Radar ensemble precipitation estimation
- a new topic on the radar horizon

Urs Germann, MeteoSwiss
M Berenguer, D Sempere-Torres, G Salvade

Stimulated by many discussions with I Zawadzki, G Lee, E Cassiraga, X Llort, R Sanchez-Diezma, A Seed, T Einfalt

What is a *Radar Ensemble*?

MeteoSwiss radar on La Dole, 1675m, near Geneva, Photo Charvet
Why not deterministic radar estimate?

high hardware stability and

sophisticated error correction algorithms

(Jürg Joss’ 40 years of efforts and experience)
Many years of progress

Veriﬁcation
3 radars, 58 gauges (whole Switzerland), all (!!) days of May-Oct

Automatic hardware calibration + noise monitoring

Summer 1997

<table>
<thead>
<tr>
<th>Bias</th>
<th>Scatter</th>
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<tbody>
<tr>
<td>0.50</td>
<td>2.7</td>
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introduce visibility map correction
7-step ground clutter elimination
correction for vertical reﬂectivity proﬁle
global + local bias correction (long-term gauge adjustment)

For hydrology
errors are still too large

Summer 2004

<table>
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<tr>
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missed water=2%
false water=1‰
polarimetry in the Alps? (Katja Friedrich)

Germann et al., 2006, QJRMS
Solution 1: Detailed information on error sources

Receiver noise

Scan geometry

Visibility map

Maps of total clutter and residual clutter

Z-R variability

Error distribution

Confusing, and too complex for most applications.
Solution 2: Generate an ensemble of radar fields

Idea
Generate set of perturbation fields and add perturbation to original radar rainfall field.

Easy to understand and easy to use.

Variability among ensemble members represents uncertainty in radar estimates.

Use ensemble in hydrological (!) and meteorological (?) models.
There are different approaches to obtain estimates of error variances and covariances. There are two main approaches:

1. **Deterministic**
   - Estimate of radar error for each point in space and time (error variances).
   - Estimate of how errors are correlated in space and time (error covariances).
   - Stochastic simulation of error field.
   - Perturbation field with correct space-time variances and covariances.

2. **Probabilistic**
   - Original field (unperturbed).
   - Ensemble member (perturbed).
2 ways to estimate radar errors

1 Measurement theory and simulations

Examine all sources of error separately using measurement theory and error simulations.

+ Rigorous, based on physics
- Tedious, extrapolation needed, superposition???

2 Comparison with ground-truth

Use radar-gauge agreement as estimate of overall uncertainty in radar rainfall estimate.

+ Simple, fast, direct estimate of overall uncertainty.
- includes gauge errors, interpolation + extrapolation needed.
Recipe

- Estimate of radar error for each point in space and time (error variances)
- Estimate of how errors are correlated in space and time (error covariances)

There are different approaches for the stochastic simulation

Stochastic simulation of error field

Original field (unperturbed) + Perturbation field with correct space-time variances and covariances = Ensemble member (perturbed)
Stochastic variations
### Stochastic simulation of perturbation field

**1 Spectral approach (FFT, DCT)**

- **Step 1:** Initialise perturbation field with N(0,1) white noise
- **Step 2:** Low-pass filter to impose space-time autocorrelation
- **Step 3:** Add mean and variance
- **Step 4:** Add perturbation field to original radar rainfall field

**perturbation field is 2nd-order stationary**

**2 LU decomposition (Cholesky)**

- **Step 1:** Simulate perturbation field
  \[
  \delta_i = \mu + L \varepsilon_i \\
  LL' = C, \quad \text{where}
  \]
  - \(\delta\) is desired perturbation vector,
  - \(\mu\) is vector of mean perturbation,
  - \(C\) is error covariance matrix,
  - \(L\) is lower-triangular matrix of \(C\),
  - \(\varepsilon\) is N(0,1) white noise vector.

**Step 2:** Add \(\delta_i\) to logarithm of original radar rainfall field
\[
\log(R'_i) = \log(R_0) + \delta_i
\]

**full flexibility for \(C\) and \(\mu\)**
Error covariance matrix

Suppose we divide the basin into 11 pixels ...

Error variances at all 11 pixels

Error covariances for pixel 4

Error covariances for all pixel pairs

Full error covariance matrix

Covariance between error at pixel 4 and error at pixel 1
Does perturbation generator reproduce C matrix?

- Error covariance matrix as input to stochastic simulation
- Error covariance matrix from 1000 simulated realisations

YES

900 basin pixels

![Low variance](image1)

![High variance](image2)

Synthetic values, just for testing
Does error variance depend on location?

Germann et al., 2006, QJRMS

May-Oct04
Does error covariance depend on location?

- Low spatial correlation e.g. around Zurich

May-Oct 2003-2005
Does error covariance depend on location?

- High spatial correlation, e.g., within the Alps

May-Oct 2003-2005
Does error covariance depend on location?

In flat region?
Variance-covariance structure less complex, but also strongly location-dependent, because of increase of pulse volume and height above ground with distance.
water trio
3 rivers

3 rivers Maggia-Verzasca-Ticino:
2800km²-catchment, S-Alps, 1 radar, 31 gauges, 6 months of data, lake 200m; mountains >3000m

Goal: generate ensemble of daily (hourly) radar precipitation fields.

Assumption: uncertainty defined as log(radar/gauge) is correlated random field.

Step 1: determine radar error covariance matrix $C$ from 6-month radar-gauge agreement.

Step 2: determine $L$ from $C$ using Cholesky decomposition (modified Cholesky for numerical stability), or SVD

Step 3: simulate perturbation vector $\delta_i$ using $\delta_i = \mu + L\epsilon_i$

Step 4: calculate ensemble member $R'_i$ by adding $\delta_i$ to original radar field $R_0$ in logarithmic domain $\log(R'_i) = \log(R_0) + \delta_i$
Interpolation + extrapolation

From radar-gauge agreement we can directly estimate variances and covariances at gauge locations. Interpolation is needed to obtain variances and covariances at all basin pixels (here 2km).

31 gauges

average distance between 2 gauges is 9.5km

697 basin pixels

C and µ from 6-month data set Extrapolation real-time event
Mean error at basin pixels
Error standard deviation at basin pixels
Error correlation (1)
Error correlation (2)
Error correlation (3)
Original radar rainfall estimate

Swiss Radar 19Aug2005 2300UTC – 20Aug2005 0000UTC (1h)
3 ensemble members (example)

perturbation fields (from stochastic simulation)

original field (unperturbed)

ensemble members (perturbed precipitation fields)
downscaling fugue
31 gauges: daily records only. We only get an estimate of radar errors for 24h periods!

But, we have 8 gauges with 10min resolution ...
the unfinished
Next steps

**Downscaling:** determine error covariance matrix for 1h periods.

**Time:** introduce time
- either by extending dimension of covariance matrix,
- or by using an auto-regressive model

**Conditioning:** explore possibility of conditioning error covariances

**Validation** with hydrological model for level of Lago Maggiore in MAP D-PHASE forecast demonstration project in summer-fall 2007: [http://www.map.meteoswiss.ch/map-doc/dphase/dphase_info.htm](http://www.map.meteoswiss.ch/map-doc/dphase/dphase_info.htm)

\[\text{the unfinished}\]
Summary

2800 km² catchment

The radar ensemble

downscaling fugue

MAP D-PHASE  http://www.map.meteoswiss.ch/map-doc/dphase/dphase_info.htm