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Multi-criteria evaluation for parameter uncertainty assessment and ensemble runoff forecasting in a snow-dominated basin

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Abstract: The increase in global temperatures undesirably affects the ever-growing world population and reveals the significance of hydrology science. Hydrological models might estimate spatial and temporal variability in hydrological components at the basin scale, which is critical for efficient water resource management. Satellite data sets with enhanced snow mapping with high spatial and temporal resolutions have been developed. The potential of these satellite data sets is evaluated in this study for multi-criteria evaluation of a conceptual hydrological model to improve model performance and reduce uncertainty.

The upstream part of the transboundary Coruh River is selected for this study because snowmelt contributes a significant portion of the streamflow feeding major reservoirs during the spring and early summer months. The region's snow cover dynamic has been analyzed using a combination of two satellite products. Hydrologic modeling is performed using the HBV model for the 2003–2015 water years (01 Oct–30 Sep). The Monte Carlo method is used for multi-criteria optimization exploiting satellite snow cover data besides runoff data. The sensitivity and uncertainty analysis on the model parameters indicate that multi-criteria calibration effectively reduces the uncertainty of the parameters and increases the model performance. Moreover, ensemble runoff forecasts are generated with several best model parameters using 1-day and 2-day lead time numerical weather prediction data for the snowmelt period (March–June) of the 2015 water year.

The results indicate that the use of multiple remote sensing products in combination better represents the snow-covered area for the region. Additionally, including these data sets into hydrological models enhances the representation of hydrological components while reducing runoff prediction uncertainty.

Keywords: Snow cover; Multi-criteria calibration; Uncertainty; Runoff forecast; Coruh basin.

INTRODUCTION

Climate change, combined with an ever-increasing population, severely impacts water supplies today. Conservation and efficient use of natural resources are becoming increasingly important to mitigate these adverse effects. In order to predict the consequences on water resources, most applications of hydrological design and forecasting require the use of hydrological models. Particularly, hydrological modeling studies in the snow-dominated areas can help to increase the efficiency of reservoir operations and flood control studies in mountainous regions (e.g. Anghileri et al.,2016; Şensoy et al., 2018; Sleziak et al., 2020).

Despite their utility, model simulation results may still be uncertain due to uncertainty in model inputs, model parameters, and model structure (Efstratiadis and Koutsoyiannis, 2010; Parajka et al., 2007; Sahraei et al., 2020; Thornton et al., 2021; Tong et al., 2021; Wagener and Montanari, 2011). In hydrological modeling, there are several types of methods for estimating model parameters (Blasone et al., 2007; Duan et al., 2006; Silvestro et al., 2015). Due to the limited information content or accessible "number of degrees of freedom," calibration has an ill-posed nature, which results in parameter uncertainty. Consequently, it is frequently impossible to come up with a single, definitive response for a model parameter set during calibration. As a result, various sets of calibrated parameters may give an equivalent model performance, which is known as equifinality (Beven, 2006). The degree of parameter uncertainty (increased with observation errors, model complexity, and parameter interdependence) coming from equifinality has a significant impact on how efficiently model parameters can be transposed in time and space (Foulon and Rousseau, 2018). Therefore, hydrological reasoning is required to be incorporated into the calibration process to prevent the equifinality problem. Incorporating additional data into the calibration procedure can be one way to address this (Boyle et al., 2000; Efstratiadis and Koutsoyiannis, 2010).

In literature, there are a number of studies showing multi-criteria calibrations to help constrain hydrologic models for minimizing uncertainty and improving runoff and/or model state (e.g. snow, soil moisture) predictions. The majority of these studies focused on the importance of constraining models with signatures of runoff using various objective functions (Adeyeri et al., 2020; Her and Seong, 2018; Huo and Liu, 2020; Ji et al., 2019; Sahraei et al., 2020; Zhang et al., 2018) or others concentrated on additional variables, such as groundwater data (Beldring, 2002; Madsen, 2003; Seibert, 2000), soil moisture data (Budhathoki et al., 2020; Kuban et al., 2022; Kundu et al., 2017; Li et al., 2018; Parajka et al., 2009; Rajib et al., 2016; Tong et al., 2021), and snow/ice data (Di Marco et al., 2021; Duethmann et al., 2014; Finger et al., 2011; Finger et al., 2015; Han et al., 2019; Nemri and Kinnard, 2020; Parajka and Blöschl, 2008; Tong et al., 2021; Tuo et al., 2018; Şorman et al., 2009; Udnæs et al., 2007). Although some of the above-mentioned studies paved way to improvements in modeling, a better understanding of the potential contribution of multi-criteria (using runoff as well as additional variables by satellite observations) analysis is still challenging and necessary especially when there are: data scarce regions and advances in satellite technology. One of the most efficient ways for monitoring the change in snow cover on a spatial basis is to use

earth observation data. Moreover, technological advancements serve users with freely available high temporal/spatial resolution satellite images. Multi-satellite usage or blended products may provide several benefits such as decreasing revisit time for the area of interest or obtaining cloud-free datasets.

Numerous studies demonstrate that including snow data other than runoff in the process of model calibration improves runoff and other simulations while also enhancing the model's reliability and lowering uncertainty. The first examples of these studies (Duethmann et al., 2014; Finger et al., 2011; Şorman et al. 2009; Udnæs et al., 2007) demonstrated the value of additional satellite snow data for model calibration. These studies were forced to employ a small number of catchments and a short calibration period in their analysis due to a shortage of data. Some of these research (Han et al., 2019; and Tuo et al., 2018; Nemri and Kinnard, 2020) concentrated on observed snow water equivalent (SWE) values in multi-criteria calibration, on the other hand, observed SWE values are typically not available for mountainous regions. The majority of research using optic satellites was constrained by the difficulty in acquiring cloud-free datasets, which results in long time intervals between satellite observations. In the majority of these studies, researchers either used eighth daily composite images of MODIS (Han et al., 2019), discarded the cloudy days from the time series of snow cover data sets (Di Marco et al., 2021; Etter et al., 2017; Finger et al., 2015), combined only two sensors (Aqua and Terra) of MODIS (Tong et al., 2021) or applied cloud removal algorithms to MODIS data sets (Parajka and Blöschl, 2008). In order to further enhance the snow cover dataset and accurately examine the impact of snow cover on multi-criteria calibration as well as to boost accuracy and decrease the uncertainty, we combined two separate satellite data sets (IMS and MODIS) in this study. Additionally, the research area in this application is entirely mountainous with no glaciers and has a relatively scarce monitoring network in comparison to other studies. Nearly all of these studies have as their main objective to see the contribution of snow data as an additional variable into multi-criteria calibration on output or state variables of a hydrological model (Duethmann et al., 2014; Etter et al., 2017; Finger et al., 2011; Şorman et al., 2009; Tong et al., 2021; Tuo et al., 2018; Udnaes et al., 2007), a few of these studies also incorporate sensitivity analysis (Nemri and Kinnard, 2020; Parajka and Blöschl, 2008), and only a very small number of them address uncertainty (Di Marco et al., 2021) or the effects of climate change (Etter et al., 2017; Han et al., 2019). On the other hand, we also consider parameter sensitivity and uncertainty analysis together with their impact on daily runoff prediction in our study. Moreover, an ensemble of runoff forecasts is generated and presented utilizing multi-criteria model parameter sets, parameter uncertainty analysis, and numerical weather forecast data.

In this study, multi-criteria hydrological modeling is implemented in a mid-sized mountainous basin located towards the northeastern part of Turkey with high snowmelt contribution. Being located at an elevated region, limited ground observations are present, hence satellite imagery is one of the best ways to obtain areal snow cover. For hydrological simulations, HBV, one of the well-known models in the literature, is utilized as it seems to provide satisfactory performance at snow-dominated mountainous catchments. Predicting runoff in the region is critical especially during the snowmelt season of spring and early summer months where there are several large dams situated at the downstream of the basin. In the end, short term Numerical Prediction Weather (NWP) data is exploited within the calibrated hydrological model in order to forecast valuable runoff that could be used to optimize reservoir operations. Hence, the objectives as well as the novelty of the study are to i) utilize two different satellite snow products in a combined manner and monitor long term cloud-free snow extent for a mountainous catchment, ii) implement a multi-criteria approach (high/low runoff and snow) to improve model states and outputs and decrease model parameter uncertainty, iii) forecast streamflow ensembles using multi-criteria calibration data sets and short term Numerical Weather Prediction data.

STUDY AREA AND DATA

Study area

Coruh River, forming a transboundary watercourse, rises from the Mescit Mountains above altitudes of 3250 m in the Eastern Anatolia Region, flows through the Coruh Valley, one of the deepest valleys in Turkey to end up with a delta in Georgia. Despite the region's importance in terms of water resources, there is a lack of hydrological modeling studies conducted in the area so far. However, the basin necessitates proper hydrological modeling to efficiently operate the water structures downstream of the Coruh basin. Therefore, the headwaters of the Coruh River basin, the Upper Coruh basin, where most runoff occurs due to snowmelt in spring and early summer, is selected as the study area.

The Upper Coruh basin has a drainage area of 1783 km^2, with a stream gauging station E23A004, and is bounded by coordinates 40º02’ N to 40º24’ N latitudes and 40º12’ E to 41º10’ E longitudes, as shown in Figure 1. Elevation ranges from 1537 and 3244 m with a hypsometric mean of 2190 m. The mean slope of the basin is about 35%. The major land cover types are pasture/grassland (41.2%), bare land (32.6%), agricultural area (20.9%), forested land (4.8%) and urban areas (0.5%). Much of the watershed has steep slopes at high elevations and is almost non-urbanized. Therefore, the catchment is mountainous, and snow plays a significant role in the annual runoff volume. Concerning the rough topography and relatively infrequent observation network, satellite remote sensing provides the most appropriate monitoring method over the region.

Hydro-meteorological data

The meteorological data were obtained from 15 meteorological stations (altitudes range from 1223 m to 2666 m) located in the vicinity of the Upper Coruh basin (Figure 1). The number of stations within the basin is somewhat limited, but the neighboring stations were also used in the analysis. Meteorological data, especially the ones in the city centers, is almost entirely available (~99%) for an extended period (1980–2016). Still, concerning the availability of daily satellite snow data (MODIS) and missing flow data, the application period is selected as 2003–2015. According to the analysis of hydro-meteorological data of the basin, the annual average precipitation is around 463 mm, and the annual average temperature is 7.0 ºC for the study period of 2003–2015 water years (01 Oct–30 Sep). Moreover, about 70% of the annual runoff volume is fed by snowmelt and rainfall during the melting season.

Satellite snow cover data

Satellite technology is used in many scientific and engineering studies since it provides spatial and temporal data variations. In particular, snow hydrology studies (e.g. Dong, 2018; Duethmann et al., 2014; Parajka and Blöschl, 2008) use satellite data to determine the variation of snow properties in the basin over time. In this study, two different satellite images (MODIS and IMS) are used to identify the snow-covered area in the basin.

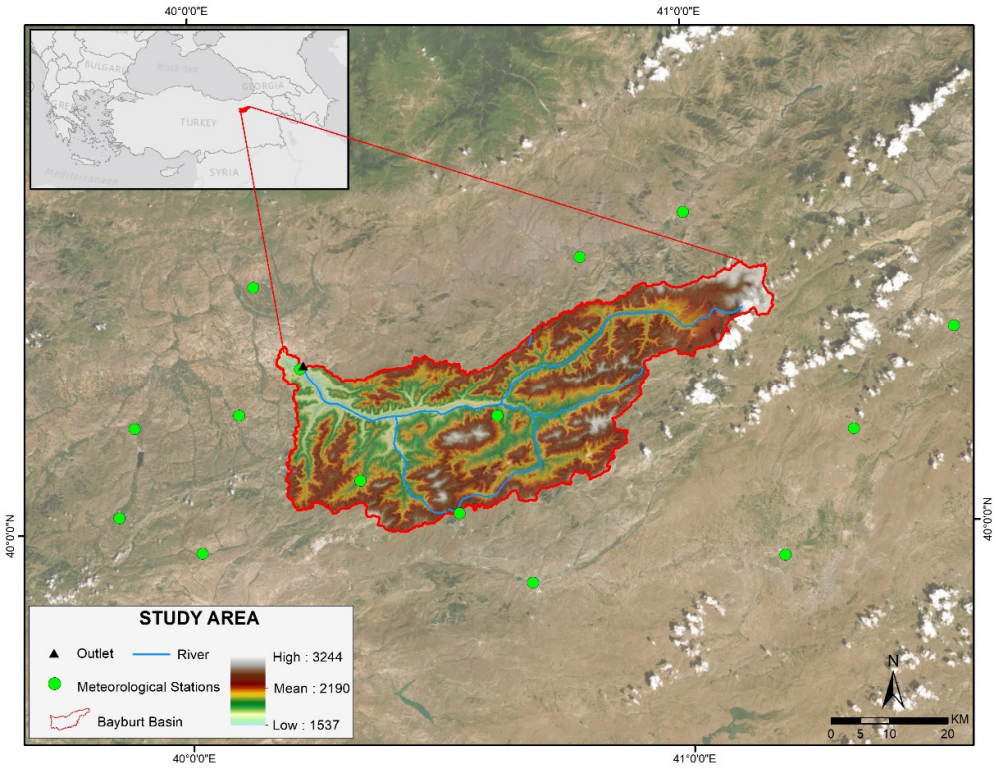


Fig. 1. Location, DEM and meteorological network of the Upper Coruh basin.

MODIS snow product

Moderate Resolution Imaging Spectroradiometer (MODIS) is an imaging spectroradiometer to provide imagery of the Earth's surface and clouds in 36 discrete, narrow spectral bands from approximately 0.4 to 14.4 μm (Barnes et al., 1998). The US National Aeronautics and Space Administration (NASA) launched the MODIS sensor on 18 December 1999, on the Terra platform and 4 May 2002 Aqua platform as part of the EOS program. Having two transition times (Terra in the morning, Aqua in the afternoon) increases the likelihood of obtaining clearer images of the snowpack because the location and spatial distribution of clouds may change within 3 hours (Hall et al., 2002). However, since MODIS is an optical satellite, cloud cover must still be considered in the data analysis. The mapping approach exploits the high reflectance in the visible and the low reflectance in the shortwave infrared part of the spectrum by the Normalized Difference Snow Index (NDSI) (Hall et.al., 1995). In this study, MODIS daily snow product with 500 m spatial resolution is utilized. There are ten classes of classification in MODIS snow algorithm, but these classes are reduced to three (snow, cloud and land) in this study for simplification.

IMS snow product

Interactive Multisensor Snow and Ice Mapping System (IMS) products have been produced weekly at 190 km spatial resolution since 1966. Three different versions of IMS data have been developed to date. The first version, 24 km spatial and daily temporal resolution, has been produced since 4 February 1997. The second version has been provided since 23 February 2004 with 4 km spatial and daily temporal resolution. The latest and new version of IMS (after December 2014) is at 1 km spatial and daily temporal resolution. The inputs used to produce all three versions vary depending on the changes and data sources (URL-1). Snow cover area analysis was carried out with the available spatial resolutions during the model application period (24 km for 2003–2004, 4 km for 2004–2015). Since it is a blended product, IMS imagery is not affected by clouds and therefore, the utilized dataset in this study is cloud-free.

The satellite snow products mentioned above are shown on the basin and surrounding area for 14 March 2014 in Figure 2.

Numerical weather prediction data

Numerical Weather Prediction (NWP) system is developed to collect actual weather observations from meteorological stations and process them with specific atmospheric models to predict future weather. In this study, deterministic NWP data for daily average temperature and daily total precipitation with a lead time of 1 and 2 days are obtained from Weather Research and Forecasting (WRF) model and used for runoff forecasting in conjunction with the hydrological model. The WRF model is a new generation of medium-scale numerical weather prediction systems (URL-2). WRF provides raster data with a spatial resolution of 4 km, and a temporal resolution of 1 hour. For hydrological modeling forcing, variables are aggregated in daily average and total values for temperature and precipitation respectively.

METHODOLOGY

Satellite data analysis

Due to the reflective properties of snow, snow-covered surfaces are monitored in the visible (VIS) and near-infrared (NIR) regions of the electromagnetic spectrum. However, the monitoring of snow cover by optical imagers is hindered by cloud conditions. For MODIS optical imagery, in this study, a

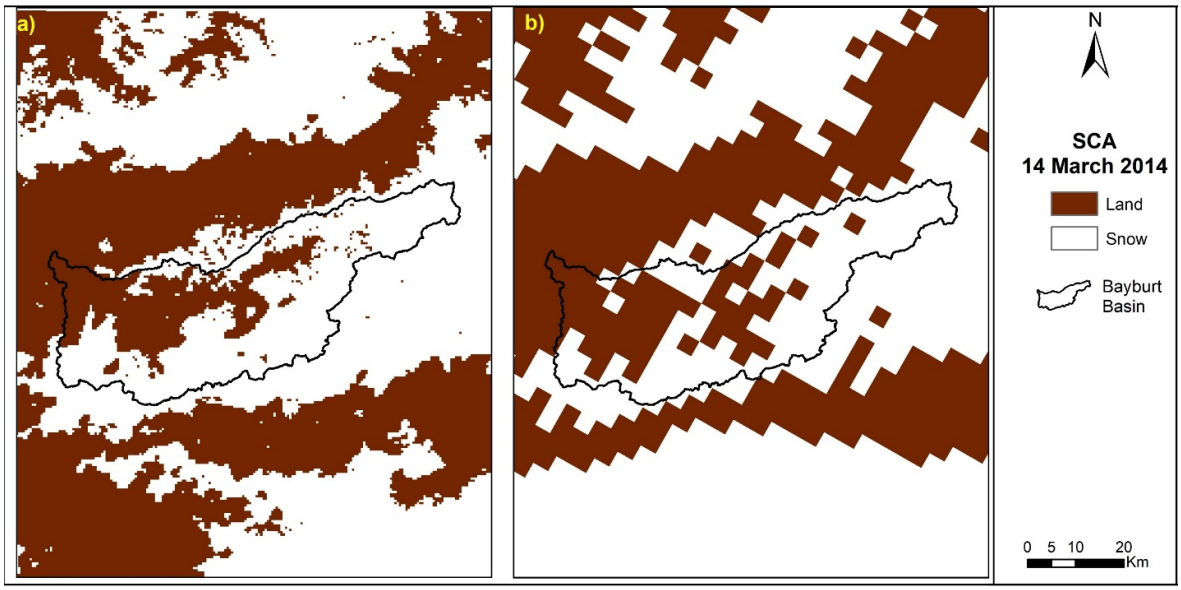


Fig. 2. Satellite snow cover images for 14 March 2014 a) MODIS, b) IMS.

cloud filtering methodology based on spatial/temporal/elevational algorithms, similar to Krajčí et al. (2014), Sorman and Yamankurt (2011), Gafurov and Bárdossy (2009), Wang et al. (2009), and Parajka and Blöschl (2008), is implemented in order to reduce cloudiness by replacing cloud pixels with snow or land. In the end, a cloud-free daily MODIS snow cover image with 500 m resolution is attained. Conversely, IMS products are already blended images from several different satellite platforms, hence, they offer daily cloud-free snow extent at 24 km and 4 km resolutions for this study period.

When the two cloud-free snow cover products are compared over the area of interest (Upper Coruh basin) for the study period of 2003–2015, several differences are observed, as exemplified by the snow season of 2012 in Figure 3a. Since IMS products utilize passive microwave images, which are not affected by clouds even during snowfall events, usually for the snow accumulation period from October to December, IMS images respond to the increase of snow extent faster than MODIS. This is largely because MODIS cloud filtering algorithm is only able to remove clouds once it sees a clear image either before or after the snowfall event. On the contrary, MODIS images are much more responsive to snow cover variations during maximum snow extent (January to March) as well as in the depletion season (March-onwards) due to the higher spatial resolution of the product (Figure 2) and shorter cloud coverage durations for the considered period. Therefore, by utilizing the advantages of both satellite imagery, a combined snow cover area (SCA) curve, primarily using IMS in the snow accumulation phase and MODIS in the full snow coverage along with snow depletion stage, offers a better timing response and a more realistic continuous SCA curve. Figure 3b, depicts the overall average combined SCA from 2003–2015 snow seasons to indicate how snow extent typically varies during a snow season in the Upper Coruh basin.

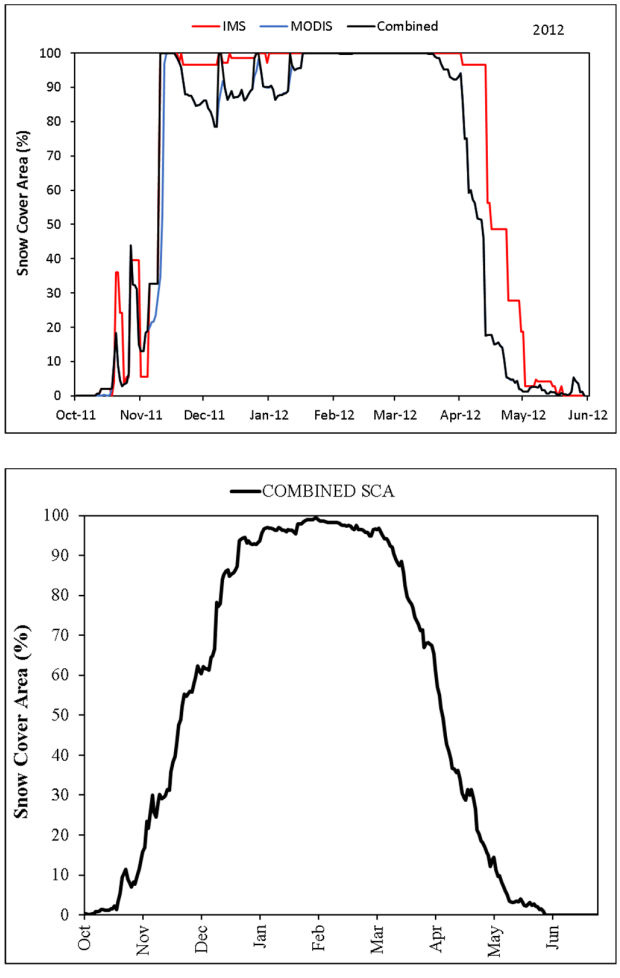


Fig. 3. a) An example of combined snow covered area for MODIS and IMS during 2012 snow season b) Average seasonal snow covered area from 2003 to 2015 years in the Upper Coruh basin.

Hydrological model

HBV (Hydrologiska Byrans Vattenbalansavdelning) is a conceptual and semi-distributed hydrologic model developed in 1972 by Swedish Meteorological and Hydrological Institute (SMHI) due to the need for runoff prediction and early flood warning Bergström (1976).

The HBV model distributes precipitation, temperature, and potential evapotranspiration based on elevation and vegetation zones to perform flow simulation. When different elevation zones are used, the temperature and precipitation for each zone are generally computed from some catchment-average value and a lapse rate (Lopez et al., 2020). In this study, daily total precipitation data was distributed by Thiessen Polygons weights and the resultant time series was assigned to the average altitude of gages. Daily average temperature time series were calculated for the same altitude using daily lapse rates between gages. Both precipitation and temperature are corrected for elevation zones using a gradient and a lapse rate, respectively. Long-term monthly mean values of potential evaporation are estimated using pan evaporation data (e.g. Häggström et al., 1988; Reynolds et al., 2017; Seibert et al., 2010). Therefore, evapotranspiration was measured at only one station and used as potential evapotranspiration. The model simulates daily runoff by calculating snow and soil moisture layers on elevation zones and runoff on a catchment-wide basis. Since continuity is considered in the model, the state variable can be tracked in each elevation zone. 10 vertical elevation zones having equal areas are used for snow and soil moisture calculations. The runoff routine (upper and lower) is treated as a lumped manner by the model. A single set of model parameters are taken for each elevation zone but model variables differ according to lapse rate. The HBV model used in this study is the HBV-Light version (Fig. 4) developed by Seibert and Vis (2012), which has a user-friendly graphical interface and an automatic calibration option. This version of HBV provides snow water equivalent (SWE) and snow cover area (SCA) for each elevation zone as well as the whole catchment. The basin average values are used in the analysis.

Single and multi-criteria model calibration

As the first step of the study, the Genetic Algorithm and Powell (GAP) optimization method (Seibert, 2000) is used to determine the best parameter set (objective function in Equation (1)). Secondly, the Monte Carlo (MC) methods, which generate random model parameter sets compatible with the normal distribution, are used for single and multi-criteria optimization by selected objective functions (Equations (1) to (3)) and their combinations (Table 1). In the multi-criteria evaluation (MC), the ranges of parameters are restricted (Table 3) according to the parameter set range which give a Reff above 0.3 in GAP analysis. Using MC, the best parameter sets for the basin are obtained with the ranking of objective function criteria run on the model. Furthermore, in the name of reliability and internal function of the model, sensitivity and uncertainty analysis are performed with the best parameter sets obtained using the MC method.

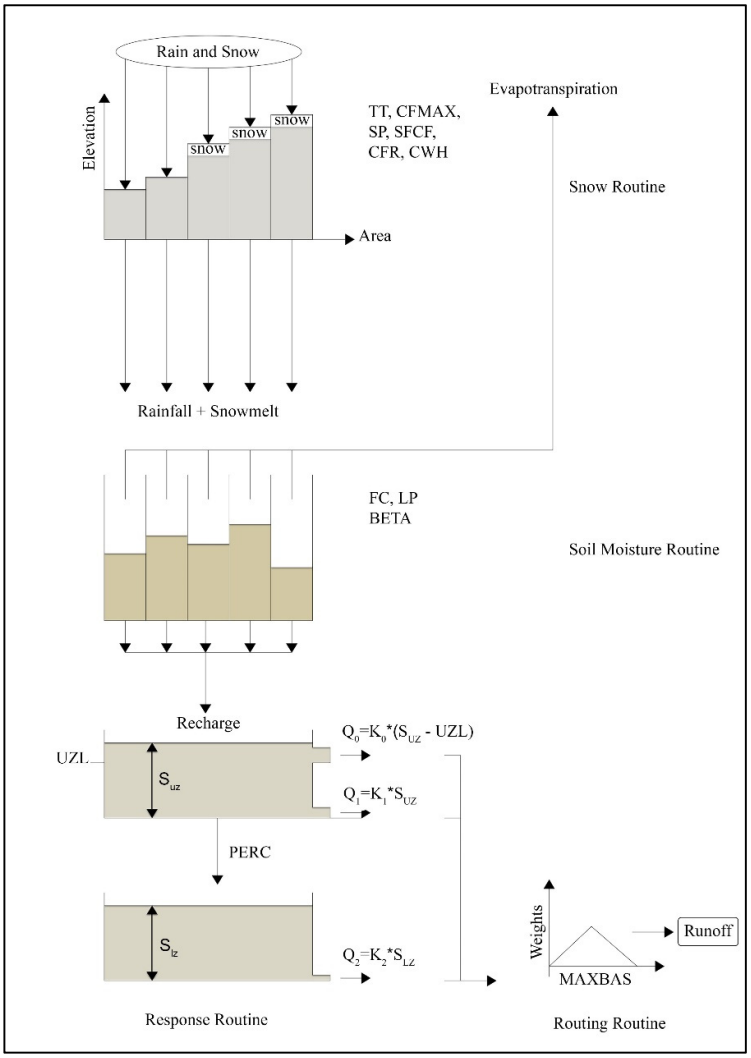


Fig. 4. HBV Light model structure (Seibert and Vis, 2012).

Table 1. Single and multi-criteria functions used for calibration study with Monte Carlo (MC) method.

Reff (R)
SCA (S)
MARE (M)
SCA + MARE (S+M)
Reff + MARE (R+M)
Reff + SCA (R+S)
Reff + SCA + MARE (R+S+M)

Selection of objective functions

Different objective functions (Equations (1) to (3)) are considered to evaluate the model's performance, consisting of single or multiple criteria that assess the agreement between observed and modeled data.

$$\text{Reff (NSE)} = 1 - \frac{\sum(Q_{obs} - Q_{Sim})^2}{\sum(Q_{obs} - \overline{Q_{obs}})^2} \quad (1)$$

$$\text{SCA}_{\text{RMSE}} = 1 - \sqrt{\frac{1}{n}\sum(C_{sim} - C_{obs})^2} \quad (2)$$

$$\text{MARE} = 1 - \frac{1}{n}\sum\frac{|Q_{obs} - Q_{Sim}|}{Q_{obs}} \quad (3)$$

where Q_{obs}, Q_{sim} and $\overline{Q_{obs}}$ stands for observed, simulated and mean of the observed flows, C_{sim} and C_{obs} shows observed and simulated SCA, respectively. C_{sim} is provided by the model for each elevation zone and the basin, C_{obs} is calculated from the satellite data. The values are used as basin averages in calculations. n indicates days in the time series of simulation. The objective function Reff (Nash and Sutcliffe, 1970) is more sensitive to peak flows, and it can range from negatively infinite (∞) to 1, with 1 being the best model output. For SCA_RMSE (Snow Cover Area Root Mean Square), the best model output is 1. Furthermore, the MARE (Mean Absolute Relative Error) objective function is responsive to low flows (Vis et al., 2015), with 1 being the best output value.

Model performance is evaluated by computing various efficiency criteria and then using the calculated efficiencies to rank the 500,000 simulations, each corresponding to a different set of parameters. For this purpose, combinations of criteria are determined to simultaneously evaluate model performance for runoff and SCA data (Table 1).

The 500,000 simulations are ranked by assigning rank 1 to the best simulation (Equation (4)), concerning each efficiency criterion, and then to the combined criteria. P_r^i, the ranking value is specified for each run, r, and efficiency criterion, i to achieve this goal (Finger et al., 2011 and 2015).

$$P_r^i = \frac{(N+1) - R_r^i}{N} \quad (4)$$

According to Equation (4), R_r^i remains for the rank of the run under consideration with respect to criterion i and N is the total number of runs performed. 500,000 MC simulations were done and each model run was ranked between 1 and 500,000 with this Equation (4). After the ranking values are obtained, the objective functions are ranked in a general way according to the multi-criteria that occur singularly or in combinations. Normalization in Equation (4) allows the rank to be independent of the total number of runs used. This, in turn, enables the calculation of combined rank values for each observed variable, i.e. P_r^R for high flows, P_r^S for snow cover and P_r^M for low flows, by simply averaging the relevant P_r^i terms. The model's performance with respect to the observational datasets considered in this study can be measured by the overall ranking P_r^{OA}, defined in Equation (5).

$$P_r^{OA} = \frac{(P_r^R + P_r^S + P_r^M)}{3} \quad (5)$$

As a result, the parameter sets with the highest P_r^{OA} have the best overall performance. The P_r^{OA} of the best runs selected using single or combined observational data sets are then calculated by sorting the combined ranking values for each data set in descending order.

RESULTS

Model results

In this study, the model was calibrated (2003–2009) with the GAP method by using the parameter ranges proposed in previous HBV Light studies (Seibert, 2000), and then they were validated for 2010–2015 (Figure 5). According to Reff, the performance in terms of model efficiency is calculated as 0.90 for the calibration period and 0.88 for the validation period when employing the GAP methodology.

Continuous satellite data of snow-covered area (SCA) and snow water equivalent (SWE), especially in snow-fed basins, are valuable independent validation variables for efficient water resources management in mountainous areas. Figure 6 shows modeled and observed values of snow-covered area in the basin for the entire model application period. The model results have a high level of accuracy, as shown in Table 3. The hit rate is derived by dividing the total number of hits (snow-snow and no snow-no snow match) by the total data set.

In this study, a multi-criteria calibration/validation approach is carried out by considering both low and high flow compliance and agreement with observed daily snow cover area processed using the combination of two different satellites. For this purpose, 500,000 MC simulations were performed during the calibration period covering 2003–2009 water years. In the given calibration period, the parameter ranges used for the MC simulation are given in Table 2.

In the hydrological modeling phase with the targeted multi-criteria structure, simulations are produced for the best 10 and 100 parameter sets with the highest performance for 500,000 MC. Using the best 10 parameter set it is found to be practical since the results are insensitive to a greater number of parameter sets (100), and reduced numbers minimize computational efforts in modeling and forecasting studies. To this end, Figure 7 represents the overall performance rankings of the best 10 parameter sets obtained with the objective functions and their combinations used during the calibration period concerning the basin representation. The best 10 parameter sets from each performance criterion obtained in the calibration studies are used in the validation. Moreover, calibration and validation graphs are each formed by the best 10 parameter sets from the combination of multi-criteria (R+S+M) is shown in Figure 8.

The overall performance of the model may vary depending on the objective functions used. If the parameter sets selected when calibrating the model are based on only one objective function, the model's overall performance appears to be lower. Therefore, it is found that when multi-criteria is preferred instead of a single objective function in the calibration process, the model

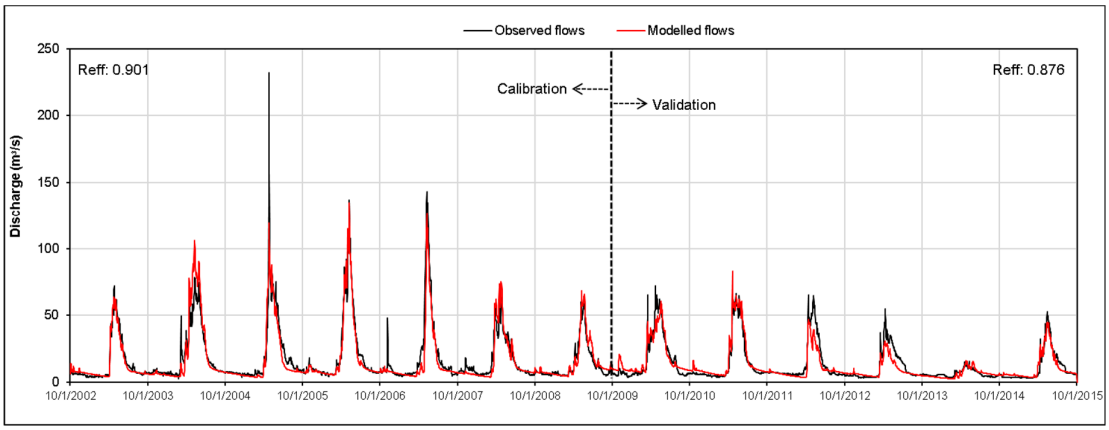


Fig. 5. Comparison of observed and modeled flows for calibration (2003–2009) and validation (2010–2015) with GAP Method.

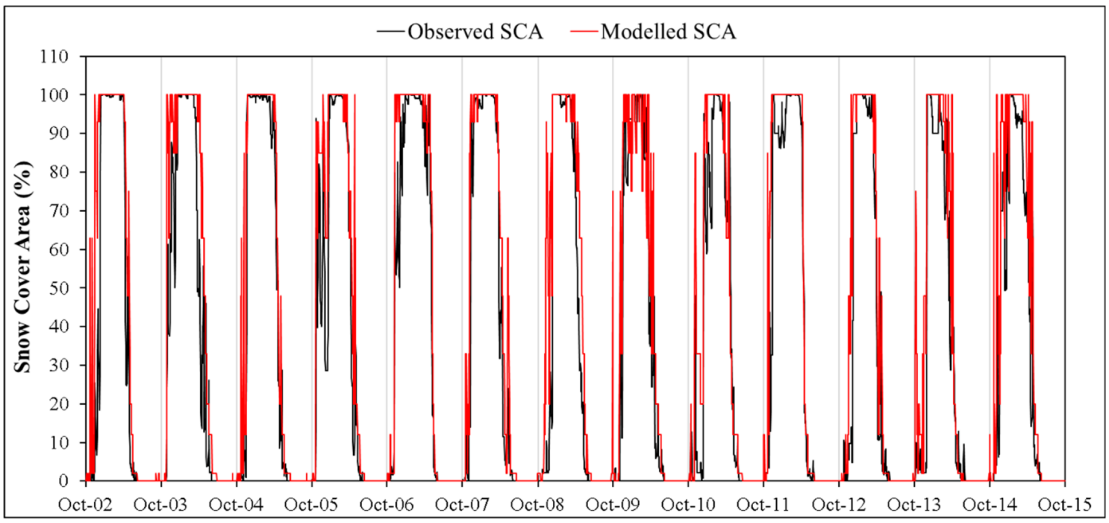


Fig. 6. Comparison of observed and modeled snow cover area for calibration (2003-2009) and validation (2010–2015) with GAP Method.

Table 2. Parameter ranges specified for MC method.

Class	Parameter	Explanation	Unit	Min	Max
Snow routine	TT	Threshold temperature	°C	–1	1
	CFMAX	Degree-day factor	mm/day °C	1.5	4.5
	SP	Seasonal variability of degree-day factor	–	0.5	1
	SFCF	Snowfall correction factor	–	0.7	1.2
	CWH	Water holding capacity	–	0.01	0.05
	CFR	Refreezing coefficient	–	0.001	0.1
Soil routine	FC	Maximum of SM (storage in soil box)	mm	80	300
	LP	The threshold for reduction of evaporation (SM/FC)	–	0.2	1
	BETA	Shape coefficient	–	0.5	2.5
	CET	Correction factor for potential evaporation	1/°C	0.1	0.3
Response routine	PERC	Maximal flow from upper to the lower box	mm/day	0.5	5
	UZL	Threshold for the K0-outflow	mm	5	50
	K0	Recession coefficient (upper storage)	1/day	0.2	0.6
	K1	Recession coefficient (upper storage)	1/day	0.02	0.1
	K2	Recession coefficient (lower storage)	1/day	0.001	0.06
Routing routine	MAXBAS	Routing, length of weighing function	day	1	2
Catchment properties	PCALT	Altitude correction factor for precipitation	%/100 m	3	8
	TCALT	Altitude correction factor for temperature	°C/100 m	0.6	0.8

Table 3. Consistency analysis of modeled and observed SCA.

Number of days (2003–2015)		Observed SCA			Hit rate	Reff	R^2	RMSE (%)
		Snow	No snow	Total				
Model-SCA	Snow	2365	279	2644	0.93	0.86	0.90	16.1
	No snow	32	2072	2104				
	Total	2397	2351	4748				

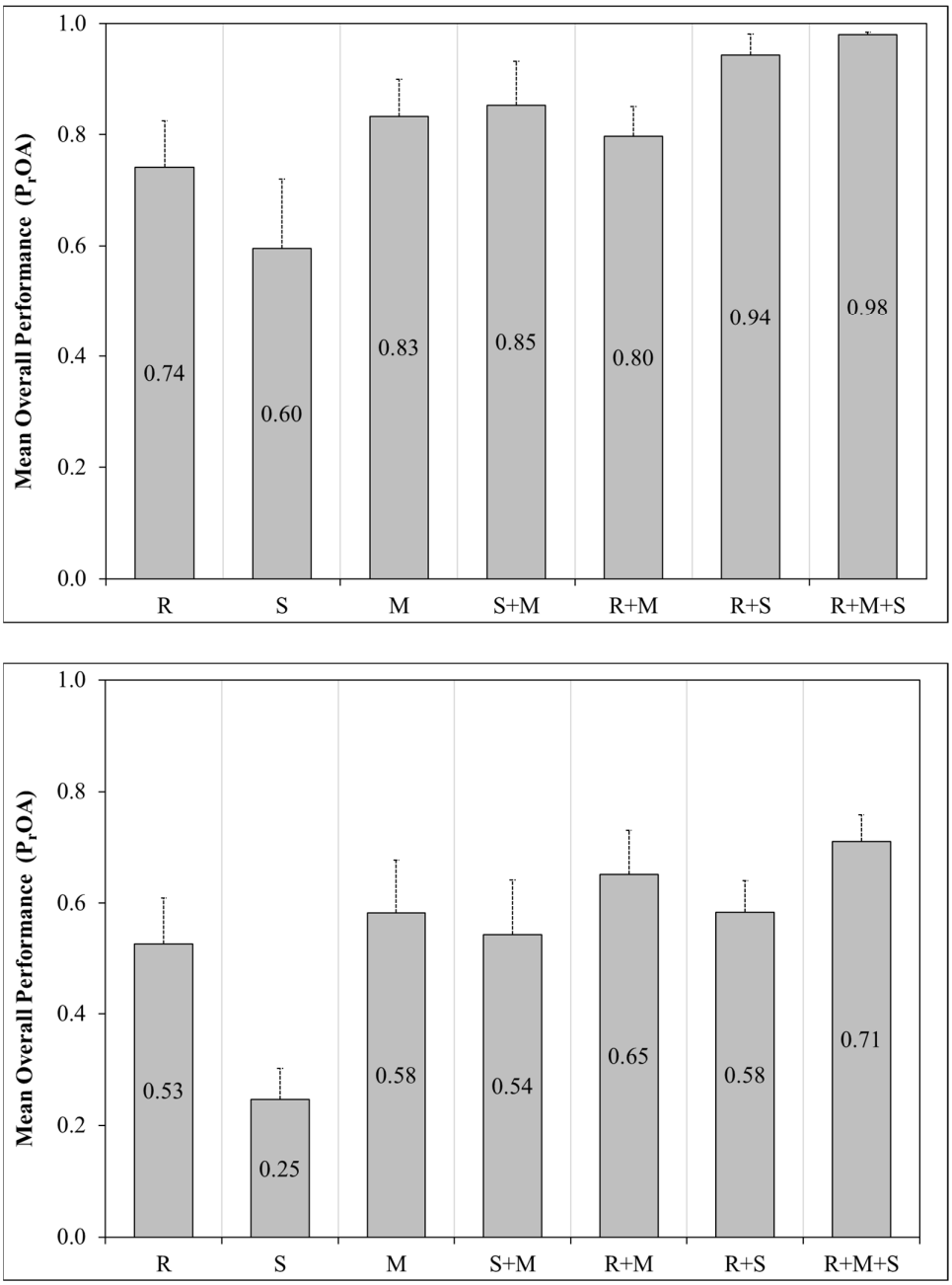


Fig. 7. Ranking Results of the MC method for calibration (on the top) and validation (on the bottom) periods.

performance is increased, and the uncertainty range of the model (error bars of the Fig. 7 graphs) is decreased, as shown in the plots. In addition, 7x10 parameter sets that obtained each performance criterion, as shown in Table 1, are ranked as the top 10 sets in the ranking for all conditions and finally, the top 10 parameter sets are used in the runoff forecasting study.

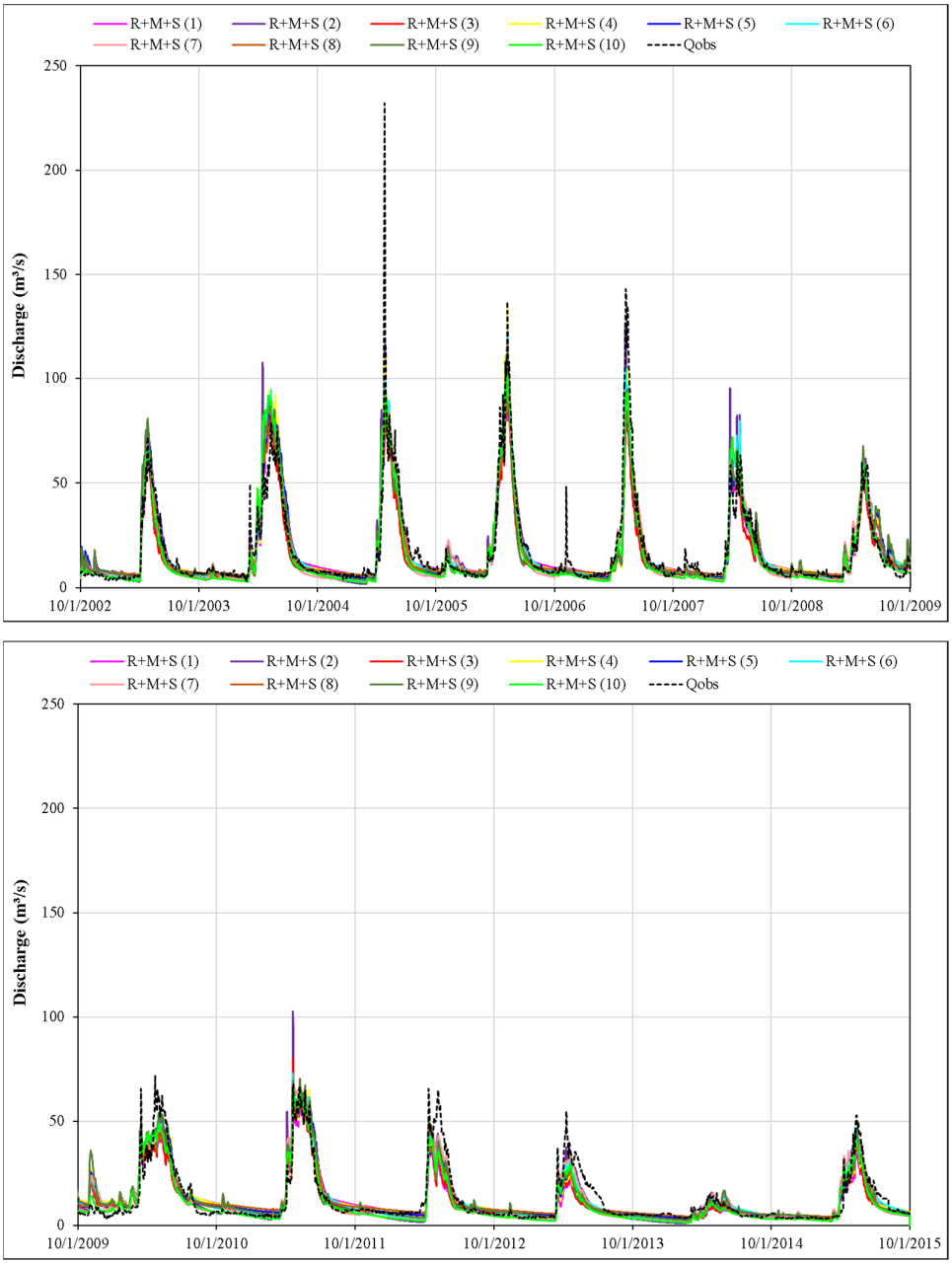


Fig. 8. Comparison of observed and modeled flows for calibration (on the top) and validation (on the bottom) with the best 10 parameter set by R+M+S, respectively.

Sensitivity and uncertainty analysis

Sensitivity analysis

The sensitivity analyzes of each parameter (Table 2) are examined separately according to Reff, MARE and SCA objective functions as shown in Figure 9. First, all parameters are normalized to values from 0 to 1 to represent them as a typical value in this analysis. Then, while holding all variables constant, each parameter value is changed individually to observe the changes in the hydrograph with respect to the performance in the objective functions used.

The results of sensitivity analysis are also analyzed for each objective function used in the application. Finally, the sensitivity values are normalized according to the ranges between 25 and 75 percentiles and presented in Figure 10 in data color bars.

Figure 9 and Figure 10 show that the seasonal variability of degree-day factor SP, refreezing coefficient CFR, water holding capacity CWH, reservoir threshold UZL, recession coefficient K0, routing function MAXBAS, and correction factor for potential evaporation CET are insensitive to all objective functions. The result of parameter sensitivity based on the Reff objective function reveals that snowfall correction factor SFCF of the snow routine and parameters PERC, K1 and K2 of the response routine seem to be the most influential parameters controlling the high flows. Threshold temperature TT and degree-day factor CFMAX parameters of the snow routine are moderately and slightly sensitive to the high and low flow series, respectively, but they are significantly affected by the snow cover area contribution in the objective function. One of the soil moisture parameters, FC plays a vital role in transferring the effective precipitation to the flow routine.

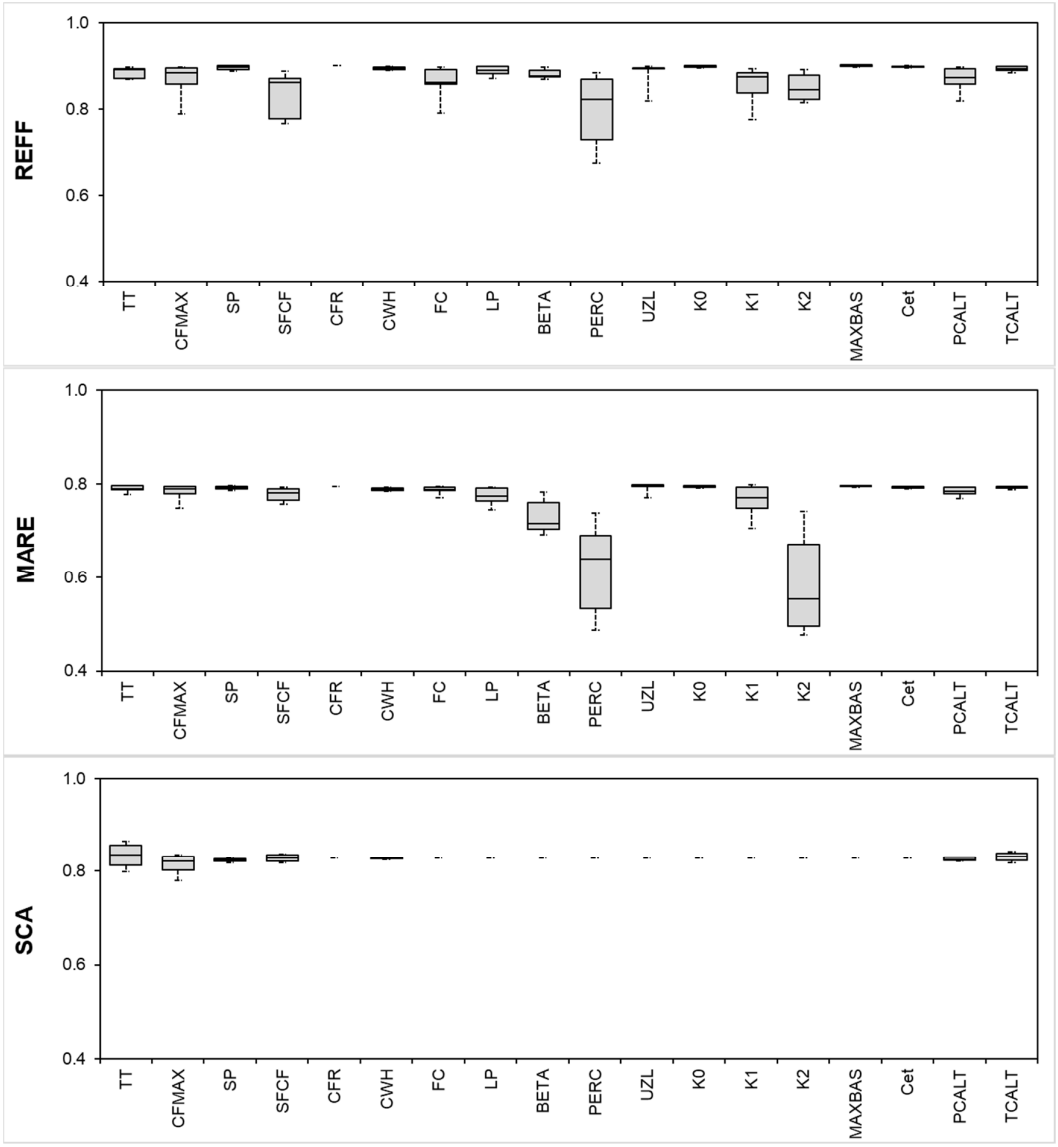


Fig. 9. Sensitivity plots of parameters with reference to objective functions a) Reff, b) MARE, c) SCA.

Process	Parameter	R	S	M	R+S	R+M	S+M	R+S+M
Snow Routine	TT							
	CFMAX							
	SP							
	SFCF							
	CFR							
	CWH							
Soil Moisture Routine	FC							
	LP							
	BETA							
Response Routine	PERC							
	UZL							
	K0							
	K1							
	K2							
Routing Routine	MAXBAS							
Other	Cet							
Catchment Properties	PCALT							
	TCALT							

Fig. 10. Comparison of model parameter sensitivity ranges according to objective functions.

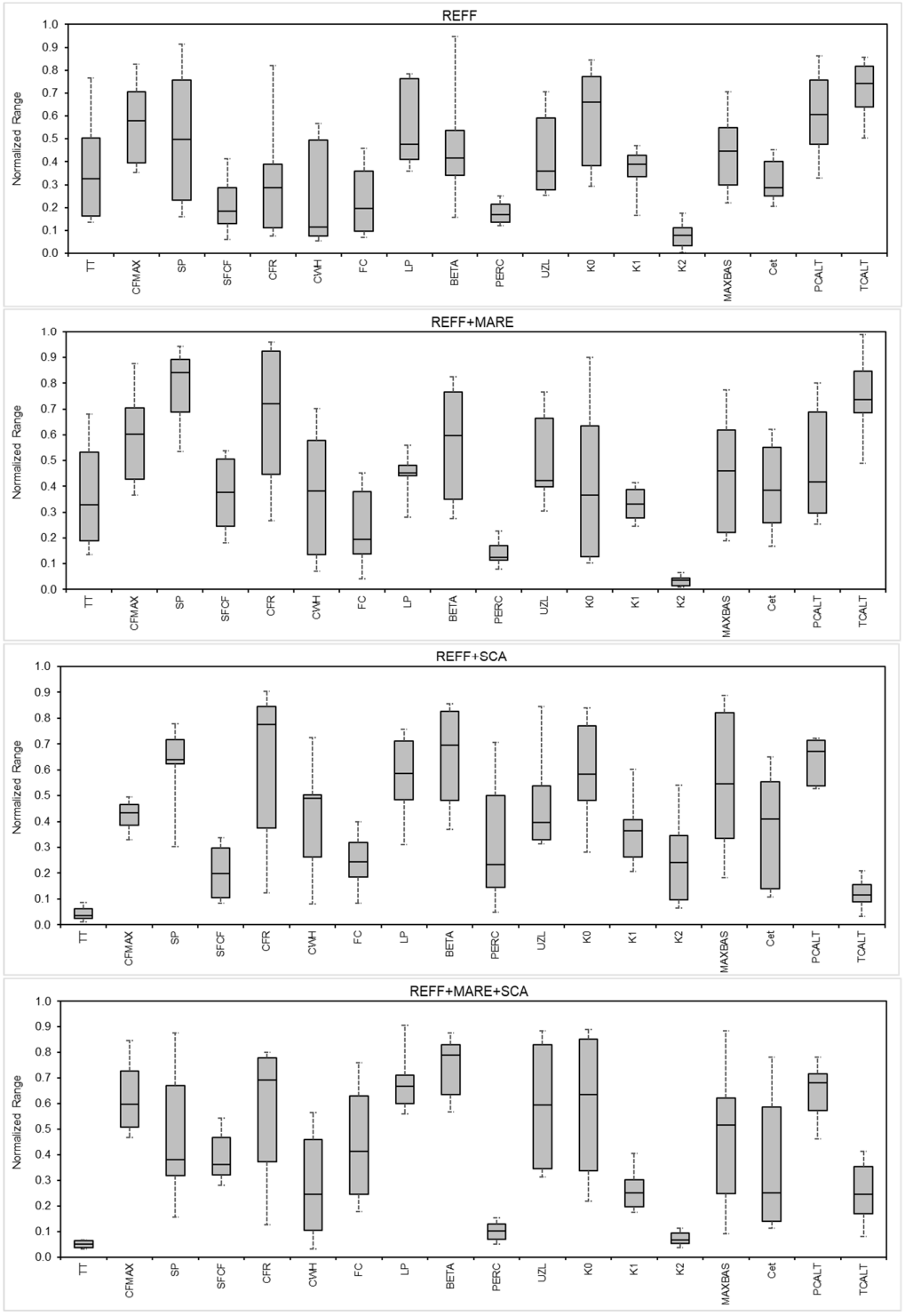


Fig. 11. Uncertainty plots of parameters with reference to objective functions.

Therefore, FC is the most influential parameter for hydrograph shape in soil moisture routine and moderately sensitive to high flows. The threshold for reducing the evaporation parameter, LP, is slightly sensitive to the high and low flows. Another soil moisture parameter, BETA, represents the ratio of soil moisture to the field capacity. It affects the partitioning of net precipitation into a response routine. Therefore, it is one of the most sensitive parameters affecting the low-flow series in the basin. From the structure of the HBV model, it can be seen that the recession coefficient of interflow, K1, and baseflow from deep groundwater, K2, in combination with percolation rate from an exchange, PERC, are parameters that play a role in the response routines. Thus, they are exceptionally responsive to both high and low-flow series. However, both soil moisture and response routine parameters have no impact when it comes to the snow cover area. The physical features of the basin (PCALT and

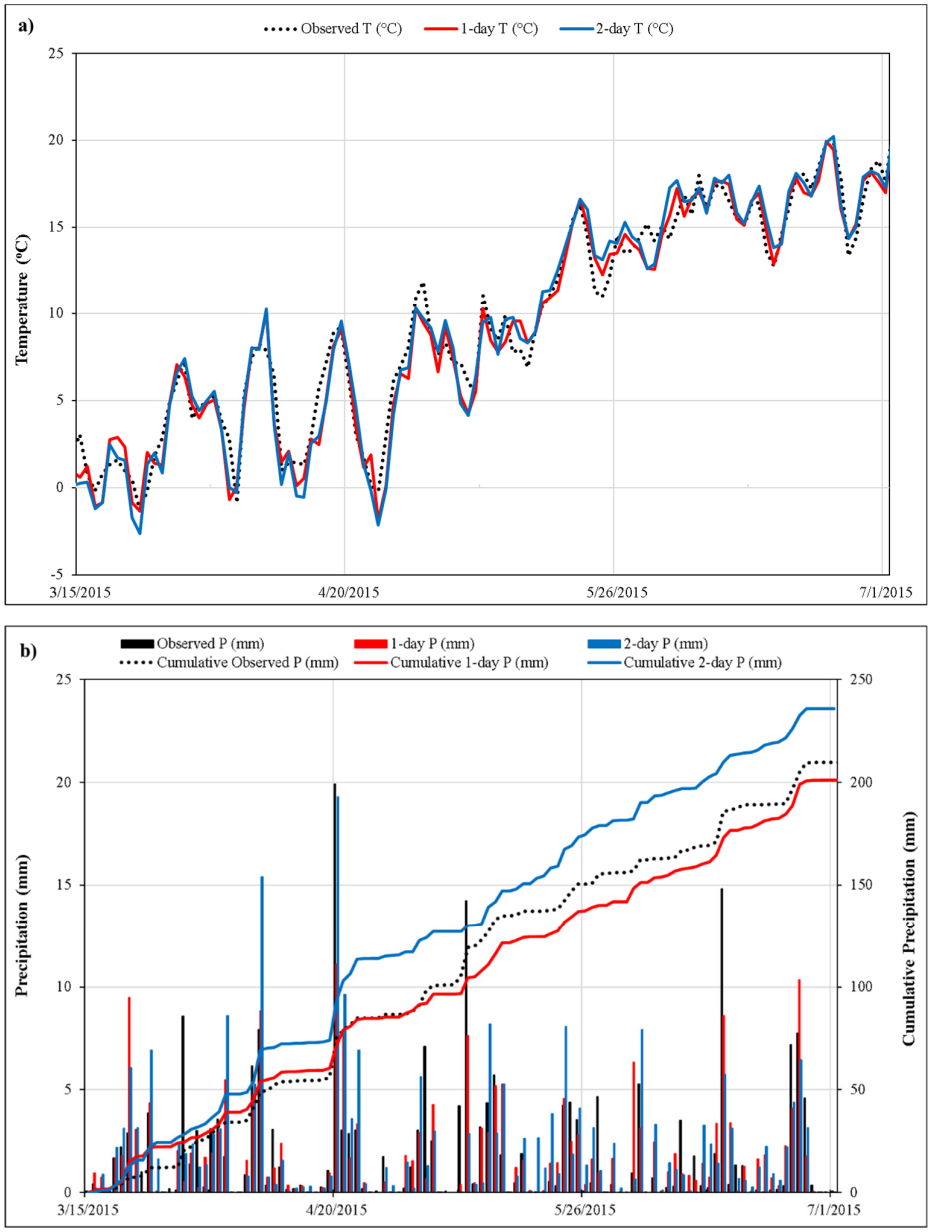


Fig. 12. Comparison of WRF and observed data for the basin a) Temperature data, b) Precipitation data.

TCALT) contribute to calculating the best number of elevation zones. However, when compared to Reff, their sensitivity rate for affecting the shape of the hydrograph is not high.

These sensitivities are weighted for the combination of objective functions in Figure 10; accordingly, PERC and K2 of response function are the most sensitive parameters when runoff signatures and snow cover is considered together in the calibration. Then, parameters SFCF, K1, CFMAX, and TT come next in sensitivity. As a result of these findings, it is clear that calibrating the model without considering objective function division of the parameters and using only single objectives would result in more uncertainty in the model performance.

Uncertainty analysis

Model uncertainty analysis is used to evaluate the model parameters' uncertainties to the model's various objective functions.

The best 10 parameter sets obtained with MC simulation during the calibration period are used for model uncertainty studies. In accordance with this goal, the uncertainties of the parameter set generated by the Reff, SCA, and MARE objective functions and their combinations are investigated. Figure 11 shows the uncertainty analysis of the 18 parameters used in this study, represented by box plots, with the boxes representing values between the first quarter (25%) and third quarter (75%) of each parameter. In addition, the error bars at the two ends of the boxes reflect 10–25% and 75–90%, respectively, of the best 10 parameter sets. Thus, box plots, representing the best 10 parameter sets, show where the values affecting 50% of the parameters are settled and how their average values are changed.

The uncertainty of the model parameters is assessed using various objective function criteria to explore model dependability for forecasting research. Based on singular and multi-criteria objective functions, the best 10 parameter sets, which were previously defined by MC simulations, are used in this analysis.

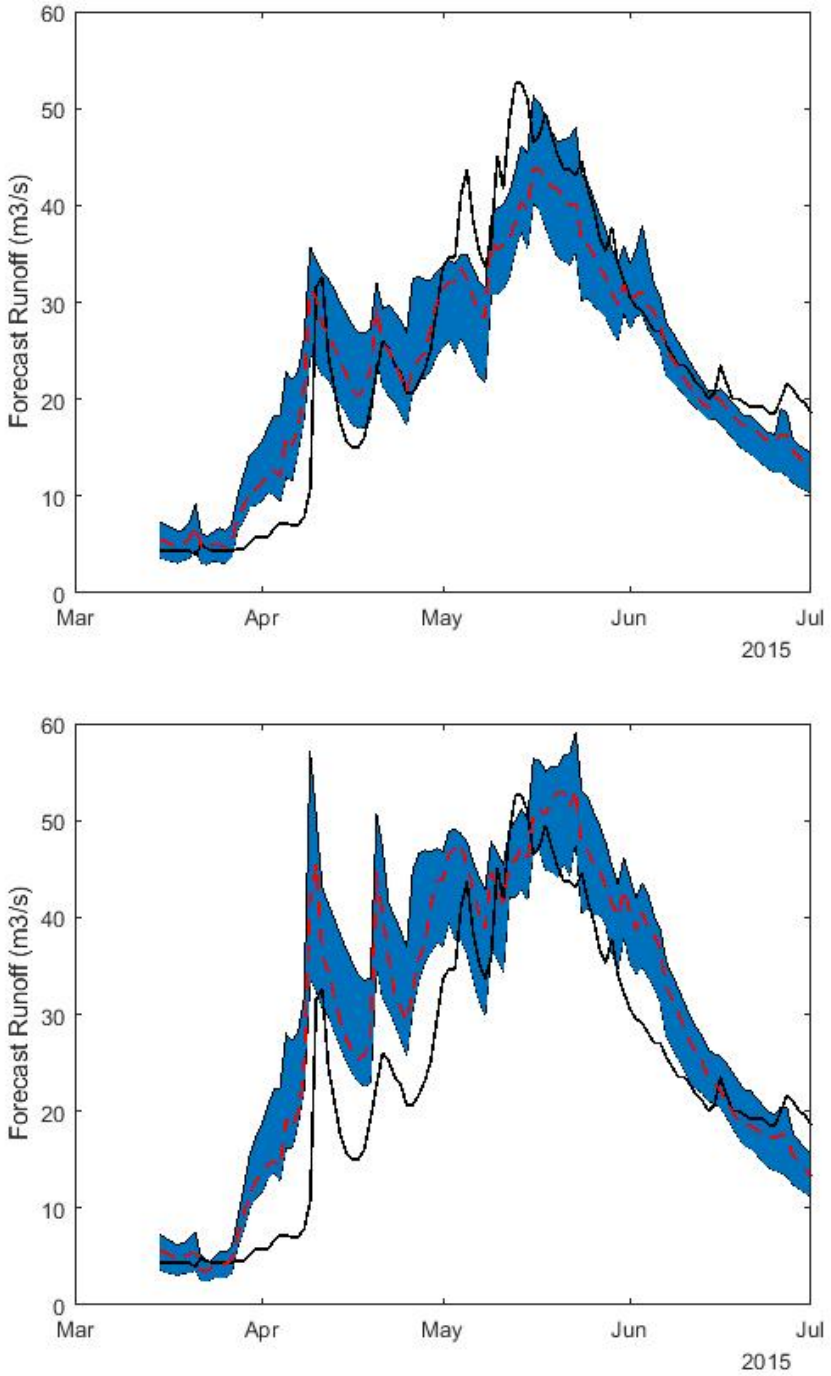


Fig. 13. Runoff forecast performances; a) 1-day ahead WRF data, b) 2-day ahead WRF data (black is observed, red is median of ensembles and blue is the range of ensemble forecasts).

For this reason, the uncertainty analysis graphs show that a single objective function (e.g., Reff) used in the model resulted in the increased uncertainty, especially for the upper and lower bounds of parameters, as indicated in Figure 11. Multi-criteria structures are used to reduce the model uncertainty by integrating multiple objective functions. The graph illustrates that utilizing multi-criteria techniques reduces or maintains the variance of the model's parameters. CFR and MAXBAS parameters, on the other hand, are found to be uncertain in multi-criteria systems because they have previously been identified as insensitive. As a result, these parameters should be kept constant in this analysis.

The uncertainty of parameters is evaluated overall, giving weights to each parameter according to its sensitivity. R+S+M reduces the parameter uncertainty 29.8%, for the range of 25 and 75 percentile, and 35.5% for the range of 10 and 90 percentile, compared to calibration only with R. This overall reduction in uncertainty indicates how superior the multi-criteria calibration R+S+M compared to a single case.

Runoff forecasting

The ensemble runoff forecasts are produced using 1-day and 2-day ahead WRF data for the snowmelt period (March–June) of the 2015 water year. First, the NWP data are compared with the observed basin average meteorological data (temperature and precipitation) for the specified period and presented in Figure 12.

The comparison graph clearly shows that WRF data and observed data are very compatible with each other for the application period. Though temperature values are consistent with the observed ones on both the 1st and 2nd lead day forecasts (Figure 12.a), consistency in precipitation forecasts are lower compared to observed ones where there seems to be a slight underestimation on the first lead day and significant overestimation on the second lead day (Figure 12.b).

Runoff forecasts are carried out as ensembles and the aim is to reduce the uncertainty of the prediction. 10 best model parameter sets based on single and multi-calibration periods are used to generate forecast ensembles. The compliance of the ensemble runoff forecasts (given in range with blue color) obtained using these parameters with the observed discharge is shown in Figure 13a and Figure 13b for 1 and 2-day predictions, respectively. The runoff forecasts were calculated using the direct insertion method of updating (Magnusson et al., 2017; Mazzoleni et al., 2018) with seven days period. Within this scope, the overall ensemble runoff forecast performance, with the first day ahead WRF data (Figure 13a), can be evaluated as very good since Reff changes in between 0.75–0.86 based on the performance criteria given by Moriasi et al. (2007) (Very Good for $0.75 < \text{Reff} < 1.00$). The median of the ensembles provides Reff of 0.85 (Figure 13a). Moriasi (2007) suggests these measures for the conventional model simulations, concerning uncertainties and inconsistencies in the deterministic NWP data, the runoff forecast performance is naturally expected to be somewhat lower. Since there is an undercatch in 1-day forecasted precipitations at the beginning of May (Figure 12b), slightly lower peak values occur in the forecasted runoff hydrograph (Figure 13a). The ensembles' performance in terms of SCA-MARE is between 0.78 to 0.84, indicating a satisfactory fit between observed and modeled SCA values.

On the other hand, 1-day ahead forecasts are better than 2-day forecasts (Figure 13). As the prediction time gets closer, it is expected that the uncertainty will decrease and the consistency will increase. The median of the ensembles provides Reff of 0.63 for 2-day lead time results (Figure 13b). The significant over-estimation in forecast precipitation values (Figure 12b) in the 2nd lead time caused an overestimation in runoff forecasts, especially for the early melting period (Figure 13b).

DISCUSSION AND CONCLUSIONS

A large part of the total annual runoff volume is caused by snowmelt during spring and early summer months in the mountainous eastern regions of Turkey. Therefore, monitoring the amount of accumulated snow in the headwaters, where Turkey's major reservoirs for hydropower and flood control are located, is crucial for efficient water resources.

The headwater of the Coruh River basin, the Upper Coruh basin, has harsh topographic conditions in high elevation ranges with virtually no urbanization. Remote sensing techniques provide the most convenient approach to monitor snow cover regarding the relatively rare observation network. Therefore, daily snow-cover area data obtained from two satellite products with different spatial and temporal resolutions were used. The combination of satellite products leads to better masking and representing heterogeneous snow cover in mountainous regions. IMS images were mostly used during the snow accumulation period as providing blended cloud-free images of several satellites. The optical satellite images were used to represent depletion seasons. Hence, the integrated snow cover series was obtained for the basin from 2003 to 2015 water years.

The primary purpose of this study is to indicate the multi-criteria calibration approach to reduce the model uncertainty and improve runoff prediction performance. In line with this objective, HBV-light hydrological model was applied in the basin to acquire a precipitation-runoff relationship. At first, the Genetic Algorithm and Powell (GAP) method was applied during the calibration period (2003–2009) to obtain the best parameter set. HBV model parameters estimated using the GAP were highly representative for the basin; however, it was carried out only for fitting observed and modeling runoff. For this reason, it was needed to improve the reliability of the model for variants of runoff signatures and other hydrological variables. In accordance with this purpose, a multi-criteria calibration study was carried out by considering the compatibility among low flows, peak flows, and daily snow-cover area used as an additional data set. The Monte Carlo (MC) simulation approach was chosen for multi-criteria calibration, which produces random model parameter sets compatible with normal distribution within the defined parameter range, constrained by GAP optimization results. Concordantly, three different objective functions (Reff, SCA and MARE) were selected in line with the specified criteria, and the performance criteria formed by their combinations were converted into the same units and used as equally weighted. Then combinations of best parameter sets are derived for further calibration/validation and forecast analysis.

From the results, it was determined that multi-criteria calibration approach improved model efficiency compared to selecting only one objective function. Additionally, overall success rate increased as more constraints are introduced in the modeling stage, which is in good agreement with the results given by previous research demonstrating the value of snow data in calibrating hydrological models using a multi-criteria approach (Di Marco et al., 2021; Duethmann et al., 2014; Etter et al., 2017; Finger et al., 2011; Finger et al., 2015; Han et al., 2019; Nemri and Kinnard, 2020; Parajka and Blöschl, 2008; Riboust et al., 2019; Şorman et al., 2009; Tong et al., 2021; Tuo et al., 2018; Udnæs et al., 2007).

The success of some research applications (Han et al., 2019; Nemri and Kinnard, 2020; Tuo et al., 2018, etc) depends on the availability of in-situ snow data. Concerning the difficulties in obtaining SWE over mountainous regions, our findings indicate that incorporating remotely sensed SCA observations with a level of spatial representability for sparse observation networks is an alternative to enhance the calibration of conceptual models in snow-dominated basins.

On the other hand, the majority of the studies discovered that cloud obstruction makes it challenging to employ optical satellite products for SCA determination in multi-criteria analysis. Researchers typically used MODIS (or AVHRR) SCA products, and to the cloud coverage, they either captured images with a defined cloud cover threshold only (Di Marco et al., 2021), preferred eight-day composite images (Han et al., 2019), or simply combined Aqua and Terra sensors (e.g. Tong et al., 2021). These works tended to have limited application periods because there was a shortage of data (e.g. Finger et al., 2011; Finger et al., 2015). Contrary to those, in our work, we have shown an alternate way by combining two different snow products (making use of different spatial/spectral resolutions) for a better representation of the SCA (especially during the accumulation and depletion phases of snow).

The sensitivity analysis showed that each of the model parameters has a certain degree of influence on simulated variables. Our study also demonstrated that both sensitivity and uncertainty analysis underlined the need for multi-criteria calibration to reduce uncertainties in HBV model predictions, as suggested by Tibangayuka et al. (2021). In summary, in contrast to the scenario where just runoff is utilized, the findings employing a multi-criteria approach lead to a reliable prediction, a decrease in model equifinality and a reduction in overall uncertainty similar to work done before by Di Marco et al. (2021), Széles et al. (2020), Demirel et al. (2019), Nijzink et al. (2018), Pan et al. (2018). Furthermore, we tried to apply the constrained model parameters within a selected best parameter set for an ensemble runoff forecasting approach.

Once the best parameter sets were derived and tested from multi-criteria calibration/validation stage, ensemble runoff forecasts were performed using 1-day and 2-day ahead WRF data for the snowmelt period (March–June) of 2015 water year. Instead of a single best parameter estimate, the range of ensemble flows exhibited a wider forecast horizon including model parameter uncertainty. Forecast results indicated a high model performance with median ensembles giving Reff:0.85 for runoff and SCA:0.82 for snow cover area using 1-day ahead WRF data as forcing into the model.

It can be said that efficient and reliable hydrological modeling can be carried out by generating various parameter sets (e.g. runoff, snow cover, etc.) that can better represent the basin, as opposed to evaluating and producing different objective functions on a single performance criterion (runoff). This study has evaluated the potential of including different runoff signatures and qualified snow data into hydrologic model calibration and its impact on ensemble runoff forecast. It would be helpful to extend this study to include other time-variant and model-sensitive variables, such as snow water equivalent and soil moisture in multi-criteria evaluation.

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