Overall Objectives:

• Develop a radar rainfall error model able to capture the different sources of uncertainty in rainfall estimations at various spatial and temporal scales.
• Study the influence of rainfall estimation error on integrated water quality models. This activity will integrate the uncertainty from rainfall data with the uncertainty in models.

Today presentation:

• Radar errors
• Radar error estimation
• Radar ensembles
• REAL ensemble generator
• New ensemble generator

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Radar Errors

- Attenuation
- Shielding
- Partial beam blocking
- Ground clutter
- Beam overshooting
- Earth curvature
- Anomalous propagation
- Bright band
- Drizzle/snow/hail
- Evaporation
- Orographic lifting
- Conversion from reflectivity to rainfall rates
- Sampling and averaging
- …..
Radar Residual Error Estimation

• How to estimate the residual errors?

1. Comparison with “true rainfall”
   • Best approximation: quality checked rain gauges

(Germann et al. 2009)
• How to estimate the errors?

2. Error by error modelling

• Physically model the error for every source

(Norman et al. 2010)
Radar Noise Estimation

• How to estimate the errors? X

3. Noise separation
• Determine which part of the radar acquisition is signal and which is noise

Noise

(Pegram et al. 2011)

PROS
• No need of reference or additional data

CONS
• Noise is not errors
• It doesn’t explain the uncertainty
• No spatial or temporal correlation
Error propagation

When we use rainfall data for hydrology we want

• A quantification of the errors
• To know how they propagate in the models

RADAR RAINFALL ENSEMBLES
“Different probable rainfall fields consistent with the observed radar rainfall maps and their error structure”
Villarini et al. 2009
Radar Ensembles
Covariance approach (REAL)

- Defining the errors

\[ \epsilon = 10 \log(G) - 10 \log(R) \]

\(G\) = Rain gauge measurement

\(R\) = radar measurement in the pixel that contains the rain gauge

! The error is positive when radar underestimates!

- Defining the error characteristics

\[ C_{kl} = \text{Cov}\{\epsilon_{x_k}, \epsilon_{x_l}\} = E[(\epsilon_{x_k} - E[\epsilon_{x_k}])(\epsilon_{x_l} - E[\epsilon_{x_l}])] \]

\(\epsilon_{x_k}, \epsilon_{x_l}\) = error measured in a position \(x_k, x_l\)

\(E[\;] = \) time mean

! If you have \(n\) rain gauges, the matrix is \(n \times n\)!

(Germann et al. 2009)
Generate the error components

- Covariance matrix decomposition

\[ C = L \cdot L^T \]
L = triangular matrix

Either Cholesky algorithm (positive definite) or SVD

\[ y_{t,i} \sim N(0,1) \]

\[ \delta_{t,i} = \mu + L y_{t,i} \]
\[ \delta_{t,i} = \text{error component for the } i^{th} \text{ ensemble at time } t \]
\[ \mu = \text{error mean vector} \]

(Germann et al. 2009)
Generate the ensembles

Ensemble error components

Original radar data

Ensembles

\[ 10 \log[\Phi_{t,i}] = 10 \log[R_{t,i}] + \delta_{t,i} \]

\( \Phi_{t,i} = \) ensemble member \( i \) at time \( t \)

! Rigorously, it should be:

\[ 10 \log[\Phi_{t,i}] = 10 \log[R_{t,i}] + \epsilon_t - \delta_{t,i} ! \]

(Germann et al. 2009)
Study Area

- >200 tbr EA raingauges
- UKMO radar mosaic @ 1km/5min
- Urban catchment: 15 flow monitors, 7 depth monitors, 4-6 raingauges

Data sets: 2007-2009
Results
Covariance approach

**Pros**
- Complete description of the errors and their spatial characteristics
- Easy to model temporal correlation too
- Widely used and tested model

**Cons**
- Large covariance matrix (time/storage)
- Unstable decomposition method
- Interpolation of the results
- Variance inflation
New method

• We are developing a new method

The basic idea is to filter a random field with a lowpass filter designed to obtain a field with the same semivariogram and variance of the measured errors

Maintaining observed spatial dependence and variance

Faster: semivariogram vs covariance

No interpolation needed

More flexible: no need of long time series
Error definition

• Defining the errors

\[ \epsilon = 10 \log(G) - 10 \log(R) \]

\( G = \) Rain gauge measurement

\( R = \) radar measurement in the pixel that contains the rain gauge

• Defining the error characteristics

\[ \gamma(d) = E \left[ (\epsilon_{x_k} - \epsilon_{x_l} + d)^2 \right] \]

\( \epsilon_{x_k}, \epsilon_{x_l} = \) error measured in a position \( x_k, x_l \)

\( E[ ] = \) mean on the pixel number

! 1D but much faster!
Error component generation

Random Gaussian field

Lowpass filter

Rescaling

\[ y_{t,i} \sim N(0,1) \]

\[ \delta'_{t,i} = h(s) \otimes y_{t,i} \]

\[ \delta_{t,i} = \delta'_{t,i} \cdot \frac{\sigma^2_{\text{target}}}{\sigma^2_{\delta_{t,i}}} \]

Random Noise

Generated Noise

semivariogram

calculated semivariogram
fitting exponential curve

distance (km)
The filter design is crucial

Polynomial FIR filters cannot reproduce the semivariogram

Filter function designed with exponential form, analogous to semivariogram shape

Filter parameters calibrated to obtain the exact result
<table>
<thead>
<tr>
<th>PROS</th>
<th>CONS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Much faster: 1/20!</td>
<td>Isotropic error</td>
</tr>
<tr>
<td>No need of interpolation</td>
<td></td>
</tr>
<tr>
<td>No need of time series</td>
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<td>Independence of the ensemble members calculation</td>
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Issues to address and future work

- Is the error model we are using appropriate (variance inflation)?
- Hydrologic application
- Real-time application
- Anisotropic filter (?)