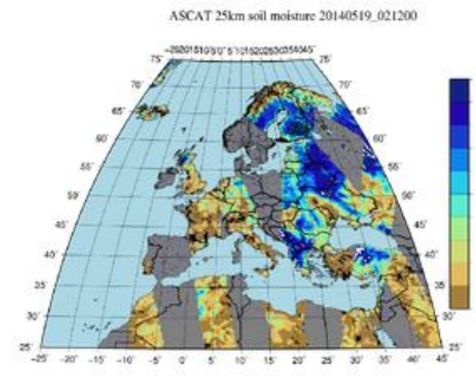
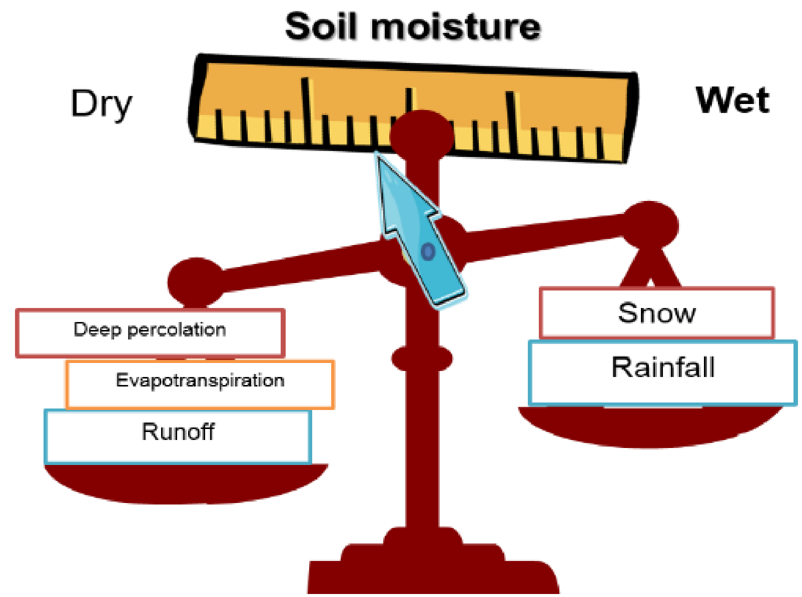
Assimilation of H-SAF soil moisture products for hydrological modelling in Mediterranean catchments

Christian Massari, Luca Brocca, Angelica Tarpanelli, Luca Ciabatta, Tommaso Moramarco
Research Institute for Geo-Hydrological Protection (IRPI),
National Research Council (CNR),
Perugia, Italy

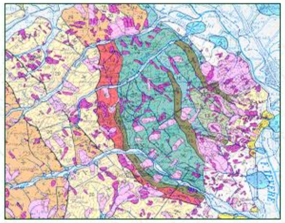


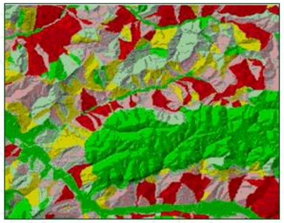
Soil moisture in the hydrological cycle …

Soil moisture plays a critical role in the hydrological cycle since it determines the partitioning of precipitation into runoff, evaporation and groundwater recharge) but also in atmosphere studies



- Numerical Weather Forecasting
- Climate Prediction
- Agriculture and Plant Production
- Shallow Landslide Forecasting
- Flood modelling and forecasting





irpi
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via della Madonna Alta, 126
06128 Perugia
Tel. +39 075 5014 411
Fax +39 075 5014 420

Added value of soil moisture observations…

1. Soil moisture important for the determination of the wetness conditions of the catchment before a flood event (**antecedent wetness conditions**)

- Brocca et al., 2009 (JHE),
- Beck et al. 2010 (AWR)
- Tramblay et al. 2012
- Cousteau et al. 2012

1st part of the presentation

2. Soil moisture used for **rainfall correction and estimation:**

- Crow et al. 2011 (WRR)
- Brocca et al. 2013, 2014 (JGR)
- Pellarin et al. (2013)

2nd part of the presentation

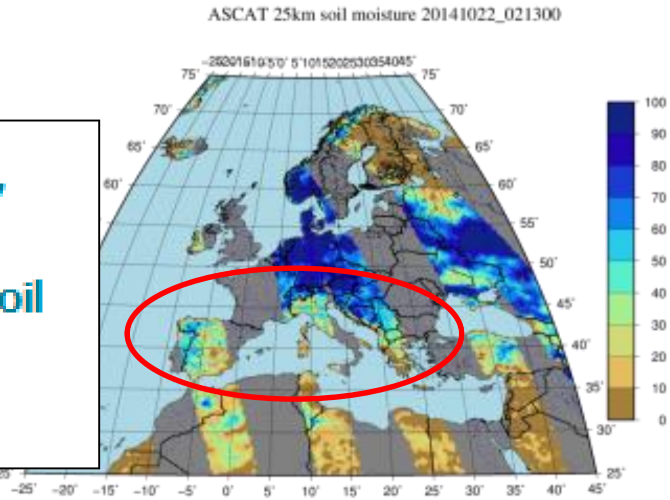
3. Soil moisture used the improvement of the modelling of the catchment hydrological response (**data assimilation**):

- Francois et al. 2003 (JoM)
- Brocca et al., 2009 (JHE), 2010 (HESS)
- Matgen et al., 2012 (HYP)
- Chen et al. 2011 (AWR)-2014(JoM)

3rd part of the presentation

SM OBS 1 - H07

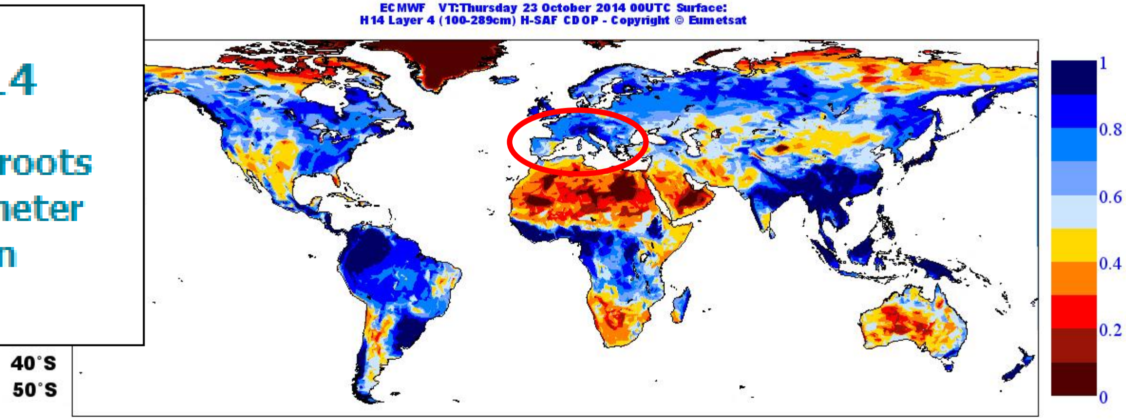
Large scale surface soil moisture by radar scatterometer



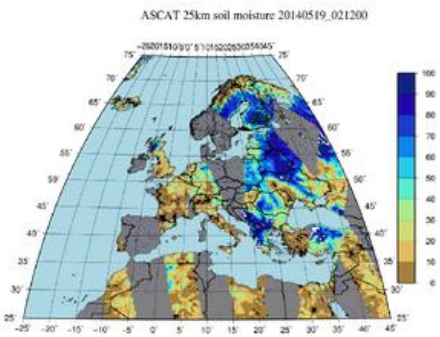
Most of the climate models projections for the Mediterranean basins have showed that the region is very sensitive to climate change.
(IPCC 2012)

SM DAS 2 - H14

Profile Index in the roots region by scatterometer data assimilation



Antecedent wetness conditions



The importance of the antecedent wetness conditions…

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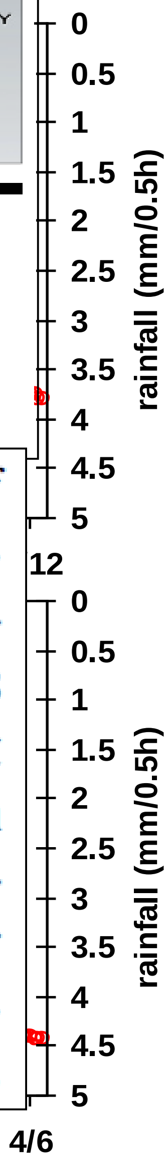
JOURNAL OF HYDROLOGY

Characterisation of selected extreme flash floods in Europe and implications for flood risk management

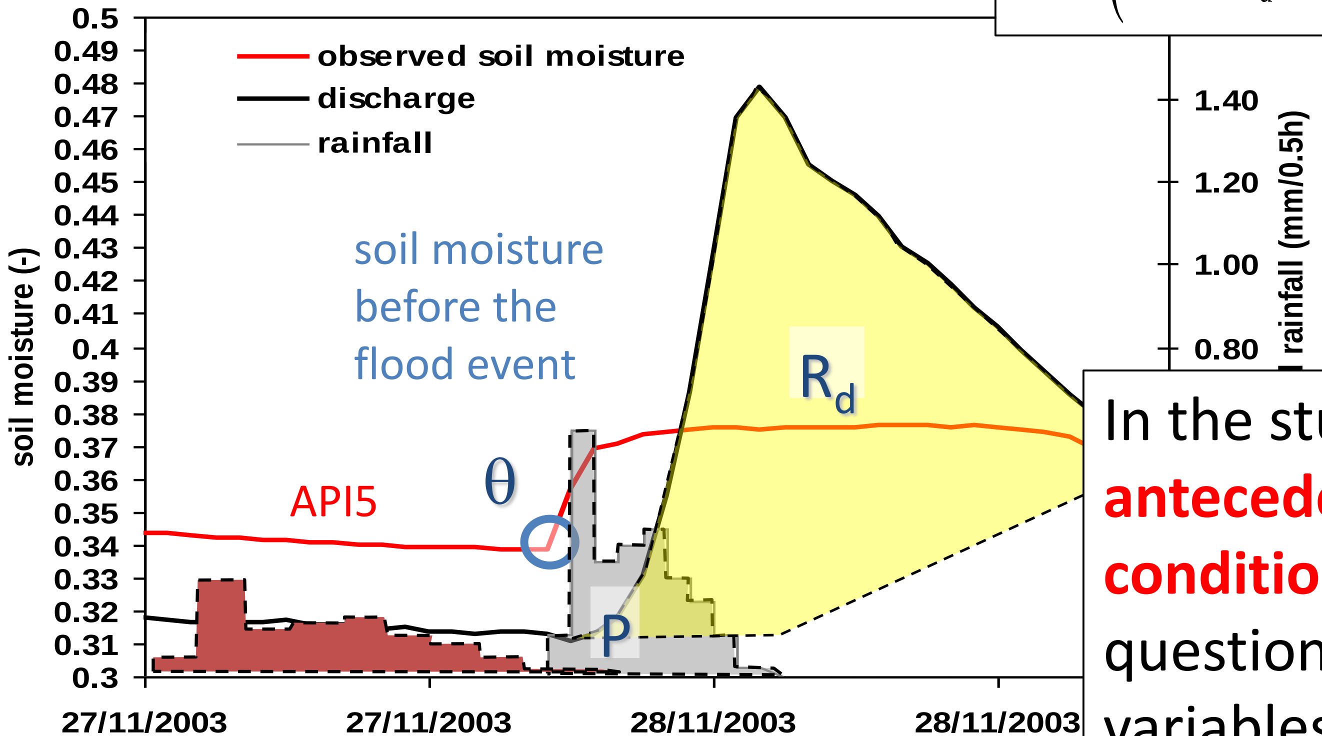
L. Marchi[a,*], M. Borga[b], E. Preciso[a], E. Gaume[c]

- The influence of antecedent saturation conditions on runoff coefficient has been analysed by considering the ratio of the precipitation in the 30 days before the event to the long-term average precipitation in the same period. Analysis of these results shows a significant impact of the antecedent conditions on event runoff coefficients. These results challenge the common wisdom that antecedent soil moisture is of little importance in determining the magnitude of extreme flash floods. Hence, accounting for antecedent soil moisture conditions is paramount for operational flash flood forecasting. In the typical data-poor conditions



… having an estimate of the wetness of the catchment before a flood event is crucial for understanding how severe will be our flood

$$S = 5\left(P + 2R_d - \sqrt{4R_d^{\ 2} + 5PR_d}\right)$$

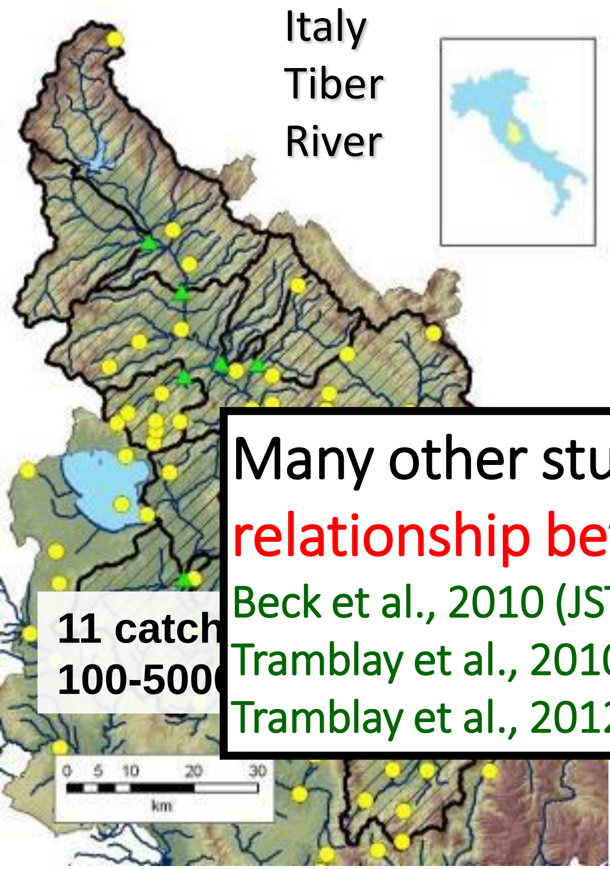


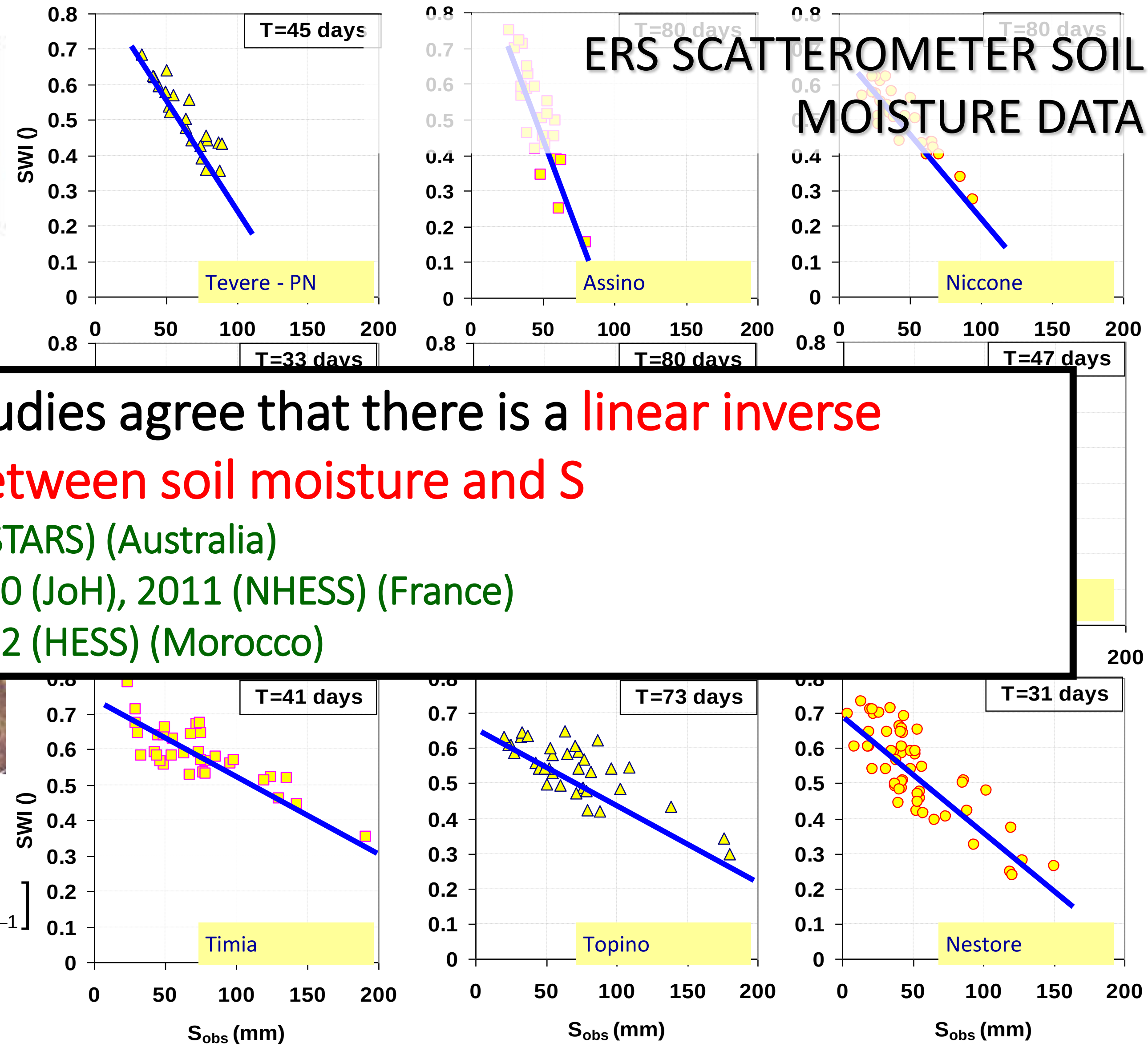
SOIL CONSERVATION SERVICE METHOD (SCS-CN)

In the study of the **antecedent wetness condition** there is the question if some variables can be used to estimate S

Brocca et al. 2009 (JoH) , 2009 (JHE)

S vs Θ relation: ERS SCAT





ERS SCATTEROMETER SOIL MOISTURE DATA

Many other studies agree that there is a **linear inverse relationship between soil moisture and S**

Beck et al., 2010 (JSTARS) (Australia)

Tramblay et al., 2010 (JoH), 2011 (NHESS) (France)

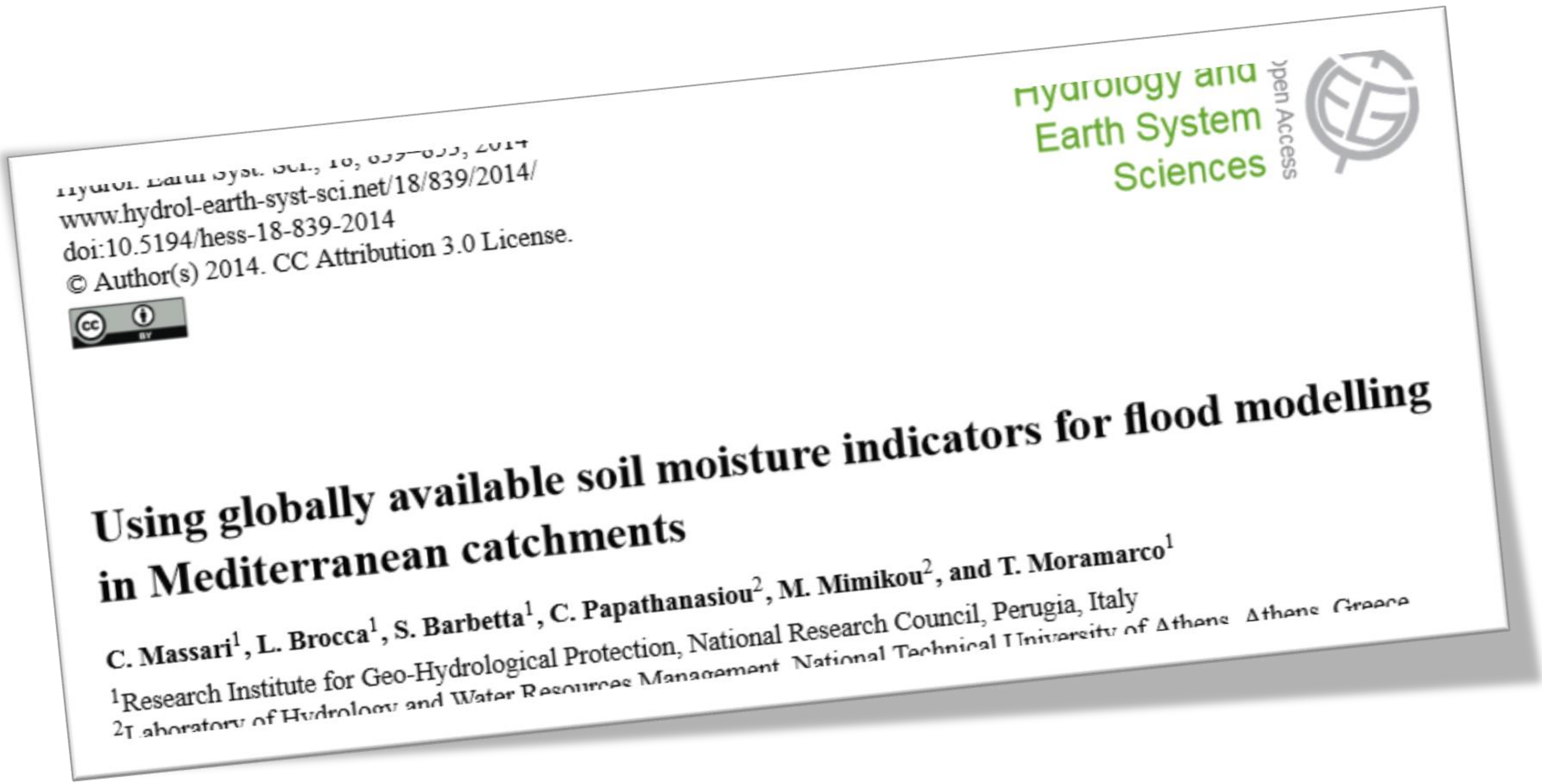
Tramblay et al., 2012 (HESS) (Morocco)

Brocca et al.,
2009 (JoH); 2009 (JHE)

$$SWI_n = SWI_{n-1} + K_n\left[m_s(t_n) - SWI_{n-1}\right]$$

$$K_n = \frac{K_{n-1}}{K_{n-1} + exp-\left(\frac{t_n - t_{n-1}}{T}\right)}$$

Why do not embed directly the relation between the parameter S and the soil moisture into the hydrological model?



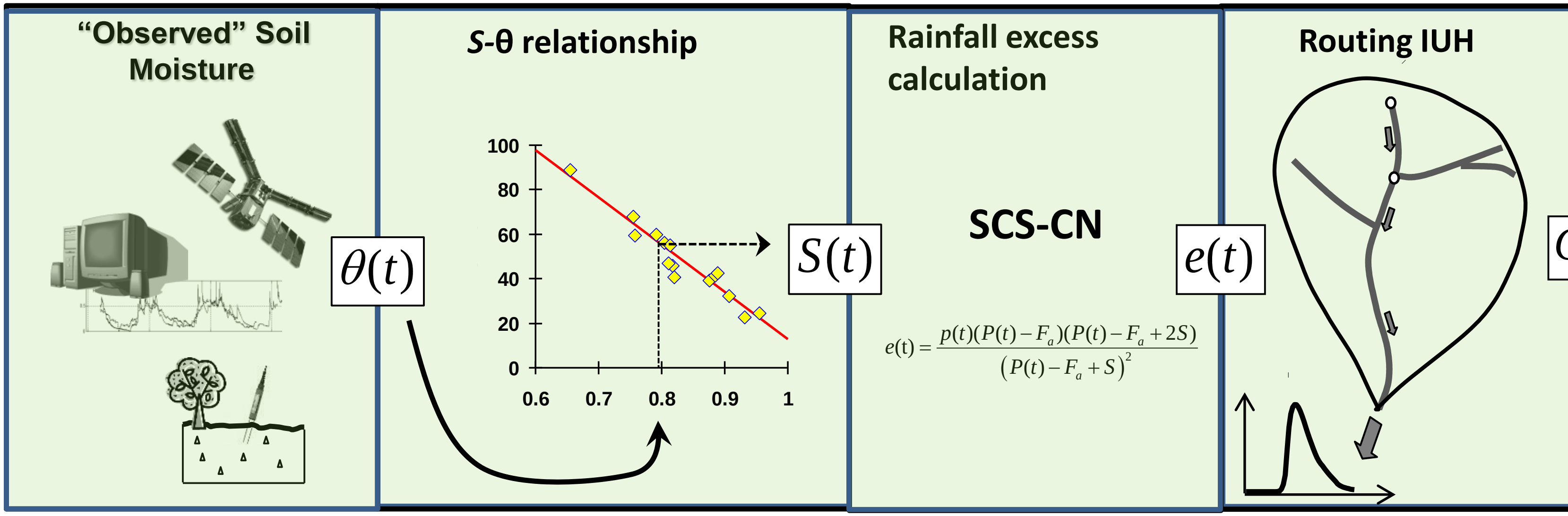
www.hydrol-earth-syst-sci.net/18/839/2014/
doi:10.5194/hess-18-839-2014

Earth System Sciences

Using globally available soil moisture indicators for flood modelling in Mediterranean catchments

C. Massari[1], L. Brocca[1], S. Barbetta[1], C. Papathanasiou[2], M. Mimikou[2], and T. Moramarco[1]
[1]Research Institute for Geo-Hydrological Protection, National Research Council, Perugia, Italy

Soil moisture estimate inside an event based model…



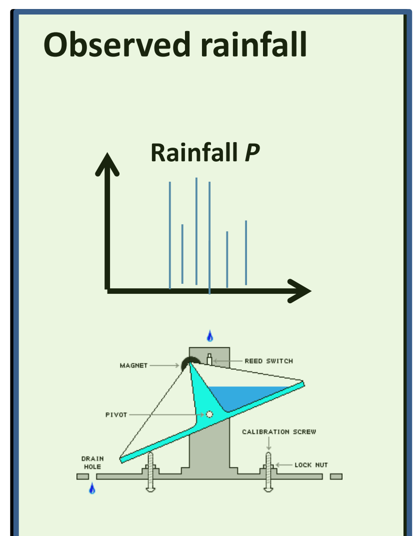
Advantages:

1) No need of continuous rainfall and evapotranspiration datasets.

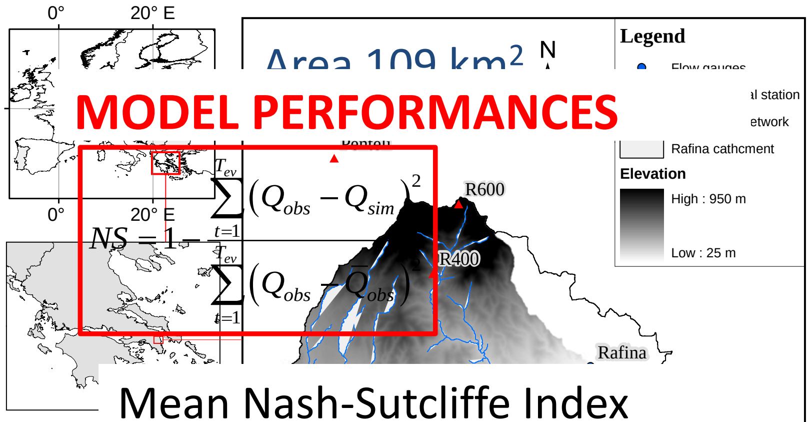
Good in poorly gauged areas.

2) Parsimony and simplicity.

Good for operational purposes.



"Simplified Continuous Rainfall Runoff" model (SCRRM, Massari et al. 2014, HESS)



MODEL PERFORMANCES

$$NS = 1 - \frac{\sum_{t=1}^{T_{ev}} (Q_{obs} - Q_{sim})^2}{\sum_{t=1}^{T_{ev}} (Q_{obs} - \overline{Q}_{obs})^2}$$

Mean Nash-Sutcliffe Index

NS=1 perfect model

NS<0 bad performance

RESULTS IN VALIDATION

Initial conditions from	NS
MISDc model (Brocca et al. 2011)	**0.55**
ERA-Land	**0.56**
ASCAT	**0.48**
AMSR-e	**0.47**
In situ	**0.43**

System for Flood and Fire

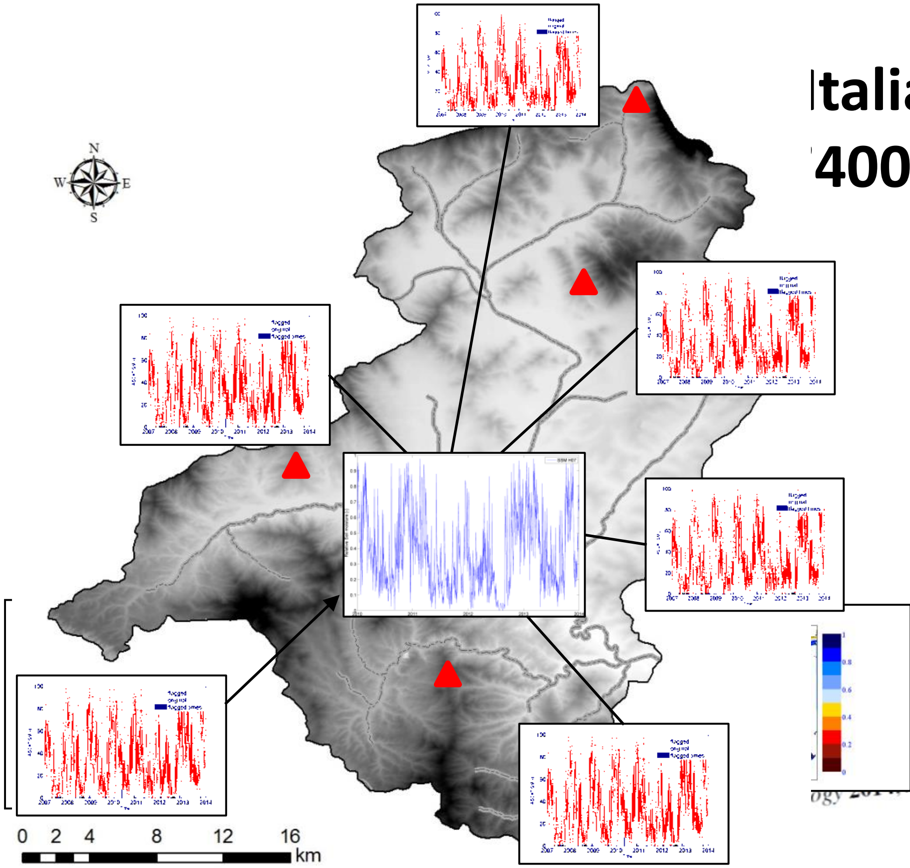
Lumped version of the model

Soil moisture indicator	LAT[1]	LON[2]	Spatial resolution	Temporal resolution	Band [GHz]	Retrieval algorithm	Depth [cm]
Remote sensing soil moisture							
In situ	37.9919	23.9194	N/A	10 min	N/A	N/A	25
ERA-Land	38.2406	23.3417	80 km	1 day	N/A	N/A	0–7, 8–28, 28–100
ASCAT	37.9326	23.8872	25 km	≈ 1 day	5.25 (C band)	WARP 5.5 v1.1	0–3
AMSR-E	37.875	23.875	56 km	≈ 1 day	6.90 (C band)	LPRM	0–3

[1] LAT = latitude, [2] LON = longitude.

MISD 6

The model has provided performances comparable with those obtained by a classical continuous model



pixels inside the catchments were averaged for obtaining a single time series

To obtain the root zone soil moisture we used the Exponential filter for H07

$$SWI(t) = \frac{\sum_i SSM_{t_i}\, exp\left(-\frac{t - t_i}{T}\right)}{\sum_i exp\left(-\frac{t - t_i}{T}\right)}$$

Wagner et al., 1999 (RSE)

and a depth parameter *z* which accounts for the information given by the layers of H14

$$\theta_{SM-DAS2} = \theta_1 \qquad : z \leq 7\text{cm}$$

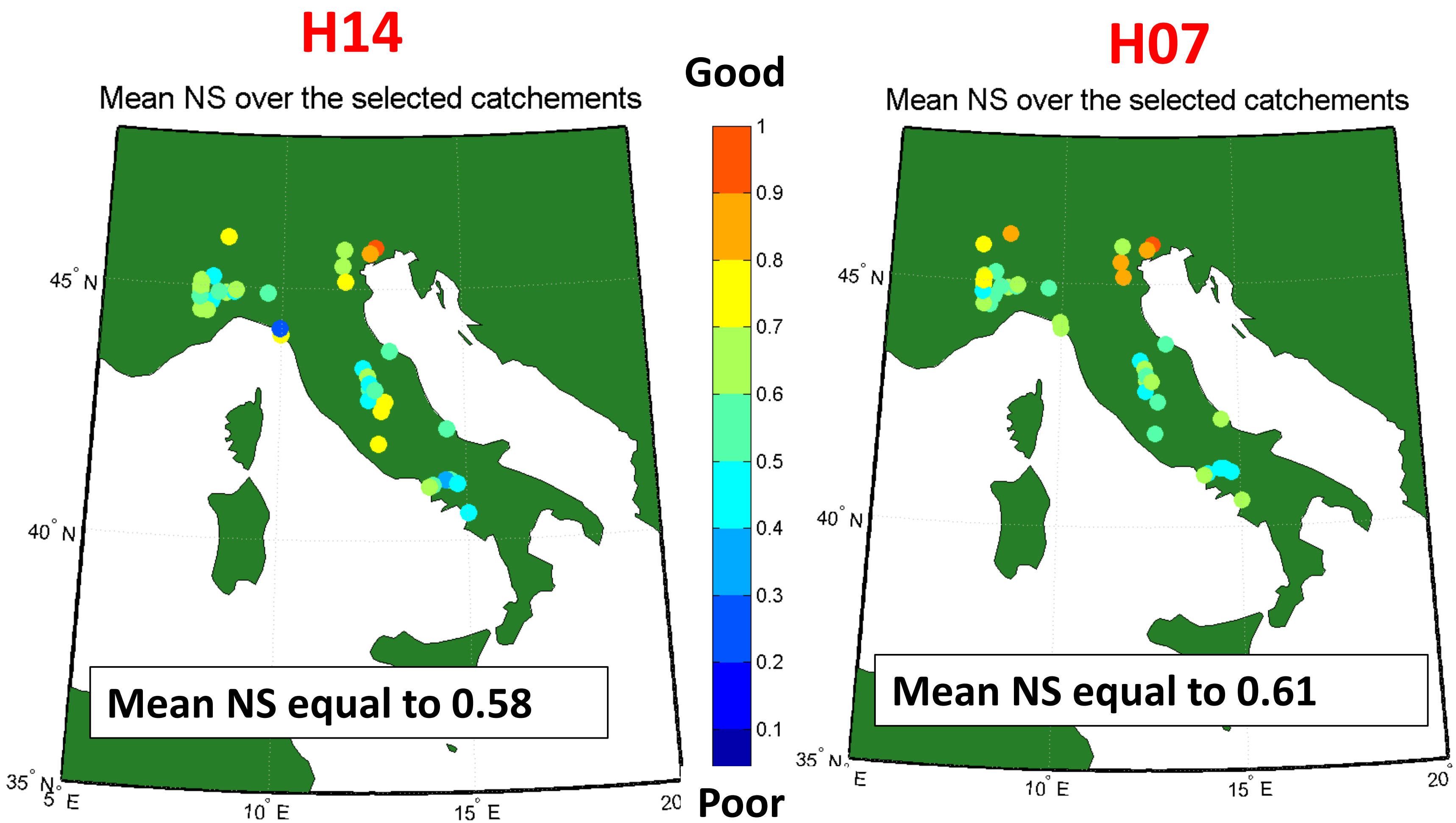
$$\theta_{SM-DAS2} = \frac{(\theta_1 0.07 + \theta_2(z - 0.07))}{z} \qquad : 7 < z \leq 28\text{cm}$$

$$\theta_{SM-DAS2} = \frac{(\theta_1 7 + \theta_2 21 + \theta_3(z - 28))}{z} \qquad : 28 < z \leq 100\text{cm}$$

$$\theta_{SM-DAS2} = \frac{(\theta_1 7 + \theta_2 21 + \theta_2 72 + \theta_3(z - 100))}{z} \qquad : 100 < z \leq 289\text{cm}$$

Application of the model to 35 Italian catchments: results

Results in terms of Nash-Sutcliffe efficiency index

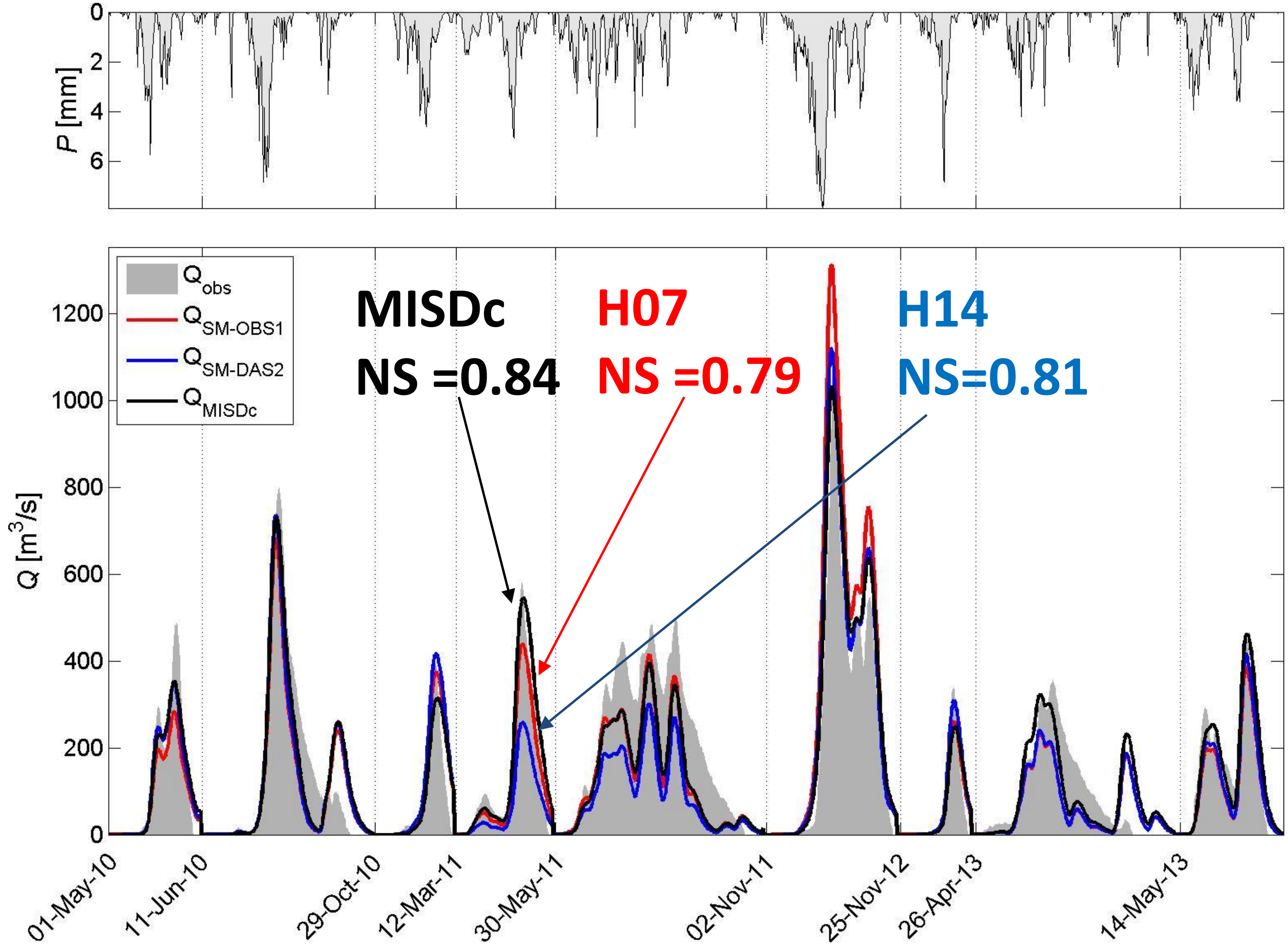


MISDc model used as benchmark NS=0.66

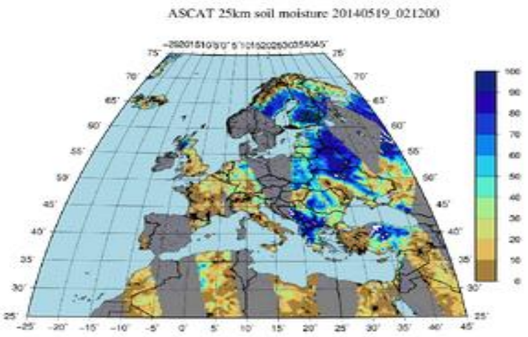
Massari et al. 2014 (Hydrology)
(Under review)

Application of the model to 35 Italian catchments

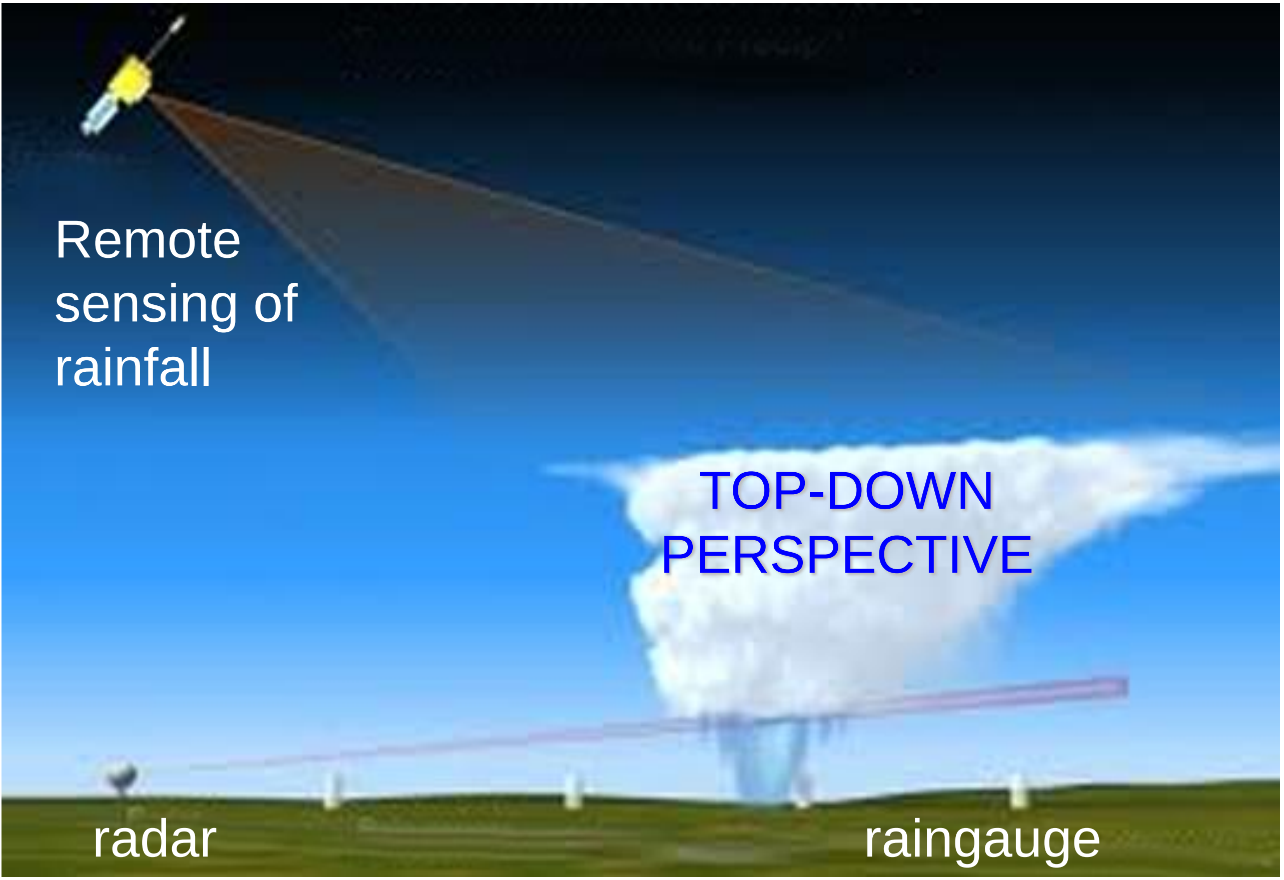
Po River at Carigliano Area=3570 km^2

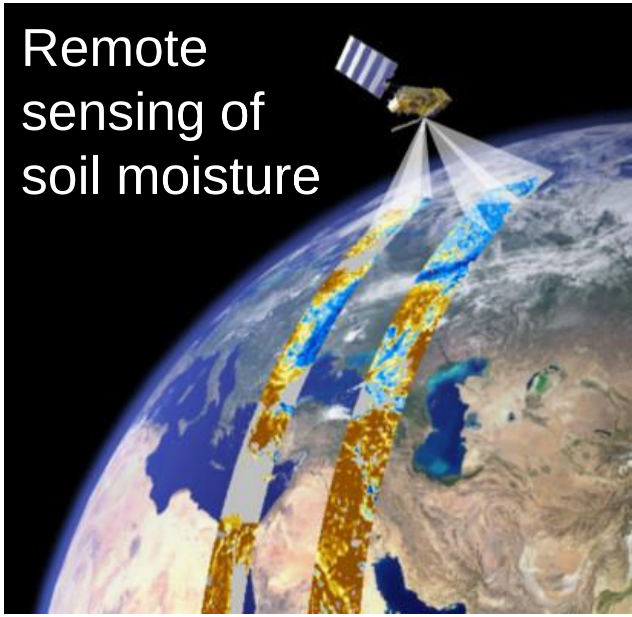


Exploiting soil moisture derived rainfall in flood modelling: SM2RAIN



Rainfall estimation: Top down vs bottom up perspective

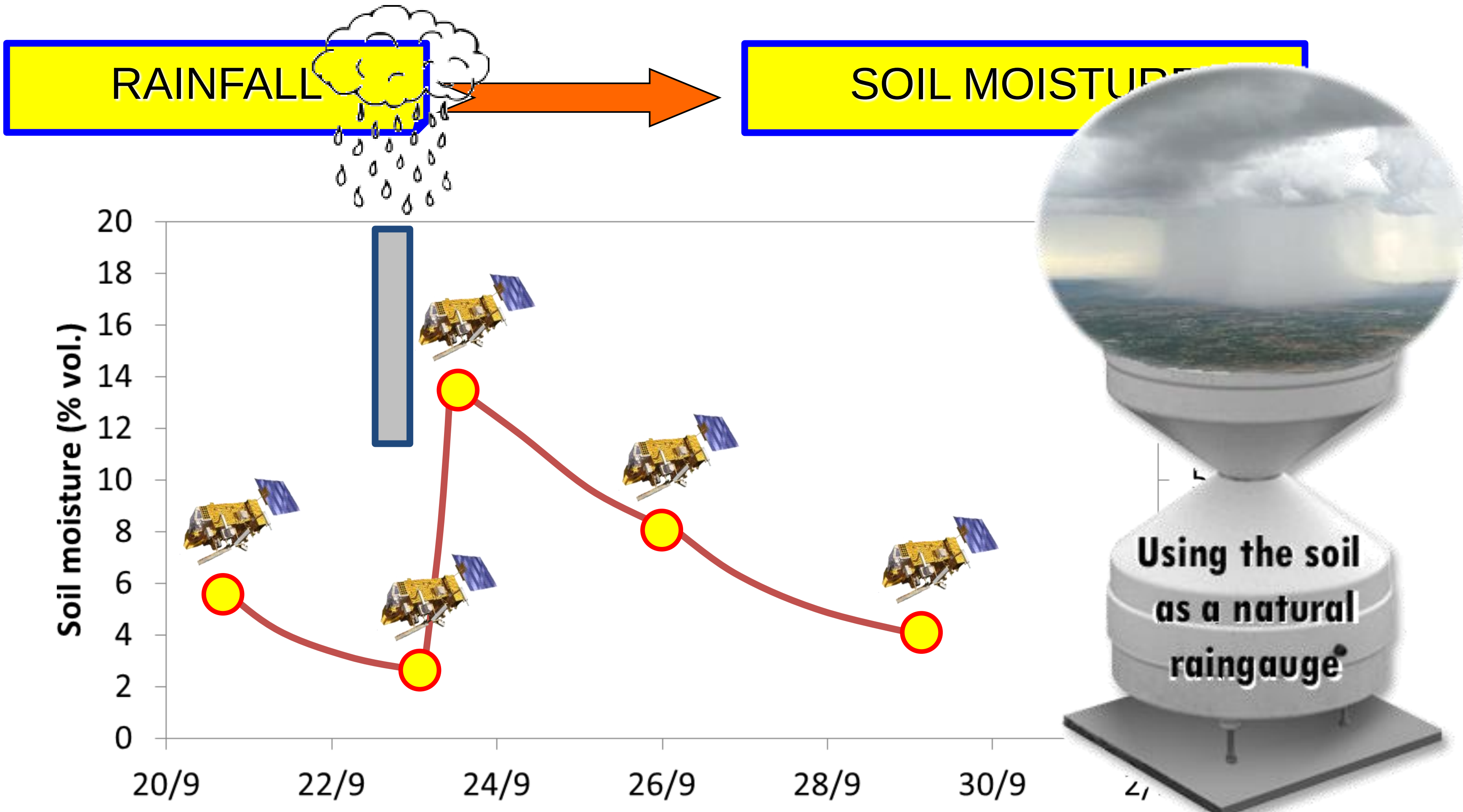




BOTTOM-UP PERSPECTIVE

CAN WE USE SOIL MOISTURE DATA TO INFER THE AMOUNT OF WATER FALLING INTO THE SOIL???

SM2RAIN concept



The soil moisture variations are strongly related to the amount of rainfall falling into the soil. Therefore, we can use soil moisture observations for estimating rainfall by considering the "soil as a natural raingauge".

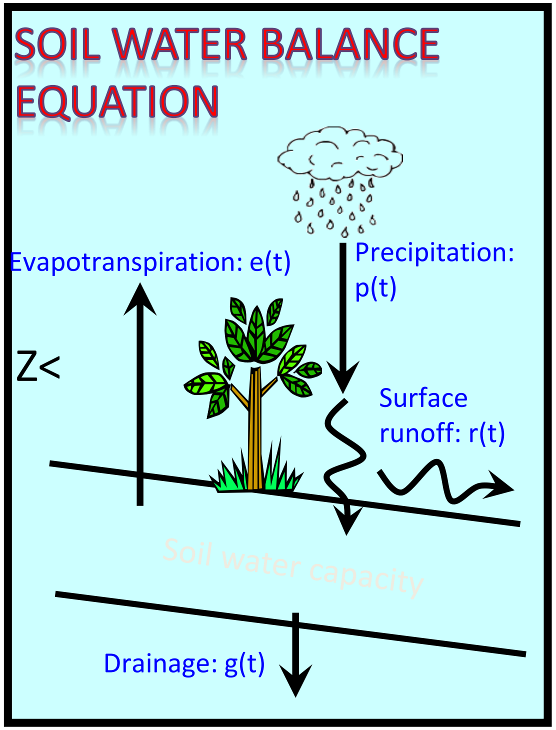
Brocca et al 2013, GRL

relative saturation, precipitation, surface runoff, drainage

$$Z\,ds(t)/dt = p(t) - r(t) - e(t) - g(t)$$

soil water capacity = soil depth X porosity

evapotranspiration



Inverting for *p(t):*

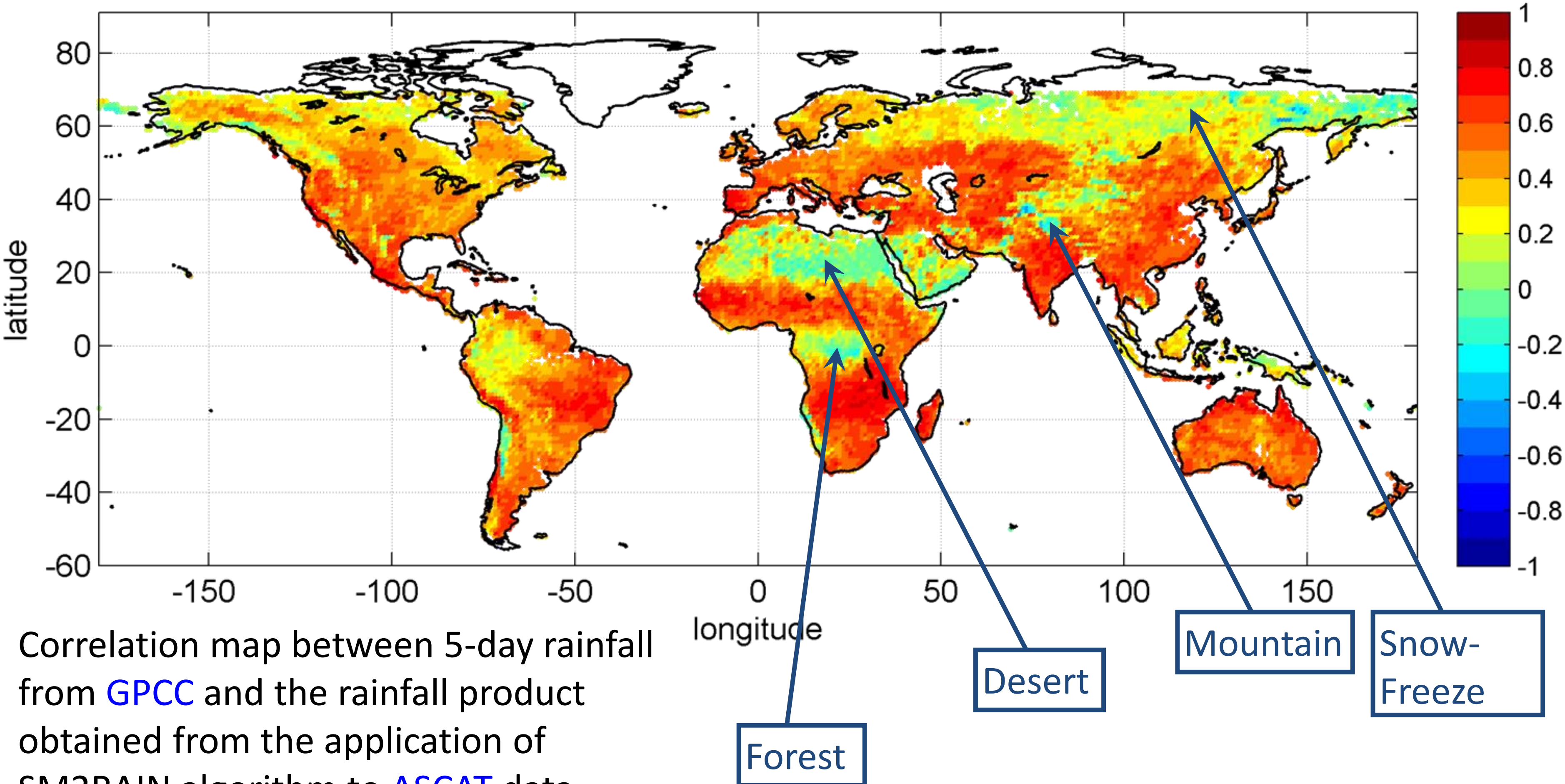
$$p(t) = Z\,ds(t)/dt + r(t) + e(t) + g(t)$$

Assuming: $g(t) = a\,s(t)^b$ + $e(t)=0$ + $r(t)=0$

during rainfall

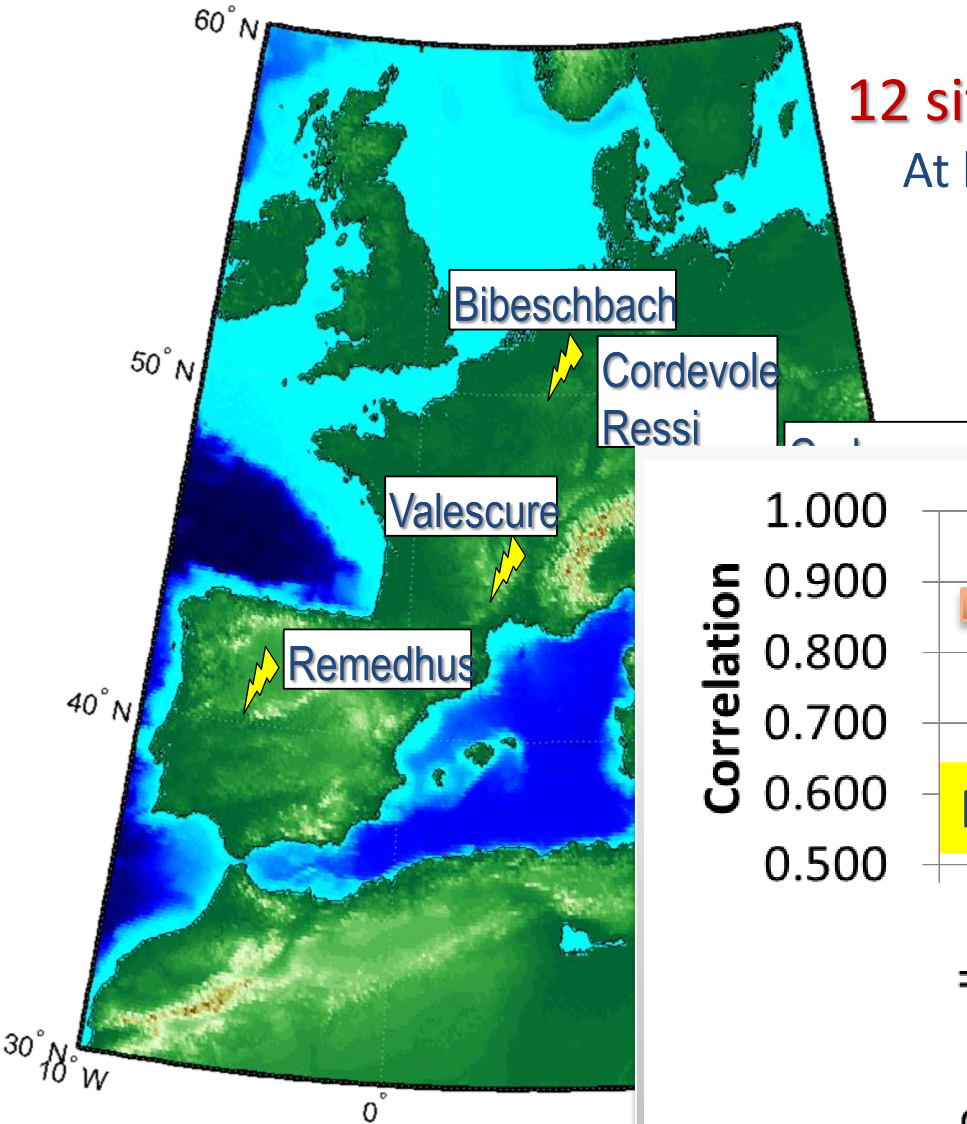
$$\boxed{p(t) \cong Z\,ds(t)/dt + a\,s(t)^b}$$

SM2RAIN Performance: satellite soil moisture data (H07)



Correlation map between 5-day rainfall from GPCC and the rainfall product obtained from the application of SM2RAIN algorithm to ASCAT data (*VALIDATION period 2010-2011*)

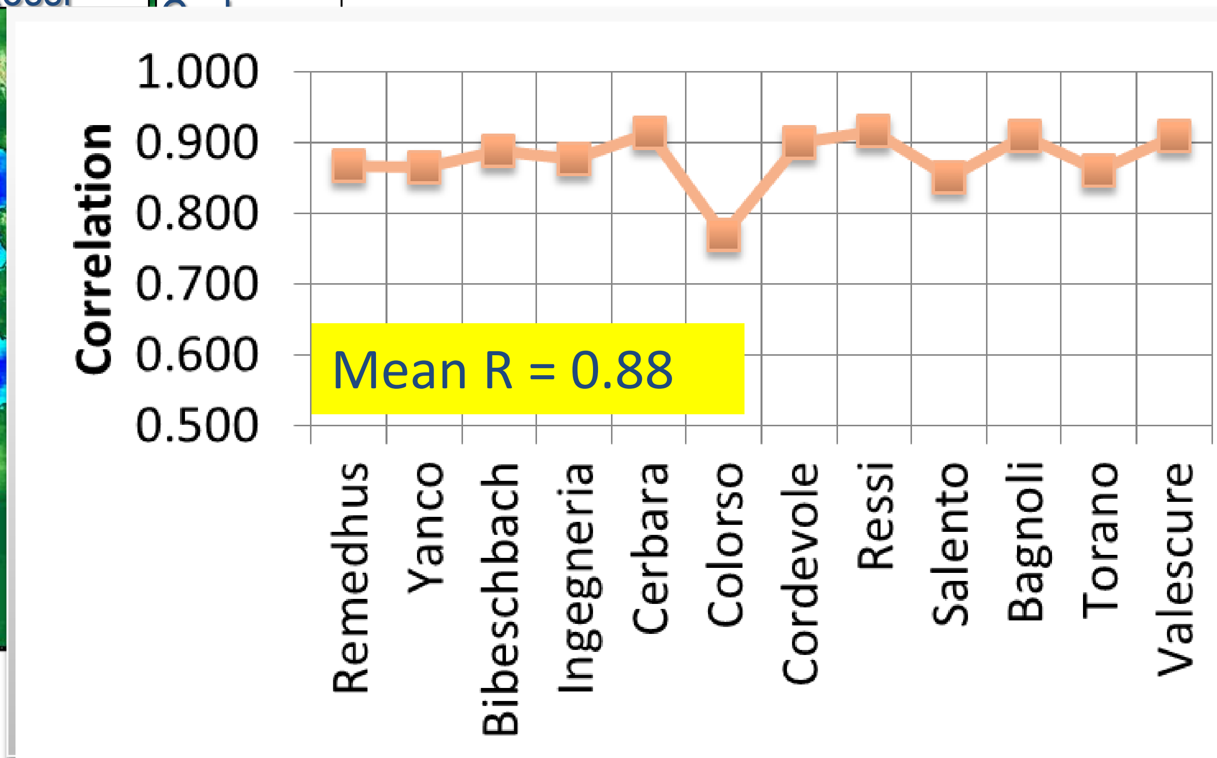
SM2RAIN Performance: in situ data



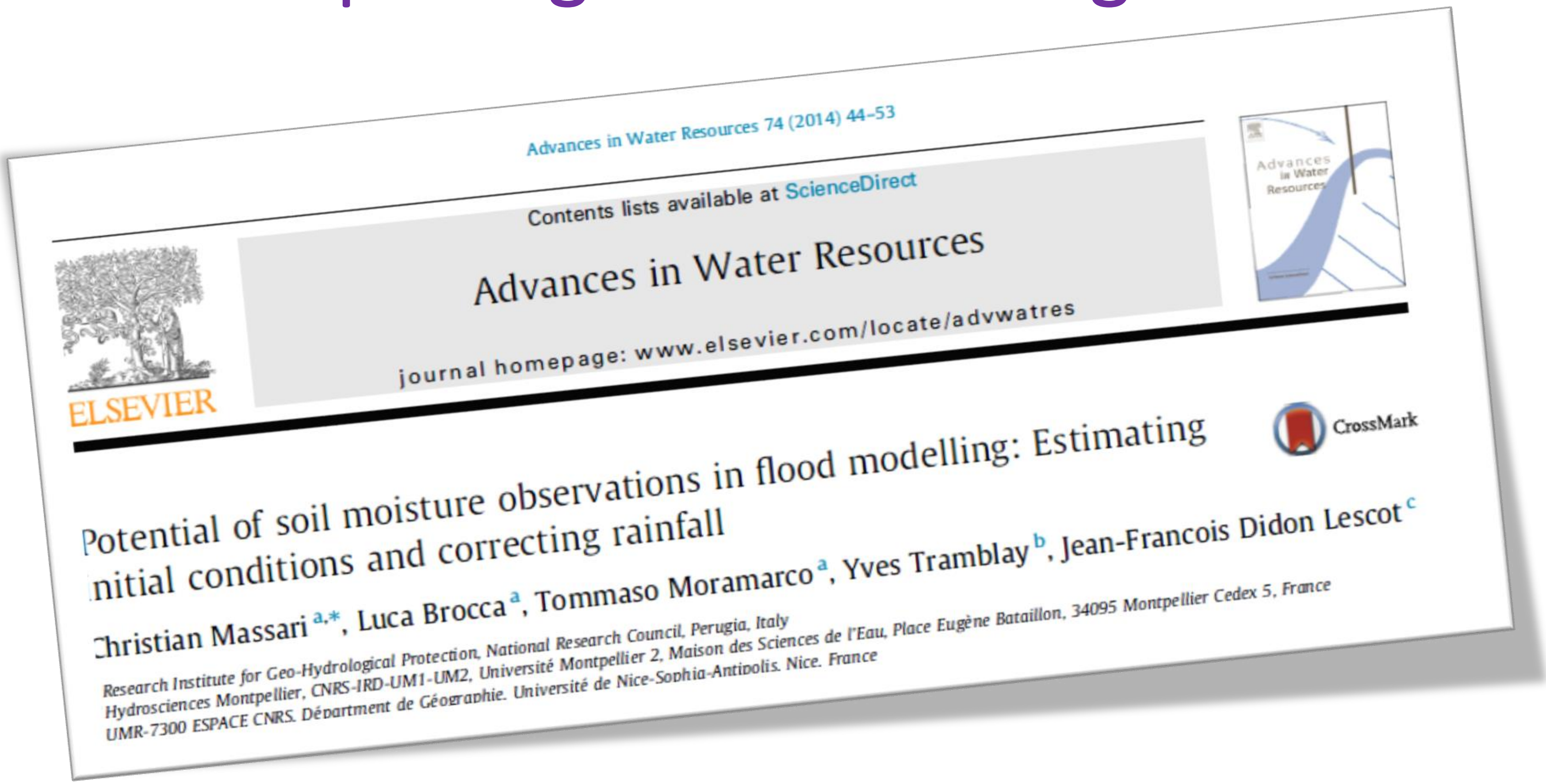
12 sites, 5 countries

At least one year of rainfall and soil moisture data at hourly time scale.

Most of the sites are located in Italy



Can we use the SM2RAIN algorithm for improving flood modelling?



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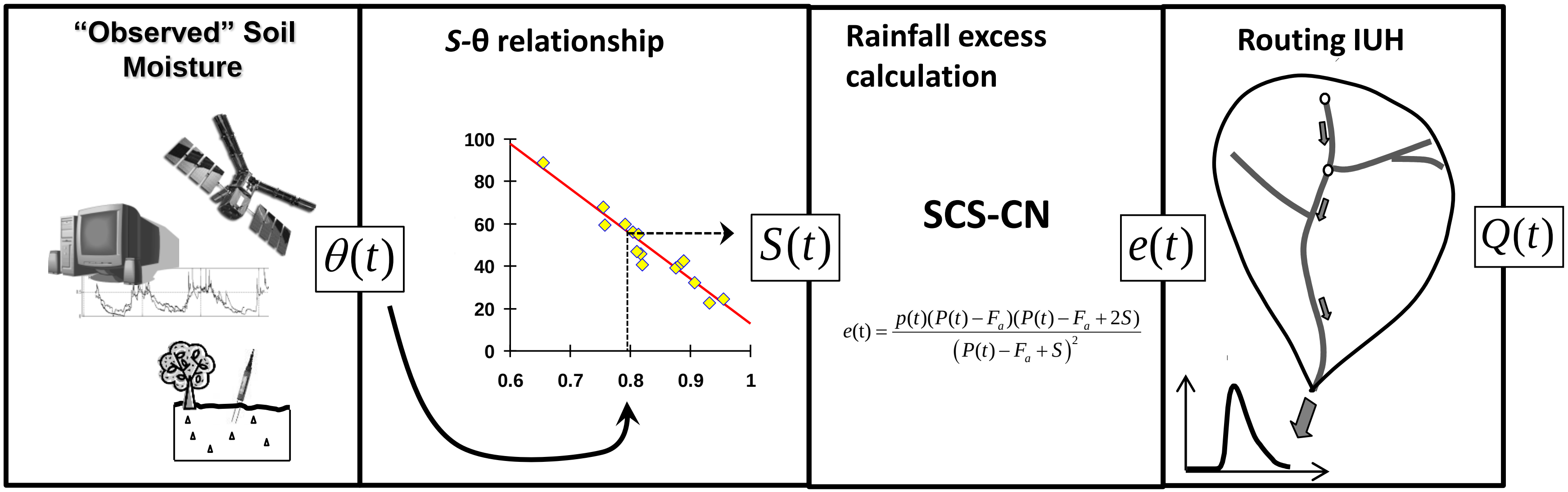
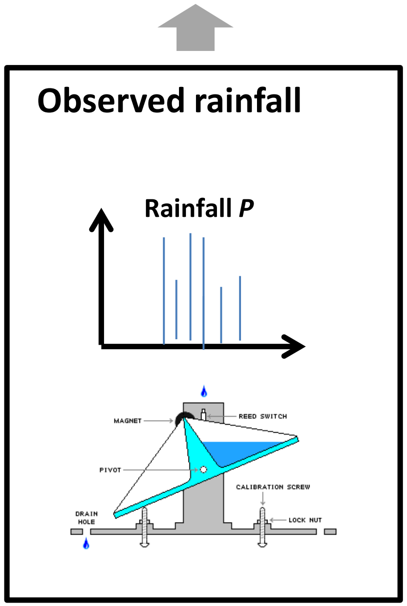
CrossMark

Potential of soil moisture observations in flood modelling: Estimating
nitial conditions and correcting rainfall

Christian Massari [a,*], Luca Brocca [a], Tommaso Moramarco [a], Yves Tramblay [b], Jean-Francois Didon Lescot [c]

Research Institute for Geo-Hydrological Protection, National Research Council, Perugia, Italy
Hydrosciences Montpellier, CNRS-IRD-UM1-UM2, Université Montpellier 2, Maison des Sciences de l'Eau, Place Eugène Bataillon, 34095 Montpellier Cedex 5, France
UMR-7300 ESPACE CNRS, Département de Géographie, Université de Nice-Sophia-Antipolis, Nice, France

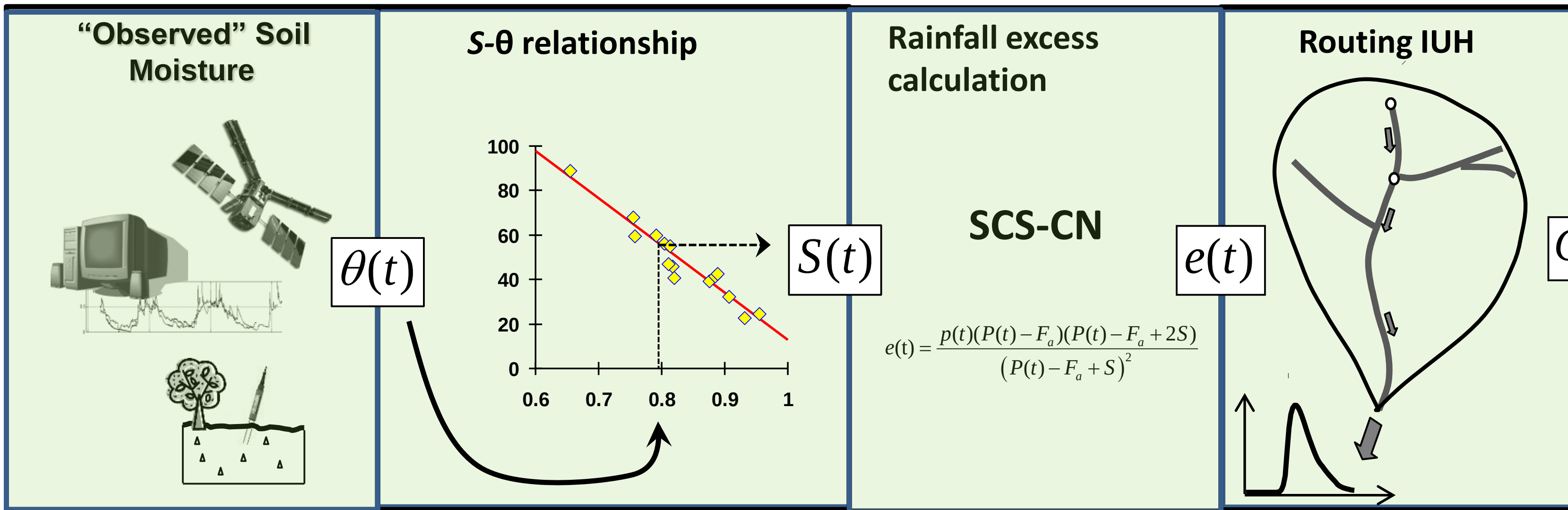




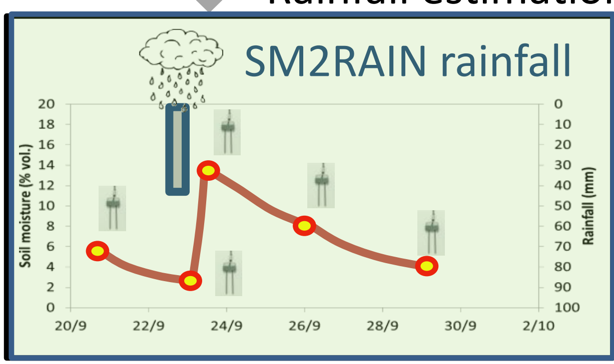
The model uses external source of soil moisture only for initialization

We considered a modified configuration of the previous model …

Initialization

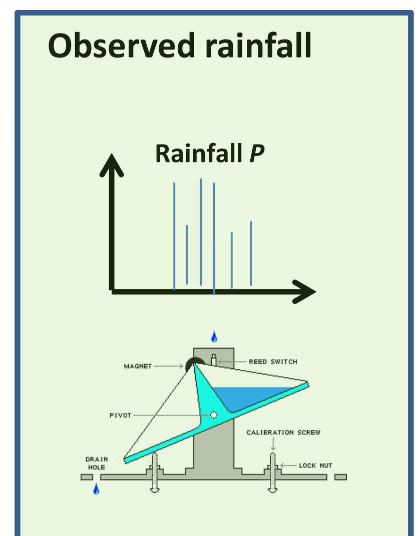


Rainfall estimation



Integrated rainfall via Nudging

$$P_{int}(t)=P_{obs}(t)+K\left[P_{SM2RAIN}(t)-P_{obs}(t)\right]$$



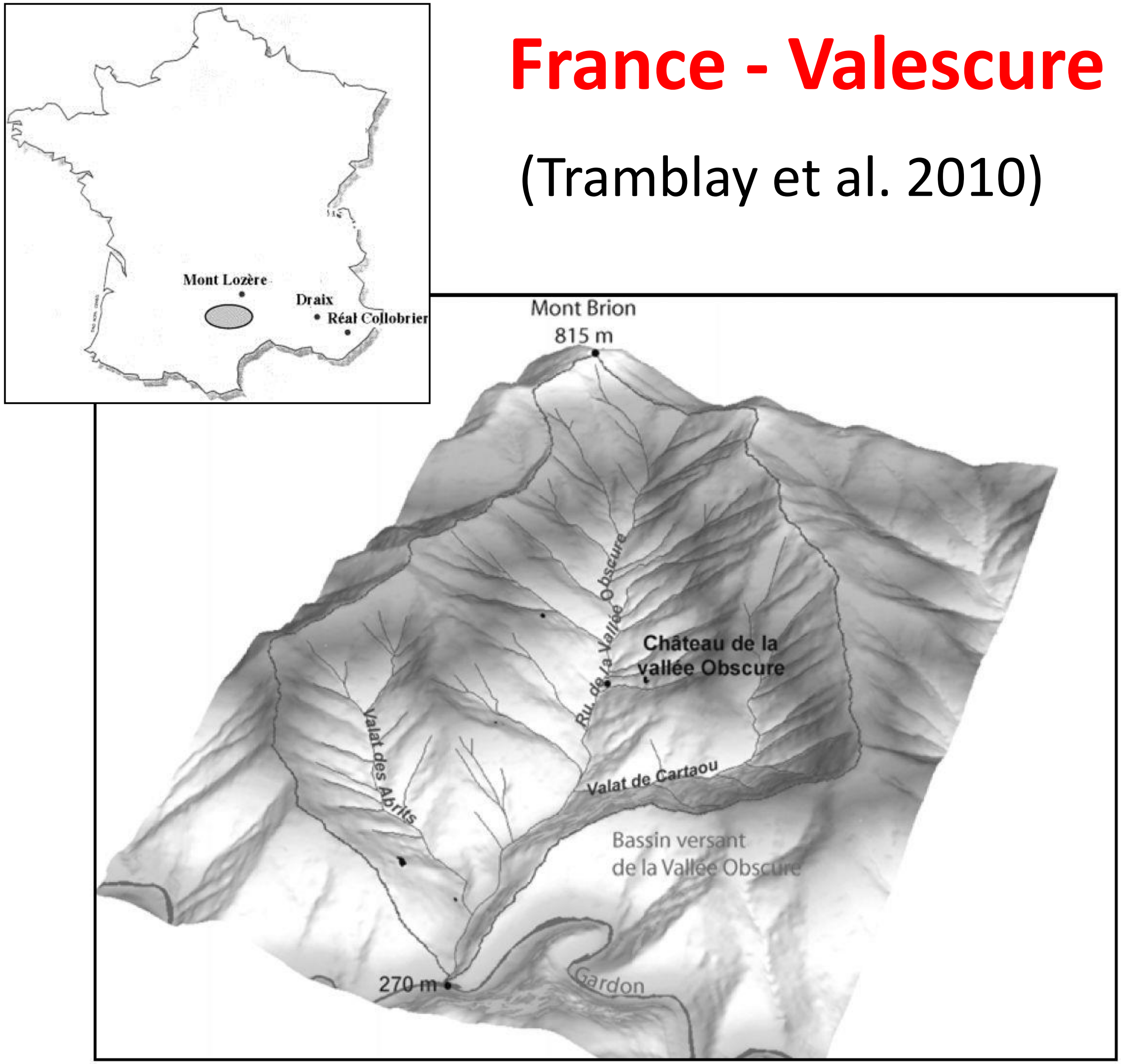
$$P_{int}(t)=P_{obs}(t)+K\left[P_{SM2RAIN}(t)-P_{obs}(t)\right]$$

K=0 → Pint=P_{obs}

K=1 → Pint=$P_{SM2RAIN}$

France - Valescure

(Tramblay et al. 2010)



Area: 3.83 km^2

Elevations:

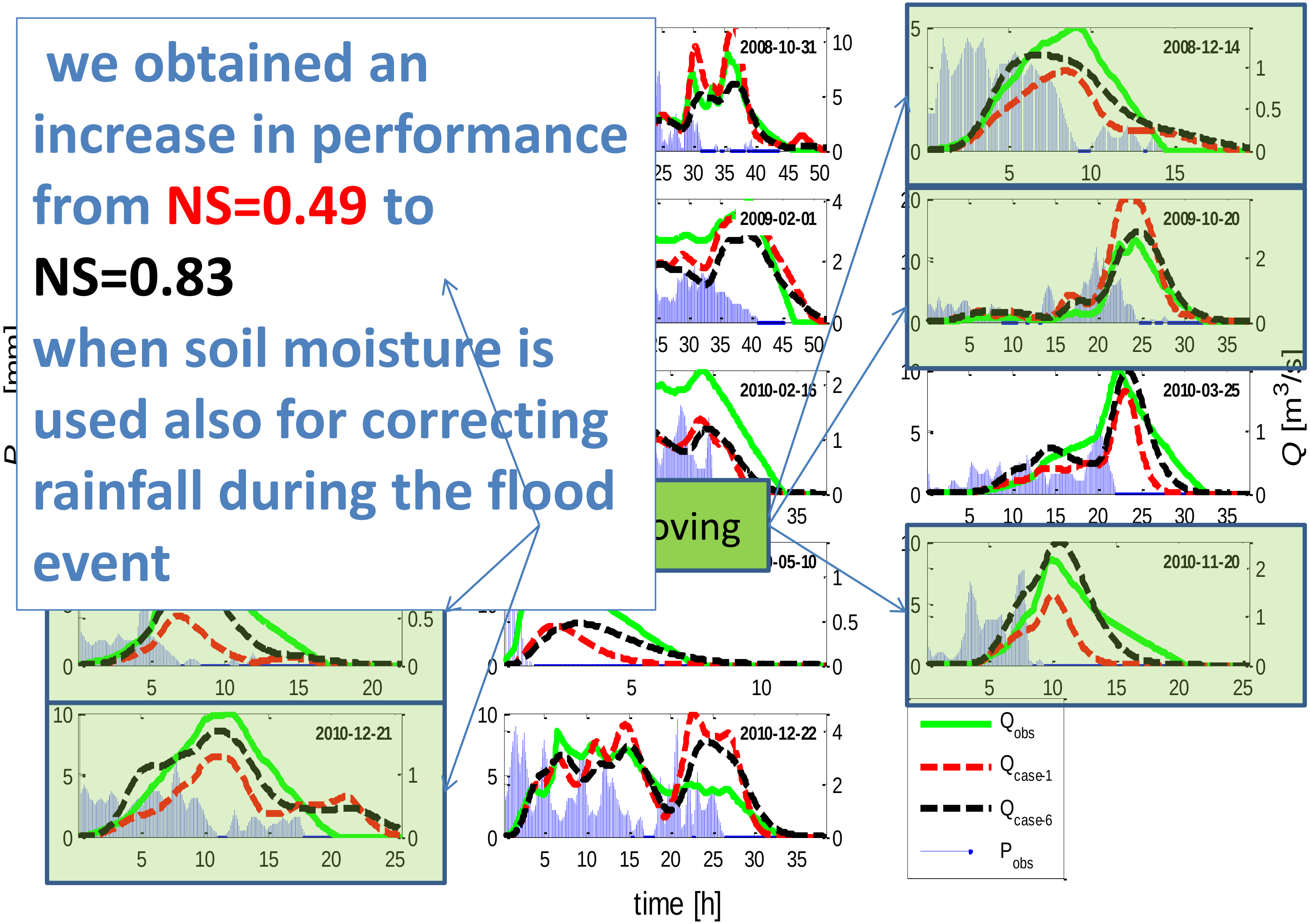
from 244 m to 815m ASL

Mean slope: 56 %

30 minutes interval recorded data of

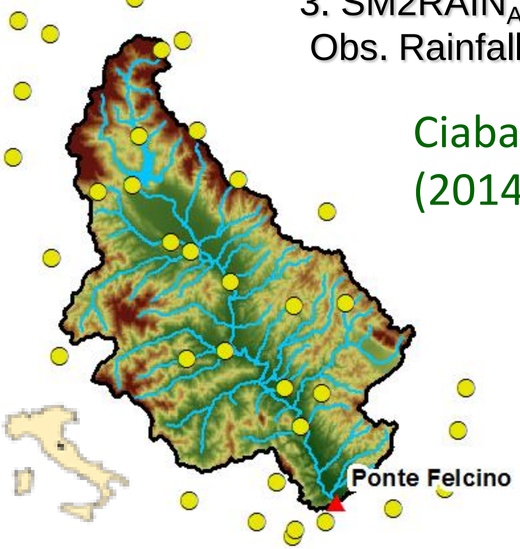
- **Rainfall**
- **Temperature**
- **Discharge**
- **Soil moisture** (30 cm depth from a representative location)

we obtained an increase in performance from NS=0.49 to NS=0.83 when soil moisture is used also for correcting rainfall during the flood event



A similar approach with satellite data

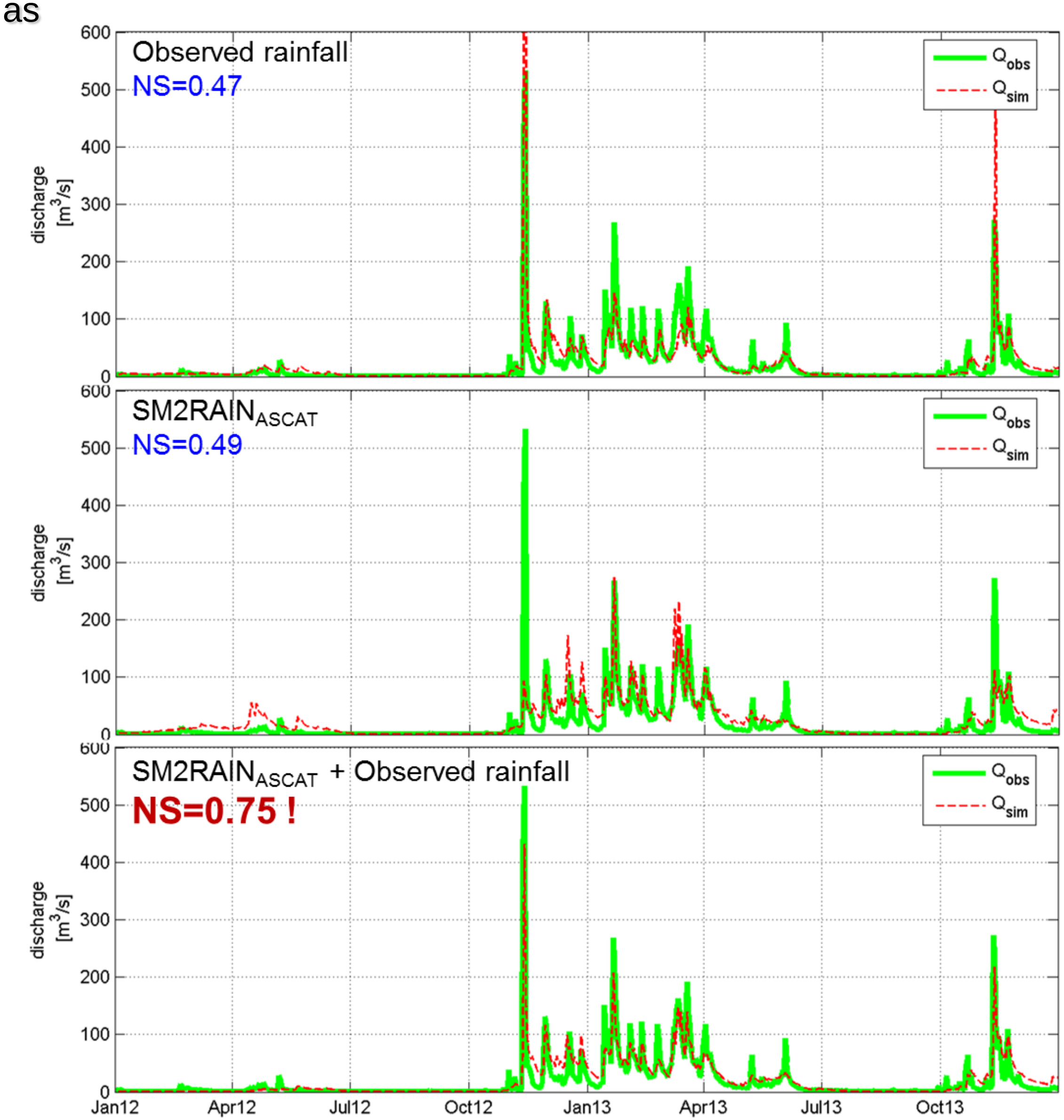
Tiber River catchment @ Ponte Felcino central Italy



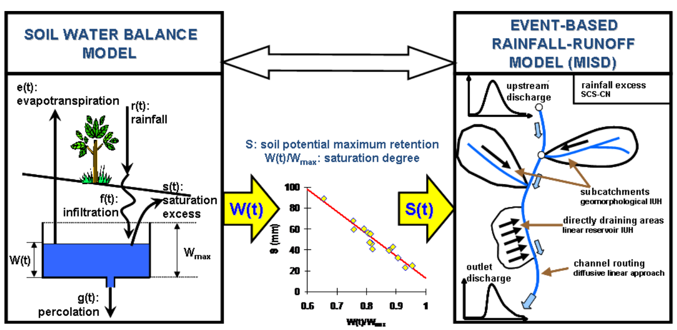
Runoff simulation by using as input

1. Observed rainfall
2. $SM2RAIN_{ASCAT}$
3. $SM2RAIN_{ASCAT}$ + Obs. Rainfall

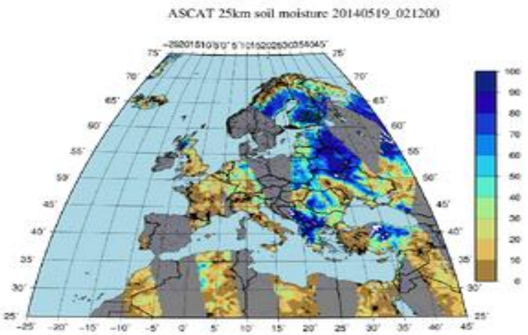
Ciabatta et al. (2014 in prep.)



MISDc rainfall-runoff model



Data assimilation of soil moisture for improving flood predictions



In rainfall-runoff modelling …

In the last decades a number studies performed **data assimilation experiments** and tested different techniques and approaches for soil moisture assimilation within rainfall-runoff modelling …

In situ soil moisture …	Satellite soil moisture …
	Brocca et al. 2012 (IEEE TGRS)
	Chen et al. 2014 (JoH)
	Garreton et al. 2014 (HESSD)

However, few studies (to our knowledge) demonstrated the real value of assimilating true soil moisture data for improving runoff prediction and there are still many controversial issues to be solved ….

Data Assimilation ingredients

Observations
1) In situ
2) Satellite data
3) Land surface model data

Assimilation technique
1) Variational
2) Sequ

Rainfall runoff model
1) Lumped
2) distributed
3) Single layer
layers

The problem is often not the ingredients but the cooking technique …

"Cooki

Bias Han
1) Varian
2) Least square rescaling
3) Cdf matching
4) Triple collocation

(SWI)
2) Others
3) No filtering

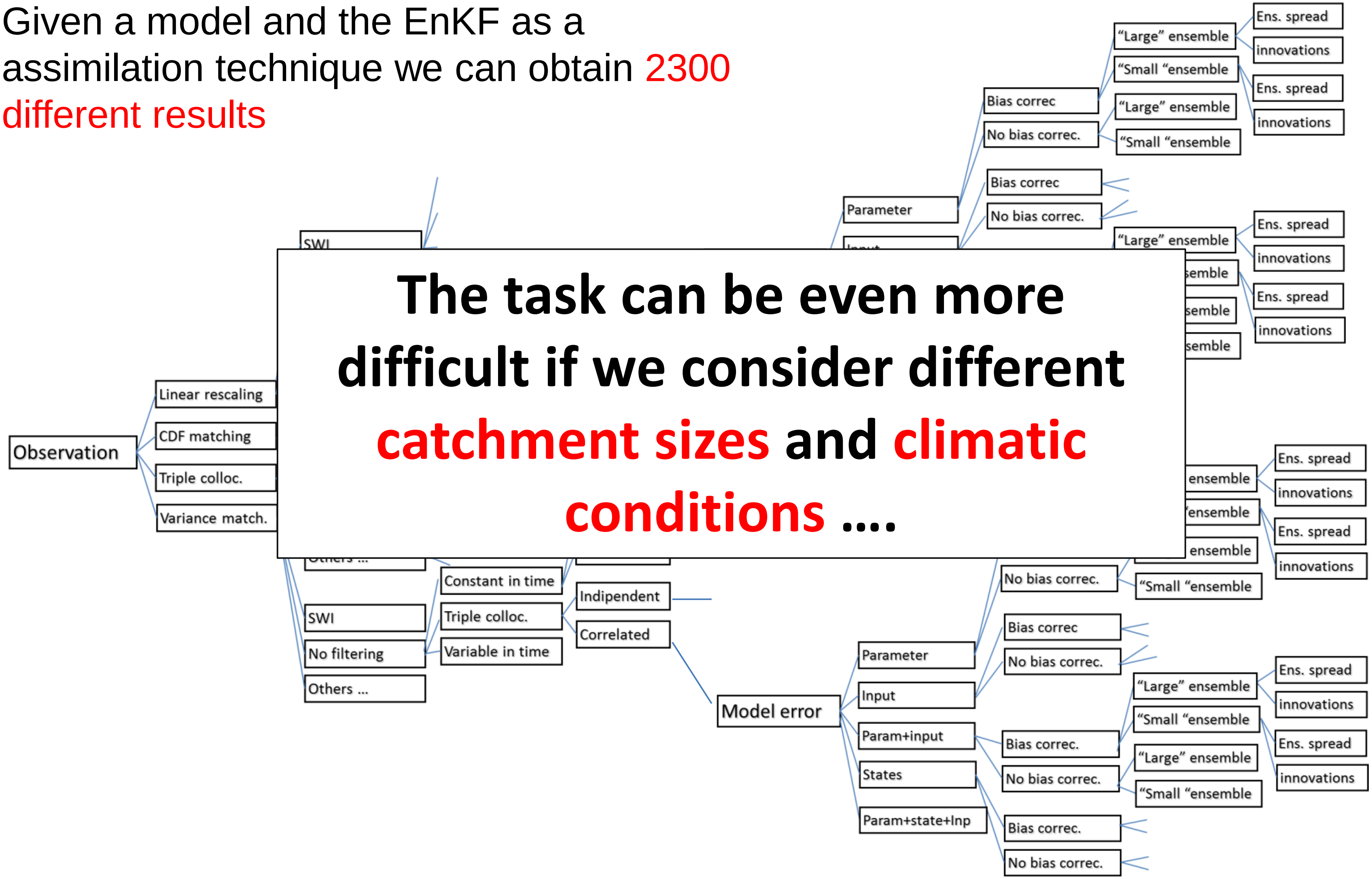
ation error
oral variability of the obs. error
2) Spatial correlation between the observations
3) Masking

Model error
1) Model error covariance estimation (i.e. EnkF: ensemble size)
2) What to perturb. (parameters, inputs, states etc …)
3) How to perturb (amount of perturbation)

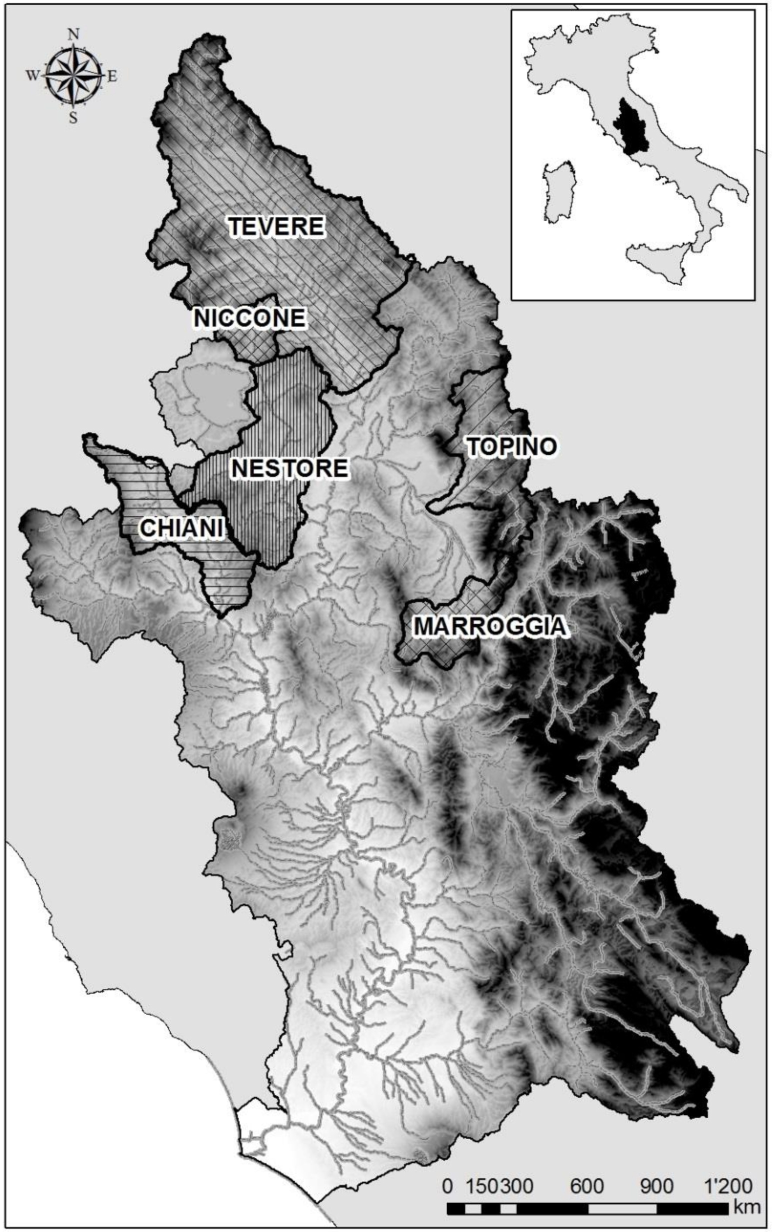
Data assimilation of soil moisture - a complex topic?

Bias handling	Filtering	Temporal variability	Spatial variability	What to perturb	Bias correction	Ensemble size	Ensemble verification

Given a model and the EnKF as a assimilation technique we can obtain 2300 different results



The task can be even more difficult if we consider different catchment sizes and climatic conditions ....



Tiber River Basin

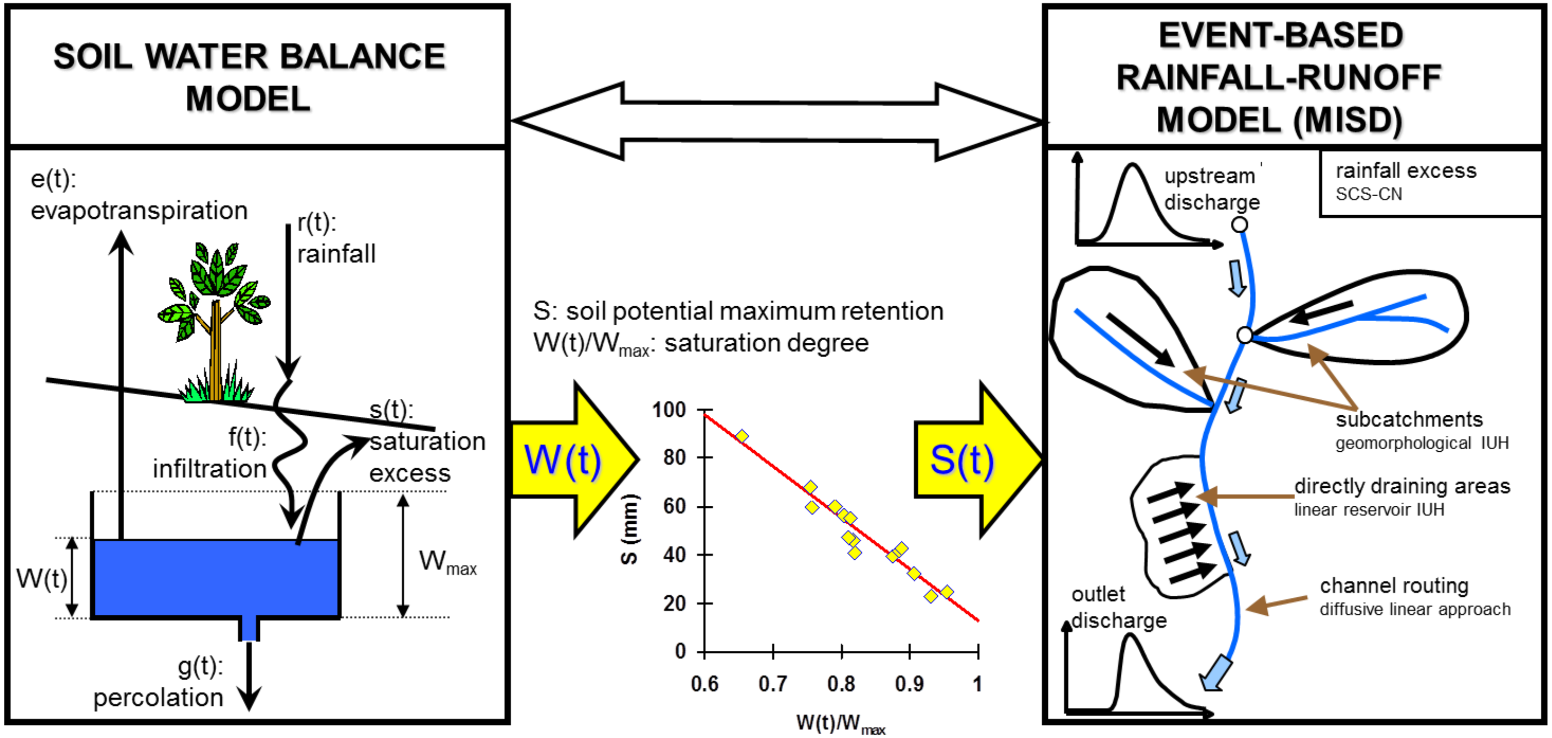
Basin	Area (km^2)
Tevere at Ponte Felcino	2080
Nestore at Marsciano	725
Chiani at Morrano	457
Topino at Bevagna	440
Marroggia at Azzano	258
Niccone at Migianella	137

6 sub-catchments (140-2080 km^2)

Rainfall-runoff data from 1989 at hourly time resolution

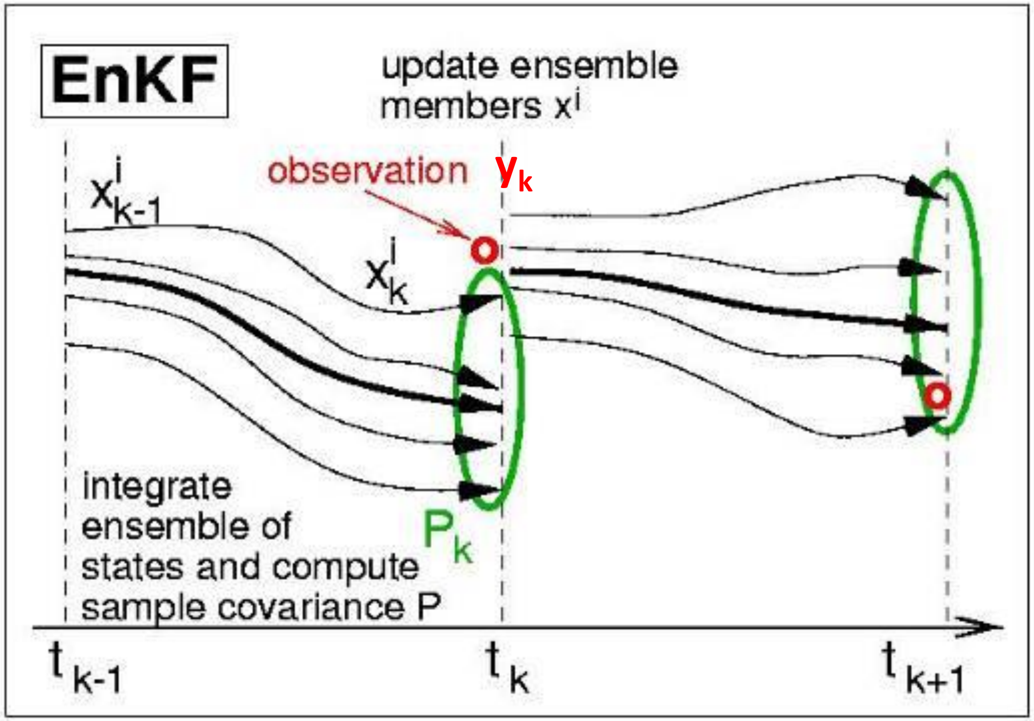
RR model with 1 layer (Brocca et al., 2010 HESS)

Lumped version



calibration period: 1989 - 2009

assimilation of H07 during 2010 - 2013



Nonlinearly propagates ensemble of model trajectories.

Can account for wide range of model errors (incl. non-additive).

Reichle et al., 2002 (MWR)

$\mathbf{x}_k^{\mathbf{i}}$	state vector (eg soil moisture)
$\mathbf{P}_k$	state error covariance
$\mathbf{R}_k$	observation error covariance

Ensemble size N=50 members

Perturbing parameters and inputs

We assume observation error constant in time

ENSEMBLE TEST

$$ensp_k = \frac{1}{N}\sum_{i=1}^{N}(Q_k^i - \overline{Q_k})^2 \qquad \frac{< ensk_k >}{< ensp_k >} \approx 1$$

$$mse_k = \frac{1}{N}\sum_{i=1}^{N}(Q_k^i - Q_{o,k})^2 \qquad \frac{< ensk_k >}{< mse_k >} \approx \sqrt{\frac{N+1}{2N}}$$

$$ensk_k = (\overline{Q_k^i} - Q_{o,k})^2$$

De Lannoy et al. 2006, JGR

FLAGGING AND AVERAGING OF THE OBSERVATION

Data removed when quality flags of H07 >1
Averaging pixels fallen inside the catchment using the weighted linear inverse method

FILTERING

$$SWI(t) = \frac{\sum_i SSM_{t_i} \exp\left(-\frac{t - t_i}{T}\right)}{\sum_i \exp\left(-\frac{t - t_i}{T}\right)}$$

Wagner et al., 1999 (RSE)

SWI:	**Soil Water Index**
t:	**time**
SSM_{ti}:	**relative Surface Soil Moisture [0,1]**
ti:	**acquisition time of SSM_{ti}**
T:	**characteristic time length**

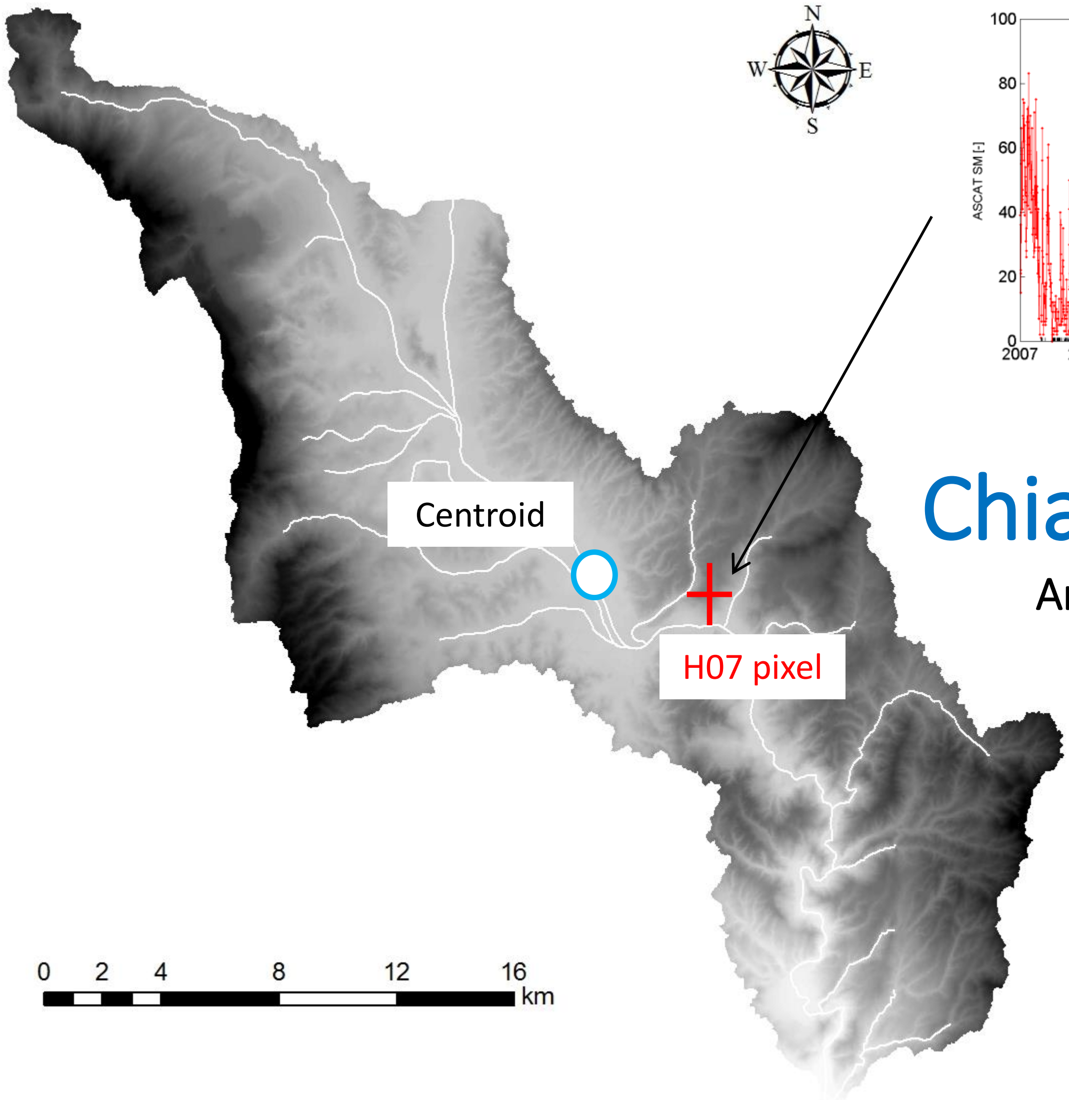
RESCALING

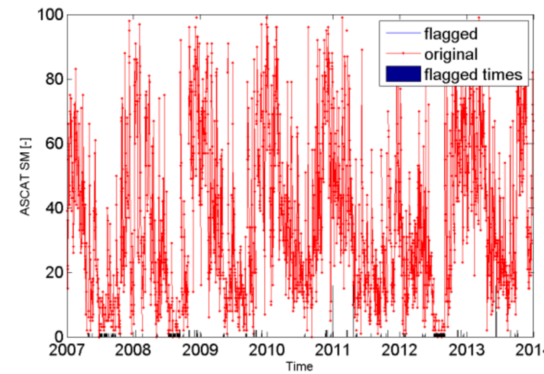
1) Variance matching (Brocca et al 2010, HESS)

2) Linear least square rescaling (Yilmaz and Crow 2012, JM)

3) CDF matching (Reichle and Koster, 2004)

Chiani catchment: results

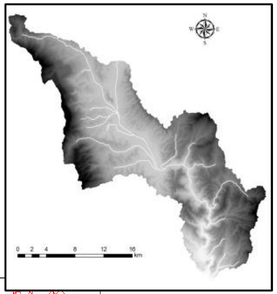




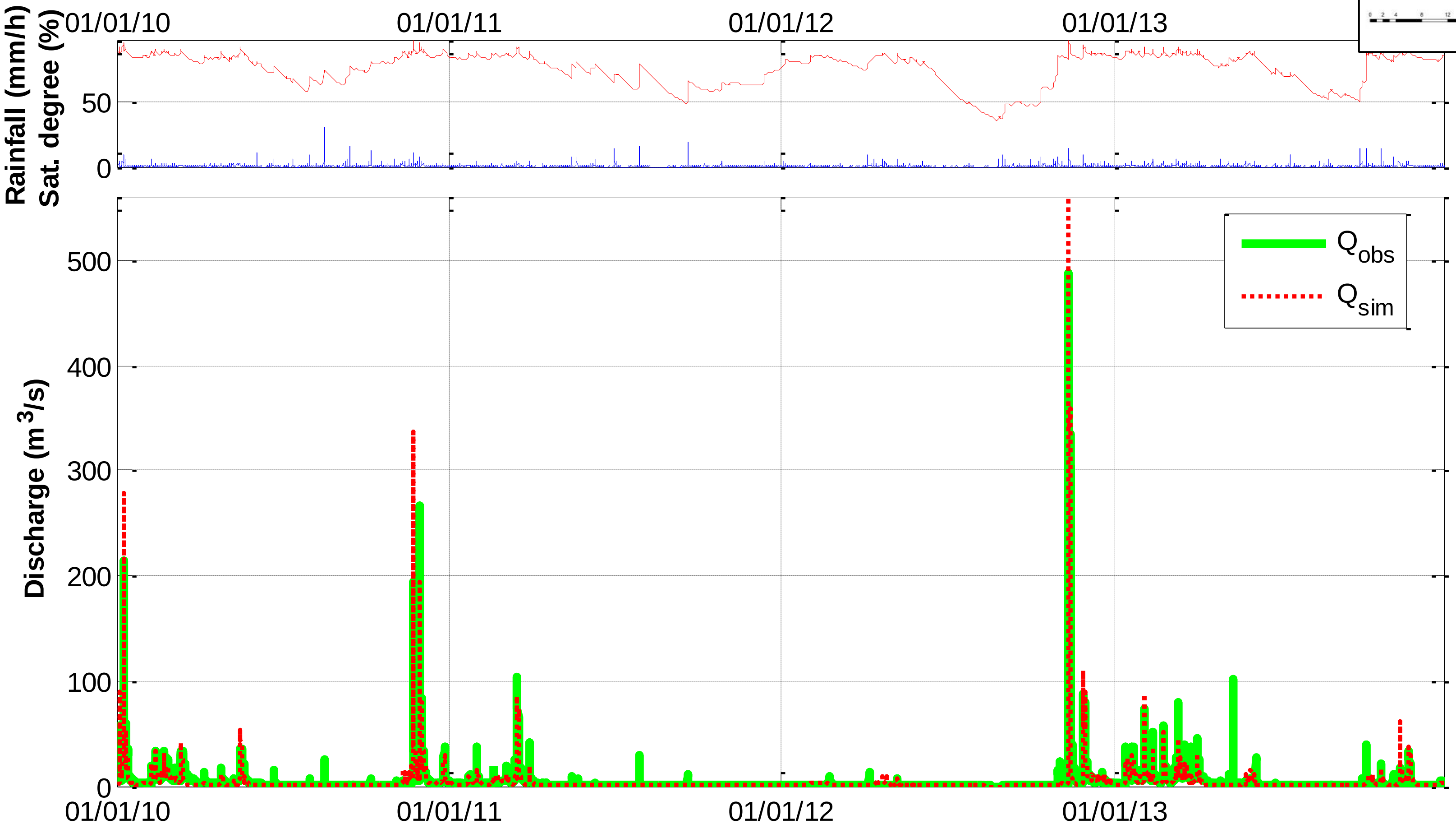
Chiani catchment

Area 457 km^2

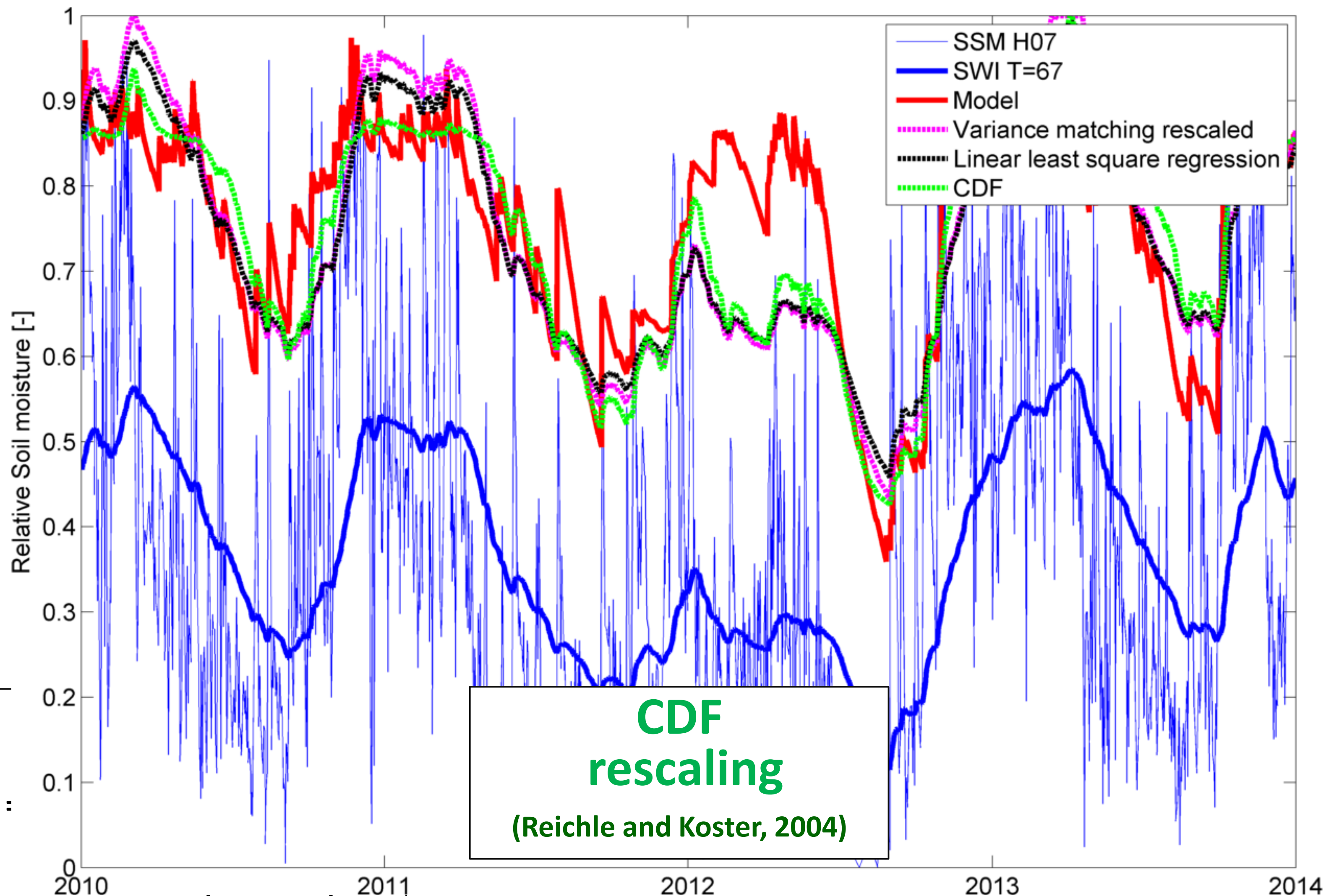
Chiani catchment



Validation 2010-2013 NS=0.72



Chiani catchment: observation handling

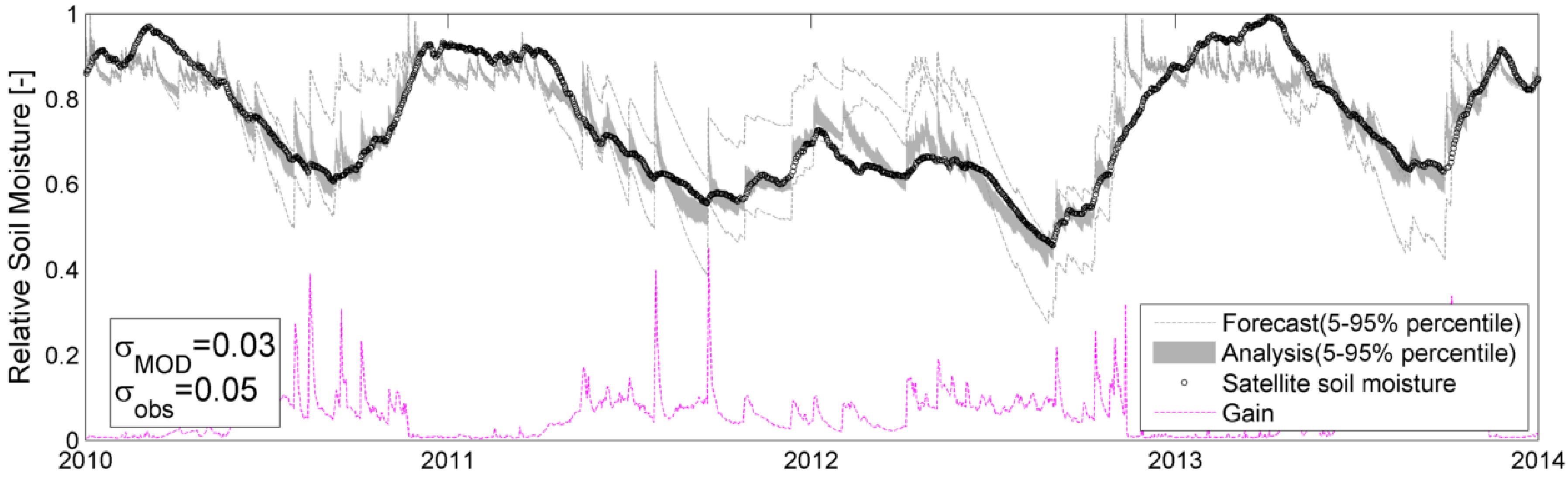


$SWI(t)=$

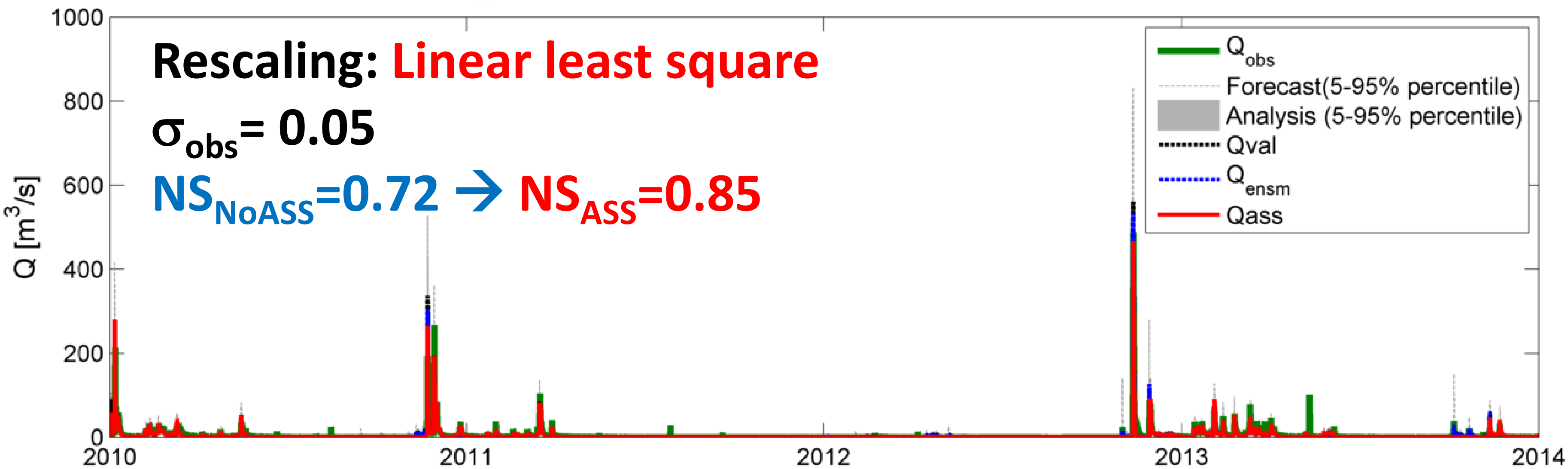
CDF rescaling

(Reichle and Koster, 2004)

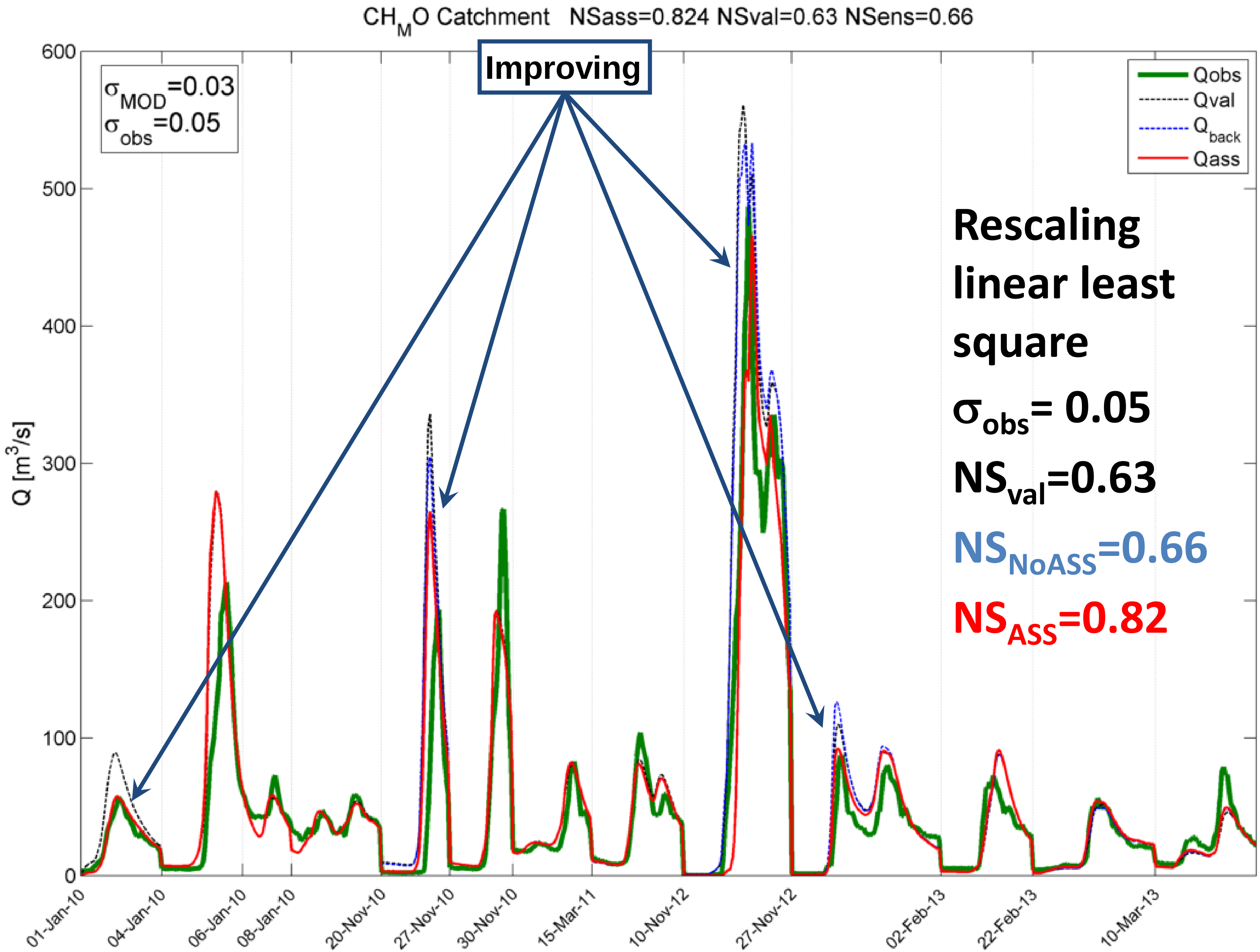
Results: Chiani river basin data assimilation



CH$_M$O Catchment NSass=0.848 NSval=0.724 NSens=0.745



Results: Chiani river basin most important flood events



Rescaling linear least square

σ_{obs}= 0.05

NS_{val}=0.63

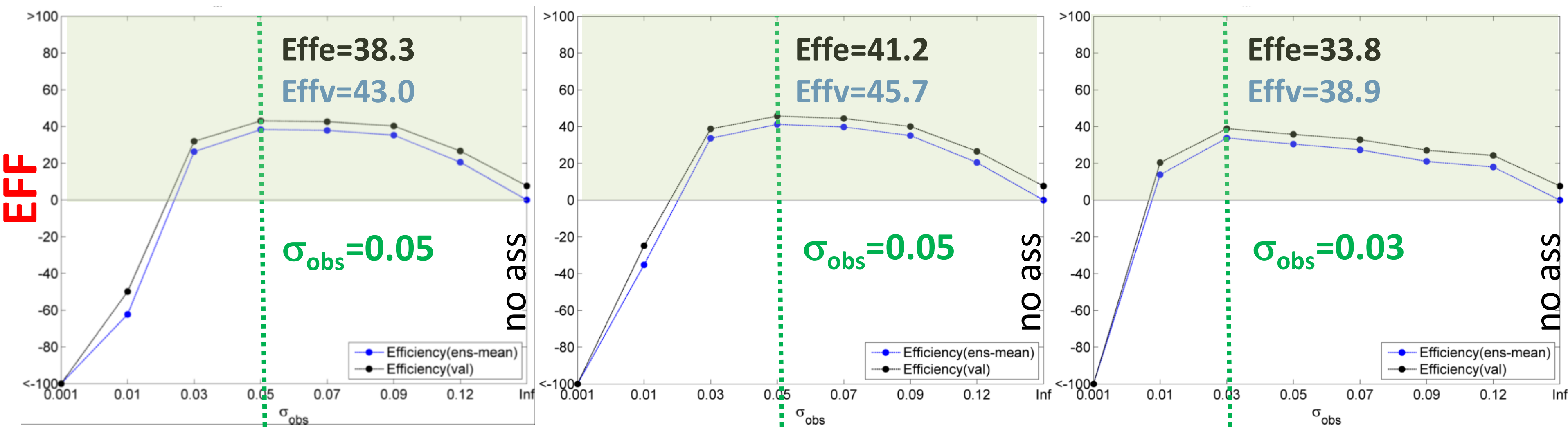
NS_{NoASS}=0.66

NS_{ASS}=0.82

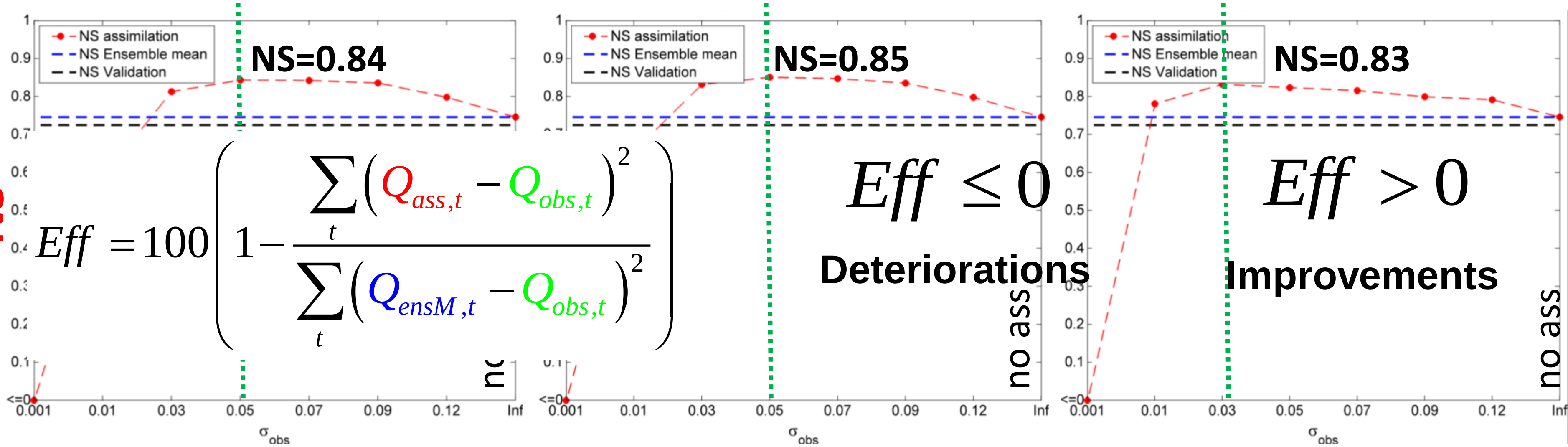
Results: Chiani river basin

Variance matching | **Linear least square** | **CDF**

EFF



NS



$$Eff = 100\left(1 - \frac{\sum_t \left(Q_{ass,t} - Q_{obs,t}\right)^2}{\sum_t \left(Q_{ensM,t} - Q_{obs,t}\right)^2}\right)$$

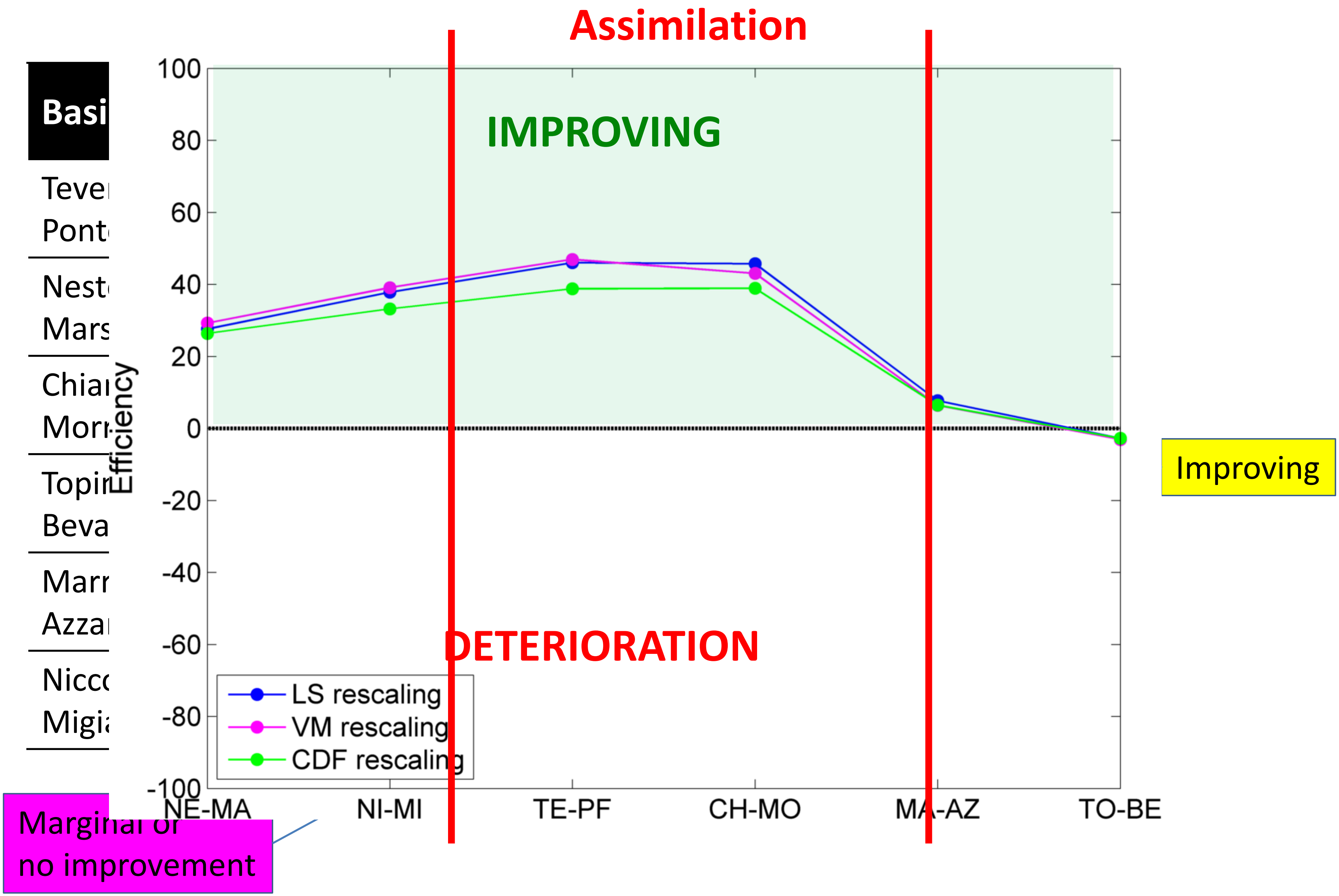
$$Eff \leq 0$$

Deteriorations

$$Eff > 0$$

Improvements

Results for all cathcments



Conclusions

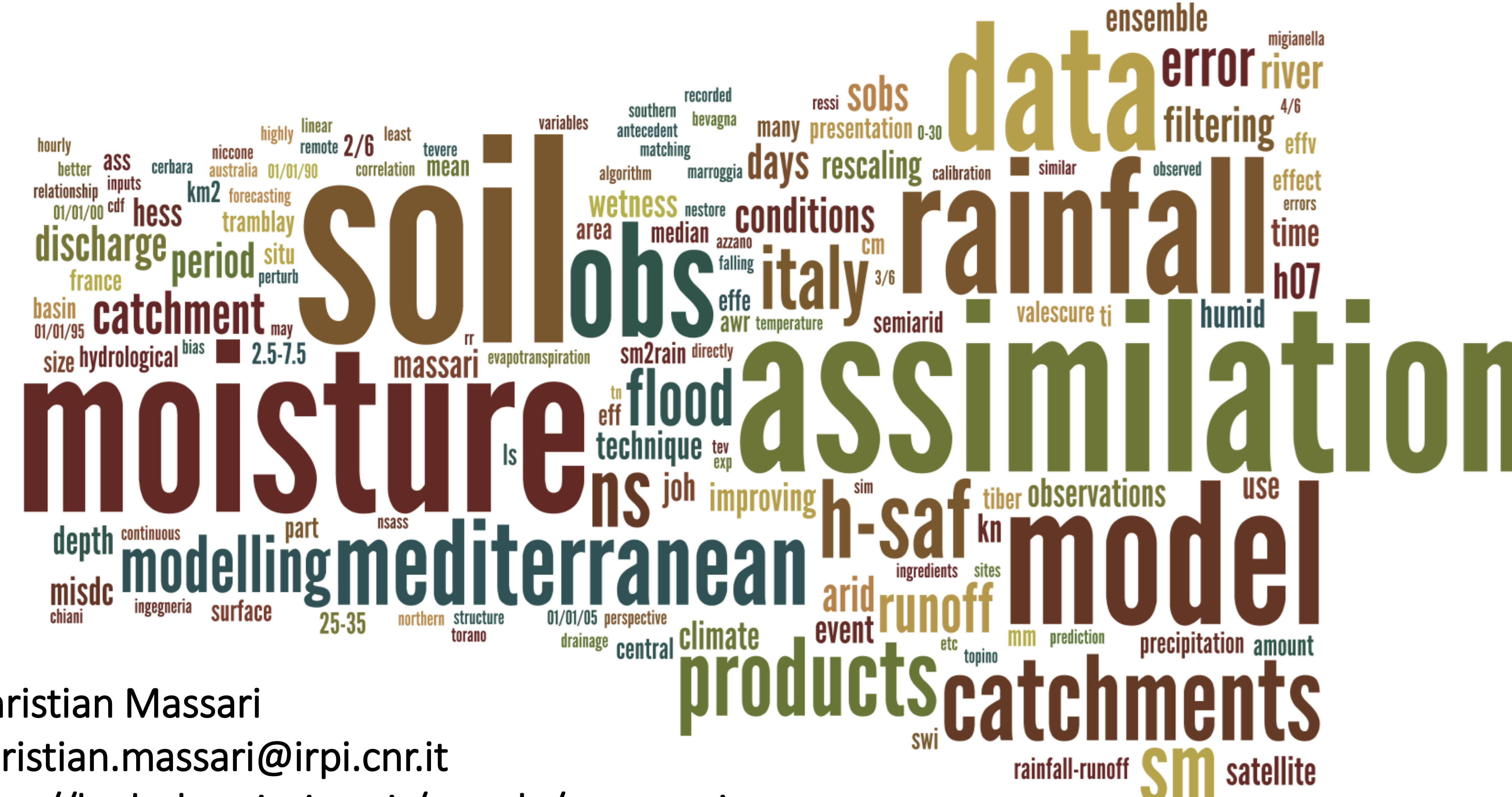
H-SAF soil moisture products may offer a great benefit in rainfall-runoff modelling in Mediterranean catchments and can be used directly both in RR modelling for operational purposes and as additional information for improving flood modelling in the contest of data assimilation in hydrological models

A lot of work remains to be done for:

- a better characterization of the errors to associate to satellite observations (there should be a stronger connection between users and developers)
- the understanding the effect of the RR model structure, rescaling, filtering on the results of the data assimilation
- exploring the potentiality for a larger range of climatic conditions and catchment characteristics

Thanks for your attention

A special thanks to Clement Albergel, Patricia De Rosnay, Silvia Puca, Simone Gabellani and Wolfgang Wagner



Christian Massari
christian.massari@irpi.cnr.it
http://hydrology.irpi.cnr.it/people/c.massari