ECMWF/ H-SAF and HEPEX Workshops on coupled hydrology
Reading, 3-6 November 2014

Assimilation of satellite soil moisture data in a distributed hydrological model: impact on the hydrological cycle in some Italian basins

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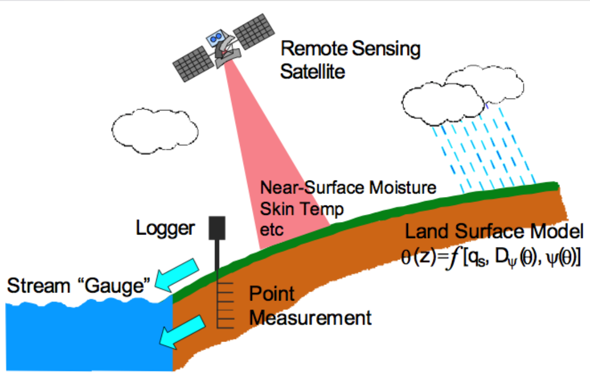
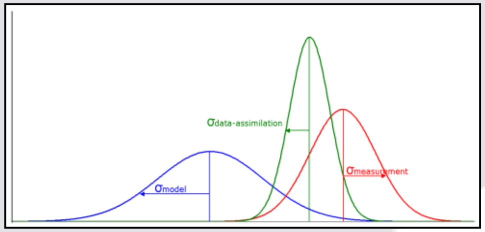
CIMA Research Foundation
International Centre on Environmental Monitoring

Osservare per prevedere, prevedere per prevenire



Data Assimilation

Data assimilation is used operationally in oceanography and meteorology, but in hydrology it is only recently that international research activities have been deployed.



(some) Open questions in DA

1. Which is the best DA techniques?
2. How can satellite data be used in a framework for DA in hydrological models?
3. Which is the proper model configuration?
4. Which is the impact of DA on the hydrological cycle?

1. Data Assimilation Technique

Direct insertion (Houser et al. 1998; Walker et al. 2001a)
Statistical correction (Houser et al. 1998)
Successive correction Bergthorsson and Döös (1955)
Analysis correction Lorenc et al. (1991)
Nudging (Stauffer and Seaman 1990)
Optimal interpolation (Lorenc et al. 1991)

Kalman Filters, simple, extended, ensemble (Evensen)
Particle filter (Kalman, 1960; Evensen 1994, Gordon et al. 1993)

SEQUENTIAL FILTERS

$$x_k^{i+} = x_k^{i-} + G_k(y_k^{i} - x_k^{i-})$$

3D & 4D var -> Var. filter

$$J = \frac{1}{2}\left(\mathbf{X}_0 - \mathbf{X}_0^b\right)^T \Sigma_0^{b^{-1}} \left(\mathbf{X}_0 - \mathbf{X}_0^b\right) + \frac{1}{2}\sum_0^{N-1}\left(\mathbf{Z}_k - \hat{\mathbf{Z}}_k\right)^T \mathbf{R}_k^{-1}\left(\mathbf{Z}_k - \hat{\mathbf{Z}}_k\right),$$

Houser, De Lannoy and Walker (2012). Hydrologic Data Assimilation, Approaches to Managing Disaster - Assessing Hazards, Emergencies and Disaster Impacts, http://www.intechopen.com/books/approaches-to-managing-disaster-assessing-hazards-emergencies-and- disaster-impacts/land-surface-data-assimilation

1. Data Assimilation Technique

The assimilation technique is particularly important in some cases

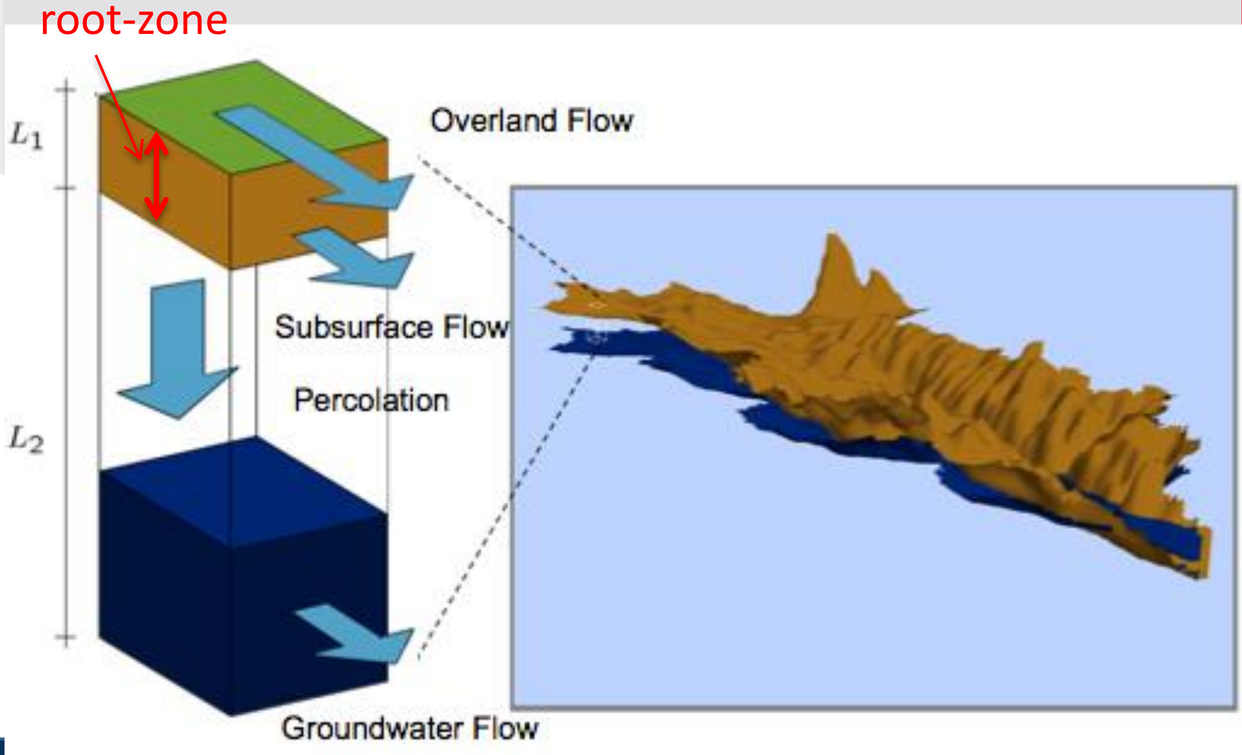
Samuel, J. et al. 2014 (JoH)
“[…] In the streamflow assimilation, soil moisture states were markedly Distorted […]”

”General filtering approaches in hydrologic data assimilation, such as the ensemble Kalman filter (EnKF), are **based on the assumption that uncertainty of the current background prediction can be reduced by correcting errors in the state variables at the same time step**. However, this assumption may not be valid when assimilating stream discharge into hydrological models to correct soil moisture storage due to the time lag between the soil moisture and the discharge …”
Li et al. 2013 (WRR)

The EnKF is designed to update model-forecasted state predictions at the same time an observation is acquired. No attempt is made to reanalyze previous model predictions in response to a particular observation. In contrast, the **Ensemble Kalman Smoother (EnKS)** can be used to update all model states predictions within a fixed lag of past time (Dunne and Entekhabi, 2005).
Crow and Ryu, 2009 (HESS)

2. How can sat. data be used in DA?

Satellite data give information of soil moisture for the first centimetres of the soil. This may not match the layer depth simulated by the model (different climatology and considerable bias)



Usually satellite soil moisture data CANNOT be directly used within hydrological models

2. How can sat. SM data be used in DA?

A. “Transform” the sat. SSM in the “same” modelled variable
   - → Filtering

B. Adjusting the observation to match the climatology of the model
   - → Bias handling

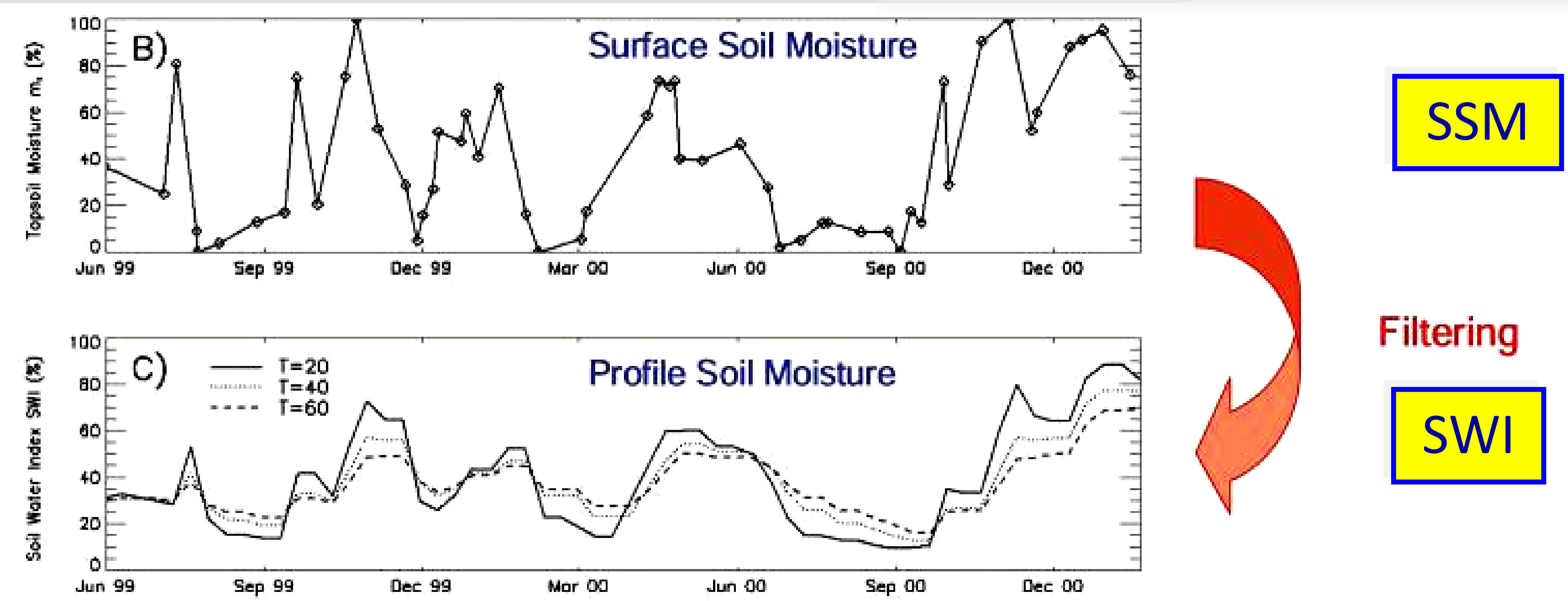
2. How can sat. SM data be used in a DA?

Filtering: A filtering technique is applied to obtain information of a deeper soil layer

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

Wagner et al., 1999, Stroud, 1999
Albergel et al., 2008

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



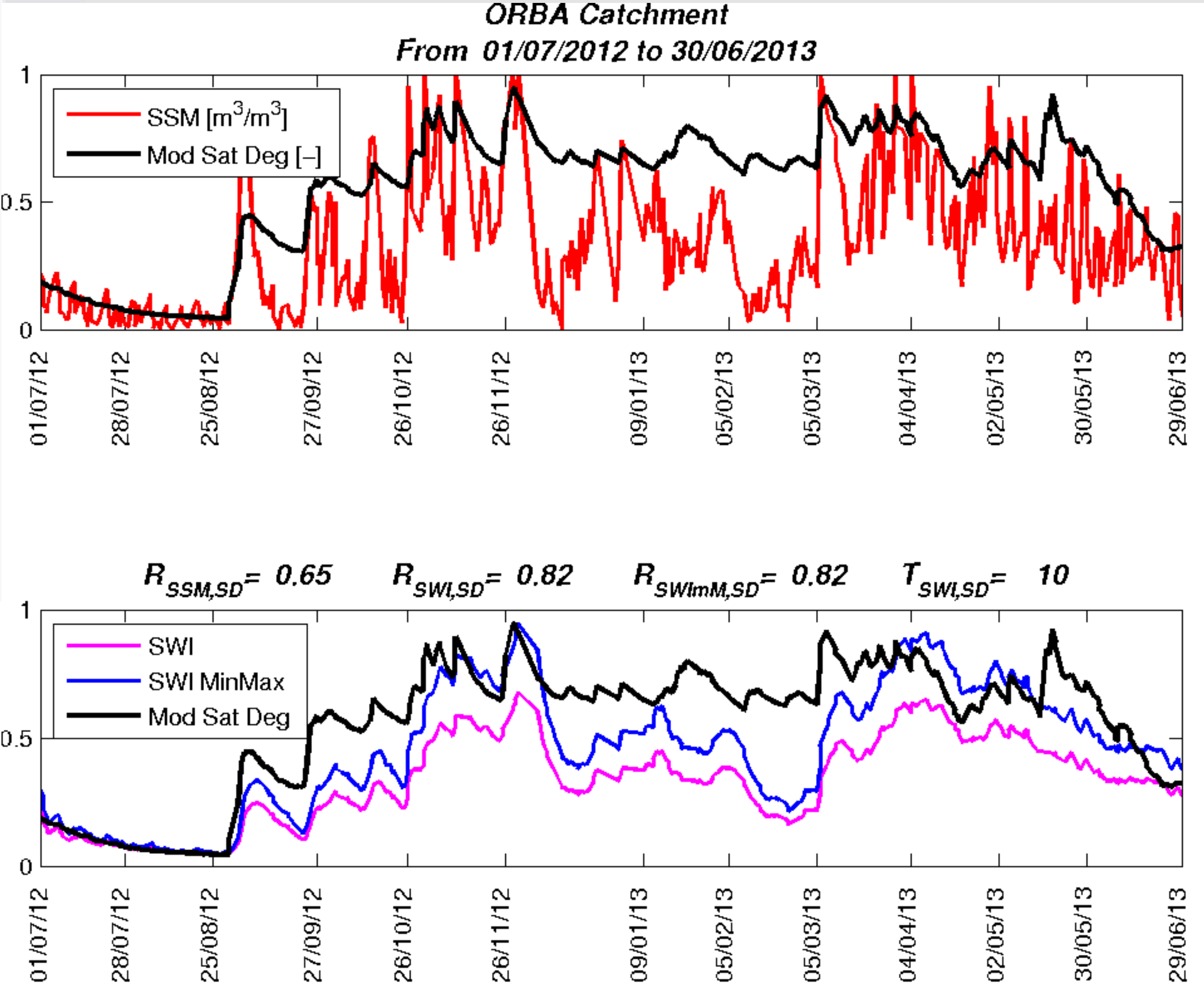
2. How can sat. SM data be used in DA?

Bias Handling: Several potential strategies exist and have been applied in hydrologic data assimilation

Variance matching (VM) (Brocca et al. 2010, 2012, Matgen et al. 2011, Chen et al. 2011)
Linear regression techniques (LR)
Cumulative distribution function matching (CDF) (Reichle and Koster 2004)
Anomaly based cumulative distribution (aCDF)
Triple collocation analysis-based approach (TCA) (Stoffelen 1998, Yilamz and Crow 2013)

There many methods their optimality (for real cases) in terms of error analysis in an assimilation framework has not been yet analysed

2. How can sat. SM data be used in DA?



1. **Filtering -> SWI**
2. **Bias handling**

$$SAT^* = \frac{SAT - \mu(SAT)}{\sigma(SAT)} \cdot \sigma(SD_{\mathrm{mod}}) + \mu(SD_{\mathrm{mod}})$$

$$SAT^* = \frac{SAT - \min(SAT)}{\left[\max(SAT) - \min(SAT)\right]} \cdot \left[\max(SD_{\mathrm{mod}}) - \min(SD_{\mathrm{mod}})\right] + \min(SD_{\mathrm{mod}})$$

2. How can sat. SM data be used in DA?

3-D EnKF

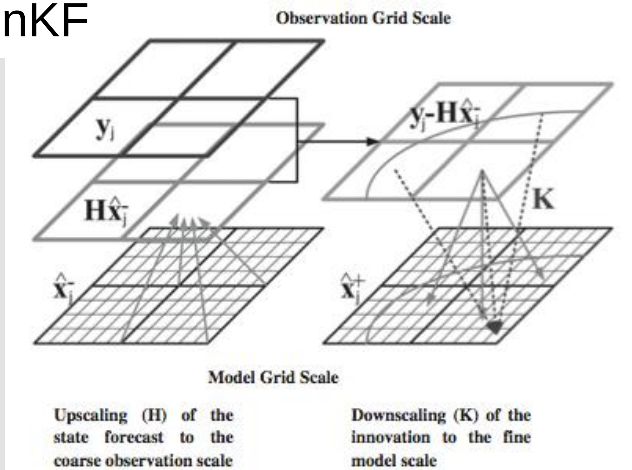


Fig. 2. A schematic diagram of the 3-D EnKF approach illustrated for four coarse-scale pixels, each containing 4 × 6 fine-scale pixels.

Advances in Water Resources 52 (2013) 19–33
Contents lists available at SciVerse ScienceDirect
Advances in Water Resources
journal homepage: www.elsevier.com/locate/advwatres

Assimilation and downscaling of satellite observed soil moisture over the Little River Experimental Watershed in Georgia, USA

Alok Kumar Sahoo [a,*], Gabriëlle J.M. De Lannoy [b,c], Rolf H. Reichle [c], Paul R. Houser [d]

Sahoo et al., 2013

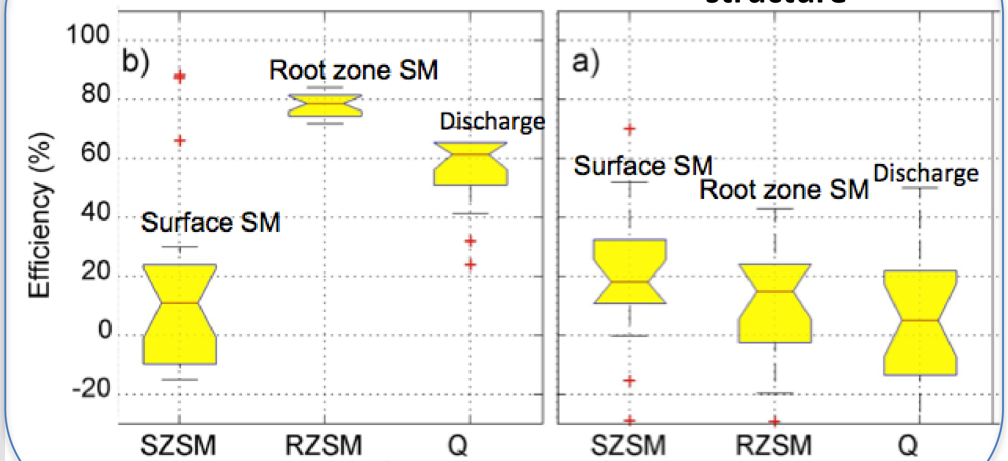
After the assimilation the analysis is bias-corrected to bring the output to the true climatology

The 1-D EnKF application assimilates a priori partitioned observations at the fine scale model grid cells.
The 3-D EnKF algorithm downscales the coarse observations within the assimilation scheme and uses multiple coarse observation grid cells, as shown in Fig. 2.

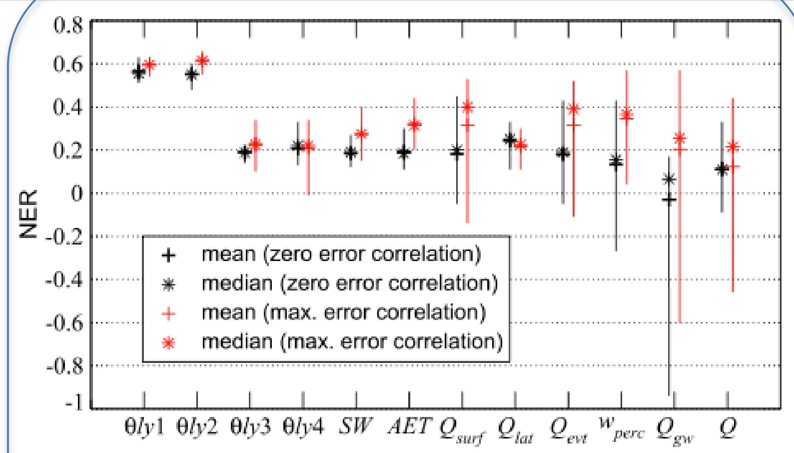
Both the EnKF algorithms produce fine-scale results that are closer to the in situ data than either the model open loop or the satellite observations alone. The 3-D EnKF slightly outperforms the 1-D EnKF and better preserves realistic spatial patterns because of the colored spatial error correlations and the corresponding impact of multiple coarse observation grid cells

3. Proper model configuration

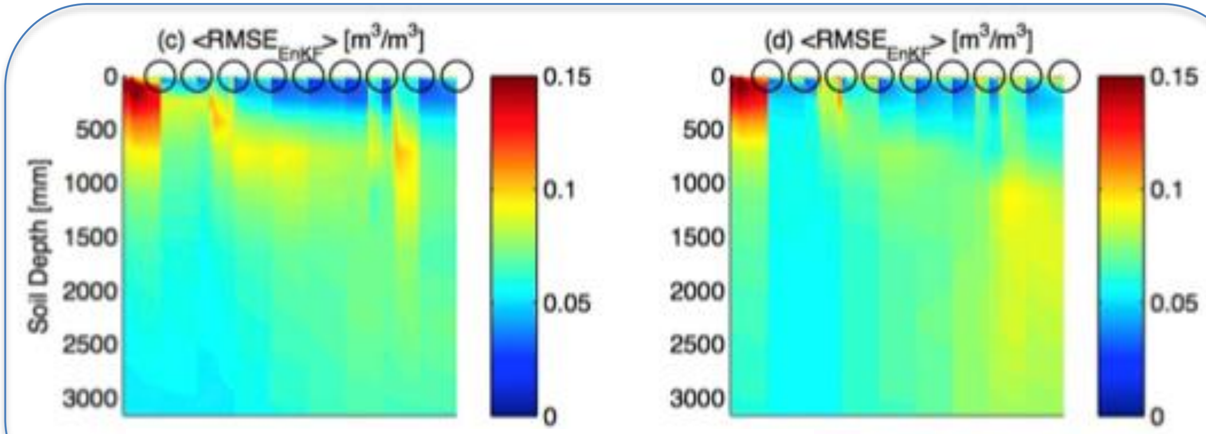
Filtering the observation **Modifying the model structure**



Brocca et al. 2012 (IEEE ToGRS)



Chen et al. 2011 (AWR)



Flores et al. 2012 (WRR)

4. Which is the impact of DA on the hydrological cycle?

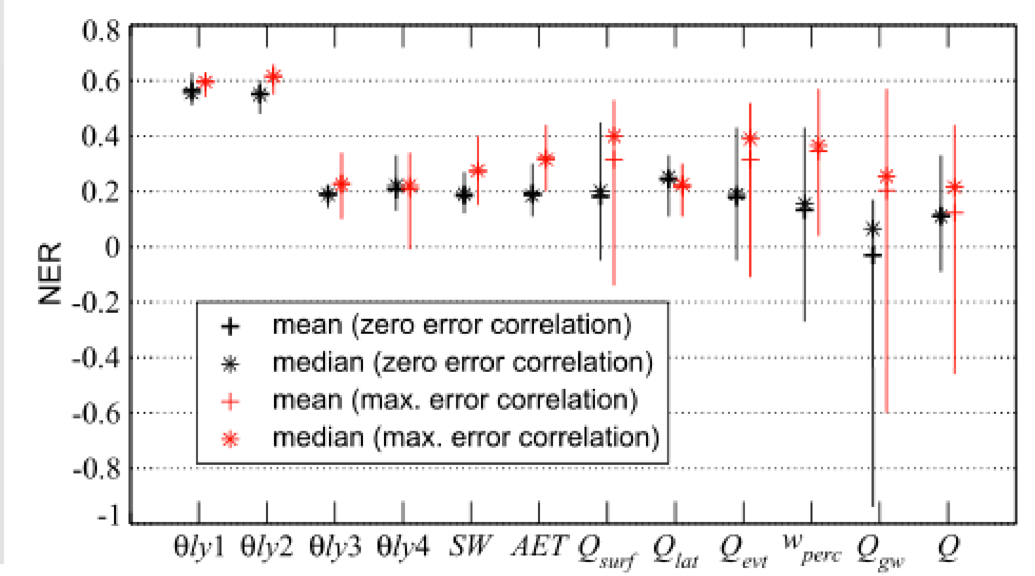
Many of the hydrologic DA studies reported in the literature focused on advancing the theoretical development of DA techniques using **synthetic experiments** (e.g., Andreadis et al., 2007; Kumar et al., 2009; Crow and Ryu, 2009).

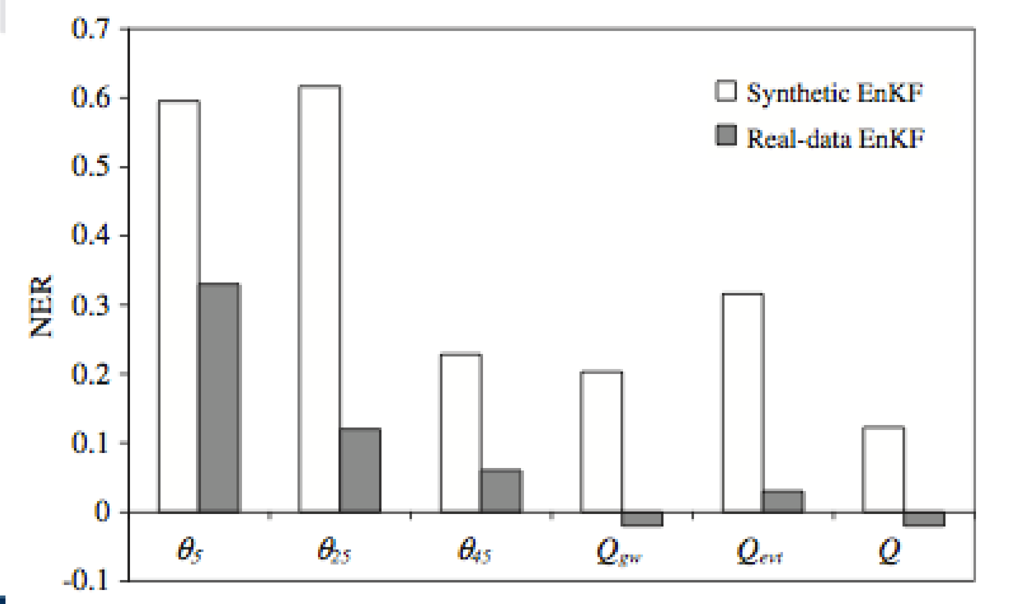
- diagnostic and design purposes such as assessing the impact of improper characterization of model and observation errors (e.g., Crow and Van Loon, 2006; Reichle et al., 2008
- evaluating the potential benefits of future satellite missions (e.g., Matgen et al., 2010)

Only a few formulated DA in an operational setting and attempted to evaluate the performance gain from DA in **real cases** (e.g., as a result of better characterized initial conditions) studies (e.g., Seo et al., 2003, 2009; Thirel et al., 2010; Weerts et al., 2010; DeChant and Moradkhani, 2011, Brocca et al. 2012)

> "There is a strong need to estimate soil moisture content through assimilating remotely sensed soil moisture **into a long-term, physically based distributed catchment scale hydrologic model**. Most of the previous studies that explored DA for runoff simulation used **conceptual rainfall-runoff models** (Aubert et al. 2003; Weerts and El Serafy, 2006; Crow and Ryu, 2009; van Delft et al. 2009) or **lumped models** (Jacobs et al 2003) or for short-term period with real measurements (Pauwels et al. 2001)". **Han et al. 2012**

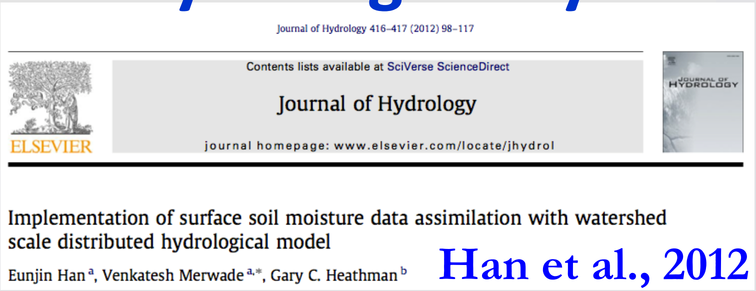
4. Which is the impact of DA on the hydrological cycle?





Chen et al. 2011 (AWR)

4. Which is the impact of DA on the hydrological cycle?



Journal of Hydrology 416–417 (2012) 98–117

Contents lists available at SciVerse ScienceDirect

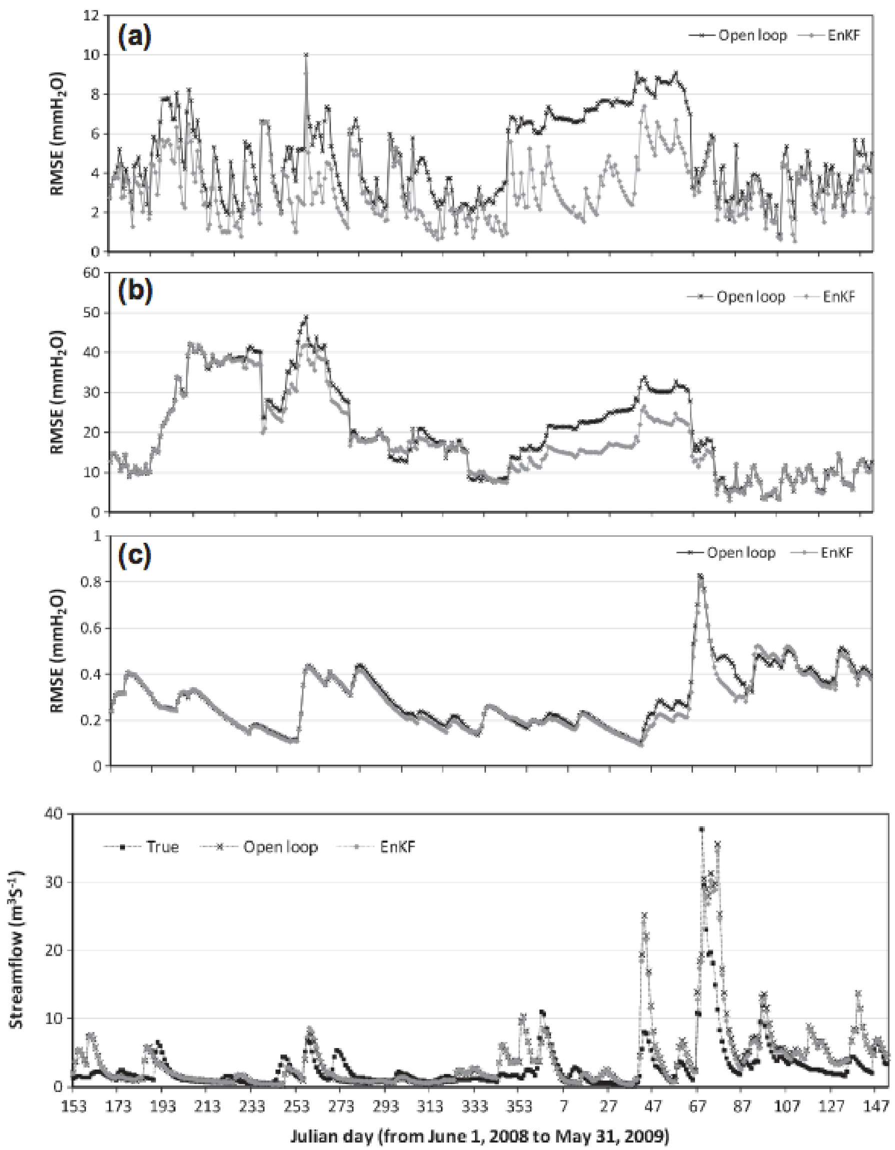
Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Implementation of surface soil moisture data assimilation with watershed scale distributed hydrological model

Eunjin Han [a], Venkatesh Merwade [a,*], Gary C. Heathman [b]

Han et al., 2012



Synthetic experiments using SWAT model Results of assimilation:

- great impact on soil moisture
- small impact on discharge
- impact on discharge is a function of soil type
- the capability of the SSM assim. for improving streamflow is constrained by the accuracy of precipitation

1) Model predicted antecedent soil moisture is less than the true soil moisture ($\theta_{predicted} < \theta_{true} \approx \theta_{EnKF}$) and current precipitation is overestimated.
2) Model predicted antecedent soil moisture is greater than the true soil moisture ($\theta_{predicted} > \theta_{true} \approx \theta_{EnKF}$) and current precipitation is overestimated.
3) Model predicted antecedent soil moisture is less than the true soil moisture ($\theta_{predicted} < \theta_{true} \approx \theta_{EnKF}$) and current precipitation is underestimated.
4) Model predicted antecedent soil moisture is greater than the true soil moisture ($\theta_{predicted} > \theta_{true} \approx \theta_{EnKF}$) and current precipitation is underestimated.

Continuum model

MAIN CHARACTERISTICS:

- Simple but complete description of Hydrological Cycle
  - Schematization of vegetation interception and water table
  - Tank schematization of overland and channel flows
- Mass Balance and Energy Balance completely solved
- Fully Distributed
- River network derived from a DEM
- Spatial-temporal evolution of:
  - Streamflow
  - Evapotranspiration
  - Vegetation retention
  - Land Surface Temperature
  - Soil Moisture
  - Water table

- It can be **calibrated using only satellite data** (e.g. surface temperature or soil moisture). Model suitable for application in data scarce environments

Hydrol. Earth Syst. Sci., 17, 39–62, 2013
www.hydrol-earth-syst-sci.net/17/39/2013/
doi:10.5194/hess-17-39-2013

Hydrology and Earth System Sciences

Exploiting remote sensing land surface temperature in distributed hydrological modelling: the example of the Continuum model

F. Silvestro[1], S. Gabellani[1], F. Delogu[1], R. Rudari[1], and G. Boni[1,2]
[1]CIMA research foundation, Savona, Italy
[2]DIBRIS, University of Genova, Genova, Italy
Correspondence to: F. Silvestro (francesco.silvestro@cimafoundation.org)

Received: 24 May 2012 – Published in Hydrol. Earth Syst. Sci. Discuss.: 14 June 2012
Revised: 12 December 2012 – Accepted: 20 December 2012 – Published: 11 January 2013

Silvestro et al., 2013

The model Fortran code is open and can be requested to: http://www.cimafoundation.org/cima-foundation/continuum/

Hydrol. Earth Syst. Sci. Discuss., 11, 6215–6271, 2014
www.hydrol-earth-syst-sci-discuss.net/11/6215/2014/
doi:10.5194/hessd-11-6215-2014

Hydrology and Earth System Sciences Discussions
Open Access

This discussion paper is/has been under review for the journal Hydrology and Earth System Sciences (HESS). Please refer to the corresponding final paper in HESS if available.

Uncertainty reduction and parameters estimation of a distributed hydrological model with ground and remote sensing data

F. Silvestro[1], S. Gabellani[1], R. Rudari[1], F. Delogu[1], P. Laiolo[1], and G. Boni[1,2]
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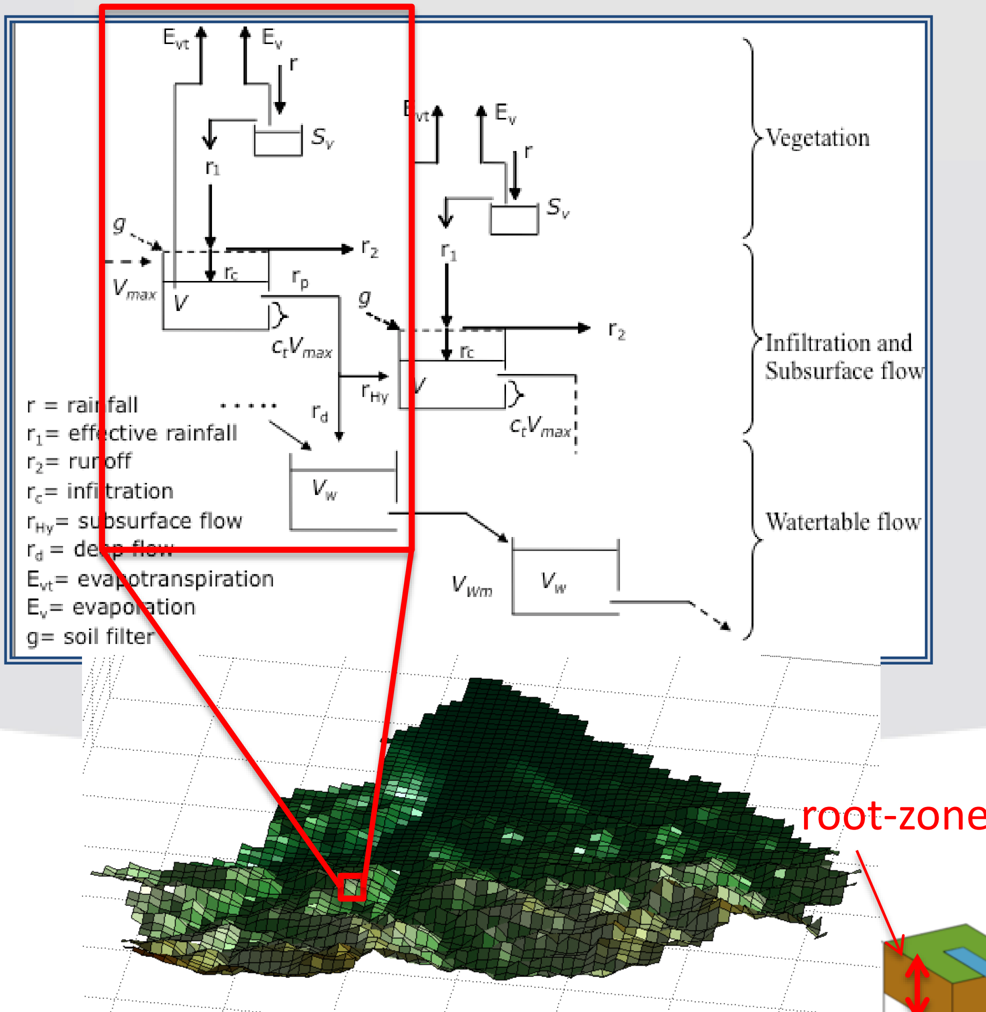
Received: 14 May 2014 – Accepted: 15 May 2014 – Published: 13 June 2014
Correspondence to: F. Silvestro (francesco.silvestro@cimafoundation.org)
Published by Copernicus Publications on behalf of the European Geosciences Union.

Silvestro et al., 2014

Continuum



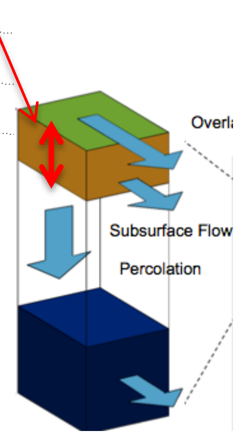
Saturation Degree of root zone

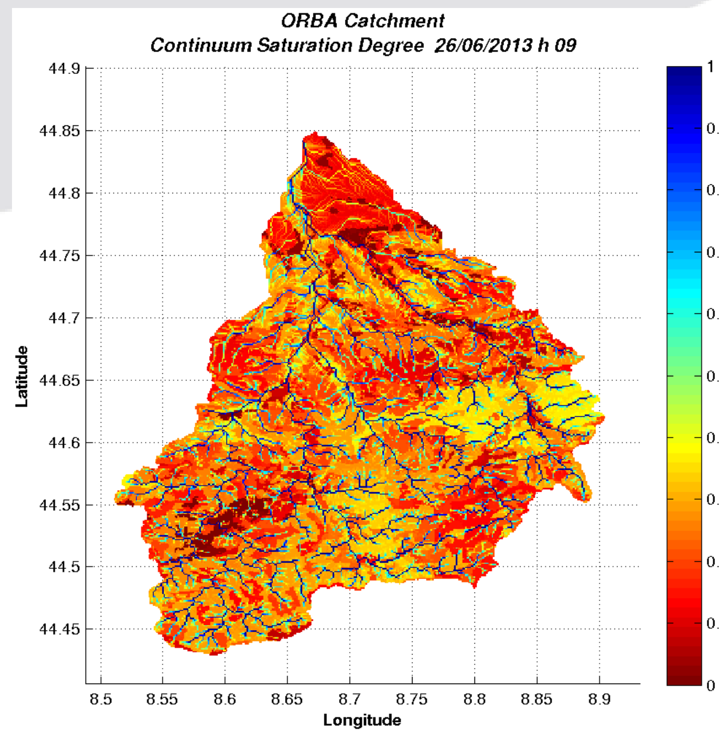
$$SD = \frac{V(t)}{V_{max}}$$

$0 £ SD £ 1$

V(t)= <u>Actual water volume</u>

V_{max}= <u>Max soil retention capacity</u> (related to soil type and land use through the CN)



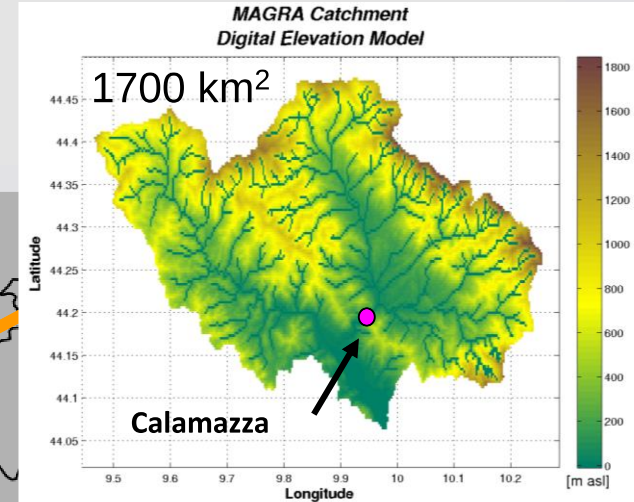


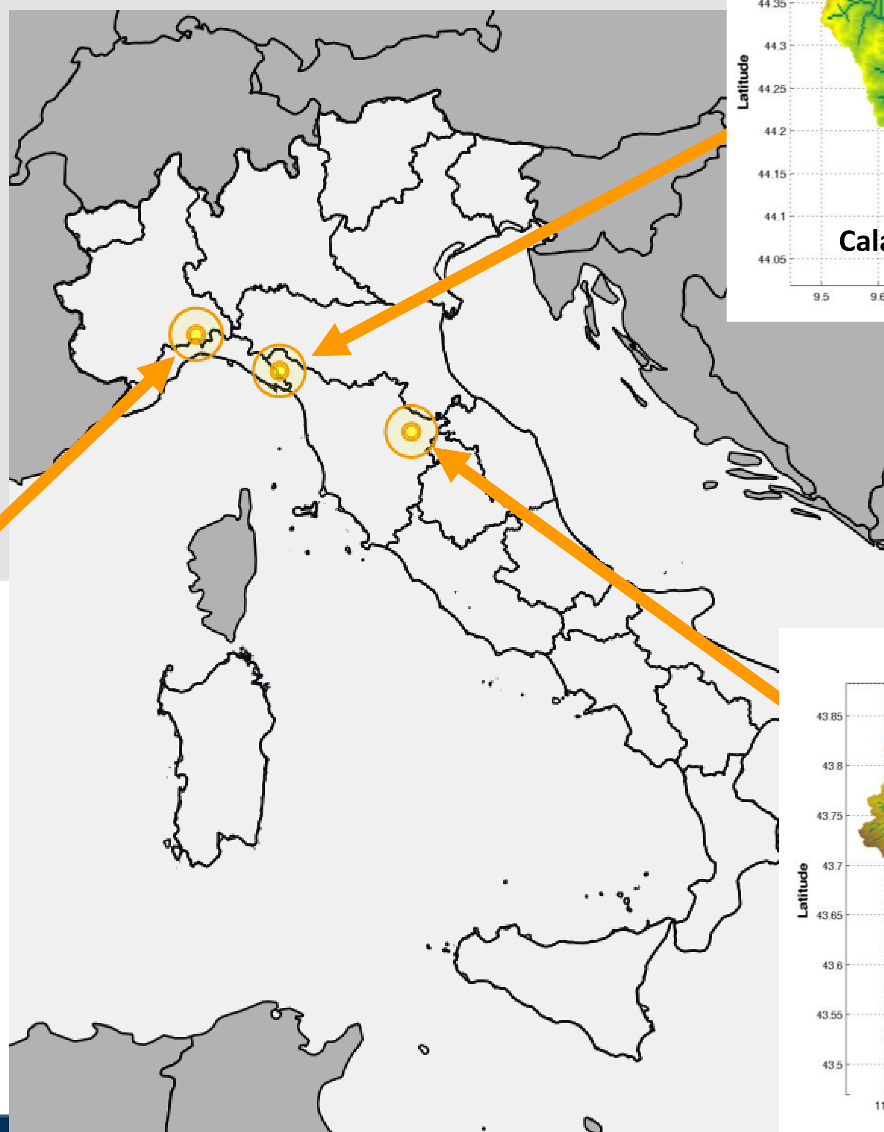
<u>Time frequency</u>: Hourly map

<u>Resolution</u>: 100 m

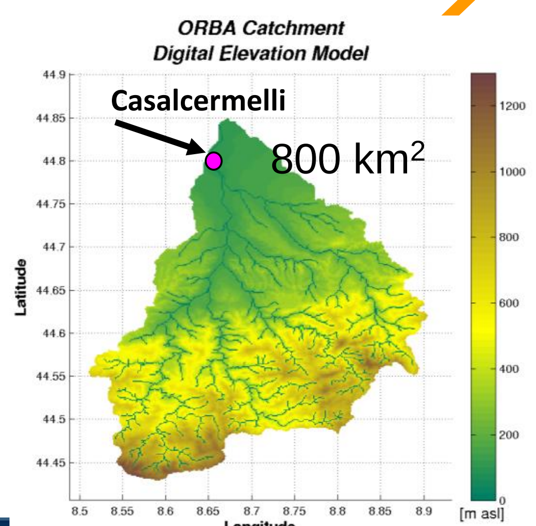
Italian test basins

MAGRA river

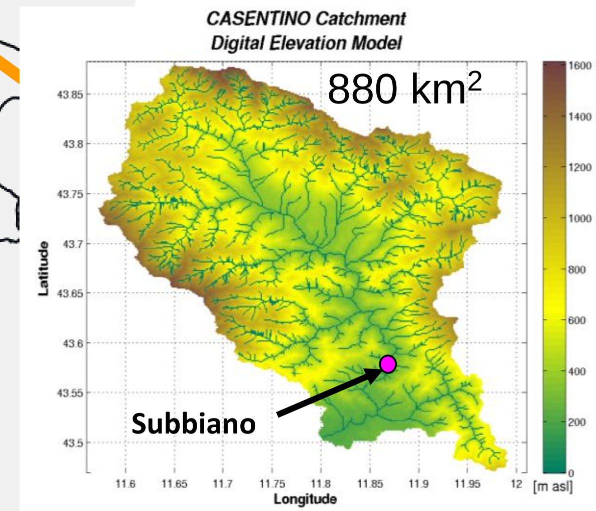




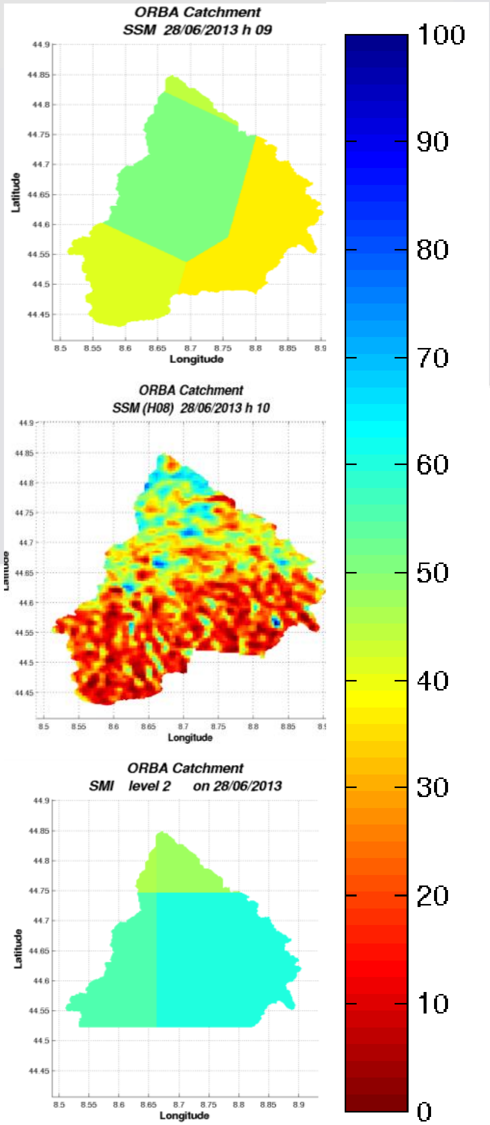
ORBA river



CASENTINO river



H-SAF Soil Moisture products



• SM-OBS-1 (H07)

Large-scale surface soil moisture (SSM) [-]

Time frequency: 2 maps per day, 1-2 days revisit time
Spatial coverage: Strips of 1000 km swath covering the whole globe
Resolution: 25 km

• SM-OBS-2 (H08)

Small-scale surface soil moisture (SSM) [-]

Time frequency: 2 maps per day, 1-2 days revisit time
Spatial coverage: Strips of 1000 km swath crossing the H-SAF area
Resolution: 1 km

• SM-DAS-2 (H14)

Profile Soil Moisture Index (SMI) in the roots region [-]

Time frequency: Daily map (at 00.00)
Spatial coverage: Globe
Horizontal resolution: 25 km
Vertical resolution: 4 layers (0-7 cm, **7-28 cm**, 28-100 cm, 100-289 cm)

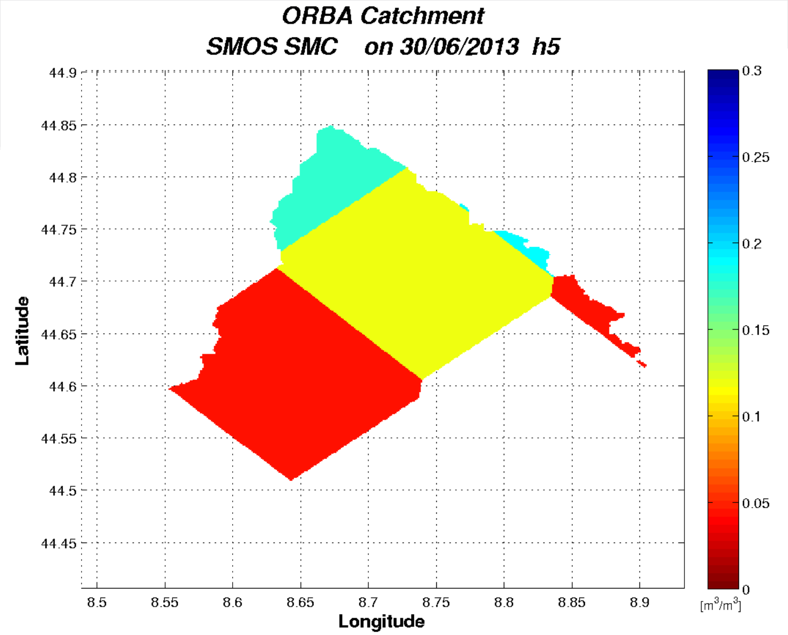
SMOS soil moisture product

- ## Level 2 Soil Moisture

volumetric soil moisture content (SMC) [m^3/m^3]

Time frequency: 2 maps per day, max 3 days revisit time

Spatial coverage: 600 km swath covering the whole globe
Resolution: 43 km in average, 35 km (centre of field of view)



Data Preparation

- Satellite soil moisture data **regridded** to Continuum grid using **nearest neighbour method**
- Assimilation of the **mornig passes** only
- Discarded H07 data with high quality flag
- Discarded SMOS data with DQX>=0.045 and RFI/200>1

Normalization:

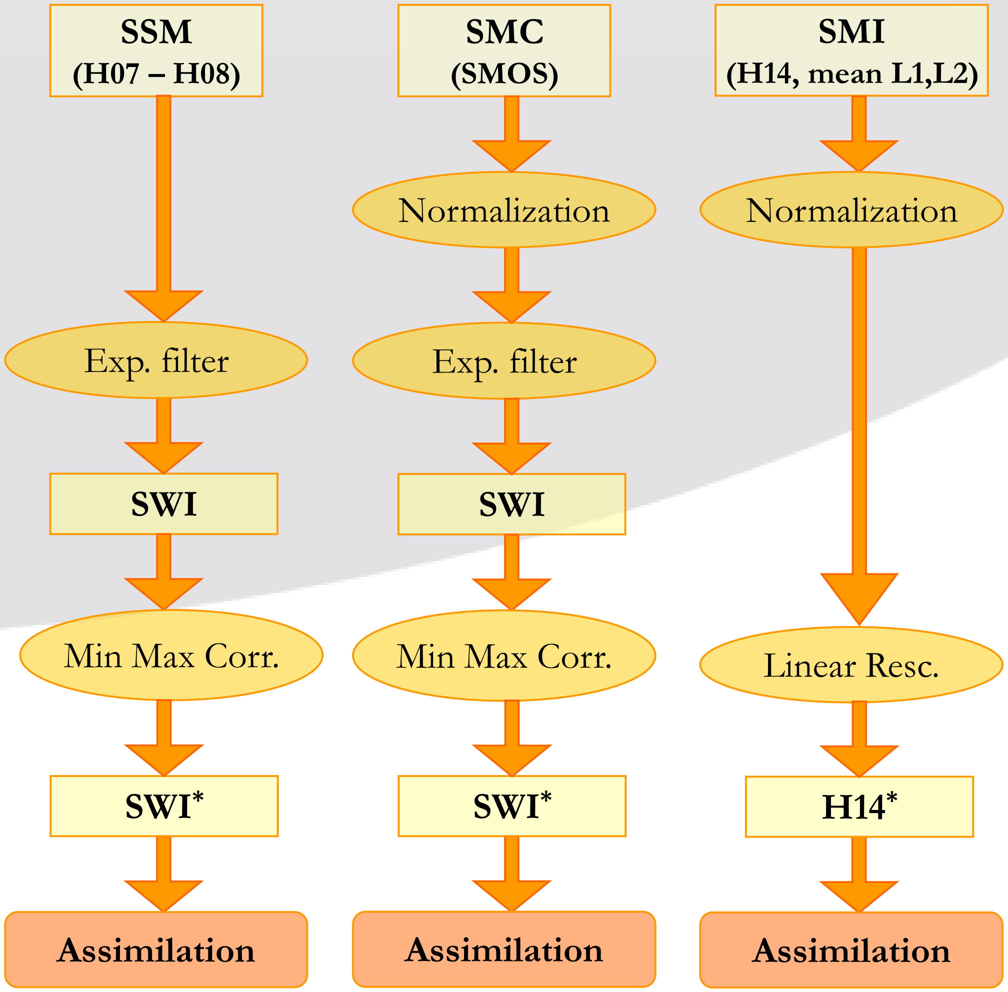
$$SAT_{norm} = \frac{SAT - \min(SAT)}{\max(SAT) - \min(SAT)}$$

Linear Rescaling (H14)

$$SAT^{*} = \frac{SAT - \mu(SAT)}{\sigma(SAT)} \cdot \sigma(SD_{\mathrm{mod}}) + \mu(SD_{\mathrm{mod}})$$

Min Max correction (H07, H08 and SMOS)

$$SAT^{*} = \frac{SAT - \min(SAT)}{[\max(SAT) - \min(SAT)]} \cdot [\max(SD_{\mathrm{mod}}) - \min(SD_{\mathrm{mod}})] + \min(SD_{\mathrm{mod}})$$



Assimilation in Continuum model

- Assimilation of the four SSM products

1. **Model scale →** Re-grid of Sat. data at model's resolution, filtering and bias handling and Assimilation

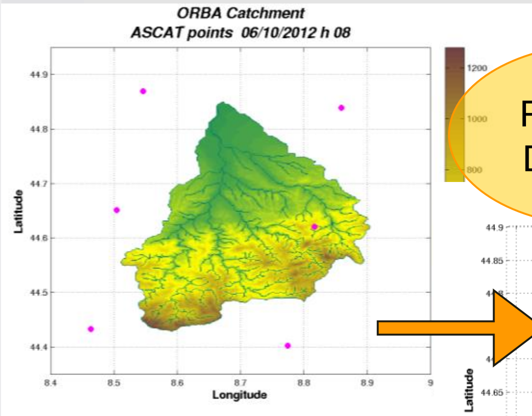
2. **Sat. scale →** Re-grid of Model's state at Sat. resolution, filtering and bias handling, Assimilation and then downscaling of assimilated state to model's resolution

Nudging

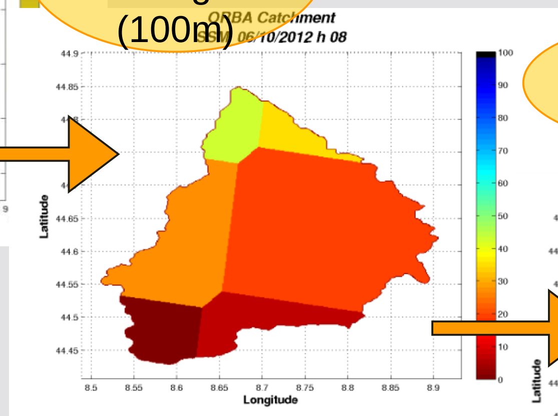
3. **Model scale →** Re-grid of Sat. data at model's resolution and Assimilation

Ensemble

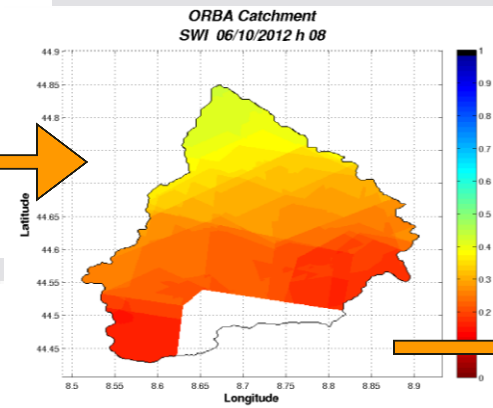
1. **Model Scale** → Re-grid of Sat. data at model's resolution and Assimilation



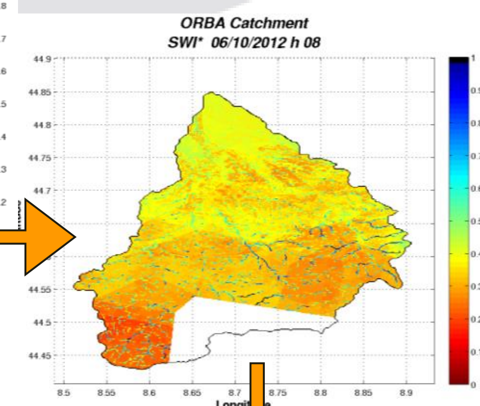
H07 Regrid on DEM grid (100m)



Data flag + Exp. Filter



MinMax correction

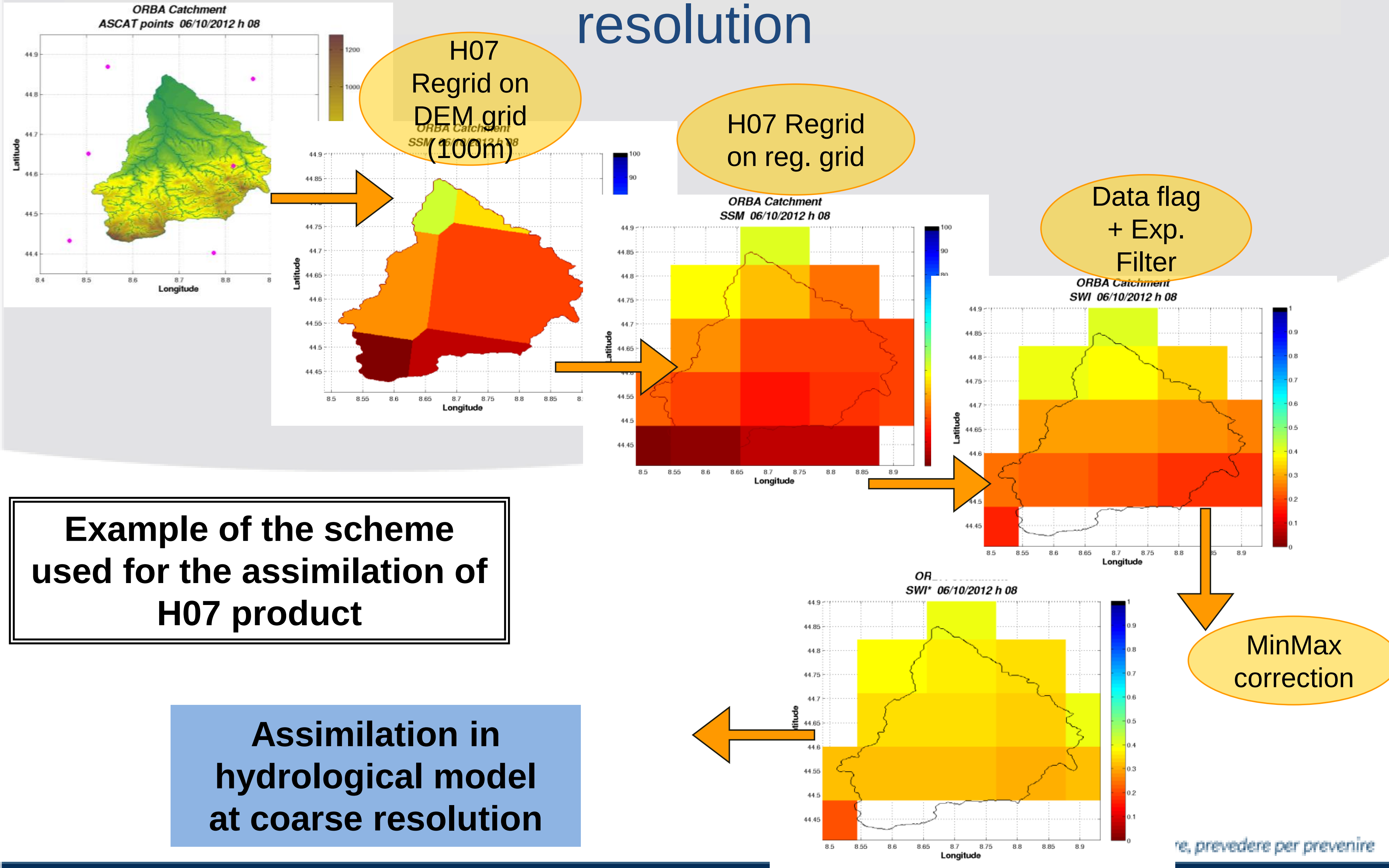


Assimilation in hydrological model

Example of the scheme used for the assimilation of H07 product

Osservare per prevedere, prevedere per prevenire

2. **Sat. Scale** → Re-grid of Model's state at Sat. resolution, Assim. and then downscaling to model's resolution



Example of the scheme used for the assimilation of H07 product

Assimilation in hydrological model at coarse resolution

1. **Model Scale** → Re-grid of Sat. data at model's resolution and Assimilation

$$\boxed{X^{+}_{\mathrm{mod}}(t) = X^{-}_{\mathrm{mod}}(t) + G \cdot \left[X_{obs}(t) - X^{-}_{\mathrm{mod}}(t)\right]}$$

Nudging assimilation scheme

X^{+}_{mod} = **New** Saturation Degree

X^{-}_{mod} = **Background modeled** Saturation Degree

X_{obs} = **Observed** Saturation Degree
- SWI* (H07, H08, SMOS)
- SMI* (H14)

No assimilation over urban areas and rivers

G = Gain

$$G = \frac{RMSD_{\mathrm{mod}}}{RMSD_{\mathrm{mod}} + RMSD_{obs}}$$

$RMSD_{\mathrm{mod}}$ = **Root Mean Square Difference** of X^{-}_{mod} = 0.092

(Estimated from a study over modeled soil moisture outputs)

$RMSD_{\mathrm{obs}}$ = **Root Mean Square Difference** of X_{obs}

- **$RMSD_{H14}$**: 0.22 [-]
  (SOURCE: Albergel validation work presented during H-SAF meeting in Budapest 2013)
- **$RMSD_{SWI.HSAF}$**: 0.12 [-] for H07 and H08
  (SOURCE: Brocca et al. 2011)
- **$RMSD_{SWI.SMOS}$**: 0.24 [-]
  (SOURCE: Albergel et al. 2012)

Nudging assimilation scheme

Satellite scale

$$X^{+}_{\text{mod}}(t) = X^{-}_{\text{mod}}(t) + S \times R \times G \cdot \left[X_{obs}(t) - H \times X^{-}_{\text{mod}}(t) \right]$$

X^{+}_{mod} = **New** Saturation Degree

X^{-}_{mod} = **Background modeled** Saturation Degree

X_{obs} = **Observed** Saturation Degree → SWI* (H07. H08. SMOS) / SMI* (H14)

G = **Gain** value

$$G = \frac{RMSD_{\text{mod}}}{RMSD_{\text{mod}} + RMSD_{obs}}$$

G = 0.3 (H14)
G =0.43 (H07 and H08)
G = 0.28 (SMOS)

H = **Observation operator** (allow to obtain the map at 12.5 km resolution from that at 100 m resolution)

R = **Regrid operator** (allow to obtain the map at 100 m resolution from that at 12.5 km resolution)

S = **Spatialization operator** (allow to redistribute the correction on the 100 m grid. The correction depends on the ratio between the value of X^{-}_{mod} at each 100 m pixel and the mean soil moisture value at the corresponding 12.5 km pixel)

Bayesian assimilation scheme

Model scale

$$SD_{ass}(t) = \langle SD | SD_{obs} \rangle = \left(P^{-1} \cdot m + R^{-1} \cdot SD_{obs}\right) \cdot \left(P^{-1} + R^{-1}\right)^{-1}$$

SD_{ass}= **Posterior mean** of Saturation Degree

$SD_{mod}(t)$ = **Modeled** Saturation Degree

$SD_{obs}(t)$ = **Observed** Saturation Degree → SWI, SMI (H-14)

R = **Variance of** SD_{oss} = 0.04 (assumption)

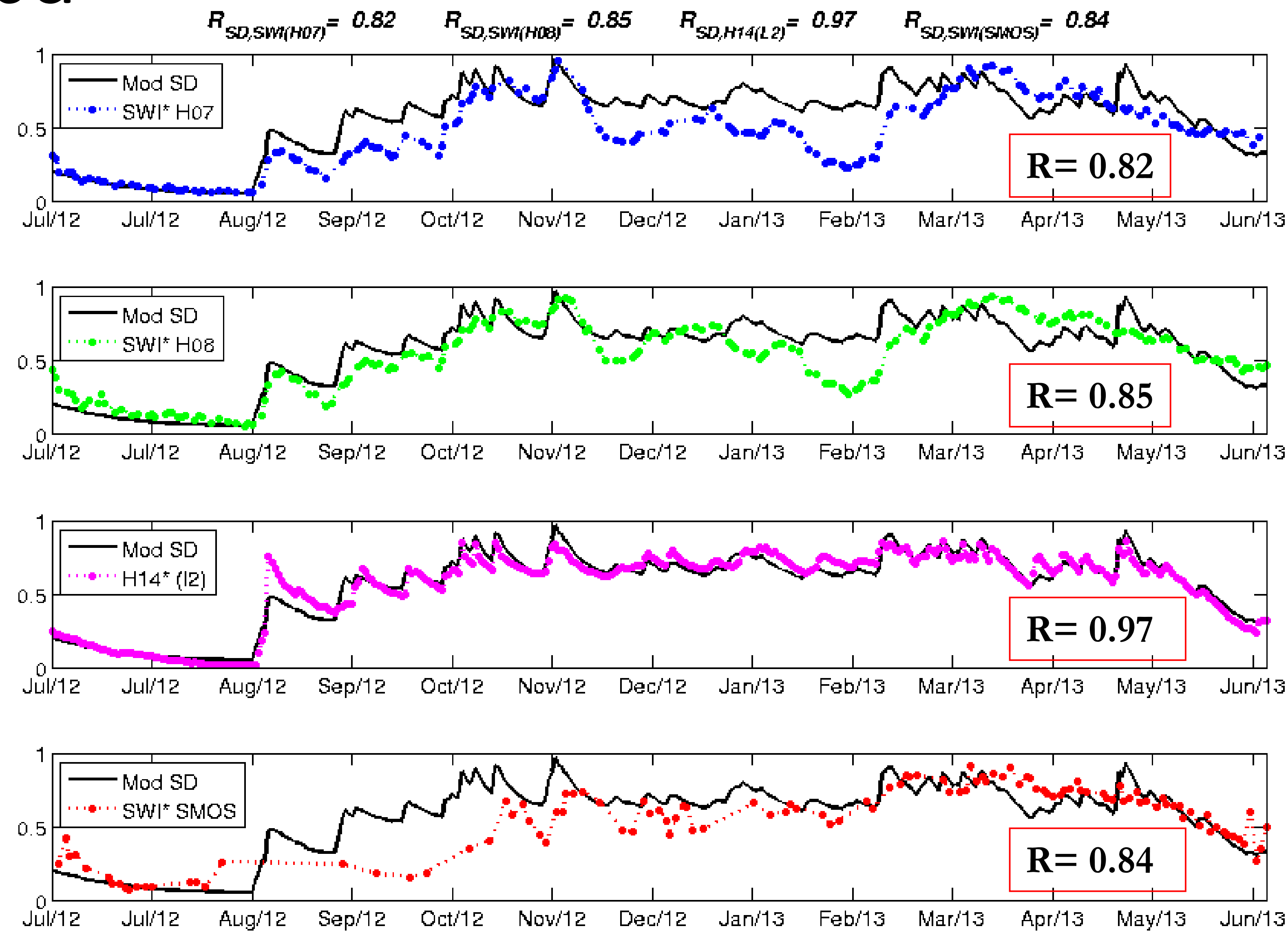
m = **Expected value of** SD_{mod} → $m(t) = \frac{1}{N}\sum_{i=1}^{N} SD_{\mathrm{mod},i}(t)$ **N = 20 parameters sets**

P = **variance of** SD_{mod} → $P(t) = \sigma^2[SD_{\mathrm{mod}}] = \frac{1}{N-1}\sum_{i=1}^{N}\left[\left(SD_{\mathrm{mod},i}(t) - m(t)\right)^2\right]$

Soil moisture basin scale comparison

Orba

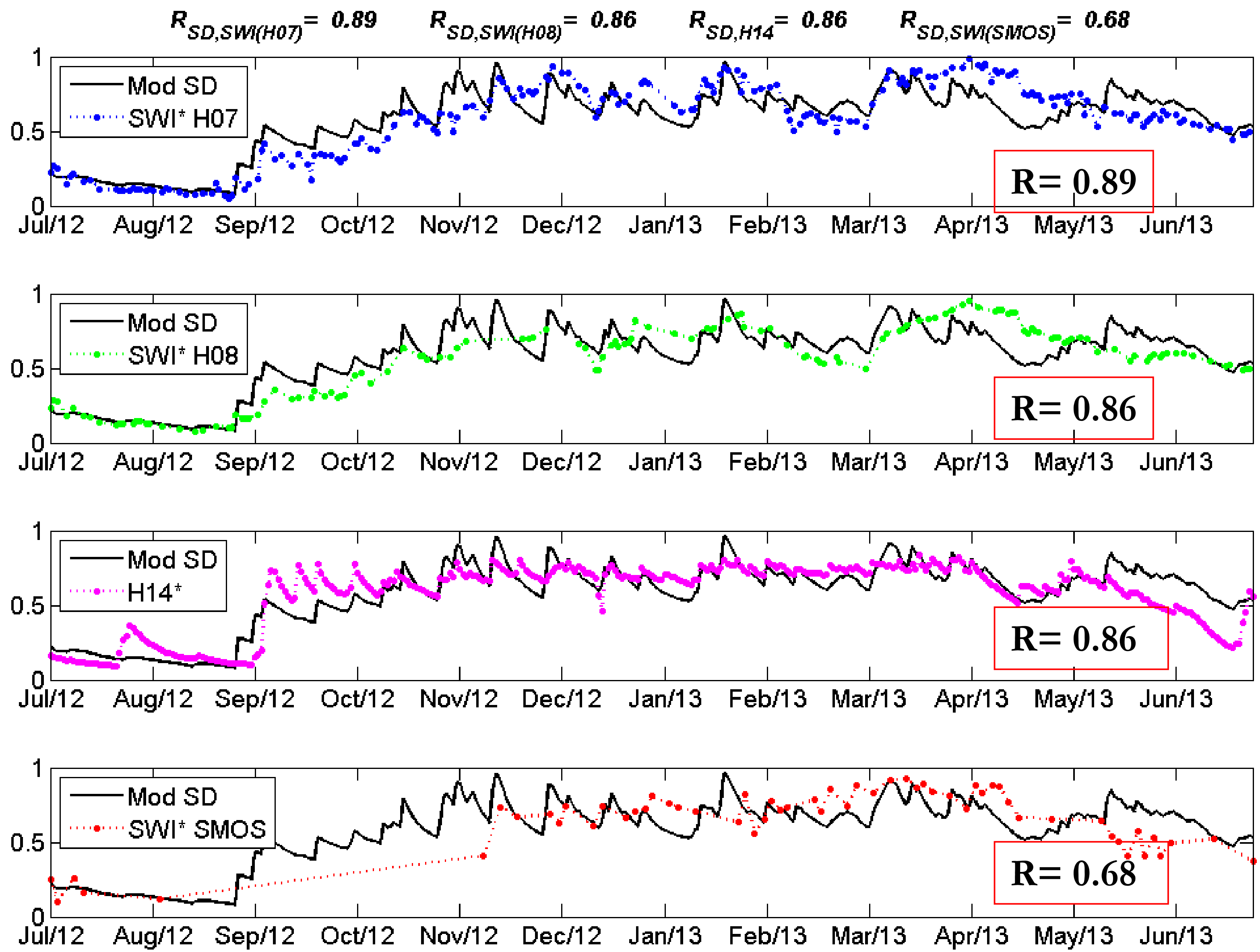
Period: July 2012 – June 2013



Soil moisture basin scale comparison

Casentino

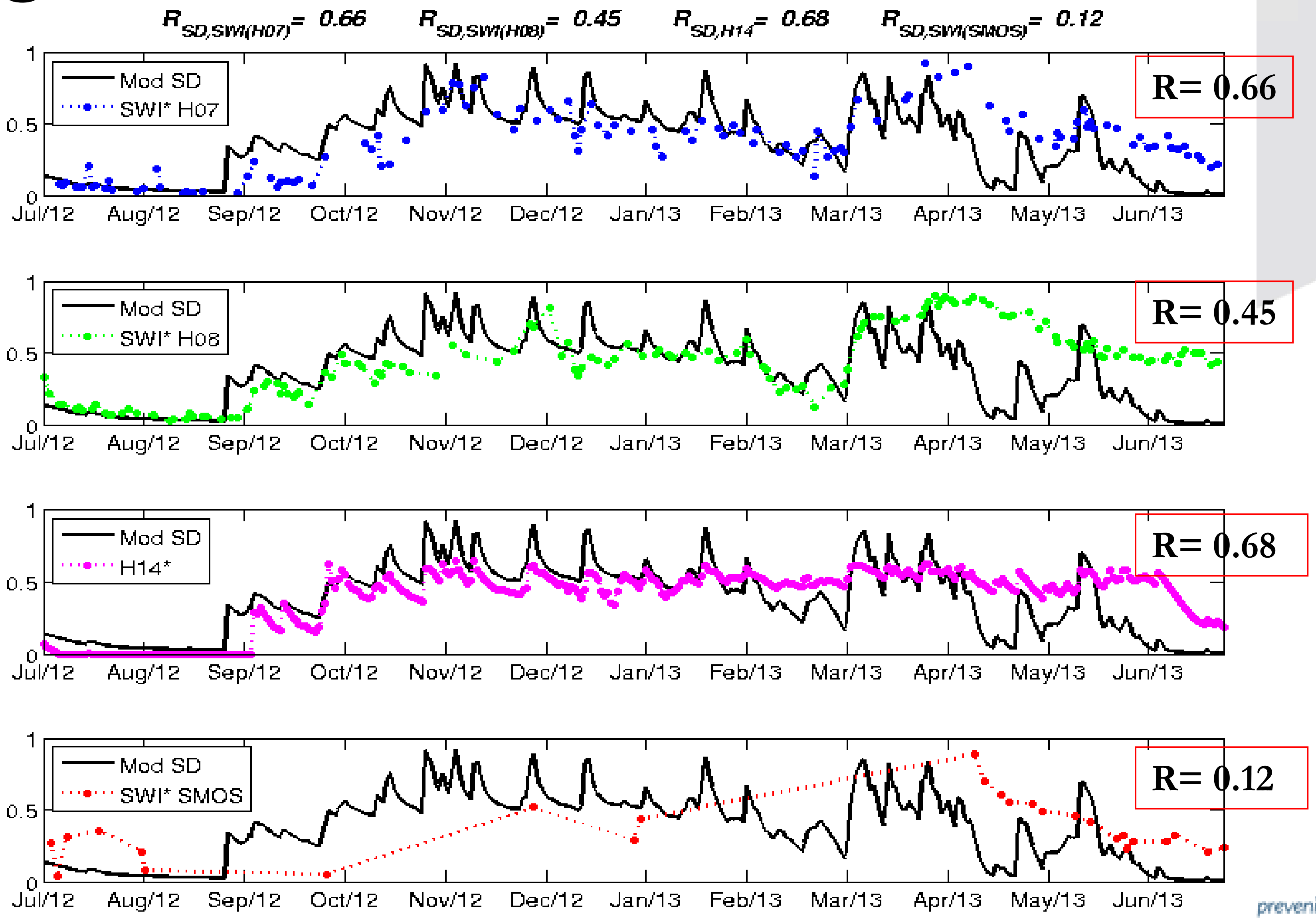
Period: July 2012 – June 2013



Soil moisture basin scale comparison

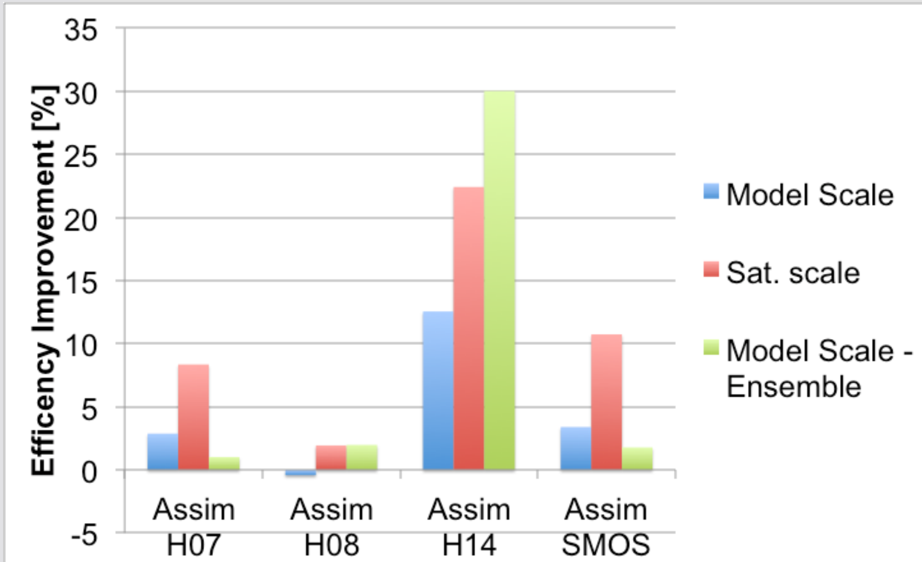
Magra

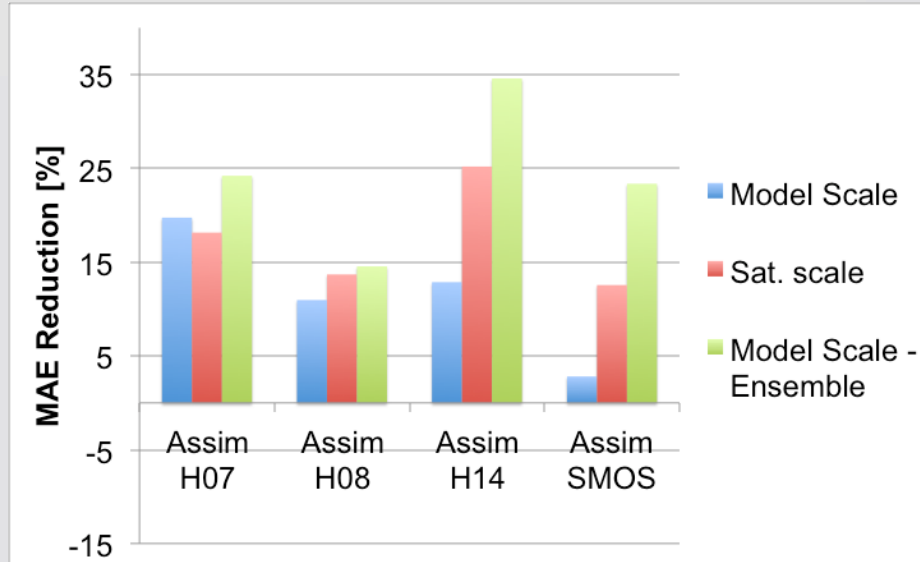
Period: July 2012 – June 2013

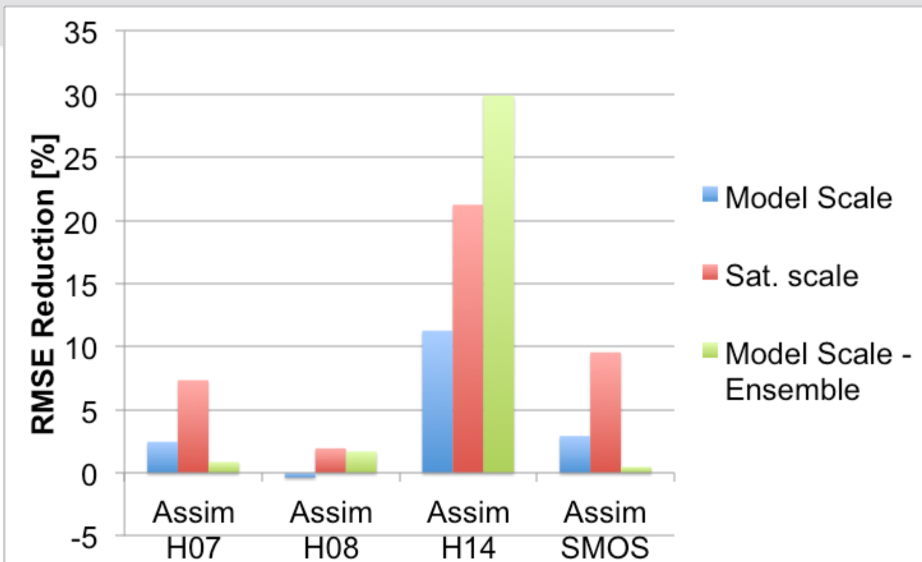


prevenire

Annual results - Orba







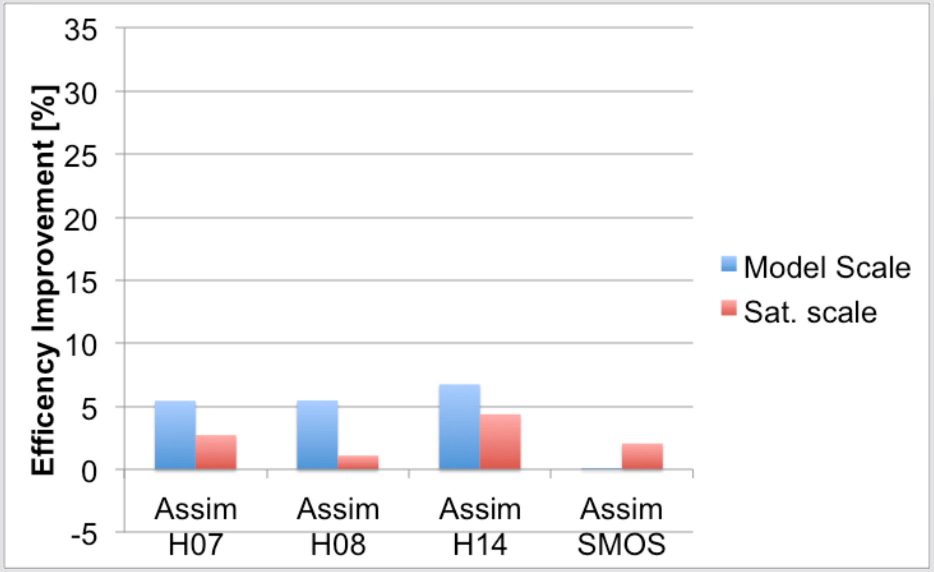
E_{OL} = 0.63
MAE = 17.4 [m^3/s]
RMSE = 25.3 [m^3/s]

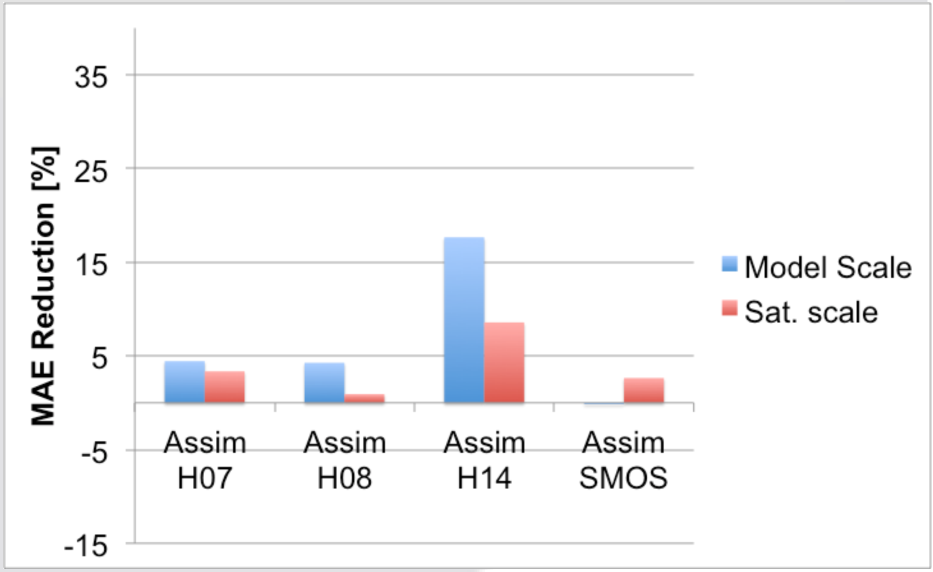
$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Qs_i - Qo_i\right| \qquad RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Qs_i - Qo_i\right)^2}$$

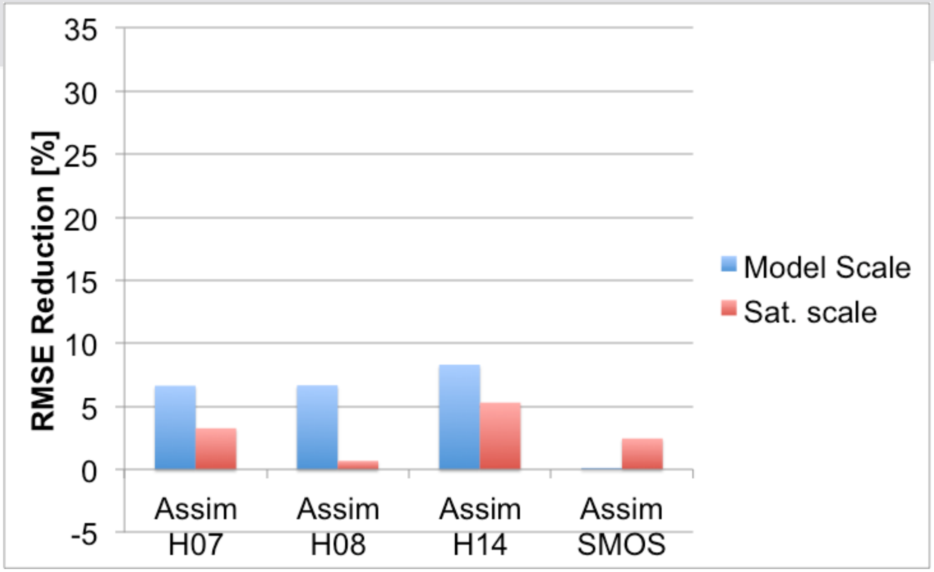
$$E = 1 - \frac{\sum_{i=1}^{n}\left(Qo_i - Qs_i\right)^2}{\sum_{i=1}^{n}\left(Qo_i - \overline{Qo}\right)^2}$$

Q_{si} – simulated values
Q_{oi} – observed value

Annual results - Casentino

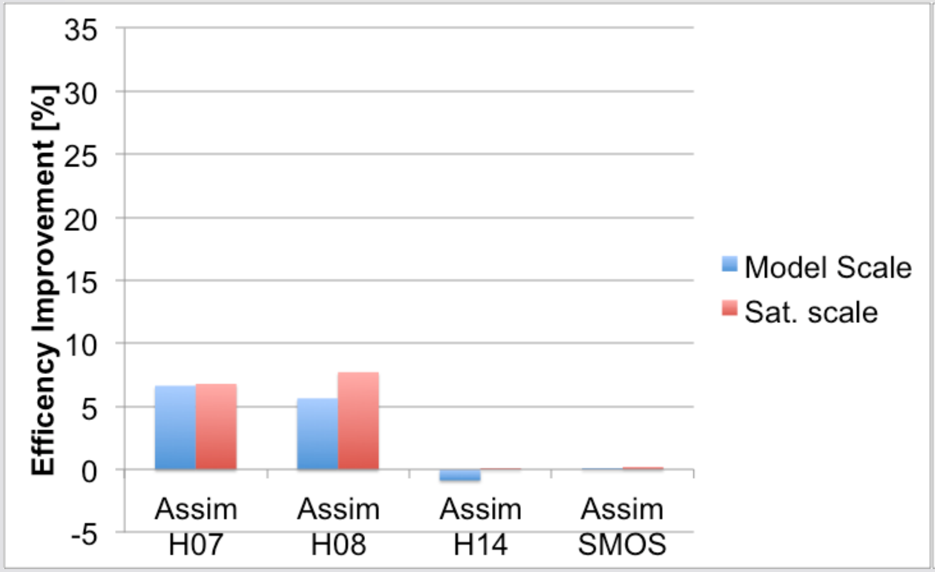


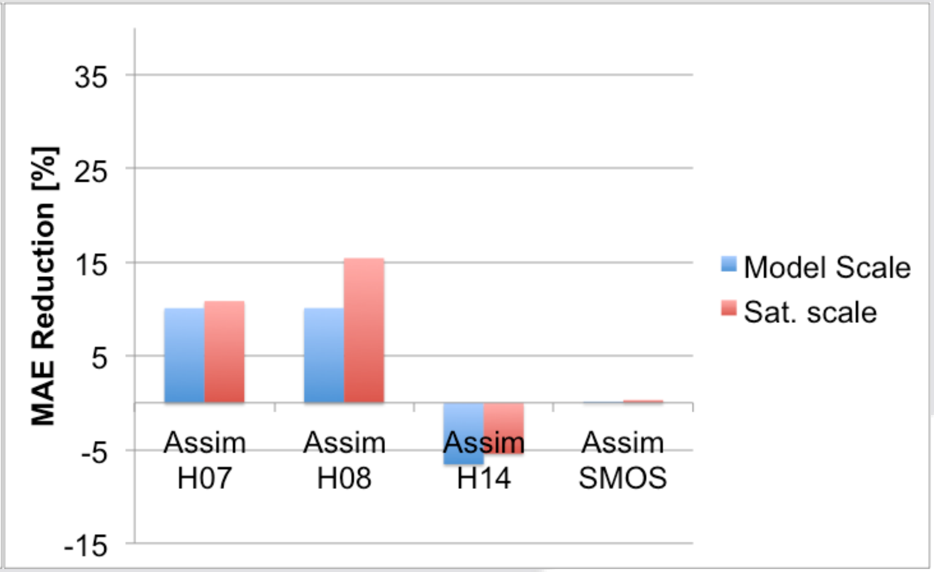


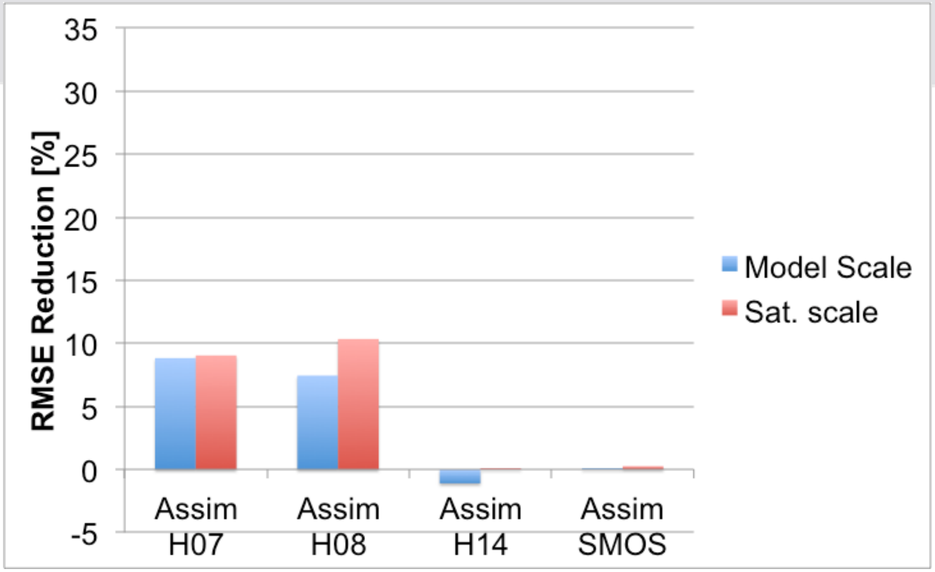


E_{OL} = 0.70
MAE = 14.3 [m^3/s]
RMSE = 21.6 [m^3/s]

Annual results - Magra



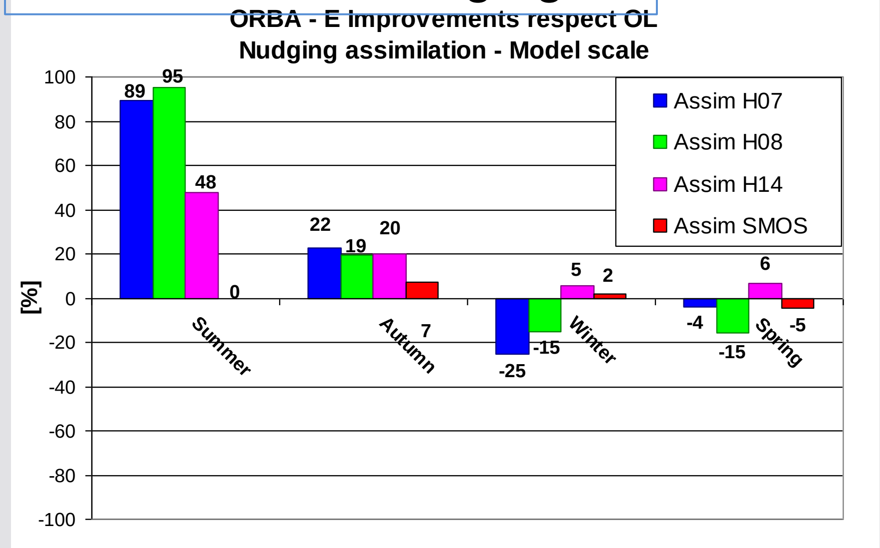




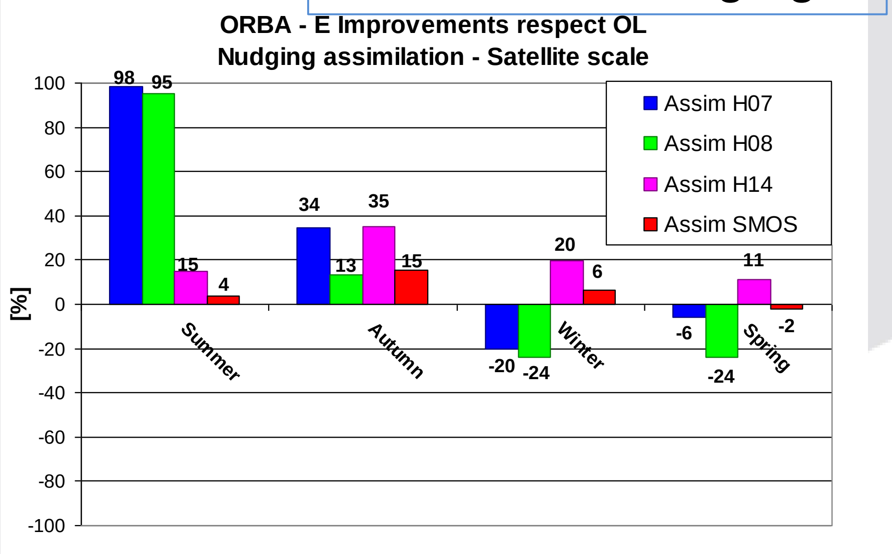
E_{OL} = 0.72
MAE = 28.4 [m^3/s]
RMSE = 46.7 [m^3/s]\

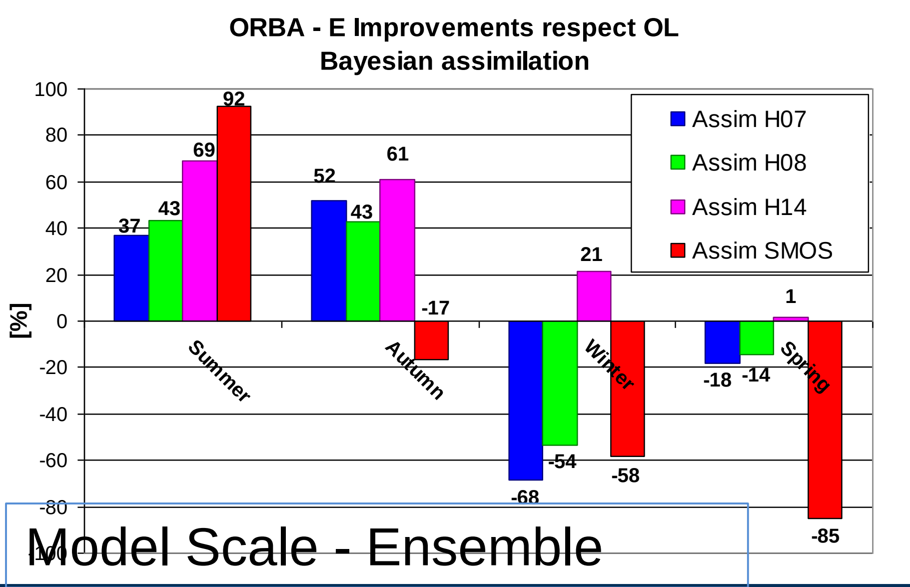
Seasonal results - Orba

Model Scale - Nudging



Sat. Scale - Nudging

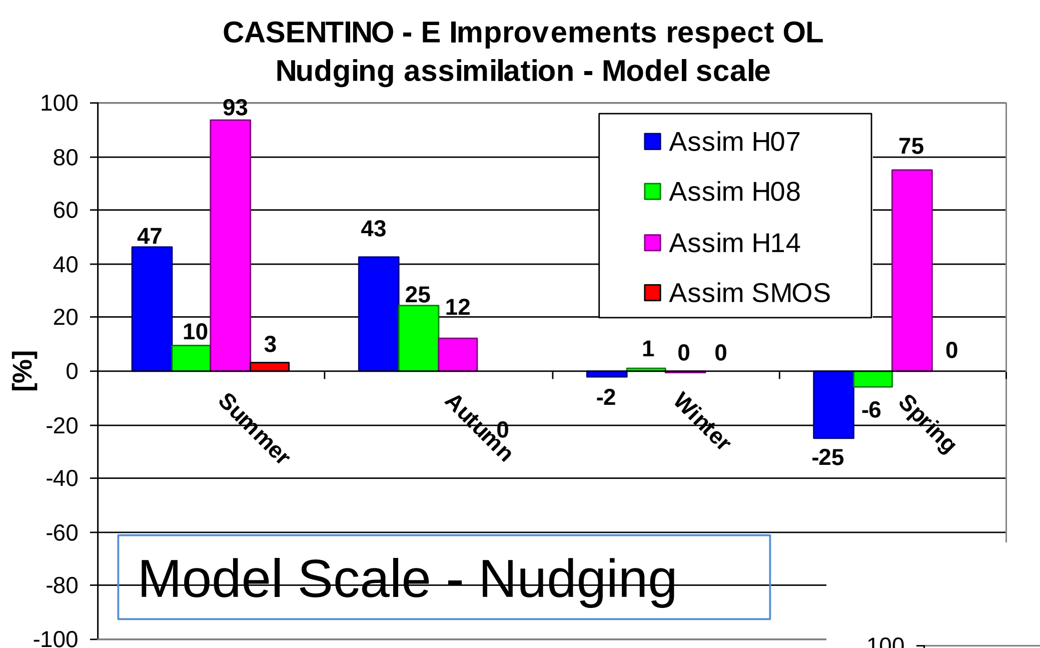




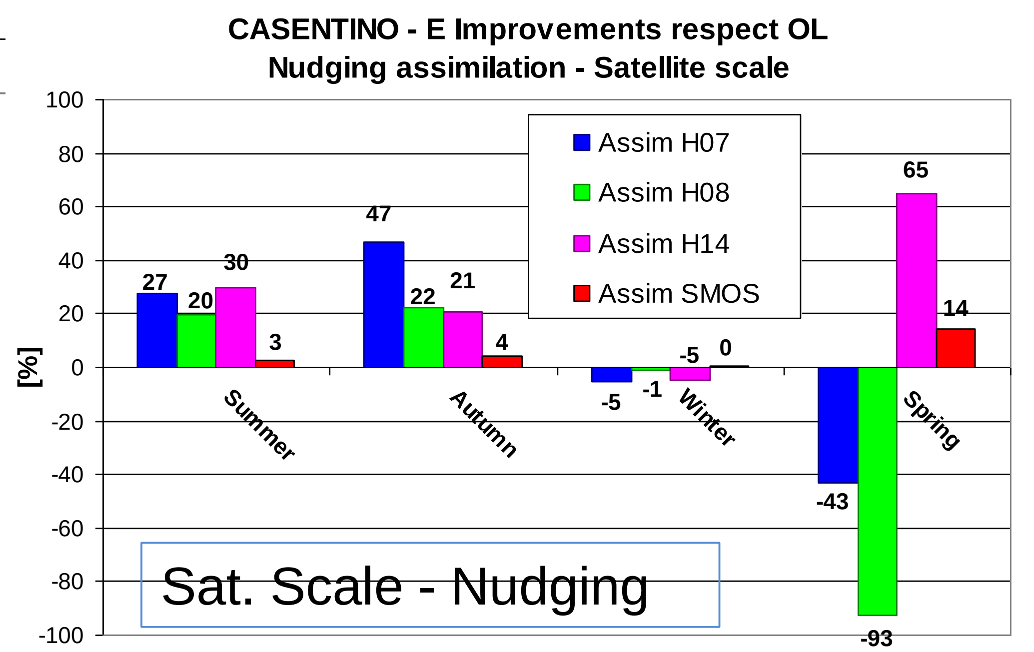
Model Scale - Ensemble

Summer	Autumn	Winter	Spring
-2.64	0.57	0.52	0.78

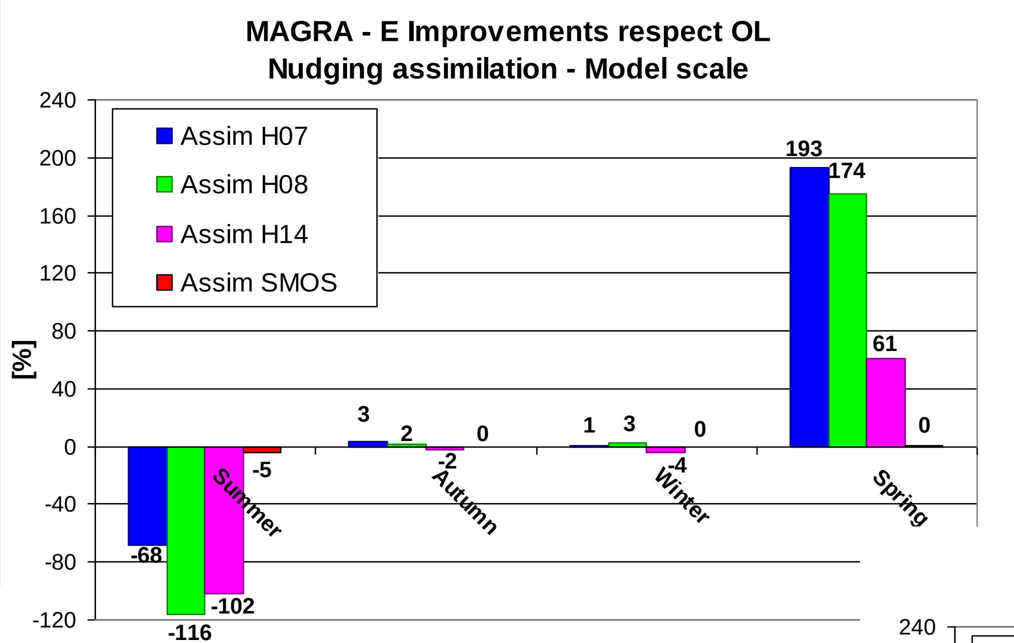
Seasonal results - Casentino



Summer	Autumn	Winter	Spring
-1.50	0.50	0.86	-0.64

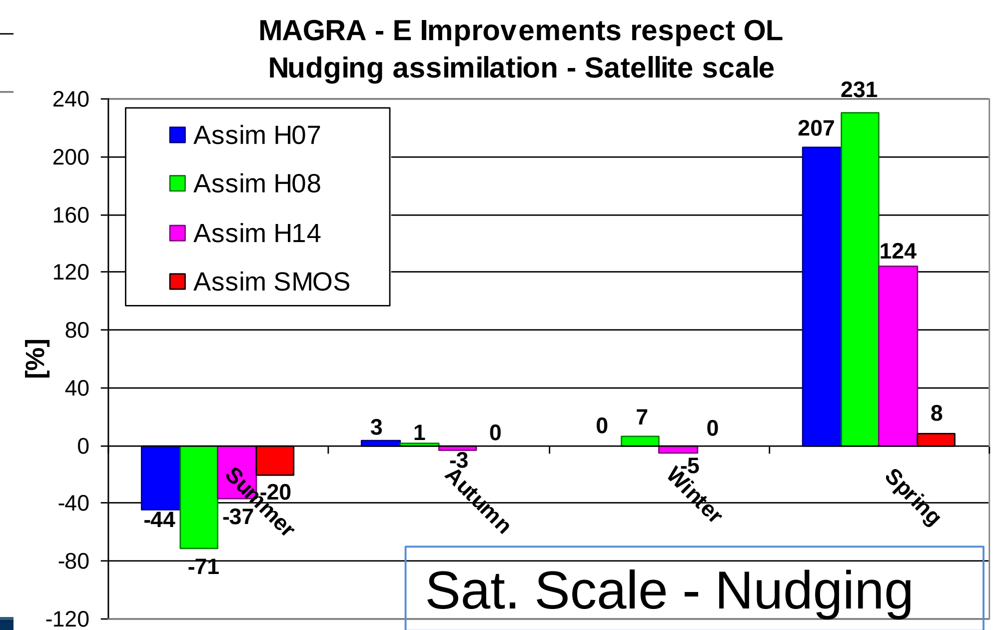


Seasonal results - Magra



Model Scale - Nudging

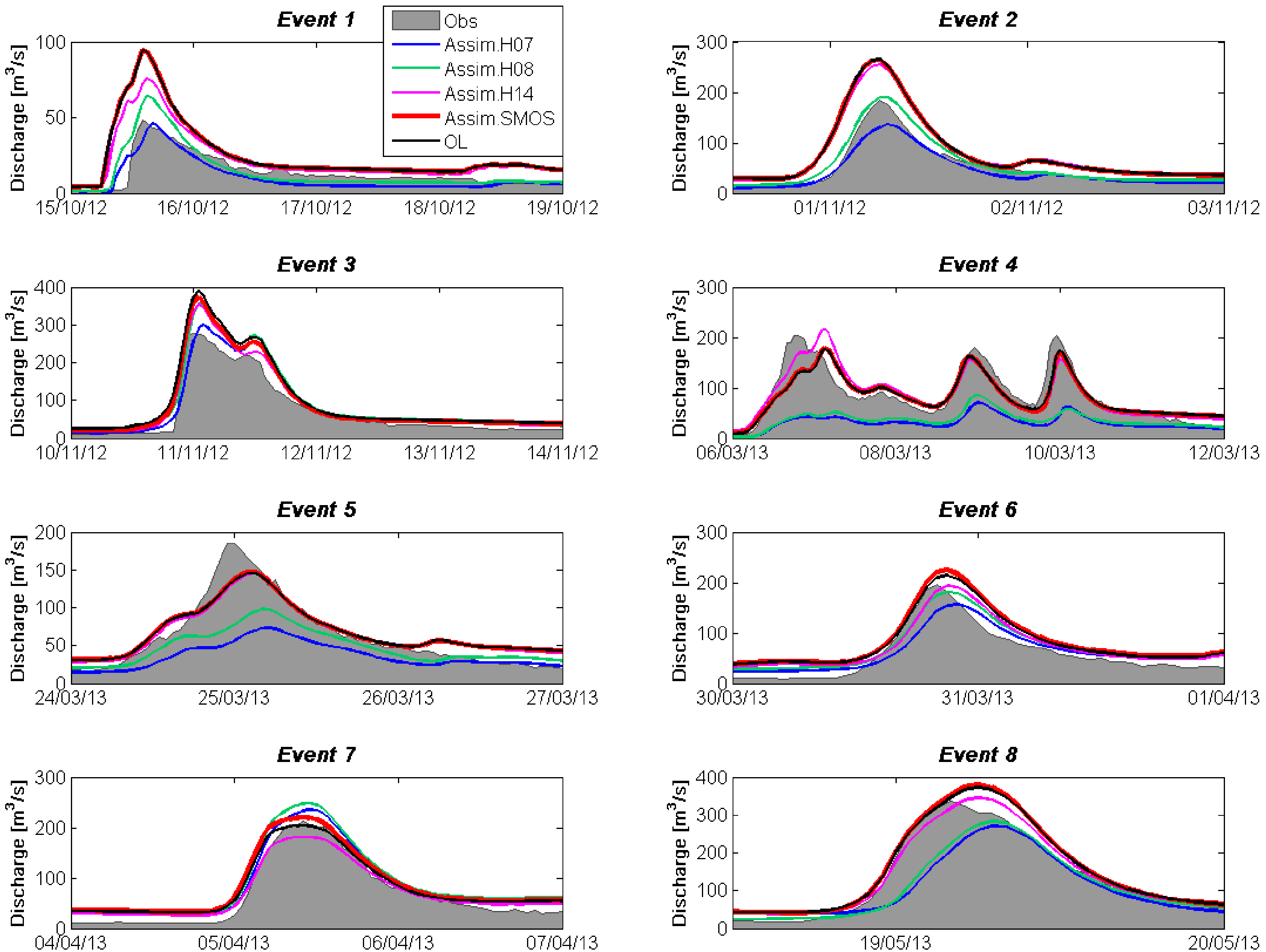
Summer	Autumn	Winter	Spring
-0.18	0.84	0.60	0.24



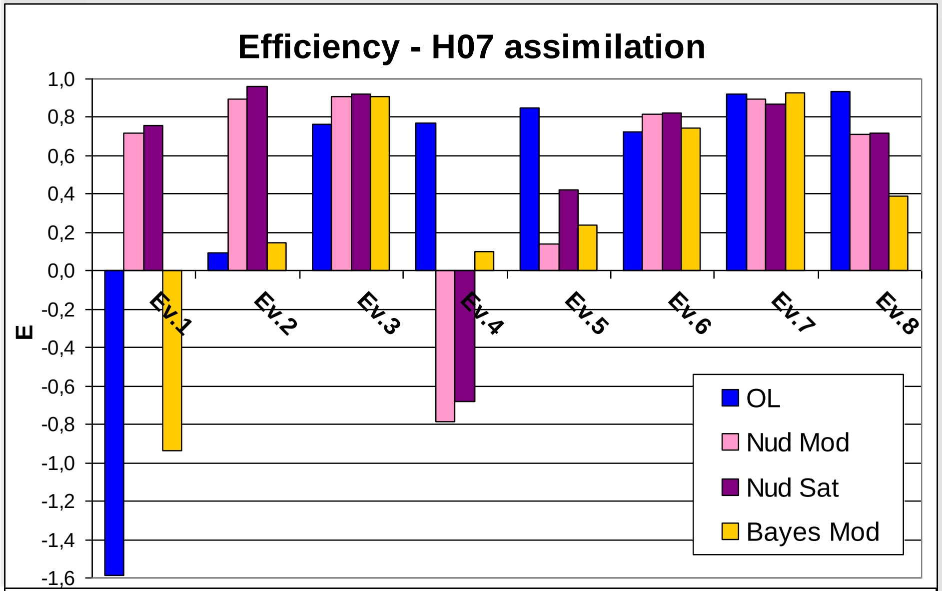
Sat. Scale - Nudging

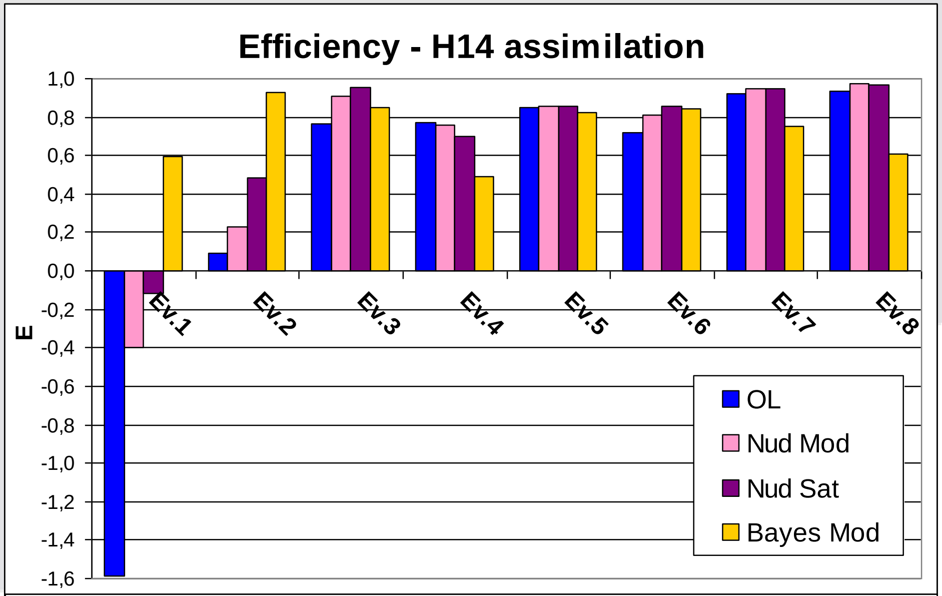
Discharge events results - Orba

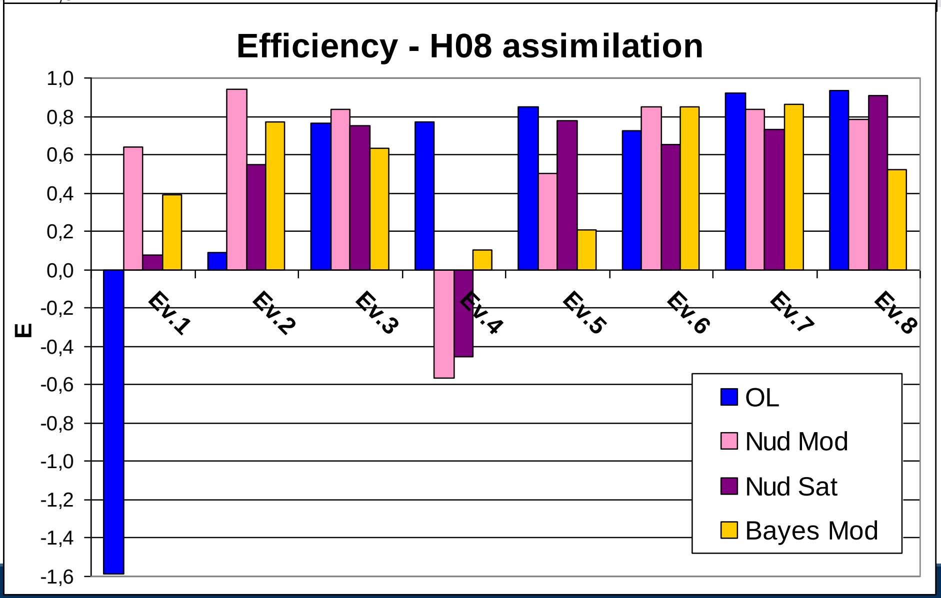
Nudging – Model scale

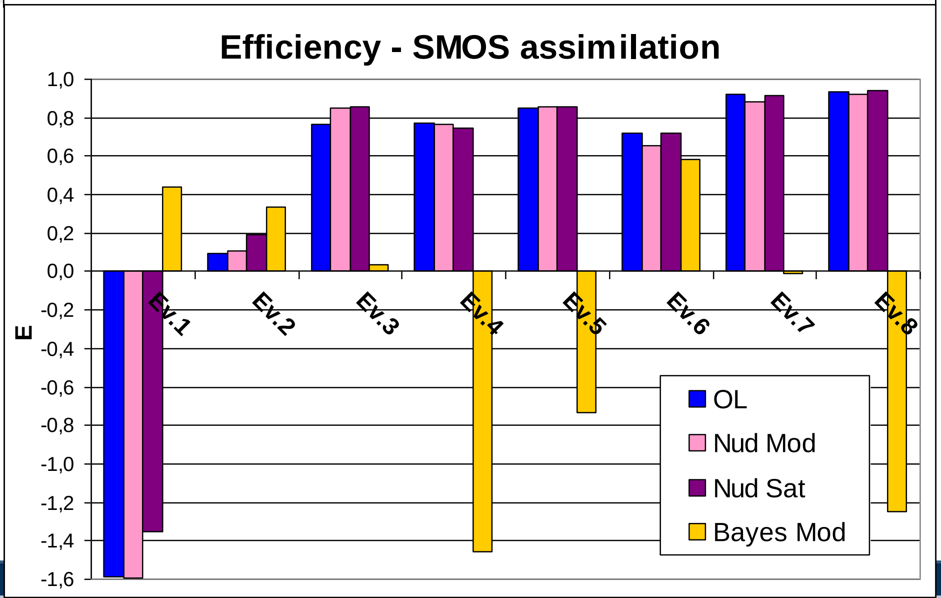


Discharge events results - Orba



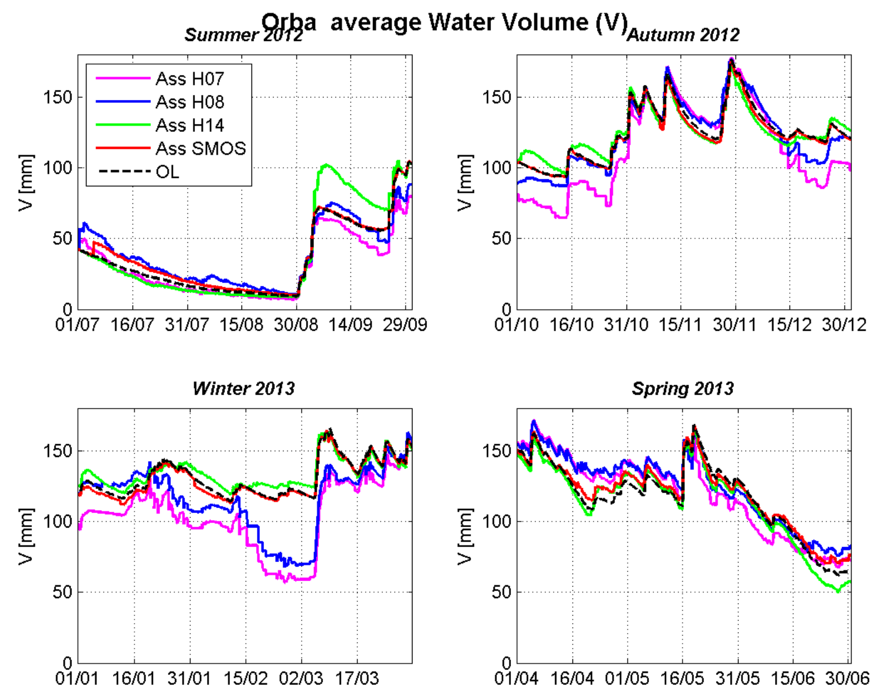


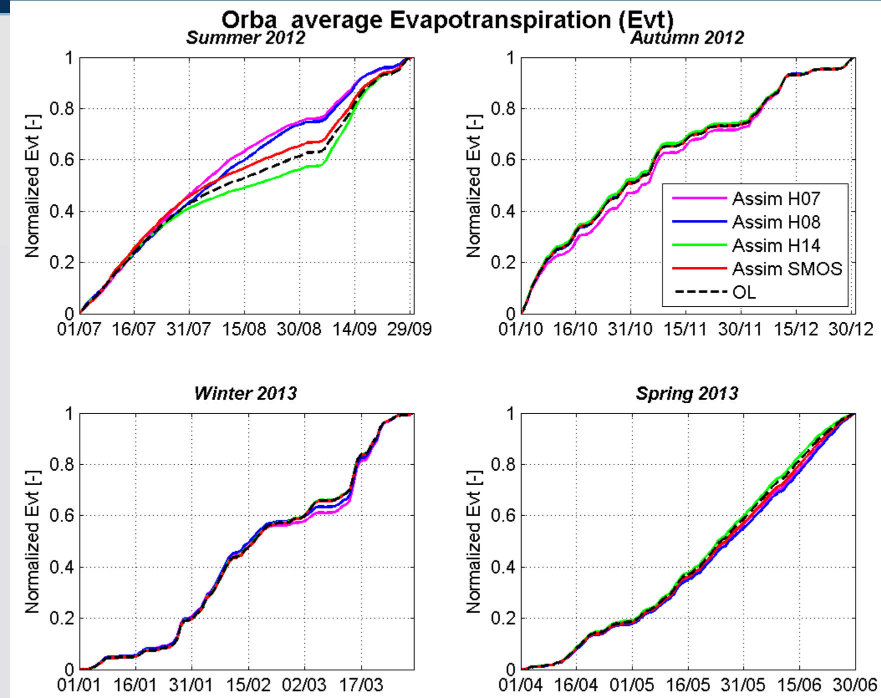


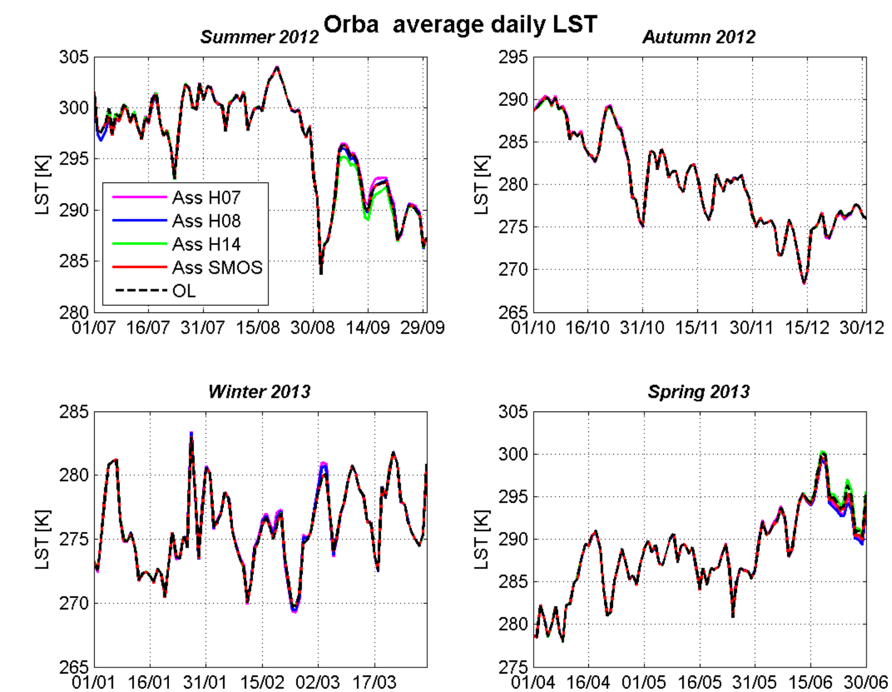


Impact of assimilation on other state variables

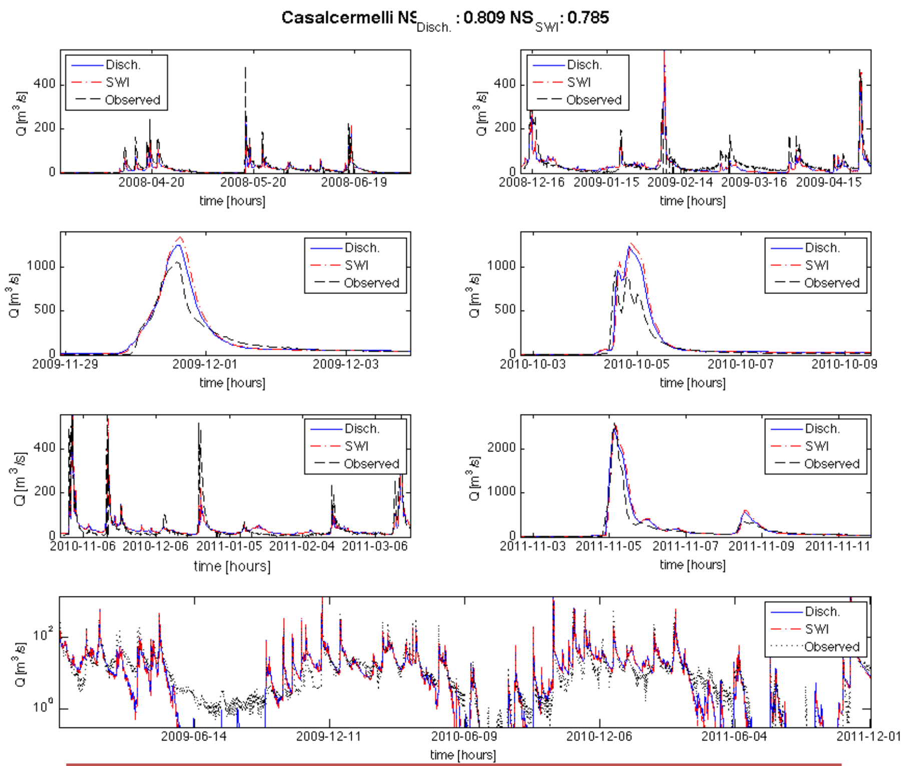
- Water Volume (V)
- Evapotranspiration (Evt)
- Land Surface Temperature (LST)







Model calibration with satellite data



Val. Period: 1/06/2009 – 31/12/2011

Hydrol. Earth Syst. Sci. Discuss., 11, 6215–6271, 2014
www.hydrol-earth-syst-sci-discuss.net/11/6215/2014/
doi:10.5194/hessd-11-6215-2014

Hydrology and Earth System Sciences
Discussions

Uncertainty reduction and parameters estimation of a distributed hydrological model with ground and remote sensing data

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Received: 14 May 2014 – Accepted: 15 May 2014 – Published: 13 June 2014

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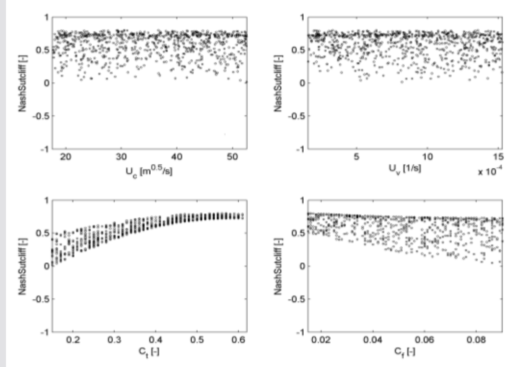
Published by Copernicus Publications on behalf of the European Geosciences Union.

Parameter calibration using SWI(H07)



Satellite data reduced hydrological uncertainty and could be used to calibrate models

Calibration results using only geomorphology (DEM) and **SWI** from H07

Nash and Sutcliffe's efficiency coefficient	
NS_{Disch}	0.81
NS_{SWI}	0.79

Osservare per prevedere, prevedere per prevenire

Conclusions

- Annual evaluation
  - Assimilations of Soil moisture products improved the performances
  - “Sat. Scale” is better than “Model Scale” for Magra and Orba
  - The Ensemble method is promising on Orba
- Seasonal evaluation
  - Summer and Autumn benefit most from assimilation
  - “Sat. Scale” is better than “Model Scale” for Magra and Orba
- Events evaluation
  - H14 leads to improvement in 90% of cases
  - H07 and H08 lead improvement in 50% of cases
  - SMOS lead improvement in 35% of cases

Thanks to L. Campo, F. Silvestro, F. Delogu, R. Rudari, L. Pulvirenti, G. Boni, N. Pierdicca, L. Brocca, C. Massari, L. Ciabatta, S. Hasenauer, S. Puca

CIVIL PROTECTION
DISASTER RISK REDUCTION
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Thank you!

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