SEQUENTIAL AND VARIATIONAL ASSIMILATION OF SATELLITE SNOW DATA THROUGH A CONCEPTUAL HYDROLOGICAL MODEL IN A MOUNTAINOUS CATCHMENT

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A European network for a harmonised monitoring of snow for the benefit of climate change scenarios, hydrology and numerical weather prediction

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Outline

1. **Introduction**
2. **Methodology**
   - Data assimilation (DA)
     - Variational DA (Moving Horizon Estimation)
     - Sequential DA (Ensemble Kalman Filter)
   - Hydrological model (HBV)
3. **Study Area, Data, Model**
   - Upper Euphrates Basin
   - Data (Hydro-meteorological & Satellite)
   - Hydrological model application
4. **Implementation of DA Application**
5. **Results & Comparison**
6. **Conclusion**

1. Introduction (1)

Satellite based data…

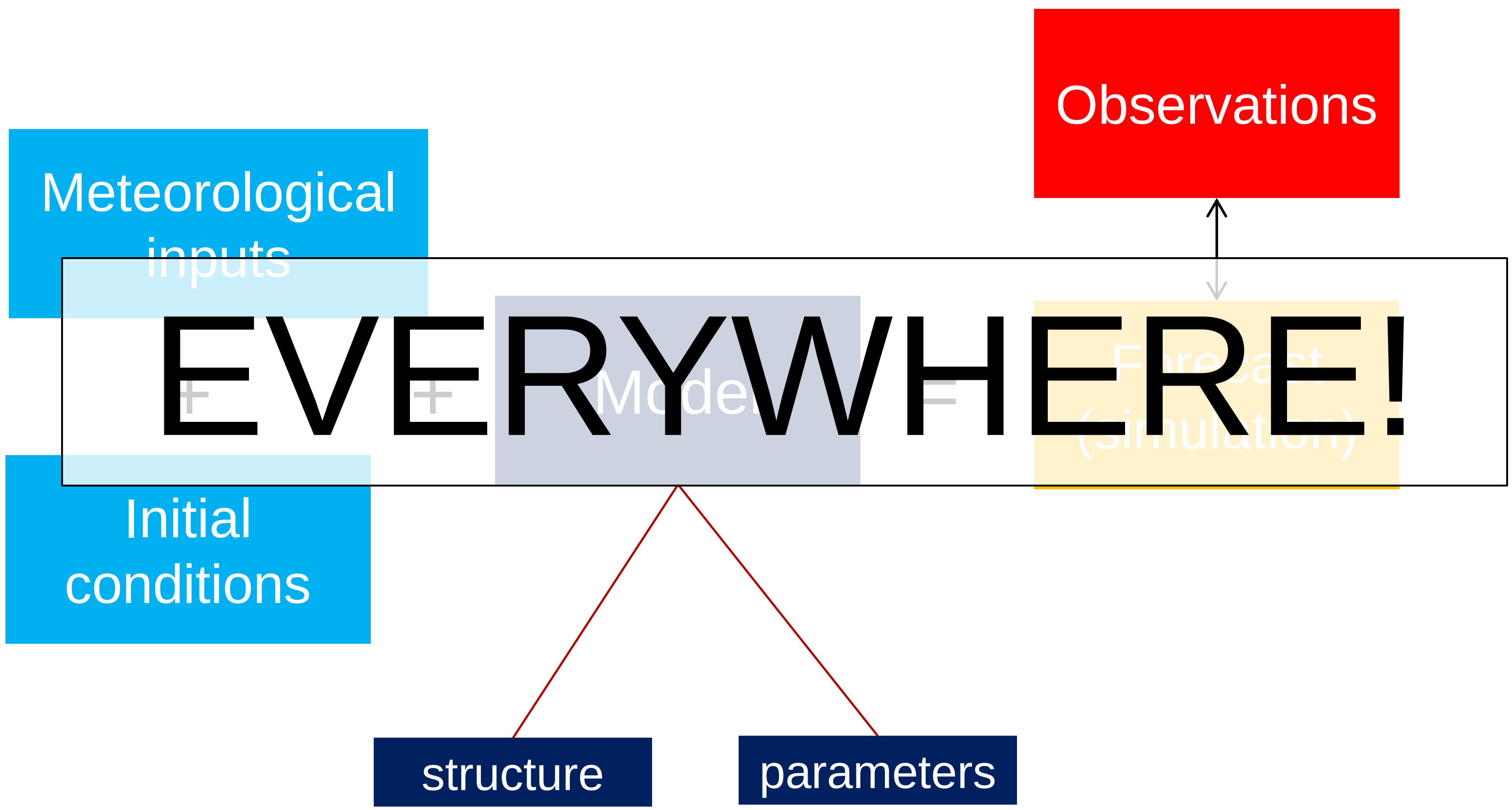
Class	Observation	Ideal Technique	Ideal Time Scale	Ideal Space Scale	Currently available data
Parameters	Land cover/change	optical/IR	daily or changes	1km	AVHRR, MODIS, NPOESS
	Leaf area & greenness	optical/IR	daily or changes	1km	AVHRR, MODIS, NPOESS
	Albedo	optical/IR	daily or changes	1km	MODIS, NPOESS
	Emissivity	optical/IR	daily or changes	1km	MODIS, NPOESS
	Vegetation structure	lidar	daily or changes	100m	ICESAT
	Topography	in-situ survey, radar	changes	1m-1km	GTOPO30, SRTM
Forcings	Precipitation	microwave/IR	hourly	1km	TRMM, GPM, SSMI, GEO-IR, NPOESS
	Wind profile	Radar	hourly	1km	QuickSCAT
	Air humidity & temp	IR, microwave	hourly	1km	TOVS, AIRS, GOES, MODIS, AMSR
	Surface solar radiation	optical/IR	hourly	1km	GOES, MODIS, CERES, ERBS
	Surface LW radiation	IR	hourly	1km	GOES, MODIS, CERES, ERBS
States	Soil moisture	microwave, IR change	daily	1km	SSMI, AMSR, SMOS, NPOESS, TRMM
	Temperature	IR, in-situ	hourly-monthly	1km	IR-GEO, MODIS, AVHRR, TOVS
	Snow cover or SWE	optical, microwave	daily or changes	10m-100m	SSMI, MODIS, AMSR, AVHRR, NPOESS
	Freeze/thaw	radar	daily or changes	10m-100m	Quickscat, IceSAT, CryoSAT
	Ice cover	radar, lidar	daily or changes	10m-100m	IceSAT, GLIMS
	Inundation	optical/microwave	daily or changes	100m	MODIS
	Total water storage	gravity	changes	10km	GRACE
Fluxes	Evapotranspiration	optical/IR, in-situ	hourly	1km	MODIS, GOES
	Streamflow	microwave, laser	hourly	1m-10m	ERS2, TOPEX / POSEIDON, GRDC
	Carbon flux	In-situ	hourly	1km	In-situ
	Solar radiation	optical, IR	hourly	1km	MODIS, GOES, CERES, ERBS
	Longwave radiation	optical, IR	hourly	1km	MODIS, GOES
	Sensible heat flux	IR	hourly	1km	MODIS, ASTER, GOES

Table 1. Characteristics of remotely sensed hydrological observations potentially available within the next decade.

Houser et al. (2012)

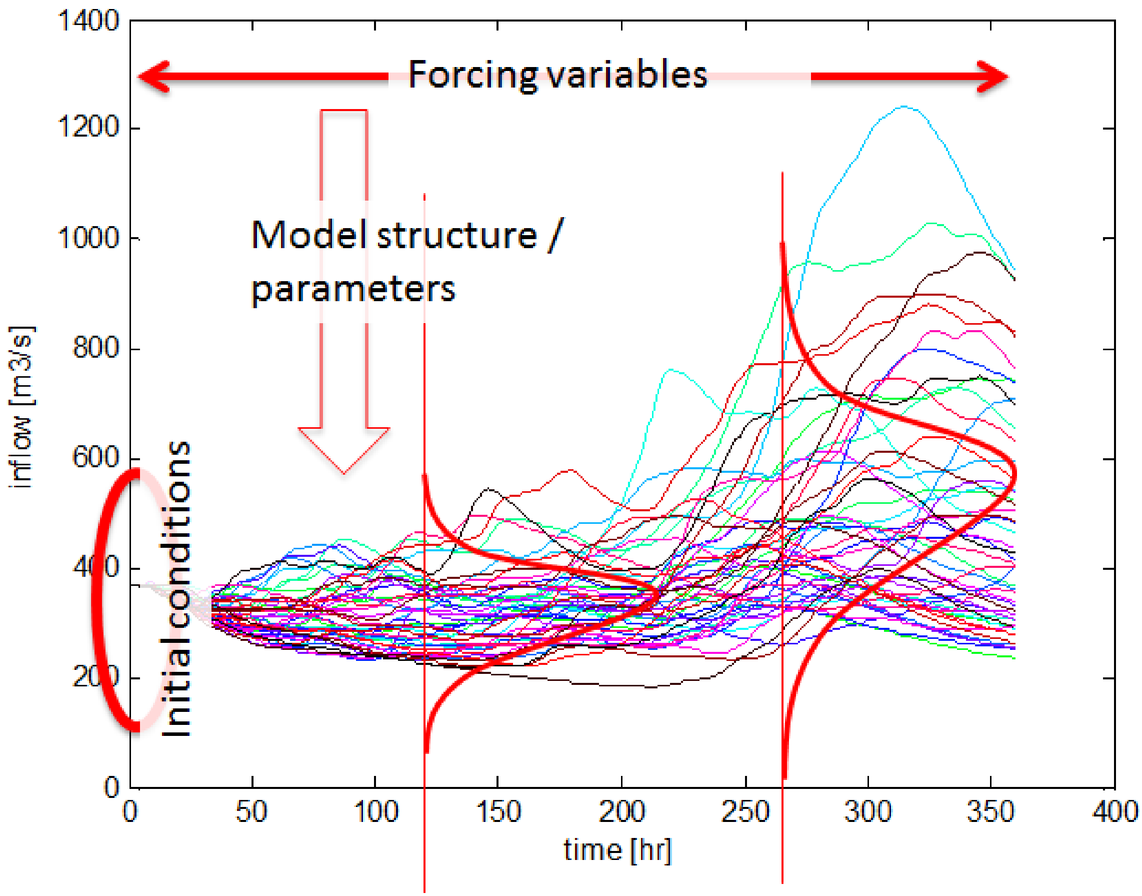
1. Introduction (2)

How to produce a forecast?



Indicate the sources of uncertainty!

Sources of uncertainty



Prediction of Hydrological System (HS) are often poor due to

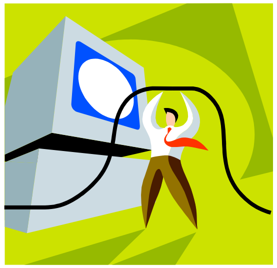
- Initial conditions,
- Forcing errors,
- Inadequate model structure and parameters

“ **Both model predictions and observations are IMPERFECT** and we wish to use both synergistically to obtain a more accurate result”. (Walker & Hoser, 2007)

1. Introduction (4)

Data Assimilation (DA)

- …holds considerable potential for improving hydrological predictions….



information present in imperfect models

+

uncertain data

to produce

optimal

physically consistent representations

estimates of the dynamical behavior of a system

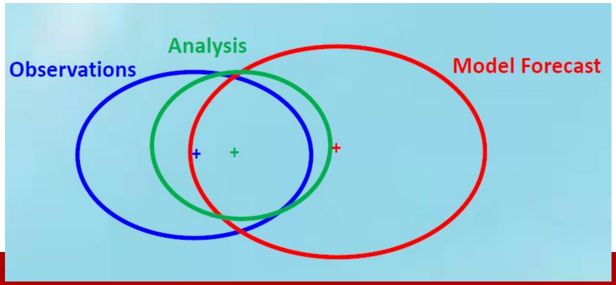
1. Introduction (5)

The aim of the study

1) to evaluate the feasibility of assimilating snow satellite data (SCA & SWE) through a conceptual hydrological model,
2) to apply different assimilation techniques,
3) to assess H SAF products in Real Time DA Tools

2. Methodology: DA (1)

DA challenge



<u>The purpose</u> is ***to improve the initial state of the model***, which later makes a forecast for the next time step.

<u>Given:</u> a (noisy) model of system dynamics
<u>Find:</u> the best estimates of system states X from (noisy) observations Z.

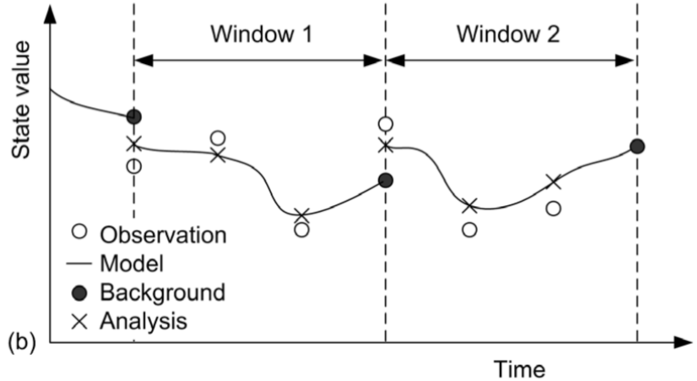
1. Variational Data Assimilation (VarDA):

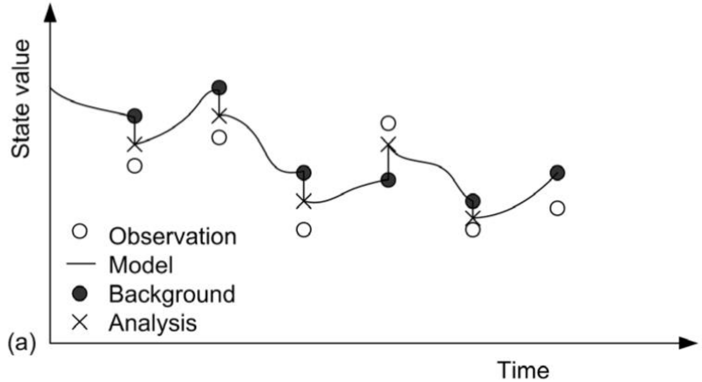
- Correction of initial conditions of a model and obtaining the best overall fit of the state to the observations by minimizing over *space and time an objective function*
- Behavior of the system is driven by accuracy of initial conditions.

2. Sequential Data Assimilation (SeqDA):

- Observations are used as soon as they are available to correct the present state of a model (sequentially updated).
- Suitable when the system is driven by boundary conditions.

Houser et al. (2012)





2. Methodology: Hydrological Model (1)

Conceptual Model: **HBV**

HBV hydrological model is used for rainfall-runoff relationship:

Forcing (model inputs):

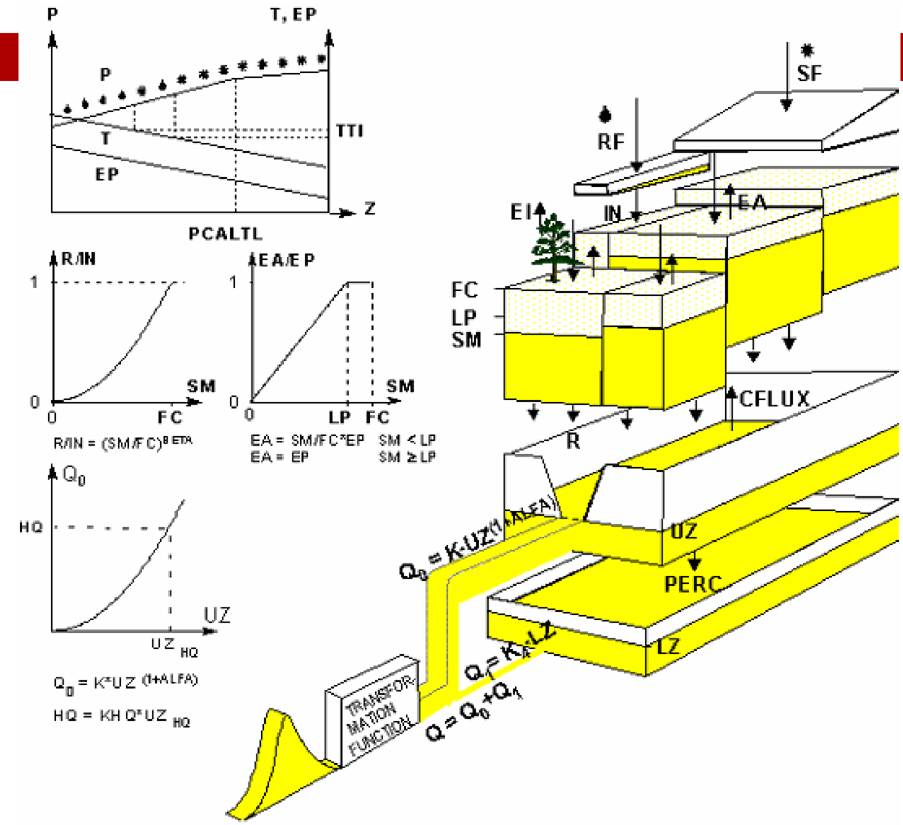
- Precipitation (P)
- Temperature (T)
- Potential Evapotranspiration (PET)

State variables:

- Snow water equivalent (SWE)
  (snow pack SP + water content WC)
- Interception storage (IC)
- Soil moisture (SM)
- Upper zone storage (UZ)
- Lower zone storage (LZ)

Output variables:

- Discharge (Q)



P = Precipitation
T = Temperature
SF = Snow
RF = Rain
Z = Elevation
PCALTL = Threshold for altitude correction
TTI = Threshold temperature interval
IN = Infiltration
EP = Potential evapotranspiration
EA = Actual evapotranspiration
EI = Evaporation from interception
SM = Soil moisture storage
FC = Maximum soil moisture storage
LP = Limit for potential evapotranspiration

BETA = Soil parameter
R = Recharge
CFLUX = Capillary transport
UZ = Storage in upper response box
LZ = Storage in lower response box
PERC = Percolation
K, K_4 = Recession parameters
ALFA = Recession parameter
Q_0, Q_1 = Runoff components
HQ = High flow parameter
KHQ = Recession at HQ
HQ_{UZ} = UZ level at HQ

Schematic structure of HBV-96 model (Lindström et al., 1997)

2. Methodology: *Imp. of DA into HBV (1)*

VarDA implementation by MHE

The implementation of the HBV model follows:

Simulated variable

Forward Model

Noise (to forcing/states)

External forcing vectors

states

output variable

$$\boxed{x_k} = \boxed{\tilde{x}_k} + \boxed{\eta_k} = \boxed{M_k}\left(x_{k-1}, \boxed{\mu_k}, \boxed{\delta_k}\right) + \eta_k$$

$$\boxed{z_k} = \boxed{\tilde{z}_k} + \boxed{\varepsilon_k} = \boxed{H_k} \cdot x_k + \varepsilon_k$$

Observation operator

Model and observation error with coveraince Q & R, respectively

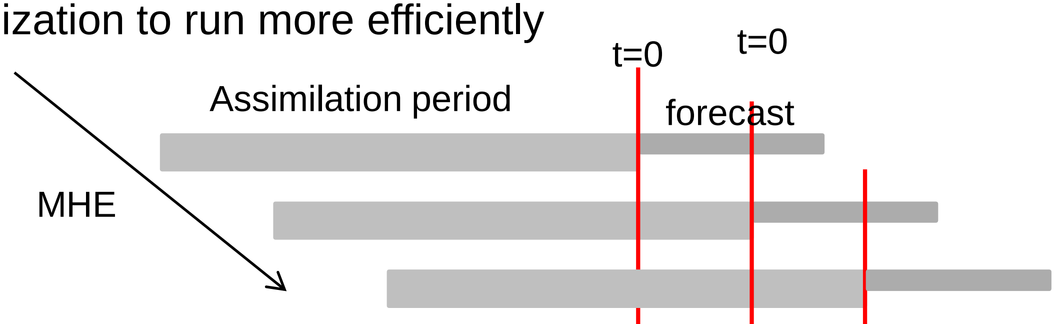
The moving horizon estimation (MHE) for a forecast *Tk=0* over an assimilation period *k=[-N+1,0]* is defined as:

Observations

$$\min_{\mu} J = \min_{\mu} \sum_{k=-N+1}^{0} \left(w_z \left\| \boxed{z_k} - \tilde{z}_k \right\| + w_x \left\| \boxed{x_k} - \tilde{x}_k \right\| + w_\mu \left\| \mu_k \right\| \right)$$

Objective function

- Adjoint models are required for the optimization to run more efficiently



Alvarado-Montero et al., 2016

2. Methodology: Imp. of DA into HBV (2)

SeqDA implementation by Kalman Filter

Ensemble Kalman Filter is the most commonly applied DA in hydrological sciences (Liu et al. 2012).

- It estimates the model (co)-variances by <u>perturbing model forcings</u> and <u>sampling the model states</u>.

$$\boxed{J = \frac{(True - Obs)^2}{\sigma^2_{obs}} + \frac{(True - Model)^2}{\sigma^2_{Model}}}$$

Objective function!

$$\frac{dJ}{dTrue} = 0 = \frac{(True - Obs)}{\sigma^2_{obs}} + \frac{(True - Model)}{\sigma^2_{Model}}$$

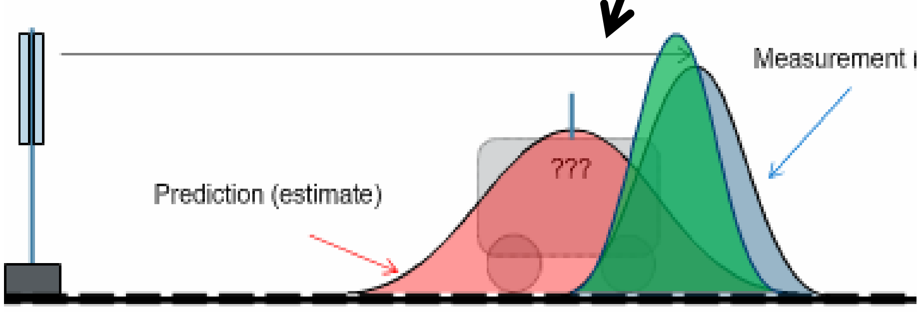
$$\sigma^2_{Model}(True - Obs) + \sigma^2_{obs}(True - Model) = 0$$

$$True(\sigma^2_{Model} + \sigma^2_{obs}) = Obs \cdot \sigma^2_{Model} + Model \cdot \sigma^2_{obs}$$

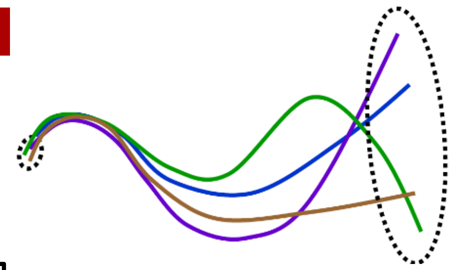
$$True = \frac{Obs \cdot \sigma^2_{Model} + Model \cdot \sigma^2_{obs}}{(\sigma^2_{Model} + \sigma^2_{obs})} = \boxed{Model + K \cdot (Obs - Model)}$$

$$K = \frac{\sigma^2_{Model}}{(\sigma^2_{Model} + \sigma^2_{obs})}$$

Improved estimate!



SeqDA implementation by Kalman Filter



Perturbations

Forcing vector

$$\delta_k^i = \delta_k + \xi_k^i \quad \text{with: } \xi_k^i \approx N\left(0, U_k\right)$$

Covariance of δ_k

The states are obtained: $x_k^{-,i} = M\left(x_{k-1}^{+,i}, \delta_k^i, u_k^i\right)$

The state updating from the implementation of the EnKF:

$$x_k^{+,i} = x_k^{-,i} + K_k \cdot d_k^i$$

Kalman gain

distance between observed and simulated

$$K_k = E\left[x_k^-, z_k^-\right] \cdot \left(E\left[z_k^-, z_k^{-,T}\right] + R_k\right)^{-1}$$

$$d_k^i = z_k - \varepsilon_k^i - H_k \cdot x_k^{-,i}$$

Alvarado-Montero et al., 2017

2. Methodology: Imp. of DA into HBV (4)

Comparison of both techniques

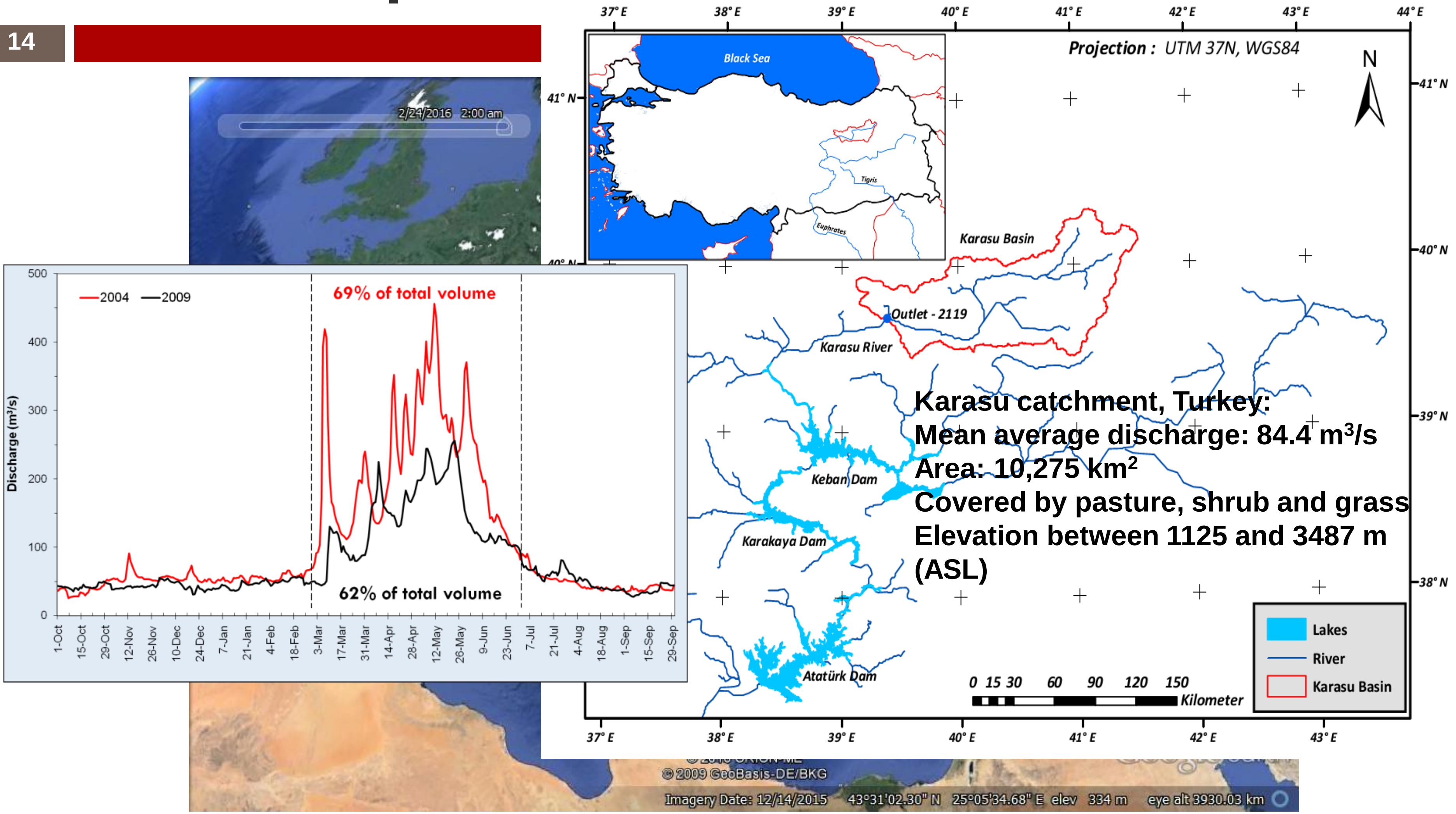
Variational DA:

- + simultaneous technique over several time steps
- + suitable for reanalysis
- - requires first-order sensitivities, i.e. adjoint code, and preferably a smooth model
- - deterministic approach

Ensemble Kalman DA:

- + applicable on black-box models, simple to implement
- + probabilistic approach
- - sequential technique, has issues with time lags

Selected pilot basin



Karasu catchment, Turkey:
Mean average discharge: 84.4 m³/s
Area: 10,275 km²
Covered by pasture, shrub and grass
Elevation between 1125 and 3487 m (ASL)

- Large dam reservoirs (Keban, Karakaya, Atatürk…) are located at the downstream of the basin

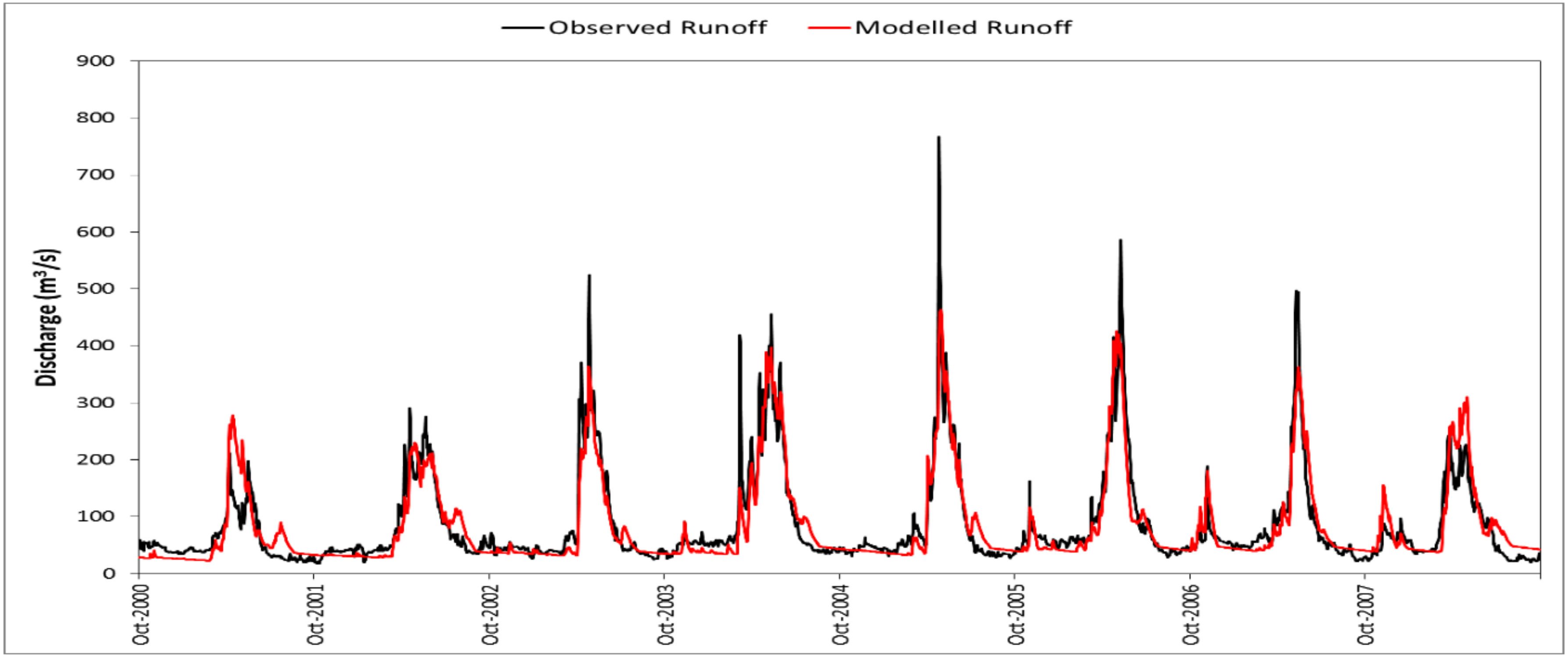
3. Model Setup (2)

Data

- Ground Data: 18 Climate & AWOS
- 10 elevation zones (within 1125 – 3487 m)
- 1 land use type
- Model inputs:
  - Precipitation
  - Temperature
  - Potential Evapotranspiration
- Model outputs:
  - Discharge
  - SWE & SCA

3. Model setup (3)
Model parameters

- Calibrated btw 01/10/2001 to 30/09/2008 (NSE* of 0.84)
- Validated btw 01/10/2008 to 30/09/2012 (NSE* of 0.74)

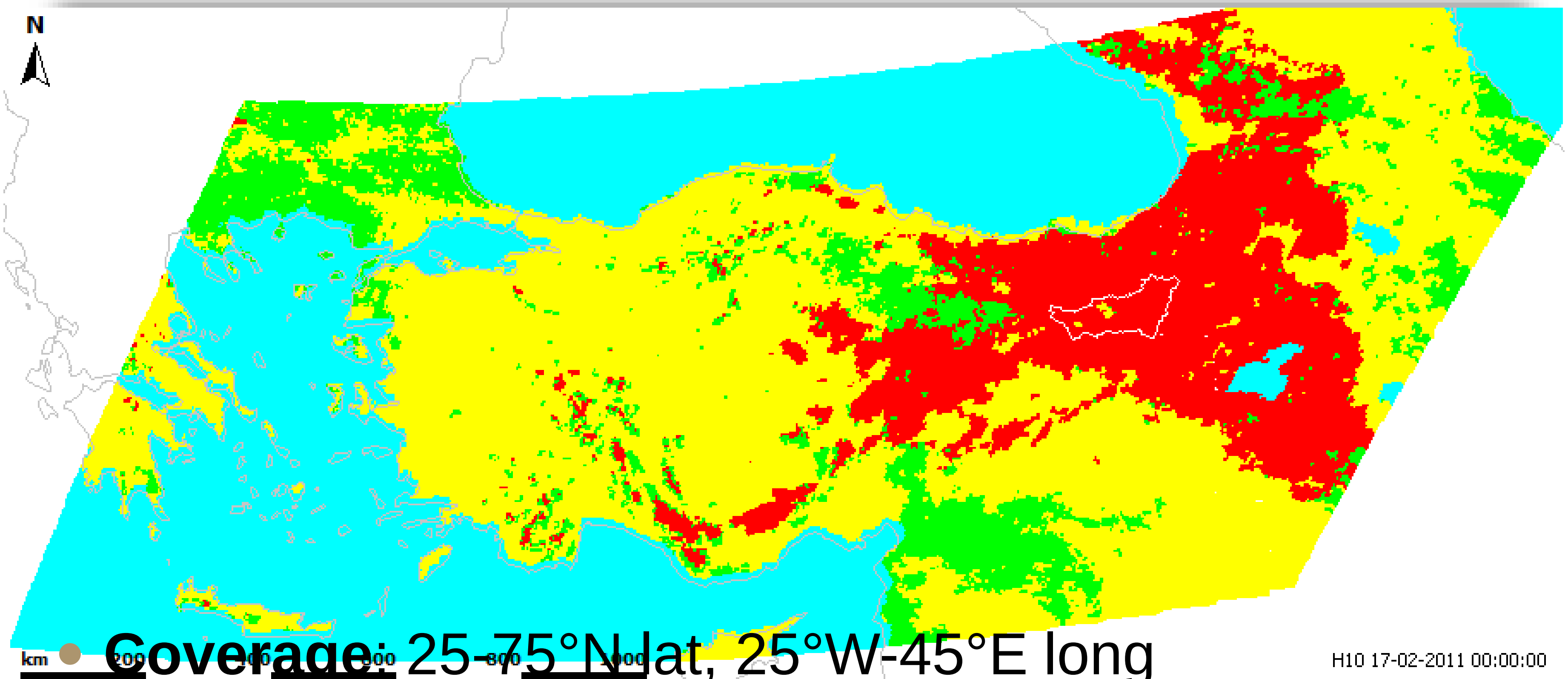


Daily Observed and simulated discharge with the HBV model for the calibration period

**Nash-Sutcliffe Efficiency (NSE)*

3. Model setup (4)

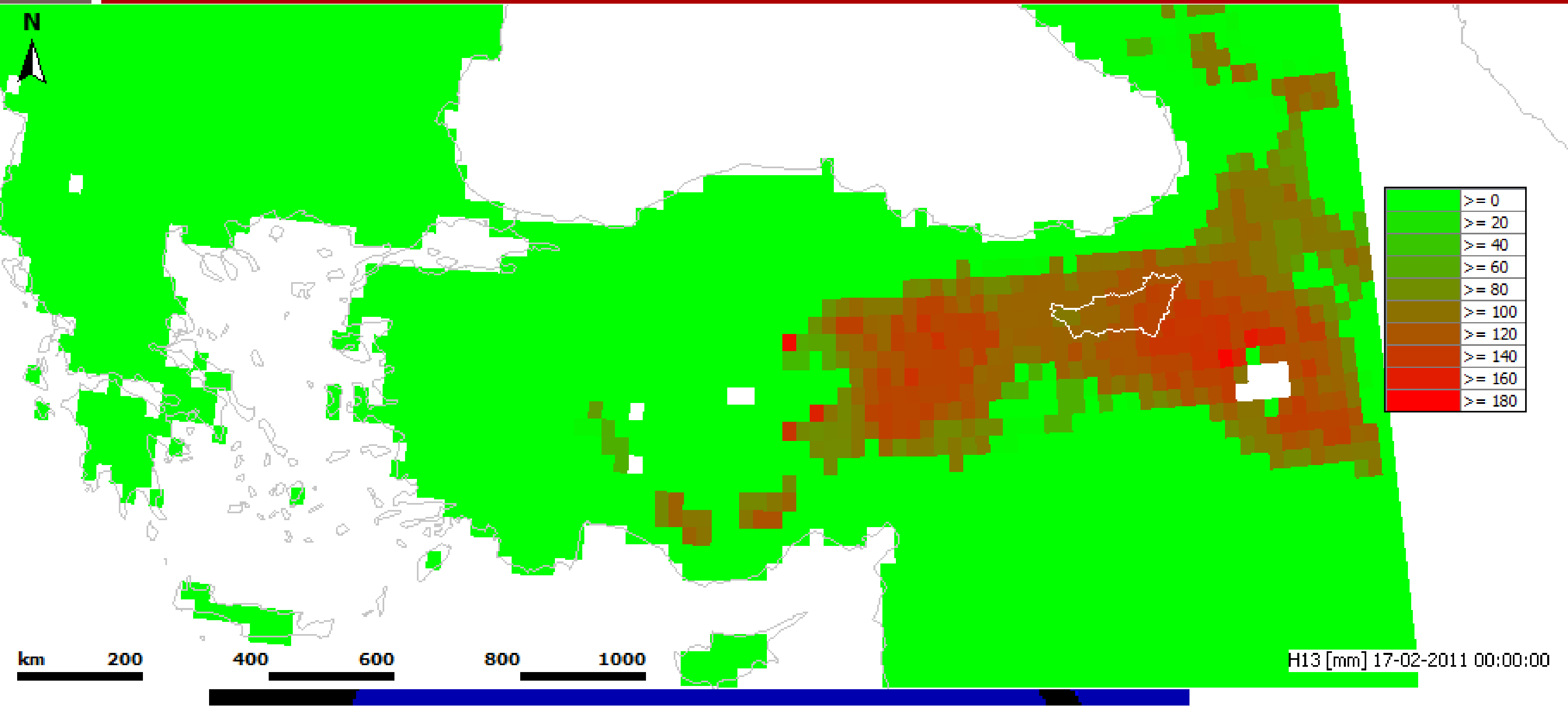
Snow Recognition Product, H10



- **Coverage**: 25-75°N lat, 25°W-45°E long
- **Cycle**: Daily
- **Resolution**: 1 to 5 km
- **Accuracy**: POD 95 %, FAR 10 %

3. Model setup (5)

Snow Water Equivalent, H13



- **Coverage**: 25-75°N lat, 25°W-45°E long
- **Cycle**: Daily
- **Resolution**: 10-30 km (0.25 degrees)

4. DA Application (1)
In general

- Hindcasting period:
  - 2015-2016 (2 water years)
- Assimilated observations:
  - Discharge (Q) & SCA (H10) with both methods
  - Q & H10 & SWE (H13) with VarDA
- Forcings:
  - *Perfect forecast* (Prec., Temp.)
- Warm-up (+ assimilation window in VarDA)
  - 180 days
- Lead time:
  - 10 days

4. DA Application (2)
VarDA

- Noise terms introduced both for forcings and states
- Variables and objective function terms in the MHE
- Observation uncertainty: Q, SCA, Q+SCA, Q+SWE, Q+SCA+SWE

Variable		**Objective Function Term**
Model Inputs	Precipitation (*P*)	$w_P(\Delta P^k)^2$
	Temperature (*T*)	$w_T(\Delta T^k)^2$
Model States	Snow Water Equivalent (*SWE* = *SP* + *WC*)	$w_{SWE}(\hat{s}^k_{SWE} - s^k_{SWE})^2$
	Soil Moisture (*SM*)	$w_{SM}(\hat{s}^k_{SM} - s^k_{SM})^2 + w_{\Delta SM}(\Delta s^k_{SM})^2$
	Upper Zone Storage (*UZ*)	$w_{\Delta UZ}(\Delta s^k_{UZ})^2$
	Lower Zone Storage (*LZ*)	$w_{\Delta LZ}(\Delta s^k_{LZ})^2$
Model Outputs	Snow Covered Area (*SCA*)	$w_Q(\hat{A}^k_{SCA} - A^k_{SCA})^2$
	Discharge (*Q*)	$w_Q(\hat{Q}^k - Q^k)^2$

SeqDA

- Stability & to properly capture uncertainty
  - Selected ensemble member: 100 (probabilistic technique)
- Observation uncertainty: Q, SCA, Q+SCA
- Perturbations: P, T

4. DA Application (4)
Model Interfaces & performance metric

- **VarDA Implementation:** Deltares RTC-Tools (Schwanenberg and Bernhard, 2013),
- **EnKF Implementation:** Python
- **Model performance:** Continuous Ranked Probability Skill Score, CRPS.
  - Zero CRPS is desired.
  - Both for discharge, SCA and SWE.

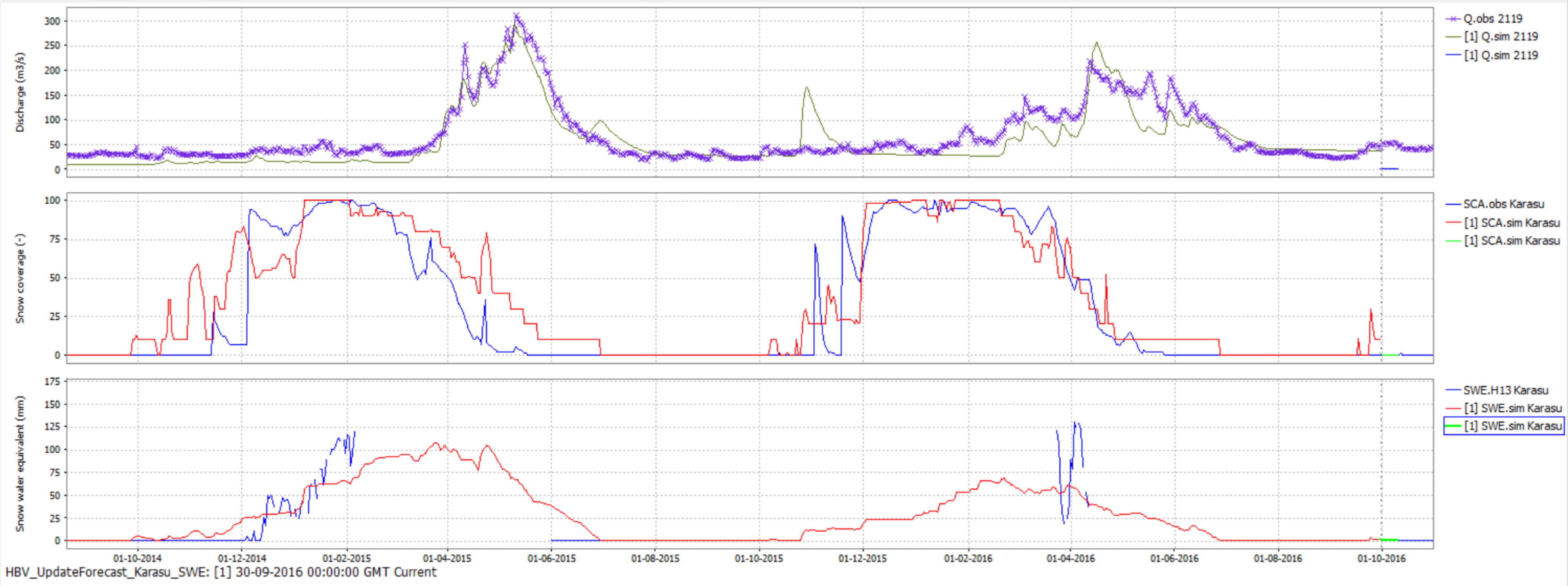
$$CRPS_L = \frac{1}{n}\sum_{k=1}^{n}\left[\int_{-\infty}^{+\infty}\left(F_t(y_{k,L}) - \Gamma(y_{k,L} \geq \hat{y}_k)\right)^2 dy\right]$$

where $y_{k,L}$ represents the value of the forecast k-L with a leadtime L, k is the indicator of the forecast, n is the number of ensembles, F is the cumulative distribution function, and Γ is a function which assumes probability 1 for values higher or equal to the observation and 0 otherwise.

5. Results & Comparison (1)

No DA simulation (2015-2016)

- The reference hindcasting simulation to represent the model performance without DA application (having
- For Q: NSE= 0.76, mae= 22.48 cms ≈ 0.20 mm/day
- For SCA: NSE=0.79, mae= 11.64 %



5. Results & Comparison (2)
An exemplary hindcasting result

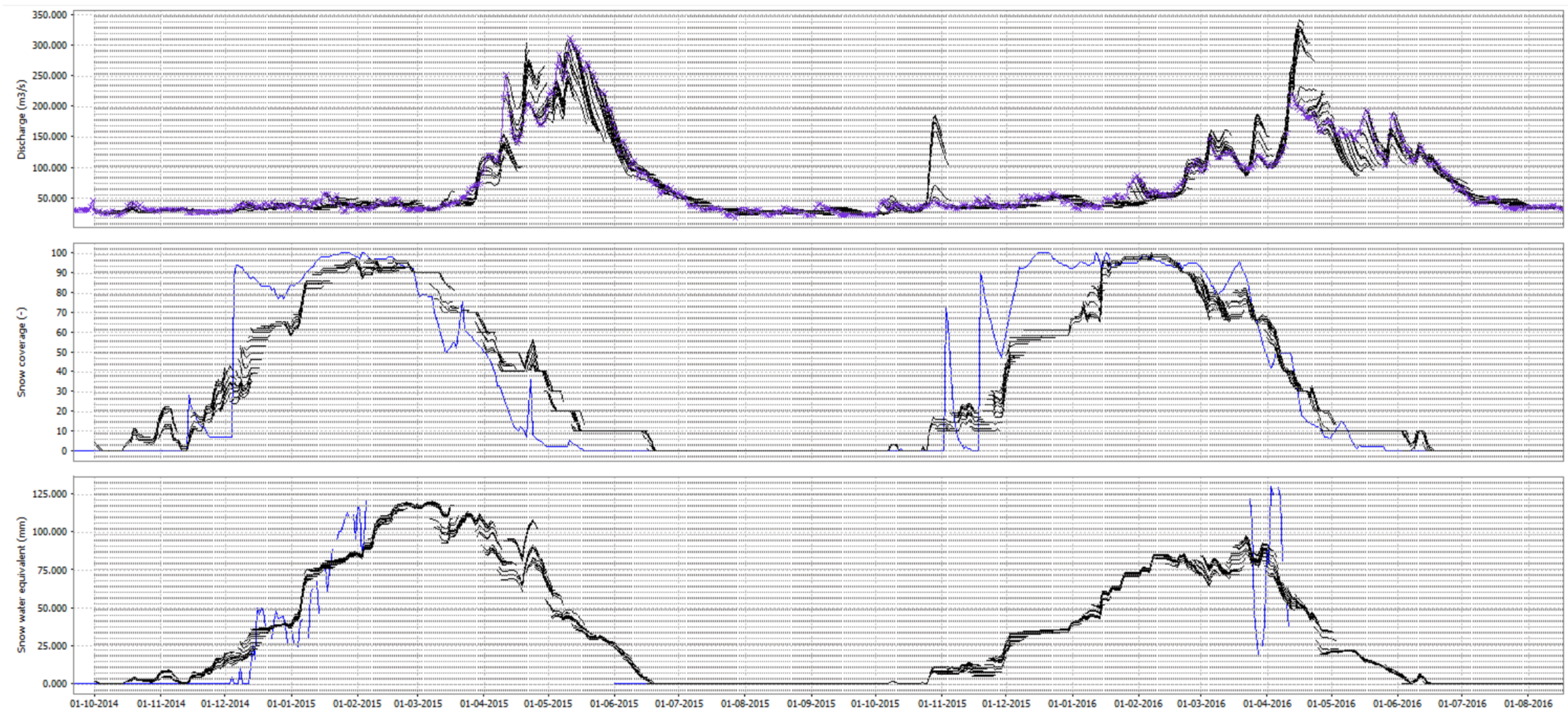
- Var DA application

Assimilating: Q+SCA[H10]+SWE[H13]

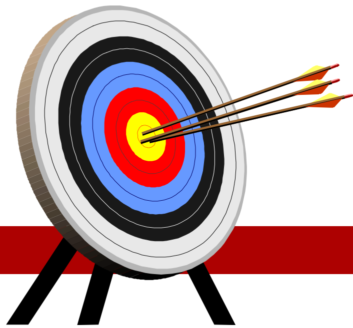
Q

SCA

SWE



6. Conclusion (1)



1. Uncertainty

Even providing perfect input to the model, the model outputs contain many uncertainties due to model and observation errors.

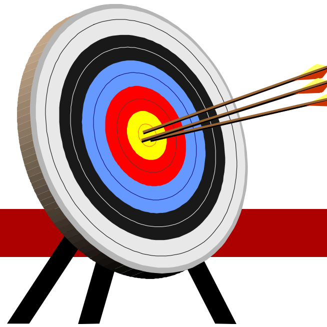
2. Data Assimilation

The study is conducted to improve the consistency of the streamflow forecasts with the observations, thus different data assimilation techniques are employed in a mountainous basin where major part of the discharge is originated from snow melting.

3. Various observations

Applied DA techniques consider not only discharge but also snow observations provided from satellites.

6. Conclusion (2)



4. Added value of DA

Consideration of snow observations (H SAF products) in DA together with discharge IMPROVES both discharge + snow output performances in comparison with No DA control simulation.

5. Lead time performance

Due to the nature of initial conditions, the performance of the result decreases with respect to lead time.

6. VarDA vs. SeqDA

Moving Horizon based Variational method performances are higher than Sequential Kalman Filtering method.

7. Outlook

a. The models will be extended using numerical weather predictions (deterministic & probabilistic) for real time forecasting application.

b. Improved forecasts will be main input to reservoir control models for better decision making!

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