MULTI-PARAMETRIC VARIATIONAL DATA ASSIMILATION OF MODIS SNOW COVER DATA THROUGH HBV MODEL IN MOUNTAINOUS UPPER EUPHRATES RIVER 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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Progresses and gaps on monitoring of snow and its components at the local-, regional to global scale and its applications to support weather, hydrological and climate science, as well as monitoring of natural hazards

Outline

1. **Introduction**
2. **Methodology**
   - Multi-parametric VarDA (MP-VarDA)
   - Hydrological model (HBV)
3. **Study Area, Data, Model**
   - Upper Euphrates Basin
   - Data (Hydro-meteorological & Satellite)
   - Hydrological model application
4. **Implementation of MP-VarDA Application**
5. **Results & Comparison**
6. **Conclusion**

1. Introduction (1)

Satellite based data…

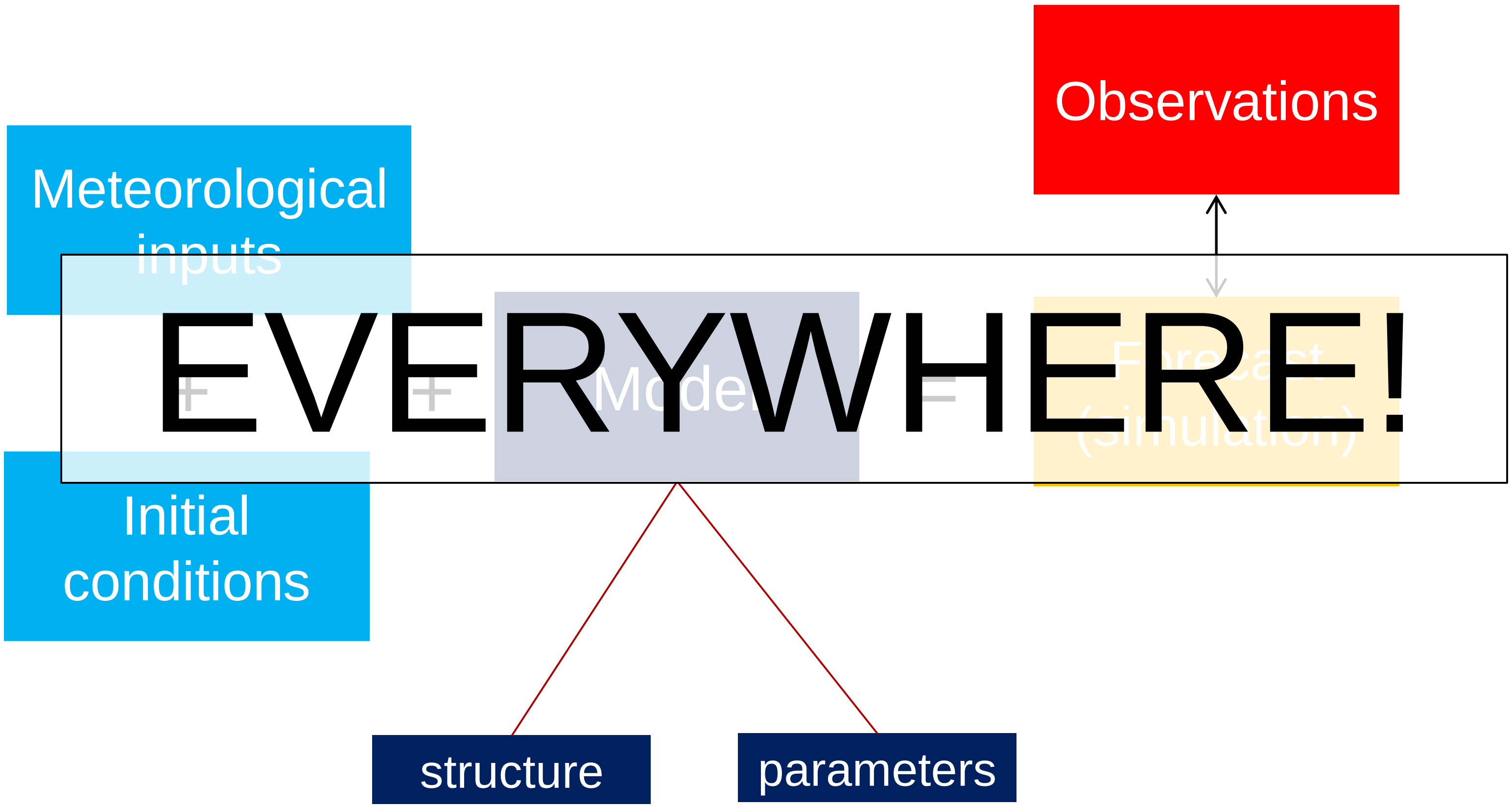
Class	Observation	Ideal Technique	Ideal Time Scale	Ideal Space Scale	Currently available data
Parameters	Land cover/change	optical/IR	daily or changes	1km	AVHRR, MODIS, NPOESS
	Leaf area & greenness	optical/IR	daily or changes	1km	AVHRR, MODIS, NPOESS
	Albedo	optical/IR	daily or changes	1km	MODIS, NPOESS
	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)

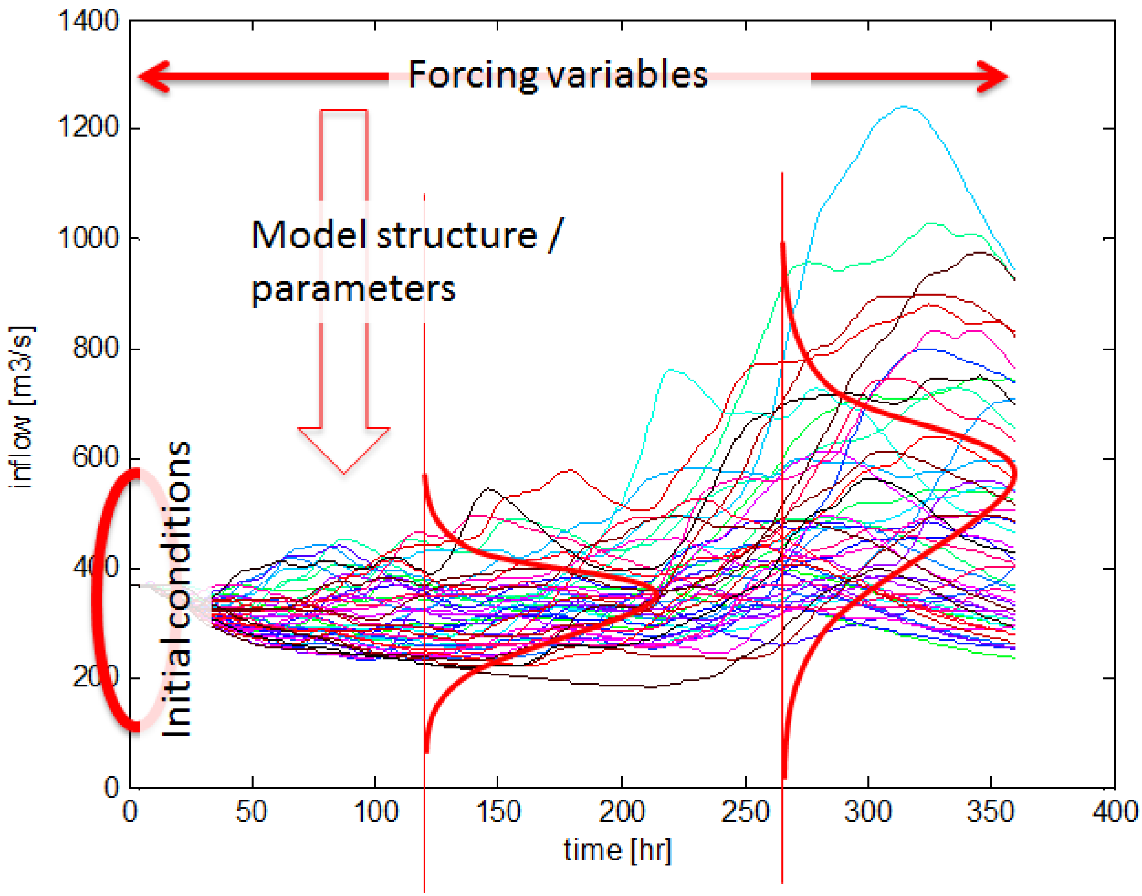
How to produce a forecast?



Indicate the sources of uncertainty!

1. Introduction (3)

Sources of uncertainty



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

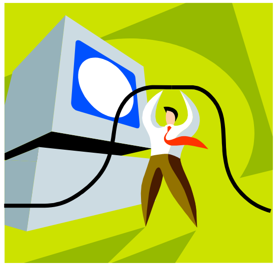
- Initial conditions,
- Forcing errors,
- Inadequate model structure and parameters

" **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

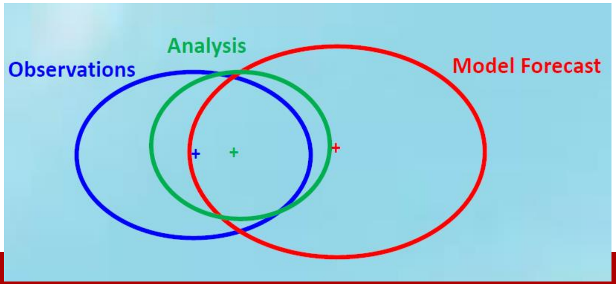
optimal

physically consistent representations

estimates of the dynamical behavior of a system

2. Methodology: Var-DA (1)

DA challenge



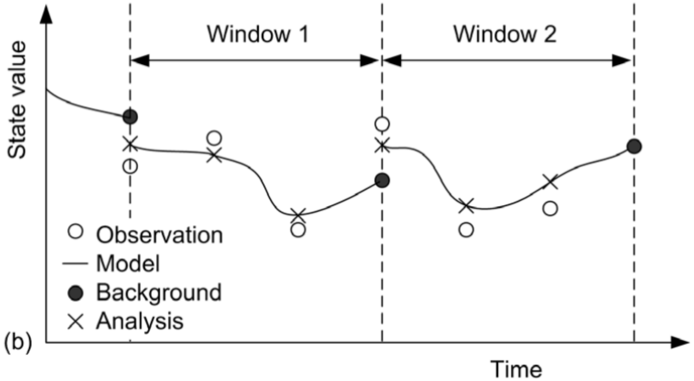
The purpose is ***to improve the initial state of the model***, which later makes a forecast for the next time step.

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

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.

Question: Can we merge DA with model uncertainty?



Houser et al. (2012)

2. Methodology: MP-VarDA (1)

The aim of the study

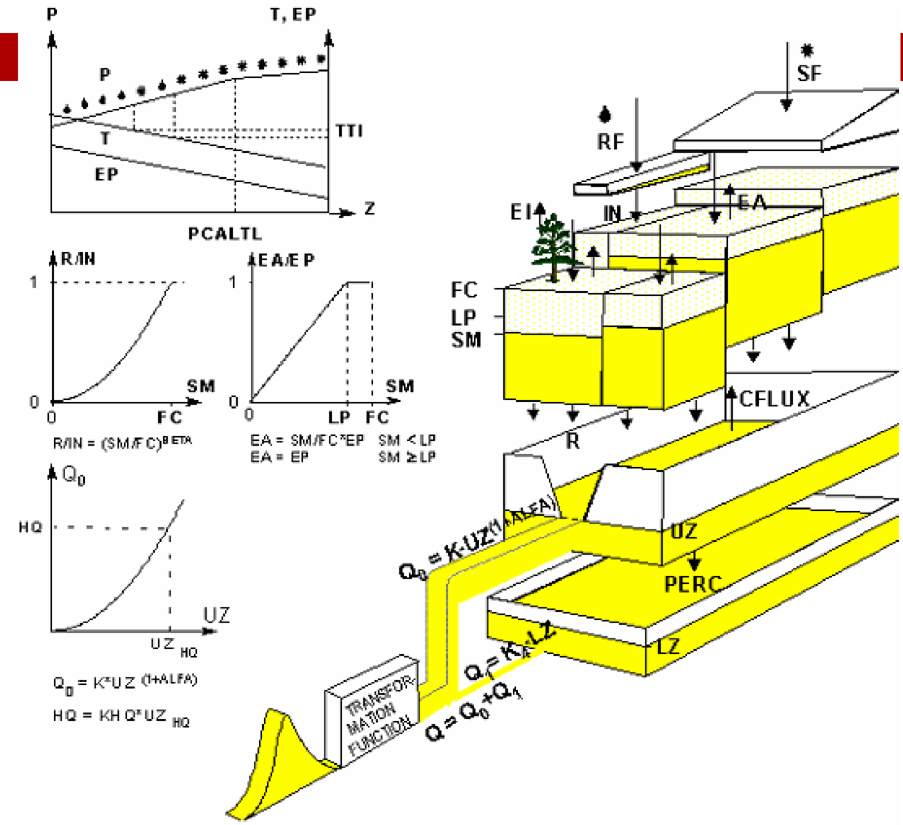
- **The uncertainties of the model structure** is very important since in each implementation of DA same model and same parameter sets are used.
- In this study, the problem is re-analyzed by considering both:
  - **improving initial conditions**
  - **considering model uncertainty**

  to improve the modelled discharges and snow cover data
- **Method:** Hydrological Model + Multi-parametric Variational DA

2. Methodology: Hydrological Model (1)

Conceptual Model: **HBV**

HBV hydrological model is used for rainfall-runoff relationship:



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)

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)

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

MP-VarDA implementation by MHE

The implementation of the HBV model follows:

$$x^k = f\left(x^{k-1}, u^k, d^k, p\right)$$

$$y^k = g\left(x^k, v^k, d^k, p\right)$$

- x, y, d are the state, output and external forcing vectors, respectively,
- u, v are noise terms, p is the model parameters vector, f() and g() are functions representing arbitrary linear or non-linear components of the model, and
- k is the time step index.

MP-VarDA to assimilate information into a pool of M number of model instances, according to below Objective Function & Constraints

$$\min_{u,v} \sum_{m=1}^{M} \left(p_m \sum_{k=-N+1}^{0} \left(w_x \left\| \hat{x}^k - x^{k,m}(u) \right\| + w_y \left\| \hat{y}^k - y^{k,m}(u,v) \right\| + w_u \left\| u^k \right\| + w_v \left\| v^k \right\| \right) \right)$$

$$u_L \leq u^k \leq u_U$$

$$v_L \leq v^k \leq v_U$$

Alvarado-Montero et al., 2017

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

MP-VarDA implementation by MHE

- Model Pool

Generalized Likelihood Uncertainty Estimation (GLUE) (Beven, 2009) is used to create a model pool based on previously calibrated model.

the modified parameter bounded to the lower and upper bounds

a variation factor

$$-p_{i,cal} * F_{var} \leq p_{i,m} \leq p_{i,cal} * F_{var}$$

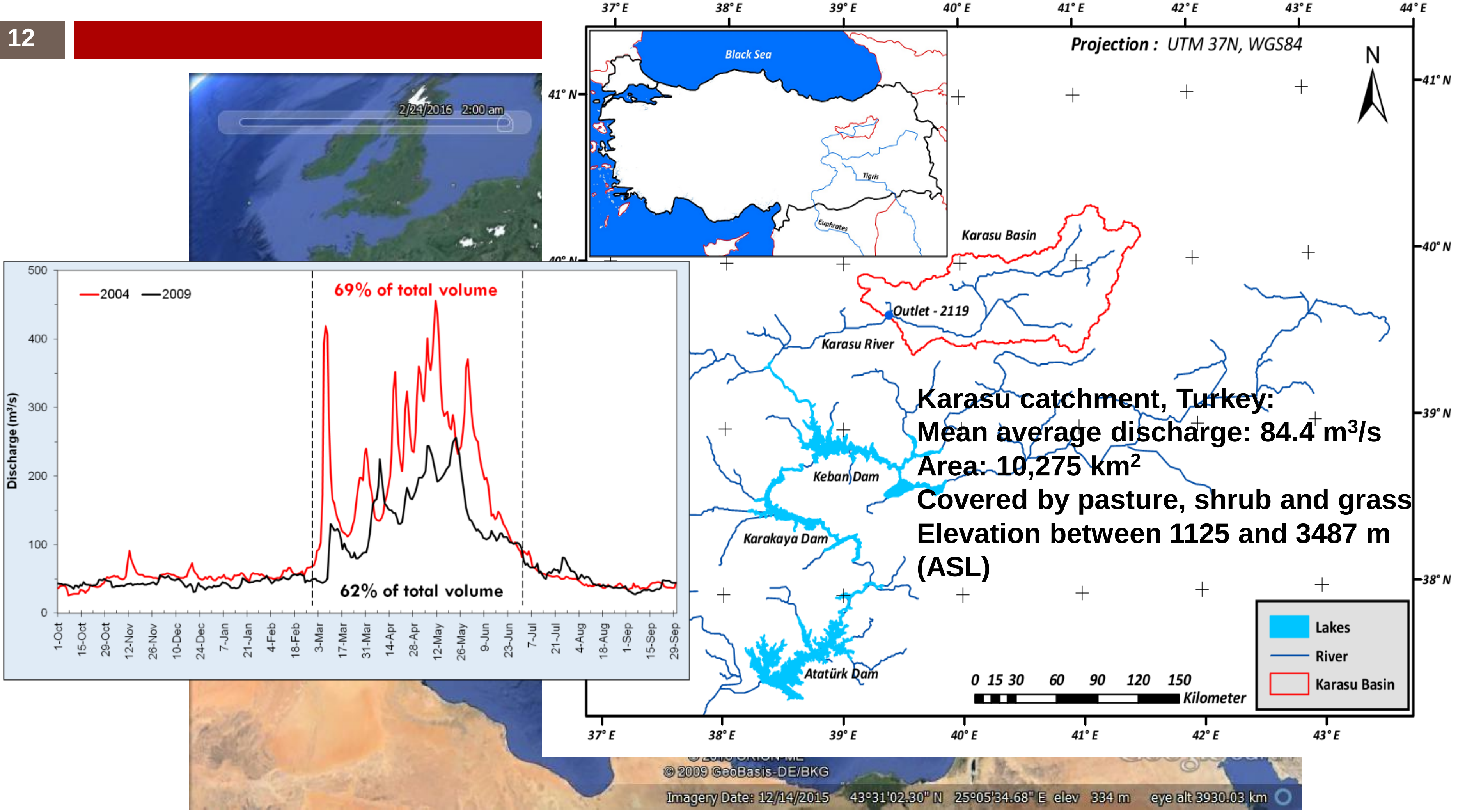
$$p_{i,L} \leq p_{i,m} \leq p_{i,U}$$

the parameter i of the calibrated set

Parameters are generated using Monte-Carlo approach

Alvarado-Montero et al., 2017

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)

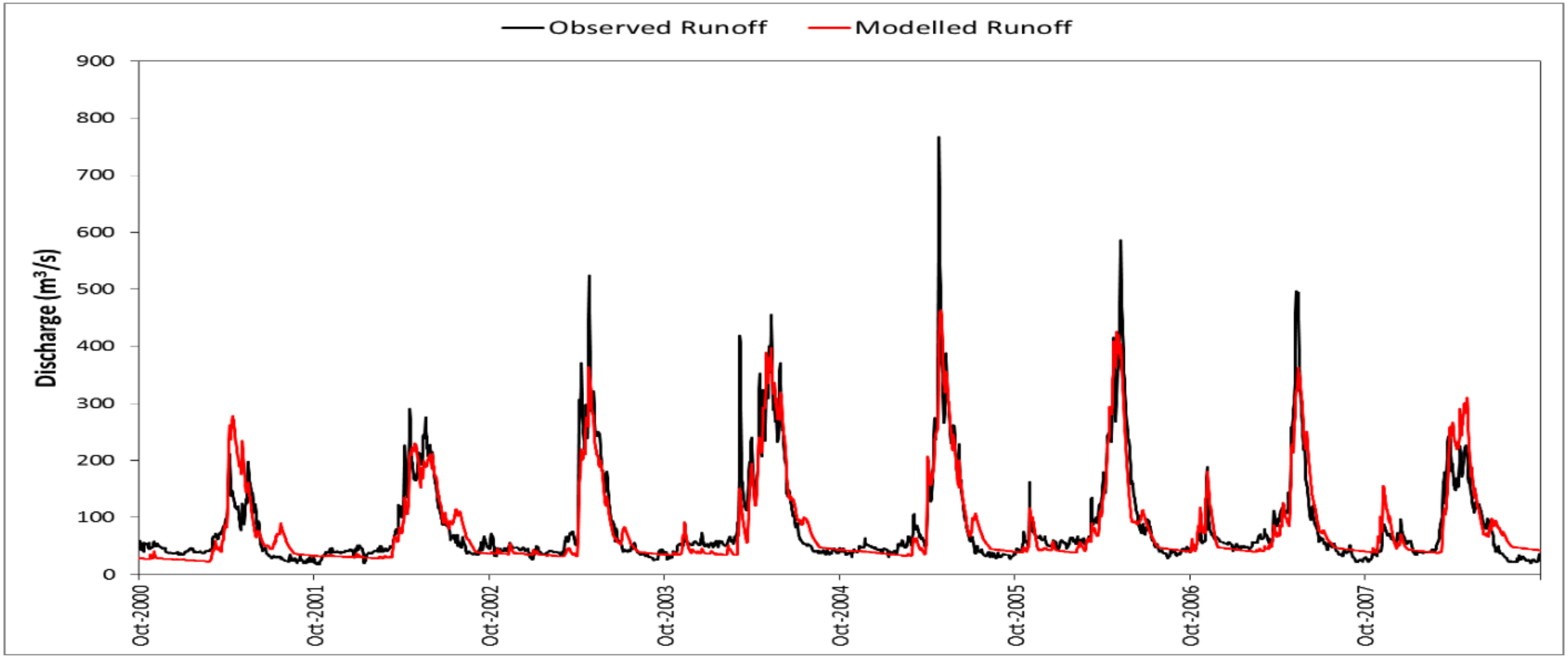
Data

- Ground Data: 18 Climate & AWOS (+2000m)
- 10 elevation zones (within 1125 – 3487 m)
- 1 land use type
- Model inputs:
  - Precipitation
  - Temperature
  - Potential Evapotranspiration
- Model outputs:
  - Discharge
  - SWE and Snow Covered Area (SCA)

3. *Model setup (3)*

Model parameters

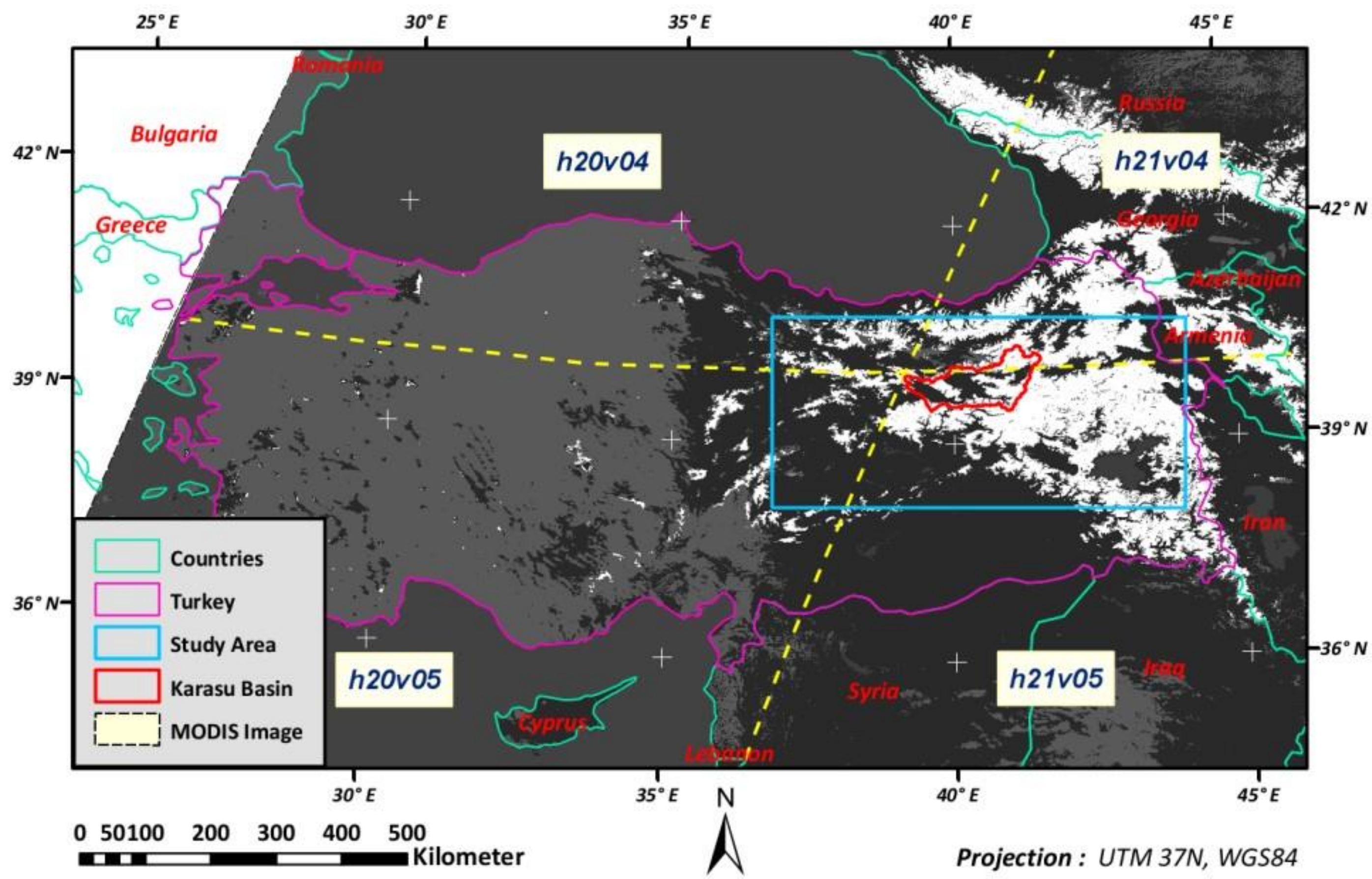
- Calibrated btw 01/10/2001 to 30/09/2008 (NSE* of 0.84)
- Validated btw 01/10/2008 to 30/09/2012 (NSE* of 0.74)



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

**Nash-Sutcliffe Efficiency (NSE)*

3. Model setup (4)
Snow Cover Area (SCA) MODIS



- **Temporal Resolution**: Daily
- **Spatial Resolution**: 500 m

Şorman et al., 2019

4. MP-VarDA Application (1)

- Results are conducted for: VarDA (Uysal et al. 2019) & MP-VarDA
- Test simulation: 2007 (demo)
- Hindcasting period:
  - 2015-2016 (2 water years)
- Assimilated observations:
  - Only Discharge (Q)
  - Q & SCA (MODIS)
- Forcings:
  - *Perfect forecast* (Prec., Temp.)
- Warm-up (+ assimilation window in VarDA and MP-VarDA)
  - 180 days
- Lead time:
  - 10 days

4. MP-VarDA Application (2)

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

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*)	$w_{SWE}(\hat{s}_{SWE}^k - s_{SWE}^k)^2$
	Soil Moisture (*SM*)	$w_{SM}(\hat{s}_{SM}^k - s_{SM}^k)^2 + w_{\Delta SM}(\Delta s_{SM}^k)^2$
	Upper Zone Storage (*UZ*)	$w_{\Delta UZ}(\Delta s_{UZ}^k)^2$
	Lower Zone Storage (*LZ*)	$w_{\Delta LZ}(\Delta s_{LZ}^k)^2$
Model Outputs	Snow Covered Area (*SCA*)	$w_Q(\hat{A}_{SCA}^k - A_{SCA}^k)^2$
	Discharge (*Q*)	$w_Q(\hat{Q}^k - Q^k)^2$

4. MP-VarDA Application (3)

Model Interfaces & performance metric

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

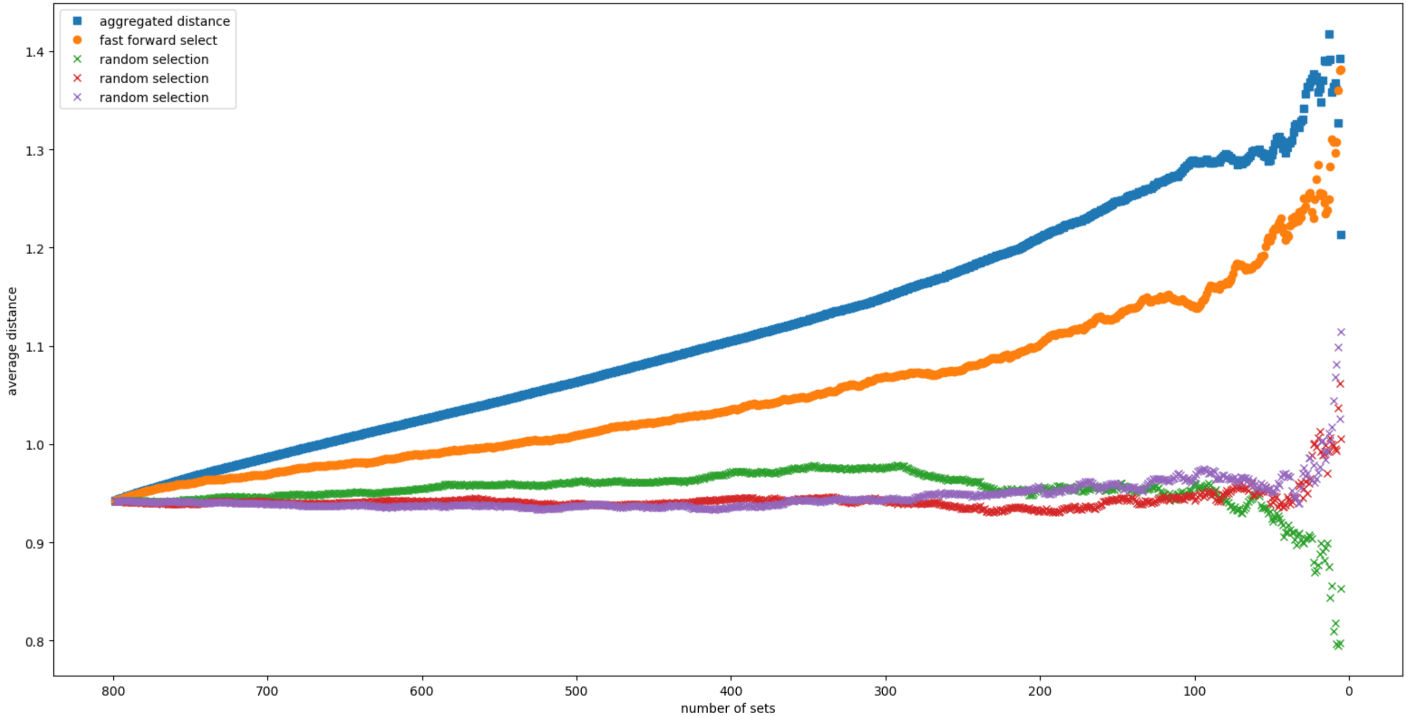
$$CRPS_L = \frac{1}{n}\sum_{k=1}^{n}\left[\int_{-\infty}^{+\infty}\left(F_t(y_{k,L}) - \Gamma(y_{k,L} \geq \hat{y}_k)\right)^2 dy\right]$$

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)

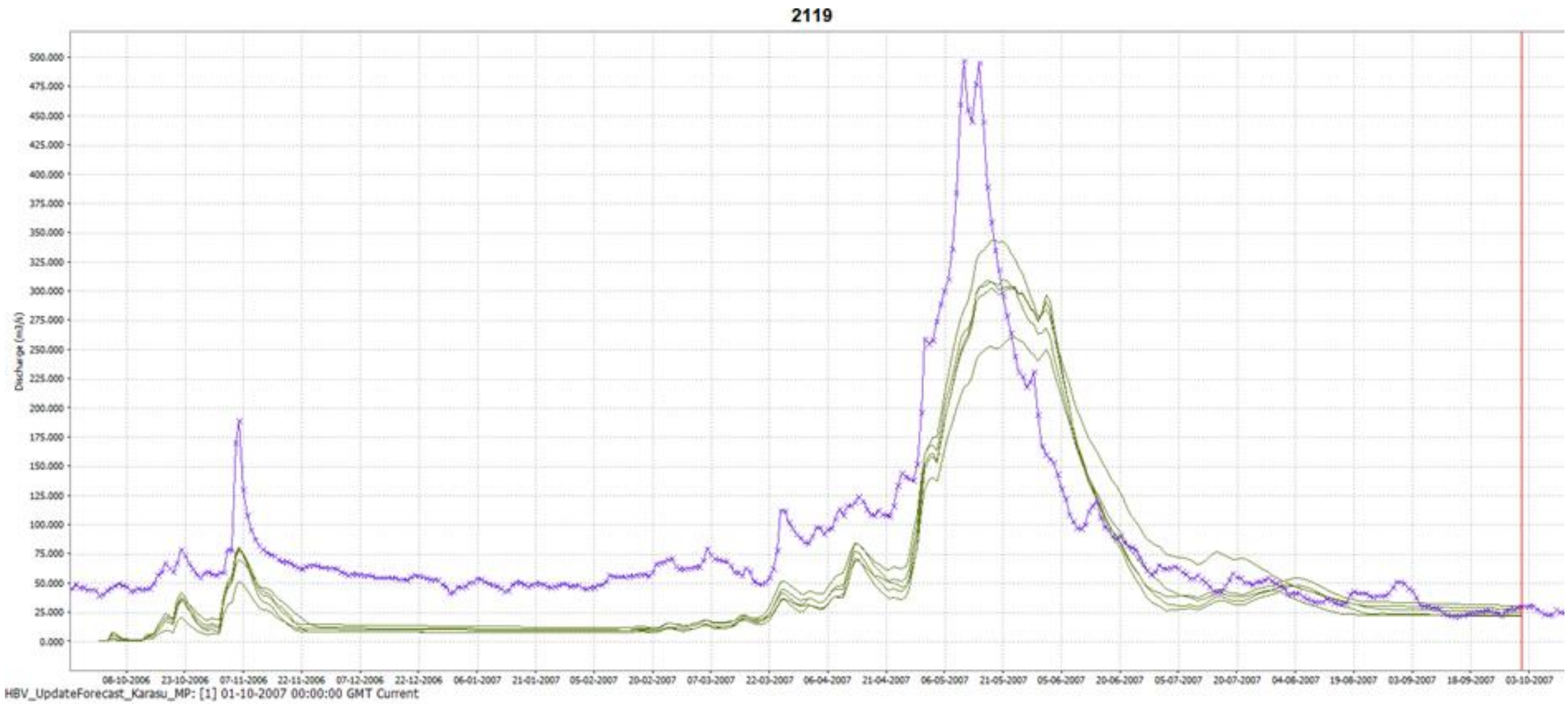
Generating model pool (parameter instances)

- Single Model Pool is derived by GLUE (Beven, 2009)
- 1000 Monte Carlo simulation (F_{var}=30%)
- Later, the parameters are reduced to five instances based on two different (FF and AD) techniques and 3 random selection.



5. Results & Comparison (2)
(example from 2007 water year, NoDA)

- Multi-parametric modelling simulation application using model pool parametrization (5 instances)

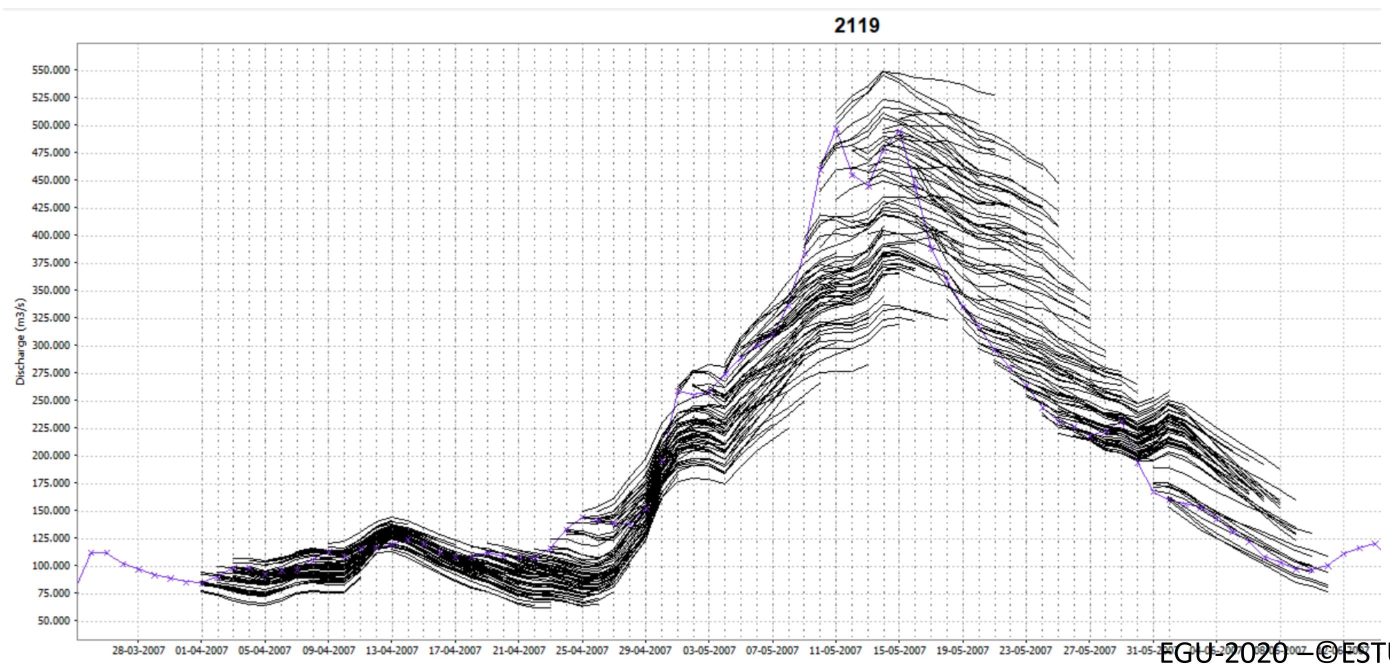


5. Results & Comparison (3)

Ensemble discharge forecasts

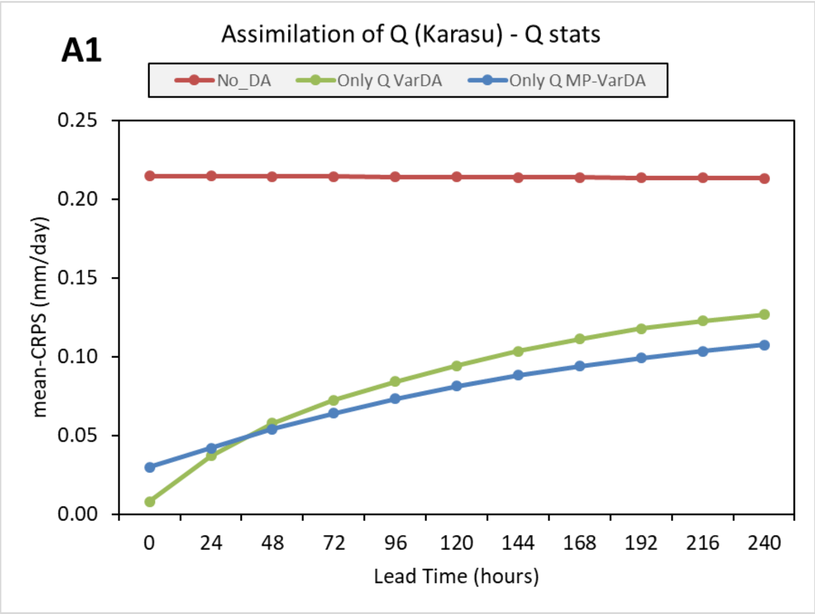
- Figure represents different time step ensemble discharge forecasts based on MP-VarDA updates for the initial states.
- MP-VarDA can provide more robust results by having probabilistic initial states (covering initial state uncertainty) and ensemble forecasts (covering model based uncertainty) rather than single trajectory generated by VarDA method.

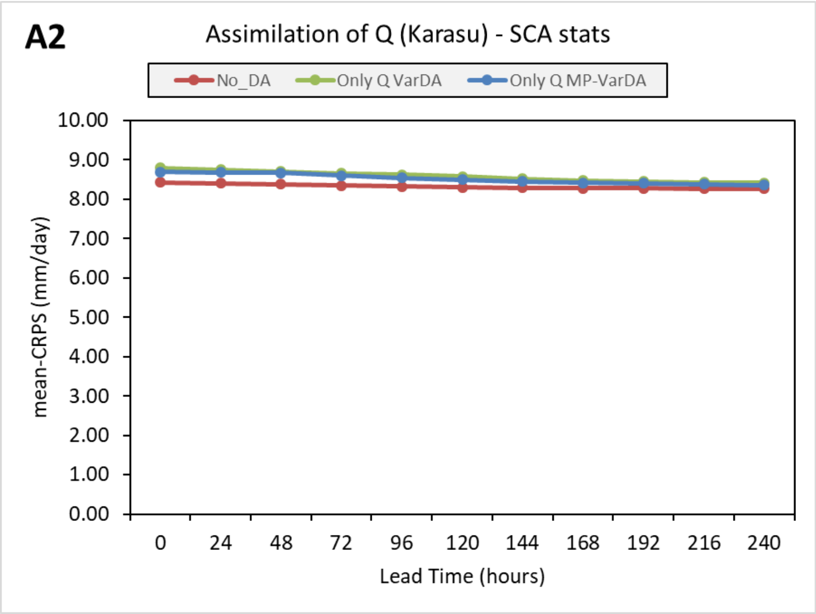
Q



5. Results & Comparison (4)

Comparison of VarDA & MP-VarDA (2009-2012) (Assimilation of Q observations)



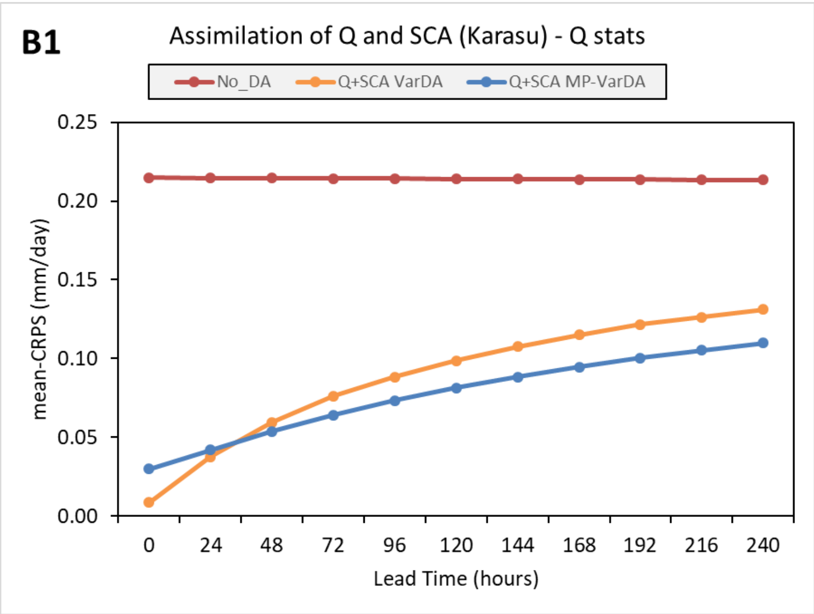


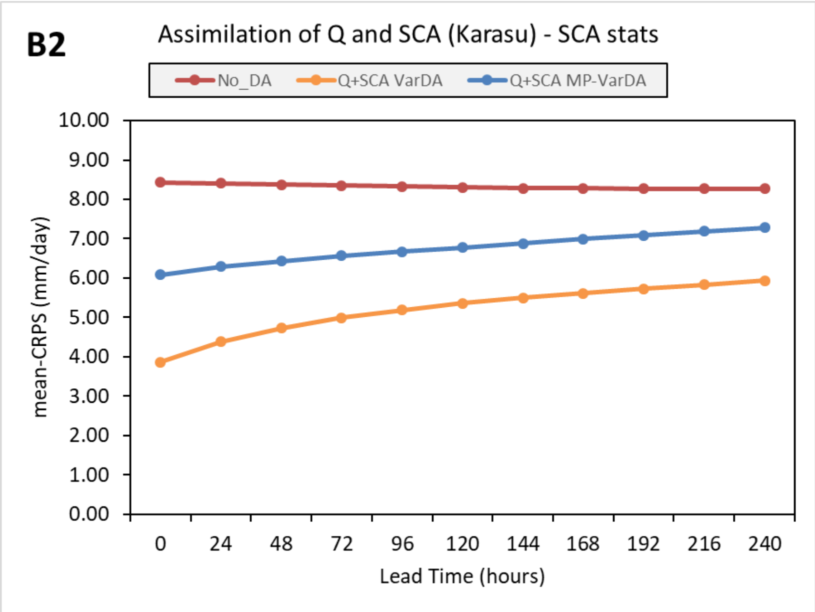
Q (m^3/s)	Q (mm/day)
10	0.08
100	0.84
1000	8.43
Q (mm/day)	Q (m^3/s)
0.03	3.56
1.00	100.00
1.50	1000.00

Note;
VarDA crps=mae
(since not ensemble method)

5. Results & Comparison (5)

Comparison of VarDA & MP-VarDA (2009-2012) (Assimilation of Q & SCA observations)





Q (m^3/s)	Q (mm/day)
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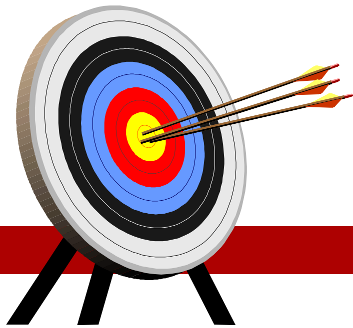
6. Conclusion (1)



1. Uncertainty

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

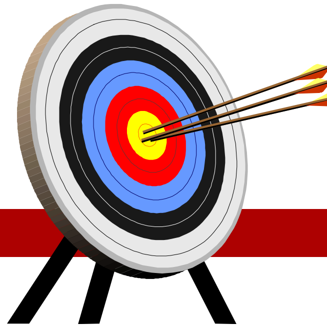
2. Data Assimilation

The study is conducted to improve the consistency of the streamflow forecasts with the observations, thus variational data assimilation technique is improved. And the model is tested 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 (MODIS products).

6. Conclusion (2)



4. Added value of MP-VarDA

- Preliminary results show that consideration of model pool in VarDA (which turns to a stochastic approach) provides better discharge performances.
- Snow observations (MODIS SCA products) in DA together with discharge requires further analyses.
- Both methods (VarDA & MP-VarDA) are better compared to 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. Outlook

a. The models desired to be extended using NWP (deterministic & probabilistic) *for real time forecasting application*.

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

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