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(Bits and pieces of research for) Improving urban pluvial flood modelling, forecasting and management

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6th December 2013

PWG Seminar, University of Sheffield, UK

Contents

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URBAN PLUVIAL FLOODING

Extreme rainfall events exceed the capacity of the drainage system

URBAN PLUVIAL FLOODING

- Insufficient capacity of sewer system
- Surface flow (overland system)

- Dynamic interactions between the two systems
- It's localised and happens quickly – "flash floods"

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Model Assembly for Pluvial Flood Modelling, Forecasting and Management

Rainfall Estimation / Forecasting → Flood Modelling / Forecasting → Management (urban planning, emergency)

Supported by data (monitoring)

Same "framework" as other types of flooding, but for urban pluvial flooding each step is a bit more complex

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Rainfall Estimation / Forecasting → Flood Modelling / Forecasting → Management (urban planning, emergency)

- The rainfall events which generate pluvial flooding are often associated with **thunderstorms of small spatial scale** (~ 10 km), whose magnitude and spatial distribution are **difficult to monitor and predict** (also: <u>lead time vs. accuracy</u>)

- Rainfall estimates/forecasts with fine spatial and temporal resolution are required, given small scale and fast response of urban catchments

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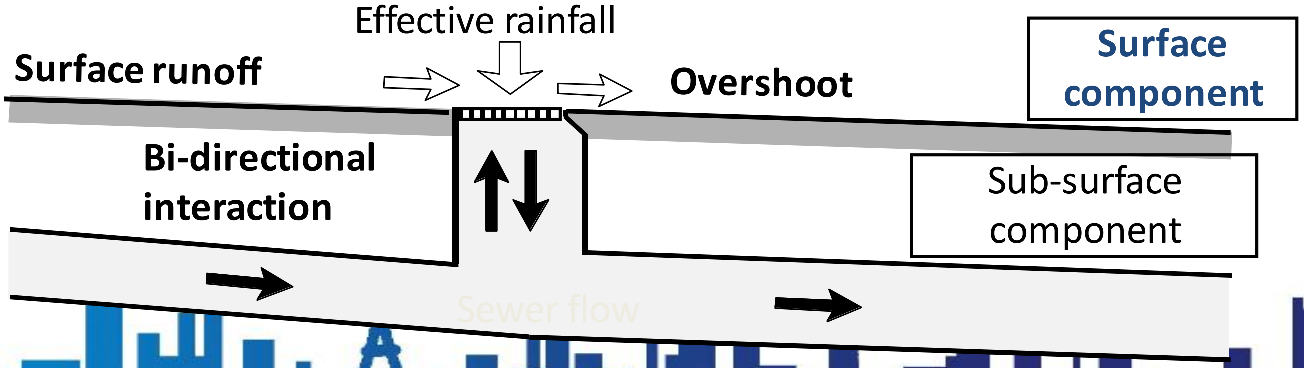
Rainfall Estimation / Forecasting

Flood Modelling / Forecasting

Management (urban planning, emergency)

- Urban "jungle" is complex
- Interaction of sewer and overland systems
- Since flooding is localised, models must have fine spatio-temporal resolution
- Model detail vs. Runtime



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Rainfall Estimation / Forecasting → **Flood Modelling / Forecasting** → Management (urban planning, emergency)

- Urban catchments **change** constantly
- Complete **flood records** for calibration and verification are seldom available
- High **uncertainty in boundary conditions**
- High **operational uncertainty** (blockages, pipe burst, pump failure, change in geometry of roads and other channels, etc.)
- **Individual sources of uncertainty are magnified by small scale**

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Rainfall Estimation / Forecasting → Flood Modelling / Forecasting → **Management** (urban planning, emergency)

- **Uncertainty** in modelling and forecasting **hinders decision making**
- **Low awareness**
- Given rapid onset and short forecasting lead-times, the **public become the principal responders**, but they are not so willing to respond
- **Lack of coordination** between stakeholders involved
- **Budgetary cuts**
- …

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Our work: Tackling some of these challenges

Rainfall Estimation / Forecasting → Flood Modelling / Forecasting → Management (urban planning, emergency)

RainGain

FRMRC flood risk management research consortium

belspo

PLURISK:
Forecasting and management of extreme rainfall induced risks in the urban environment

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Our work: Tackling some of these challenges

Rainfall Estimation / Forecasting

Flood Modelling / Forecasting

Management (urban planning, emergency)

LIPEN

SUSANA

Radar rainfall processing for urban hydrological applications

Li-Pen Wang
Hydraulics Laboratory, KU Leuven, Belgium

Contents

1. Introduction
2. Spatial downscaling using Multifractals
3. Radar-raingauge data merging
   - Incorporation of local singularity analysis
4. Radar rainfall nowcasting
5. Conclusions & on-going research

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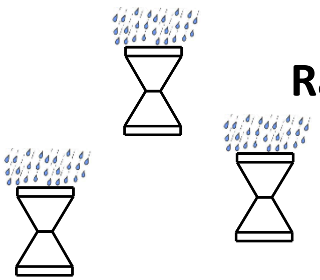
1. Introduction

Two essential characteristics of rainfall estimates

- **Accuracy (getting the values right):** this is critical! Especially for urban hydrological applications, where errors in rainfall estimates are magnified by the small scale

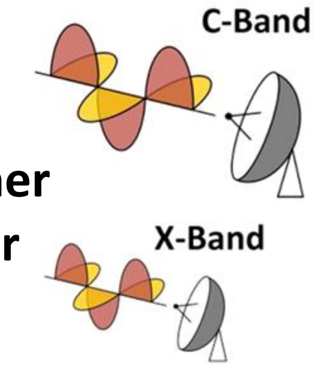
- **Resolution (spatial & temporal):** for urban hydrological applications spatial and temporal resolution must be high

Sensors commonly used for estimation of rainfall at catchment scales



Raingauge

Weather Radar



	RAINGAUGE	RADAR
Accuracy		
Coverage, spatial characterisation of rainfall field		
Resolution		

Further processing of radar rainfall estimates can improve its applicability (in terms of accuracy and resolution) to urban hydrological applications

My work focuses on improving the applicability (in terms of accuracy and resolution) **of radar rainfall estimates for urban hydrological applications:**

- **Improving accuracy:** Gauge-based adjustment of radar rainfall estimates
- **Improving resolution:** Rainfall downscaling

A big portion of my work is based upon the theory of fractals and multifractals

What are fractals/multifractals ?

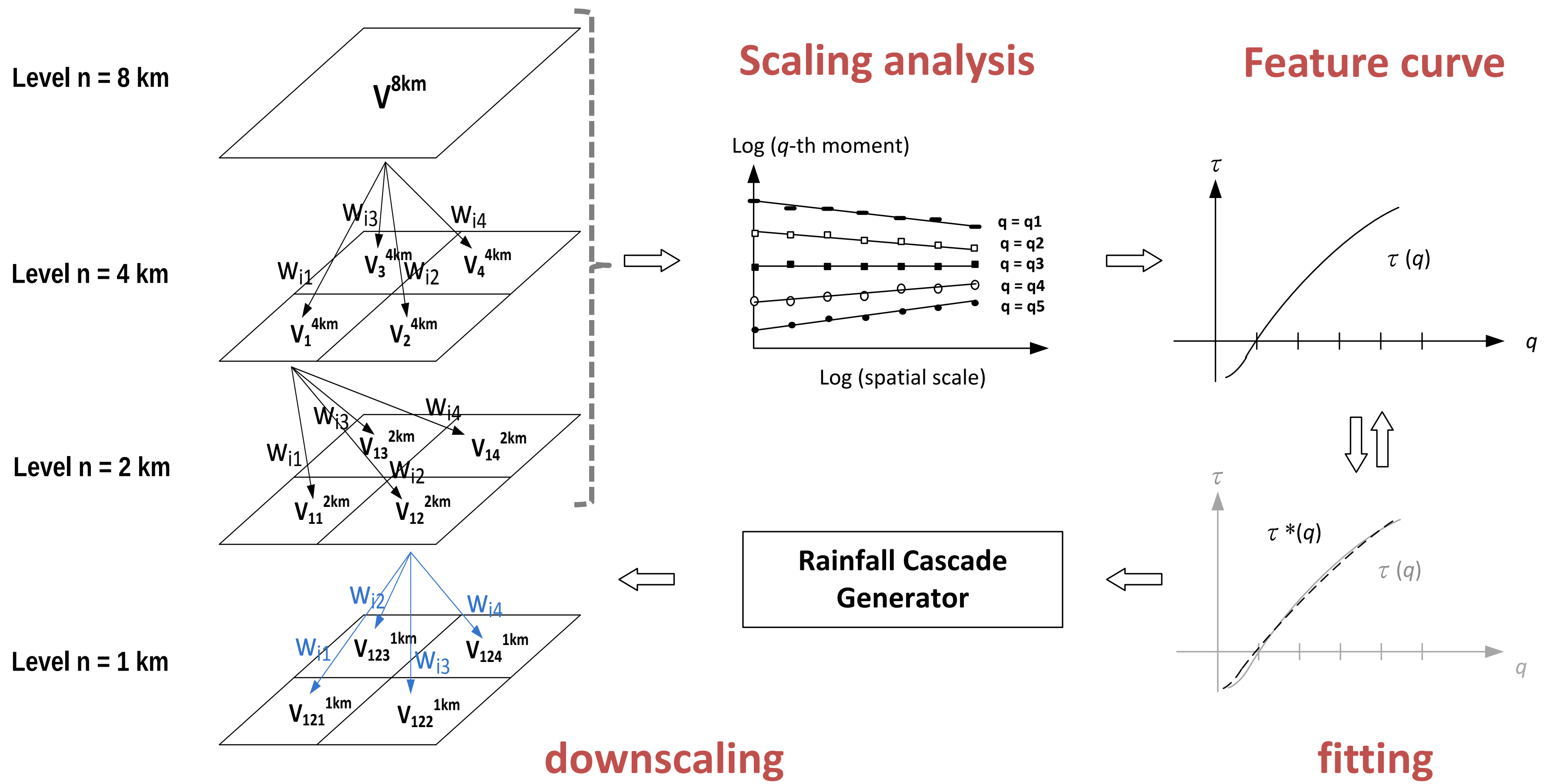
- **Fractals**
  - Fractals are non-regular geometric shapes that have the same degree of non-regularity on all scales. This degree can be in general investigated through the power relation between observations and scales (i.e. **scaling law**), and quantified by a constant value (called fractal dimension or singularity index).
- **Multifractals**
  - A multifractal system is a generalization of a fractal system in which a single fractal dimension is not enough to describe its dynamics; instead, a continuous spectrum of exponents (the so-called multifractal or singularity spectrum) is needed

Why fractals/multifractals ?

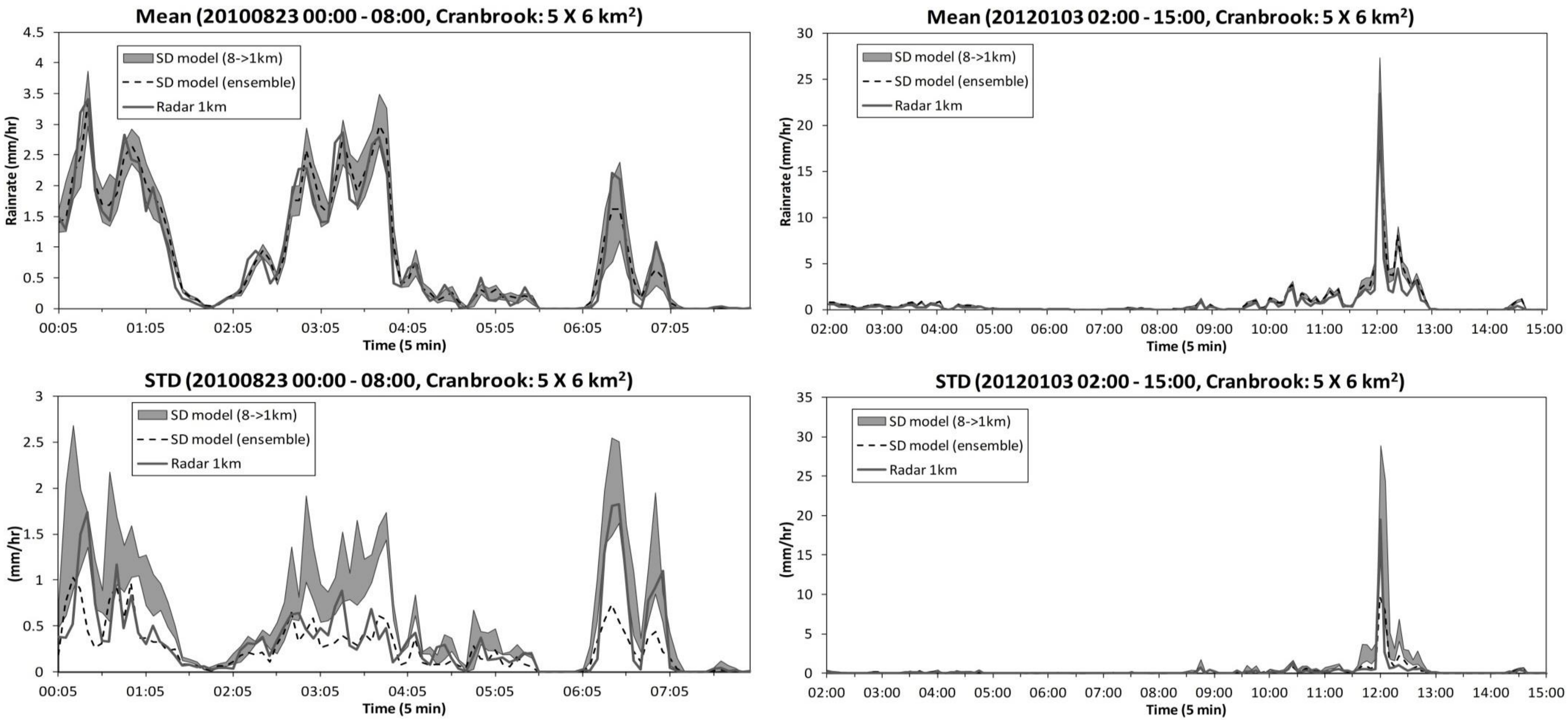
- Fractals everywhere!
  - Widely observed in nature, e.g., hydrology and atmosphere.
- Solid mathematical framework, linking fractals/multifractals with physics and statistics
- Scaling invariance enables the ‘prediction’ of estimates at finer scales.
- Characterise a continuous range of statistical features (or moments) of observations, which enables the preservation of extreme values.

2. Spatial downscaling using multifractals

Principle of cascade based spatial downscaling



Radar rainfall downscaling: 8 -> 1 km



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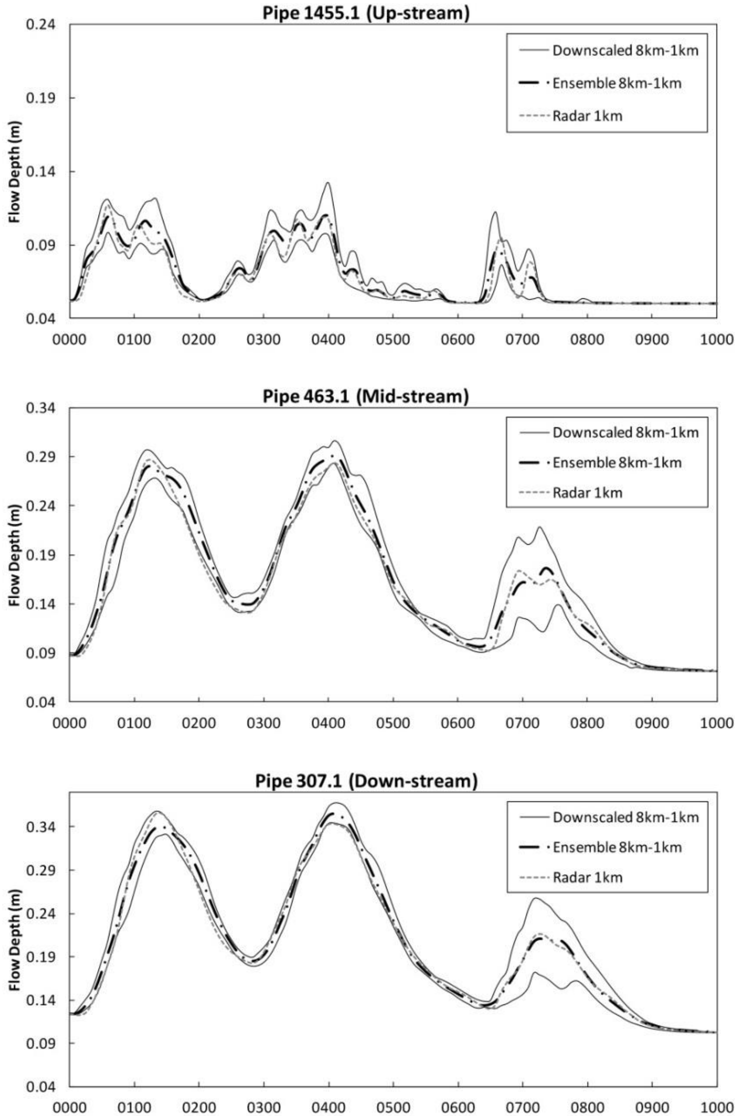
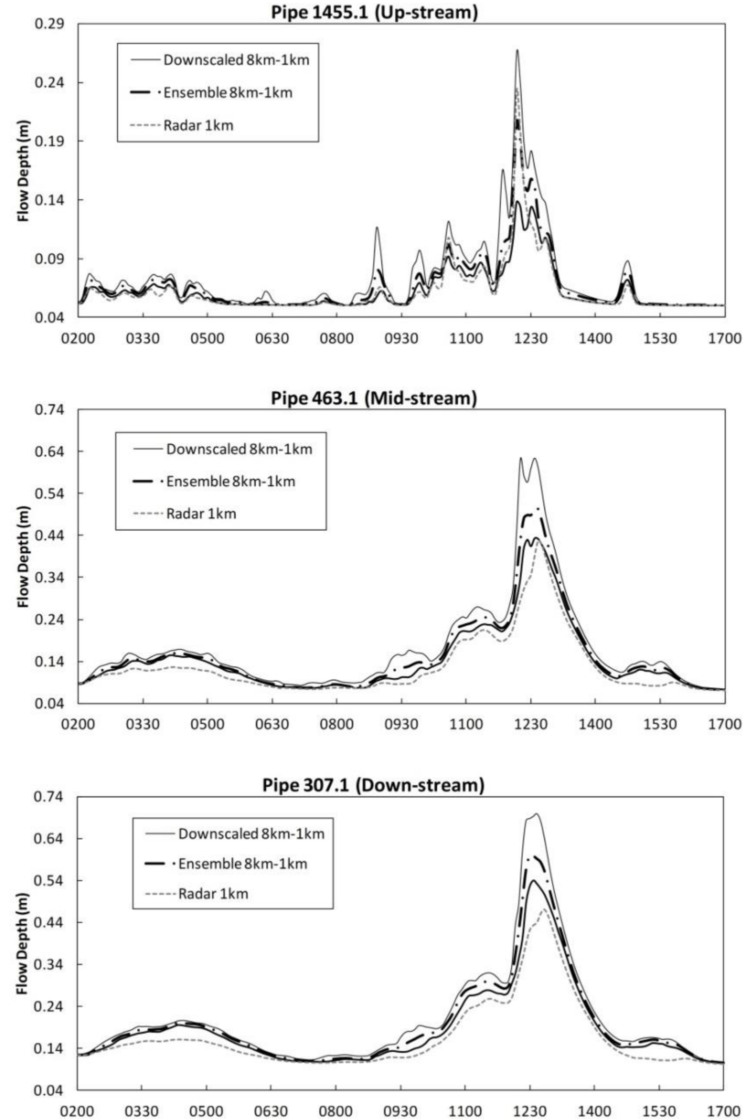
Subsequent hydraulic outputs: 8 -> 1 km

20100823 event



20120103 event

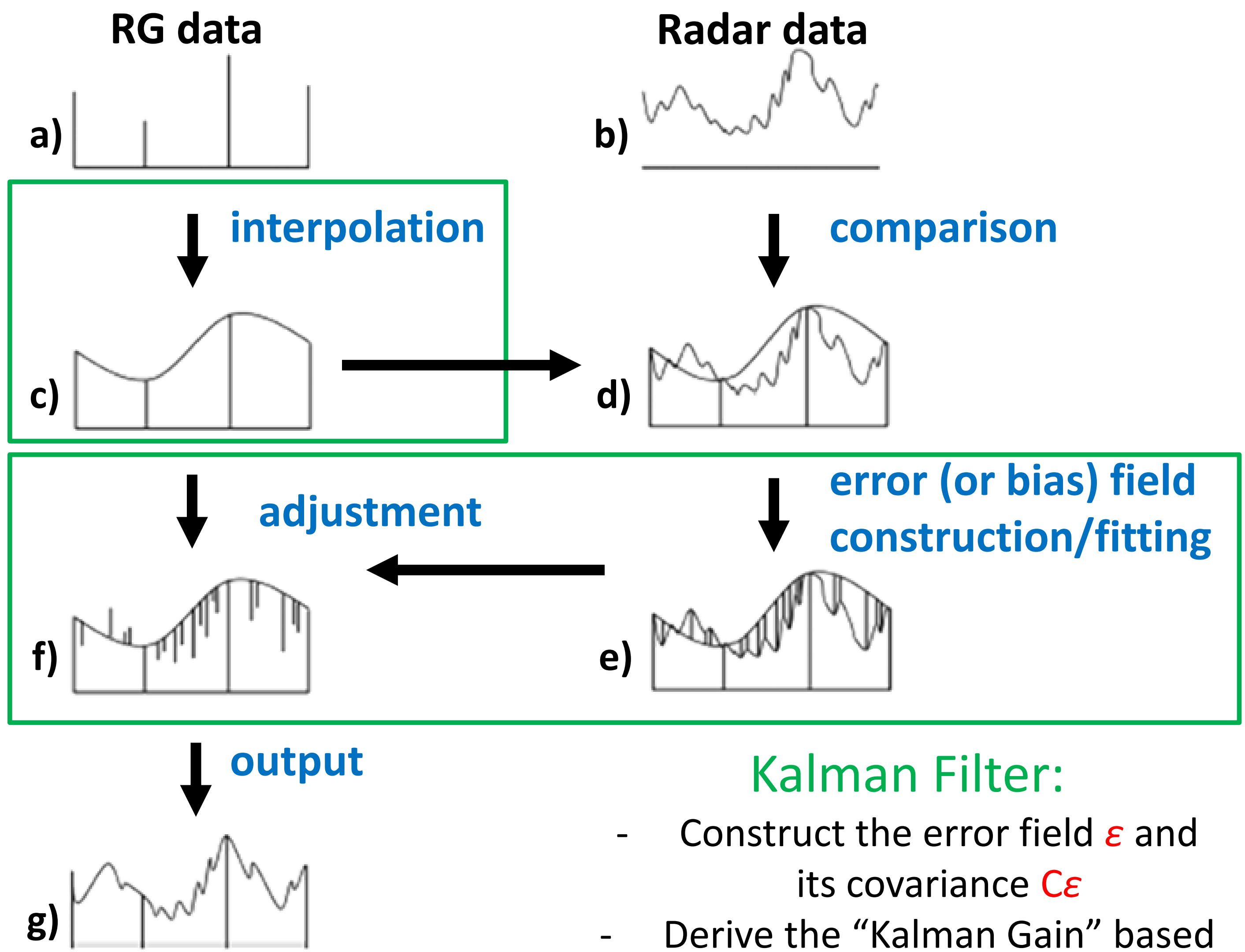


3. Radar-raingauge data merging

Principle of radar-raingauge data merging technique

Block-Kriging Interpolation:

- RG field y^G
- estimation error covariance $C\varepsilon_G$

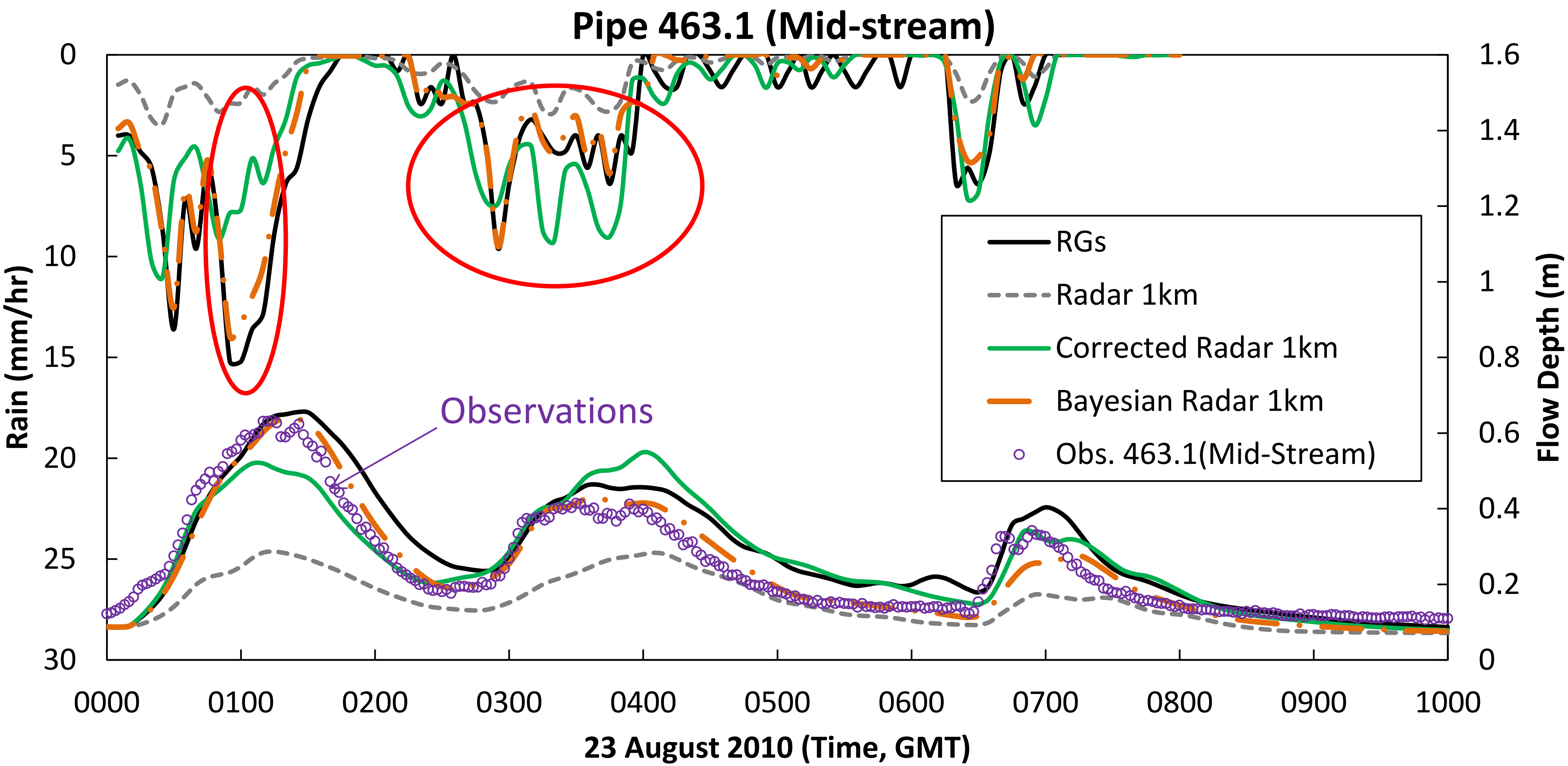


Kalman Filter:

- Construct the error field ε and its covariance $C\varepsilon$
- Derive the "Kalman Gain" based upon $C\varepsilon_G$ and $C\varepsilon$

(Todini, 2001; Ehret et al., 2008)

Simulation of flow depths is substantially improved by using merged rainfall data as input (23/08/2010 event)

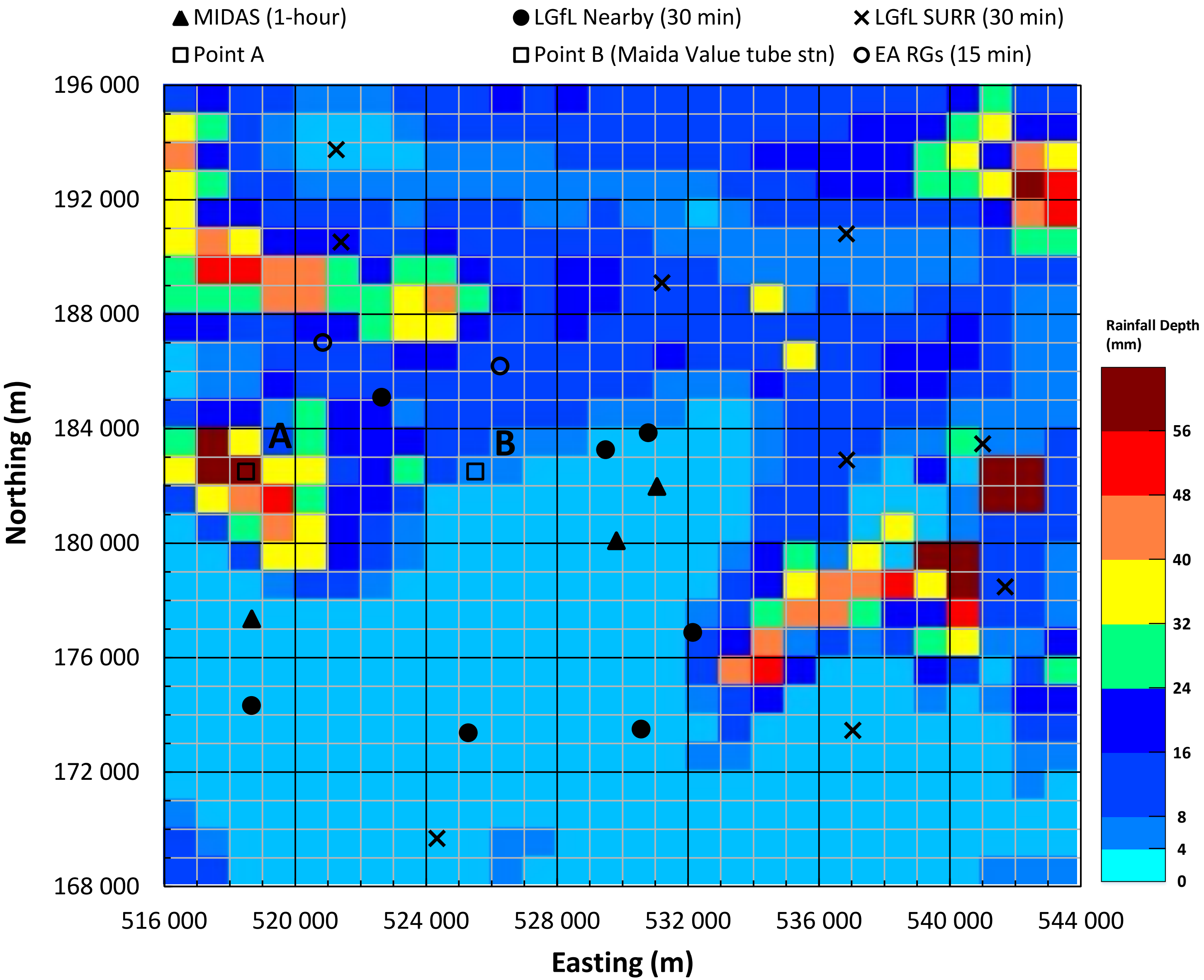


Reconstruction of a 2009 summer storm crossing Central London area

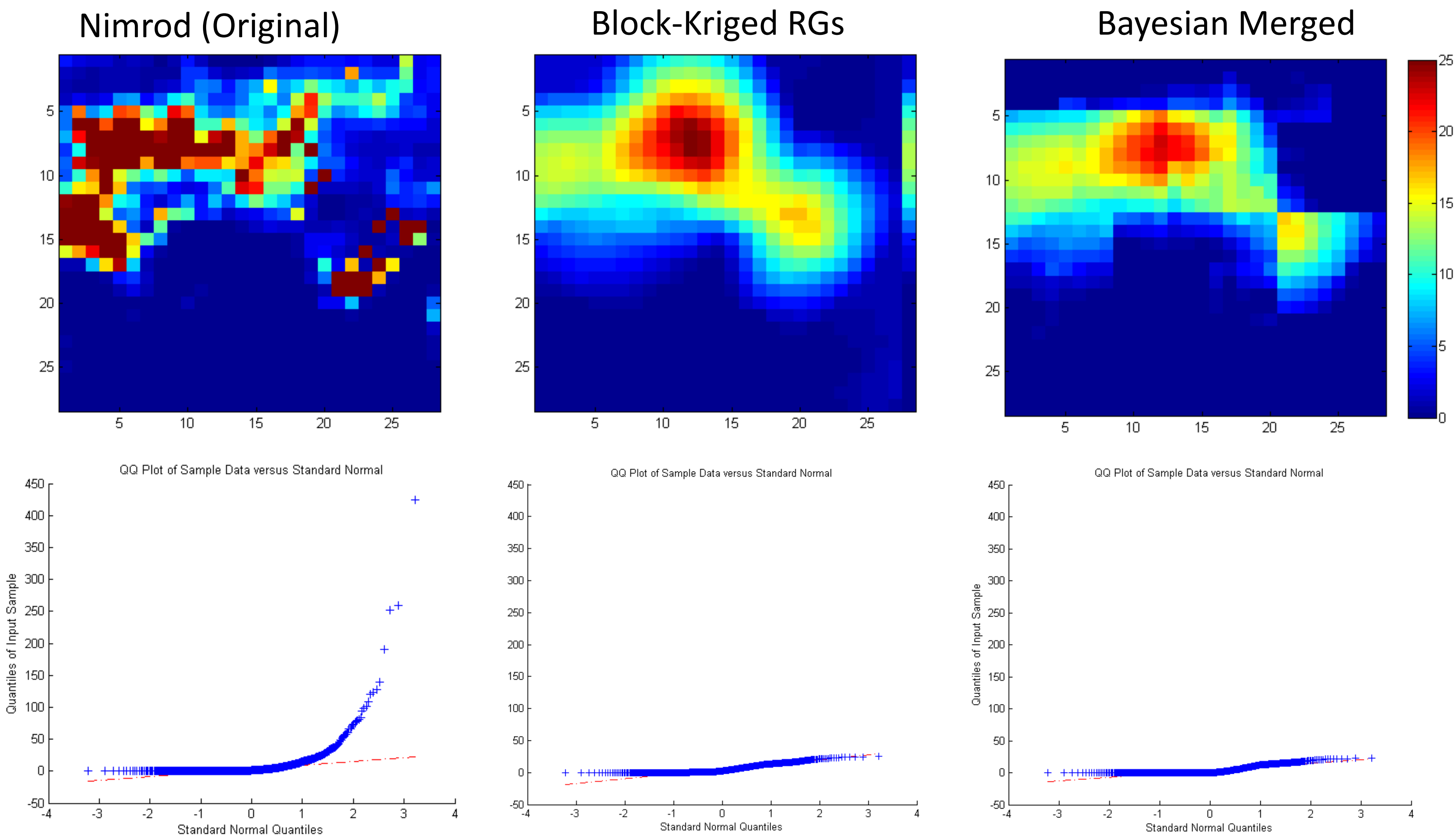
RESULTS

- *This storm led to flooding in North-West London*
- *The water company of the area wants to reconstruct this storm in order to improve the design of the sewer system (they are interested in appropriately estimating the return period of the storm)*
- *Original radar QPEs underestimate rainfall depths: when inputting the radar QPEs into the hydraulic model of the area, no flooding is observed.*
- *The Bayesian merging led to smoothening of the convective cells initially observed in the radar images (although the radar estimates were inaccurate, the shape of the convective cells was properly captured by it)*
- *Local Singularity Analysis was applied with the aim of better preserving the intense precipitation areas during the Bayesian merging*

Deployment of rain gauges, backgrounded by radar rainfall accumulations over the event period

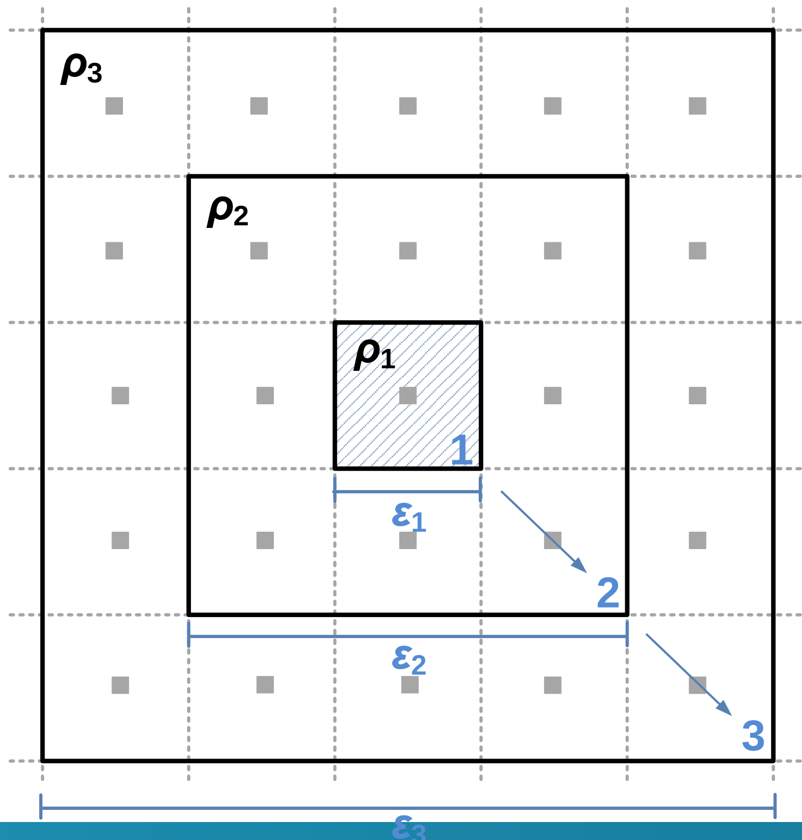


The Bayesian method tends to 'trust' (interpolated) raingauge data, which are usually of better normality. This may smooth off local rainfall peak intensities.



Local singularity analysis

Local singularity analysis decomposes a geo-value into a singular and a non-singular components



Mass density

The "singularity" component, of which the value varies at different scales according to local singularity exponent, termed α(x)

$$\boxed{\rho(x)} = \boxed{c(x)}\boxed{\varepsilon^{\alpha(x)-E}}$$

Non-singularity component: The Background magnitude that does not change as scale varies

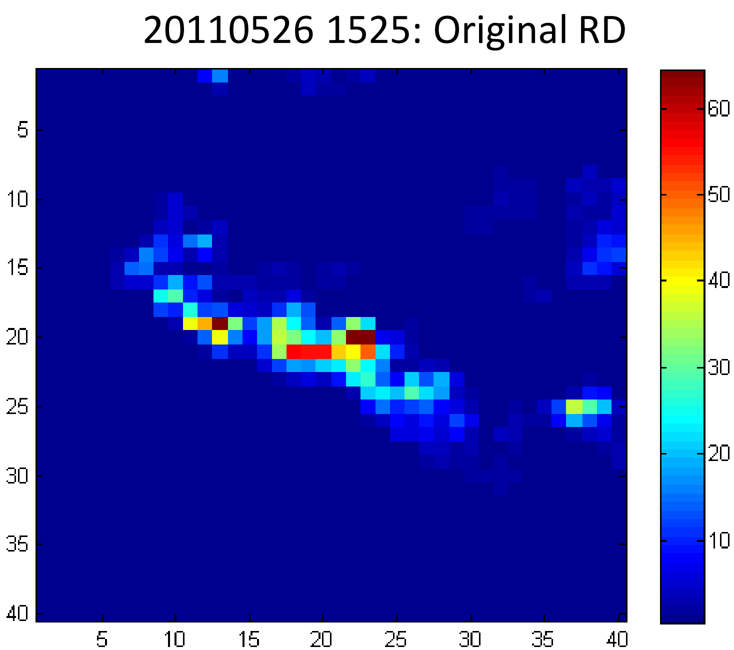
$\alpha = 2$, no singularity exists

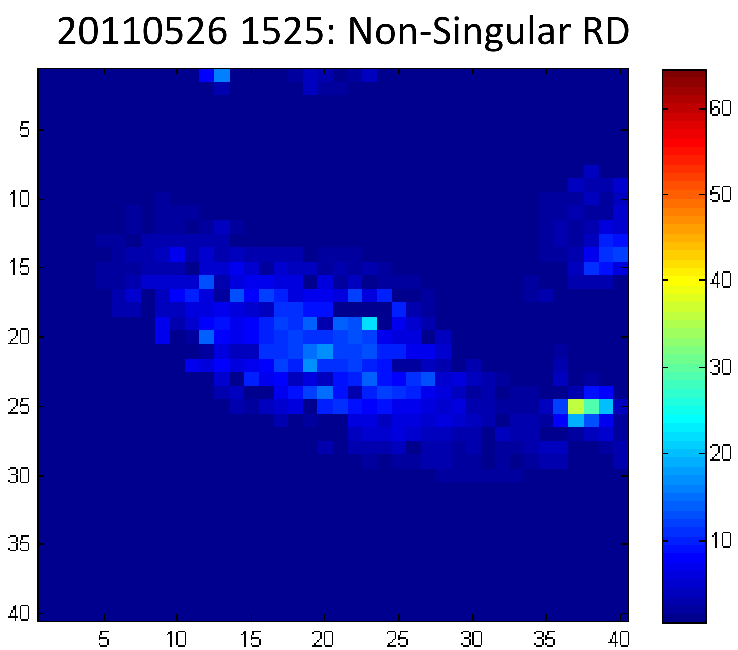
$\alpha \neq 2$, singularity exists

$\alpha > 2$, local depletion

$\alpha < 2$, local enrichment

As compared to the original radar (RD) field, the Non-Singular (NS) one is smoother and more symmetric





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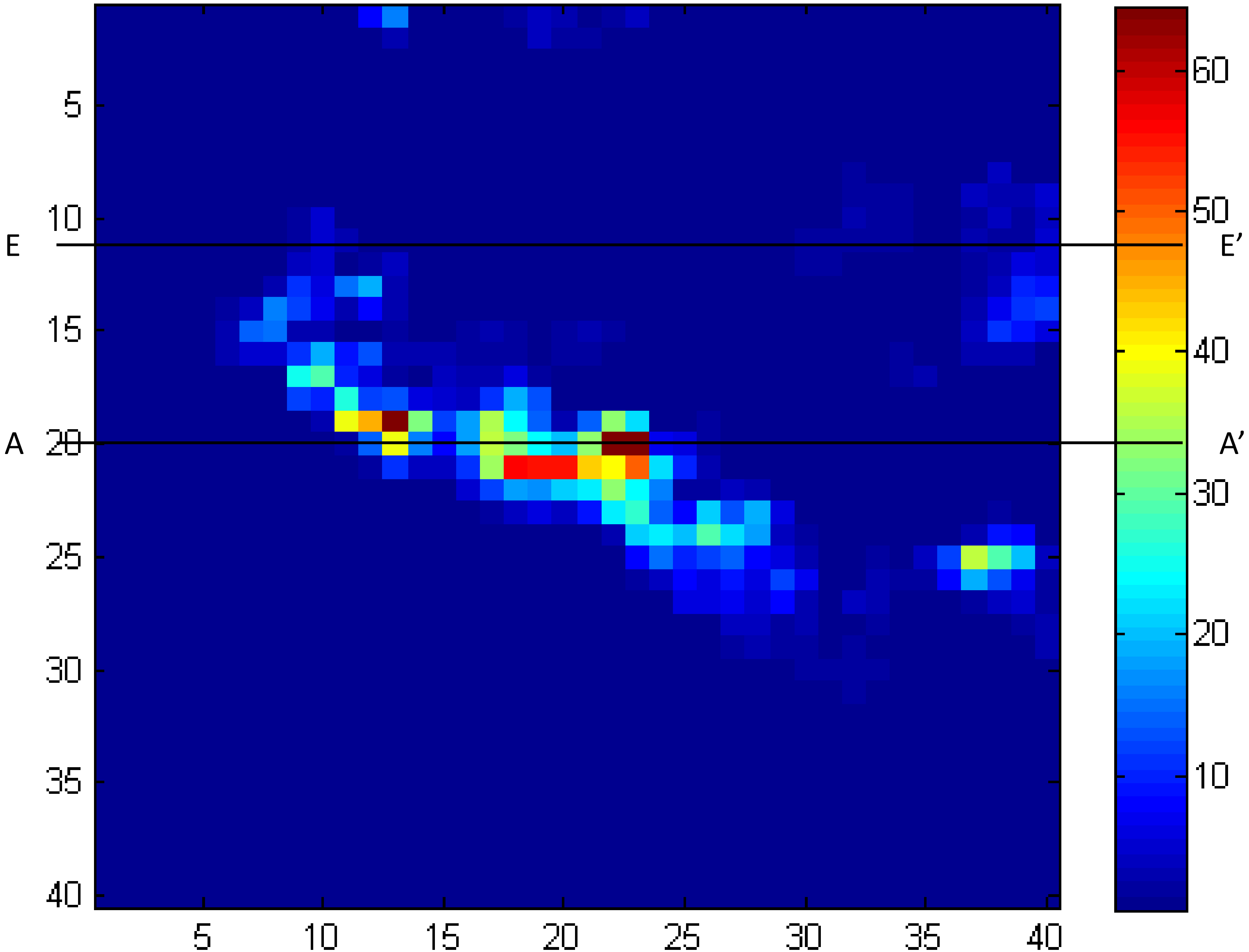

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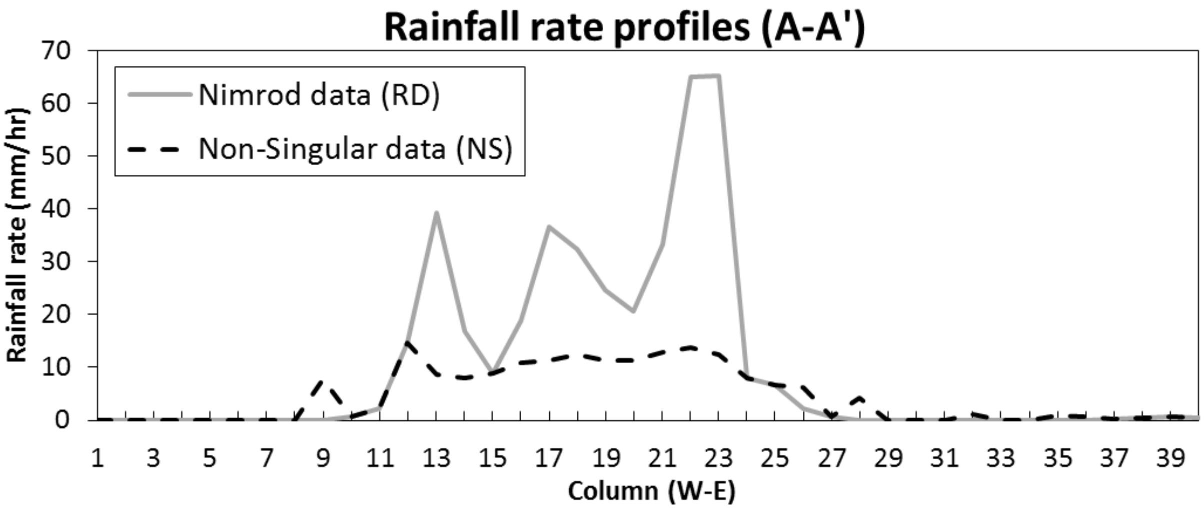
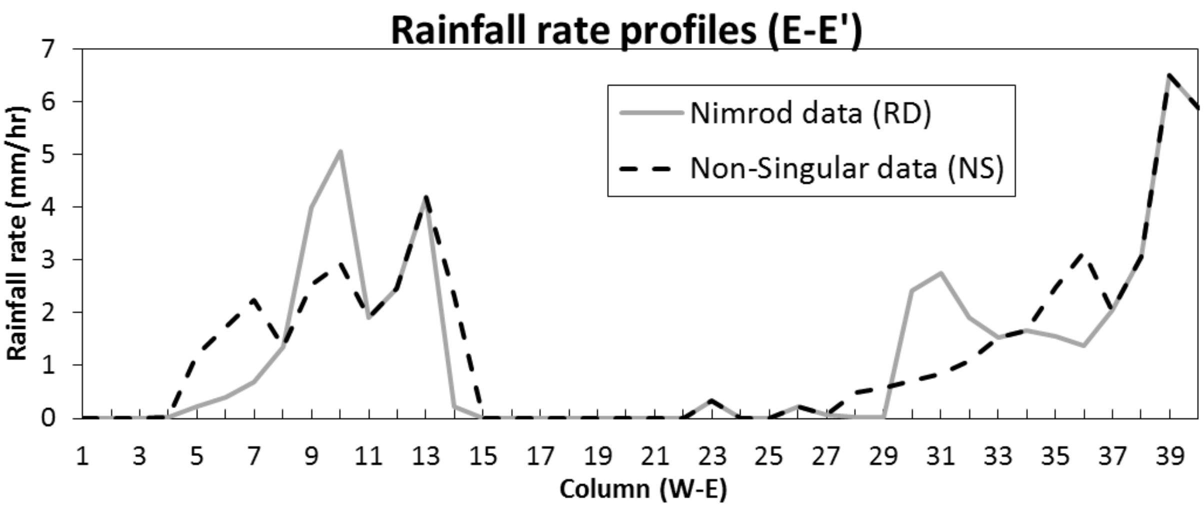
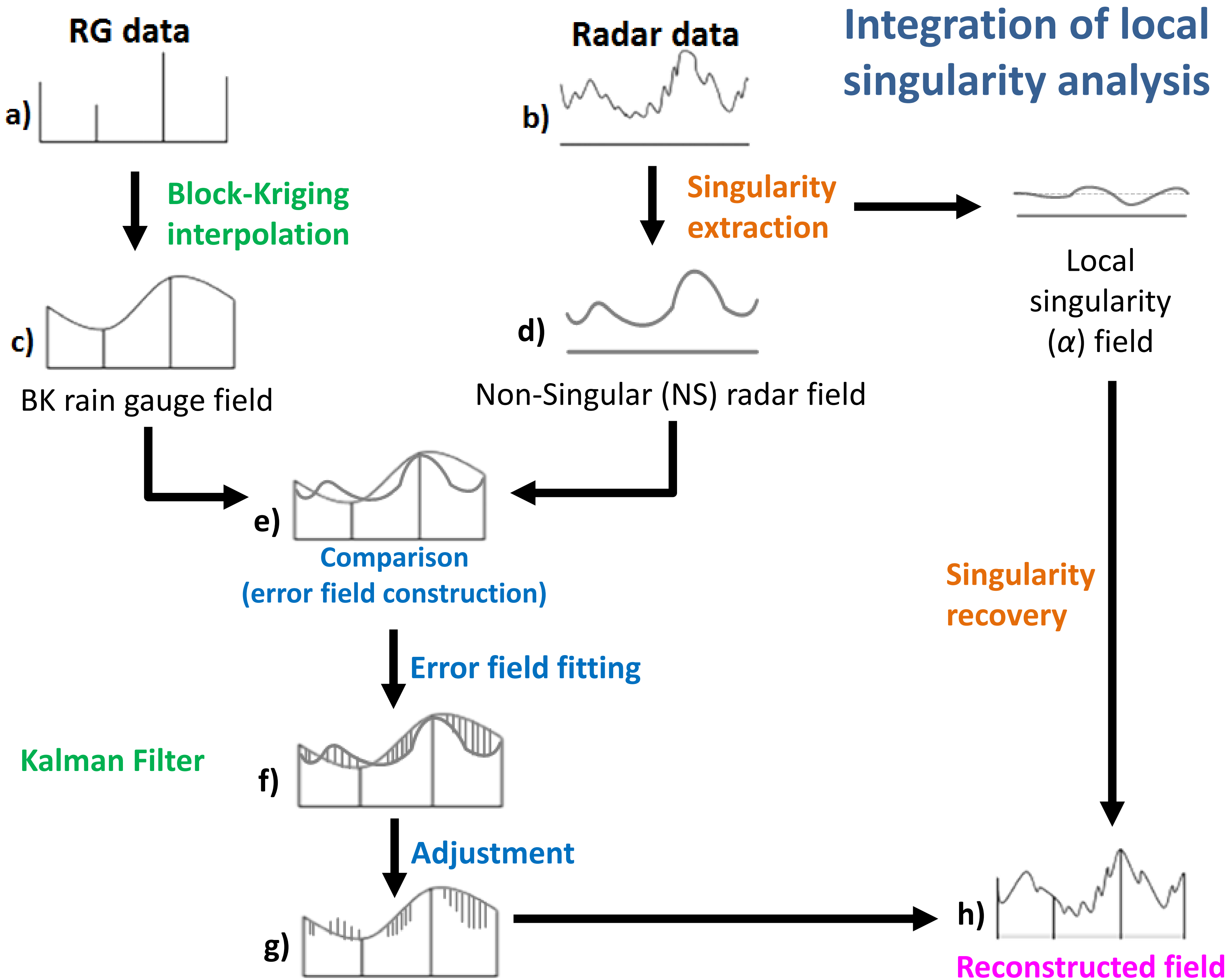
The degree of “smoothing” is in particular strong at the locations where more local extreme magnitudes are seen

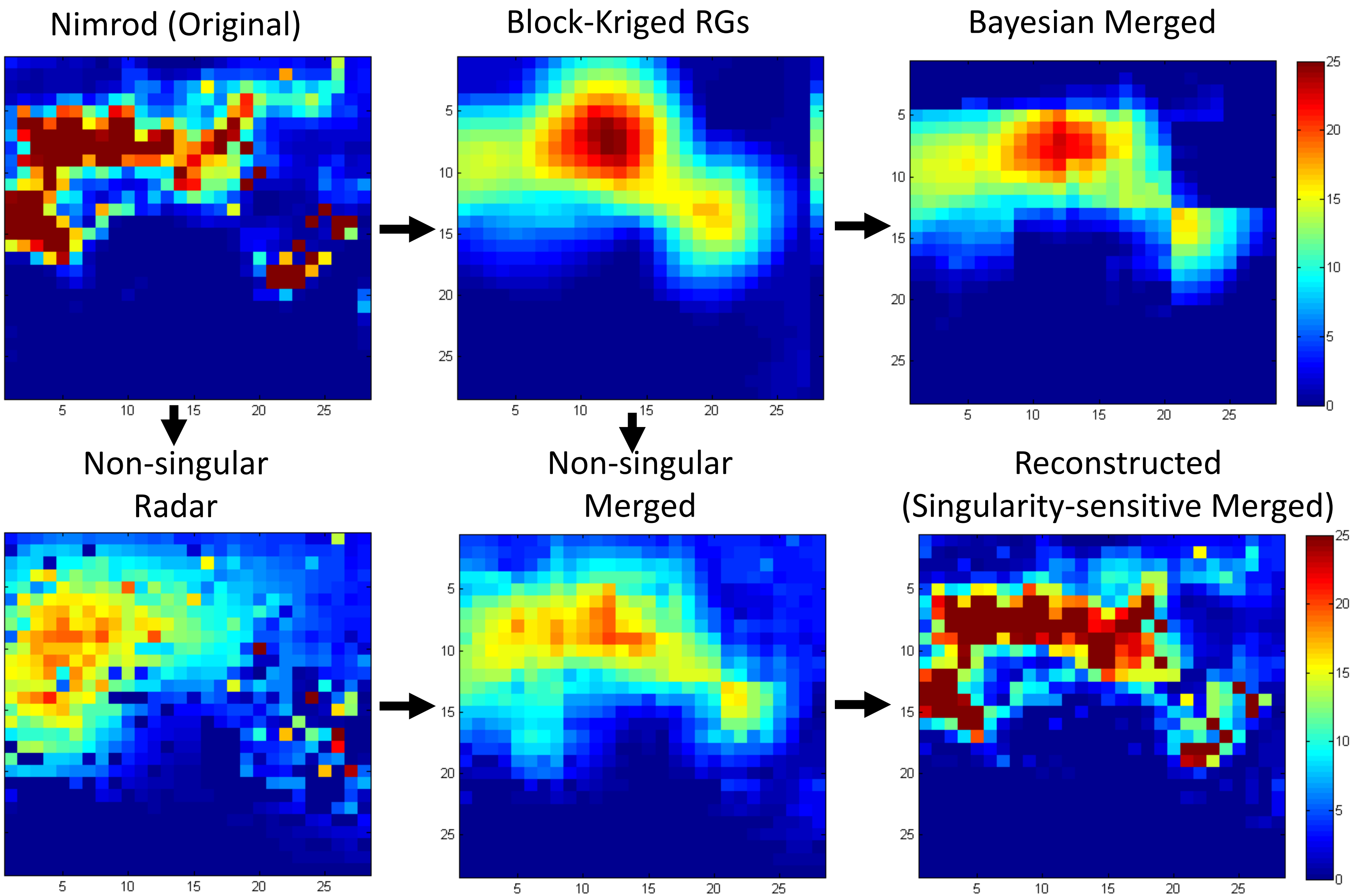






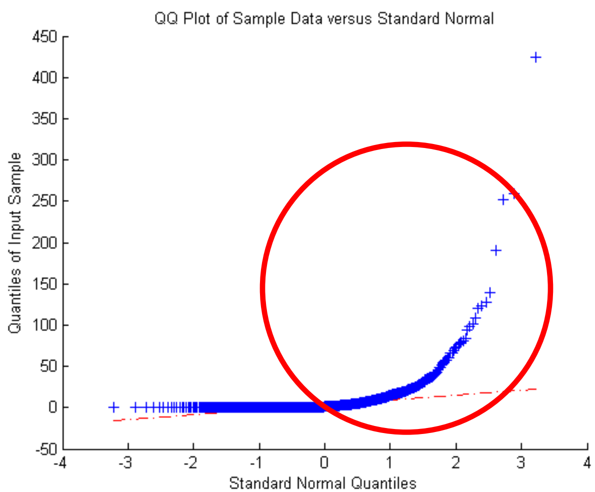
Integration of local singularity analysis
RG data
a)
Radar data
b)
Block-Kriging interpolation
Singularity extraction
Local singularity (α) field
c)
BK rain gauge field
d)
Non-Singular (NS) radar field
e)
Comparison (error field construction)
Singularity recovery
Error field fitting
Kalman Filter
f)
Adjustment
g)
h)
Reconstructed field

Images at each step of the Bayesian data merging with/without local singularity analysis

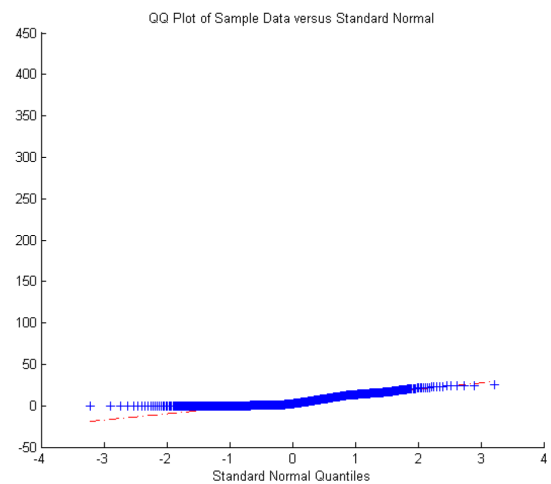


Quantile-quantile plots at each step of the Bayesian data merging with/without local singularity analysis

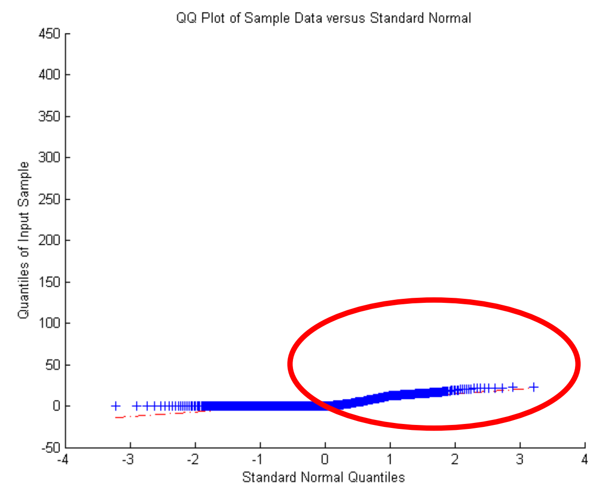
Nimrod (Original)



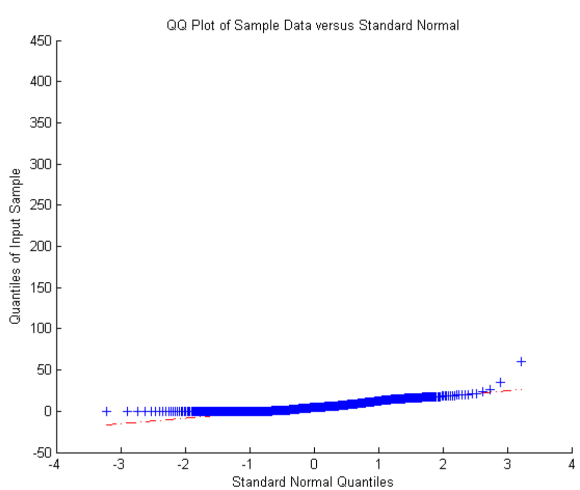
Block-Kriged RGs



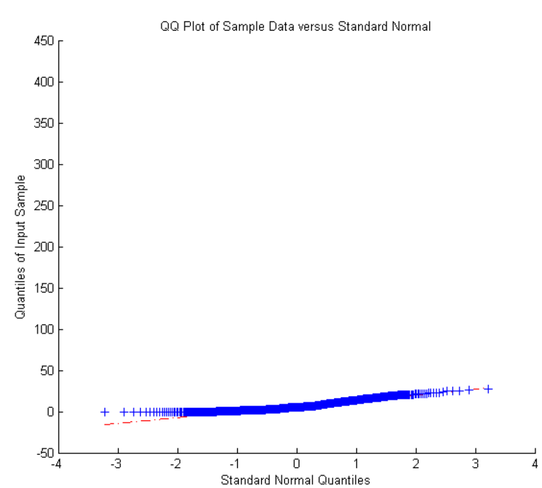
Merged



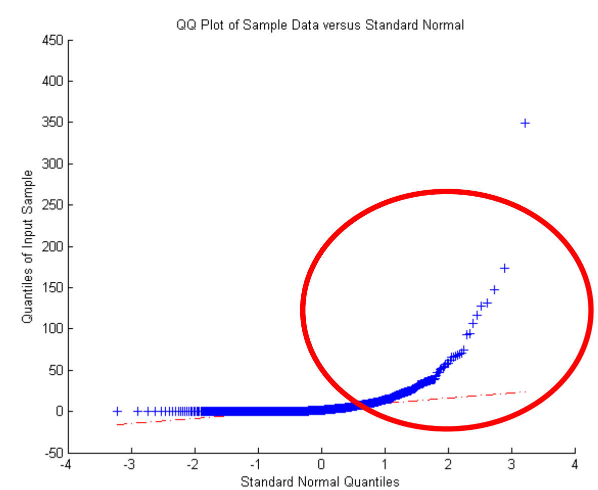
Non-singular Radar



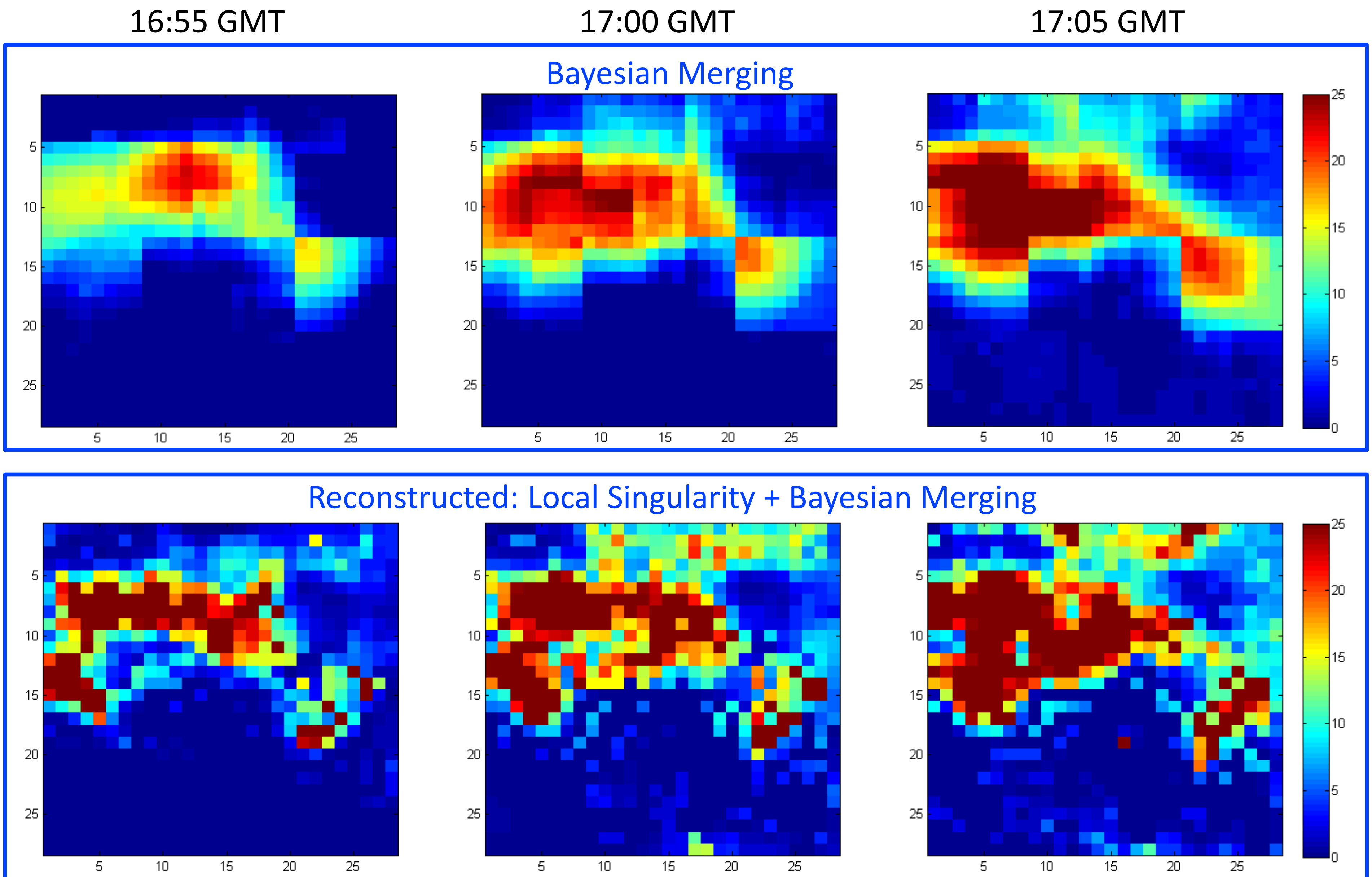
Non-singular Merged



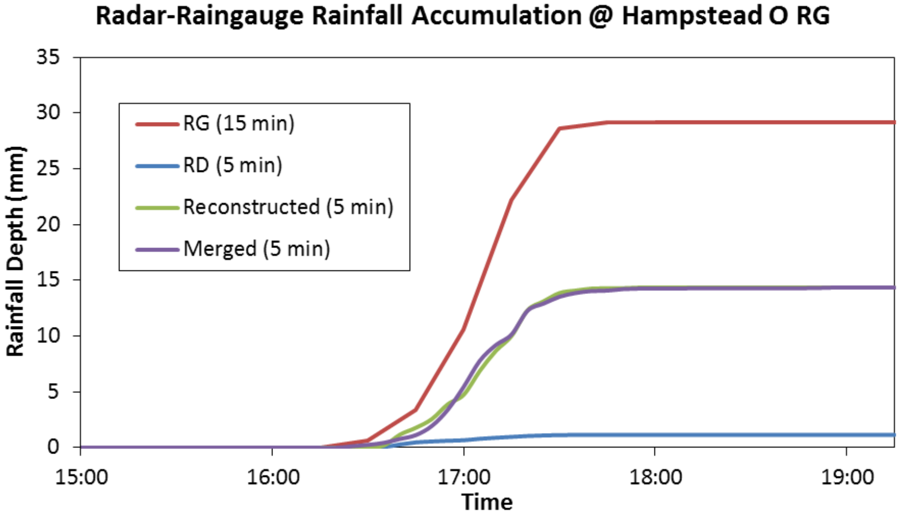
Reconstructed

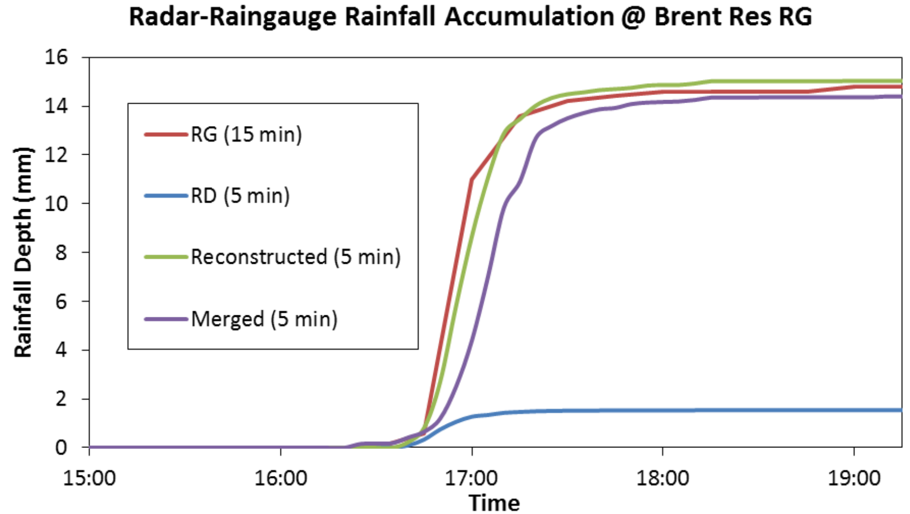


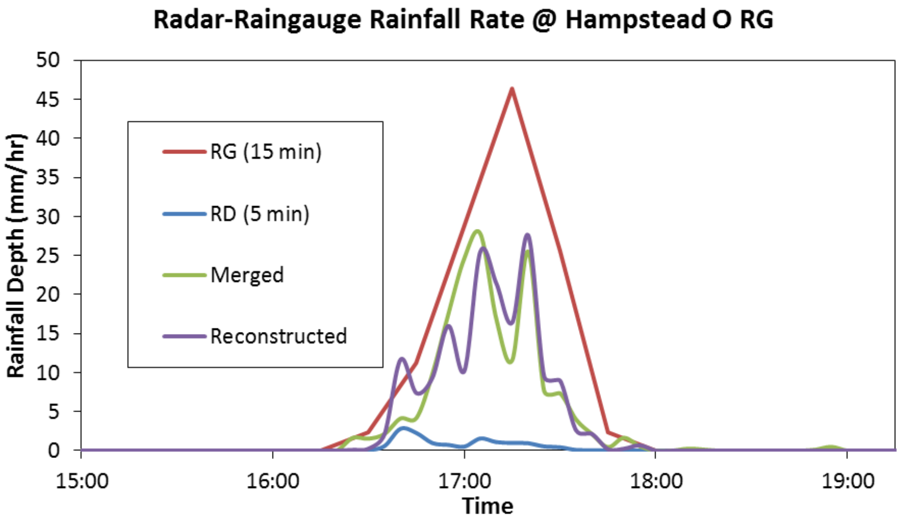
Merged radar rainfall estimates with local singularity analysis are visually more realistic and show better temporal continuity

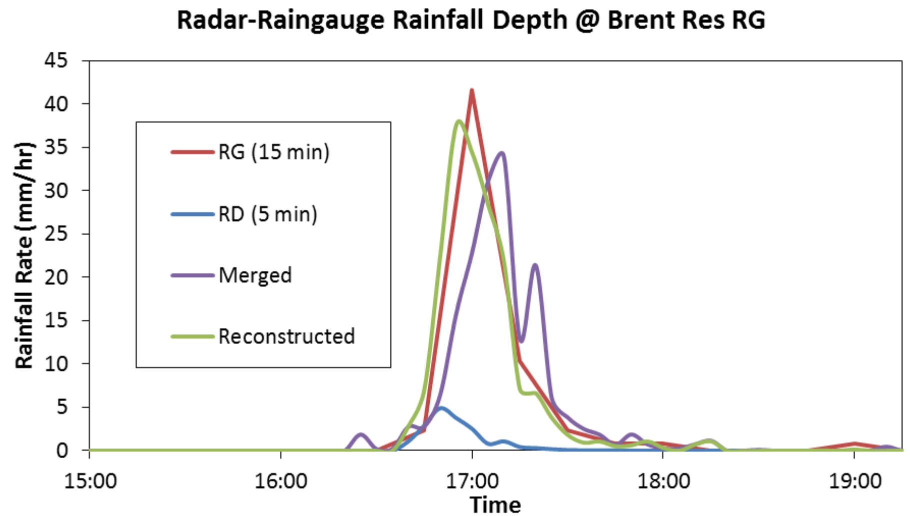


Comparison of the merged radar rainfall accumulations and rates against independent EA raingauge records









4. Radar rainfall Nowcasting

Radar rainfall nowcasting

- **Definition:**
  - The basic idea of nowcasting is to 'extrapolate' future rainfall rates according to current available radar images, so its accuracy largely depends on the quality of input radar estimates and the extrapolation techniques used to characterise the variation of storms.
- **Assumption:**
  - In short term, the variation of a storm is dominated by its movement (mainly caused by wind advection), so the evolution (i.e. the growth or decay) of storm cells is usually neglected or simulated by rainfall cell merging or separation.
- **Categories:**
  - Storm cell tracking (Dixon and Wiener, 1993)
  - Tracking radar echoes by correlation (TREC: Reinhart, 1981)
  - Variational echo tracking (VET: Laroche and Zawadzki, 1994)

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Characteristics of nowcasting techniques

- **(Object-based) storm cell tracking**
  - Subjective thresholds, suitable for small-scale but ‘relatively large displacement’ applications
  - Cartesian -> polar coordinate systems
- **(Block-based) TREC methods**
  - Easy and effective, ‘Holes’ in the wind field, lack of (spatial) continuity, suitable for large-scale applications
  - COTREC (TREC + minimisation of the divergence of the velocities of adjacent blocks), MTREC (Multi-scale TREC)
- **(Block-based) VET methods**
  - Smooth (continuous) wind field, numerically time-consuming, unable to handle too large displacement between two consecutive images
  - Optical flow techniques (used in STEPS)

Optical flow techniques

- **Optical flow constraint (OFC):**

$$R(x, y, t) = R(x + u\Delta t, y + v\Delta t, t + \Delta t) \Longrightarrow \frac{\partial R}{\partial x}u + \frac{\partial R}{\partial y}v + \frac{\partial R}{\partial t} = 0$$

  – Rainfall objects are assumed to remain constant in intensity, and only change in shape

  -> **this may not be the case, especially for thunderstorms.**

- **Smoothness assumption:**

$$\nabla^2 \mathbf{V} \Longrightarrow u(x, y) - \frac{u(x + h, y) + u(x, y + h) + u(x - h, y) + u(x, y - h)}{4}$$

  – Minimisation of the difference between the velocity of each pixel and the average velocity of its neighbouring pixels.

Possible improvements for Optical Flow techniques

- **Gradient constancy assumption**

$$\nabla R(x, y, t) = \nabla R(x + u\Delta t, y + v\Delta t + t + \Delta t)$$

  - This allows small variations in rainfall intensity and is helpful to determine the displacement vector by providing an additional criterion.

- **Multi-scale calculation**
  - Numerical estimation of wind velocities from coarse to fine (spatial) scales
  - This will improve the applicability of OF techniques to large-displacement cases.

Summary of on-going research

- **Fractals/multifractals**
  - Continuous testing of singularity-sensitive data merging techniques in different catchments
  - Extending to work with other existing merging methods, e.g., KED and KRE.
  - Development of spatial downscaling models based upon local multifractals.
- **Radar rainfall nowcasting**
  - Improved optical flow technique that enables the prediction of larger displacement of small-scale rainfall cells.
  - Comparison/combination of block- and object-based nowcasting methods.

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Thank you for your attention

Quantification and reduction of uncertainty in urban pluvial flood modelling and forecasting based upon improved rainfall estimates

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Contents

1. Testing and assessment of the suitability of different rainfall estimates for:
    a) Urban pluvial flood modelling
    b) Urban pluvial flood forecasting
2. Uncertainty-based calibration of urban drainage models based upon improved rainfall estimates

1. Testing and assessment of the suitability of different rainfall estimates

Including raingauge, radar and merged products

Objective: selecting best rainfall estimates with which we should continue to work

*"... **Rainfall** is the main input for urban pluvial flood models and the uncertainty associated to it dominates the overall uncertainty in the modelling and forecasting of these type of flooding..."*

(Golding, 2009)

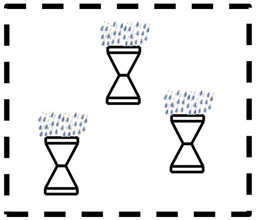
We really need to get the rainfall right!

(a) Assessing the suitability of different rainfall estimates for urban pluvial flood modelling applications, including:

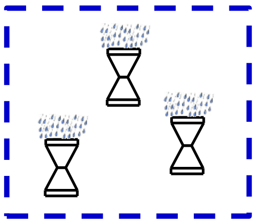
- Reconstruction of storm events in urban catchments
- Calibration/verification of urban storm-water drainage models
- Real time simulation of storm events

GENERAL METHODOLOGY

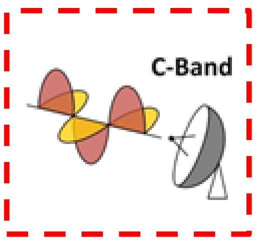
Different Rainfall Inputs



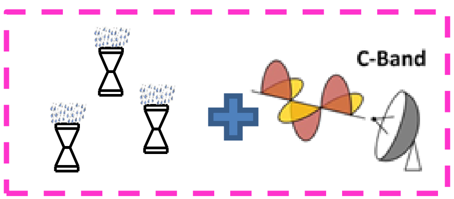
Original raingauge (RG)



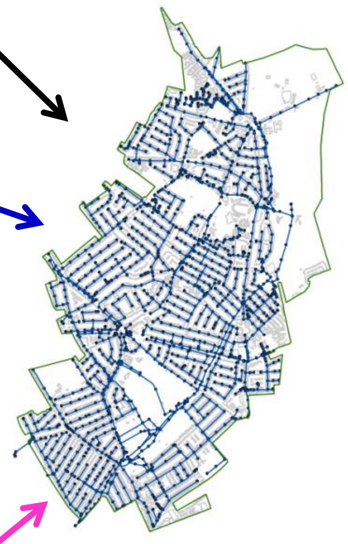
Block-Kriging Interpolated raingauge (RG)



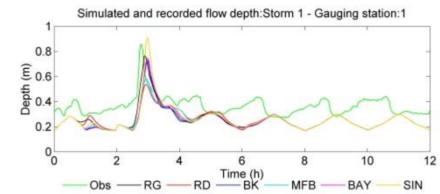
Original Radar (RD)



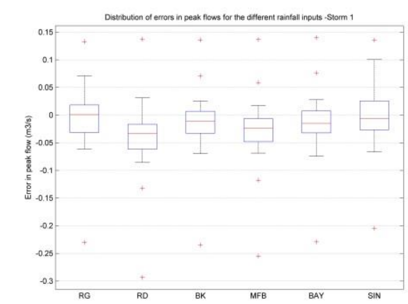
3 Merged rainfall products



Comparison of hydraulic outputs



NSE, Correlation, Relative Error in peaks, Error in time to peak



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Gauge-based adjusted rainfall estimates included in this analysis:

- **Mean field bias (MFB) adjusted**

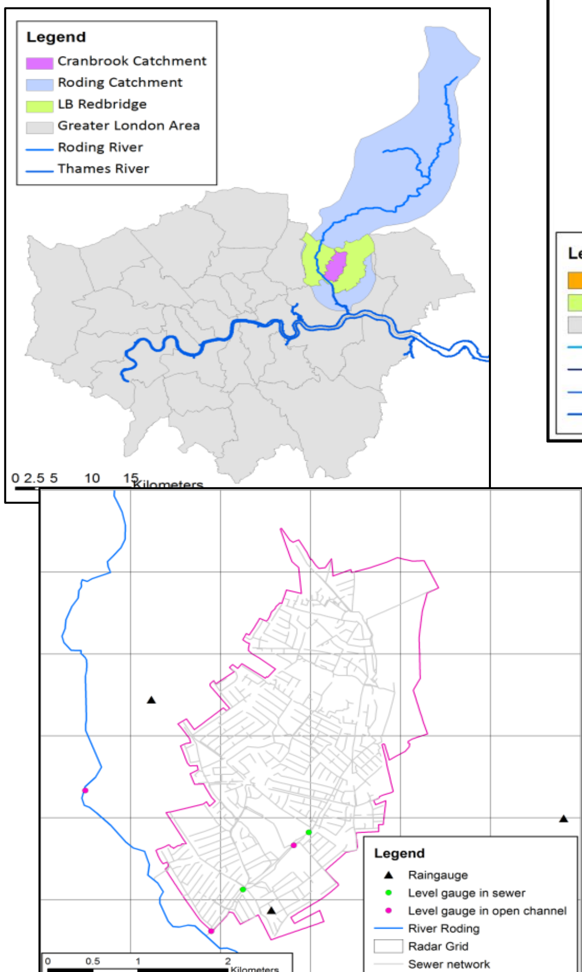
$$Bias_{last\ 1h} = \frac{\sum All\ raingauges\ in\ domain_{last\ 1h}}{\sum All\ radar\ grids\ in\ domain_{last\ 1h}}$$

- **Bayesian (BAY) adjusted**

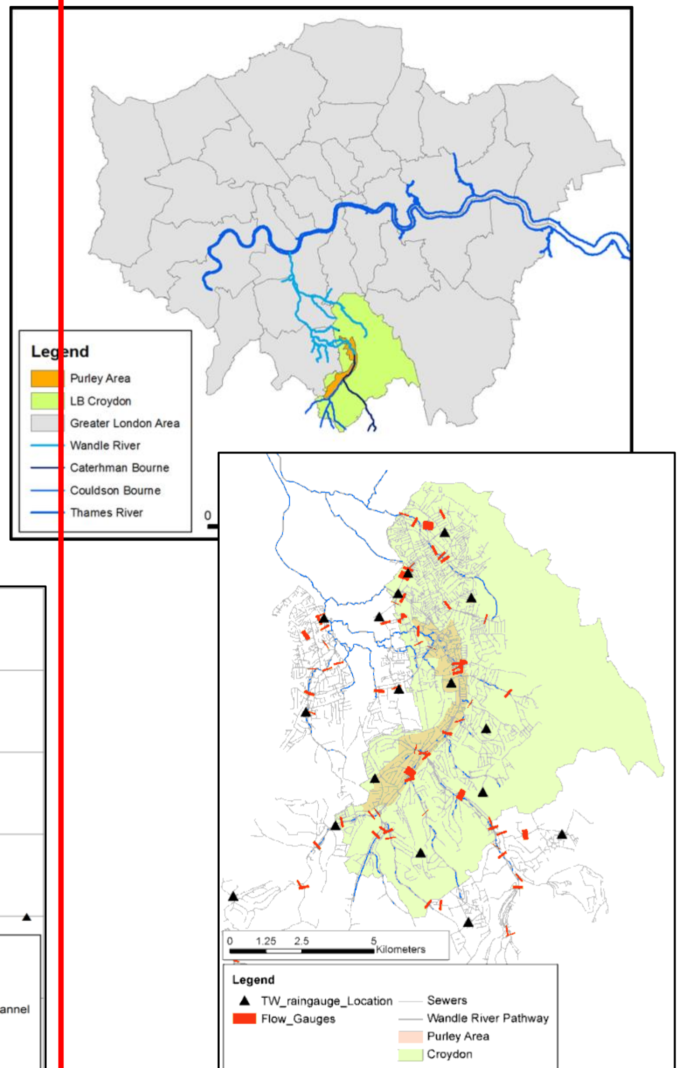
- **Singularity-Sensitive Bayesian (SIN) adjusted**

TEST CATCHMENTS

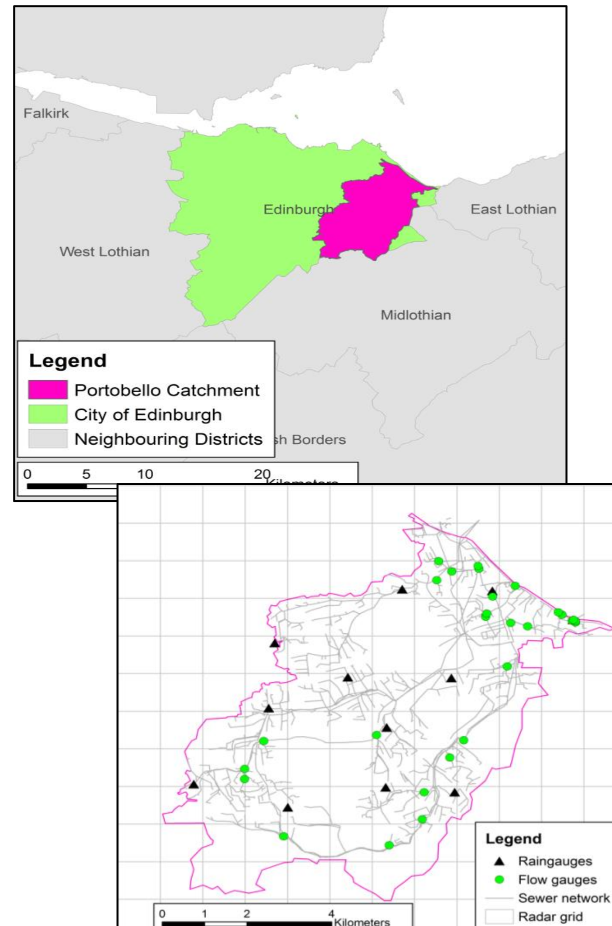
Cranbrook, NE London
9 km^2
3 RG, 1 depth gauge



Croydon, S London
64 km^2
18 RG, 78 flow/depth gauges



Portobello, E Edinburgh
53 km^2
12 RG, 32 flow/depth gauges



Storm events analysed in this study

Event	Date (duration)	RG Total (mm)	RG Peak Intensity (mm/h)
Storm 1	23/08/2010 (8h)	23.53	15.20
Storm 2	26/05/2011 (9h)	15.53	36.00

These events are different from those used in the verification of the model

PORTOBELLO CATCHMENT, EDINBURGH

Storm events analysed in this study

Event	Date (duration)	RG Total (mm)	RG Peak Intensity (mm/h)
Storm 1	06-07/05/2011 (7h)	9.25	11.21
Storm 2	23/05/2011 (24h)	7.70	5.03
Storm 3	21-22/06/2011 (24 h)	32.96	8.46

These events were the very same events used in the verification of the model (which was done using raingauge (RG) data as input)

RESULTS – RAINFALL ESTIMATES

- Rainfall depth accumulations
- Spatial structure of rainfall fields
- Ability of different rainfall estimates to reproduce rainfall rates in comparison to raingauges

Areal average total rainfall accumulations

	CRANBROOK CATCHMENT		PORTOBELLO CATCHMENT		
Rainfall Estimates	**Storm 1**	**Storm 2**	**Storm 1**	**Storm 2**	**Storm 3**
RG	23.53	15.53	9.25	7.70	32.96
RD	6.80	4.77	9.67	10.80	25.85

Areal average total rainfall accumulations

	CRANBROOK CATCHMENT		PORTOBELLO CATCHMENT		
Rainfall Estimates	Storm 1	Storm 2	Storm 1	Storm 2	Storm 3
RG	23.53	15.53	9.25	7.70	32.96
RD	6.80	4.77	9.67	10.80	25.85
RG/RD BIAS	3.46	3.26	0.96	0.71	1.28

The RG/RD bias is event varying

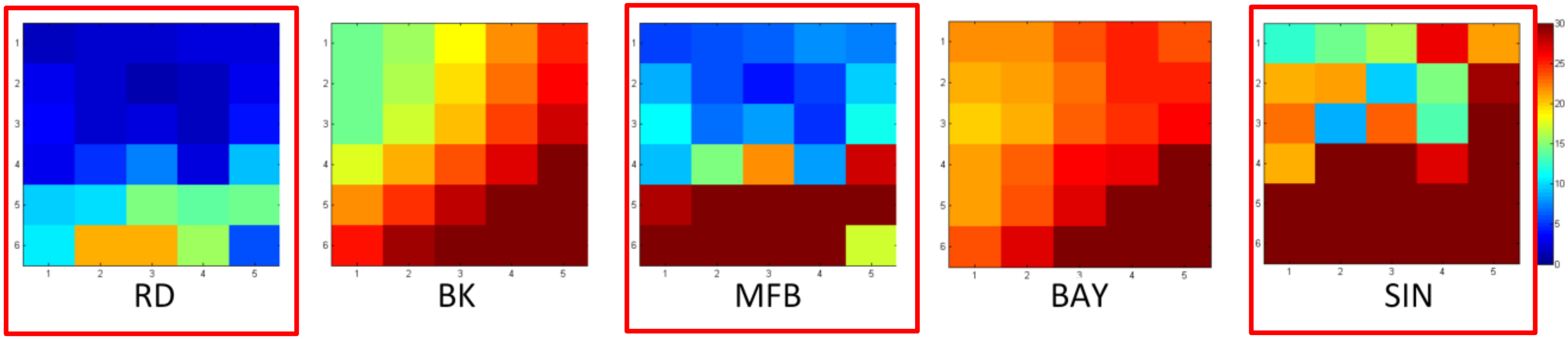
Need for dynamic and local adjustment

Areal average total rainfall accumulations

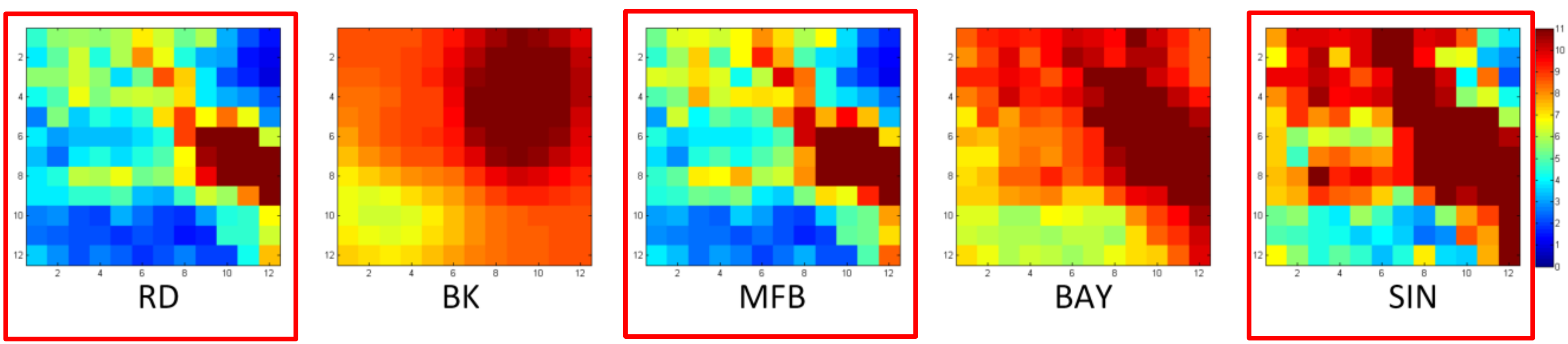
	CRANBROOK CATCHMENT		PORTOBELLO CATCHMENT		
Rainfall Estimates	Storm 1	Storm 2	Storm 1	Storm 2	Storm 3
RG	23.53	15.53	9.25	7.70	32.96
RD	6.80	4.77	9.67	10.80	25.85
BK	22.23	12.75	9.02	7.50	30.69
MFB	18.06	11.11	8.47	7.13	31.94
BAY	18.8	12.31	8.80	7.51	26.94
SIN	19.47	14.07	9.66	7.56	33.73

All adjustment methods can, in general, reduce RG/RD cumulative bias, leading to areal total accumulations similar to those recorded by raingauges

Cranbrook catchment – peak intensity image (Storm 2)

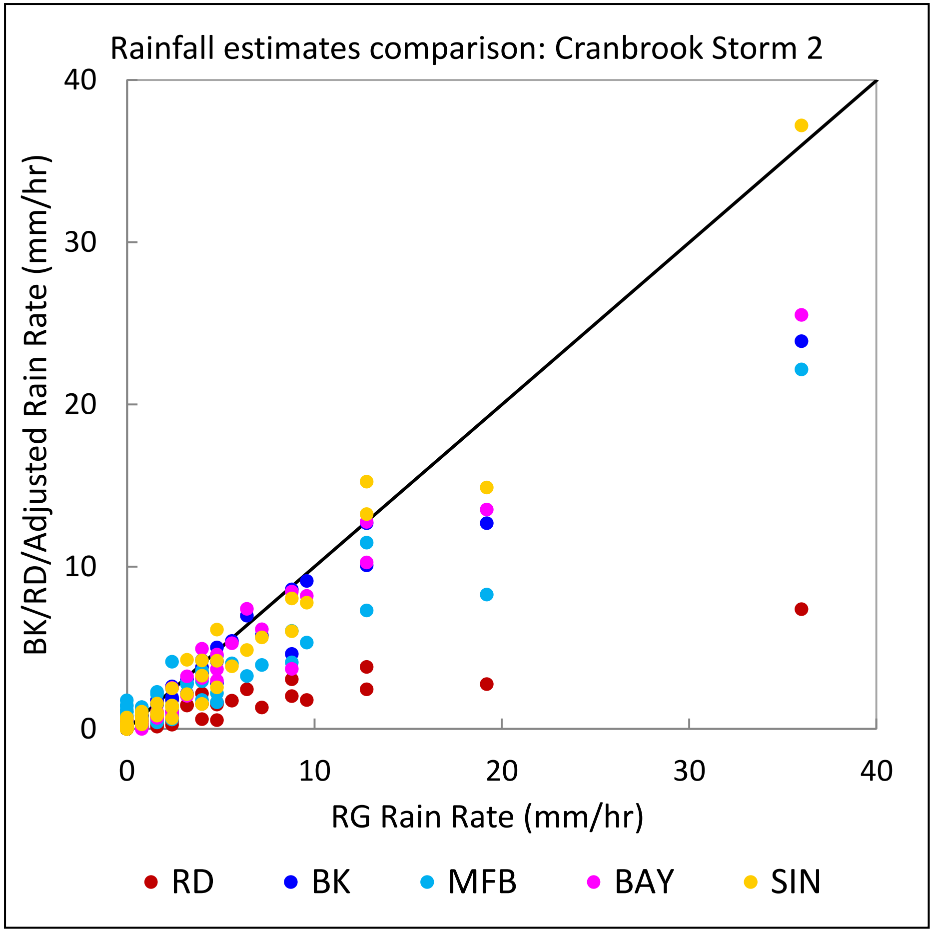


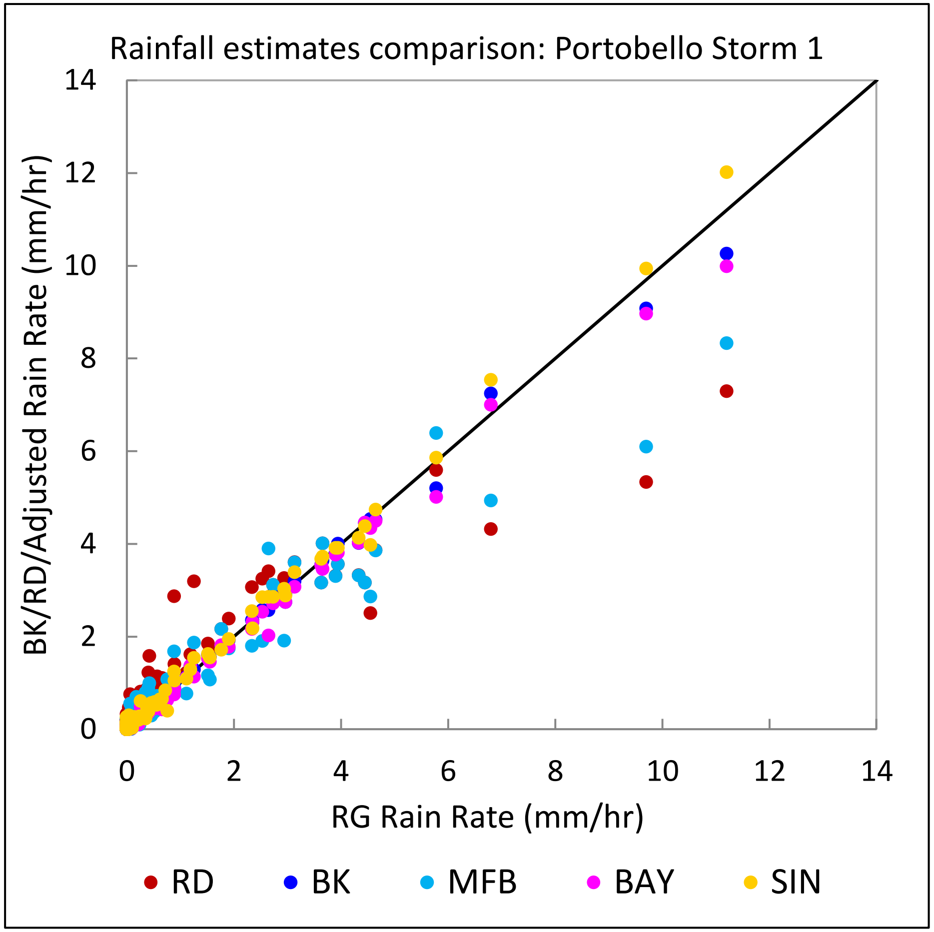
Portobello catchment – peak intensity image (Storm 1)



MFB and BAY methods can better preserve the spatial variability of the rainfall field, as originally captured by the radar

Comparison of areal average RG rain rates VS. areal average rain rates of radar and merged estimates

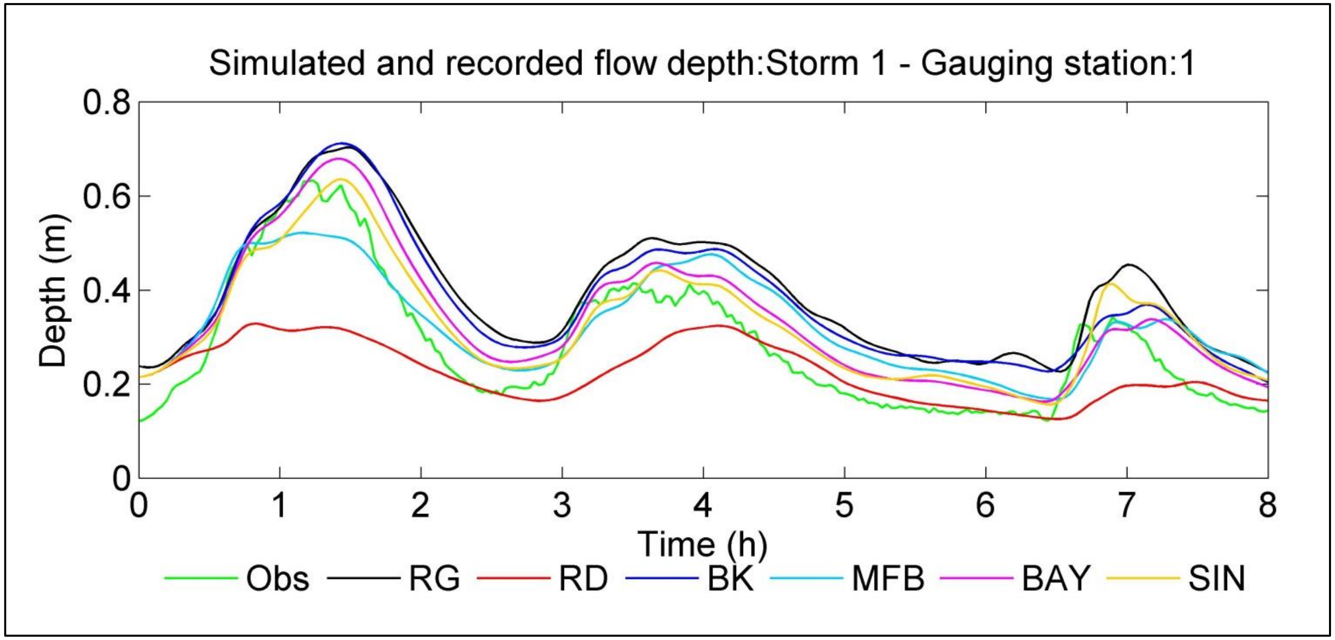


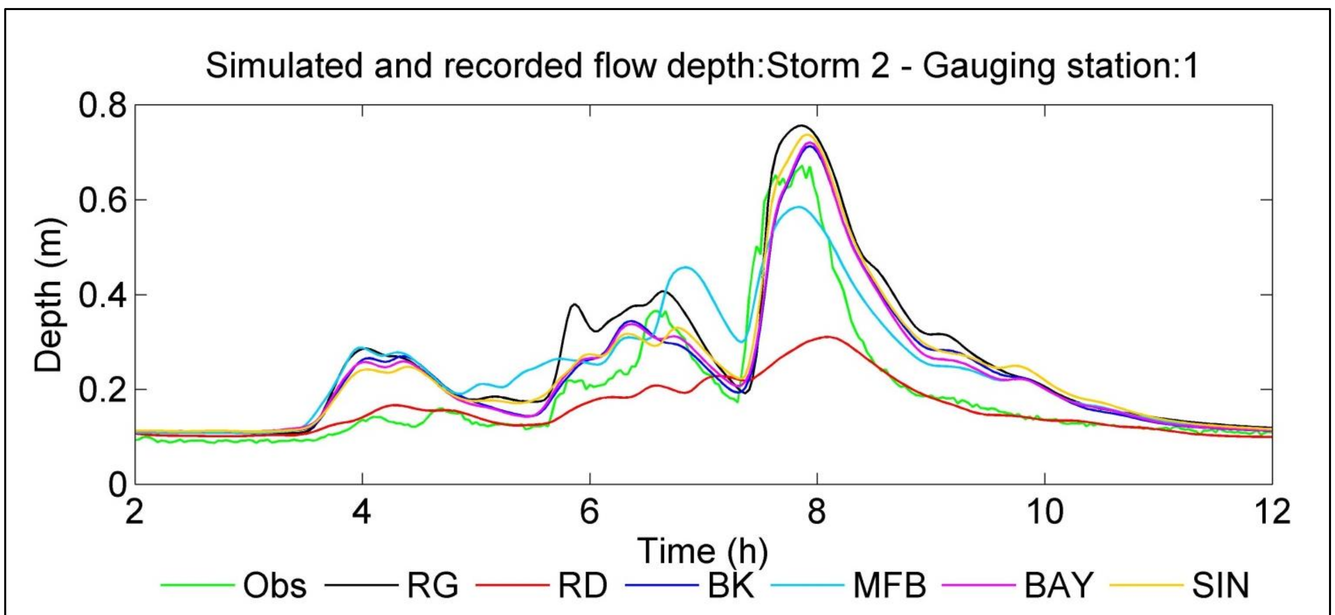


- Radar (RD) accuracy in terms of rainfall rates is poor
- MFB does not provide significant improvement in this regard
- Bayesian techniques (especially SIN) can properly reproduce low as well as high intensities

RESULTS – HYDRAULIC OUTPUTS

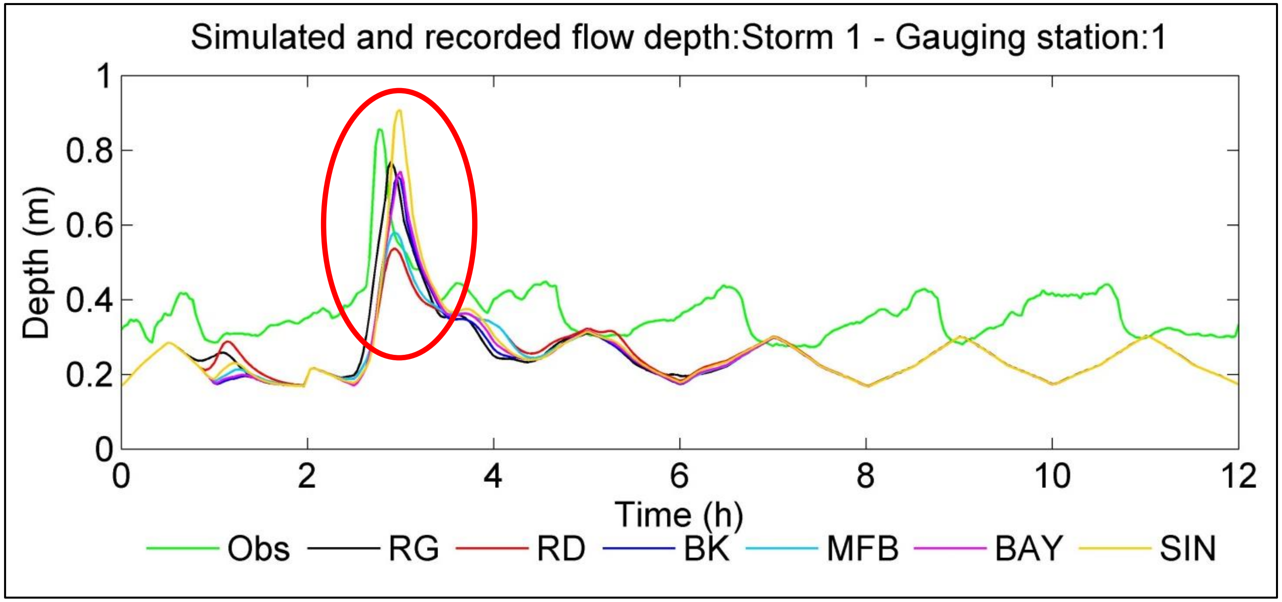
CRANBROOK CATCHMENT: Observed vs. Simulated flow depth at mid-stream gauging station (Storms 1 and 2)

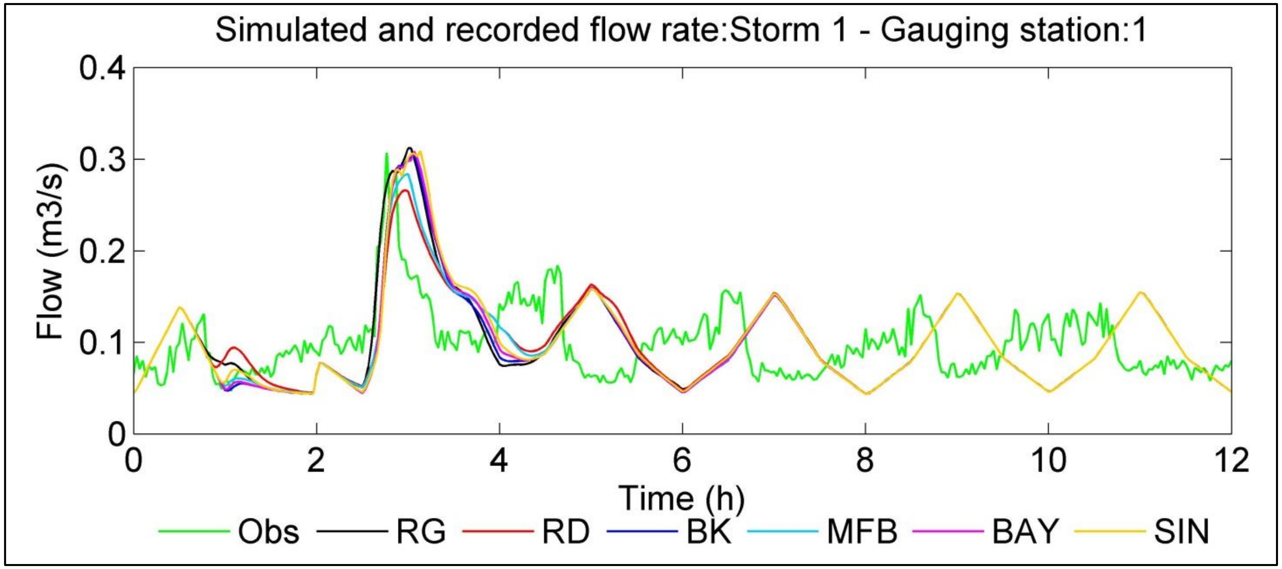


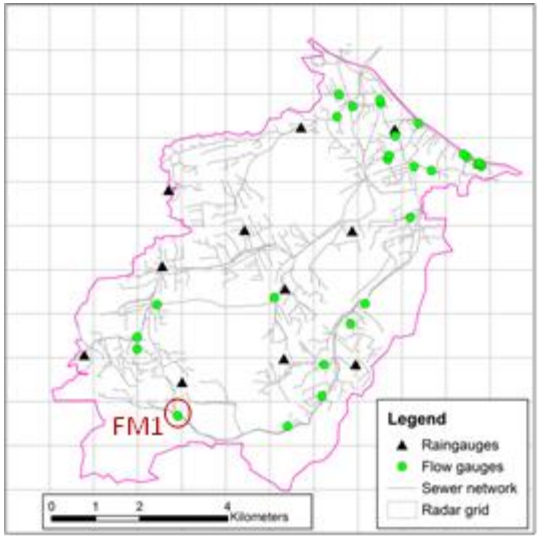


- RD largely underestimates
- MFB not enough
- BAY and SIN perform very well, even better than original RG

PORTOBELLO CATCHMENT (Storm 1): Observed vs. Simulated flow depth and rate at up-stream gauging station

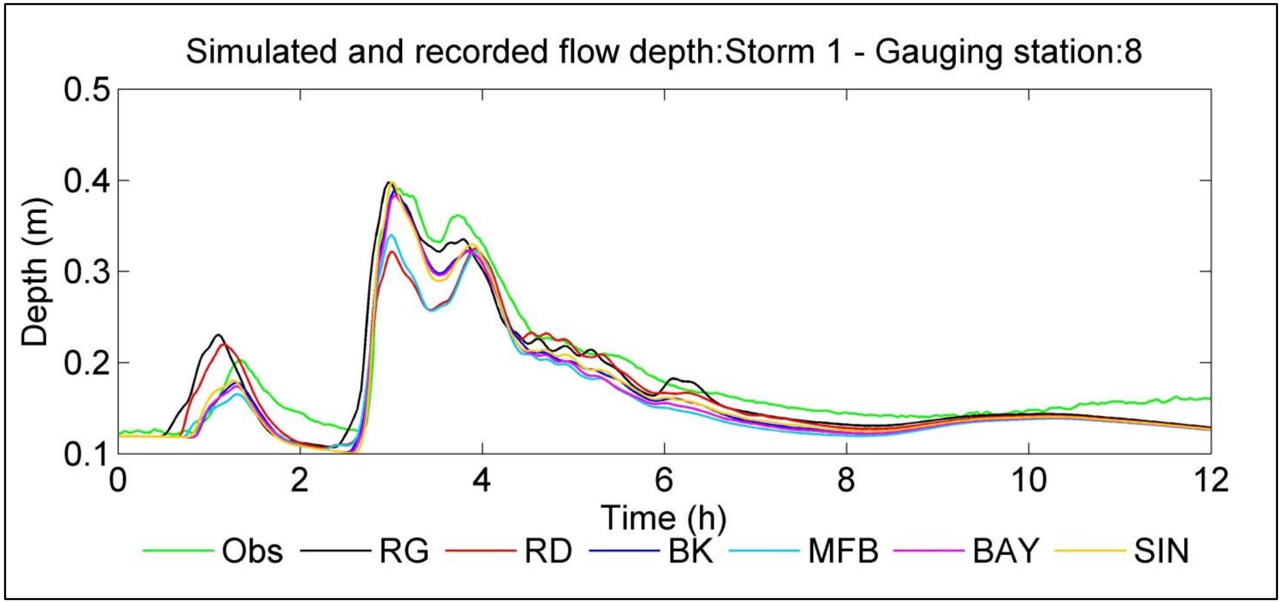


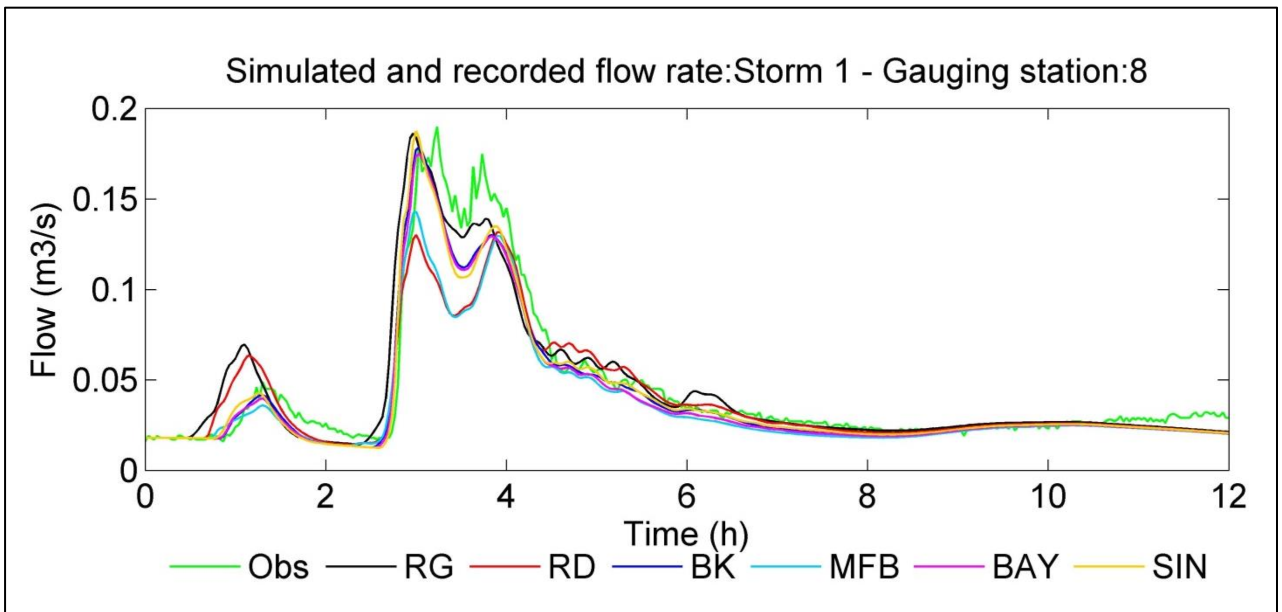


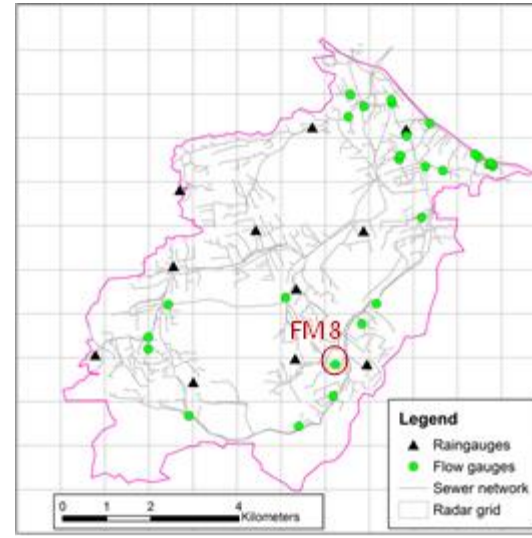


- In spite of small RG/RD bias, RD underestimates peaks
- MFB not enough
- BAY ok
- SIN better at capturing peak

PORTOBELLO CATCHMENT (Storm 1): Observed vs. Simulated flow depth and rate at mid-stream gauging station

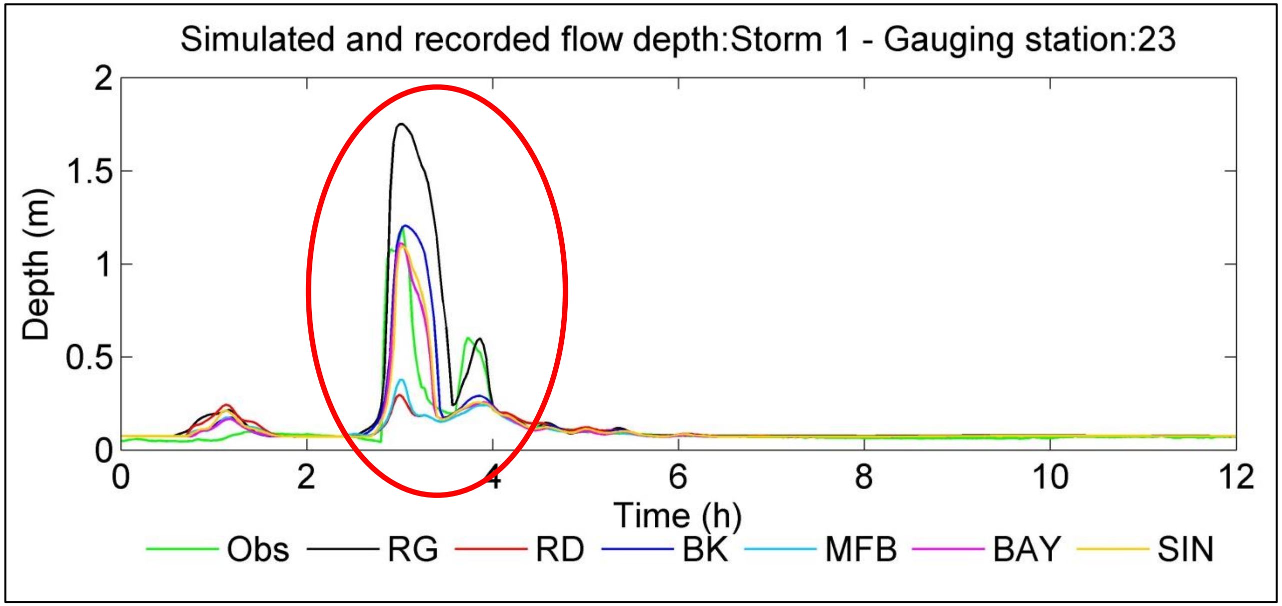


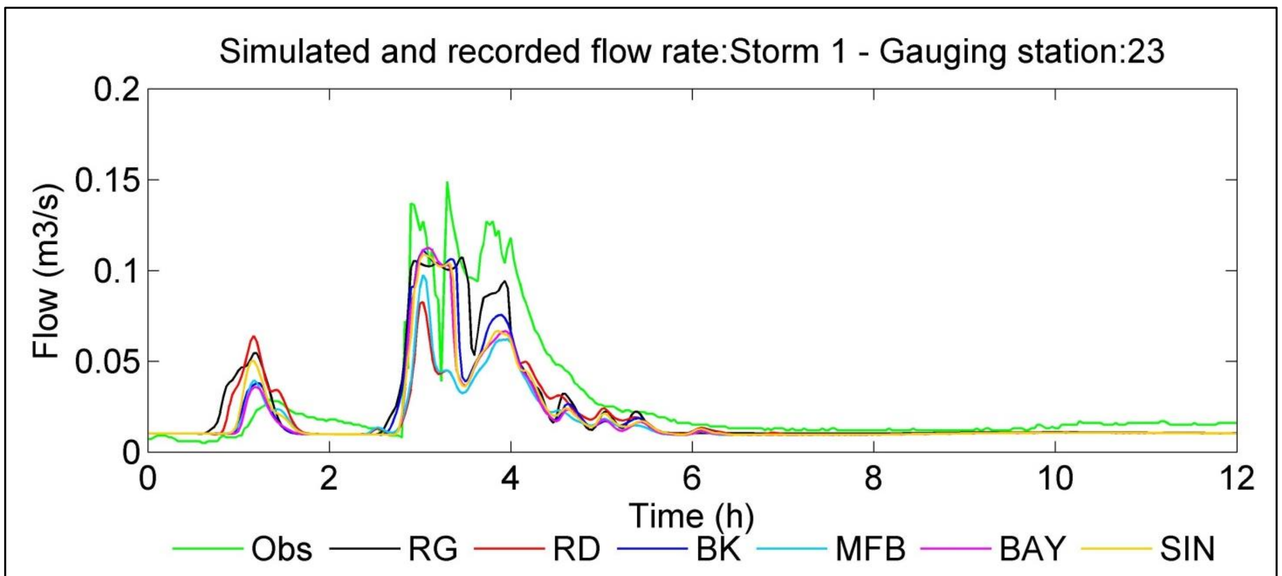


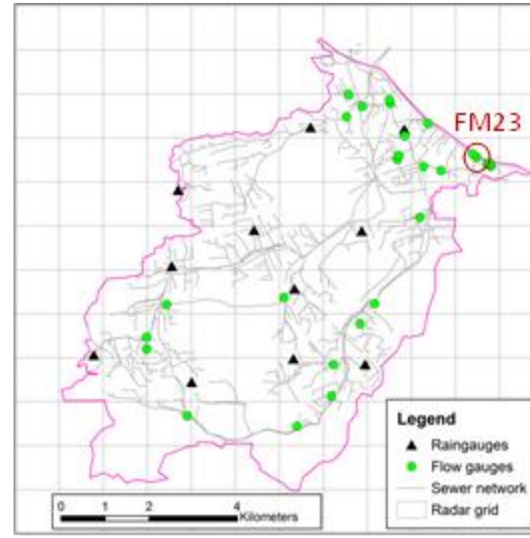


- In spite of small RG/RD bias, RD underestimates peaks
- MFB not enough
- BAY and SIN perform well

PORTOBELLO CATCHMENT (Storm 1): Observed vs. Simulated flow depth and rate at down-stream gauging station







- RD underestimates even more (cumulative effect?)
- MFB not enough
- RG overestimates peak
- **Even BK performs better than RG**
- BAY and SIN perform well

Conclusions

- In general, **all adjustment methods improve the applicability of the original RD rainfall estimates** to urban hydrological applications, although the degree of improvement provided by each adjustment method is different.

- **MFB is insufficient** for satisfactorily correcting the errors in RD estimates and this is evident in the associated hydraulic outputs -> **more dynamic and spatially varying adjustment** methods are required for urban hydrological applications.

- Overall, **the BAY and SIN rainfall estimates lead to significantly better simulation results** than the MFB adjusted estimates and the original RD estimates, with the **SIN estimates performing particularly well at reproducing peak depths and flows**.

Conclusions:

- **The benefits of merging are more evident in the Cranbrook catchment, for which storm events different from those used in the verification were tested.** In this case, the BAY and SIN merged estimates led to simulation results even better than those obtained when using point RG estimates as input.

- In the Portobello catchment (storm events analysed were same as those used in the verification) the merged estimates also performed in general better than original RD estimates, but **the real benefit of the merged products is likely to become more evident when the models are re-verified** or **when storm events different from those used in the verification are reconstructed**.

(b) Assessing the suitability of different rainfall estimates as starting point for short-term nowcasting and associated urban pluvial flood forecasting

Sources of uncertainty in flood forecasting

(Todini, 2004):

i. Uncertainties in **input measurements**; i.e. Quantitative Precipitation Estimates (QPEs);

ii. Uncertainties in **meteorological models**, namely **radar nowcasting** or **Numerical Weather Prediction (NWP)** models, used to generate Quantitative Precipitation Forecasts (QPFs);

iii. Uncertainties in **hydrological models** (parametric uncertainty, uncertainty in model structure and solution, and uncertainty in the measurement of responses used for calibration).

Todini, E. 2004. Role and treatment of uncertainty in real-time flood forecasting. Hydrological Processes ***18****(14), 2743-6*

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Dominant sources of uncertainty in urban runoff / urban pluvial flood forecasting (Golding, 2009)

iii. Uncertainties in **hydrological models** (parametric uncertainty, uncertainty in model structure and solution, and uncertainty in the measurement of responses used for calibration).

*Golding, B. W. 2009. Uncertainty propagation in a London flood simulation. Journal of Flood Risk Management **2**(1), 2-15*

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For urban pluvial flooding: **Nowcasting** forecasts are generally **more suitable** than NWP forecasts (Liguori et al., 2012)

Liguori S. et al. 2012. Using probabilistic radar rainfall nowcasts and NWP forecasts for flow prediction in urban catchments. Atmospheric Research ***103****, 80-95.*

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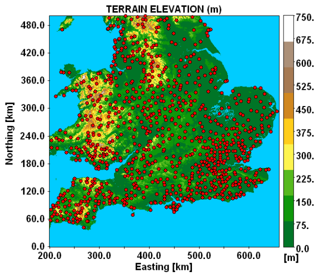
Nowcasting: extrapolation of radar images → **Quality of forecast highly dependent on quality of radar QPEs (i)!**

Radar rainfall estimates are subject to significant uncertainties

The accuracy of radar rainfall estimates is usually insufficient, particularly in the case of extreme rainfall magnitudes
(Einfalt et al., 2005)

Possibility to overcome this problem: dynamically adjusting radar estimates based on raingauge measurements (e.g. Wang et al., 2013)

Benefits of radar-raingauge rainfall adjustment in terms of Quantitative Precipitation Forecasts (QPFs) not yet explored



Radar (Nimrod) and raingauge measurements (domain: 500 km x 500 km)

↓

Gauge-based adjustment: Mean field bias & KED

↓

Assessment of QPEs at small scale using Cranbrook local raingauges

↓

Generation of QPFs with STEPS Nowcasting model

↓

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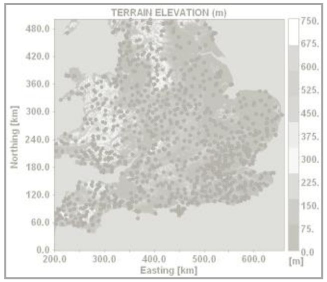
↓

Runoff forecasts – inputting QPFs to InfoWorks model of Cranbrook catchment

↓

Assessment of runoff forecasts using Cranbrook local water depth gauges



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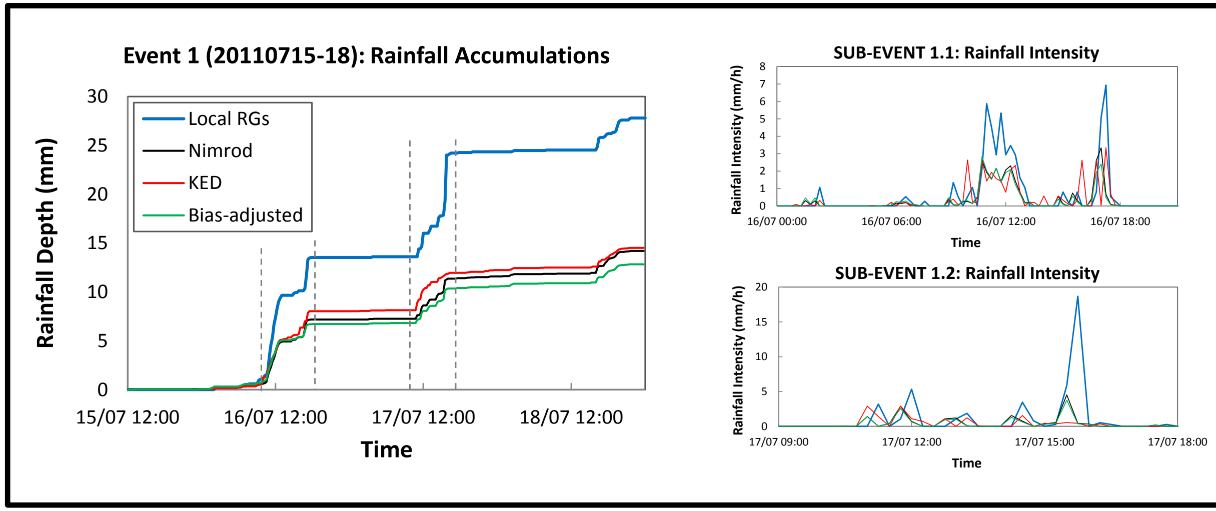
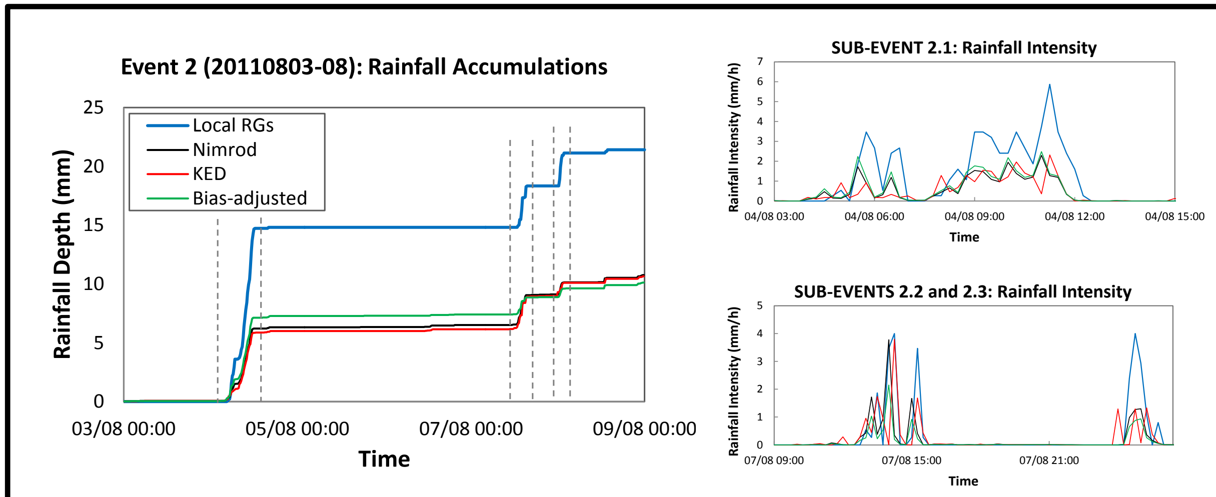
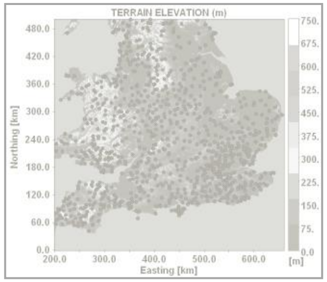




- Radar largely underestimate rainfall over the Cranbrook area (this seems to be due to radar beam blocking)
- Adjustments were done at too large scales and no improvements were achieved at the local scale of urban catchments
- Need to apply adjustment (both mean bias and KED) at smaller domains – our previous work supports this statement



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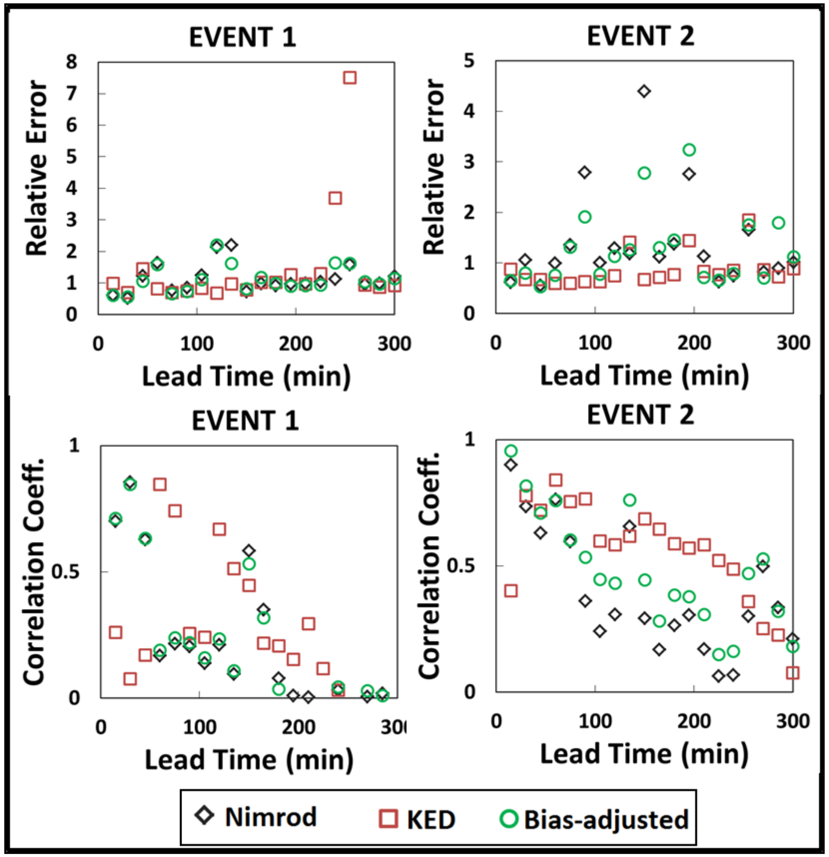
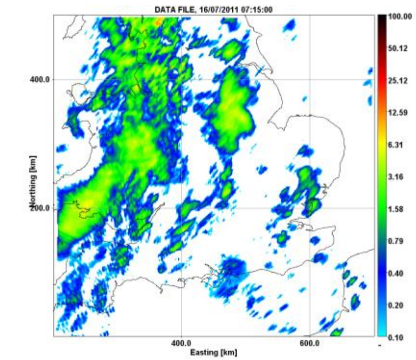
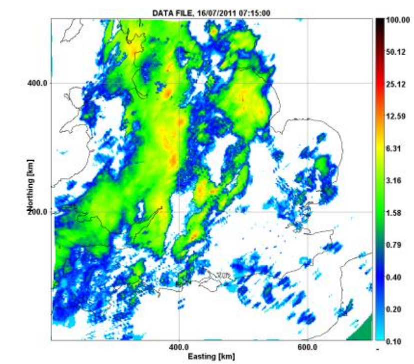




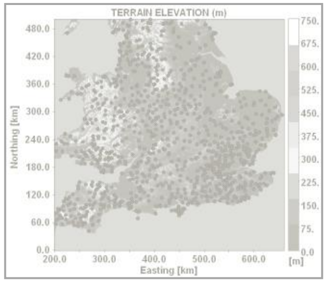
Nimrod Forecasts



KED Forecasts

- **Quantitatively:** all QPFs perform badly – mainly due to underestimation of QPEs

- **In terms of correlation and storm movement:**
  - Nimrod and bias adjusted QPFs present consistent behaviour
  - KED QPFs present inconsistent behaviour, the storm even changes direction – reason: KED adjustment does not take into account the temporal correlation of the radar rainfall field; therefore, the adjustment affects the rain field in the time domain . Consequently, the nowcasting model is not able to properly capture the movement the storm



Radar (Nimrod) and raingauge measurements (domain: 500 km x 500 km)

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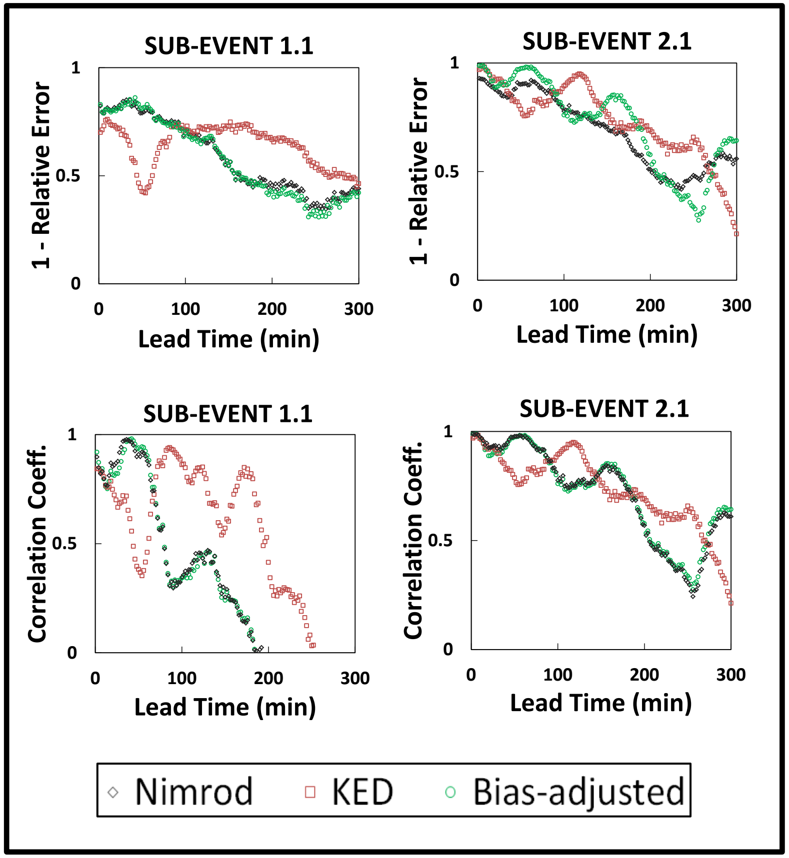
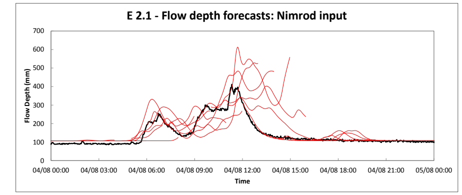
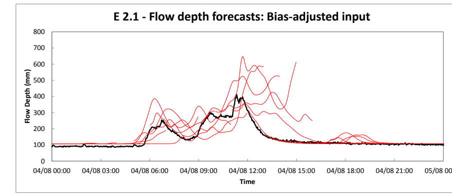
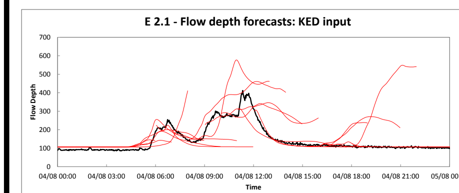




Water depth forecast – Nimrod QPFs



Water depth forecast – Bias-adj QPFs



Water depth forecast – KED QPFs

- **Quantitatively:** better results (than QPFs alone)
- **In terms of correlation and consistency:**
  - Nimrod and bias adjusted QPFs present consistent behaviour
  - KED QPFs present inconsistent behaviour

GENERAL CONCLUSIONS

- Need to do adjustment at smaller domains
- KED adjusted radar rainfall fields may not be appropriate for generating QPFs
- Need to analyse more storms, adjustment methods and way of applying these

Next steps in this direction:

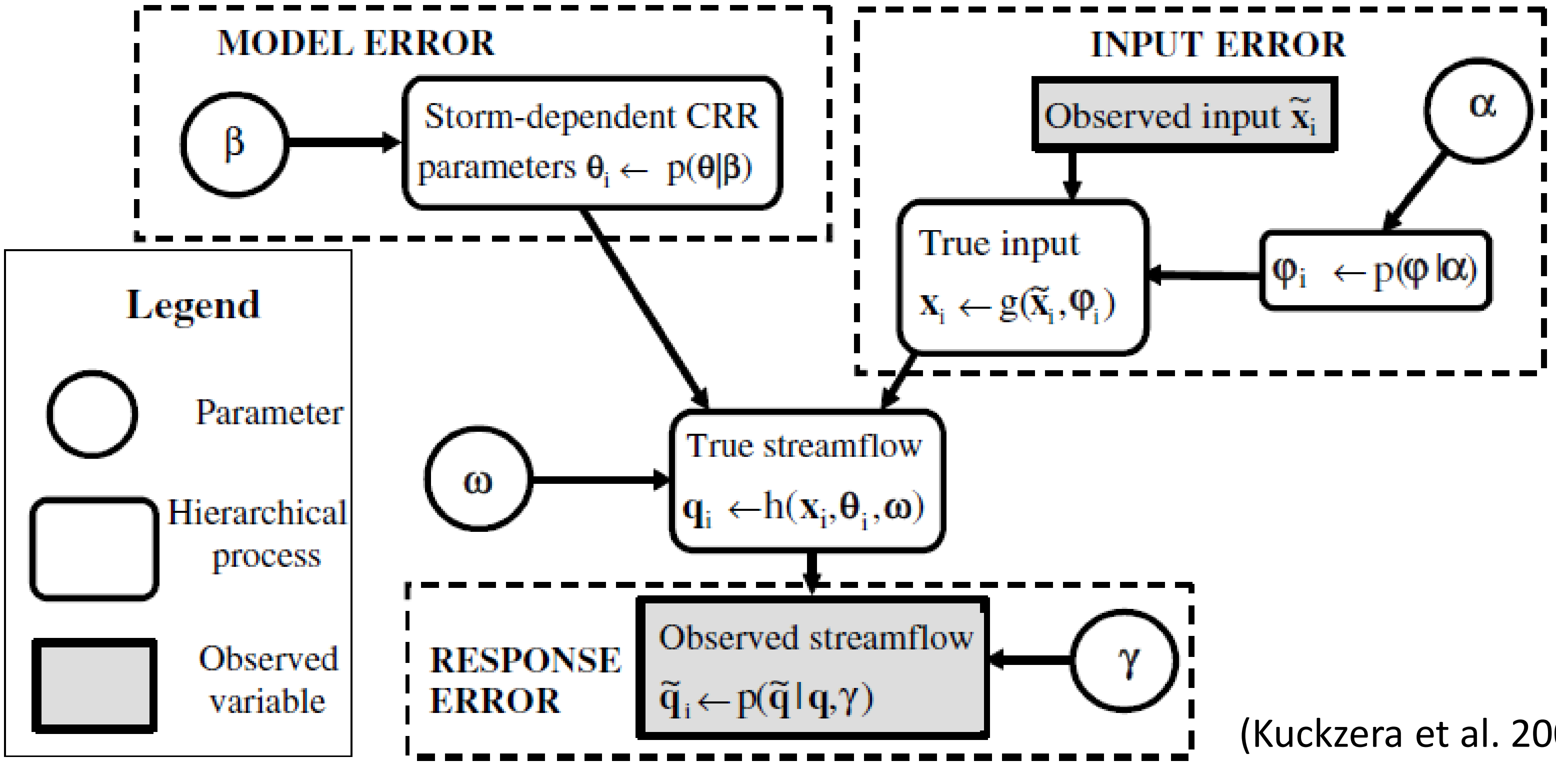
- Testing will continue in both areas (i.e. estimates/modelling and forecasting), critical aspects that must be analysed include:
  - Scale at which adjustment must be done
  - Effect of the density of gauges
  - Conservation of temporal correlation of rainfall fields (so that nowcasting models can properly capture storm movement)
- More merging techniques will be included in the analysis in both contexts (including testing of sensitivity of the Singularity method)
- Based on results, **the best rainfall estimates will be selected** and will constitute the starting point for the uncertainty analysis

2. Uncertainty-based calibration of urban drainage models based upon improved rainfall estimates

Uncertainty-based calibration of urban storm water drainage models explicitly disaggregating input, model and response error using Bayesian strategies.

- In traditional calibration approaches only parametric uncertainty is considered and it is ustilised to represent all sources of error
- Lumping of the different sources of error may lead to parameter bias and may limit the use of hydrological models for predictive tasks
- **Proposal**: apply the **Bayesian Total Error Analysis** framework, which allows disaggregating and separately quantifying the three main sources of uncertainty (i.e. input, model and response uncertainties)

Bayesian Total Errors Analysis (BATEA) framework:



(Kuckzera et al. 2006)

- Error models are formulated for rainfall inputs, hydraulic/hydrological models and response measurements (i.e. flows and depths).
- The posterior distributions of the parameters of the error models are estimated through calibration, thus allowing quantification of the uncertainty associated to each component

Advantages/Applications of this approach

- Allows explicit quantification and thus comparison of the magnitude of different sources of uncertainty
- Improves applicability of models for predictive purposes
- Allows objective comparison of the performance of different rainfall products
- Allows quantification of model structural errors, thus allowing objective comparison between different model structures

Next steps in this direction

- Development of error models for:
  - Rainfall inputs: based on selected rainfall estimates
  - Response measurements: based on calibration of flow and depth gauges
  - Model structure: need to adapt existing approaches applied to large river catchments to urban drainage models
- Implementation of sampling method in order to derive the posterior distribution of the different parameters – this will be computationally demanding, a PC cluster is likely to be used

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Thank you for your attention