation of the complex interactions between rainfall and catchment scales and it allows to derive the required rainfall resolution, given rainfall and catchment characteristics.

The third parameter, α_3 combines both temporal and spatial rainfall and catchment scales. This scale factor, however, seems also to not be the most appropriate parameter to represent hydrological response sensitivity, since ire present low values of specificity. It is worth noting that when the characterizations of all the available scale is included, it leads to additional potential noise. In particular, temporal rainfall characterization has shown to not be able to properly represent some aspects, such as rainfall intermittency, that are relevant for the identification of hydrological response sensitivity. Hence, α_2 is preferred to represent the interactions between rainfall and catchment scales and to identify the required rainfall resolution.

Thresholds were derived for the proposed scale factors, that identify the required rainfall resolution, depending on the required model performance. Thresholds were derived for the small basin of Cranbrook and then their applicability was tested for Little Sugar Creek. This demonstrated the applicability of scale factors and related performance thresholds to different catchment scales and different geomorphological and climatological areas. The scale factor α_2 presented low values of specificity, especially when comparing results to local measurements. Acceptable values are obtained also for α_3, although the performance is generally worse than α_2.

6.2. RECOMMENDATIONS

6.2.1. PRACTICAL RECOMMENDATIONS

MINIMUM REQUIRED RAINFALL MODEL-INPUT RESOLUTION FOR URBAN HYDROLOGICAL APPLICATIONS

Rainfall resolution plays a fundamental role in the definition of the hydrological response. Using a too coarse resolution could lead to a wrong estimation of the runoff generation, especially in urban areas, where the catchment scale is particularly small. In this work, we have shown the importance of considering spatially and temporally distributed rainfall data at high resolution to have a good estimation of the hydrological response. When aggregating in space and time radar rainfall rate to a coarser resolution, losses in terms of rainfall peak can be quite high. In the Cranbrook study case, results showed that using a common operational radar network (1000 m - 5 min resolution) can result in a rainfall peak loss of 70% compared to the use of high resolution 100 m - 1 min. This highlights how in most of the operational cases, the used rainfall resolution is not able to properly capture rainfall peaks, suggesting the need of investing in new high resolution instruments to measure rainfall in urban areas.

The proposed scale factors are a powerful tool to identify whether the available radar resolution is sufficient to be used for hydrological applications, given catchment characteristics and storm scale typical of the local climatological regime, or, in case no radar is available, what radar resolution is required for the selected area. If a weather radar is already installed in the selected area, scale factors can identify the level of model performance that can be obtained using the radar rainfall data. The model performance is expressed with the coefficient of determination. Depending on applications, the designer should evaluate whether the obtained model performance is good enough.

IMPLEMENTATION OF URBAN HYDROLOGICAL AND HYDRODYNAMICAL MODELS

As already mentioned in the previous section, one of the fundamental starting points for this study was the availability of high resolution and high detailed hydrological models. These models were previously developed and calibrated, with a good representation of the surface characteristics and a good incorporation of the drainage network. For the aim of this study, the model quality was generally sufficient. However, well-calibrated models are not often used by municipalities and not always available for research activities. Municipalities should invest more in the implementation and calibration of their hydrological models. A good hydrological model can be a fundamental help in pluvial flooding prediction, reducing risk for the citizen.

6.2.2. FUTURE RESEARCH DEVELOPMENTS

The proposed scale factors have shown to be a powerful tool to investigate the influence of rainfall and catchment scales on hydrological response sensitivity. They allow to identify the minimum required resolution for a specific area, given physiographies and climatological characteristics. Scale factors also allow to verify if the available rainfall resolution is sufficient to properly estimate the hydrological response. However, further developments could be done in order to improve the performance of scale factors and to verify their applicability for different catchment and rainfall scales and characteristics. Deeper analysis should involve the improvement of rainfall spatial and temporal scale classification, including rainfall characteristics that have shown to have a strong influence on sensitivity of hydrological response (i.e. intermittency), and the evaluation of different temporal catchment scales.

SCALE FACTORS APPLICABILITY

Scale factors and related thresholds were developed for Cranbrook, where local rainfall and flow measurements were not available. Subsequently, they were tested for Little Sugar Creek, in order to evaluate their applicability at a large urban scale. Moreover, Little Sugar presents different climatological and physical characteristics and rainfall and flow observations are available at high resolution. It was, hence, possible to evaluate the developed approach for both model-based and observation-based analysis. Although results have shown a good applicability of the scale factors to Little Sugar Creek, more study cases need to be investigate in order to generalize the developed method for different spatial and temporal rainfall and catchment scales. In particular, different locations, with local measurements of the hydrological response, should be investigated and used for testing and validating the new methodology proposed in this work.

IMPROVEMENT OF RAINFALL SPATIAL AND TEMPORAL SCALE CLASSIFICATION

Rainfall spatial and temporal classifications are two key elements in the definition of scale factors. The spatial rainfall classification proposed in this work, showed some improvements compared to the generally used semi-variogram and to other classifications available in the literature. It allows to obtain, in a fast and easy way, an estimation of the dimension of the rainfall core. However, some small improvements could be made. For example, the situation in which more than one cluster is covering the catchment at the same time step. In this study, the percentage of these cases was small, but it is a problem that should be investigated.

Large improvements should be made for the temporal rainfall classification, which does not show to have large influence on sensitivity to hydrological response. The maximum wet period above the selected thresholds is, indeed, not able to properly account for rainfall intermittency. This parameter should be incorporated in the definition of the temporal rainfall scale, and consequently in the definition of the scale factors.

Moreover, the influence of other rainfall characteristics, such as rainfall maximum intensity, total depth, storm direction and storm velocity should be more deeply investigated. Some of these elements were investigated in this study and have shown to strongly influence the hydrological response sensitivity. Some others, like storm velocity and direction should be evaluated, and eventually included in the scale factor definition.

EVALUATION OF TEMPORAL CATCHMENT SCALE

Another important aspect that needs further investigation is the temporal characterization of catchment scale, which is described by the response time of the catchment. In this work, we selected the lag time, defined as the difference in time between the centroid of the hyetograph and the centroid of the hydrograph. This parameter is widely used in the literature to classify the response time of the catchment. Centroid to centroid lag time takes into account spatial characteristics, such as drainage area, slope and degree of imperviousness. Berne et al. (2004) highlighted the power law relation between lag time and drainage area, and this relation was confirmed in this study for the selected catchments.

However, this factor depends also on the rainfall event and it is not always representative of response time of the system. If we consider, for example a multi-peak event, peak to peak lag time could be a more appropriate choice. Different possible characterizations of the response time of the catchment are available in the literature and their possible interactions with rainfall scale and the effects on the hydrological response sensitivity should be investigated.

For many events presented in this study, however, the interpretation of the hydrological response was complex and the response time was not properly represented by any of the existing methods. Hence, we recommend to consider the development of a new and better method to characterize catchment response time. This thesis provides the starting points and general directions for such future research.

7

List of Symbols & Abbreviations

Catchment scale		
L_s	[L]	Length scale proposed by Julien & Moglen (1990)
d	[T]	Rainfall event duration
i	[L T^{-1}]	Rainfall intensity
s_0	[]	Average slope
n	[]	Average roughness
t_c	[T]	Time of concentration
t_{ch}	[T]	characteristic time of a system (Berne et al. 2004)
t_e	[T]	Time of equilibrium
T_s	[T]	Time scale proposed by Morin et al. (2001)
t_{lag}	[T]	Lag time centroid to centroid
A	[L^2]	Total catchment area
A_d	[L^2]	Drainage area

Weather Radar		
R	[L T^{-1}]	Estimated rainfall
Z	[L^6 L^{-3}]	Reflectivity
a	[T L^3]	Parameter to estimate rainfall from reflectivity
b	[-]	Parameter to estimate rainfall from reflectivity
λ	[L]	Wavelength
ν	[f]	Frequency
ł	[L]	size of the antenna

Model Characterization		
FD		Fully distributed model
L_C	[L]	Characteristic length of the catchment
L_{RA}	[L]	Spatial resolution of the runoff model
L_S	[L]	Sewer length
SD1		Low resolution semi-distributed model
SD2		High resolution semi-distributed model
GSSHA		Gridded Surface Subsurface Hydrological Analysis

Rainfall Resolution		
N_{tot}	[-]	Total number of pixels over the catchment
Δs	[L]	Spatial rainfall resolution
Δt	[min]	Temporal rainfall resolution

Variogram		
A_r	[L^2]	Areal average of spatial rainfall structure
n	[-]	Number of radar pixel
R	[L T^{-1}]	Rainfall Rate
r	[L]	Variogram range
r_c	[L]	Characteristic length scale

$\lvert\bar{v}\rvert$	[L T^{-1}]	Storm motion
γ		Climatological semi - variogram
Δs_r	[L]	Minimum required spatial resolution
Δt_r	[T]	Minimum required temporal resolution

	Spatial Variability Index	
I_σ	[L T^{-1}]	Spatial variability index
R_t	[L T^{-1}]	Spatially averaged rainfall intensity
σ_t	[L T^{-1}]	Standard deviation of spatially distributed hourly rainfall

	Statistical indicators	
P_{st}	[L T^{-1}]	Peak of aggregated rainfall
P_{ref}	[L T^{-1}]	Measured rainfall peak (100 m - 1 min)
Re_Q	[-]	Relative error on maximum flow peak
Re_R	[-]	Peak attenuation ratio
R^2_Q or R^2	[-]	Coefficient of determination for flow
R^2_R	[-]	Coefficient of determination for rainfall

	Cluster	
$\%cov$	[-]	Percentage of coverage
$\%T$	[-]	Percentage of wet periods
N_t	[-]	Number of pixel above Z at each time-step
S_Z	[L^2]	Cluster dimension above Z
Z	[L T^{-1}]	Selected threshold
Tw_{max}	[T]	Maximum wet period above Z
Td_{max}	[T]	Maximum dry period above Z
Z_x	[L T^{-1}]	Threshold above the x-%ile, with $x \in [25, 50, 75, 95]$
S_{Zx}	[L^2]	Cluster dimension above the threshold Z_x, with $x \in [25, 50, 75, 95]$
Tw_{Zx}	[T]	Maximum wet period above Z_x over d, with $x \in [25, 50, 75, 95]$
Td_{Zx}	[T]	Maximum dry period above Z_x over d, with $x \in [25, 50, 75, 95]$

	Scale factors	
s	[-]	Subscript for spatial factors
t	[-]	Subscript for temporal factors
st	[-]	Subscript for combined scale factors
H_t	[T]	Anisotropy coefficient
λ_s	[-]	Scaling factor in space, used for the anisotropy factor
λ_t	[-]	Scaling factor in time, used for the anisotropy factor
δ	[-]	Rainfall scale factor using S_{Z75}
γ	[-]	Model scale factor
Θ	[-]	Rainfall scale factors proposed by Ochoa Rodriguez et al. (2015)
R_s	[T]	Rainfall spatial scale
R_t	[T]	Rainfall temporal scale
C_s	[T]	Catchment spatial scale

7

C_t	[T]	Catchment temporal scale
α_1	[-]	Scale factor that combines δ_S and γ_S
α_2	[-]	Scale factor that combines δ_S and γ_T
α_3	[-]	Scale factor that combines δ_{ST} and γ_{ST}

Applicability of scale factors	
$T+$	True Positive Values
$T-$	True Negative Values
$F+$	False Positive Values
$F-$	False Negative Values
S_e	Sensitivity
S_p	Specificity
P_p	Positive Predictive Values
P_n	Negative Predictive Values

A

HYDROLOGICAL AND HYDRODYNAMICAL MODELS

In this work, different models and software have been used to represent the proposed study cases. Three hydrodynamical models were build up in InfoWorks ICM for Cranbrook and a Gridded Surface Subsurface Hydrologic Analysis (GSSHA) model was employed for Little Sugar Creek. A short description of the the main characteristics of these different models is presented in this Appendix.

A

A.1. INFOWORKS ICM

Infoworks ICM (Integrated Catchment Modelling) is a commercial tool developed by Innovyze and largely used in the UK, Belgium and other European countries. Infoworks ICM is an integrated modelling platform, that allows to incorporate both urban and river catchments in one single model. It was derived from the fusion of InfoWorks CS (urban sewer network modelling) and InfoWorks RS (river systems) into a single powerful platform. Infoworks ICM is generally used by engineers and researchers for different hydrological purposes, including:

- river, drainage and sewerage master planning studies;
- effective implementation of sustainable urban drainage systems (SUDS / BMPs);
- development of solutions to existing flooding problems;
- flooding and pollution prediction under complex urban and river interaction;
- flood flow planning and management.

With this platform it is possible to model 1D and 2D surface and subsurface hydrological phenomena and to combine them with sewer network and structures. Models can be generated in a semi-distributed or fully distributed way. In the semi-distributed modelling package, the total area is divided into subcatchments, each one associated with manholes or inflow nodes. Rainfall is applied to each subcatchment, as average of all the rainfall pixels above the subcatchment or considering only the rainfall cell corresponding to the subcatchment centroid. Fully distributed modelling package, instead, enables to derive the runoff generation, taking into account the spatial variability of catchment characteristics. The module for 2D simulation of overland flow enables to use a triangular mesh with flexible resolution and an implicit solution of the full shallow water and it provide a precise modelling of flows through complex geometries. The flexible resolution of the triangular mesh allows to represent points of particular interest with high resolution and, at the same time, to keep the computational time low.

Manholes, pipes, and inlets can be represented in the model and combined with channels and natural elements. Bridges, sluices, weirs and pumps can also be introduced in the model, in order to recreate realistic conditions. Flow in sewer pipes is modelled with the de Saint-Venant equations using the dynamic wave approximation. Flow estimation is solved with a finite implicit differential scheme. When the flow is pressurised, in case of sewer surcharge, the model can use different simplified approaches to simulate the flow: lost volume, virtual reservoir and virtual water column.

More information about InfoWorks ICM can be found at Innovyze's website (http://www.innovyze.com/).(Innovyze 2014)

A.2. GSSHA: Gridded Surface Subsurface Hydrologic Analysis

The gridded surface subsurface hydrologic analysis model (GSSHA) is a physically based, distributed-parameter hydrologic model, that is used to simulate a hydrological response to a given hydrometeorological inputs. This model was developed in the US from the implementation of the CASC2D model (Ogden & Dawdy 2002). Originally written in FORTRAN, the code was then reformulated in C by Dr. Saghafian at the U.S. Army Construction Engineering Research Laboratorie. Compared to CASC2D, GSSHA model is capable to better estimate the runnof mechanisms and it can include infiltration excess.

The model includes the major hydrological processes, such as spatially and temporally varying precipitation, interception, infiltration, evapotranspiration, surface runoff routing, saturated and unsaturated groundwater flow, sediment and contaminant transport and deposition. The spatially distributed character of the model was particularly relevant for this study. Rainfall from multiple rain gauges (or from radar grid) can be used as input for the model and rainfall data can be interpolated to the grid cells with Thiessen polygons or inverse distance-squared. This and all the other selected hydrological processes are defined in project file, which contains all data required to run the simulation. The catchment is represented using a 2D rectangular grid that cover the entire area. Parameter describing catchment characteristics are associated to each cell.

In GSSHA, infiltration can be simulated with a 1-D formulation of Richards' equation or using simplified approaches traditional Hortonian Green and Ampt methods. The GSSHA model allows three optional Green and Ampt based methods to calculate infiltration:

- traditional Green and Ampt infiltration;
- multi-layer Green and Ampt;
- Green and Ampt infiltration with redistribution.

The model is able to combine surface runoff with channel hydraulics, where the flow is simulated as a 1-D finite volume system of links and nodes. Channel routing is simulated using a diffusive wave approach, that enables to overcome the problem of pits or depressions. The relation between depth and discharge is expressed with Manning formula.

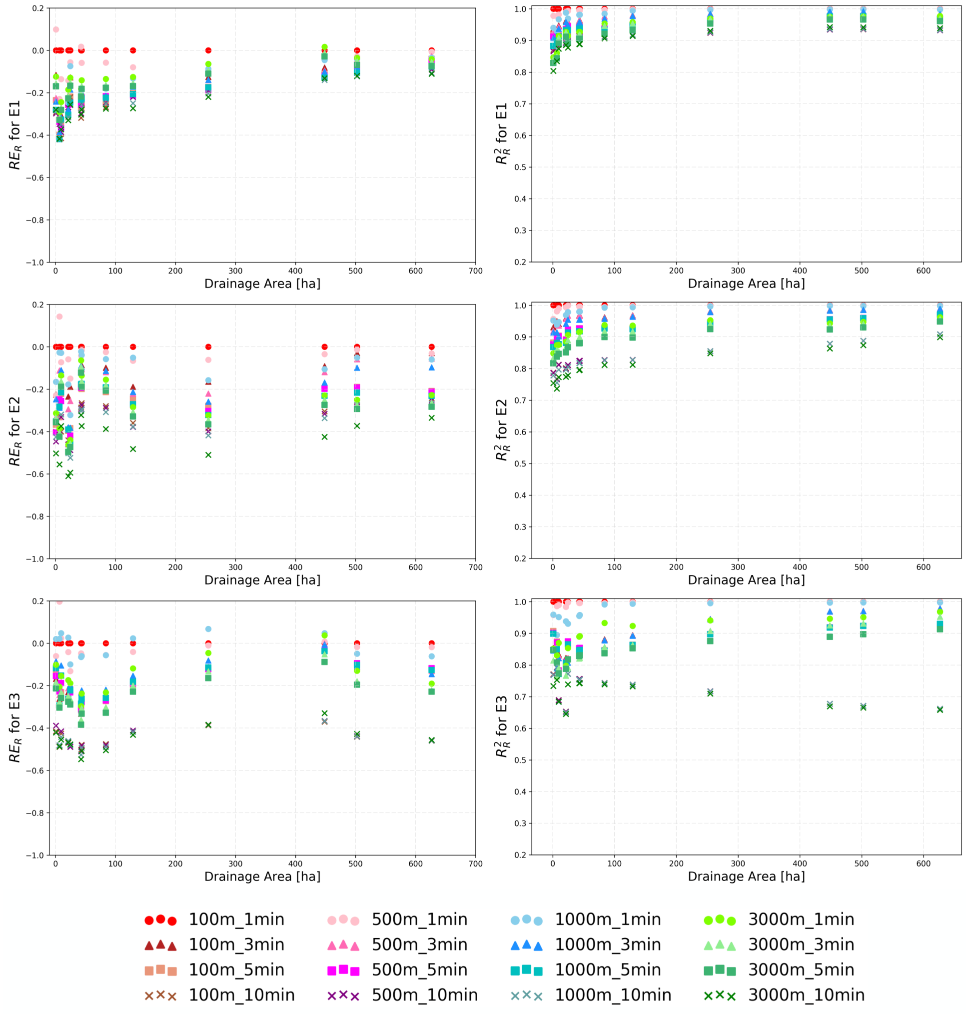
This model was developed for large scale applications in natural environments, and it mainly focuses on stream flow modelling. In this work, the model was applied to an urban environment. The model for Little Sugar Creek had been improved in a previous work (Wright, Smith & Baeck 2014), in order to include a representation of the drainage system. A network of open channels represents the sewer system. The model was previously calibrated and it showed good performance in estimating the runoff and stream flow generation. More information can be found at https://www.gsshawiki.com

B

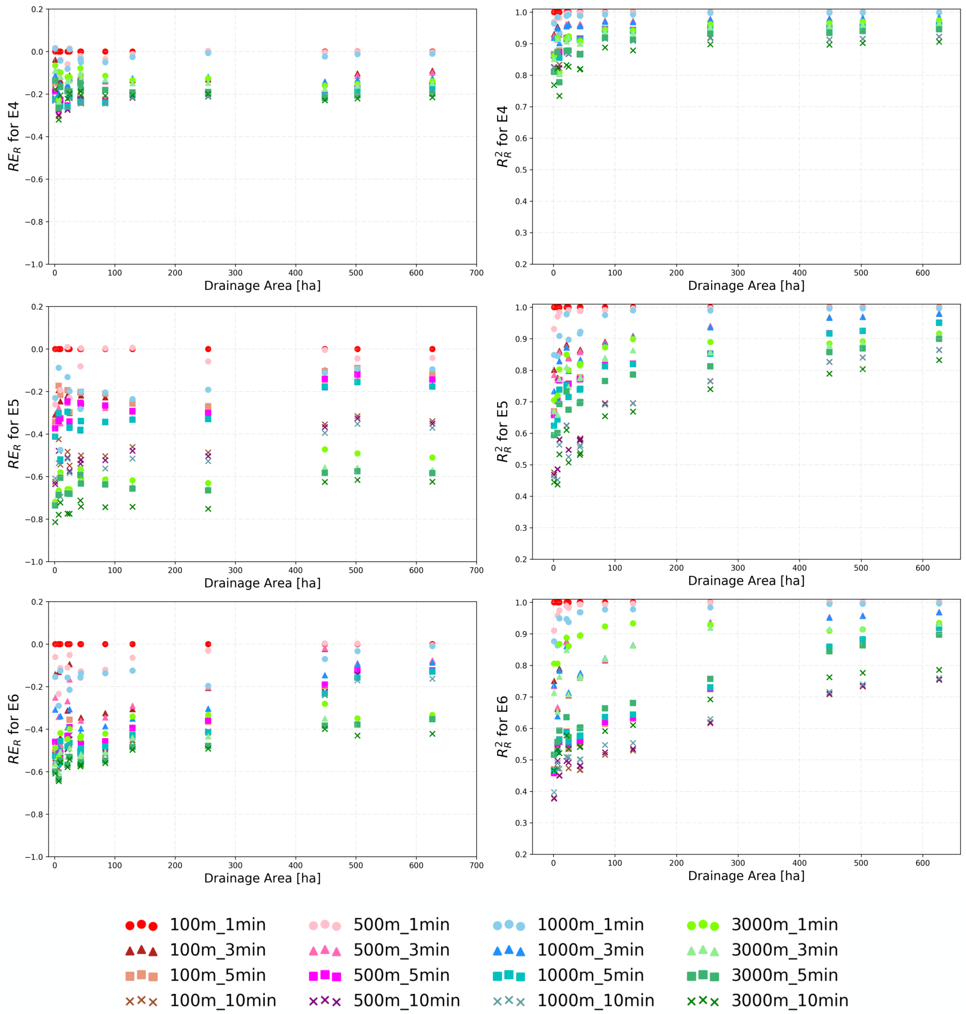
SUPPLEMENT MATERIAL

In Chapter 2, results were presented and discussed only for selected rainfall events. In this appendix, results are presented for all scenarios. In particular, Fig. B.1 shows the influences of spatial and temporal aggregation on rainfall sensitivity. Re_R and R_R^2 are presented for all the selected rainfall events, as function of the drainage area. Fig. B.2 presents the sensitivity of hydrological response to different rainfall resolutions used as input of the hydrological model. Re_Q and R_Q^2 are investigated in relation to the drainage area. Fig. B.3 plots the influences of rainfall spatial and temporal characterization on the hydrological response sensitivity: spatial and temporal required resolution, Spatial Variability Index, dimension of cluster above Z_{75} and Z_{95} and maximum wet period above Z_{75} are shown for all 13 locations.

B



RE_R for E1
R_R^2 for E1
RE_R for E2
R_R^2 for E2
RE_R for E3
R_R^2 for E3
Drainage Area [ha]
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min



RE_R for E4
R_R^2 for E4
RE_R for E5
R_R^2 for E5
RE_R for E6
R_R^2 for E6
Drainage Area [ha]
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min

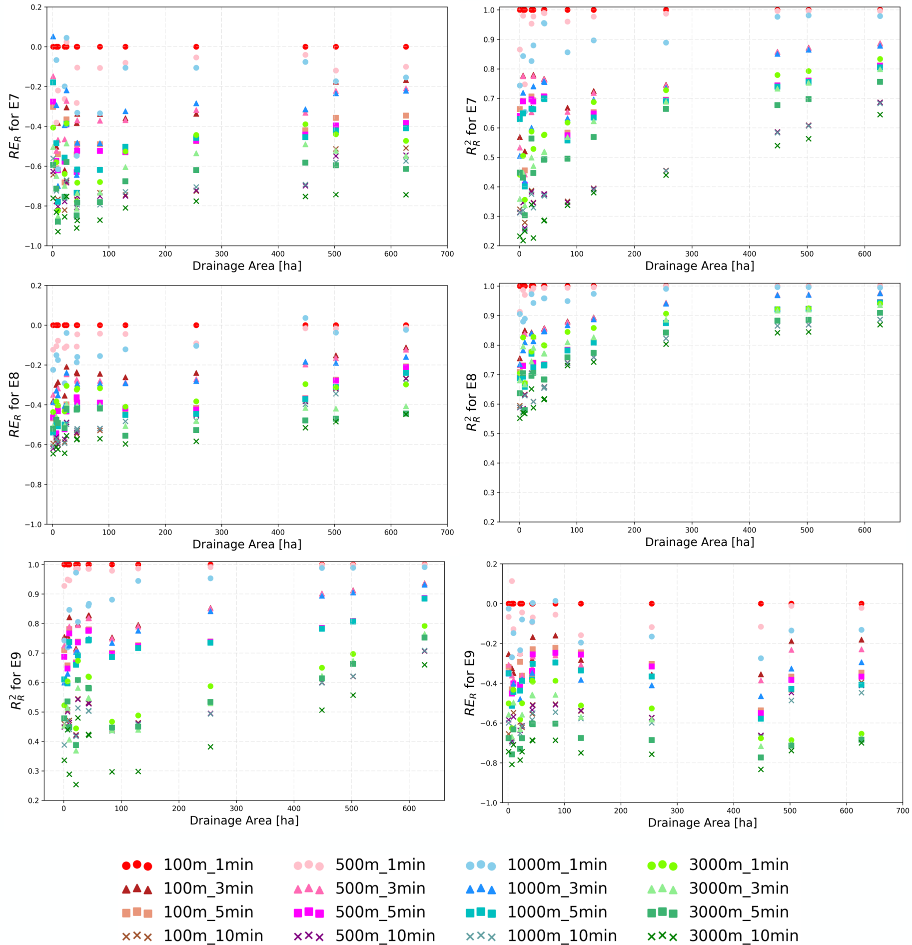
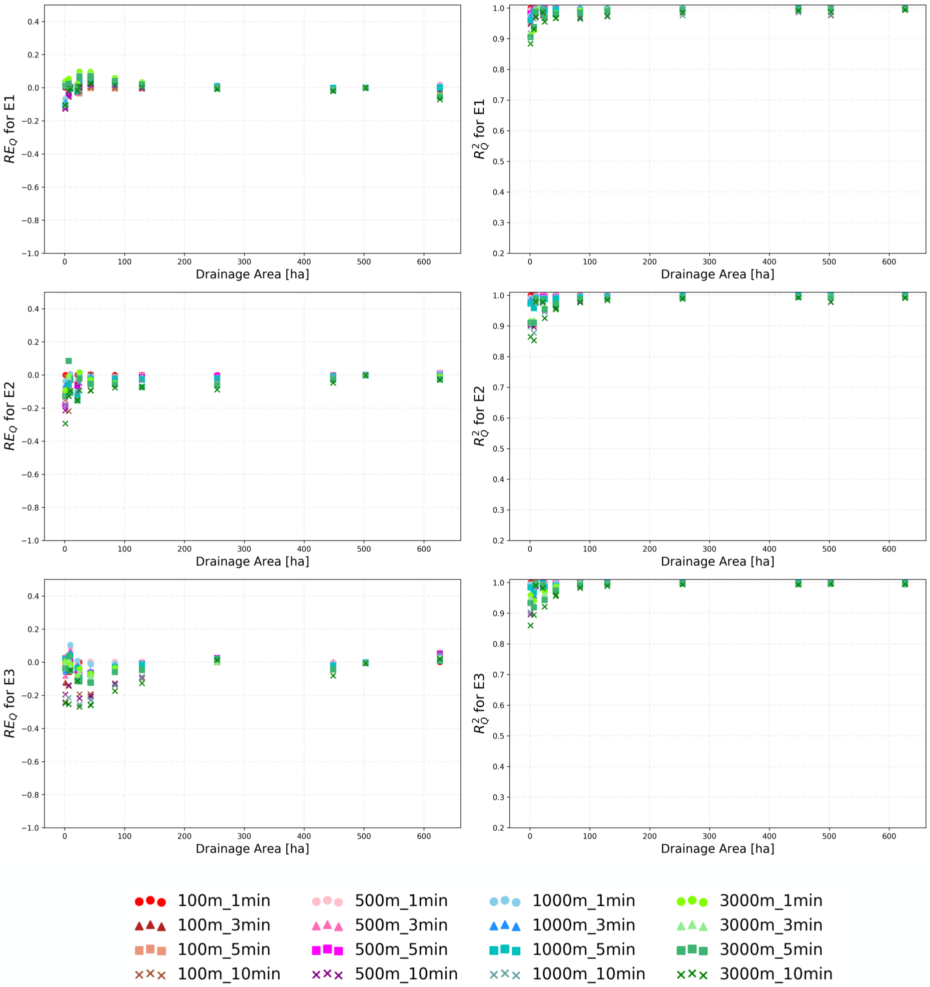
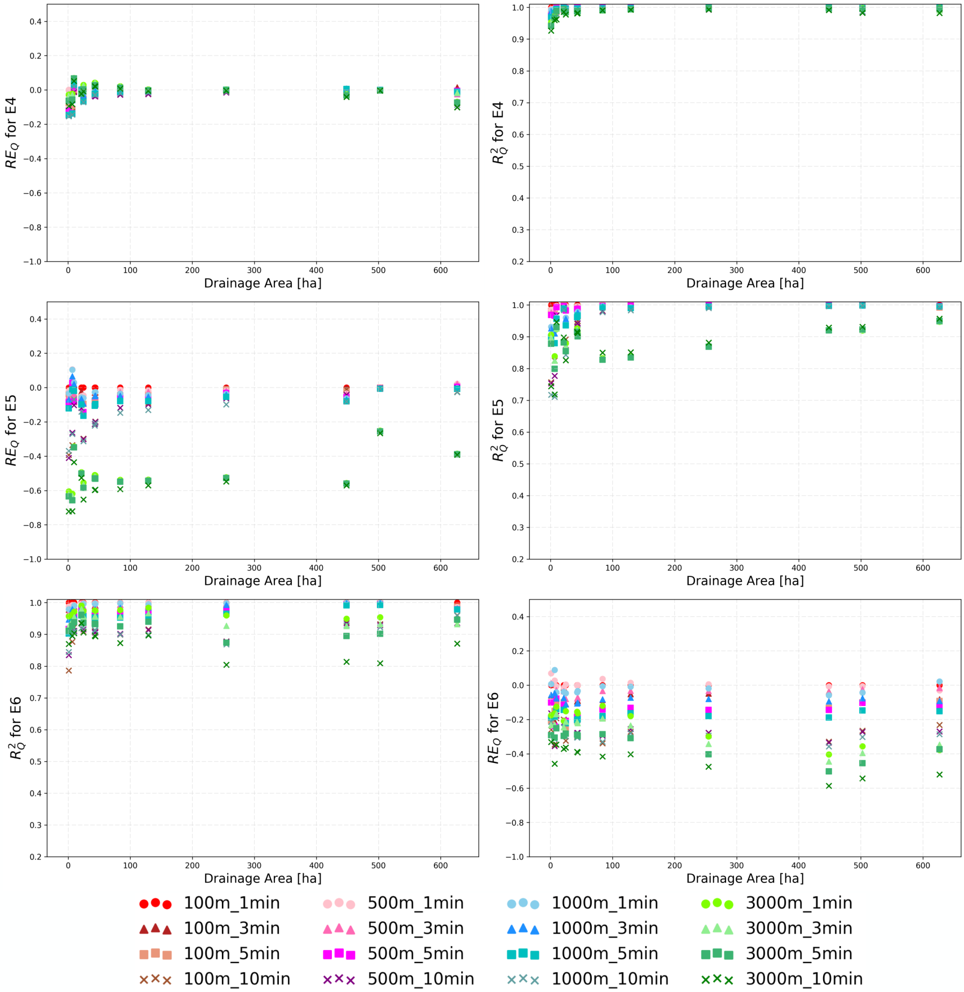


Figure B.1: Impact of aggregation in space and time on rainfall peak (Re_R, left column) and overall pattern (R_R^2, right column), as function of sub-catchment size (A_d). All 9 rainfall events are investigated.


RE_Q for E1
R_Q^2 for E1
RE_Q for E2
R_Q^2 for E2
RE_Q for E3
R_Q^2 for E3
Drainage Area [ha]
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min


RE_Q for E4
R_Q^2 for E4
RE_Q for E5
R_Q^2 for E5
R_Q^2 for E6
RE_Q for E6
Drainage Area [ha]
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min

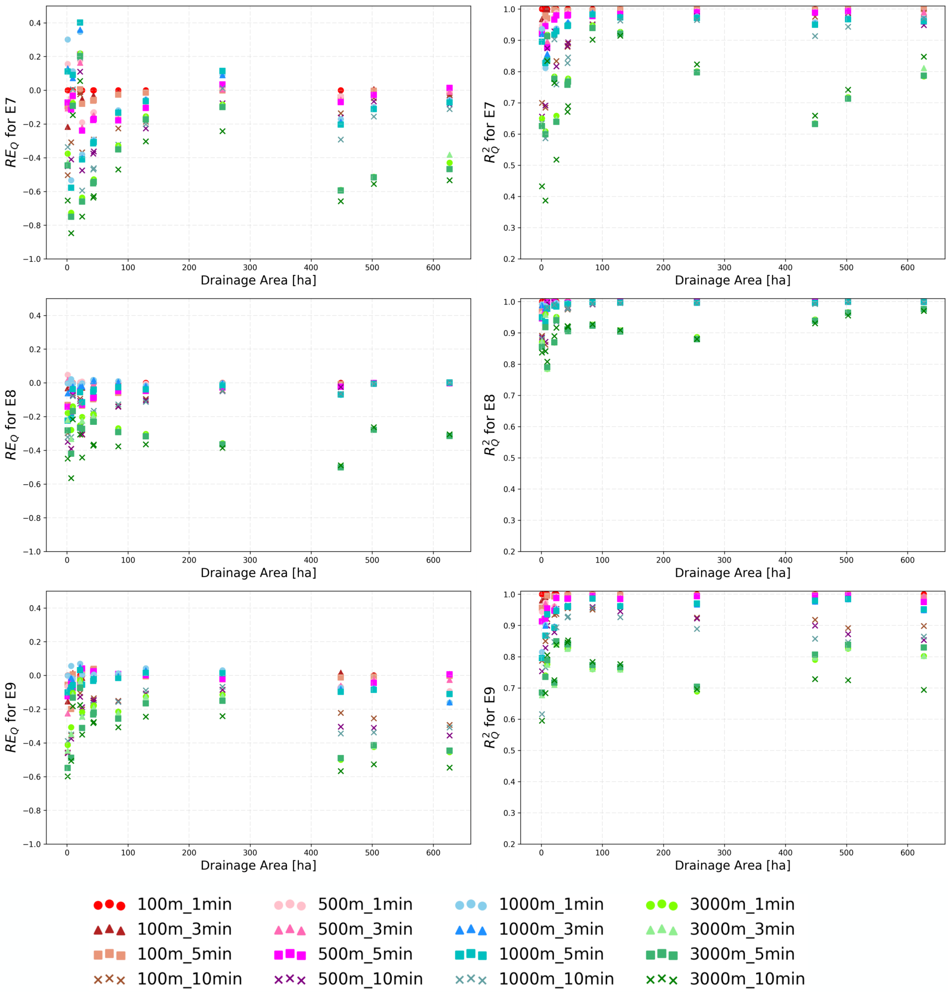
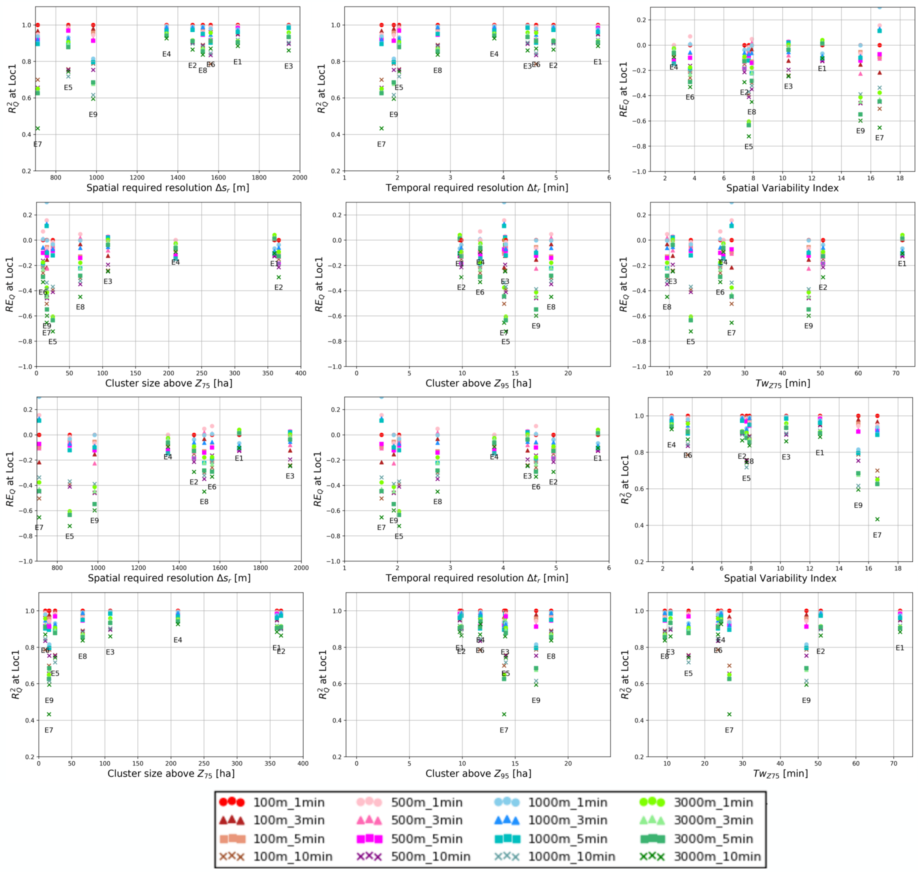
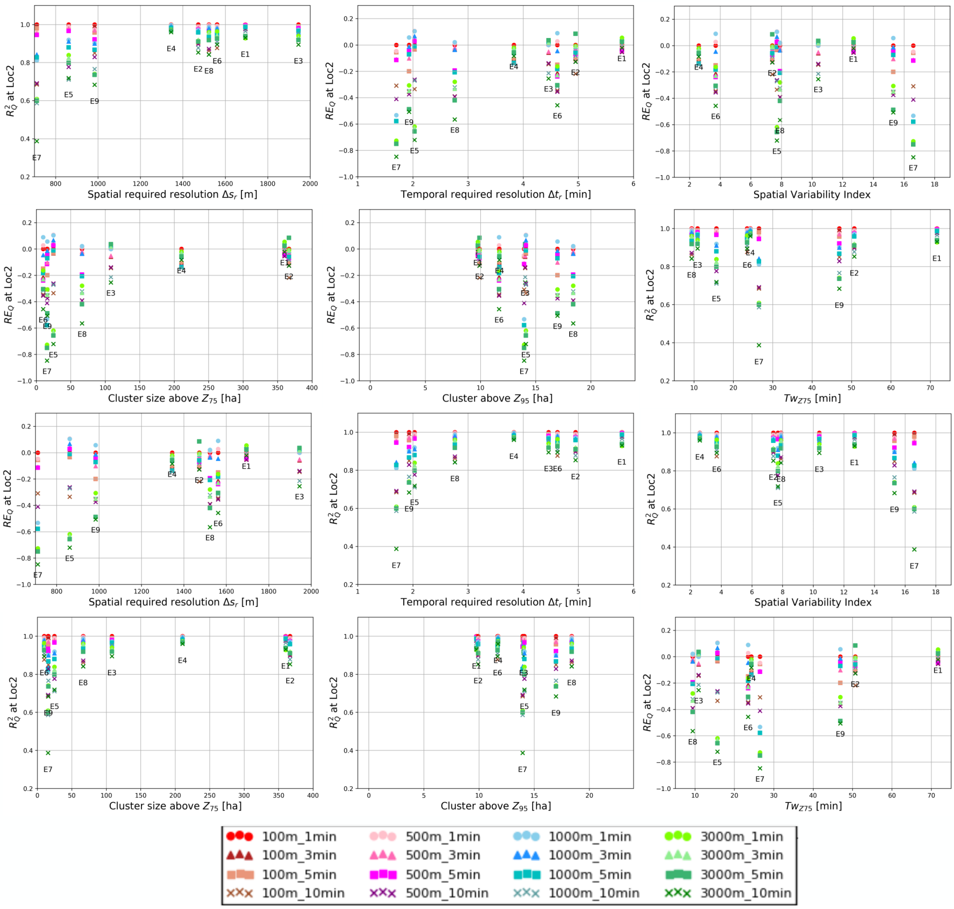


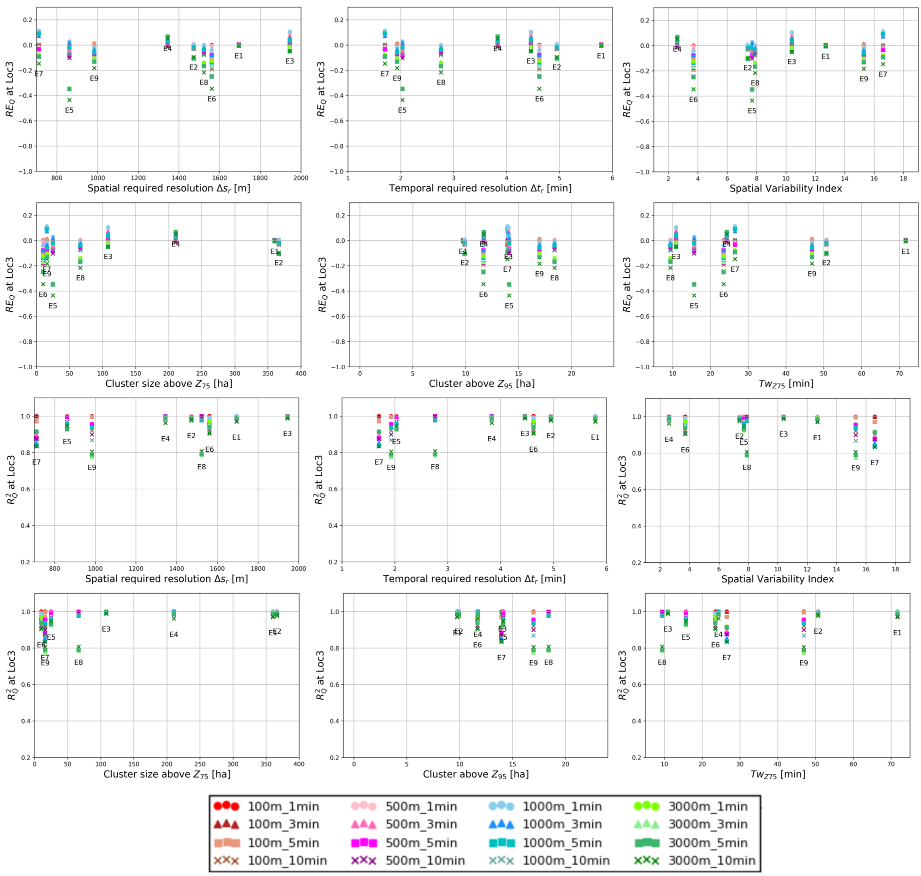
Figure B.2: Relative error in peak Re_Q (left column) and coefficient of determination R_Q^2 (right column) for SD2, plotted as function of A_d, for the sixteen combinations of rainfall input resolutions. All 9 rainfall events are investigated.

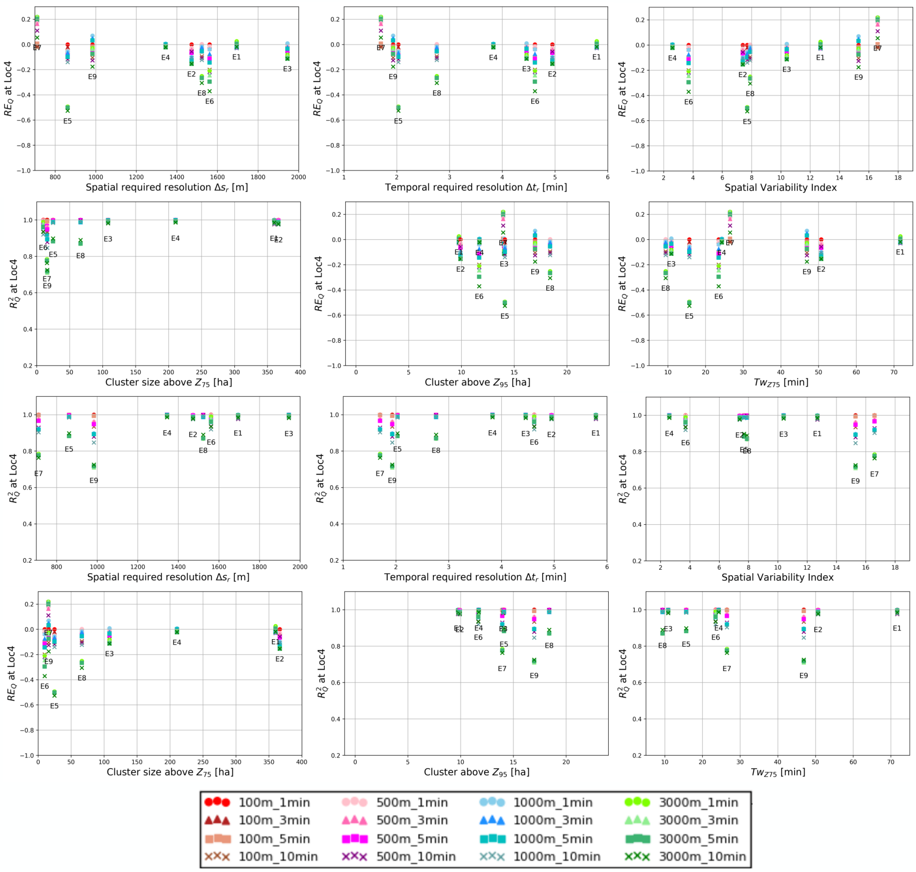
B


R_Q^2 at Loc1
RE_Q at Loc1
Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster size above Z_{75} [ha]
Cluster above Z_{95} [ha]
Tw_{Z75} [min]
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min

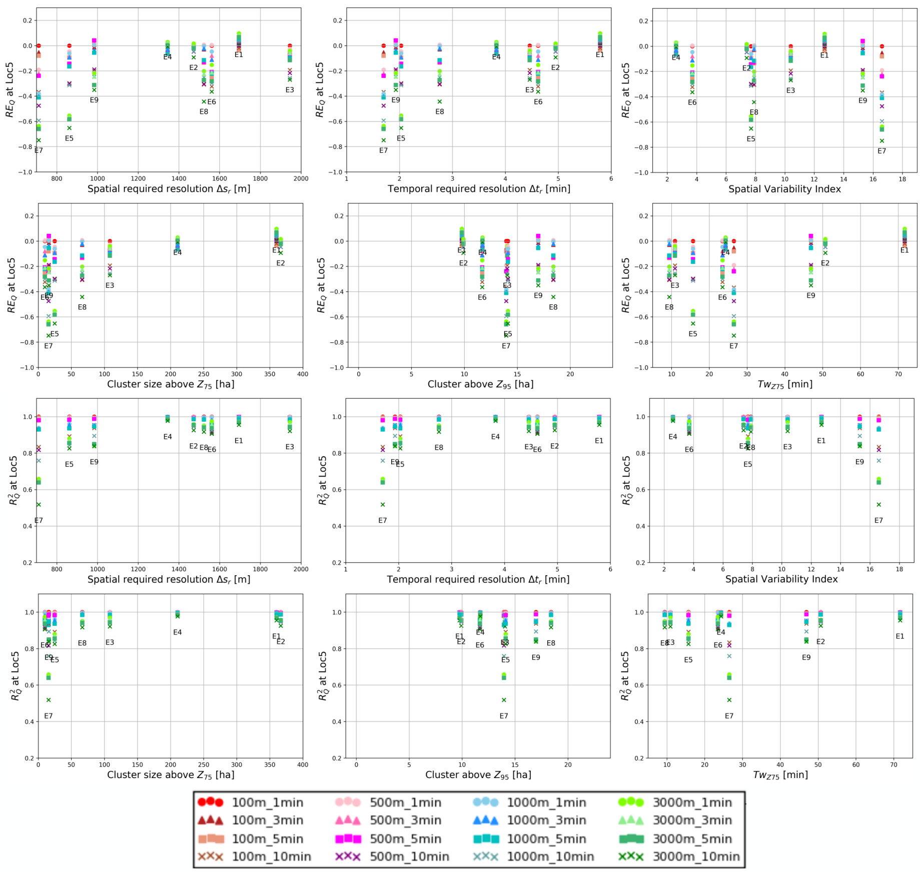


R_Q^2 at Loc2
RE_Q at Loc2
Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster size above Z_{75} [ha]
Cluster above Z_{95} [ha]
Tw_{Z75} [min]
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min

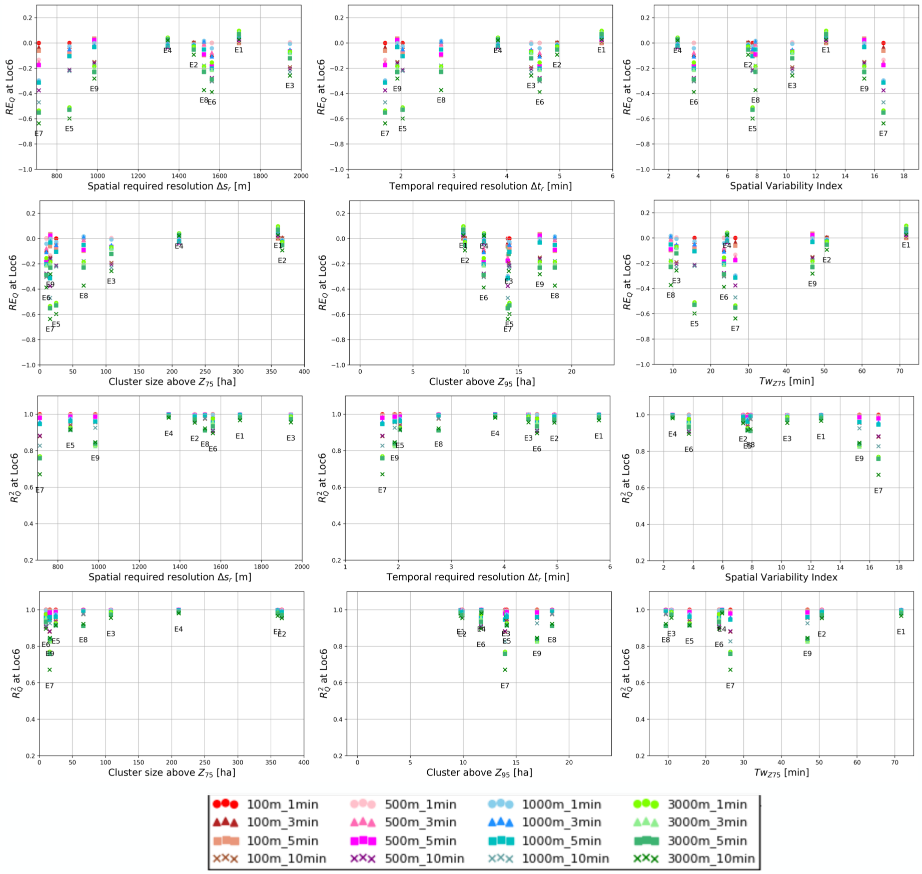

RE_Q at Loc3
R_Q^2 at Loc3
Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster size above Z_{75} [ha]
Cluster above Z_{95} [ha]
Tw_{Z75} [min]
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min

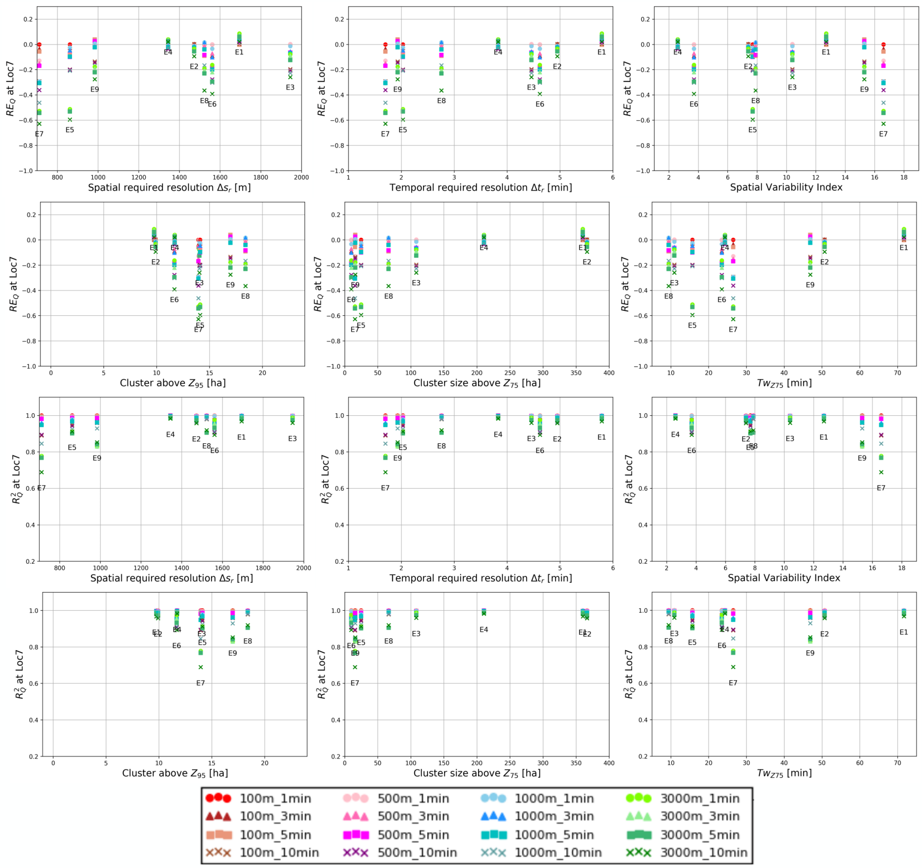

Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster size above Z_75 [ha]
Cluster above Z_95 [ha]
Tw_Z75 [min]
RE_Q at Loc4
R²_Q at Loc4
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min

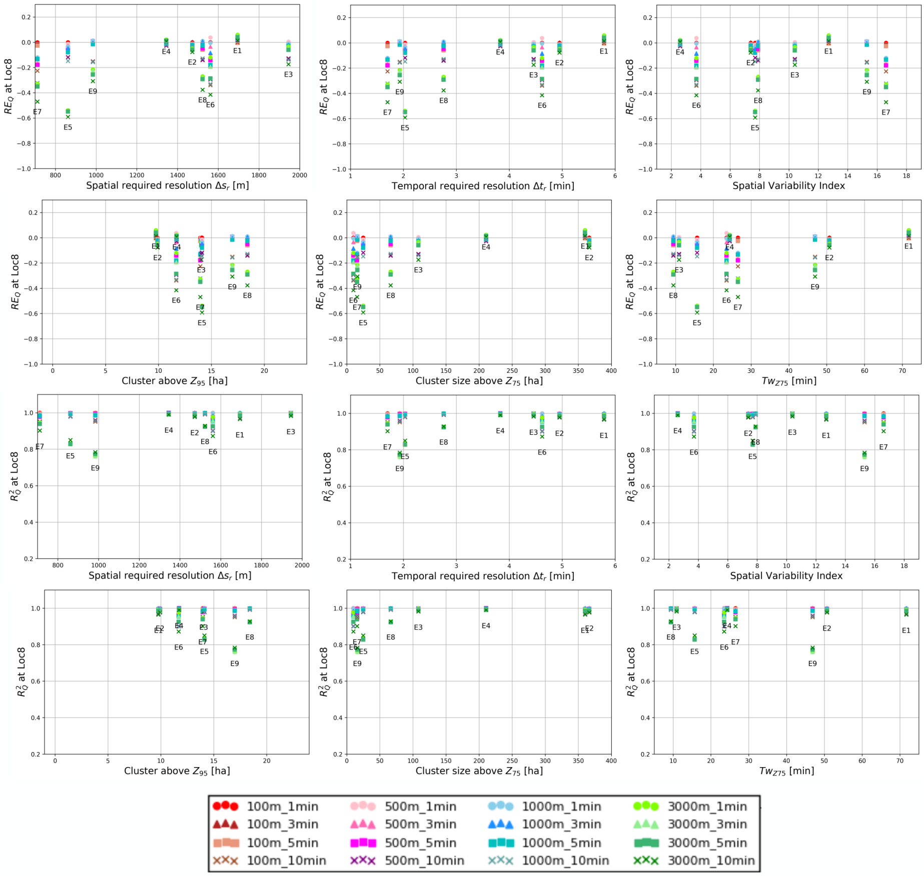
B



Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster size above Z_{75} [ha]
Cluster above Z_{95} [ha]
Tw_{Z75} [min]
RE_Q at Loc5
R^2_Q at Loc5
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min


RE_Q at Loc6
Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster size above Z_{75} [ha]
Cluster above Z_{95} [ha]
Tw_{Z75} [min]
R_Q^2 at Loc6
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min


Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster above Z_95 [ha]
Cluster size above Z_75 [ha]
Tw_Z75 [min]
RE_Q at Loc7
R²_Q at Loc7
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min


RE_Q at Loc8
R^2_Q at Loc8
Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster above Z_{95} [ha]
Cluster size above Z_{75} [ha]
Tw_{Z75} [min]
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
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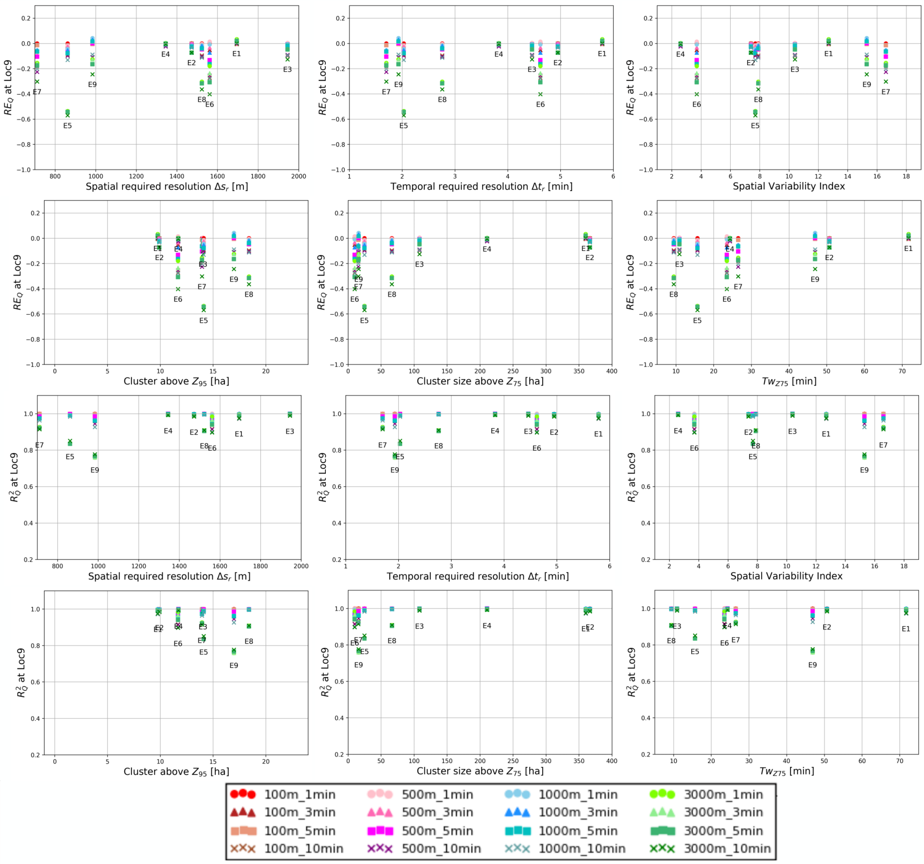
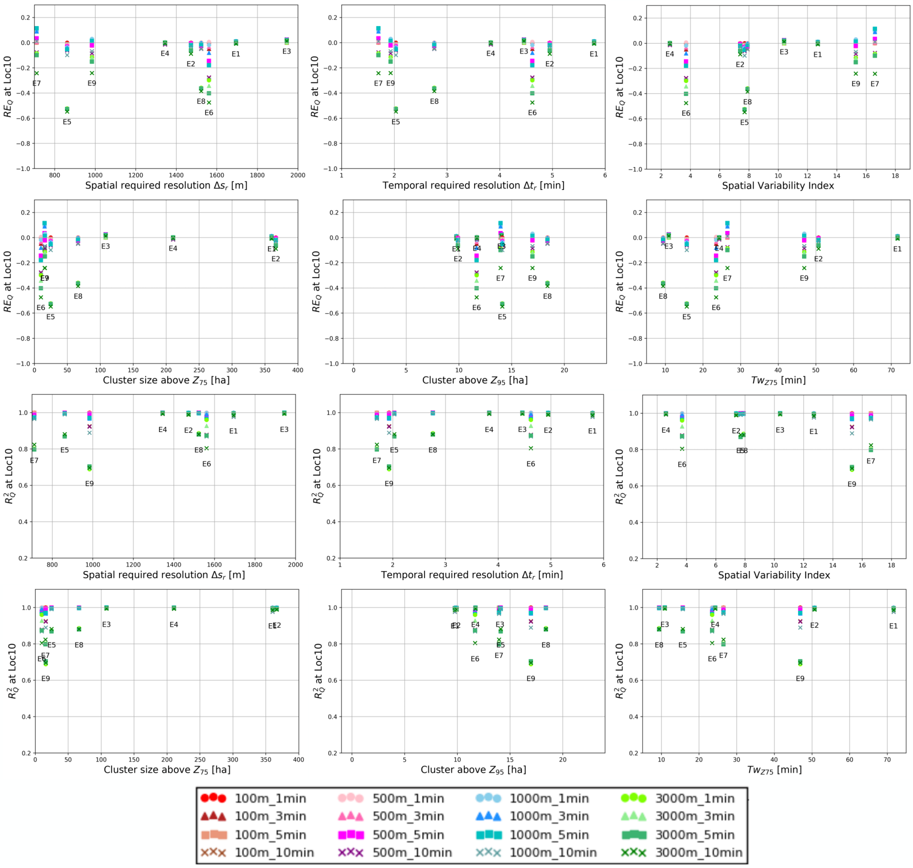
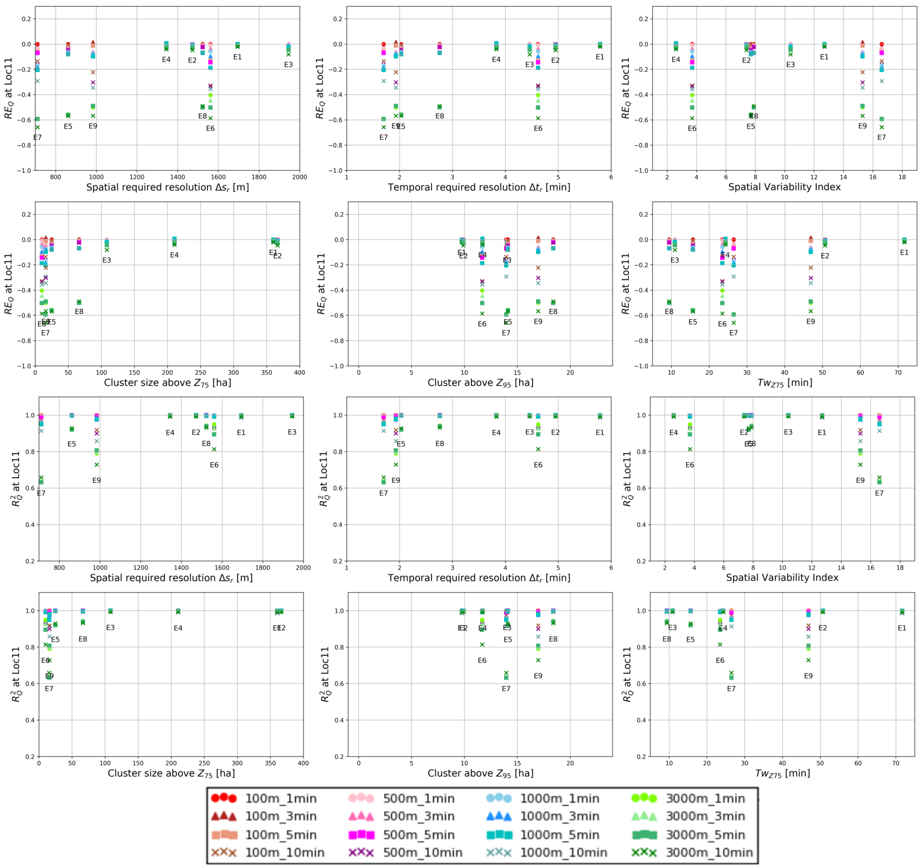
3000m_5min
3000m_10min



RE_Q at Loc9
R_Q^2 at Loc9
Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster above Z_{95} [ha]
Cluster size above Z_{75} [ha]
Tw_{Z75} [min]
E1
E2
E3
E4
E5
E6
E7
E8
E9
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min

B


Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster size above Z_{75} [ha]
Cluster above Z_{95} [ha]
Tw_{Z75} [min]
RE_Q at Loc10
R^2_Q at Loc10
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
1000m_1min
1000m_3min
1000m_5min
1000m_10min
3000m_1min
3000m_3min
3000m_5min
3000m_10min


RE_Q at Loc11
R_Q^2 at Loc11
Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster size above Z_{75} [ha]
Cluster above Z_{95} [ha]
Tw_{Z75} [min]
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
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1000m_3min
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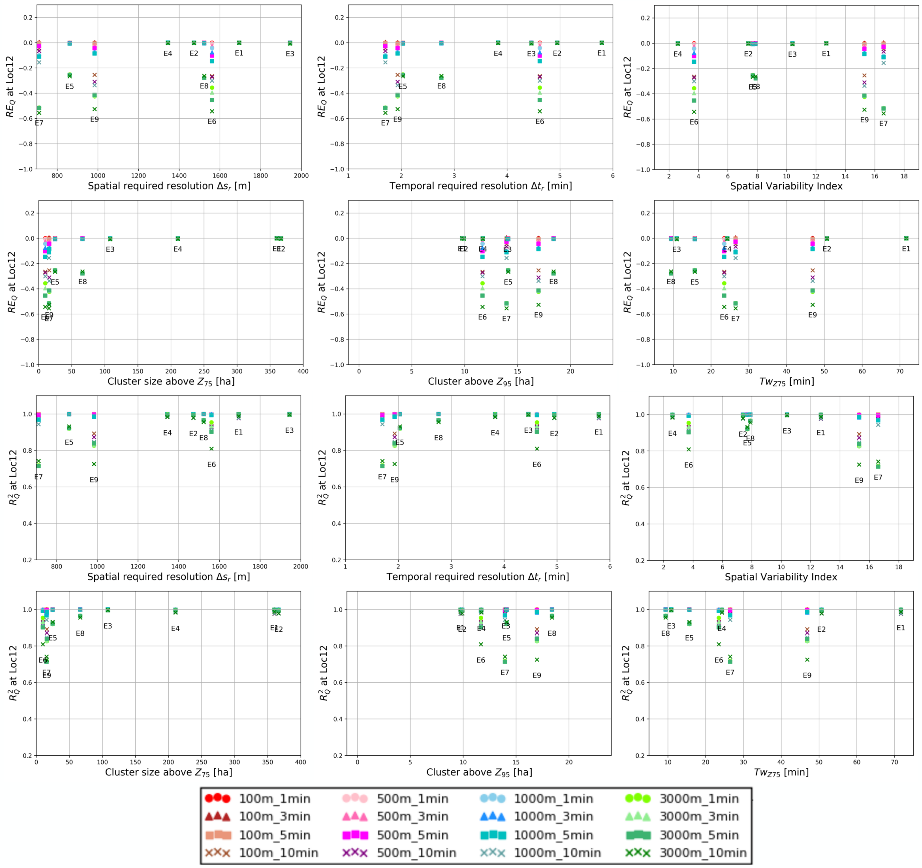
3000m_3min
3000m_5min
3000m_10min



RE_Q at Loc12
R_Q^2 at Loc12
Spatial required resolution Δs_r [m]
Temporal required resolution Δt_r [min]
Spatial Variability Index
Cluster size above Z_{75} [ha]
Cluster above Z_{95} [ha]
Tw_{Z75} [min]
E1
E2
E3
E4
E5
E6
E7
E8
E9
100m_1min
100m_3min
100m_5min
100m_10min
500m_1min
500m_3min
500m_5min
500m_10min
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3000m_5min
3000m_10min

B

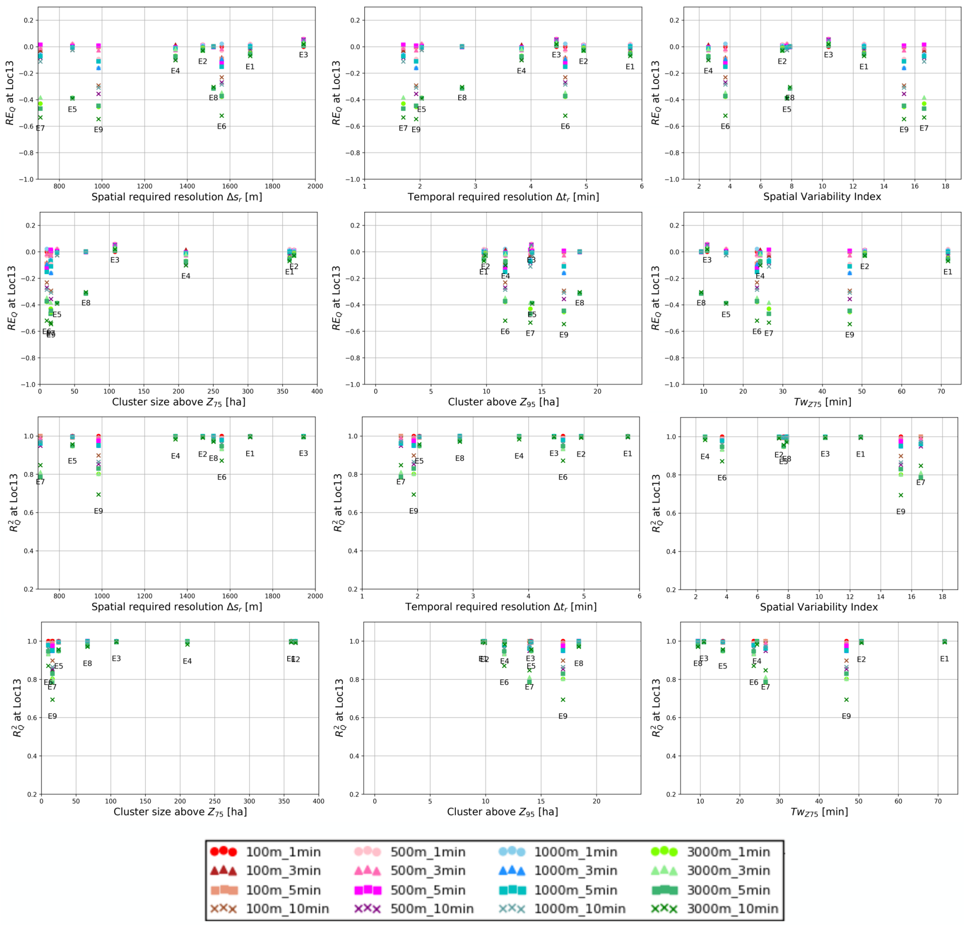

Figure B.3: Influences of rainfall spatial and temporal characterization on the hydrological response sensitivity. R^2_Q at all 13 locations for different rainfall resolution, plotted against different rainfall characterising scales: spatial and temporal required resolution, Spatial Variability Index, dimension of cluster above Z_{75} and Z_{95} and maximum wet period above Z_{75}.

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List of Publications

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- **E. Cristiano**, ten Veldhuis M.-c., Gaitan, S., Ochoa-Rodriguez, S. & van de Giesen, N., *Critical scales to explain urban hydrological response: an application in Cranbrook, London*, Hydrology and Earth System Sciences **22(4)**, 2425-2447 (2018).

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- **Cristiano, E.,** ten Veldhuis, M.-c., Wright, D. B., Smith, J. A., and van de Giesen, N., *Investigating the sensitivity of hydrological response modelling to critical rainfall and catchment scales in the (semi-) urbanised Charlotte area*, ERAD2018, Wageningen (NL), 2018. ORAL PRESENTATION

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- **Cristiano, E.**, ten Veldhuis, M.-c., Ochoa-Rodriguez, S., and van de Giesen, N., *Comparing rainfall variability, model complexity and hydrological response at the intra-event scale,* EGU2017, Vienna, 2017. POSTER
- **Cristiano, E.**, ten Veldhuis, M.-c., and van de Giesen, N., *Influence of high resolution rainfall data on the hydrological response of urban flat catchments,* EGU2016, Vienna, 2016. POSTER
- **Cristiano, E.**, ten Veldhuis, M.-c. & van de Giesen, N.,*Effects of different spatial and temporal rainfall data resolution on hydrological response in flat urban catchments*, UrbanRain15, Pontresina (CH), 2015. ORAL PRESENTATION
- **Cristiano, E.**, ten Veldhuis, M.-c., and van de Giesen, N., *Spatial and temporal resolution effects on urban catchments with different imperviousness degrees,* EGU2015, Vienna, 2015. POSTER