SHORT TERM SCIENTIFIC MISSION (STSM) – SCIENTIFIC REPORT

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

Action number: COST Action ES1404
STSM title: Hydrological Data Assimilation
STSM start and end date: 05/08/2018 to 15/08/2018
Grantee name: Antonio-Juan Collados-Lara

PURPOSE OF THE STSM

The Short Term Scientific Mission (STSM) has been raised to provide the grantee useful knowledge about Data Assimilation (DA) techniques applied to hydrological models. The host advisor is Rodolfo Alvarado who has a high experience in these topics and the host institution is Deltares, located in Delft (The Netherlands), which is an independent institute for applied research in the field of water and subsurface.

In Alpine catchments snow dynamic plays an important role in the streamflow forecasting. Snow information can be incorporated into the models using DA techniques. DA techniques hold considerable potential for improving hydrologic predictions as demonstrated in numerous research studies in the in the last times (Reichle, 2008). The purpose of the STSM is to have an application of hydrological DA using two different techniques: ensemble Kalman Filters and variational methods. The first one relies on a sequential type of data assimilation, commonly applied in hydrological forecasting applications (Liu et al., 2012). The second one is an innovative approach recently developed and tested by Alvarado-Montero et al. (2016) which relies on the assimilation of observation within an assimilation window and perturbing internal model states together with model forcing to get a better match between observed and simulated variables. The objective is to apply the DA techniques to assimilate discharge observations and snow cover area (SCA) for the case of study of the Canales basin which is an alpine basin located in the headwaters of the Genil River in the northern flank of the Sierra Nevada Mountain (south of Spain) (see Figure 1). The Canales basin covers a surface area of around 176 Km² and has a mean elevation of 2050 m.a.s.l. with elevations ranging from 850 and 3443 m.a.s.l. Sierra Nevada enjoys a high-mountain Mediterranean climate with a relatively dry summer, and a wetter winter during which the majority of precipitation falls as snow. Thus the dynamics of snowfall is essential to the availability of water in the Canales basin. For this study we used a lumped HBV conceptual rainfall-runoff model to simulate conditions at a basin scale.

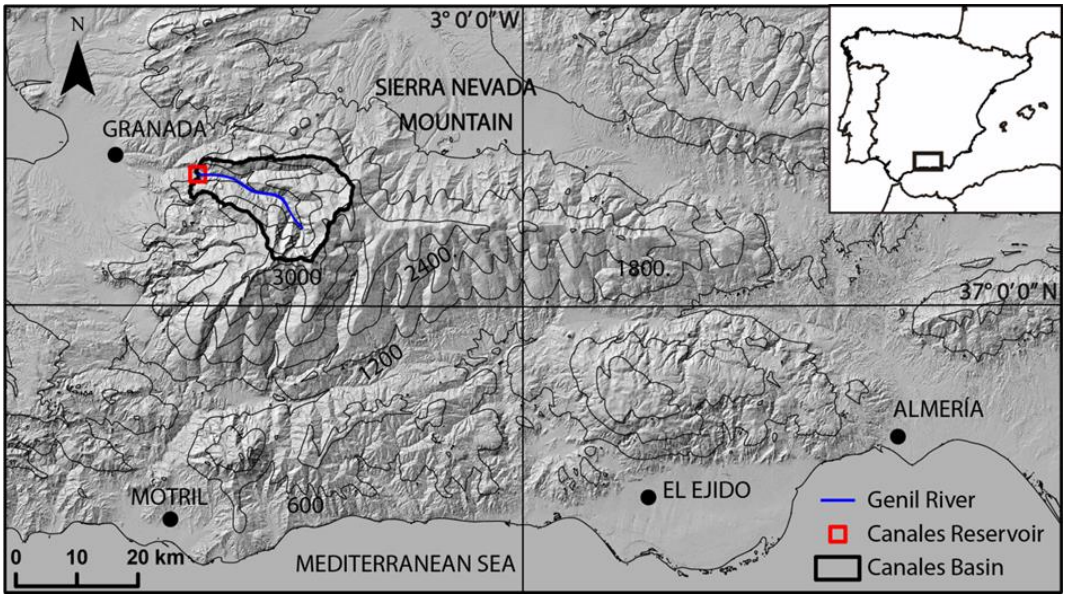

Figure 1. Location of the Canales basin.

DESCRIPTION OF WORK CARRIED OUT DURING THE STSM

Previously to the STSM a lumped HBV conceptual rainfall-runoff model (Lindström et al., 1997), has been calibrated (for the period 01/10/2000 to 30/09/2010) and validated (for the period 01/10/2010 to 30/09/2014) for the Canales basin. A subdivision according to elevation zones (< 1200, 1200-1700, 1700-2200, 2200-2600, > 2600 m) was adopted to represent the characteristics of the catchment and later combined to compute the response of the model.

The objective of the STSM is to apply the DA techniques to assimilate discharge and SCA observations for the case of study of the Canales basin in the period 01/10/2010 to 30/09/2014. During the STSM the following activities have been done to reach the main objective:

- Configuration of a sequential DA approach (ensemble Kalman Filter) to assimilate discharge and SCA observations.
- Configuration of a variational DA approach (Var1D) to assimilate discharge and SCA observations.
- Implementation of hindcast experiments to assess the performance of each assimilation technique using perfect forecast data.
- Implementation of different experiments of sequential DA (assimilating discharge and assimilating both discharge and SCA) varying the perturbations to model inputs, the number of members of the ensembles and the observation error of the observations.
- Implementation of different experiments of variational DA (assimilating discharge and assimilating both discharge and SCA) varying the noise to model inputs, the noise to models states and the weights of the observations.
- Assessment of results using forecast validation metrics (CRPS, BSS, MAE, rank histograms, ROC, etc.).

DESCRIPTION OF THE MAIN RESULTS OBTAINED

(max. 500 words)

The performance of the different experiments for calibration and validation of the HBV conceptual rainfall-runoff model was evaluated using the Nash-Sutcliffe efficiency coefficient. For the case study we obtained a NSE of 0.69 in the calibration period and 0.58 in the validation period. The simulation of the complete calibration period is showed in Figure 2. According to the classification of Moraisi et al. (2007) the

performance of the calibrated HBV model for the case study can be considered good.

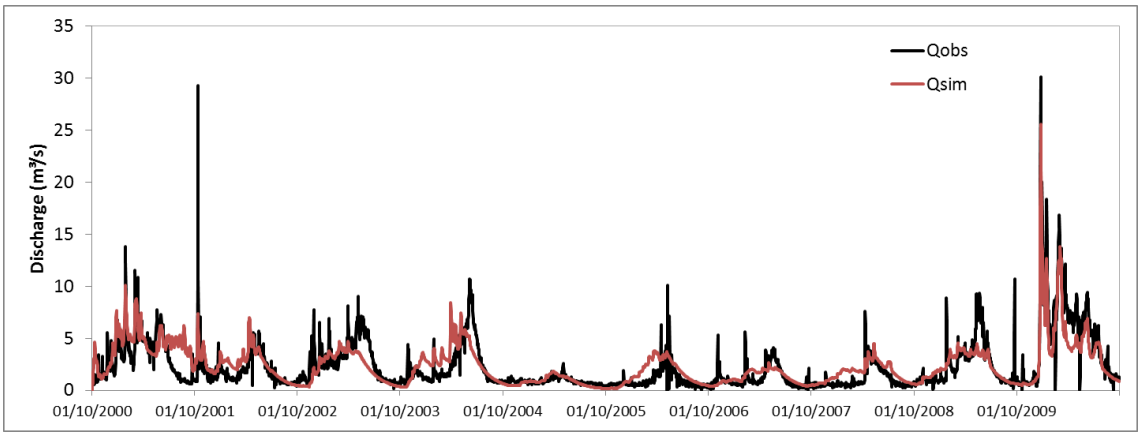

Figure 2. Daily Observed and simulated discharge with the HBV model for the calibration period (01/10/2000 to 30/09/2010).

Regarding the DA approaches, the setups of the different experiments tested for the case study are showed in Table 1 and the complete lists of the performed experiments are showed in Table 2 (sequential experiments) and Table 3 (variational experiments).

Sequential EnKF DA	**Variational DA**
Warm-up period of 6 months	Assimilation window of 180 days
Perturbations to model inputs (μ) - Precipitation: normal distr. N(0, ± 10%,15%), tail limits at ± 30% - Temperature: normal distr. N(0,± 0.5°C) , tail limits at ± 2.0, 3.0, 4.0 °C Updates the complete matrix of model states	Noise to model inputs (μ) - Precipitation: bounded to ± 15, 20, 30, 40 % - Temperature: bounded to ± 1.0, 2.0, 3.0 °C Noise to model states (η) - Soil moisture: bounded to ± 1.0, 3.0, 4.0, 5.0 mm - Upper zone: bounded to ± 1.0, 3.0, 4.0, 5.0 mm - Lower zone: bounded to ± 1.0, 3.0, 4.0, 5.0 mm
Tests using 50, 100 and 200 members Observation error for Q: 1, 2, 3, 5 % Observation error for SCA: 5, 10, 12, 15 %	Deterministic method Observation mismatch weights for Q from 1 to 200 Observation mismatch weights for SCA from 0 to 1 model noise weights kept constant at 1.0

Table 1. Setups of the different DA experiments.

Members	**Uncertainty Observations**		**Uncertainty Perturbations**		**NoID**
	Q	**SCA**	**P**	**T**	
50	5%	-	15%	3°C	01_Canales_Seq_50_5_-_15_3
50	5%	5%	15%	3°C	02_Canales_Seq_50_5_5_15_3
50	2%	-	15%	3°C	03_Canales_Seq_50_2_-_15_3
50	2%	10%	15%	3°C	04_Canales_Seq_50_2_10_15_3
100	2%	-	15%	3°C	05_Canales_Seq_100_2_-_15_3
100	2%	10%	15%	3°C	06_Canales_Seq_100_2_10_15_3
200	2%	-	15%	3°C	07_Canales_Seq_200_2_-_15_3
200	2%	10%	15%	3°C	08_Canales_Seq_200_2_10_15_3
100	2%	15%	15%	3°C	09_Canales_Seq_100_2_15_15_3
100	3%	15%	15%	3°C	10_Canales_Seq_100_3_15_15_3
100	1%	15%	15%	3°C	11_Canales_Seq_100_1_15_15_3
100	2%	12%	15%	3°C	12_Canales_Seq_100_2_12_15_3
100	2%	15%	20%	4°C	13_Canales_Seq_100_2_15_20_4
100	2%	15%	10%	2°C	14_Canales_Seq_100_2_15_10_2

100	2%	15%	15%	2°C	15_Canales_Seq_100_2_15_15_2
100	2%	15%	10%	3°C	16_Canales_Seq_100_2_15_10_3
200	2%	15%	10%	3°C	17_Canales_Seq_200_2_15_10_3
100	2%	-	10%	2°C	19_Canales_Seq_100_2_-_10_2

Table2. Complete list of the performed experimens for the sequential approaches.

Weight of Observations		Range of Noise Terms (weight at 1.0)					NoID
Q	SCA	P	T	SM	UZ	LZ	
5	1	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	01_Canales_Var_5_1_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	02_Canales_Var_10_1_30_2_5_5_5
20	1	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	03_Canales_Var_20_1_30_2_5_5_5
1	0	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	04_Canales_Var_1_0_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	05_Canales_Var_1_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	06_Canales_Var_50_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	07_Canales_Var_100_1_30_2_5_5_5
20	1	1.3, 0.7	2.0, -2.0	1.0, -1.0	1.0, -1.0	1.0, -1.0	08_Canales_Var_20_1_30_2_1_1_1
200	1	1.3, 0.7	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	09_Canales_Var_200_1_30_2_5_5_5
20	1	1.3, 0.7	2.0, -2.0	3.0, -3.0	3.0, -3.0	3.0, -3.0	10_Canales_Var_20_1_30_2_3_3_3
20	1	1.2, 0.8	1.0, -1.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	11_Canales_Var_20_1_20_1_5_5_5
20	1	1.4, 0.6	3.0, -3.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	12_Canales_Var_20_1_40_3_5_5_5
20	1	1.3, 0.7	3.0, -3.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	13_Canales_Var_20_1_30_3_5_5_5
20	1	1.15, 0.85	3.0, -3.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	14_Canales_Var_20_1_15_3_5_5_5
20	1	1.15, 0.85	2.0, -2.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	15_Canales_Var_20_1_15_2_5_5_5
20	1	1.15, 0.85	1.0, -1.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	16_Canales_Var_20_1_15_1_5_5_5
20	1	1.3, 0.7	1.0, -1.0	5.0, -5.0	5.0, -5.0	5.0, -5.0	17_Canales_Var_20_1_30_1_5_5_5
20	1	1.3, 0.7	2.0, -2.0	4.0, -4.0	4.0, -4.0	4.0, -4.0	18_Canales_Var_20_1_30_2_4_4_4
20	1	1.25, 0.75	2.0, -2.0	4.0, -4.0	4.0, -4.0	4.0, -4.0	19_Canales_Var_20_1_25_2_4_4_4
20	1	1.20, 0.80	2.0, -2.0	4.0, -4.0	4.0, -4.0	4.0, -4.0	20_Canales_Var_20_1_20_2_4_4_4
1	0	1.3, 0.7	2.0, -2.0	4.0, -4.0	4.0, -4.0	4.0, -4.0	21_Canales_Var_1_0_30_2_4_4_4

Table 3. Complete list of the performed experimens for the variational approaches.

Some configurations from the different DA experiments performed for the case study assimilating only discharge or both discharge and SCA have been selected to point the main results in this report. The comparison of these experiments (see Figure 3) is done in terms of Continuous Ranked Probability Score (CRPS) which is a measure of the integrated squared difference between the cumulative distribution function of the forecasts and the corresponding cumulative distribution function of the observations. When only discharge is assimilated Sequential DA shows a better CRPS of discharge than Variational DA for the first lead times (from 0 to 72 hours) and for the last lead times (from 120 to 216) Variational DA shows better results (see Figure 3A). However Variational DA provides better results in terms of CRPS of SCA than Sequential DA (see Figure 3C).On the other hand if discharge and SCA are assimilated Variational DA shows better results for discharge metric (see Figure 3B). The change in the performance of forecasts expressed in % when discharge and SCA are assimilated instead assimilating only discharge can be observed in Table 4. For the SCA metric only for the first lead time Sequential DA provides better results than Variational DA (see Figure 3D).

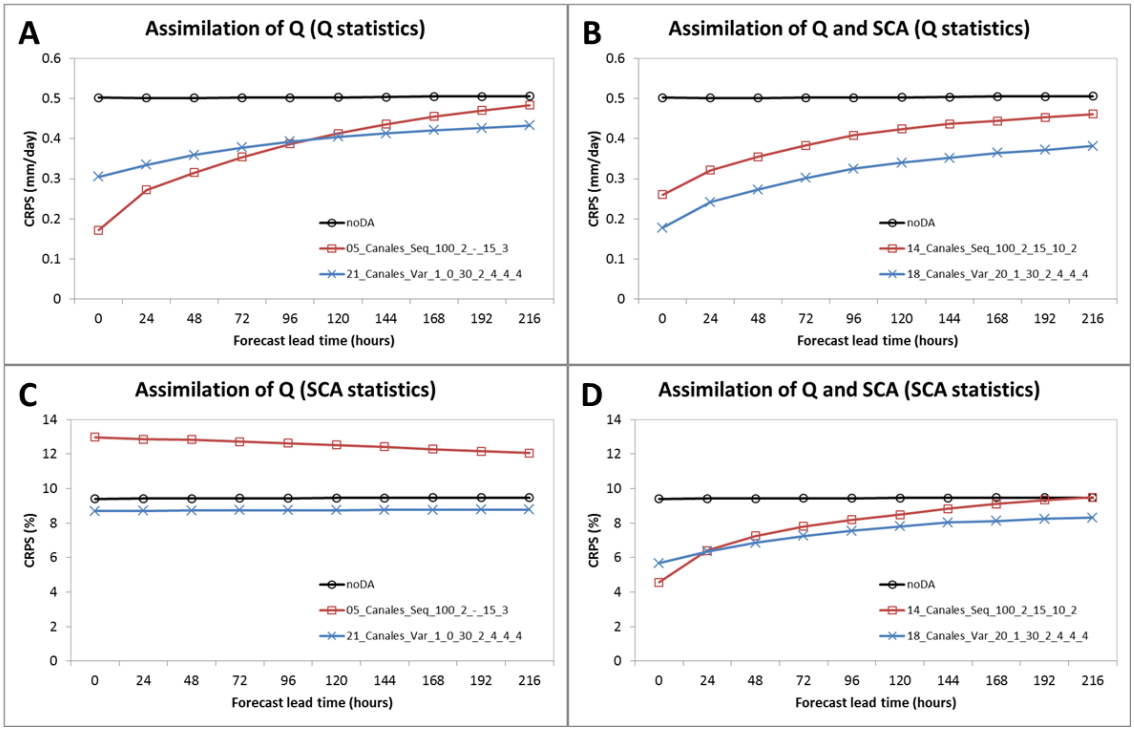

Figure 3. CRPS of discharge and SCA for the best experiments of sequential and variational DA. A) CPRS of Q assimilating Q. B) CPRS of Q assimilating Q and SCA. C) CPRS of SCA assimilating Q. D) CPRS of SCA assimilating Q and SCA.

Lead time (hours)	Sequential approach	Variational approach
0	51.8	-41.8
24	18.1	-27.7
48	12.6	-23.9
72	8.2	-20.0
96	5.6	-17.2
120	2.7	-16.0
144	0.0	-14.8
168	-2.3	-13.5
192	-3.6	-12.7
216	-4.7	-11.9

Table 4. Change in the performance of the forecasts (expressed in %) when discharge and SCA are assimilated compared to assimilate only discharge (negative values indicate an improvement).

FUTURE COLLABORATIONS (if applicable)

It is expected to publish a paper where the results obtained for the Canales basin will be compared to the results obtained for the Karasu basin which is located in the headwaters of Euphrates Basin in the eastern part of Turkey. The results for this basin have been obtained by Gokcen Uysal and Aynur Sensoy during a similar STSM in Deltares with Rodolfo Alvarado as host advisor too. On the other hand in the different meetings developed during the STSM (see Figure 4) future lines of research were raised. Therefore future collaborations are expected. Among them, the following topics were discussed:

- Development of additional data assimilation techniques: particle filters, multi-modelling techniques, asynchronous ensemble Kalman filter, ensemble variational, etc.
- Development of the perfect initial conditions.
- Test dual state-parameter estimation.

- Development of model calibration using Bayesian estimation.

Figure 4. Photo during one of the meetings developed in the STSM.

REFERENCES

Lindström, G., Johansson, B., Persson, M., Gardelin, M., Bergström, S., 1997. Development and test of the distributed HBV-96 hydrological model. J. Hydrol., 201, 272–288.

Liu, Y., Weerts, A., Clark, M., Hendricks Franssen, H., Kumar, S., Moradkhani, H., et al., 2012. Advancing data assimilation in operational hydrologic forecasting: progresses, challenges, and emerging opportunities. Hydrol. Earth Syst. Sci., 16 (10), 2012.

Montero, R. A., Schwanenberg, D., Krahe, P., Lisniak, D., Sensoy, A., Sorman, A. A., & Akkol, B. (2016). Moving horizon estimation for assimilating H-SAF remote sensing data into the HBV hydrological model. Adv. Water Res., 92, 248–257.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D. and Veith, T.L., 2007. Model evaluation guidelines for systenatic quantification of accuracy in whatershed simulations. American Society of Agricultural and Biological Engineers, 50(3), 885−900.

Reichle, R.H., 2008. Data assimilation methods in the Earth sciences. Adv. Water Res., 31, 1411–1418.