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Numerical Weather Prediction and Relative Economic Value framework to improve Integrated Urban Drainage- Wastewater management

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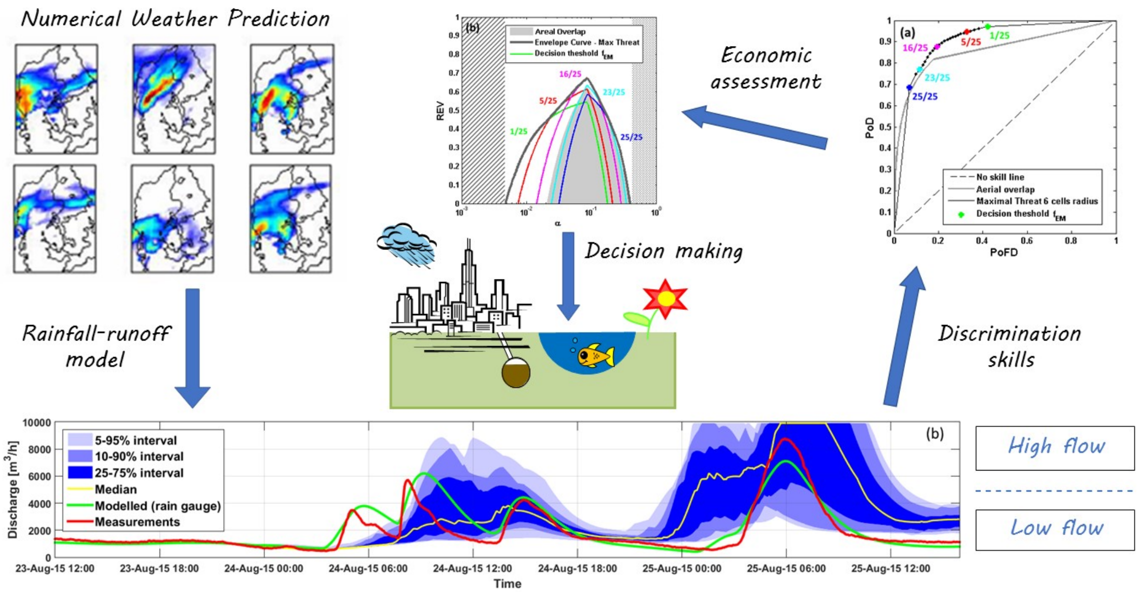

Vianney Courdent
Ph.D. Thesis
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DTU Environment
Department of Environmental Engineering

Numerical Weather Prediction and Relative Economic Value framework to improve Integrated Urban Drainage-Wastewater management.

Vianney Courdent

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The synopsis part of this thesis is available as a pdf-file for download from the DTU research database ORBIT: http://www.orbit.dtu.dk.

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Preface

This thesis is based on the scientific results obtained during an industrial PhD (Erhvervs PhD) project at Krüger A/S and the Department of Environmental Engineering (DTU Environment), Technical University of Denmark (DTU) in the period from April 2014 to June 2017. The project was conducted under the supervision of Professor Peter Steen Mikkelsen from DTU Environment former Innovation Manager Morten Grum (until March 2016) and Senior Engineer Thomas Munk-Nielsen (from April 2016) from Krüger A/S. The PhD project was funded by Krüger A/S and the Innovation Fund Denmark.

The content of the thesis is based on the results presented in four scientific papers, which have been published or are in preparation for peer reviewed journals. These will be referred by their paper number written with the Roman numerals I-IV.

I. **Courdent V.**, Vezzaro L., Mikkelsen P.S., Mollerup A.L., Grum M. (2015): Using ensemble weather forecast in a risk based real time optimization of urban drainage systems, *La Houille Blanche*, (2), 101–107. http://doi.org/10.1051/lhb/20150025

II. **Courdent, V.**, Grum, M., Mikkelsen, P.S. (2016): Distinguishing high and low flow domains in urban drainage systems 2 days ahead using numerical weather prediction ensembles, Journal of Hydrology, doi: http://dx.doi.org/10.1016/j.jhydrol.2016.08.015

III. **Courdent, V.**, Grum, M., Munk-Nielsen, T. and Mikkelsen, P. S. (2017): A gain–loss framework based on ensemble flow forecasts to switch the urban drainage–wastewater system management towards energy optimization during dry periods, Hydrol. Earth Syst. Sci., 21(5), 2531–2544, doi:10.5194/hess-21-2531-2017.

IV. Courdent, V., Munk-Nielsen, T. and Mikkelsen, P. S. (2017): Use of the Relative Economic Value (REV) approach to optimise the benefit of flow forecasting for activation of wet weather operation of wastewater treatment plants. Manuscript.

The papers above are not included in this www-version but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or upon request to DTU Environment, Technical University of Denmark, Miljoevej, Building 113, 2800 Kgs. Lyngby, Denmark, reception@env.dtu.dk.

In addition, the following publications, not included in this thesis, were also produced during this PhD study.

- Bjerg, J. E., Grum, M., **Courdent, V.**, Halvgaard, R., Vezzaro, L., & Mikkelsen, P. S. (2015). Coupling of Weather Forecasts and Smart Grid-Control of Wastewater inlet to Kolding WWTP (Denmark). 10th International Urban Drainage Modelling Conference, Mont Sainte-Anne, Québec, Canada, 20th-23rd September 2015, pp. 47–59.
- **Courdent V.**, Grum M., Mikkelsen P.S. (2015): Using Numerical Weather Prediction ensembles to distinguish urban drainage flow domains 2 days ahead. 10th International Urban Drainage Modelling Conference, Mont Sainte-Anne, Québec, Canada, 20th-23rd September 2015, pp. 123–126.
- Meneses, E. J., Löwe, R., Brødbæk, D., **Courdent, V.** and Petersen, S. O (2015). SURFF - Operational flood warnings for cities based on hydraulic 1D-2D simulations and NWP. 10th International Urban Drainage Modelling Conference, Mont Sainte-Anne, Québec, Canada, 20th-23rd September 2015, pp. 97–104.
- **Courdent V.**, Grum M., Mikkelsen P.S. (2015): On extracting information from numerical weather prediction ensemble precipitation forecasts to anticipate urban runoff flow domains. 10th International Workshop on Precipitation in Urban, Pontresina, Switzerland, 1st-5th December 2015, pp. 1-2.
- Vezzaro L., Pedersen J.W., **Courdent V.**, Löwe R, Mikkelsen P.S. (2017): Towards a domain-based framework for use of rainfall forecasts in control of integrated urban wastewater systems. 12th IWA Specialized Conference on Instrumentation, Control and Automation, Québec City, Québec, Canada, 11th-14th June 2017, pp. 1-8.
- **Courdent, V.**, Pedersen, J.W., Munk-Nielsen, T. and Mikkelsen, P. S. (2017): Using a time-lagged method to enhance Numerical Weather Prediction for urban drainage applications. 14th IWA/IAHR International Conference on Urban Drainage, Prague, Czech Republic, 10th-15th September 2017, pp. 1-4. (Accepted abstract)

- Lovring M.M., Löwe R., **Courdent V**., Meneses E.J., Petersen S.O., Vedel H., Petersen H.M., Mikkelsen P.S. (2017): Comparison of radar and numerical weather model rainfall forecasts in the perspective of urban flood prediction. 14^{th} IWA/IAHR International Conference on Urban Drainage, Prague, Czech Republic, 10^{th}-15^{th} September 2017, pp. 1-4. (Accepted abstract).
- Pedersen J.W., **Courdent V**., Vezzaro L., Vedel H., Madsen H., Mikkelsen P.S. (2017): Spatial bias and uncertainty in numerical weather predictions for urban runoff forecasts with long time horizons. 14^{th} IWA/IAHR International Conference on Urban Drainage, Prague, Czech Republic, 10^{th}-15^{th} September 2017, pp. 1-5. (Accepted abstract).

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I would also like to thank my friends from DTU volley. It was always nice to play with you after a long day. Special thanks to Martine and Alæssåndrø, who were very supportive and helped proof-reading of this thesis. Thanks also to my amazing DTU Environment Volleyball team mates: Ioannis, Arda and Giulia.

Last be not least I would like to thanks my family who, despite being further away, were very supportive, sending biscuits and chocolate by mail which were very welcome during the café break.

Summary

Integrated urban drainage-wastewater systems (IUDWSs) are challenged by the need for higher environmental and health standards and the increased frequency of heavy rain storms caused by climatic change. Real-time control (RTC) offers an alternative to the construction of costly facilities in cities where space is scarce and large-scale construction work a nuisance. This thesis focuses on flow domain predictions of IUDWS from numerical weather prediction (NWP) to select relevant control objectives for the IUDWS and develops a framework based on the relative economic value (REV) approach to evaluate when acting on the forecast is beneficial or not.

Rainfall forecasts are extremely valuable for estimating near future stormwater-related impacts on the IUDWS. Therefore, weather radar extrapolation “nowcasts” provide valuable predictions for RTC. However, radar nowcasts are limited by their prediction horizon of 1 to 2 hours and RTC of IUDWS could benefit from longer forecast horizons. The development of NWP models in parallel to the increase in computational power has led to limited area models (LAM) with increasingly finer spatial-temporal resolution, opening the possibility to use such weather forecast products in urban water management. NWPs are complementary to radar forecasts, providing predictions on a longer time scale (days). However, atmospheric motions are chaotic and highly nonlinear. Applying NWP to urban catchments, which often have a similar size to a single NWP grid cell, is limited by scientific gaps on how to deal with this poor spatial and temporal resolution for urban hydrology application, its predictive skills and uncertainty, etc. Forecast uncertainty is commonly described by meteorologist using ensemble prediction systems (EPS). This thesis used the outcome of the DMI-HIRLAM-S05 model which generates an EPS of 25 members. Each forecast ensemble provides hourly time step predictions over a forecast horizon of 54 hours with a horizontal resolution of 0.05° (approx. 5.6 km).

In order to evaluate the predictions based on the end-user perspective, namely the flow in the IUWDS, a case study was established for the urban catchment of Damhuså in Copenhagen, Denmark, and a rainfall-runoff model associated to it was developed. Hence, the predictions were therefore not assessed against observed rainfall but against observed flow at the end of the coupled hydro-meteorological model chain. The predictions were assessed based on flow domain prediction, distinguishing between high and low flow events. The combination of the different possibilities between observations and fore-

casts can be summarised in the 2x2 contingency table containing the four possible pairs of forecast-observation: hits (correct positives), false alarms (false positives), misses (false negatives) and correct negatives. The outcome of the contingency table were used to calculate skill scores like the probability of detection (PoD) and the probability of false detection (PoFD), and to plot the relative operating characteristic (ROC) diagram illustrating the discrimination skill of the NWP EPS prediction.

Using verification methods from meteorology on flow predictions showed that NWPs have poor precision at such fine resolution. Therefore, NWP post-processing methods are necessary to cope with this limitation, getting the most out of the NWP to enhance its EPS, especially towards reducing the occurrence of missed events. This thesis investigates two NWP post-processing approaches: The neighbourhood method which includes predicted rainfall from nearby grid cells, and the time lagged ensemble (TLE) which utilises the overlap between consecutive NWP generations to expand the EPS. Both approaches have shown to be beneficial to enhance the NWP EPS, reducing the occurrence of missed events. However these approaches can lead to a large increase of the EPS size. The maximal threat neighbourhood method developed in this thesis improved the EPS discrimination skill with a limited increase of the EPS size.

Despite these improvements, the high uncertainty embedded in NWP prevents the use of quantitative rainfall values directly for an urban catchment. NWP should be used, instead, in connection with a domain-based decision framework, predicting for which domain the IUDWS should be optimized. The following domain-based framework was suggested, distinguishing between 4 operational domains: (i) dry weather conditions with storage basins empty, (ii) dry weather conditions with stored water, (iii) wet weather conditions within the system capacity and (iv) wet weather conditions that exceed the system capacity.

Handling uncertainty is challenging for decision makers. Tools are necessary to provide insight on when acting based on uncertain forecast data is beneficial or not. The REV framework developed in this thesis provides a tool to evaluate the added benefit of using control strategies based on uncertain forecast information, to select the most relevant control parameters and to compare different control strategies.

This REV framework was applied on two case studies. The first one used NWP EPS to predict low flow domains during which the IUDWS can be coupled with the electrical smart grid to optimise its energy consumption. The REV framework was used to determine which decision threshold of the EPS (i.e. number of ensemble members predicting an event) provides the highest benefit for a given situation. In the second case study, the REV framework was used to evaluate the current control strategy switching the WWTP to wet weather operation and to assess other control parameters and strategies. The analysis of the current control showed a significant number of false alarms, and the REV framework was used to calibrate the threshold on radar flow prognosis and to test new control strategies to solve this problem.

Uncertainty communication to end-users is a critical and challenging part of forecast usage. It can be achieved through the REV framework, which includes the possibility of considering management mistakes due to erroneous forecast. The REV framework assesses the overall benefit including these potential mismanagements, hence, maintaining the operator trust in the control.

Dansk sammenfatning

Integrerede urbane afløbs- og spildevandssystemer er udfordret af strengere miljø- og sundhedskrav samt hyppigere tilfælde af kraftig regn drevet af klimaændringer. Realstidsstyring (eng: real time control, RTC) er her et alternativ til at bygge nye, dyre anlæg i byer, hvor der er mangel på plads og store anlægsprojekter er til gene. Denne afhandling fokuserer på forudsigelser af flowdomæner baseret på numeriske vejrprognoser (eng: numerical weather predictions, NWP) for at kunne foretage kvalificerede styringsbeslutninger. Derudover udvikles et rammeværktøj baseret relativ økonomisk værdisætning (eng: relative economic value, REV) til at vurdere, hvornår det er gavnligt at reagere på en prognose.

Regnprognoser er ekstremt værdifulde, når man skal estimere regnpåvirkningen af afløbs- og spildevandssystemer i den umiddelbare fremtid. "Nowcasts" baseret på ekstrapolering af vejrradarsignaler er derfor vigtige for RTC. De kan dog kun levere forudsigelser med en tidshorisont på 1-2 timer, og RTC systemer vil kunne drage nytte af længere horisonter. Udviklingen af vejrmodeller har sammen med større regnekraft i computere ført til detaljerede vejrmodeller for begrænsede områder med en høj opløsning i tid og sted, som muligvis kan bruges inden for den urbane vandbranche. Numeriske vejrmodeller leverer forudsigelser på længere tidshorisonter (dage) og kan derfor supplere brugen af radarprodukter. Disse modeller forsøger imidlertid at beskrive de fysiske processer i atmosfæren, der er kendt som kaotiske og stærkt ikke-lineære, og brugen af vejrmodeller inden for urban hydrologi er begrænset af mangel på videnskabeligt funderede metoder til at håndtere den forholdsvis dårlige opløsning i tid og sted samt usikkerheden på forudsigelser. Meteorologer beskriver ofte usikkerheden i deres modeller ved hjælp af ensemble systemer, og i denne afhandling bruges vejrudsigter fra DMI-HIRLAM-S05 modellen, der indeholder 25 ensemble medlemmer. Hver modelkørsel har et-times tidsskidt over en horisont på 54 timer og er i en opløsning på 0,05 grader (ca. 5.6 km).

For at kunne evaluerer disse prognoser fra et brugersynspunkt blev en regn-afstrømningsmodel udviklet for et casestudie i Damhusåens afløbssystem i København. Regnprognoserne er derfor ikke vurderet mod målte regnmængder, men i stedet mod målt afstrømning ved enden af den hydro-meteorologiske modelkæde. Prognoserne blev vurderet på baggrund af deres evne til at skelne mellem flowdomæner hvor der er hhv. højt eller lavt flow. Evalueringen af høj/lav-prognoser kan opsummeres i en 2x2 kontingenstabel, der består af følgende dele: pletskud (korrekt positiv), falsk alarm (falsk positiv), falsk negativ og korrekt negativ. Kontingenstabeller blev brugt til at udregne sandsynlighed for detektion og for falsk detektion af ”høje” flows, der sammen beskriver en prognoses diskriminationsevne og kan illustreres med et (eng.) ”relative operating characteristic” (ROC) diagram.

Brug af evalueringsmetoder fra meteorologien på flowprognoser viste, at NWP modeller har en dårlig præcision ved meget fin opløsning. For at imødekomme dette, især i forhold til ikke at misse lokale hændelser, er efterbehandling af vejrmodellernes resultater nødvendig. Denne afhandling undersøger to efterbehandlingsmetoder: nabolagsmetoden, som inkluderer forudsigelser fra det omkringliggende område, og tidsforskydningsmetoden, der gør brug af fortløbende modelkørsler som overlapper i tid. Begge metoder har vist sig at forbedre ensembleprognoserne ved at reducere antallet af oversete hændelser (falske negativer), men de kan føre til en voldsom forstørrelse af modelensemblet. I denne afhandling er der derfor udviklet en ”største trussel i nærområdet”-metode, der forbedrer diskriminationsevnen med kun en lille forstørrelse af ensemblet.

Disse forbedringer er dog ikke nok til at overkomme den store usikkerhed, der er i vejrudsigter, og som forhindrer den direkte brug af kvantitative regnprognoser i urbane sammenhænge. Numeriske vejrmodeller bør i stedet bruges i en domænebaseret beslutningsproces, hvor de bruges til at forudse hvilket domæne, et afløbs- og spildevandssystem vil befinde sig i. Her foreslås det, at der skelnes mellem de følgende fire operationelle domæner: (i) tørvejr med tomme bassiner, (ii) tørvejr med vand i bassiner, (iii) regnvejr inden for systemets kapacitet og (iv) regnvejr, der overstiger systemets kapacitet.

Det er udfordrende for beslutningstagere at håndtere usikkerheder, hvilket gør, at der er brug for værktøjer, som kan vurdere, hvornår det er gavnligt at reagere på en prognose. Her kan relativ økonomisk værdisætning (REV) bruges til at vurdere styringsstrategier, der anvender usikre prognoser, til at vælge styringsparametre og til at sammenligne forskellige styringsstrategier.

REV metoden blev her anvendt i to casestudier. I det første blev numeriske ensemble vejrudsigter brugt til at forudsige lave flowdomæner, hvor der er mulighed for at koble styringen til det elektriske smart grid og dermed optimere systemets strømforbrug. Her blev REV brugt til at definere det mest fordelagtige antal af ensemble medlemmer, der skal forudse en hændelse, før en beslutning tages. I det andet casestudie blev REV brugt til at evaluere den nuværende styringsstrategi, hvor renseanlægget skifter til regnvejrsdrift baseret på radarprognoser, og til at vurdere andre styringsparametre. Analysen viste et stort antal falske alarmer, som kunne imødegås ved at kalibrere den flowgrænse, der definerer hvornår renseanlægget skifter til regnvejrsdrift. Derudover kunne REV metoden bruges til at teste nye styringsstrategier.

Kommunikationen af usikkerheder til slutbrugere er vigtig del af anvendelsen af vejrprognoser. Dette kan gøres gennem den relative økonomiske værdi, som kan tage hensyn til risikoen for at foretage forkerte beslutning baseret på fejlagtige prognoser. Her evalueres den samlede effekt af en styring, inklusiv eventuelle forkerte beslutninger, hvilket opretholder de lokale operatørers tillid til styringsstrategien.

Table of contents

Abbreviations

ALADIN	Aire Limitée Adaptation dynamique Développement InterNational
ATS	Aeration Tank Settling
BOD	Biological Oxygen emand
BS	Brier Score
BSS	Brier Skill Score
COMEPS	Continuous Mesoscale Ensemble Prediction System
COSMO	The Consortium for Small-scale Modeling
CRPS	Continuous Ranked Probability Score
CSI	Critical Success Index
CSO	Combined Sewer Overflow
DMI	Danish Meteorological Institute
ECMWF	The European Centre for Medium-Range Weather Forecasts
EM	Ensemble Member
EPS	Ensemble Prediction System
HIRLAM	High Resolution Limited Area Model
IFS	Integrated Forecast System
IUDWS	Integrated Urban Drainage-Wastewater System
LACE	Limited Area modelling in Central Europe
LAM	Limited Area Model
NWP	Numerical Weather Prediction
PE	Population Equivalent
PoD	Probability of Detection
PoFD	Probability of False Detection
PQPF	Probabilistic Quantitative Precipitation Forecasting
QPF	Quantitative Precipitation Forecasting
REV	Relative Economic Value
ROC	Relative Operating Characteristic
ROCA	Relative Operating Characteristic Area
RPS	Ranked Probability Score
SVK	Spildevandskomiteen (Water Pollution Committee of the Danish Engineers Society)
UD	Urban Drainage System
WFD	Water Framework Directive
WWTP	WasteWater Treatment Plant

1 Introduction

1.1. Integrated Urban Drainage-Wastewater Systems

An integrated urban drainage-wastewater system (IUDWS) includes four components as illustrated on Figure 1: The surface rainfall-runoff, the urban drainage system (UDS), the waste water treatment plant (WWTP) and the receiving water bodies.

UDSs are mostly underground closed systems composed of sewer collectors, networks of pipes, manholes, pumping stations, detention basins, etc., which collect and transport wastewater from households, industries, infiltrating groundwater and, depending on the type of UDS, stormwater. Indeed, UDSs can be either combined or separated. Combined sewage systems carry wastewater and stormwater in a single pipe, whereas separated sewage systems transport wastewater and stormwater through independent pipe networks. In the case of combined sewage systems, during a rainstorm, combined wastewater flows can overload the system capacity, producing combined sewer overflows (CSOs) that pollute receiving water bodies.

WWTPs treat the wastewater before it is discharged into water bodies. WWTPs have become complex systems to operate and manage. They are subject to strict legislation to meet requirements such as the EU Water Framework Directive (WFD) 2000/60/EC (European Commission, 2000). In Denmark, a ‘green’ tax is applied to the effluent discharges of organic material (BOD - biological oxygen demand), nitrogen, and phosphorous from WWTP (ECOTEC, 2001). Municipal WWTPs commonly employ biological treatment as a secondary treatment process. The activated sludge process is widely used for secondary treatment; this process requires a critical focus on the current and future state of the activated sludge, especially on the secondary clarifiers to avoid sludge escape which can cause large pollution events.

There is a growing interest in integrated systems approaches to improve the IUDWS efficiency. Synergies can be developed by combining the management of UDSs and WWTPs, which have traditionally been handled independently of each other. The storage available in the UDS can e.g. be utilized as a buffer to control the inflow to the WWTP to improve its efficiency. Bach et al. (2014) further describes the evolution towards integrated systems in urban water modelling and clarifies the terminology.

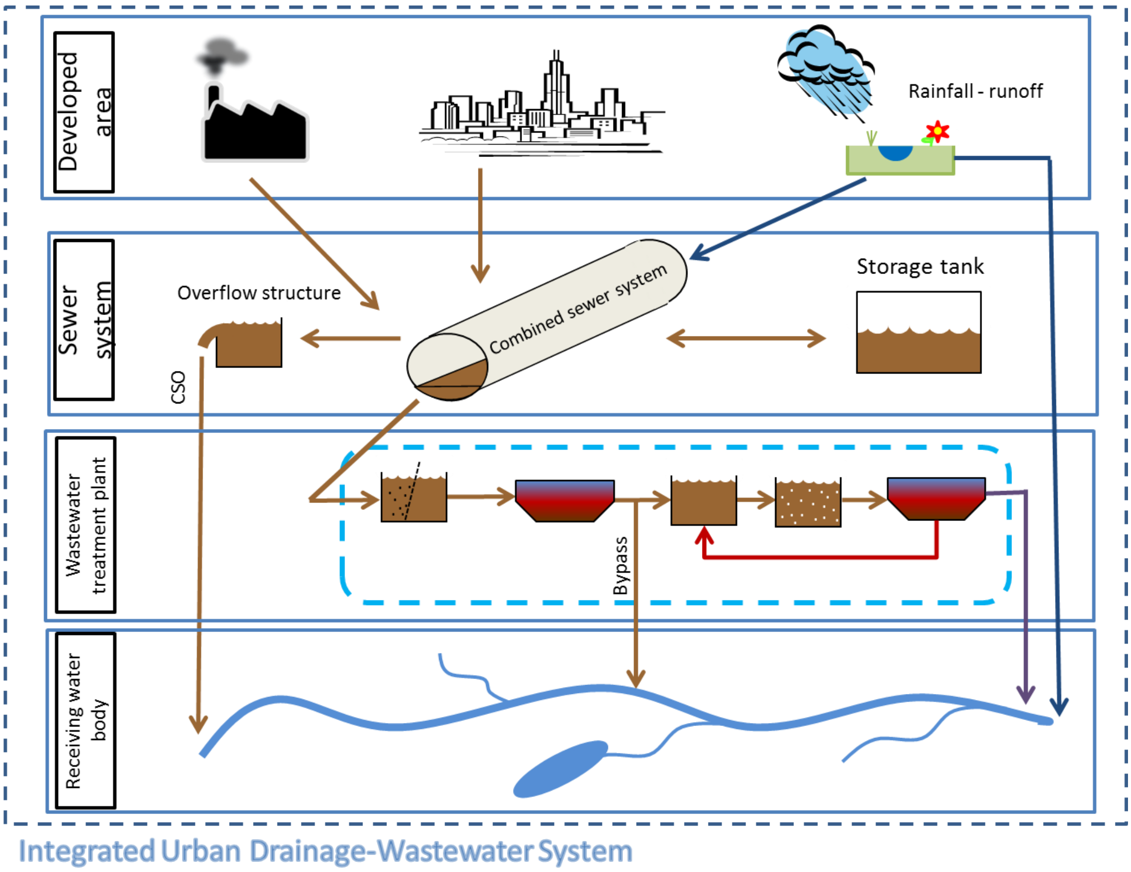

Figure 1: Illustration of different components of the IUDWS.

1.2. Forecasting and real-time control of IUDWS

New challenges arise with the recognition of the need for higher environmental and health standards and the increased frequency of heavy rain storms caused by climatic change. It is therefore crucial to improve IUDWSs and their management. Various solutions are available for this, which in the case of CSO mitigation can be achieved through three main alternatives: (i) enlarging the infrastructure of the sewer system, (ii) developing stormwater source control and (iii) implementing intelligent control systems to operate IUDWS.

The objective for real-time control (RTC) is to efficiently use the existing infrastructure to reduce environmental and/or economic impacts of CSO, sludge escape from the secondary clarifiers at the WWTP, energy consumption, etc. RTC therefore offers an alternative to the construction of costly facilities in cities where space is scarce and construction works unwelcome, e.g. (Beeneken et al., 2013; Dirckx et al., 2011; García et al., 2015).

The simplest real-time control strategies optimize IUDWSs according to their current status (e.g. known flows and water levels) as informed by monitoring without providing any forecast information about the future, e.g. (de Rooij and van Heeringen, 2013; Schütze et al., 2004; Vanrolleghem et al., 2005).

The development of techniques for extrapolating weather radar images into the future, called "nowcasting", has opened the possibility to utilise rainfall forecasts in control strategies (Thorndahl and Rasmussen, 2013). A standard deterministic radar-based nowcast can predict rainfall for a lead time between less than 30 min (small convective cells) and more than 2 h (large-scale slow moving weather systems) (Thorndahl et al., 2017). Such forecast data are for instance used to prepare WWTPs in time to cope with increasing inflows due to storm events (Heinonen et al., 2013; Munk-Nielsen et al., 2015) or to equalise the utilisation of storage in IUDWS (Grum et al., 2011). The Dynamic Overflow Risk Assessment (DORA) strategy, used as reference in **Paper I**, uses up to 2-hour radar nowcasts to optimize UDSs in real time (Vezzaro and Grum, 2014). Nevertheless, the operational time scale of IUDWS is longer than 2 hours, emptying of detention basins in large catchments can for example take many hours. Furthermore, exploiting the synergies between the energy consumption in the IUDWS, the power production at the WWTP and the power supply systems (electrical smart grid) also requires longer forecast horizon. Thus, there is a high interest in increasing the forecast horizon used for real time control in order to improve the IUDWS management. **Paper I** investigates the potential of using a longer forecast horizon when optimising the control of wastewater storage to mitigate CSO events based on the DORA framework. **Paper I** underlines the risk of mismanagement resulting from using (too) short forecast horizons in the case of long and/or combined rainfall events. Numerical weather prediction (NWP) models can provide such longer forecast horizon (Huang et al., 2012; Liguori et al., 2012). However, the implementation of numerical weather forecasts at an urban scale is limited by scientific gaps in how to deal with the poor spatial and temporal resolutions of the NWP model, its predictive skills and uncertainty, the handling of ensemble data, etc.

1.3. Operational domains and control objectives

IUWDS are operated in various types of situations. In **Paper I** we distinguished 3 modes of operation in relation to the degree of freedom for CSO mitigation: “Dry”, “No CSO” and “CSO mode”. Different cost functions were used in the optimization routine based on the current status of the IUDWS and the forecasted runoff. In Vezzaro et al. (2017) we further develop the concept and we suggest a domain-based framework distinguishing between 4 operational domains: (i) dry weather conditions with storage basins empty, (ii) dry weather conditions with stored water, (iii) wet weather conditions within the system capacity and (iv) wet weather conditions that exceed the system capacity. The IUWDS control objectives depend on the operational domain at hand. Mollerup et al. (2016) developed a time-dependent control hierarchy framework for sewage systems (Figure 2). The control objectives are here determined at the top of the hierarchy. They define the overall scope and targets for the control schemes operating at lower levels in the hierarchy.

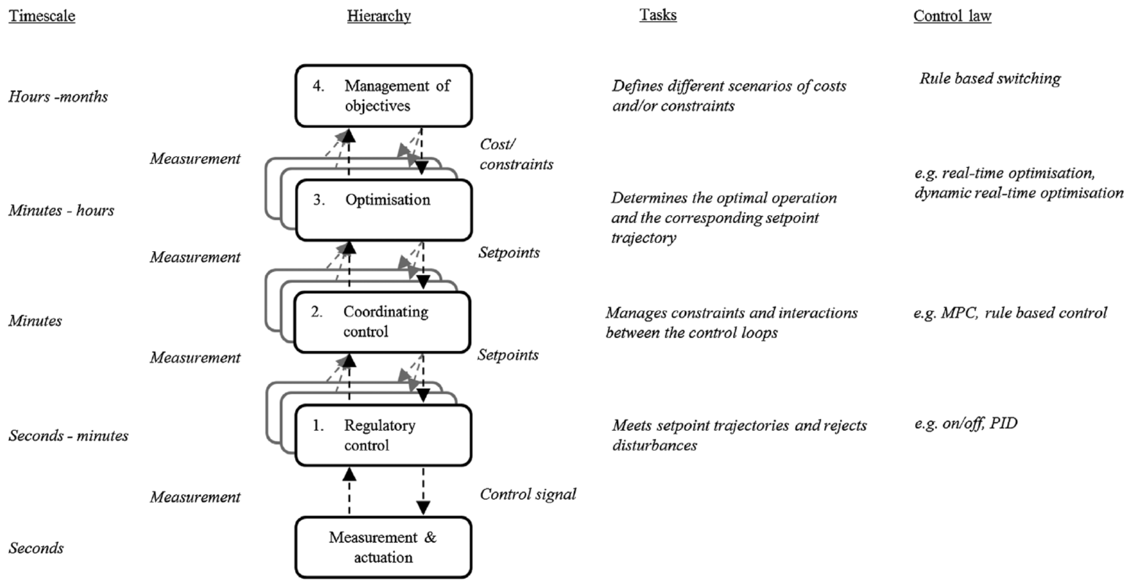

Figure 2: Time-scale dependent control hierarchy for a sewage system. From the left: the first column shows the timescales, the second column shows the layers in the control hierarchy, the third column shows the tasks performed in these layers and the fourth column shows examples of control techniques used. The output and input information to each layer is also presented (Mollerup et al., 2016).

The control objectives should be selected based on the current and near future state of the IUDWS. NWPs may provide predictions of the IUWDS domain status for forthcoming days and could be used to select the relevant objectives for a given situation. Similarly, radar extrapolation nowcasts may provide finer predictions for the forthcoming hours, which can be used e.g. to prepare the WWTP to cope with increased flows. Using forecast data, uncertain by nature, in a control strategy requires a decision-making framework that can help determining if acting based on the forecast is beneficial and how to best use is. The relative economic value (REV) approach developed by Richardson (2000) associates each course of action with a cost and an economic benefit or loss depending on the observed outcome. The benefit of using the forecast can thus be quantified by considering the occasions when the forecast was beneficial, neutral or detrimental with respect to the process of decision making. This framework can also be used to compare control strategies and to determine the control parameters leading to the highest benefit.

1.4. Objective of PhD project

The overall purpose of this PhD is to address the scientific gaps related to the use of NWP in urban hydrology, to lay the first stone towards the development of IUDWS control strategies using input data from NWP models, and to develop a decision-making framework based on the REV approach to provide a tool to evaluate control strategies, assessing when acting on the forecast is beneficial or not.

The PhD study has the following specific objectives:

1. To establish a case study for an urban catchment and to develop a rainfall-runoff model associated to it, in order to evaluate the predictions based on the end-user perspective, namely the flow in the IUWDS.
2. To identify the potential and the challenges of using NWP output for IUDWS applications, and to identify and develop methodologies which enhance NWP output towards their usage in urban hydrology.
3. To develop a decision-making framework based on the REV approach, assessing when using the forecast is beneficial (or not) and evaluating the control strategies to select the most appropriate control parameters. This framework will be applied on two control schemes: one based on low flow forecasts from NWP EPS (a) and another one based on high flow forecasts from weather radar extrapolation nowcast (b).
    a. Prediction of dry weather flow based on ensembles of NWP data to determine when the objective of the IUDWS could be switched to energy optimisation, utilising the electrical smart grid.

b. Switch to wet weather operation at the WWTP based on weather radar extrapolation nowcast: Evaluation of the current control scheme and suggestion for improvements.

Table 1 displays the relationship between these specific objectives and the papers included in this thesis.

Table 1: The specific objectives of this thesis paired with the relevant papers.

	Paper			
	I	II	III	IV
Obj. 1		X	X	
Obj. 2	X	X		
Obj. 3			X	X
3a			X	
3b				X

1.5. Thesis Outline

This thesis is structured as follows. This chapter provides the background and the objectives of the PhD. Chapter 2 gives an overview of NWP models and the NWP data used in the PhD. Chapter 3 describes the catchment, the developed rainfall-runoff model and the WWTP used as a case study throughout the thesis. Chapter 4 presents the forecast verification methods that are used and developed in the next chapters. Chapter 5 explains the NWP post-processing methods used and discusses their skills for urban applications. Chapter 6 develops the REV framework and its application in two different situations: dry weather flow predictions for energy optimisation and switching to wet weather operation at the WWTP. Finally, Chapters 7 concludes the thesis with reference to the objectives defined in section 1.3 and chapter 8 provides an outlook for future work.

2 Numerical weather prediction

2.1. NWP and EPS

The concept that the future state of the atmosphere could be determined based on the knowledge of its initial state and physical equations of motion originates from a paper by Vilhelm Bjerkness (1904). How to solve these equations numerically was first suggested by Lewis Richardson (1922) and implemented years later when modern computers allowed it. The first real-time forecasts were made in Stockholm in 1954 (as cited in (Bauer et al., 2015)).

Today, a hierarchy of many models with different levels of complexity exists covering the full range from global climate projections, global weather prediction to limited area modelling. The limited area models (LAM) are nested into global weather model which provide their boundary conditions. For a more detailed review of mesoscale models, the reader is referred to (Dudhia, 2014). NWP models are not to be confused with climate models. The difference between weather and climate is the measure of time. The weather describes the conditions of the atmosphere over a limited period of time, whereas the climate characterizes the atmosphere behaviour over relatively long periods of time.

Lorenz (1969) showed the limits to predictability of atmospheric circulations. The atmospheric motions are highly nonlinear and complex, implying that infinitesimal differences of initial conditions may lead to a completely different forecast (as cited in (Cloke and Pappenberger, 2009)). The exact state of the atmosphere is therefore impossible to predict. Even with the best estimates of the initial conditions and the most accurate NWP models, nonlinearities combined with unavoidable uncertainty (initial condition, model structure) are the cause of forecast errors. Forecasters as well as users of weather forecasts know from experience that there is always some uncertainty associated with a forecast (Morss et al., 2008). Hence, without specifying their uncertainty, NWP forecasts may be considered incomplete. Forecast uncertainty is commonly described by meteorologists through Ensemble Prediction Systems (EPS) based on a practical Monte Carlo framework of NWPs suggested by Leith (1974) (as cited in (Feddersen, 2009)).

Atmospheric initial conditions are considered as the major source of uncertainty. 1-dimensional EPS are based on the perturbation of initial conditions which evolved to be motion dependent and to favour fast growing modes to maximize the ensemble dispersion. Hence, individual ensemble members are more likely to represent extreme outcomes than a random approach. 2-dimensional EPS also consider uncertainty in the model physics and dynamics using for example multi-models, multi-physics, stochastic physics, etc. However, EPS does not incorporate all sources of uncertainty. They remain generally under-dispersive and exhibit systematic bias, which implies potential for missing events. For more information on uncertainty and EPS see (Du, 2007).

The reader is referred to (Bauer et al., 2015) for a further description on the fundamental scientific basis of NWP and the recent advances and perspective in this field. For further details on the history of NWP, the reader is referred to (Cressman, 1996) and to (Lorenz, 2006).

2.2. The DMI-HIRLAM-S05

Most of the meteorological institutes are gathered in a consortium to gain synergy in developing weather models. There are five limited area model (LAM) consortia in Europe (ALADIN, COSMO, HIRLAM, LACE and Met Office). The Danish Meteorological Institute (DMI) is part of the HIRLAM consortium which has engaged in a close collaboration with the ALADIN consortium since 2005 to develop and maintain a new mesoscale LAM model for short-range NWP called HARMONIE (http://www.hirlam.org/).

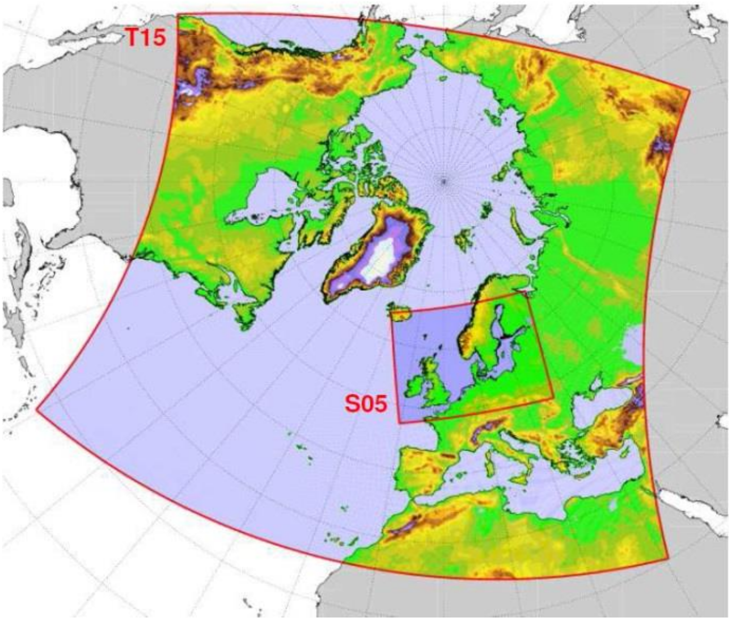

Figure 3: Geographical domains of the DMI-HIRLAM S05 and T15 models (Feddersen, 2009).

This PhD used data from the HIRLAM EPS generated by the DMI: DMI-HIRLAM-S05. This model covers the Scandinavian countries and northern Europe, see Figure 3, with a horizontal resolution of 0.05° (approx. 5.6 km). To estimate the boundary conditions, this model is nested into the coarser (0.15° horizontal resolution) and larger DMI-HIRLAM-T15 model (Mahura et al., 2006), which is itself nested into the global ECMWF IFS model (http://www.ecmwf.int).

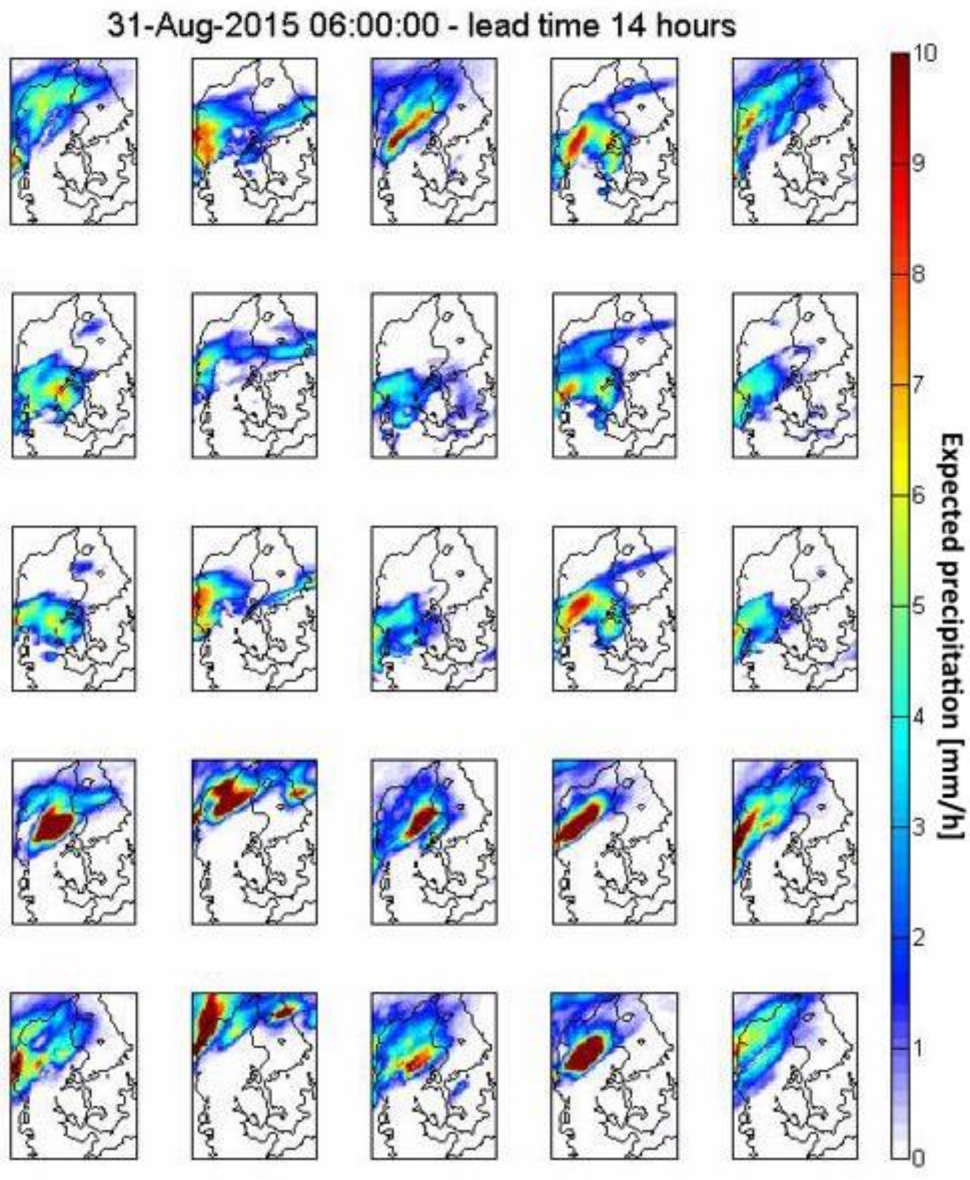

Figure 4: Example of DMI-HIRLAM-S05 EPS at a given time step over Denmark. Each row corresponds to a set of initial conditions and each column to a model structure.

Each forecast provides hourly time step predictions over a forecast horizon of 54 hours. Forecasts are generated every 6 hours at 0h, 6h, 12h and 18h UTC. The DMI-HIRLAM-S05 ensemble is a 2-dimensional EPS comprising 25 members based on a pairing of 5 different set of initial conditions and 5 different model structures. Figure 4 displays an example of the difference predictions from these 25 ensemble members, showing the potential disparities between the location and the intensity of the predicted rainfall event. Further information on the model is provided in the report by Feddersen (2009), in the HIRLAM technical documentation (Unden et al., 2002) and on the HIRLAM website (http://www.hirlam.org/). Table 2 presents the periods of NWP EPS data used in the project.

Table 2: Periods of NWP data used in **Papers I-III** (**Paper IV** did not use any NWP data)

	Periods used in the papers
Paper I	May 2012 to March 2013
Paper II	June 2014 to January 2016
Paper III	June 2014 to May 2016

Examples of animated EPS quantitative precipitation forecast for different rainfall processes (convective, stratiform) over Denmark are displayed in appendix A.

2.3. Use of NWP in other fields

NWPs are already in use for forecasting in various fields. Renewable energy forms (wind and solar power) are conditioned by the weather with high variability and uncertainty, which have significant impact on the electrical system (smart grid). Al-Yahyai et al. (2010) made a review on the use of NWP for wind energy assessment and Diagne et al. (2013) reviewed the solar irradiance forecasting methods. NWPs are also widely used in hydrology e.g. for reservoir operations (Collischonn et al., 2007; Zhao and Zhao, 2014), for river flood forecasting (Cloke and Pappenberger, 2009) and more broadly for streamflow forecasting (Cuo et al., 2011; Shrestha et al., 2013). The specificity of this thesis in comparison to these examples is the use rainfall predictions at high NWP spatial and temporal resolution for urban catchments with sizes near grid cell size.

2.4. Challenges for NWP use in urban applications

The use of NWP for urban hydrology application faces numerous challenges.

Precipitation is one of the most difficult variables to forecast on an urban scale due to its large variability in space, time and intensity leading to the following errors: (i) the event localisation, an error of a few kilometres can lead to precipitation in the wrong catchment; (ii) the timing of the events, since urban catchment are characterised by short response time; (iii) the precipitation intensity.

NWP spatial and temporal resolutions have improved significantly along with the increase of computational power. However, a bottleneck remains for the application of NWP on urban catchments, which can be of similar size (or even smaller) as a single grid cell. Ochoa-Rodriguez et al. (2015) investigated the impact of rainfall input resolution on the outputs of detailed hydrodynamic models considering a spatial resolution between 100m and 3000m and a temporal resolution between 1 and 10 minutes. For comparison, the resolution of the DMI-HIRLAM-S05 model is currently above the upper range of resolutions considered.

The continuous improvement of NWP makes their use in urban hydrology increasingly more suitable. Their development is referred to as a "quiet revolution" by Bauer et al. (2015). E.g. the new NWP RA3 model from DMI assimilates precipitation rates derived from weather radar observations and has a horizontal resolution of 0.03º (ca. 3.3 km) and a 10 minutes temporal resolution (Korsholm et al., 2015; Olsen et al., 2015). This spatial and temporal resolution matches the upper range of the interval mentioned above and used by (Ochoa-Rodriguez et al., 2015).

3 Case Study and rainfall-runoff model

3.1. Damhuså catchment

The Damhuså catchment is located in western Copenhagen. This 67 km^2 highly urbanized catchment, equipped with a combined sewer system, is mostly composed of compact residential housing. This catchment was chosen for the absence of major flow-control infrastructures affecting the hydraulic response upstream the Dæmning CSO infrastructure (red hexagon in Figure 5) and because the Damhuså WWTP has two different operation modes during dry and wet weather flow. The flow is measured at Dæmning by the utility company HOFOR using an electromagnetic flow meter with a 2 minutes temporal resolution. The combined sewer interceptor pipe has a maximum capacity of 10,000 m^3/h. Once this threshold is reached, overflowing water is discharged untreated into a nearby small river (Damhuså). The rainfall-runoff model developed in this project (see section 3.2) aims at representing the hydraulic response of the catchment at this location. This choice was made to simplify the modelling approach. The hydraulics downstream from Dæmning are more complex, including several pumping stations. Therefore, the flow at the WWTP can be higher than 10,000 m^3/h.

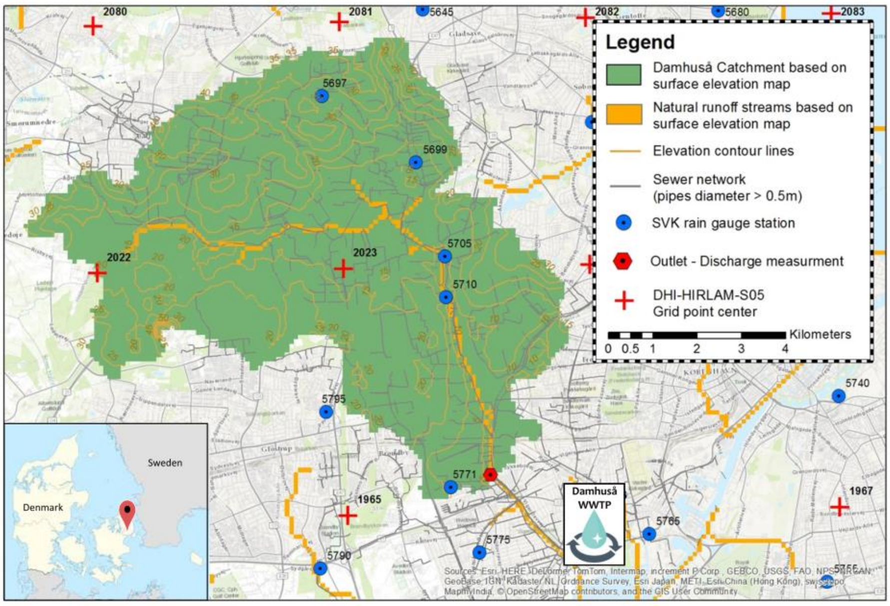

Figure 5: The upstream Damhuså urban drainage catchment (Copenhagen, Denmark) with the location of the flow gauge at Dæmning (red hexagon), the WWTP, the rain gauge stations (blue circles) and the center of the DMI-HIRLAM-S05 grid cells (red crosses).

Rainfall observation data were obtained from the national Danish SVK rain gauge network (blue circles in Figure 5) which is operated by the Danish Meteorological Institute (DMI) and the Water Pollution Committee of the Danish Society of Engineers (SVK – Spildevandskomiteen, in Danish). The rainfall measurements were recorded with a 1 min temporal and a 0.2 mm volumetric resolution; for more information see (Jørgensen et al., 1998).

The inflow to the WWTP consists of wastewater, surface rainfall-runoff and infiltration inflow (especially in the winter months). The Damhuså WWTP has a capacity of 350 000 PE (population equivalent). In 2015, the WWTP treated 33,390,000 m^3 and consumed 8,735MWh of electricity, which corresponds to a ratio of 0.261 kWh/m^3 (BIOFOS, 2015). Treated and bypassed wastewater is discharged into the Øresund at a maximal flow rate of 18,000 m^3/h. If this pumping capacity is exceeded, the treated wastewater is stored in a 45,000 m^3 basin which overflows near the WWTP. Figure 6 shows the flow diagram of the Damhuså WWTP.

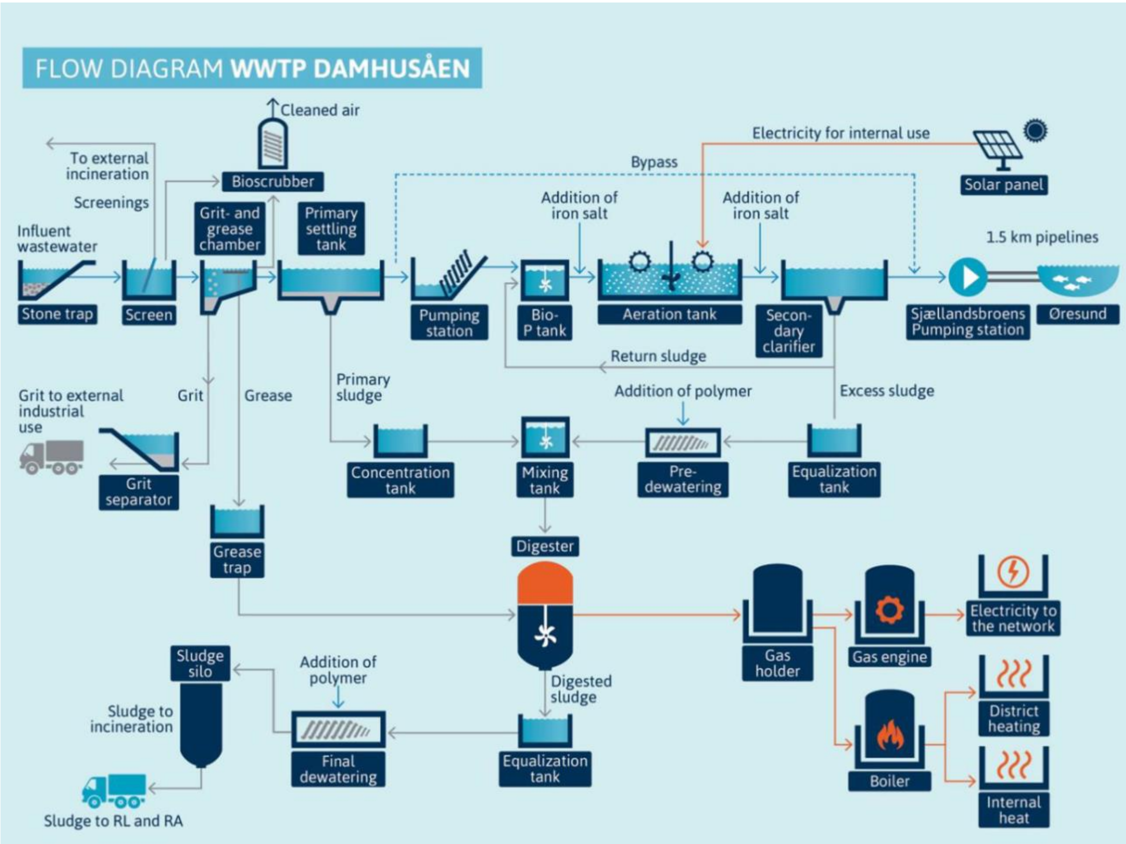

Figure 6: Process diagram of the Damhuså WWTP (BIOFOS and HOFOR, 2016).

3.2. Hydrologic model description

A hydrological rainfall-runoff model was developed to assess the predictive performance of the NWP EPS based on one of the main variables of interest in IUDWS, namely the discharge at the catchment outlet, rather than on the rainfall. The hydrological model was composed of 3 main conceptual parts describing (i) wastewater flow from households, (ii) fast surface runoff from impervious areas and (iii) slow runoff caused e.g. by infiltration-inflow and correlated to the potential evaporation (Figure 7).

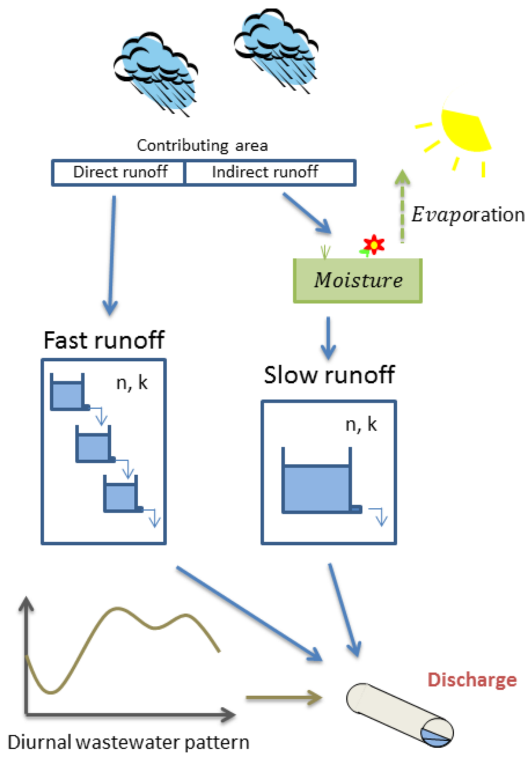

Figure 7: Overall scheme of the conceptual hydrological model (**Paper II**)

The pattern of the wastewater, ww(t) from household and industries was assumed to be constant throughout the year and was modelled using a second order Fourier transform, see equation (2.1) where a_0, a_1, b_1, a_2 and b_2 are the Fourier series parameters and w the frequency of the pattern (e.g. (Langergraber et al., 2008)).

$$ww(t) = a_0 + a_1\cos(wt) + b_1\sin(wt) + a_2\cos(2wt) + b_2\sin(2wt) \qquad (2.1)$$

The rainfall-runoff processes was modelled using a lumped conceptual model based on the Nash linear reservoir cascade (Nash, 1957). Hence, the catchment response was represented by a set of reservoirs in series with a linear relationship between the reservoir outflow, $Q(t)$, and the amount of water stored, $S(t)$, as shown in Eq. 2.2.

$$S(t) = K.Q(t) \tag{2.2}$$

Assuming continuity, the instantaneous unit hydrograph (IUH) is described by Eq. 2.3 with two hydrologic model parameters: the number of linear reservoirs, n, and the storage coefficient, K.

$$IUH(t) = \frac{1}{K^n}.\frac{1}{\Gamma(n)}.t^{n-1}.\exp(-\frac{t}{K}) \tag{2.3}$$

where $\Gamma(n)$ is the gamma function defined by $\Gamma(n) = \int_0^{+inf} e^{-t} * t^{n-1} * dt$, which can be simplified to $\Gamma(n) = (n-1)!$ if n is an integer.

Different runoff patterns were observed at the Dæmningen location during winter and summer months. During the summer period, the discharge reverts to the dry weather condition only a few hours after the rainfall event (up to 10 hours), whereas during the winter period a rainfall event impacts the discharge during several days (up to 10 days). These different behaviours were assumed to relate to the infiltration rate and the potential evaporation. They were modelled by combining two runoff processes, one fast and one slow. Thereby the fast runoff has a constant pattern throughout the year, whereas the slow runoff relates to the wetness index which is calculated based on potential evaporation and previous rain events (catchment's memory). Such a simple lumped conceptual model fits the purpose at hand and is fast to run. A more detailed model is not necessary due to the coarse temporal and spatial characteristics of the rainfall inputs (NWP). This model was developed in MATLAB® and based on matrices to minimize the calculation time. Figure 8 shows an example of a flow prediction at the catchment outlet. The hydrological model and its calibration are further described in **Paper II**.

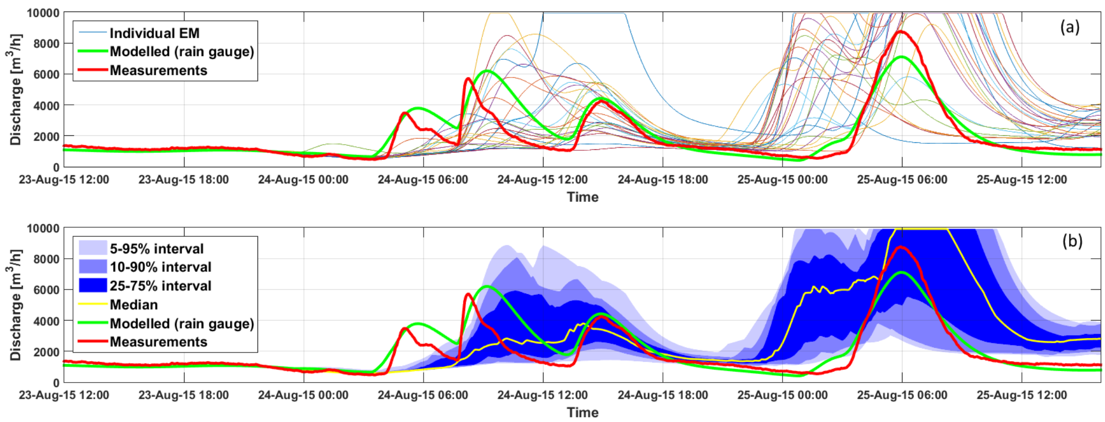

Figure 8: Example of flow predictions for each ensemble member (a) and using EPS quantiles (b).

3.3. Wet weather operation of the WWTP

The Damhuså WWTP has two modes of operation. Under dry weather condition the biological treatment has a maximal hydraulic capacity of 6,400 m^3/h and under wet weather condition, when the aeration tank settling (ATS) is activated, the maximal hydraulic capacity is increased to 10,000 m^3/h. The ATS operation (Bundgaard et al., 1996; Nielsen et al., 1996, 2000) increases the hydraulic capacity of the WWTP during wet weather periods by reducing the suspended solids and hydraulic loads to the secondary settlers. For optimal performance, the ATS mode has to be started before the hydraulic load increases in order to have enough time to transfer sludge from the secondary clarifiers into the aeration tanks. This requires between 20 and 120 minutes of flow forecast (Munk-Nielsen et al., 2015). Settling is then introduced in the aeration tanks at the end of each treatment cycle. This allows the plant to run at very low flow rates of return activated sludge from the secondary settlers and therefore at a higher hydraulic rate. If the sludge levels in the secondary clarifiers reach a critical level and suspended solids start occurring in the discharge the flow rate needs to be reduced to avoid sludge escape. The ATS operation was introduced at the Damhuså WWTP in 2013. Flow prognoses based on radar extrapolation forecasts were introduced in September 2014 with 30 minutes lead time, which was extended to 120 minutes in June 2015. The flow forecast is generated by a conceptual rainfall-runoff model that is auto-calibrated based on Maximum a Posteriori estimation as described in (Pedersen et al., 2016).

The control of ATS operation (activation and deactivation) at the Damhuså WWTP is based on the flow measurement upstream (at Dæmning) and at the WWTP, and on the flow prognosis using weather radar extrapolation nowcast.

Figure 9 shows an example of how the current ATS control switch works. The WWTP is first under dry weather operation (a), then the ATS operation is triggered by the radar flow forecast which provides enough lead time to fully prepare the WWTP before the flow increase (b). The WWTP is thereafter under ATS operation (c). The sludge blanket level later reaches a critical level and to avoid sludge escape from the secondary clarifier, the maximal hydraulic capacity is reduced (d).

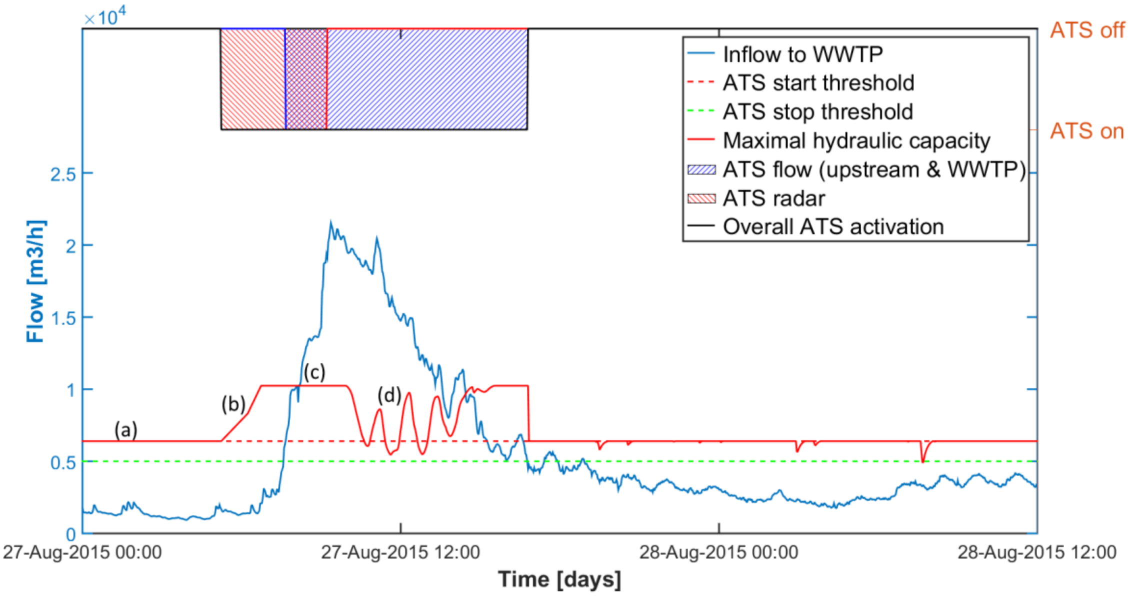

Figure 9: Example of ATS control switch from flow measurement and radar flow prognoseis, and maximal hydraulic capacity under different conditions (a) dry weather, (b) preparation of the ATS operation, (c) ATS operation, (d) critical sludge blanket level in secondary settlers (**Paper IV**).

The ATS operation is further described in **Paper IV**. The historical data were obtained via the advanced real time online STAR Control® platform with a 2-minute resolution for 2 years period from June 2015 to June 2017.

4 Forecast verification

Forecast verification is largely developed in the weather and climate forecasting literature. This section focuses on the verification of quantitative precipitation forecasts (QPF) in meteorology and for flow forecasts in IUDWS. A more general description of the issues of forecast verification can be found in two textbooks: “Forecast Verification – A Practitioner’s Guide in Atmospheric Science” by Jolliffe and Stephenson (2012); and “Statistical methods in the atmospheric sciences: An introduction” by Wilks (2011) and in various articles as shown in the review by Casati et al. (2008).

4.1. Forecast verification in meteorology

A good understanding of outputs from NWP models is critical to properly interpret and use such data. As explained in section 2, NWP is based on very complex models. Understanding their model structure requires a certain level of expertise in the field. However, the expected skills of NWP model output and the mind-set of the meteorologists who developed them can be assessed by studying the verification methods that they are using, providing insight on how to use the outputs of their models.

4.1.1. Quantitative precipitation forecast verification

Quantitative precipitation forecasts (QPF) are the prime variables of interest of NWP models for IUWDS applications. Unlike most other meteorological variables, precipitation has both a quantitative and an on/off component.

The world meteorological organisation recommends in their report (WWRP/WGNE, 2009) to use 24-hour accumulation as the primary temporal scale for rainfall verification. They also specify that adding a higher temporal resolution (6h or 12h) is highly desirable, especially for high resolution models, but optional. They recommend running the model-oriented verification on a common 0.5° latitude/longitude grid (1.0° for ensembles). They also recommend that verification data and results should be stratified by the following observed rainfall intensity thresholds: 1, 2, 5, 10, 20 and 50 mm d^{-1}. Meteorological forecast verifications for precipitation are thus based on categorical evaluations defined by a threshold with a relatively coarse resolution. This stands in contrast to the resolution currently available (see section 2) and required for the use of NWP in urban hydrology. Forecast verification for fine resolution is challenging for meteorologists. High resolution forecasts are more realistic but getting the forecast exactly right at fine scales is extremely difficult due to the chaotic nature of the atmosphere. Hence high-resolution forecasts are usually interpreted with caution (i.e. “around this place”, “about this time”, “about this magnitude”), rather than at face value (Jolliffe and Stephenson, 2012).

Therefore, point verification scores can be worse for higher-resolution models than for lower-resolution models. Here, misplacements of an event in space and/or time are penalized twice, for predicting an event which did not occur and again for failing to predict an event. This is known as the ‘double penalty’ problem (Mass et al., 2002; Rossa et al., 2008). Meteorologists developed new forecast verification methods to cope with this, e.g. the neighbourhood verification method assumes that forecast values in nearby grid boxes are equally likely and allows these ‘close’ forecasts to be considered as well (Ebert, 2008) and the object oriented verification method based on weather pattern recognition (Ebert and McBride, 2000).

The analysis of the forecast verification methods shows that meteorologists and urban hydrologists have two different mind-sets regarding weather forecast. The first ones are concerned by modelling correctly the processes, getting the weather patterns correct even if they are slightly misplaced whereas the second one, due to the size of their hydraulic catchment, are concerned about the specific value of given grid cells. This difference in mind-sets can lead to misuse of NWP outputs by urban hydrologists.

4.1.2. Meteorological verification from a hydrological perspective

Weather forecast verification requires a common spatial and temporal definition between observations and predictions. The two common approaches are (i) the model-oriented verification which includes processing the observation data to match the spatial and temporal scales of the model and (ii) the user-oriented verification which interpolates the model output to match the observation scales. Both approaches are embedded with assumptions and add uncertainty during the data processing, e.g. when point measurements from rain gauge stations are compared to average rainfall prediction over a grid cell or vice versa. However, these methods are based on variables of meteorological relevance. The purpose of our study is not to predict rainfall but the flow inside the IUDWS. Hence, as suggested by (Pappenberger et al., 2008) the prediction skills should be evaluated on flow forecast by coupling meteorological and hydrological models. The evaluations thereby become based on discharge predictions and discharge observations rather than precipitation forecasts and observations. Such an integrated approach lessens spatial and temporal scale issues and incorporates the effect of dominant hydrological processes. This method allows the evaluation of application-specific performance of meteorological predictions, but requires acknowledging the addition of the hydrological model uncertainty into this model cascade. The uncertainty propagation in hydro-meteorological forecasting chains is further discussed in (Beven and Lamb, 2017; Zappa et al., 2010). The forecast evolution presented in this work is based on the rainfall-runoff model developed in section 3.2 and in **Paper II**.

4.2. Scoring rules for forecast verification

This section introduces the common forecast verification scores applied in this thesis. For an overview of the measures that can be used for evaluating environmental models, the reader is referred to (Bennett et al., 2013).

4.2.1. Categorical forecast scores

A categorical dichotomous statement is a simple "yes" or "no" statement. It means that the observed data (the forecast) is below or above a pre-defined threshold. The combination of the different possibilities between observations and forecasts defines a 2x2 contingency table containing the four possible pairs of forecast-observation: hits (correct positives), false alarms (false positives), misses (false negatives) and correct negative (see Table 3).

Table 3: Schematic contingency table for deterministic forecasts of a sequence of n binary events. The numbers of observations/forecasts in each category are represented by a, b, c and d.

		Event observed		
		Yes	No	
Event forecast	Yes	hits (a)	false alarms (b)	$a+b$
	No	misses (c)	correct negatives (d)	$c+d$
		$a+c$	$b+d$	$a+b+c+d=n$

Various scores have been developed to evaluate categorical forecasts (Table 4). The proportion correct (PC) gives a fraction of all correct forecasts (both events and non-events). This simple measure can be misleading, the correct "yes" and "no" are equality rewarded and hence, for the common case of rare occurrence of events, non-events have an often too high influence on this score.

The critical success index (CSI) is defined as hits divided by the sum of hits, false alarms and misses. The correct forecasts of non-events (correct negatives) are not included in this skill score. This is especially relevant for rare events for which the PC is mostly driven by the correct negative ($a \ll d$). CSI is sensitive to hits and penalizes both misses and false alarms, but does not distinguish the source of the forecast error.

The probability of detection (PoD) measures the fraction of observed events that were correctly forecasted. The probability of false detection (PoFD) measures the fraction of forecasted events that were observed to be non-events. PoD and PoFD should be examined together, as neither provides a complete description. PoD is sensitive to hits but does not take false alarms into account, whereas PoFD is sensitive to false alarms and does not take misses into account.

Table 4: Verification measures based on the contingency table.

Score	**Formula**	**Range**	**Perfect**
Proportion Correct, *PC*	*(a+d)/n*	[0,1]	1
Critical success index, *CSI*	*a/(a+b+c)*	[0,1]	1
Probability of detection, *PoD*	$a/(a+c)$	[0,1]	1
Probability of false detection, *PoFD*	$b/(b+d)$	[0,1]	0
Occurrence frequency of events, μ	$(a+c)/n$	[0,1]	na

4.2.2. Probabilistic forecast verification

As mentioned in sections 2, EPS are generated to characterise NWP uncertainty. Assuming an equal likelihood between the ensemble members, forecast probabilities can be extracted from an EPS. The ensemble-based probability is the average of the binary probabilities for each individual member depending on the occurrence (1) or non-occurrence (0) of an event defined by the exceedance of a specified threshold (q), Eq. (4.1).

$$EM_{k,i} = \begin{cases} 1 & if \;\; F_{k,i} \geq q \\ 0 & if \;\; F_{k,i} < q \end{cases} \quad (4.1)$$

where F is the predicted flow at the ith time step for the kth ensemble member.

The ensemble probability, also called fraction of positive EM (f_{EM}), at the ith time step is computed as a mean value, Eq. (4.2).

$$f_{EM,i} = \frac{1}{N} \sum_{k=1}^{N} EM_{k,i} \quad (4.2)$$

where N is the number of members in the ensemble.

4.2.2.1 Relative operating characteristic diagram

The relative operating characteristic (ROC) diagram is obtained by plotting PoD (vertical-axis) versus PoFD (horizontal-axis) and describes the ability of the forecast to discriminate between the occurrence and the non-occurrence of an event. For an EPS with N ensemble members, N increasing probability levels can be defined based on the fraction of ensemble members predicting an event, f_{EM} (also called the weight of evidence). For each given $f_{EM,k}$, the EPS can be turned into a single categorical yes/no forecast and the skill score, developed in the previous section. 4.2.1, can be applied, e.g. $PoFD_k$ and PoD_k. Hence, the ROC curve for probabilistic forecasts is defined as the curve from (0,0) to ($PoFD_k$, PoD_k) for each $f_{EM,k}$ from 1/N to 1, and to finally (1,1) – see Figure 10. ROC diagrams are further developed in **Paper II**.

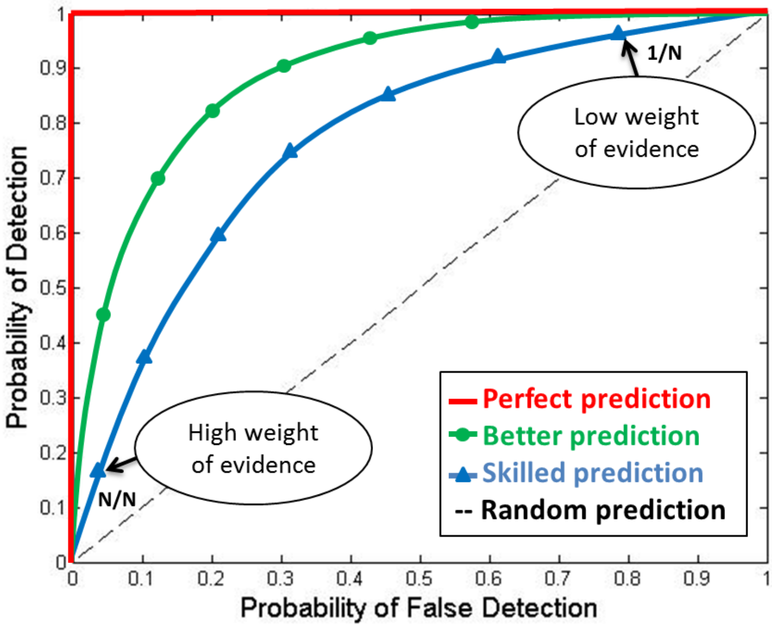

Figure 10: Illustration of the relative operating characteristic (ROC) diagram for different theoretical EPS with higher or lower skills.

4.2.2.2 Brier skill score

The Brier Score (Brier, 1950) assesses the quality of discrete probability forecasts predicting categorical outcomes (i.e. “events” and “non-events”) and is comparable to the mean squared error. For a given ith forecast time step, the forecasted probability of an event ($0 \leq f_{EM,i} \leq 1$) is compared to the observation (y_t). If the ith observation is an event (or non-event) then $y_i = 1$ (or else $y_i = 0$).

$$BS = \frac{1}{n}\sum_{i=1}^{n}(f_{EM,i} - y_i)^2 \tag{4.3}$$

The Brier Skill Score (BSS) is a skill score related to a reference forecast (BS_{ref}). The reference forecast is based on the frequency of occurrence of events during the recorded forecast period (μ). A positive value of the BSS indicates that forecast is beneficial compared to the reference forecast.

$$BSS = 1 - \frac{BS}{BS_{ref}} \quad \text{with} \quad BS_{ref} = \frac{1}{n}\sum_{i=1}^{n}(\mu - y_i)^2 \tag{4.4}$$

4.2.2.3 Continuous ranked probability score

The Continuous Ranked Probability Score (CRPS) is defined as the integrated squared difference between the cumulative forecast and the observation distribution (Eq. 4.5).

$$CRPS = \frac{1}{n} * \sum_{i=1}^{n}\int_{-\infty}^{\infty}[F_i(u) - H(u - y_i)]^2\, du \tag{4.5}$$

where H denotes the Heaviside function, F_i is the cumulative distribution, y_i the observation and n the number of forecasts. The CRPS can be interpreted as a probabilistic generalization of the mean absolute error, see Figure 11. Better forecasts yield lower differences between the two distributions, thus lower CRPS values correspond to better performance.

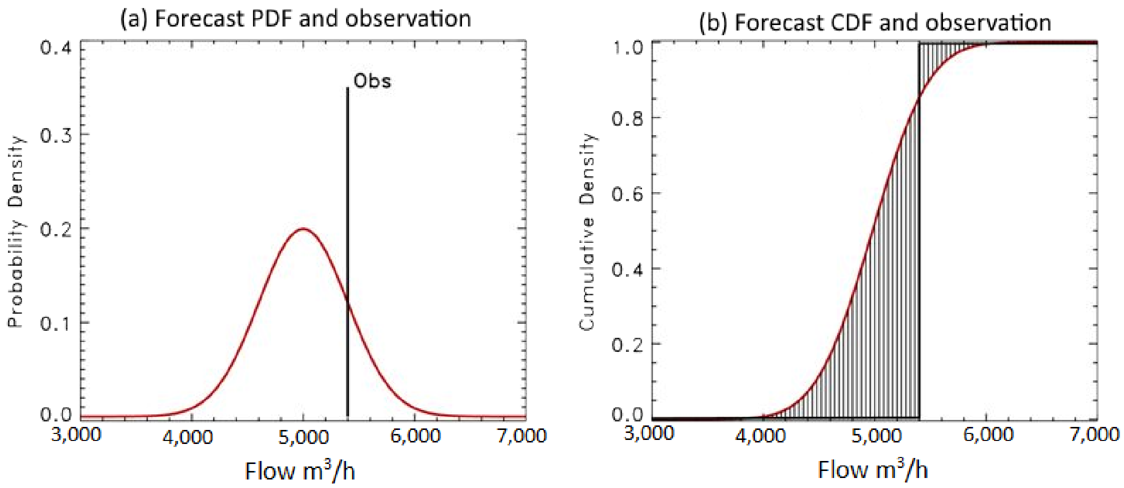

Figure 11: Illustration of the CRPS calculation. The CRPS is based on the square of the hatched area in the right plot.

5 NWP post-processing methods

Post-processing approaches attempt to improve the raw output of the NWP model. This is either done by expanding the amount of used information or by correcting the model output with various statistical techniques. It is referred to as *post*-processing in the meteorological literature as NWP model *outputs* are corrected, while it sometimes in the hydrological literature is referred to as *pre*-processing as the variable of interest from this point of view is a model *input*. This section describes two post-processing techniques that originate from the meteorological community. The choice of techniques is motivated by practicality as they are reasonably straightforward to implement and do not involve complicated statistical output-corrections. This will hopefully help with the adoption of NWP forecasts by IUDWS practitioners. These techniques exploit two features of the LAM NWP model: spatial neighbourhoods and time-lagged forecasts. The neighbourhood approach makes use of the spatial variability of the LAM NWP model output, while the time-lagged approach takes advantage of consecutive forecast overlaps. The maximal threat method developed in this thesis is inspired by the neighbourhood approach but aims at limiting the EPS size expansion.

5.1. Spatial neighbourhood approach

5.1.1. Methods

The simulation of convective storms by high resolution NWP models are often off a by few hours and/or few tens of kilometres away from the observed storm event (Bernardet et al., 2000). The neighbourhood approach is thus based on the assumption that the inclusion of forecasts from neighbouring grid cells can improve predictions by compensating for inherent spatial misplacement of the rainfall event. **Paper II** investigated the neighbourhood approach for the urban catchment of the case study, including neighbouring grid cells up to a radius of six cells (~33 km) from the centre of the catchment (Figure 12). Three methods were compared, (i) the weighted areal overlap method which only includes the rainfall prediction from the grid cells overlapping the catchment, (ii) the neighbourhood inclusion method which expands the EPS with predictions from neighbourhood grid cells, and (iii) the maximum threat method which assesses the worst case scenario within the given surroundings.

The aim of the second approach is to investigate to what extent inclusion of rainfall predictions from neighbouring grid cells is able to compensate for the spatial errors of the NWP model and, thus, improve its skill (e.g. ROC diagram). This approach was first developed by Theis et al. (2005) as a pragmatic, low-budget post-processing procedure to generate "probabilistic" precipitation forecasts from a deterministic forecast. The concept was further developed by Ben Bouallègue et al. (2013) and Schaffer et al. (2011) to expand EPS generating a ''super-ensemble''. The surrounding areas used for the neighbourhood ensemble expansion method were defined based on a circle centred in the catchment. Figure 12 displays the size of the neighbourhood for the case study, from the smallest vicinity in dark grey to the largest vicinity (radius of 6 grid cells) in light grey. The radii and corresponding number of ensemble members are shown in Table 5.

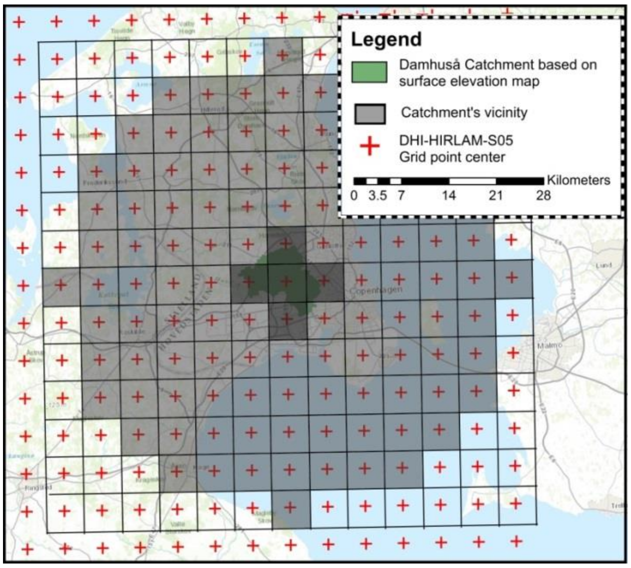

Figure 12: Illustration of the grid cells used for the smallest expansion (dark grey) and the largest expansion (light grey) in the neighbourhood ensemble expansion approach (**Paper II**)

Table 5 : Variation of EPS size with neighbourhood radius in grid cell (**Paper II)**

Radius of neighbourhood (in grid cells)	0	1	2	3	4	5	6
EPS size	25	125	325	625	1225	1825	2825

As shown in Table 5, the size of the EPS is quickly expanding. To limit the ensemble size, considering that a hydrological simulation needs to be run for each ensemble member, the third method is based on the worst case scenario within the area defined by the inclusion radius. For each ensemble member and at each time step the highest rainfall intensity with the considered area was selected. The aim was here not to produce QPF but to assess the maximal threat within a given surrounding in order to reduce missed events with a limited expansion of the EPS size.

5.1.2. Results

The analysis of the results, Figure 13, showed different evolution of the forecast skill for each hourly time step through the forecast horizon depending on the method and the radius of the neighbourhood. The two panels on the left show the evolution PoD and PoFD with increasing lead time for different decision threshold (i.e. numbers of ensemble members predicting an event) for the baseline scenario solely considering overlapping grid cells. As mentioned in section 4.2.1, PoD and PoFD relate to each other and should be examined together. For the lowest decision threshold (1EM, i.e. only one ensemble member is required to predict an event), the PoD remains stable through the time horizon at the expense of a PoFD increase. And on contrary for a higher decision threshold (16EM) the PoFD remains stable through the time horizon but the PoD decreases.

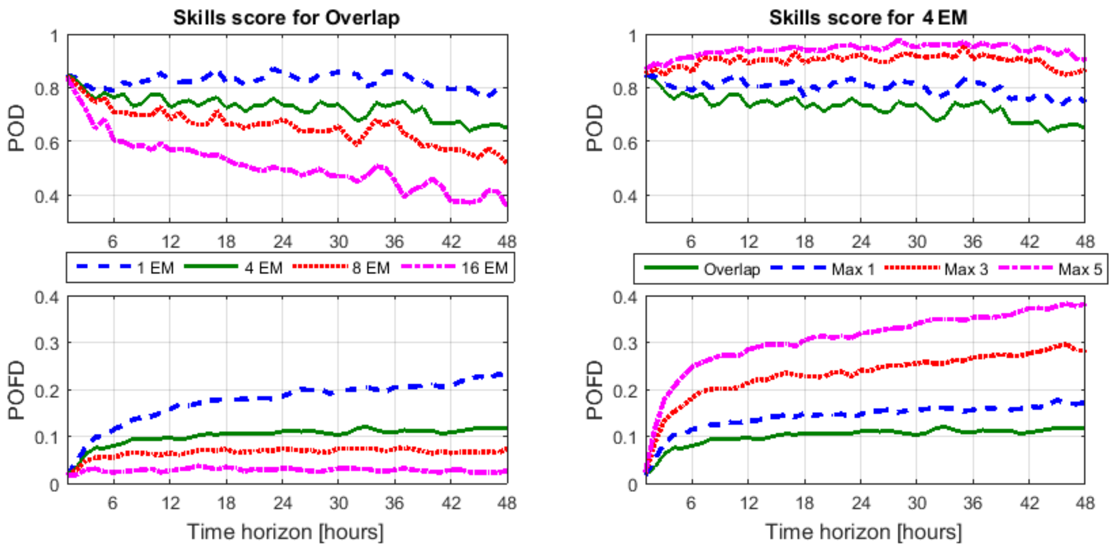

Figure 13: Variation of predictive skill with forecast lead time for a flow threshold of 4,000 m^3/h. Left: PoD and PoFD for different number of ensemble members (iEM) predicting an event using the weighted aerial overlap method. Right: PoD and PoFD for the weighted aerial overlap method and the maximal threat EPS method with different radii based on the same fraction of ensemble members (4EM) (**Paper II**).

The two right panels show the evolution PoD and PoFD with increasing lead time for different neighbourhood radii (for a decision threshold of 4EM). Overall, Figure 13 shows that most conservative approaches, aiming at avoiding missed events, maintained their PoD skills through the time horizon but their PoFD increase significantly with the lead time.

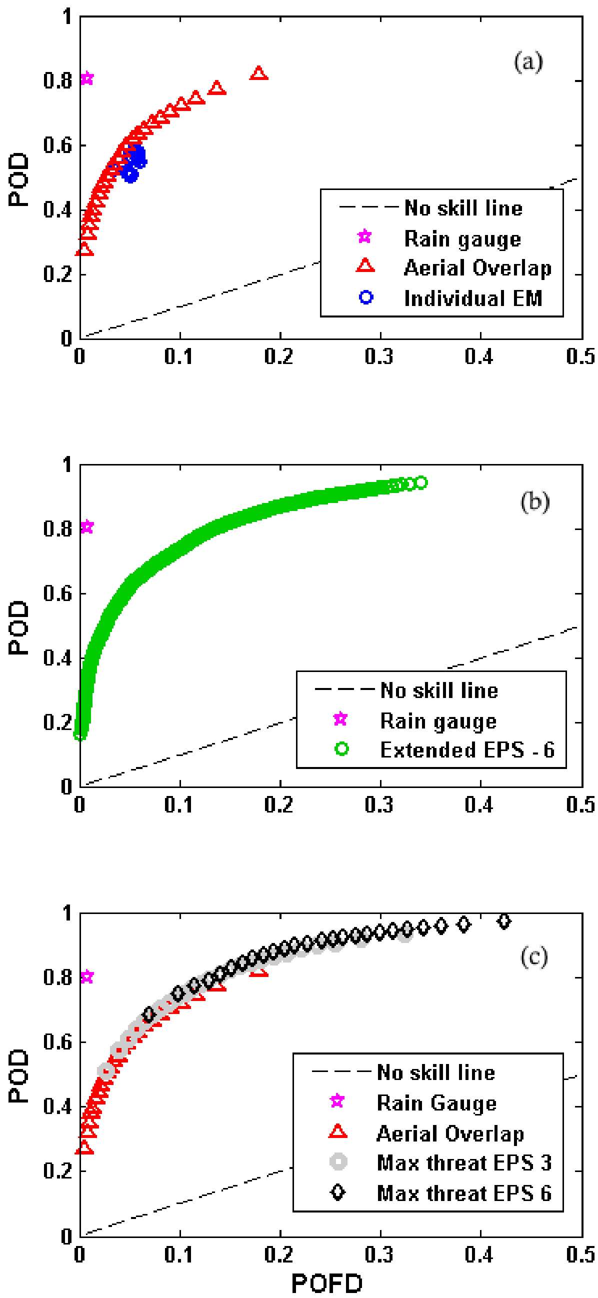

Figure 14: ROC diagram for different NWP post-processing strategies: catchment overlap with 25 EM (a); expended neighbourhood EPS with 2825 EM (b); and maximal threat approach with 3x25 EM (c) (**Paper II**).

Figure 14 shows the discrimination skill for the different neighbourhood approaches, aggregating hourly time steps through all forecast horizons. Figure 14a underlines the benefit of using EPS rather than individual ensemble members. EPS gives the opportunity to select the fraction of EMs predicting an event that most appropriately balances PoD against PoFD for the prediction purpose at hand. However, Figure 14a which represents the results from the first approach based on weighted catchment overlap achieved at best a PoD of 81.9%, hence a significant proportion of high flow events are missed by the predictions using this approach. Figure 14b and Figure 14c show that the two other approaches provide a larger range of discrimination skills with a PoD up to 97.0%. Furthermore, the third approach based on the maximal threat achieved results comparable to the conventional neighbourhood approach with a significant smaller size EPS. For further results and analysis, the reader is referred to **Paper II**.

5.2. Time-lagged approach

5.2.1. Methods

NWPs have long forecast horizons and because their forecasts are renewed often there will be periods where old and new forecasts overlap - see the first two panels in Figure 15. In this case, the NWP has a forecast horizon of 54 hours and the whole ensemble is renewed every 6 hours. Hence the expected precipitation for a given time step at a given grid point is predicted by the 25 ensemble members nine times.

As underlined by Pappenberger et al. (2011) the forecast (in)consistency can either be seen as a curse or a blessing. As mentioned in section 2, NWPs are highly sensitive to their initial conditions as tiny differences here may lead to a completely different evolution of the forecast over time. This is especially true for the high-resolution forecasts required for urban hydrology applications, while coarser-resolution models tend to smooth out the potential differences. Hence consecutive forecast may contradict each other, leading to forecast inconsistency also known as “jumpiness”. Forecast (in)consistency is not to be confused with internal EPS (in)consistency, which relates to the spread between ensemble members. However, the problem of forecast inconsistency is to some extent eased through ensemble forecasting as the ensemble will intrinsically “blend out” individual jumpy forecasts.

Forecast inconsistency can be seen as a curse as it may generate erratic decision making or warnings, leading to the end-user losing confidence in the forecast skills. On the other hand, as argued by Persson (2015), a consistent forecast may deceive forecasters into a false sense of confidence in the reliability of their model. Thereby forecast inconsistencies can also be seen as beneficial if it results in the forecaster being cautious about its interpretation. This way inconsistency can be used as measure of forecast uncertainty.

For example, Bartholmes et al. (2009) and Thielen et al. (2009) integrated the forecast (in)consistency (they call it persistency) into the decision-making process. Their flood warning was postponed to gain confidence in the prediction following the principal of ‘Let’s wait and see the next forecast’. They decide that at least three consecutive flood forecasts must predict that the discharge at the same river stretch will exceed a critical threshold before a flood warning is issued. These studies showed that the use of forecast consistency reduces the number of false alarms with a minimal loss on the overall probability of detection. This methodology is especially of relevance for hydro-meteorological forecast models which have to cope with highly uncertainty and rare events like flooding. For further discussion on forecast (in)consistency and suggestions for a code of practice the reader is referred to (Pappenberger et al., 2011).

Another way to handle forecast “jumpiness” is to combine the most recent forecast with the previous ones. On average, the most recent NWP forecast is expected to yield better predictions than older forecasts as they contain new observations. Nonetheless, there are cases where previous forecasts were more accurate. Previous forecasts can be regarded as additional ensemble members that have started from slightly different initial conditions. Hence previous forecast can be combined together with the latest one into a consensus forecast, a time-lagged ensemble (TLE), as developed by Mittermaier (2007) and illustrated in Figure 15.

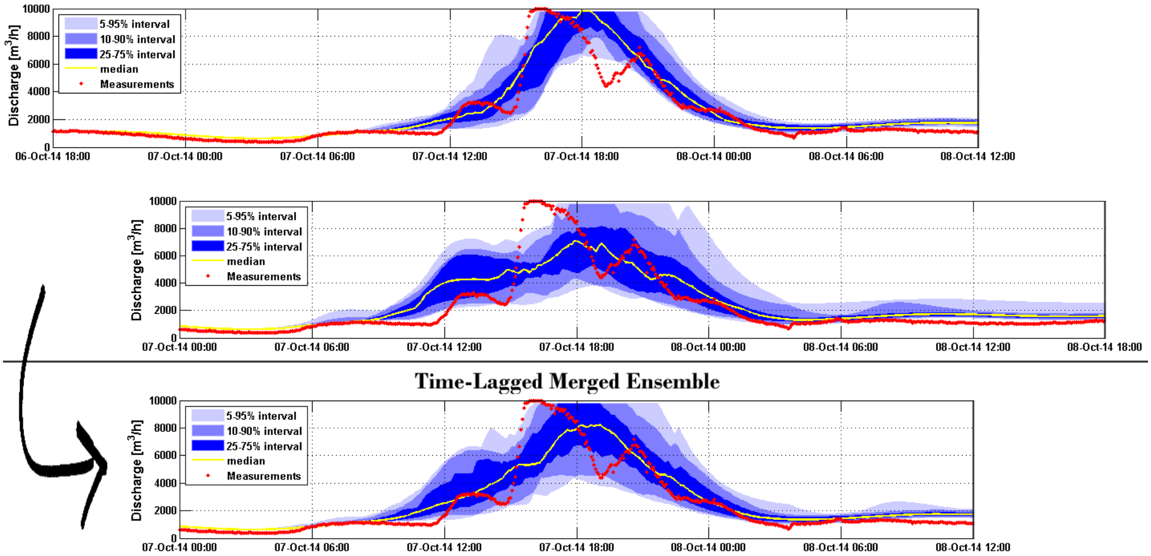

Figure 15: Two consecutive ensemble discharge forecasts of 25 ensemble members – the two upper panels - are merged into a TLE of 50 ensemble members – the lower panel (Courdent et al., 2017).

It should be noted that using the TLE approach to expand the size of the EPS reduces the forecast horizon to the common forecast window shared by all the forecasts. This is seen in Figure 15 where the lower panel is shorter than the two upper panels.

5.2.2. Results

The time-lagged approach increases the overall skill of discharge prediction as shown in Table 1 with the CRPS as scoring rule. The most significant improvement is achieved by adding the predictions from the closest previous forecast. Hence, a trade-off between the benefit of expanding the EPS size and the computational cost of a larger ensemble has to be evaluated for a given case.

Table 6: Evolution of the CRPS in regard to the number of overlaps included, aggregating hourly time step through the full time horizon (Courdent et al., 2017).

Time-Lags (number of overlaps)	0	1	2	3	4
EPS Size	25	50	75	100	125
CRPS of the discharge [m^3/hr]	601.76	590.60	586.62	584.69	583.87

As shown in Figure 16, the TLE approach improves the discrimination skill, providing a larger range of predictions. Hence the TLE approach reduces the proportion of missed forecast events.

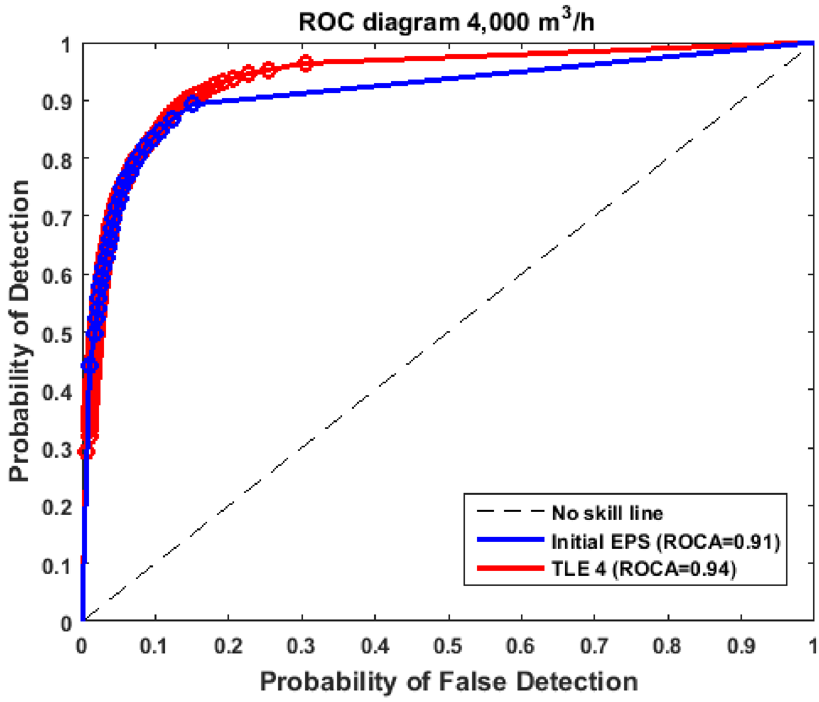

Figure 16: ROC diagram comparing the discrimination skill of the initial EPS and the expanded TLE including 4 overlaps (125 members), (Courdent et al., 2017).

5.3. Discussion

The analysis of discharge predictions from hydro-meteorological models showed that using NWP outputs directly, considering solely the newest predictions directly above the catchment area, leads to a significant proportion of miss-predicted events. As displayed on Figure 14a, 18.9% of the high flow events were missed by all of the 25 ensemble members. This can be explained by the very fine resolution required as input to the hydrological model and the limitation of the EPS to represent the full uncertainty.

Both NWP post-processing approaches presented above (spatial neighbourhood and time-lagged) improve the discriminative skill, reducing the amount of missed events. These computationally inexpensive methods maximise the use of the NWP output to get the most out of it (e.g. spatial variability, forecast overlap) and provide enhanced EPS.

However, the results show that even with post-processing, it is challenging for NWPs to provide reliable values for urban catchments with near grid cell dimension. But NWPs do provide valuable information about the future state of the IUWDS (e.g. high or low flow). Such prediction can help to improve the IUDWS management.

Hence NWP can be used in a domain-based framework. We are suggesting in (Vezzaro et al., 2017), a domain-based framework distinguishing between 4 operational domains: (i) dry weather conditions with empty storage basins, (ii) dry weather conditions with stored water in basins, (iii) wet weather conditions within system capacity and (iv) wet weather conditions exceeding system capacity. The municipality of Aarhus (Denmark) has developed a similar concept to characterize the relevant level of modelling according to the operating conditions. They defined 5 operating conditions: dry weather, everyday rain, rainfall corresponding to design capacity, controlled cloudburst and uncontrolled cloudburst (Aarhus Vand, 2016). Each of these domains has its own specificity which should addressed by the control objectives. E.g. Tik et al. (2015) specifically addressed the optimal management for emptying the retention tank of combined sewer. And in the control strategy developed by Pleau et al. (2005), two different operating modes are defined based on the hydraulic status in the sewer network. Specific control objectives are defined for these two operating modes. For the dry weather conditions, the objective is to maximize the life expectancy of mechanical devices and to minimize energy consumption. And, for the wet weather conditions, the objective is to minimize overflows and to maximize the use of the WWTP capacity.

The predictions of these domains using NWP are useful to select the relevant control objective to apply according to the current situation (e.g. energy optimization during dry weather, CSO mitigation during wet weather within the system capacity, flooding prevention during wet weather exceeding the system capacity). Figure 17 shows an example of switches between control strategies according to flow domain prediction in the IUDWS.

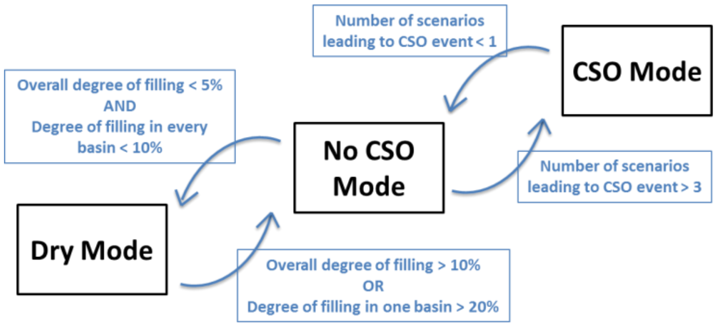

Figure 17: Decision tree for switches between control strategiy modes (**Paper I**).

Forecast data are by nature uncertain; their usage in a control scheme may lead to mismanagement. It should therefore be evaluated if the benefits from using forecasts overcome this risk. Furthermore, as shown on the ROC diagrams and expressed in (Richardson, 2000), EPS provides a large range of potential decision thresholds (one for each dot on the ROC diagram). An evaluation of forecast skills combined with a given control scheme is necessary to assess if using the forecast is beneficial and, if so, to select the most relevant EPS decision threshold. The next chapter develops a framework based on the relative economic value (REV) to assess control schemes using uncertain forecast and to evaluate the control parameters leading to the highest benefit.

6 Relative Economic Assessment

As described in the previous section, NWP EPS enhanced with a post-processing method and coupled with a hydrological model can provide valuable predictions of flow domains in IUDWS. EPS provide a large range of potential decision thresholds. Hence a framework is required to manage these predictions in the best way possible, assessing the trade-off between gains resulting from correct forecasts and losses caused by incorrect forecasts. Similarly, the switch to wet weather operation at the Damhuså WWTP also utilises uncertain data (flow prognosis from radar forecast) and should be evaluated as well. Additionally, such framework can be used to assesses the control parameters (e.g. probability thresholds of the EPS, flow threshold) to select the most relevant one for a given situation.

6.1. Theoretical background

A proper evaluation of the benefits of a forecast system should not only consider the forecasts skill. A detailed knowledge of the decision making process is needed to answer the question: “how does this skill translate to the economic value of a forecast?”. Furthermore, when using ensemble forecasts, the following question should be answered as well: “which decision threshold and NWP post-processing method for the EPS is the most beneficial for my purpose?”.

The gain-loss relative economic value (REV) framework developed in this study and implemented in **Paper III** and **IV** is inspired by the cost-loss ratio decision model introduced by Richardson (2000). Richardson developed this approach to assess the economic value of taking costly actions to mitigate the consequences of forecasted adverse weather events in order to reduce the potential losses associated with them. The decision threshold that can empirically be shown to lead to the lowest expense in the long term should be adopted. Richardson illustrated his approach for the problem of road gritting to prevent ice formation. Subsequently Roulin (2007) used this approach to investigate the benefit of river-flood mitigation measures for two catchments in Belgium, and Chang et al. (2015) applied it to assess the relevance of typhoon mitigation measures in Taiwan.

The REV associates each course of action with a cost and an economic benefit or loss depending on the observed outcome. The task is thus to choose the appropriate actions that will maximize the expected gain or minimize the expected loss. The usefulness of a control strategy can be quantified empirically by considering the occasions when the control was beneficial, detrimental or neutral. The REV compares the economic value of a given control strategy ($E_{forecast}$) to the economic value of baseline scenario which do not used any forecast and is used as reference ($E_{reference}$). This value is then normalised based on the expected economic value achieved with a perfect forecast ($E_{perfect}$) as expressed in Eq. 6.1.

$$REV = \frac{E_{forecast} - E_{reference}}{E_{perfect} - E_{reference}} \tag{6.1}$$

This REV framework was applied and further developed in the context of two case studies summarized in Table 7 which outlines how $E_{forecast}$, $E_{perfect}$ and $E_{reference}$ were formulated for each example, what forecast data and model was used and what main control parameters were evaluated.

Table 7: Summary of the two REV analyses

Energy optimisation during low flow periods. *Actions taken when no-events are forecasted*	High flow prediction for WWTP wet weather operation. *Actions taken when events are forecasted*
Control strategies – Economic assessment	
$E_{forecast}$ • Gain from *correct negatives* (energy consumption improved). • Loss from *misses* (IUDWS jeopardized by energy optimisation during wet weather). $E_{perfect}$ • Perfect predictions of dry weather flow periods $E_{reference}$ • Either never, or always, switch to wet weather operation.	$E_{forecast}$ • Gain from *hits* (WWTP in the correct wet weather mode). • Loss from *false alarms* (loss of efficiency at the WWTP due to unnecessary switches to wet weather mode). • Loss from *misses* (WWTP not ready to cope with high flow). $E_{perfect}$ • Ideal switches to wet weather operations (based on perfect flow forecast) $E_{reference}$ • Either never, or always, switch to wet weather operation.
Forecast and model	
NWP EPS	Weather radar extrapolation nowcast
June 2014 to January 2016	June 2015 to June 2017
Rainfall-runoff model developed in MATLAB® (see section 3.2)	Runoff model developed by (Pedersen et al., 2016) in WaterAspect®
Main control parameters	
• Probability threshold (f_{EM}), i.e. number of ensemble members predicting high flow.	• Flow threshold on radar flow prognosis at the WWTP • Flow threshold on upstream flow measurements

The first one assessed low flow predictions based on NWP EPS data as basis for switching to energy optimisation. The second one assessed high flow prediction based on weather radar extrapolation data as basis for switching to wet weather operation at Damhuså WWTP. These two case studies are further detailed in section 6.2 and 6.3.

6.2. Low flow prediction for energy optimisation

This case study investigates the use of NWP EPS for urban flow domain prediction in order couple the IUWDS with the electric smart grid during dry weather flow periods. For further details, the reader is referred to **paper III**.

6.2.1. Concept and application

Denmark has the political ambitions to have a fossil fuel free energy system by 2050, which requires the development of renewable energy sources (Ministry of Foreign Affairs of Denmark, 2016). However, renewable energy like wind and solar power are by nature intermittent, which generates strains on the electrical network. The electrical smart grid is designed to handle this issue. It provides a framework in which both energy producers and consumers can be proactive to balance the fluctuating power production. Energy markets are developed, as part of the smart grid, to align electricity production and consumption through bids and offers. The electricity price is based on supply and demand, creating an economic incentive to distribute the energy consumption in time (e.g. shifting non-essential energy consumption out of the consumption peaks). For further detailed history and description of electricity markets, the reader is referred to (Weron, 2006).

IUDWSs have the potential to be proactive on these energy markets, taking advantage of the energy price variation both regarding its energy production (e.g. biogas production) and its energy consumption (e.g. aeration). During dry periods, the unused storage in the IUDWS can be used as a buffer to control the timing of the energy consumption associated with wastewater transportation and treatment as suggested in (Bjerg et al., 2015; Halvgaard et al., submitted 2017). The aeration process represents between 50 and 70 % of the WWTP process energy consumption (Rosso and Stenstrom, 2005), and the wastewater load to the aeration tank can be controlled as a function of the daily variation of the power rate to reduce the average power costs (Leu et al., 2009). Figure 18 highlights that both wastewater production and energy consumption are driven by human activities and therefore have similar daily patterns. This means that the energy is generally more expensive when the need for wastewater transportation and treatment is peaking. The hourly energy price is also impacted by other parameters such as the wind as shown by its high standard deviation of 11.5 €/MWh.

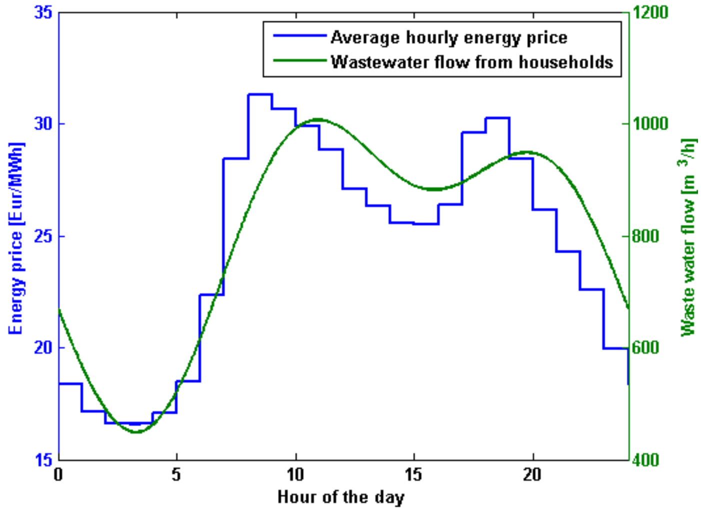

Figure 18: Annual average (2015) of hourly energy price for the energy market DK2 covering the Copenhagen region (in blue, data from http://www.nordpoolspot.com/) and daily variation of the dry weather flow for the Damhuså catchment (green) (**Paper III**).

During low flow periods, when no rain events are forecasted, the management objective of the IUDWS can be switched to optimisation of the energy consumption by utilising the smart grid energy market. Depending on the daily variation and the share of wind power, this optimisation can generate a variable gain (G). On the other hand, missing high flow events will jeopardise the IUDWS management as e.g. the detention basins may not be empty in time to cope with high flow generated by a storm event. These negative outcomes are represented by a loss (L). In case of forecasted events (hits and false alarms) the IUWDS stays under normal operation. The economic outcome of these two situations remains the same and therefore a null value is assigned to them, Table 8.

Previous studies using REV (e.g. (Chang et al., 2015; Roulin, 2007)) considered adverse events which can be mitigated at a cost, reducing the loss associated with these events. Their decision models are therefore based on a cost-loss ratio. This study investigates a different perspective. Instead of taking mitigating measures when adverse events are predicted, the system is optimized when no events are predicted in order to achieve a positive gain. It is left under its traditional management when events are predicted. Furthermore, this study considers the possibility of a time-dependent gain–loss ratio. The gain (G) from switching the management objectives to energy optimization depends on the state of the energy market at the given time. Similarly, the loss (L) resulting from miss predicted events could be related to the current status of the IUWDS, e.g. the volume of water stored. The events are characterised by hourly time step and assessed based on their average flow.

Table 8: Economic values assigned to the different outcomes of the contingency table (L:loss; G:gain) for the decision “activate energy optimisation”.

		Event observed		
		Yes	No	
Event forecast	Yes	hits (*a*) **0**	false alarms (*b*) **0**	$a + b$
	No	misses (*c*) **L**	correct negatives (*d*) **G**	$c + d$
		$a + c$	$b + d$	$a + b + c + d = n$

Base on Table 8 the different elements of the REV (Eq. 6.1) can be expressed as follow:

$$E_{forecast} = \frac{d*G-c*L}{n} \tag{6.2}$$

$$E_{perfect} = d*\frac{G}{n} = (1-\mu)*G \tag{6.3}$$

Where μ is the empirical frequency of occurrence of an event. $E_{reference}$ represents the (theoretical) baseline scenarios which are not using any forecast: either never or always operate the IUDWS in energy optimisation mode. $E_{reference}$ considers the baseline providing the highest economic value (max).

$$E_{reference} = \max(G-\mu*L, 0) \tag{6.4}$$

The REV expressed by Eq. 6.1 can be reformulated using Eq. 6.2, Eq. 6.3 and Eq. 6.4 and expressed as a function of the PoD, the $PoFD$, the frequency of occurrence (μ) and the gain-loss ratio ($\alpha = \frac{G}{L}$) as shown by Eq. 6.5 (**Paper III**).

$$REV = \frac{\alpha*(1-\mu)*(1-PoFD)-(1-PoD)*\mu-\max(\alpha-\mu,0)}{\alpha*(1-\mu)-\max(\alpha-\mu,0)} \tag{6.5}$$

6.2.2. Results and discussion

The possible value of the REV ranges from 1, corresponding to a perfect forecast, to minus infinity. In the case of a positive REV, the use of the forecast is beneficial. A negative REV indicates that using statistical information and either always or never optimizing the IUDWS yields a better economic value than using the weather forecast. Hence the REV can be divided in 3 domains (Figure 19b): (i) the interval on the right of the curve in which it is preferable to always optimize (dotted domain on the right side), (ii) the interval with positive REV covered by the curve in which using the forecast is beneficial (middle domain in Figure 19b) and (iii) the interval on the left in which it is preferable to never optimize (crosshatched domain on the left side).

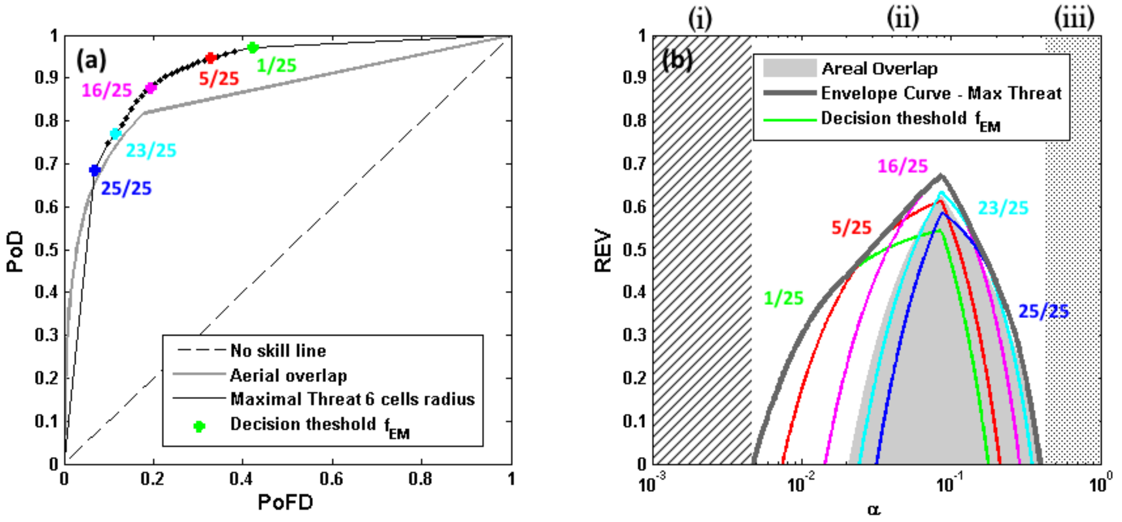

Figure 19: ROC and REV diagram for a flow threshold of 4,000 m^3/h. The flow forecasts are based on the two NWP post-processing methods: the maximal threat EPS method with a neighbourhood radius of 6 grid cells in colour and the catchment weighted areal overlap method in grey colour as background (**Paper III**).

Figure 19 shows the benefit of using NWP post-processing methods as underlined in section 5. The ROC curve provided by the maximal threat method results in the extension of the α-interval with positive REV, which characterizes the range of beneficial forecast usage. For a given α-value, representing the ratio between gain and loss, the REV indicates which decision threshold (f_{EM}) should be used to maximize the overall benefit of the control strategy. If no positive REV is available for the selected α-value, then the corresponding baseline control (either (i) or (iii)) provides a better result than using the forecast.

The comparison between these two NWP-post processing approaches using the Brier Skill Score (BSS), Table 9, shows a deterioration of the forecast skill when the maximal threat approach is used. This result underlines the need to assess the forecast skill together with the specific control objectives rather than purely on common forecast skill scores.

Table 9: *BSS* and *REV* characteristics for the two different NWP post-processing methods (**Paper III**).

	ROCA	α-interval		*BSS*
		Lower bound	Upper bound	
Weighted areal overlap	0.86	0.0208	0.3955	0.14
Maximal threat 6 cells radius	0.91	0.0049	0.3940	-1.52

Figure 20 provides an example of a prediction. The first panel (Figure 20a) displays the energy market, providing insight on the variation of the energy price and the proportion of wind energy which is assumed to be correlated with CO_2 footprint. The fluctuation of the energy market for both parameters illustrates the variation of the potential gain (G) and therefore the α-ratio during a given period. The next two panels represent the flow forecast based on the catchment weighted areal overlap approach (Figure 20b) and based on the maximal threat EPS approach with a 6-grid-cell radius (Figure 20c). The last panel (Figure 20d) shows examples of decision making based on the two different post-processing methods and different decision thresholds (weights of evidence f_{EM}).

This case study only investigates the flow domain prediction to trigger the energy consumption optimisation. The full energy optimisation scheme was not developed in this study. Halvgaard et al. (submitted 2017) presents a model predictive control (MPC) scheme to control the power consumption of pumps in a sewer system and of the treatment processes at the WWTP (aeration tanks) according to electricity prices and effluent quality (nitrogen) based on another case study at Kolding, Denmark. Assuming dry weather flow periods, the controller is able to balance electricity costs and treatment quality. The methods introduced here and elaborated in **Paper III** operate in layer 4 of the control hierarchy illustrated in Figure 2, and they are necessary to know when, based on the NWP EPS, this control strategy on energy optimisation (which operates in layer 3) can be activated.

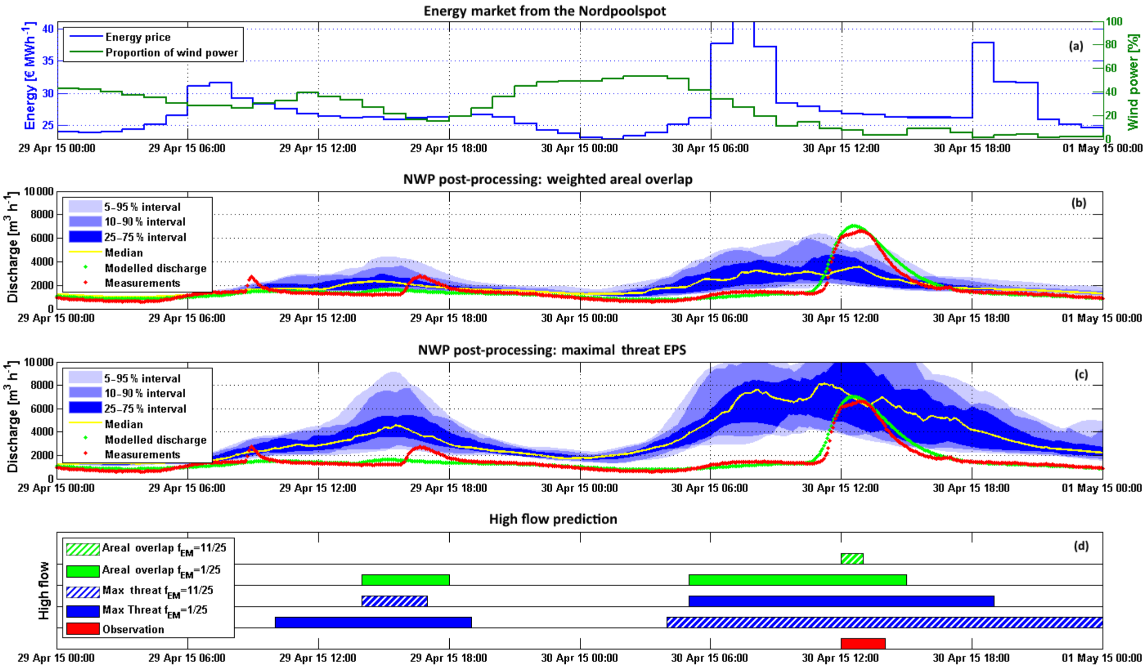

Figure 20: Example illustration of the EPS flow prediction system for 2 selected days, 29–30 April 2015. Energy market parameters, energy price and proportion of wind power (a), ensemble flow predictions using the areal average (b) and maximal threat (c) post-processing methods, and (d) flow domain predictions for the two post-processing methods and for two decisions thresholds (coloured areas imply that an event is predicted, otherwise not) (**Paper III**).

6.3. High flow prediction for WWTP wet weather operation

This case study investigates the switch to ATS mode at the Damhuså WWTP when high stormwater flows are predicted. The predictions are based on radar extrapolation forecast and upstream measurements. Thus it illustrates how the REV approach can be used to assess and improve a control strategy. For further details, the reader is referred to section 3.3 and to **paper IV**.

6.3.1. Concept and application

As mentioned in section 3.3, the ATS operation needs to be started prior to the increase in hydraulic load in order to reach its full potential. Therefore, as described in (Munk-Nielsen et al., 2015), flow forecasts based on radar extrapolation are used to trigger the ATS in advance.

As underlined by the study of NWP data earlier in this thesis, forecasts are by nature uncertain and can therefore lead to mismanagement. Hence the benefit of using the forecast needs to be evaluated in comparison to the potential impact of mismanagement.

The first step towards evaluating the current ATS control (described in **Paper IV**) was to define the perfect ATS assuming a perfect flow forecast. Thereafter, using this perfect ATS as reference (similar to the use of flow observations in the previous example), the current and several alternative control strategies were evaluated using the REV as objective function.

In order to apply the REV approach, economic values were assigned to the four different outcomes of the contingency table, see Table 10. Contrary to the previous case study, both false alarms and misses lead to costly negative outcomes: false alarms unnecessarily trigger the ATS operation jeopardizing the WWTP efficiency (L_1) and misses lead to an unprepared WWTP (L_2). In order to use the gain-loss ratio ($\alpha = \frac{G}{L}$), an overall loss value is defined as $\mathrm{L} = \mathrm{L}_1 + \mathrm{L}_2$ with the ratio between the two losses defined by k as $\mathrm{L}_1 = \mathrm{k} * \mathrm{L}$ and $\mathrm{L}_2 = (1 - \mathrm{k}) * \mathrm{L}$.

Table 10: Contingency table with economic values assigned to the different outcomes of the contingency table for the decision “switching to wet weather operation”.

		Perfect ATS Control		
		ATS on	ATS off	
Real / Simulated ATS Control	ATS on	hits (*a*) **G**	false alarms (*b*) **L_1**	$a + b$
	ATS off	misses (*c*) **L_2**	correct negatives (*d*) **0**	$c + d$
		$a + c$	$b + d$	$a + b + c + d = n$

Base on Table 10 the different elements of the REV (Eq. 6.1) can be expressed as:

$$E_{forecast} = \frac{a*G - b*L_1 - c*L_2}{n} \tag{6.6}$$

$$E_{perfect} = \mu *. G \tag{6.7}$$

Here $E_{reference}$ represents the (theoretical) baseline scenario in case no forecast is available: either always or never operate in ATS mode. $E_{reference}$ considers the baseline providing the highest economic value.

$$E_{reference} = \max(\, G * \mu - L_1 * (1 - \mu), 0) \qquad (6.8)$$

The REV expressed by Eq. (6.1) can be reformulated using Eqs. (6.6), (6.7) and (6.8) and expressed as a function of the PoD, the PoFD, the frequency of occurrence (μ), the loss ratio (k) and the gain–loss ratio ($\alpha = \frac{G}{L}$) as shown by Eq. (6.9).

$$REV = \frac{PoD\, \alpha\, \mu - [PoFD\, (1 - \mu)\, k + (1 - PoD)\, \mu\, (1 - k)] - \max((\alpha\, \mu - (1 - \mu)\, k, 0)}{\alpha\, \mu - \max((\alpha\, .\, \mu - (1 - \mu)\, k, 0)} \qquad (6.9)$$

6.3.2. Results and discussion

The evaluation of the current ATS control in comparison to the perfect ATS control, displayed by the contingency table (Table 11), underlines the limitations of the current control switch - especially the proportion of false alarms. After further investigation, it was found that the majority of these false alarms are generated by the radar flow forecast. The flow threshold on the radar flow forecast used to start the ATS mode is the most influencing control parameters in regard of forecast uncertainty.

In order to limit these false alarms, the REV was used as a framework to calibrate the threshold on radar flow prognosis. The calibration was performed based on the fminsearch function in MATLAB® assessing the threshold value providing the lowest result for objective the function (1-REV). Also, a new strategy based on the introduction of a time component on the radar flow threshold, which aims at moving towards a volume based control was tested. Such an approach delays the switch to ATS given that part of the forecast lead time is required to convert flow into volume. A balance is necessary between the prediction lead time and duration of the accumulated volume (for further details the reader is referred to **Paper IV**).

Table 11: Contingency table of the current control strategy in comparison to the perfect control strategy showing the percentage of occurrence of each outcome. (**Paper IV**)

		Perfect ATS Control	
		ATS on	*ATS off*
Current Control	*ATS on*	0.1413	0.0766
	ATS off	0.0084	0.7737

Considering the gain-loss ratio α and the loss ratio k a 3D plot can be generated to represent the REV response surface of the current control, which is displayed on Figure 21. The α and k values for which the REV is positive represent the range for which the current control switch is beneficial.

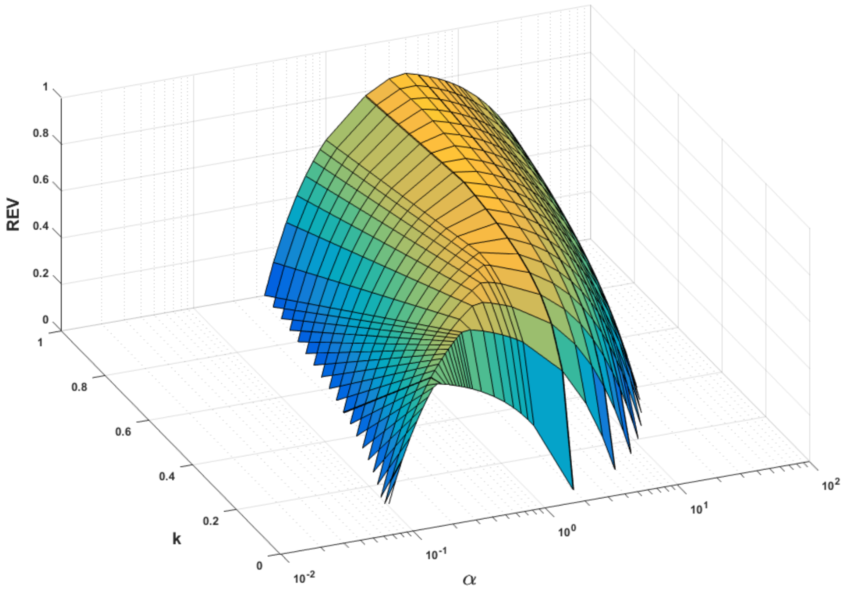

Figure 21: REV response surface for the current ATS control switch, with k as the loss ratio between impact of false alarms and misses and α as the ratio between gain and loss (**Paper IV**).

The pair (α, k) represents the relationship between the economic values of the different potential outcomes. Each set (α, k) corresponds to one point on the REV response surface. Given a specific (α, k)-pair the objective is to select and use the control parameters providing the highest REV for this situation. Hence the control parameters (here the threshold on radar flow prognosis) can be calibrated using the REV as objective function.

Figure 22 shows an example of calibration for two (α, k) pairs equal to (1, 0.8) and (1, 0.2), and compares these control strategies to the current control.

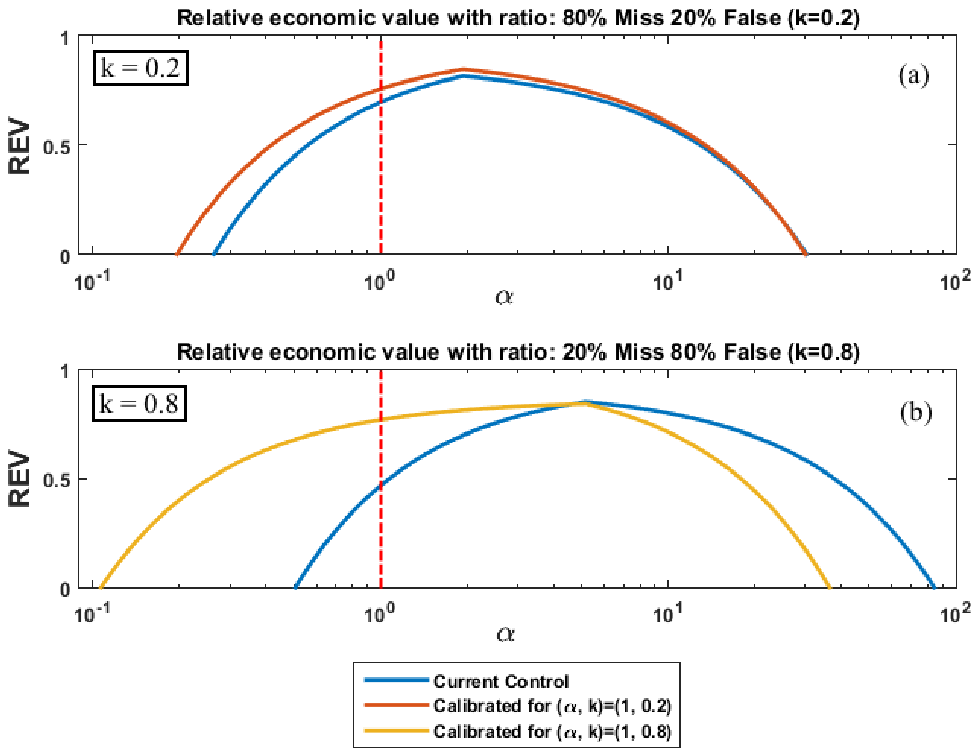

Figure 22: Cross section of the REV response surface for given k values (a) k = 0.2 and (b) k = 0.8 and for different sets of control parameters calibrated for each situation. The vertical red dotted line represents α = 1 (**Paper IV**).

Depending on the impact of the outcomes of the control strategy, defined by the α and k ratios, the control parameters should be calibrated to yield the best benefit possible (REV). In the case of (α, k) = (1, 0.2), which corresponds to high negative impact of misses, the highest REV based on the calibration is reached for threshold on radar flow prognosis of 9,500 m^3/h. In the other situation, of (α, k) = (1, 0.8), which corresponds to a situation with high negative impact from false alarms, the calibration gives a threshold on radar flow prognosis of 16,875 m^3/h which is significantly high and could indicates that flow prognosis from radar nowcast should not be used in this case.

6.4. Discussion

Using uncertain data in a control scheme may result in occasional mismanagement due to forecast error (false positives or misses). Such situations can create distrust of the control strategy among the operators. Additionally as underlined by Kox et al. (2014) which investigated the perception and use of weather prediction uncertainty by emergency services, decision making based on uncertain data is challenging for the operators. This advocates for a framework to support the decision making. The REV framework evaluates the overall performance of a control strategy during a selected period, assessing if the benefit achieved from using the forecast overcomes the drawbacks. Hence, the REV framework is a useful tool to maintain the operators' trust in the control strategy despite potential mismanagements due to erroneous forecasts.

The REV framework can also be used to compare different control parameters. E.g. in the first case study, EPS NWPs were used to predict low flow domains in order to determine when the control objective of the IUWDS can be switched to energy optimisation, and the REV framework was used to determine which decision threshold of the EPS provides the highest benefit for a given situation. The REV diagram underlines the benefit of NWP post-processing methods which extend the range in which using the forecast is beneficial (REV>0) as shown in Figure 19. In the second case study, the REV framework was used to evaluate the current control strategy switching the WWTP to wet weather operation and to assess other control parameters and strategies.

The purpose of the reference economic value ($E_{reference}$) is to visualise, with positive REV values, when using the evaluated control strategy is more beneficial than using the reference strategy selected. Different reference strategies can be selected according to the comparison whished. E.g. the reference strategy can be based on the two theoretical extreme baseline scenarios: to either always or never activate the ATS in order to assess the overall benefit of the control scheme (Figure 21 and Figure 22). Or to assess specifically the addition of the radar flow prediction to the control scheme, the reference strategy could be the control strategy solely based on flow measurement. The REV framework is based on empirical data and real life applications are therefore limited by the period of data availability. Furthermore, the REV approach requires expressing the economic value of the different outcomes of the contingency table (how beneficial is it to have the ATS operation running when it should be off? How detrimental is it to activate the ATS operation when it is not required?) or at least to determine the ratio between these (the gain-loss ratio α). As mentioned in (Richardson, 2000) these cost and losses for particular uses may be difficult to determine. Such difficult analysis can be highly subjective and has a high impact on the REV results. Therefore, these values (or the ratio) should be carefully assessed together with the operators. Furthermore as explained by (Campisano et al., 2013) one of the reasons for the relatively limited implementation of RTC techniques in IUWDS is the reluctance of wastewater operators to introduce complexed advanced technology. This underlines the importance of involving operators in the developing process to ensure their understanding and trust.

7 Conclusions

The work presented in this thesis builds the foundation for including data from numerical weather prediction (NWP) models in the control of integrated urban drainage-wastewater system (IUDWS). This is achieved by predicting flow-domains and thus allowing selecting the relevant management objective based on the actual state of the IUWDS and a flow forecast up to two days ahead. The use of uncertain forecasts can however lead to wrong decisions due to forecast error. A decision framework based on the relative economic value (REV) was thus developed to assess how to use the forecast and when acting on it is beneficial or not.

Meteorologists and urban hydrologists have two different mind-sets in regard to weather forecast. The objective of meteorologists is to capture and predict the weather pattern whereas urban hydrologists focus on the predicted values at specific grid cells. The fine spatial and temporal resolution required for urban applications however come at the cost of large uncertainties only partly captured by the NWP ensemble prediction systems (EPS), in the sense that (too) many verifying observations fall outside the ensemble range. Therefore, outputs from NWP EPS are not to be used with overconfidence.

The partnership with the Danish Meteorological Institute (DMI) was productive, providing nearly 32 months of historical NWP EPS data. This data was used throughout the PhD project and may be used for further investigations. A conceptual rainfall-runoff model of the upstream part of the Damhuså catchment was furthermore developed in MATLAB® and used to evaluate the prediction based on the end-user objective, the flow in the IUDWS. This model was sufficiently accurate for the purposes at hand, but other more details models potentially including stochastic terms and data assimilation may be needed for application in practice.

NWP post-processing approaches are necessary to enhance the EPS, reducing the occurrence of missed events and overcoming some NWP limitations. The “double penalty” effect, which corresponds to a rainfall event correctly forecasted but slightly misplaced in space or/and in time and therefore is penalised twice, can be mitigated with the neighbourhood methods. Consecutive NWPs are overlapping and can potentially contradict each other, leading to inconsistency; this can be address with the time lagged approach. However, these types of post-processing can expand the size of the EPS significantly which can become a computational issue. The maximal threat method developed in this thesis provides similar improvement on the EPS discrimination skill with a limited increase of the EPS size, as showed on the relative operating characteristic (ROC) diagram.

Despite these improvements, the high uncertainty embedded in NWP prevents the use of quantitative rainfall values directly for an urban catchment. NWP may be used, instead, in connection with a domain-based decision framework, predicting for which domain the IUDWS should be optimized (e.g. when to optimise energy consumption or when to prepare the WWTP for high flows).

Based on empirical data, the REV approach assesses the trade-off between benefits and drawbacks from using the forecast. The REV framework provides a tool to evaluate the added benefit of using control strategies based on uncertain forecast information, to select the most relevant control parameters and to compare different control strategies. E.g. in the first case study, EPS NWPs were used to predict flow domains in order to determine when the control objective of the IUWDS can be switched to energy optimisation. The REV framework was used to determine which decision threshold of the EPS provides the highest benefit for a given situation. In the second case study, the REV framework was used to evaluate the current control strategy switching the WWTP to wet weather operation and to assess other control parameters and strategies. The analysis of the current control showed a significant number of false alarms. The REV framework was used to calibrate the threshold on radar flow prognosis and to test new control strategies to solve this problem.

Uncertainty communication to end-users is a critical and challenging part of forecast usage. It can be achieved through the REV framework, which includes the possibility of considering management mistakes due to forecast uncertainty (errors). The REV demonstrates the overall benefit despite these potential mismanagements, hence, maintaining the operator trust in the control.

The potential from using NWP data in IUDWS is foreseen to increase in the years to come along with the continuous improvement of NWP models (with data assimilation from radar extrapolation, improved computational power and the new generation of non-hydrostatic NWP models).

8 Recommendations for future research

Based on the work done during this PhD study, the following further research is recommended.

- The skill of the runoff-model influences the overall skill of the hydro-meteorological model. It would be interesting to develop a stochastic rainfall-runoff model including data assimilation to improve the forecasting of low flows.
- This thesis assesses two NWP post-processing approaches (neighbourhood and time-lagged). It would be of interest to investigate the best practice to combine these two approaches (e.g. are they redundant or complementary?). More sophisticated post-processing method based on statistical analysis like the ensemble model output statistic (EMOS) which fit a parametric predictive distribution using summary statistics from the ensemble could be assessed as well (e.g. (Gneiting et al., 2005; Scheuerer, 2014)).
- DMI recently announced the release of a new forecast product: COMEPS. One of the particularities of COMEPS is to generate a sliding EPS. The ensemble members are generated consecutively rather than all at the same time. In the case of COMEPS, 4 members are generated every hour during a 6 hours cycle providing a total of 24 ensemble members (DMI, 2017). It would be of interest to assess this new method of EPS generation using the ROC diagram and the REV method presented in this thesis.
- In order to comply with new regulations on CSO, a major project is currently under development, planning to construct two large pipes upstream of the Damhuså WWTP inlet. These pipes would have a volume equivalent a full day’s worth of dry weather flow (Anders Breinholt, personnel communication, November 17, 2017). This large storage volume provides great opportunity for a real life application of the energy optimisation strategy developed in this thesis and in (Halvgaard et al., submitted 2017). It would be interesting to pursue this perspective in a study where $E_{perfect}$ in the REV is based on simulation using a details model and rain gauge data as input.
- The ATS operation aims at increasing the hydraulic capacity of the WWTP. However, the hydraulic capacity is also dependant on the level of the sludge blanket in the secondary clarifiers. In order to prevent sludge escape from the secondary clarifiers, the hydraulic capacity of the biological treatment is reduced when the sludge level is too high. New sensors

are being installed in secondary clarifiers at the Damhuså WWTP to monitor the sludge level. It would be of interest to assess how these new data can be integrated in the ATS switch decision framework.

- The domain-based framework could be applied to the Dynamic Overflow Risk Assessment (DORA) strategy (Vezzaro and Grum, 2014). Using NWP to predict flow domains in order to adapt the formulation of the objective function to the current situation, avoiding mismanagement in the case of long and/or a sequence of rainfall events (beyond the forecast horizon of weather radar extrapolation nowcast).
- The REV framework requires empirical data and it is computationally too demanding for meteorological institutes to re-run their model for long periods of time. Hence it is recommended to store NWP data for future evaluation, maintaining a contact with the meteorological institute to be aware of any major changes in their model. Flow domain predictions from NWP should be included in the STAR Control® platform in addition to weather radar extrapolation "nowcast".

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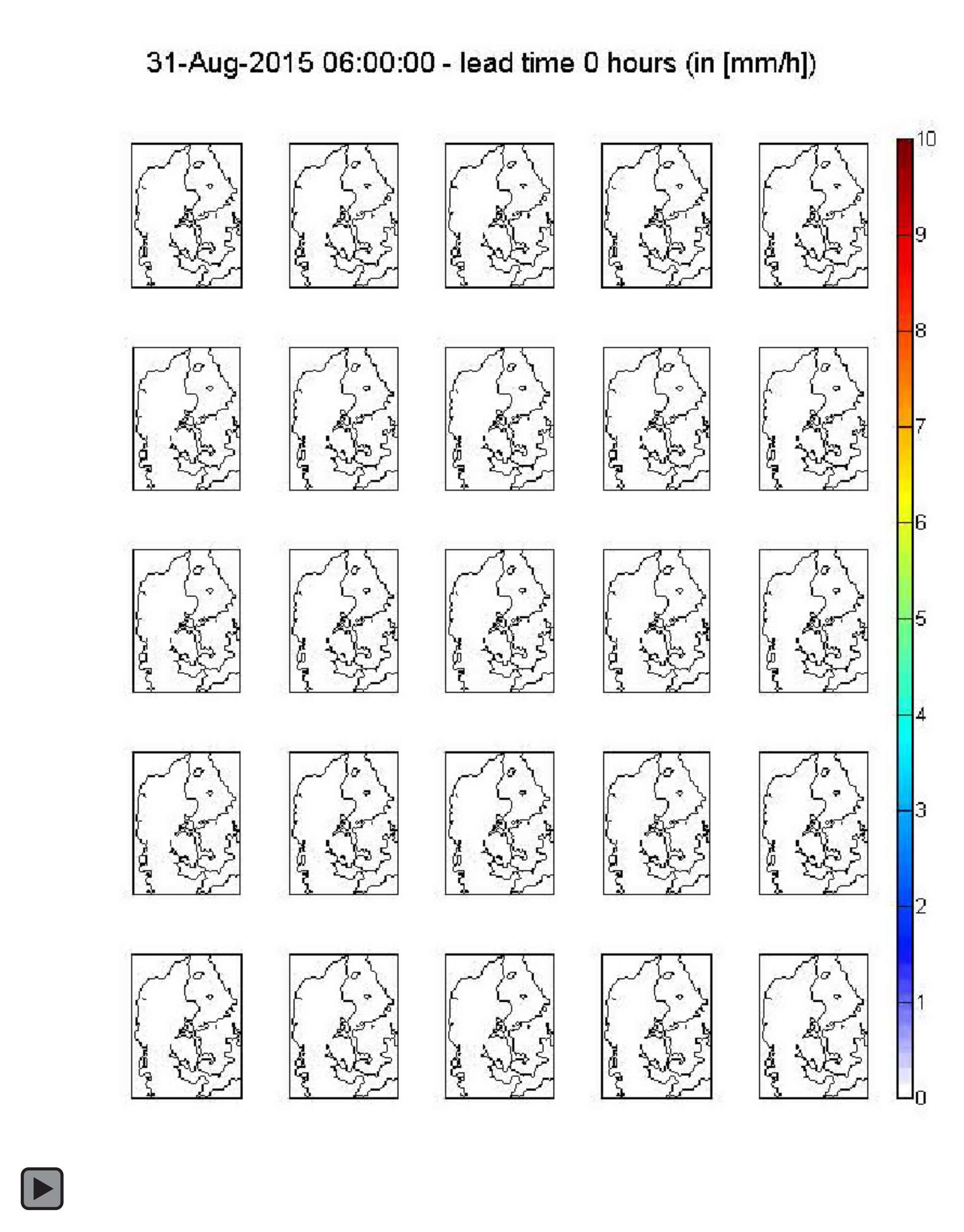
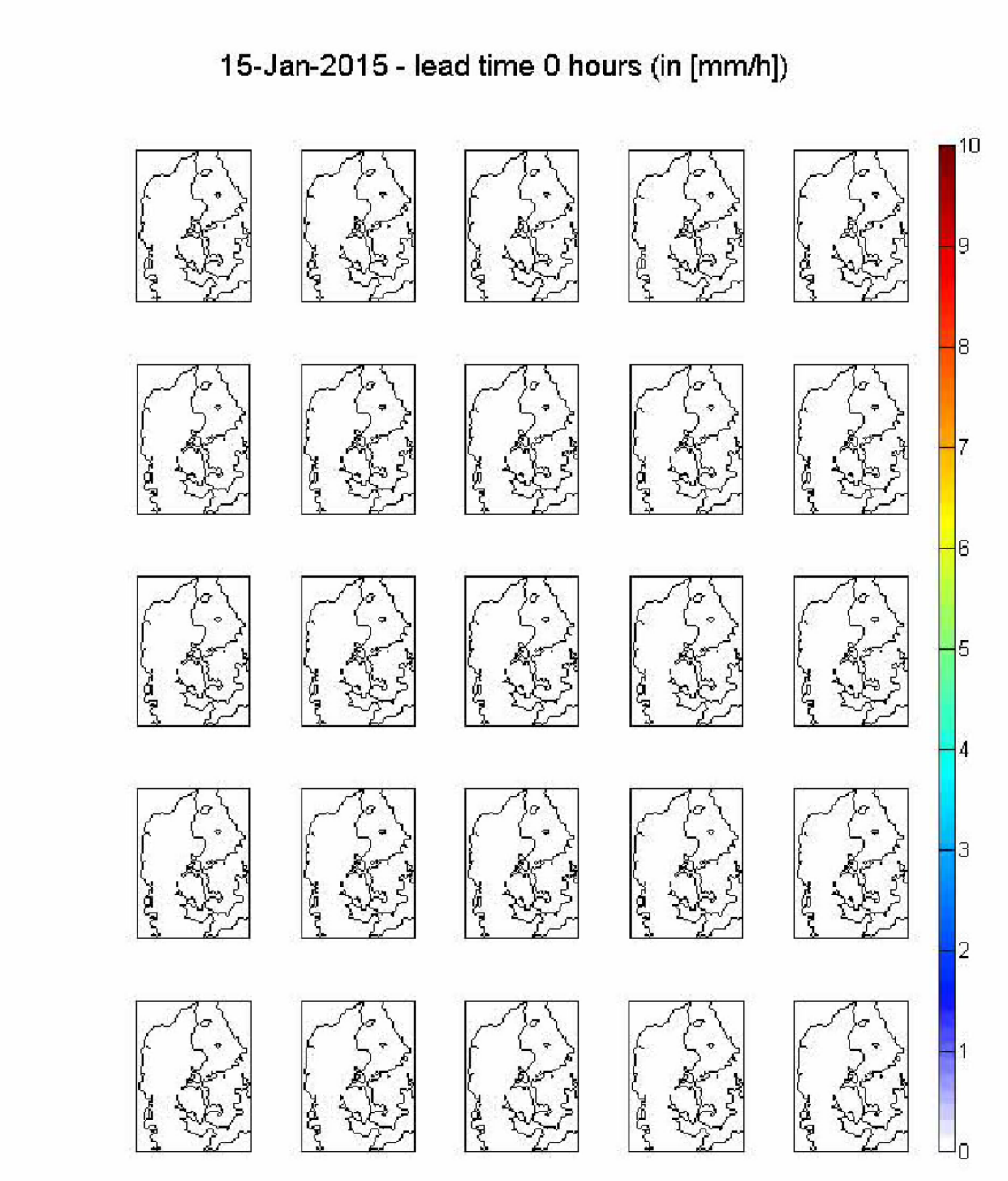
Appendix A – Animations of NWP EPS

A1 - Animation of the NWP EPS for a convective rainfall event (readable from the digital version)



A2 - Animation of the NWP EPS for a stratiform rainfall event (readable from the digital version)



Papers

I. **Courdent V.**, Vezzaro L., Mikkelsen P.S., Mollerup A.L., Grum M. (2015): Using ensemble weather forecast in a risk based real time optimization of urban drainage systems, *La Houille Blanche*, (2), 101–107. http://doi.org/10.1051/lhb/20150025

II. **Courdent, V**., Grum, M., Mikkelsen, P.S. (2016): Distinguishing high and low flow domains in urban drainage systems 2 days ahead using numerical weather prediction ensembles, Journal of Hydrology, doi: http://dx.doi.org/10.1016/j.jhydrol.2016.08.015

III. **Courdent, V.**, Grum, M., Munk-Nielsen, T. and Mikkelsen, P. S. (2017): A gain–loss framework based on ensemble flow forecasts to switch the urban drainage–wastewater system management towards energy optimization during dry periods, Hydrol. Earth Syst. Sci., 21(5), 2531–2544, doi:10.5194/hess-21-2531-2017.

V. Courdent, V., Munk-Nielsen, T. and Mikkelsen, P. S. (2017): Use of the Relative Economic Value (REV) approach to optimise the benefit of flow forecasting for activation of wet weather operation of wastewater treatment plants. Manuscript.

In this online version of the thesis, **paper I-IV** are not included but can be obtained from electronic article databases e.g. via www.orbit.dtu.dk or on request from.

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