Calibration of a Distributed Hydrological Model (VIC-3L) Based On Global Water Resources Reanalysis Dataset

Sakineh Koohi

IKIU: Imam Khomeini International University

Asghar Azizian (✉ asgharazi@gmail.com)

Imam Khomeini International University <https://orcid.org/0000-0002-6556-2931>

Luca Brocca

CNR-ISE: Istituto di Ricerca sulle Acque Consiglio Nazionale delle Ricerche Sede di Verbania

Research Article

Keywords: VIC-3L Hydrological Model, Remote Sensing, Re-analysis, Surface Soil Moisture, Evapotranspiration, Surface Runoff

Posted Date: October 25th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-852004/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Version of Record: A version of this preprint was published at Water Resources Management on February 19th, 2022. See the published version at <https://doi.org/10.1007/s11269-022-03081-9>.

Abstract

The lack of observed flow datasets for calibration of rainfall-runoff models imposes fundamental problems for the applicability of them in most catchments, especially in poorly gauged or ungauged river basins. By developing satellite technologies over the past decades, several water balance components globally databases by remote sensing and data assimilation techniques have been developed and provided to researchers. This study performs various products of surface soil moisture (ASCAT, HTESSSEL, HBV, and LISFLOOD), evapotranspiration (W3RA, GLEAM, HBV and Ensemble), and surface runoff (SURFEX-TRIP and Ensemble) to the calibration of the macro-scale hydrological model (VIC-3L) over the SefidRood basin (SRB) in Iran. Results show that using the distributional approach and applying LISFLOOD lead to an acceptable performance in the flow hydrograph simulation than others with Nash-Sutcliffe (NS) values of 0.68 and Root Mean Square Error (RMSE) values of 64.84 m³/s. Among the studied evapotranspiration sources, the GLEAM daily and monthly time scales with NS values of 0.59 and 0.51, respectively, have better performance than other products in the simulation of flow hydrograph. Based on the results, the application of evapotranspiration has been better than soil moisture and surface runoff in estimating low-flows. Finally, results indicated that the multi-objective approach (GLEAM and ASCAT) had better performance than single-objective calibration to estimate runoff volume with Relative Error = 9.1 %. This study encourages applying the re-analysis database to hydrological models' calibration process to estimate discharge in data-limited areas.

1. Introduction

Grey box or conceptual models, including hydrological models, simulate a watershed hydrological cycle, which have a structure consisting of simple conceptual components such as linear and non-linear reservoirs and streams (WMO 2008). In these models, physical equations and structures are used along with experimental equations. Although the basin's physical details are also included in the conceptual models, these details are insufficient to obtain all the model parameters by direct measurement. Therefore, it is necessary to estimate some parameters of conceptual models using the calibration process. In Iran, hydrological models' calibration is carried out, usually using streamflow values recorded by the hydrometric station at the basin outlet. Disadvantages of this method can be referred to the non-calibration of some important hydrological components, leading to an improper simulation of the hydrological processes governing the watershed and flow hydrograph (Wanders et al. 2014). Considering that evapotranspiration and soil moisture play an important role in hydrological cycle simulation, their utilization in hydrological models may be associated with improving these models' performance.

On the other hand, due to increasing remote sensing technologies over the past years, several satellite-based datasets estimate meteorological and hydrological variables such as precipitation, evapotranspiration, temperature, soil moisture, runoff, etc. at a global scale. The application of the recently developed global earth observations and re-analysis products to calibrate hydrological models is one of the most appropriate solutions for achieving data with spatial and temporal resolution, especially in data-limited areas or regions where ground observations are sparsely-distributed or insufficient.

Another advantage of using remote sensing sources is considering the spatial variability of the model input parameters, which reduces the uncertainty of the results. Besides, the use of these resources by extracting of the spatial pattern of calibration model parameters over the catchment will provide a better view of the hydrological processes of the watershed (Hafeez et al. 2011; Kite and Droogers 2000; Seneviratne et al. 2010; Vereecken et al. 2008).

In recent years, several studies have been carried out on the calibration of hydrological models using balance components (Brocca et al. 2010; Corbari and Mancini 2014; Franco and Bonumá 2017; Immerzeel and Droogers 2008; Isenstein et al. 2015; López et al. 2017; Rientjes et al. 2013; Sutanudjaja et al. 2014). For instance, (Corbari and Mancini 2014) calibrated the distributed hydrological model (FEST-EWB) using MODIS land surface temperature (LST) for the upper Po River basin (Italy) from 2000–2003 and Compared the results with traditional calibration. Results showed that relative errors in the combined LST and Q calibration improved 11–14% in simulating the volume discharge and 10% in ET estimates, so one of the suggestions of the researchers of this research is combined calibration based on satellite land surface temperature and ground discharge in order to improve reproduce flow volume and also spatially distributed maps of representative equilibrium temperature and evapotranspiration. The results also indicated that in studies where the primary purpose of modeling is to simulate evapotranspiration fluxes, the soil surface parameter calibration should be done with satellite LST. (Rientjes et al. 2013) investigated the MODIS sensor's evapotranspiration during the HBV rainfall-runoff model's calibration process in the daily step. Results showed that in case the model performance improvement in simulating the time series of streamflow and evapotranspiration is used as the calibration target, it leads to the hydrological model's proper operation to simulate water balance. While calibration based streamflow or evapotranspiration only resulted in poor reproduction of the water balance. (Sutanudjaja et al. 2014) assessed the possibility of using remotely sensed soil moisture and observing river discharge to calibrate a large extent-physically based hydrological model PCR-GLOBWB-MOD over Rhine-Meuse basin order to simulate the groundwater level. They found that the Soil Water Index (SWI) derived from the soil moisture data ERS sensor can be used to calibrate upper soil hydraulic conductivities to determine the amount of groundwater recharge. However, to constrain aquifer transmissivities and diffusion of runoff and infiltration, discharge data should be used in the calibration process. They concluded that using both discharge and soil moisture data can predicting groundwater head dynamics with acceptable accuracy. (Isenstein et al. 2015) calibrated the variable infiltration capacity (VIC) model in the Arkansas catchment using the fractional snow-covered area (SCA) and using a Genetic Algorithm (GA). Findings indicated that using the SCA dataset, which is estimated by the MODIS sensor, is suitable for calibration and validation of the VIC model (NS = 0.91 and NS = 0.78) and in the case of using SCA images and the value of this index is 0.58 and 0.65. These results illustrate SCA's potential use for hydrological models' calibration in conditions where there is no access to observed streamflow. (Lopez Lopez et al. 2017) calibrated model parameters of PCR-GLOBWB based on evapotranspiration observations acquired by GLEAM and soil moisture from ESA CCI over Moroccan Oum Er Rbia basin (1979–2010). These researchers carried out the calibration model in a variety of one-objective and multi-objective scenarios. They concluded that although the best result is related to the model's calibration based on the streamflow observations. However, multi-objective

calibration using soil moisture and evapotranspiration images with NSE values from 0.5 to 0.75 leads to reasonable performance in the runoff estimation. However, calibration based on only evapotranspiration or soil moisture has less improvement in the model results.

The studies carried out indicated the high efficiency of remote sensing datasets such as precipitation, soil moisture, evapotranspiration, and land surface temperature to improve hydrological models' performance to flood simulation. Unfortunately, despite the expansion of these resources in the hydrological simulation of the watershed worldwide, there is little research about the performance of these resources in Iran's watersheds. In contrast, these resources' application can be handy, especially when there is limited access to observation data with proper spatial and temporal resolutions. Thus the aim of this study is a comprehensive assessment of the efficiency of satellite products and re-analysis datasets: surface soil moisture (SSM) (ASCAT, HTESSSEL, HBV, and LISFLOOD), evapotranspiration (W3RA, GLEAM, HBV, and Ensemble), and surface runoff (SURFEX-TRIP, Ensemble) for calibration process of the large-scale hydrological model VIC-3L and simulating the streamflow during different scenarios over the SefidRood basin (SRB).

2. Materials And Methods

2.1. Study Area

The study area is the SefidRood basin (SRB), which is situated in the north-western region of Iran (Fig. 1). Drainage of this basin, one of the most important basins in the country, is done by the SefidRood river. The SefidRood is the second largest river in Iran, with a total length of 670 km. The basin's topography ranges from -31 m in basin outlet to 4300 m in the highest location above mean sea level. The basin is positioned between coordinate: 46° 30' E and 51° 13' E longitudes and 34° 55' N and 37° 52' N latitudes. The watershed covers about 59500 km², and its perimeter is approximately 1650 km. Due to this basin's extent, the variety of climate, vegetation, and soil type are observed, which is one of the reasons for the importance of the SefidRood catchment. The observed river discharge data from the Gilvan hydrometric station located at the basin outlet in daily and monthly time scales are used to evaluate the VIC 3L hydrological model's performance.

2.2. Macro Scale Hydrological Model: VIC-3L

The Macro-scale hydrological model variable infiltration capacity (VIC-3L) (Liang, Wood, and Lettenmaier 1996) was used at a spatial resolution of 0.25°×0.25° (approximately 27.7 km ×27.7 km). This model, capable of solving water and energy balances. In the VIC-3L model, each cell is modeled separately, and grid cells do not interact or current transfer with each other. Meteorological input data for model: precipitation (mm), humidity (vapor pressure), wind speed (m/s), daily maximum and minimum temperature (°C) are drawn from local synoptic and rain gauge stations within the catchment, then application of Inverse Distance Weighting (IDW) interpolation method has been extracted for each cell of the basin computing network. Leaf area index, albedo coefficient, minimum stomatal resistance,

architectural resistance, roughness length, displacement length, and the relative fraction of roots in each soil layer include the model parameters related to the catchment's vegetation. In this research, after classifying and determining the type of coverage based on Advanced Very High-Resolution Radiometer (AVHRR), these parameters have been estimated according to the values provided by (Su et al. 2005). Determination of some soil parameters (such as porosity fraction, saturated hydraulic conductivity, field capacity, bulk density, wilting point, the slope of retention curve) in order to implement the model is possible using library functions, for which it is necessary to determine the soil texture of the study catchment. In this study, soil types are obtained from the Iranian National Soil Conservation Service (INSCS) soil map. According to the values provided by (Rawls, Gimenez, and Grossman 1998), the characteristics and parameters of each soil texture are extracted. However, most of the model parameters can be derived from remote sensing and in-situ measurement observation. Some of them are conceptual and have non-physical values, so their estimation is feasible during the calibration process. The studies indicate the high importance of some soil parameters in estimating soil layers moisture and surface and subsurface runoff modeling (Guo, Liang, and Leung 2004; Nijssen et al. 1997): b_{inf}) The infiltration parameter which controls the partitioning of rainfall (or snowmelt) into infiltration and direct runoff [0.01–0.4]. D_{smax}) The maximum base-flow velocity [0.01–30]. D_s) The fraction of maximum base-flow velocity where non-linear base flow begins [0.01–1]. W_s) The fraction of maximum soil moisture where non-linear base flow occurs [0.01–1]. C) Power used in base discharge curve [0.01–2]. d_2 and d_3) The thickness of the second and third soil layer [0.1–2.5 and 0.1–1.5].

2.3. Remote-sensing and Re-analysis data used

2.3.1. ASCAT Surface Soil Moisture Database

Advanced SCATterometer (ASCAT) is a radar system operating in the C-band (5.255 GHz) onboard the Metop satellite since 2006. The scientific basis for retrieving the soil moisture from ASCAT scatterometer data is based on a change detection method (CDM) (Bartalis et al. 2008). This method is mathematically less complicated than the radiation transmission model can be analyzed in inverse. Therefore, the soil moisture content can be estimated directly by measuring the sensor without needing the correction process. Thus, in order to estimate the recovery error for each cell at ground level is quite straightforward. It is noted that one of the disadvantages of the CDM is the integrated representation of the measurement process. In other words, there is no distinct portion to the retrieving and observation of soil, vegetation, and soil-vegetation interactions. The algorithm for processing the scatterometer data is called soil Water Retrieval Package (WARP), Which is provided in the WARP6 software package (Naeimi et al. 2009). Soil moisture values of this sensor are associated with the depth of 2 cm of soil (topmost) with 3-days/ ~25 km temporal/ spatial resolution (Wanders et al. 2014)

2.3.2. A Global Water Resources Reanalysis Database: The earth2Observe

In the re-analysis database using data assimilation techniques and meteorological forcing data, climate data are re-analyzed. In general, a constant model and available observational data are used during the re-analysis process. Climate re-analysis databases are continually being updated by monitoring data measured by satellites, radiosondes, and so on. In these databases, using observation data, data simulated by the models are corrected and debug. One of the features of this data is its spatial scale diversity. The Earth2Observe dataset (<http://wci.earth2observe.eu/>), recently developed by the EU Water Resources/Remote Sensing Research (2017), is one of these re-analysis databases, which consisted of an ensemble of ten global hydrological and land surface models with a different spatiotemporal resolution for the 1979–2014 period using a meteorological forcing dataset based on re-analysis. In this database, error reduction uses meteorological observation and data assimilation techniques (Dutra, Balsamo, and Calvet 2017). In the next section, the modeling protocol of global hydrological and land surface models in this database, which simulated data has been used in the present study, has been described.

2.3.2.1. The LISFLOOD Model

The LISFLOOD model is a distributed large-scale hydrological rainfall-runoff model that has been developed by the floods group of the Natural Hazards Project of the Joint Research Centre (JRC) of the European Commission to simulate water balance of catchment. The basis of this model is the division of the catchment into several cells. To implement the LISFLOOD model can be used a range of grid cells of as little as 100 m for medium-sized catchments to around 10 km for large scale catchments (Burek, Knijff, and De Roo 2013). LISFLOOD is one of the models that can simulate water balance (on a daily time step) and individual flood events (on hourly time intervals, or even smaller). In this model, two layers are considered for the simulation of groundwater and subsurface flow. Also, using a sub-model, surface runoff is routed to the nearest river channel. With the Arno routing model (Todini 1996; Zhao and Liu 1995), the flow is directed to the basin's outlet. The processes that are simulated by the model include snowmelt, infiltration, interception of rainfall, evapotranspiration, surface runoff, and exchange of soil moisture between the two soil layers, etc. One of the limitations of this hydrological model is its non-application in dry areas due to the lack of simulation of capillary ascent and groundwater at great depths (van der Knijff, Younis, and de Roo 2010). This model's surface soil moisture data have been used to calibrate the VIC 3L model in the present study.

2.3.2.2. The HTESSEL Model

Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land (HTESSEL) is a distributed land surface model that simulates the land surface's response to weather conditions and components related to water and energy balance. The model can also simulate soil temperature changes, soil moisture, surface / sub-surface runoff, and improve the model's performance by considering different vegetation and snow cover conditions (Dutra et al. 2017). In general, in this model, for the surface layer, six tiles including bare ground, low and high vegetation, intercepted water and shaded and exposed snow, and two over water including open and frozen water (Balsamo et al. 2009). The vertical discretization has soil

layers below ground at 7 cm for the top layer and 21, 72, and 189 cm as suggested in (Deardorff 1978) that can be covered by a single layer of snow (The presence of a snow layer depends on the study area, which can be zero). In the HTESSEL model, Subsurface water fluxes are determined by Darcy's law. In this research, surface soil moisture data of this model have been used.

2.3.2.3. The HBV Model

The HBV model is a semi-distributed conceptual model generated by the Swedish Meteorological and Hydrological Institute (SMHI) by (Bergström and Forsman 1973) to simulate runoff, forecasting, and water balance studies. The model simulates daily discharge using rainfall and temperature (daily) and potential evaporation (monthly) as input. This model with a simple structure and low inputs simulate the most critical variables relating to water balance components, including the river discharge, precipitation, evapotranspiration, soil moisture, and water storage that contribute to runoff formation. In this model, the basin is divided into hydrological units based on height variations and vegetation type. Snowmelt simulation in the HBV model is computed by a degree-day method. The HBV-light version provides the possibility to include observed groundwater levels and use a different response routine with a delay parameter. In this study, surface soil moisture and evapotranspiration data of this model have been used.

2.3.2.4. The W3RA Model

The World-Wide Water (W3RA) model is one of the distributed large-scale hydrological models based on the landscape hydrology component model of the AWRA system, developed by the Australian Meteorological Agency. This model's snowmelt simulation is based on the HBV model's thought, and the model is implemented at a spatial resolution of 0.5 degrees (Dutra et al. 2017). The vertical discretization is considered a 3-layer soil with different depths. In each grid box, two vegetation types are present: deep-rooted tall vegetation type and shallow-rooted short vegetation type. The energy balance determines actual evaporation. In this model, humans' changes and systems, such as irrigation, are not considered (Van Dijk, 2010). In this study, evapotranspiration data of this model have been used.

2.3.2.5. The GLEAM Model

The Global Land Evaporation Amsterdam Model (GLEAM) was developed by VU Amsterdam in collaboration with Ghent University in Belgium and the European Space Agency to estimate evapotranspiration (Miralles et al. 2011). In each grid cell includes 4 types of coverage: bare soil, short vegetation, tall vegetation, open water. The amount of evapotranspiration in this model is calculated based on the equation presented by (Priestley and Taylor 1972) and according to air temperature and net surface radiation. The actual evaporation for each pixel results from aggregating the total of each land cover type weighted by the percentage of each cover type within the pixel. GLEAM data is included daily with a spatial resolution of 0.25 degrees from 1980 to 2016.

2.3.2.6. The SURFEX-TRIP Model

The SURFEX-TRIP model is a distributed model coupling with the ISBA land surface model to compute water and energy balance. In the SURFEX-TRIP model, 14 layers are considered for the soil. The total

runoff results from total surface runoff, subsurface flow in the upper soil layer, and free drainage in the soil's lower hydrological column. In this land surface model, the TRIP routing model collects runoff from the cells and transfers water to the basin outlet. The simulation of hydrological components is carried out at the 0.25° resolution and daily time scale (Decharme et al. 2010). In this research, surface runoff data of this model have been used.

2.3.2.7. The Ensemble Model

In addition to the above models, the results of all hydrological and land surface models available in the Earth2Observe database are averaged and presented as a new product called Ensemble or Earth2Observe. In this research, evapotranspiration and surface runoff data (in daily time scale) of this database have been used to calibrate the VIC-3L model.

Table 1
The database used in this research.

Model name	Data provider (s)	Model type	Routing	Data used	Reference(s)
ASCAT	IPF/TU Wien	-	-	SSM	(Wagner et al. 1999)
LISFLOOD	Joint Research Centre (JRC)	GHM	Double kinematic wave	SSM	(van der Knijff, Younis, and de Roo 2008)
HTESSEL	European Centre for Medium-Range Weather Forecasts (ECMWF)	LSM	CaMa-Flood	SSM	(Balsamo et al. 2009)
HBV	Swedish Meteorological and Hydrological Institute	GHM	Muskingum	SSM & ET	(Bergström 1972)
W3RA	Australian National University (ANU) and Commonwealth Scientific and Industrial Research Organization (CSIRO)	GHM	Cascading linear reservoirs	ET	(Van Dijk 2010)
GLEAM	VU Amsterdam in collaboration with Ghent University in Belgium and the European Space Agency	-	-	ET	(Miralles et al. 2011)
SURFEX-TRIP	Météo France	LSM	TRIP with stream	Surface Runoff	(Decharme et al. 2010)

2.3. Rescale Surface Soil Moisture

Usually, due to data characteristics or differences in layer depth, systematic biases, and differences between the values of the surface moisture of the observed (SSM of ASCAT, HTESSEL, HBV, and LISFLOOD) and modeled (SSM of VIC-3L) may exist. Several methods can be used to overcome these

errors and match the observed and modeled values, such as the cumulative distribution function (CDF) or a mean-standard deviation (Draper et al. 2009; Reichle and Koster 2004). It was decided in order to overcome these errors and match the SSM of the VIC-3L model and the remote sensing sources, the mean-standard deviation be used. The amount of corrected SSM in this way is calculated based on Eq. 1 (Draper et al. 2009).

$$\theta'_{sim} = \frac{\sigma_{\theta_{obs}}}{\sigma_{\theta_{sim}}} \times (\theta_{sim} - \bar{\theta}_{sim}) + \bar{\theta}_{obs} \quad (1)$$

θ'_{sim} : the adjusted simulated surface soil moisture value, θ_{sim} : the simulated (VIC-3L) soil moisture values, $\bar{\theta}_{sim}$ and $\bar{\theta}_{obs}$: the means of the simulated and observed (ASCAT, HTESSEL, HBV, and LISFLOOD) soil moisture values, $\sigma_{\theta_{sim}}$ and $\sigma_{\theta_{obs}}$: the standard deviations of the simulated and observed soil moisture values.

2.4. Calibration Strategy

Despite the different approaches, the Generalized Likelihood Uncertainty Estimation (GLUE) probabilistic method that had a much simpler operational process, especially in the Linux operating system and was first proposed by (Beven and Binley 1992), was used. This method is a combination of the Monte Carlo thought and the Bayesian paradigm, which has high efficiency in calibration and analysis of uncertainty. The fundamental idea behind the Monte Carlo technique is choosing sample points randomly over the desired range to approximate their results (Goodarzi, Ziaei, and Teang Shui 2013). Independent on the calibration parameters is one of the GLUE's hypotheses. The parameters that are not correlated with each other are selected for calibration using this method. The steps for implementing the GLUE method are as follows:

- 1) Defining the initial domain of calibration parameters, The calibration parameters and their range of variations are mentioned in Sect. 1–3.
- 2) Generate 1000 random variables for each parameter with uniform distribution (due to the lack of a prior distribution of a parameter).
- 3) Use the set of random parameters, the VIC-3L hydrological model was implemented on a daily scale.
- 4) Calculate the likelihood index such as Nash-Sutcliffe efficiency (Beven and Freer 2001) according to the simulated and observational values in each cell of the basin computing network.
- 5) Opt the most proper set of parameters with the highest Nash-Sutcliffe value (higher than 0.6) as the optimal value of each cell's calibrated parameters.
- 6) Optimal surface and sub-surface runoff from each grid cell's of basin routed to the outlet.

2.5. Performance Metrics

The performance of the VIC-3L hydrological model in simulating basin river discharge has been evaluated based on indexes, including Pearson Correlation Coefficient (CC), Nash-Sutcliffe (NS), Kling-Gupta (KGE), and Root Mean Square Error (RMSE), in this research. CC is a dimensionless index that is used for investigating the relationship between two variables. It has a value between + 1 (perfectly positively linearly related) and – 1 (entirely negatively linearly related) and is equal to zero if two variables do not have any linear relation whatsoever. NS is a normalized statistic to determine the residual variance's relative magnitude compared to the observed data variance. NS = 1 means a perfect match of the model to the observed data. RMSE measures how much error there is between two data sets. It is close to zero indicates a more accurate model in the simulation of river discharge. Kling-Gupta is an index based on the NS index and the Mean Squared Error (MSE), which facilitates the analysis of the relative importance of its different components (correlation, bias, and variability) in the context of hydrological modeling. These statistics are calculated in Table 2.

Table 2
The statistical indexes which are used in this study

Statistical Index	Formula	Reference(s)
Correlation Coefficient	$CC = \frac{\sum_{i=1}^n (O_i - \bar{O}) (S_i - \bar{S})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (S_i - \bar{S})^2}}$	(Pearson 1896)
Nash-Sutcliffe	$NS = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$	(Nash and Sutcliffe 1970)
Root Mean Square Error	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - S_i)^2}$	(Hyndman and Koehler 2006)
Kling-Gupta	$KGE = 1 - \sqrt{(\beta - 1)^2 + (\alpha - 1)^2 + (CC - 1)^2}$ <hr/> $\beta = \frac{\bar{S}}{\bar{O}}$ <hr/> $\alpha = \frac{\sigma_{S_i}}{\sigma_{O_i}}$	(Gupta et al. 2009)

O_i and S_i are observed and simulated variable, $\bar{O}$ and $\bar{S}$ are the mean of observed and simulated data, σ_{O_i} and σ_{S_i} are the standard deviations of the observed and simulated variable; n is the total number of observations.

2.6. Scenarios

The use of river discharge recorded in the basin outlet is one of the hydrological model's standard calibration methods. Moreover, remote sensing data and re-analysis datasets are the calibration methods that calibrate the model's cell by cell. Therefore in the present research, in addition to calibrating the VIC 3L model based on the observed stream flows of SRB outlet, soil moisture, evapotranspiration, and surface runoff during single-objective and multi-objective approaches to cell by cell calibration, this hydrological model were evaluated. These experiments were carried out for five different calibration scenarios: S1) in this scenario, which is also the basic scenario, calibration using river discharge time series observed of Gilvan hydrometric station. S2) calibration using the surface soil moisture time series of each source: ASCAT, HTESSSEL, HBV, and LISFLOOD. S3) calibration using W3RA, GLEAM, HBV, and Ensemble evapotranspiration. S4) use SURFEX-TRIP and Ensemble surface runoff time series to calibration. S5) simultaneous calibration using ASCAT surface soil moisture GLEAM evapotranspiration time series.

S1 aims to calibrate the hydrological model using river discharge observations, following the traditional calibration approach. In scenarios 2 to 4, the time series of surface soil moisture, evapotranspiration, and surface runoff obtained from remote sensing and re-analysis Earth2observe datasets were considered observational values for each SRB grid cell. In other words, improvement of model performance in estimating the time series of SSM, ET, or surface runoff for each grid cell is considered the objective function. While in S5, the matching of the ET and SSM simulated time series with GLEAM ET and ASCAT SSM at the same time is the objective function. Calibration S5 represents the multi-objective calibration approach that combines the strengths of calibration S2 and S3. In general, the scenarios evaluated in the present study can be categorized according to Table 3. The flowchart of the research process is presented in Fig. 2.

Table 3
The scenarios which are used in this study

Scenario	Objective functions	Products
1	River Discharge	in-situ streamflow
2	Surface Soil Moisture (SSM)	ASCAT
		HBV
		HTESSEL
		LISFLOOD
3	Evapotranspiration (ET)	W3RA
		HBV
		GLEAM
		Ensemble
4	Surface Runoff	SURFEX-TRIP
		Ensemble
5	SSM & ET	ASCAT & GLEAM

3. Results

3.1. Evaluation of VIC-3L Model Performance in Simulation of flow hydrographs

Model parameters were calibrated using basin outlet streamflow, surface soil moisture, evapotranspiration, and surface runoff through five different calibration scenarios. In this section, the VIC 3L hydrological model's performance in simulating the basin flow hydrograph on daily and monthly time scales is evaluated. For the statistical measures, the Taylor diagrams provide a graphical way of summarizing the results in terms of the correlation coefficient, root-mean-square error, and standard deviations. This diagram for the simulated flows using VIC-3L daily and monthly scales is shown in Fig. 3. Also, the value of the NS index for all scenarios is presented in Fig. 4. The green contours in Fig. 3 indicate the RMSE values, and it can be seen that in cases of application of Ensemble and HVB ET have the highest RMSE than other scenarios and products on daily and monthly scales. The standard deviation of these is greater than the observed standard deviation indicated by the dashed arc in the daily river discharge and on a monthly scale, more than other calibration approaches. The maximum correlation on a daily scale (0.84 and 0.83) corresponds with S2_LISFLOOD and S1, on a monthly scale (0.92 and 0.90), correspond with S1 and S2_LISFLOOD.

Findings indicate that in daily and monthly times, application of HBV and LISFLOOD SSM and using S5 calibration approach after the first scenario, it has a good performance in simulating the flow hydrograph of the basin ($NS > 0.60$ and $NS > 0.70$ on a daily and monthly time scale, respectively). In contrast, the application of Ensemble and HBV ET to calibration VIC-3L model has the lowest NS and was so weak (see Fig. 4).

In Fig 5, the observed and simulated hydrographs for five scenarios and products are presented. Results showed that the simulated flow hydrograph after calibration of VIC-3L based on HBV, LISFLOOD SSM, and GLEAM, W3RA ET datasets with the KGE value of 0.58, 0.56, and 0.53 are the best matching with observed hydrograph after implementing the basic scenario for calibration of the hydrological model (using discharge recorded in Gilvan hydrometric station). Furthermore, assessments demonstrate that surface soil moisture and surface runoff products have led to overestimation in low-flow. At the same time, ET datasets are more effective for these. Which can be attributed to the following factors: since for some times after the occurrence of large-flood, the soil is saturated, and since changes in soil moisture in these conditions are meaningless, so the use of SSM sources has to lead to errors in hydrograph simulated by VIC-3L after the event of the large-flood. Furthermore, when the soil moisture basin is low, evapotranspiration has a more significant impact on the balance parameters. This approach for calibration of hydrological models can be more effective for low-flow simulation. As can be seen in Fig 5, the difference between the simulated and observed flows is decreasing over time. If the length of the period is more considerable, the possibility of matching simulated flow with the observed does seem to be expected. It should be noted that the performance of the hydrological model after applying the distributive approach and the surface runoff products have decreased. One of the reasons for this is that in the VIC 3L hydrological model, the surface and subsurface runoff is routed from the computational network cells to the basin's outlet. Therefore, in S4 that only the model performance improvement in surface runoff estimation is the objective calibration function associated with overestimation in the hydrograph simulation.

Figure 6 displays the scatter plots of simulated stream flows during 2001–2004, against observing records at a monthly timescale. As shown in Fig. 3, the CC value in all scenarios is greater than 0.7, indicating a good correlation between the simulated and observational flows. However, this correlation does not mean the acceptable hydrological model performance in all scenarios because the Nash-Sutcliffe (which indicates the overall performance of the model) and Kling-Gupta illustrate the use of surface runoff, ET, ASCAT and HTESSSEL SSM overestimation and deviation of the simulated flows. While the application of HBV and LISFLOOD surface soil moisture values (S2) with an improvement of about 5 and 2% in the KGE value, respectively, compared to the basic scenario (S1), it has had a good efficiency in estimating the SRB monthly flow. It should be noted that despite the lower performance of the VIC-3L model in the case of ET as well as ASCAT SSM data, if the combination of GLEAM evapotranspiration and ASCAT surface soil moisture as the objective function for cell by cell calibration hydrological model, simultaneously, the NS and KGE are 0.71 and 0.60, respectively, which means the excellent effective this scenario for hydrologic simulation on a monthly scales. After that, the application of Scenario 1 (with KGE = 0.59) has a good performance in estimating the monthly basin flow.

3.2. Evaluation of VIC-3L Model Performance in Simulation of FDC and Runoff Volume

Flow Duration Curves (FDC) are useful and graphical tools to show the basin's hydrological response. The upper part of this curve represents the flood regime, and the tail-end shows the inherent characteristics of the basin to sustain the flow in times of water shortage and basic-flow supply (Vogel and Fennessey 1994). The FDC represents the relationship between the magnitude and frequency of river flow (Vogel and Fennessey 1995). Figure 7 shows the daily flow FDCs in various scenarios. According to the S1 FDC shape, flows (lesser than $240 \text{ m}^3/\text{s}$) were very similar in the observed FDC. It can be concluded that this scenario has led to a reduction in currents above than $240 \text{ m}^3/\text{s}$ and a slight increase in the low-currents estimation. After that, the FDC simulated in Scenario 5 has relatively good matching with the observation curve, especially in the range of 50 to $240 \text{ m}^3/\text{s}$. The use of soil surface moisture and surface runoff to calibrate the hydrological model (S2 and S4), the use of different sources in these scenarios, have had similar results. As it has been associated with underestimation in large-flows and overestimation in simulating low-flows.

A high slope observed FDC on the upper part of this curve represented that the low-flow during the dry seasons can be small. This section of the curve is better simulated by evapotranspiration sources (scenario 3) than other scenarios. This occurrence can be mostly due to ET's more significant influence on the balance than other components when the flow is low. In addition, the use of GLEAM datasets has less deviation than other products.

The Relative Error in the estimation of runoff volume was calculated, the results of which are shown in Fig. 8. The finding indicates that the use of recorded flow data to VIC-3L model calibration (Scenario 1) has led to good performance, as the RE value is 4.6 %. Also, the use of GLEAM ET and ASCAT SSM datasets in scenario 5, with an average error of 9.1 %, is considered appropriate and better than other scenarios. In contrast, each of these sources alone did not efficiently estimate the basin's runoff volume. In other scenarios, the value of error in estimating the runoff volume overtakes more than 25 % and even to about 70 %, which is not satisfactory.

3.3. Investigation of optimum parameters and their spatial distribution

The values of calibrated parameters after the implementation of scenario 1 presented in Table. 4. Since in scenarios 2 to 5, the VIC-3L hydrological model has been calibrated cell-by-cell; therefore, the spatial distribution of calibration parameters is available in these scenarios. Due to the high number of calibration parameters and the studied datasets, the spatial distribution of all calibration parameters have been refused. The map of spatial variations related to the 2 parameters (d_2 and W_s), which according to the research conducted by (Azizian and Shokoohi 2017), have a more significant impact on the performance of the VIC 3L model, are presented (see Figs. 9 and 10).

Table 4
Calibrated parameters of the VIC-3L model in scenarios 1

Scenario	b_{inf}	D_s	D_{smax} (mm/day)	W_s	C	$d_2(m)$	$d_3(m)$
1	0.05	0.24	5.22	0.89	1.02	0.73	0.11

According to the results, it is clear that the range changes of the second layer of soil thickness after calibration base on ET and surface runoff have increased, and in some cases, the maximum value reaches more than 1.5 m. For example, as can be seen, using surface runoff values of SURFEX-TRIP and HBV evapotranspiration sources, this parameter is 0.24 m to 1.53 m and 0.11 m to 1.67 m, respectively. In comparison, the application of HBV and LISFLOOD surface soil moisture (which have a good performance in estimating river discharge on a daily and monthly scale), this parameter's value is less and close to its value if scenario 1 is implemented. Therefore, it can be concluded that excessive increasing d_2 , in other scenarios, can be one of the reasons for the weakening of the hydrological model in simulating the flow hydrograph.

As shown in Fig. 10, if calibration VIC-3L hydrological model based on SSM datasets (S2), the value of W_s in the north, north-west, and west of SRB is increased, also in the S4 (using surface runoff for calibration process), the value of this parameter has increased in the whole basin. Since W_s specifies the amount of water stored in the soil and its contribution to base-flow rate, increasing it increases the base-flow and decreases the large-flood. The low value of this parameter using evapotranspiration resources (S3), can be one reason to match the FDC with the observation curve in the high flow range (see Fig. 7).

4. Discussion And Conclusion

This study investigates alternative ways to calibrate the VIC-3L hydrological model using earth observations available for the SRB in north-west Iran. During the research, 4 surface soil moisture (ASCAT, LISFLOOD, HBV, and HTESSSEL), 4 evapotranspiration (HBV, W3RA, GLEAM, and Ensemble), and 2 surface runoff (SURFEX-TRIP and Ensemble) were followed to calibrate the VIC-3L hydrological model in 5 scenarios (in single-objective and multi-objective scenarios). River discharge recorded in the basin's outlet also was used for the calibration process as a traditional and basic method. Results demonstrated that the traditional calibration had the highest model performance, as expected. On daily and monthly time scales, the simulated flow had a good correlation with the observed values. The performance of the model in simulating flow less than $400 \text{ m}^3/\text{s}$ is acceptable. Another point is the ability to estimate the runoff volume with acceptable accuracy by the model in this scenario (RE = 4.6 %).

Calibration results based on only SSM sources show, LISFLOOD and HBV have the best performance in VIC-3L model calibration and flow hydrograph simulation. When using remote sensing and re-analysis databases of surface soil moisture, the correlation rate is high ($CC > 0.75$), and this shows the efficiency of these sources in calibrating the hydrological model. The use of SSM sources leads to overestimation

in runoff simulation until times after the occurrence of large currents, so surface soil moisture has less effect on the large-flow simulation. In comparison, the use of ET sources have more effective for the improvement of low-flow simulation. These results are consistent with the findings by (Liu, Wang, and Liu 2018; Lopez Lopez et al. 2017). Among evapotranspiration products, only the use of GLEAM data has better performance in terms of NS, CC, and RMSE for hydrograph simulation on a daily time scale. The results showed that since the VIC-3L model surface and subsurface runoff are routed to the basin outlet, only surface runoff values as a calibration goal function have reduced the hydrological model performance. We expect it to increase the model's performance in simulation by adding subsurface runoff as the objective function at the surface runoff. Results show the approach using evapotranspiration (GLEAM), and soil moisture (ASCAT) data combines the benefits of both products getting a better simulation performance than when they are separately used (especially in estimating the runoff volume).

In general terms, this paper has highlighted the role of globally available datasets such as remote-sensing and re-analysis to calibrate large-scale hydrological models and simulate flow as a suitable and practical solution, particularly in the cases of ungauged catchments or data restricted areas.

Declarations

Funding

Not applicable.

Author information

Affiliations

1&2- Water engineering Dept., Imam Khomeini International University (IKIU), Qazvin, Iran.

3- Researcher, Research Institute for Geo-Hydrological Protection IRPI, Perugia, Italy.

S. Koohi, A. Azizian & L. Brocca

Contributions

S. Koohi: Development of the original concepts, scope of the work and modeling setup; Running the VIC-3L model, writing, review and editing.

A. Azizian: Data and GIS maps preparation, modeling setup; data acquisition and preparation, writing initial draft preparation, software application, Text editing and draft preparations.

L. Brocca: data acquisition and preparation, writing initial draft preparation, software application, Text editing and draft preparations.

Corresponding author

Correspondence to A. Azizian

Ethics declarations

Ethical Approval

Not applicable.

Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

Conflict of Interest

The authors declare that there is no conflict of interest.

Competing Interests

The authors declare no competing interests.

Data Availability

Data and material are available upon request to the corresponding author.

References

1. Azizian A and Alireza Shokoohi (2017) Evaluating and Sensitivity Analysis of a Macro Scale Hydrological Model (VIC-3L) for Simulation of Stream Flow at Different Time Scales. *Journal of Civil Environmental Engineering* 47(2):39–52
2. Balsamo G, Beljaars A, Scipal K, Viterbo P, Bart van den Hurk M, Hirschi, Betts AK (2009) "A Revised Hydrology for the ECMWF Model: Verification from Field Site to Terrestrial Water Storage and Impact in the Integrated Forecast System." *Journal of Hydrometeorology* 10(3):623–43
3. Bartalis Z, Naeimi V, Hasenauer S, Wagner W (2008) *ASCAT Soil Moisture Product Handbook. ASCAT Soil Moisture Report Series, No. 15*
4. Bergström S (1972) "Utveckling Och Tillämpning Av En Digital Avrinningsmodell (Development and Application of a Digital Runoff Model, in Swedish)." 22
5. Bergström S, Forsman A (1973) Development of a Conceptual Deterministic Rainfall-Runoff Model. *Nord Hydrol* 4(3):147–170

6. Beven K, Binley A (1992) The Future of Distributed Models: Model Calibration and Uncertainty Prediction. *Hydrol Process* 6(3):279–298
7. Beven KJ, Freer JE (2001) "Equifinality, Data Assimilation, and Uncertainty Estimation in Mechanistic Modelling of Complex Environmental Systems Using the GLUE Methodology". *J Hydrol* 249:11–29
8. Brocca L, Melone F, Moramarco T, Wagner W, Naeimi V, Bartalis Z, Hasenauer S (2010) Improving Runoff Prediction through the Assimilation of the ASCAT Soil Moisture Product. *Hydrol Earth Syst Sci* 14(10):1881–1893
9. Burek P, Van Der Knijff J, Arie De R (2013) LISFLOOD - Distributed Water Balance and Flood Simulation Model. Publications Office of the European Union
10. Corbari C, Mancini M (2014) Calibration and Validation of a Distributed Energy-Water Balance Model Using Satellite Data of Land Surface Temperature and Ground Discharge Measurements. *J Hydrometeorol* 15:376–392
11. Deardorff JW (1978) Efficient Prediction of Ground Surface Temperature and Moisture, with Inclusion of a Layer of Vegetation. *J Geophys Res* 83(C4):1889
12. Decharme B, Alkama R, Douville H, Becker M, Cazenave A (2010) Global Evaluation of the ISBA-TRIP Continental Hydrological System. Part II: Uncertainties in River Routing Simulation Related to Flow Velocity and Groundwater Storage. *J Hydrometeorol* 11(3):601–617
13. Van Dijk AIJM (2010) "The Australian Water Resources Assessment System: Technical Report 3. Landscape Model (Version 0.5) Technical Description." *WIRADA/CSIRO Water for a Healthy Country Flagship, Canberra*. (June):86
14. Draper C, Walker JP, Steinle PJ, de Jeu RA, Holmes TR (2009) An Evaluation of AMSR-E Derived Soil Moisture over Australia. *Remote Sens Environ* 113:703–710
15. Dutra E, Balsamo G, Jean-Christophe Calvet (2017) "Report on the Improved Water Resources Reanalysis." (June):94
16. Franco ACL, Bonumá NB (2017) "Multi-Variable SWAT Model Calibration with Remotely Sensed Evapotranspiration and Observed Flow." *Brazilian Journal of Water Resources* 22(35)
17. Goodarzi E, Ziaei M, and Lee Teang Shui (2013) Introduction to Risk and Uncertainty in Hydrosystem Engineering, vol 22. Springer Netherlands, Dordrecht
18. Guo J, Liang X, Leung L (2004) Impacts of Different Precipitation Data Sources on Water Budgets. *J Hydrol* 298:311–334
19. Gupta HV, Kling H, Yilmaz KK, Martinez GF (2009) Decomposition of the Mean Squared Error and NSE Performance Criteria: Implications for Improving Hydrological Modelling. *J Hydrol* 377(1–2):80–91
20. Hafeez M, van de Giesen N, Bardsley E, Seyler F, Pail R, Taniguchi M (2011) *GRACE, Remote Sensing and Ground-Based Methods in Multi-Scale Hydrology: Proceedings of Symposium J-H01 Held during IUGG2011*. IAHS Publications

21. Hyndman RJ, Koehler AB (2006) Another Look at Measures of Forecast Accuracy. *Int J Forecast* 22(4):679–688
22. Immerzeel WW, Droogers P (2008) Calibration of a Distributed Hydrological Model Based on Satellite Evapotranspiration. *J Hydrol* 349(3–4):411–424
23. Isenstein EM, Wi S, Ethan Yang YC, Casey Brown (2015) "Calibration of a Distributed Hydrologic Model Using Streamflow and Remote Sensing Snow Data." *World Environmental and Water Resources Congress 2015: Floods, Droughts, and Ecosystems* (May):973–82
24. Kite G, Droogers P (2000) Comparing Evapotranspiration Estimates from Satellites, Hydrological Models and Field Data: Preface. *J Hydrol* 229(1–2):3–18
25. van der Knijff JM, Younis J, J. de Roo AP (2008) LISFLOOD: A GIS-Based Distributed Model for River Basin Scale Water Balance and Flood Simulation. *Int J Geogr Inf Sci* 24:189–212
26. van der Knijff JM, Younis J, J. de Roo AP (2010) LISFLOOD: A GIS-Based Distributed Model for River Basin Scale Water Balance and Flood Simulation. *Int J Geogr Inf Sci* 24(2):189–212
27. Liang X, Wood EF, Lettenmaier DP (1996) "Surface Soil Moisture Parameterization of the VIC-2L Model: Evaluation and Modification". *Global Planetary Change* 13(1–4):195–206
28. Liu Y, Wang W, Liu Y (2018) ESA CCI Soil Moisture Assimilation in SWAT for Improved Hydrological Simulation in Upper Huai River Basin. *Advances in Meteorology* 2018:27–31
29. Lopez Lopez, Patricia E, Sutanudjaja J, Schellekens G, Sterk, Bierkens M (2017) "Calibration of a Large-Scale Hydrological Model Using Satellite-Based Soil Moisture and Evapotranspiration Products." *Hydrology and Earth System Sciences Discussions* (January):1–39
30. López P, López EH, Sutanudjaja J, Schellekens G, Sterk, Marc FP, Bierkens (2017) Calibration of a Large-Scale Hydrological Model Using Satellite-Based Soil Moisture and Evapotranspiration Products. *Hydrol Earth Syst Sci* 21(6):3125–3144
31. Miralles DG, De Jeu RAM, Gash JH, Holmes TRH, Dolman AJ (2011) Magnitude and Variability of Land Evaporation and Its Components at the Global Scale. *Hydrol Earth Syst Sci* 15(3):967–981
32. Naeimi V, Scipal K, Bartalis Z, Hasenauer S, Wagner W (2009) An Improved Soil Moisture Retrieval Algorithm for ERS and METOP Scatterometer Observations. *IEEE Transaction on Geoscience Remote Sensing* 47:1999–2013
33. Nash JE, Sutcliffe JV (1970) River Flow Forecasting through Conceptual Models, Part I - A Discussion of Principles. *J Hydrol* 10:282–290
34. Nijssen B, Lettenmaier DP, Liang Xu, Wetzel SW, Wood EF (1997) Streamflow Simulation for Continental-Scale River Basins. *Water Resour Res* 33(4):711–724
35. Pearson K (1896) "Mathematical Contributions to the Theory of Evolution.–On a Form of Spurious Correlation Which May Arise When Indices Are Used in the Measurement of Organs." *Proceedings of the Royal Society of London* 60:489–98
36. Priestley CHB, Taylor J (1972) "On the Assessment of Surface Heat Flux and Evaporation Using Large Scale Parameters". *Mon Weather Rev* 100(2):81–92

37. Rawls WJ, Gimenez D, Grossman R (1998) "USE OF SOIL TEXTURE, BULK DENSITY, AND SLOPE OF THE WATER RETENTION CURVE TO PREDICT SATURATED HYDRAULIC CONDUCTIVITY." *Transactions of the ASAE* 41(4):983–988
38. Reichle RH, Koster RD (2004) "Bias Reduction in Short Records of Satellite Soil Moisture." *Geophysical Research Letters* 31
39. Rientjes THM, Muthuwatta LP, Bos MG, Booij MJ, Bhatti HA (2013) Multi-Variable Calibration of a Semi-Distributed Hydrological Model Using Streamflow Data and Satellite-Based Evapotranspiration. *J Hydrol* 505:276–290
40. Seneviratne SI, Corti T, Davin EL, Hirschi M, Jaeger EB, Irene Lehner, Boris Orlowsky, and Adriaan J. Teuling. 2010. "Investigating Soil Moisture-Climate Interactions in a Changing Climate: A Review." *Earth-Science Reviews* 99(3):125–61
41. Su F, Adam JC, Bowling LC, Lettenmaier DP (2005) Streamflow Simulations of the Terrestrial Arctic Domain. *Journal of Geophysical Research D: Atmospheres* 110(8):1–25
42. Sutanudjaja EH, Van Beek LPH, De Jong SM, Van Geer FC, Bierkens MFP (2014) Calibrating a Large-Extent High-Resolution Coupled Groundwater-Land Surface Model Using Soil Moisture and Discharge Data. *Water Resour Res* 50(1):687–705
43. Todini E (1996) The ARNO Rainfall–Runoff Model. *J Hydrol* 175:339–382
44. Vereecken H, Huisman JA, Bogaen H, Vanderborght J, Vrugt JA, Hopmans JW (2008) "On the Value of Soil Moisture Measurements in Vadose Zone Hydrology: A Review." *Water Resources Research* 44(4)
45. Vogel RM, Fennessey NM (1994) Flow-Duration Curves. i: New Interpretation and Confidence Intervals. *J Am Water Resour Assoc* 120:485–504
46. Vogel RM, Neil M, Fennessey (1995) Flow Duration Curves li: A Review of Applications in Water Resources Planning. *J Am Water Resour Assoc* 31(6):1029–1039
47. Wagner W, Lemoine G, Borgeaud M, Rott H (1999) A Study of Vegetation Cover Effects on ERS Scatterometer Data. *IEEE Trans Geosci Remote Sens* 37:938–948
48. Wanders N, Bierkens MFP, de Jong SM, de Roo A, Karssenberg D (2014) The Benefits of Using Remotely Sensed Soil Moisture in Parameter Identification of Large-Scale Hydrological Models. *Water Resour Res* 50(8):6874–6891
49. WMO (2008) *Guide to Hydrological Practices*. 6th ed. edited by W. M. Organization
50. Zhao RJ, Liu XR (1995) "The Xinanjiang Model. In: Singh, V.P. (Ed.)." *Computer Models of Watershed Hydrology* 215–32

Figures

Figure 1

The geographic location of the study area

Figure 2

Flow chart for research process

Figure 3

The Taylor diagrams of flow hydrograph simulated in different scenarios.

Figure 4

NS statistics in different scenarios.

Figure 5

Simulated and observed flow hydrographs at different scenarios (daily time scale)

Figure 6

Simulated runoff at different scenarios versus observed flow (at monthly time scale)

Figure 7

Flow duration curve simulated at different scenarios

Figure 8

The relative error in the estimation of runoff volume at different optimization scenarios

Figure 9

Spatial distribution of d2 parameter of the VIC-3L model at different scenarios

Figure 10

Spatial distribution of WS parameter of the VIC-3L model at different scenarios