Comparison of polarimetric techniques for operational precipitation estimation in complex orography scenarios

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Outline of the presentation

- ***Introduction:***
  - Motivation
  - Environmental scenario
  - Radar system
- ***Data processing chain***
  - Clutter mitigation & Partial Beam Blocking correction
  - Φ_{dp} processing → K_{dp} estimation
  - Attenuation correction
  - Vertical Profile of Reflectivity (VPR) and Kdp (VPK) reconstruction
  - Rainfall estimation: power-law & neural network
- ***Results***
- ***Conclusions***

Acknowledgement

Thank you Andrea!!

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Motivation

- Integrating a previous work (Vulpiani et al., JAMC, 2012) on the same topic (operational polarimetric rainfall estimation in complex orography)
- In Vulpiani et al. (2012):
  - a new K_{dp} retrieval technique was proposed
  - the K_{dp}-based rainfall algorithm was found to generally outperform the considered Z-R relationship
  - $R(K_{dp})$ was found less sensitive to range distance
  - $R(K_{dp})$ was found sensitive to ice contamination
- In the present work the following tasks are accomplished:
  - considering more rainfall events (5 more events for a total of 12)
  - tuning of the K_{dp} retrieval technique
  - retrieval of the vertical profile of K_{dp} and ground-projection of K_{dp} fields
  - evaluation of a neural network algorithm employing Z and K_{dp} for better dealing with DSD variations

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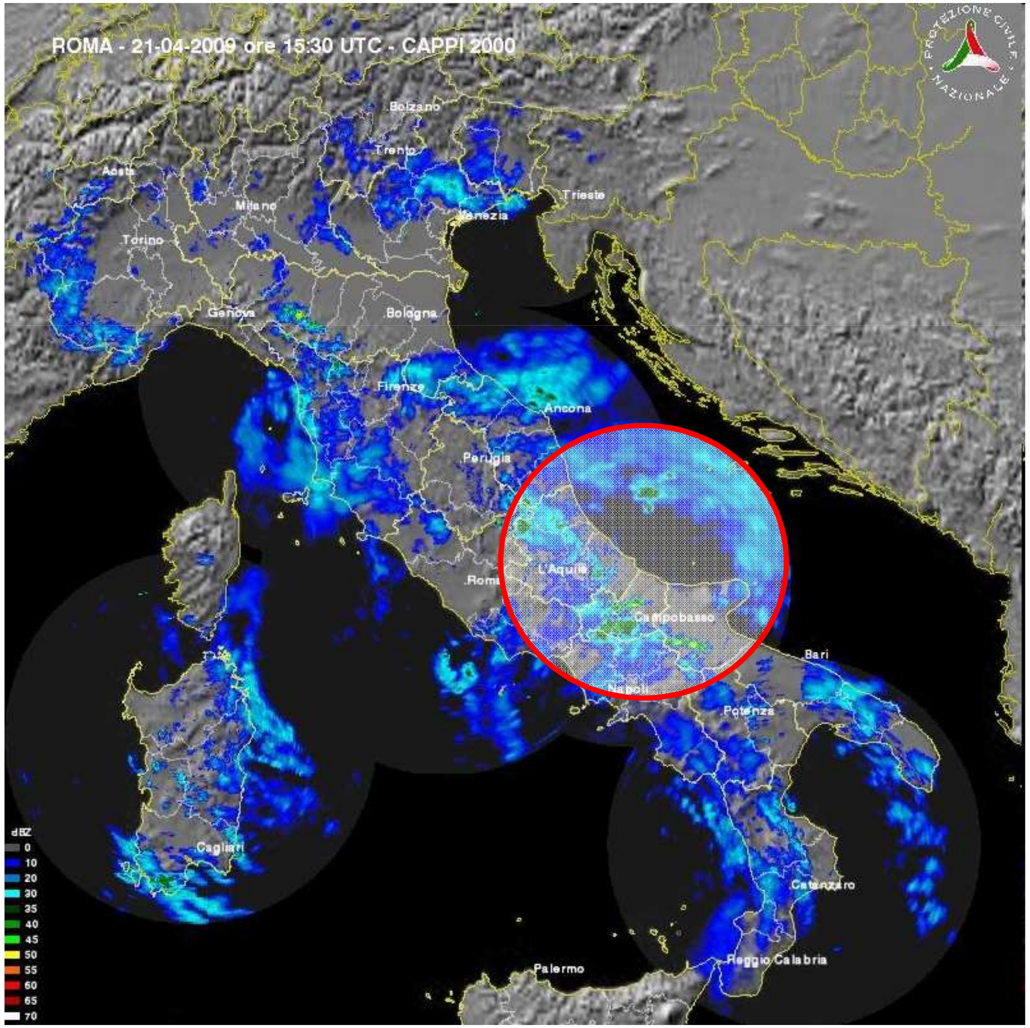
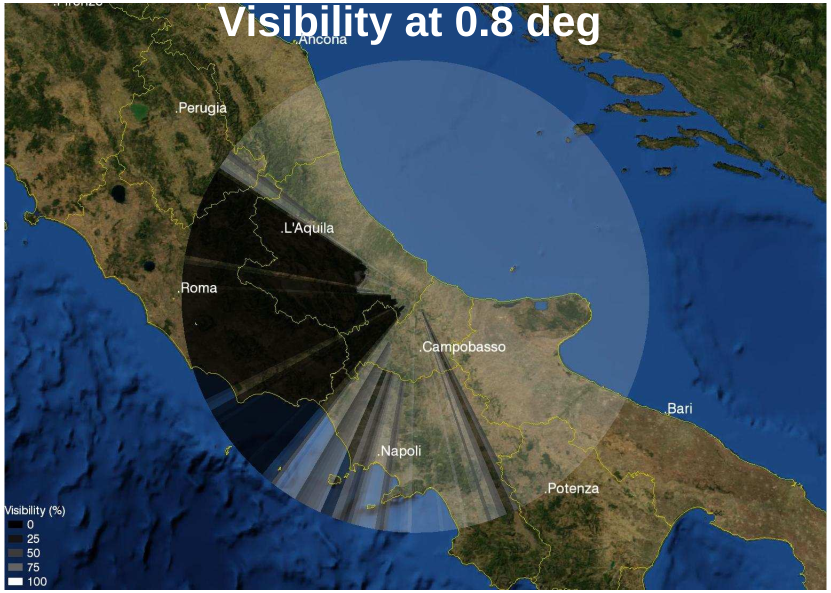
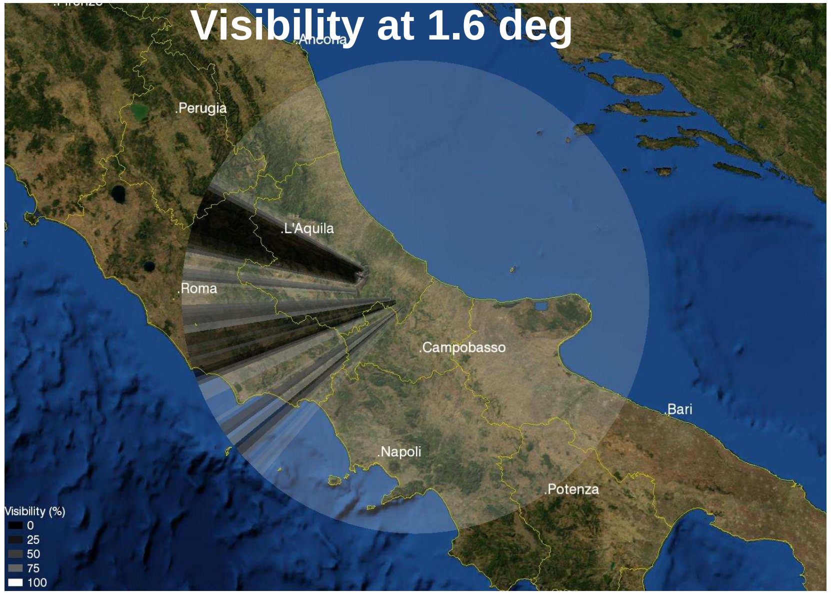
Introduction

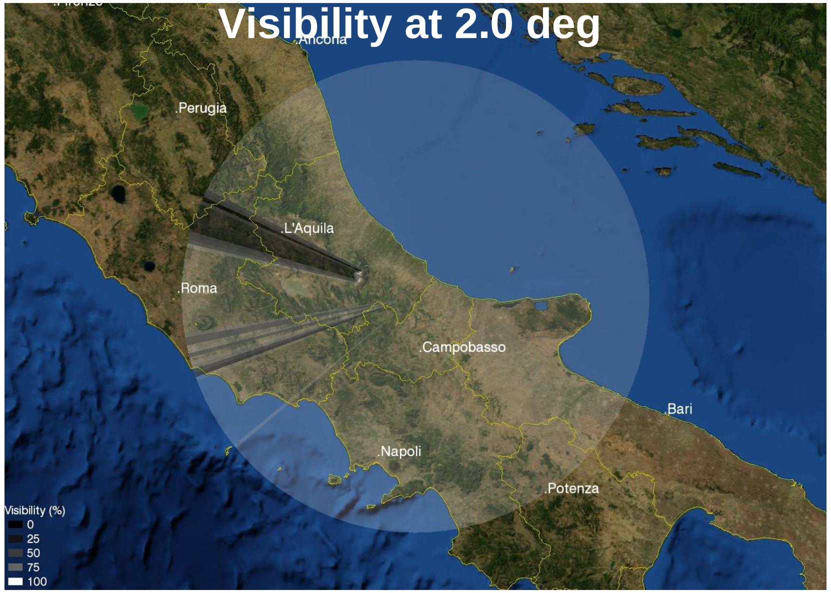
- *Italy has Iper-complex orography*, a lot of small basins→need to have a dense network
- *Federated national weather radar network coordinated (at central level) by the Department of Civil Protection*
- *18 C-Band and 4 X-Band radars +3 more planned C-band*
- *The radar data used in this work* come from the operational Polarimetric Doppler Radar System located in Central (PDRS1)



Environmental scenario







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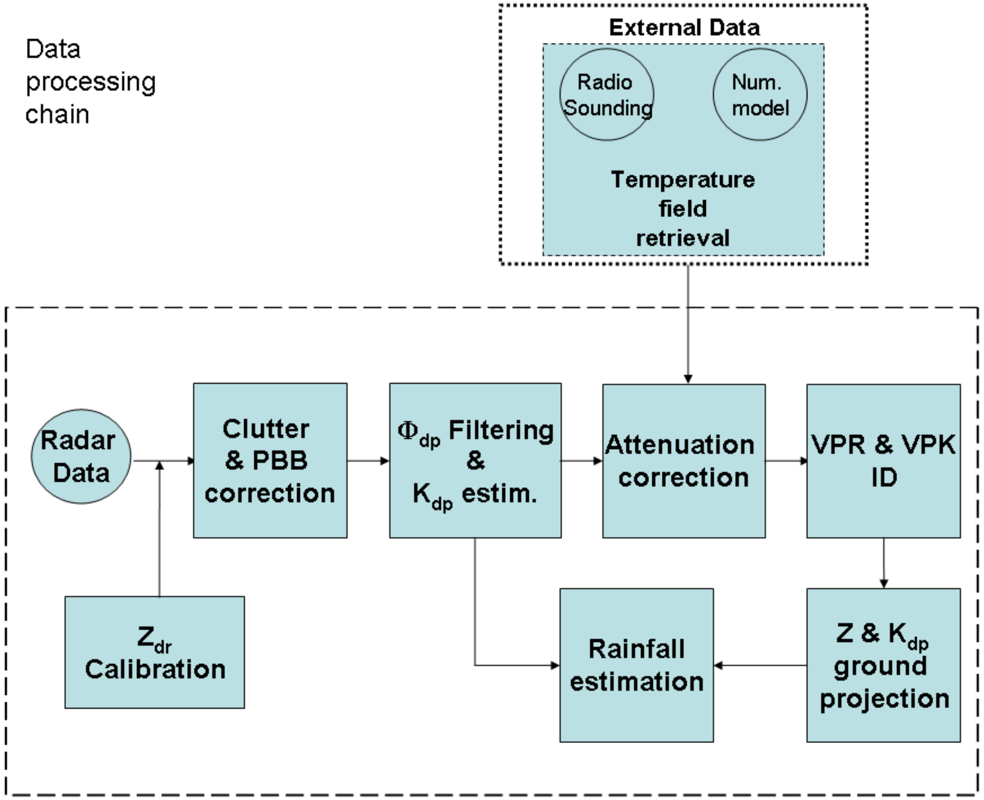
Data processing chain

Data processing chain



- **Clutter removal**: data quality concept
- **PBB correction**: Bech et al., (2003)
- **Φ_{dp} filtering and K_{dp} estimation:** new technique
- **Attenuation correction:** Vulpiani et al., (2008)
- **VPR reconstrution**: real-time mean VPR computation
- **VPK reconstrution**: VPK computation on a daily basis
- **Rainfall estimation:**
  - Z-R (Marshall and Palmer, 1948) applied to ground-projected VMI
  - **R_{BC01}**: R-K_{dp} (Bringi and Chandrasekar, 2001)
  - **R_{BR11}**: R-K_{dp} (Bringi et al., 2011)
  - **R_{NN}(Z, Kdp): Neural Network**

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Data processing chain: clutter removal

Identification by resorting to the data quality concept based on the following input (X_j):

- Empirical CLUTTER **Map** (X_1)
- Radial velocity, **Vr** (X_2)
- Texture of: $\mathbf{Z_{dr}}$ (X_3), ρ_{hv} (X_4), $\mathbf{\Phi_{dp}}$ (X_5)

Degree of membership to the non-meteorological class (d_j) as derived by the j-th input

$$d_i = \begin{cases} 0 & \text{if } X_j < X_{1,j} \text{ or } X_j > X_{4,j} \\ (X_j - X_{1,j})/(X_{2,j} - X_{1,j}) & \text{if } X_{1,j} < X_j < X_{2,j} \\ (X_{4,j} - X_j)/(X_{4,j} - X_{3,j}) & \text{if } X_{3,j} < X_j < X_{4,j} \\ 1 & \text{if } X_{2,j} < X_j < X_{3,j} \end{cases}$$

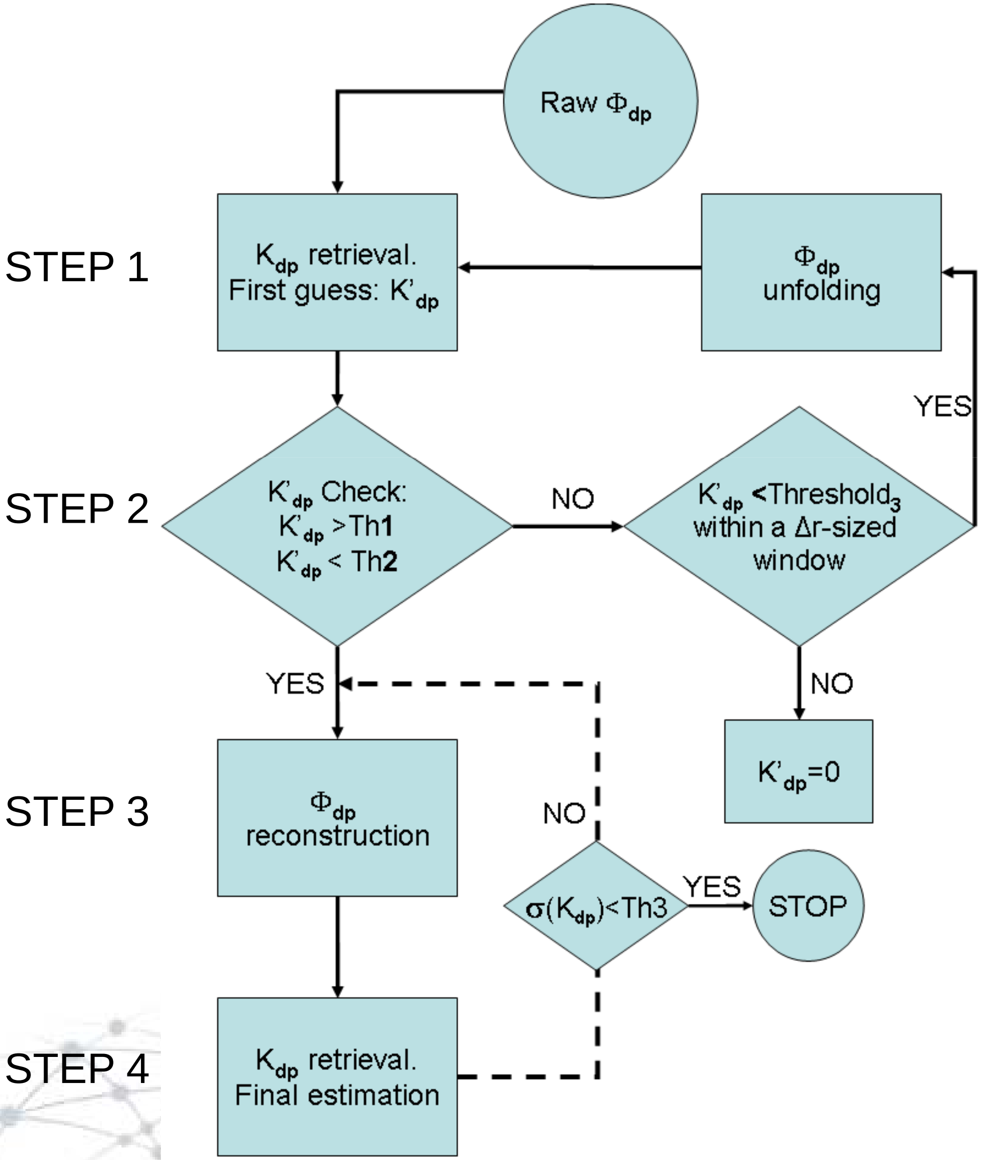
Relative quality index q_j

$q_j = 1 - d_j$

Overall quality

$$q_{clutter} = \frac{\sum_j^n w_j q_j}{\sum_j^n w_j}$$

Data processing chain: Φ_{dp} filtering and K_{dp} estimation



Notes:

- it can be demonstrated that:

$$\sigma\left(K_{dp}\right)=\frac{1}{\sqrt{2N}}\frac{\sigma\left(\Psi_{dp}\right)}{L}$$

$\sigma(K_{dp})$ is about 0.05 deg km^{-1} for $\sigma(\Phi_{dp})$ = 3 deg and L=7 km

- $\sigma(K_{dp})$ can be further reduced by iterating steps 3-4 :

$$\sigma\left(K_{dp}{}^{(I)}\right)=\frac{1}{\sqrt{2N^{I}}}\frac{\sigma\left(\Psi_{dp}\right)}{L}$$

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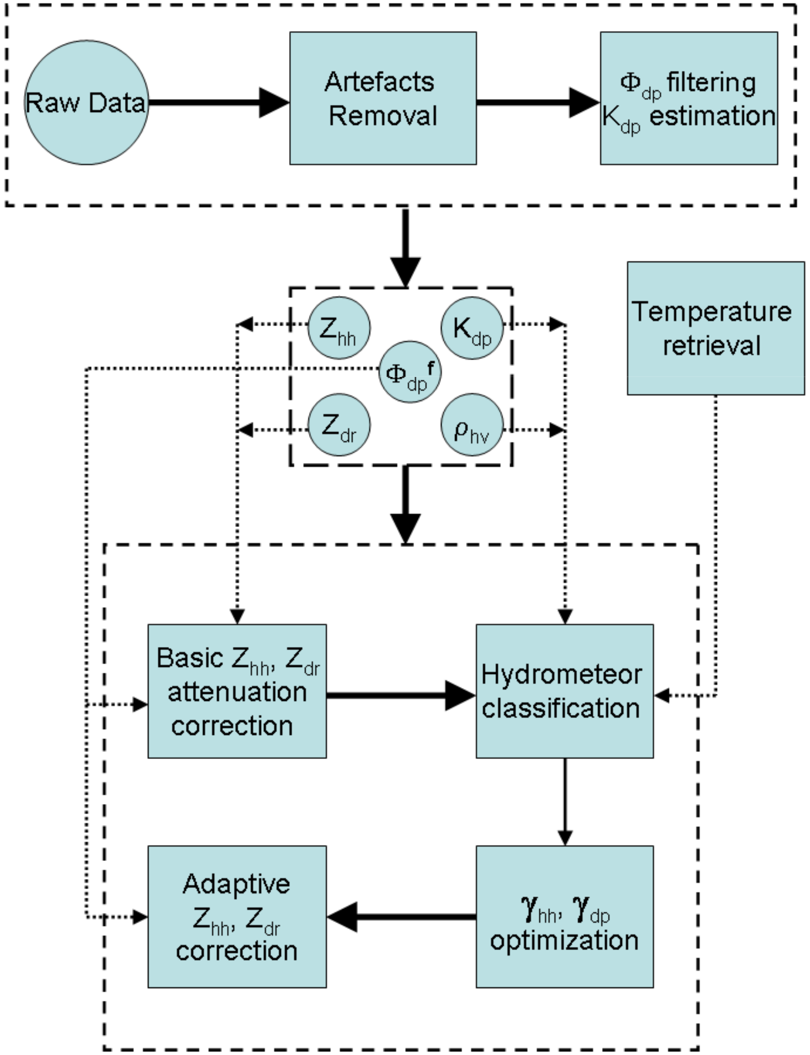
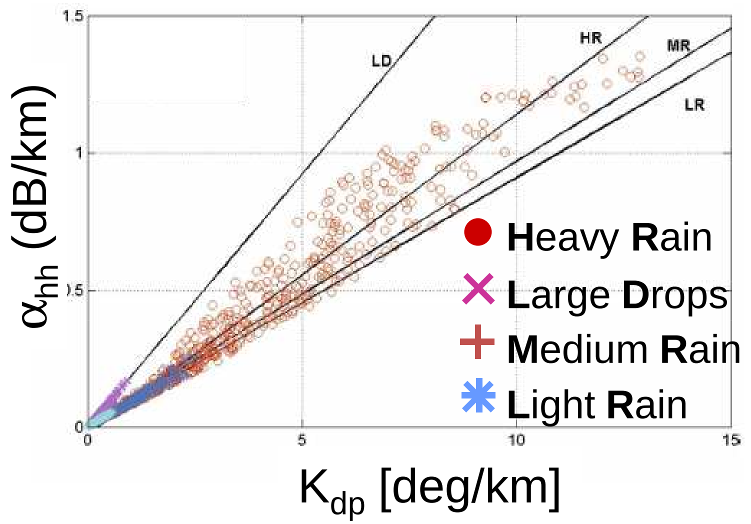
Data processing chain: attenuation correction





Attenuation correction based on Φ_{dp} measurements: ***APDP*** (*Vulpiani et al. 2008*)

- Linear relationship: $\alpha_{hh,dp} = \gamma_{hh,dp} K_{dp}$ [dB/km]
- $\gamma_{hh,dp}$ *depend on drop size, shape and tempertaure*
- $\gamma_{hh,dp}$ *are optimized through an iterative hydrometeors classification*

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Rainfall Estimation

Algorithms

- **R_{MP}**(f(Z)): Marshall and Palmer (1948)
  with f(Z)= **VPR**(**VMI**(Z))
- **R_{BC01}**(g(K_{DP})): Bringi and Chandrasekar (2001)
- **R_{BR01}**(g(K_{DP})): Bringi et al. (2011)
  with g(K_{DP})= **LBM**(K_{DP})
- R_{NN}(Z,K_{dp}), neural networks

Radar Gauge Comparison

- Best-matching radar bins

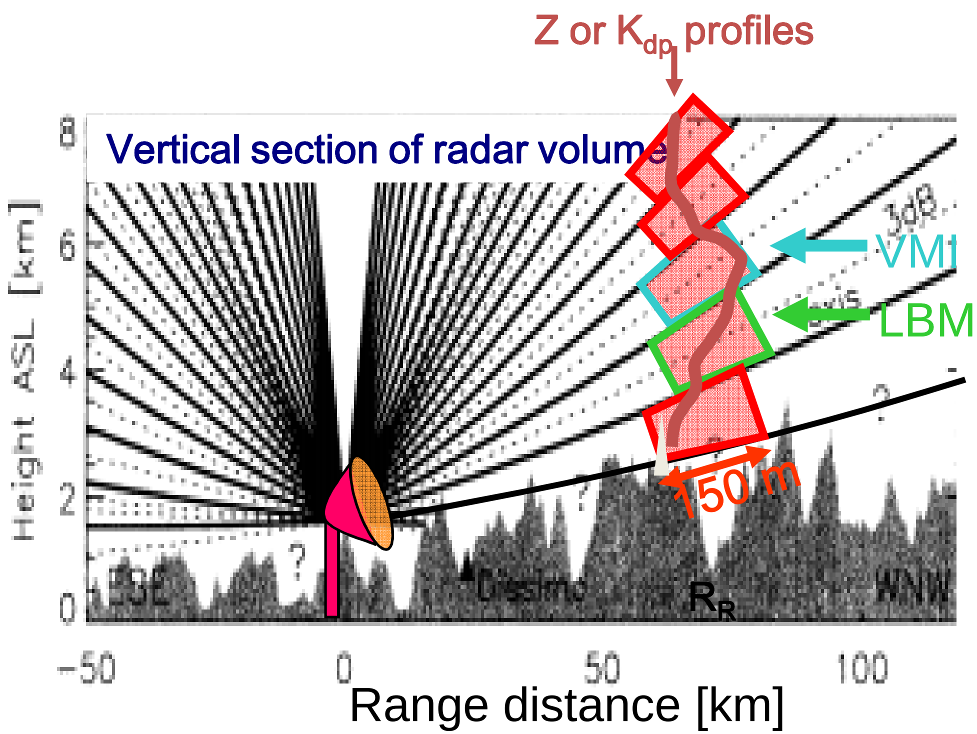
within 25 km^2 area around gauge position are compared with gauges (Silvestro et al., 2008)

Performance analysis

- BIAS: R_G/R_R,
- FSE: RMSE/<R_G>
- Correlation coefficient

➢VPR retrieved for each volume scan

➢VPK retrieved on a daily basis



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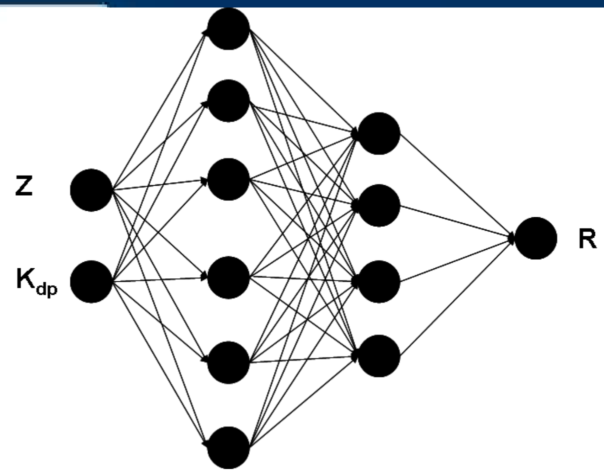
Neural Network: $R_{NN}(Z,K_{dp})$



Architecture

Multi Layer Perceptron (MLP) composed by

- 6 nodes at the 1° hidden layer
- 4 nodes at the 2° hidden layer

Training

- The network is trained using **supervised learning**, with a training set D = (xi, ti) of known inputs and targets. Weights and biases are iteratively adjusted in order to minimize the network performance function, which normally is the sum square error.
- The minimization is based on repeated evaluation of the gradient of the performance function using **back-propagation**
- **Regularization** by input perturbation + considering an additional **term** within the objective function,e.g. $(1-\gamma)E_W$ where E_W is the sum of squares of the network's weights and biases.

Training data set

Simulations by means of the T-matrix scattering model.

Assumptions:

Axis ratio: Brandes et al. (2002)

- Temperature: T=10 ° C
- RSD shape: $N(D)=Nw\,(D/D0)^{\mu}\exp(-(3.67+\mu)D/D0)$
  with 0.5<=D0<=3.5 mm, 2<=log(Nw)<=5, $-1<=\mu<=5$
- Canting angle: Gaussian distribution mean=0 deg, std=10deg

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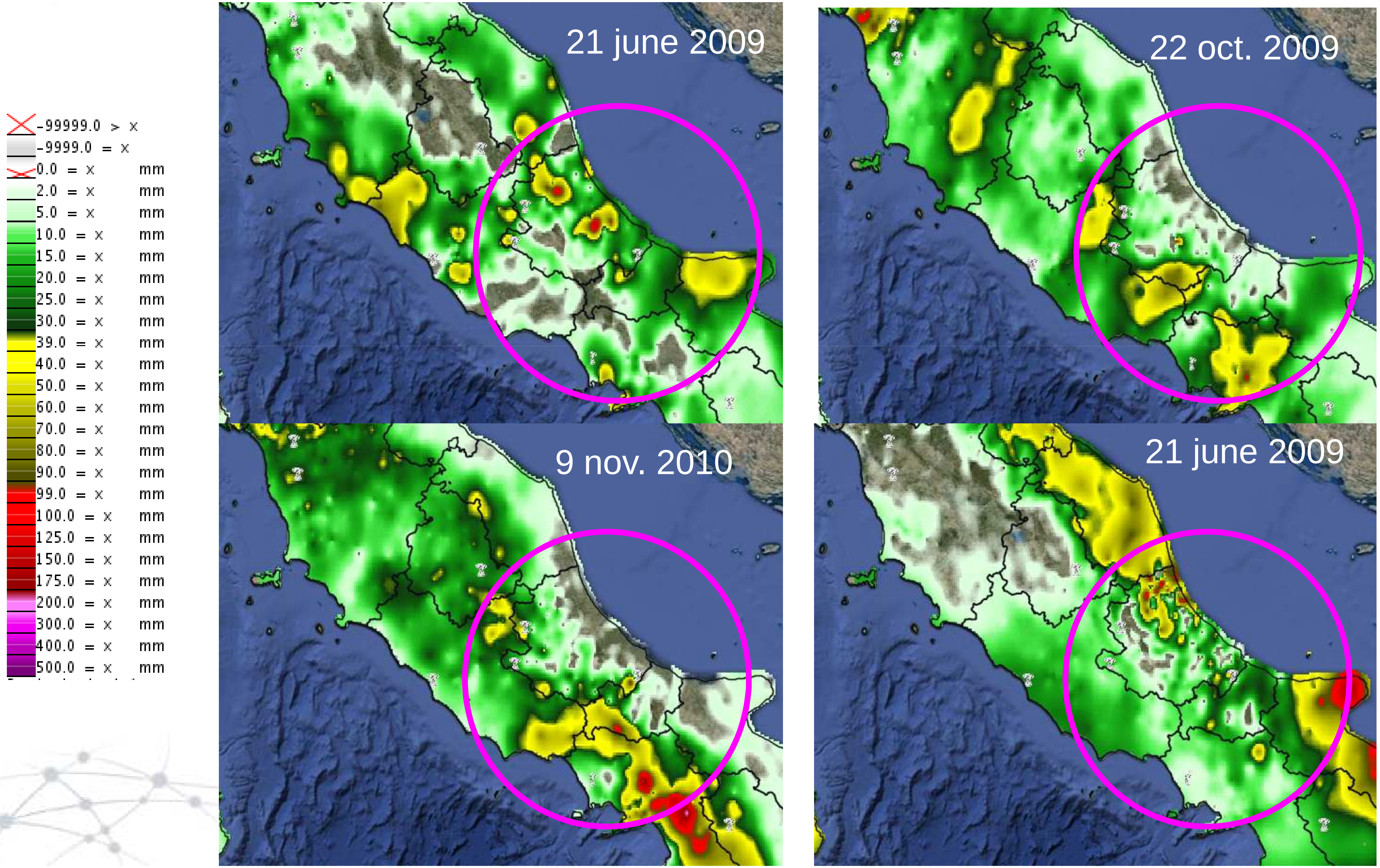
Data set: 12 events



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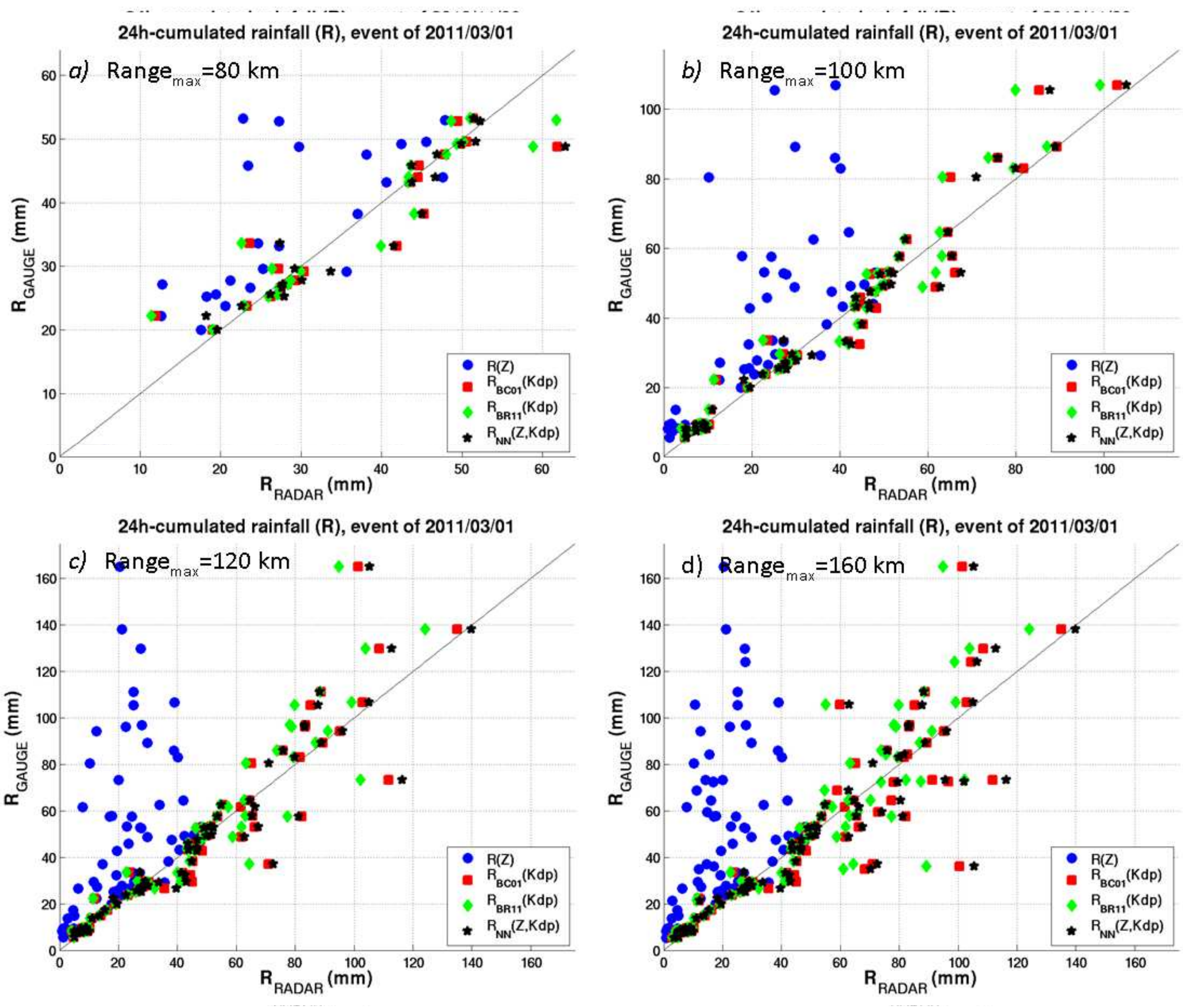
Results: range dependency

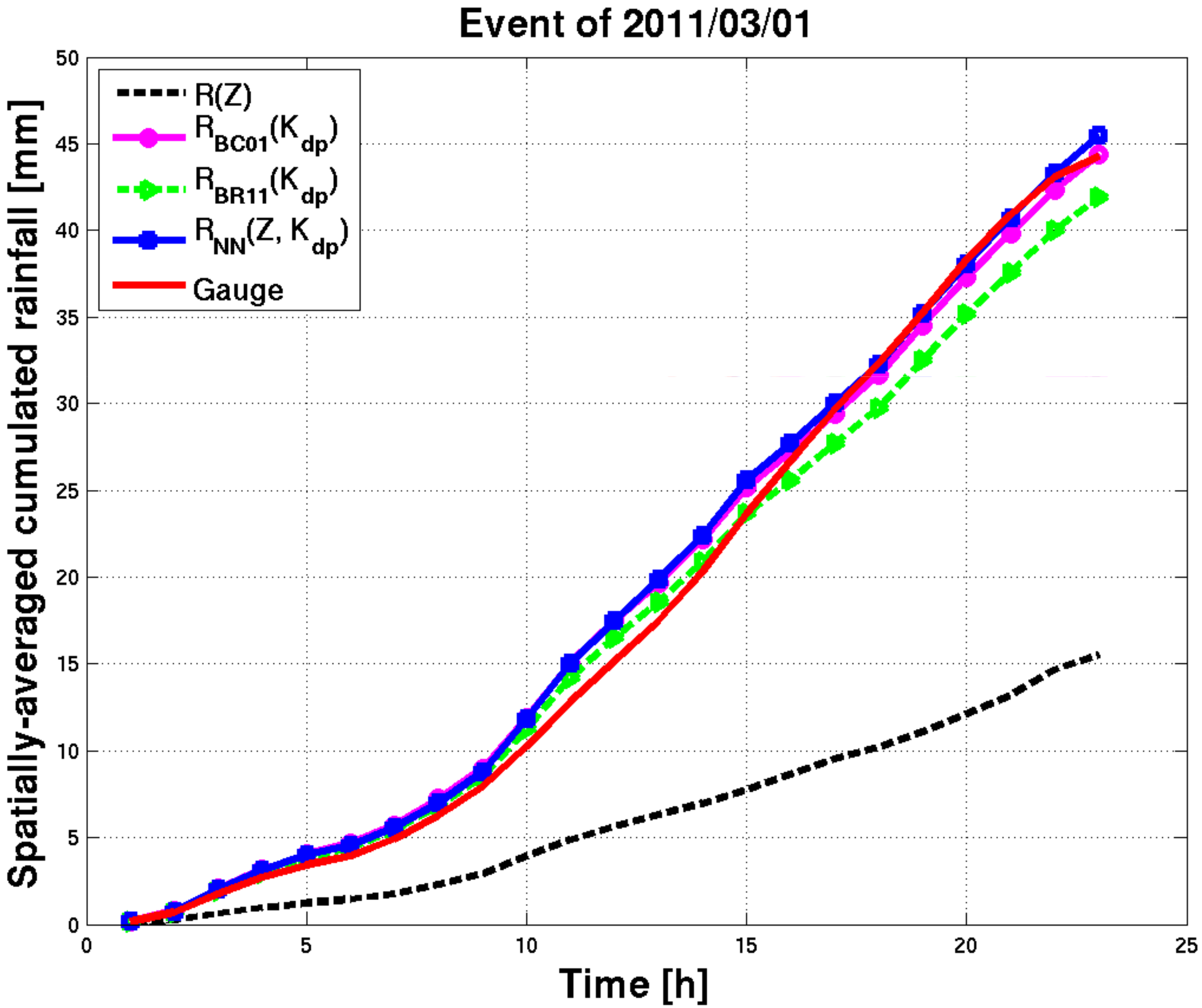
24-h cumulated rainfall

- R(Z)
- $R_{BC01}(K_{dp})$
- $R_{BR11}(K_{dp})$
- $R_{NN}(Z,K_{dp})$



Results:
spatially-averaged cumulated rainfall

Z & K_{dp} are projected at ground



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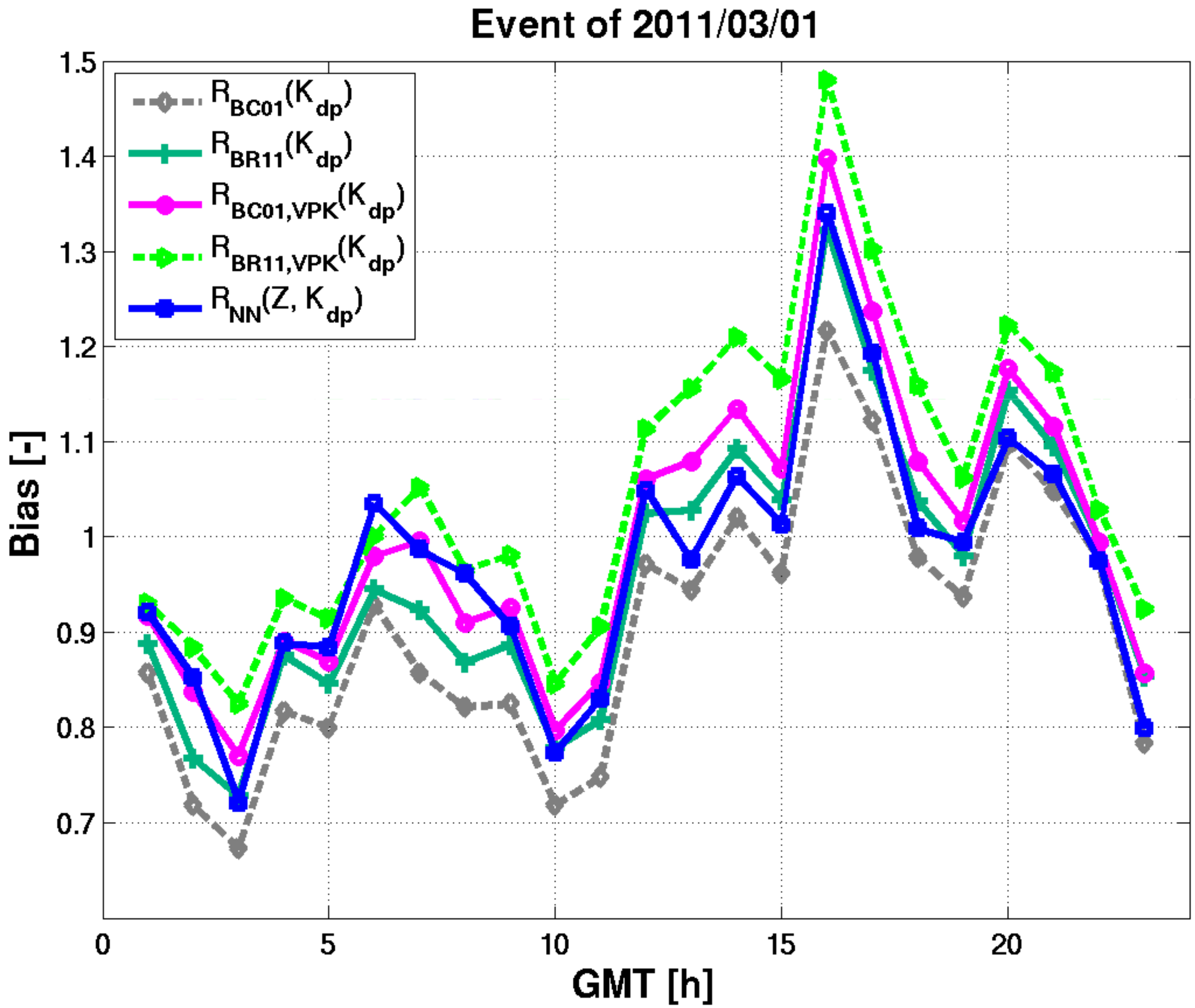
Results: Mean Bias

Threshold on the estimated 1-h rainfall:

Th= 0.2 mm



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Conclusions

- K_{dp} can be used successfully used for operational rainfall estimation in complex terrain conditions, it being immune to partial PBB and attenuation
- K_{dp}-based algs perform relatively well even at far ranges
- In about 70 % of the cases the ground-projection of K_{dp} by means Vertical Profile of K_{dp} (VPK) improved the rainfall estimation reducing the ice-contamination effects
- The neural network algorithm $R_{NN}(Z,K_{dp})$ generally outperformed the considered K_{dp}-based rainfall algorithm

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Questions?

“The important thing is not to stop questioning. Curiosity has its own reason for existing.”
- Albert Einstein

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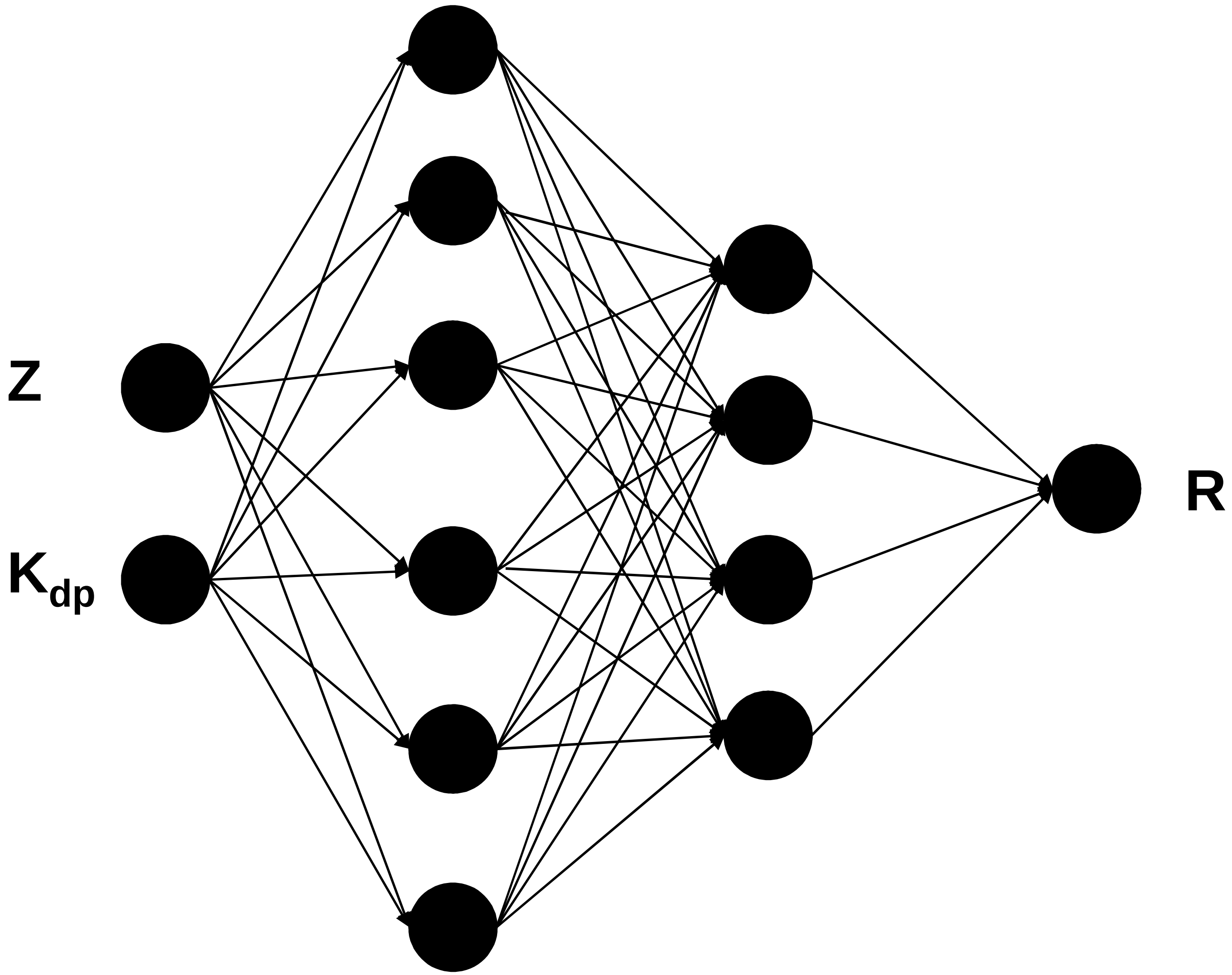
Error scores

Date	Score	R(Z)	$R_{BC01}(K_{dp})$	$R_{BR11}(K_{dp})$	$R_{NN}(Z, K_{dp})$
2009/06/01	FSE	0.54	0.14	0.18	0.10
	CC	0.71	0.97	0.95	0.98
	Bias	2.33	1.03	1.06	1.01
2009/06/21	FSE	0.43	0.42	0.49	0.34
	CC	0.89	0.88	0.84	0.93
	Bias	1.67	1.16	1.22	1.08
2009/09/21	FSE	0.53	0.11	0.21	0.08
	CC	0.82	0.99	0.98	0.99
	Bias	1.56	1.01	1.04	0.99
2009/10/22	FSE	0.72	0.24	0.28	0.21
	CC	0.32	0.89	0.86	0.91
	Bias	2.78	1.11	1.17	1.04
2009/10/23	FSE	0.49	0.17	0.20	0.17
	CC	0.54	0.91	0.88	0.91
	Bias	1.95	1.07	1.10	1.04
2010/09/10	FSE	0.57	0.42	0.47	0.34
	CC	0.60	0.73	0.67	0.80
	Bias	2.30	1.65	1.79	1.34

Date	Score	R(Z)	$R_{BC01}(K_{dp})$	$R_{BR11}(K_{dp})$	$R_{NN}(Z, K_{dp})$
2010/09/11	FSE	0.60	0.53	0.58	0.48
	CC	0.75	0.70	0.66	0.74
	Bias	2.66	1.98	2.14	1.75
2010/11/01	FSE	0.70	0.42	0.47	0.38
	CC	0.18	0.62	0.56	0.69
	Bias	2.59	1.18	1.27	1.11
2010/11/02	FSE	0.76	0.38	0.45	0.34
	CC	0.47	0.65	0.50	0.73
	Bias	3.58	1.37	1.50	1.30
2010/11/09	FSE	0.70	0.43	0.47	0.38
	CC	0.02	0.38	0.31	0.46
	Bias	3.22	1.45	1.57	1.32
2011/03/01	FSE	0.79	0.34	0.35	0.34
	CC	0.31	0.63	0.59	0.63
	Bias	4.06	1.21	1.29	1.20
2011/03/02	FSE	0.67	0.34	0.38	0.30
	CC	0.53	0.56	0.49	0.65
	Bias	3.30	1.31	1.41	1.25


Z
Kdp
R

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Artificial Neural Networks

What a NN is?

Biological model of human brain able to learn from experience →A Powerful inversion technique

An artificial neural network is a non-linear parameterized mapping from an input x to an output y=NN(x; w, M)

where w=vector of parameters relating the input x to the output y,
M=functional form of the mapping (i.e., the architecture of the net).

The multi-layer perceptron architecture (MLP), considered here, is a mapping model composed of several layers of parallel processors.

It has been theoretically proven that one-hidden layer MLP networks may represent any non-linear continuous function (Haykin, 1995), while a two-hidden layer MLP may approximate any function to any degree of non-linearity taking also into account discontinuities (Sontag, 1992).

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Artificial Neural Networks

NN Training

- The network is trained using supervised learning, with a training set D = (xi, ti) of inputs and targets. During training the weights and biases are iteratively adjusted in order to minimize the so called network performance function, which normally is the sum squared error:

- The minimization is based on repeated evaluation of the gradient of the performance function using back-propagation, which involves performing computations backwards through the network

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Neural Network Optimization: minimization and regularization techniques

MINIMIZATION

- The performance of the algorithm is very sensitive to the proper setting of the learning rate. For this reason, a back propagation training with an adaptive learning rate is crucial. Battiti's "bold driver" technique has been implemented in this work. It can be summarized as follows.

First, the initial network output and error are computed for a given value of η0. If the performance function decreases, the learning rate is then increased by a factor ρ (=1.1). On the contrary, if E_D increases this is taken as an indication that the step made was too large and η0 is decreased by a factor σ(=0.7), the last change is cancelled, and the search process is continued. The process of reduction is repeated until a step is found that decreases the performance function.

- Gradient descent may get stuck in local minima of the performance function. The best strategy in this case is to orient the search towards the local minima, but the form of the error function may be such that the gradient does not point in this direction. Following the gradient direction can lead to large oscillations of the search process. The problem can be overcome by including a momentum term in the weight updates. Momentum can be added to back propagation learning by making weight changes equal to the sum of a fraction of the last weight change and the new change suggested by the back propagation rule

$$\Delta w_{ij}(t) = (m-1)\eta_0 \frac{\partial E_D}{\partial w_{ij}} + m\Delta w_{ij}(t-1)$$

REGULARIZATION

- The procedure to improve generalization, called regularization, adds an additional term to the objective function which becomes

$$E_R = \gamma\, E_D + (1-\gamma)E_W$$