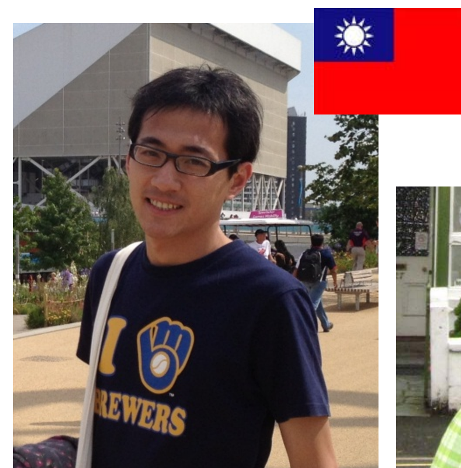
Imperial College
London

9th International Conference on Urban Drainage Modelling
Belgrade 2012

Radar-raingauge data combination techniques:

A revision and analysis of their suitability for urban hydrology



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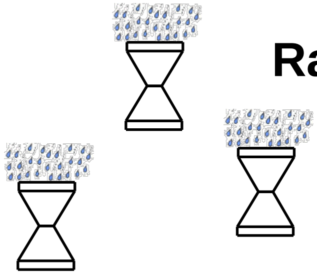
4th September 2012, Belgrade

*"… **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 types of flooding… "*

(Golding, 2009)

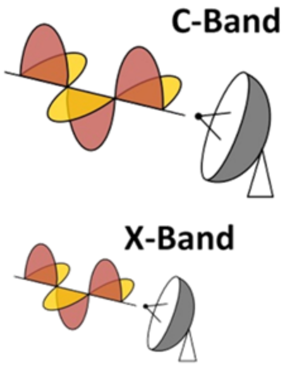
We really need to get the rainfall right!

Sensors commonly used for estimation of rainfall at catchment scales



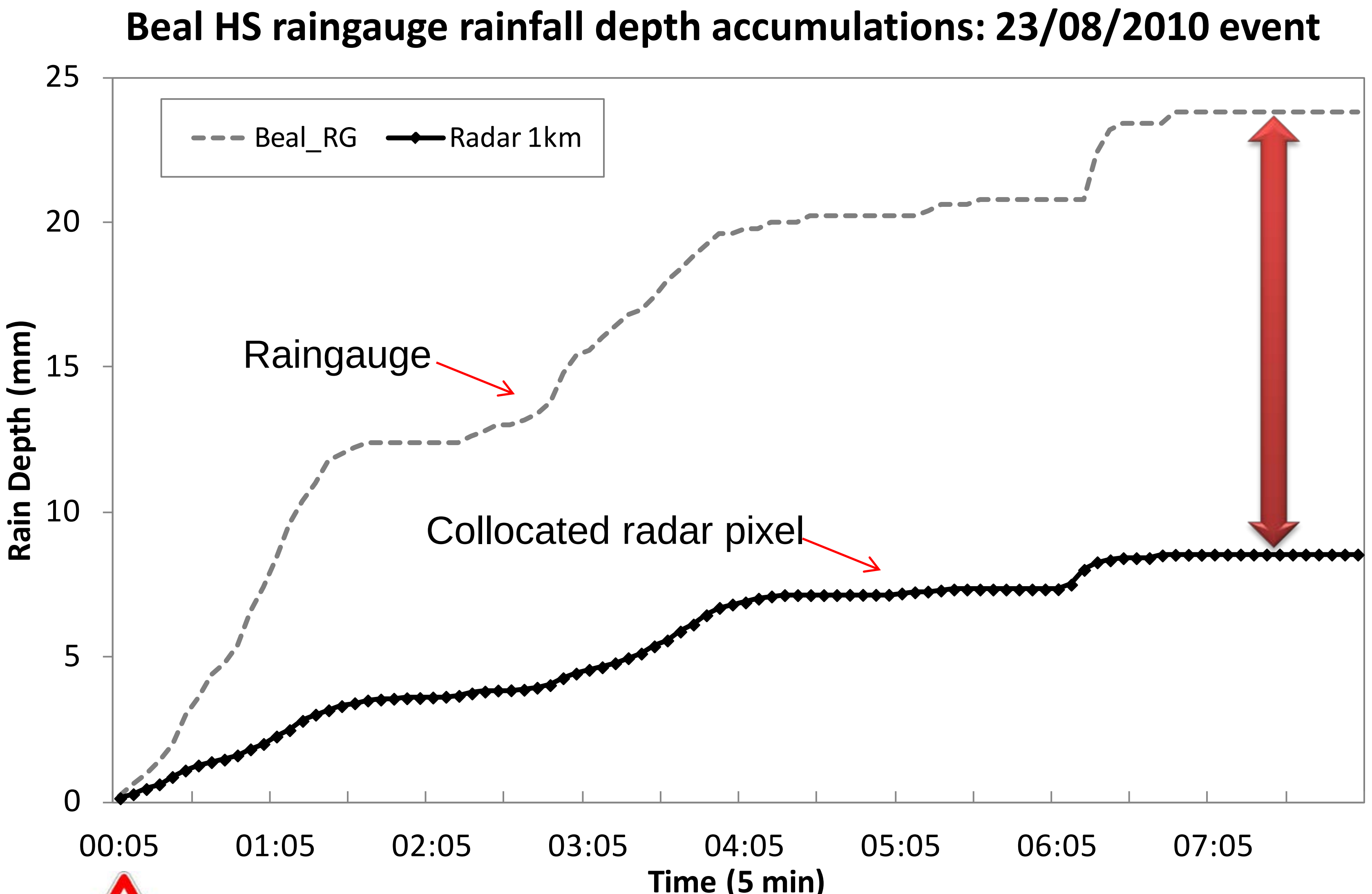
Raingauge

Weather Radar



	RAINGAUGE	RADAR
Accuracy		
Coverage, spatial characterisation of rainfall field		

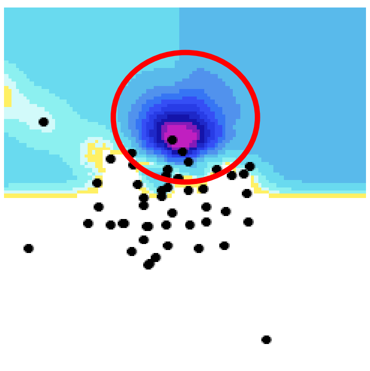
Why we need to adjust radar rainfall data?



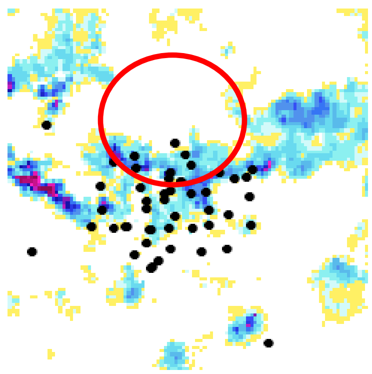
Urban drainage models are normally calibrated using raingauge data

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

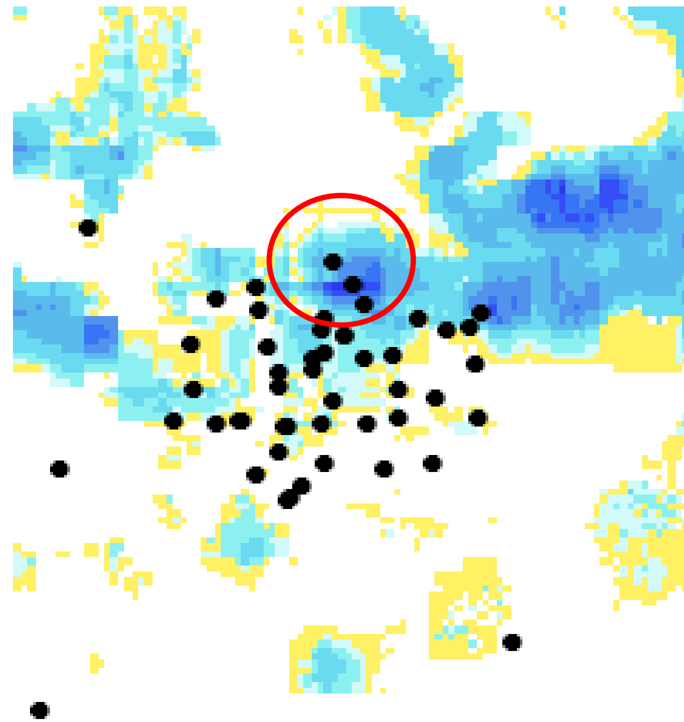
Interpolated rainfall field



Radar image



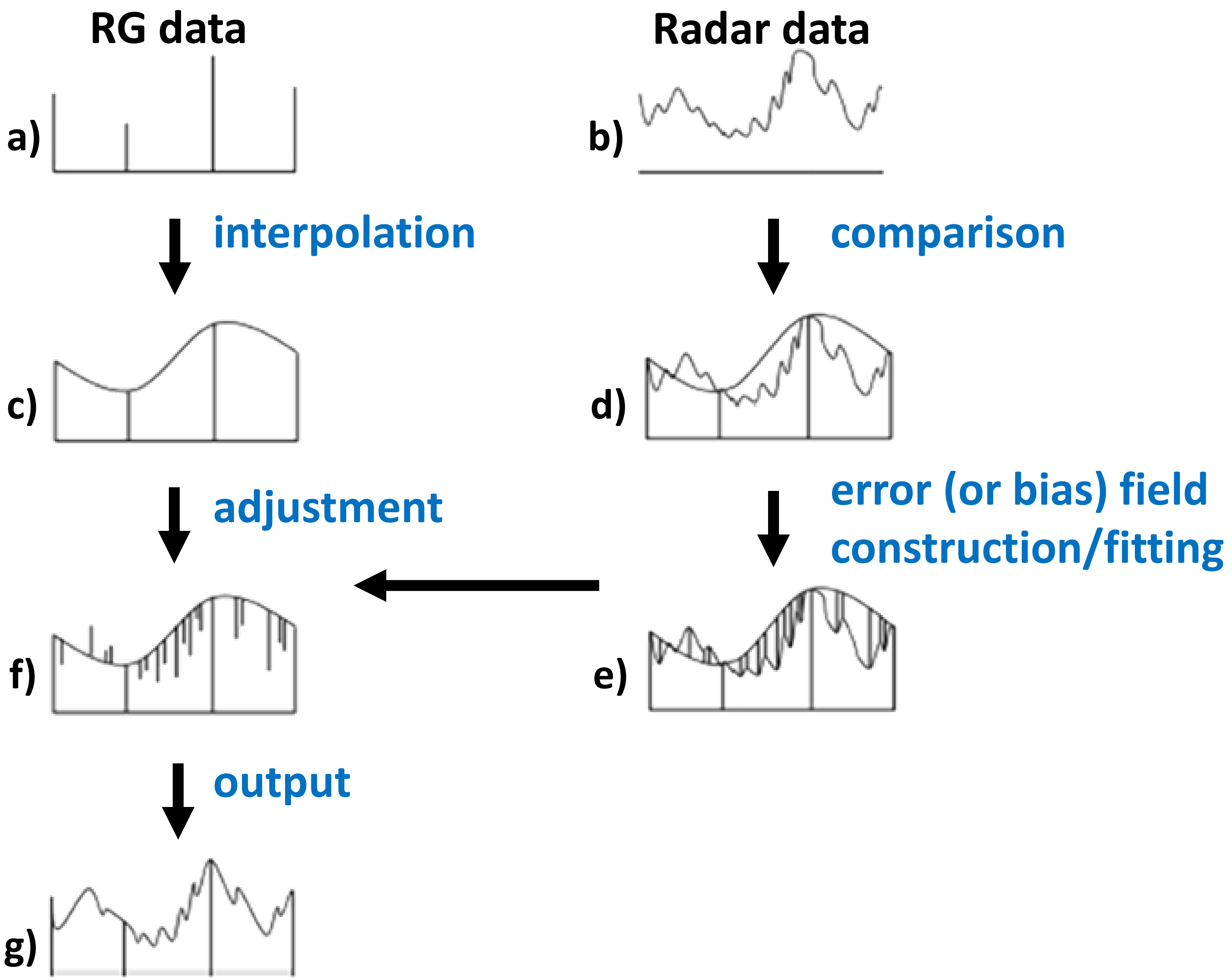
Output rainfall field



Contents

1. Basic principle of gauge-based radar rainfall adjustment techniques
2. Mean bias correction methods
   - Sample bias ratio
3. Error variance minimisation methods
   - Bayesian data combination
4. Case study
   - Cranbrook catchment (5 X 6 km^2) in London, UK
   - Adjusted rainfall fields
   - Subsequent hydraulic outputs
5. Conclusions and future work

1. Basic principle of gauge-based radar rainfall adjustment techniques



[Source: Ehret et al., 2008]

Based on their assumption, gauge-based radar rainfall adjustment techniques can be classified into two types

Mean Bias Correction

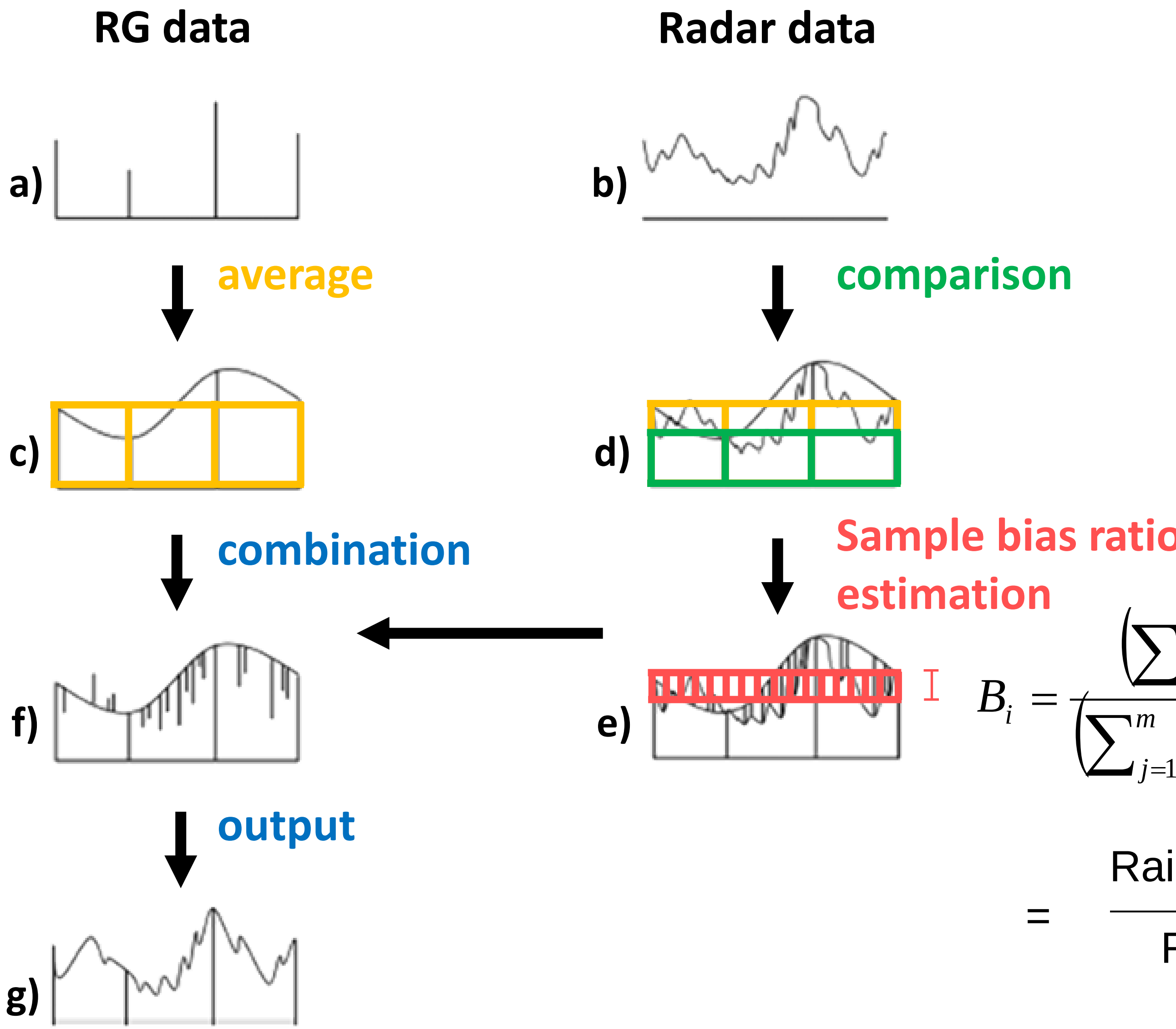
Error Variance Minimisation

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

2. MEAN BIAS CORRECTION

- Raingauge mean records are fully trusted
- After adjustment: radar data must have the same mean as raingauge data

Example: Sample Bias Ratio Adjustment



$$B_i = \frac{\left(\sum_{j=1}^{m} RG_{ij}\right)/m}{\left(\sum_{j=1}^{m} R_i\left(x_j, y_j\right)\right)/m}$$

$$= \frac{\text{Raingauge Mean}}{\text{Radar Mean}}$$

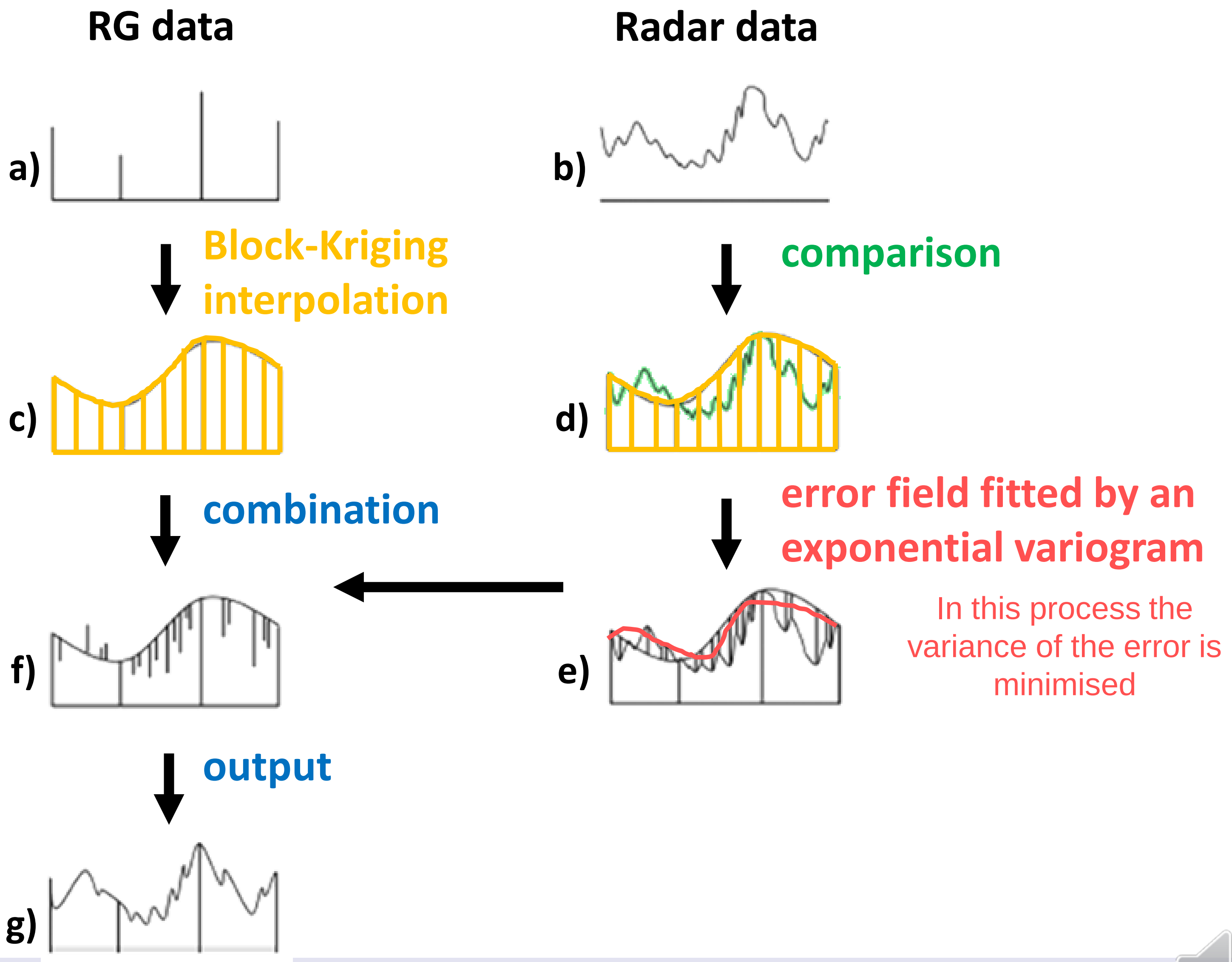
[Source: Smith et al., 2007]

The differences between radar and interpolated raingauge rainfall estimates (i.e. errors) are assumed to be an intrinsic random field, which can be characterised by mathematical models with 2nd moment complexity (variance)

3. ERROR VARIANCE MINIMISATION

- Neither raingauge nor radar rainfall are assumed to be truth
- Error field is fitted by a mathematicl model and its variance is minimised

Example: Bayesian Data Combination

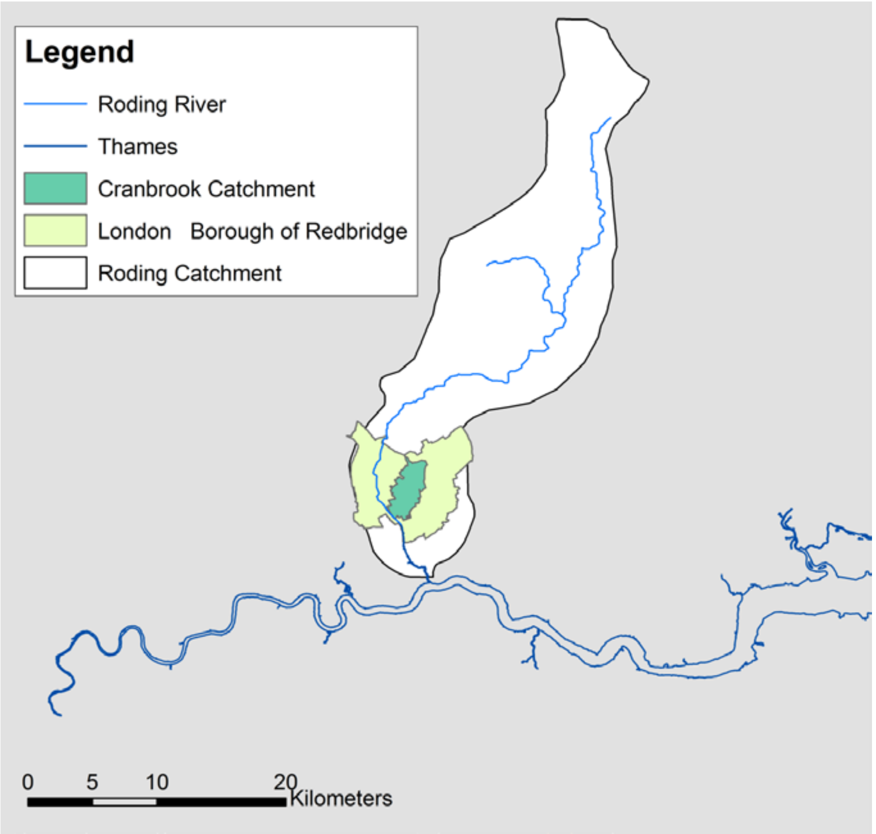


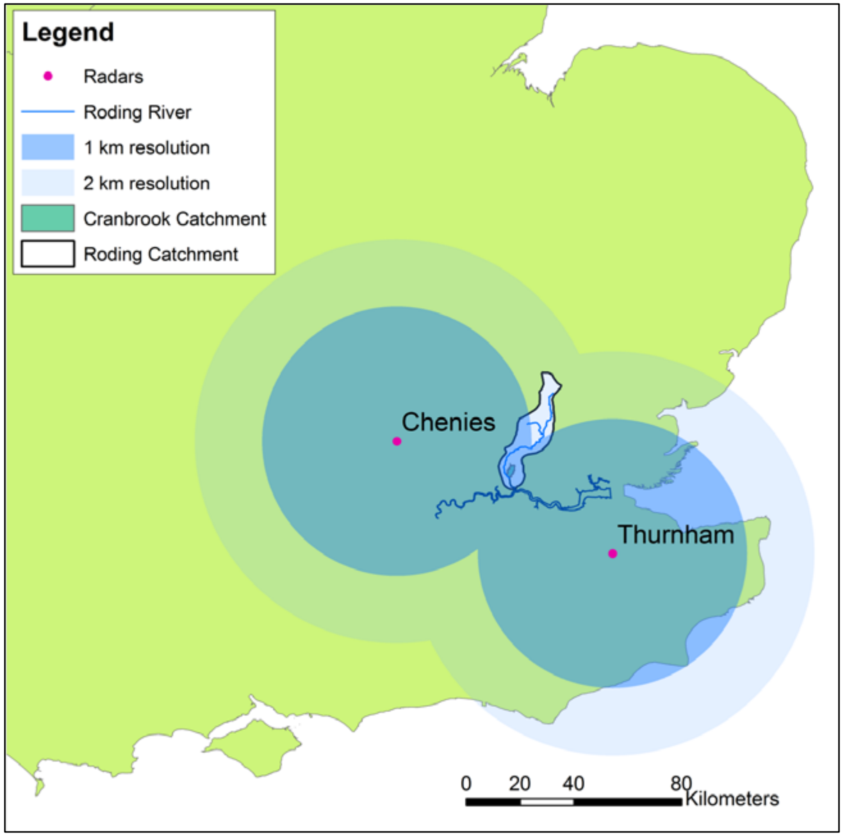
[Source: Todini, 2001]

Cranbrook catchment (London), UK

4. CASE STUDY

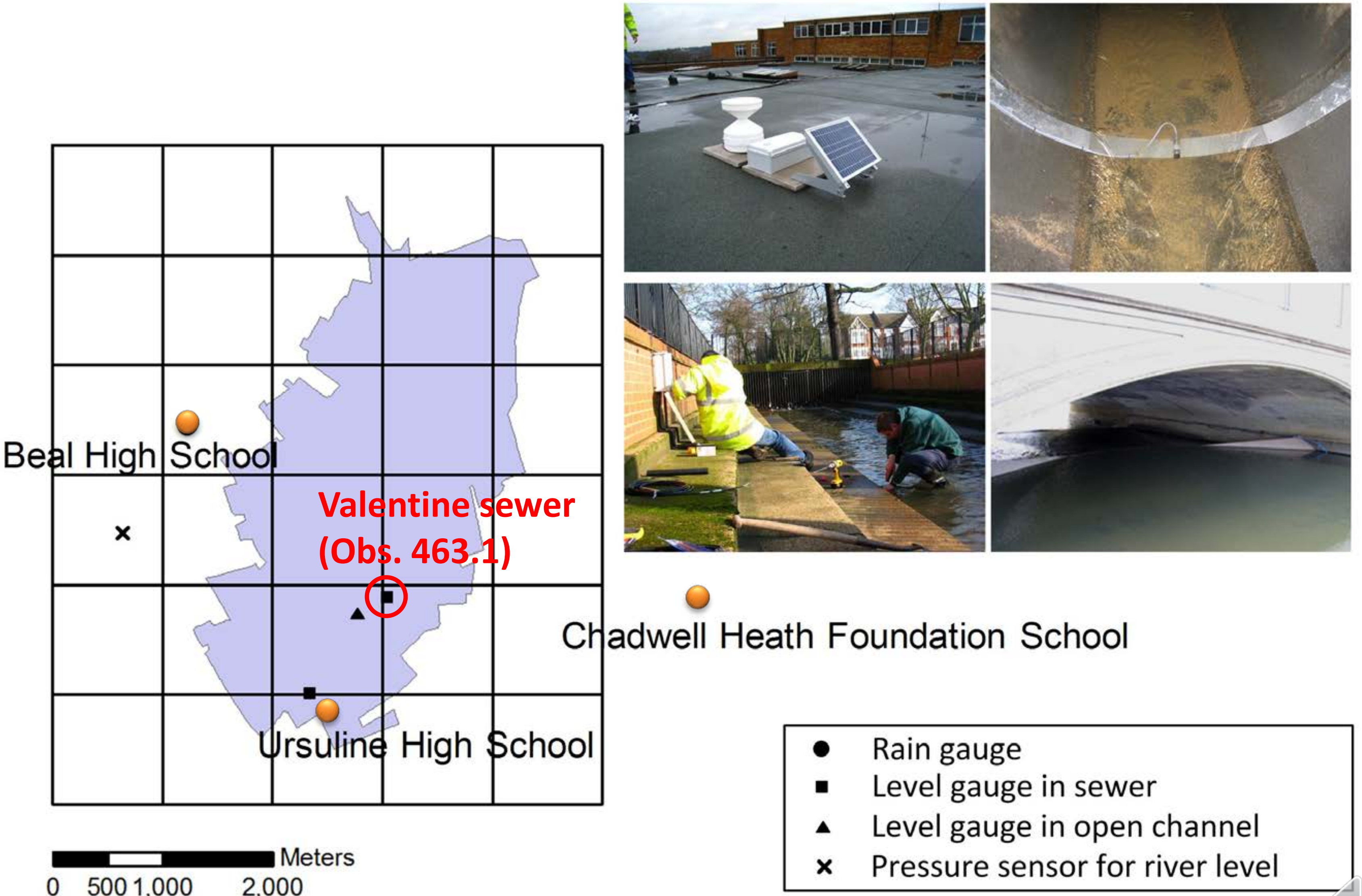
Cranbrook catchment, UK





The drainage area of the Cranbrook catchment is approximately 910 hectares; the main water course is about 5.75 km long, of which 5.69 km are piped or culverted.

A real time accessible monitoring system is installed in the Cranbrook catchment.



Rainfall data used in the analysis

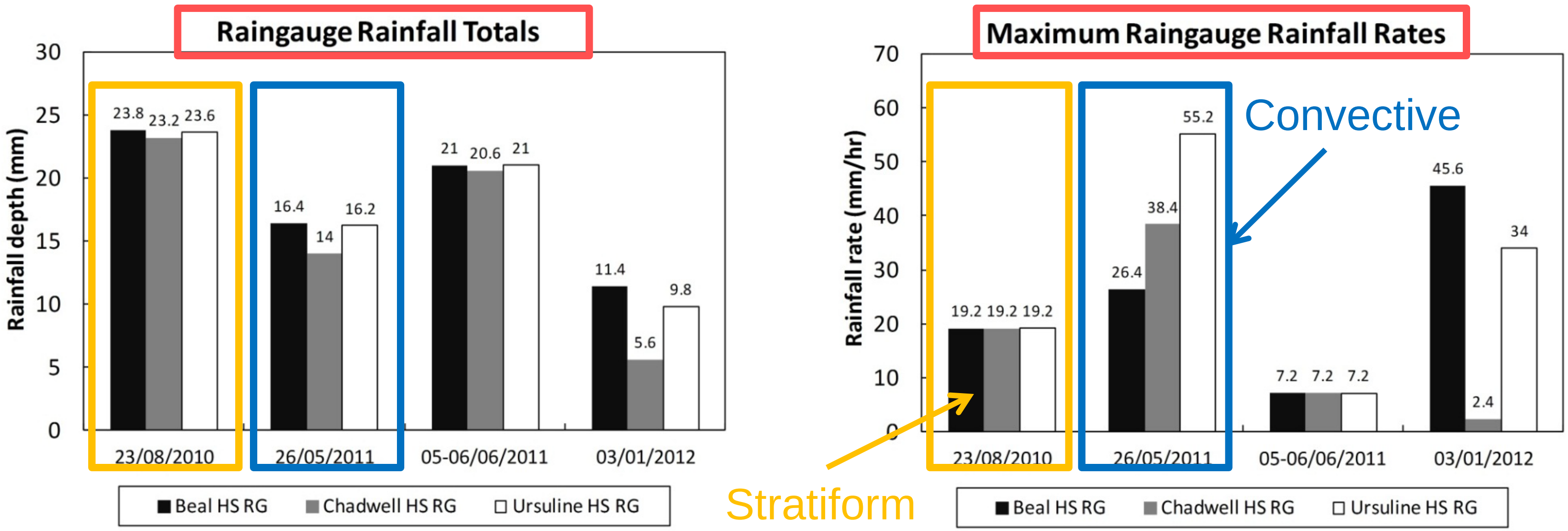
- 3 tipping bucket raingauges with 5 min temporal resolution

- Composite quality controlled radar data with 1 km and 5 min resolution provided by the UK Met Office

Resulting adjusted rainfall data field

- The resulting adjusted rainfall field has a spatial resolution of 1 km and a temporal resolution of 5 min

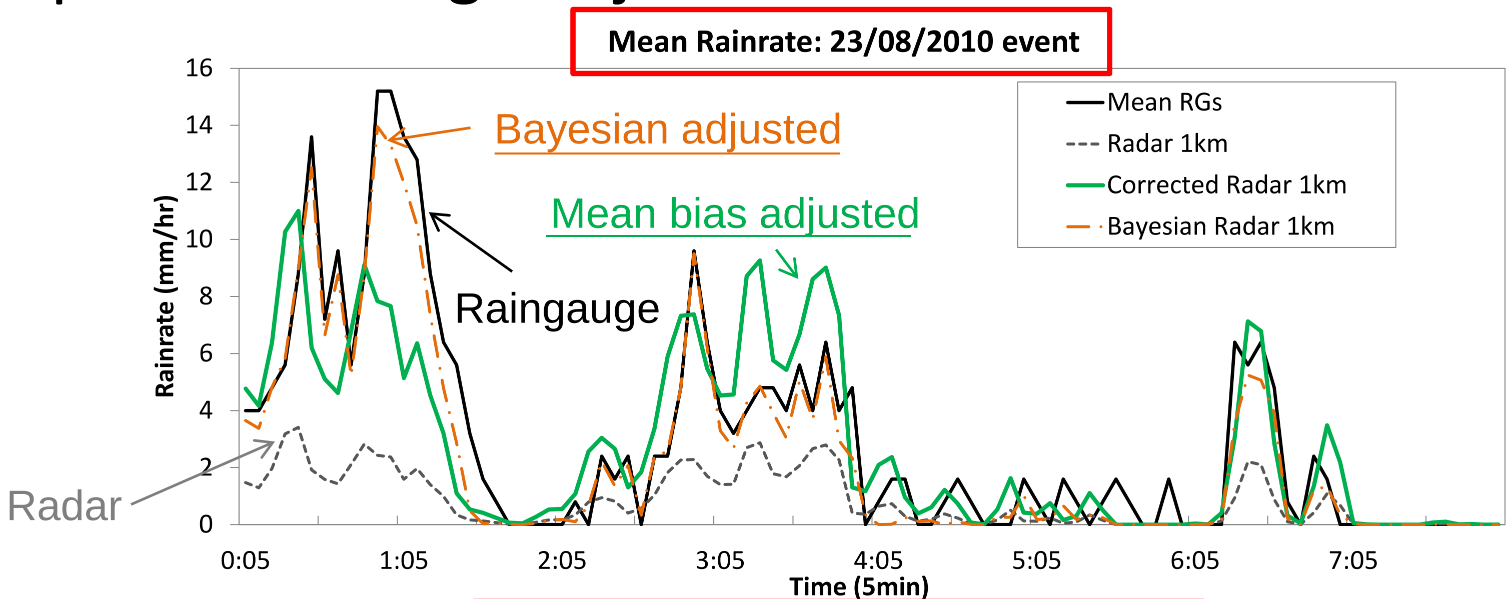
Four recorded events in the period of 2010 – 2012 passing Cranbrook catchment were studied

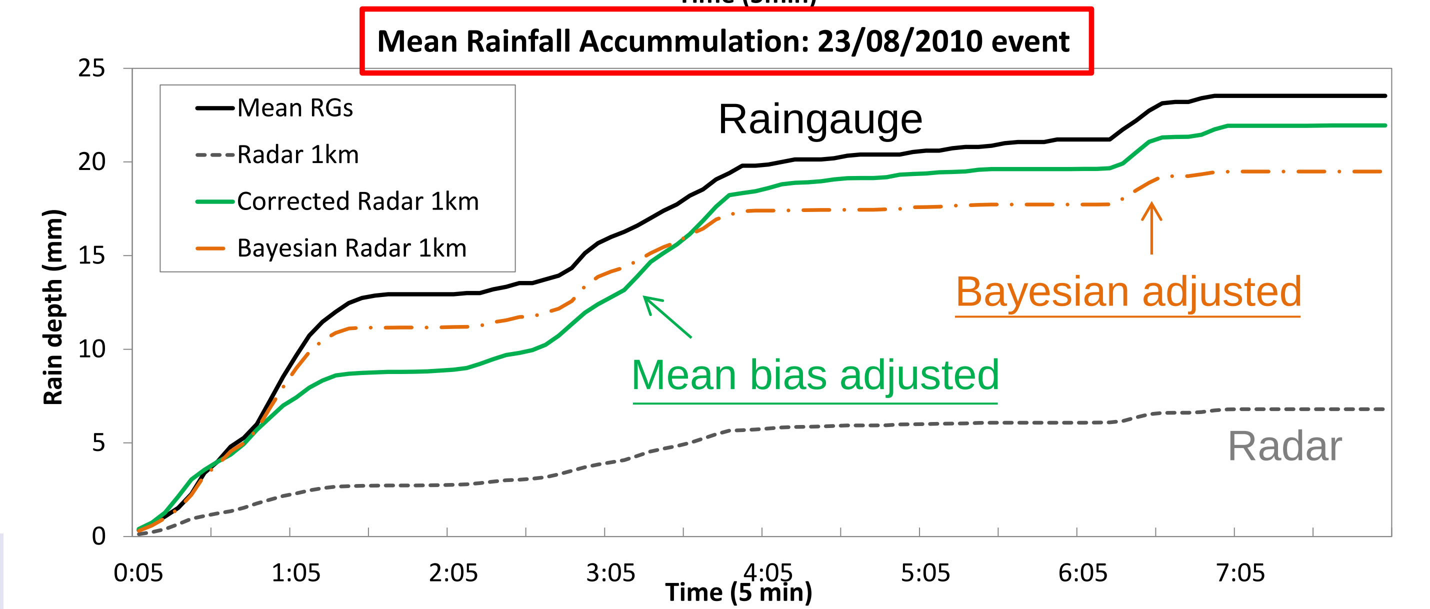


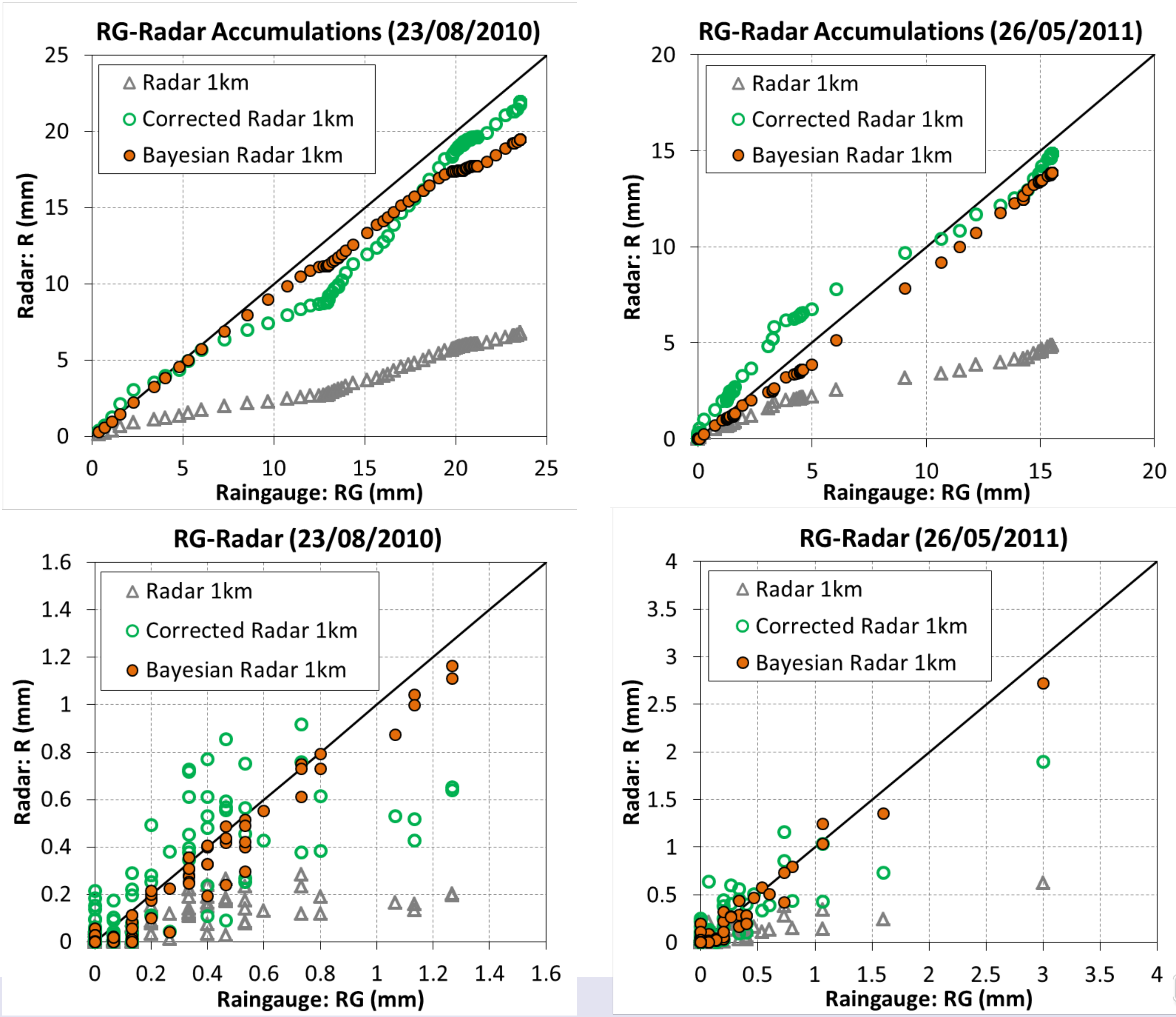
Event	Duration	RG total(1) (mm)	Radar@RG total(2) (mm)	Radar total (mm)	Sample bias $B_i = (1)/(2)$
23/08/2010	8 hr	23.53	7.29	6.80	3.23
26/05/2011	9 hr	15.53	5.10	4.88	3.04
05/06/2011	24 hr	20.87	9.43	9.48	2.21
03/01/2011	13 hr	8.93	7.72	7.55	1.16

Bias is event-varying, separate adjustment for each event is required

Both rainfall profiles and accumulations can be significantly improved through adjustment







RG-Radar Accumulations (23/08/2010)
Radar 1km
Corrected Radar 1km
Bayesian Radar 1km
Radar: R (mm)
Raingauge: RG (mm)
RG-Radar Accumulations (26/05/2011)
Radar 1km
Corrected Radar 1km
Bayesian Radar 1km
Radar: R (mm)
Raingauge: RG (mm)
RG-Radar (23/08/2010)
Radar 1km
Corrected Radar 1km
Bayesian Radar 1km
Radar: R (mm)
Raingauge: RG (mm)
RG-Radar (26/05/2011)
Radar 1km
Corrected Radar 1km
Bayesian Radar 1km
Radar: R (mm)
Raingauge: RG (mm)

Statistics of rainfall estimates: 23/08/2010 event (Whole Cranbrook catchment)

- **R^2 and β:** obtained from the linear regression between coincidental, instantaneous raingauge rainfall rate (x-axis) and the original and adjusted radar (y-axis) rainfall estimates

- **rmse:** root mean square error

Data Type	Total (mm)	Max. (mm/hr)	R^2	β	rmse
Cranbrook catchment					
RG	23.53	11.09	-	-	-
Radar 1km	6.80	3.41	0.57	0.18	3.71
Corrected Radar 1km	21.95	14.08	0.57	0.57	2.47
Bayesian Radar 1km	19.49	13.96	0.88	0.78	0.91

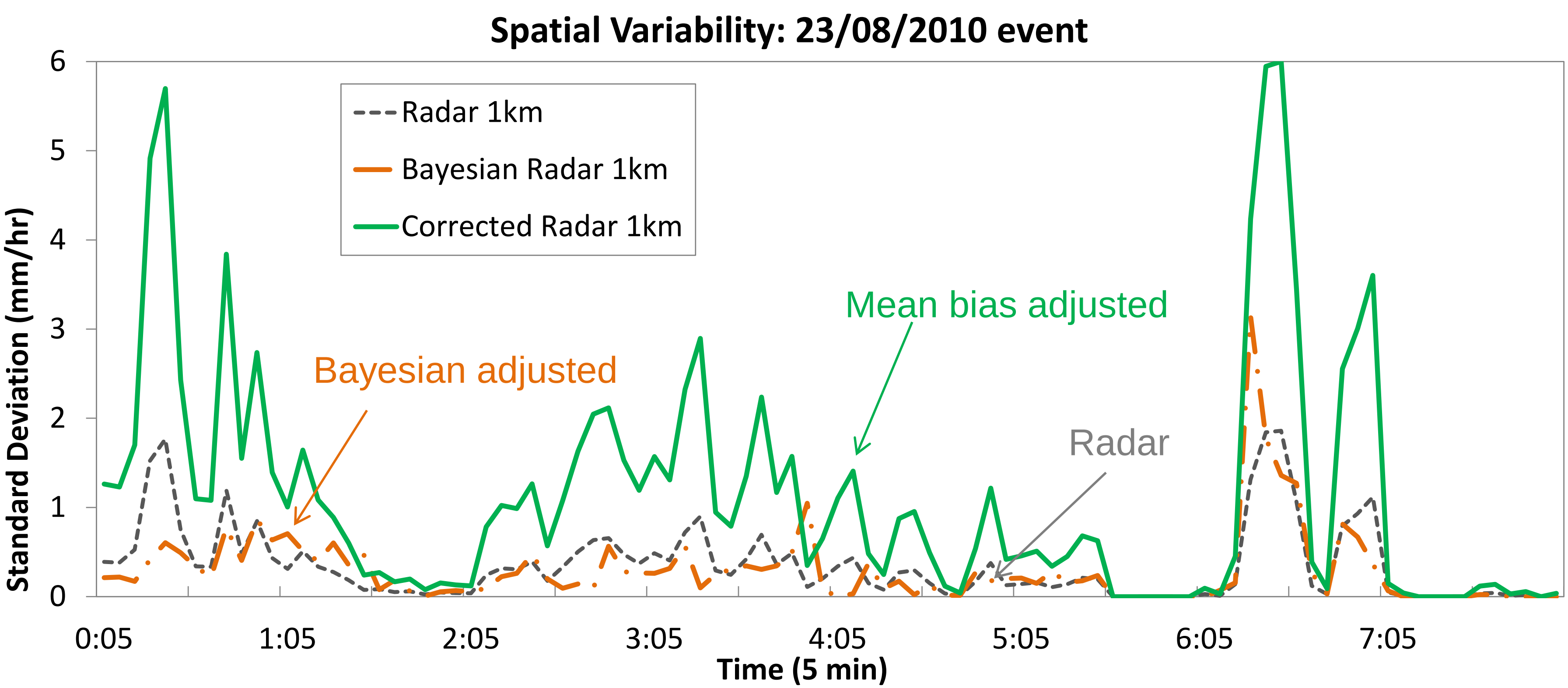
Data Type	Total (mm)	Max. (mm/hr)	R^2	β	rmse
RG - Beal HS					
RG	23.80	19.20	-	-	-
Radar 1km	8.54	3.73	0.43	0.15	4.13
Corrected Radar 1km	27.56	12.04	0.43	0.49	3.08
Bayesian Radar 1km	20.36	13.25	0.74	0.71	2.14
RG – Chadwell Heath HS					
RG	23.20	19.20	-	-	-
Radar 1km	5.79	3.39	0.36	0.14	3.38
Corrected Radar 1km	18.69	10.94	0.36	0.44	4.23
Bayesian Radar 1km	18.35	14.32	0.79	0.72	1.99
RG – Ursuline HS					
RG	23.60	19.20	-	-	-
Radar 1km	7.55	3.83	0.56	0.21	3.89
Corrected Radar 1km	24.37	12.36	0.56	0.66	2.79
Bayesian Radar 1km	20.25	15.28	0.86	0.81	1.60

Statistics of rainfall estimates: 26/05/2011 event

Data Type	Total (mm)	Max. (mm/hr)	R^2	β	rmse
Cranbrook catchment					
RG	15.53	36.00	-	-	-
Radar 1km	4.88	7.47	0.66	0.14	3.80
Corrected Radar 1km	14.85	22.76	0.66	0.42	2.28
Bayesian Radar 1km	13.84	32.61	0.75	0.55	0.90

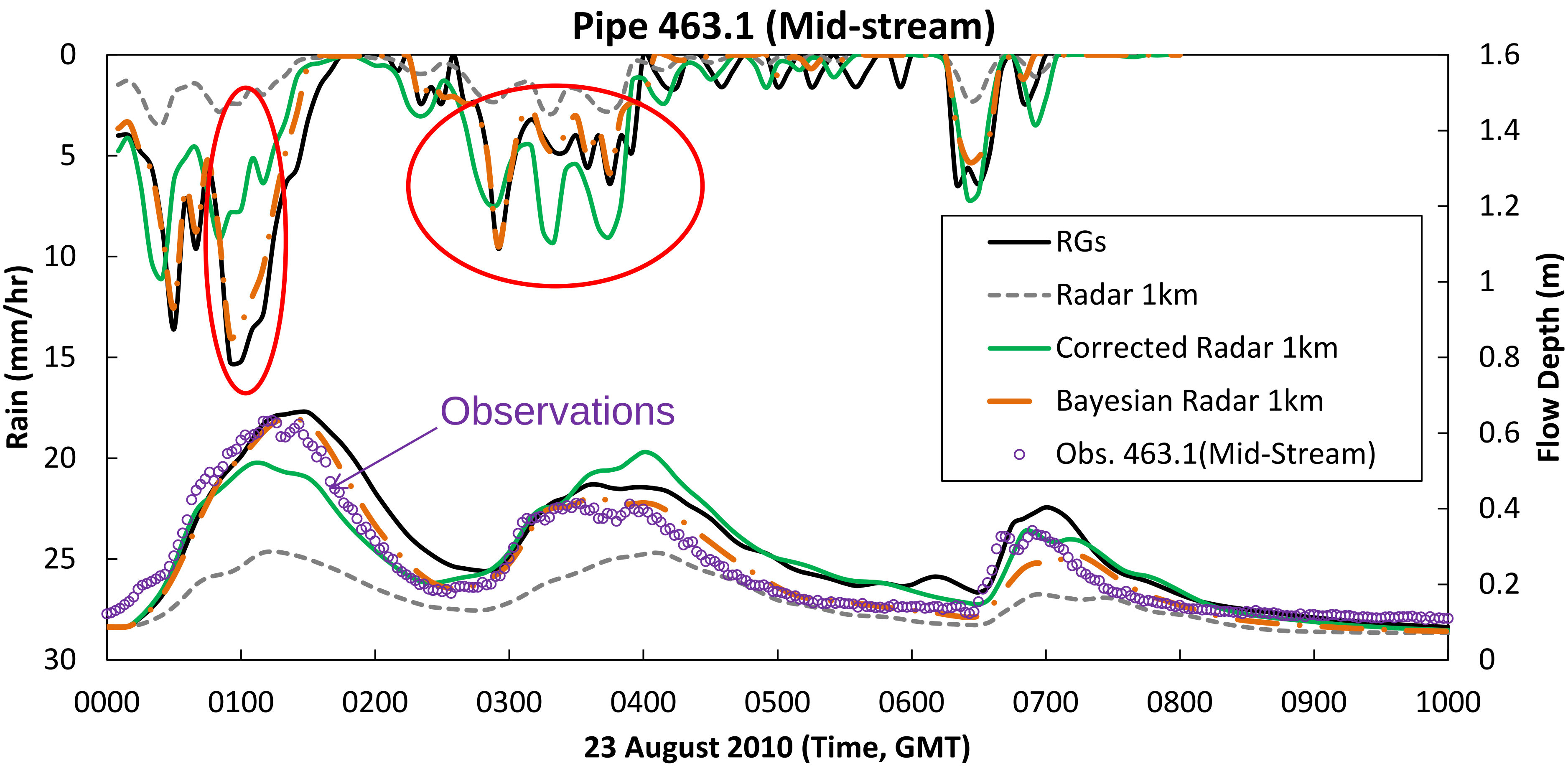
Data Type	Total (mm)	Max. (mm/hr)	R^2	β	rmse
RG - Beal HS					
RG	16.40	26.40	-	-	-
Radar 1km	4.31	8.48	0.71	0.23	3.61
Corrected Radar 1km	13.12	25.81	0.71	0.71	2.34
Bayesian Radar 1km	17.83	29.83	0.74	0.83	2.26
RG – Chadwell Heath HS					
RG	14.00	38.40	-	-	-
Radar 1km	4.70	7.53	0.46	0.18	4.20
Corrected Radar 1km	14.32	22.93	0.46	0.54	3.60
Bayesian Radar 1km	14.37	30.70	0.87	0.78	1.79
RG – Ursuline HS					
RG	16.20	55.20	-	-	-
Radar 1km	6.29	10.89	0.52	0.20	5.50
Corrected Radar 1km	19.16	33.16	0.52	0.62	4.66
Bayesian Radar 1km	13.76	34.40	0.83	0.60	3.19

Spatial variability of radar rainfall fields can be somewhat reflected in the merged rainfall fields

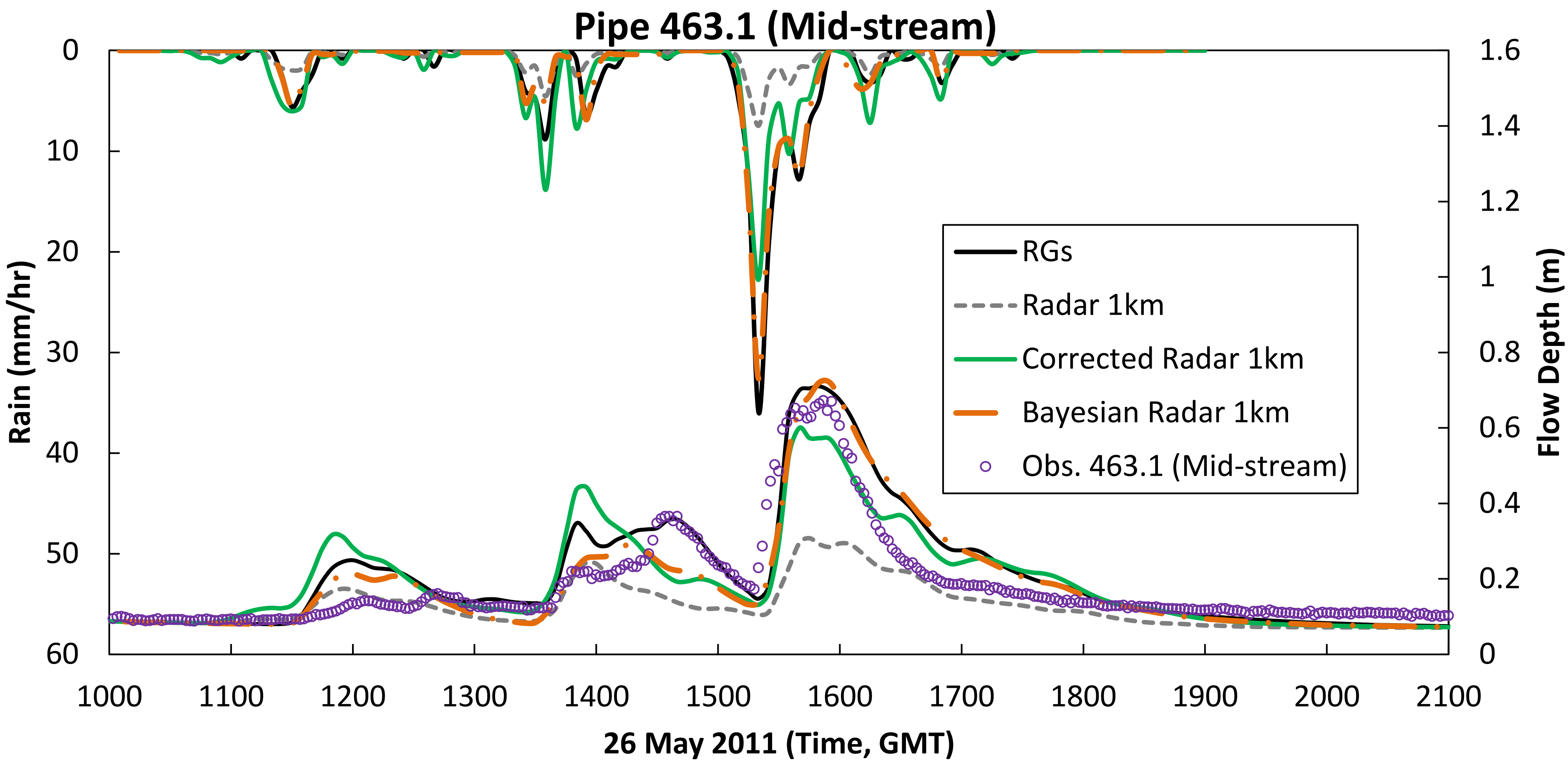


The Bayesian adjustment method preserves better the spatial structure of the original radar rainfall esimates

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



Simulation of flow depths is substantially improved by using merged rainfall data as input (26/05/2011 event)



5.1 Conclusions

- Gauge-based rainfall adjustment is implemented to combine the advantages of raingauge and radar data and overcome their shortcomings

- The existing adjustment methods can be categorised into two types: **mean bias correction and error variance minimisation**, according to the assumption behind them.

5.1 Conclusions

- The results suggest that, in addition to the total rainfall volume (mean bias) adjustment, **the spatial and temporal variability** of rainfall distribution is also very important for **short-term urban pluvial flood modelling**.
- Considering this, the error variance minimisation methods (e.g. Bayesian adjustment) seem to be more suitable for **urban hydrological applications**.
- Adjustment methods are highly sensitive to the quality of the input data; therefore, **data quality control** routines must be implemented before adjustment is conducted.

5.2 Future Work

- The Bayesian adjustment technique is now being tested in a larger area with the purpose of carrying out the following tasks:
  - Cross validation testing
  - Analysis of the uncertainty associated to the merging process
  - Assessment of the feasibility of using merged rainfall fields for improving real-time rainfall nowcasting.
- Other applications of data combination techniques are also being developed and tested, such as NWP data assimilation to enable better prediction of convective storms.

5.2 Future Work

- The improvement of rainfall interpolation and error field characterisation techniques using models which can better capture extreme and non-linear values is being investigated.

QUESTIONS

THANK YOU!

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