Development of an Artificial Intelligence Model for Improving Snow Simulation in SWAT

Our research team!

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Previous works

Open Access Article

SWAT Modeling of Non-Point Source Pollution in Depression-Dominated Basins under Varying Hydroclimatic Conditions

by Mohsen Tahmasebi Nasab [1], Kendall Grimm [1], Mohammad Hadi Bazrkar [1], Lan Zeng [1], Afshin Shabani [2], Xiaodong Zhang [2] and Xuefeng Chu [1,*]

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Evaluating the Performance of Soil and Water Assessment Tool (SWAT) in a Snow-Dominated Climate (Case Study: Azna–Aligoudarz Basin, Iran)

by Yaser Sabzevari [1,2], Saeid Eslamian [1], Saeid Okhravi [2] and Mohammad Hadi Bazrkar [3,*]

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Research gaps

Improving snow simulation can help improve hydrologic modeling in SWAT.

Research objectives

The objective of this study is to improve snow simulation in SWAT by developing AI-based models to simulate SWE in a cold, snow-dominated region.

Previous works

- Mital et al. (2022) used random forest (RF) to model the spatial distribution of SWE by integrating meteorological and satellite data.
- Thapa et al. (2024) used Long Short-Term Memory (LSTM) to predict SWE by recognizing patterns in snow accumulation and snowmelt data.
- Duan et al. (2024) estimated daily SWE using deep learning models.

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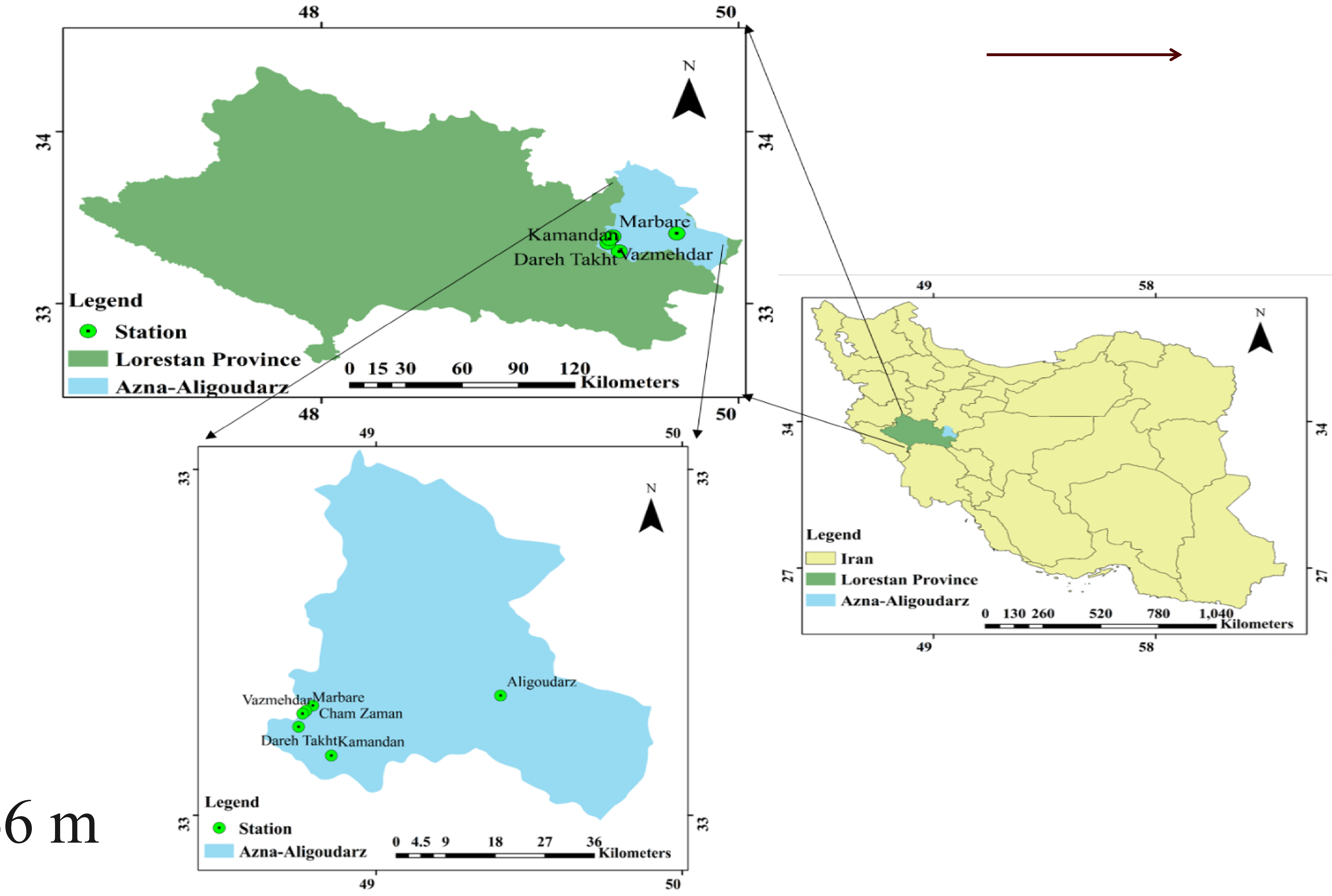
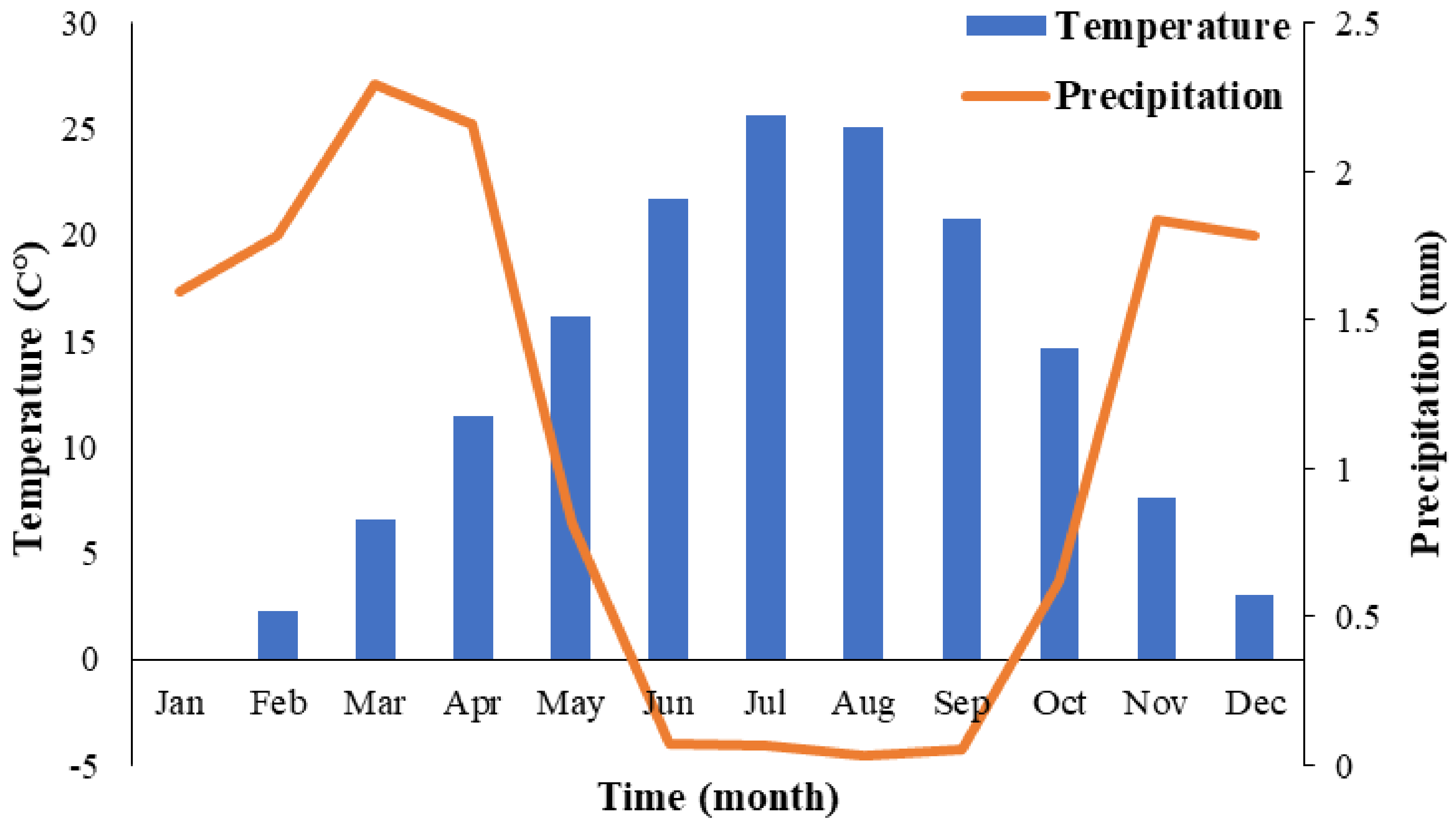
This study is structured into five main steps:

- The first step investigates the influence of various parameters on SWE.
- The second step focuses on identifying modeling input patterns based on the most influential parameters affecting SWE.
- The third step presents the modeling of SWE using the selected input patterns. The fourth section compares the performance of the models and introduces the most accurate model for SWE simulation.
- The fifth step, incorporate the improved model and see how it improves snow simulation in SWAT.

Study area

- Azna–Aligoudarz Basin
- Location: Western Iran
- Area: 1,218.9 km²
- Elevation range: 1,818 m – 3,746 m





Station	Station's Type	Establishment	Altitude(m)	Latitude	Longitude
Aligoudarz	Synoptic	1985	1980	33°24′	49°42′
Kamandan	Hydrometry Rain Gauge	1967	2050	33°18′14″	49°25′36″
Dareh Takht	Hydrometry Rain Gauge	1955	1940	33°21′14′	49°22′23″
Marbare	Hydrometry	1958	1820	33°22′52″	49°24′6″
ChamZaman	Hydrometry	1961	1870	33°23′36″	49°23′27″
Vazmehdar	Snow Gauge	1974	1912	33°22′35″	49°22′47″

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Model set up

SWAT 2012

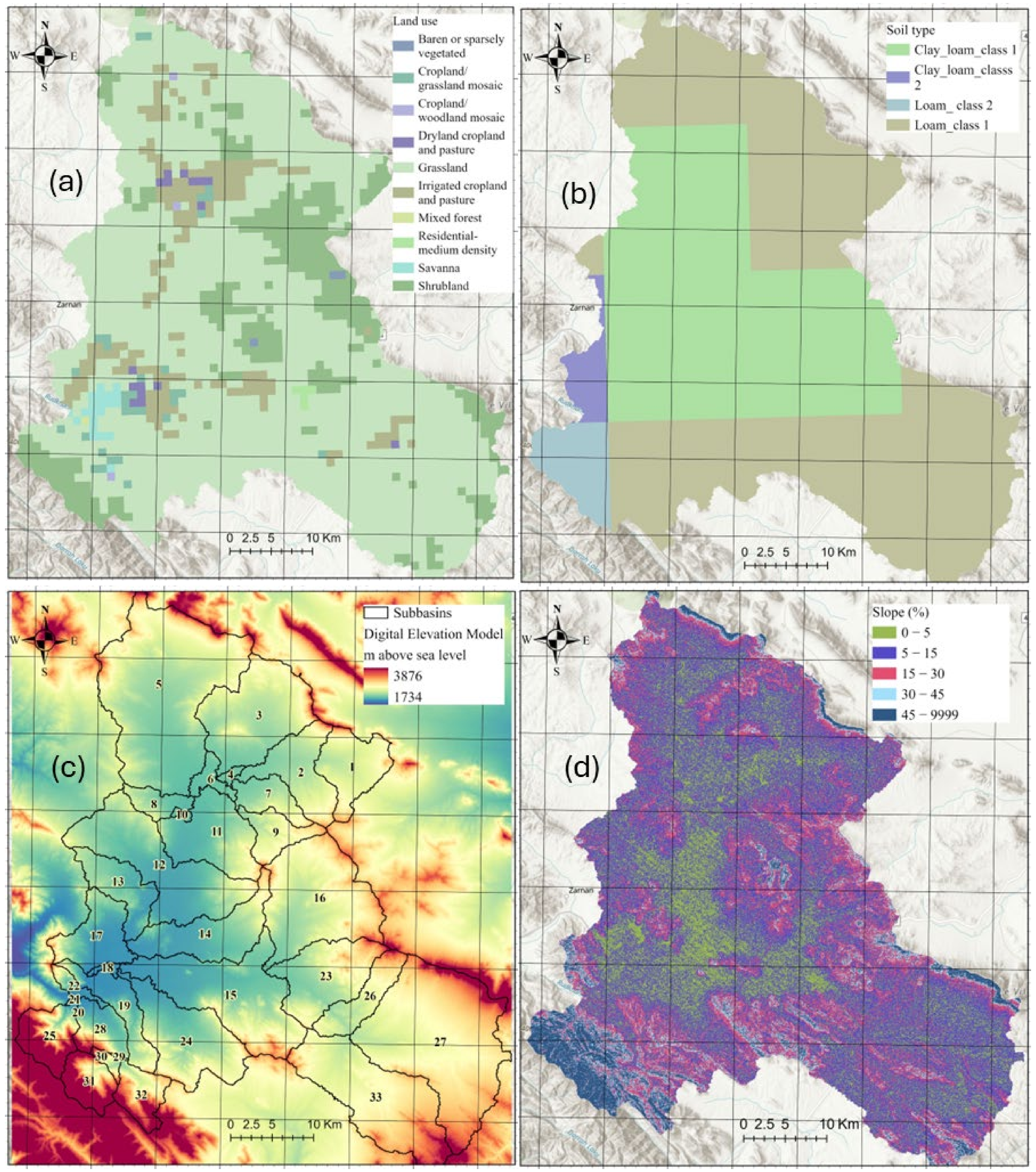
Warm-up period: 1991-1992

Calibration period: 1993-2016

Validation period: 2017-2023

33 subbasins

Data used for training and testing AI models: 1980-2019



Input maps of (a) land use, (b) soil class, (c) digital elevation map and sub-basins. (d) slope of the study area.

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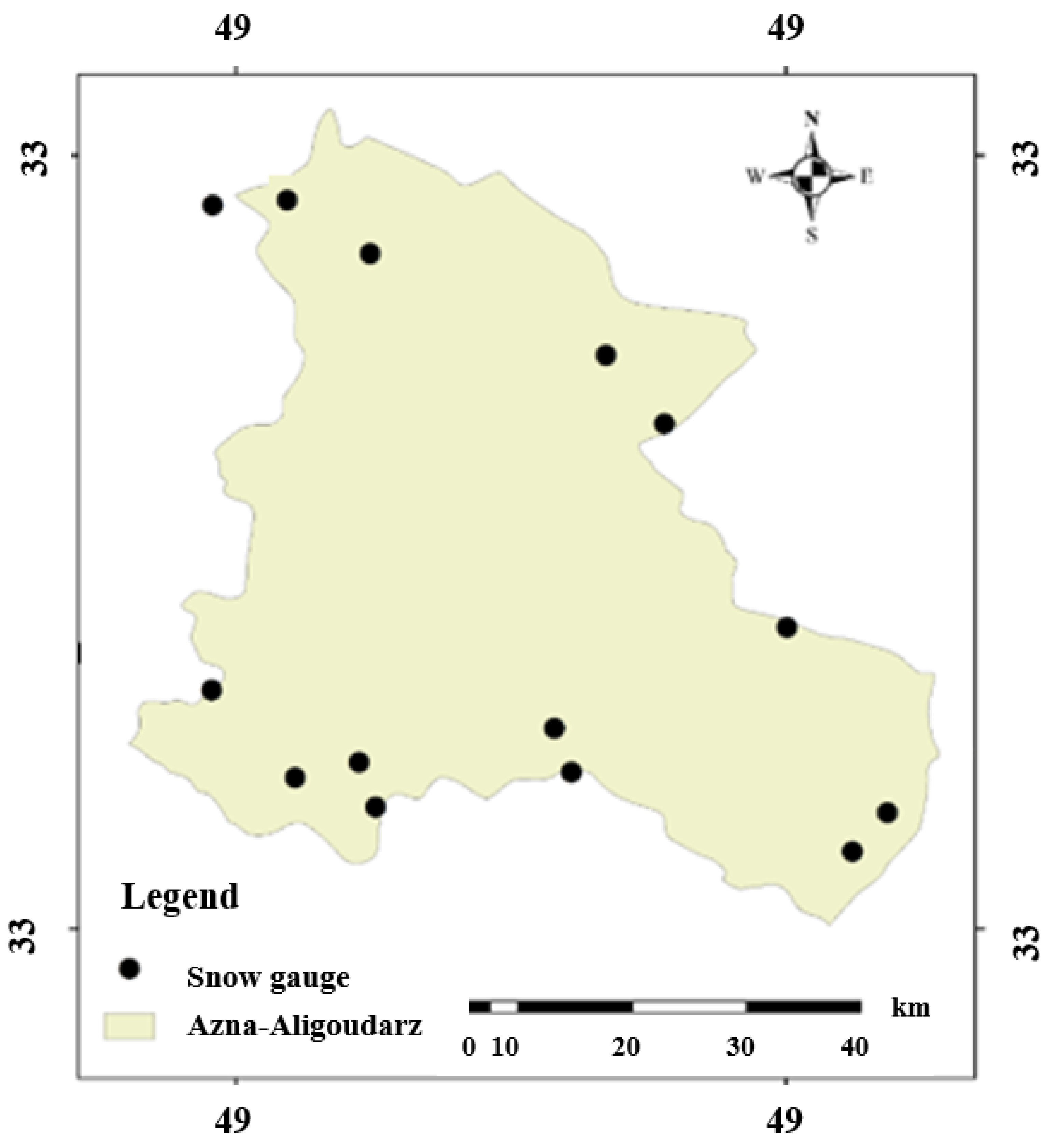
Snow measurement stations

Longitude	Latitude	Elevation (m)	Establishment Year	Station Name
49°41′24″	33°38′24″	2064	1983	Domsiah-Javadieh
49°22′47″	33°22′35″	1912	1974	Vazmeh Dar
49°15′12″	33°24′19″	1996	1974	Qaleh Rostam
49°53′03″	33°14′57″	2468	1983	Khalileh
49°39′46″	33°18′42″	2400	1974	Chahar Cheshmeh
49°29′45″	33°19′10″	2440	1984	Dalouni
49°30′31″	33°17′04″	2330	1974	Aziz Abad
49°52′03″	33°18′32″	2510	1974	Farsesh
49°45′29″	33°56′12″	2141	1983	Bahram Abad
49°44′38″	33°01′32″	2525	1974	Chalghou
49°22′50″	33°45′29″	2336	2001	Palangdar
49°44′10″	33°35′10″	2336	1974	Barfian
49°38′59″	33°20′47″	2260	2001	Ghelavarde
49°49′58″	33°25′33″	2490	1974	Gardaneh Khomein



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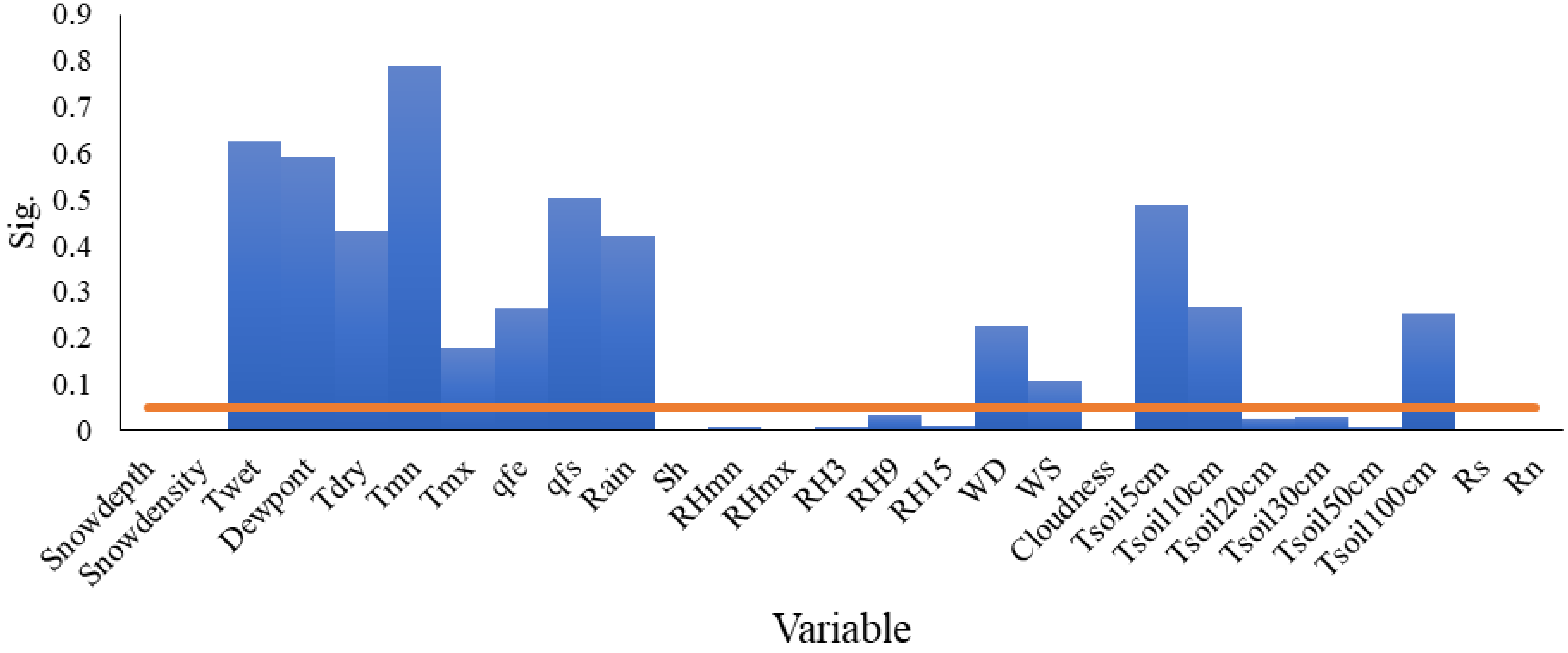
Significance levels of the correlations of various parameters and SWE at the 95% confidence level

These parameters included: snow depth, snow density, wet-bulb temperature, dew point temperature, dry-bulb temperature, minimum and maximum temperature, station pressure, sea-level pressure, precipitation, number of sunshine hours, minimum and maximum relative humidity, relative humidity at 3 a.m., 9 a.m., and 3 p.m., wind speed, wind direction, cloudiness, soil temperature at depths of 5, 10, 20, 30, 50, and 100 cm, total radiation and net radiation, Julian day, and latitude.

Significance levels of the correlations of various parameters and SWE at the 95% confidence level



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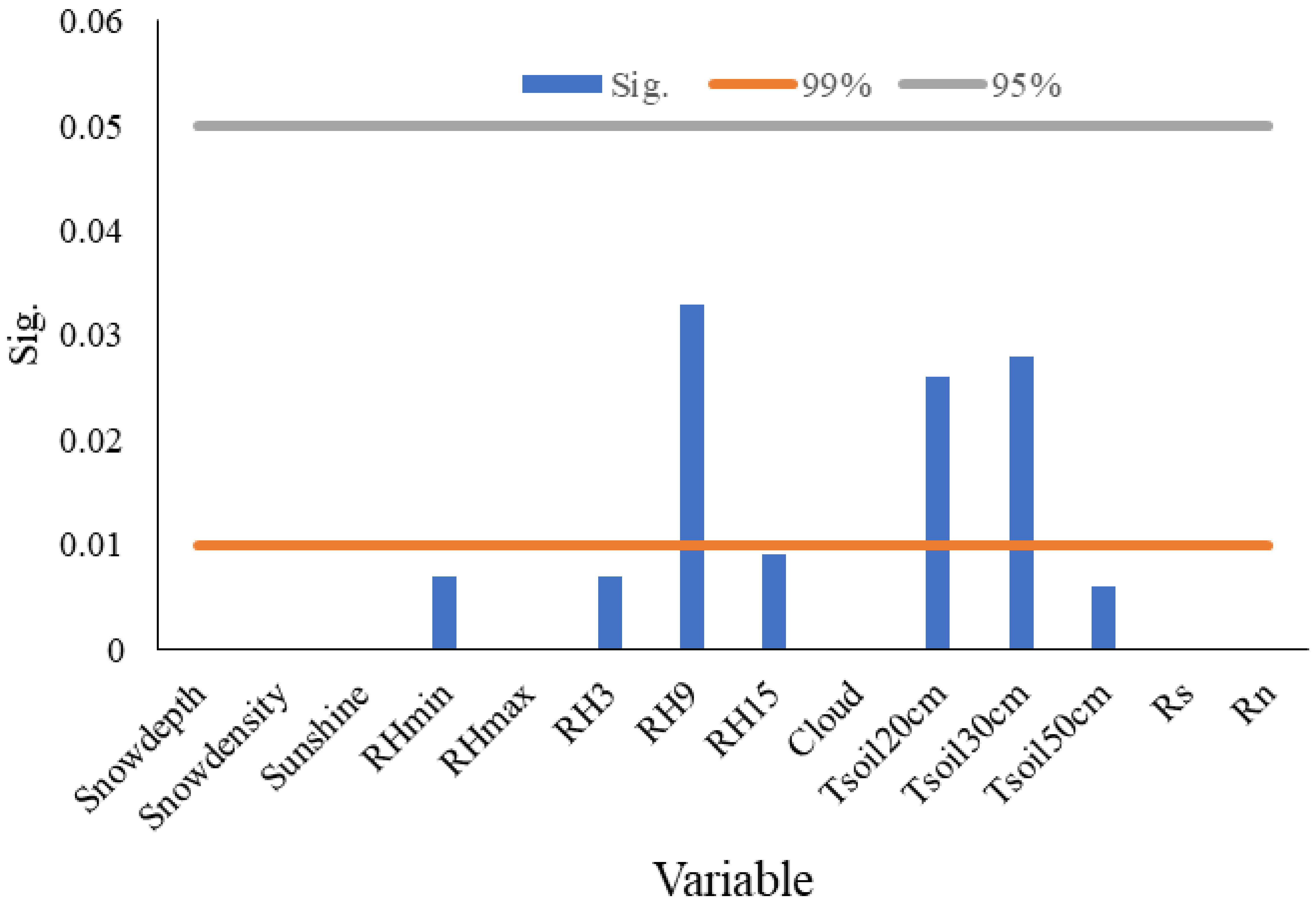
Correlation analysis for the selected parameters (P values below 0.05)

Among these, three parameters had a significant correlation with SWE at the 95% confidence level, while the rest showed significant correlation at the 99% confidence level.

These parameters included: snow depth, snow density, number of sunshine hours, minimum and maximum relative humidity, relative humidity at 3 a.m., 9 a.m., and 3 p.m., cloudiness, soil temperature at depths of 20, 30, and 50 cm, total radiation, and net radiation.



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Modeling input patterns resulting from the correlation test

Based on the results of the correlation test and the impact of various parameters on the SWE, input patterns for the models selected to estimate SWE were determined. For this purpose, 11 input patterns were considered for modeling. The table shows these 11 input patterns used for modeling.

Pattern	Name
['Snowdepth']	M1
['Snowdepth', 'Snowdensity']	M2
['Snowdepth', 'Snowdensity', 'Rhmax']	M3
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness']	M4
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs']	M5
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh']	M6
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn']	M7
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn', 'TmeanSoil50cm']	M8
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn', 'TmeanSoil50cm', 'RH3']	M9
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn', 'TmeanSoil50cm', 'RH3', 'Rhmin']	M10
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn', 'TmeanSoil50cm', 'RH3', 'Rhmin', 'TmeanSoil30cm']	M11

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Tested AI models

- **Stepwise Regression (SR) Model**

This method allows for the simultaneous analysis and examination of multiple predictor variables.

- **Gene Expression Programming (GEP)**

GEP is a hybrid and extended method combining Genetic Algorithms (GA) and Genetic Programming (GP), introduced by Ferreira in 1999. In this method, simple linear chromosomes of fixed length, similar to those in Genetic Algorithms, are combined with branching structures of varying sizes and shapes, similar to parse trees in Genetic Programming.

- **Group Method of Data Handling (GMDH) Algorithm**

Rosenblatt introduced the concept of the perceptron in 1958 based on the functioning of neurons (Nasrolahi et al., 2025). GMDH is a combination of neurons, and its modified versions have been applied for various modeling purposes.

- **Bayesian Regression Model (BR)**

In this study, the BR model is used as a probabilistic method for uncertainty analysis and predicting the behavior of variables affecting SWE. BR is an extension of classical regression that, by considering probability distributions for the model coefficients, allows better uncertainty analysis and provides more robust estimates.

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GMDH Model

Features	Pattern
['Snowdepth', 'Snowdensity']	M1
['Snowdepth', 'Snowdensity', 'Rhmax']	M2
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness']	M3
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs']	M4
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh']	M5
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn']	M6
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn', 'TmeanSoil50cm']	M7
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn', 'TmeanSoil50cm', 'RH3']	M8
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn', 'TmeanSoil50cm', 'RH3', 'Rhmin']	M9
['Snowdepth', 'Snowdensity', 'Rhmax', 'Cloudness', 'Rs', 'Sh', 'Rn', 'TmeanSoil50cm', 'RH3', 'Rhmin', 'TmeanSoil30cm']	M10

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Best results (M10 from MGDH)

Rs = total radiation (millijoules per square centimeter per day),
Sh = number of sunshine hours (hours),
Rn = net radiation (watts per square meter),
Tsoil30cm = average soil temperature at 30 cm depth (°C),
Tsoil50cm = average soil temperature at 50 cm depth (°C),
Snowdepth = snow depth (cm),
Snowdensity = snow density (grams per cubic centimeter),
Cloudness = cloudiness percentage (%),
RHmax = maximum relative humidity (%),
RH3 = relative humidity at 3 a.m. (%),
RHmin = minimum relative humidity (%).

Equation	Pattern
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M1
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M2
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M3
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M4
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M5
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M6
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M7
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M8
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M9
SWE = -0.0040 + 0.0002 * (Snowdepth) + 0.0002 * (Snowdensity) + 0.0100 * (Snowdepth*Snowdensity) + -0.0000 * (Snowdepth^2) + -0.0000 * (Snowdensity^2)	M10

Selected SWE equation

$$\text{SWE} = -0.0040 + 0.0002 * (\text{Snowdepth}) + 0.0002 * (\text{Snowdensity}) + 0.0100 * (\text{Snowdepth} * \text{Snowdensity}) + -0.0000\ 1 * (\text{Snowdepth}^2) + -0.00001 * (\text{Snowdensity}^2)$$

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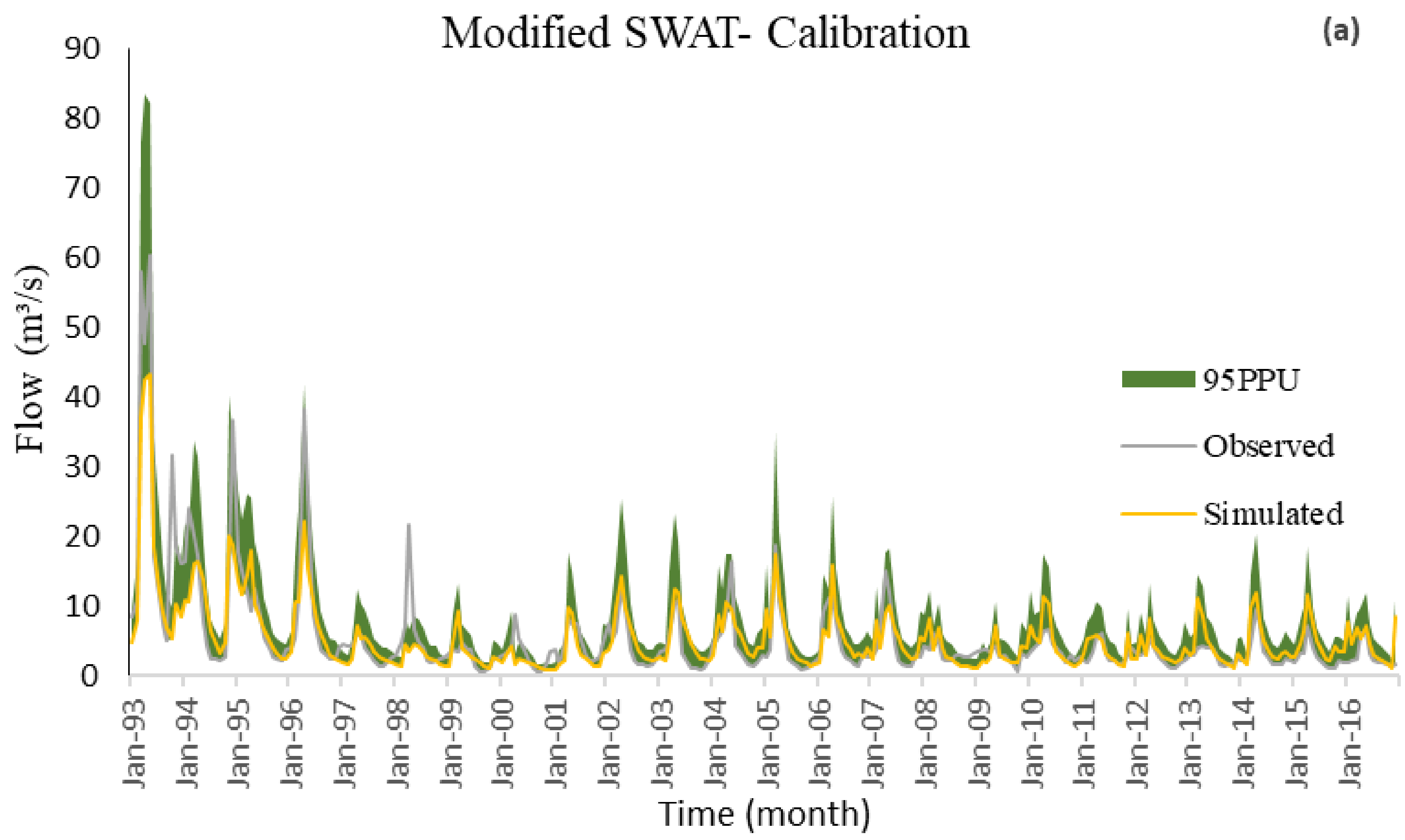
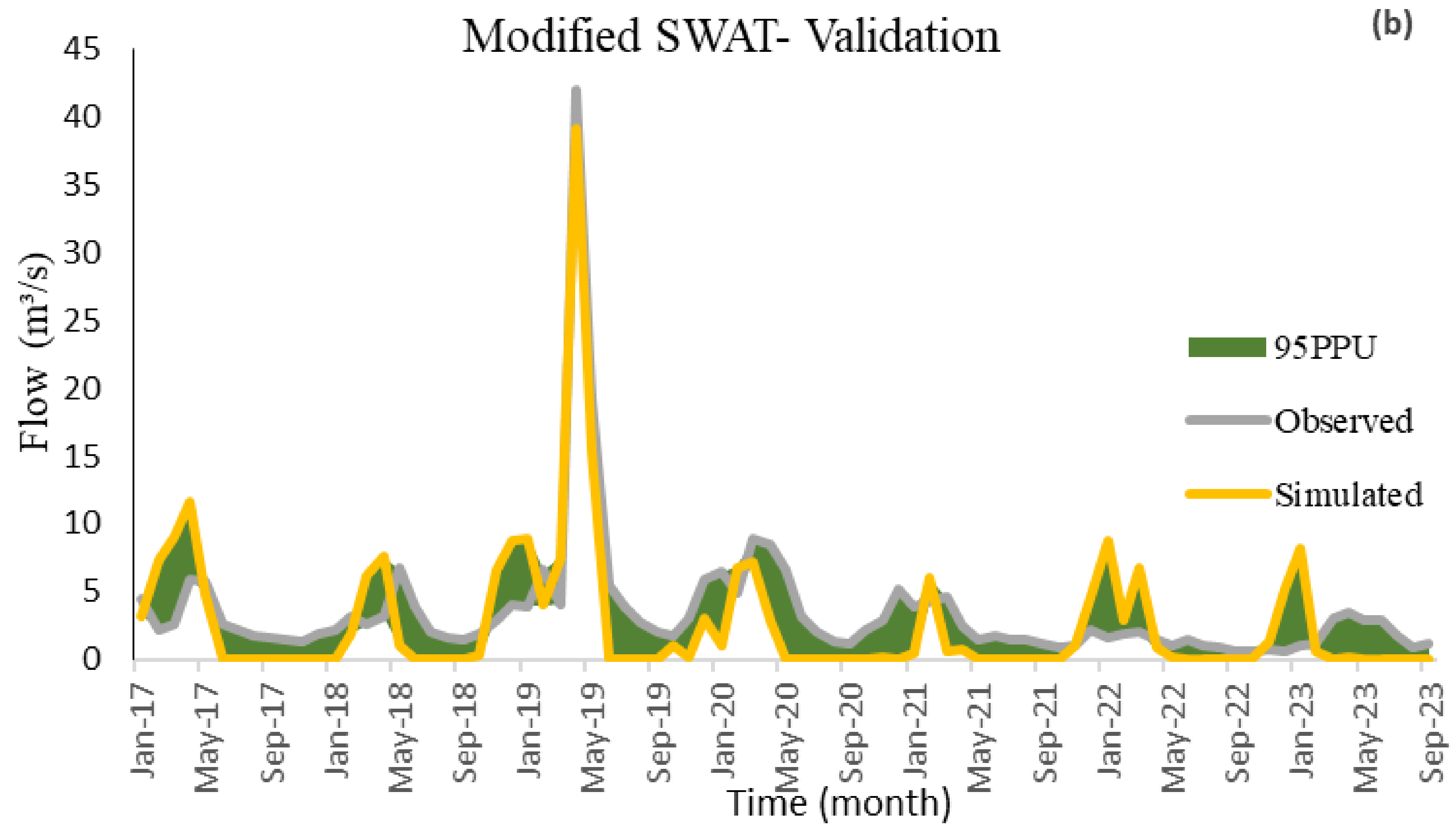
Calibrated parameters

Parameter	Opt.	Min.	Max.	Var. Type
SFTMP.bsn	5.75	5.6	5.9	Replace
TLAPS.sub	−9.72	−9.72	−9.72	Replace
SMTMP.bsn	−9.89	−9.89	−9.89	Replace
SNOCOVMX.bsn	−35.03	−35.15	−35.02	Replace
CH_K2.rte	37.2	36.8	55.6	Replace
REVAPMN.gw	1.34	1.32	1.56	Replace
CN2.mgt	0.03	0.01	0.07	Multiply
SOL_BD(..).sol	−0.52	−0.52	−0.52	Multiply
ALPHA_BNK.rte	0.04	0.04	0.04	Replace
GWQMN.gw	1.72	1.71	1.83	Replace
OV_N.hru	−0.01	−0.02	−0.01	Multiply
GW_REVAP.gw	0.02	0.00	0.03	Replace
ALPHA_BF.gw	0.18	0.18	0.19	Replace
PLAPS.sub	−13.34	−13.34	−13.34	Replace
SLSUBBSN.hru	0.22	0.22	0.22	Multiply
GW_DELAY.gw	305.03	304.83	305.59	Replace
SURLAG.bsn	14.76	14.76	14.76	Replace
ESCO.hru	0.98	0.8	1.00	Replace
SNOEB(..).sub	310.65	310.64	310.64	Replace
CH_N2.rte	0.16	0.01	0.2	Replace
SOL_AWC(..).sol	-0.05	-0.09	-0.05	Multiply

Calibration and validation of modified SWAT





	R^2	NS	r-Factor	p-Factor	R^2	NS	r-Factor	p-Factor
SWAT	0.32	0.28	0	0.14				
Modified SWAT	0.65	0.68	0.21	0.73	0.72	0.74	0.46	0.52

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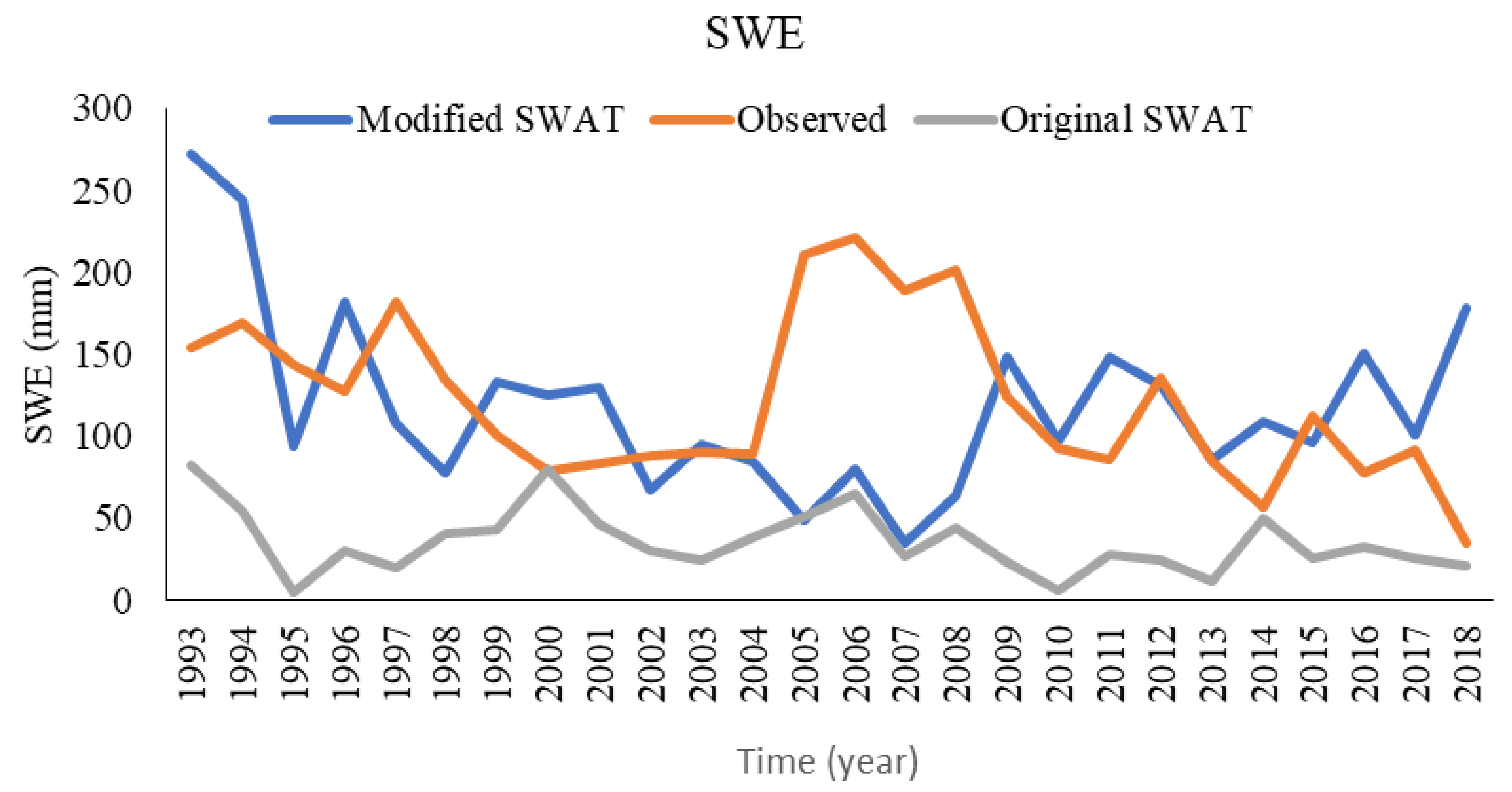
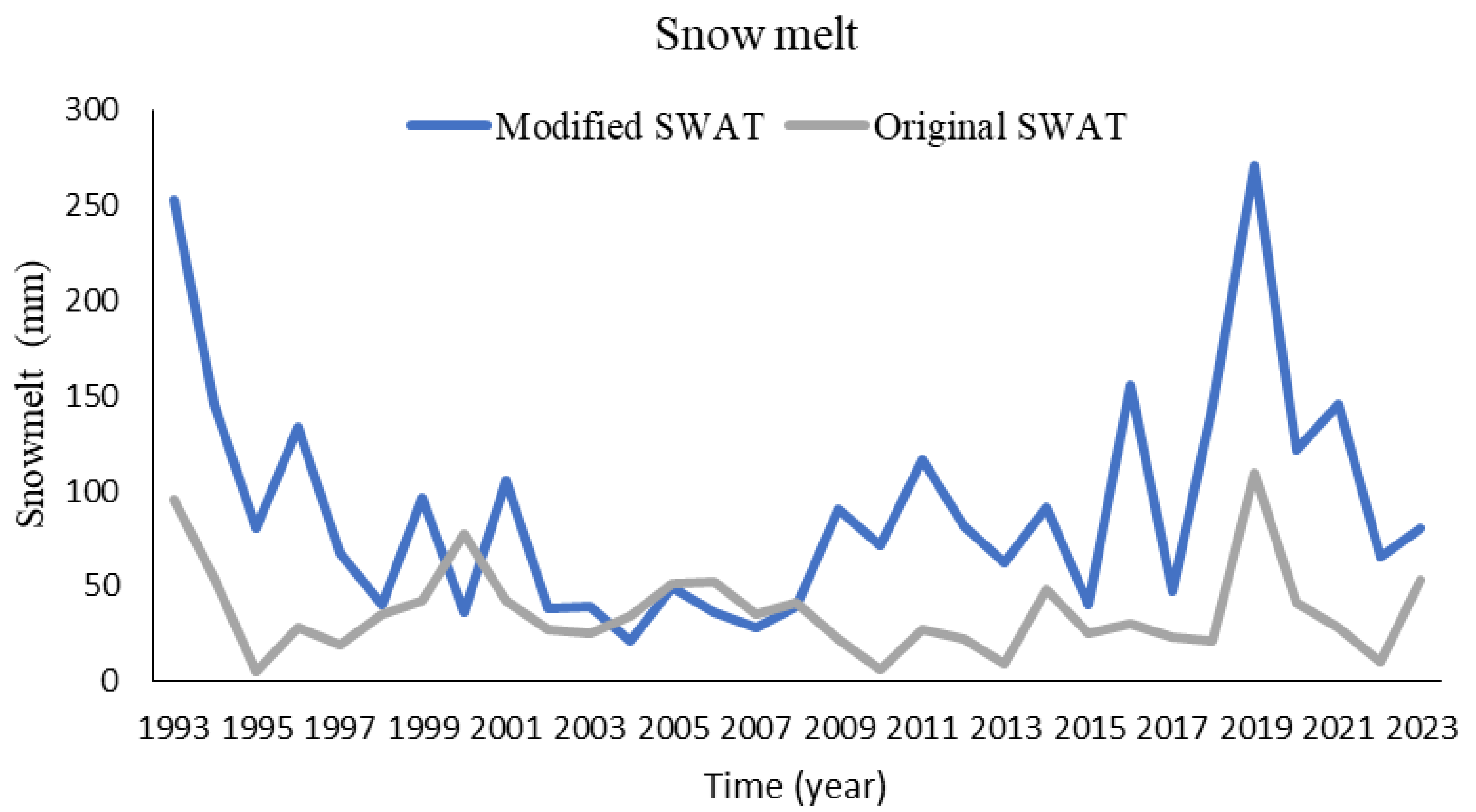
Comparison of simulated and observed SWE and snowmelt





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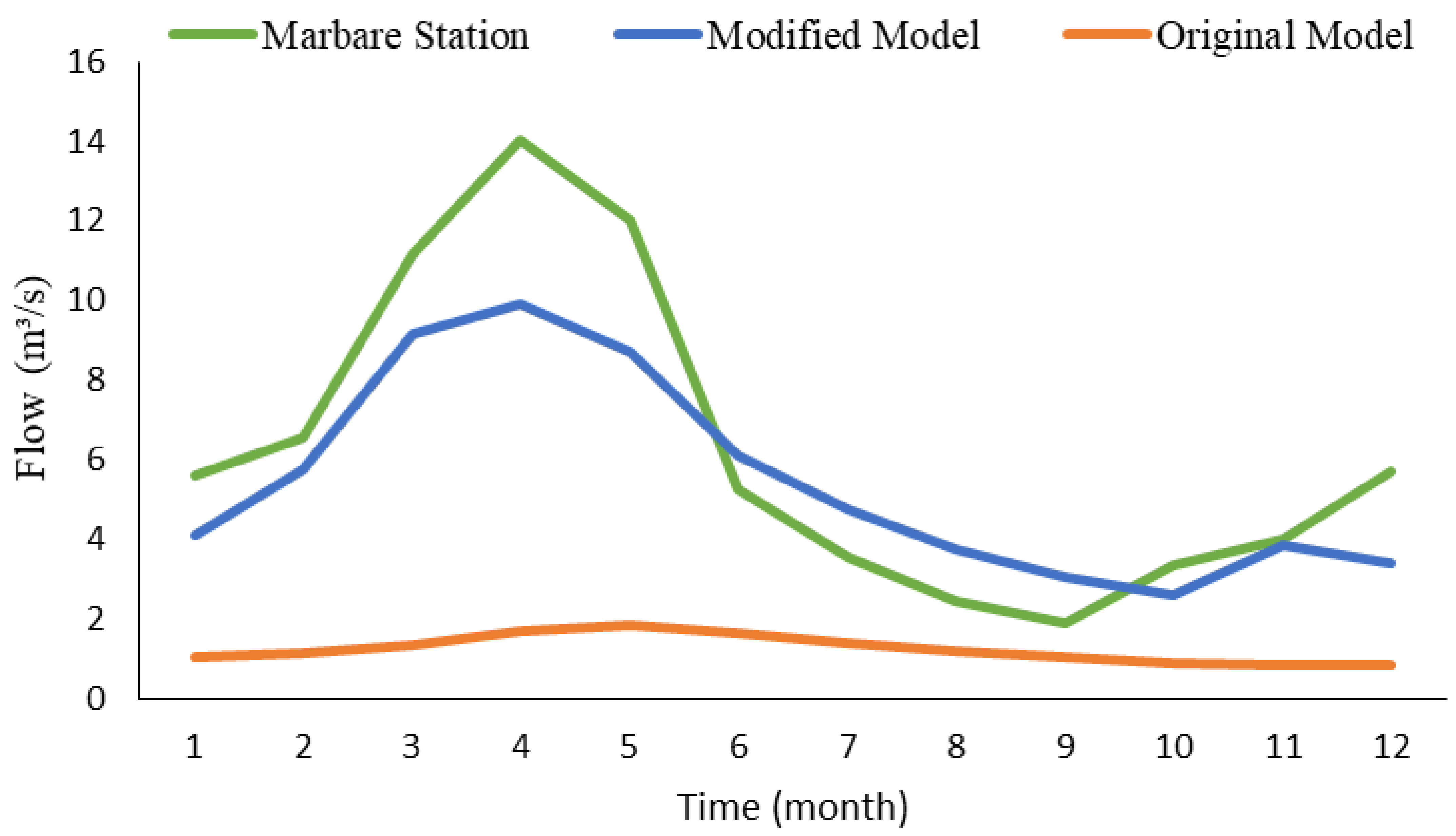
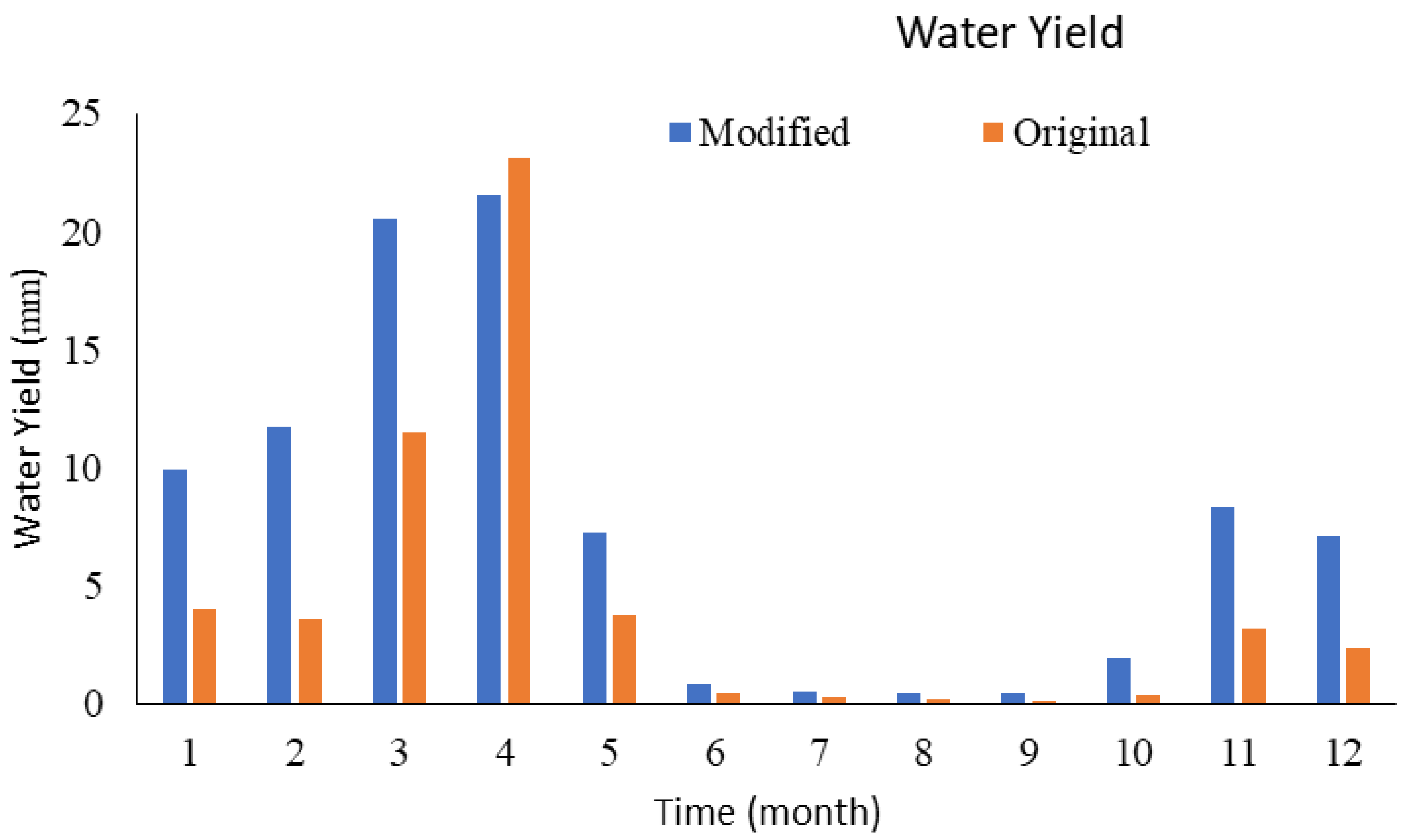
Montly flow and water yield





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Conclusions

Based on the correlation analysis and the eleven identified patterns, the parameters that significantly affect SWE at the 95% confidence level are snow depth and snow density (GMDH AI model).

The SWAT model's performance in simulating snow processes, runoff, and discharge improved after the modifications.

Some limitations remain, particularly during hot seasons with no rainfall events, when the model tends to underestimate flow.

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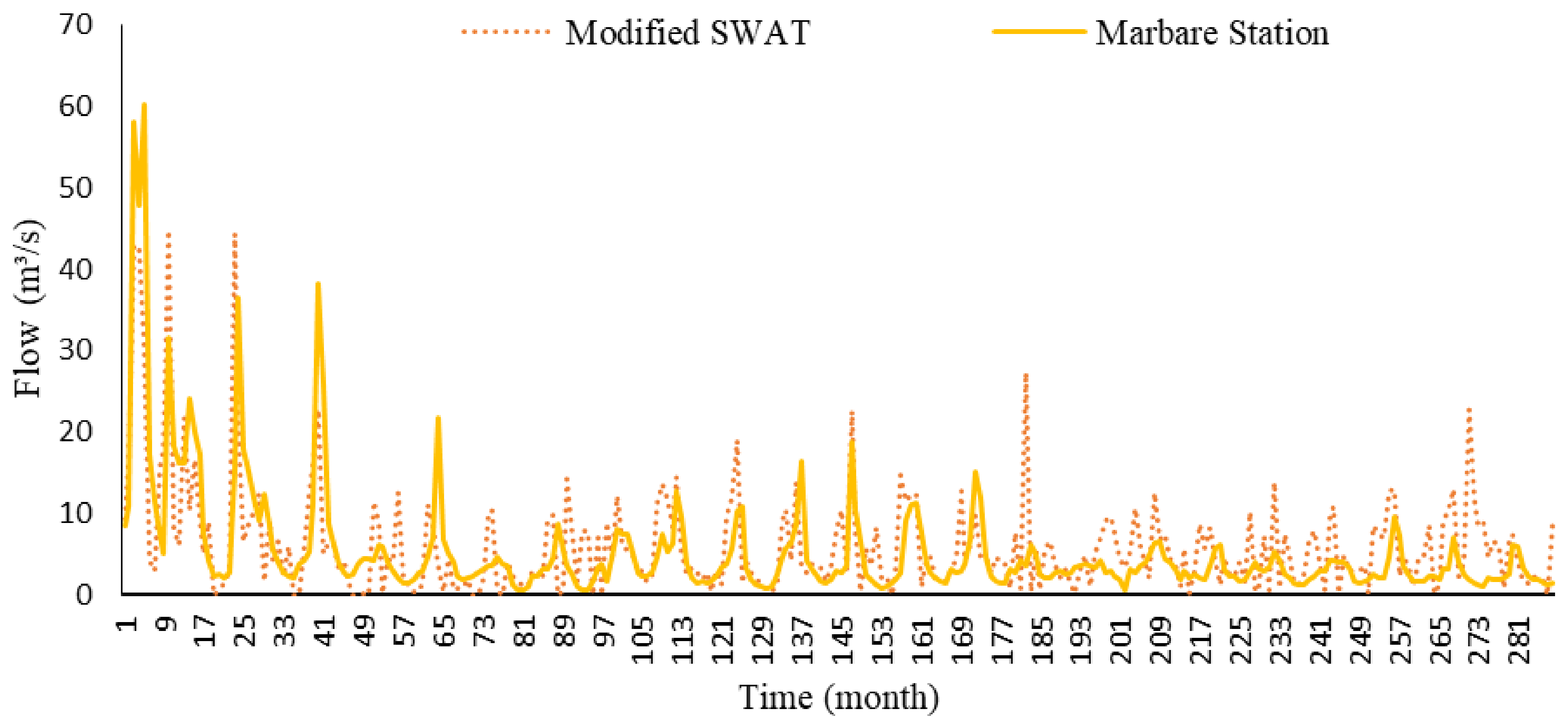
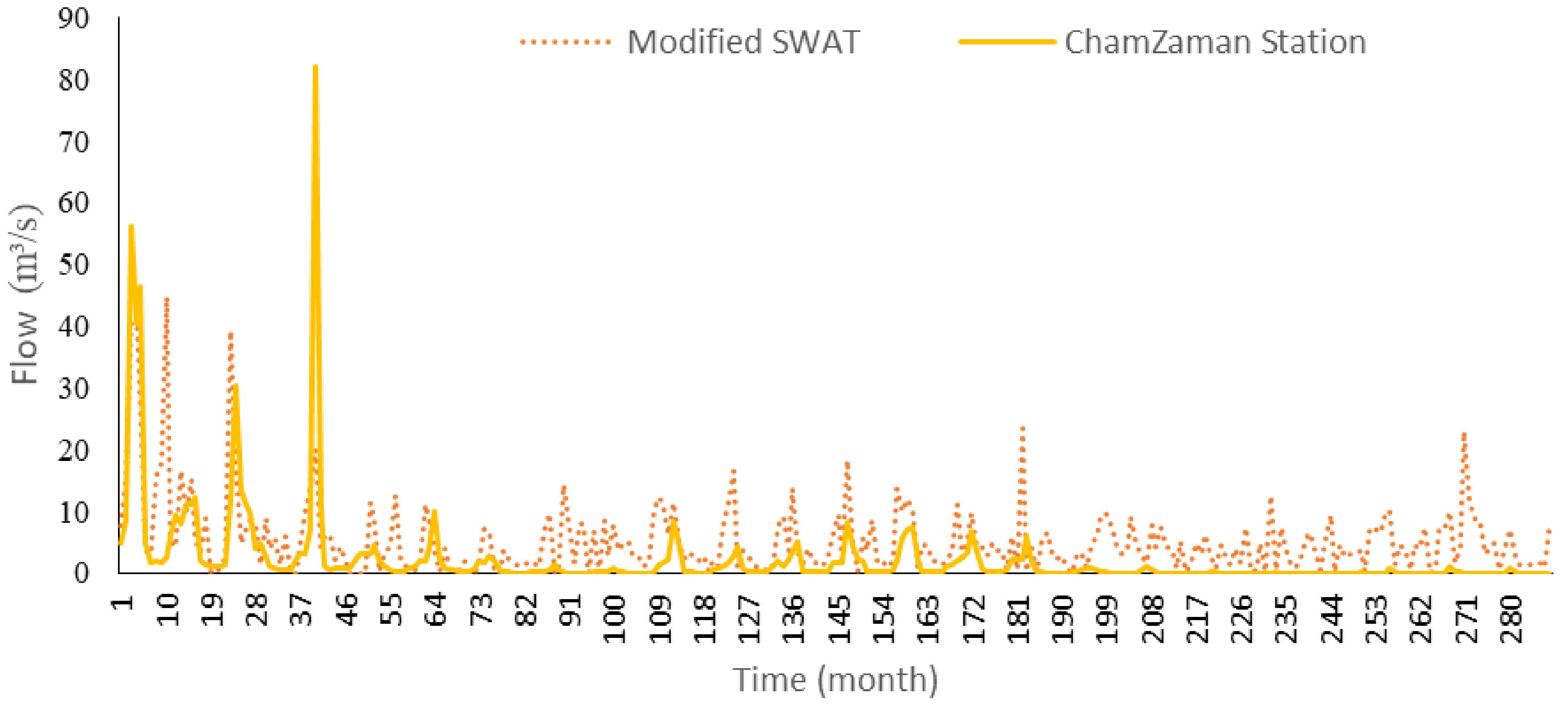
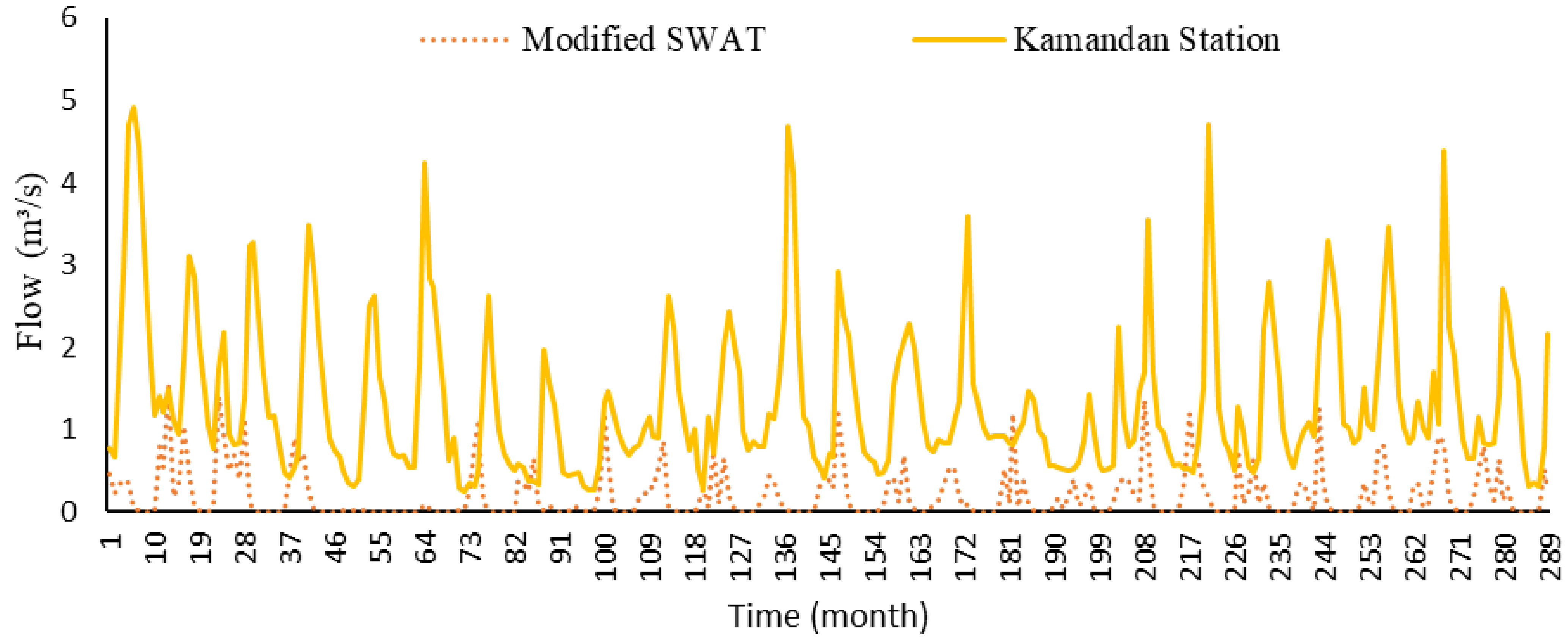
Thank you! Any questions?

Simulated and observed flow in different stations







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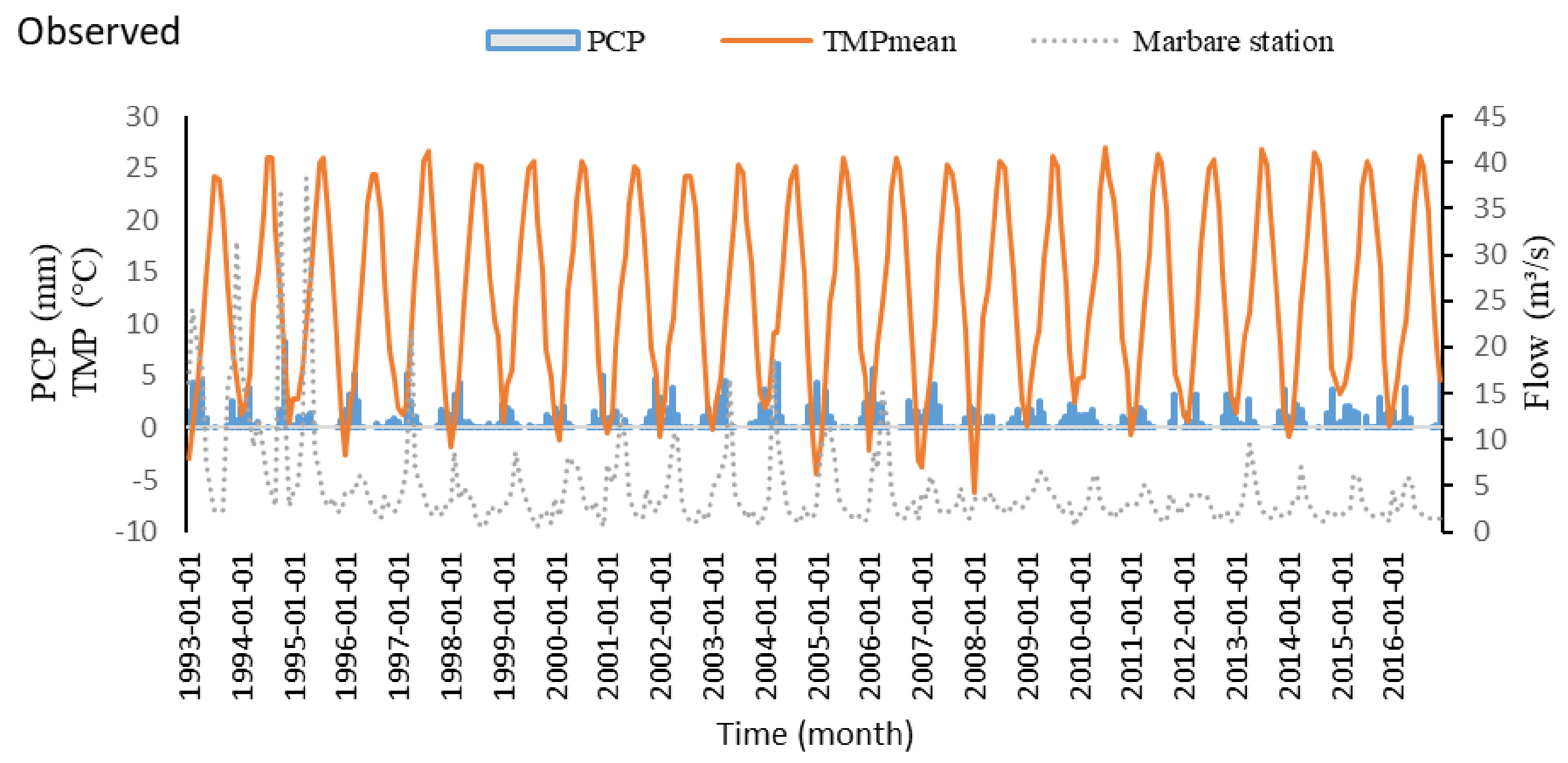
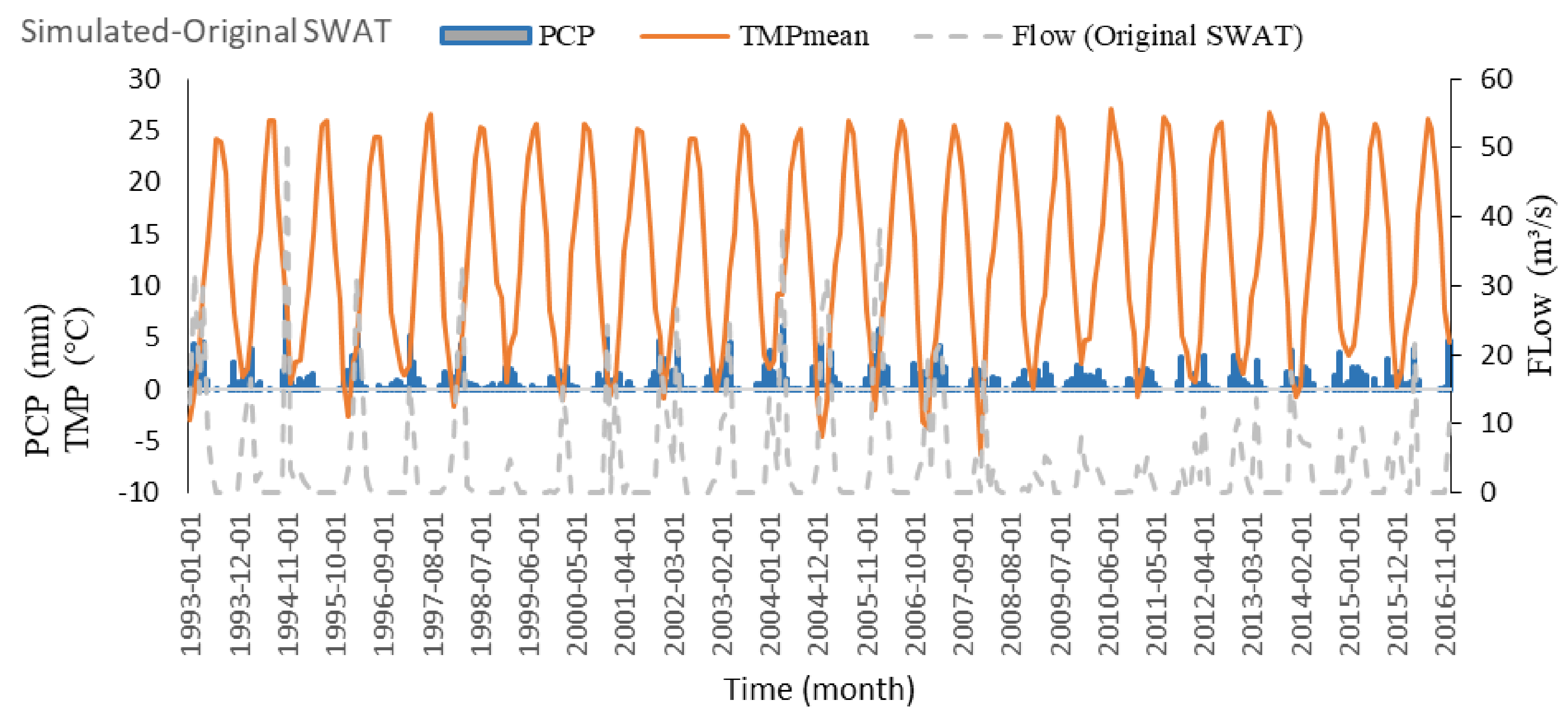
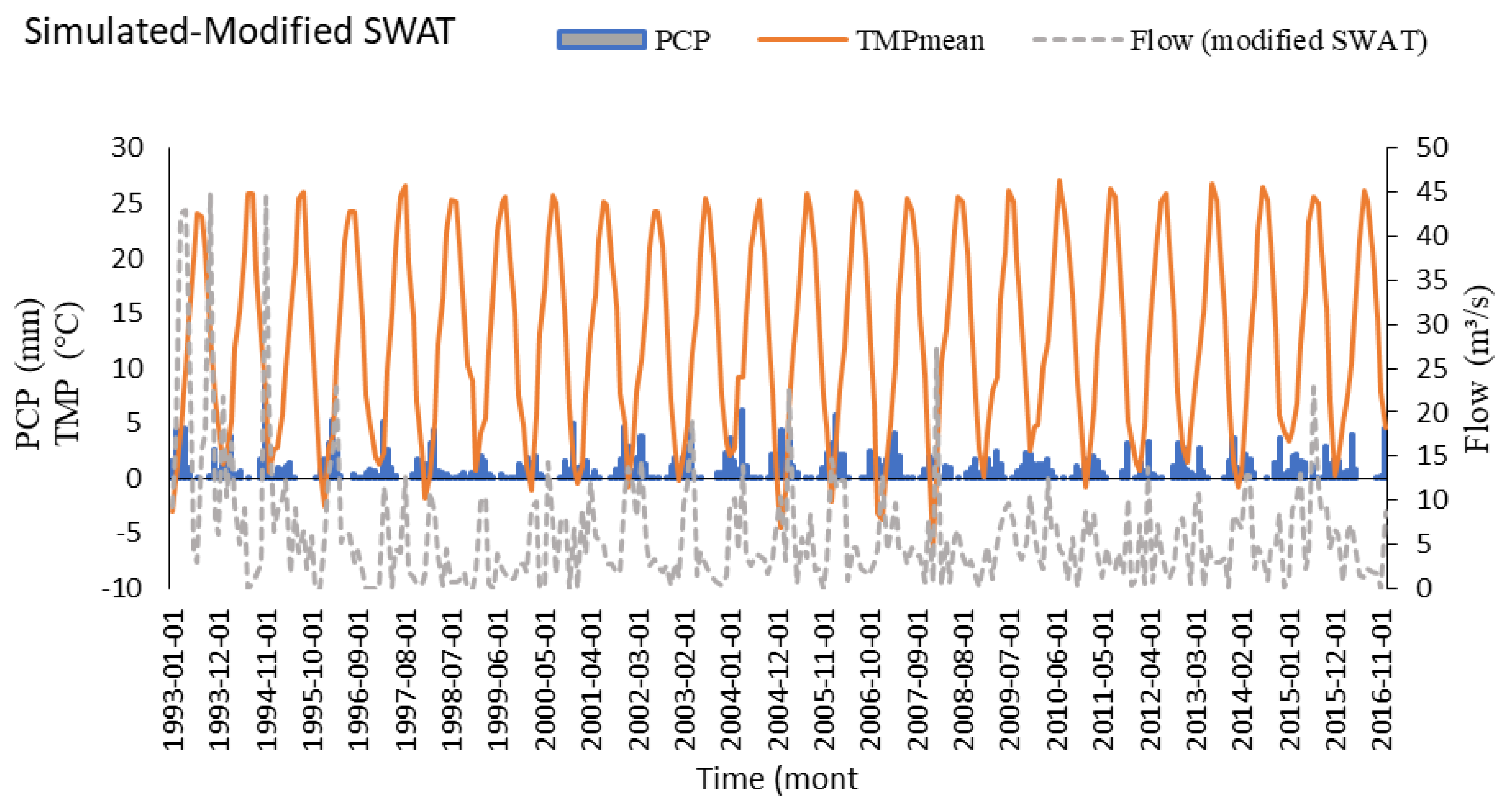
and Observed and simulated flow in SWAT and Modified SWAT







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