DATA ASSIMILATION OF SATELLITE SNOW PRODUCTS THROUGH HYDROLOGICAL MODELLING IN MOUNTAINOUS CATCHMENTS

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COST ACTION ES1404: Towards a better harmonization of snow observations, modeling and data assimilation in Europe,
20-21 Oct 2018, Budapest-HUNGARY

MOTIVATION

SNOW D

EUROPEAN COOPERATION
IN SCIENCE & TECHNOLOGY

SHORT TERM SCIENTIFIC MISSION (STSM) – SCIENTIFIC REPORT

The STSM applicant submits this report for approval to the STSM coordinator

Action number: ES1404
STSM title: Data Assimilation of Satellite Snow Products through Hydrological Modelling
STSM start and end date: 05/08/2018 - 11/08/2018
Grantee name: Assoc. Prof. Dr. Aynur ŞENSOY ŞORMAN

PURPOSE OF THE STSM/

Analyzing and forecasting the temporal and spatial variability of snow is important for hydrological purposes as well as for weather prediction and climatic models especially in mountainous regions. Snow observations are necessary for running hydrological and meteorological models for calibration, validation

OVERVIEW

- **FOCUS:**

The use of data assimilation in the context of hydrological operational forecasting systems

- **OBJECTIVE:**

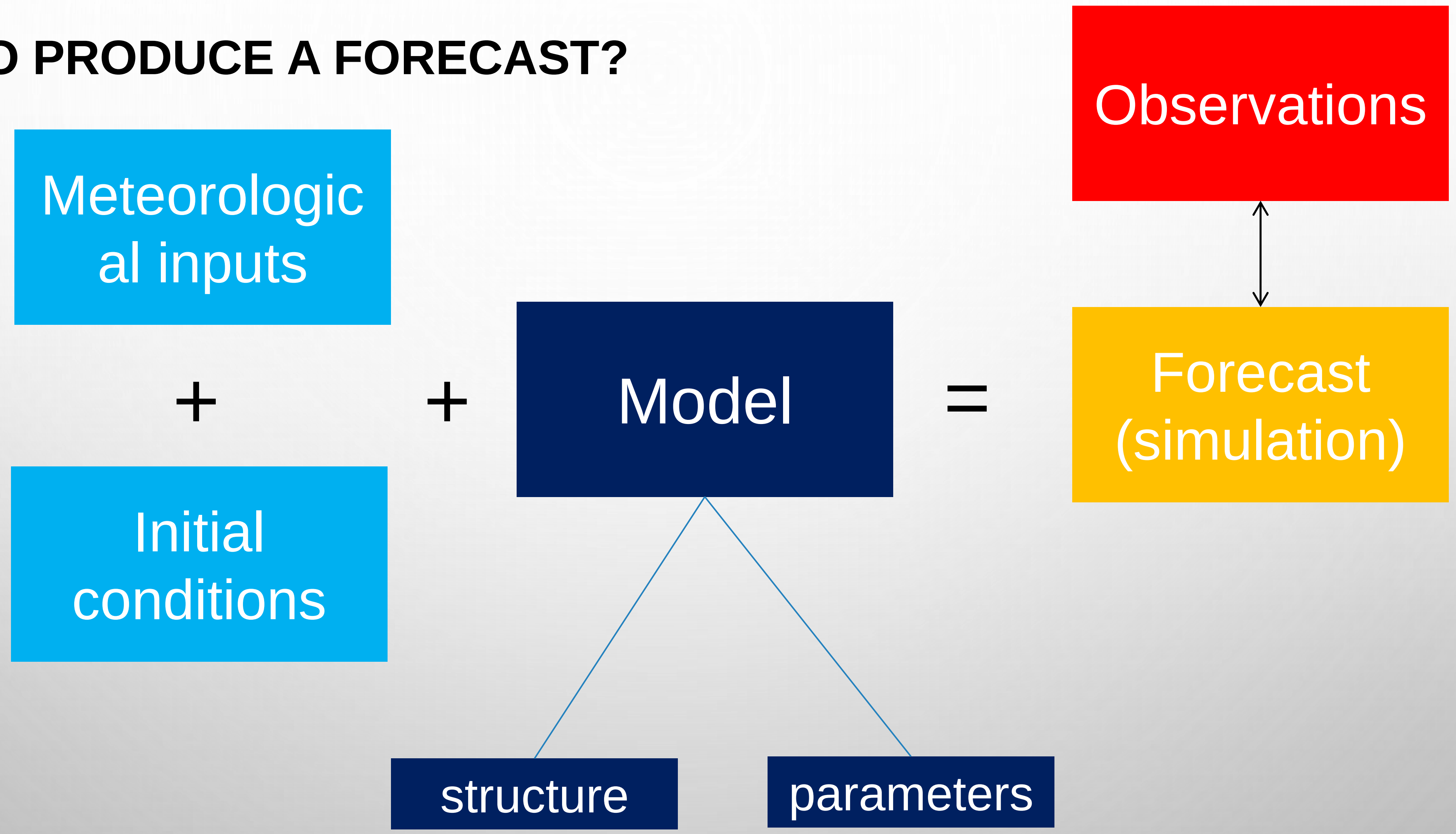
How to assimilate data (snow) in applications using conceptual hydrological modelling (HBV)

- **SPECIFIC:**

- Implementation of the Ensemble Kalman Filter, as it is perhaps the most widely used sequential data assimilation method
- Implementation of the variational data assimilation approach
- Get exposed to forecasting systems and produce forecasts based on assimilated snow products
- Assess the performance skill of the forecasts

INTRODUCTION

HOW TO PRODUCE A FORECAST?



INTRODUCTION

INDICATE THE SOURCES OF UNCERTAINTY!

Observations

Meteorological inputs

+

+

Model

=

Forecast (simulation)

EVERYWHERE!

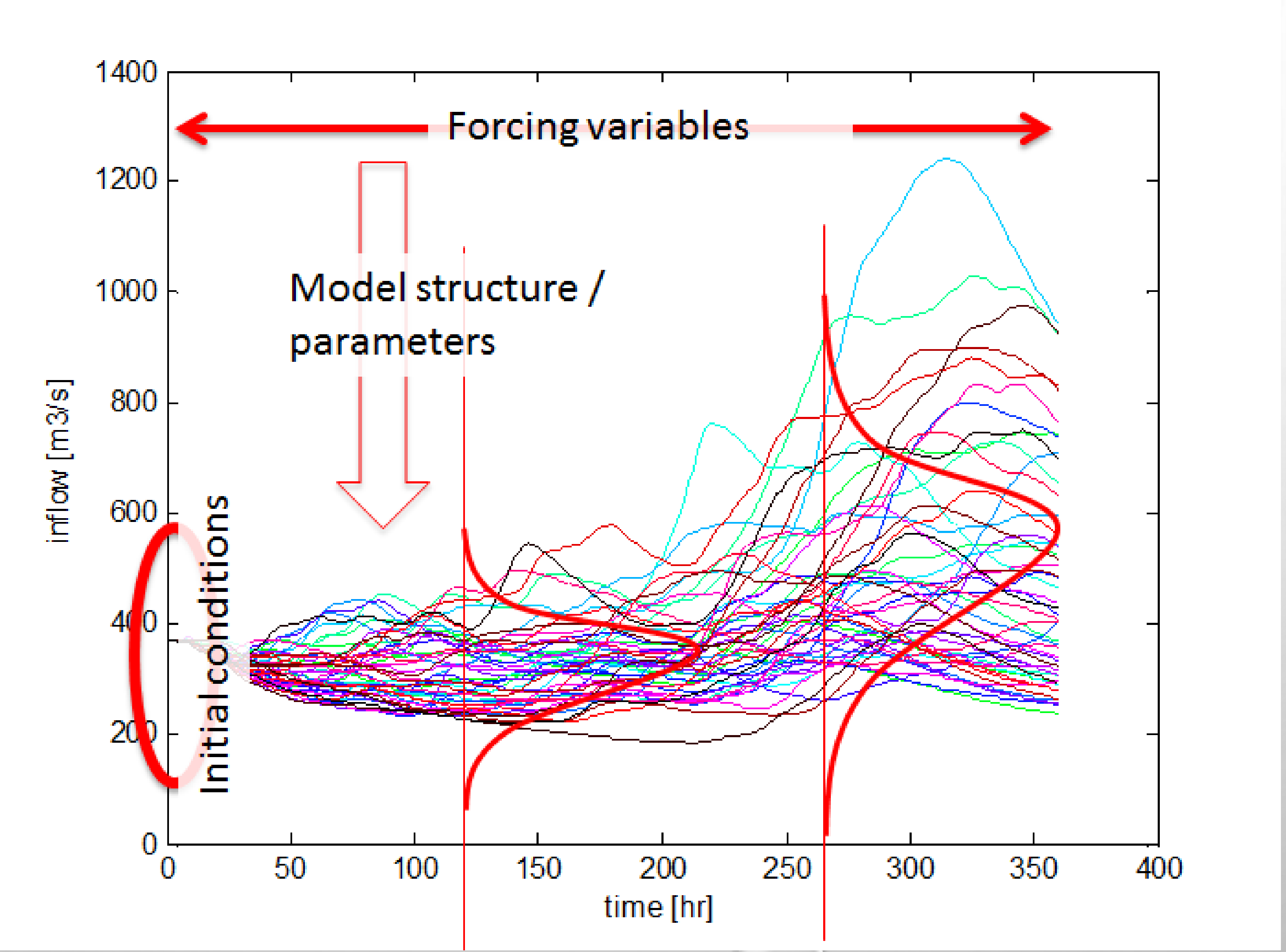
Initial conditions

structure

parameters

INTRODUCTION

UNCERTAINITY



INTRODUCTION

DATA ASSIMILATION

"Procedures that aim to produce physically consistent representations or estimates of the dynamical behavior of a system by merging the information present in imperfect models and uncertain data in an optimal way to achieve uncertainty quantification and reduction."

(Definition by Liu Y. and Gupta H., 2007, underlined is added)

METHODOLOGY-1 (HYDROLOGICAL MODEL)

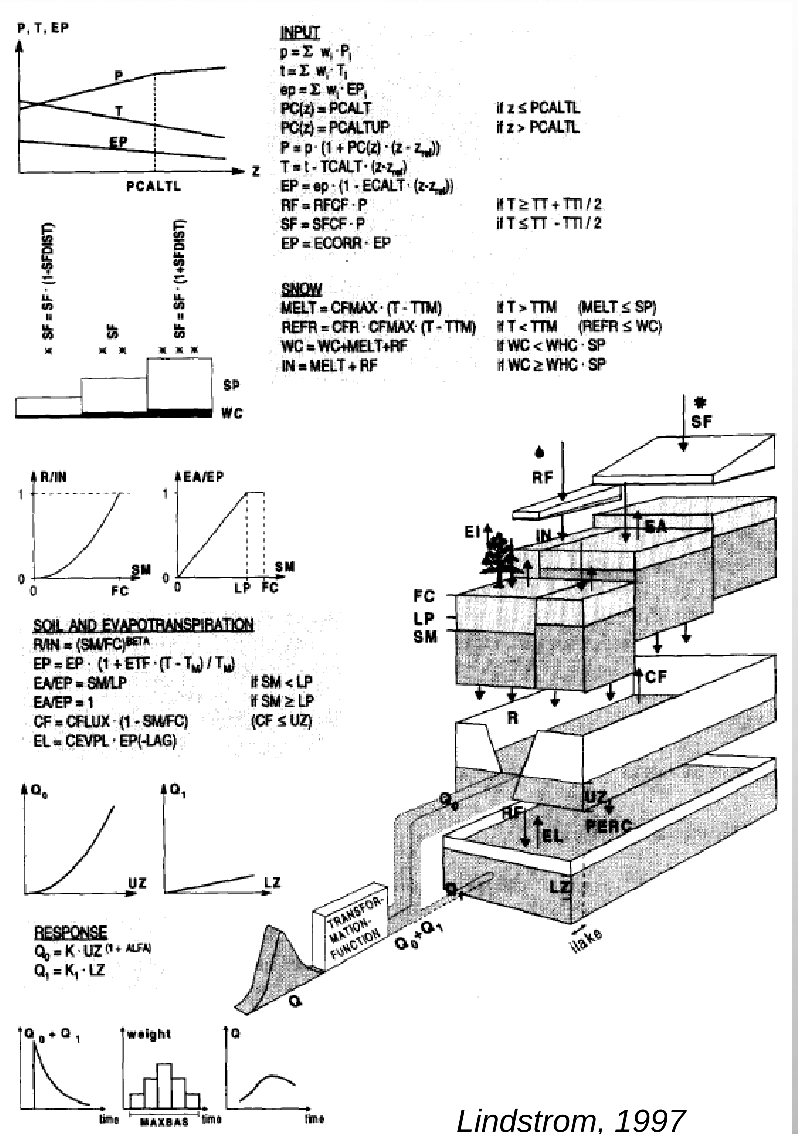
HBV model is selected as the conceptual hydrological model

Forcing (model inputs):

- Precipitation
- Temperature
- Evapotranspiration

State variables:

- Snow water equivalent
  (snow pack + water content in snow)
- Interception storage
- Soil moisture
- Upper zone storage
- Lower zone storage



Lindstrom, 1997

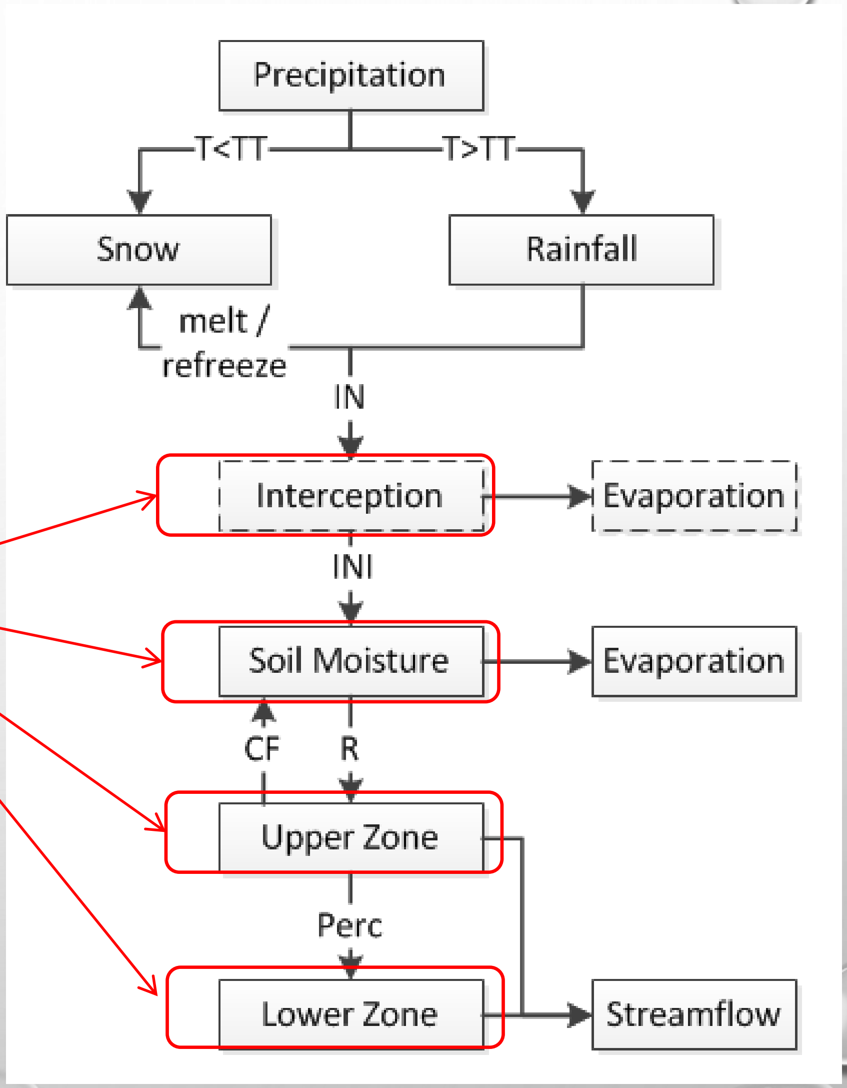
METHODOLOGY-1(HYDROLOGICAL MODEL)

- The model structure allows extensive modifications by DA
- DA works well from a technical perspective, even for a long assimilation horizons of up to 40 years in a single assimilation run
- High computational performance enables the operational application of the approach and supports the execution of hindcast experiments

IDENTIFY:

FLUX VARIABLES

STORAGE VARIABLES



METHODOLOGY-2 (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 perturbing model forcings and sampling the model states.

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

Objective function!

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

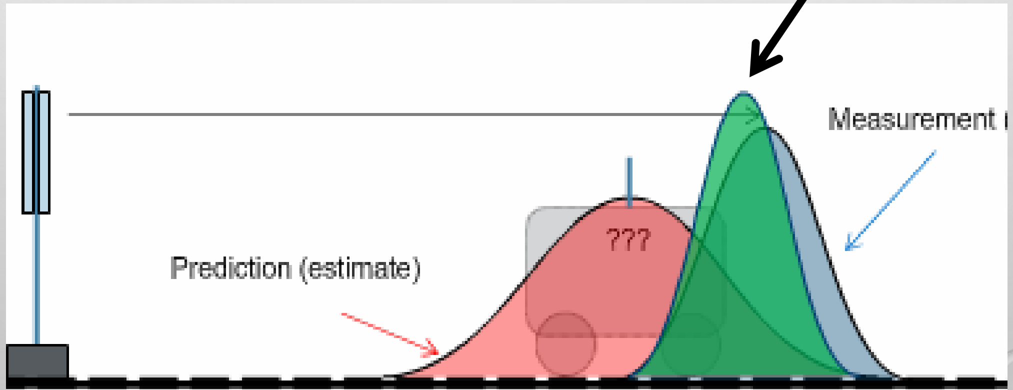
$$\sigma^2_{Model}(True - Obs) + \sigma^2_{obs}(True - Model) = 0$$

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

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

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

Improved estimate!



METHODOLOGY-3 (MHE)

The implementation of the HBV model follows:

Disturbance/forcing vector

states $\rightarrow$ $x^k = f(x^{k-1}, d^k, u^k)$

noise vectors

output variable $\rightarrow$ $y^k = g(x^k, d^k, v^k)$

Linear and non-linear functions of HBV model

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

Observations

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

Objective function

$$\text{subject to} \quad u_L \leq u^k \leq u_U$$

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

Hard constraints

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

METHODOLOGY-3 (MHE)

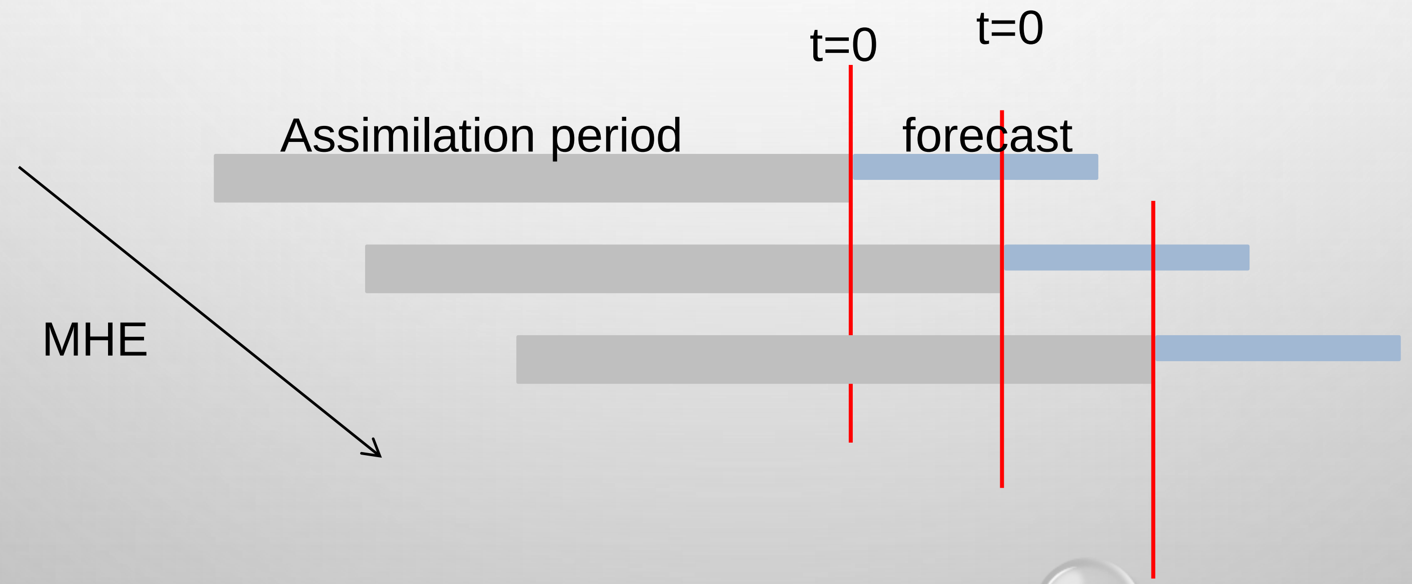
Variables and objective function terms in the MHE

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)	$w_Q(\hat{Q}^k - Q^k)^2$

METHODOLOGY-3 (MHE)

Variational data assimilation by moving horizon estimation (MHE):

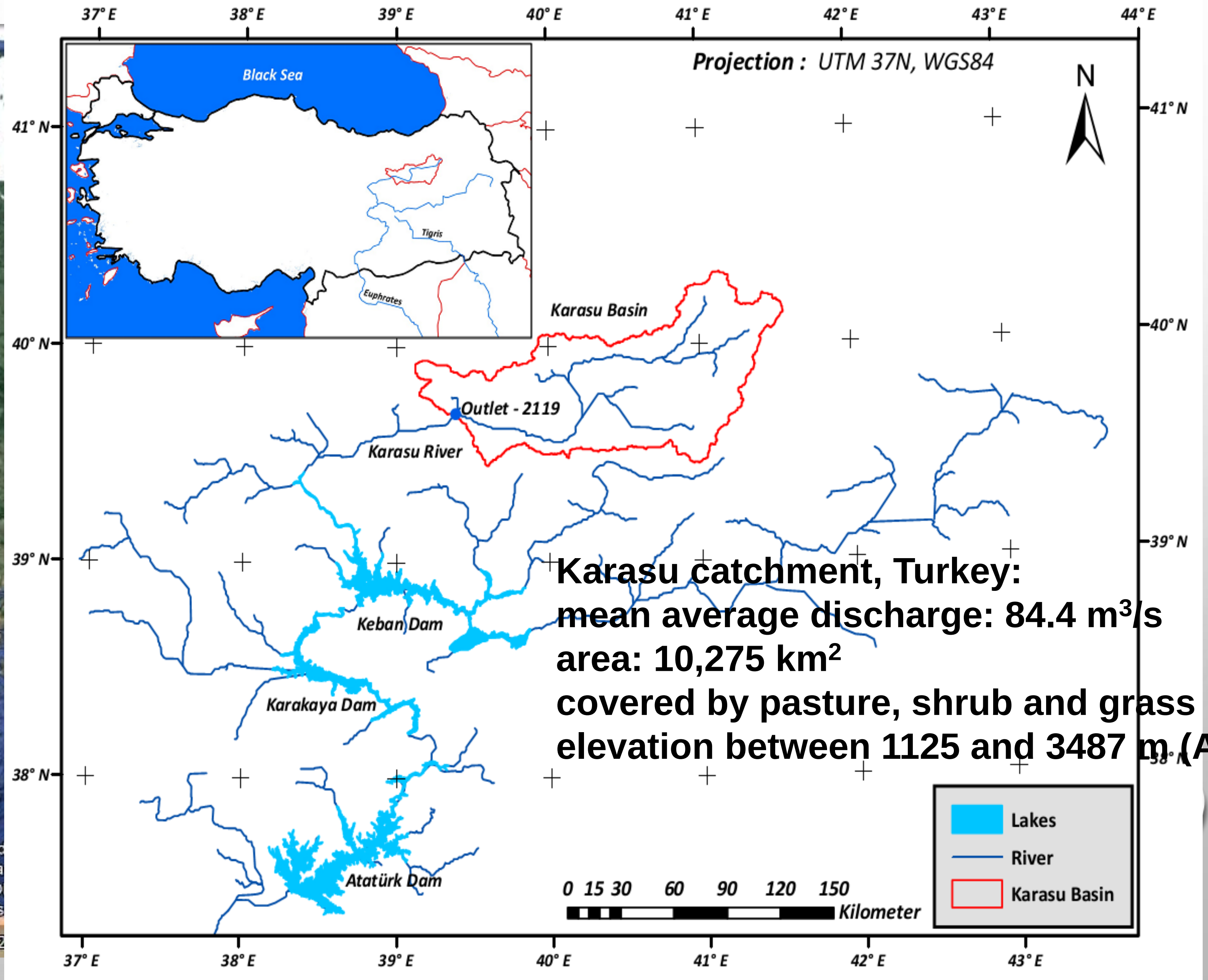
- Model simulation over an finite-time assimilation period,
- Cost function with penalty on deviations between observed and simulated quantities and the update of model inputs and states,
- Minimize the cost function by an optimization algorithm,
- Apply the assimilated states as initial condition of a forecast and
- Repeat the procedure at every forecast time



- 4DVar:
- + 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 KF:
- + applicable on black-box models, simple to implement
- + probabilistic approach
- - sequential technique, has issues with time lags

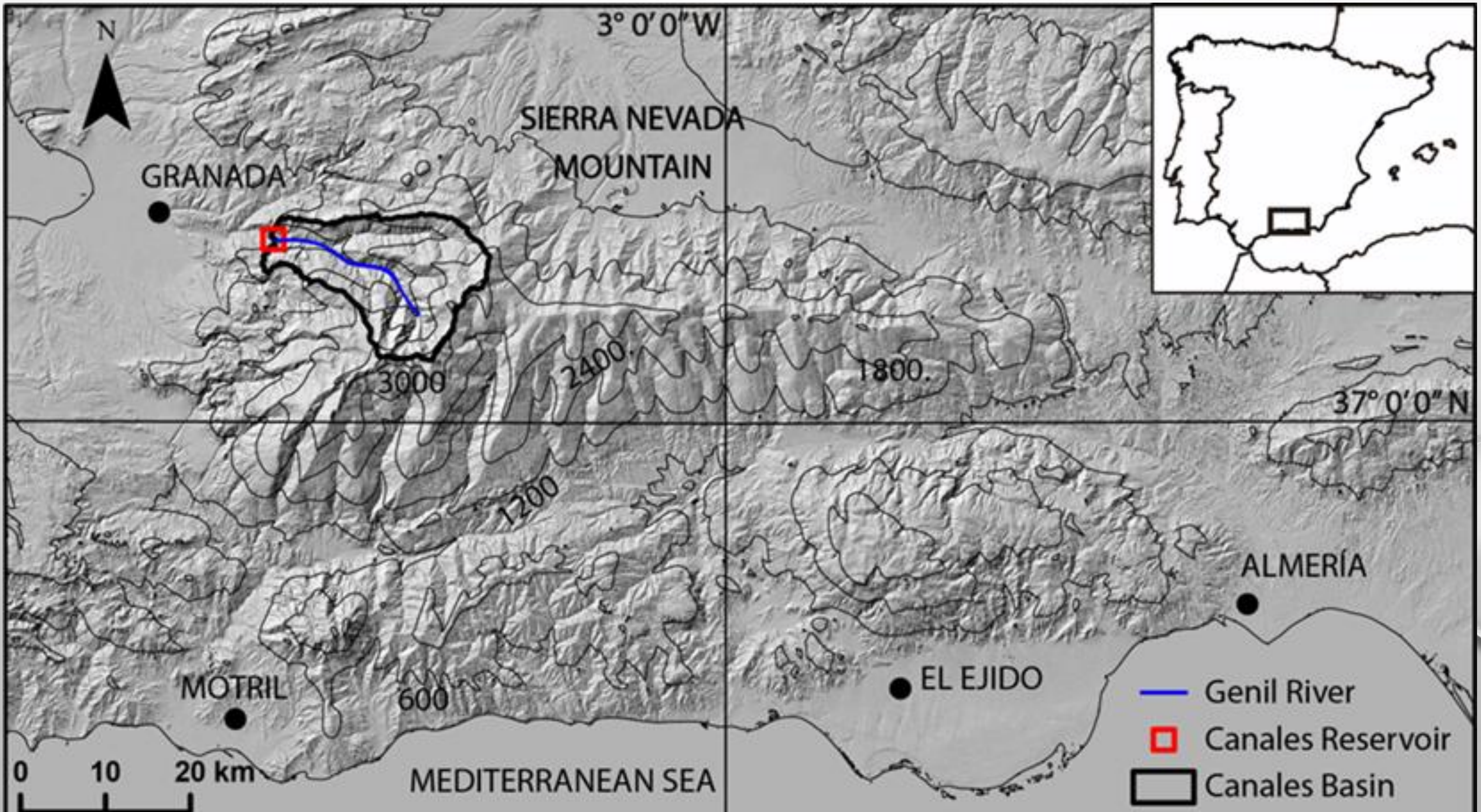
STUDY AREA 1 (KARASU BASIN - TURKEY)



Karasu catchment, Turkey:
mean average discharge: 84.4 m^3/s
area: 10,275 km^2
covered by pasture, shrub and grass
elevation between 1125 and 3487 m (A

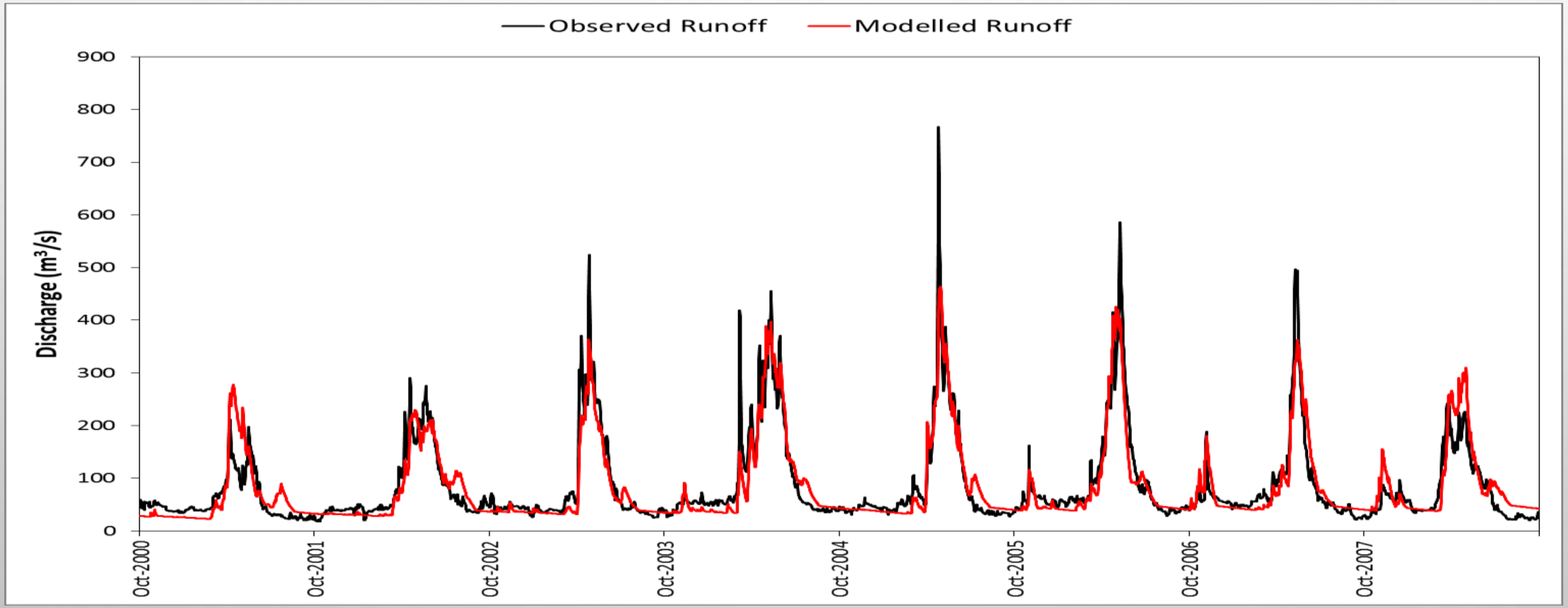
STUDY AREA 2 (CANALES BASIN - SPAIN)

- Alpine basin
- Headwaters of the Genil River (Northern flank of the Sierra Nevada Mountain, Southern Spain)
- Surface area = around 176 Km^2
- Mean elevation of 2050 m.a.s.l. (ranging from 850 and 3443 m.a.s.l)



MODEL SETUP FOR KARASU BASIN:

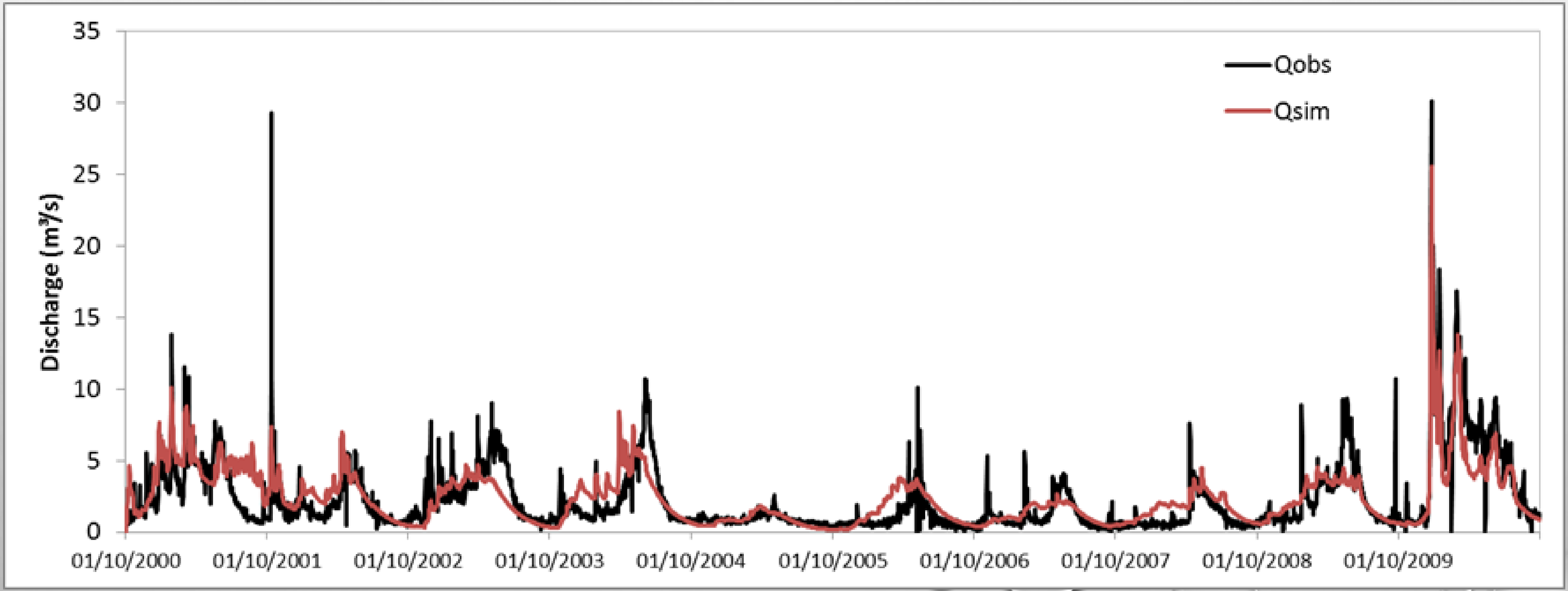
- 10 elevation zones and 1 land use type
- Cal period 01/10/2001 to 30/09/2008 (NSE of 0.84)
- Val period 01/10/2008 to 30/09/2012 (NSE of 0.74)



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

MODEL SETUP FOR CANALES

- 5 elevation zones and 1 land use type
- Cal period 01/10/2000 to 30/09/2010 (NSE of 0.69)
- Val period 01/10/2010 to 30/09/2014 (NSE of 0.58)



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

MODEL SETUP MATRIX FOR DA APPLICATION

Sequential experiments

Members	Uncertainty Observations		Uncertainty Perturbations		Limits of Tails		Test case	Local folder - NoID
	Q	SCA	P	T	P	T		
100	0.1%	0.05%	1mm	0.25°C	1000mm	0.5°C	Karasu	40_Karasu_Seq_100_0.1_0.05_1mm_0.25°C_1000mm_0.5
100	1%	5%	1mm	0.25°C	1000mm	0.5°C	Karasu	41_Karasu_Seq_100_1_5_1mm_0.25°C_1000mm_0.5°C
100	1%	5%	3mm	0.25°C	1000mm	0.5°C	Karasu	42_Karasu_Seq_100_1_5_3mm_0.25°C_1000mm_0.5°C
100	1%	5%	1mm	0.5°C	1000mm	1.0°C	Karasu	43_Karasu_Seq_100_1_5_1mm_0.5°C_1000mm_1.0°C
100	1%	5%	1mm	0.25°C	100mm	0.5°C	Karasu	44_Karasu_Seq_100_1_5_1mm_0.25°C_100mm_0.5°C
100	2%	5%	1mm	0.25°C	1000mm	0.5°C	Karasu	45_Karasu_Seq_100_2_5_1mm_0.25°C_1000mm_0.5°C
100	1%	1%	1mm	0.25°C	1000mm	0.5°C	Karasu	46_Karasu_Seq_100_1_1_1mm_0.25°C_1000mm_0.5°C
100	1%	15%	1mm	0.25°C	1000mm	0.5°C	Karasu	47_Karasu_Seq_100_1_15_1mm_0.25°C_1000mm_0.5°C
100	0.1%	5%	1mm	0.25°C	1000mm	0.5°C	Karasu	48_Karasu_Seq_100_0.1_5_1mm_0.25°C_1000mm_0.5°C

Variational experiments

Weight of Observations		Range of Noise Terms (weight at 1.0)					Test case	Local folder
Q	SCA	P	T	SM	UZ	LZ		
10	0	1.3, 0.7	2.0, -2.0	1.0, -1.0	1.0, -1.0	1.0, -1.0	Karasu	01_Karasu_Var_10_0_30_2_1_1_1
10	1	1.3, 0.7	2.0, -2.0	1.0, -1.0	1.0, -1.0	1.0, -1.0	Karasu	02_Karasu_Var_10_1_30_2_1_1_1
10	0	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	Karasu	03_Karasu_Var_10_0_30_2_5_5_5
10	1	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	Karasu	04_Karasu_Var_10_1_30_2_5_5_5
100	1	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	Karasu	05_Karasu_Var_100_1_30_2_5_5_5
50	1	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	Karasu	06_Karasu_Var_50_1_30_2_5_5_5
1	1	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	Karasu	07_Karasu_Var_1_1_30_2_5_5_5
200	1	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	Karasu	08_Karasu_Var_200_1_30_2_5_5_5

PERFORMANCE MEASURE

- THE *CONTINUOUS RANKED PROBABILITY SCORE* (CRPS) GENERALIZES THE MAE TO THE CASE OF PROBABILISTIC FORECASTS. THE CPRS IS ONE OF THE MOST WIDELY USED ACCURACY METRICS WHERE PROBABILISTIC FORECASTS ARE INVOLVED.

$$CPRS_L = \frac{1}{n}\sum_{k=1}^{n}\left[\int_{-\inf}^{\inf} F_t \;\; y_{k,L} \;\; - \Gamma \;\; y_{k,L} \geq \hat{y}_k \;\;^{2} dy\right]$$

SUMMARY

- Data assimilation increases the streamflow forecast accuracy in both methods.
- Including satellite snow products increases the forecast accuracy of streamflow together with SCA forecasts.
- Significant improvement is seen in the variational method by assimilating snow. It produces estimates that improves discharge and snow forecast.
- Sequential method produces relatively poor performance of forecasted snow by assimilating either Q only or Q and SCA.
- Strong tradeoff between improvement of forecasted Q and reduction of SCA forecast skill in sequential assimilation
- Other performance indicators capturing additional properties of the ensemble (e.G. Brier score, ROC curves) could contribute to the effects produced by

FUTURE WORKS

- Other satellite products could also be applied for DA, for instance snow water equivalent, soil moisture.
- In-situ observations of snow (e.g. depth, swe, etc.) could also be used in DA
- Enhancement in real-time runoff forecast can improve the reseroir operation
- Multi-parametric variational assin

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Multi-parametric variational data assimilation for hydrological forecasting

R. Alvarado-Montero [a, d], D. Schwanenberg [b], P. Krahe [c], P. Helmke [c], B. Klein [c]

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THANK YOU!

In Preparation:

Sequential and variational assimilation of discharge and snow data using hydrological lumped models in mountainous catchments

Rodolfo Alvarado Montero, Gokcen Uysal, Antonio Collados, David Pulido Velázquez, Aynur Sensoy