

Calculating the hydrological response of a mountain catchment using conventional and unconventional (CML) rainfall observations: the case study of Mallero catchment

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RAINFALL MONITORING - why and how?

Rainfall is the main downward forcing of the hydrological cycle and exhibits large variability in space and time. For this, an accurate monitoring of precipitation is fundamental for:

- weather forecasting;
- prediction of extreme events;
- prevention of hydrogeological instability;
- mitigation of hydrogeological risk.

Traditional instruments for rainfall monitoring are:



Rain gauge



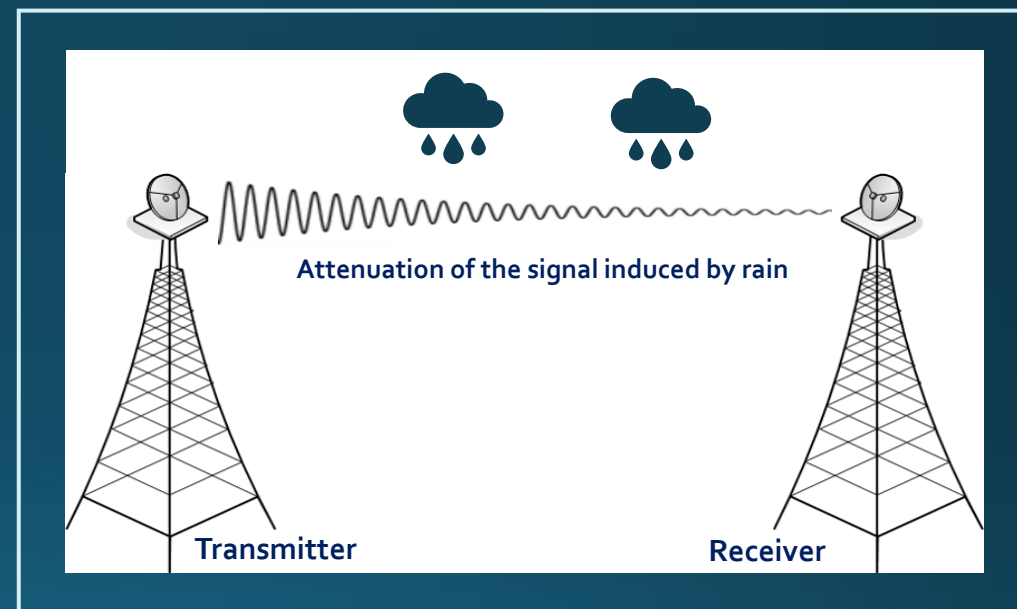
Disdrometer



Weather radar

Rain gauges and disdrometers provide single point measurements while weather radars give observed rainfall aloft.

An alternative approach relies on measurements of the signal loss induced by rain on commercial microwave links owned by cellular companies.



They are called opportunistic sensors because it is possible to get rainfall intensity information coming from data generated for another purpose that is link quality verification.

WHAT WE DO - MOPRAM PROJECT

In our project MOPRAM (Monitoring of PRecipitation through A network of Microwave radio links) we aim to assess the use of real CML rainfall data into a hydrological model. We check if their use, applied to a specific case study, could provide performances comparable with those obtained through traditional instruments.

Our activity is divided into 2 main tasks:

1. Meteorological task

EGU AS1.36

R. Nebuloni et al., <<Rainfall estimate using commercial microwave link (CML): first outcomes of the MOPRAM project>>

1.1

Estimation of rainfall intensity from CML attenuation signals

1.2

Comparison of CML data with traditional instruments (rain gauges and disdrometers)

2. Hydrological task

2.1

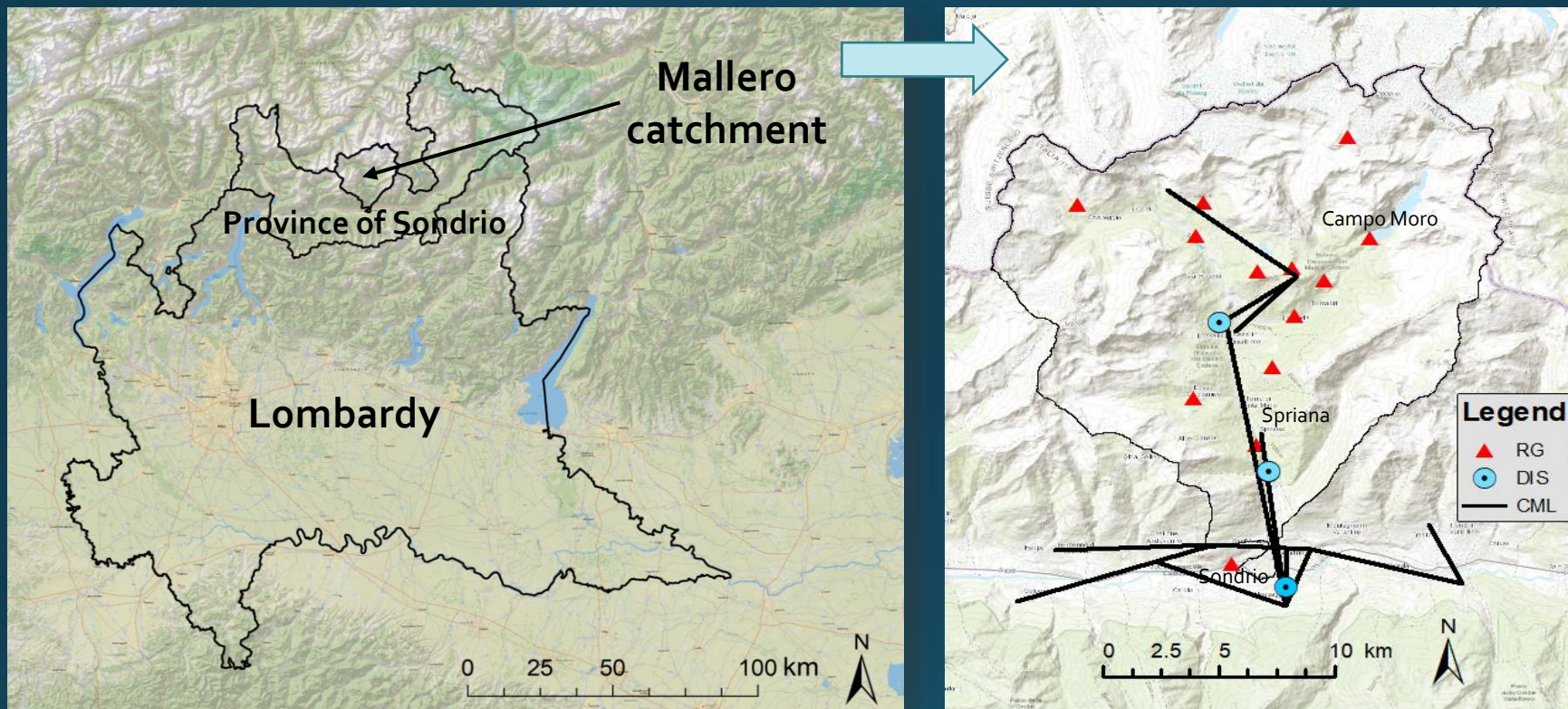
Integration of CML data into a hydrological model

2.2

Check of hydrological response

In this slideshow, we will focus on this second task.

CASE STUDY - MALLERO CATCHMENT



The case study area is the Mallero catchment (right figure), located in the province of Sondrio, in Lombardy (Italy). This area is of great hydrological and geological interest, since it includes a narrow and steep valley crossed by Mallero river, where floods and landslides are very frequent. The catchment area is 320 km² and the minimum and maximum altitudes are respectively 282 and 4018 m a.s.l..

The area is equipped with different rainfall observation instruments: 13 rain gauges (RG), 3 disdrometers (DIS) and 12 commercial microwave links (CML). Unfortunately, most of these sensors are installed in the valley area while there is a lack of rainfall data in the mountain part.

THE HYDROLOGICAL MODEL

We have implemented a hydrological model to predict river discharge at the fluvial section in Sondrio (red point in figure). The model is semi-distributed: the catchment area is subdivided into 12 Hydrological Response Unit (HRU) [1]. For each HRU we assume the homogeneity of *input variables*, *soil and land use parameters* and *hydrological processes*.

- Runoff R in each HRU is calculated through **SCS-CN method** [2]:

$$R = \frac{(P - 0.2 * S)^2}{P + (1 - 0.2) * S}$$

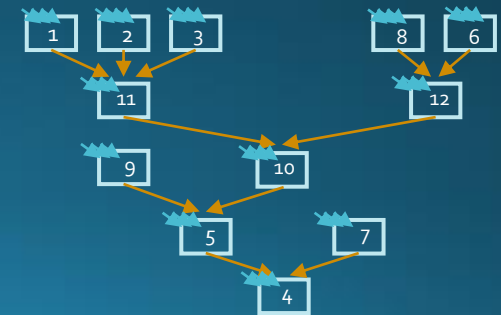
$\left\{ \begin{array}{l} R \text{ (mm)} = \text{direct runoff} \\ P \text{ (mm)} = \text{total rainfall} \\ S \text{ (mm)} = \text{maximum soil potential retention (function of Curve Number)} \end{array} \right.$

- The output hydrograph $q(t)$ is evaluated assuming that each HRU works as a **linear reservoir**:

$$q(t) = \int_0^t r(\tau) * A * \frac{1}{k} * \exp\left(-\frac{t-\tau}{k}\right) d\tau$$

$\left\{ \begin{array}{l} q \text{ (m}^3\text{/s)} = \text{discharge} \\ r \text{ (m/s)} = \text{runoff rate} \\ A \text{ (m}^2\text{)} = \text{HRU area} \\ k \text{ (s)} = \text{lag time} \end{array} \right.$

- The 12 HRU work in series or in parallel following this pattern:



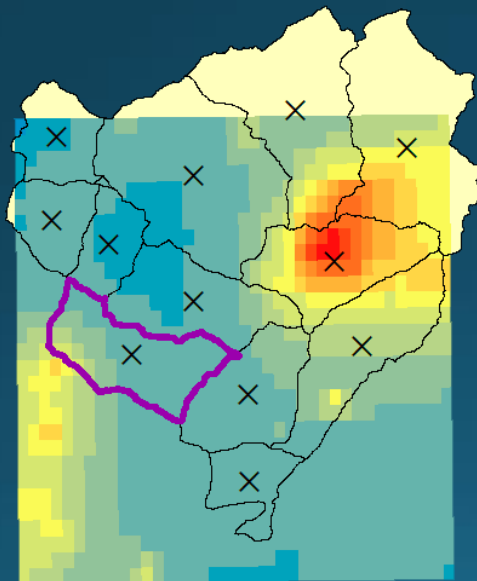
RAINFALL INPUT DATA

The hydrological model requires as input data a single value of rainfall intensity per each HRU, which is assumed uniform over the HRU area. We have tested four methods to evaluate the interpolated rainfall in the 12 HRU.

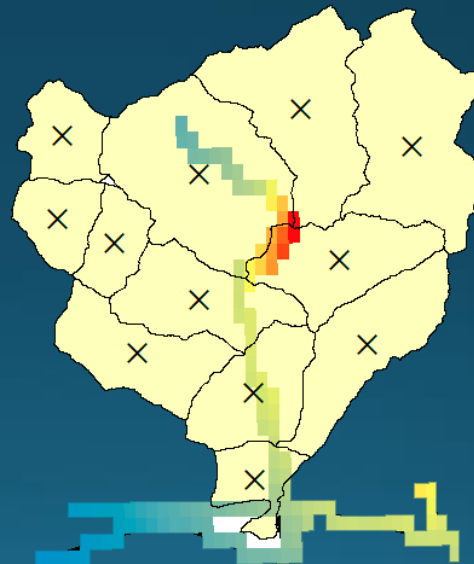
S1. RG + DIS, *IDW*



S2. RRF, *average*



S3. ERG, *IDW*



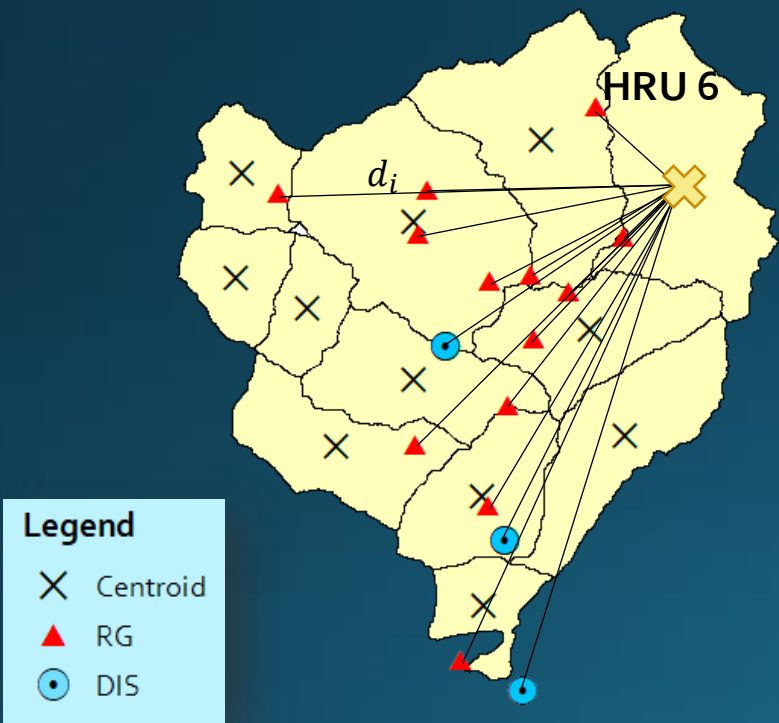
S4. RG + DIS + ERG, *IDW*



RAINFALL INPUT DATA

S1. RG + DIS, IDW

We use the network of traditional sensors (13 RG + 3 DIS, when available) to get rainfall observations. The value of spatial interpolated rain rate in each HRU is calculated with the inverse square distance weighting (ISDW) method, considering all the observations available:



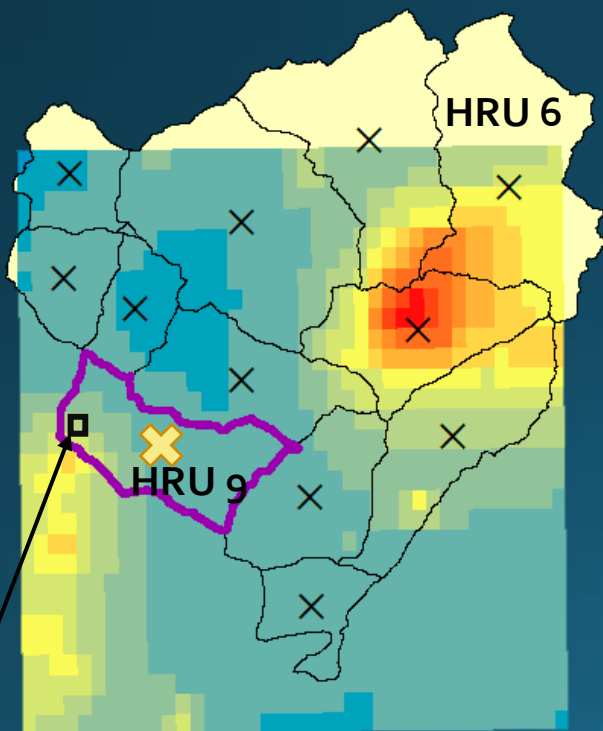
$$P_{HRU} = \frac{\sum_i^{n_{sensors}} p_i \frac{1}{d_i^2}}{\sum_i^{n_{sensors}} \frac{1}{d_i^2}}$$

Rainfall at HRU (points to P_{HRU})
Rainfall observed by i-th sensor (points to p_i)
Euclidean distance between i-th sensor and HRU centroid (points to d_i)

RAINFALL INPUT DATA

S2. RRF, average

We exploit a 2D reconstructed rainfall field (RRF). It is retrieved over the area covered by the network of 12 CML with a rainfall field reconstruction algorithm (RRA, see next slide for further information). The rainfall intensity value representative of the single HRU, is calculated as the average value among cells of the RRF that are inside the same HRU.



i – th pixel inside HRU 9

$$P_{HRU} = \frac{1}{n_{cells}} \sum_{i=1}^{n_{cells}} p_i$$

*Number of cells
inside HRU*

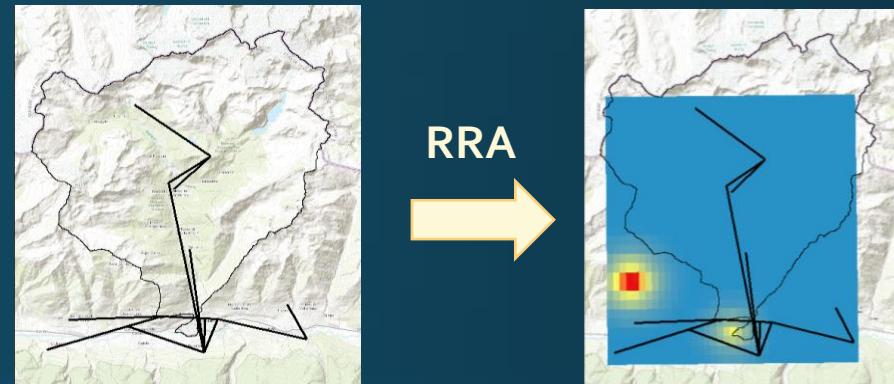
*Rainfall reconstructed
in i-th pixel*

! For HRU where RRF does not cover the whole area (as for HRU 6) we compute the interpolated value of rainfall using only cells where rainfall intensity is available, assuming no information in the outstanding area.

RAINFALL INPUT DATA

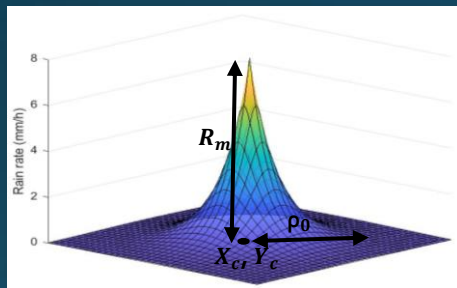
Rainfall field reconstruction algorithm (RRA)

From the received signal level of a CML it is possible to retrieve the average rainfall intensity across its propagation path. Given a set of rain intensity estimations from a network of CML we reconstruct a 2D rainfall field (RRF) using the RRA. It is a physically-based tomographic algorithm that aims at optimizing set of parameters [3].



Spatial distribution of rain rate is modelled by **N** negative exponential rain cells, each one described by **4** parameters:

- peak intensity R_m (mm/h);
- radius ρ_0 (km);
- x position of cell center X_c (km);
- y position of cell center Y_c (km).



Attenuation calculated - for i-th CML - by numerical integration over the reconstructed rainfall field

Attenuation experienced over i-th CML

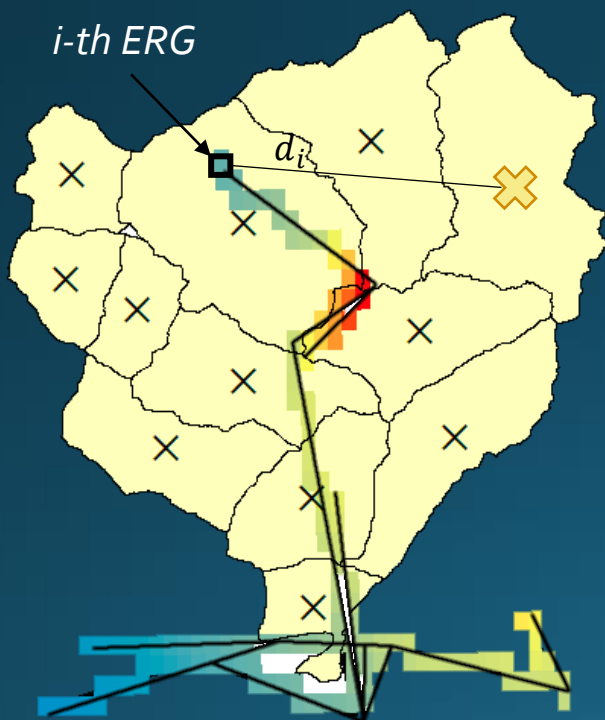
The **4xN** parameters are retrieved by iteratively minimizing this cost function: $err(R_m, \rho_0, X_c, Y_c) = \sum_{i=1}^{n_{CML}} (k_i(R_m, \rho_0, X_c, Y_c) - \bar{k}_i)^2$

The algorithm's goodness depends on the CML network topology and the CML density over the area. Moreover, in each reconstructed map, the most reliable values of rainfall intensity are in cells close to the position of CML.

RAINFALL INPUT DATA

S3. ERG, IDW

In this case we use rainfall cells reconstructed with RRA only over the CML, that is where the cost function is minimum. These cells are called equivalent rain gauges (ERG), since we deal with them as single point measurements. As done in S1, we calculate the rainfall interpolated in each HRU using IDW.



Rainfall observed by i-th ERG

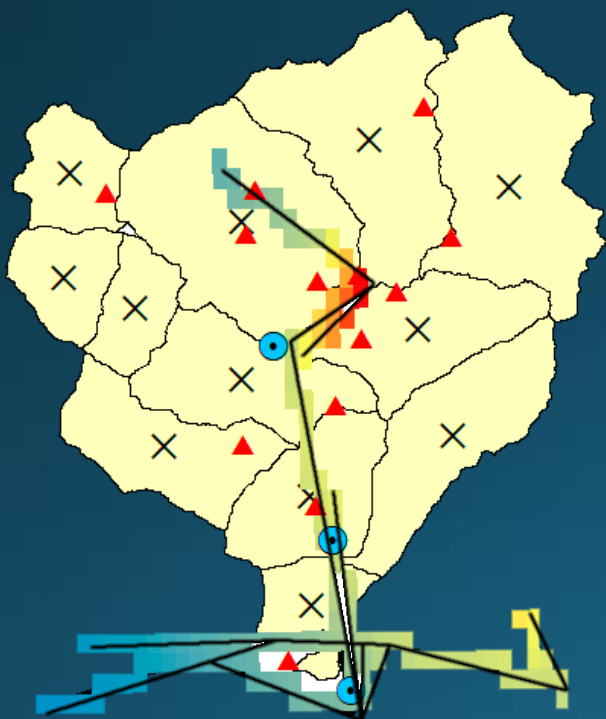
$$P_{HRU} = \frac{\sum_i^{n_{sensors}} p_i \frac{1}{d_i^2}}{\sum_i^{n_{sensors}} \frac{1}{d_i^2}}$$

Euclidean distance between i-th ERG and HRU centroid

RAINFALL INPUT DATA

S4. ERG + RG + DIS, IDW

For this solution we use all point estimations/measurements available for this case study (ERG, RG and DIS). The spatial interpolation method is again ISDW.



Rainfall observed by i -th ERG/RG/DIS

$$P_{HRU} = \frac{\sum_i^{n_{sensors}} p_i \frac{1}{d_i^2}}{\sum_i^{n_{sensors}} \frac{1}{d_i^2}}$$

Euclidean distance between i -th ERG/sensor and HRU centroid

CHECK OF HYDROLOGICAL RESPONSE

In order to check the hydrological response of the model using different types of rainfall data observations we have chosen 10 intense liquid precipitation events for 2019 and 1 historic event in 2016. These are the steps leading to the evaluation of hydrological response performances for each rainfall event:

1. evaluation of average rainfall intensity from attenuation signal data, for each CML;
2. assessment of rainfall spatial interpolation using the 4 methods (S1-S4) presented in previous slides;
3. use of the interpolated values of rainfall as input into the hydrological model;
4. calculation of the output discharge for the 4 methods;
5. separation of total observed discharge from baseflow to evaluate the contribution due to direct runoff;
6. estimation of Nash-Sutcliffe index between observed (depurated from baseflow) and simulated discharge to define the performance of the prediction.

In next slides we will observe in detail results for 3 events. Finally, we will summarize the performances of S1-S4 for all the 11 events.

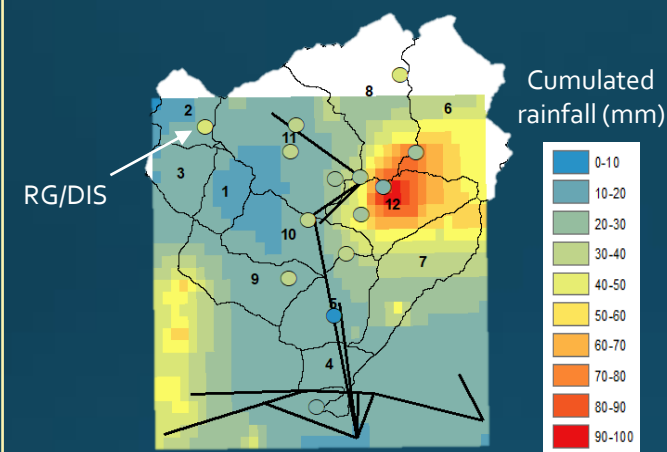
CHECK OF HYDROLOGICAL RESPONSE

Rainfall data

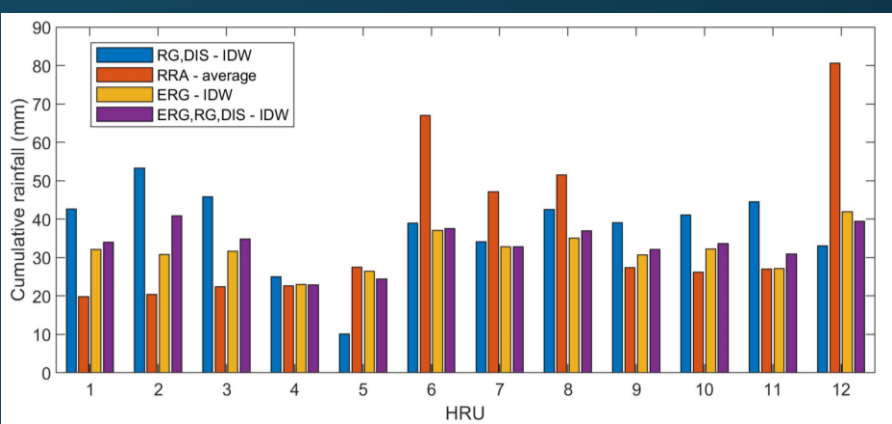
Description of rainfall event

Period: 6-7 August 2019
Type: moderate, divided in different episodes, overall catchment area is involved
Max observed rain rate: 45 mm/h
Max observed discharge: 32.4 m³/s

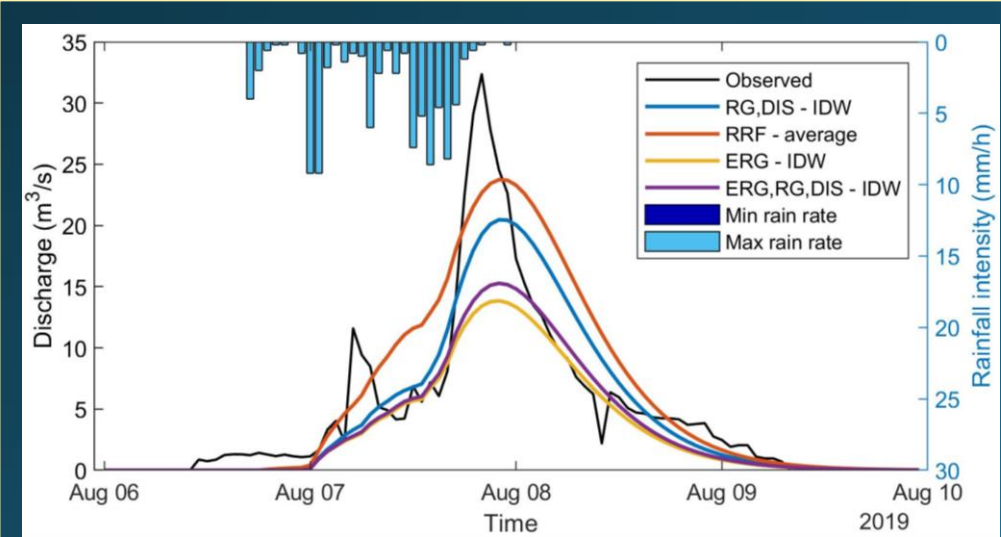
RRF and observations from RG and DIS



Cumulated rainfall in each HRU



Observed vs Simulated Discharge



Model performance

Rainfall input	Nash-Sutcliffe index
S1. RG,DIS – ISDW	0.77
S2. RRA – average	0.66
S3. ERG – ISDW	0.62
S4. ERG,RG,DIS – ISDW	0.68

CHECK OF HYDROLOGICAL RESPONSE

Rainfall data

Description of rainfall event

Period: 18-22 August 2019

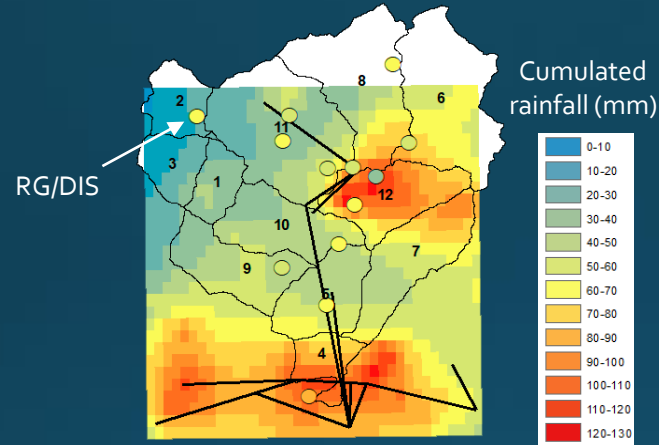
Type: intense, divided in 4 main episodes, patchy distribution of rainfall

Max observed rain rate: 120 mm/h

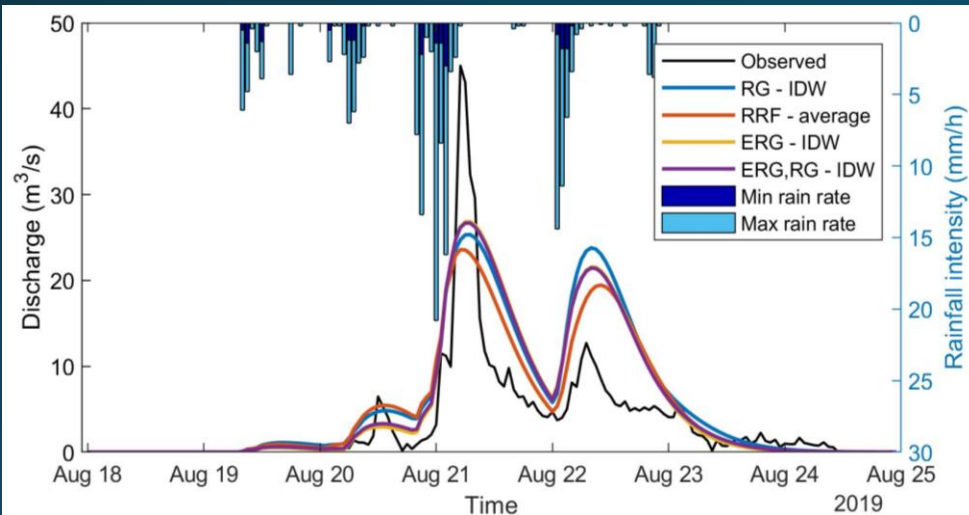
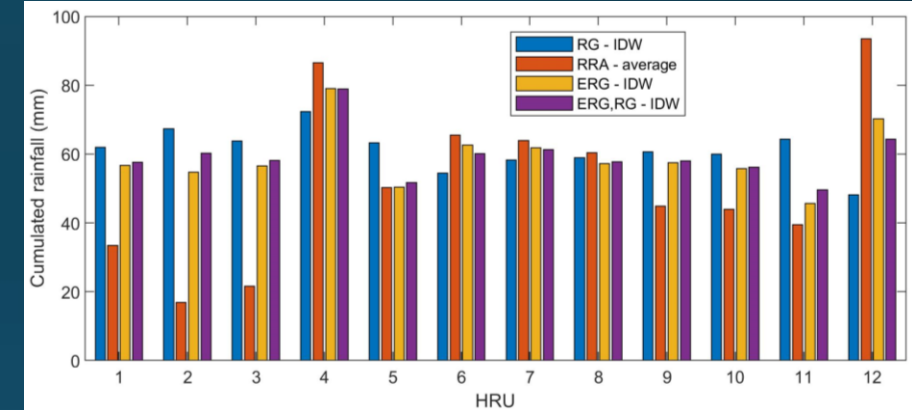
Max observed discharge: 45.0 m³/s

Observed vs Simulated Discharge

RRF and observations from RG and DIS



Cumulated rainfall in each HRU



Model performance

Rainfall input	Nash-Sutcliffe index
S1. RG, DIS – ISDW	0.53
S2. RRF – average	0.53
S3. ERG – ISDW	0.32
S4. ERG, RG, DIS – ISDW	0.33

CHECK OF HYDROLOGICAL RESPONSE

Rainfall data

Description of rainfall event

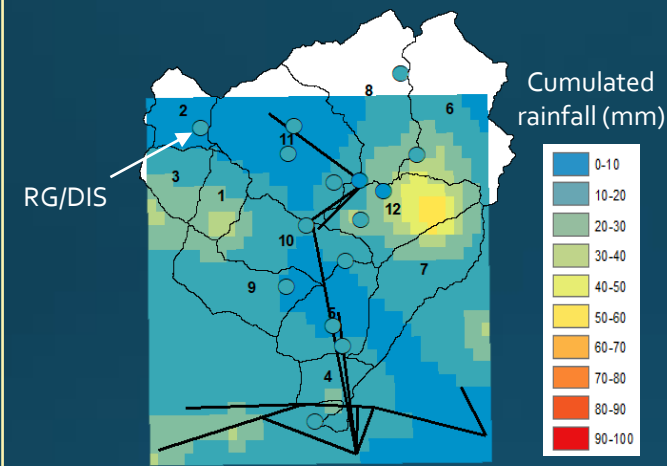
Period: 1-2 October 2019

Type: : one short convective event

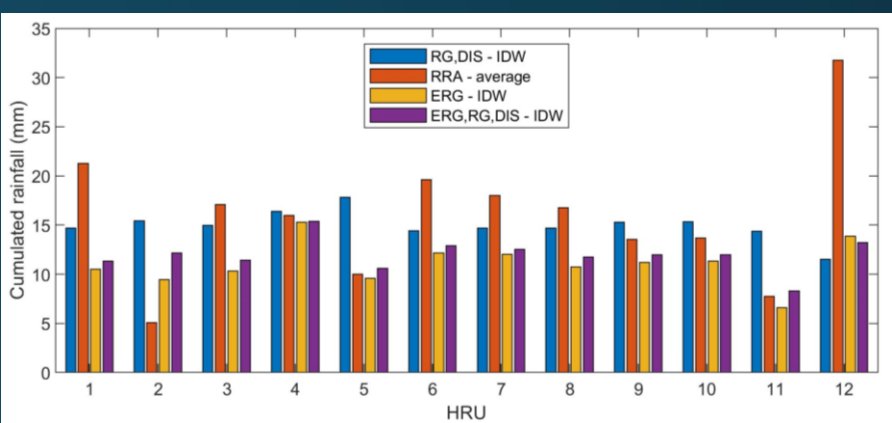
Max observed rain rate: 60 mm/h

Max observed discharge: 5.7 m³/s

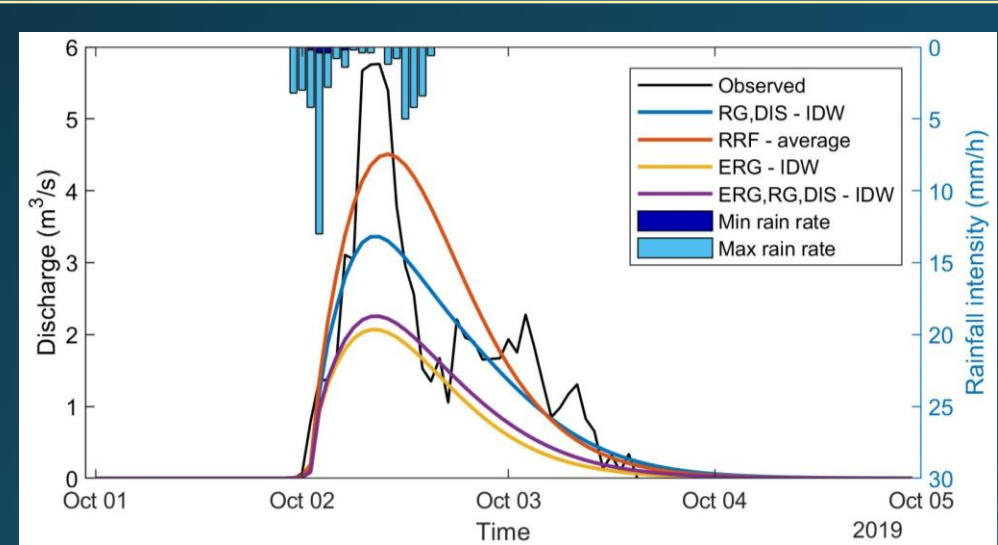
RRF and observations from RG and DIS



Cumulated rainfall in each HRU



Observed vs Simulated Discharge



Model performance

Rainfall input	Nash-Sutcliffe index
S1. RG,DIS – ISDW	0.66
S2. RRF – average	0.57
S3. ERG – ISDW	0.17
S4. ERG,RG,DIS –ISDW	0.29

SIMULATED DISCHARGE PERFORMANCE - Overview

	<i>Nash-Sutcliffe index</i>			
EVENT	s1. RG, DIS IDW	s2. RRF average	s3. ERG IDW	s4. ERG, RG, DIS IDW
13-18 October 2016	0.52	-0.43	0.49	0.61
14-15 July 2019	-0.69	-4.03	-0.88	-0.73
25-26 July 2019	0.34	0.02	0.24	0.33
6-7 August 2019	0.77	0.66	0.62	0.68
11-13 August 2019	-0.04	-1.52	-0.41	-0.25
18-22 August 2019	0.53	0.53	0.32	0.33
25-26 August 2019	-7.07	-17.45	-3.45	-3.57
22-23 September 2019	-1.51	0.20	-0.60	0.08
1-2 October 2019	0.66	0.57	0.17	0.29
15-16 October 2019	0.66	0.18	-0.71	-0.41
18-24 October 2019	0.77	-0.06	0.46	0.57

In green are the solutions that provide admissible values of N-S index (> 0.40).

If we consider only events which have at least one solution providing good values of N-S index, we observe that in most of them performances which implies the use of CML (s2, s3, s4) are comparable with those obtained from traditional rainfall detection instruments. However, the best solutions come from RG and DIS. This is surely due to the unfavourable network configuration of CMLs which are only located in the valley part of the catchment and do not provide information in the mountain region.

CONCLUSIONS



Using CML rainfall data into the hydrological model results in performances comparable to those achieved with traditional instruments (RG and DIS).



Reconstructed 2D maps (RRF) suffer from the CML configuration but could be useful in case of lack of traditional instruments.



N-S index shows a great variability in model performance. The unfavourable network configuration of all monitoring sensors (CML, RG, DIS) is probably one of the reasons.

Future steps



- Increase statistics considering new rainfall events for year 2020, when data will be available.
- Implement a new hybrid method (S_5) to evaluate rainfall at HRU. It could rely on a combination among RG/DIS observations and the RRF.
- Carry out same analysis in catchments with a more uniform distribution and a higher density of CML.

THANK YOU BY THE MOPRAM TEAM!



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- [1] Carrara, A. (2004). «Generazione delle linee di impluvio e displuvio e calcolo dei parametri morfologici dei sottobacini elementari appartenenti al territorio collinare-montano della Regione Lombardia», CNR-IEIT Bologna.
- [2] Natural Resources Conservation Service (NRCS) (2001). «Section 4: Hydrology» National Engineering Handbook, Natural Resources Conservation Service, U.S. Department of Agriculture, Washington, DC.
- [3] D'Amico, M. et al. (2018). «Tomographic reconstruction of rainfall fields using heterogeneous frequency microwave links», IEEE Statistical Signal Processing Workshop, Freiburg, Germany.