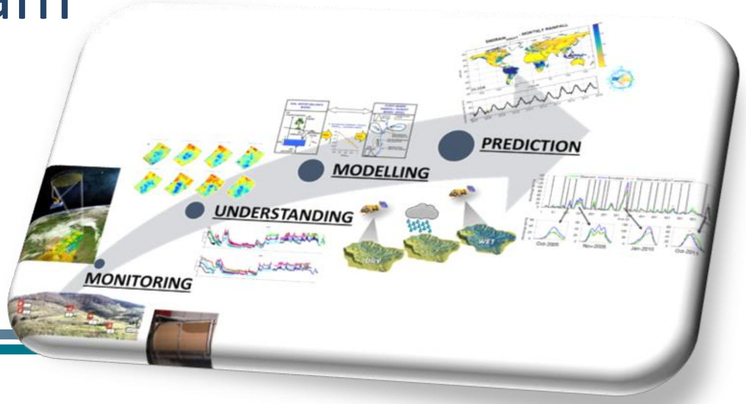
H SAF SOIL MOISTURE WEEK 2019
4-8 November 2019

Flood prediction through H SAF satellite soil moisture products

Introduction

Luca Brocca and the Hydrology Team
IRPI CNR



Which processes contribute to floods?

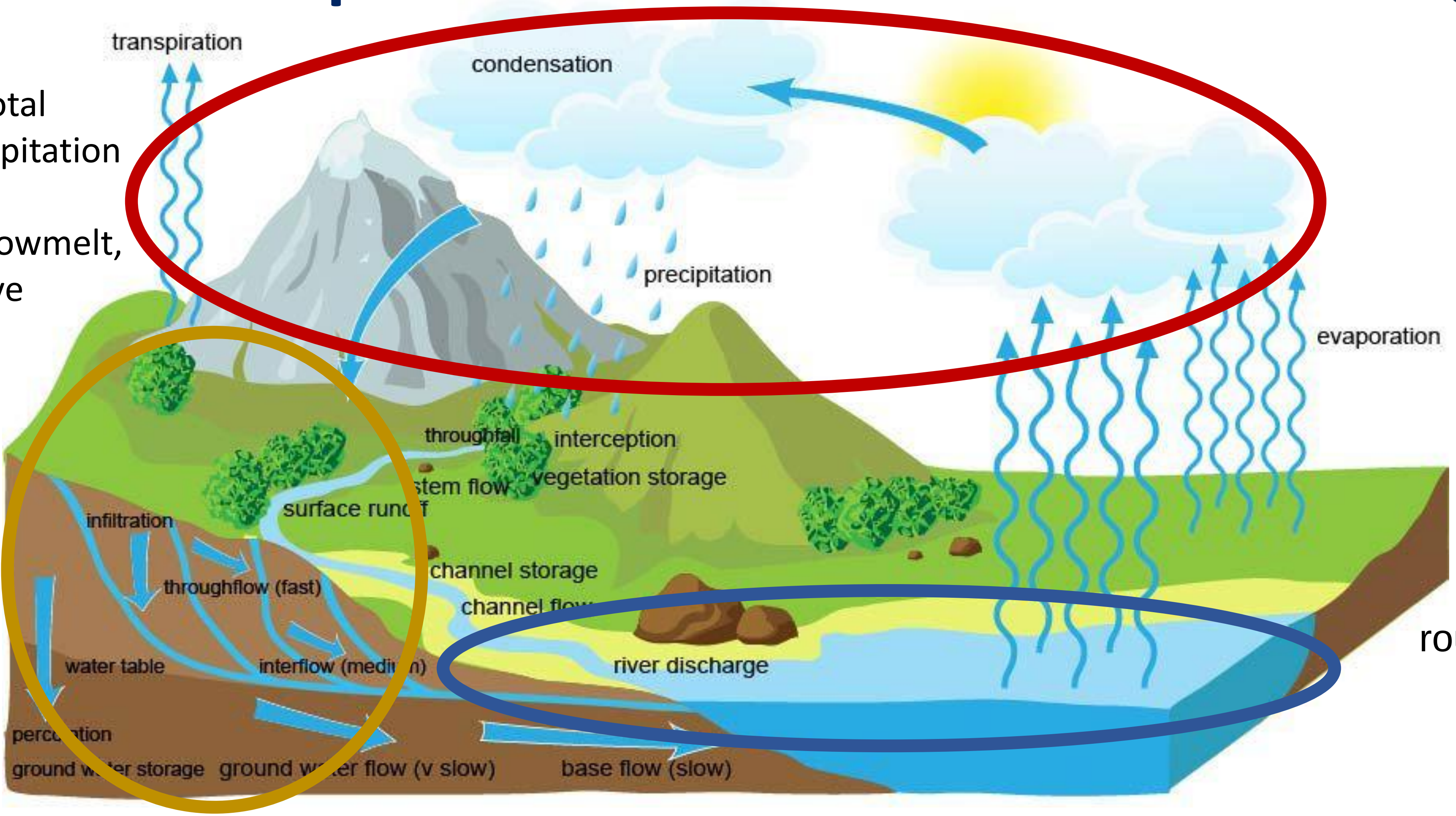
EUMETSAT H SAF

ATMOSPHERE

Air temperature, total precipitation, precipitation intensity/duration, snow cover and snowmelt, short and long-wave radiation

CATCHMENT

Infiltration capacity, runoff coefficient, water storage capacity, evapotranspiration



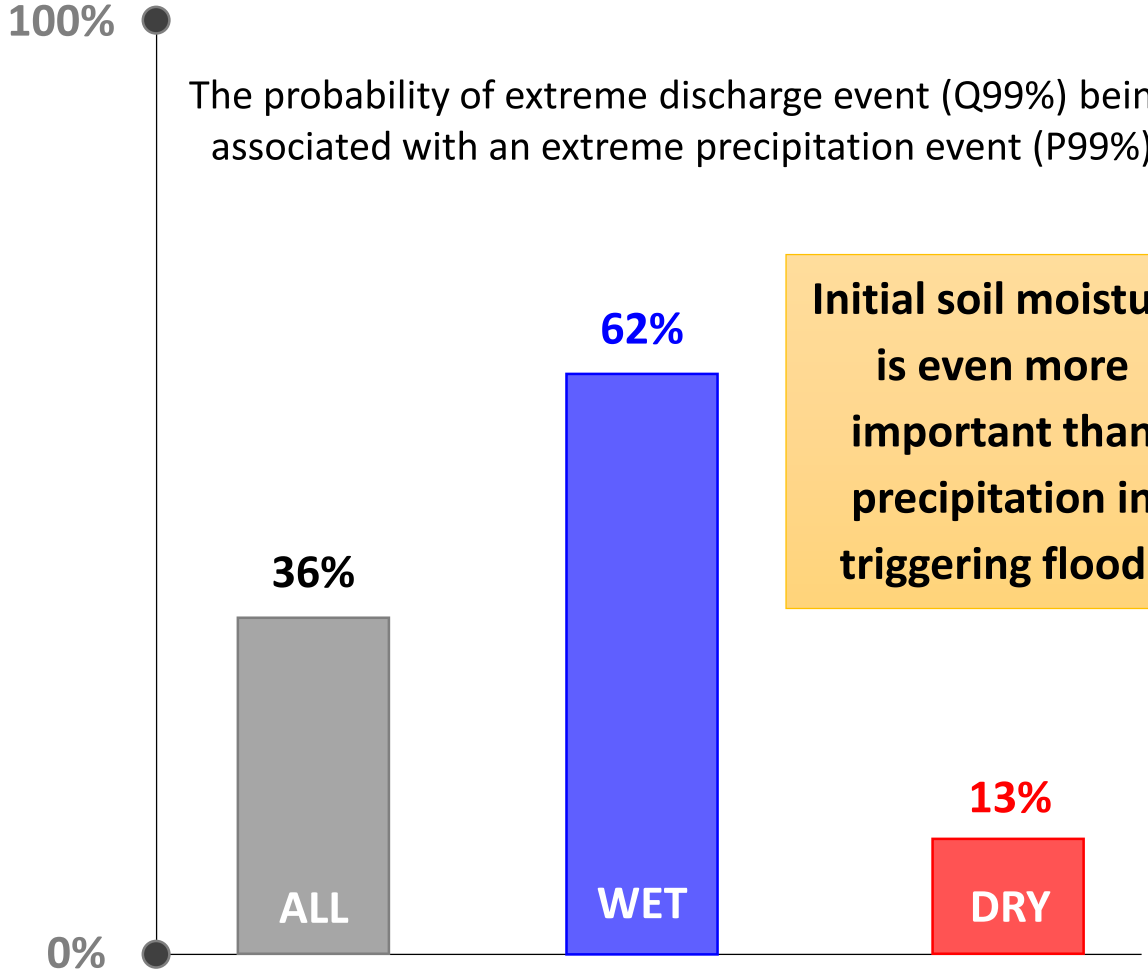
RIVER

River morphology, conveyance, roughness, water level, runoff, floodplain storage, river channel vegetation

The processes in all three compartments affect the characteristics of river floods. The relative importance of individual drivers depends on the local and on the boundary conditions.

Which processes contribute to floods?

The probability of extreme discharge event (Q99%) being associated with an extreme precipitation event (P99%)



Initial soil moisture is even more important than precipitation in triggering floods


Water Resources Research
AN AGU JOURNAL
Commentary | Free Access
If precipitation extremes are increasing, why aren't floods?
Ashish Sharma, Conrad Wasko, Dennis P. Lettenmaier
First published: 05 November 2018 | https://doi.org/10.1029/2018WR023749
This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1029/2018WR023749
PDF TOOLS SHARE

Across all sites only 36% of extreme precipitation events lead to a corresponding extreme discharge

When the precipitation is conditioned on the catchment being wet before the start of the event, this number increases to 62%...

...contrasted with only 13% when the moisture conditions before the storm are dry

Sharma at al. (2018, WRR)
Ivancic and Shaw (2015, WRR)

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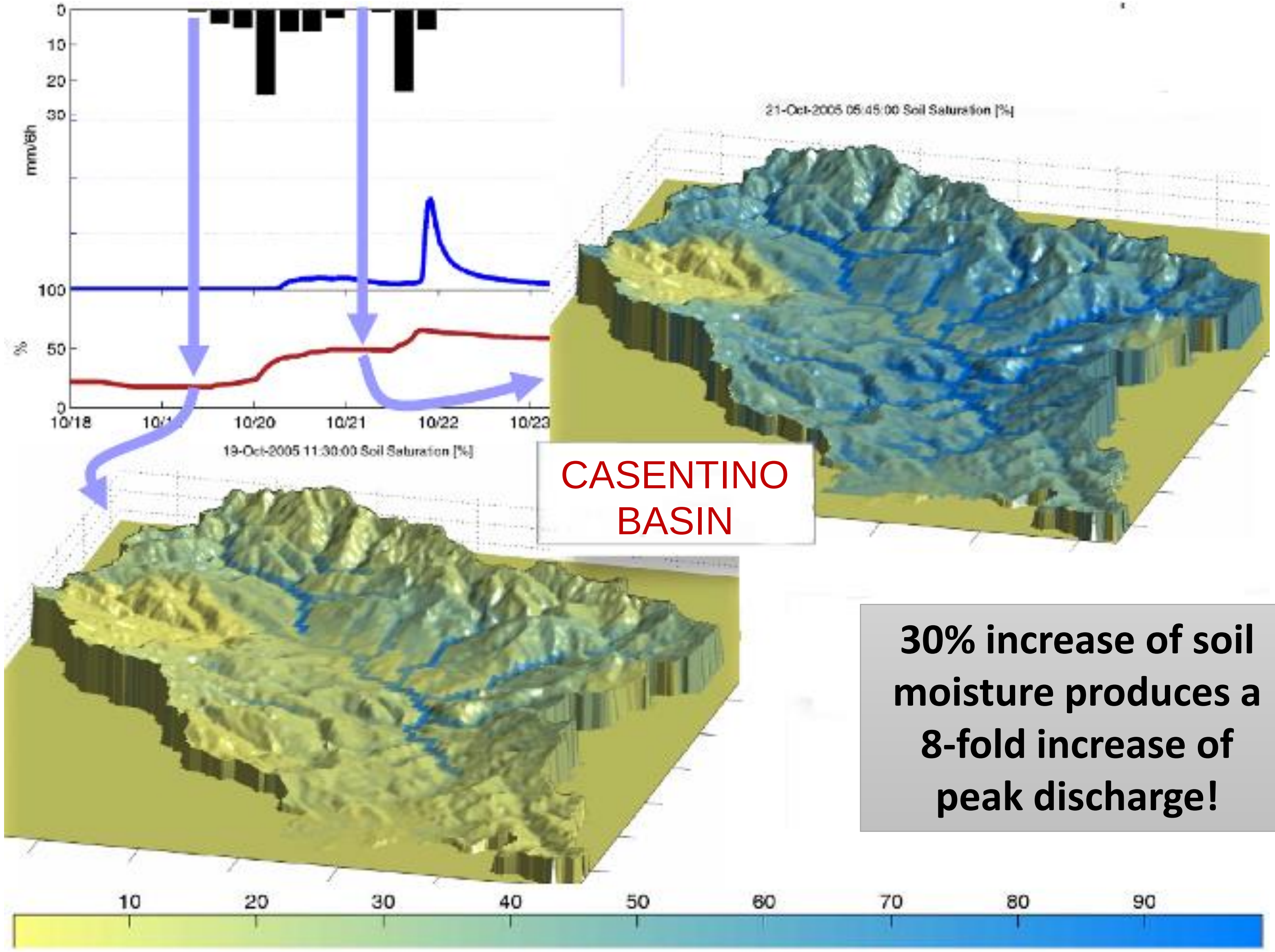
Why soil moisture for flood?



30% increase of soil moisture produces a 8-fold increase of peak discharge!

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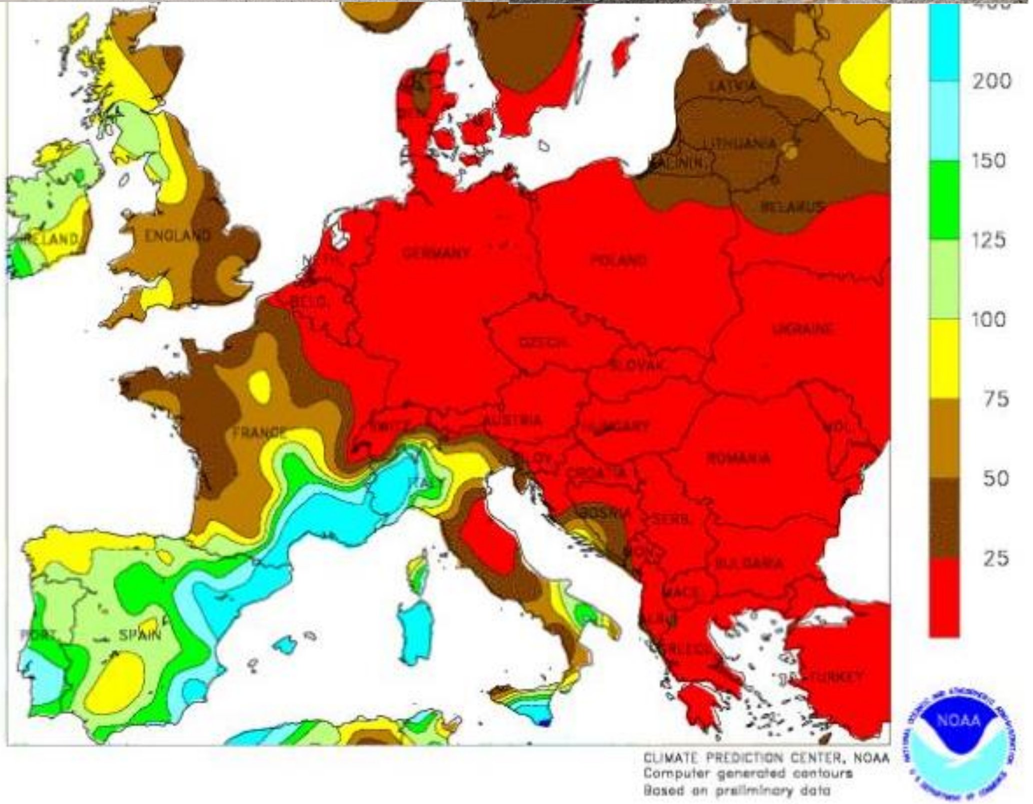
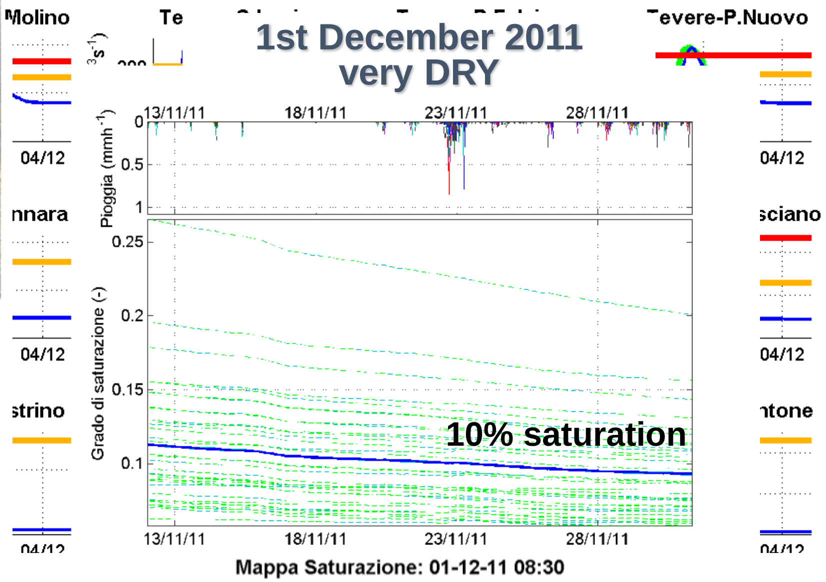
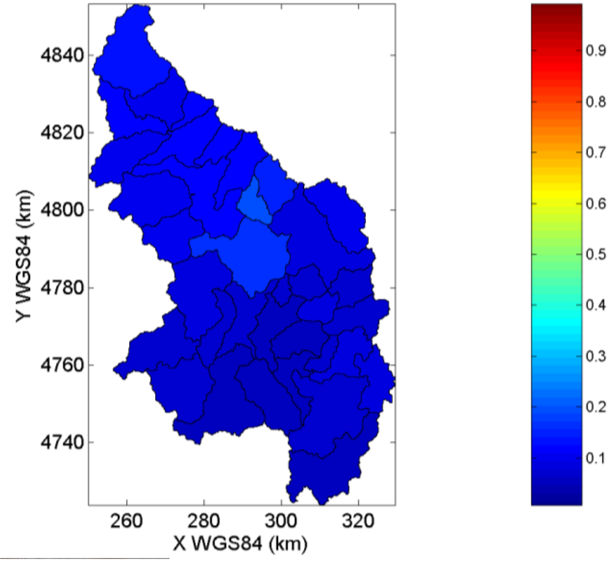
Why soil moisture for flood?







Brocca et al. (2011, HYP)
doi:10.1016/j.rse.2011.08.003

EUMETSAT H SAF

Why soil moisture for flood?

Brocca et al. (2011, HYP)
doi:10.1016/j.rse.2011.08.003

EUMETSAT H SAF

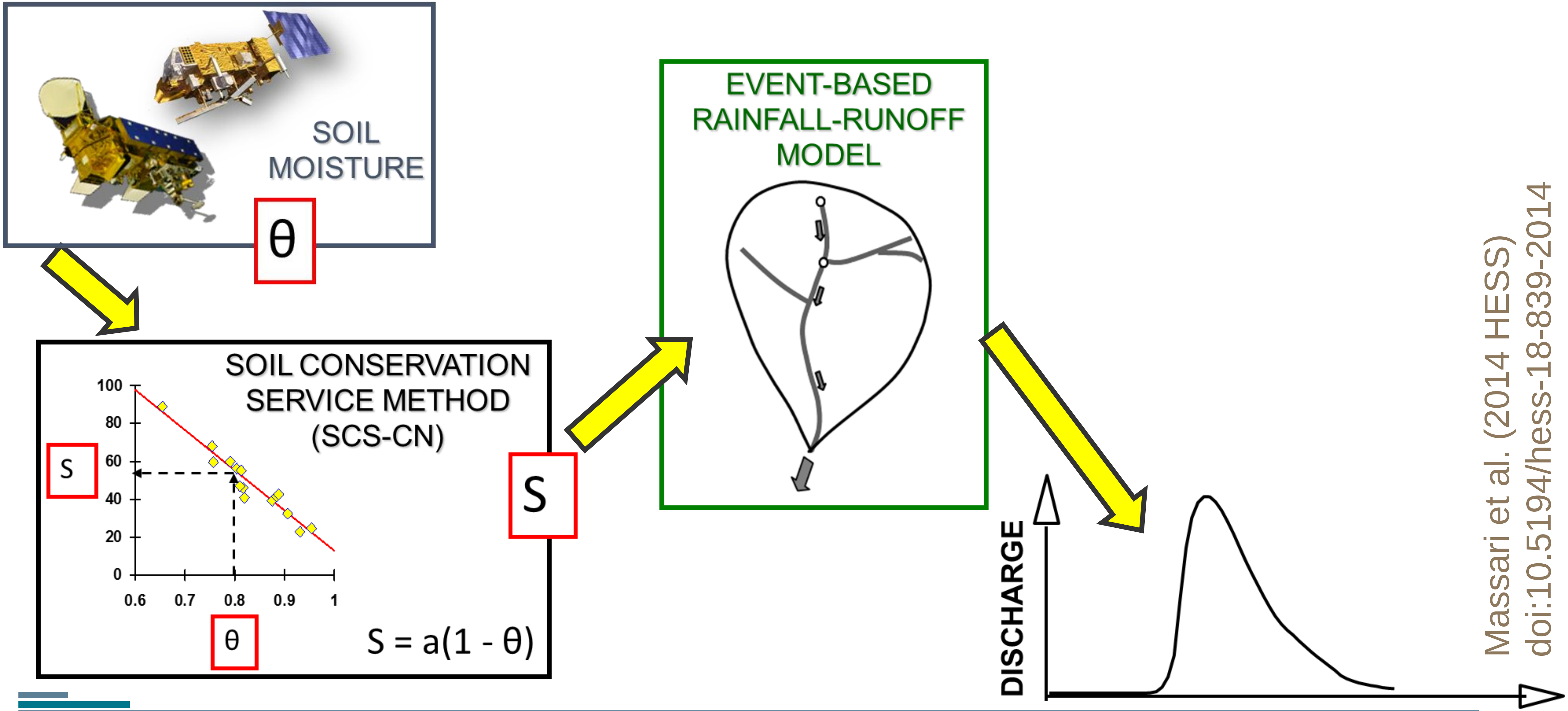
Soil moisture for hydrological alert

Satellite soil moisture products for the operational applications of civil protection: Training and Demonstration

Exploiting satellite soil moisture for flood

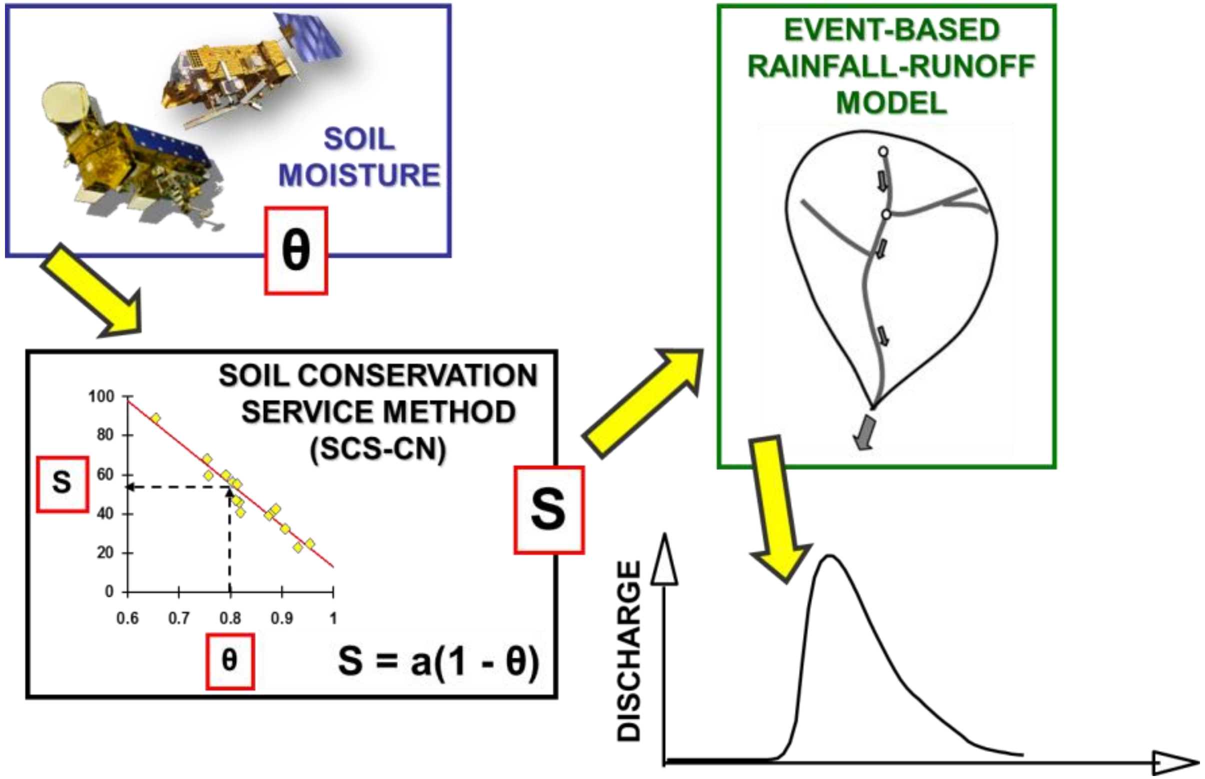
- Data Assimilation
  (this morning, Gabellani - CIMA)
- Setting initial soil moisture conditions for flood simulation
- Improving\correcting rainfall through SM2RAIN

Initial soil moisture conditions for flood



Massari et al. (2014 HESS)
doi:10.5194/hess-18-839-2014

Initial soil moisture conditions for flood



INPUT DATA:
- RAINFALL (only during floods)
- SOIL MOISTURE

OUTPUT DATA:
- DISCHARGE (only during floods)

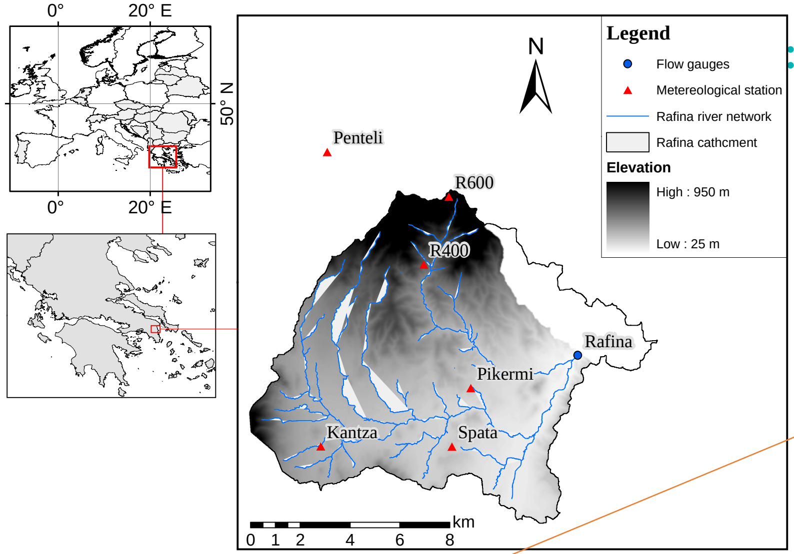
2 PARAMETERS TO BE ESTIMATED

STRENGTHS

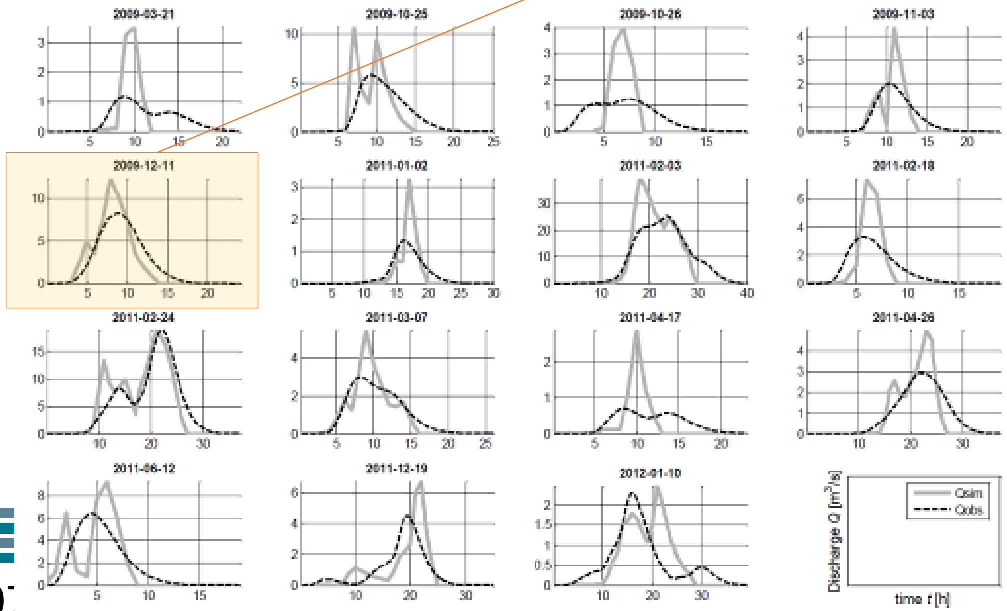
1) No need of continuous rainfall and evapotranspiration datasets.
Good in poorly gauged areas!
2) Parsimony and simplicity.
Good for operational purposes!

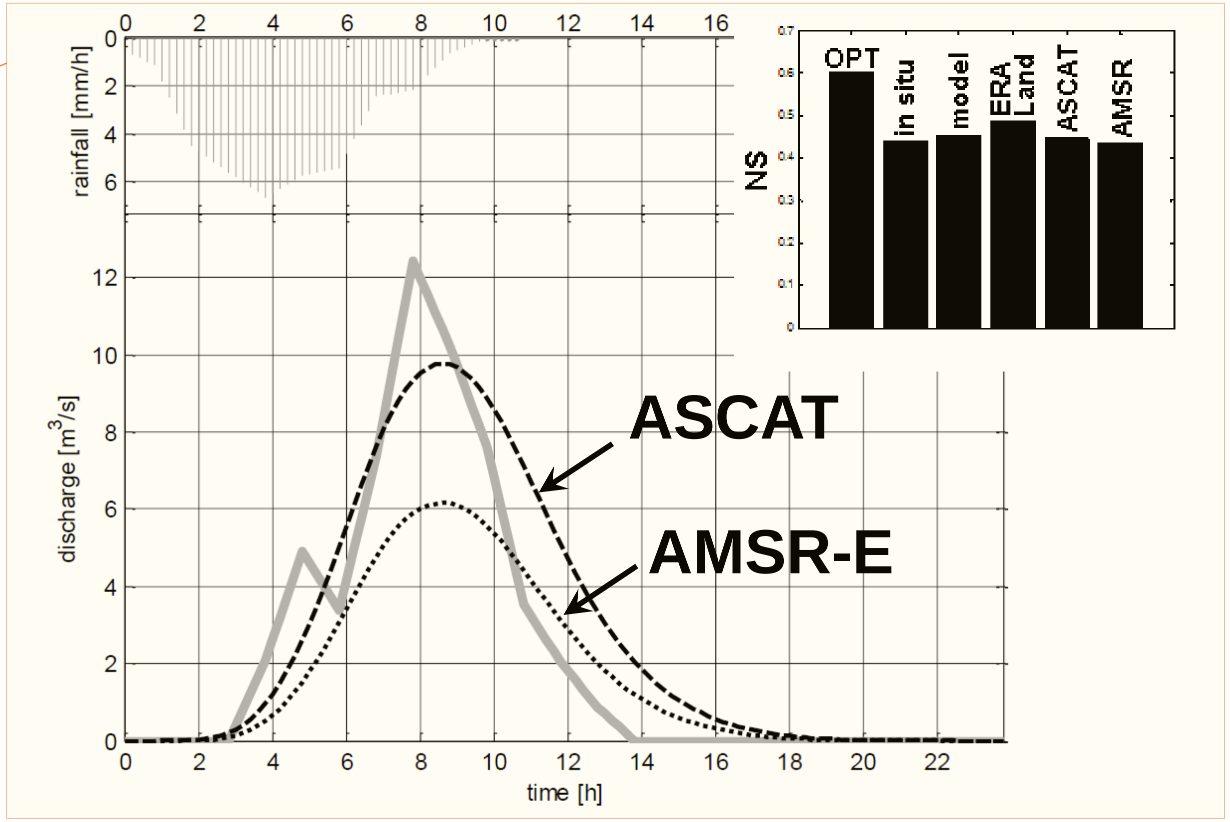
Massari et al. (2014 HESS)
doi:10.5194/hess-18-839-2014

Initial soil moisture conditions for flood



Early Warning System for Flood and Fire forecasting





Massari et al. (2014 HESS)
doi:10.5194/hess-18-839-2014

Initial soil moisture conditions for flood


Hydrology 2014, xx, 1-x; doi:10.3390/——
OPEN ACCESS
hydrology
ISSN 2306-5338
www.mdpi.com/journal/hydrology

Article

The use of H-SAF soil moisture products for operational hydrology: flood modelling over Italy

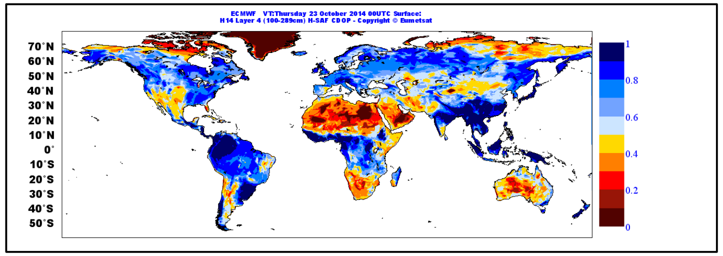
Christian Massari [1,*], Luca Brocca [1], Luca Ciabatta [1], Tommaso Moramarco [1], Simone Gabellani [2], Clement Albergel [3], Patricia De Rosnay [3], Silvia Puca[4] and Wolfgang Wagner [5]

The model was applied to 35 Italian catchments

- areas ranging from 800 to 7400 km^2
- Period 2010-2013
- 593 flood events
- We used H07 and H14 (~ H113 and H27)

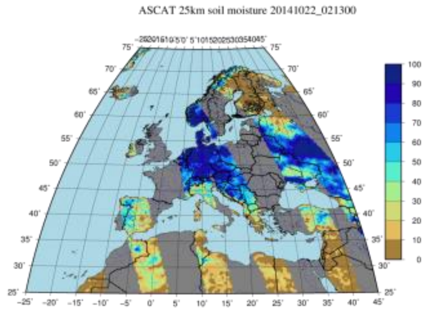
SM DAS 2 - H14

Profile Index in the roots region by scatterometer data assimilation



SM OBS 1 - H07

Large scale surface soil moisture by radar scatterometer



Massari et al. (2015 HYDROLOGY)
doi:10.3390/hydrology2010002

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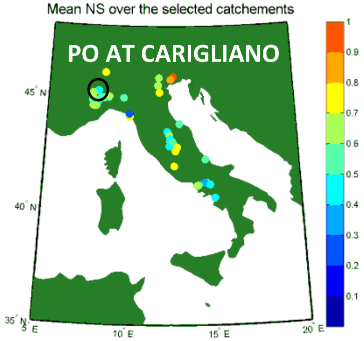
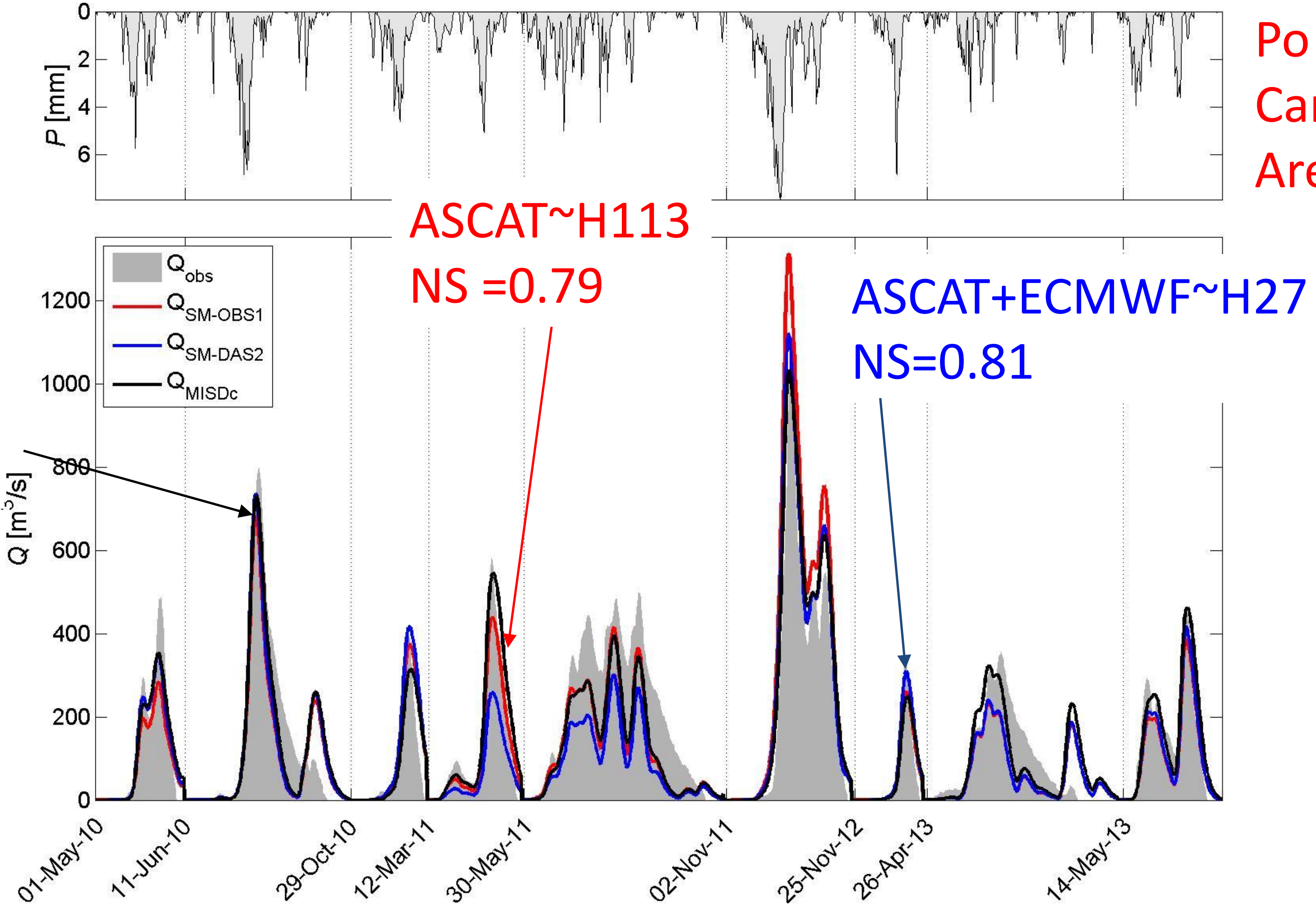
Initial soil moisture conditions for flood



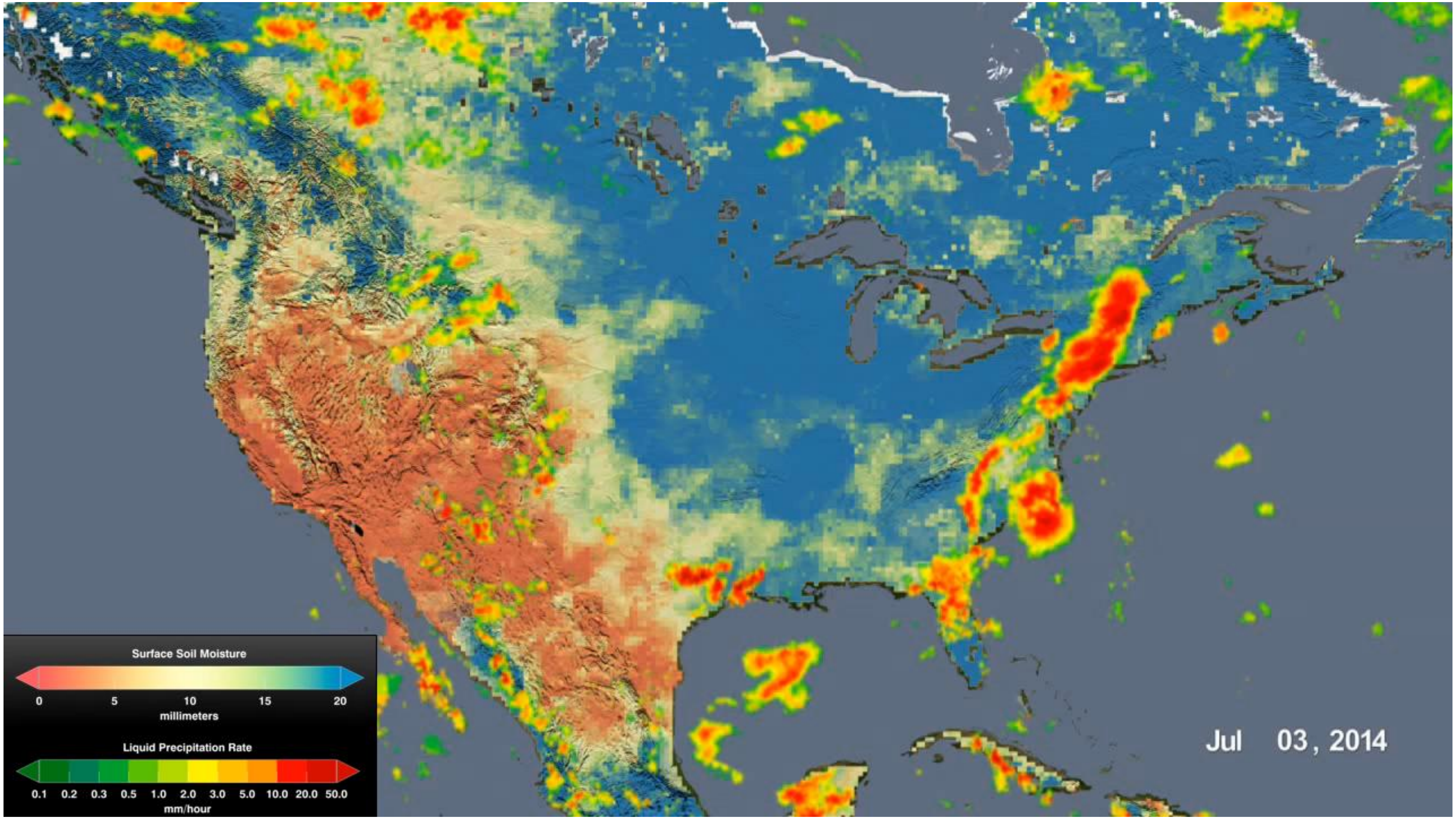


MISDc
NS =0.84

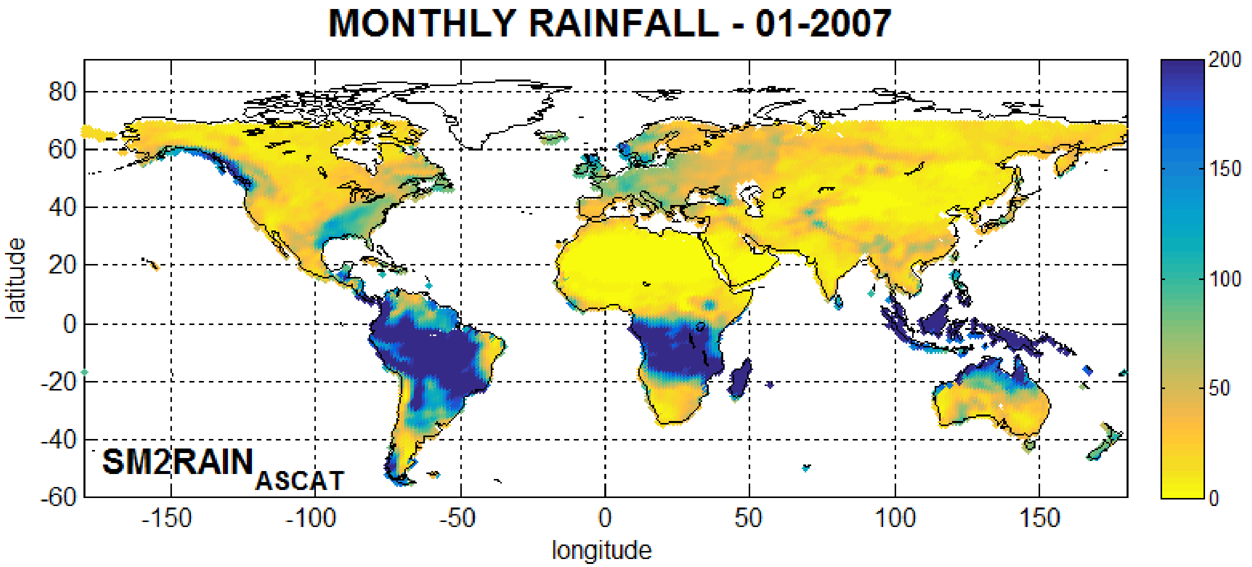
Po River at Carigliano
Area=3570 km^2

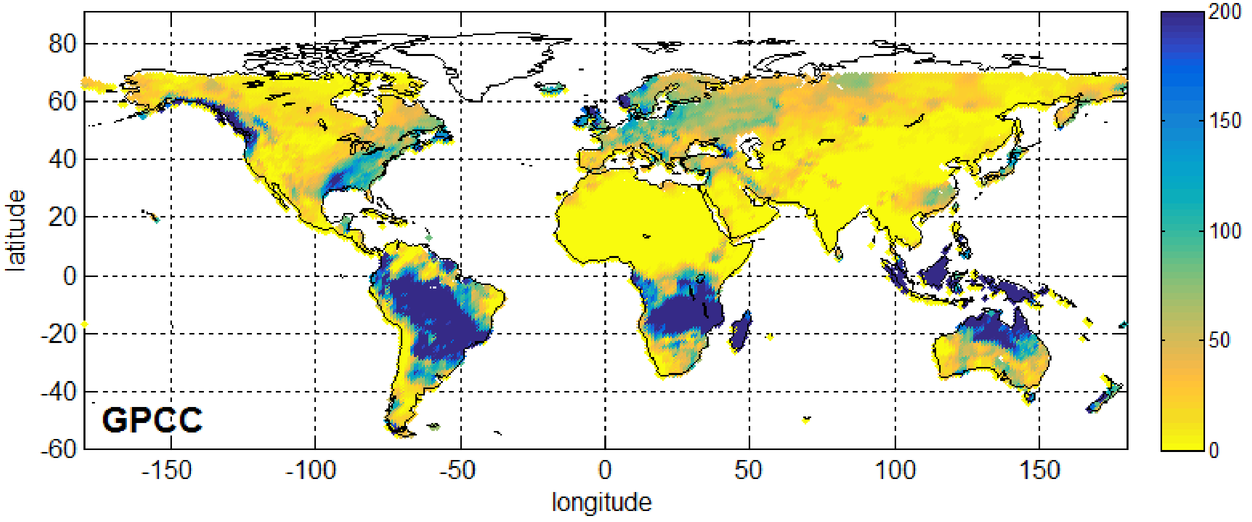
Massari et al. (2015 HYDROLOGY)
doi:10.3390/hydrology2010002

Soil Moisture and Rainfall: SM2RAIN



SM2RAIN: rainfall from the bottom up






RESEARCH HIGHLIGHTS Selections from the scientific literature

ATMOSPHERIC SCIENCE

Detecting rainfall from the bottom up

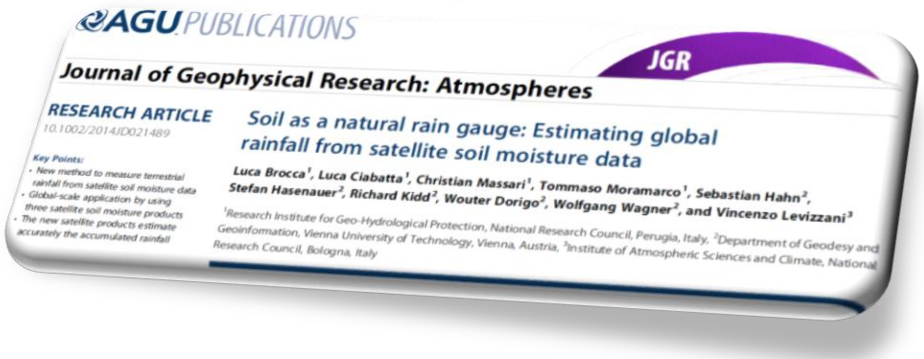
A method that allows researchers to estimate global rainfall levels using soil-moisture data could help to improve hazard planning for floods and landslides.

To estimate rainfall in places that lack ground-based rain gauges, researchers rely on satellite data of atmospheric moisture, but this is notoriously inaccurate. Luca Brocca at the National Research Council in Perugia, Italy, and his colleagues developed an algorithm that calculates rainfall amounts on the basis of satellite data on soil moisture. They compared their estimates with rain-gauge data and found that their method accurately estimates rainfall in several regions around the world.

Moreover, their algorithm is better than a state-of-the-art method at detecting light rainfall events and precipitation at high latitudes.

J. Geophys. Res. Atmos. http://doi.org/sp7 (2014)

262 NATURE VOL 509 | 15 MAY 2014


AGU PUBLICATIONS

Journal of Geophysical Research: Atmospheres

JGR

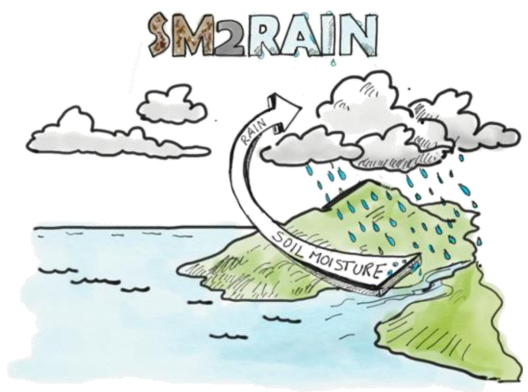
RESEARCH ARTICLE
10.1002/2014JD021489

Key Points:
- New method to measure terrestrial rainfall from satellite soil moisture data
- Global-scale application by using three satellite soil moisture products
- The new satellite products estimate accurately the accumulated rainfall

Soil as a natural rain gauge: Estimating global rainfall from satellite soil moisture data

Luca Brocca[1], Luca Ciabatta[1], Christian Massari[1], Tommaso Moramarco[1], Sebastian Hahn[2], Stefan Hasenauer[2], Richard Kidd[2], Wouter Dorigo[2], Wolfgang Wagner[2], and Vincenzo Levizzani[3]

[1]Research Institute for Geo-Hydrological Protection, National Research Council, Perugia, Italy, [2]Department of Geodesy and Geoinformation, Vienna University of Technology, Vienna, Austria, [3]Institute of Atmospheric Sciences and Climate, National Research Council, Bologna, Italy

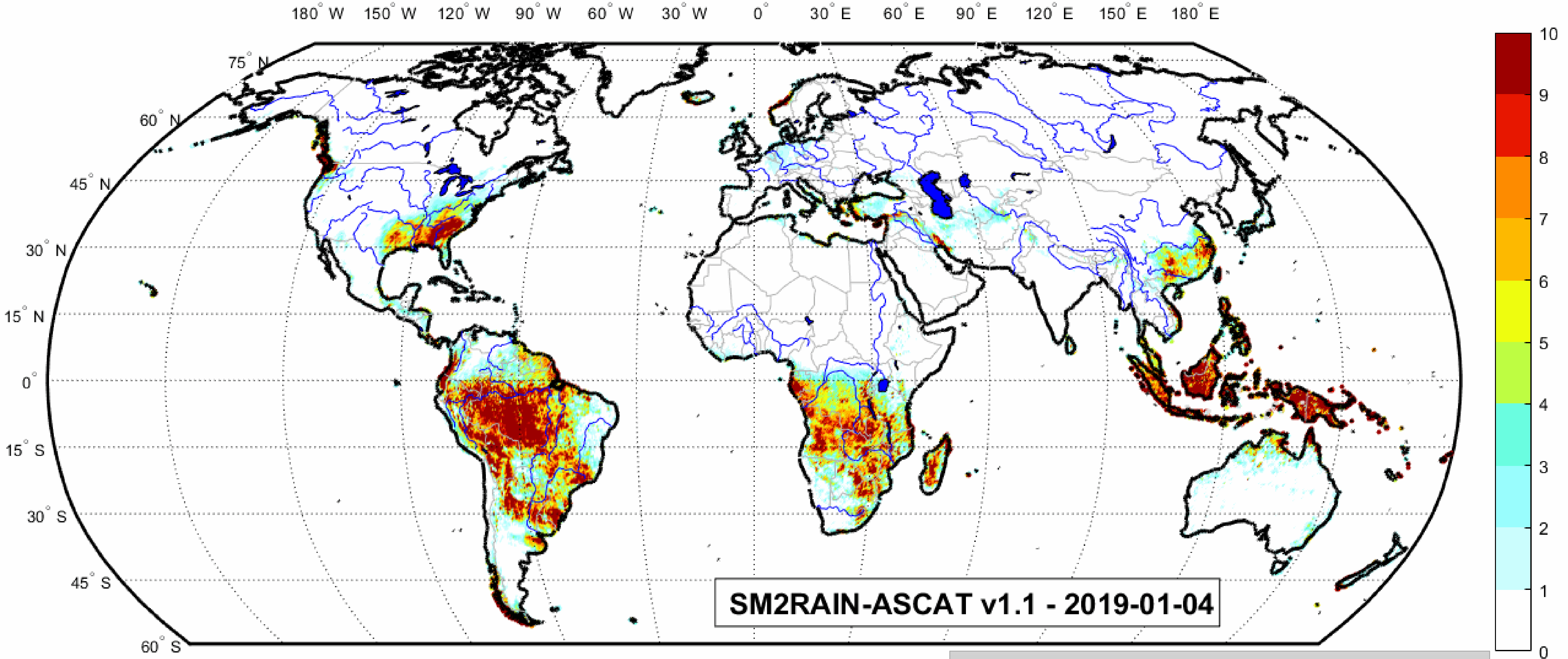


SM2RAIN is a new "bottom-up" approach (Brocca et al., 2014 JGR) for estimating the <u>ACCUMULATED RAINFALL</u> from satellite (and in situ) soil moisture observations

Brocca et al. (2014 JGR)
doi:10.1002/2014JD021489

SM2RAIN: rainfall from the bottom up

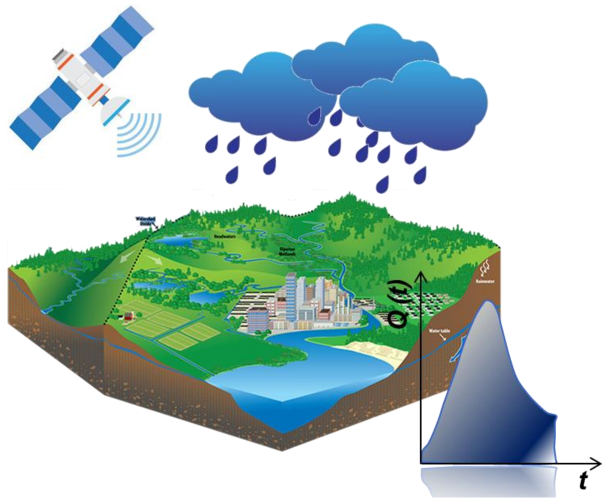
Data Period: January 2007-August 2019 - Spatial\Temporal Resolution: 12.5 km\1-day



Brocca et al. (2019 ESSD) doi:10.5194/essd-11-1583-2019

Freely available @ Zenodo
https://zenodo.org/record/3405563

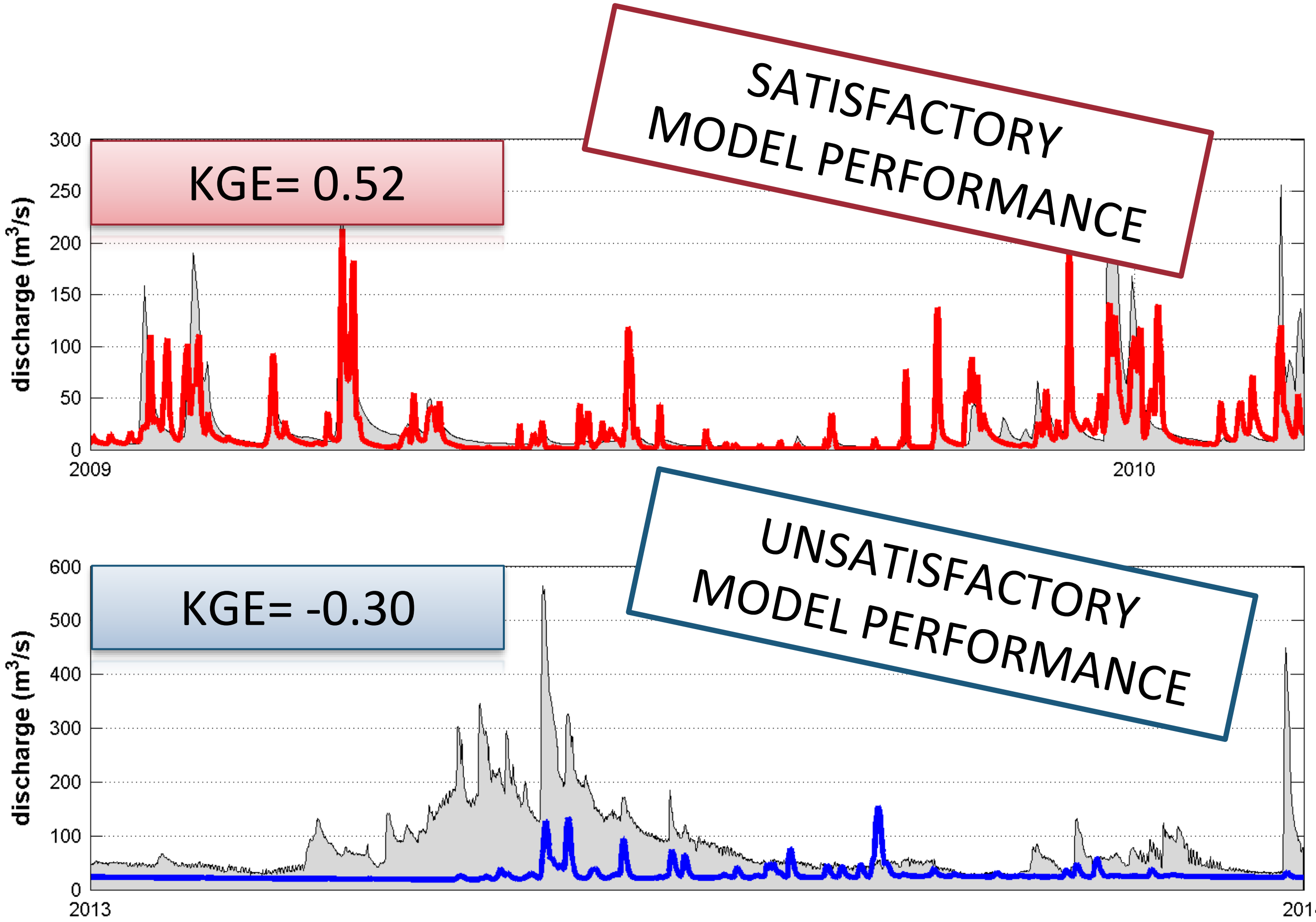
KGE Performance Score for Floods



Kling-Gupta Index
(Gupta et al., 2009)

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2}$$

r = correlation coefficient
α = relative variability between observed and simulated discharge (i.e., conditional bias index)
β = bias normalized by the standard deviation.

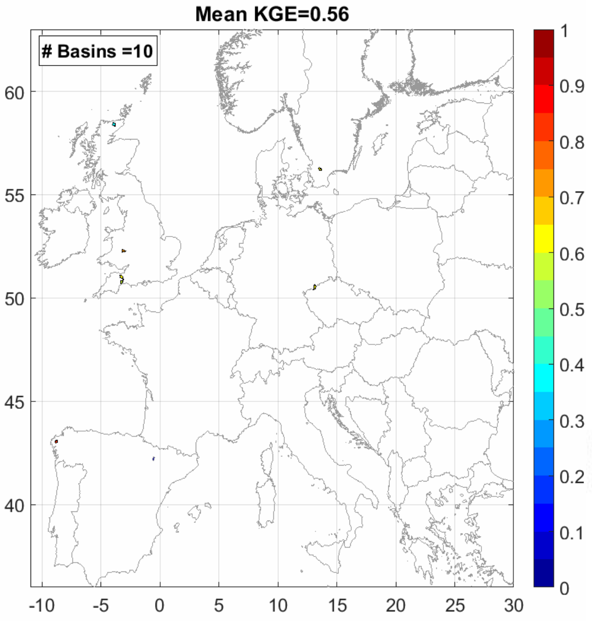


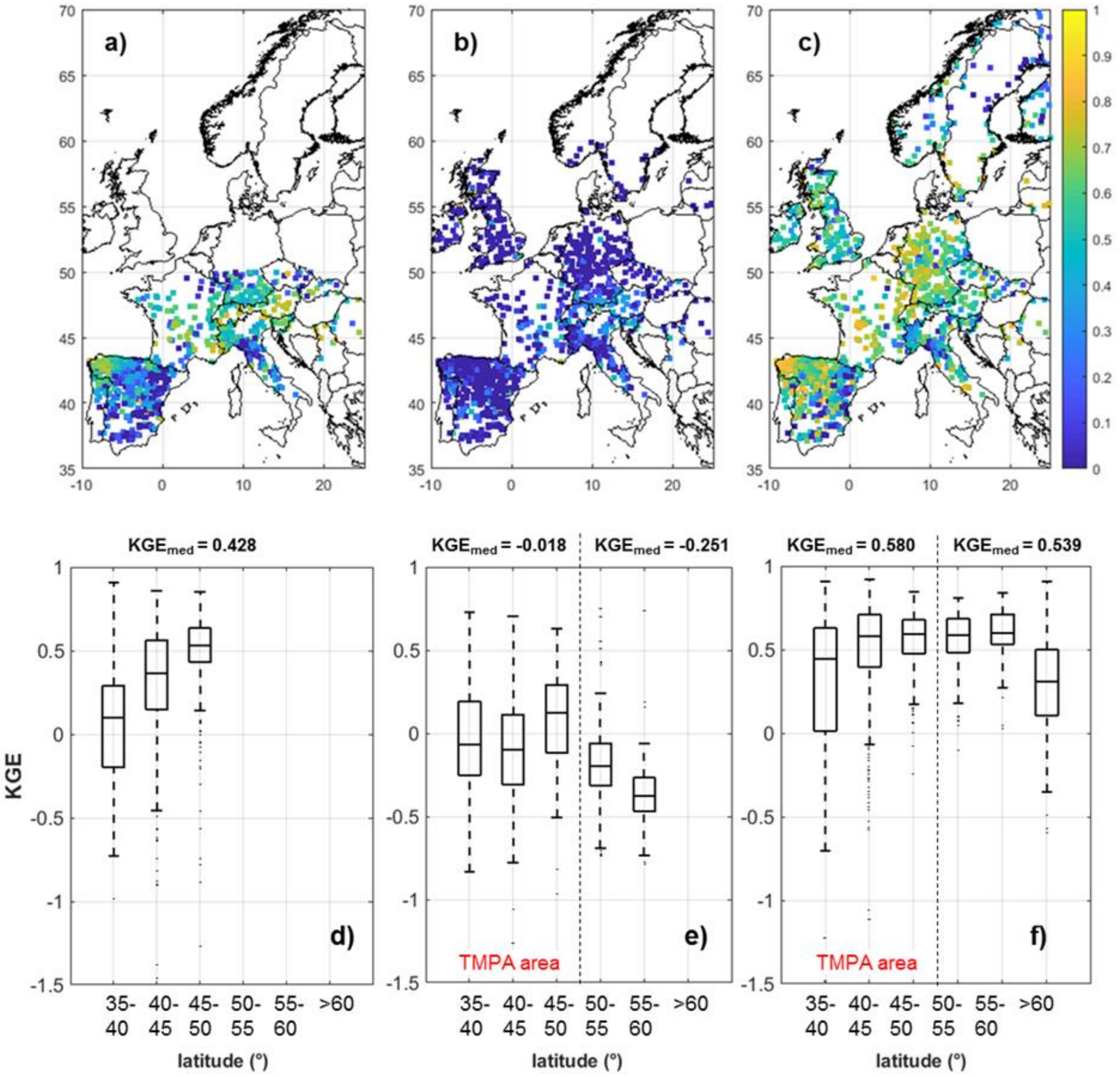
-∞ <KGE≤ 0.3	0.3 <KGE≤ 0.7	0.7 <KGE≤ 1
UNSATISFACTORY MODEL RESULTS	ACCEPTABLE/GOOD MODEL RESULTS	VERY GOOD MODEL RESULTS

Camici et al. (2018 JoH)
doi:10.1016/j.jhydrol.2018.06.067

Improving flood simulation via SM2RAIN

Simulation of floods over 1318 basins in Europe through TMPA, CMORPH and SM2RAIN-ASCAT precipitation

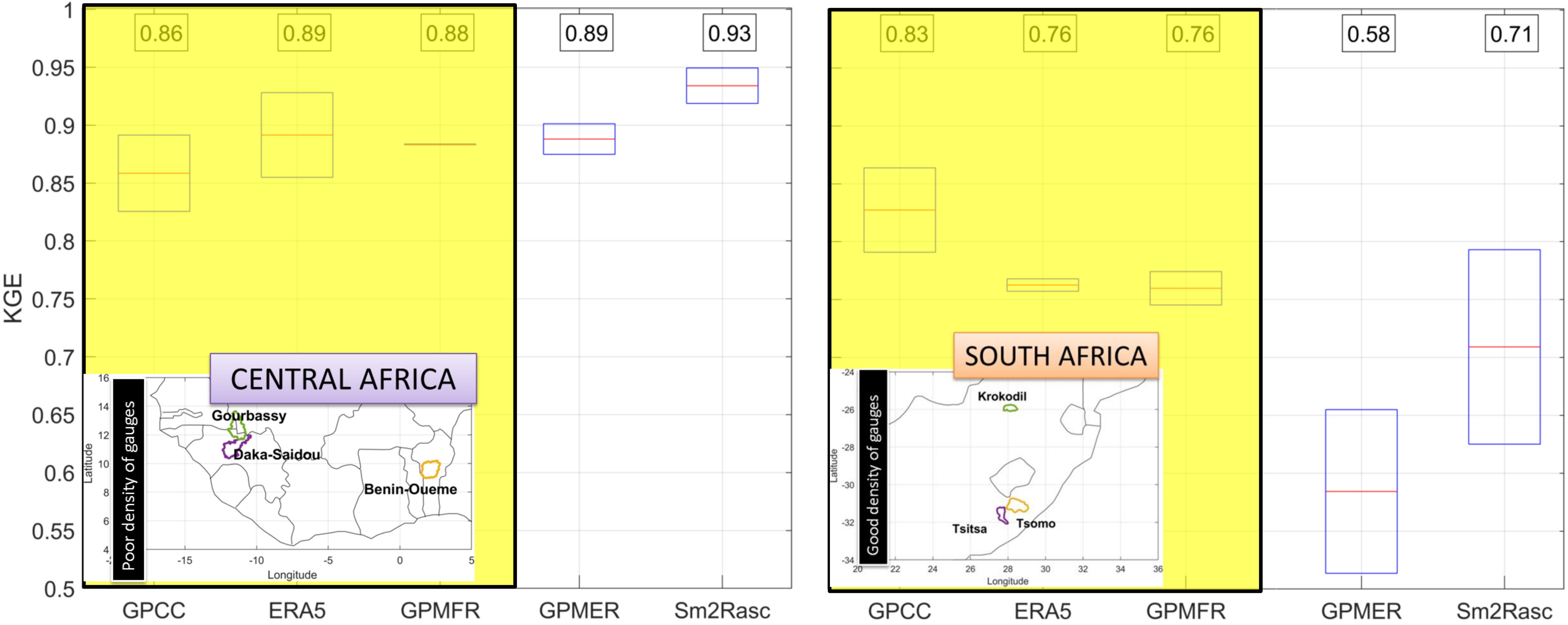




SM2RAIN-ASCAT outperforms (significantly) TMPA and CMORPH, particularly in the Mediterranean Area (KGE=0.49 vs 0.15 with TMPA)

Camici et al. (2018 JoH)
doi:10.1016/j.jhydrol.2018.06.067

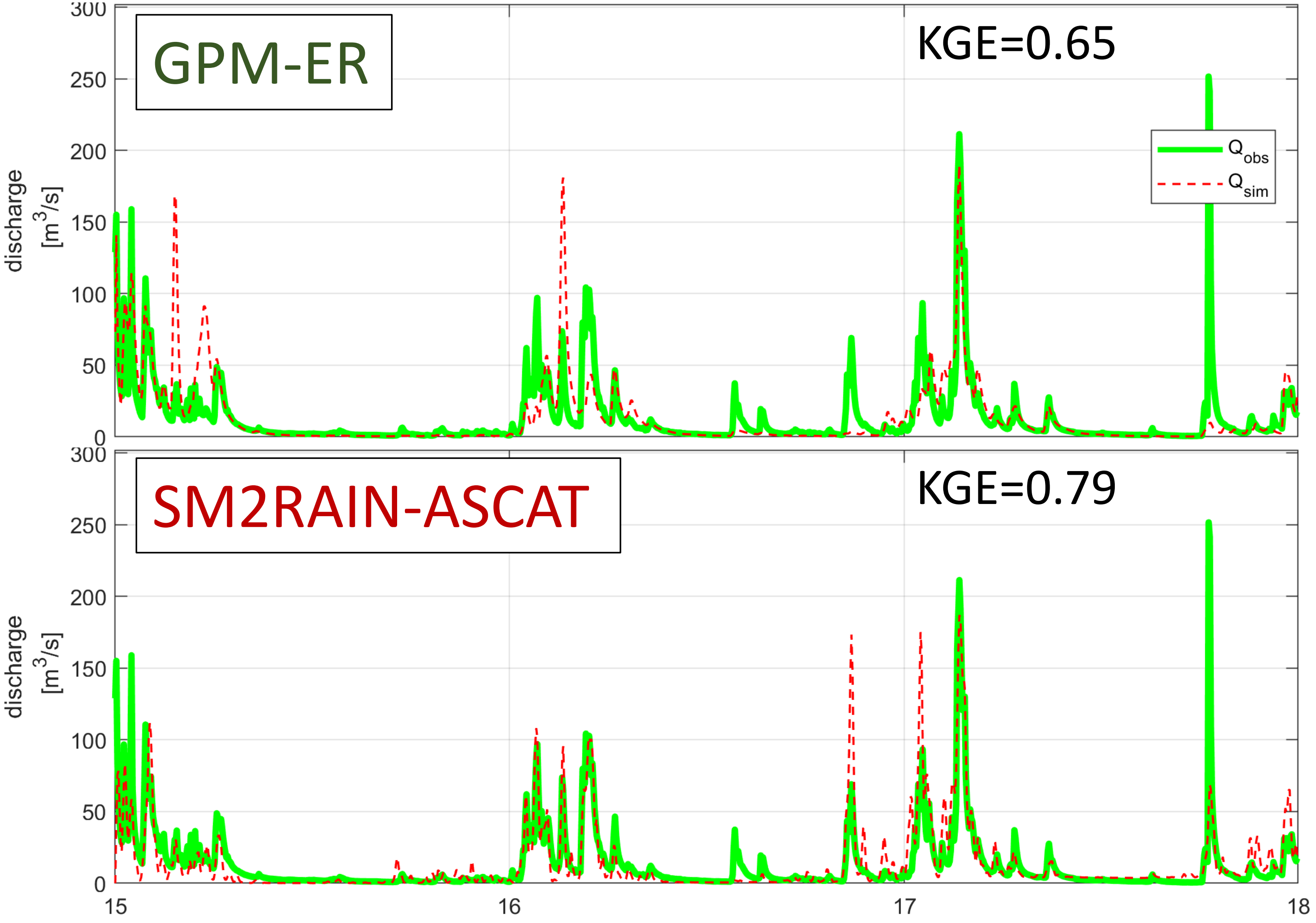
Improving flood simulation via SM2RAIN



Brocca et al. (2019, SREP submitted)

- ❑ Long latency products (GPCC, ERA5, GPMFR) cannot be used for flood prediction
- ❑ SM2RAIN-ASCAT outperforms GPM-ER in Africa also for flood prediction

Improving flood simulation via SM2RAIN



TSITSA BASIN
SOUTH AFRICA

Brocca et al. (2019, SREP submitted)

EUMETSAT H SAF

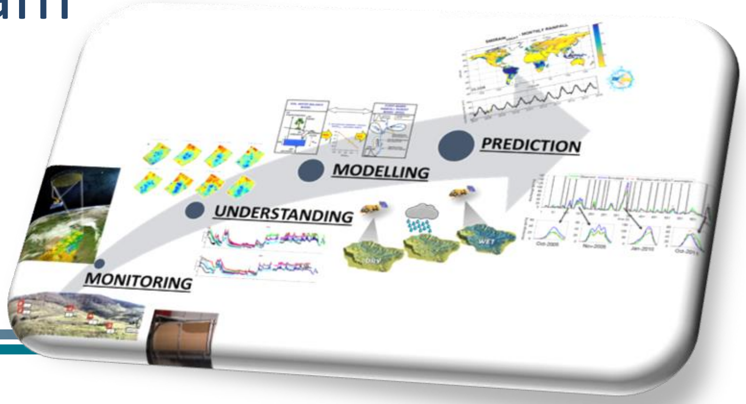
H SAF SOIL MOISTURE WEEK 2019
4-8 November 2019

Flood prediction through H SAF satellite soil moisture products

Laboratory

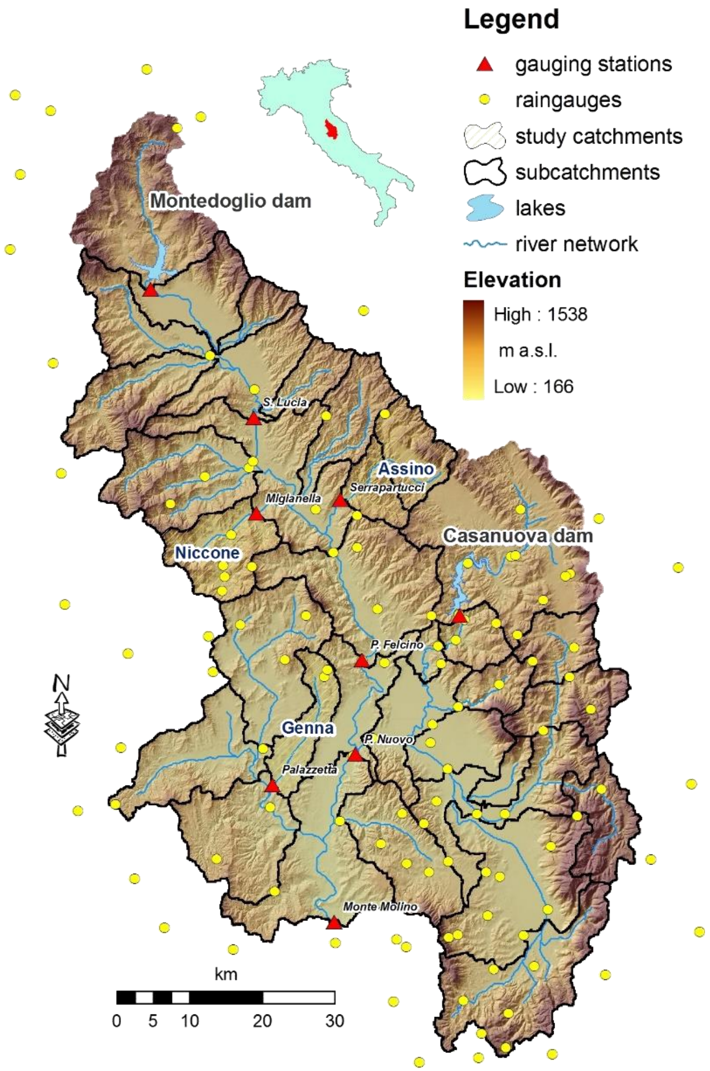
https://github.com/H-SAF/eumetrain_sm_week_2019/tree/master/FloodLab

Luca Brocca and the Hydrology Team
IRPI CNR



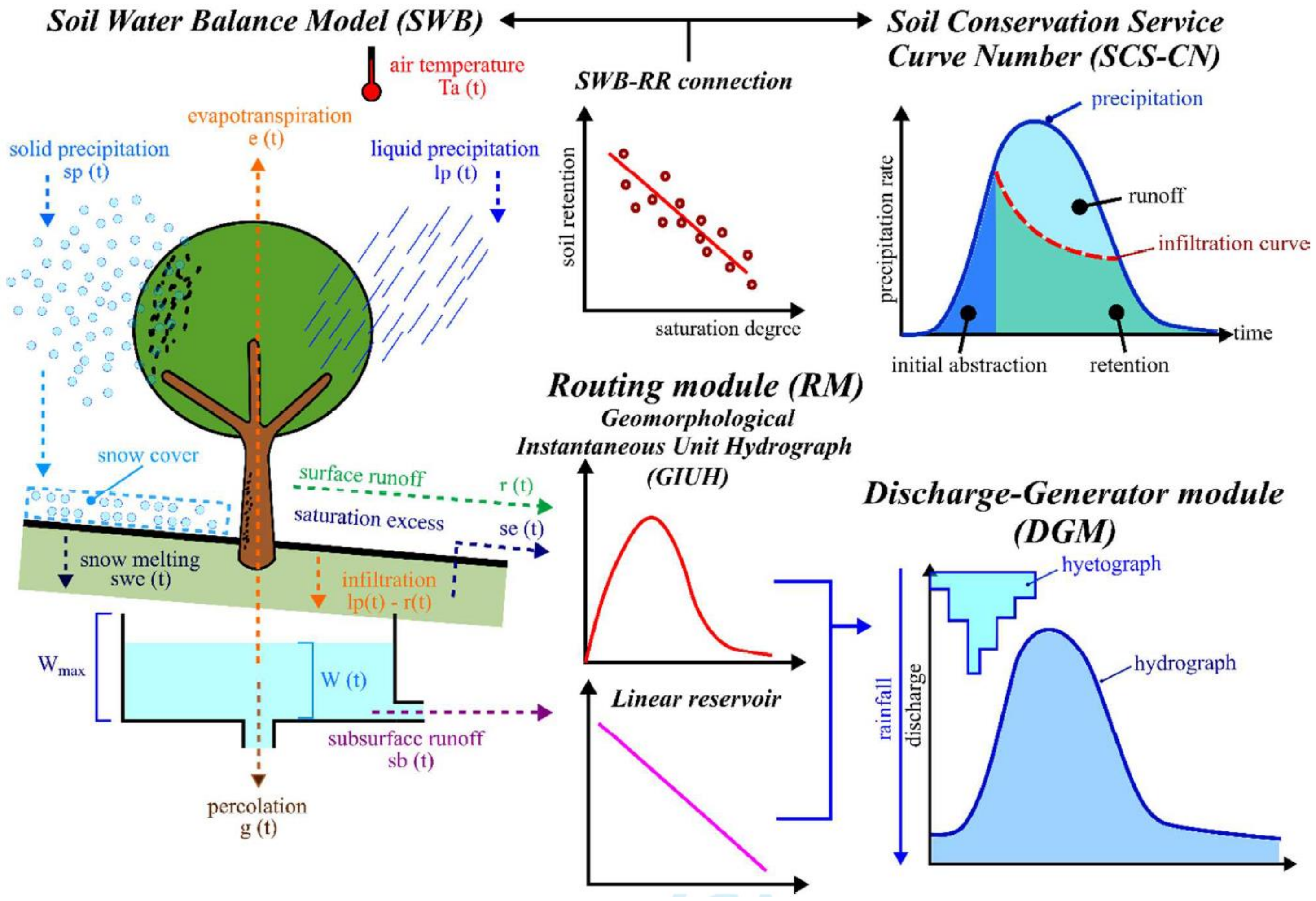
Introduction to the exercise

Tiber River Basin



Area=5270 km²

Introduction to the exercise



MISDc Rainfall-Runoff Model

Continuous and semi-distributed rainfall-runoff model.

INPUT:
- Precipitation
- Air temperature

OUTPUT:
- River discharge
- Root-zone soil moisture
- Actual and potential evapotranspiration

Recent review paper of MISDc performance:
Masseroni et al. (2017 HYD RES, doi: 10.2166/nh.2016.037)

Brocca et al. (2011, HYP) doi:10.1016/j.rse.2011.08.003

Introduction to the exercise

Satellite-based Soil Moisture

H113 = ASCAT
Surface soil moisture data record, based ONLY on satellite soil moisture data from ASCAT

H27 = ASCAT+ECMWF
Root-zone soil moisture obtained from the assimilation of ASCAT soil moisture into ECMWF IFS (Integrated Forecasting System). **4 layers**

Rainfall

P = ERA5 reanalysis rainfall

SM2R = SM2RAIN-ASCAT satellite rainfall obtained from H SAF ASCAT soil moisture

MERG =
MERGED DATASET = 0.85*ERA5 + 0.15*SM2RAIN-ASCAT

Air Temperature dataset

T = Obtained from the interpolation of meteorological stations

River Discharge

Q = Obtained from the gauging station at Monte Molino (Tiber River)

Introduction to the exercise

All the datasets are available at daily time scale from January 2007 to December 2014.
The data are spatially averaged at the basin scale and saved in the file «TEVERE_DATA_NEW.txt» = Matrix 2922 rows (dates) x 11 columns (see below)

	P	T	Q	H113	H27_1	H27_2	H27_3	H27_4	SM2R	MERG
2007-01-01 00:00:00	3.202349	8.140181	10.079916	46.676248	0.731786	0.748055	0.679018	0.691044	0.000000	2.657950
2007-01-02 00:00:00	7.674754	5.520864	9.934817	40.011059	0.767268	0.754463	0.681876	0.692929	0.000000	6.370046
2007-01-03 00:00:00	0.053418	1.178245	9.789718	32.062826	0.760015	0.751631	0.681094	0.692376	0.000000	0.044337
2007-01-04 00:00:00	0.877974	2.309108	9.644619	17.218505	0.500714	0.686350	0.662666	0.680064	0.000000	0.728718
2007-01-05 00:00:00	0.105998	3.835236	8.970421	21.853204	0.660676	0.720025	0.672820	0.686809	0.138724	0.111561
2007-01-06 00:00:00	0.015409	2.906701	8.465723	20.258275	0.503481	0.679019	0.661218	0.679051	0.505477	0.098721
2007-01-07 00:00:00	0.402833	6.070475	8.875051	27.481828	0.647051	0.710425	0.670801	0.685421	5.055940	1.193861
2007-01-08 00:00:00	1.825983	6.976988	8.891839	41.147828	0.729952	0.729314	0.676806	0.689404	8.566163	2.971814
2007-01-09 00:00:00	0.014361	5.740076	9.584285	53.950983	0.775157	0.742349	0.681023	0.692197	6.455199	1.109303
2007-01-10 00:00:00	0.060421	4.639126	10.388340	52.978213	0.766440	0.743236	0.681758	0.692666	2.553935	0.484318

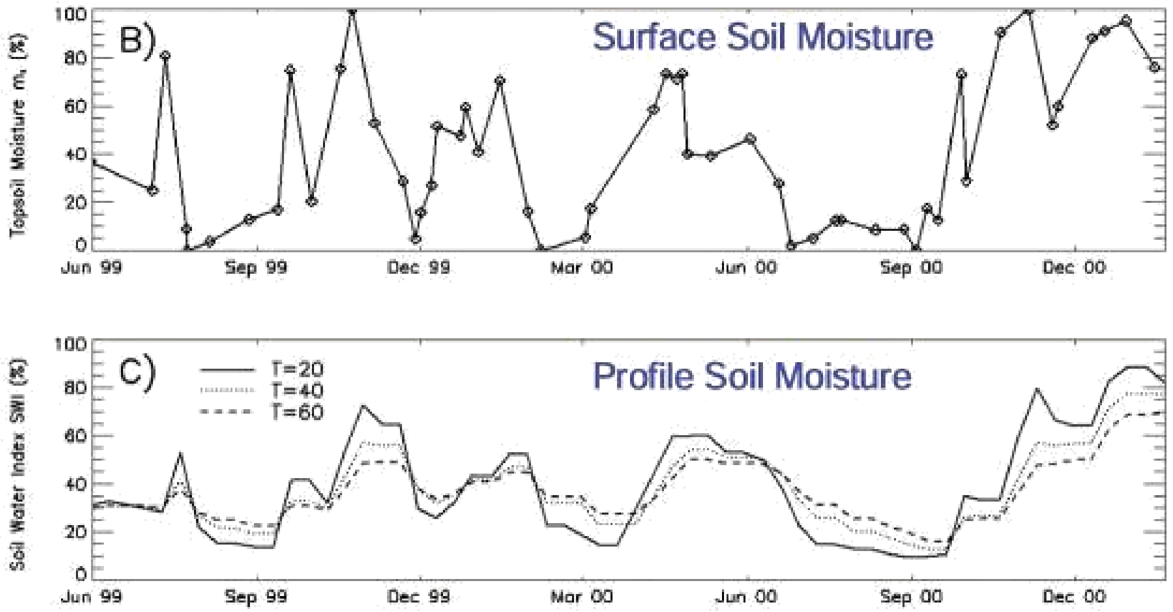
Introduction to the exercise

RECURSIVE FORMULATION; easier to implement!

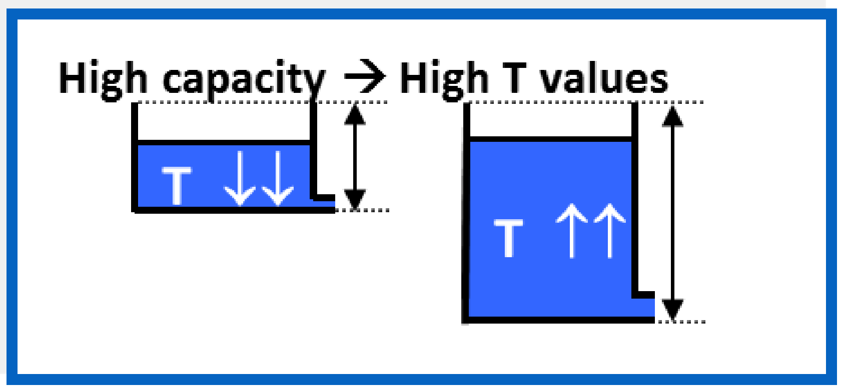
$$\mathrm{SWI}_{(n)} = \mathrm{SWI}_{(n-1)} + K_n \left(\mathrm{ms}(t_n) - \mathrm{SWI}_{(n-1)} \right)$$

$$K_n = \frac{K_{n-1}}{K_{n-1} + e^{-\frac{(t_n - t_{n-1})}{T}}}$$

Soil Water Index



Filtering



Introduction to the exercise

Soil Moisture Event Week

Flood prediction through H SAF SM products

1. Impact of initial soil moisture conditions on flood simulation

In this exercise we will

- run the MISDc rainfall-runoff model over the Tiber River Basin with ERA5 rainfall product
- extract the modelled soil moisture data to be compared with satellite-based products (H113 and H27)
- perform linear rescaling and filtering to satellite-based products to make them usable for rainfall-runoff simulation
- perform flood simulation with different soil moisture initial conditions

All the data are stored in the text file "TEVERE_DATA_NEW.txt".

We will use two satellite-based soil moisture products:

- H113 = surface soil moisture data record, based ONLY on satellite soil moisture data from ASCAT
- H27 = root-zone soil moisture obtained from the assimilation of ASCAT soil moisture into ECMWF IFS (Integrated Forecasting System)

MISDc: Discharge simulation 2007-2014

Import the necessary python libraries

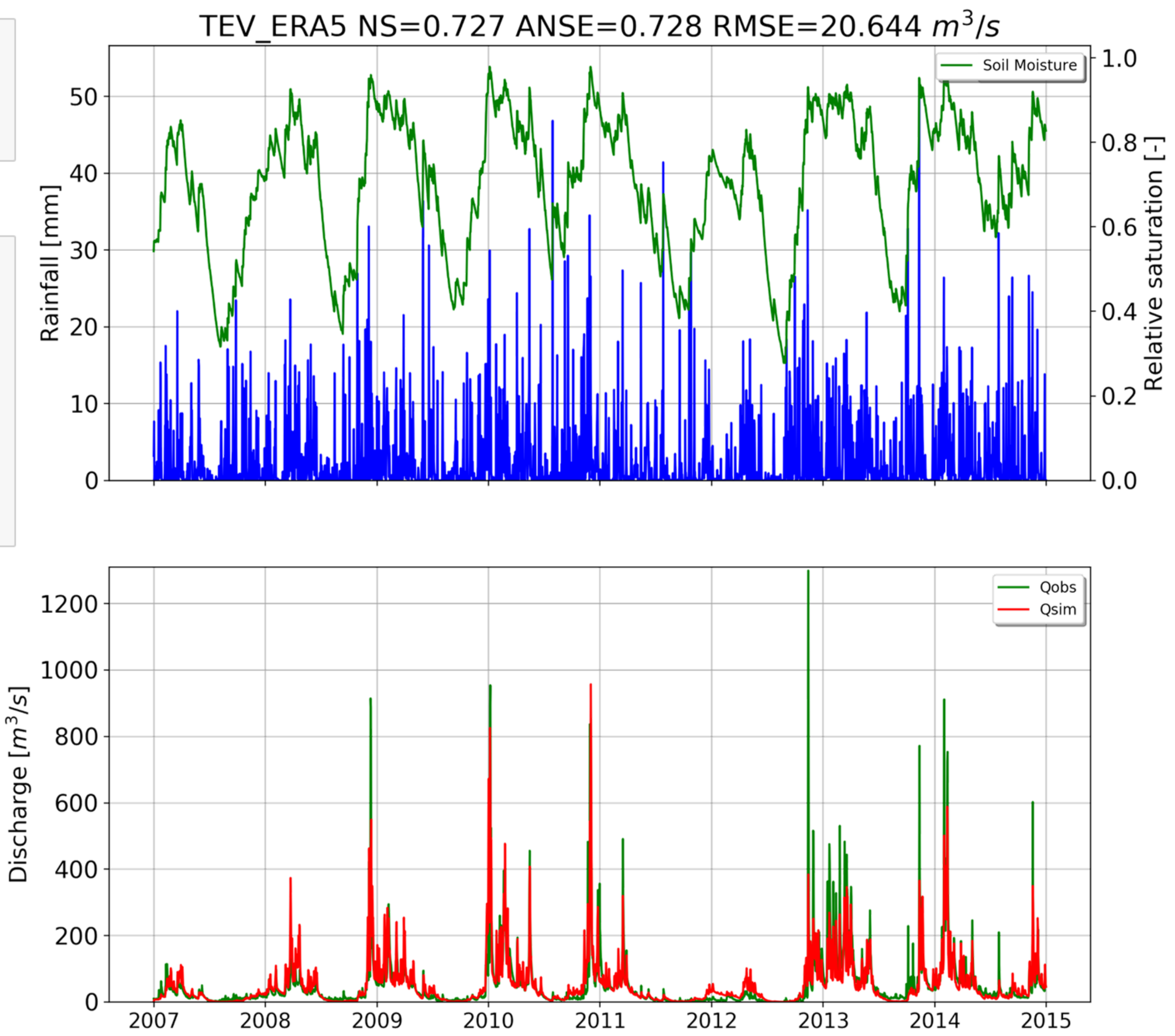
```
from MILc_2 import *
from pytesmo import temporal_matching
from pytesmo import metrics
import ascat
from pytesmo import scaling
from pytesmo.time_series.filters import exp_filter
```

Loading ground and satellite data into the workspace for the Tiber River Basin.

```
name='TEVERE'
data_input=pd.read_csv(name+'_DATA_NEW.txt',index_col=0,header = None, names = ['P','T',
                                                                              'Q','H113',
                                                                              'H27_1',
                                                                              'H27_2',
                                                                              'H27_3',
                                                                              'H27_4',
                                                                                 'SM2R',
                                                                                  'MERG'],
                       na_values='nan')

PAR=np.loadtxt(name+'_PAR_ERA5.txt')
Ab=5270
fig=1
```

Model run over the entire analysis with as input precipitation ERA5 reanalysis rainfall data (1st column named 'P').



Model performance are satisfactory with Nash-Sutcliffe Efficiency (NSE) = 0.727 and ANSE (high flow NSE) = 0.728.

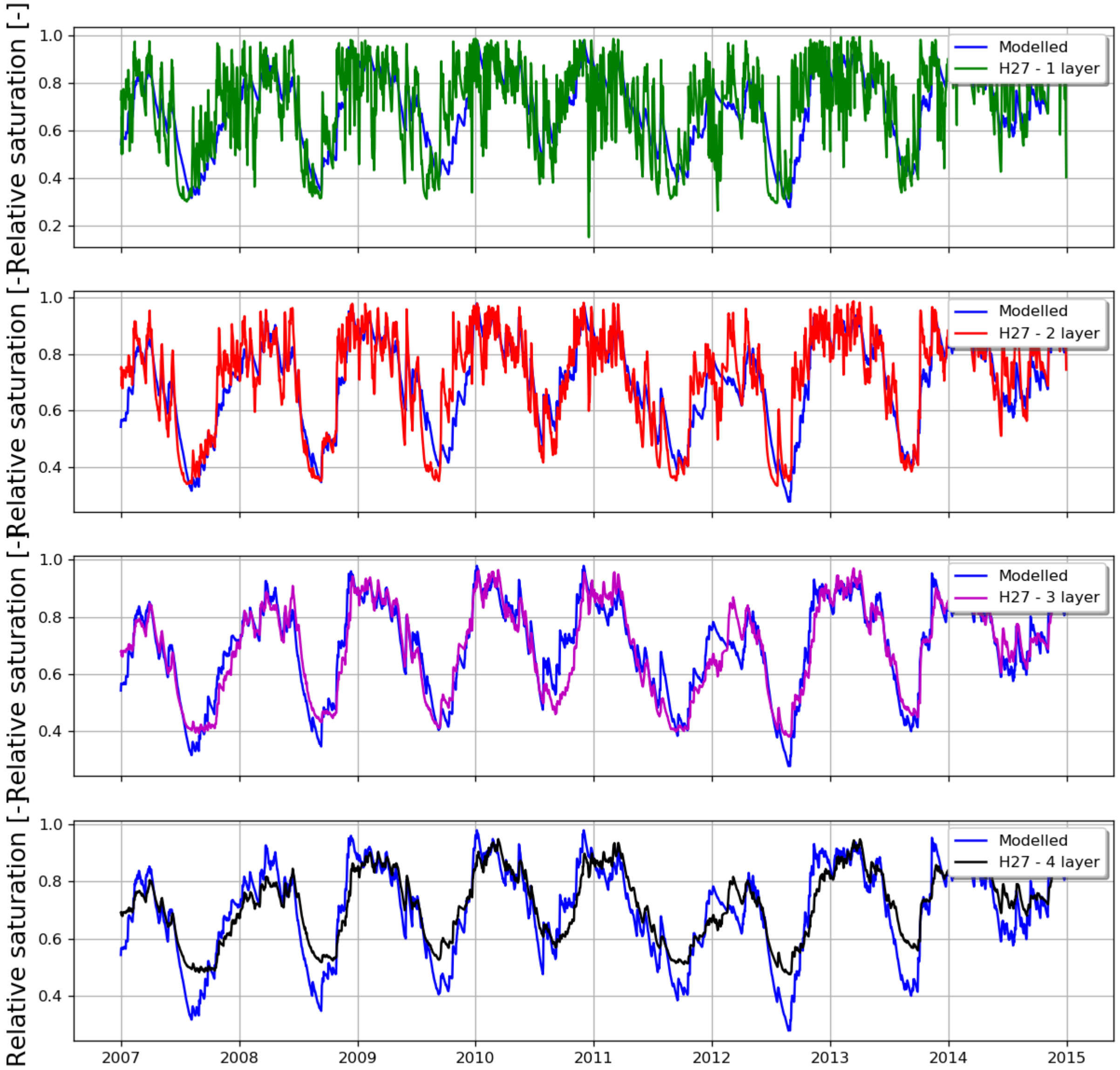
H27 (ASCAT+ECMWF) vs Modelled SM

The figure shows the temporal comparison between modelled and H27 soil moisture timeseries. Specifically, the soil moisture values over the H27 four layers are compared against the model outcomes. The Pearson's correlation coefficient is used to highlight this temporal agreement.

```
f, ax = plt.subplots(4, sharex=True, figsize=(12, 12))
ax[0].tick_params(axis='x', labelsize=14)
ax[0].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[0].plot(data.index, data_input['H27_1'].values,label='H27 - 1 layer',color='g')
ax[1].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[1].plot(data.index, data_input['H27_2'].values,label='H27 - 2 layer',color='r')
ax[2].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[2].plot(data.index, data_input['H27_3'].values,label='H27 - 3 layer',color='m')
ax[3].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[3].plot(data.index, data_input['H27_4'].values,label='H27 - 4 layer',color='k')
ax[0].set_ylabel('Relative saturation [-]', fontsize=16)
ax[1].set_ylabel('Relative saturation [-]', fontsize=16)
ax[2].set_ylabel('Relative saturation [-]', fontsize=16)
ax[3].set_ylabel('Relative saturation [-]', fontsize=16)
ax[0].grid(True)
ax[1].grid(True)
ax[2].grid(True)
ax[3].grid(True)
ax[0].legend(loc='upper right', shadow=True)
ax[1].legend(loc='upper right', shadow=True)
ax[2].legend(loc='upper right', shadow=True)
ax[3].legend(loc='upper right', shadow=True)
R_1=metrics.pearsonr(data['W'].values,data_input['H27_1'].values)
R_2=metrics.pearsonr(data['W'].values,data_input['H27_2'].values)
R_3=metrics.pearsonr(data['W'].values,data_input['H27_3'].values)
R_4=metrics.pearsonr(data['W'].values,data_input['H27_4'].values)
print(R_1)
print(R_2)
print(R_3)
print(R_4)
f.savefig('SMsim_H27vsModel', dpi=120)
```

```
(0.7245530733774587, 0.0)
(0.8785742781377508, 0.0)
(0.9386188931231921, 0.0)
(0.9135554053374679, 0.0)
```

The higher correlation (R=0.939) is obtained with the third layer (0-100cm) that will be used in the flood simulations.



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SWI-H113 (ASCAT) vs Modelled SM

irpi

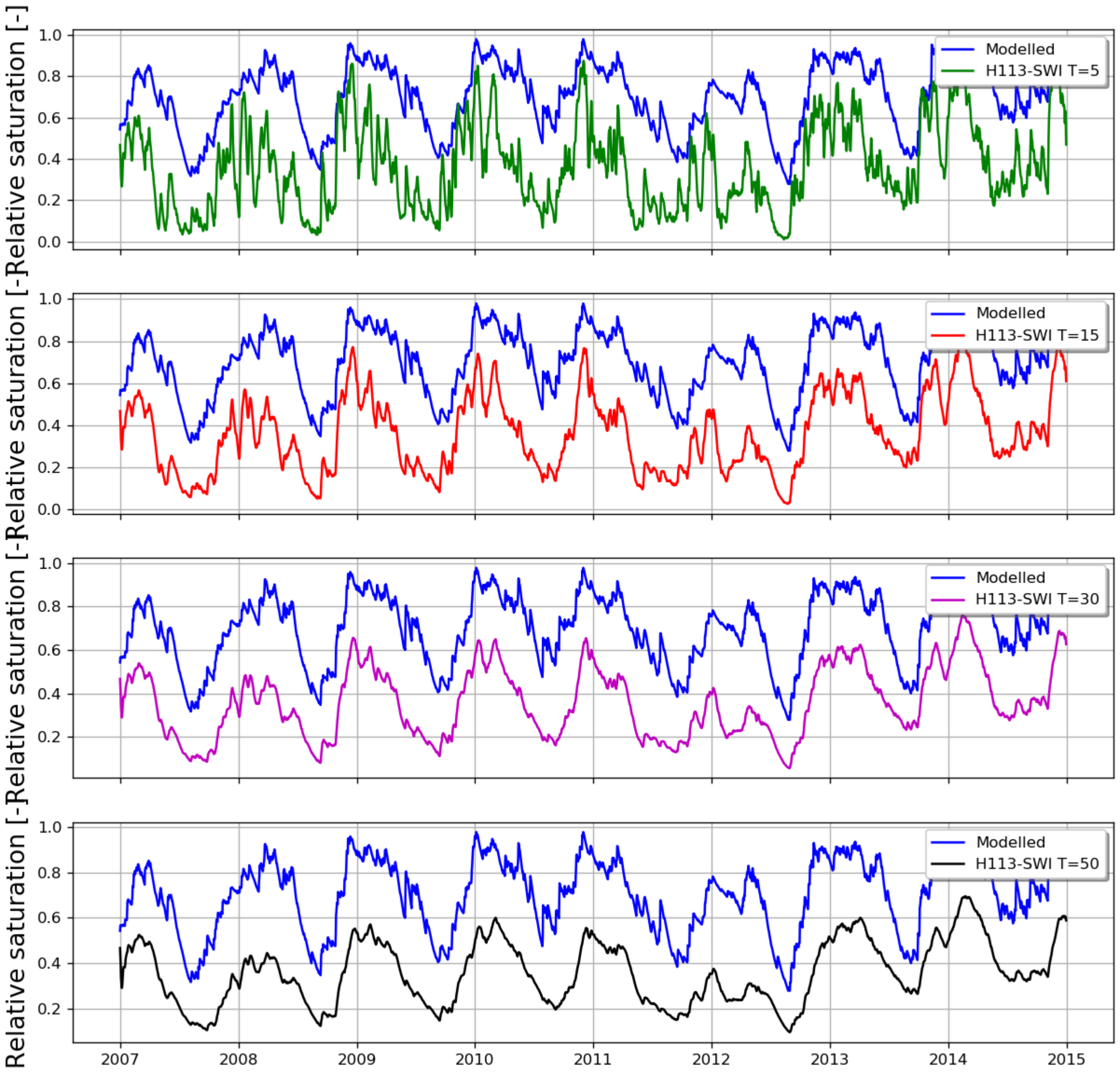
In this step, the exponential filter is applied to H113 surface soil moisture timeseries in order to match the temporal variance of the satellite soil moisture observations with the one of the modelled soil moisture. In order to define the optimal filter parametrization, estimate several Soil Water Index (SWI) timeseries, by changing the "ctime" parameter.

```
jd = data.index.to_julian_date().get_values()
SWI_5=exp_filter(data_input['H113'].values/100, jd, ctime=5)
SWI_15=exp_filter(data_input['H113'].values/100, jd, ctime=15)
SWI_30=exp_filter(data_input['H113'].values/100, jd, ctime=30)
SWI_50=exp_filter(data_input['H113'].values/100, jd, ctime=50)
```

The figure shows the temporal agreement between modelled and SWI timeseries. Specifically, the SWI estimated in the previous step is compared against the model outcomes and the Pearson's correlation coefficient is used to evaluate the temporal agreement between the two.

```
f, ax = plt.subplots(4, sharex=True, figsize=(12, 12))
ax[0].tick_params(axis='x', labelsize=14)
ax[0].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[0].plot(data.index, SWI_5,label='H113-SWI T=5',color='g')
ax[1].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[1].plot(data.index, SWI_15,label='H113-SWI T=15',color='r')
ax[2].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[2].plot(data.index, SWI_30,label='H113-SWI T=30',color='m')
ax[3].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[3].plot(data.index, SWI_50,label='H113-SWI T=50',color='k')
ax[0].set_ylabel('Relative saturation [-]', fontsize=16)
ax[1].set_ylabel('Relative saturation [-]', fontsize=16)
ax[2].set_ylabel('Relative saturation [-]', fontsize=16)
ax[3].set_ylabel('Relative saturation [-]', fontsize=16)
ax[0].grid(True)
ax[1].grid(True)
ax[2].grid(True)
ax[3].grid(True)
ax[0].legend(loc='upper right', shadow=True)
ax[1].legend(loc='upper right', shadow=True)
ax[2].legend(loc='upper right', shadow=True)
ax[3].legend(loc='upper right', shadow=True)
R_5=metrics.pearsonr(data['W'].values,SWI_5)
R_6=metrics.pearsonr(data['W'].values,SWI_15)
R
R
```

The higher correlation (R=0.880) is obtained with T=30 days, SWI(T=30) will be used in the flood simulations.



SWI applied to H113

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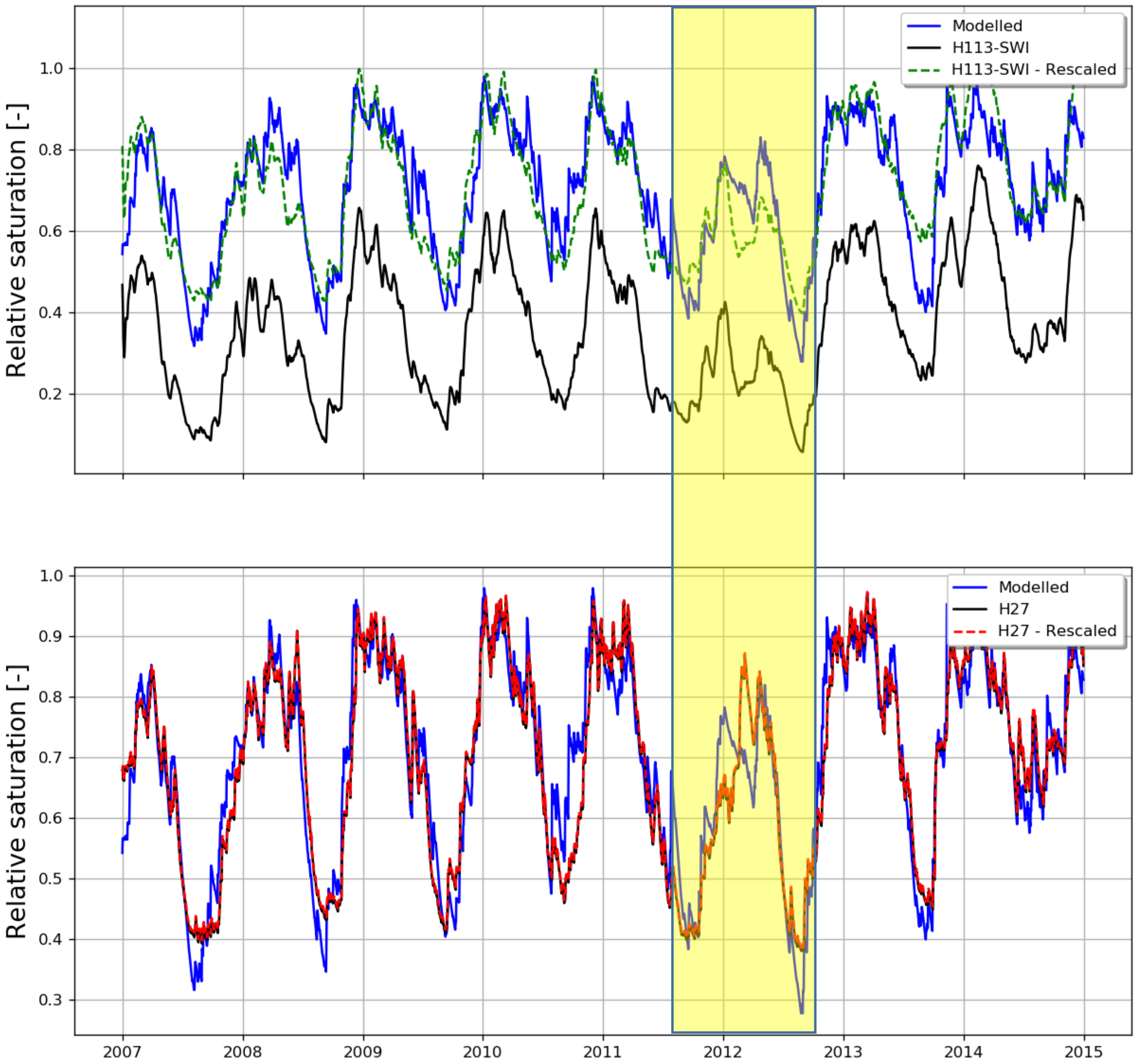
Linear Rescaling

In this step, a simple mean-variance linear rescaling technique is applied to the optimal H27 and SWI timeseries in order to match their mean and variance with the one of the modelled soil moisture. DATA_SAT dataframe is created storing all the needed soil moisture data

```
SWI_best=SWI_30
H27_best=data_input['H27_3'].values
SAT_scaled=scaling.mean_std(SWI_best,data['W'].values)
H27_scaled=scaling.mean_std(H27_best,data['W'].values)

DATA_SAT=pd.DataFrame({"H113": data_input['H113'].values/100, "SWI": SWI_best, "SWI_rescaled": SAT_scaled,
                       "H27": H27_best, "H27_rescaled": H27_scaled}, index=data.index)
```

The figure shows the satellite-based soil moisture datasets before and after the linear rescaling step.

```
f, ax = plt.subplots(2, sharex=True, figsize=(12, 12))
ax[0].tick_params(axis='x', labelsize=14)
ax[0].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[0].plot(data.index, SWI_best,'k',label='H113-SWI',color='k')
ax[0].plot(data.index, SAT_scaled,'g--',label='H113-SWI - Rescaled',color='g')

ax[1].plot(data.index, data['W'].values,label='Modelled',color='b')
ax[1].plot(data.index, H27_best,'k',label='H27',color='k')
ax[1].plot(data.index, H27_scaled,'r--',label='H27 - Rescaled',color='r')
ax[0].set_ylabel('Relative saturation [-]', fontsize=16)
ax[1].set_ylabel('Relative saturation [-]', fontsize=16)
ax[0].grid(True)
ax[1].grid(True)
ax[0].legend(loc='upper right', shadow=True)
ax[1].legend(loc='upper right', shadow=True)

f.savefig('SMsim_H113_H27_resvsModel', dpi=120)
```



The rescaling has a greater effect on H113 wrt H27. Now the data are ready to be used for flood simulations.

Larger differences in 2012

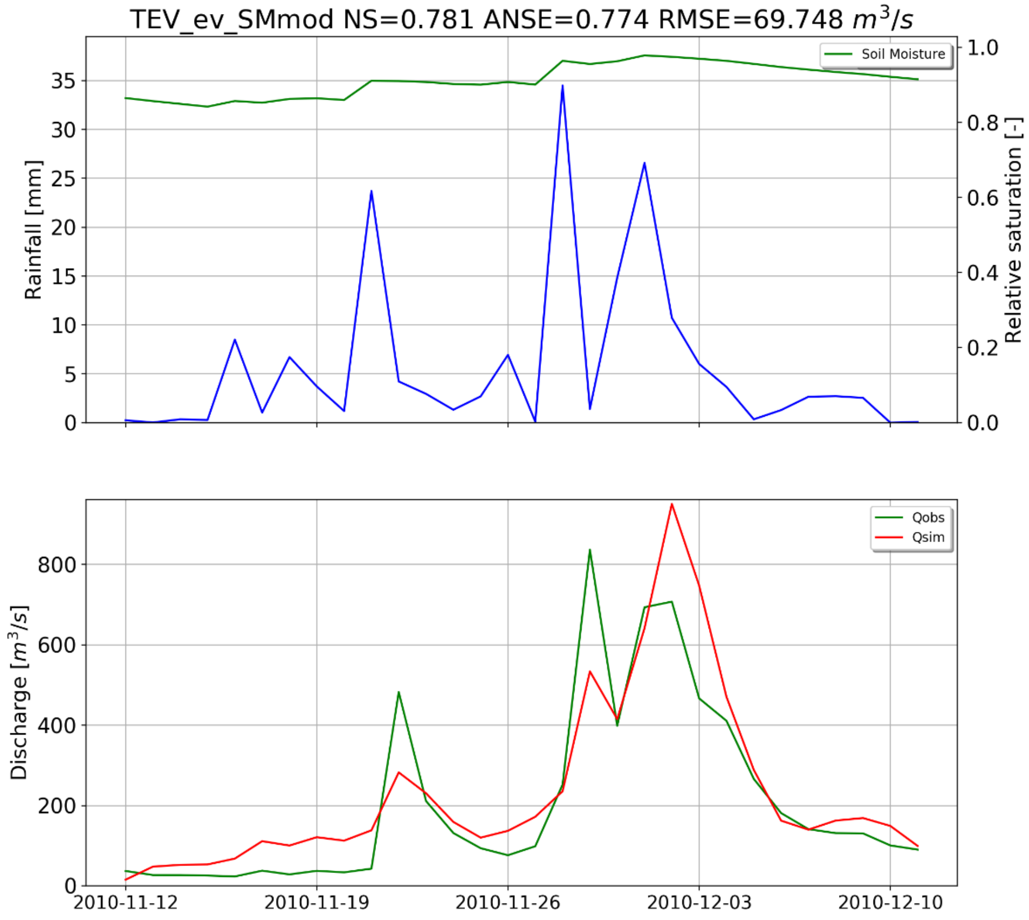
Flood simulation: SM from model

In this step, the model is run for a flood event identified by a start ("start_ev1" variable) and end date ("end_ev1" variable). The soil moisture conditions at the beginning of the flood event are set equal to the ones provided by the model simulation, in order to obtain a reference run.

```
start_ev1='2010-11-11'
end_ev1='2010-12-11'
mask_ev1=(data.index > start_ev1) & (data.index <= end_ev1)
Ev1=data_input.iloc[mask_ev1]
```

```
PAR[0]=data['W'].iloc[mask_ev1][0]
print('Initial Soil Moisture from Model='+str(PAR[0]))
QobsQsim,data=MILC('TEV_ev_SMmod',Ev1,PAR,Ab,fig)
Data_1=pd.DataFrame(data['W'].values, index=data.index)
Data_1.columns=['W_MOD']
Data_1=Data_1.join(data['S'])
Data_1.rename(columns={'S':'S_MOD'},inplace=True)
```

```
Initial Soil Moisture from Model=0.8723968455202379
```



MISDc model is run for the period from 11-Nov-2010 to 11-Dec-2010. Initial soil moisture from the model is equal to 0.87.

Flood simulation: SM from ASCAT

In this step, the soil moisture conditions at the beginning of the flood event are set equal to the ones provided by the SWI applied to H113.

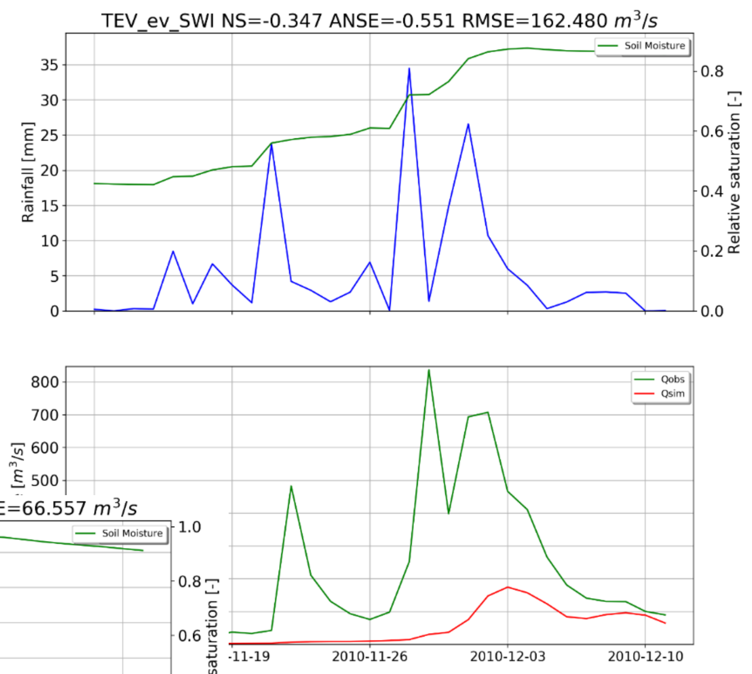
```
PAR[0]=DATA_SAT.iloc[mask_ev1]['SWI'][0]
print('Initial Soil Moisture from SWI='+str(PAR[0]))
QobsQsim,data=MILC('TEV_ev_SWI',Ev1,PAR,Ab,fig)
Data_1=Data_1.join(data['W'])
Data_1.rename(columns={'W':'W_SWI'},inplace=True)
Data_1=Data_1.join(data['S'])
Data_1.rename(columns={'S':'S_SWI'},inplace=True)
```

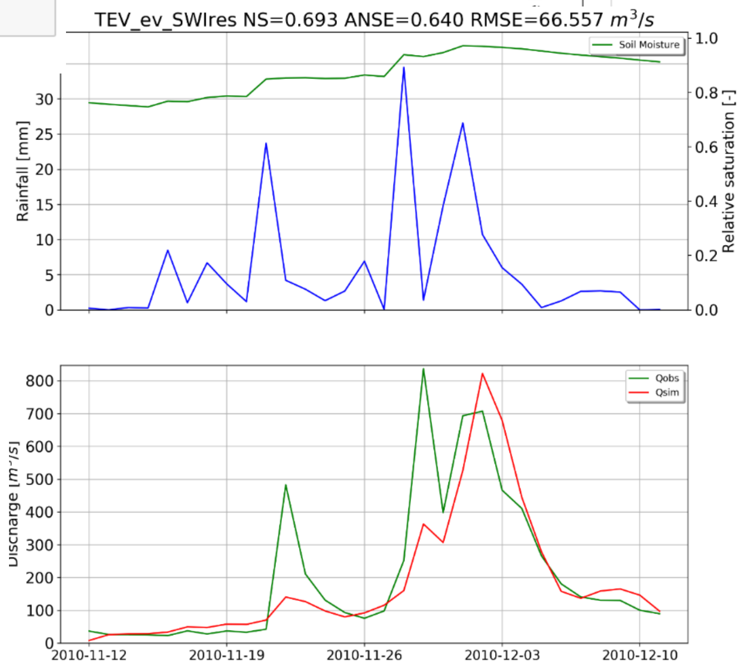
```
Initial Soil Moisture from SWI=0.4259260297805447
```

In this step, the soil moisture conditions at the beginning of the flood event are set equal to the ones provided by the SWI rescaled estimates. Which is the impact of the changed initial soil moisture condition in terms of discharge simulation?

```
PAR[0]=DATA_SAT.iloc[mask_ev1]['SWI_rescaled'][0]
print('Initial Soil Moisture from SWi Rescaled='+str(PAR[0]))
QobsQsim,data=MILC('TEV_ev_SWIres',Ev1,PAR,Ab,fig)
Data_1=Data_1.join(data['W'])
Data_1.rename(columns={'W':'W_SWI_rescaled'},inplace=True)
Data_1=Data_1.join(data['S'])
Data_1.rename(columns={'S':'S_SWI_rescaled'},inplace=True)
```

```
Initial Soil Moisture from SWi Rescaled=0.7672590804612407
```





Simulation with H113 is wrong!

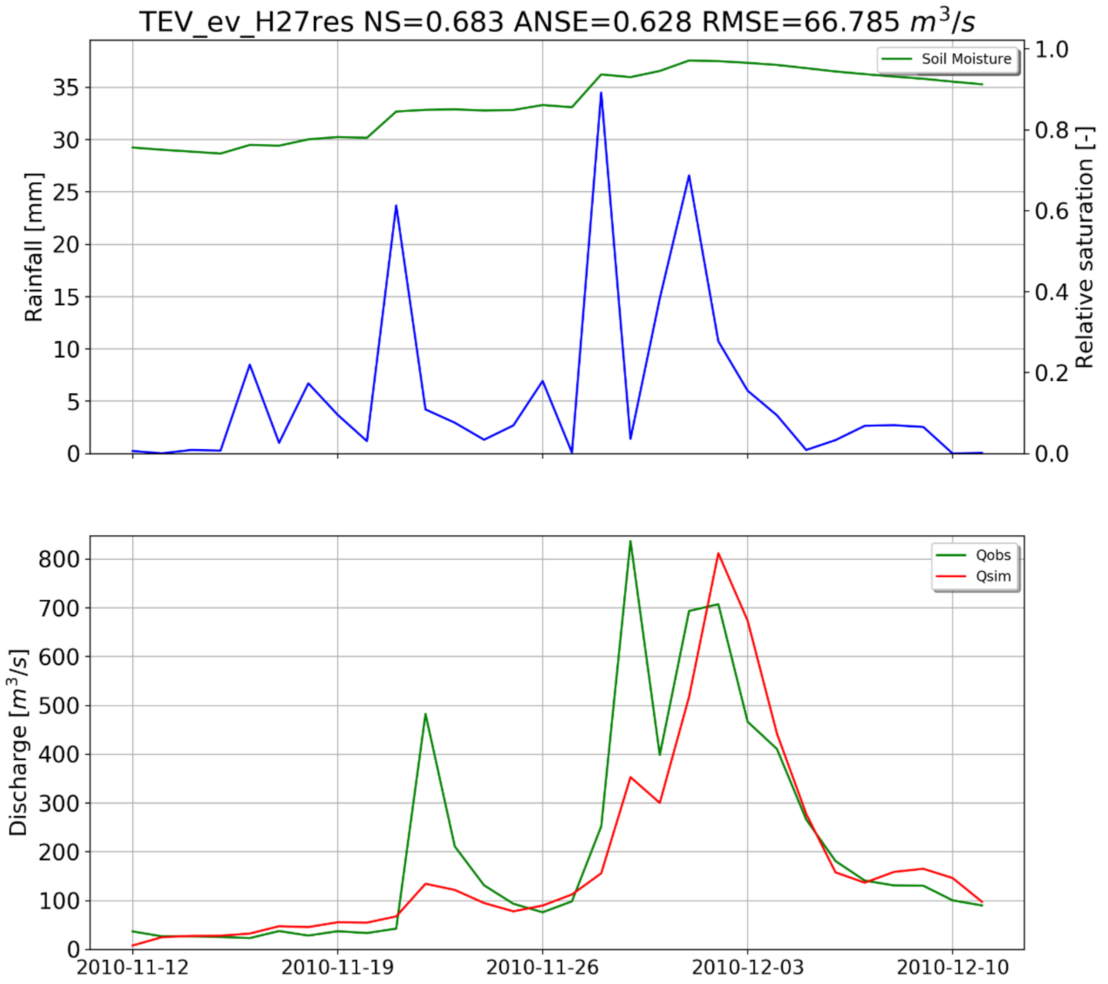
MISDc model is run with the initial soil moisture from SWI-H113 before (0.43) and after (0.77) rescaling.

Flood simulation: SM from ASCAT+ECMWF

In this step, the soil moisture conditions at the beginning of the flood event are set equal to the ones provided by the H27 rescaled estimates.

```
PAR[0]=DATA_SAT.iloc[mask_ev1]['H27_rescaled'][0]
print('Initial Soil Moisture from H27 Rescaled='+str(PAR[0]))
QobsQsim,data=MILC('TEV_ev_H27res',Ev1,PAR,Ab,fig)
Data_1=Data_1.join(data['W'])
Data_1.rename(columns={'W':'W_H27_rescaled'},inplace=True)
Data_1=Data_1.join(data['S'])
Data_1.rename(columns={'S':'S_H27_rescaled'},inplace=True)
```

```
Initial Soil Moisture from H27 Rescaled=0.7610395299622494
```

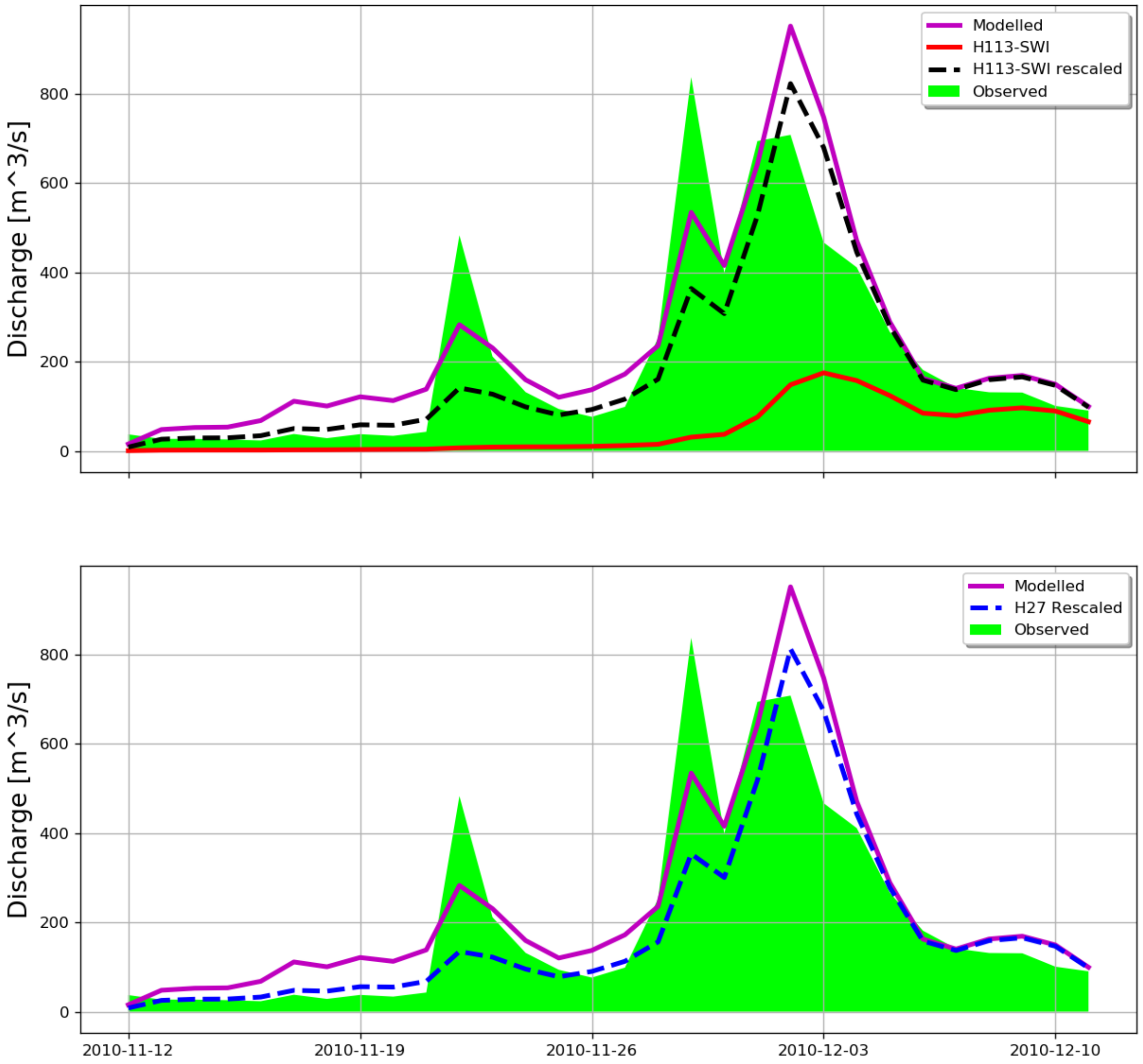


MISDc model is run with the initial soil moisture from H27 after rescaling (0.76).

Impact of SM on Flood Simulation

After the different model runs, identify the soil moisture initial condition that provided the best NS value.

```
f, ax = plt.subplots(2, sharex=True, figsize=(12, 12))
ax[0].tick_params(axis='x', labelsize=14)
ax[0].fill_between(Ev1.index, Ev1['Q'].values,label='Observed',facecolor=(0, 1, 0))
ax[0].plot(Data_1.index, Data_1['S_MOD'].values,label='Modelled',color='m',linewidth=3.0)
ax[0].plot(Data_1.index, Data_1['S_SWI'].values,label='H113-SWI',color='r',linewidth=3.0)
ax[0].plot(Data_1.index, Data_1['S_SWI_rescaled'].values,'r--',label='H113-SWI rescaled',color='k',linewidth=3.0)

ax[1].fill_between(Ev1.index, Ev1['Q'].values,label='Observed',facecolor=(0, 1, 0))
ax[1].plot(Data_1.index, Data_1['S_MOD'].values,label='Modelled',color='m',linewidth=3.0)
ax[1].plot(Data_1.index, Data_1['S_H27_rescaled'].values,'r--',label='H27 Rescaled',color='b',
        linewidth=3.0)
ax[0].set_ylabel('Discharge [m^3/s]', fontsize=16)
ax[1].set_ylabel('Discharge [m^3/s]', fontsize=16)
ax[0].grid(True)
ax[1].grid(True)
ax[0].legend(loc='upper right', shadow=True)
ax[1].legend(loc='upper right', shadow=True)
f.savefig('Qsim_Event_SMcond', dpi=120)
```



MISDc is run with different initial soil moisture conditions. You can test the sensitivity by yourself!
What is the impact of initial soil moisture?

EUMETSAT H SAF

Flood Simulation: P from ERA5

2. Satellite Soil Moisture for Improving Rainfall through SM2RAIN

In this exercise we will run the MISDc rainfall-runoff model over the Tiber River Basin with different rainfall products as input:

- ERA5 reanalysis rainfall
- SM2RAIN-ASCAT satellite rainfall obtained from H SAF ASCAT soil moisture
- merged rainfall product P-MERG= 0.85 x ERA5+0.15 x SM2RAIN-ASCAT

We will compare the performance of each product to assess the potential benefit of correcting rainfall with satellite soil moisture through SM2RAIN.

All the data are stored in the text file "TEVERE_DATA_NEW.txt".

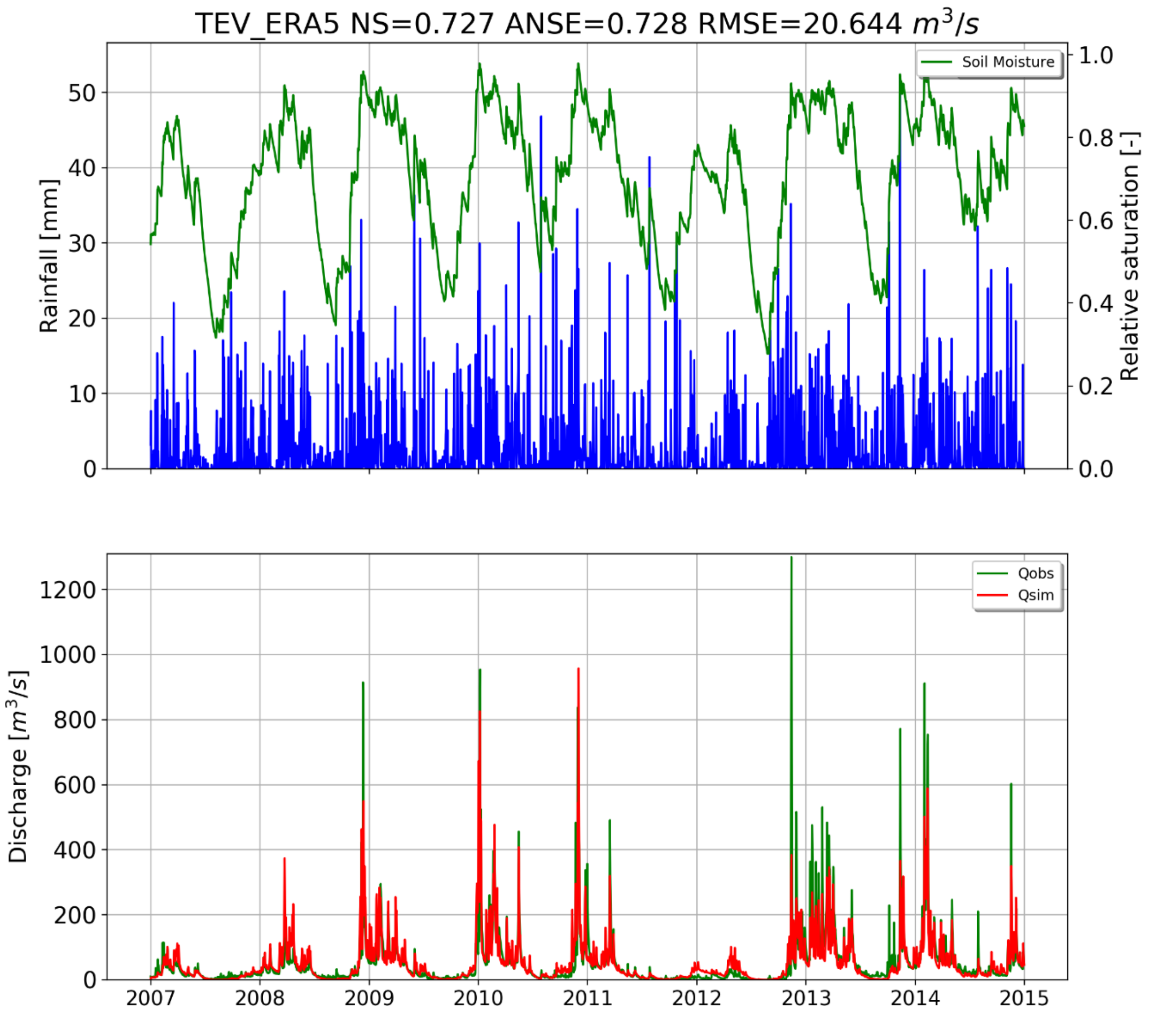
Import the necessary python libraries

```
from MILc_2 import *
from pytesmo import temporal_matching
from pytesmo import metrics
import ascat
from pytesmo import scaling
from pytesmo.time_series.filters import exp_filter
```

Loading ground and satellite data into the workspace for the Tiber River Basin.

```
name='TEV_ERA5'
data_input=pd.read_csv('TEVERE'+'_DATA_NEW.txt',index_col=0,header = None, names = ['P','T',
                                                                                    'Q','H113',
                                                                                    'H27_1',
                                                                                    'H27_2',
                                                                                    'H27_3',
                                                                                    'H27_4',
                                                                                        'SM2R',
                                                                                         'MERG'],
                         na_values='nan')

PAR_ERA5=np.loadtxt('TEVERE'+'_PAR_ERA5.txt')
PAR_SM2R=np.loadtxt('TEVERE'+'_PAR_SM2R.txt')
```

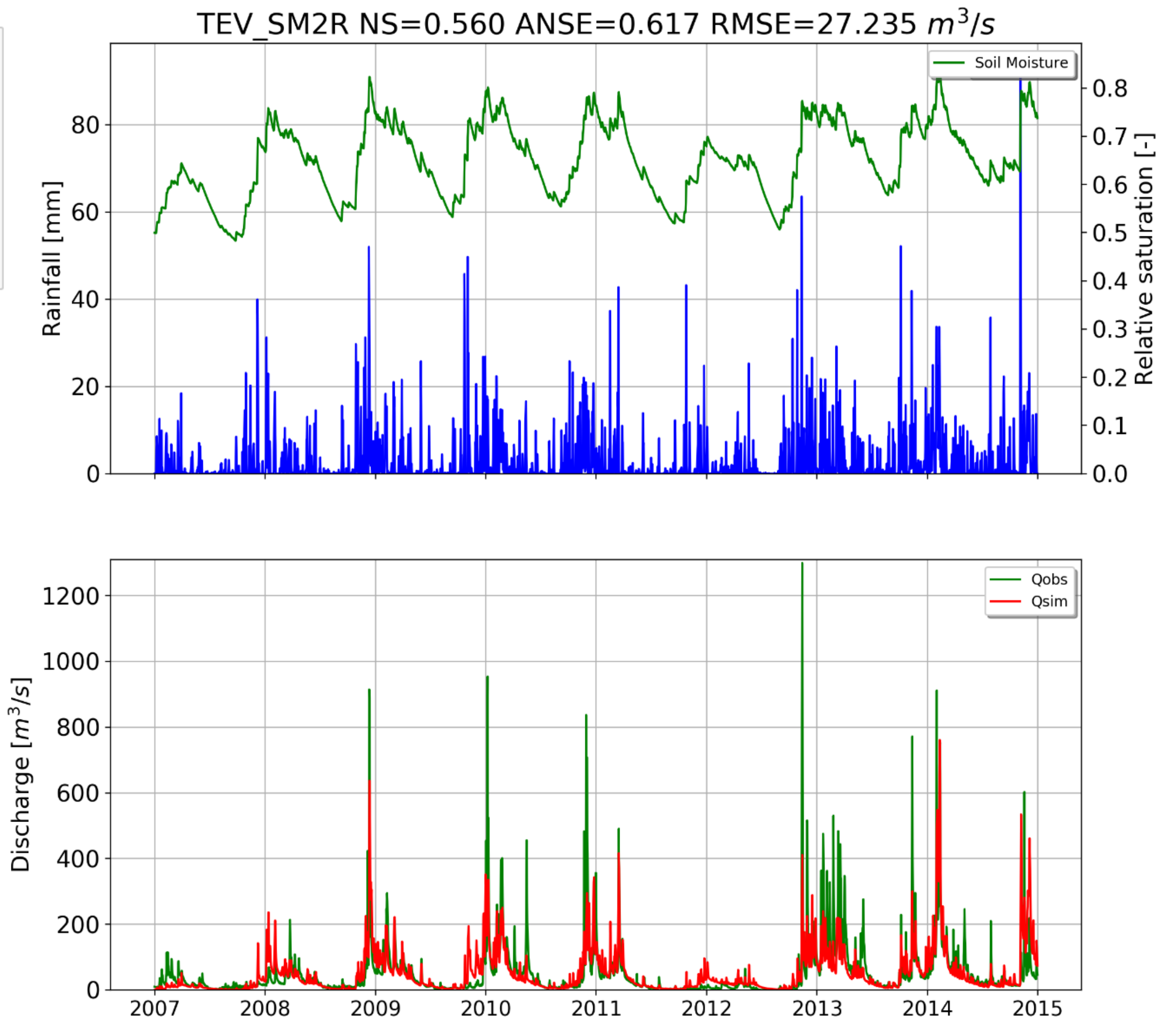
MISDc is run with ERA5 reanalysis rainfall, this is the reference simulation: NSE=0.727.



Flood Simulation: P from SM2RAIN-ASCAT

Model run over the entire analysis with as input precipitation SM2RAIN-ASCAT rainfall data.

```
name='TEV_SM2R'
data_input1=pd.read_csv('TEVERE'+'_DATA_NEW.txt',index_col=0,header = None, names = ['PERA5','T',
                                                                                        'Q','H113',
                                                                                        'H27_1',
                                                                                        'H27_2',
                                                                                        'H27_3',
                                                                                        'H27_4',
                                                                                           'P',
                                                                                            'MERG'],
                        na_values='nan')
QobsQsim,data_SM2R=MILC(name,data_input1,PAR_SM2R,Ab,1)
```

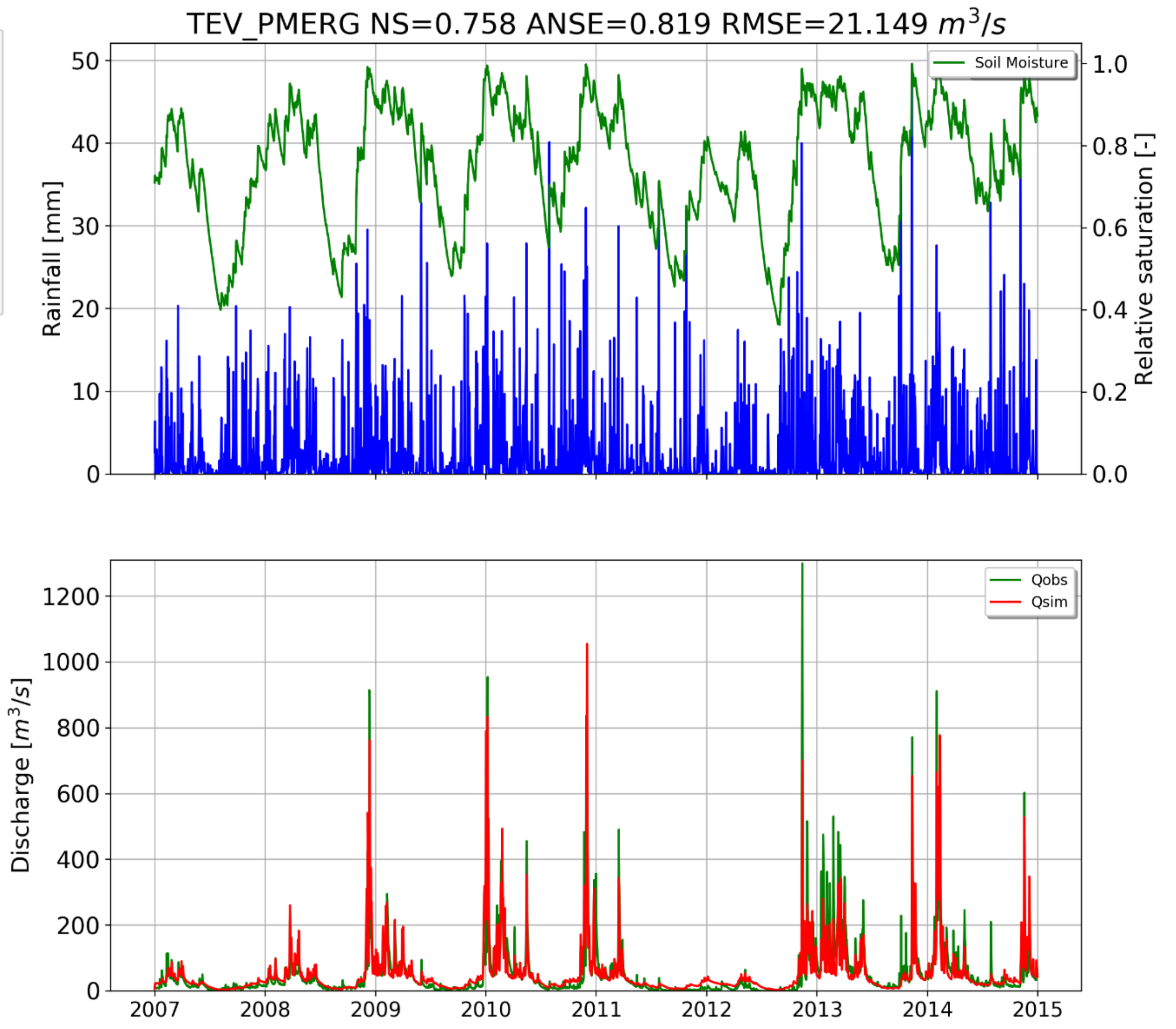


MISDc is run with SM2RAIN-ASCAT rainfall, performances are lower with NSE=0.560.

Flood Simulation: P from ERA5+SM2RAIN

The figures show observed and simulated discharge for the different run in two subperiods.

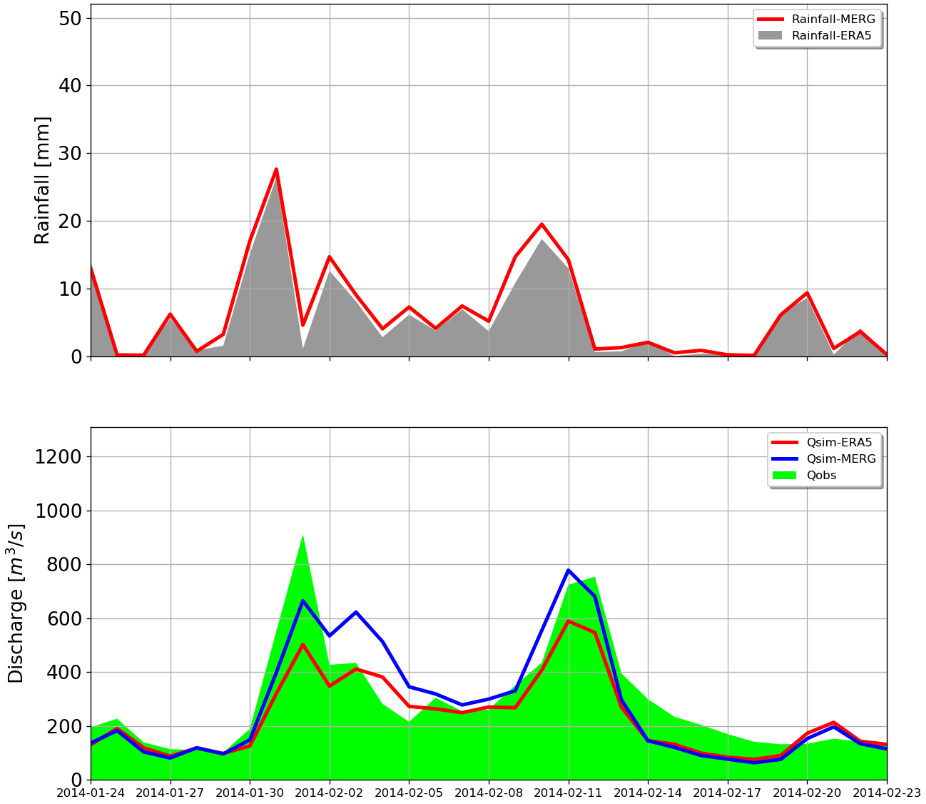
```
name='TEV_PMERG'
data_input2=pd.read_csv('TEVERE'+'_DATA_NEW.txt',index_col=0,header = None, names = ['PERA5','T',
                                                                         'Q','H113',
                                                                         'H27_1',
                                                                         'H27_2',
                                                                         'H27_3',
                                                                         'H27_4',
                                                                             'SM2R',
                                                                              'P'],
                              na_values='nan')

QobsQsim,data_MERG=MILC(name,data_input2,PAR_MERG,Ab,1)
```

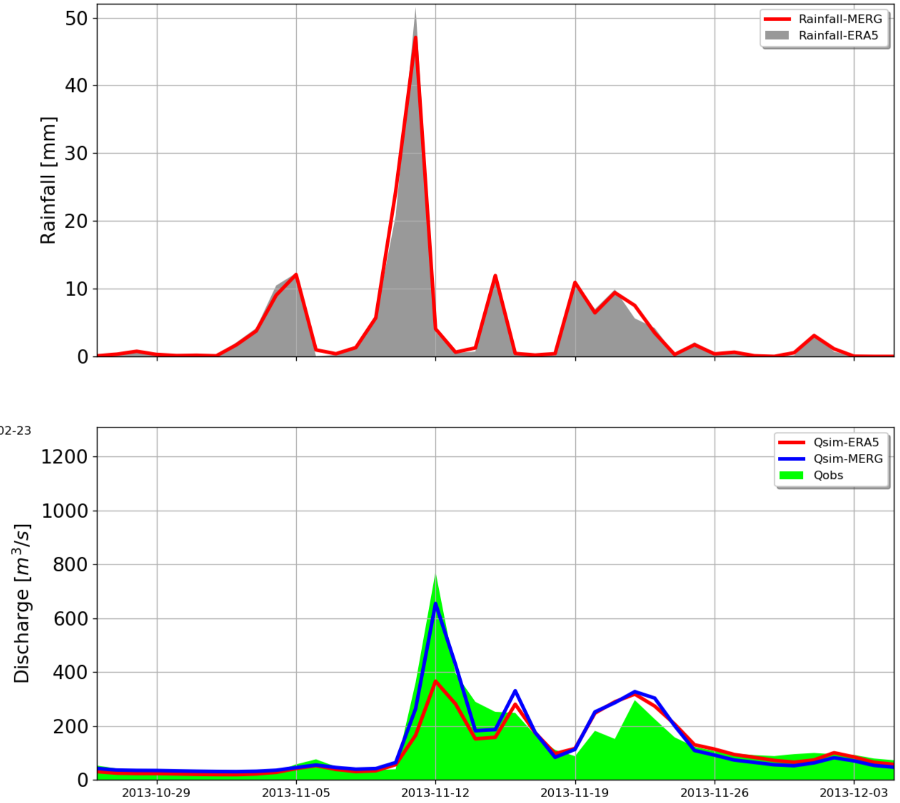


MISDc is run with the merged rainfall integrating SM2RAIN-ASCAT and ERA5, performances improve (NSE=0.758), particularly in terms of ANSE.

Flood Simulation: P from ERA5+SM2RAIN

```
ID0=2490
ID1=2530

f, ax = plt.subplots(2, sharex=True, figsize=(12, 12))
ax[0].fill_between(data_MERG.index, data_ERA5['P'].values,label='Rainfal
ax[0].plot(data_MERG.index, data_MERG['P'].values,label='Rainfall-MERG',
ax[0].set_ylim(0,np.max(data_MERG['P'].values)+5)
ax[0].set_xlim(data_MERG.index[ID0],data_MERG.index[ID1])
ax[0].set_ylabel('Rainfall [mm]', fontsize=16)
ax[0].grid(True)
ax[0].tick_params(axis='y', labelsize=16)
ax[0].legend(loc='upper right', shadow=True)

ax[1].fill_between(data_MERG.index, data_MERG['Q'].values,label='Qobs',f
ax[1].plot(data_ERA5.index, data_ERA5['S'].values,label='Qsim-ERA5',colo
ax[1].plot(data_MERG.index, data_MERG['S'].values,label='Qsim-MERG',colo
ax[1].set_xlim(data_MERG.index[ID0],data_MERG.index[ID1])
ax[1].set_ylim(0,np.max(data_MERG.max())+10)
ax[1].set_ylabel('Discharge [$m^3/s$]', fontsize=16)
ax[1].grid(True)
ax[1].tick_params(axis='y', labelsize=16)
ax[1].legend(loc='upper right', shadow=True)

f.savefig('Qsim_nov2013', dpi=120)
```





The larger improvements are obtained in the period 2013-2014 (SM2RAIN-ASCAT is more accurate).

What is the benefit of SM2RAIN for improving floods?