Ensemble radar precipitation estimation in a mountainous region

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Uncertainty in radar precipitation estimates

1 Sources of uncertainty in radar estimates

Hardware failure and instability, for example:

- power failure
- aging TR-cell
- antenna pointing error
- miscalibration

Limitations of observing technique, for example:

- undersampling (space+time)
- limited visibility
- non-weather echoes
- reflectivity-to-rain conversion

1

40 years of experience

2 How do we use uncertainty information

Step 1: to reduce uncertainty

- Hardware calibration
- ground echo elimination
- correction of beam shielding
- etc

10 years of progress

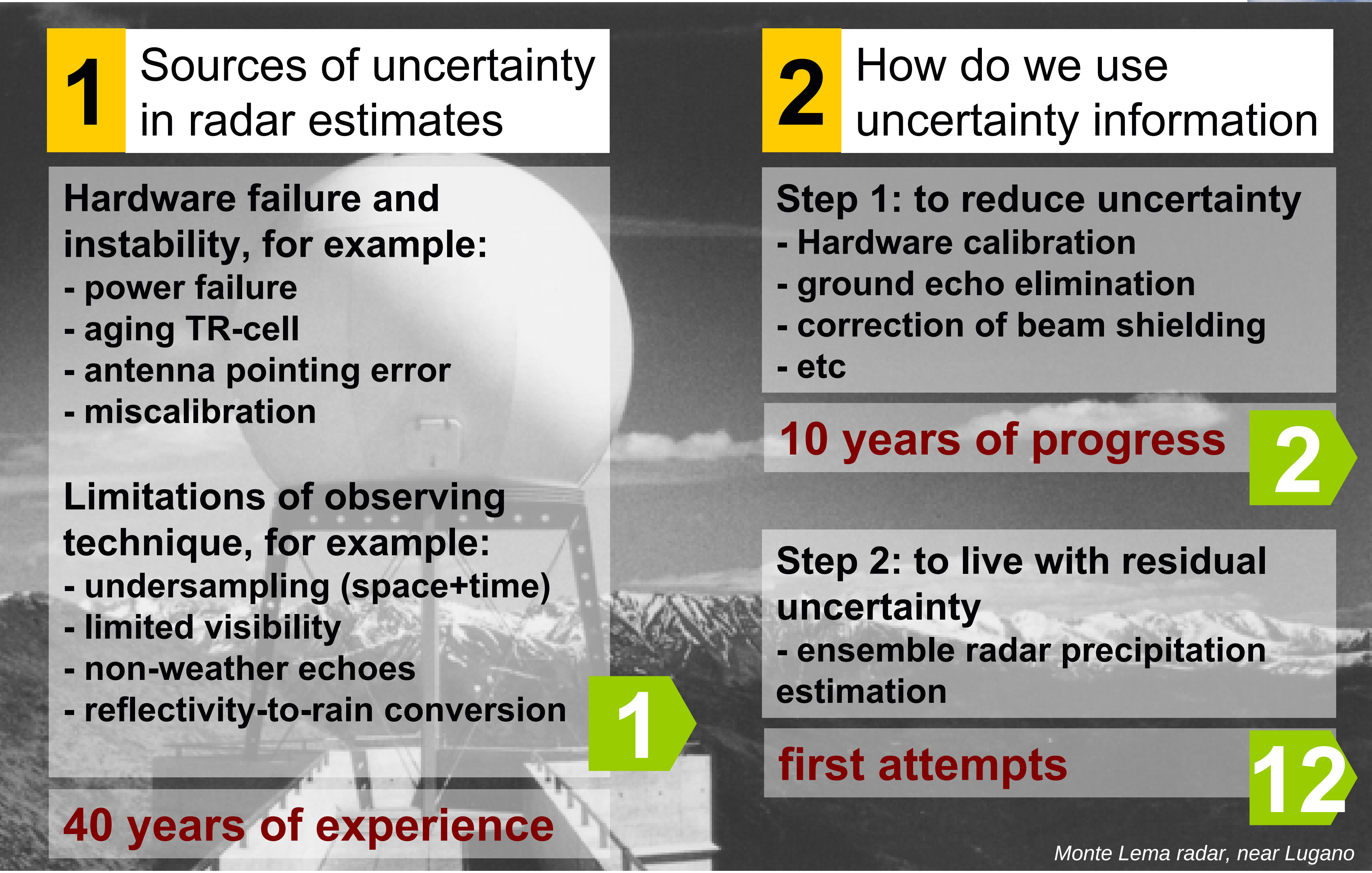
2

Step 2: to live with residual uncertainty

- ensemble radar precipitation estimation

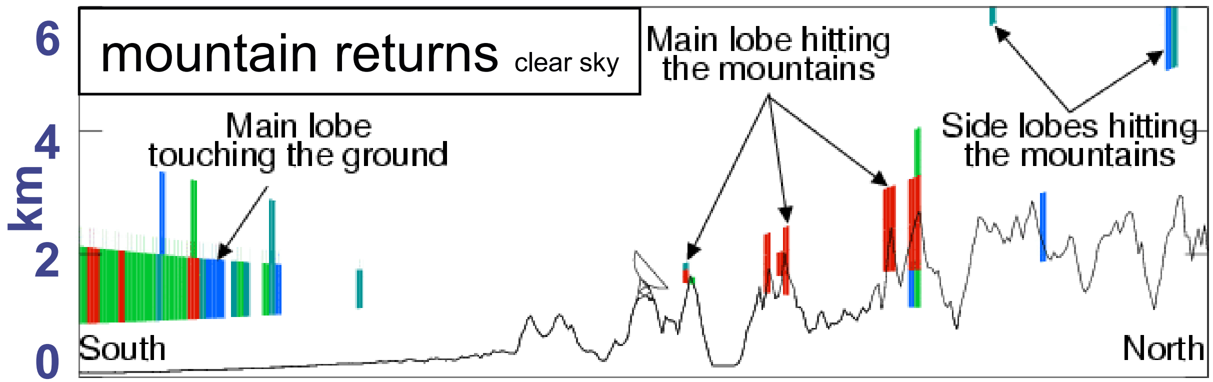
first attempts

12



Monte Lema radar, near Lugano

Challenge of using radar in mountains



many elevations in short time needed

strong returns from mountains (clutter)

shielding of radar beam by mountains

Germann and Joss, 2004
Ed P Meischner, Springer

10 years of progress: radar-gauge verification

3 Swiss radars, 58 gauges, all (!!) days of May-October

	Bias	Scatter	POD	FAR	ETS
	in terms of water amounts		for 0.3mm daily rainfall		
hardware calibration + monitoring since 1993					
Summer 1997	0.50	2.7	84	34	40
introduce visibility map correction					
Summer 1998	0.63	2.7	87	30	39
improve ground echo elimination					
Summer 1999	0.34	3.6	73	8	53
introduce correction for vertical reflectivity profile					
Summer 2001	0.36	2.1	75	8	57
introduce global bias correction					
Summer 2004	0.87	2.0	89	14	62
introduce local bias correction (training with 2003 data)					
Summer 2004	1.003	1.7	90	15	63
	Factor	Factor	%	%	%

subjective data set 1.4

missed water=2%

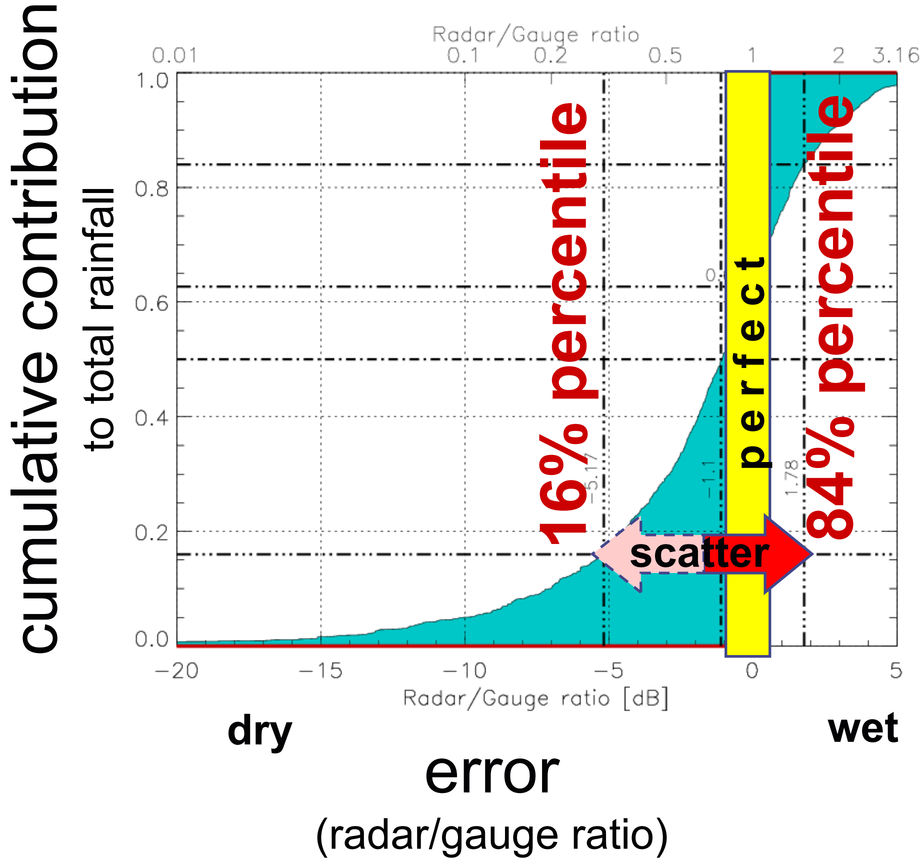
false water=1‰

Germann et al., 2006, QJRMS

Quality descriptors

Bias: radar/gauge
(accumulation over whole season)

Scatter: variation of daily radar/gauge ratio



By the way: at this scale (6 months x 58 gauges) radar errors are approx Gaussian, see plot above.

10 years of progress: radar-gauge verification

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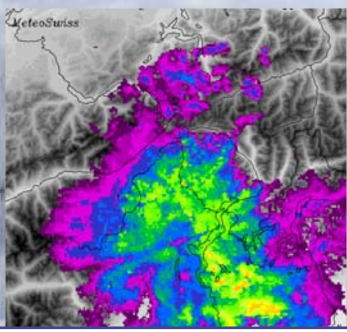
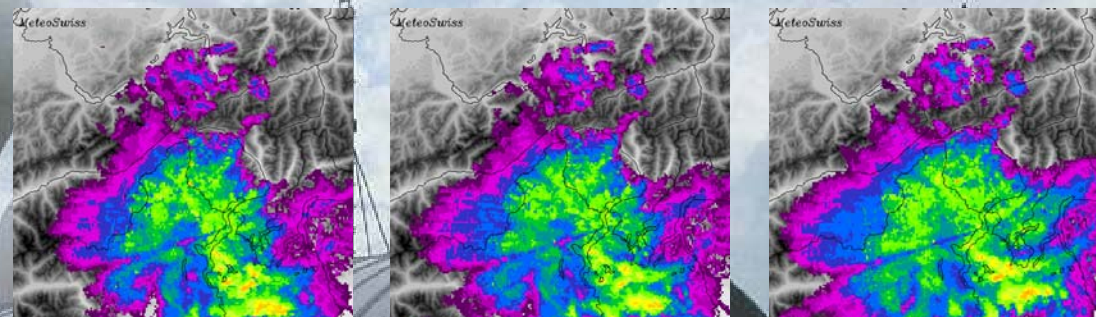
Ensemble radar precipitation estimation

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



best estimate



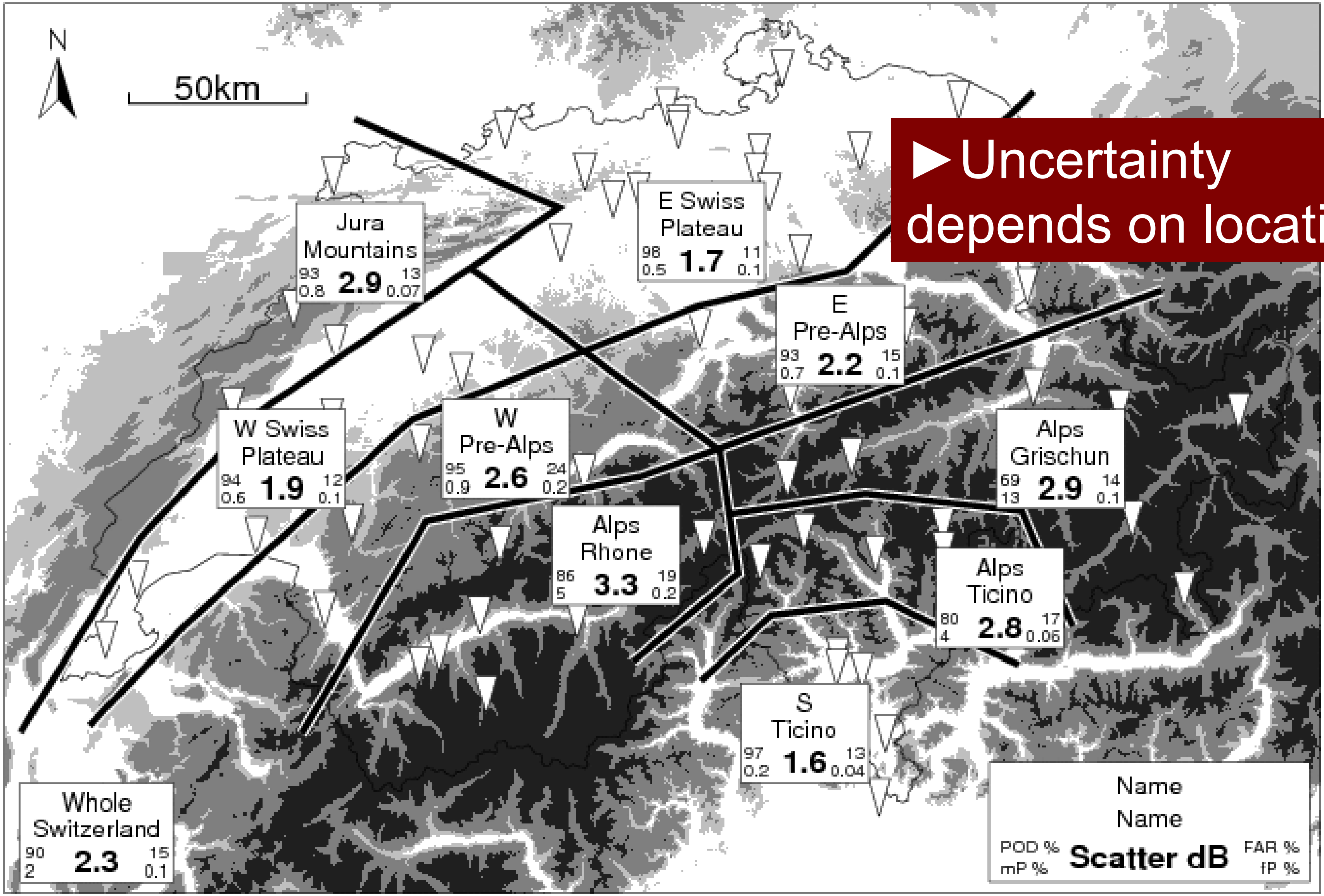
ensemble

Ensemble represents uncertainty in radar estimates

► **use ensemble in hydrological (!) and meteorological (?) models**

La Dole radar, near Geneva

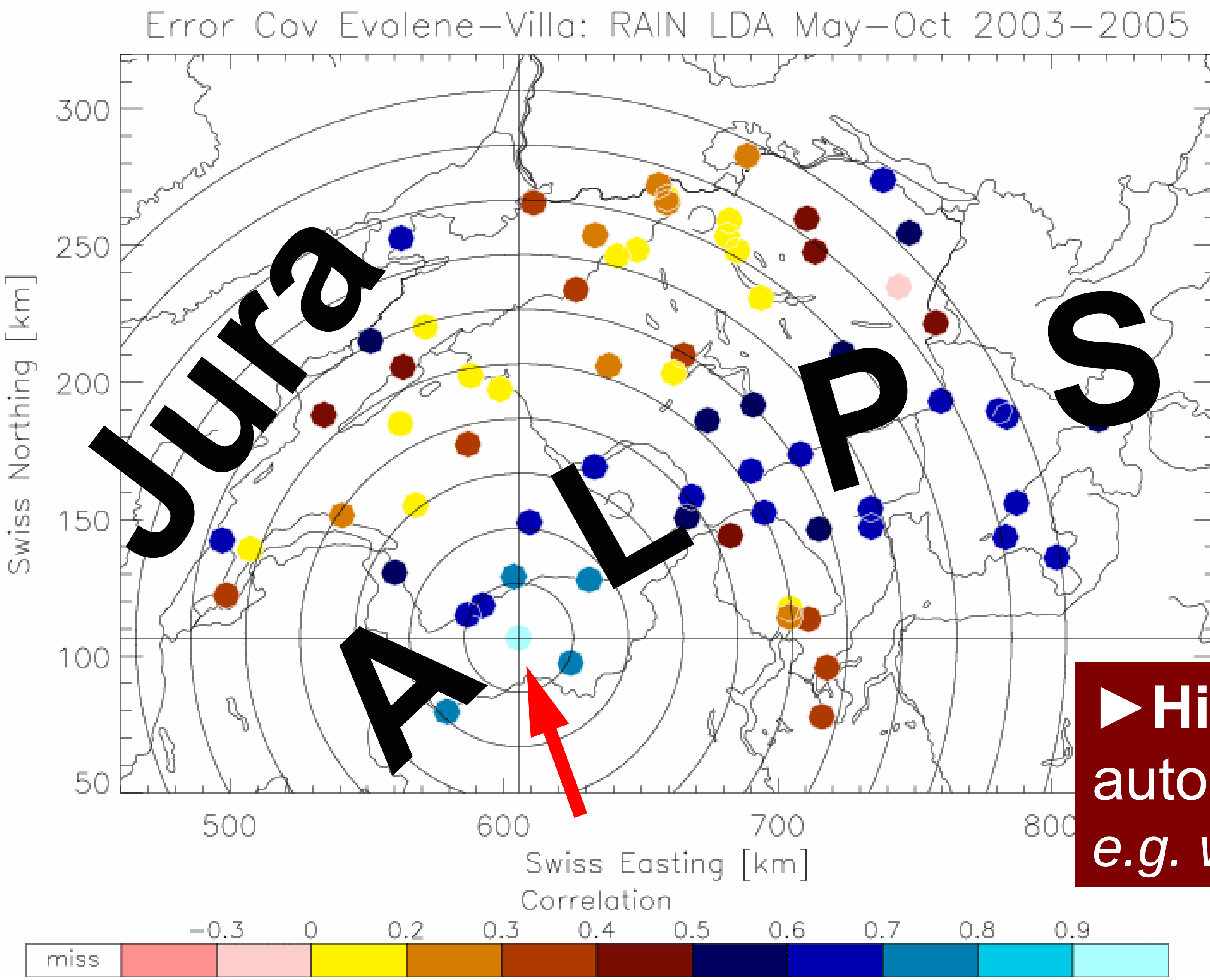
Uncertainty geography



► Uncertainty depends on location

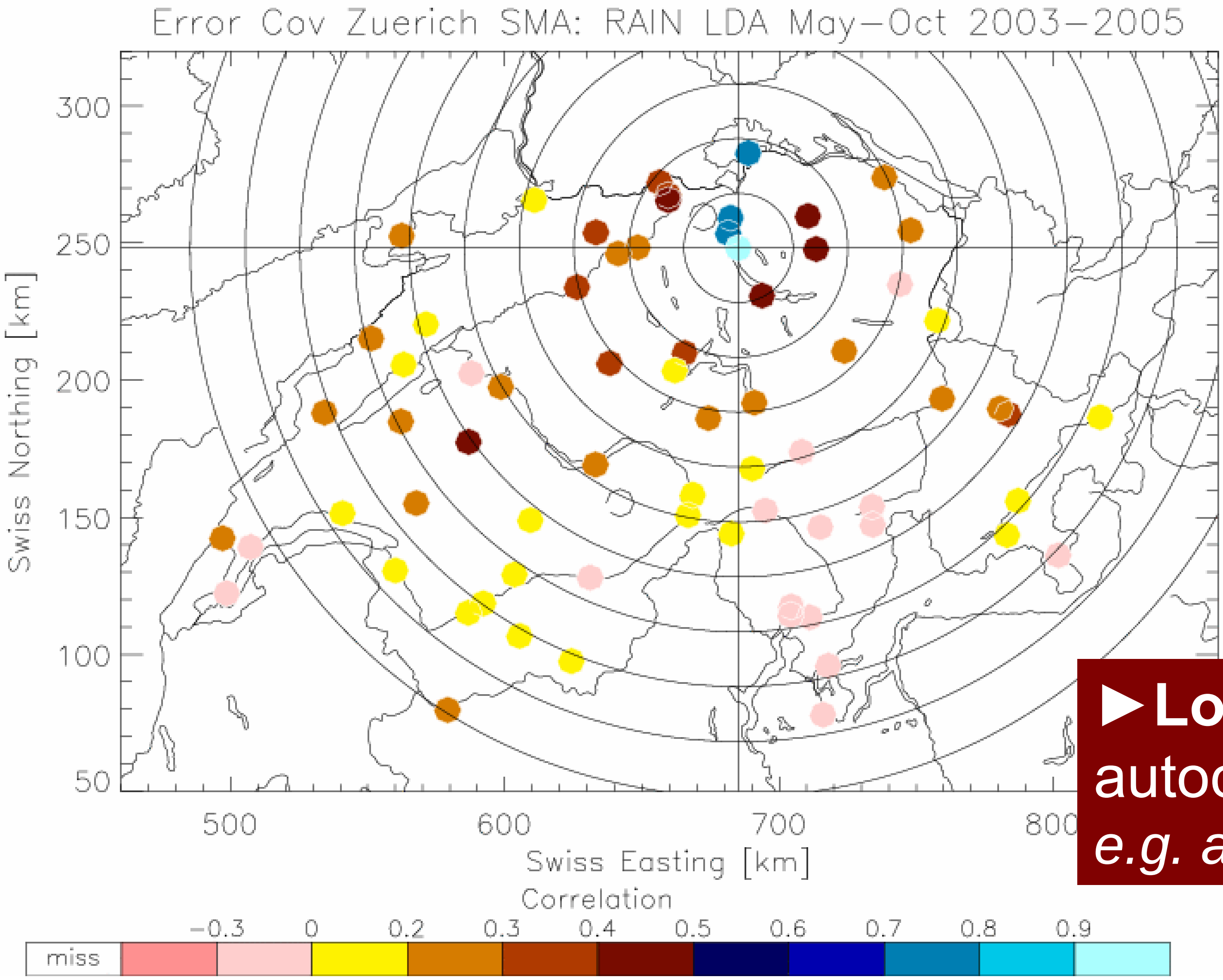
Germann et al., 2006, Q JRMS

Uncertainty auto-covariance depends on location



► **High** spatial autocorrelation *e.g. within the Alps*

Uncertainty auto-covariance depends on location



► **Low** spatial autocorrelation *e.g. around Zurich*

Albis radar, near Zurich

Generation of perturbation field

1 Estimate variance-covariance matrix

Two approaches:

- use **radar-gauge** agreement as estimate of total radar uncertainty

- **examine all sources of error separately** and compute sum of errors
 (e.g. uncertainty in reflectivity-to-rainrate conversion, uncertainty in vertical reflectivity profile, attenuation, etc)

2 Generate multi-Gaussian perturbation by Cholesky decomp.

$\boldsymbol{\delta} = L\boldsymbol{\varepsilon}$, where

$\boldsymbol{\delta}$ is desired perturbation vector (correlated multi-Gaussian),

$\boldsymbol{\varepsilon}$ is Gaussian white noise vector,

L is lower-triangular matrix of C

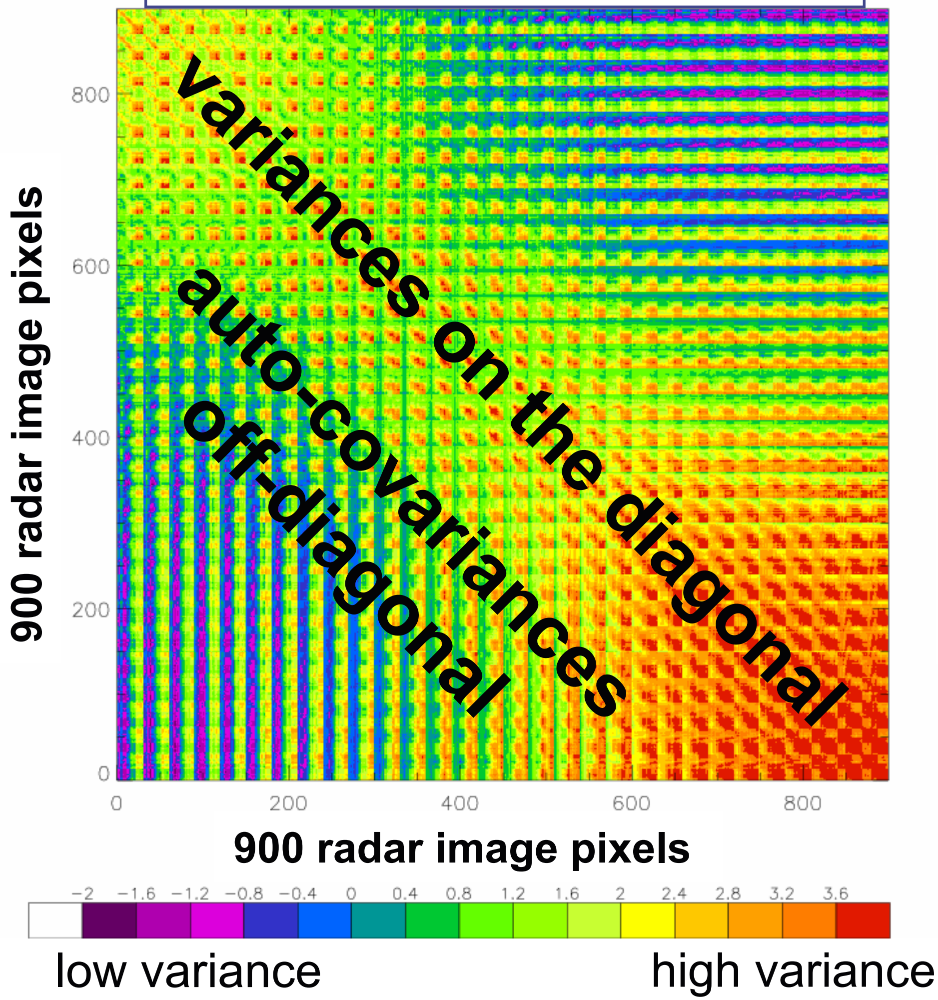
$LL^T = C$, where

C is variance-covariance matrix.

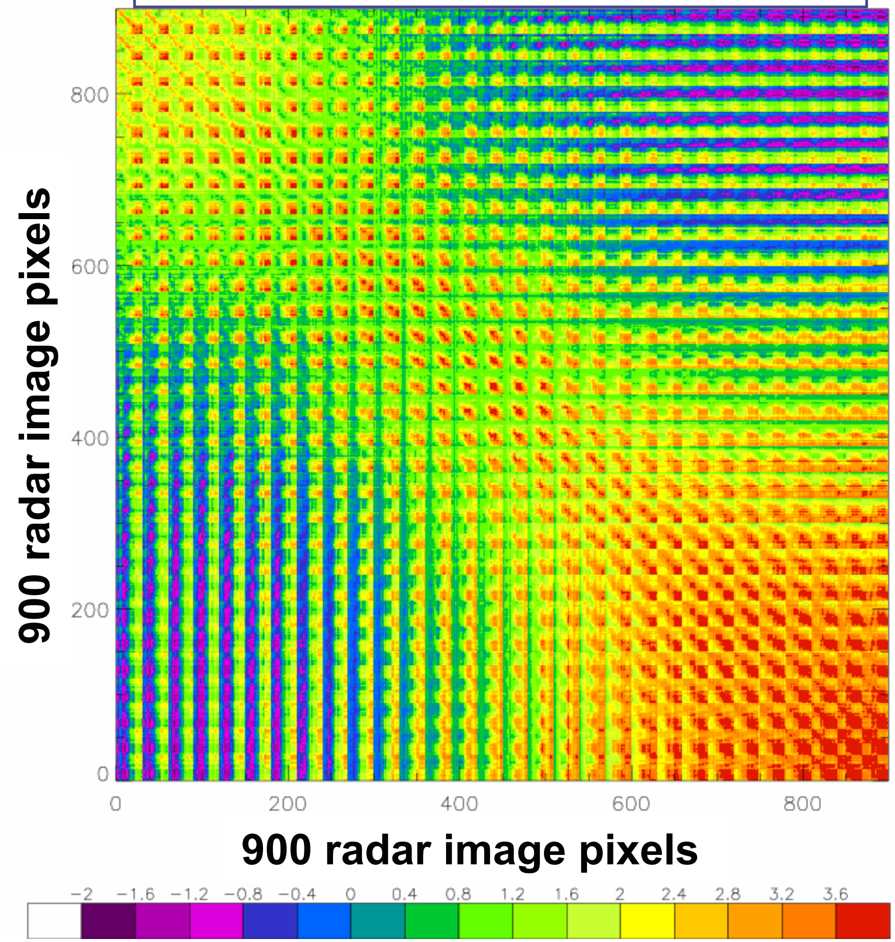
full flexibility for C
(as opposed to spectral approach)

Does it reproduce the variance-covariance matrix?

Variance-covariance matrix
as input to stochastic simulation

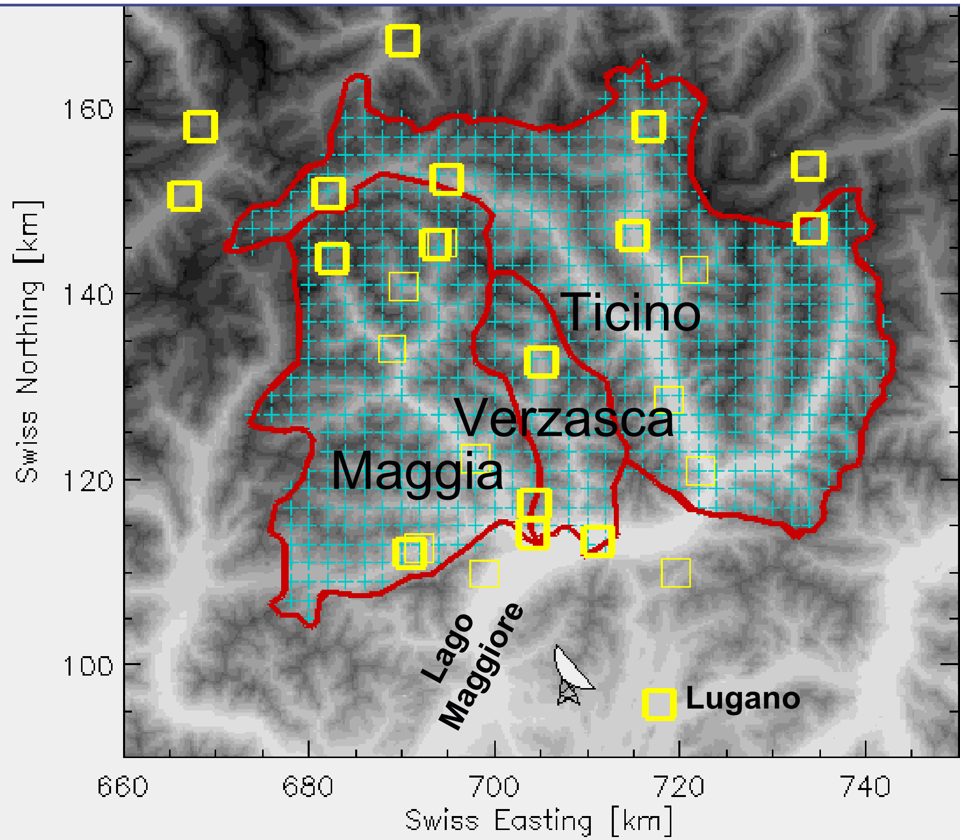


Variance-covariance matrix
from 1000 simulated realisations



Experiment set-up

3 rivers Maggia-Verzasca-Ticino:
2800km²-catchment southern Alps,
1 radar, 18 (27) gauges, 6 months of data
Lake 200m; mountain peaks >3000m



Goal: generate ensemble of hourly radar precipitation fields

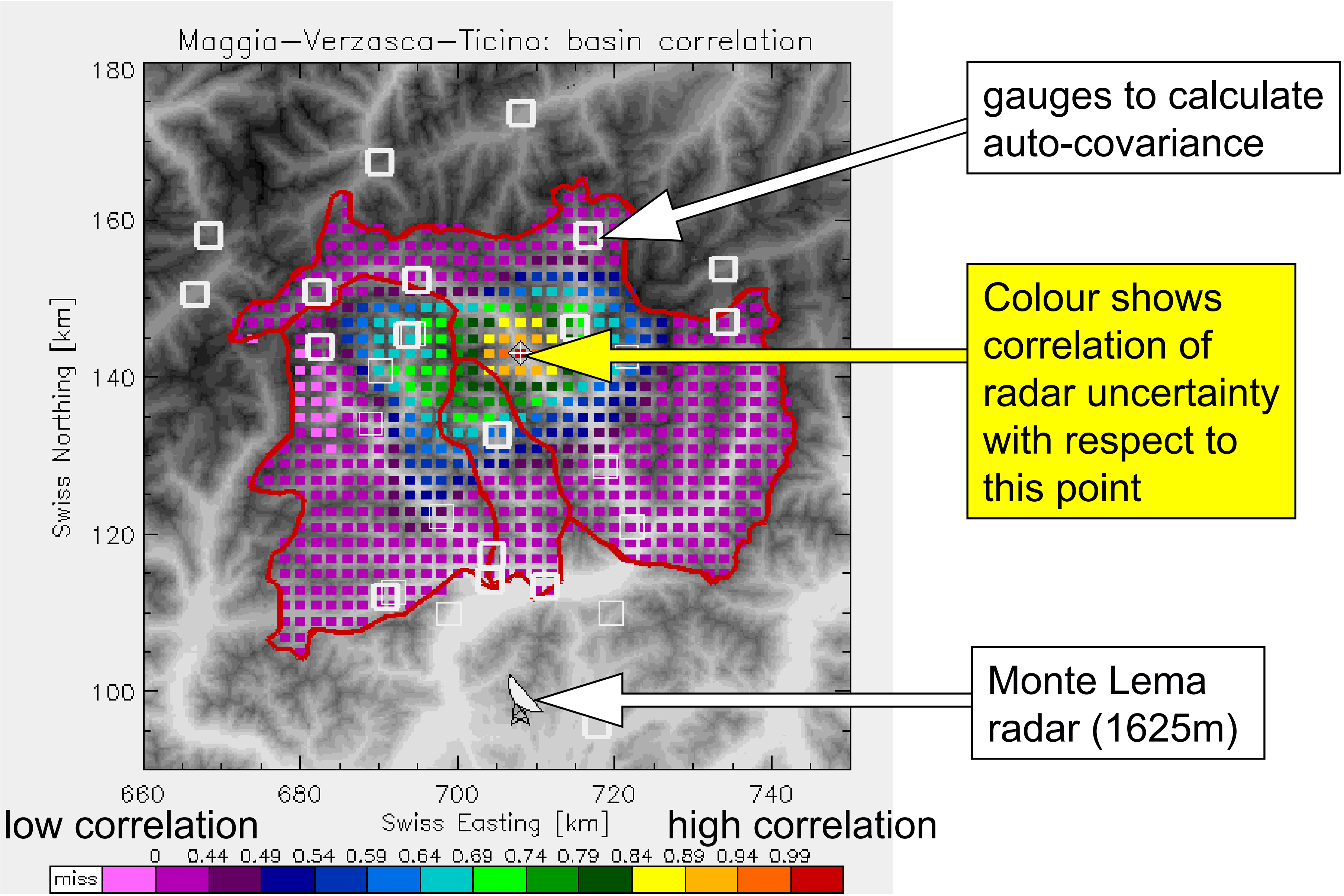
Assumption: uncertainty defined as log(radar/gauge) is correlated random

C is obtained from radar-gauge.
L from Cholesky decomp. of C.
Use *modified* Cholesky algorithm to avoid numerical instability.

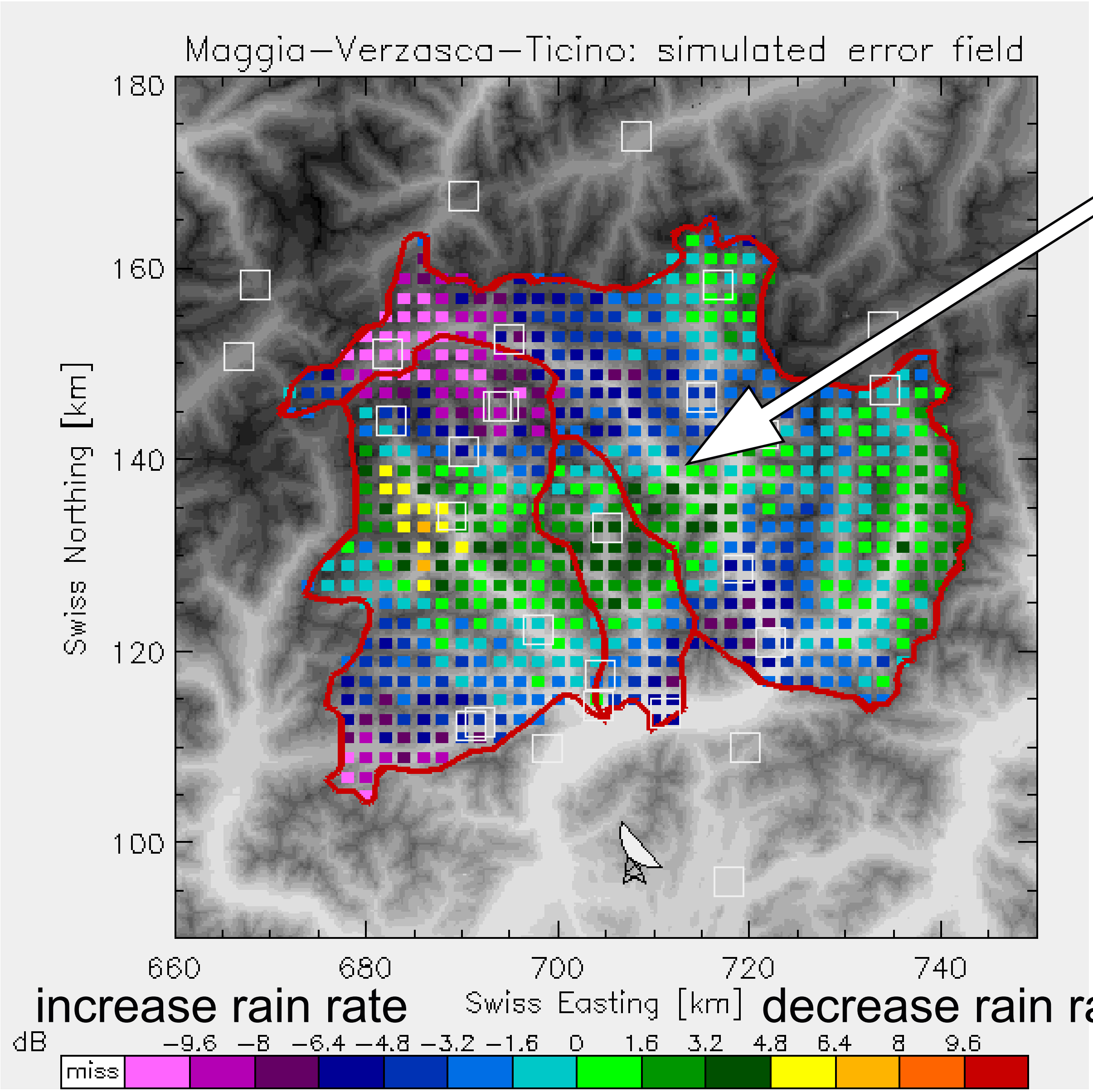
Thus: we simulate perturbation $\boldsymbol{\delta}_i$ using $\boldsymbol{\delta} = L\boldsymbol{\varepsilon}$ and obtain ensemble member $\mathbf{R'}_i$ by adding $-\boldsymbol{\delta}_i$ to logarithm of original radar field $\mathbf{R}_0$

$$\log(R'_i) = \log(R_0) - \delta_i$$

Example of auto-correlation for given location



Example of perturbation field

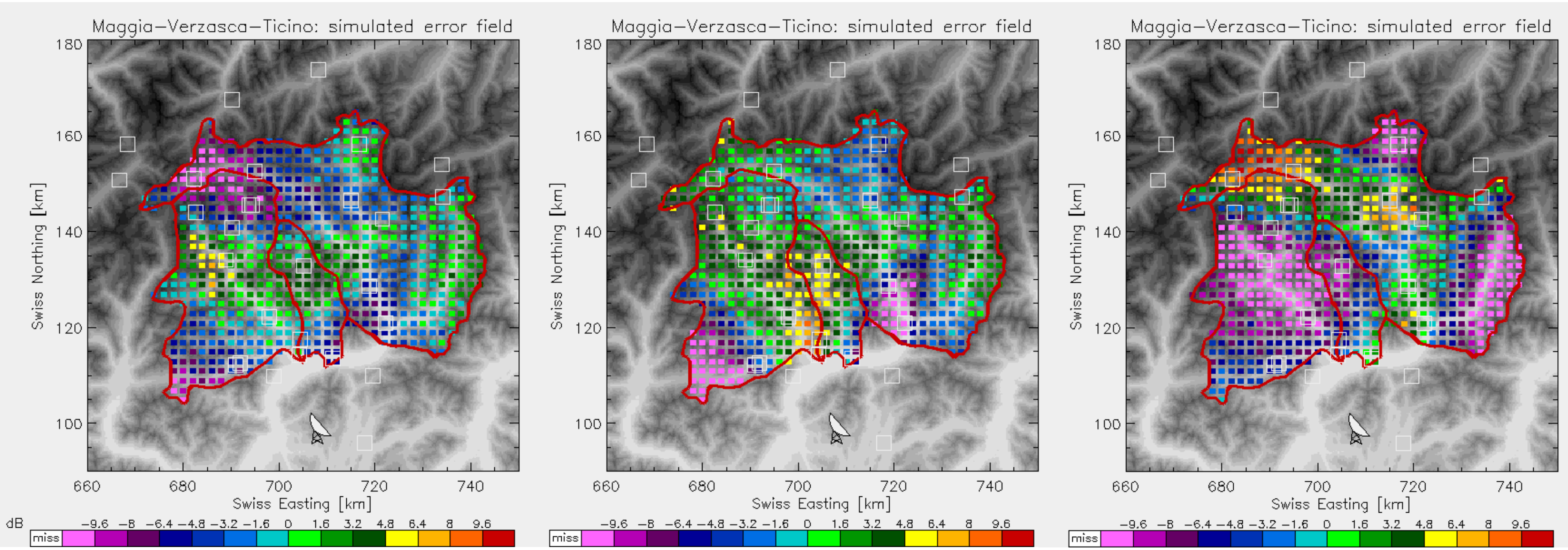


700 catchment pixels, each 2km x 2km

increase rain rate

decrease rain rate

Three realisations of perturbation field



increase rain rate

decrease rain rate

We have a flexible ensemble generator ...

What next?

Add time using auto-regressive model.

Add physics to estimate variance-covariance matrix.

Conditioning of stochastic simulation with any type of knowledge (e.g. uncertainty at given point).

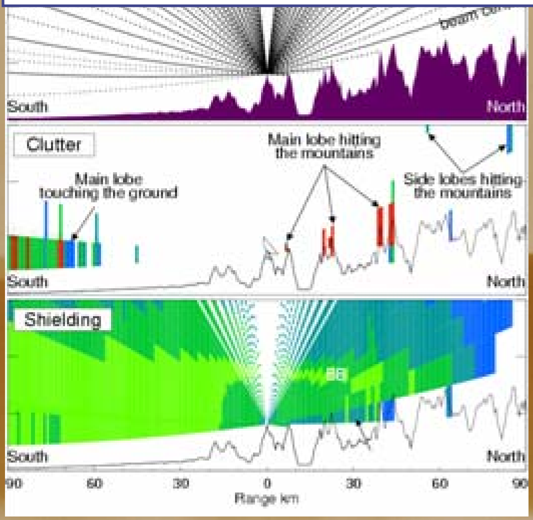
Select relevant members depending on sensitivity of given application.

Test during MAP D-PHASE meteo-hydrological forecast demonstration project in fall 2007.

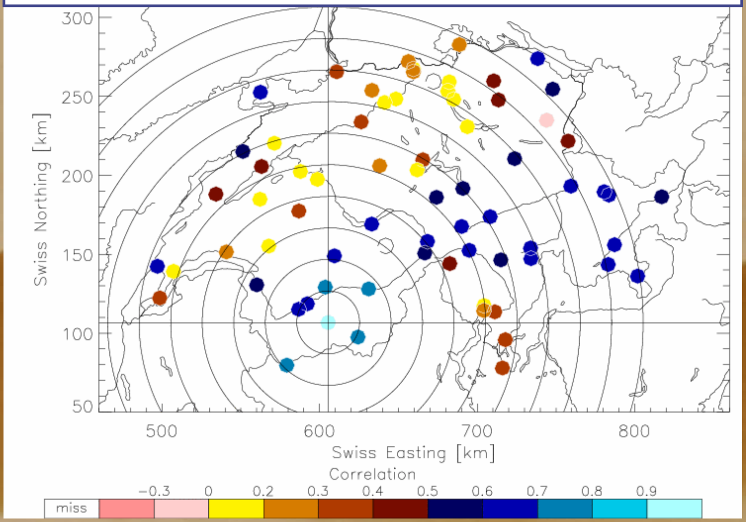
Discuss within COST-731.

Summary

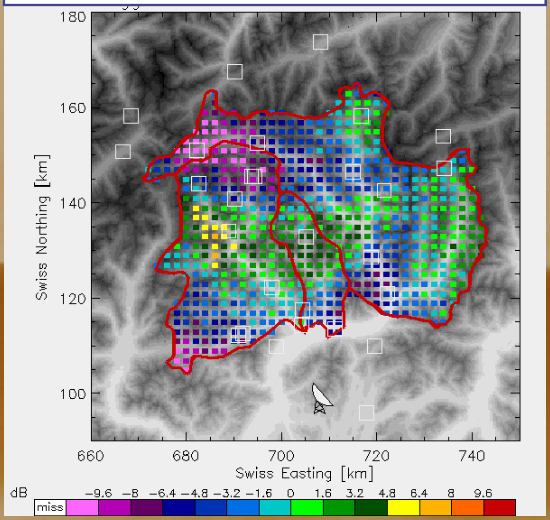
Challenge of radar in the Alps



Auto-correlation of radar uncertainty



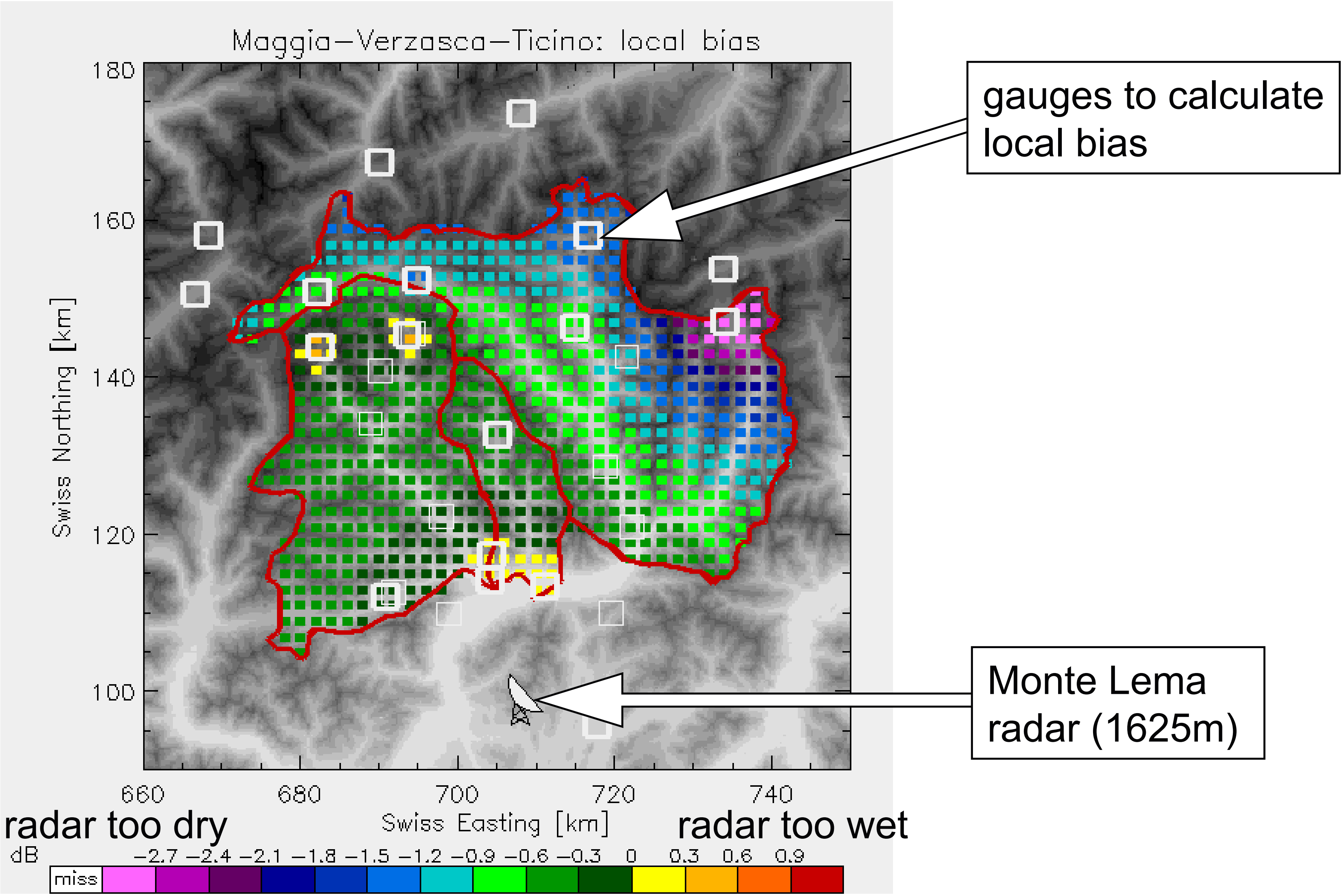
Simulated perturbation field



Thank you!

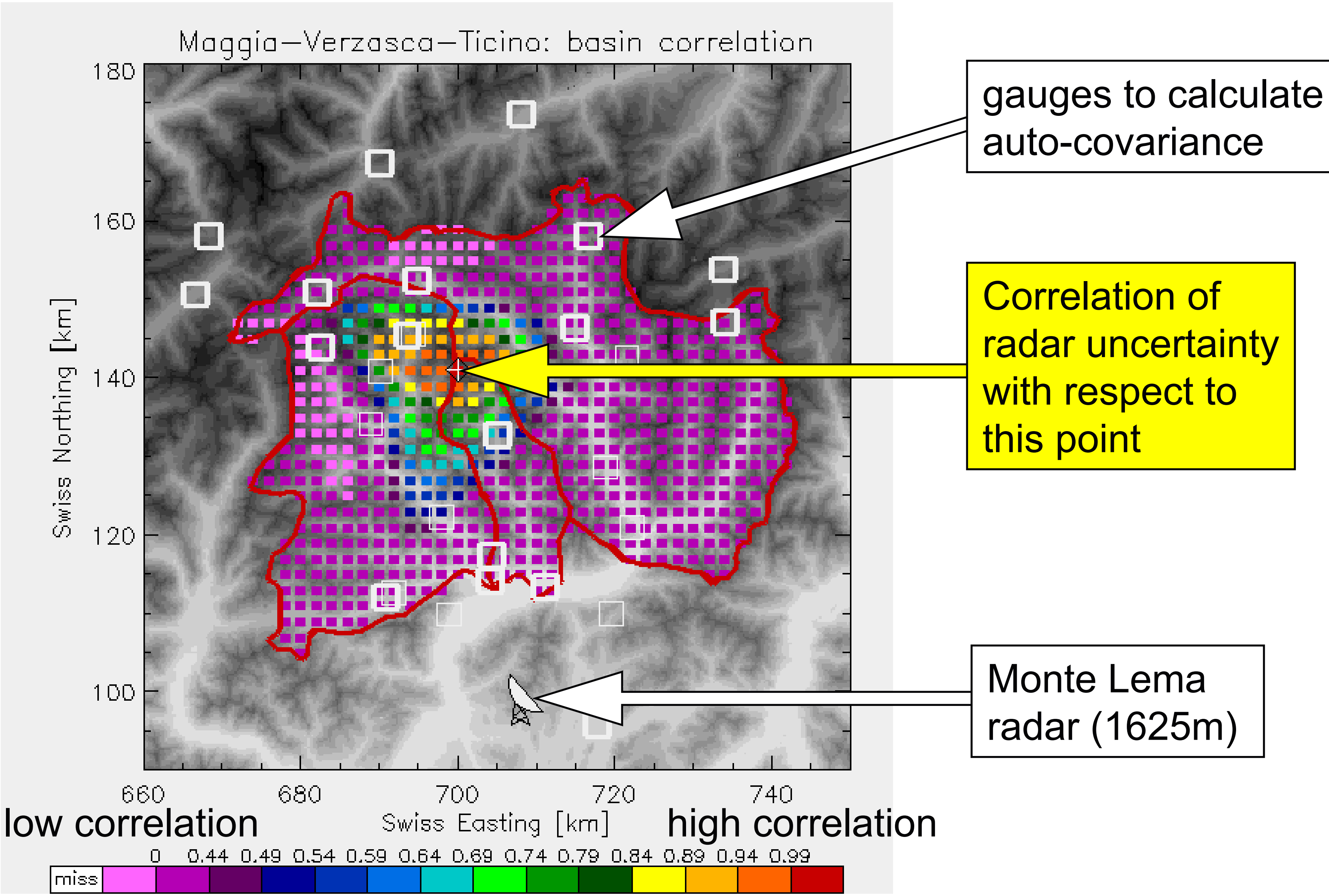
Collaboration: MeteoSwiss, GRAHI UPC Barcelona, McGill Montreal

Local bias

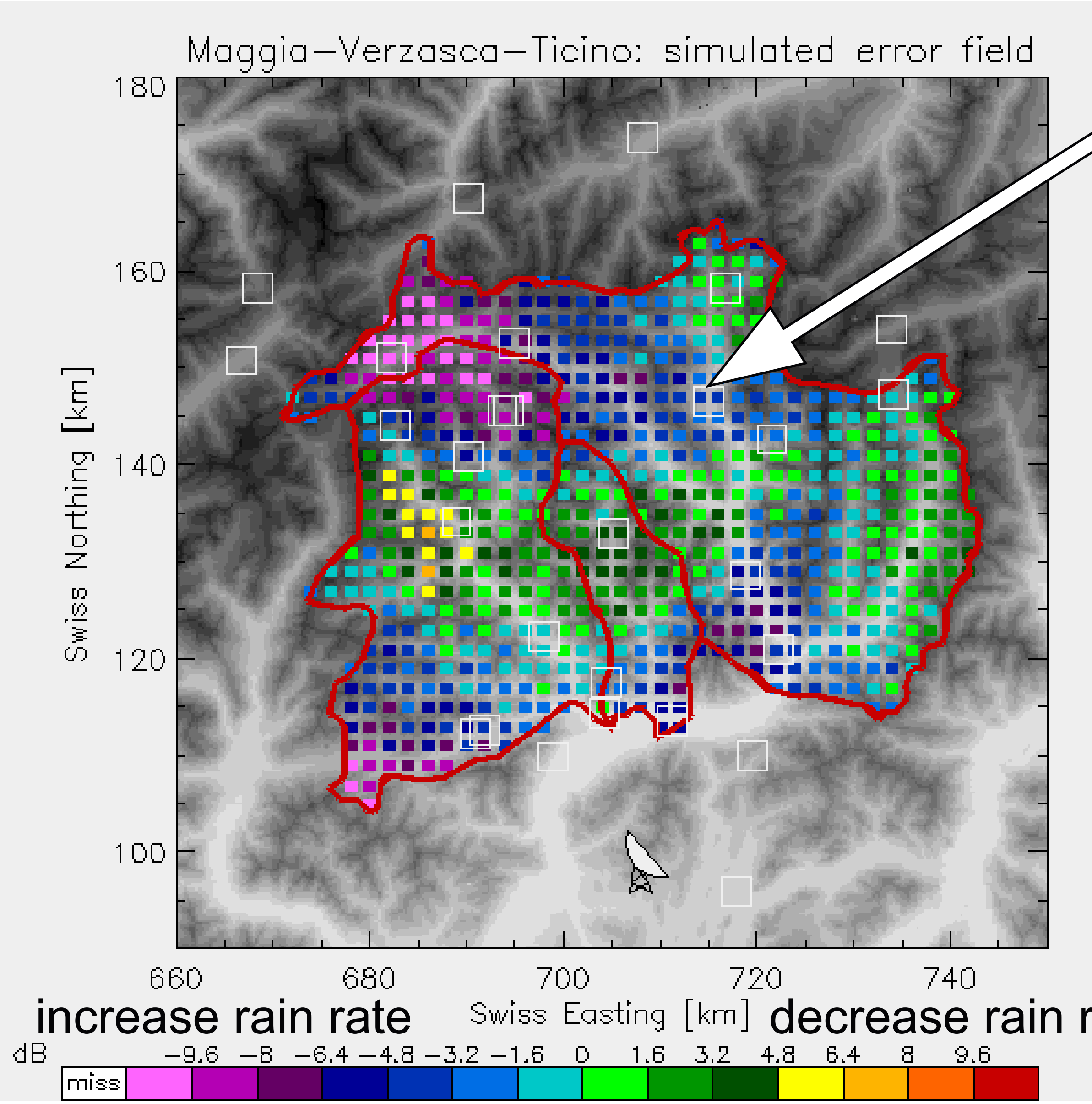


Maggia–Verzasca–Ticino: local bias
180
160
140
120
100
Swiss Northing [km]
660
680
700
720
740
Swiss Easting [km]
gauges to calculate local bias
Monte Lema radar (1625m)
radar too dry
radar too wet
dB
–2.7 –2.4 –2.1 –1.8 –1.5 –1.2 –0.9 –0.6 –0.3 0 0.3 0.6 0.9
miss

Example of auto-correlation for given point



Example of perturbation field



700 catchment pixels, each 2km x 2km

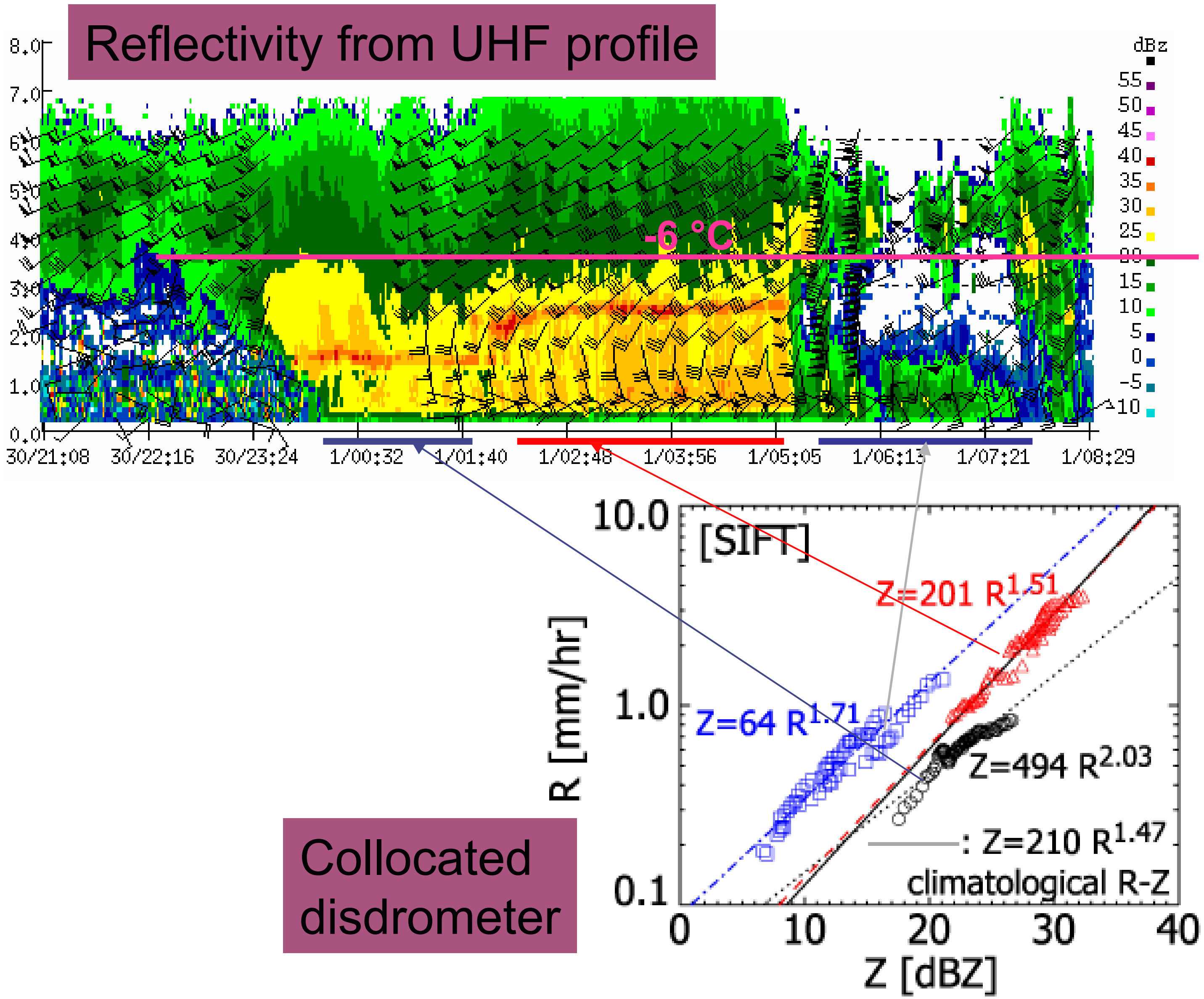
Major assumptions:

- radar-gauge ratio is good estimate of overall radar uncertainty

- uncertainty defined as log(radar/gauge) is correlated random

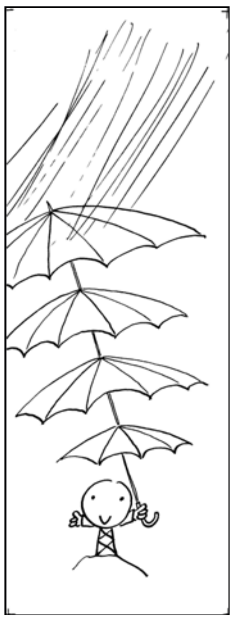
- uncertainty in summer 2005 is representative for particular event

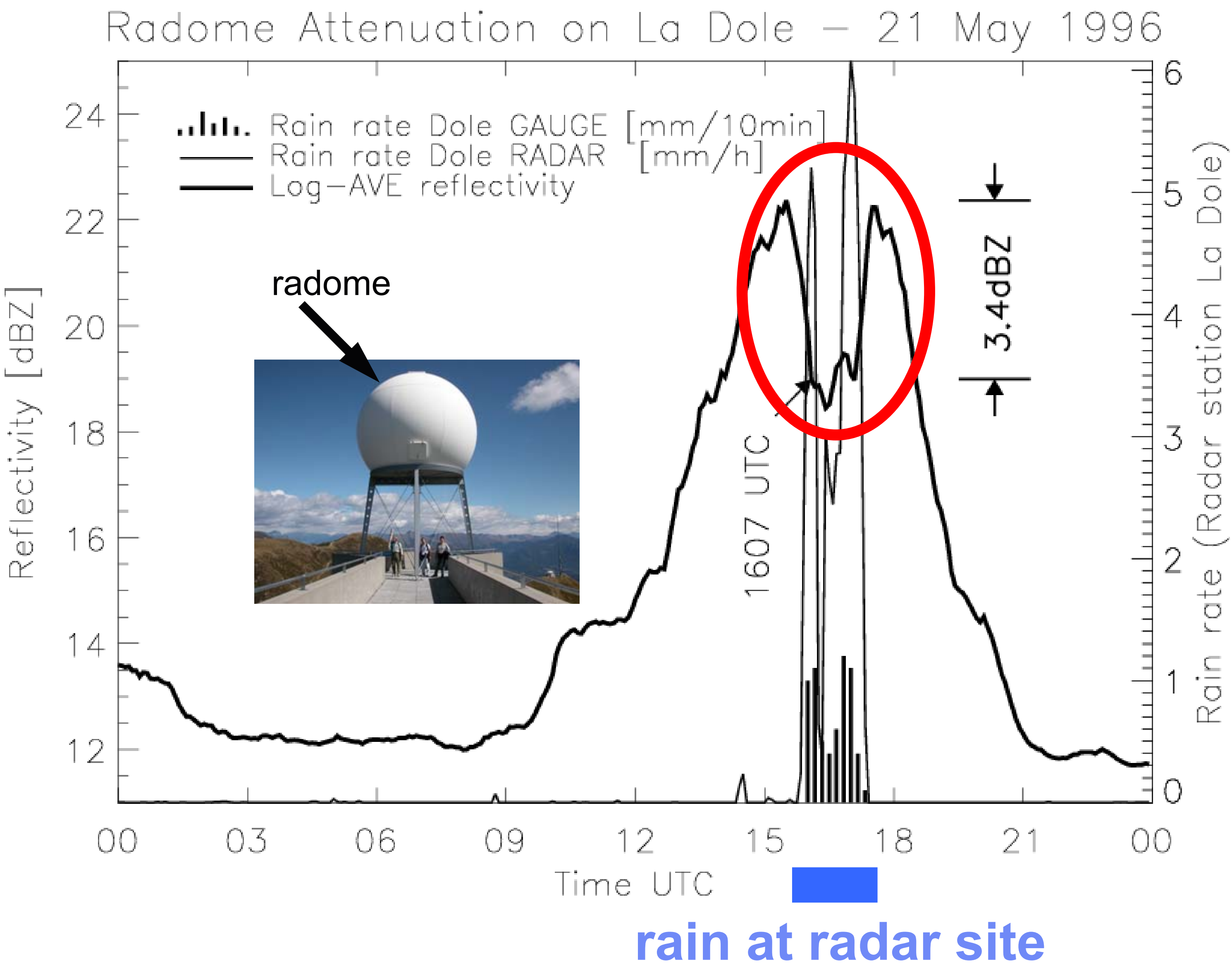
From reflectivity to precipitation (Z-R)



Courtesy: Lee+Zawadzki, J Appl Meteorol, 2005

Attenuation by water on radome

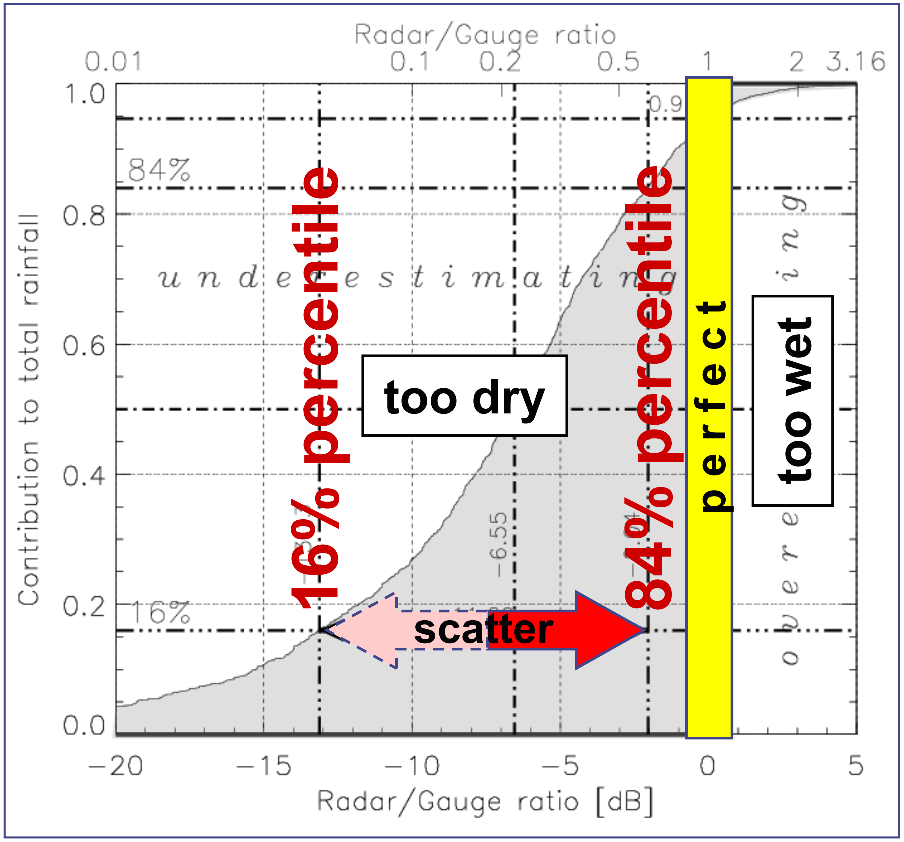




Germann, Meteorol Z, 1999

1999 versus 2004 (whole Switzerland)

Summer 1999

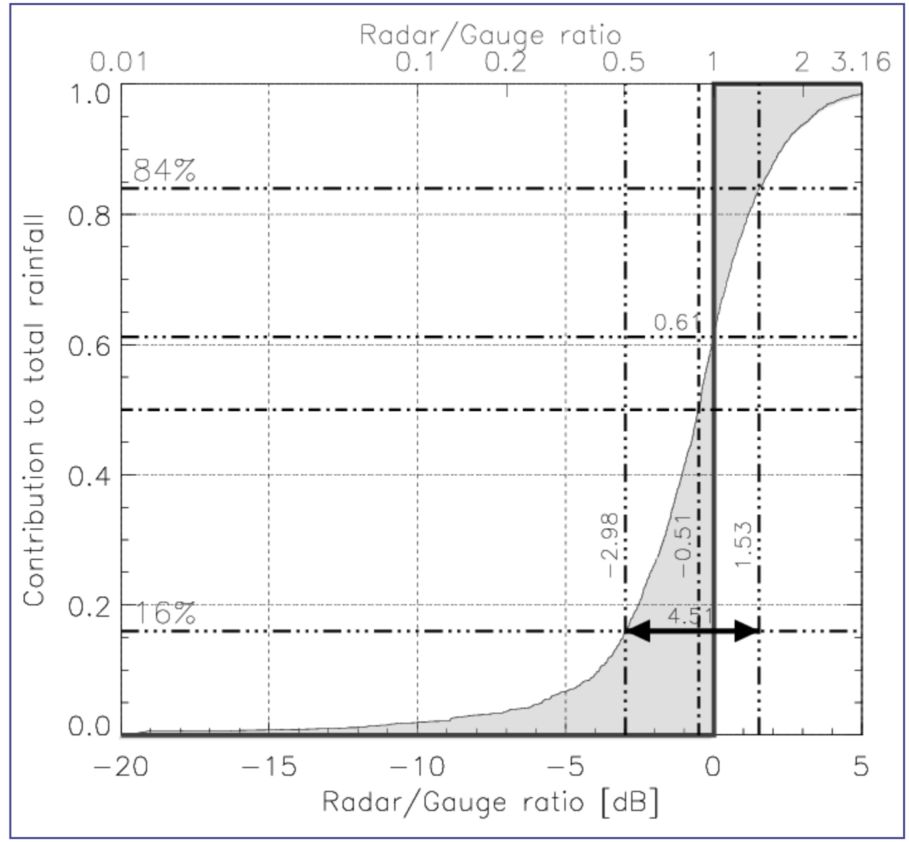


Bias: 0.34 (-66%)

Scatter: 68% of rainfall within factor of **3.6**

Summer 2004

(after correction of local bias as observed in 2003)



Bias: 1.003 (0%)

Scatter: 68% of rainfall within factor of **1.7**

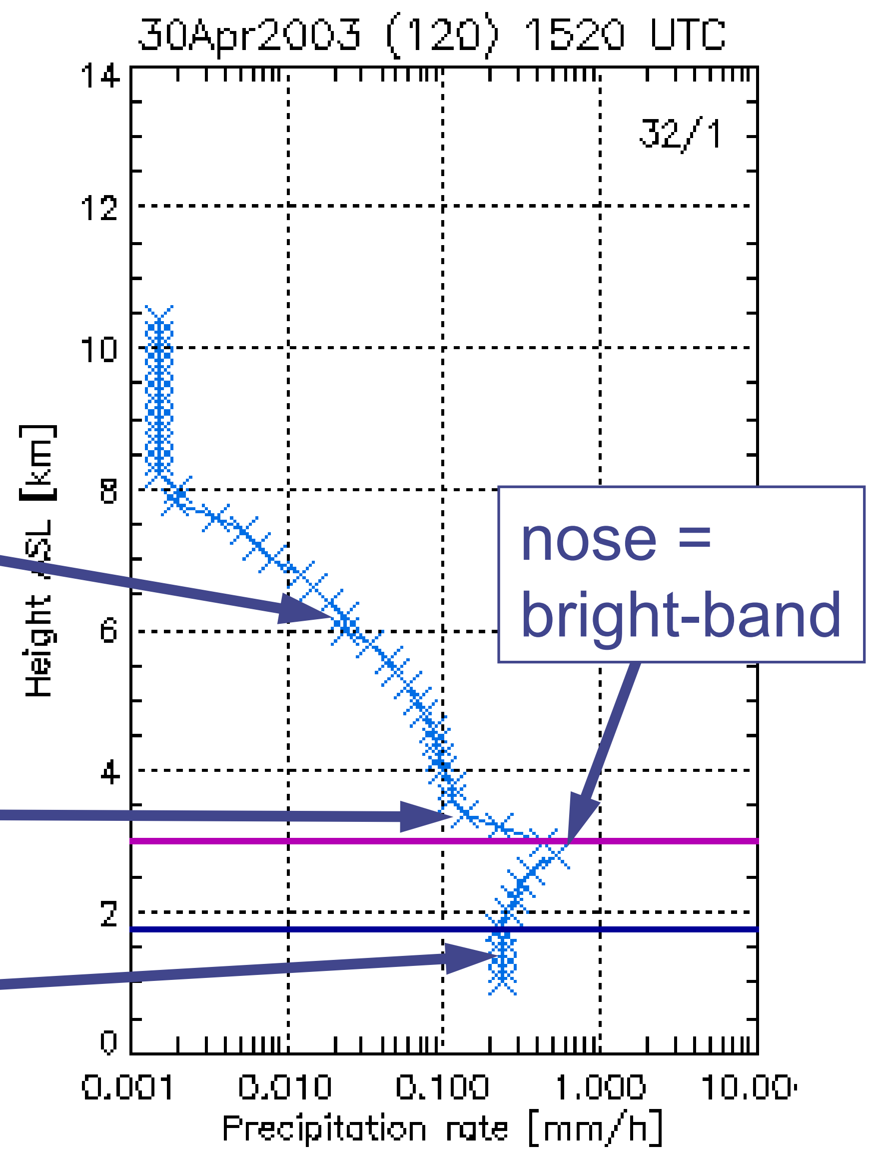
Germann et al, 2004

Extrapolation from aloft

growth in ice phase

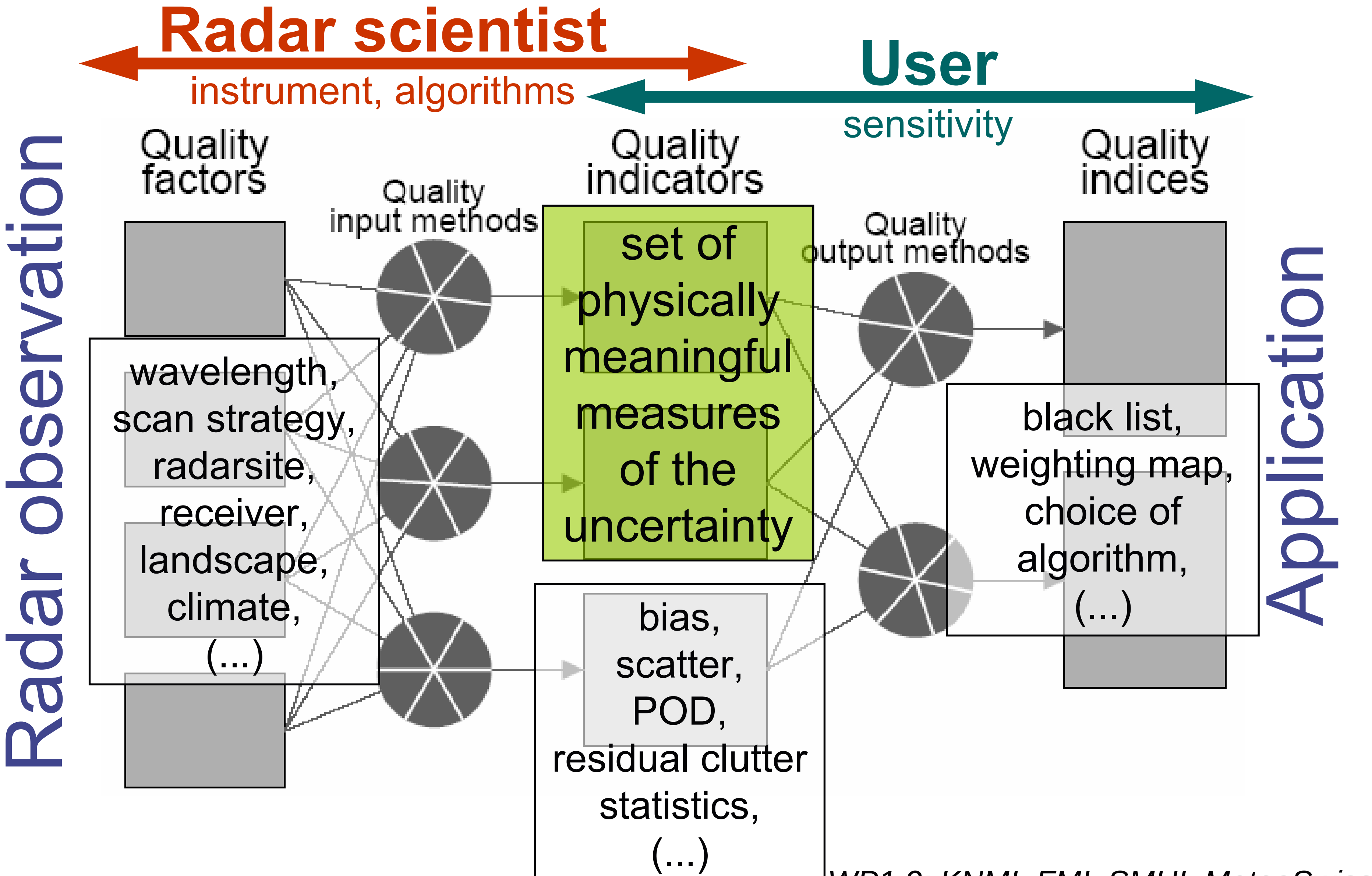
zero-degree isotherm

falling rain



Bellon et al., 2005; Germann and Joss, 2002, J Appl Meteorol

OPERA WP1.2E



WP1.2: KNMI, FMI, SMHI, MeteoSwiss