Verifying Urban Drainage Models with Variable Rainfall Input

Presenter: Andrew Bailey

Authors: Andrew Bailey, Susana Ochoa-Rodriguez, Li-Pen Wang, Alma Scherllart, Christian J. Onof, Patrick Willems

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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

<table>
<thead>
<tr>
<th>Accuracy</th>
<th>RAINGAUGE</th>
<th>RADAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coverage, spatial characterisation of rainfall field</td>
<td>☹</td>
<td>☺</td>
</tr>
</tbody>
</table>

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)

Original Radar (RD)

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.

\[ \text{Bias}_{\text{last 1h}} = \frac{\sum \text{All raingauges in domain}_{\text{last 1h}}}{\sum \text{All radar grids in domain}_{\text{last 1h}}} \]

\[ \text{Adjusted RadarField}_t = \text{Bias}_{\text{last 1h}} \cdot \text{Original Radar Field}_t \]
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 \(\lambda_{i}^{KED}\) 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

In this process the variance of the error is minimised.

[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.
3. EXPERIMENTAL CATCHMENTS AND DATASETS

- Cranbrook catchment, London
- Portobello catchment, Edinburgh
SW BIRMINGHAM

- **Drainage area:** 67 km²
- **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
PORTOBELLO CATCHMENT, EDINBURGH

Storm events used in this study

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

*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

<table>
<thead>
<tr>
<th>Rainfall Estimates</th>
<th>CRANBROOK CATCHMENT</th>
<th>PORTOBELLO CATCHMENT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Storm 1</td>
<td>Storm 2</td>
</tr>
<tr>
<td><strong>RG</strong></td>
<td>23.53</td>
<td>15.53</td>
</tr>
<tr>
<td><strong>RD</strong></td>
<td>6.80</td>
<td>4.77</td>
</tr>
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</table>
The RG/RD bias is event varying

Need for dynamic and local adjustment
## Areal average total rainfall accumulations

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</tr>
<tr>
<td>BK</td>
<td>22.23</td>
<td>12.75</td>
</tr>
<tr>
<td>MFB</td>
<td>18.06</td>
<td>11.11</td>
</tr>
<tr>
<td>BAY</td>
<td>18.8</td>
<td>12.31</td>
</tr>
<tr>
<td>SIN</td>
<td>19.47</td>
<td>14.07</td>
</tr>
</tbody>
</table>

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

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

- 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

Depth (m)

Errors in peak flow rates

Flow rate (m$^3$/s)

NSEs for simulated flow depths

NSE coefficient

NSEs for simulated flow rates

NSE coefficient
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
sochoaro@imperial.ac.uk
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

- Block-Kriging interpolation
- Singularity extraction
- Local singularity ($\alpha$) field
- Singularity recovery

**Comparison (error field construction)**

Error field fitting

Combination (Kalman filter)

Reconstructed field

- BK rain gauge field
- Non-Singular (NS) radar 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

Bayesian Merged

Singularity-sensitive Merged

Nimrod (Original)