Article

Effect of Model Structure and Calibration Algorithm on Discharge Simulation in Acısu Basin, Türkiye

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Abstract: In this study, Acısu Basin, i.e. headwater of Gediz Basin, in Türkiye, was modelled using three types of hydrological models and three different calibration algorithms. A well-known lumped model (GR4J), a commonly used semi-distributed (SWAT+), and a skillful distributed (mHM) hydrological models were built and integrated with Parameter Estimation Tool (PEST). PEST is a model independent calibration tool including three algorithms i.e. Levenberg Marquardt (L-M), Shuffled Complex Evolution (SCE), and Covariance Matrix Adoption Evolution Strategy (CMA-ES). Calibration period was 1991-2000, and validation results were obtained for 2002-2005. The effect of model structure and calibration algorithm selection on discharge simulation was evaluated via comparison of 9 different model-algorithm combinations. Results have shown that mHM and CMA-ES combination performed the best discharge simulation according to NSE values (calibration: 0.67, validation: 0.60). Although statistically the model results were classified as acceptable, the models mostly missed the peak values in hydrograph. This problem may be related to the interventions made in 2000-2001 years and possible to overcome by changing the calibration and validation periods, increasing the number of iterations or using the naturalized gauge data.

Keywords: Hydrological Modelling; Calibration Algorithm; GR4J; SWAT+; mHM

1. Introduction

Hydrologic models are used in various areas such as climate models, management of water resources, design of hydraulic structures, and drought/flood prediction. Capabilities of hydrologic models are limited with the used data and measurement techniques. In the circumstances that the input of model is insufficient, temporal or spatial extrapolation is used using available data. At the same time, the changes in land use and climate conditions are needed to be considered in terms of their effects on hydrologic cycle [1].

Hydrologic models classified in terms of their spatial resolutions are investigated in this study. These structures are lumped, semi-distributed, and distributed namely. Lumped models represent whole basin as a single unit by using the averages of the variables belong to the basin [2]. Distributed models split the basin into grids and conducts the process for each grid individually with the inputs and state variables belong to these grids. Semi-distributed models are presented to literature to combine the advantages of both lumped and distributed models. Instead of defining the spatial variability as continuous such as distributed models, they define the basin as integration of lumped models. In this way, it requires less computational load and smaller size data than distributed models. It also represents the characteristics and heterogeneity of the basin better than lumped models. There are numerous studies in the literature carried out about hydrologic modelling over decades [3–5]. Study of [6] focused on the changes in Lake Tana Basin, Ethiopia, using different models and their hydrologic responses. They built 2 lumped models (GR4J and IHACRES) and a semi-distributed model (SWAT) for the study area using four major gauged watersheds. Findings of the study showed that the lumped models demonstrated superior discharge simulation performance to SWAT in small catchment although the situation is vice versa in large catchments since SWAT represents the heterogeneity of these catchments. In another study, [7] aimed to test GR4J and SWAT for robustness. Both have undergone calibration and validation studies during climatically diverse time periods. Both of them exhibit relative robustness despite a greater performance decline for the GR4J model between calibration and validation. Additionally, study of [8] compared three lumped models' – GR4J, Australian Water Balance Model (AWMB), and Sacramento – discharge performances on Godavari River Basin, India, considering NSE values of calibration results. Results of the study showed that GR4J model is suggested in terms of discharge simulations for the study area. In another study of [9], 15 hydrologic model including GR4J, SWAT, and mHM was built for Lake Erie, USA, to evaluate models' capabilities on hydrologic variables such as discharge, evaporation, and soil moisture. The findings of the study demonstrated that the best hydrographs are produced by mHM model in terms of resultant NSE values.

Regardless of their classification, the non-measurable parameters of each hydrological model need to be adjusted to represent real basin characteristics. This process is known as calibration [10]. Initially, calibration process was conducted manually based on expert knowledge. Today, using automatic calibration methods with advantages of improved technology is more common. These calibration methods avoid subjective interceptions, computation load, and waste of time by using different algorithms and objective functions. Auto-calibration algorithms attain parameter values to optimize objective function value. There are two different types of auto-calibration algorithms namely local and global. Local calibration algorithms aim to converge the optimum objective function value based on 3 main criteria; movement direction of parameters, iteration number, and termination criteria. Local methods that assign gradient-based values to the parameters in their range accept the zero-slope point as the optimum value. This causes possible optimum values to be missed if more than one optimum solution is found. Global methods overcome this problem by approaching the parameter space from all sides. They manipulate parameter values in order to improve the objective function by using deterministic and probabilistic rules [11]. These algorithm types had been used with various hydrologic models in several studies. Study of [12] integrated one local (Levenberg-Marquardt (LM), and two global (Dynamically Dimensioned Search (DDS) and Shuffled Complex Evolution (SCE)) with a semi-distributed hydrologic model (HEC-HMS) built on various basins in Germany. They used an empirical combination of Nash-Sutcliffe Efficiency (NSE) and volumetric error (VoE) as objective function for discharge calibration, and found that DDS is superior to other algorithms in this study's circumstances with 0.75-0.90 in calibration and 0.57-0.73 in validation. Furthermore, study of [13] investigated the value of different soil moisture products (The Advanced Microwave Scanning Radiometer on the Earth Observing System (EOS) Aqua satellite (AMSR-E), soil moisture active passive (SMAP), and total water storage anomalies from Gravity Recovery and Climate Experiment (GRACE)) on Hydrologiska Bryåns Vattenbalansavdelning (HBV) by multi-objective calibration (discharge (Q), groundwater (GW), soil moisture (SM)) and soil for each model set-up with Levenberg-Marquardt (LM), shuffled complex evolution (SCE), and covariance matrix adoption evolution strategy (CMAES) algorithms for Moselle River Basin in Germany and France. Findings of the study demonstrated that global optimization algorithms (SCE and CMAES) outperformed the local algorithm (LM) after 3000 iterations for each method according to three different objective functions such as NSE-Q, NSE-LNQ, and CORR. Additionally, [14] compared the discharge simulation performances resulting from calibration with SCE and sequential uncertainty fitting algorithm (SUFI2) for SWAT model to assess climate change impact for Upper Coruh Basin in Türkiye under regional climate projections (RCP 4.5 and RCP 8.5). SUFI2 algorithm has 0.67 and 0.62 NSE values for calibration and validation periods respectively, SCE algorithm has shown better performance with 0.73 (calibration) and 0.79 (validation) NSE values. There have been many studies on performance comparison of similar and simple models; however, the effect of sophisticated models and global search algorithms on discharge performances in a headwater catchment has not been studied yet. Selection of model and calibration algorithm is key for discharge simulations in catchment hydrology.

In this study, we integrated three different model structures with three calibration algorithms for Acısu Basin. For that, we used PEST and ERA5 model inputs. We selected GR4J as lumped model, SWAT+ as semi-distributed model, and mHM as distributed model; Levenberg-Marquardt (LM), Shuffled Complex Evolution (SCE), and Covariance Matrix Adoption Evolution Strategy (CMAES) as calibration algorithms. The resulting discharge values were compared for all combinations. The effect of model structure and calibration algorithm on discharge performances was evaluated according to these results.

2. Materials and Methods

2.1. Study Area

Gediz Basin which is located at the Aegean Region of Türkiye has 1.703.586 km² surface area. It is one of the 5 largest basins in Türkiye. It originates from Murat Mountain in Kutahya. The longest river in the basin is Gediz River which ends in Aegean Sea from İzmir. Including 5 dams, 2 lakes and 1 hydropower plant, Gediz Basin is of capital importance in terms of water resources. Water potential of the basin consists of % 58,63 potential evapotranspiration loss, % 28,22 groundwater recharge, and % 13,15 surface flow. The Acısu Basin is a sub-basin of Gediz Basin and it has 3256 km² drainage area and 890 m height. It locates at the headwater of the Gediz Basin with its semi-arid climate. The study area belongs to the drainage area of stream gauging station 523. Study domain is given in Figure 1.

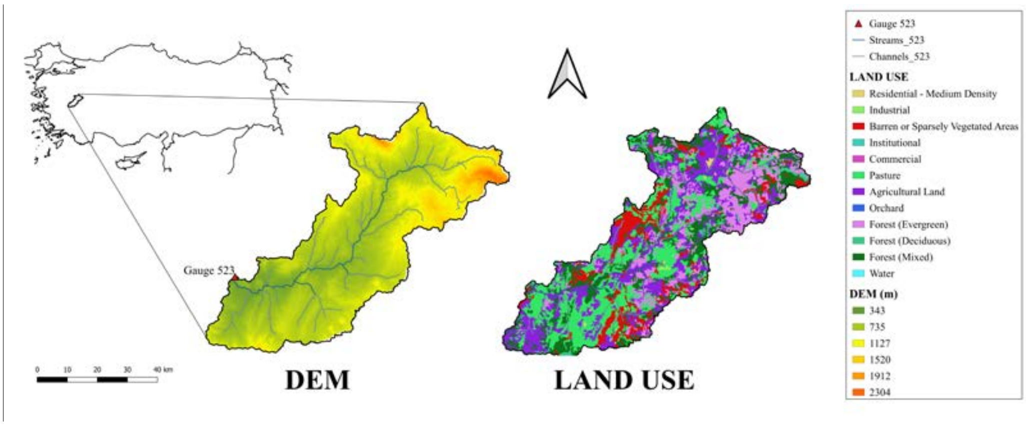

Figure 1. Study domain.

2.2. Data

In this study, common datasets are defined for each model to evaluate and compare results fairly. So, the three models are driven by ERA5 reanalysis data. Each model requires various data types in different resolutions. Therefore, the daily meteorological input - precipitation (P (mm)), potential evapotranspiration (PET (mm)), minimum and maximum temperature (T_{min} (°C), T_{max} (°C)) - obtained from ERA5 dataset is used by downscaling in line with each model's resolution. Further, measured P, $T_{average}$, T_{min}, and T_{max} data belongs to General Directorate of Meteorology of Türkiye (MGM) was used to evaluate ERA5 data (Table 1). Additionally, physically based models (SWAT+ and mHM) are driven by spatial data such as digital elevation model, land use, and soil data. DEM and land use data were shown in Figure 1 within study domain. Having 30 m spatial resolution Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) DEM data is used for SWAT+ and mHM. As land use data, Coordination of Information on the Environment (CORINE) open-source land use map with 100 m spatial resolution; as soil map, Food and Agriculture Organisation's (FAO) digital soil map of the world with 1/5.000.000 scale data is used.

Table 1. Monthly and annual data belongs to General Directorate of Meteorology of Türkiye and ERA5.

	Total Precipitation (mm)		Average Temperature (°C)		Maximum Temperature (°C)		Minimum Temperature (°C)	
	MGM	ERA5	MGM	ERA5	MGM	ERA5	MGM	ERA5
January	69.2	59.7	3.2	3.2	12.8	12.3	-10.6	-9.4
February	62.2	56.1	3.4	3.9	14.4	14.2	-8.9	-9.9
March	60.0	58.6	6.5	7.2	19.2	18.8	-6.5	-5.2
April	63.5	56.6	11.0	11.9	21.5	21.6	-1.2	-0.1
May	43.7	40.2	15.6	16.8	23.3	24.9	4.2	5.2
June	19.8	17.9	19.8	21.4	27.3	28.6	9.9	9.6
July	17.4	10.2	23.3	24.6	30.2	30.8	12.8	15.5
August	12.4	7.6	23.3	24.3	29.7	30.4	15.9	17.3
September	14.7	10.1	19.2	20.0	26.9	28.3	9.4	11.1
October	37.5	27.2	14.2	14.6	22.8	23.0	3.1	4.1
November	74.0	58.4	8.4	8.3	18.3	17.2	-2.9	-1.8
December	88.3	69.3	4.7	4.6	13.9	13.2	-5.4	-5.6
Annual	562.8	472.0	12.8	13.5	30.2	30.8	-10.6	-9.9

Precipitation and average temperature data were examined using scatter diagrams and regression equations (Figure 2) to evaluate ERA5 input and interpret the results.

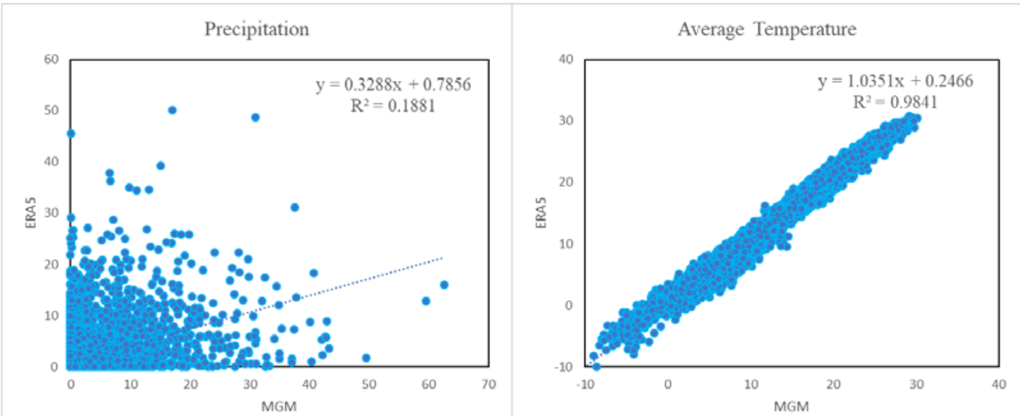

Figure 2. Comparison of MGM and ERA5 data

As discharge observation, data of stream gauge 523 -belongs to General Directorate of State Hydraulic Works. Türkiye- is used. Line graph of the discharge data is given in Figure 3.

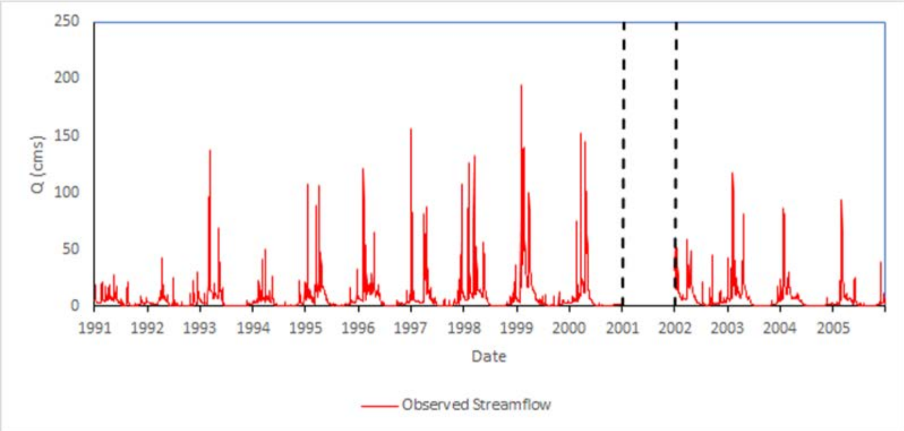

Figure 3. Observed discharge data of gauge 523.

2.3. Hydrologic Models

To compare the effect of model structure on the discharge, three different models which are classified based on their spatial resolution are set-up on Acısu Basin. GR4J is lumped, SWAT+ is semi-distributed, and mHM is distributed hydrologic model. Each model has different procedures and parametrizations to proceed hydrologic processes with different resolutions.

2.3.1. GR4J

Lumped model facilitates the use and set-up process. It shows whole basin's response to the forcing inputs. Constituting semi-distributed and distributed hydrologic models by gathering, lumped models are fundamental and starting point of these models [15]. Génie Rural â 4 Paramêtres Journalier (GR4J) is a lumped hydrologic model processing in daily time-step, presented and improved in early 2000s [16]. It requires daily P and PET as input time-series. To obtain daily data as time-series from ERA5, mean areal average values of the grids are calculated using spatial P and PET data. GR4J involve these inputs to the hydrologic processes using its 4 parameters given in Table 2.

Table 2. GR4J parameter descriptions.

Parameter	Description
X_1	Production storage capacity (mm)
X_2	Groundwater exchange coefficient (mm)
X_3	One day ahead maximum capacity of the routing store (mm)
X_4	Time base of unit hydrograph (day)

GR4J conducts the process represents rainfall-runoff relationship via 2 box model method which are called production storage and routing storage. Structure of the model is given in Figure 4. As the precipitation reaches to the surface, the first unit of the model that meets the water mass after interception process is production storage. Most amount of net precipitation after infiltration is transferred to routing storage by using unit hydrograph method. Then remaining amount of net precipitation is routed by a unit hydrograph the base width of which is twice that of the previous step. Finally, the amount of water coming from routing storage and routed part of remained net precipitation merge. Summation of these values end up with the output of GR4J which is discharge.

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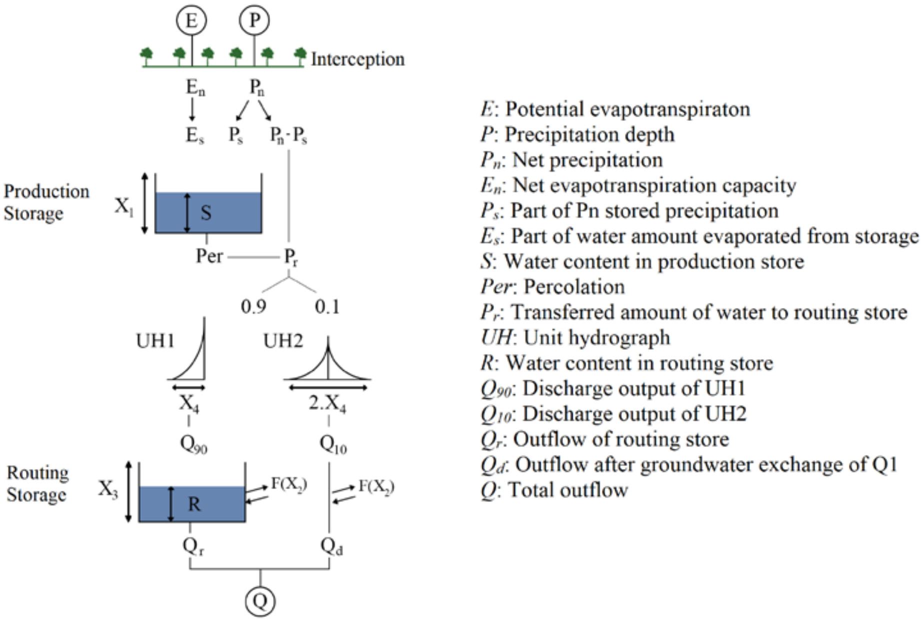

Figure 4. GR4J model structure.

During the set-up process of GR4J, we utilized R software [17] and airGR package [18] which are both open-source.

2.3.2. SWAT+

Soil water assessment tool is published by Dr. Jeff Arnold as a result of his study accomplished for USDA-ARS (U.S. Department of Agriculture – Agricultural Research Service) to foresee the effects of land use and management in a basin with heterogeneous structure [19]. Besides it is a physically based model, SWAT is semi-distributed and continuous hydrologic model working at a daily time-step which has a wide use area such as rainfall-runoff relationship, climate change, environmental studies at small or large basins [20–22]. Semi-distributed structure of the model consists of sub-basins and hydrologic response units (HRUs) in detail. In earlier versions of SWAT model, the smallest spatial subdivision of a basin is represented by HRUs. As a new feature in SWAT+, HRUs are divided in landscape units (LSUs). LSUs are divided into two part namely upland and floodplain. The HRUs are homogenous in themselves in terms of their physical characteristics [23]. We used QGIS software and QSWAT+ plugin in this study to set-up the model because of its easy-to-use interface and being the most up-to-date version of SWAT+ model. It requires DEM, land use, soil map as physical data; precipitation, temperature, wind speed, solar radiation, and relative humidity as climatic and hydrologic data. Although SWAT+ can automatically calculate PET with different methods, we added the ERA5 PET data to compare results fairly with other models. We only focused on discharge output of SWAT+ model in line with our objective. Discharge value is obtained at the outlet location by routing the output of each HRU individually through the main outlet. During the modelling process, we divided the Acısu Basin into 5 sub-basins and 1981 HRUs ranging from 6 to 60.26 km2 surface area. SWAT+ conducts the process in two phases such as land phase and routing phase. Considering the information given in [24], we used SCS-CN (Soil Conservation Service – Curve Number) method in land phase, and Muskingum method in routing phase.

2.3.3. mHM

mesoscale Hydrologic Model (mHM) is a distributed, physically based and continuous hydrologic model published by a team from UFZ (Helmholtz Centre for Environmental Research) [25,26]. Fundamental numerical approaches about hydrologic processes of

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the mHM are tested by using well-known and acknowledged lumped models such as HBV [27] and VIC [28]. Input and parameter variety for each grid of mHM is setting this model apart from other rainfall-runoff models. With this difference, changes in characteristics of the basin can be represented better as the spatial resolution of model run and forcing data increases. Model structure is given in Figure 5.

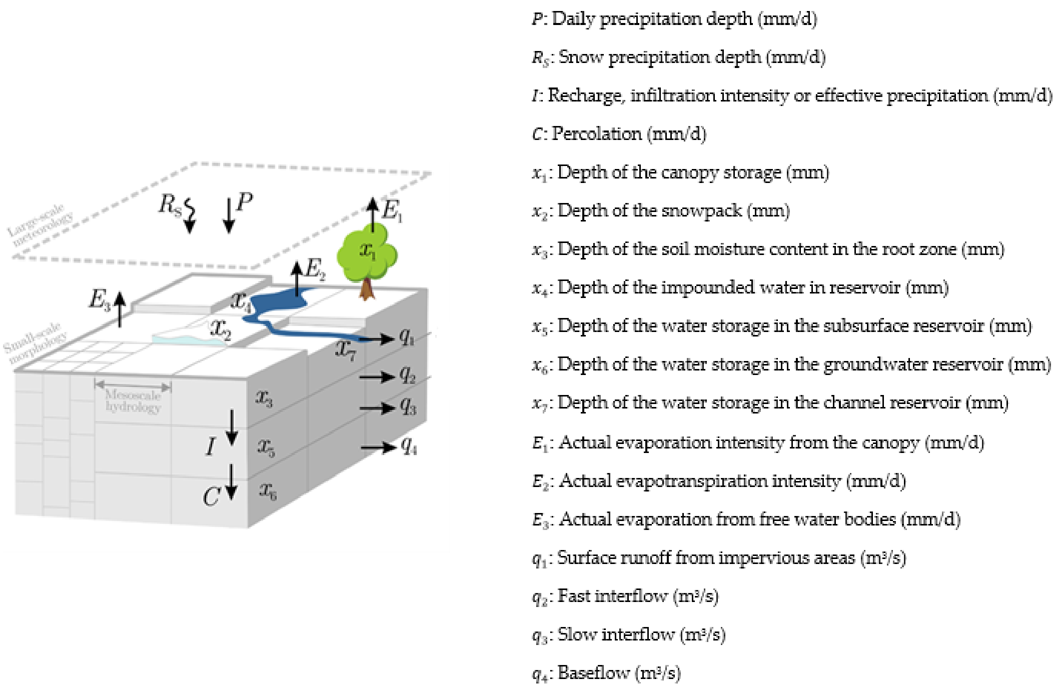

Figure 5. mHM cell structure.

All processes are applied in each cell individually and continuity of the model is provided by using ordinary differential equations (ODE). The results of ODEs obtained from each cell are routed by using Muskingum method through the main outlet [29].

In this study, open-source Fortran based code of mHM is compiled with Cygwin to run the model in Windows environment.

2.4. Calibration of Models

2.4.1. Sensitivity Analysis

Sensitivity analyses and calibrations of the examined models are performed by using Parameter Estimation Tool (PEST) which is model-independent auto-calibration tool [30]. Sensitivity analysis is used to indicate effect of a change in parameter value to objective function. Main purpose of using this method is to eliminate ineffective parameters before the calibration process to avoid the waste of time spent for unnecessary iterations. In this study, sensitivity analysis of the models' parameters is performed using the auto-sensitivity module of PEST. It is basically based on the equation given below;

$$S = \frac{\Delta\ OF\ (\%)}{\Delta\ Par\ (\%)} \tag{1}$$

where S is sensitivity value, "*ΔOF*" is change in objective function as percentage corresponding to parameter change, and "*ΔPar*" is change in parameter value as percentage.

2.4.2. Calibration Algorithms

Calibration is a process which is performed to obtain optimum results from models by adjusting parameter values. The calibration of each models' parameters was performed by using three algorithms of PEST namely Levenberg-Marquardt (LM), Shuffled Complex

Evolution (SCE), and Covariance Matrix Adoption Evolution Strategy (CMAES). These are classified as local and global algorithms. LM is a local optimization algorithm which is composed of gradient descent and Gauss-Newton methods [31]. SCE and CMAES are global optimization algorithms. SCE is combinations of the competitive evolution, the local direct search of downhill simplex method, a controlled random search, and the concept of complex shuffling [32]. Finally, CMAES is another global optimization algorithm including stochastic approaches and non-linear functions. It uses maximum likelihood method to attain parameter values giving closer results to optimum solution in previous iterations [33].

3. Results

3.1. Sensitivity Analysis

To define the effectiveness of parameters on models' objective, sensitivity analysis was performed for GR4J, SWAT+, and mHM. 4 parameters of GR4J, 20 parameters of SWAT+ affecting on discharge [34], and 66 parameters of mHM were involved to this process to eliminate unsensitive components. Sensitivity analysis of this study was completed by using auto-sensitivity analysis of PEST for the calibration period (1991-2000). The threshold of sensitivity value was selected as 0.0025 subjectively using the information shared in the study of [35]. Results of sensitivity analysis are given in Figure 6, Figure 7 and Figure 8.

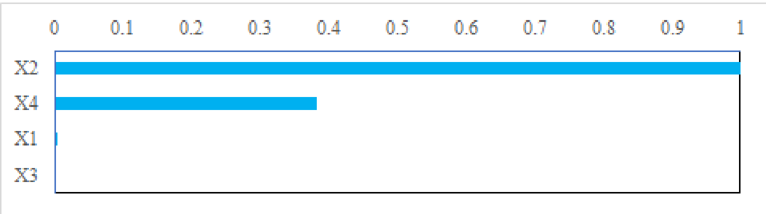

Figure 6. GR4J sensitivity analysis results.

For Acısu Basin, results of sensitivity analysis showed that the most effective parameter is "X2" which is the change in groundwater storage for GR4J, and 3 out of 4 parameters of GR4J model were defined as sensitive.

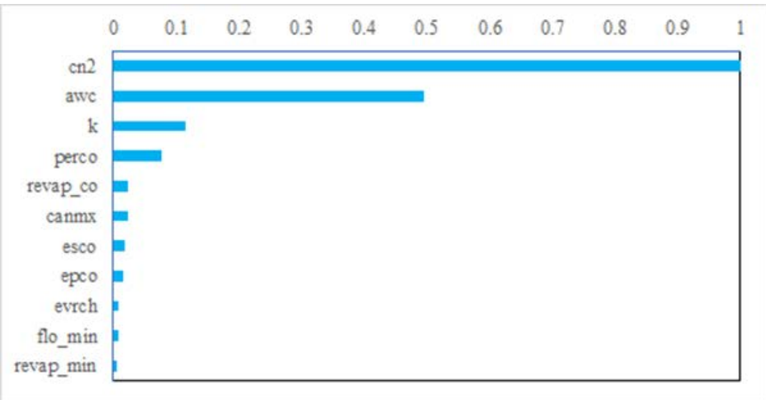

Figure 7. SWAT+ sensitivity analysis results.

SWAT+ sensitivity analysis results demonstrated that "*cn2*" (SCS curve number) is the most sensitive parameter in on discharge. Sensitivity analysis of SWAT+ performed using 20 parameters and 11 out of 20 parameters above threshold selected as sensitive. Descriptions of sensitive parameters were given in Table 3 for SWAT+.

Table 3. SWAT+ parameter descriptions

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Parameter	Desscription	Unit
cn2	SCS curve number	-
awc	Soil water content	-
k	Hydraulic conductivity of saturated soil	mm/hr
perco	Percolation coefficient	-
revap	Evaporation coefficient from shallow aquifer to root	-
canmx	Maximum canopy storage	mm
esco	Soil evaporation compensation factor	-
epco	Plant uptake compensation factor	-
evrch	Reach evaporation adjustment factor	-
flomin	Minimum amount of water to be stored in the aquifer for return flow	mm
revap_min	Minimum water depth required in shallow aquifer for "revap"	mm

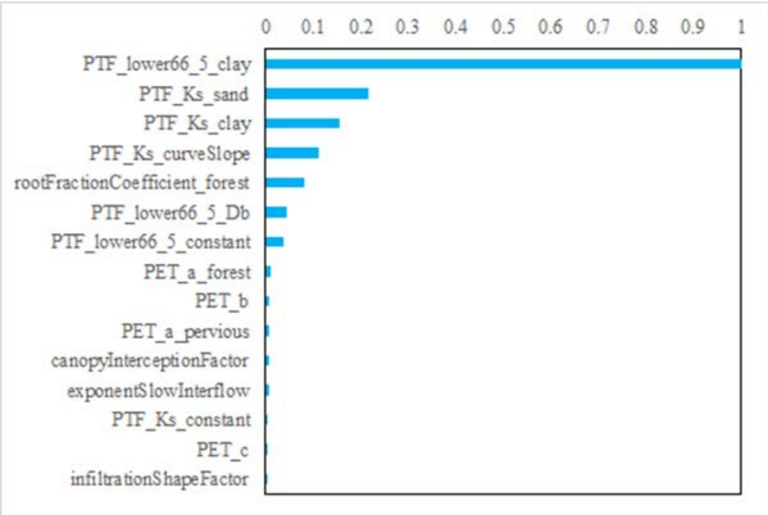

Figure 8. mHM sensitivity analysis results.

Finally, mHM sensitivity analysis resulted in 15 sensitive parameters out of 69 parameters. The most sensitive parameter of mHM is "*PTF_lower66_5_clay*" which a coefficient of Pedo-transfer function for soil including clay lower than 66.5%. Descriptions of sensitive parameters were given in Table 4 for mHM. These results show that soil related parameters at each model are dominant for the study area.

Table 4. mHM parameter descriptions

Parameter	Parameter Description
PTF_lower66_5_clay	Pedotransfer function (PTF) soil moisture constant for less than 66.5% clay
PTF_Ks_sand	PTF hydraulic conductivity constant for saturated sand
PTF_Ks_clay	PTF hydraulic conductivity constant for saturated clay
rootFractionCoefficient_pervious	Root fraction coefficient for pervious area
PTF_lower66_5_Db	PTF density constant for less than 66.5% sand
PTF_lower66_5_constant	PTF soil moisture constant for less than 66.5% sand

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PTF_Ks_constant	PTF hydraulic conductivity constant for saturated soil
rootFractionCoefficient_forest	Root fraction coefficient for forest
infiltrationShapeFactor	Shape factor that divides effective precipitation into infiltration and surface flow
PET_a_forest	Forest - PET correction factor
PET_a_pervious	Pervious area - PET correction factor
PET_b	Agricultural land - PET correction factor
PET_c	Agricultural land - PET correction factor (2)
canopyInterceptionFactor	Canopy interception factor
exponentSlowInterflow	Slow interflow exponent

3.2. Calibration and Validation

The sensitive parameters were used in calibration period from 1991 to 2000 and validation period from 2002 to 2005 with daily time-step for each model. GR4J, SWAT+, and mHM were integrated with PEST to calibrate and validate these models by using three optimization algorithms such as Levenberg-Marquardt (LM), shuffled complex evolution (SCE), and covariance matrix adoption evolution strategy (CMAES). These algorithms have some common limitations to be determined. The limitations were defined similar for each algorithm for fair comparison. Maximum iteration number was defined as 1000 and termination criteria was defined as lower than 10-6 change in objective function (NSE) through 15 successive iterations for all three algorithms.

To assess discharge simulation performance, calibration process was accomplished in daily time basis for used models. Resultant parameter values and defined parameter boundaries are given in Table 5 for GR4J, SWAT+, and mHM.

Table 5. Calibrated parameters of each model.

Model	Parameter	Calibrated Value			Limit	
		L-M	SCE-UA	CMAES	Min	Max
GR4J	X1	399.99	346.37	347.02	10	2000
	X2	0.00	0.46	0.47	-8	6
	X3	10.00	10.00	10.00	10	500
	X4	1.77	1.32	1.33	1	4
SWAT+	cn2	0.77	0.67	0.68	0.65	0.95
	awc	0.02	0.01	0.01	0.01	0.51
	k	200.40	189.18	193.07	0.00	2000.00
	perco	0.28	0.16	0.20	0.00	1.00
	revap	0.20	0.05	0.16	0.02	0.20
	canmx	19.99	23.55	22.33	0.00	100.00
	esco	0.67	0.37	0.39	0.00	1.00
	epco	0.04	0.17	0.17	0.00	1.00
	evrch	0.67	0.75	0.56	0.50	1.00
	flomin	500.00	355.52	1059.35	0.00	1250.00
mHM	PTF_lower66_5_clay	0.0017	0.0012	0.0019	0.0001	0.0029
	PTF_Ks_sand	0.0083	0.0221	0.0158	0.0060	0.0260
	PTF_Ks_clay	0.0079	0.0130	0.0124	0.0030	0.0130
	rootFractionCoefficient_pervious	0.0608	0.0095	0.0460	0.0010	0.0900
	PTF_lower66_5_Db	-0.3463	-0.2141	-0.2315	-0.5513	-0.0913
	PTF_lower66_5_constant	0.6877	0.6724	0.6750	0.5358	1.1232
	PTF_Ks_constant	-0.7105	-1.1978	-1.0251	-1.2000	-0.2850
	rootFractionCoefficient_forest	0.9401	0.9623	0.9872	0.9000	0.9990

infiltrationShapeFactor	1.9602	1.1113	1.0000	1.0000	4.0000
PET_a_forest	0.7221	1.2466	1.2885	0.3000	1.3000
PET_a_pervious	0.7414	0.3604	0.3176	0.3000	1.3000
PET_b	0.6823	0.7020	0.5982	0.0000	1.5000
PET_c	-0.9670	-0.0001	-0.0427	-2.0000	0.0000
canopyInterceptionFactor	0.1520	0.1501	0.2135	0.1500	0.4000
exponentSlowInterflow	0.1948	0.2324	0.2054	0.0500	0.3000

Using these parameter values give in the tables above, GR4J, SWAT+, and mHM were run for calibration and validation periods. According to the NSE values which were calculated for discharge outputs belong to each model-algorithm combination, Table 6 and Table 7 were arranged and given with other statistical performance indicators.

Table 6. Calibration results.

CALIBRATOIN 1991-2000	NSE	R^2	KGE	RSR	PBIAS	MSE	RMSE
mHM-CMAES	0.67	0.66	0.74	0.58	2.0	77.84	8.82
mHM-SCE	0.67	0.67	0.74	0.57	-1.9	76.59	8.75
GR4J-SCE	0.63	0.63	0.72	0.61	0.4	86.29	9.29
GR4J-CMAES	0.63	0.63	0.72	0.61	0.4	86.29	9.29
SWAT+-SCE	0.56	0.57	0.72	0.66	-2.0	102.76	10.14
SWAT+-CMAES	0.56	0.57	0.72	0.67	2.8	103.13	10.16
mHM-LM	0.54	0.55	0.71	0.68	-1.5	108.23	10.40
SWAT+-LM	0.53	0.55	0.70	0.68	-3.4	108.32	10.41
GR4J-LM	0.44	0.59	0.22	0.75	-55.5	131.05	11.45

As it is shown in Table 6 and Table 7, model-algorithm combinations were ordered by their NSE values. Calibrating respectively using LM, SCE, and CMAES, GR4J has NSE value of 0.44, 0.63, and 0.63; SWAT+ has 0.53, 0.56, and 0.56; mHM has 0.54, 0.67, and 0.67.

Table 7. Validation results.

VALIDATION 2002-2005	NSE	R^2	KGE	RSR	PBIAS	MSE	RMSE
mHM-CMAES	0.60	0.61	0.61	0.63	-9.9	52.96	7.28
mHM-SCE	0.56	0.58	0.55	0.67	-16.6	58.63	7.66
GR4J-LM	0.55	0.62	0.44	0.67	-42.7	59.24	7.70
GR4J-SCE	0.44	0.67	0.60	0.75	23.5	73.77	8.59
GR4J-CMAES	0.44	0.67	0.60	0.75	23.5	73.50	8.57
SWAT+-SCE	0.38	0.41	0.57	0.79	-2.4	81.58	9.03
SWAT+-CMAES	0.38	0.41	0.60	0.78	0.2	81.36	9.02
SWAT+-LM	0.35	0.40	0.54	0.81	-9.4	86.29	9.29
mHM-LM	0.31	0.37	0.53	0.83	-20.4	91.59	9.57

For validation period with respectively LM, SCE, and CMAES, GR4J has NSE value of 0.55, 0.44, and 0.44; SWAT+ has 0.35, 0.38, and 0.38; mHM has 0.31, 0.56, and 0.60. Iterations are continuously completed for all of the combinations with PEST. From the aspect of performance evaluation mHM-CMAES integration has shown “good” performance according to the classification given in Table 8 presented in [36].

Table 8. Classification of discharge simulation performance.

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Performance	RSR	NSE	PBIAS
Very Good	0.00 ≤ RSR ≤ 0.50	0.70 < NSE ≤ 1.00	PBIAS < ±10
Good	0.50 < RSR ≤ 0.60	0.65 < NSE ≤ 0.75	±10 ≤ PBIAS < ±15
Satisfactory	0.60 < RSR ≤ 0.70	0.50 < NSE ≤ 0.65	±15 ≤ PBIAS < ±25
Poor	RSR > 0.70	NSE ≤ 0.5	PBIAS ≥ ±25

A comparison of these statistical findings was supported with a bar chart in Figure 9 and Figure 10 to virtualize model and algorithm performances with their average NSE values for calibration and validation processes respectively.

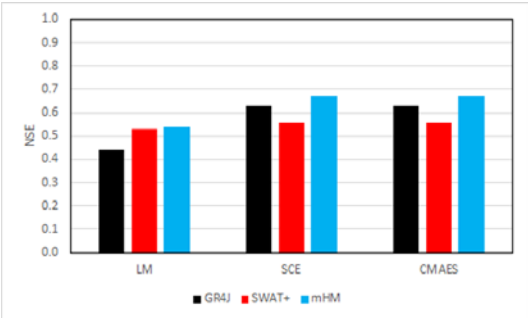

Figure 9. Calibration performance for each algorithm.

What stands out in Figure 9 is SCE and CMAES's close NSE values to each other. SCE and CMAES have average NSE values as 0.62 and outperformed LM which has 0.50 average NSE value after calibration.

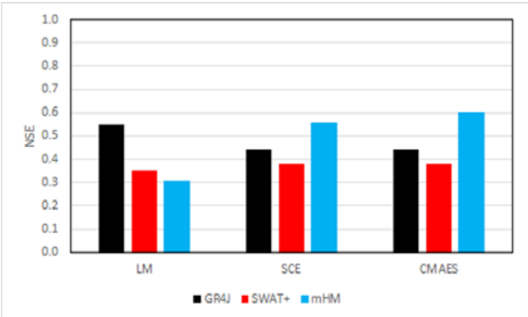

Figure 10. Validation performances for each algorithm.

CMAES dominated other algorithms in validation with average NSE value of 0.47 whilst SCE has 0.46 and LM has 0.40 average NSE values as it can be seen in Figure 10. In model basis, mHM outperformed other two models with an average NSE value of 0.63. SWAT+ and GR4J have average NSE values as 0.37 and 0.48 respectively. By the end of comparison process, hydrograph of the best combination is given in Figure 11.

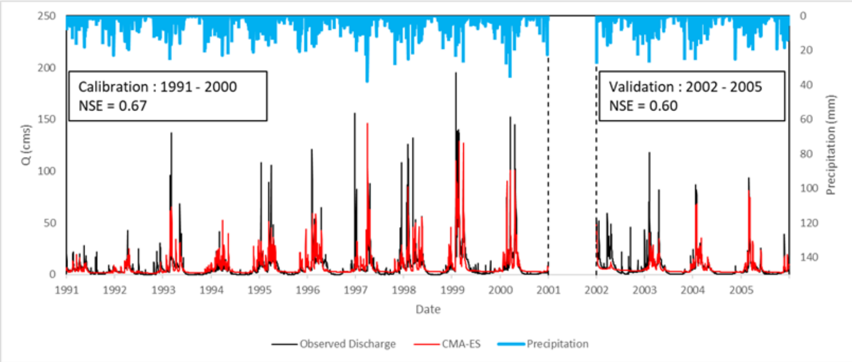

Figure 11. Comparison of observed discharge data with mHM-CMAES simulation results.

As it is shown in Figure 11, resultant hydrograph with the highest NSE value in general is mHM-CMAES combination. Besides reaching 0.67 and 0.60 NSE values for respectively, it has 0.67 and 0.61 R2 values which is given Figure 12 with scatter plots.

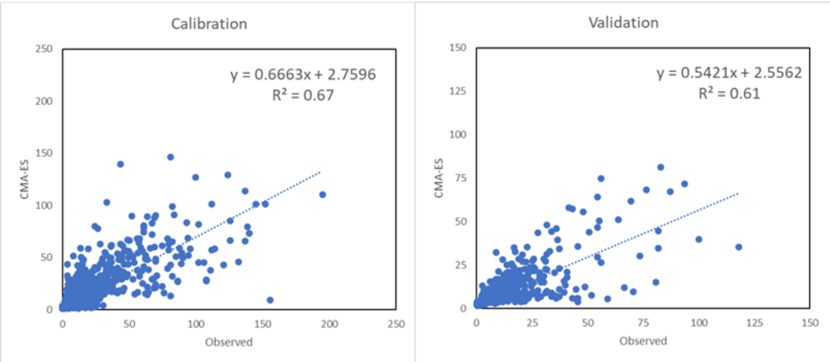

Figure 12. Scatter diagram of observed and simulated discharge data.

In line with hydrographs, distribution of calibrated and validated values demonstrates that simulated values are mostly lower than observed values.

Additionally, SWAT+ and mHM have ability to present visual results for various outputs i.e. discharge, potential evapotranspiration, snowpack, soil moisture content. In Figure 13, annual output of each model for the last year of validation (2005) were given as maps to visualize the discharge distribution in study domain. Representative map of GR4J output was given for comparing distributed structure of models.

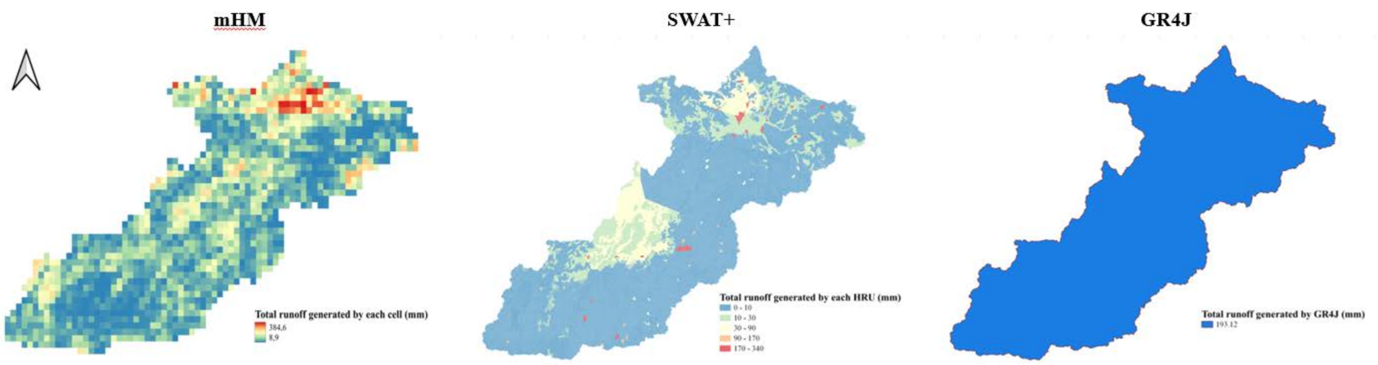

Figure 13. Map outputs of each model

4. Discussion

Hydrological model selection is a key factor for decision makers in the planning and management of water resources. Hydrologic models have various skills and limitations

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depending on their model structure, model inputs and their ability to represent the nature of the hydrological phenomenon. Basically, they convert rainfall to runoff, route in the channels, and mainly used for predictions and forecasts using forecasted weather inputs. All performed model-algorithm integrations captured the discharge pattern for Acısu Basin except for the first year of validation (Figure 11). This inaccuracy may be related to excluded period of 2001-2002. This exclusion was made to significantly avoid the negative impact of this period on the calibration process. Besides, it can be seen from the Table 1 that ERA5 dataset has almost 20% less annual precipitation and more temperature leading to more potential evapotranspiration. In line with these details, models produced less discharge than expected.

In general, the model and three different calibration algorithm capabilities were tested for the study area. Findings showed that results of the combinations are close to results of the studies performed for Acısu Basin and around [15,37] for similar methods. Main differences between the model structures in this study is their spatial resolutions and model complexity. GR4J is a lumped model whereas SWAT+ is semi-distributed model. Since mHM is a distributed hydrological model, model structure is more sensitive to the input data and its resolution for representing the characteristics of the basin. Most importantly, users can retrieve flux and state simulations from any location in the basin. On the other hand, GR4J and SWAT+ have limitations in defining meteorological inputs as spatially distributed. These models can involve meteorological inputs in the process as time series. GR4J allows users to define single time series for whole basin, while SWAT+ gives the opportunity to add inputs at different locations.

It is one of the general results encountered in the literature that the error values decrease by using the average of the spatial values of the basin in the lumped models compared to the distributed models. As a result of the analyzes in this study, contrary to the aforementioned situation, it is seen that the distributed model (mHM) shows better discharge simulation performance than the lumped and semi-distributed models according to NSE. When the obtained data and results were examined, it was concluded that this was due to the heterogeneous structure of the basin and that the model structure of mHM more successfully defines the basin characteristics in terms of the resolution of which it processes heterogeneity. Although the reanalysis data of ERA5 or coarse soil map may be insufficient as resolution or for this specific study area due to its small surface area, mHM still simulated the discharge better than other two models. The reason of this result can be the models skillful multi parameter regionalization algorithm (MPR) capturing the heterogeneity of the basin characteristics with limited number of calibrated parameters. This approach is a unique feature of mHM as compared to the other distributed models.

Modelling procedure needs fine-tuning of model parameters to get closer to the optimum. This process is known as calibration. Both local (LM) and global (SCE, CMAES) algorithms were applied to the hydrologic models in this study. Results were given in Table 6 and Table 7. Global algorithms provide comprehensive search for optimum parameter set. As it is expected considering previous studies [14,32], SCE and CMAES ended with better results than LM while CMAES was the best.

Acısu Basin has an important location at the upstream of Gediz Basin which is one of the largest basins in Türkiye. Hydrologic model studies in this region have priority for irrigation because of its agricultural potential [38–40]. For this reason, it is thought that alternative modeling approaches will guide researchers for studies to be carried out in the basin. Therefore, modelling studies can be directive for researchers for the basin. We aimed to facilitate the method selection for decision makers.

5. Conclusions

As a developing country, the population and thus the need for industrial, irrigation and drinking water is increasing rapidly in Türkiye. For this reason, the importance of studies on water resources for the effective use of water is increasing day by day. Especially the Gediz Basin has an importance in hydrological studies due to its agricultural lands and potential drought risk. To assess the future conditions, hydrologic models are preliminary tools. For the purpose of facilitating the selection of hydrologic model and its calibration algorithm, three hydrologic model structure (lumped, semi distributed, distributed) and three algorithms (LM, SCE, CMAES) were compared with 9 combinations in this study. Based on the comparison and results, following conclusions can be drawn;

1. In contrast to general findings, distributed model (mHM) simulated the discharge with higher performance than the coarser models (SWAT+ and GR4J).
2. Global optimization algorithms (CMAES and SCE) have extensive ability to search the optimum parameter set compared to local algorithm (LM). The highest performance was shown by CMAES based on average NSE through calibration and validation.
3. In terms of time efficiency, each model has different run-time for the study domain. Single run takes an average of 30 seconds for mHM, 2 minutes for SWAT+, and 4 seconds for GR4J.
4. Since mHM and SWAT+ allows to draw outputs for any sub-basin located at the upstream, it is advantageous compred to GR4J under data-limited modelling conditions.
5. Resultant hydrographs were demonstrated that simulated discharge values were lower than observed values in general. The reason for that is related to the difference between ERA5 data and MGM measurements. Direct relationship between precipitation and discharge leads the models to simulate lower values.

The results obtained with the applied models and algorithms are limited to the Acısu Basin. In order to generalize the results, it is recommended to examine the basins with different geographical, meteorological and geological characteristics with similar models and algorithms. The modelers should identify the priorities of the modeling practice and select the right model for the right purpose. Input demands can be cover by open-source global data sources and currently distributed model can easily be set up for any location in the world. However, if only flood forecasting is the aim and process understanding is not necessary, relatively simple models can be utilized for quick solution for the domain. Future work should focus on appropriate model structure selection for flood or drought forecasting using ERA5 Land inputs and ECMWF forecasted meteorological forcing.

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