





Assimilation of remote sensing observations into a continuous distributed hydrological model: impacts on the hydrologic cycle

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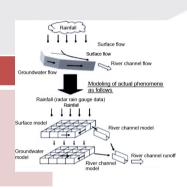
Hydrologic Data Assimilation

✓ REMOTE SENSING

Advantages	Disadvantages
•Observations over large areas	Indirect observations with long revisit time
•Possibility to have observations over	Measures referred to surface layer
ungauged basins	• Problems with roughness and/or vegetation

✓ MODELS

Advantages	Disadvantages
•Estimates over large areas (catchment)	•Problems in model initialisation
• deeper Estimates (i.e. root zone)	•Erros in the physics and input data
	•Problems in parameters determination



How to improve hydrological performances using remote sensing data?

"...an attractive prospect is to combine the strengths of hydrologic models and observations (and minimize the weaknesses) to provide a superior hydrologic state estimate. This is the goal of hydrologic data assimilation". (Houser et al. 2012)

Hydrologic Data Asssimilation

Main open questions in Hydrologic DA:

- ✓ Which is the best DA technique?
 - Sequential methods
 - Variational methods

Which is the best technique?



- ✓ How can satellite data be used in a DA into hydrological models?
 - Different spatial resolution

Satellite: ~ tens km

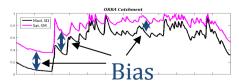
Model: ~ less than 1 km

• Estimates referred to different soil layers

Satellite: surface (2-5 cm)

Model: root zone (10-150 cm)

Different climatology and systematic bias between observations and model



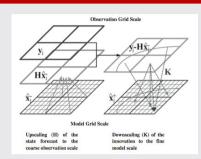
How to solve these problems?

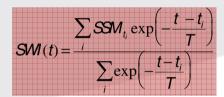
Hydrologic Data Asssimilation

Satellite soil moisture data CANNOT be directly used within hydrological models

- **✓** Possible solutions
 - Different spatial resolution
 - → SATELLITE DATA REGRID

- Estimates referred to different soil layers
 - → EXPONENTIAL FILTER





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

- Different climatology and systematic bias between observations and model
 - → Bias handling → **RESCALING TECHNIQUES**:
 - Linear rescaling
 - Cumulative distribution function matching (CDF)
 - Minimum and Maximum Correction
 - Triple collocation analysis-based approach
 - Variance matching

Assimilation experiments

- **Hydrological model used**: Continuum*
- Update of modeled soil moisture using stellite-derived data
- **Satellite-derived products**: H-SAF SM PRODUCTS (H07, H08 and H14)
- Assimilation schemes:
 - NUDGING MODEL SCALE (NudMS)
 - NUDGING SATELLITE SCALE (NudSS)
 - ENSEMBLE KALMAN FILTER MODEL SCALE (EnKF)
- Evaluation of discharge results using:
 - Observed discharge
 - Discharge modeled by "Open Loop" run (model without assimilation)

Test period: July 2012 - June 2013

Continuum model

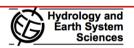


CUNTINUUM is a continuous and fully distributed hydrological model

- 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
- 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).
- Suitable for application in data scarce environments.

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Silvestro et al., 2013

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

F. Silvestro¹, S. Gabellani¹, F. Delogu¹, R. Rudari¹, and G. Boni^{1,2}

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Silvestro et al., 2015

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

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http://continuum.cimafoundation.org/

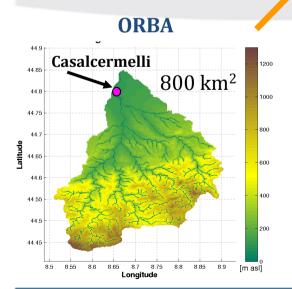
Osservare per prevedere, prevedere per prevenire

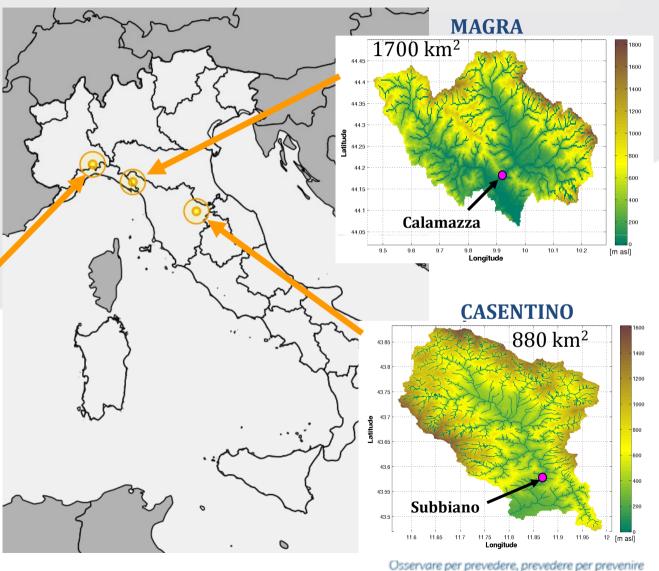
Continuum Test basins

Time resolution: 1 hour

Spatial coverage: catchment

Resolution: 100 m





H-SAF soil moisture products

• SM-OBS-1 (H07)

Large-scale surface soil moisture (SSM)

Time frequency: 2 maps per day

Spatial coverage: Globe - 2 strips of 500 km swath

Resolution: 25 km

Products derived from satellite images of the ASCAT sensor

• SM-OBS-2 (H08)

Small-scale surface soil moisture (SSM)

Time frequency: 2 maps per day

Spatial coverage: H-SAF area (Europe) - 2 strips of 500 km swath

Resolution: 1 km

Support to Operational Hycrology and Water Management

• SM-DAS-2 (H14)

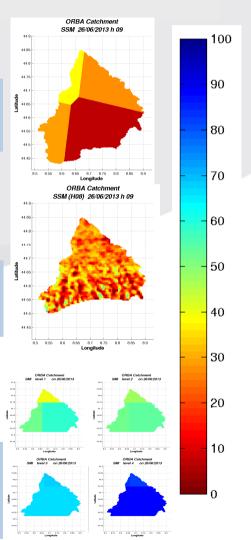
Profile Soil Moisture Index (SMI) in the root zone

Time frequency: Daily map (at 00.00)

Spatial coverage: Globe

Horizontal resolution: 25 km

Vertical resolution: 4 layers (0-7, 7-28, 28-100 and 100-289 cm)

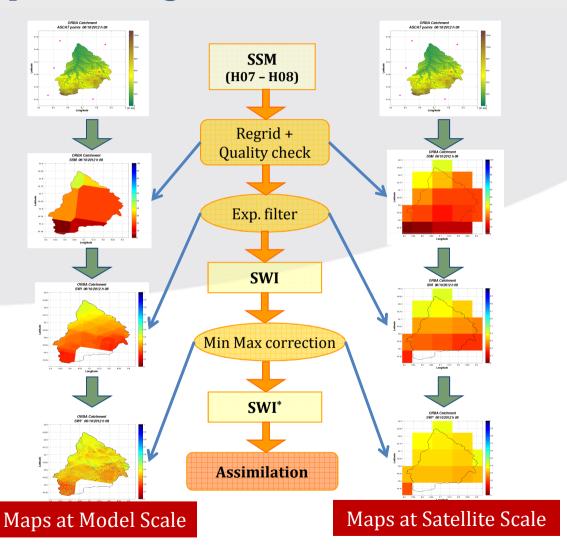


Data pre-processing – H07 and H08

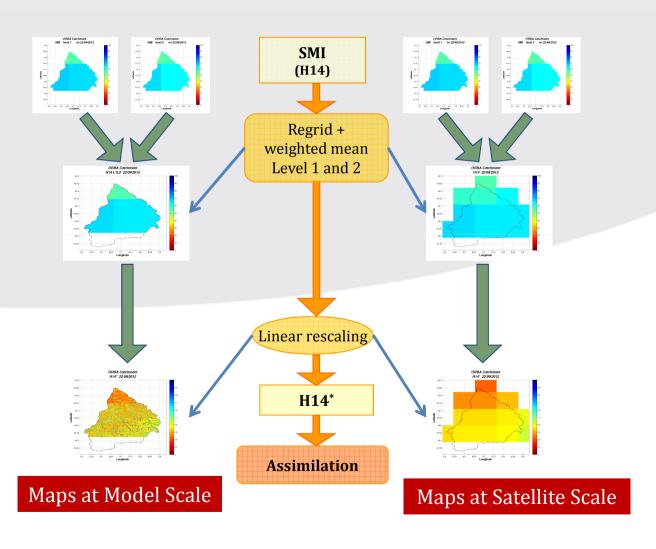
- Assimilated only mornig passes
- Quality check on H07 data: discarded data with snow cover fraction, frozen soil probability > 20%
- SWI calculated with **T=10 days** (value more suitable to reproduce modeled soil moisture)

$$SM(t) = \frac{\sum_{i} SM_{t_{i}} exp\left(-\frac{t - t_{i}}{T}\right)}{\sum_{i} exp\left(-\frac{t - t_{i}}{T}\right)}$$

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



Data pre-processing – H14



Nudging scheme

Model scale (NudMS)
$$X_{\text{mod}}^+(t) = X_{\text{mod}}^-(t) + G \cdot \left[X_{obs}(t) - X_{\text{mod}}^-(t) \right]$$

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

X⁺_{mod}= **Updated** Saturation Degree

X⁻_{mod} = **Background modeled** Saturation Degree

X_{obs}= **Observed** Saturation Degree

$$G = Gain \longrightarrow G = \frac{RMSD_{mod}}{RMSD_{mod} + RMSD_{obs}}$$

No assimilation over urban areas and rivers

 $RMSD_{mod} = Root Mean Square Difference of X_{mod}^{2} = 0.1$ (Estimated from a study over modeled soil moisture outputs)

RMSD_{obs}= Root Mean Square Difference of X_{obs} RMSD_{SWI,HSAF}: 0.22 [-] (SOURCE: Albergel et al., 2012)

RMSD_{SWI,HSAF}: 0.12 [-] for H07 and H08 (SOURCE: Brocca et al. 2011)

H = **Observation operator** (allow to obtain the map at satellite resolution from that at model resolution)

R = **Regrid operator** (allow to obtain the map at model resolution from that at satellite resolution)

S = Spatialization operator (allow to redistribute the correction on the model grid. The correction depends on the ratio between the value of X-mod at each model pixel and the mean soil moisture value at the corresponding satellite pixel)

Ensemble Kalman Filter scheme

EnKF

$$X_{\text{mod},i}^{k+}(t) = X_{\text{mod},i}^{k-}(t) + K^{k}(t) \cdot \left[Y_{i}^{k}(t) - Y_{i}^{k-}(t)\right]$$

i = ensemble member

k = single cell

t = assimilation time step

Y = observation to be assimilated

Y = observation prediction

 $\mathbf{K} = \text{Kalman gain } \mathbf{K} = \frac{P}{P + R}$

P = model error covariance

R = observation error covariance

No assimilation over urban areas, rivers and in frozen soil conditions

Assumptions:

- soil moisture observations influence only modeled saturation degree
- 20 ensemble members (N)
- Random perturbations applied to two model parameters which regulate infiltration
- Soil moisture maps firstly regridded at the fine model scale (100m) => $Y^- = X_{MOD}^-$
- P calculated as the model variance over the ensemble $P(t) = \frac{1}{N-1} \sum_{t=1}^{\infty} \left(X_{MOD,i}^{-} \overline{X_{MOD}^{-}} \right)^{2}$
- R estimated using the RMSD obtained from products validations

Evaluation metrics

Evaluations on discharge

•the Nash–Sutcliffe model efficiency coefficient (NSE) $NSE = 1 - \frac{\sum\limits_{t=1}^{n}(Qo(t) - Qs(t))^2}{\sum\limits_{t=1}^{n}(Qo(t) - \overline{Qo})^2}$ •the Root Mean Squared Error (RMSE) $RMSE = \sqrt{\frac{1}{n}\sum\limits_{t=1}^{n}(Qs(t) - Qo(t))^2}$ •the Mean Absolute Error (MAE) $MAE = \frac{1}{n}\sum\limits_{t=1}^{n}|Qs(t) - Qo(t)|$

Improvements (%) respect OL

•the Normalized Error Reduction (NER)
$$NER = 100 \cdot \left[1 - \frac{RMSE_{Assim}}{RMSE_{OL}} \right]$$

•the **Efficiency of assimilation** (Eff)

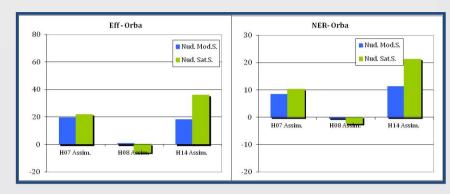
$$Eff = 100 \cdot \left| 1 - \frac{\sum_{t=1}^{n} (Q_{S_Assim}(t) - Q_{O}(t))^{2}}{\sum_{t=1}^{n} (Q_{S_OL}(t) - Q_{O}(t))^{2}} \right|$$

Assimilation improves the model if:

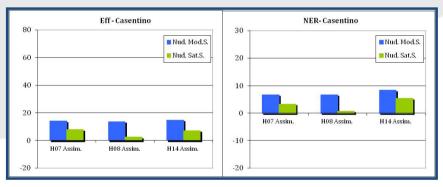
- NSE is increased respect OL
- RMSE and MAE are reduced respect OL
- Eff and NER are positive

Results: Annual analysis - Nudging

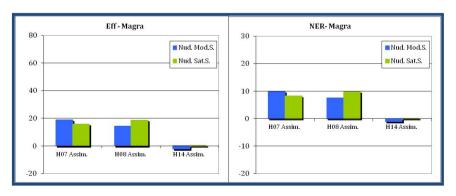
Orba	MAE		RMSE		NSE	
OL	17,4		25,3		0,63	
	NudMS	NudSS	NudMS	NudSS	NudMS	NudSS
H07 Assim	13,3	14,0	23,2	22,7	0,69	0,70
H08 Assim	15,5	17,0	25,4	25,9	0,63	0,61
H14 Assim	15,2	13,0	22,5	19,9	0,71	0,77



Casentino	MAE		RMSE		NSE	
OL	14,3		23,2		0,70	
	NudMS	NudSS	NudMS	NudSS	NudMS	NudSS
H07 Assim	13,7	13,8	21,6	22,4	0,74	0,72
H08 Assim	13,7	15,1	21,6	23,0	0,74	0,71
H14 Assim	11,8	13,1	21,2	21,9	0,75	0,73

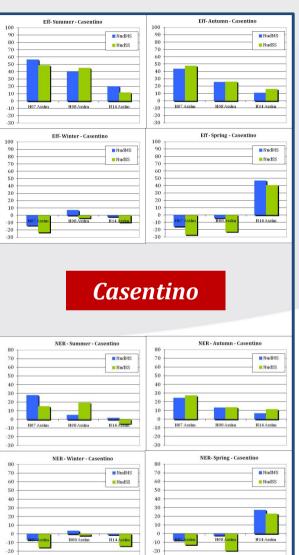


Magra	MAE 28,4		RMSE		NSE	
OL			46,7		0,72	
	NudMS	NudSS	NudMS	NudSS	NudMS	NudSS
H07 Assim	25,4	26,0	42,1	42,9	0,77	0,76
H08 Assim	25,6	24,5	43,2	42,1	0,76	0,77
H14 Assim	30,3	30,0	47,2	46,6	0,71	0,72



Results: Seasonal analysis - Nudging







Results: Comments - Nudging

ANNUAL ANALYSIS

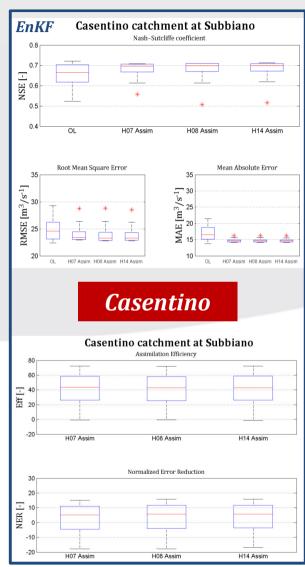
- ✓ Model improved with all the assimilations (except H08 Assim for Orba and H14 Assim for Magra)
 - NSE improved
 - Errors reduced
 - Eff and NER positive
- ✓ No significative differences between the results of the two nudging schemes

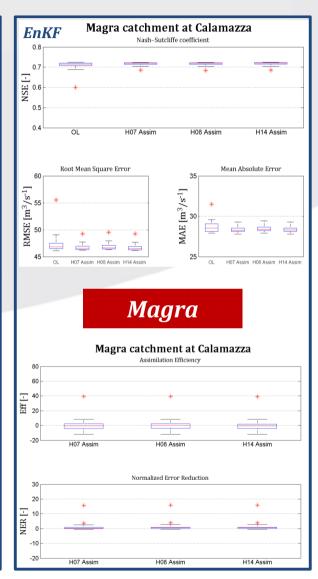
SEASONAL ANALYSIS

- Poor improvement in winter for all the catchments
- ✓ ORBA
 - Model especially improved in summer and autumn
 - •Bad performance of H07 Assim and H08 Assim in winter because of soil moisture underestimation
- ✓ CASENTINO
 - Model especially improved in summer and autumn
- ✓ MAGRA
 - Model significantly improved in spring

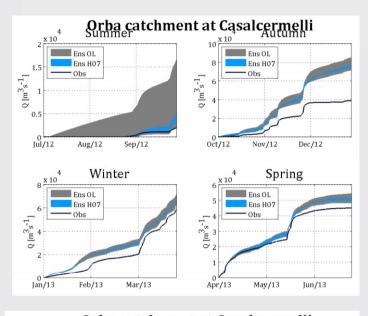
Results: Annual analysis - EnKF

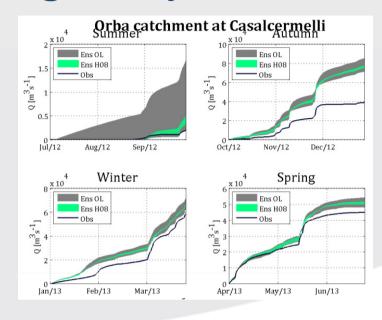


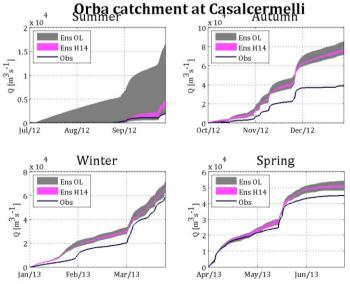




Results: Discharge analysis – EnKF Orba

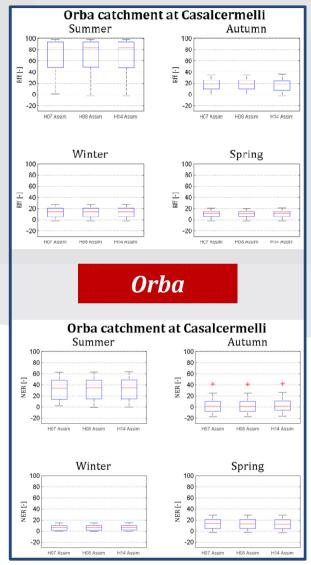


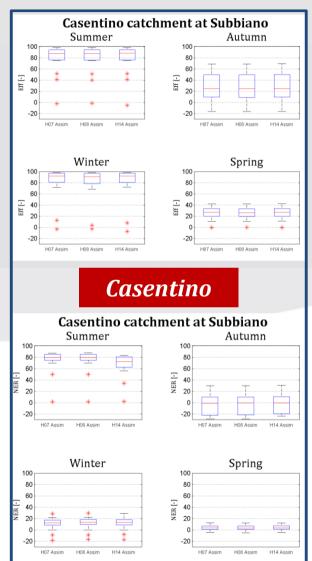


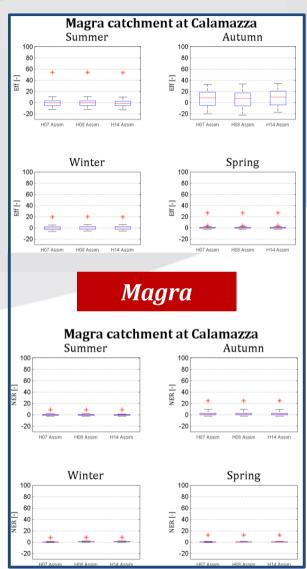


- The soil moisture update reduced the variance of the discharge ensemble
- •Similar soil moisture corrections from the three different assimilations

Results: Seasonal analysis - EnKF







Results: Comments - EnKF

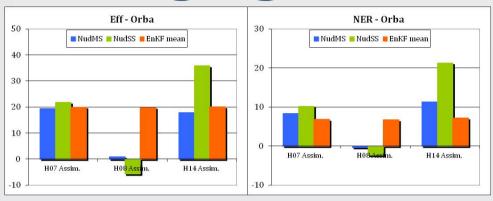
ANNUAL ANALYSIS

- ✓ Model improved with all the assimilations
- ✓ Poor improvements on Magra catchment
- ✓ Similar soil moisture corrections from the three different assimilations
- ✓ Soil moisture update reduced the variance of discharge ensemble

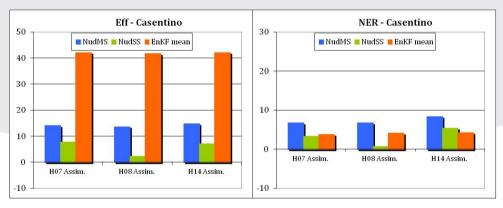
SEASONAL ANALYSIS

- ✓ ORBA
 - Model especially improved in summer and winter by $EnKF \rightarrow$ better estimation of errors respect to Nudging
- ✓ CASENTINO
 - Model especially improved in summer and winter by $EnKF \rightarrow better$ estimation of errors respect to Nudging
- ✓ MAGRA
 - Problems of satellite data spatial coverage (catchment near the sea)

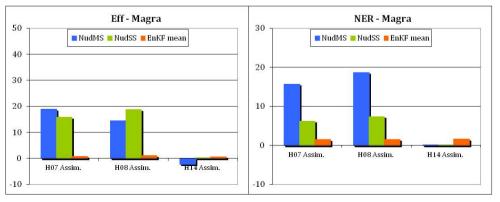
Nudging vs EnKF – Annual analysis



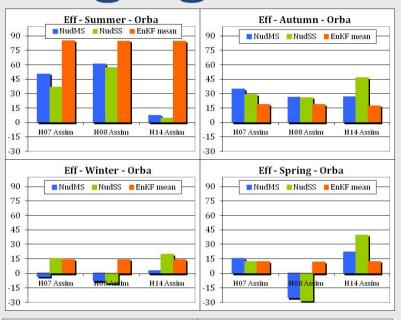
EnKF scores estimated as the average over the ensemble

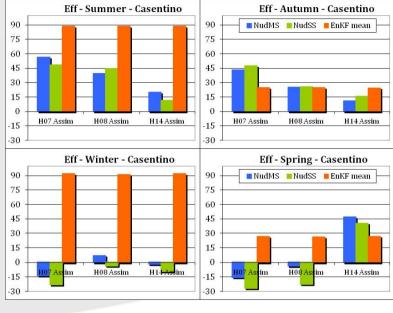


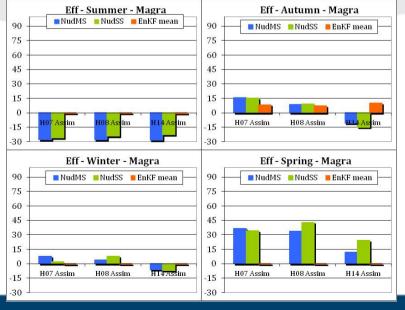
EnKF approach gave better results respect to OL only for some discharge predictions



Nudging vs EnKF - Seasonal analysis







- •EnKF approach gave better results respect to OL mainly in summer
- •Positive improvements for the model applied to Casentino catchment

Conclusions

- Satellite soil moisture data has been used to improve discharge predictions in a distributed hydrological model applied to **small** catchments at fine space and time resolutions:
 - General improvements (especially with EnKF) in transition seasons and when soil moisture is a 'limiting factor' to runoff
 - No results of general validity. Different DA schemes and SM products impacts differently the model performance in different environments
- Attention should be paid to the pre-processing of the products, taking into account:
 - the characteristics of the basin (elevation, land cover, river network),
 - the satellite retrieval problems (snow and frozen surfaces, topographic complexity)
 - the model peculiarities (space and time step and variables climatology).

CIVIL PROTECTION DISASTER RISK REDUCTION BIODIVERSITY

Thank you!

Osservare per prevedere, prevedere per prevenire



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