Verifying Urban Drainage Models with Variable Rainfall Input

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1. CONTEXT

*"… **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!

Sensors commonly used for estimation of rainfall at catchment scales

Raingauge

Weather Radar

C-Band

X-Band
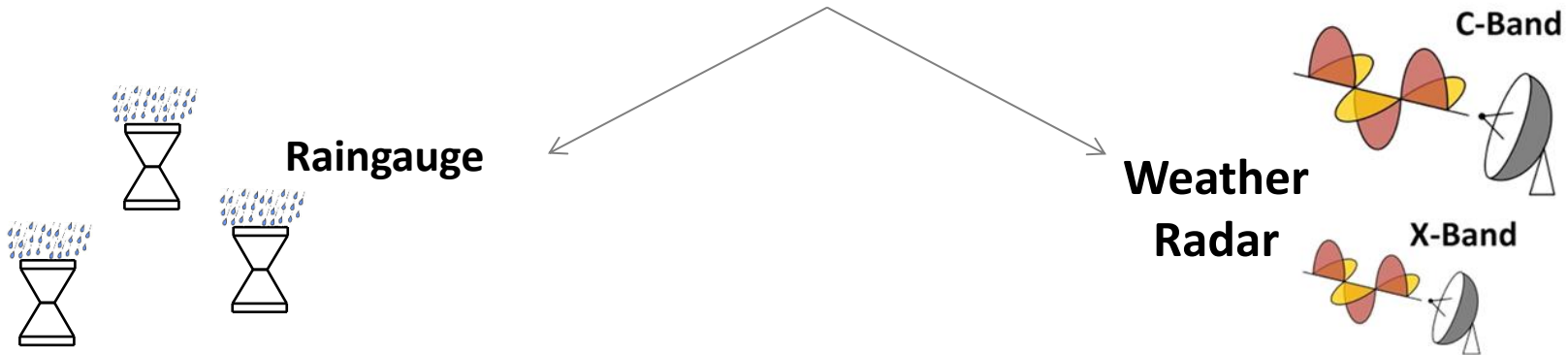
	RAINGAUGE	RADAR
Accuracy	🙂 (yellow)	😐 (green)
Coverage, spatial characterisation of rainfall field	🙁 (red)	🙂 (yellow)

In order to improve the applicability of radar rainfall estimates, these could be adjusted based on raingauge estimates

Dynamic local radar-raingauge merging or adjustment

Aim: To combine the advantages of radar and raingauge sensors to have a better spatial description and local accuracy of urban rainfall

This is not a new concept, but adjustments have been normally applied at large scales and the resulting estimates are still of insufficient accuracy for urban hydrological applications
AND
Suitability of methods for urban scales has not been explored

OBJECTIVE OF THIS WORK

Explore the possibility of improving the applicability of radar rainfall estimates through dynamic gauge-based adjustment, focusing on two aspects:
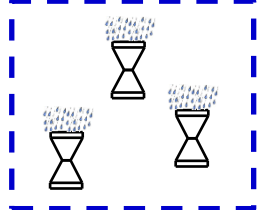
(1) Improving the verification (calibration) process
(2) Impact of gauge density on radar-rain gauge adjustment results
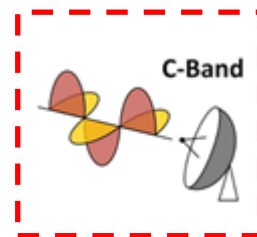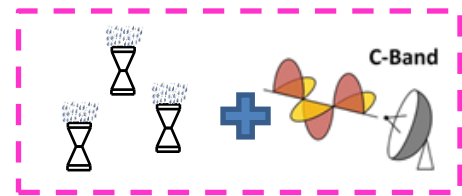
GENERAL METHODOLOGY

Different Rainfall Inputs
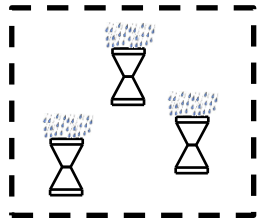
Original raingauge (RG)
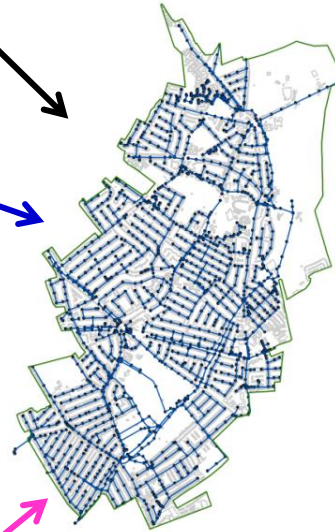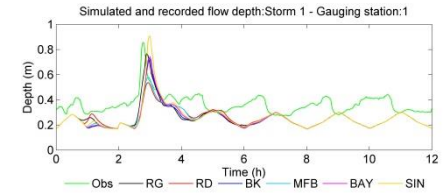
Interpolated raingauge (RG)

C-Band

Original Radar (RD)

C-Band

3 Merged rainfall products

Comparison of hydraulic outputs

NSE, Correlation, Relative Error in peaks
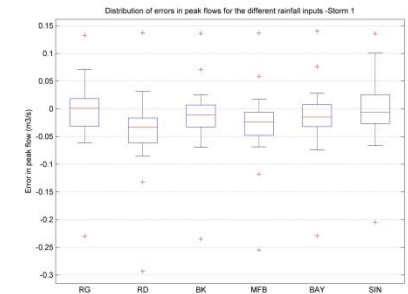
2. RAINFALL PROCESSING TECHNIQUES APPLIED IN THIS STUDY

1. **Block-kriging (BK) interpolation of raingauge values:**

   – Values at unknown locations (i.e. radar grids) are estimated based on the **linear combination** of known neighbouring values

$$Z^*(x_0) = \sum \lambda_i \cdot Z(x_i)$$

   Rainfall estimate at a given radar grid

   Weighting factor estimated based on spatial association of observations

   Known raingauge estimate

   – The interpolated field serves as **baseline for comparison** with other spatial products as well as **starting point** for some of the adjustment techniques

2. Mean field bias adjustment:

– Mean raingauge rainfall records over a specific area are assumed to be truth, able to represent the areal rainfall vol.

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

$$Adjusted\ RadarField_t = Bias_{last\ 1h} \cdot Original\ Radar\ Field_t$$

3. Kriging with External Drift (KED):

- Simple method to include radar rainfall estimates in the raingauge interpolation process

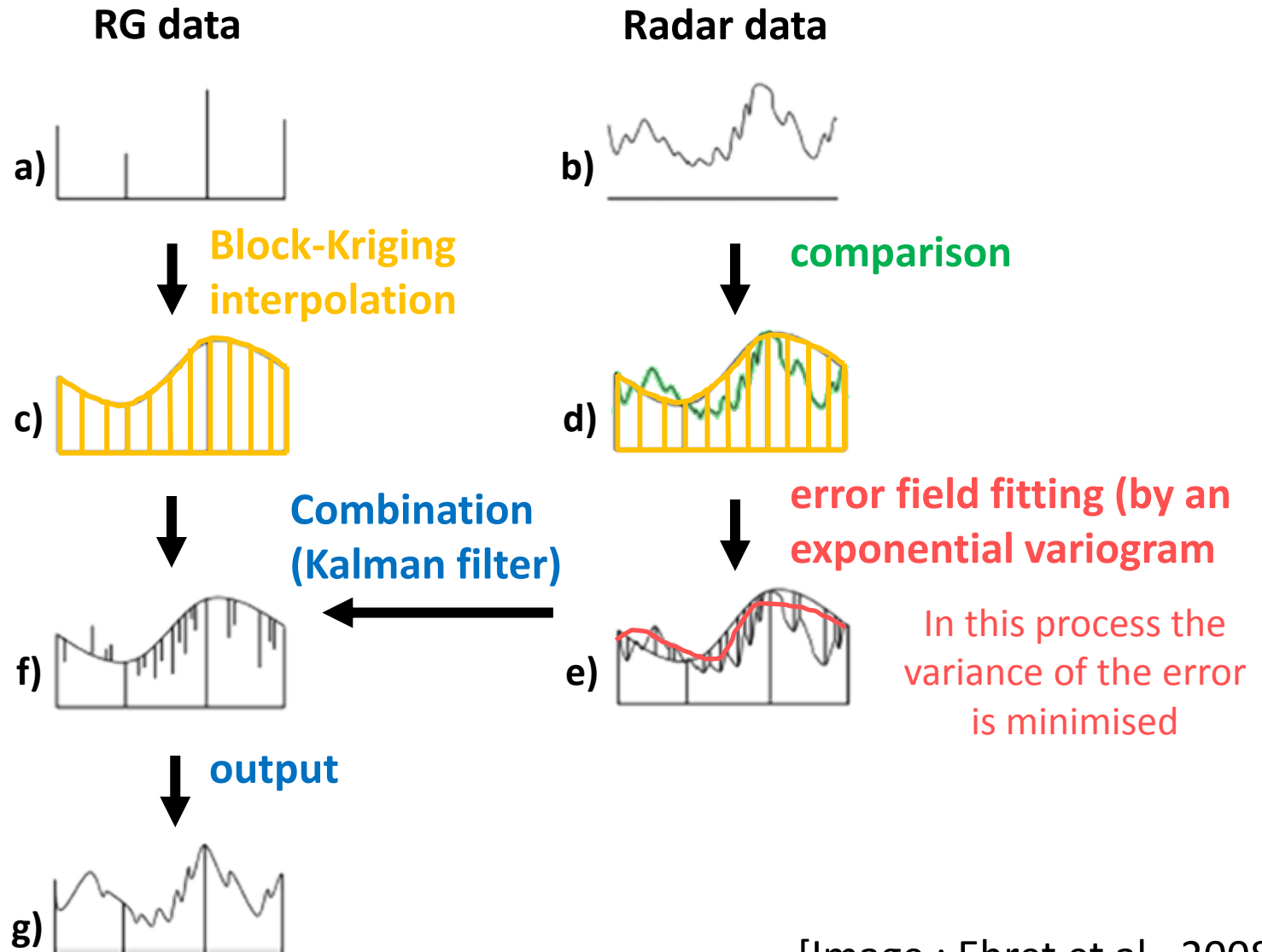- Rainfall estimate at a given point is the linear combination of known raingauge values:

$$Z_{KED}^*(x_0) = \sum_{i=1}^{n} \left(\lambda_i^{KED} \cdot Z_G(x_i) \right)$$

- The weighting factor λ_i^{KED} is constrained by the spatial association between radar values

3. Bayesian (BAY) gauge-based radar rainfall merging:

– Main idea: analyse the uncertainty of rainfall estimates from different sources (in this case radar and raingauge sensors) and combine them such that the overall uncertainty is minimised

Principle of Bayesian Data Combination

RG data

Radar data

a)

b)

Block-Kriging interpolation

comparison

c)

d)

Combination (Kalman filter)

error field fitting (by an exponential variogram

f)

e)

In this process the variance of the error is minimised

output

g)

[Image : Ehret et al., 2008]
[Source: Todini, 2001]

4. Singularity-Sensitive Bayesian (SIN) gauge-based radar rainfall merging:

– Recently developed to overcome a shortcoming of the original Bayesian (BAY) and other merging methods, which tend to smooth storm extremes initially observed in radar images

– This method identifies **local extremes** (i.e. **singular points**) and extracts them from the radar image before the merging takes place. After the merging is finished, the singularities are applied back and proportionally to the rainfall field.

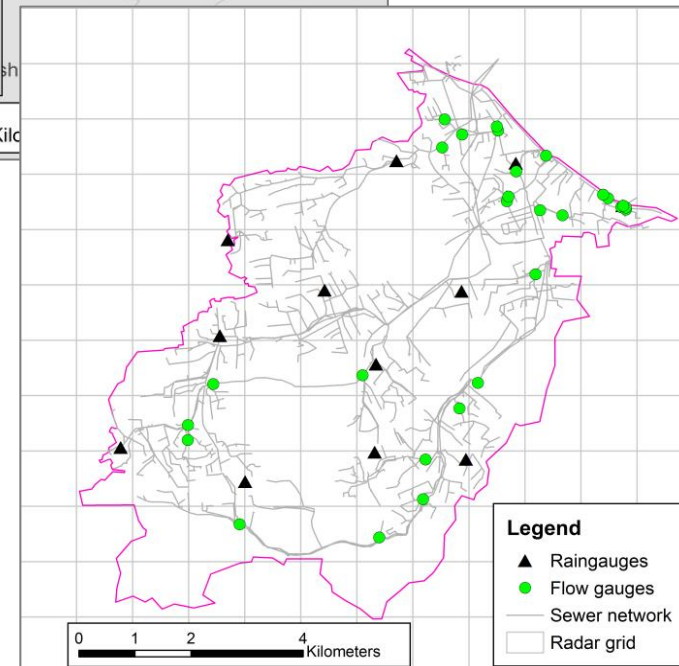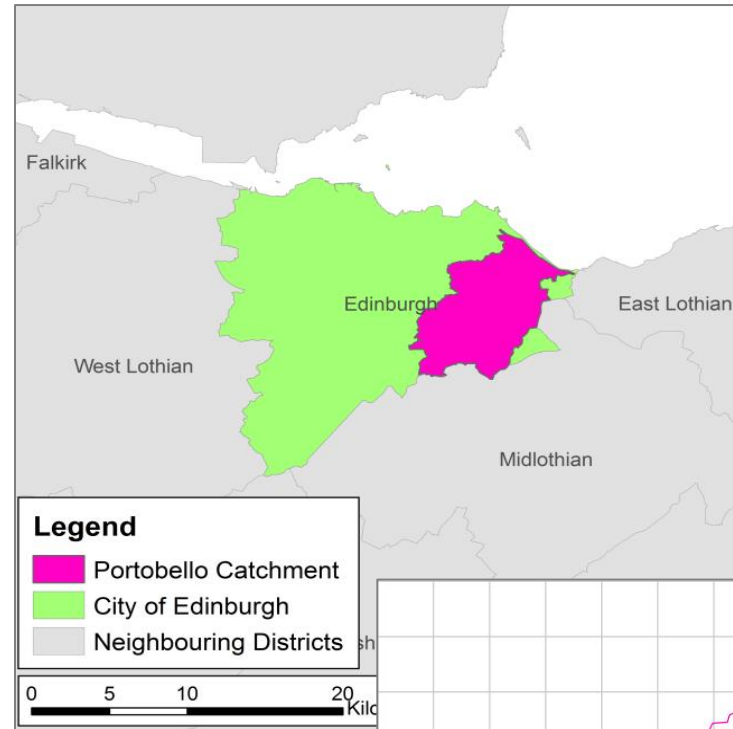Original Radar → Non –Singular Radar → Merged → Singularity Back
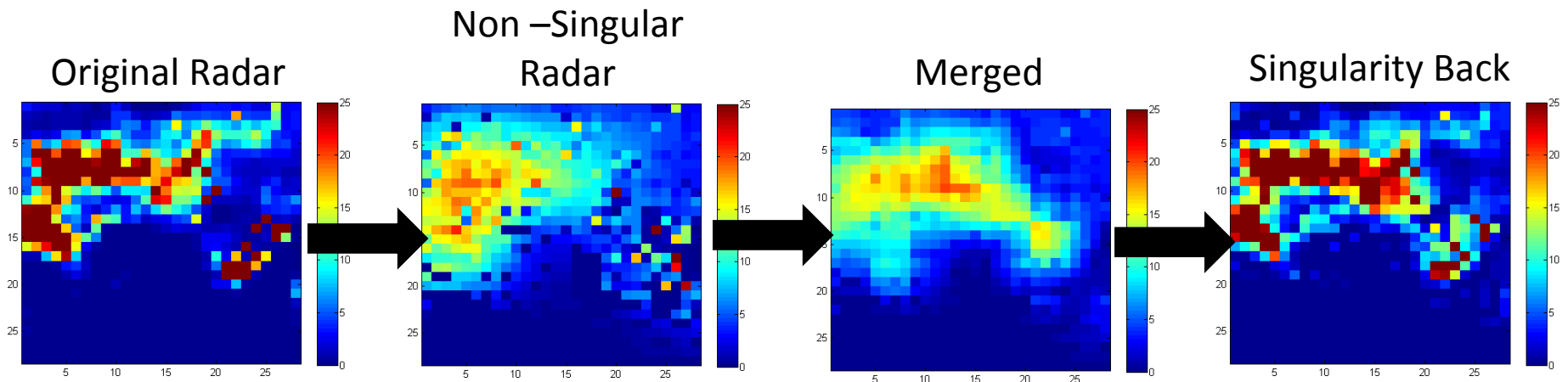
3. EXPERIMENTAL CATCHMENTS AND DATASETS

- Cranbrook catchment, London
- Portobello catchment, Edinburgh

SW BIRMINGHAM

- **Drainage area:** 67 km^2

- Urbanised

- Sewer model in InfoWorks CS:

  - 2,916 nodes and 2,906 conduits, subcatchments

  - Verified in 2011 using same flow survey used in this study

- Local monitoring data from medium term flow survey carried out between Apr-Jun'11

  - 12 raingauges

 - 32 flow gauges

Legend
- Portobello Catchment
- City of Edinburgh
- Neighbouring Districts

Legend
- ▲ Raingauges
- ● Flow gauges
- Sewer network
- Radar grid

PORTOBELLO CATCHMENT, EDINBURGH

Storm events used 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)

RADAR DATA AVAILABLE FOR BOTH CATCHMENTS

For both catchments Nimrod (multi-radar composite) data with 1 km and 5 min resolution are available
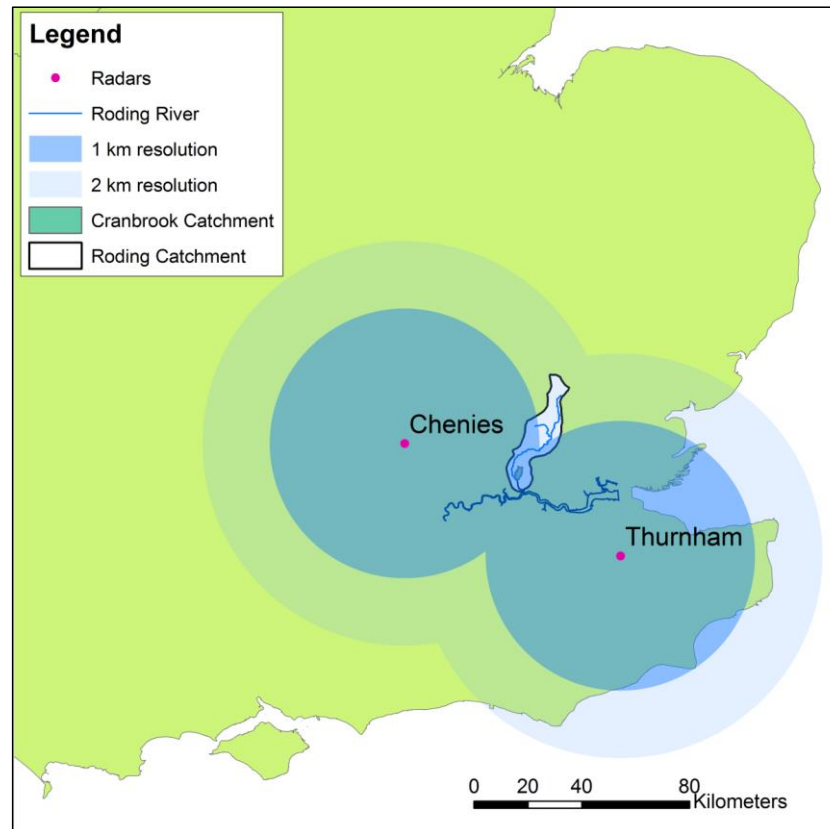
3. RESULTS - RAINFALL

- 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

Rainfall Estimates	CRANBROOK CATCHMENT		PORTOBELLO CATCHMENT		
	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

| Rainfall Estimates	CRANBROOK CATCHMENT		PORTOBELLO CATCHMENT		
	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

Rainfall Estimates	CRANBROOK CATCHMENT		PORTOBELLO CATCHMENT		
	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

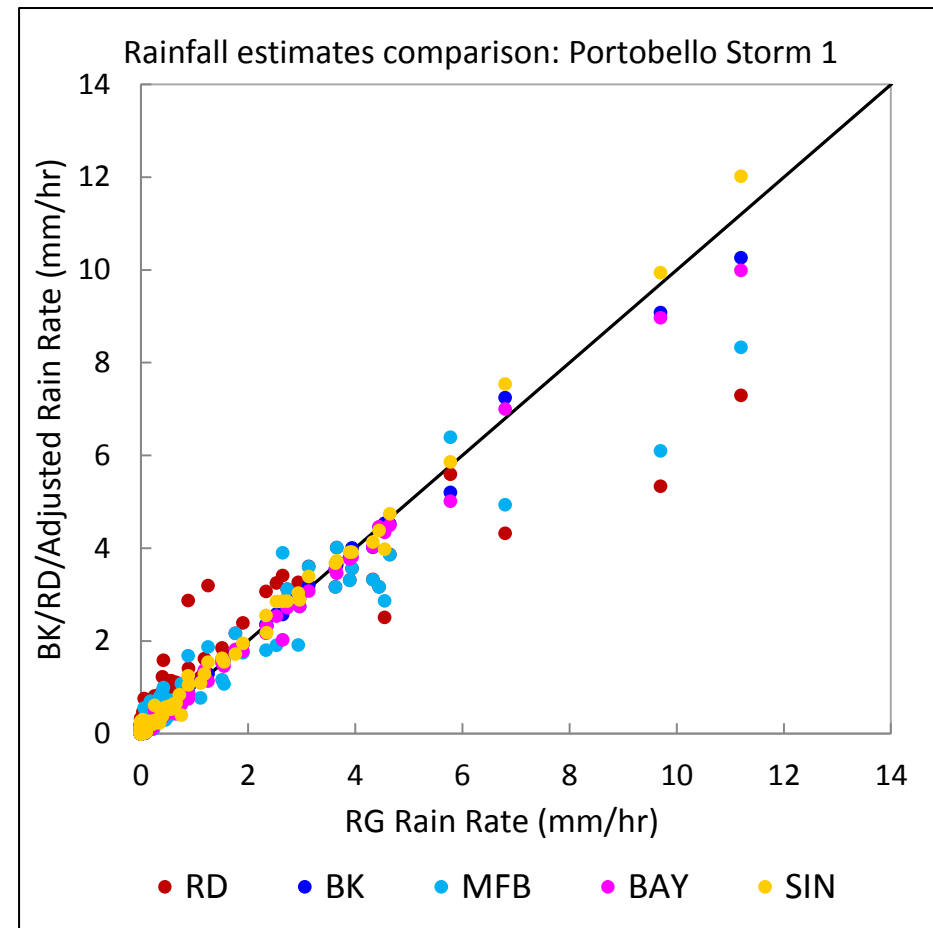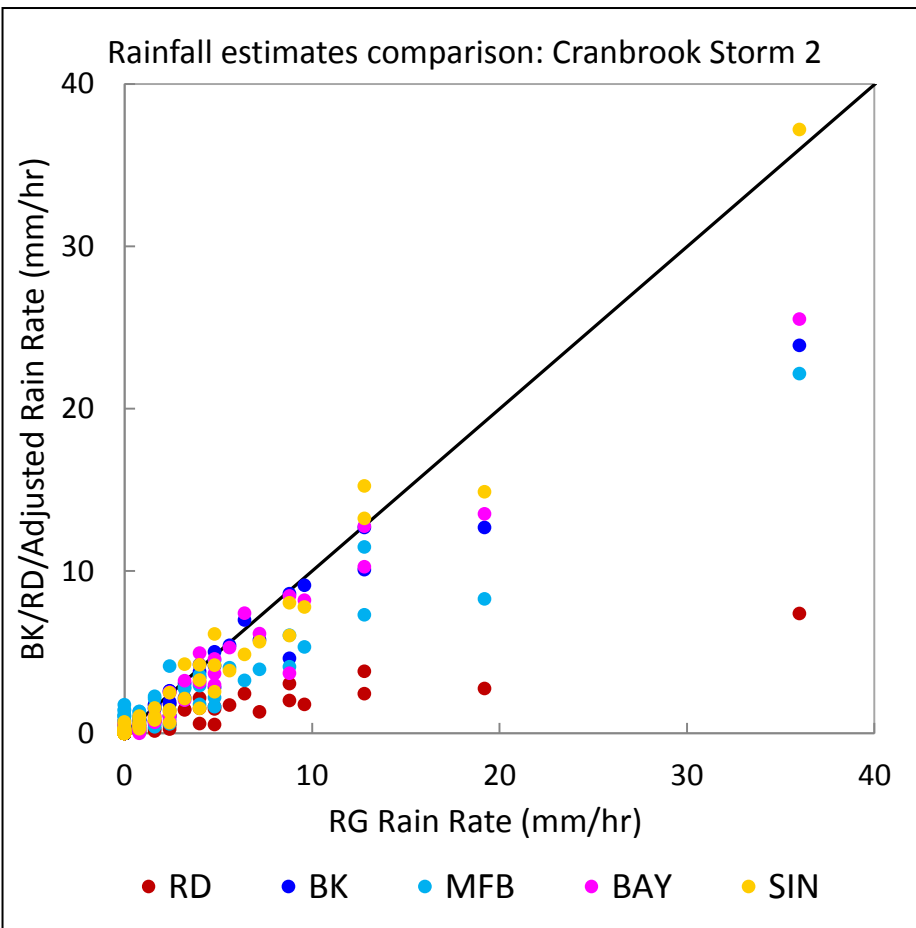# Cranbrook catchment – peak intensity image (Storm 2)

RD BK MFB BAY SIN
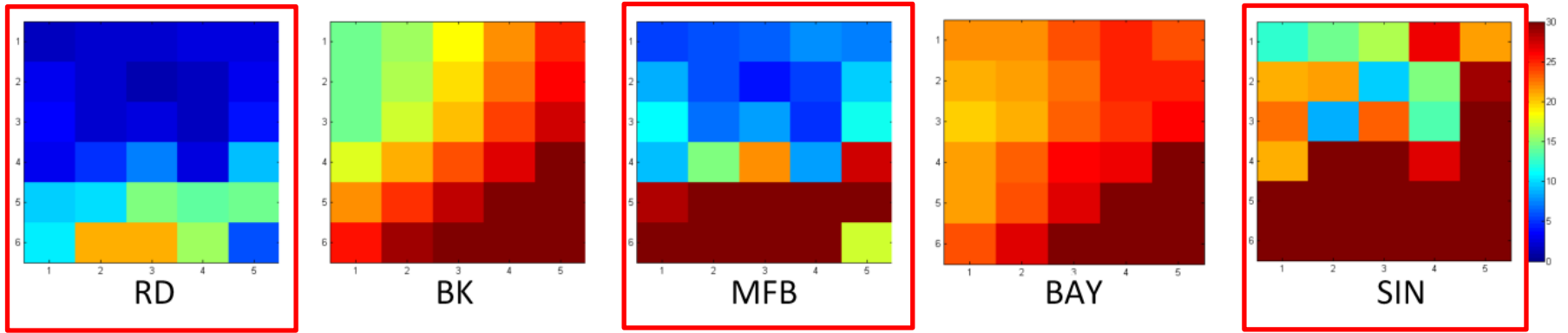
Portobello catchment – peak intensity image (Storm 1)

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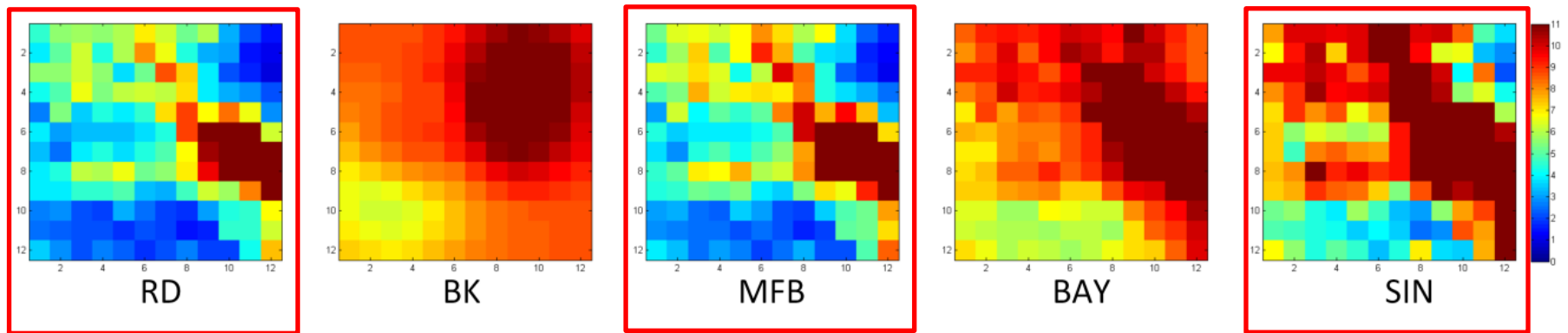
MFB and BAY methods can better preserve the spatial variability
of the rainfall field, as originally captured by the radar

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

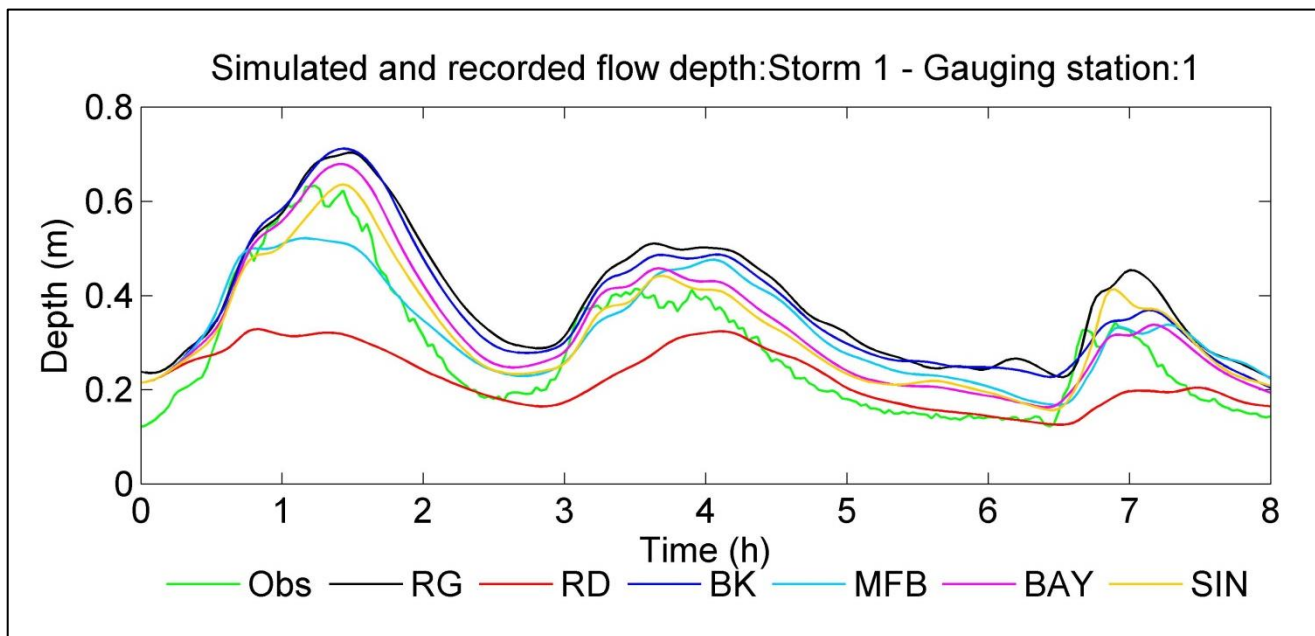- Bayesian techniques (especially SIN) can properly reproduce low as well as high intensities

4. RESULTS – HYDRAULIC OUTPUTS

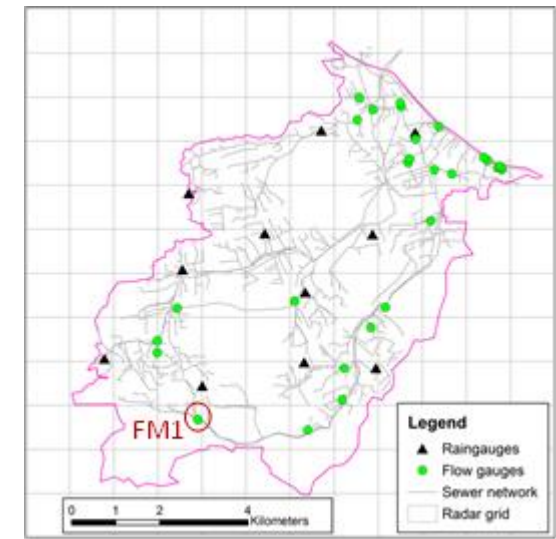# CRANBROOK CATCHMENT: Observed vs. Simulated flow depth at mid-stream gauging station (Storms 1 and 2)
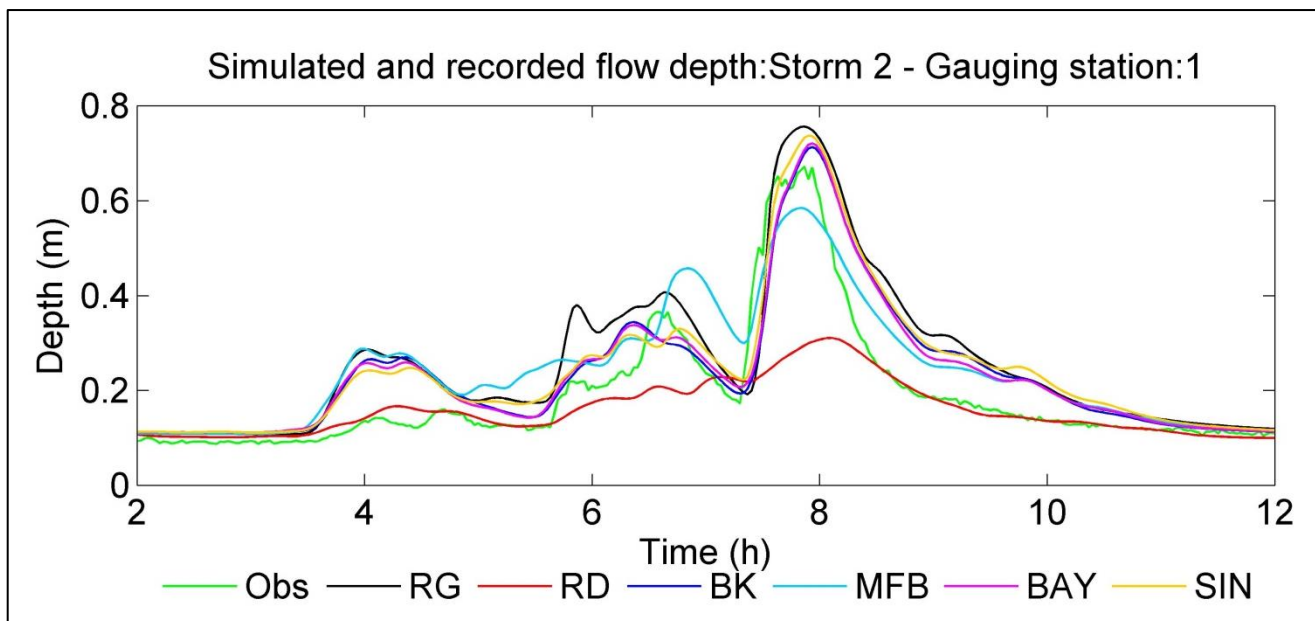

- RD largely underestimates

- MFB not enough

- BAY and SIN perform very well, even better than original RG

# CRANBROOK CATCHMENT: Performance Measures

Performance Measures/ Rainfall estimates	RG	RD	BK	MFB	BAY	SIN
Storm 1						
RE in peak depth	0.111	-0.481	0.125	-0.176	0.073	0.004
R – depth	0.874	0.618	0.881	0.814	0.913	0.902
NSE – depth	0.283	0.315	0.452	0.696	0.772	0.800
Storm 2						
RE in peak depth	0.126	-0.538	0.061	-0.130	0.072	0.098
R – depth	0.838	0.751	0.808	0.813	0.834	0.857
NSE – depth	0.522	0.492	0.680	0.658	0.711	0.676

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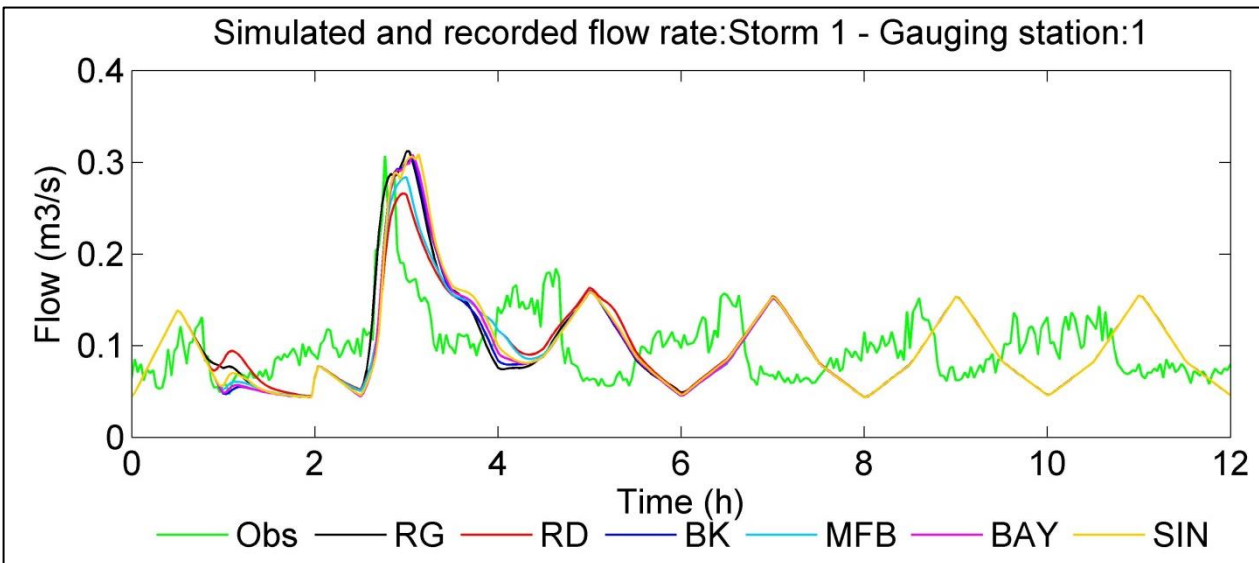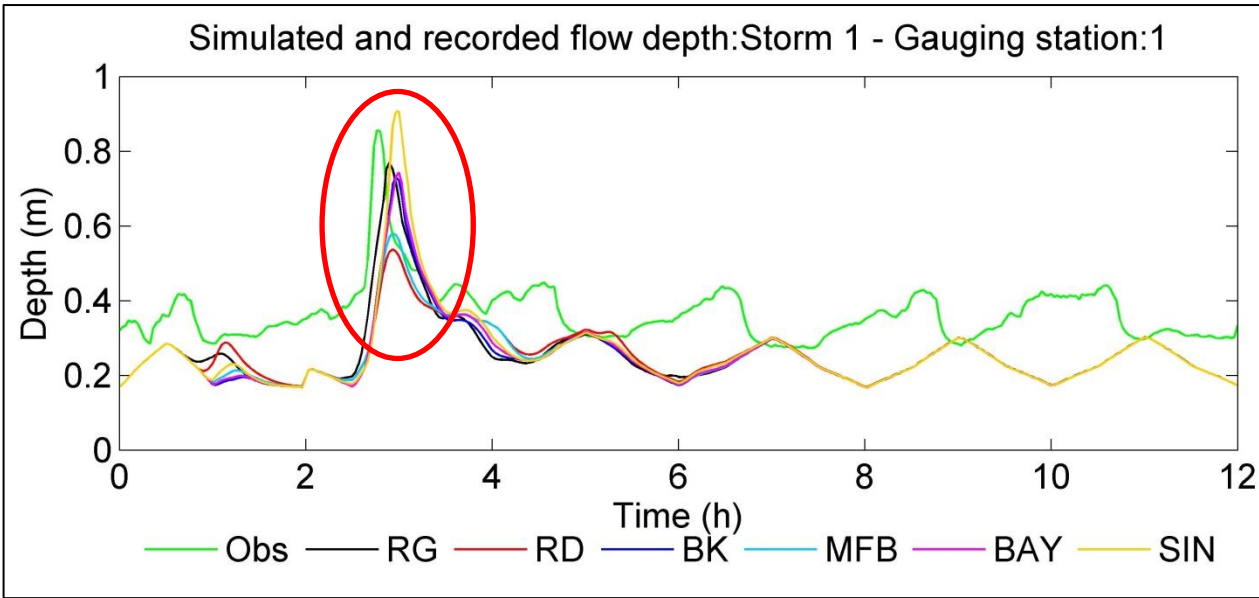

- In spite of small RG/RD bias, RD underestimates peaks

- MFB not enough

- BAY ok

- SIN better at capturing peak

PORTOBELLO CATCHMENT : Observed vs. Simulated flow depth and rate at mid-stream gauging station
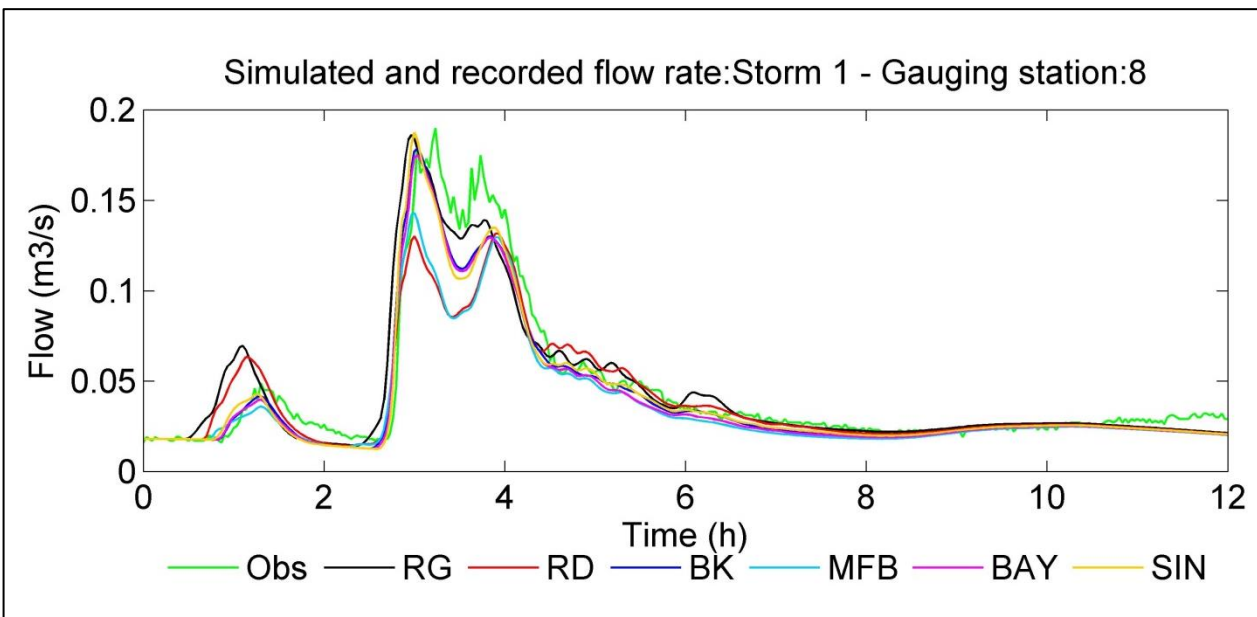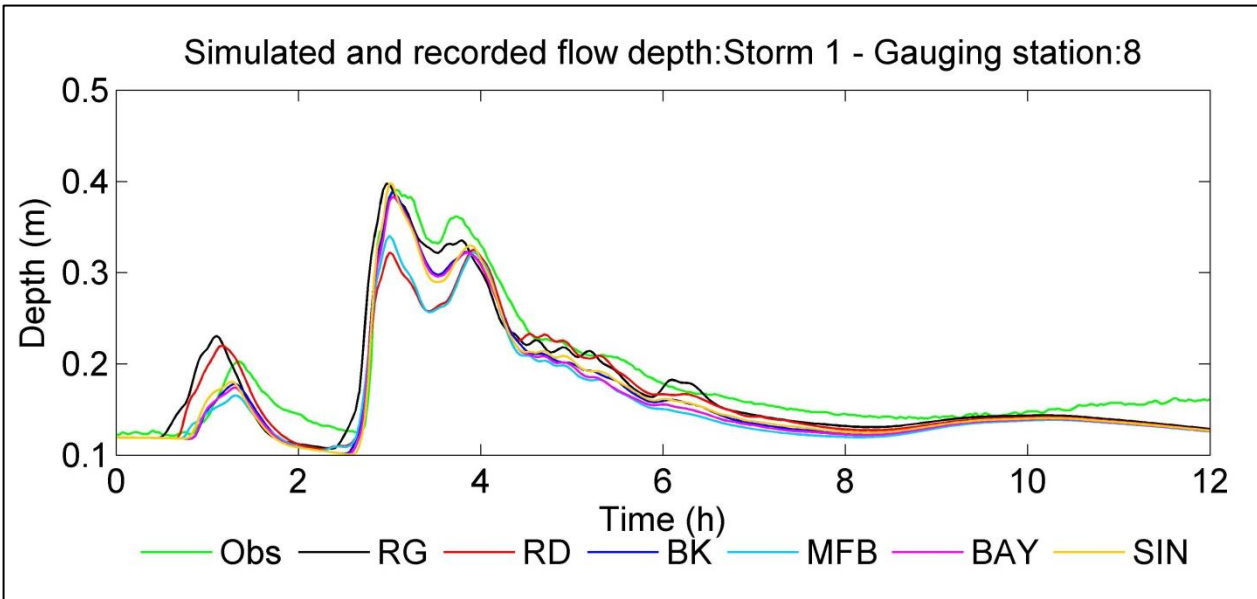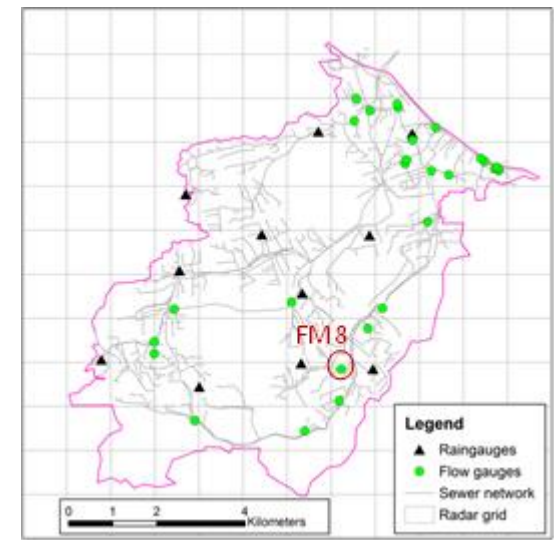
Simulated and recorded flow depth:Storm 1 - Gauging station:8

Simulated and recorded flow rate:Storm 1 - Gauging station:8

- In spite of small RG/RD bias, RD underestimates peaks
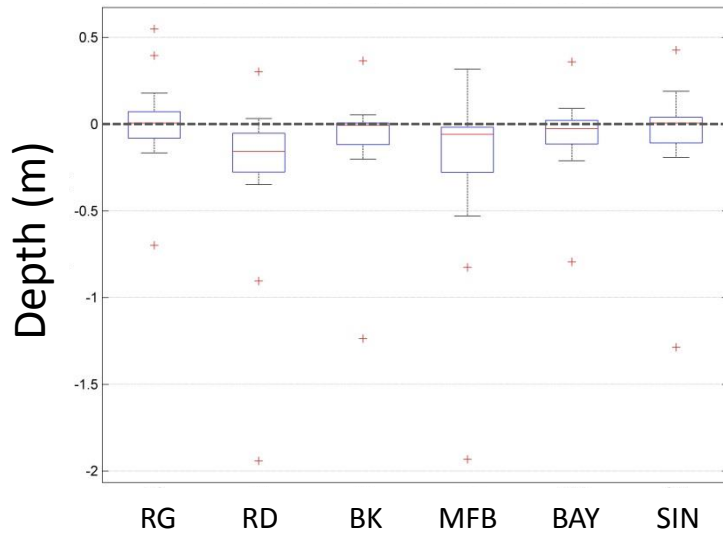
- MFB not enough

- BAY and SIN perform well

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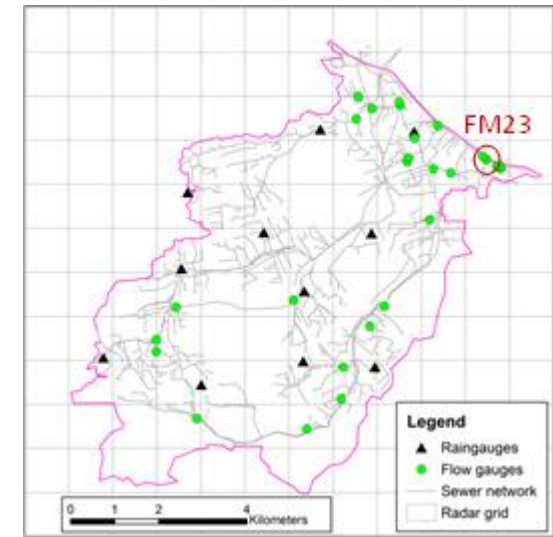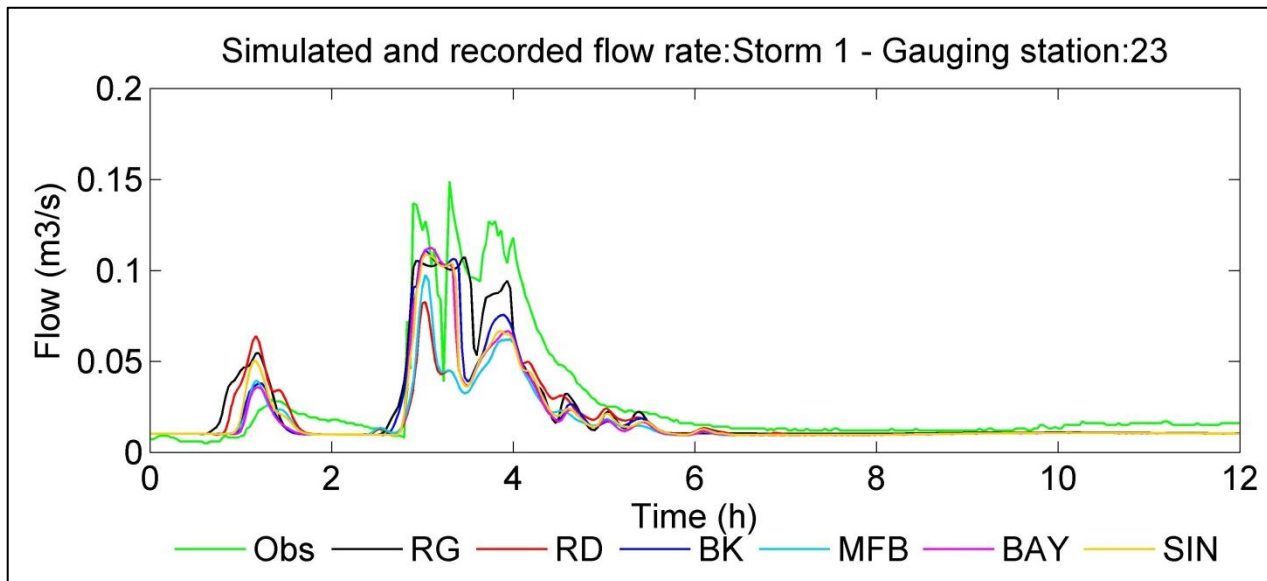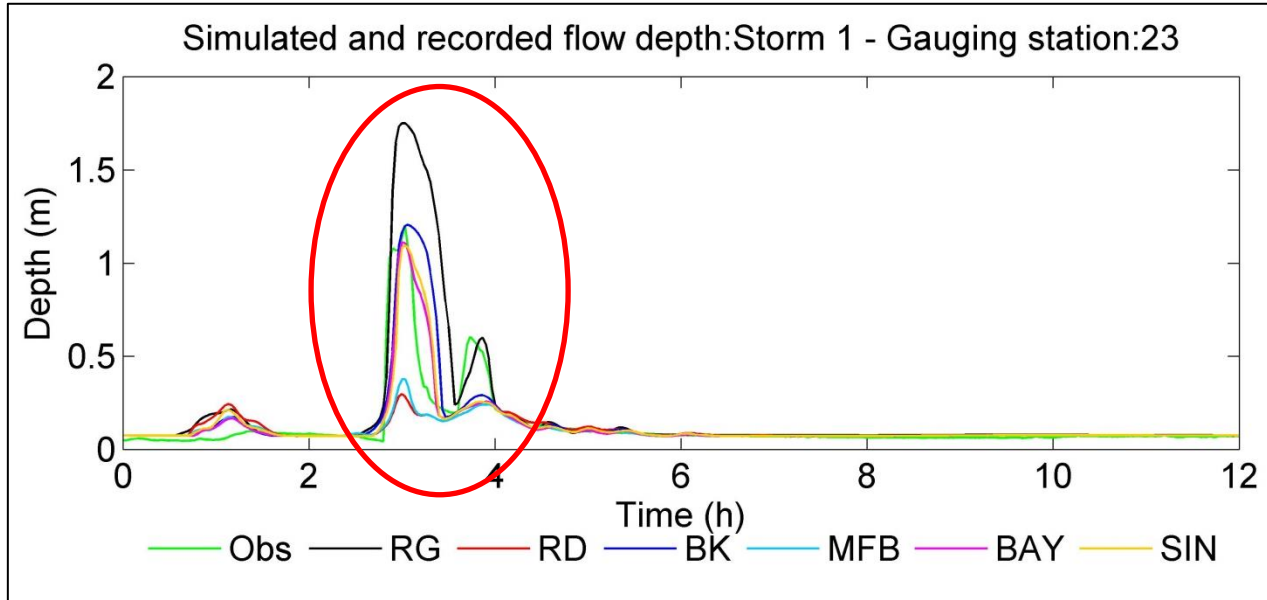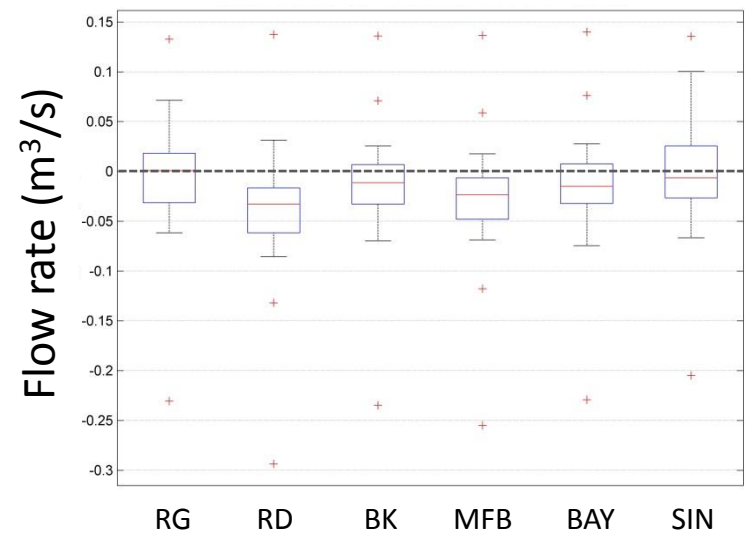

- RD underestimates even more (cumulative effect?)

- MFB not enough

- RG overestimates peak

- **Even BK performs better than RG**

- BAY and SIN perform well

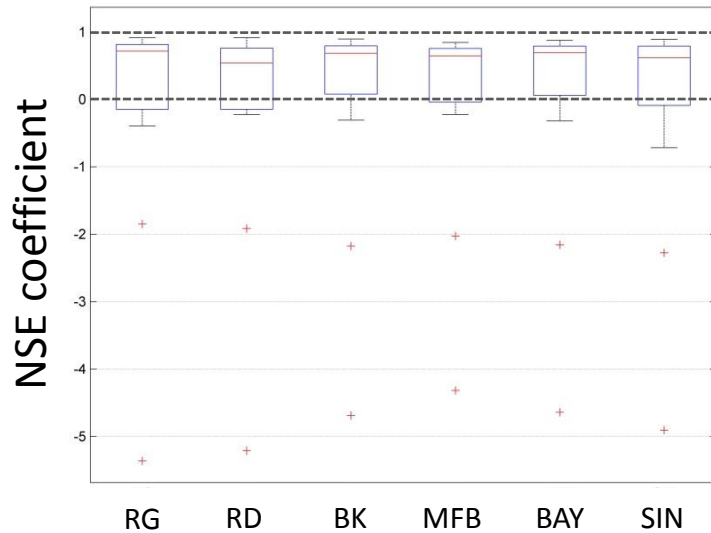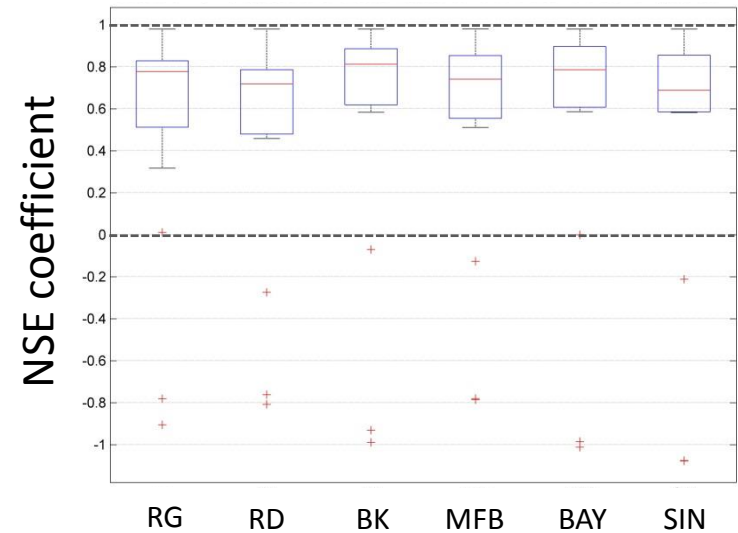# PORTOBELLO CATCHMENT: Performance Measures (Storm 1)

Errors in peak depths

Errors in peak flow rates

NSEs for simulated flow depths

NSEs for simulated flow rates

5. CONCLUSIONS AND FUTURE WORK

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 clearly evident in an operational context**, such as the one analysed in the Cranbrook catchment. 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 a **verification context** (i.e. Portobello catchment), 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**.

Future Work

- A lot more testing required!

- Re-verify models using merged estimates as input (or as an alternative data source)

- Analyse impact of raingauge density. The benefits of the merging are likely to become more evident when fewer gauges are available!

- Analyse scale at which adjustments should be applied

- Analyse sensitivity of the Bayesian singularity-sensitive to the degree of "singularity" that is removed

Main 'Message'

- Weather radar is a valuable source of data, but must be used carefully

- Merging has shown potential to improve radar estimates thus leading to improved model outputs (and very likely improved model calibration/verification), but more testing is needed

- I want you to know that there are techniques available for improving the applicability of radar estimates

- Radar has happened since 2002! maybe worth mentioning in the new code of practice?

THANK YOU

Susana Ochoa-Rodríguez

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Why we need to adjust radar rainfall data?

Beal HS raingauge rainfall depth accumulations: 23/08/2010 event
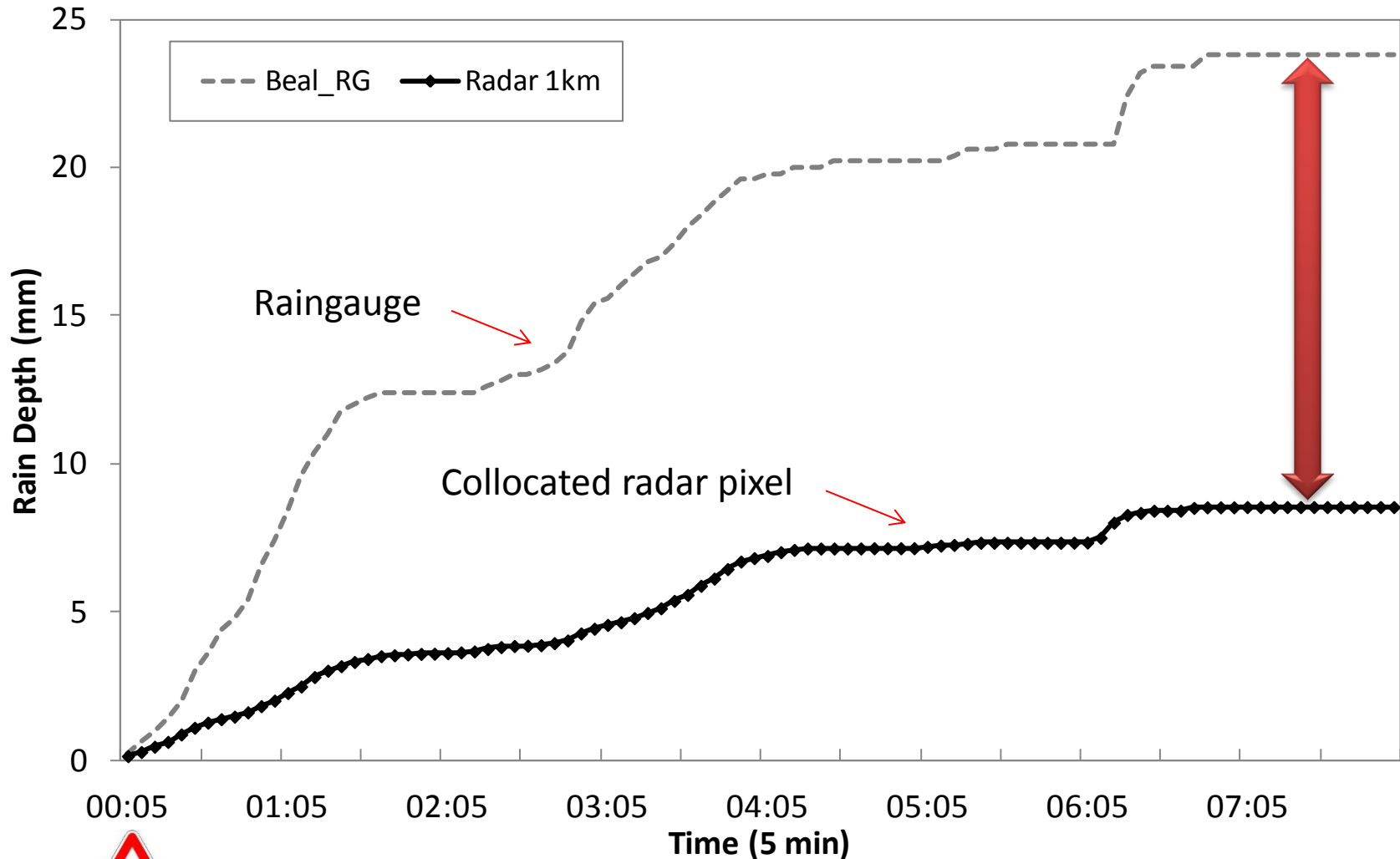
Urban drainage models are normally calibrated using raingauge data

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)

Error field fitting

f)

Singularity recovery

Combination (Kalman filter)

g)

h)

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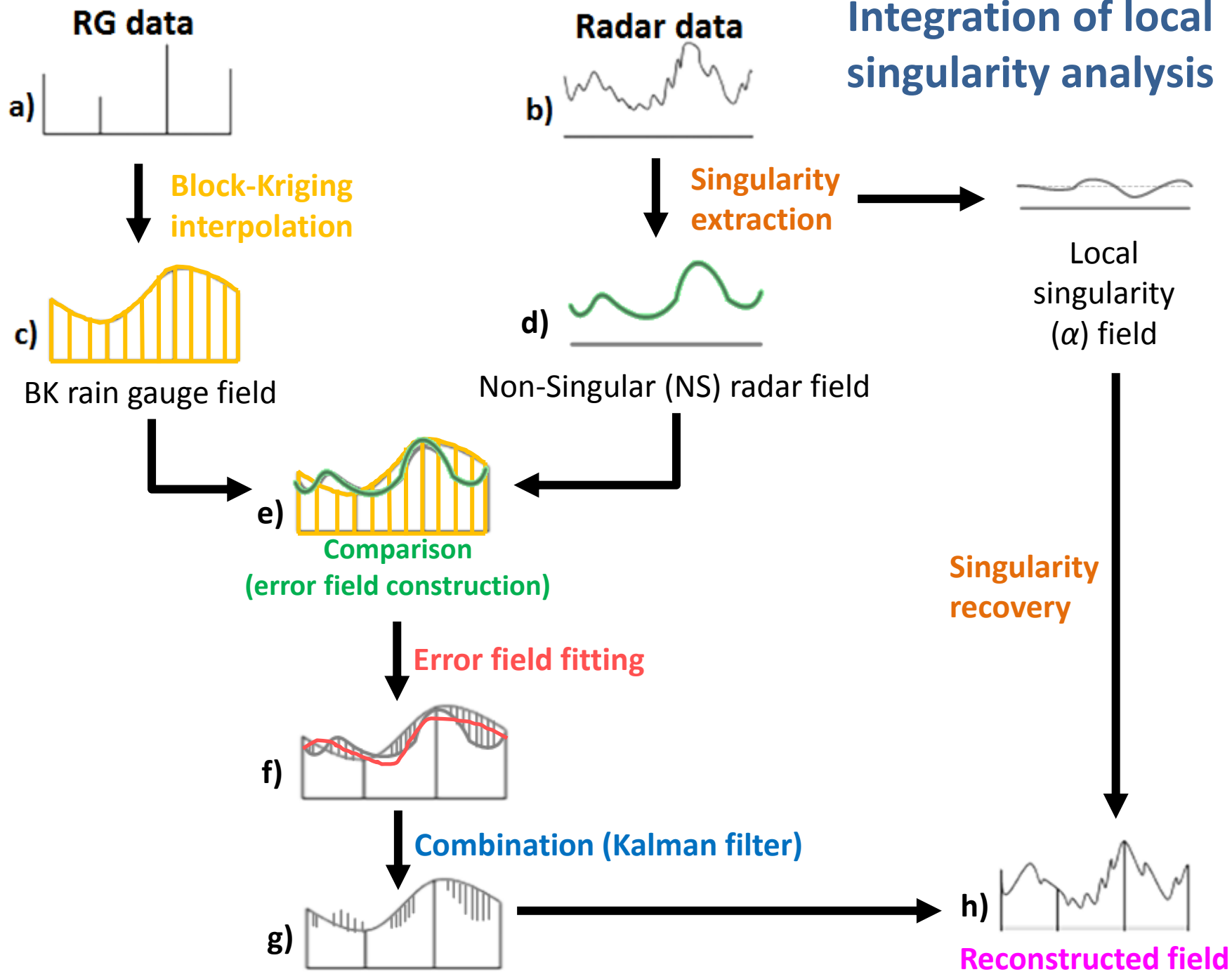
Images at each step of the Bayesian data merging with/without local singularity analysis

Nimrod (Original)
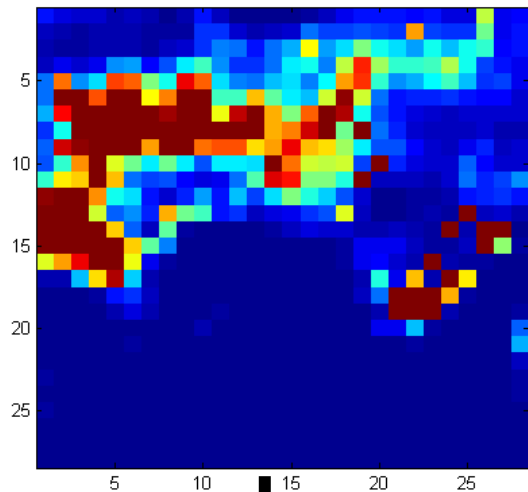
Block-Kriged RGs
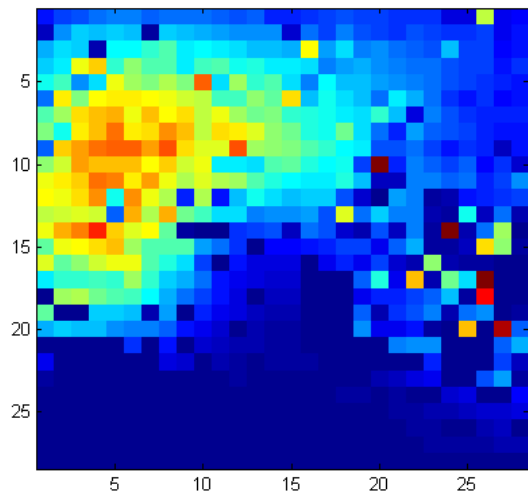
Bayesian Merged
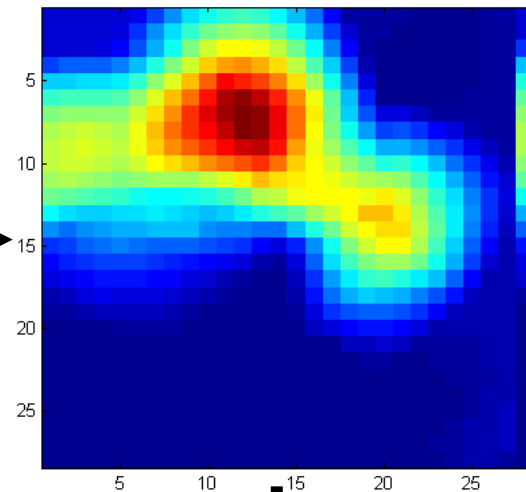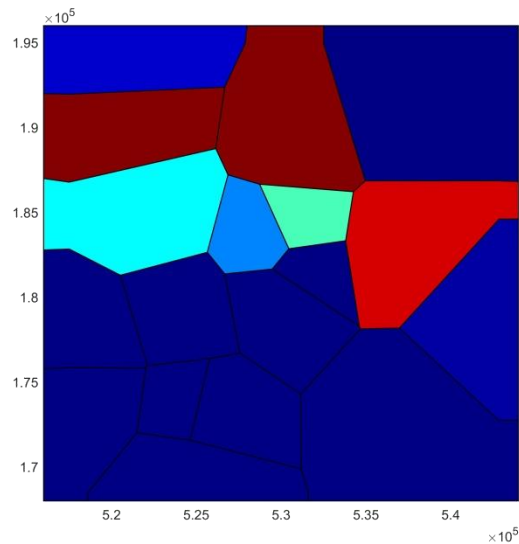
Non-singular Radar
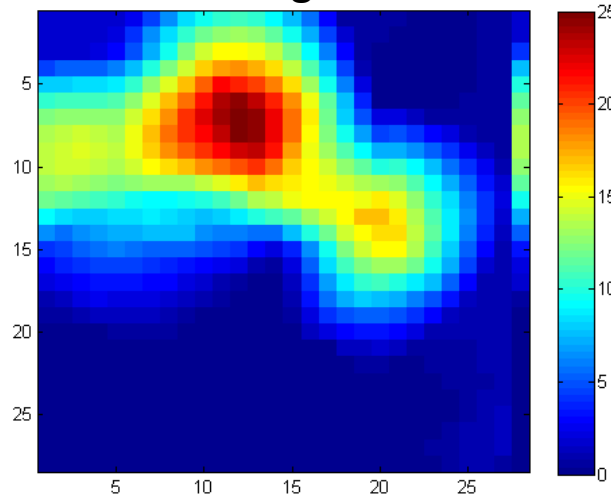
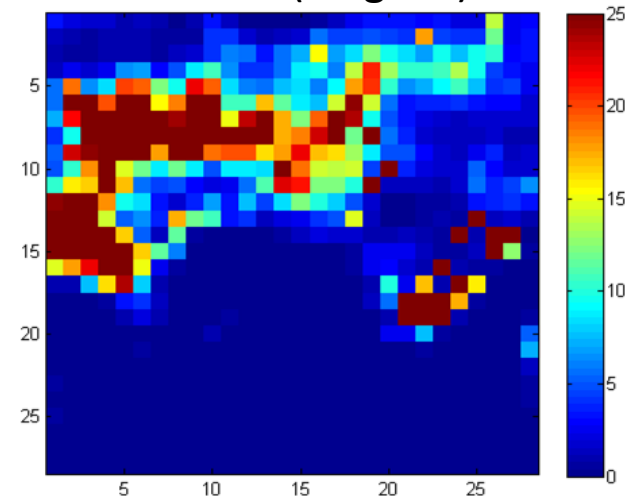Non-singular Merged
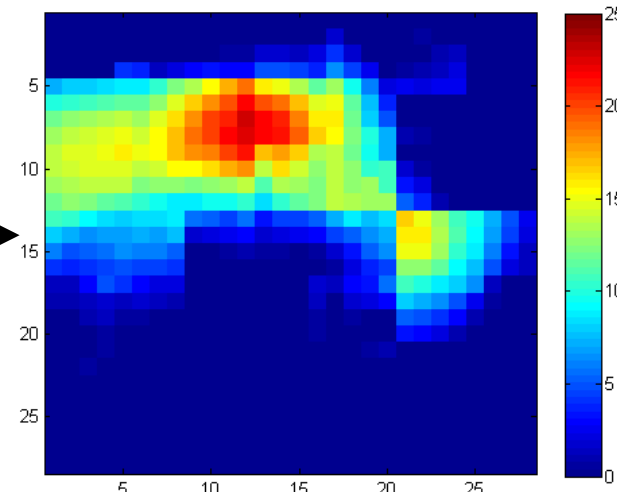
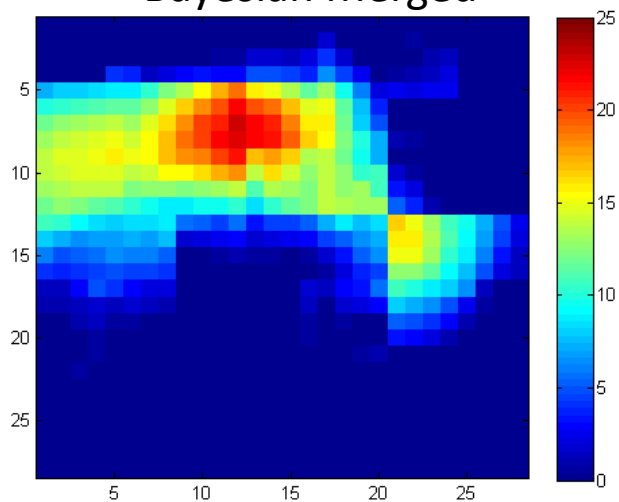Singularity-sensitive Merged

FINAL PRODUCTS

Block-Kriged RGs

Nimrod (Original)

Bayesian Merged

Singularity-sensitive Merged