# SHORT TERM SCIENTIFIC MISSION
# (STSM)
# COST ACTION ES1404

## SCIENTIFIC REPORT

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STSM Topic: Data Assimilation of Snow Observations in a Distributed Hydrological Model

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## 1. Motivation of the study

Snow accumulation and melting play an essential role within the hydrological cycle and their fluctuations can have a major impact on human activities and the environment. Therefore, analyzing and forecasting the temporal and spatial variability of snow is important for hydrological purposes as well as for weather prediction and climatic models.

Snow observations are also necessary for calibration, validation and updating of hydrological and meteorological forecast models. Furthermore, in-situ ground-truth snow observations are also necessary for developing and validating remote sensing products. As stated in the COST action, proper description and assimilation of snow cover information into hydrological models are critical to address the impact of snow on various phenomena, to predict snow water resources and to warn about snow-related natural hazards.

On the other hand, DA is a very important process in hydrological modelling due to its ability to correct the model estimates of a state by using observations. After a proper definition of accurate quantification of errors in models and measurement system, DA process achieves relatively consistent results related with snow products.

The activities being coordinated by this COST Action are multidisciplinary with topic addressing data assimilation of snow products by hydrological model. Thus, by combining WFlow and EnKF models, our main goal in this study is to assimilate Snow Water Equivalent (SWE) using point observations. Improved hydrological predictions will have a positive effect not only on the study area but also on the whole European society, economy and welfare through better safety, awareness, preparedness and adaptation. Also, this helps to encourage new generation young scientists possessing a broader viewpoint on snow science.

## 2. Study area & data

The geographical regions are divided into seven sub regions in Turkey, and one of them is Eastern Anatolia Region, which covers 21% of Turkey with a surface area as 164,000 $km^2$. Even it has a large area; the population is relatively low because of tough winter conditions. Several important streams, with the names Euphrates, Tigris, Aras and Kura are located in this region.

Mesopotamia region, home to several civilizations, owns Euphrates and Tigris Rivers, which play vital role for irrigation and energy production. These two rivers with their significant potential flow rate have a unique importance for Turkey. Euphrates has major tributaries as Murat, Karasu, Peri and Munzur. On the other hand, Tigris's major tributaries are Batman, Botan, Habur and Greater Zap.

Euphrates, which is the longest river in the Southern West Asia, has potential flow of 35.6 billion m3/month. Its total length is 2700 km and 1236 km of it is in the border of Turkey (Aytemiz and Kodaman, 2006). Keban, Karakaya, Atatürk, Birecik and Karkamış are outstanding large reservoirs located on Euphrates River.

Upper Euphrates (Karasu) Basin, which is a headwater of Euphrates River Basin, has been selected for this study. Karasu Basin is located between 39º 50' N latitude and 40º 20' E longitude (Figure 1). Its area is 10,275 $km^2$ and its elevational range is between 1125 m to 3500 m. Its mean elevation is 1983 m and its mean slope is 20 %. In addition, according to the land use maps, it consists of pasture (35%), agricultural area (31.5%), bare ground (27.5%) and water (1%).

Outlet of Karasu basin is controlled by a streamflow station (E21A019 – Kemah) which is operated by General Directorate of State Hydraulic Works. Long-term stream flow measurement shows that 60-70% of total yearly flow arises during spring and early summer (Kaya, 1999).

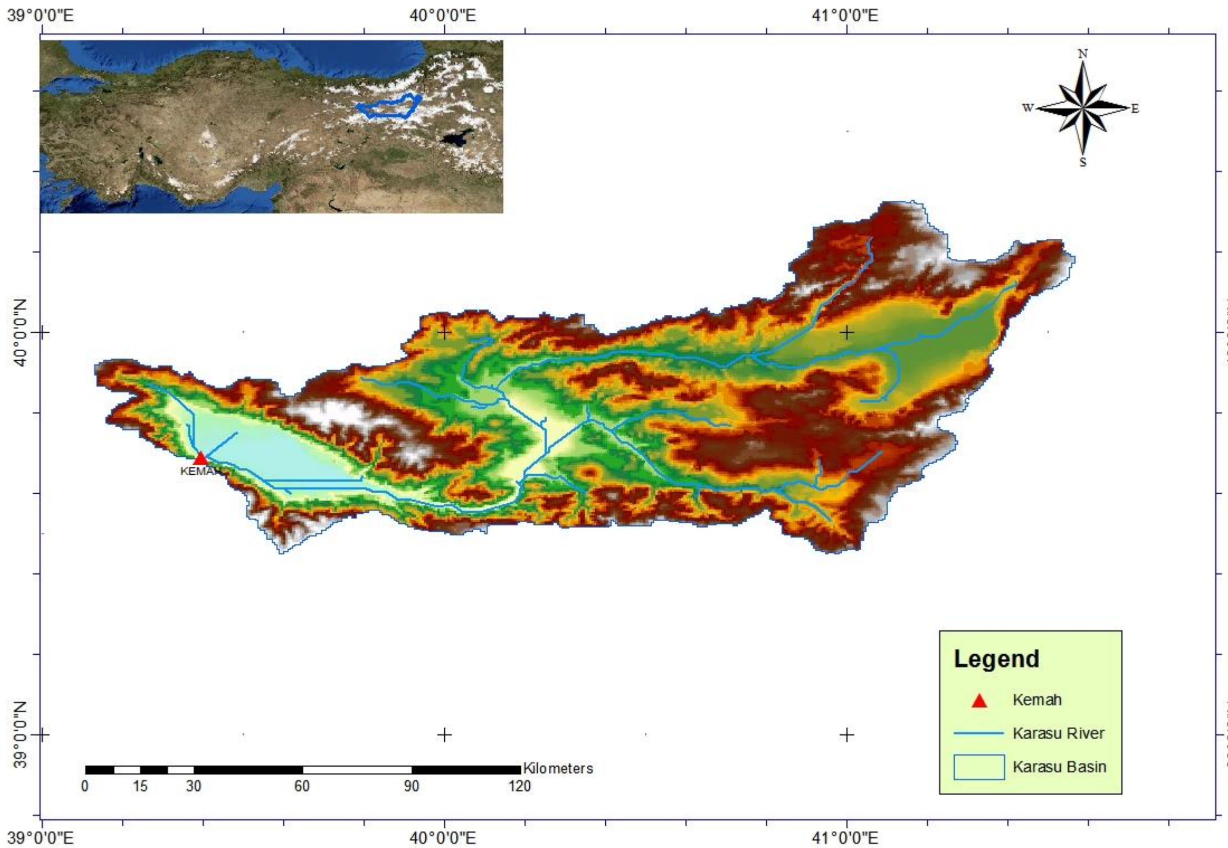


**Figure 1.** *Location and river network of Karasu Basin.*

Seventeen of meteorological stations are selected to be used in this study both inside or near outside of Karasu Basin (Figure 2)

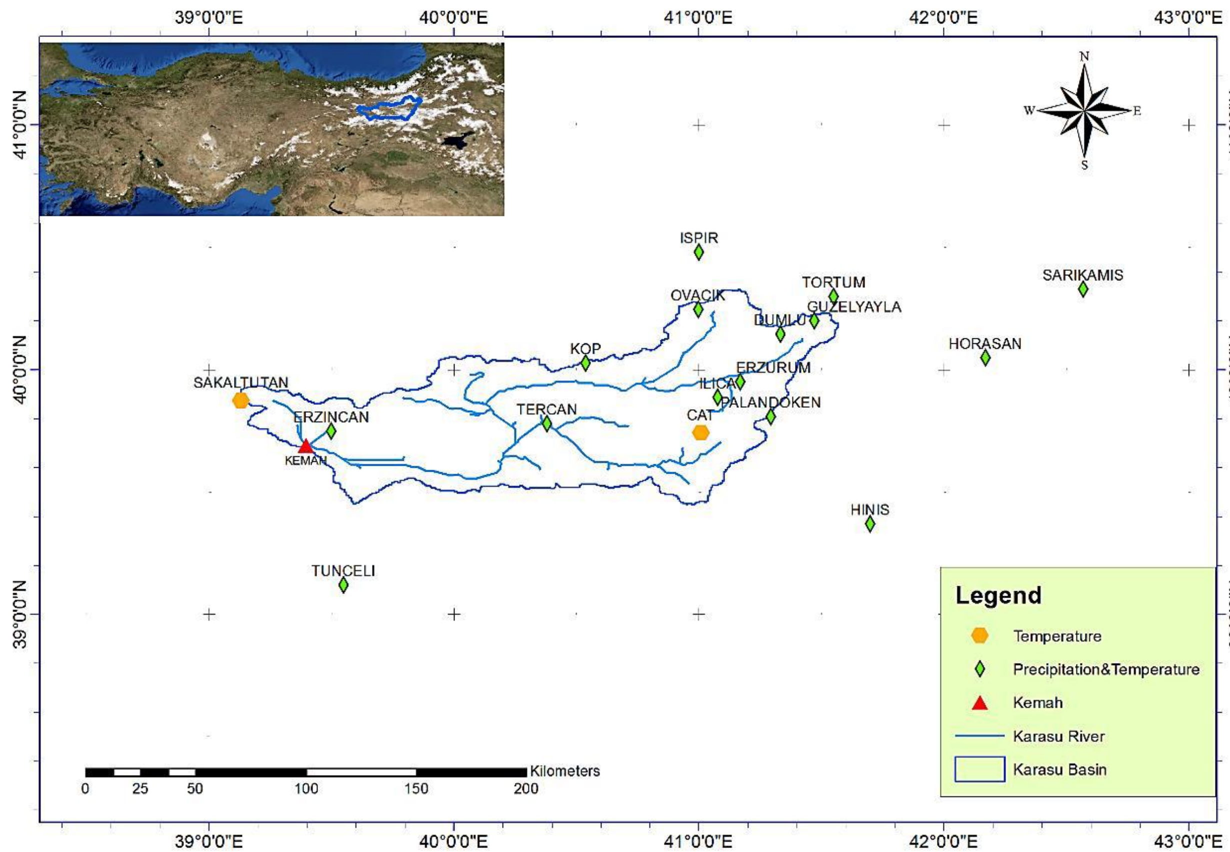


**Figure 2.** *Observation network for Karasu Basin.*

The point measurements are distributed over the catchment to obtain areal average values for the elevation zones. Several methods are being used for distribution of point observations to areal averages. Detrended Kriging (DK) is selected for the distribution of both precipitation and temperature measurements in this study. The powerful side of this technique is that it can utilize topographical information of the given DEM (Garen et al., 1994). The implicit assumption of this technique is that hydro-meteorological data and elevation have a homogenous relationship by ignoring the effect of slope, aspect and orographic regimes.

## 3. Methodology

### *HBV and WFlow Models*

WFlow as a part of the Deltares Open-Streams project (Schellekens, 2014) is a conceptual, continuous, daily and distributed model and is based on the HBV-96 model (Lindström et al., 1997). The HBV model is mainly used for runoff simulation and hydrological forecasting. The model is particularly useful for catchments where snow fall and snow melt are dominant factors.

The hydrologic process is described with twelve parameters, in which the precipitation is transformed into quick runoff and base flow and finally the total flow is route downstream in the river, this last process is changed in the WFlow model. The hydrological routing represented in HBV by a triangular function has been removed and instead, the kinematic wave function is used to route the water downstream. A catchment is divided into a number of grid cells. For each of the cells individually, daily runoff is computed through application of the HBV-96 model. The use of the grid cells offers the possibility to turn the HBV modelling concept, which is originally lumped, into a distributed model. Therefore, the WFlow hydrological model maximizes the use of available spatial data.

The land-phase of the hydrological cycle is represented by three different components: a snow routine, a soil routine and a runoff response routine (Figure 3).

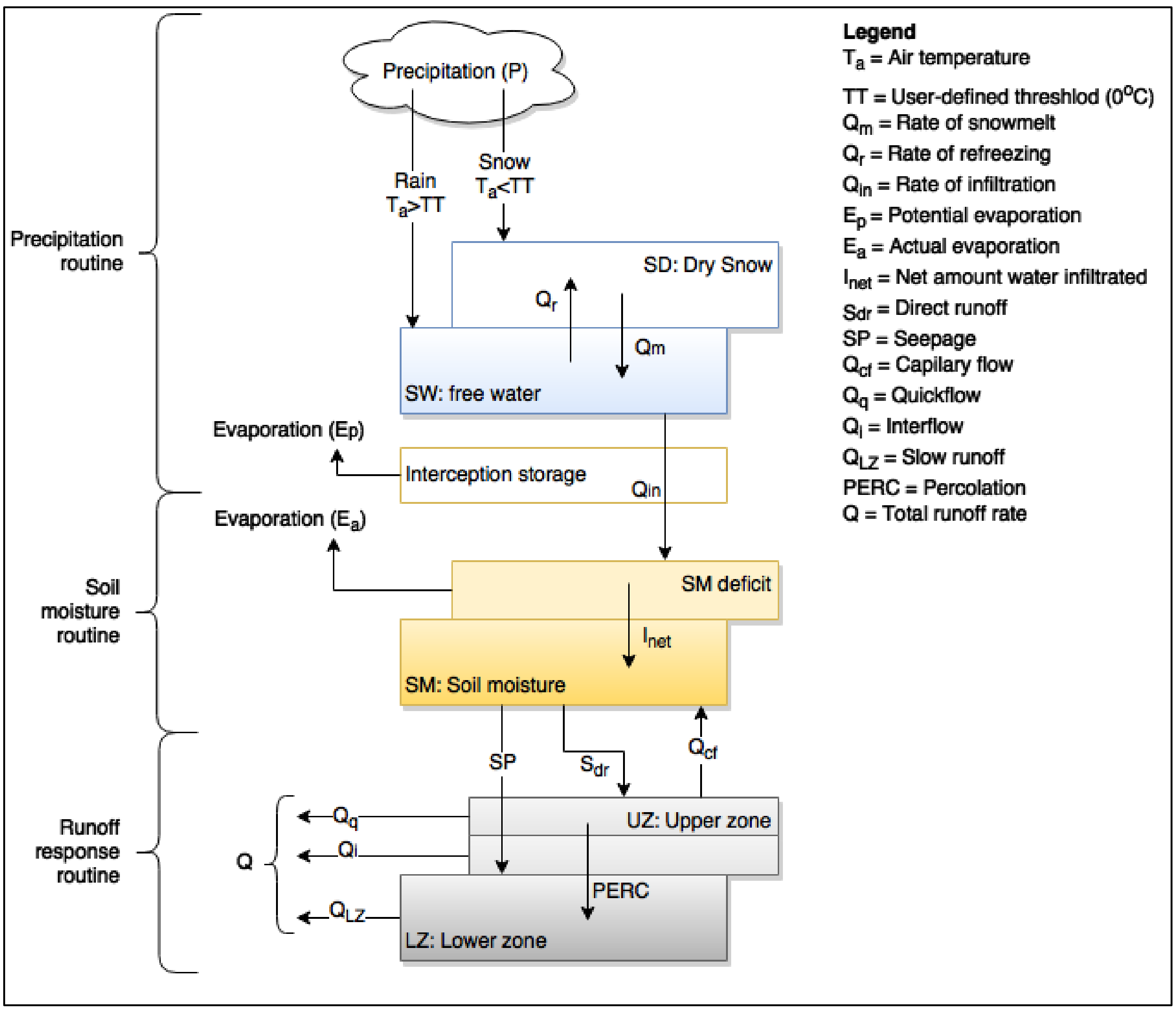


**Figure 3.** *Schematization of the WFlow HBV model, adapted from Schellekens (2014)*

### *WFlow outputs*

The WFlow module generates the following states per grid cell; these can be used to understand the model and system behavior:

- Surface runoff ($m^3$/s)
- Soil moisture (mm)
- Water level (m)
- Upper zone storage (mm)
- Lower zone storage (mm)
- Dry snow or SWE (mm)
- Interception storage (mm)
- Free water (mm)

### *Data Assimilation*

Data assimilation is an analysis technique in which the observed information is accumulated into the model state by taking advantage of consistency constraints with laws of time evolution and physical properties (Bouttier and Courtier, 1999).

Firstly, Data assimilation (DA) was started to use in meteorology and oceanography. The knowledge in these areas let the kick off the data assimilation application on hydrology. Kostov and Jackson (1993) mentioned that if hydrological model states are assimilated with proper observation, the simulation results are more accurate with actual measurements.

DA varies according to algorithm techniques, inputs used in the application and implemented hydrological models. Ensemble Kalman Filter (EnKF) DA approach was used in conceptual rainfall-runoff model for state updating (Weerts and El Serafy, 2006). Abaza et al. (2015) and He et al (2012) studied at snow dominated basins and suggested that updating model states by DA application is significant for a forecast. Besides, DA applications were conducted on snow products (for example snow water equivalent, SWE, and snow cover area, SCA) both improve forecast accuracy and improve initial states (Krysanova and Bronstert, 1999; Nagler et al. (2008); Rakovec, 2014).

### *EnKF and OpenDA*

One of the well-known data assimilation method, Kalman filter, is a statistical technique that was developed for a linear system (Kalman, 1960). It combines two estimations with own uncertainties to make the best value: like the model prediction and an observed value can be combined to get a better estimate. There are two distinct steps in the process: forecast step (or prediction step) and analysis step (or update). In the forecast step the Kalman filter produces the estimates and uncertainties of the current model states. In the analysis step these estimates are updated with the observed value. This is done based on the uncertainties of both values: the more certain the value the more weight it will receive; therefore, the new updated value will be closer to the more certain value (Mulder, 2014).

Ensemble Kalman Filter (EnKF) is an extension of the Kalman filter and was introduced by Evensen in 1994. It allows the use of the Kalman filter for nonlinear models and whereas the Kalman filter works on a single model state, the EnKF propagates an ensemble of model states (generated from model perturbations, e.g. precipitation and/or temperature noise) through time. In the forecast step the mean and covariance are calculated from ensemble of forecasts; in the analysis step the sample mean and covariance are used to calculate a Kalman gain matrix, which is in turn used to assimilate the observations to make the updated state (Mulder, 2014; Rakovec, 2014; Evensen, 2003). For the detailed theory on EnKF please refer to Evensen (2003).

OpenDA is an open interface standard that allows the user to implement data assimilation and calibration for several numerical models (OpenDA, 2012). OpenDA can be run independently and in Delft FEWS through a general adapter. OpenDA supports many DA techniques, including the EnKF.

## 4. Results

As an implementation of distributed hydrological model, WFlow, is configurated by working both Delft-FEWS platform and OpenDA. After the proper integration of the model, first step is the calibration of WFlow parameters with respect to the observed records of discharges. 01-10-2002 to 30-09-2008 is chosen as calibration period and 01-10-2009 to 30-09-2012 period is selected for validation. Regarding to the selected parameters, calibration and validation results are illustrated in Figure 4.

Correlation coefficient ($R^2$) and Nash Sutcliffe Efficiency (NSE) are selected to evaluate the performance of the model. Formulation of RMSE, $R^2$ and NSE are given in Equation 1 to 3, respectively.

$$R^2 = \frac{\sum_{t=1}^{T}(Q_o - \overline{Q_o})(Q_s - \bar{Q}_s)}{\sqrt{\sum_{t=1}^{T}(Q_o - \overline{Q_o})^2 (Q_s - \overline{Q_s})^2}} \tag{1}$$

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_o^t - Q_m^t)^2}{\sum_{t=1}^{T}(Q_o^t - \overline{Q_o})^2} \tag{2}$$

NSE value is 0.81 and $R^2$ value is 0.92 for calibration period, whilst NSE value is 0.63 and $R^2$ is 0.90 for validation periods.

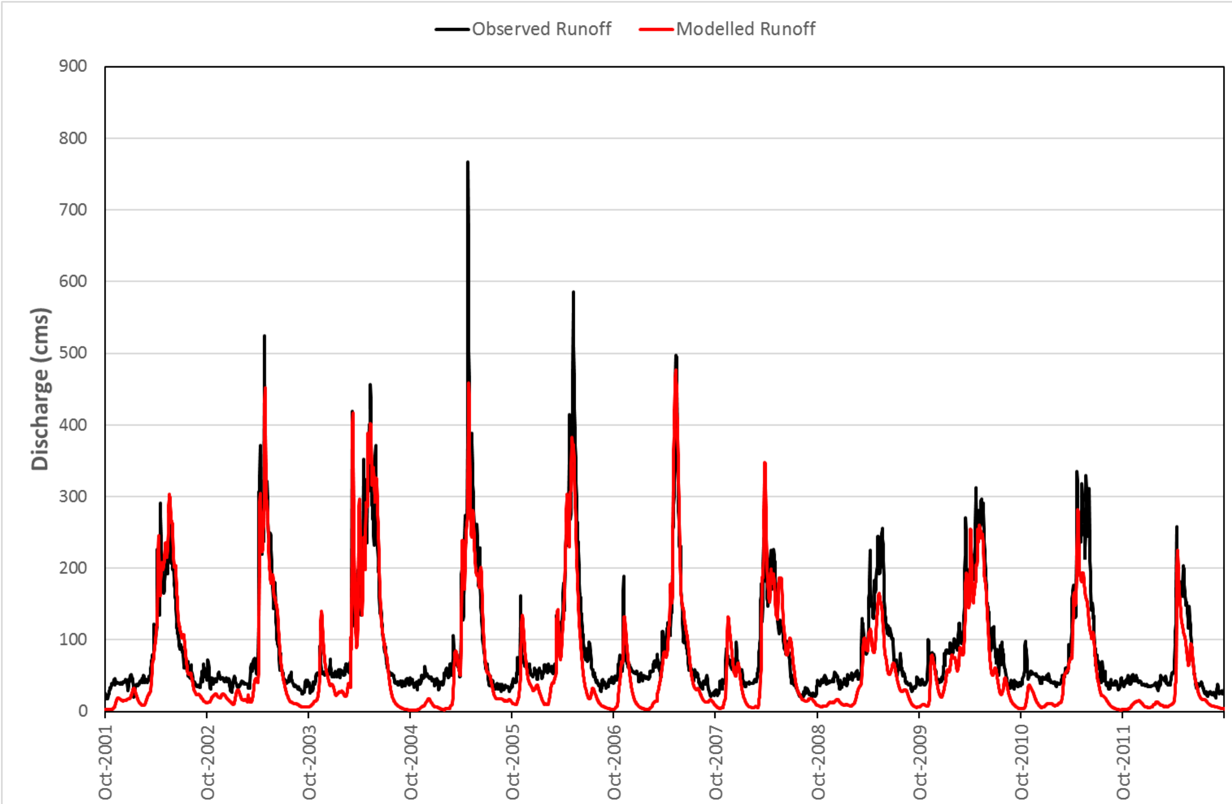


**Figure 4.** *Observed and modelled runoff for Karasu Basin, calibration and validation periods*

After all, the last experiment is conducted applying the DA method on Karasu Basin based on the discharge and snow water equivalent (SWE) observations. While discharge measurements are continuous over time, the SWE measurements are discrete snow coarse data sets over winter time. The two forcing variables, temperature and precipitation, are used as perturbation variables in objective function. Kalman gain matrix for EnKF DA application is calculated, then 16 ensemble members are generated to improve the current states according to the observations. The computation time and dispersion of members are found to be adequate for 16 ensemble members in this study.

EnKF is applied for several seasons and the results are presented for 2006 application period. For comprehensible visualization, the SWE output maps for 16 members are reduced to one by taking the average of all. Figure 5a and 5b demonstrates SWE maps with and without DA application with EnKF. It can be inferred from the figures that the snow water equivalent states of WFlow model simulation is comparatively low than the observed SWE values, therefore, EnKF results improve the state of SWE by increasing the values through the observed ones.

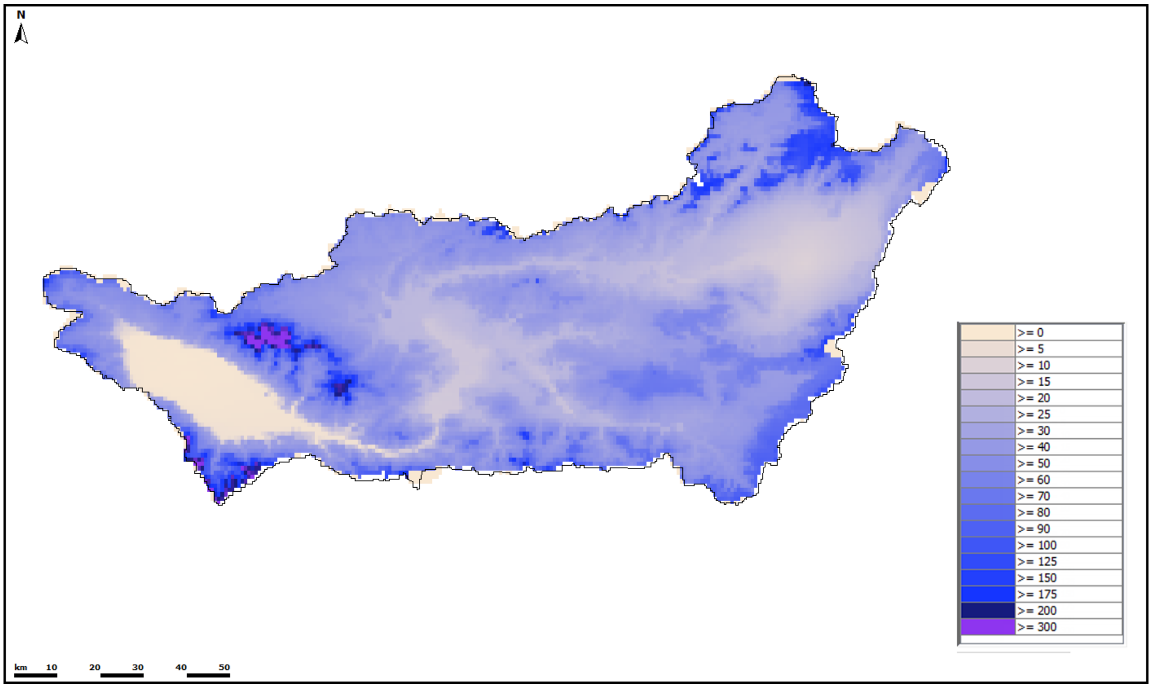


**Figure 5a.** *Modelled SWE without DA for Karasu Basin, 01-15-2006*

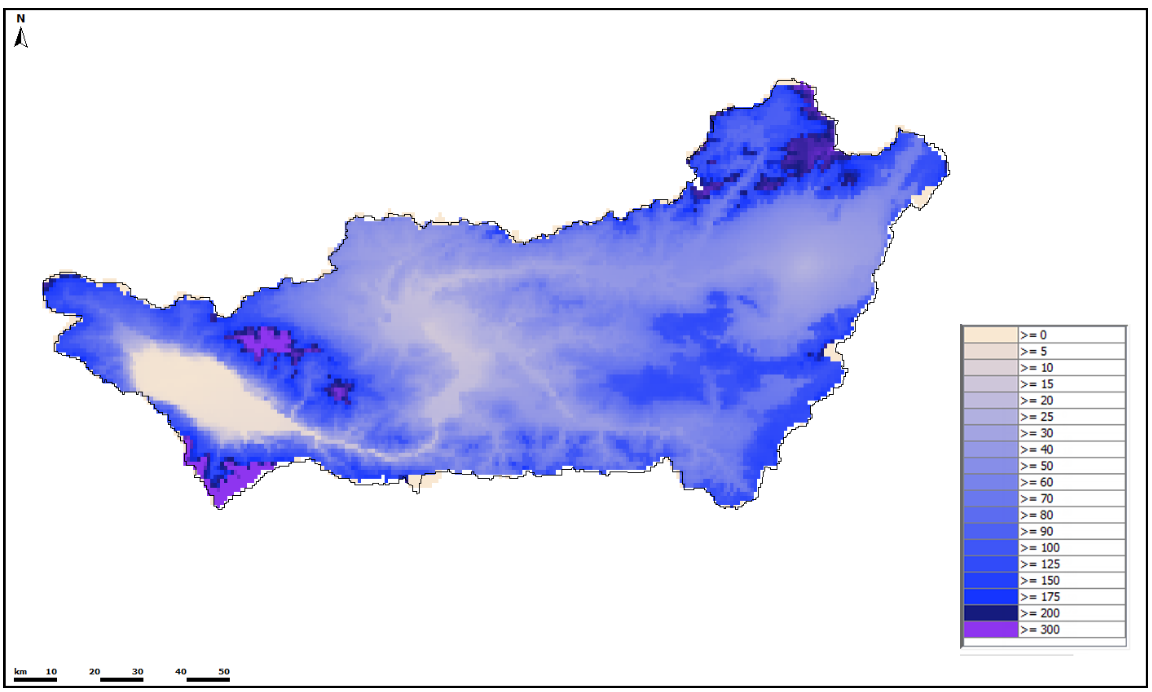


**Figure 5b.** *Modelled SWE with EnKF DA (average of SWE members) for Karasu Basin, 01-15-2006*

Discharge results of both simulations with and without EnKF are shown in Figure 6. Adding discharge observation to the objective function for calculating Kalman gain matrix has significant effect on EnKF results. While the modelled discharge is deviated from observed discharge, EnKF members tend to follow up the observed discharge.

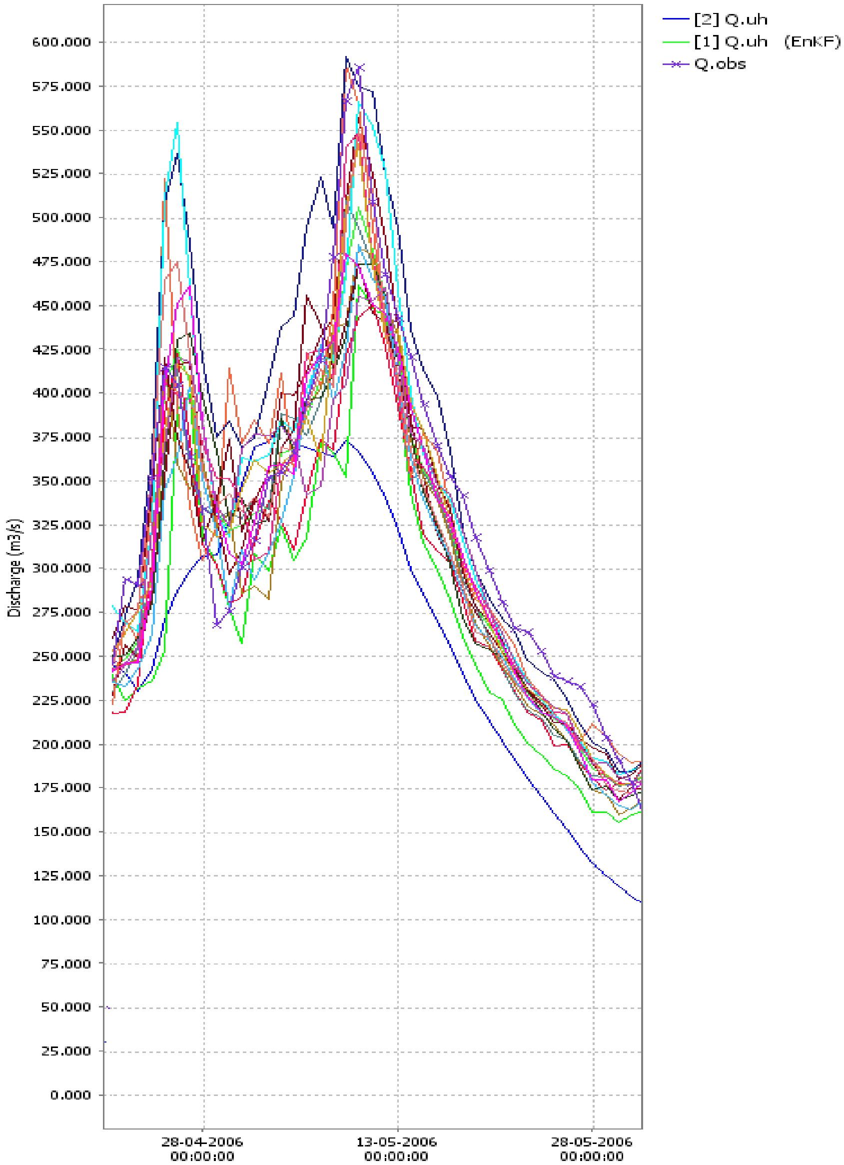


**Figure 6.** *The modelled (blue line seen below), simulated without EnKF (purple line with cross) and simulated with EnKF (Ensembles of colors), 2006*

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