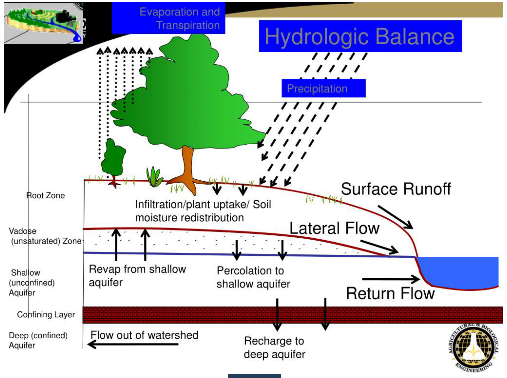
Coupling SWAT+ with LSTM for improved streamflow estimation in the Tagus Headwaters River Basin, Spain

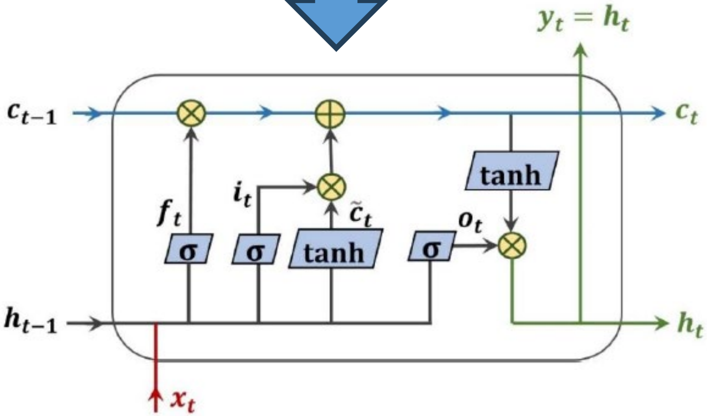
Sara Asadi, Patricia Jimeno-Saez, Adrián López-Ballesteros, Javier Senent-Aparicio

Department of Civil Engineering, Catholic University of San Antonio, Campus de Los Jeronimos s/n, 30107 Guadalupe, Murcia, Spain s.asadi370@gmail.com; sasadi@alu.ucam.edu

Objective

- Improving streamflow simulation accuracy
- Using both conceptual hydrological models and machine learning based data driven models
- SWAT: one of the process based models extensively used in the management of water resources
- LSTM AI-based model: there are studies show that LSTM model has outperformed SWAT model in simulating runoff





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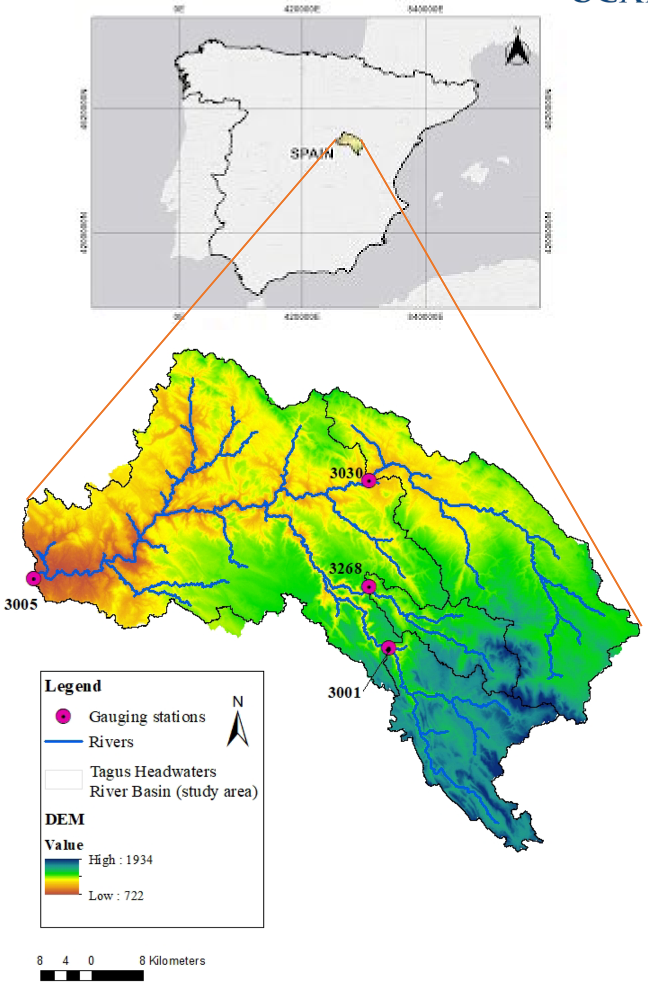
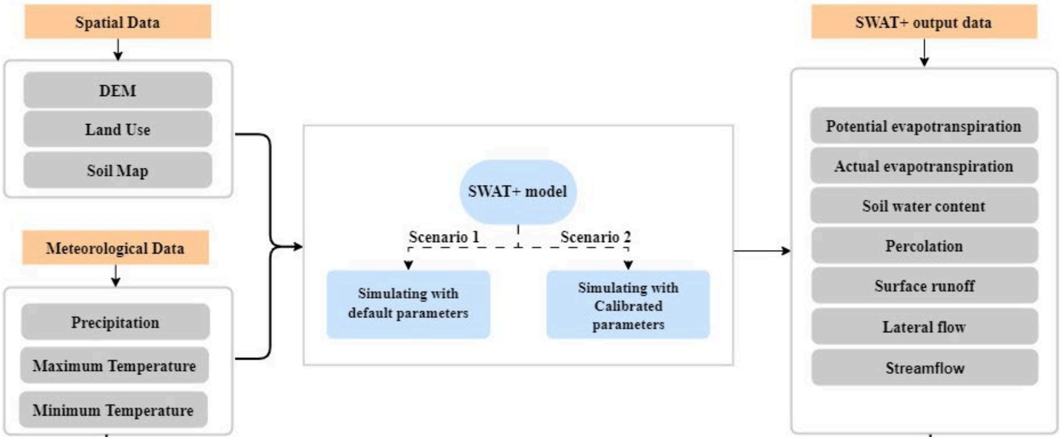
Case study

- Tagus Headwaters River Basin (THRB), Spain
- One of the most regulated rivers in Europe
- Tagus-Segura water transfer: Beyond meeting local water demands, it also diverts a portion of its supply to the Segura River Basin
- Total area of the study area: 3200 km2
- Four gauging stations recording daily flow data were utilized to determine the outlet locations for four catchments



Methodology

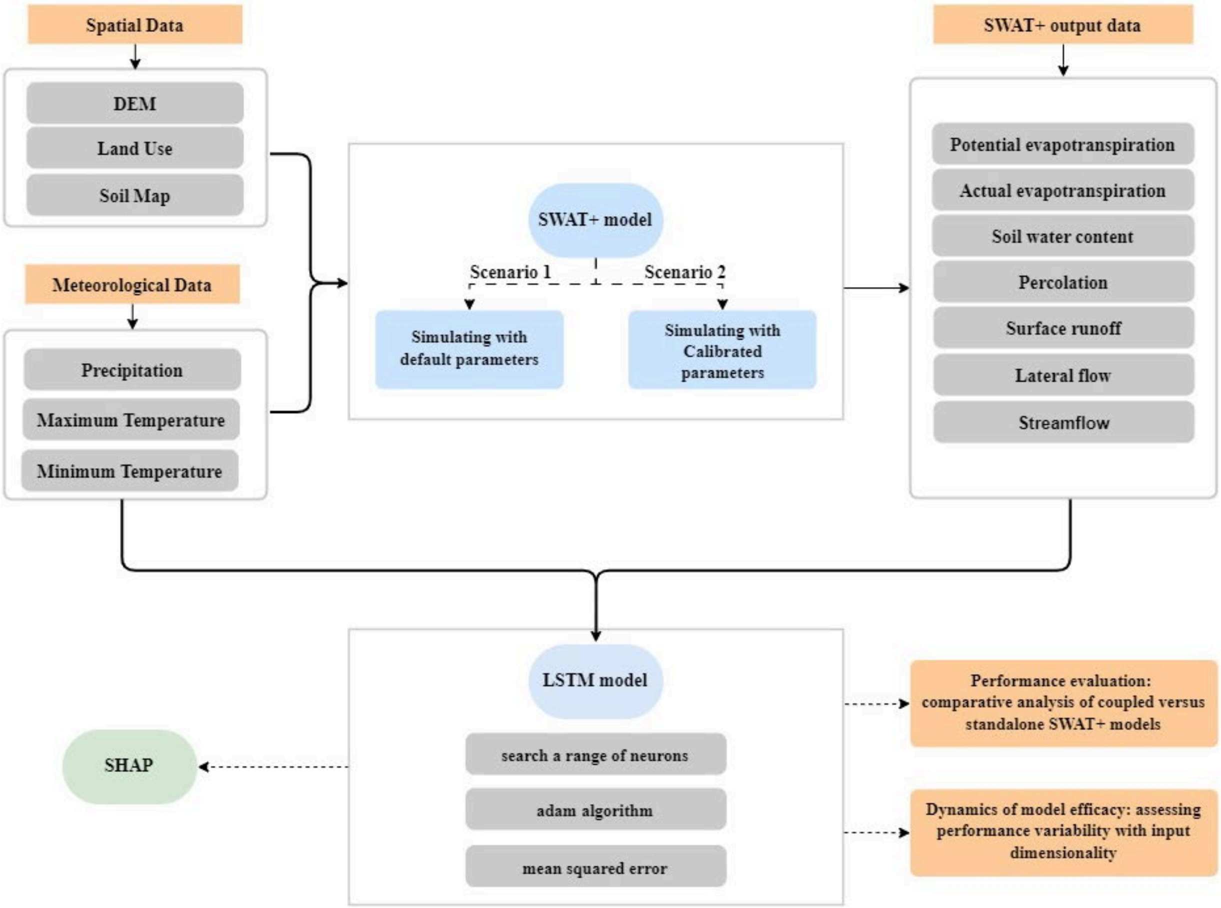
- Four different SWAT+ models for every station upstream
- Warm-up period: 1985-1989
- Calibration period: 1990-2005
- Validation period: 2006-2020
- Automatic sensitivity analysis and calibration: SWATplusCUP



Number	Parameter	Range	Gauging stations				Rank
			3001	3005	3030	3268	
	Hydrologic parameters						
1	Initial SCS curve number II (CN2)	±30%	-21.85%	-25.14%	-26.69%	-23.13%	1
2	Percolation coefficient (perco)	0-1	0.98	0.88	0.19	0.91	3
3	Slope length for lateral subsurface flow (lat_len)	1-150	92.77	109.37	62.81	73.97	5
4	Soil evaporation factor (esco)	0-1	0.49	0.55	0.83	0.36	7
5	Plant uptake factor (epco)	0-1	0.77	0.08	0.30	0.73	8
6	Manning coefficient of the main channel (chn)	0.01-0.3	0.29	0.10	0.11	0.20	11
7	Manning "n" value for surface flux (ovn)	0.01-30	2.46	10.21	10.02	26.31	12
	Soil parameters						
8	Bulk soil density (BD)	±30%	-17.47%	-3.31%	-11.71%	-4.32%	2
9	Available water capacity of the soil layer (awc)	±30%	-17.80%	9.48%	-12.64%	6.55%	14
	Groundwater parameters						
10	Specific yield (sp_yld)	0-0.5	0.33	0.25	0.05	0.04	4
11	Groundwater storage threshold for return flow to occur (flo_min)	0-10	6.21	9.98	4.99	6.73	6
12	Groundwater "revap" coefficient (revap_co)	0.02-0.2	0.11	0.19	0.11	0.20	9
13	Alpha factor for the aquifer recession curve (alpha)	0-1	0.72	0.70	0.81	0.85	10
14	Threshold of water depth in the shallow aquifer required to allow revap (revap_min)	0-10	5.80	5.55	2.26	2.86	13

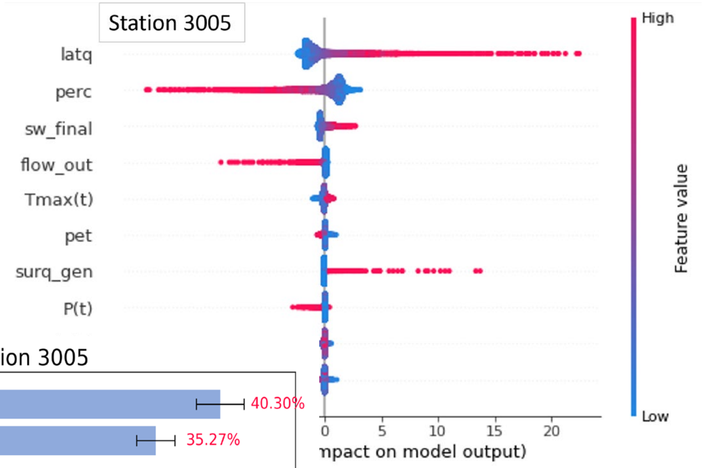
Methodology

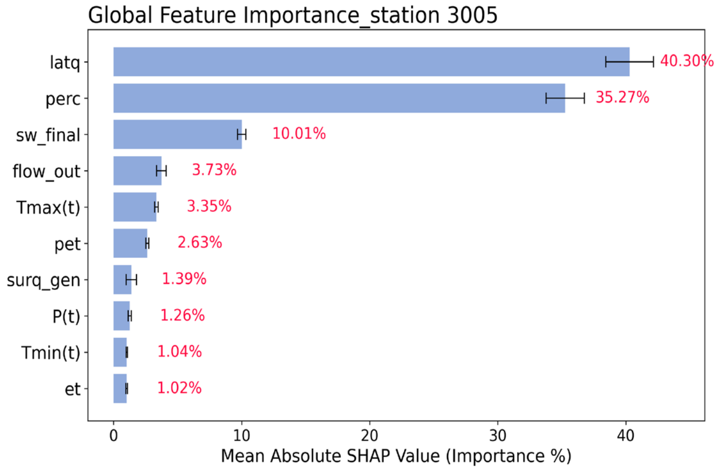
- Search a range of neurons {2, 4, 6, 8, 16, 32, 64}
- Batch size: 16
- Epoches: 100
- Adam optimization algorithm
- Loss function: mean squared error



Methodology

- Performance evaluation: NSE, RMSE, MAE, PBIAS
- Shapley Additive Explanation (SHAP) methodology: how each input feature contributes to the prediction
- SHAP: Addressing the criticism regarding the black box nature of AI-based models
- SHAP value plots and global feature importance plots



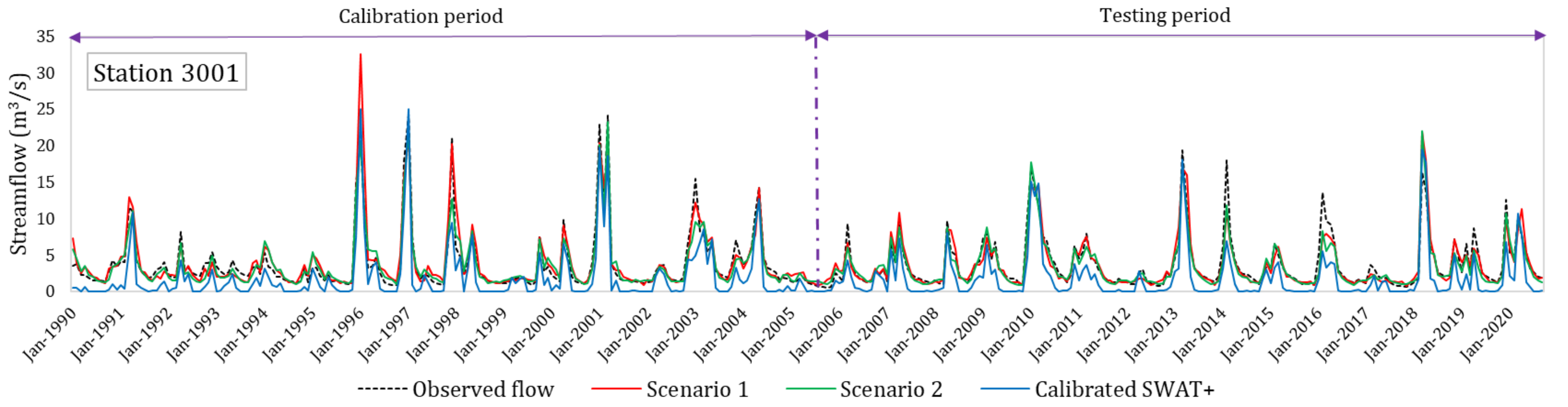


Results

Performance evaluation

Station 3001

Station 3001	Statistics	SWAT+ daily	Scenario 1	Scenario 2
Calibration	NSE	0.44	0.68 ± 0.02	0.76 ± 0.04
	PBIAS (%)	49.24	1.31 ± 4.93	0.21 ± 3.93
Validation	NSE	0.30	0.75	0.68
	PBIAS (%)	51.72	-2.07	-4.77

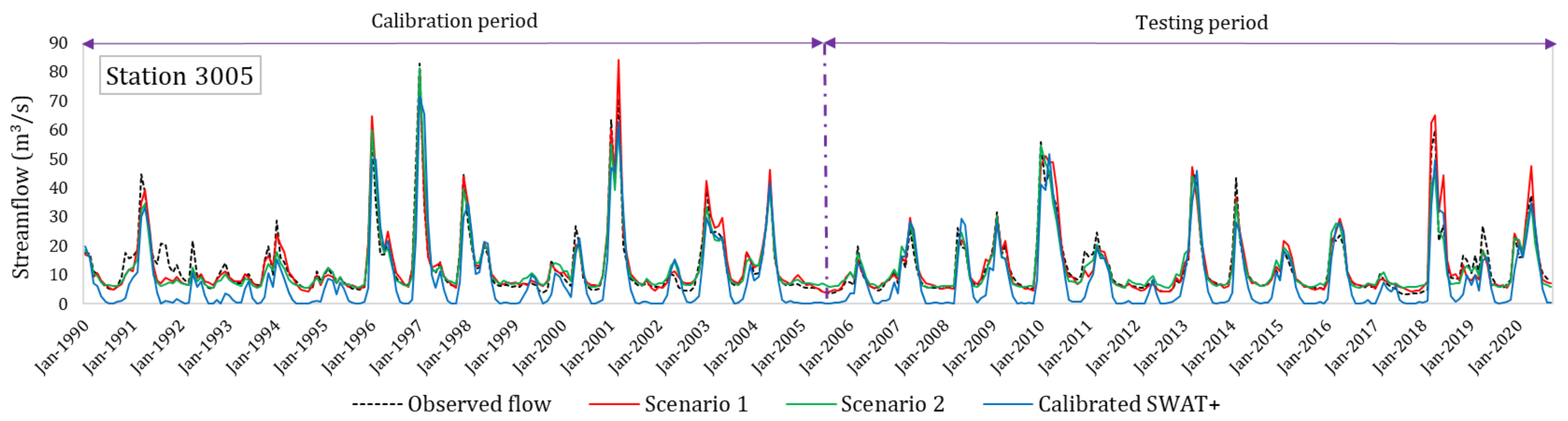


Results

Performance evaluation

Station 3005

Station 3005	Statistics	SWAT+ daily	Scenario 1	Scenario 2
Calibration	NSE	0.49	0.86 ±0.02	0.82 ±0.02
	PBIAS (%)	35.08	-0.67 ±2.14	1.24 ±1.24
Validation	NSE	0.51	0.81	0.79
	PBIAS (%)	31.97	5.86	-4.93

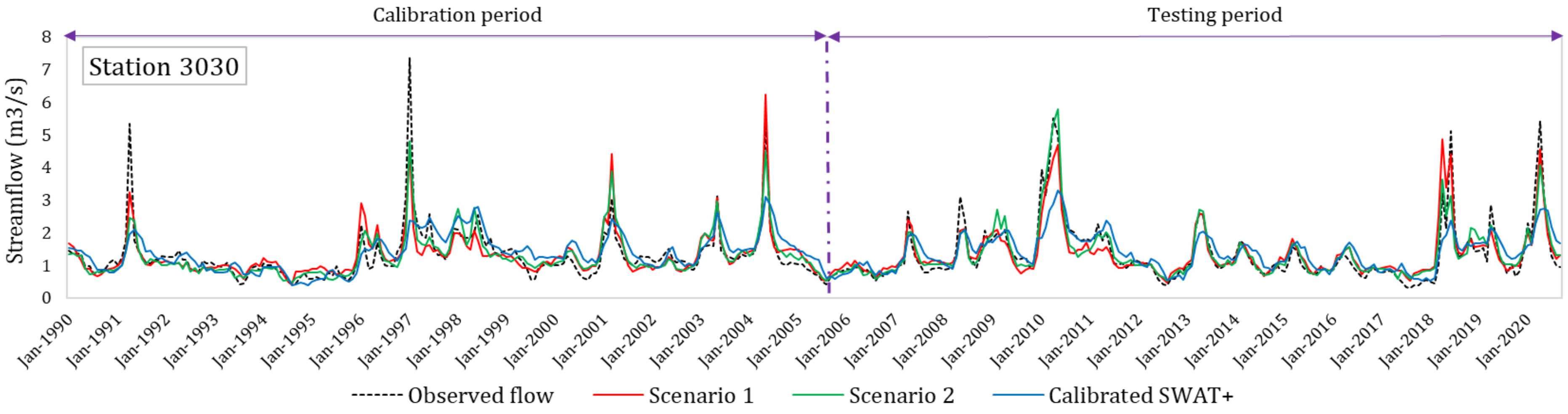


Results

Performance evaluation

Station 3030

Station 3030	Statistics	SWAT+ daily	Scenario 1	Scenario 2
Calibration	NSE	0.21	0.71 ±0.01	0.62 ±0.03
	PBIAS (%)	-6.91	0.42 ±1.59	-0.23 ±0.83
Validation	NSE	0.28	0.62	0.55
	PBIAS (%)	-3.12	9.66	6.88

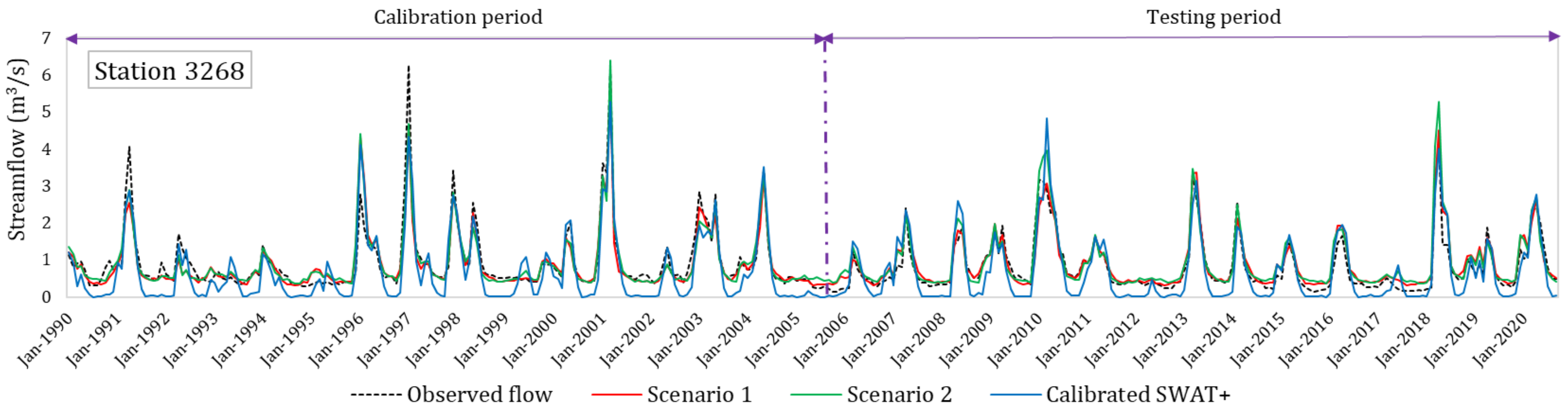


Results

Performance evaluation

Station 3268

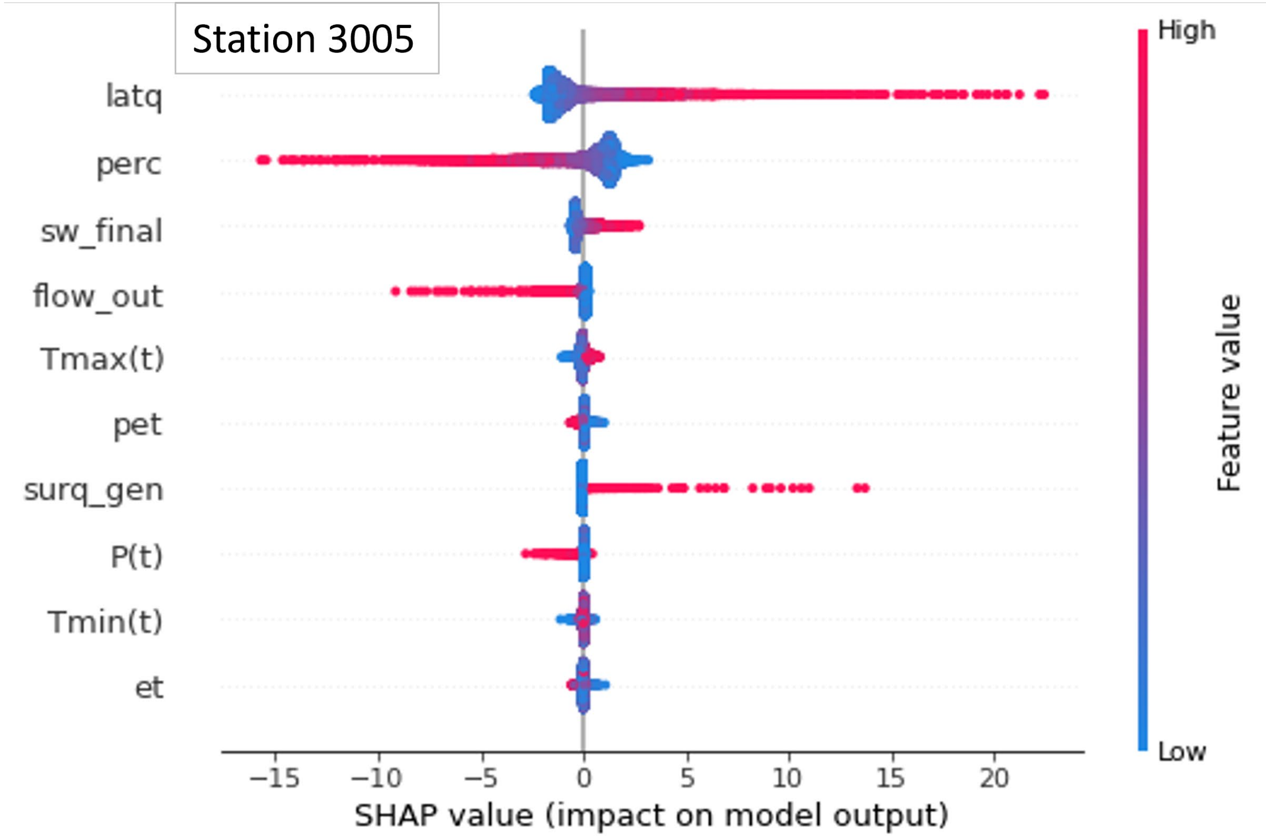
Station 3268	Statistics	SWAT+ daily	Scenario 1	Scenario 2
Calibration	NSE	0.49	0.75 ±0.02	0.79 ±0.02
	PBIAS (%)	29.19	-1.30 ±3.54	-1.73 ±2.37
Validation	NSE	0.39	0.71	0.78
	PBIAS (%)	17.44	19.57	21.36



Results

SHAP interpretation results for scenario 1

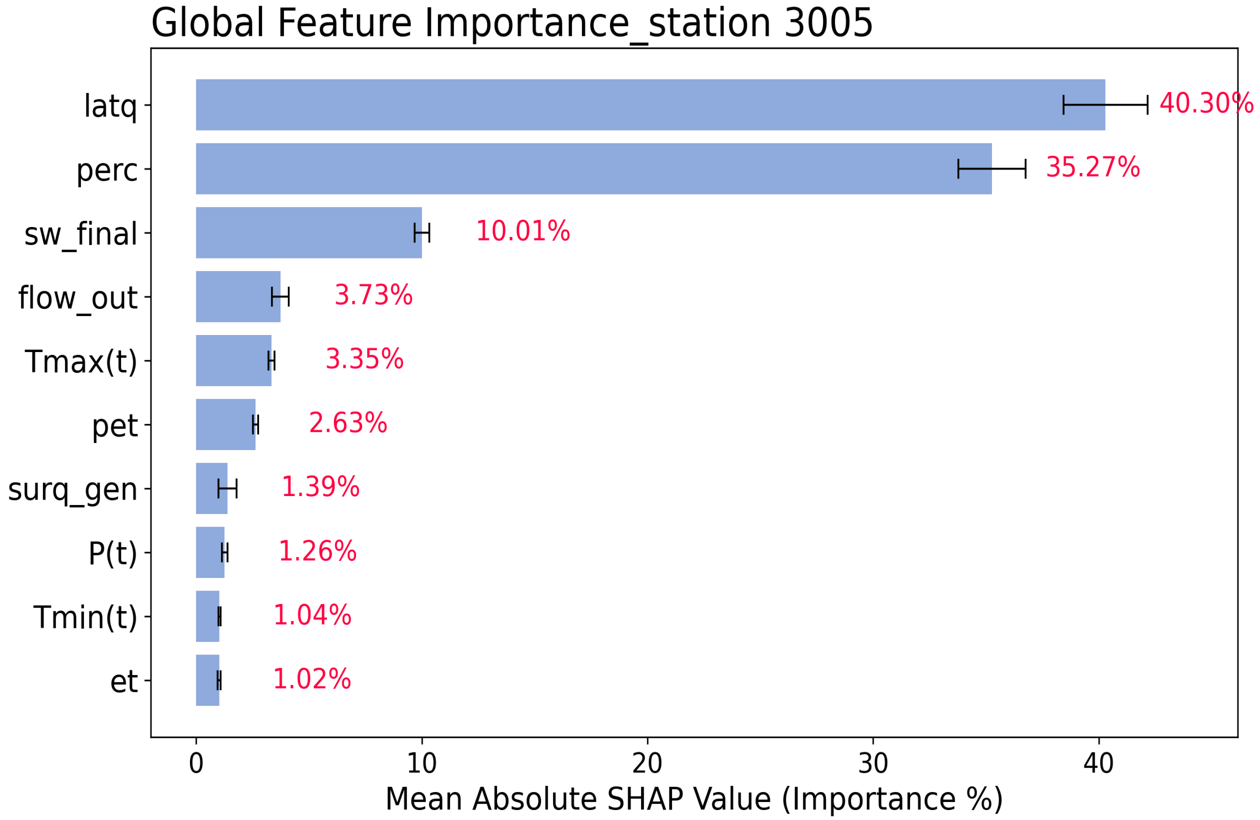
The plot shows SHAP value: how every input feature impacts on model output



Results

SHAP interpretation results for scenario 1

Global feature importance: mean absolute SHAP value (importance %) for every input feature



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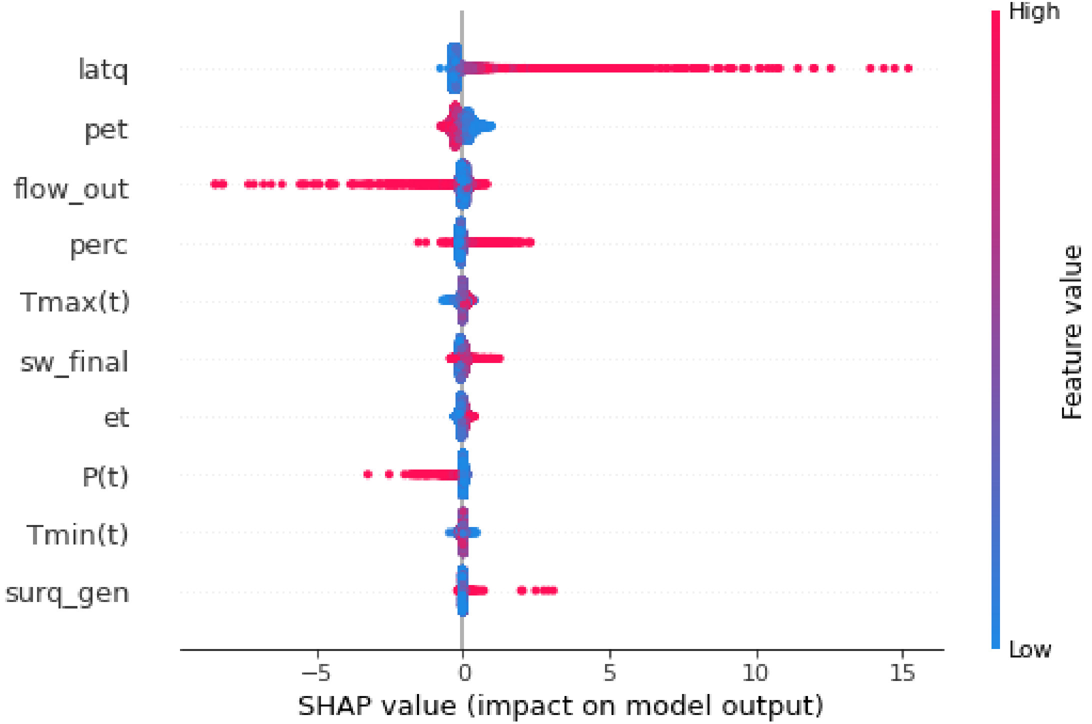
Results

SHAP interpretation results for scenario 2

The plot shows SHAP value: how every input feature impacts on model output



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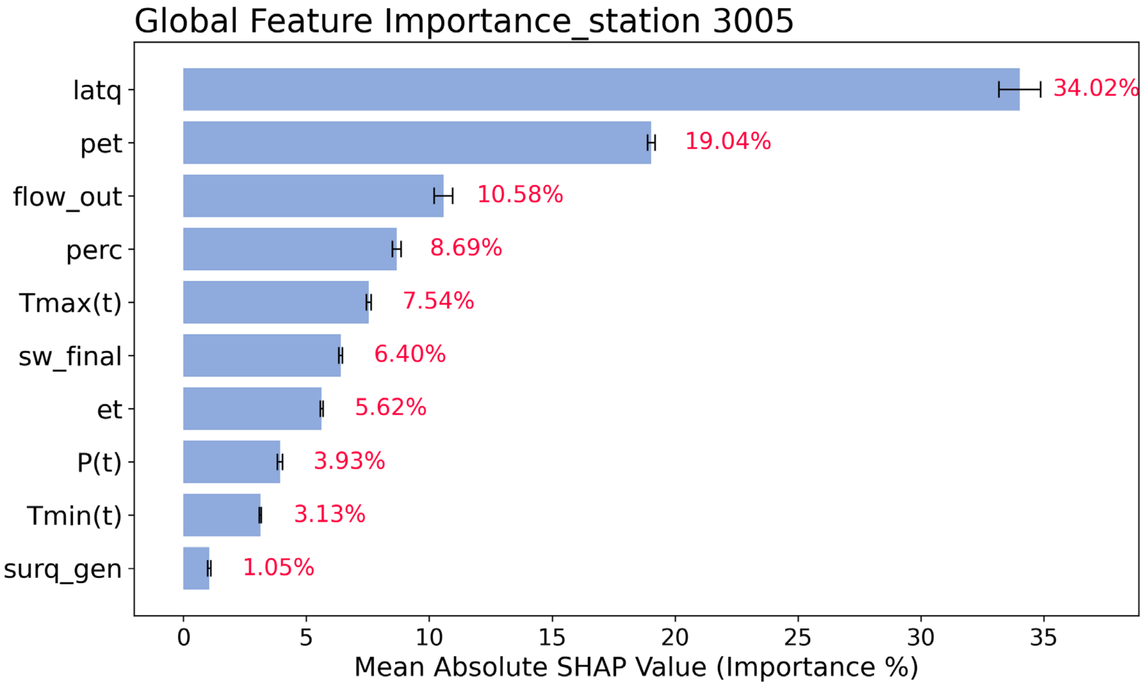
Results

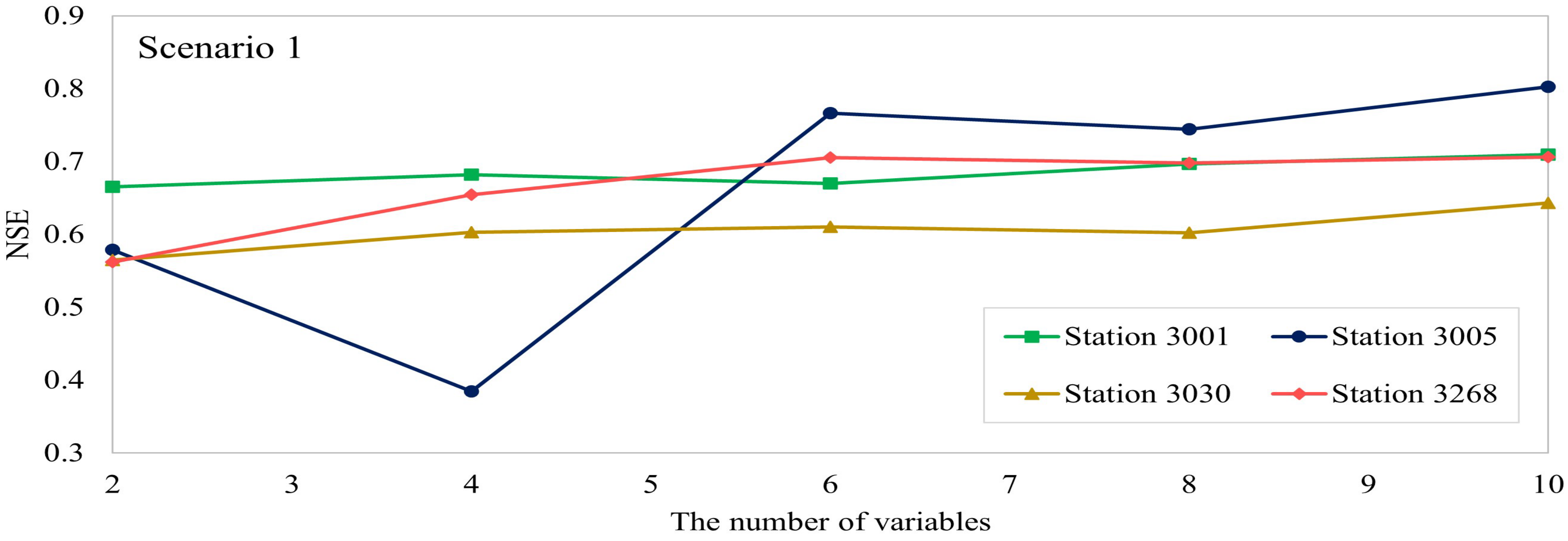
SHAP interpretation results for scenario 2

Global feature importance: mean absolute SHAP value (importance %) for every input feature



Results

SWAT+ and LSTM coupled model performance as the number of input variables changes



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Conclusion

Coupling SWAT+ and LSTM models improves streamflow prediction

Employing calibrated SWAT+ model outputs as inputs for AI-based models does not significantly affect streamflow predictions when compared to using outputs from the SWAT+ model with default parameter

SHAP methodology helps for machine learning based models interpretation

Different features including meteorological data and SWAT+ output features play differently in creating outputs of coupled models

Coupled models performance increases as we use more input features for LSTM models

Thanks for your attention

sasadi@alu.ucam.edu