EUMETSAT H SAF

Impact Studies and Snow Hydro-Validation Part I

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How to use satellite snow data

Satellite snow data have been used in hydrologic models :

a) to assign model forcing

b) to set model initial conditions

c) as time-varying state data to constrain model predictions

For the purpose of:

Flood, drought, forecasting, climate change, reservoir operation, etc.

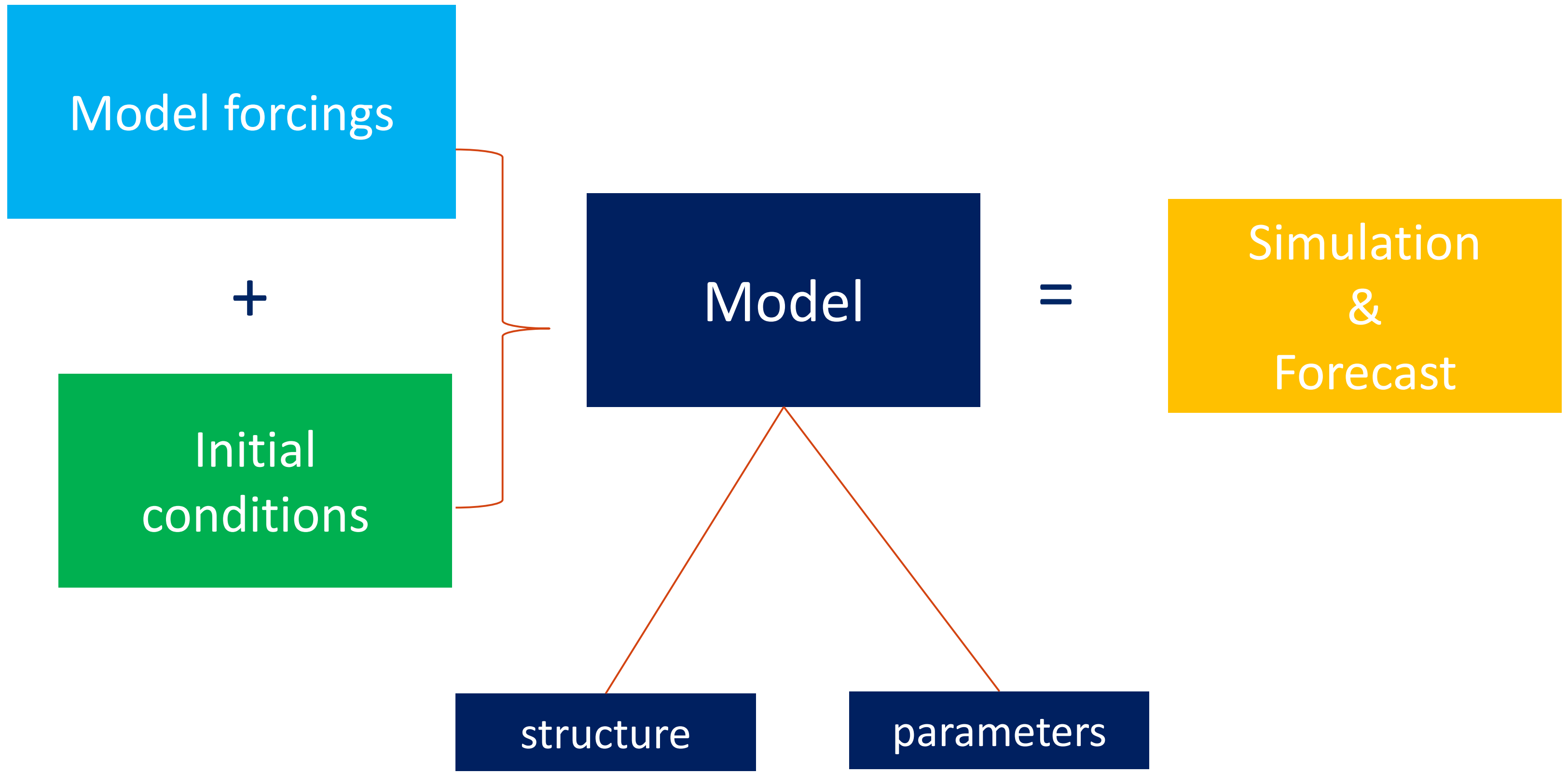
Class	Observation	Ideal Technique	Ideal Time Scale	Ideal Space Scale	Currently available data
Parameters	Land cover/change	optical/IR	daily or changes	1km	AVHRR, MODIS, NPOESS
	Leaf area & greenness	optical/IR	daily or changes	1km	AVHRR, MODIS, NPOESS
	Albedo	optical/IR	daily or changes	1km	MODIS, NPOESS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

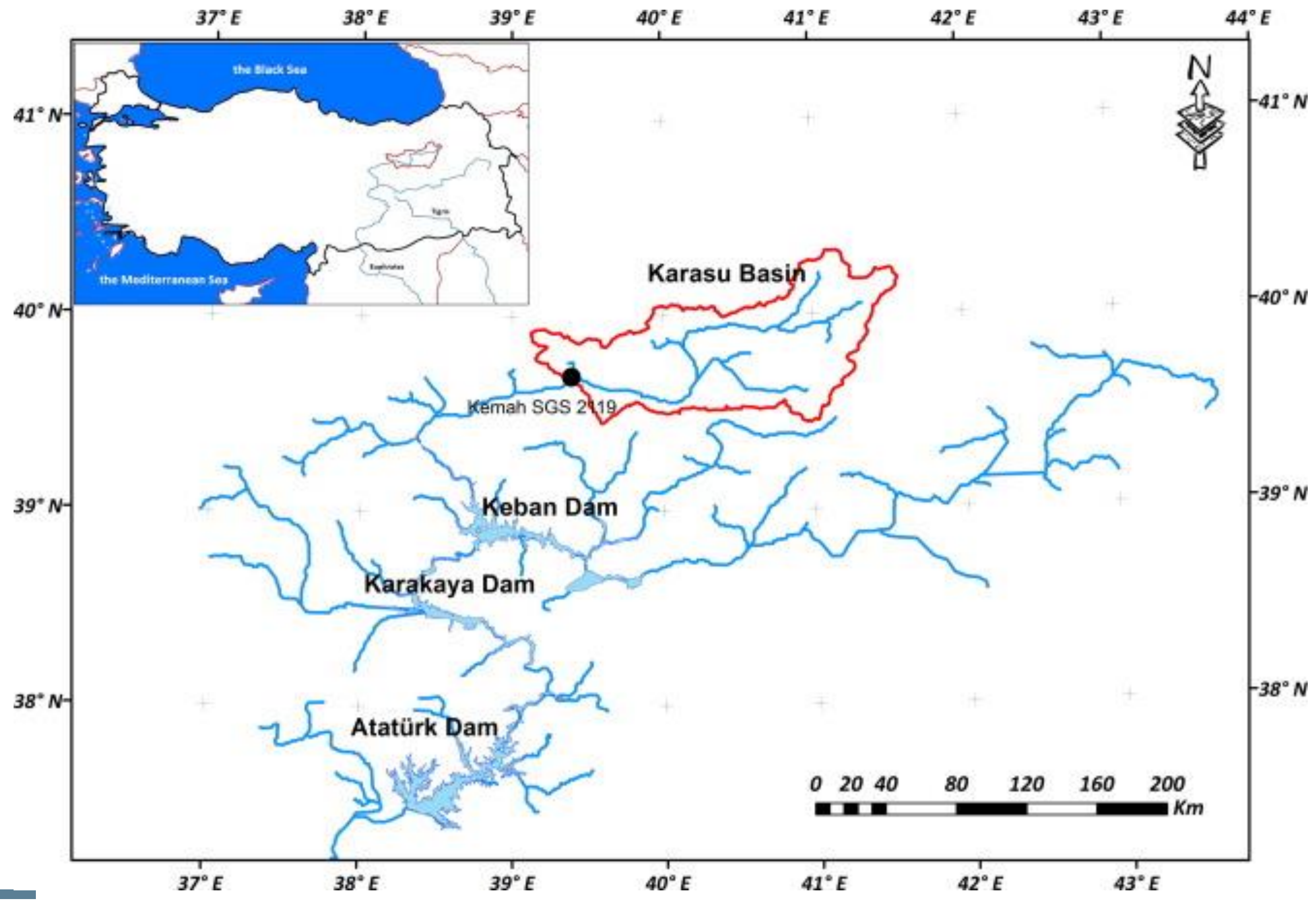
How to use satellite snow data

- Daily snow cover area (SCA) and snow water equivalent (SWE) data sets derived from SE-E-SEVIRI(H10) and SWE E(H13), respectively, are evaluated over the mountainous terrain of Eastern Turkey.
- Impact of the snow recognition product is analyzed.
- Hydro-validation of both data sets are assessed through conceptual models (SRM and HBV).
- Assimilation of snow products are shown to improve snow states of the models and lead time runoff forecasts.

How to produce a forecast



Study Area: Upper Euphrates Basin, Turkey



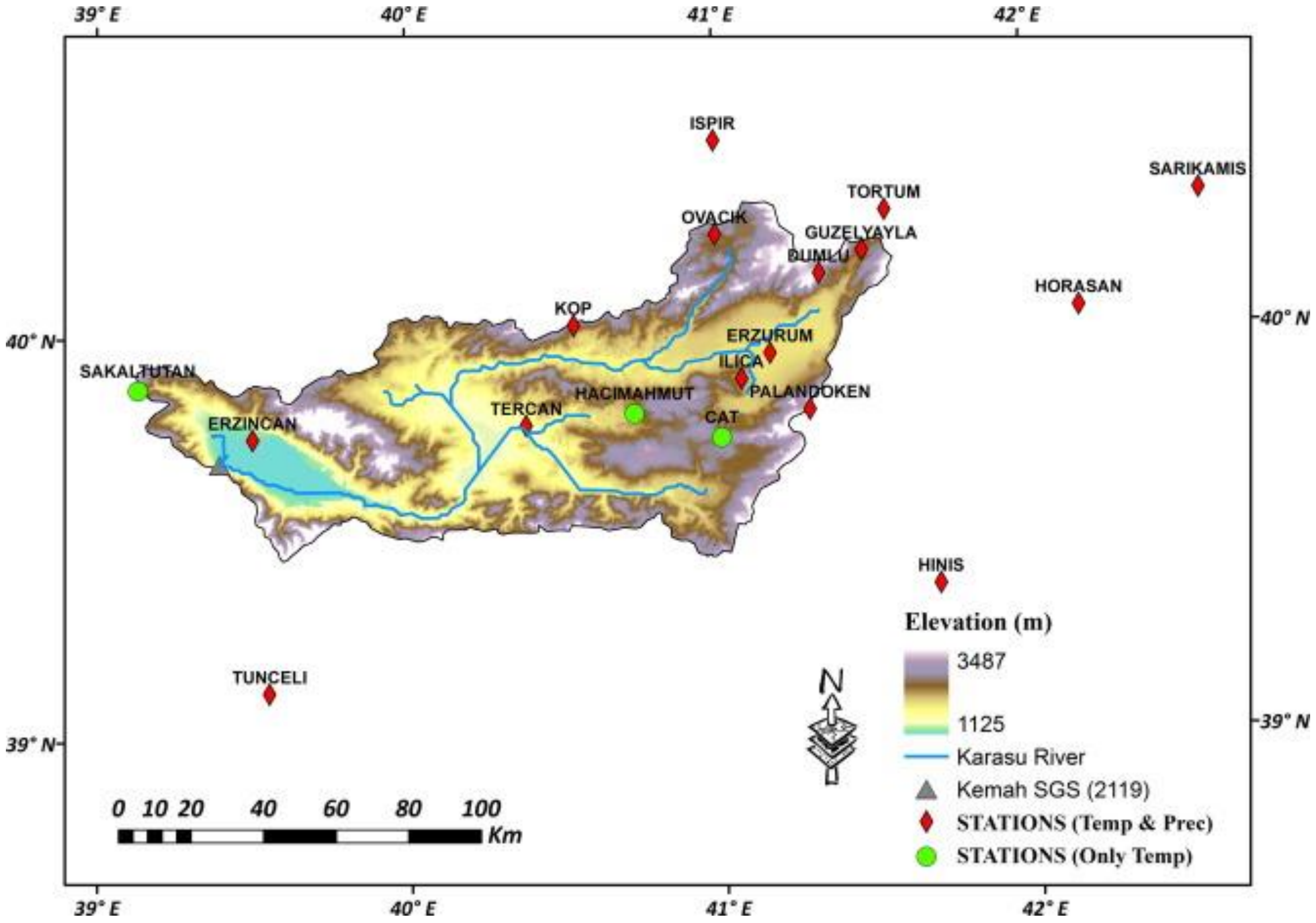
Upper Euphrates Basin (Karasu), Turkey:

Area: 10,275 km^2

Elevation between 1125 and 3487 m

Mean average discharge: 84.4 m^3/s

Hydro-Meteorological Data

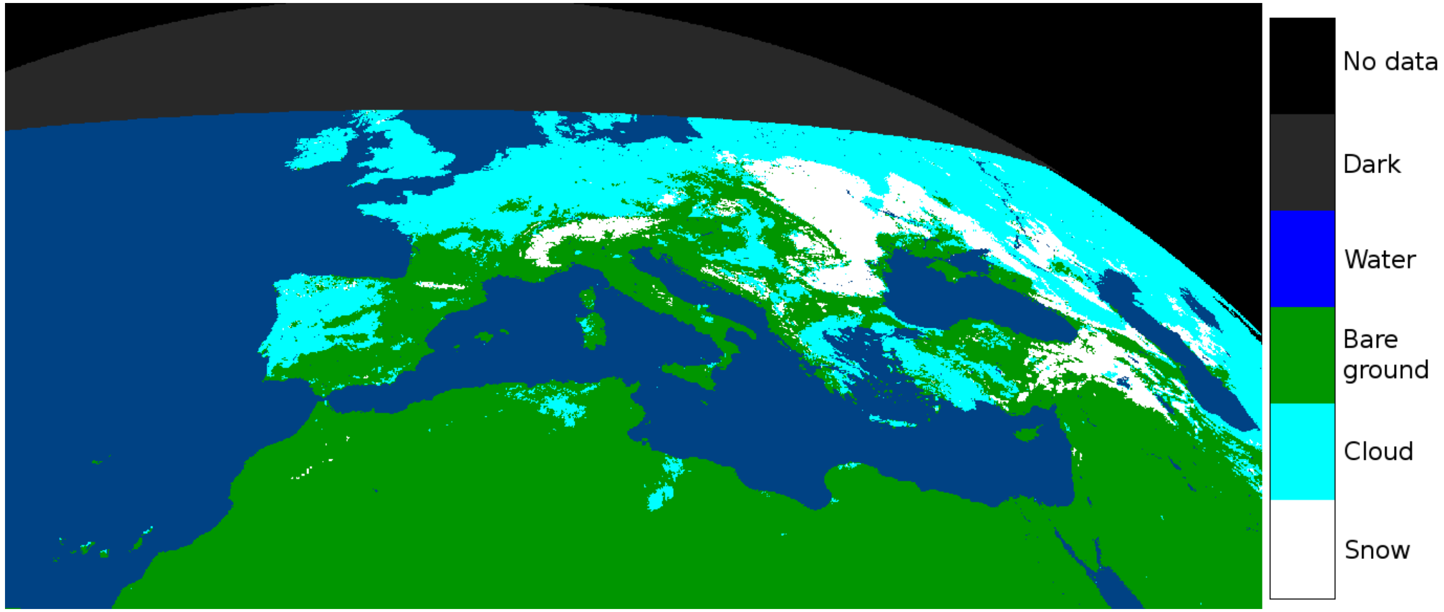


Daily total precipitation

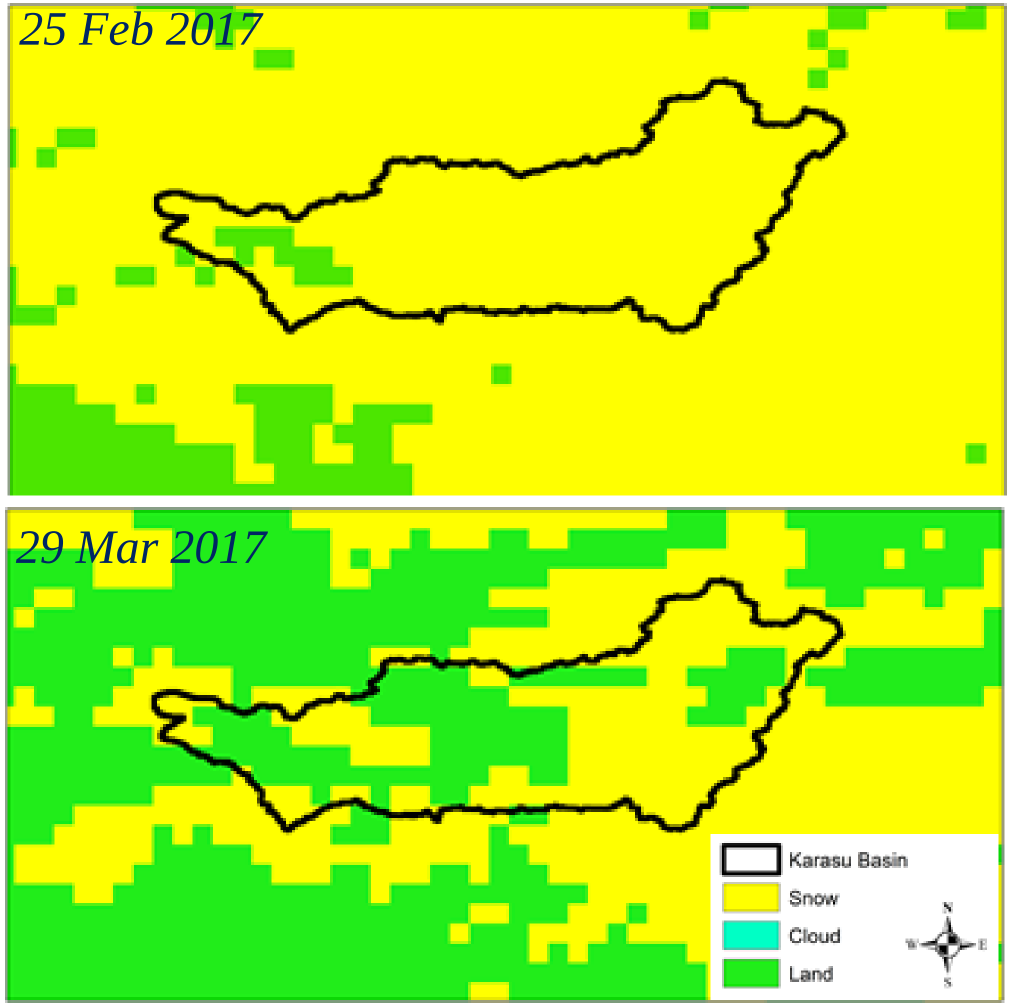
Daily average temperature

Daily average runoff

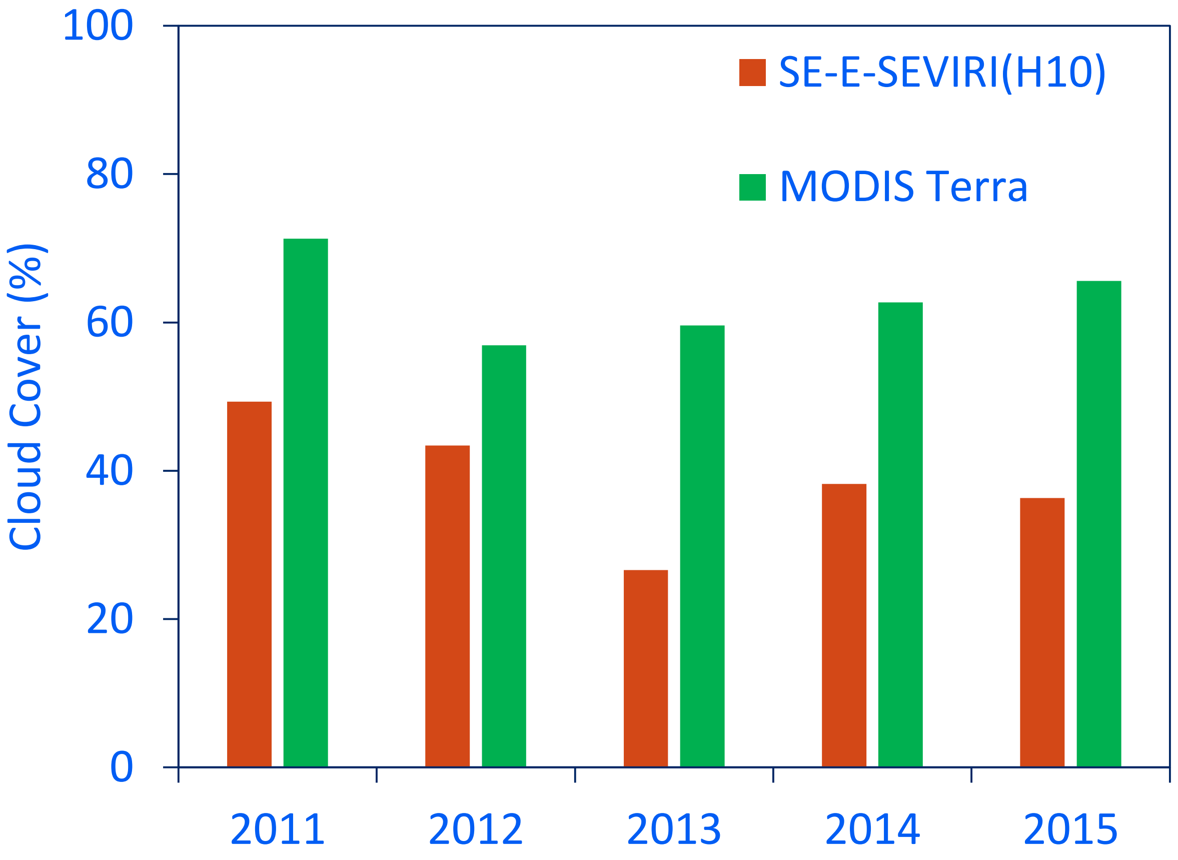
Satellite Snow Data: SE-E-SEVIRI(H10), Snow Cover Area



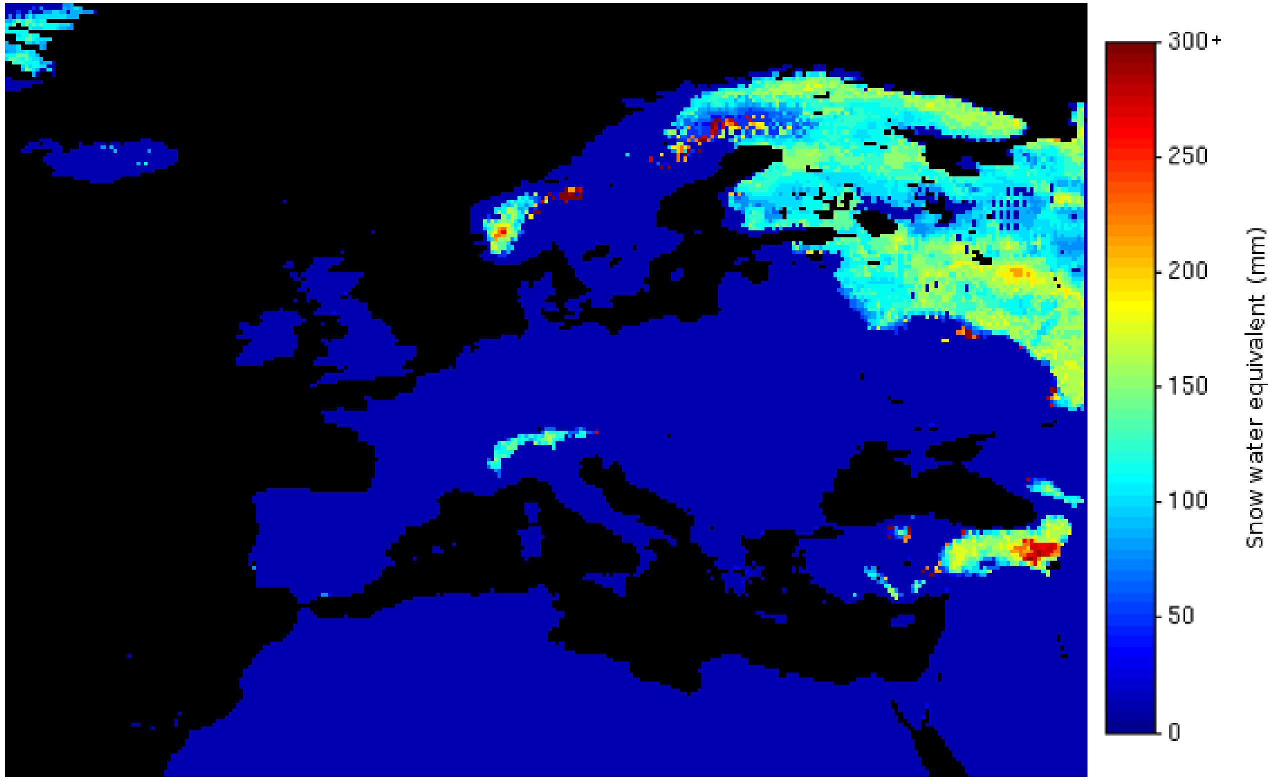
SE-E-SEVIRI(H10)



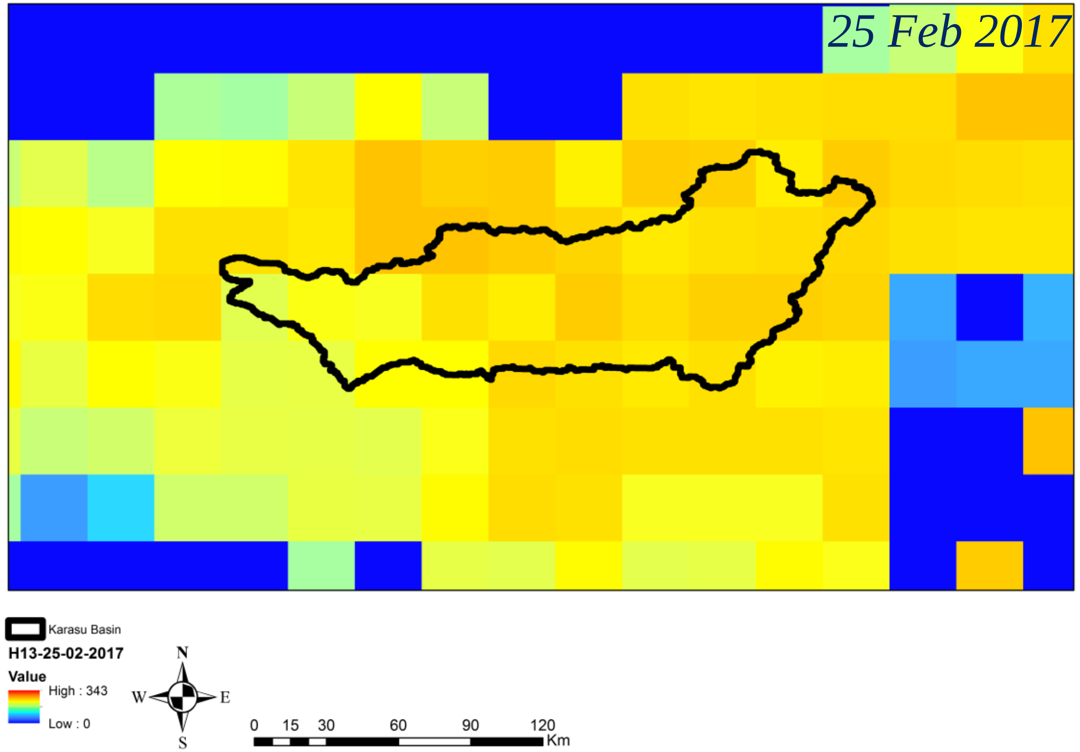
Preprocess of SE-E-SEVIRI(H10)



Satellite Snow Data: SWE-E-(H13), Snow Water Equivalent

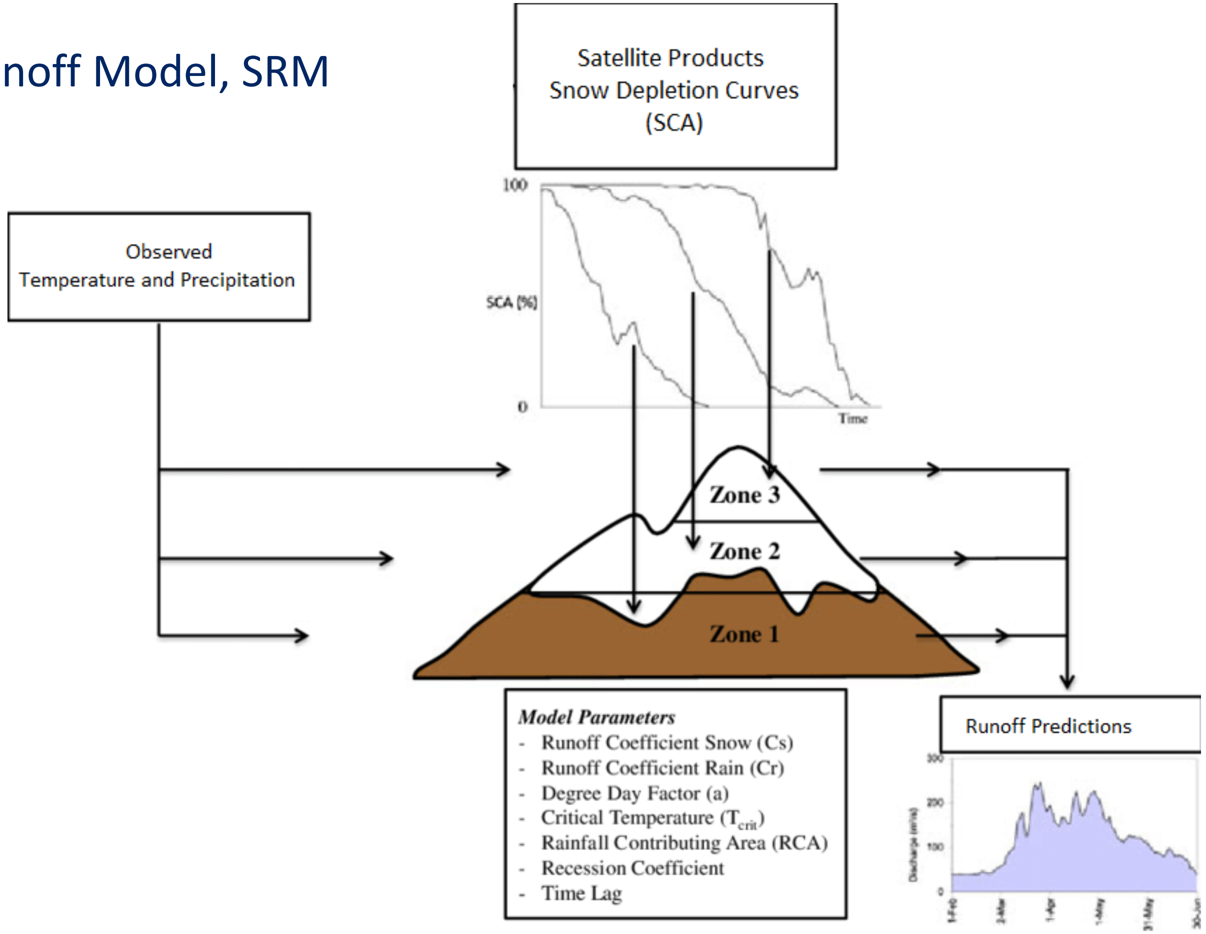


SWE-E-(H13)



Methodology

Snowmelt Runoff Model, SRM



(Martinec et al., 2008)

SRM Model

Forcing (model inputs):

- Precipitation (P)
- Temperature (T)
- **Snow Cover Area (SCA)**

Output variables:

- Discharge (Q)

$$Q_{t+1} = [c_{St}.\, a_t(T_t + \Delta T_t)S_t + c_{Rt}P_t].\,(A.\,1000/86400).\,(1 - k_{t+1}) + Q_t k_{t+1}$$

Methodology

HBV Model

Forcing (model inputs):

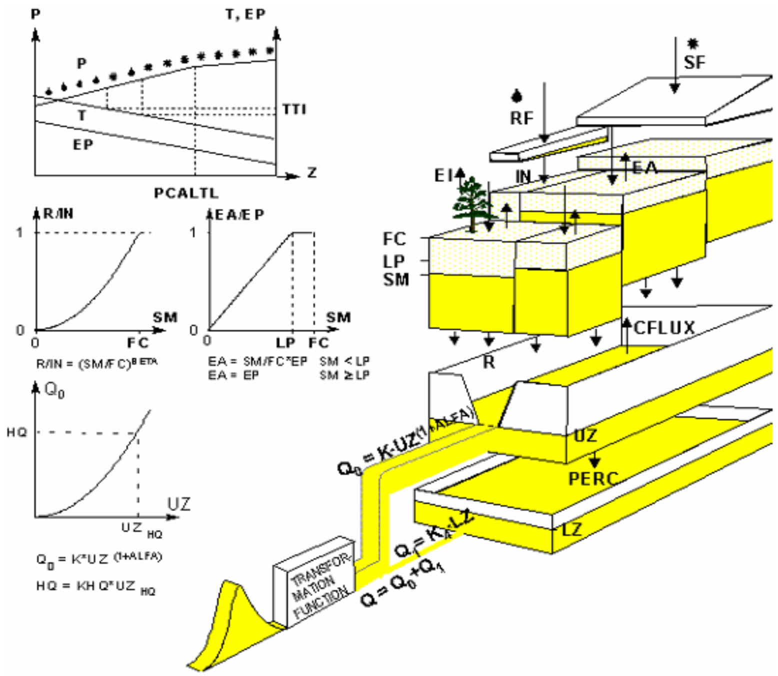
- Precipitation (P)
- Temperature (T)
- Evapotranspiration (EP)

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)



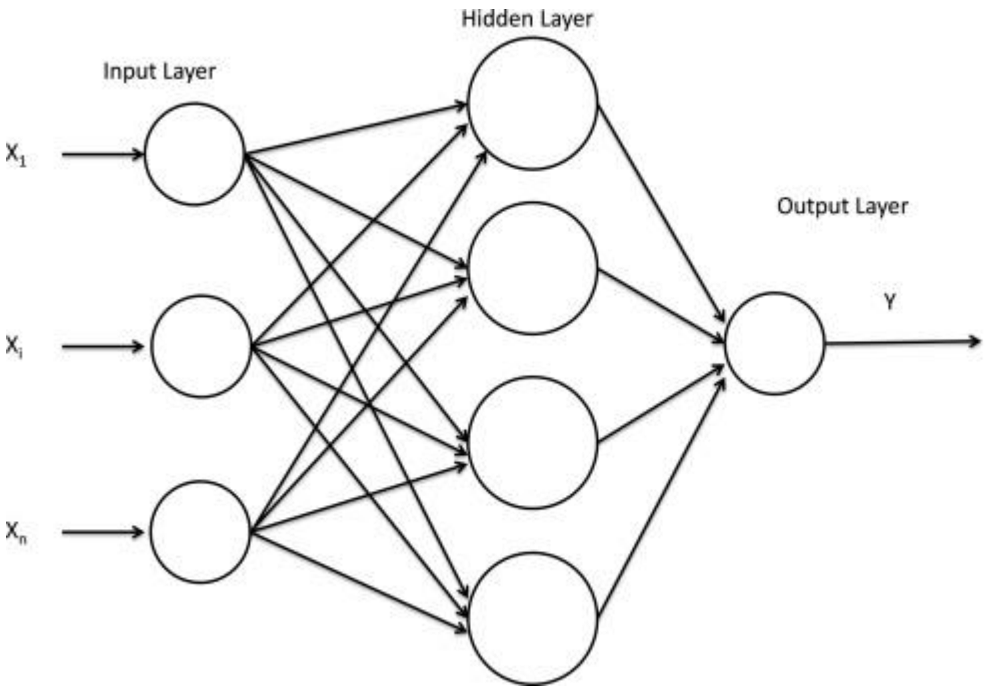
P = Precipitation
T = Temperature
SF = Snow
RF = Rain
Z = Elevation
PCALTL = Threshold for altitude correction
TTI = Threshold temperature interval
IN = Infiltration
EP = Potential evapotranspiration
EA = Actual evapotranspiration
EI = Evaporation from interception
SM = Soil moisture storage
FC = Maximum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

Methodology

ANN Model



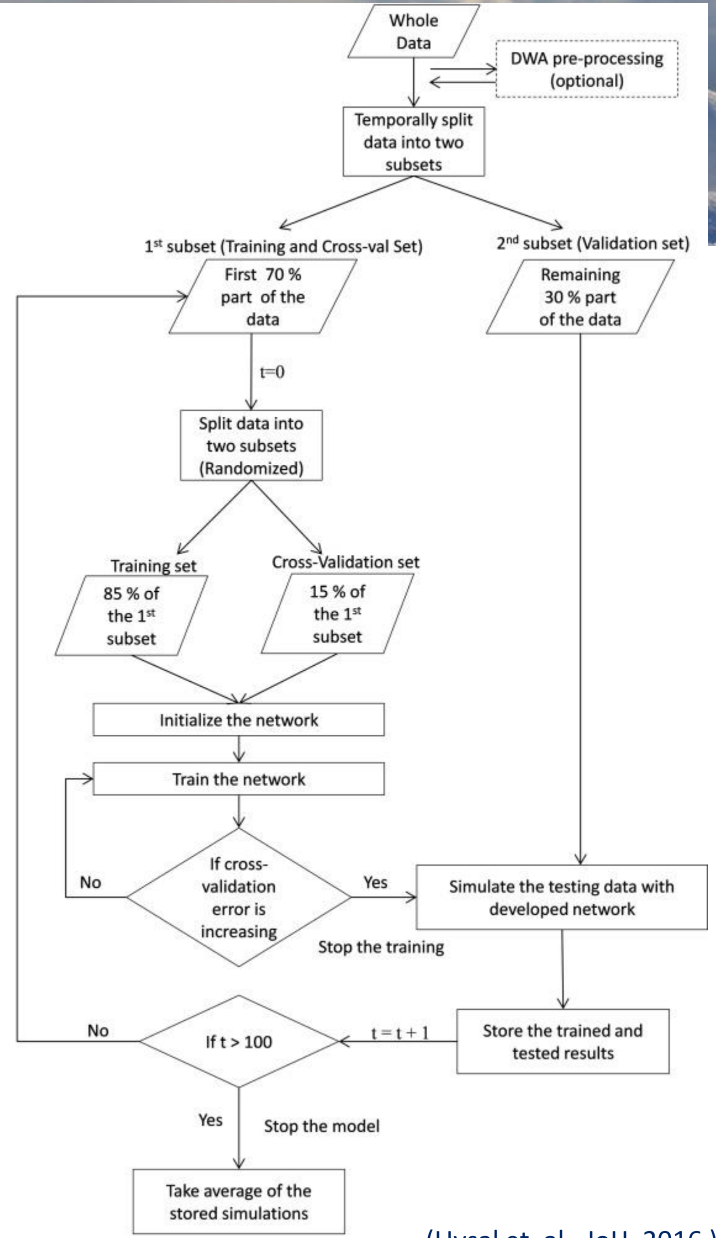
ANN Model

Forcing (model inputs):

- Precipitation (P)
- Temperature (T)
- Snow Cover Area (SCA)

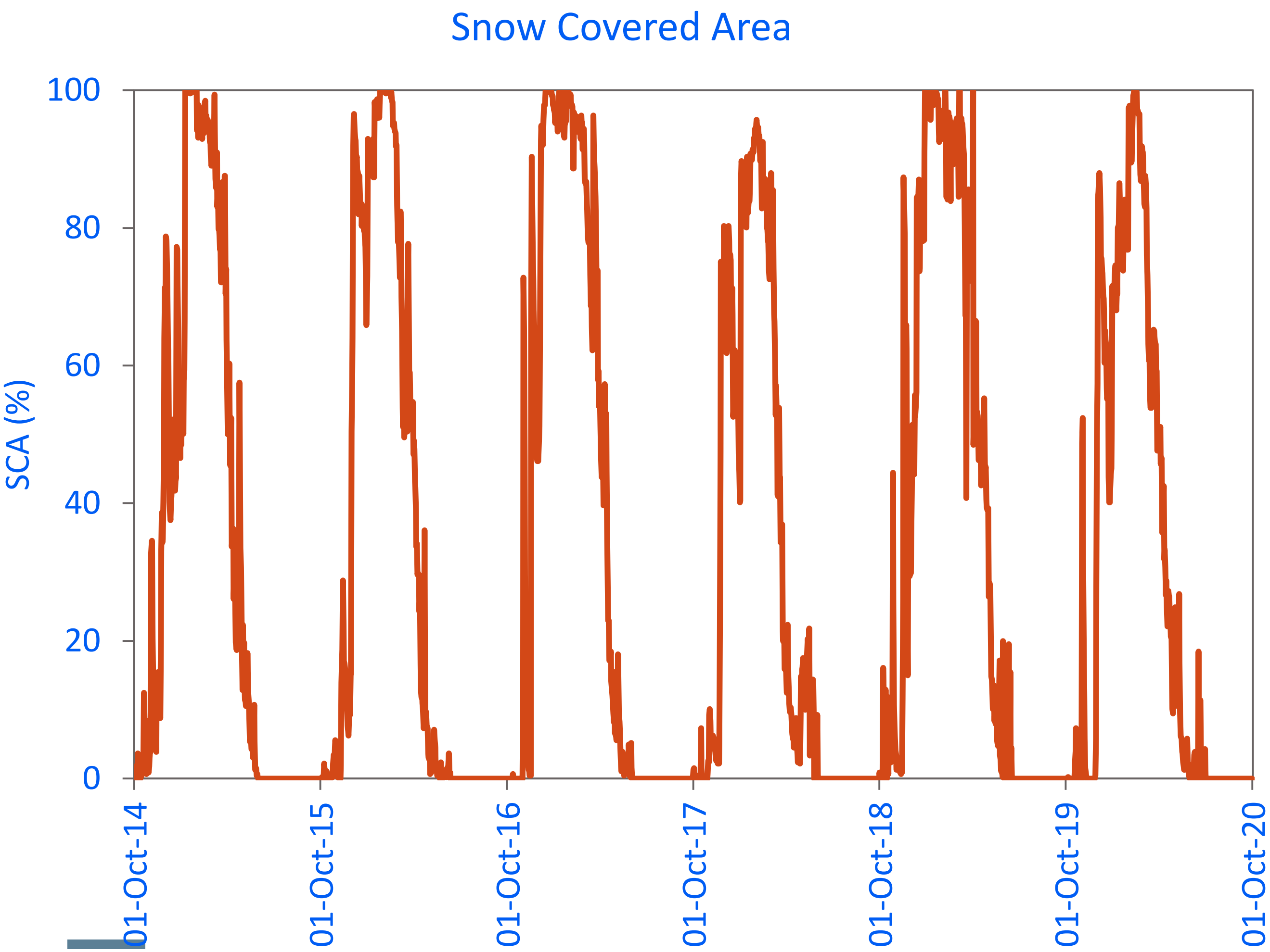
Output variables:

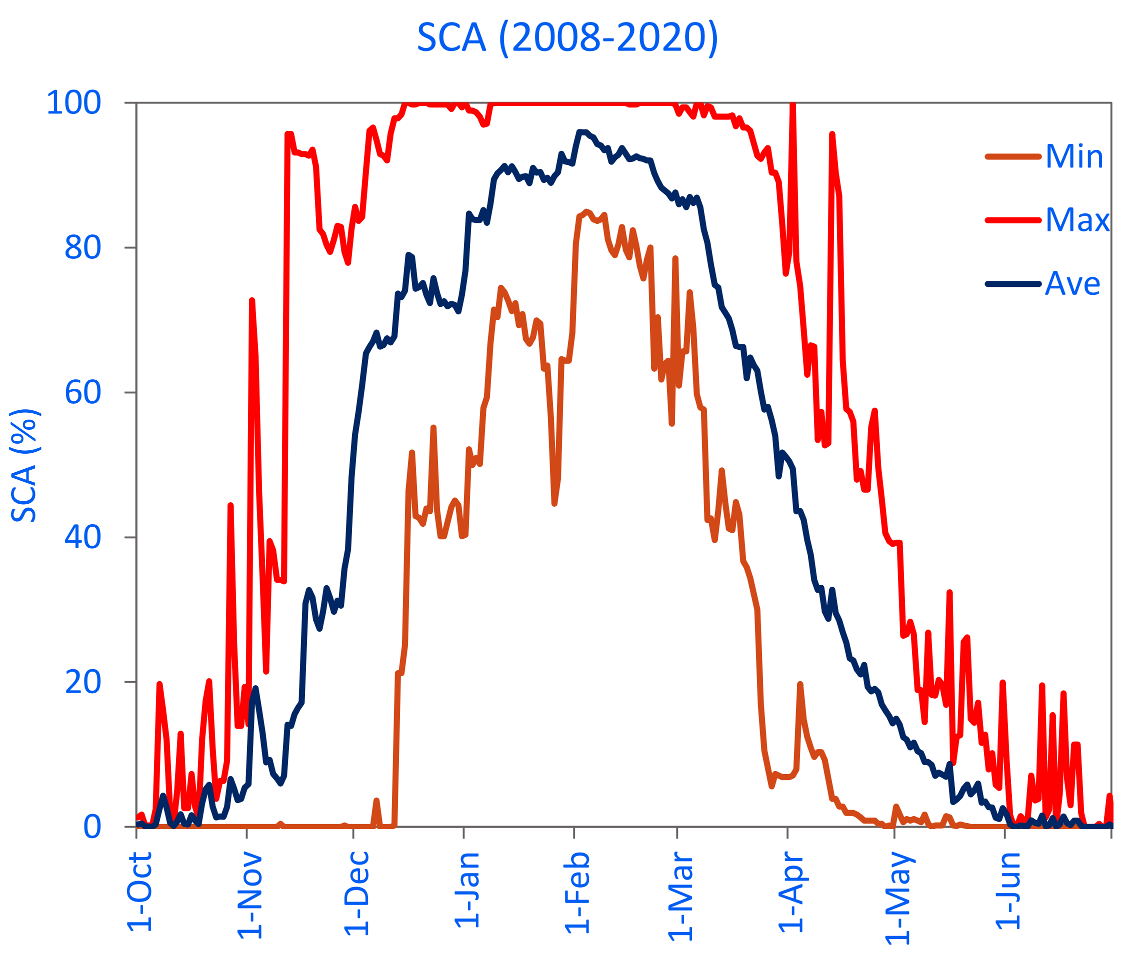
- Discharge (Q)



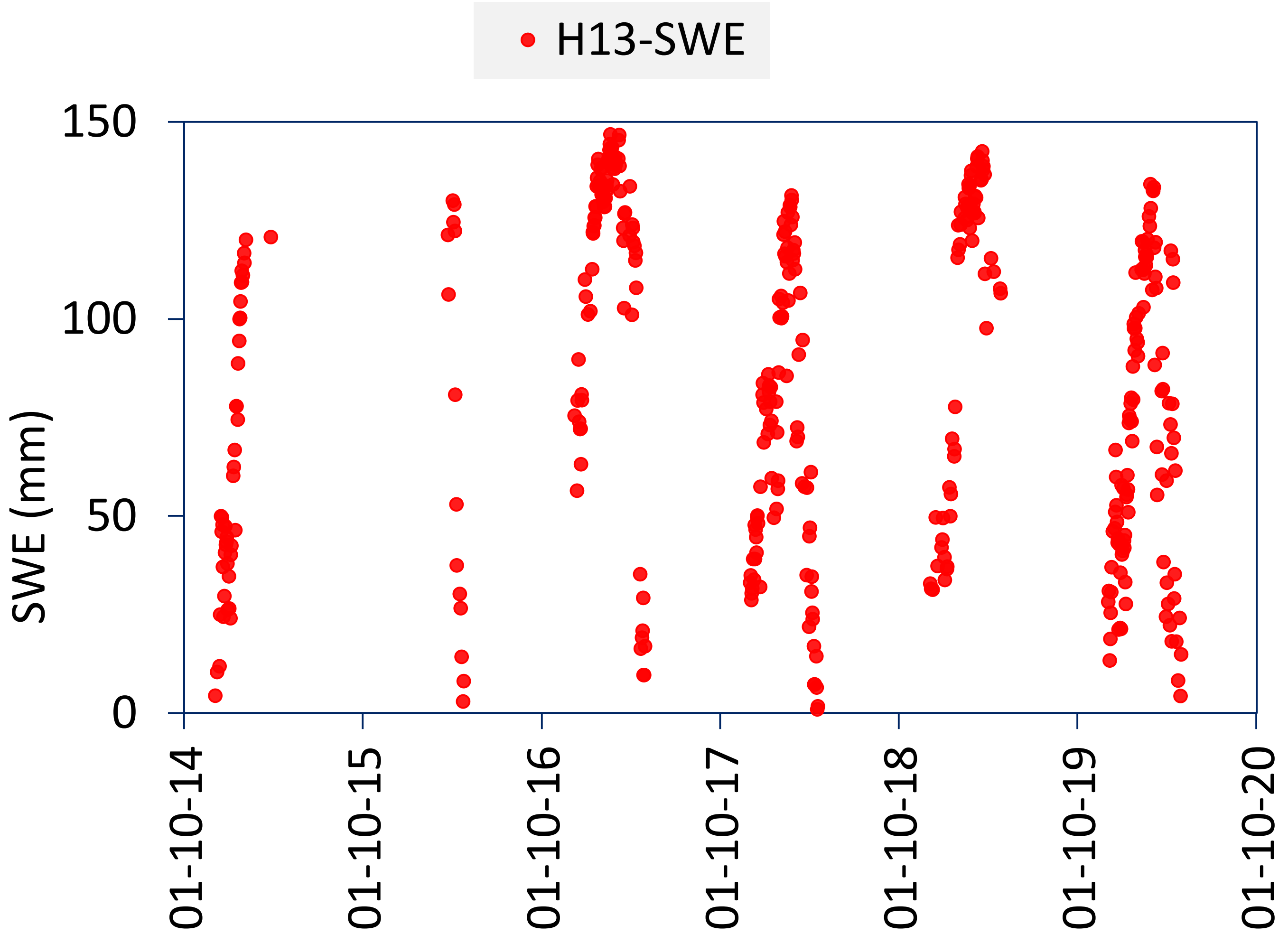
(Uysal et. al., JoH, 2016)

Time series of SE-E-SEVIRI(H10) (SCA)

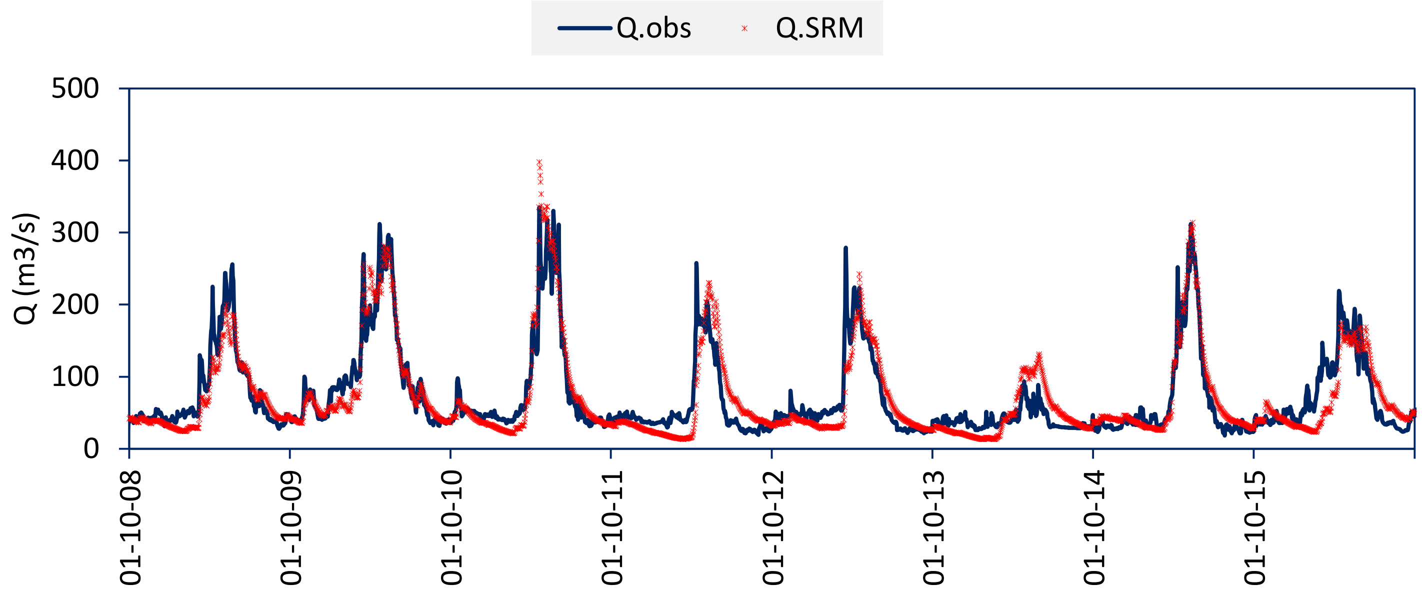


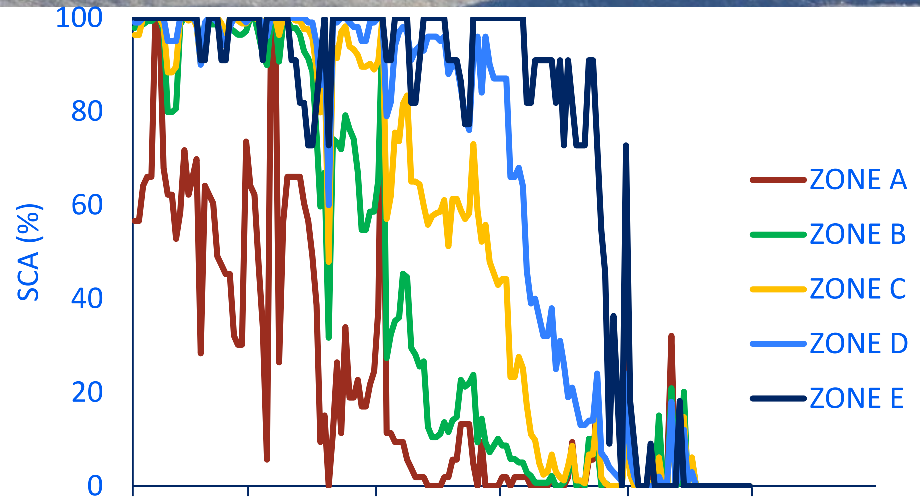


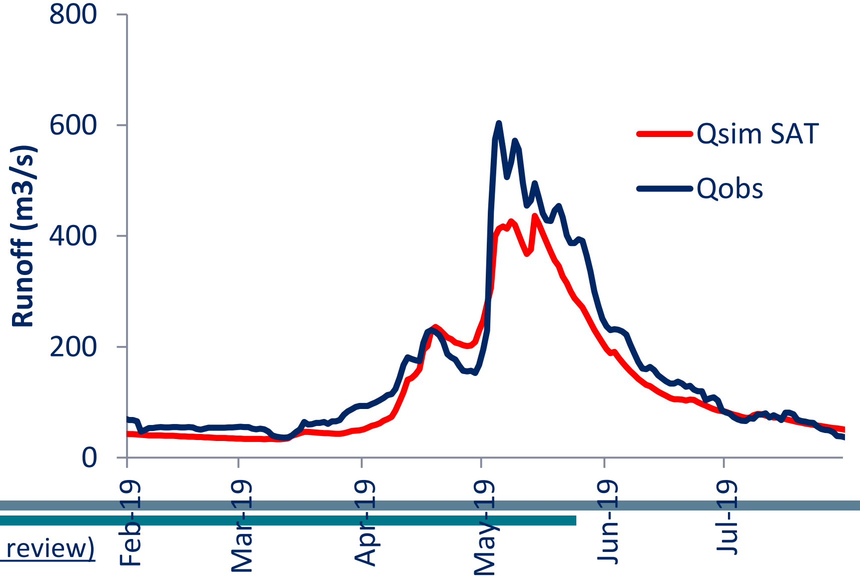
Time series of SWE-E-(H13) (SWE)



Impact study with SRM for SE-E-SEVIRI(H10)





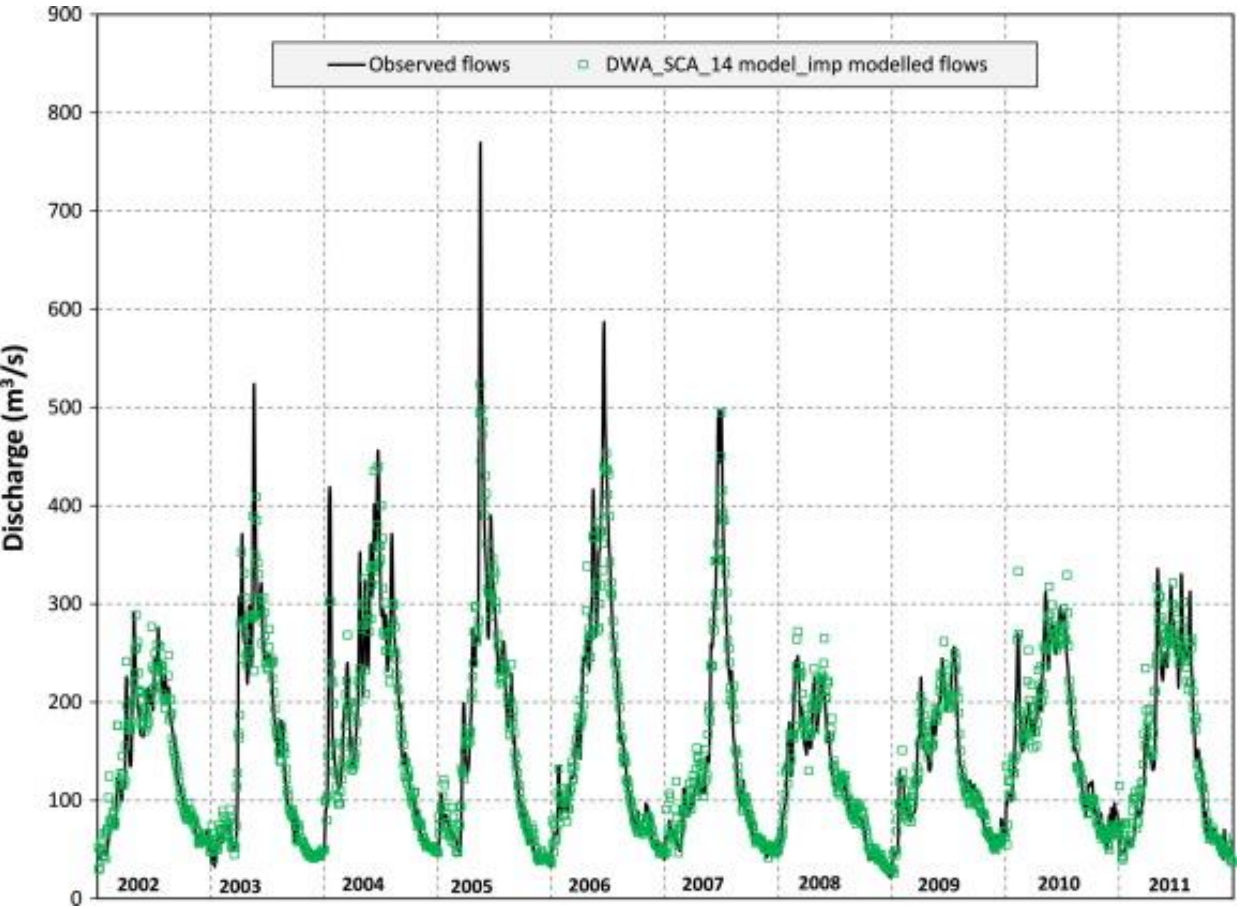


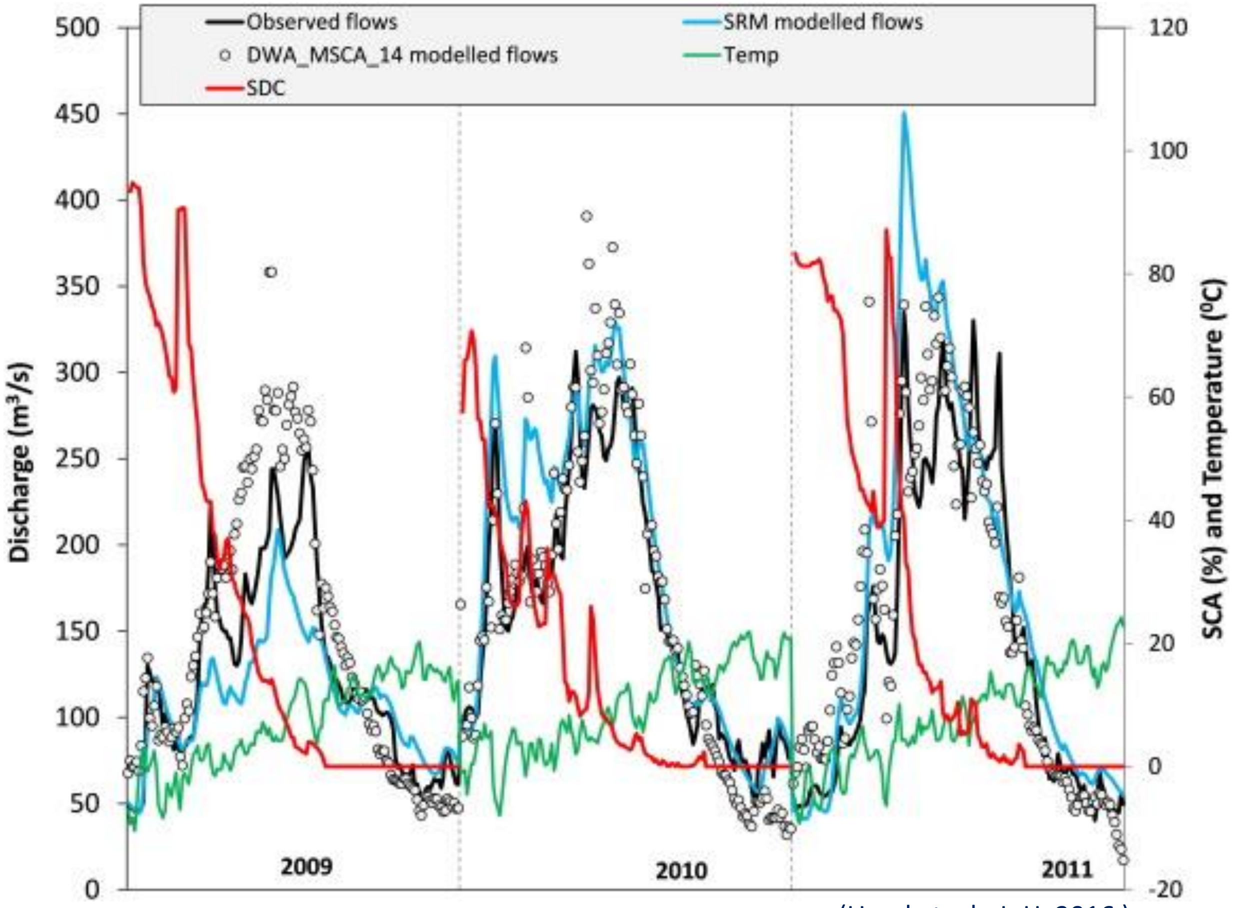
	Years	KGE	P-Bias (%)
Cal	2008-2012	0.85	-5.9
Val	2013-2019	0.82	0.8

$$KGE = 1 - \sqrt{(R-1)^2 + (\beta-1)^2 + (\alpha-1)^2}$$

(Uysal et. al., HsJ, under review)

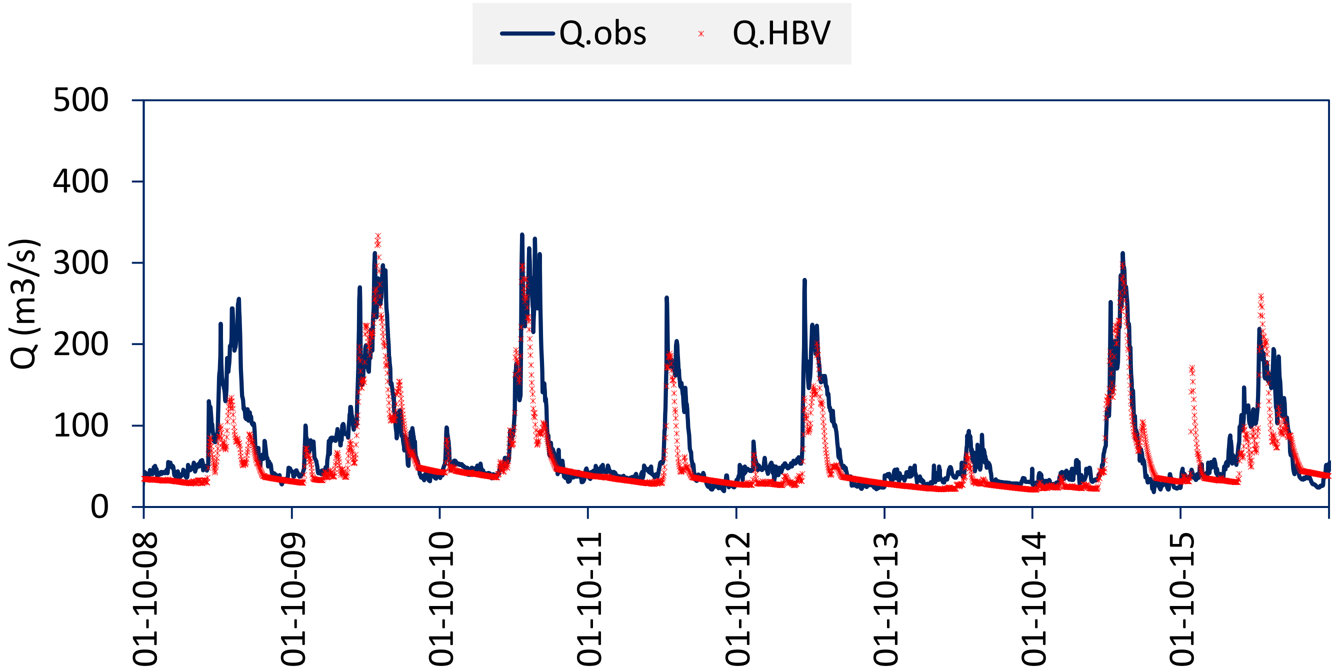
Impact study with ANN





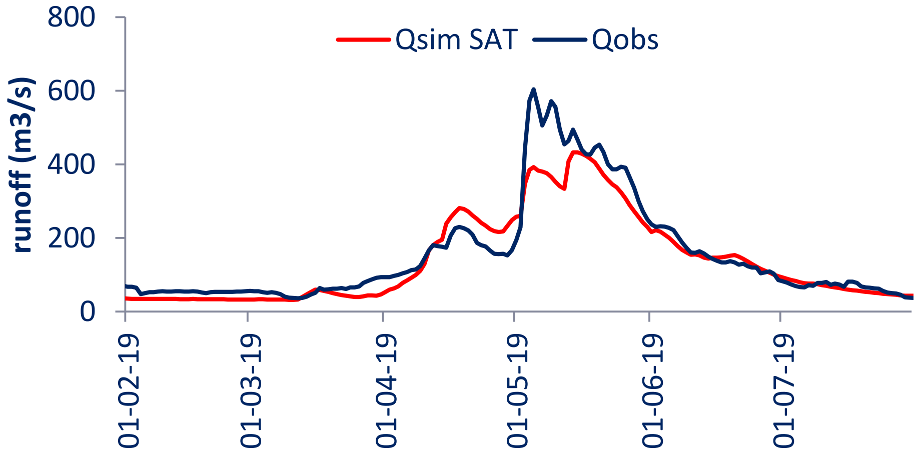
(Uysal et. al., JoH, 2016)

Hydro-validation study with HBV

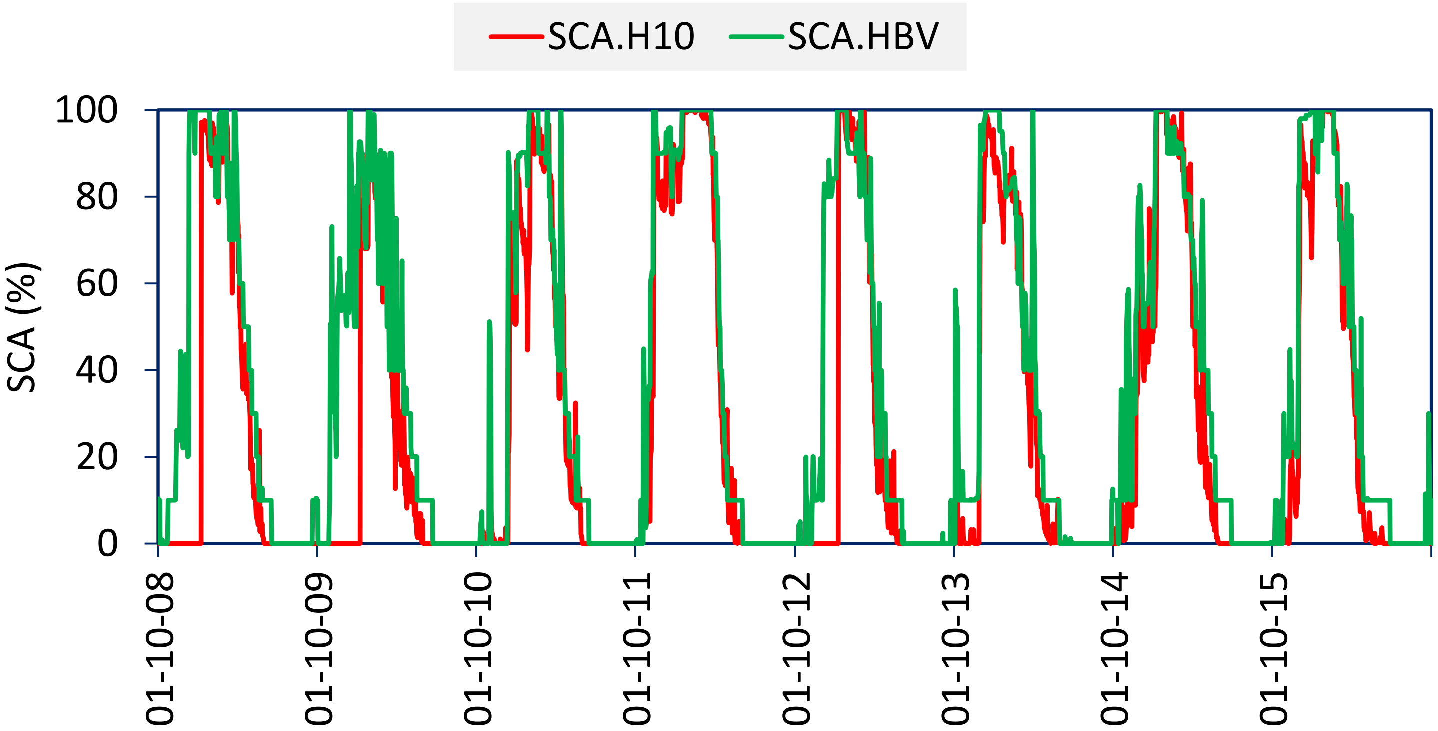


	Years	KGE	P-Bias (%)
Cal	2003-2012	0.85	-11.9
Val	2013-2019	0.82	-14.0

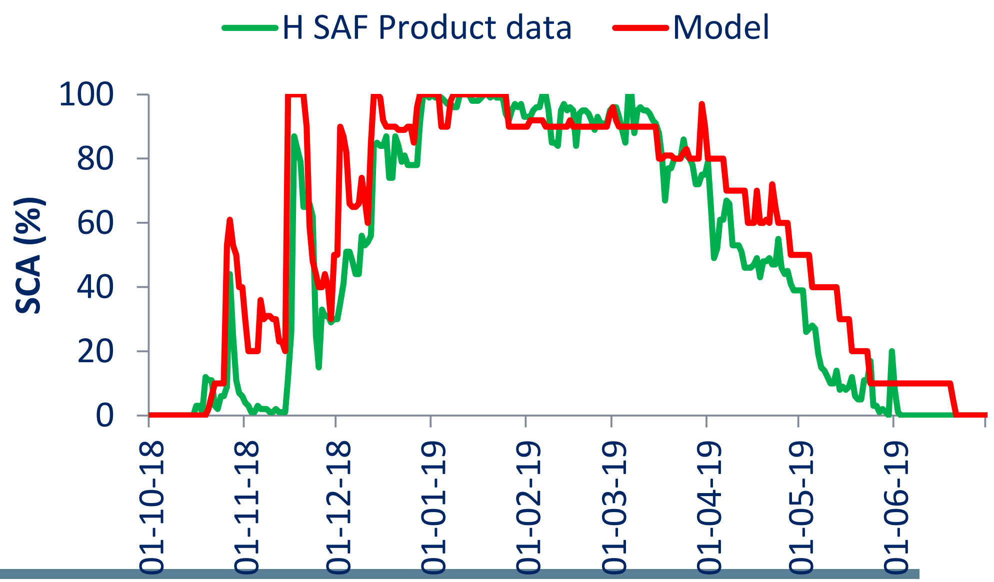
Discharge, Q



Hydro-validation study with HBV



Snow Cover Area, SCA

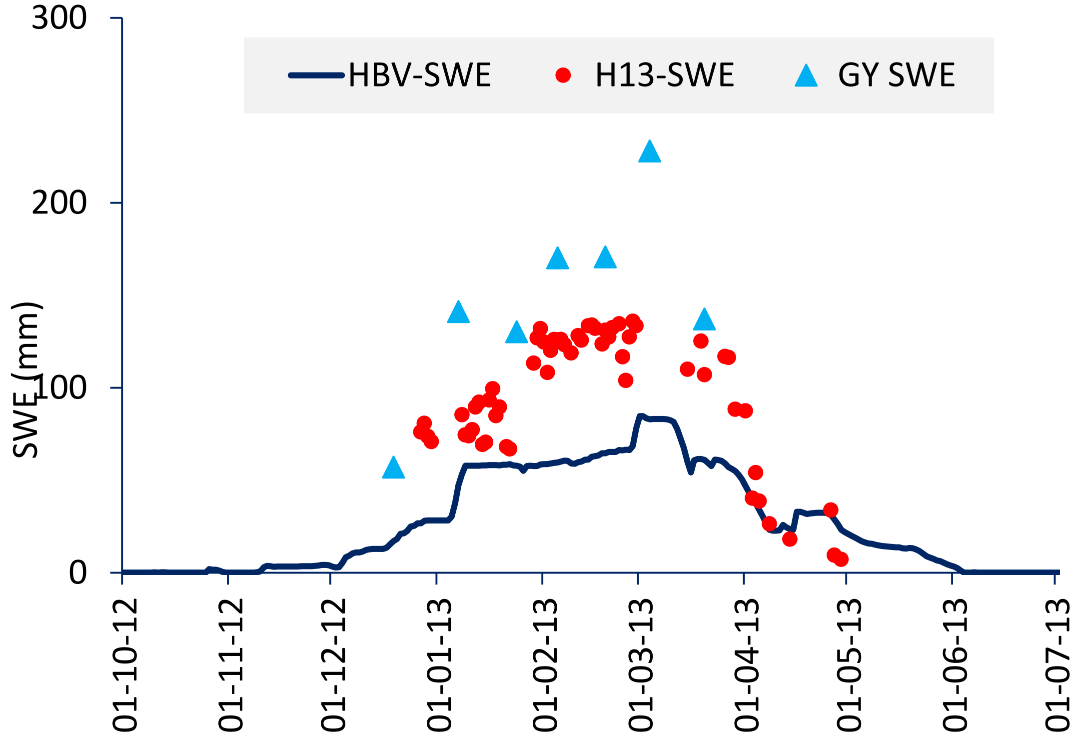


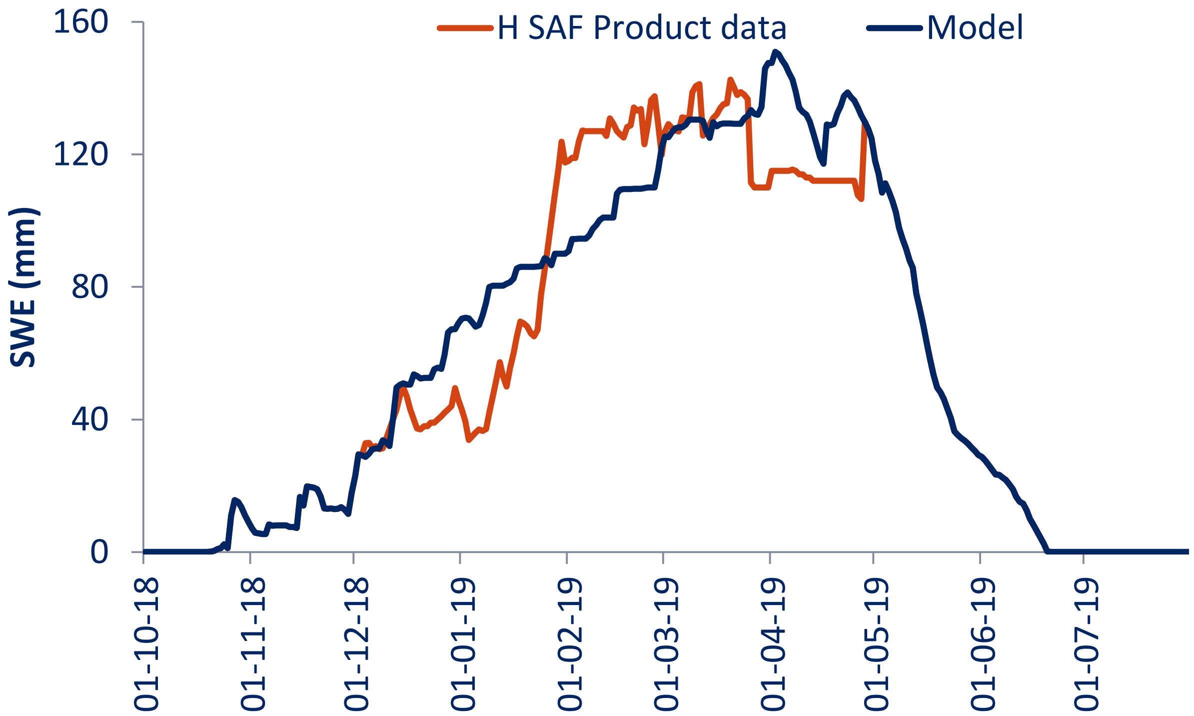
$$NSE = 1 - \frac{\sum_{t=1}^{T} (Q_O^t - Q_S^t)^2}{\sum_{t=1}^{T} (Q_O^t - \bar{Q_O})^2}$$

Period	Years	NSE	P-bias (%)
Cal	2008-2012	0.90	18.2
Val	2013-2019	0.91	18.3

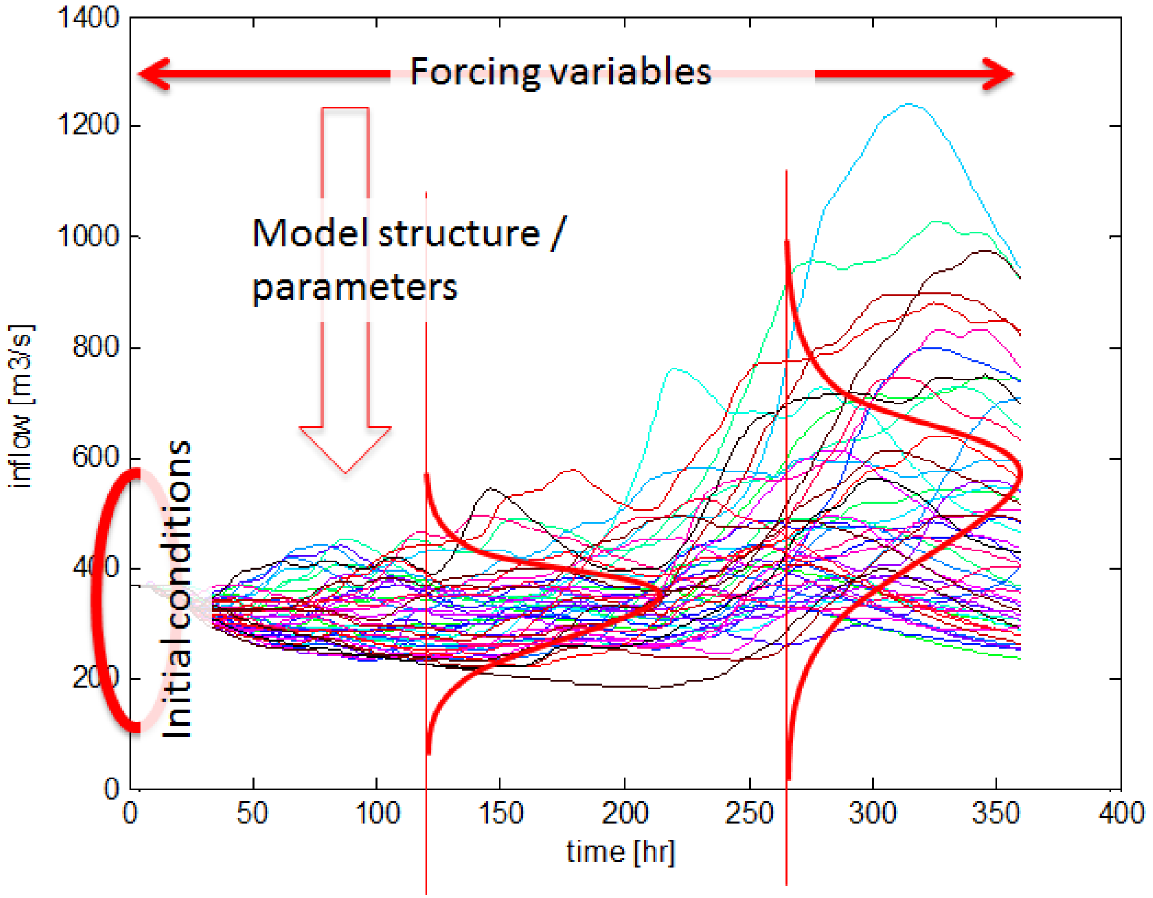
Hydro-validation study with HBV

Snow Water Equivalent, SWE





Data Assimilation



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

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

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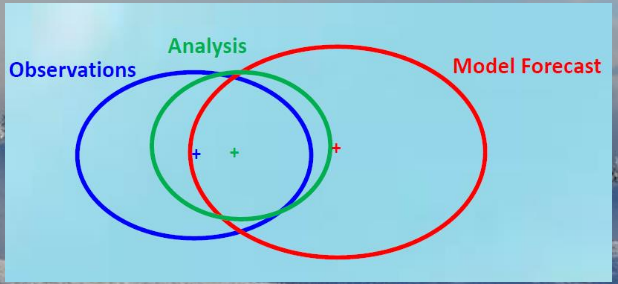
DA Challenge



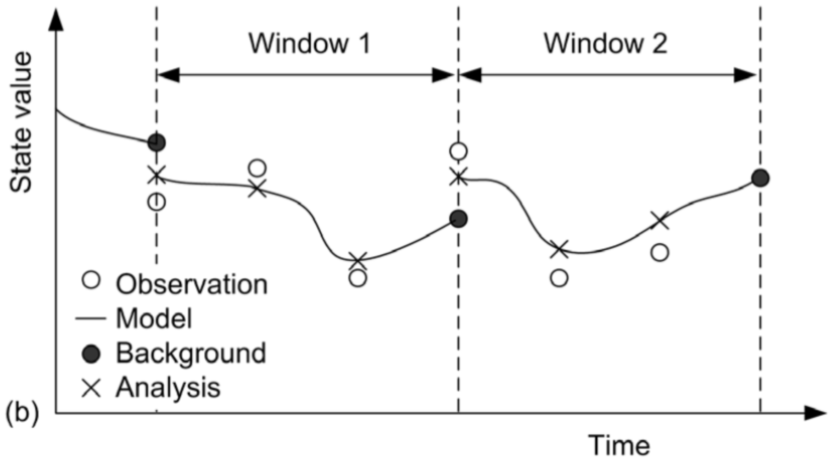
<u>The purpose</u> is ***to improve the initial state of the model***, which later makes a forecast for the next time step.

<u>Given:</u> a (noisy) model of system dynamics

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

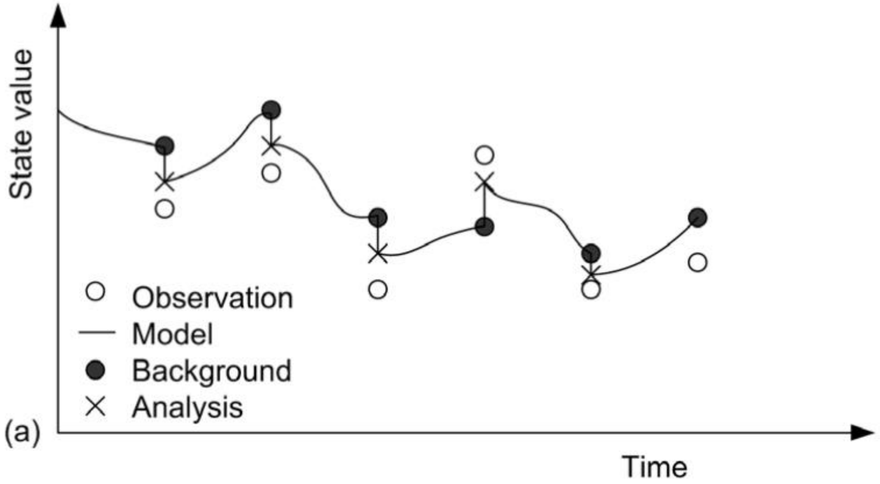
1. Variational Data Assimilation (VarDA):

- ❑ 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



Houser et al. (2012)

Comparison of both techniques

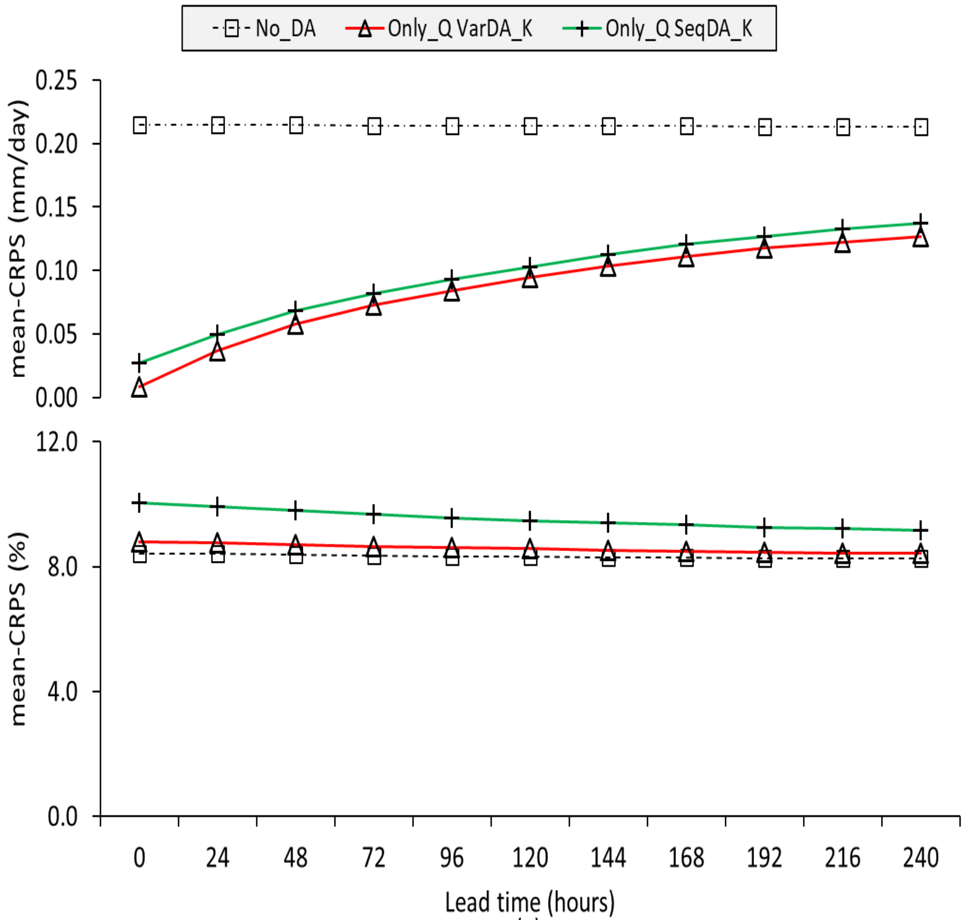
Variational DA:

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

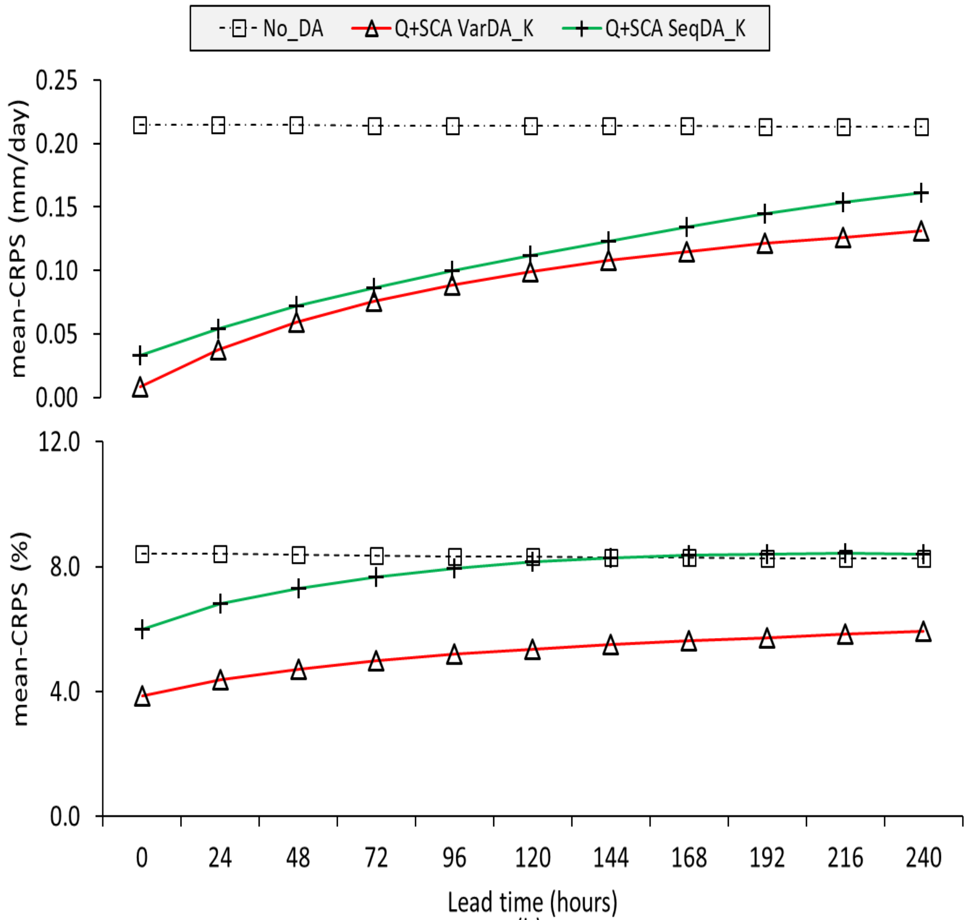
Ensemble Kalman DA:

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

DA Results



(a)



(b)

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

Conclusions

- The results show the usefulness of the data sets and methods.
- Impact and hydro-validation of products indicate their applicability in an operational hydrological framework for runoff forecasting in snow dominated regions.
- The products can also be used to improve the model output and state variables with data assimilation.
- The products are being improved in each developing phase (CDOP) of the project

Thank you..

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