University of Baghdad
College of Engineering
JE JOURNAL OF ENGINEERING

Journal of Engineering

journal homepage: www.jcoeng.edu.iq

Volume 31 Number 2 February 2025

Predicting Future Surface Runoff Delivered to the Euphrates River Using LARSWG and SWAT Models: (Sahiliya Valley in the Iraqi Western Desert as a Case Study)

Wisam Abdulabbas Abidalla, Basim Sh. Abed*

Department of Water Resources Engineering, College of Engineering, University of Baghdad, Baghdad, Al-Jadriya Campus, 10071, Iraq

ABSTRACT

The Weather Generation Model "LARSWG" and hydrological Model "SWAT" used in this study to estimate the quantity of future surface runoff in the Sahiliya Valley located within the Iraqi western desert. The weather data for the last ten years used as input in the LARSWG model to generate future weather data under the effect of climate change. In this model, the statistical test analysis done automatically, with two statistical test values, the (KS-value) test and the (p-value) test. The results of these tests are equal or close to zero (0.0) for KS-values, and equal or somewhat close to one (1.o) for p-values, which means the LARS-WG model is perfect for generating rainfall and temperature, and is more suitable in simulating the seasonal distributions. Data results from the LARSWG model used as input weather data in the SWAT model. For the SWAT model, several data are required for its software operation such as a digital elevation model, Land use-land cover, soil map, and weather data. SWAT modeling was done for watershed delineation for this valley yielding (14) sub-basins and (59) hydrological response units. To test the suitability of applying this model, two Statistical tests (Nash-Sutcliffe - NS) and Coefficient of determination - R2 test were applied for the two sets of data on Surface Runoff in both calibration and validation periods. The results of these tests are (0.72) (0.78) for calibration, and (0.64) (0.67) for validation respectively. The values of the (NS) test for both simulated and calculated data in the calibration and validation periods are somewhat similar. Also, the same goodness of results in the (R^2). The data results from SWAT modelling shows that maximum runoff occurs in October and November in winter season, and March in spring season in each year, and the runoff occurs at a rate of one to four (1-4) times annually, and in some years twice only. This means that the amount of surface runoff water added to the Euphrates River is limited from this valley.

Keywords: GIS, Iraqi valleys, LARSGW model, Surface runoff, SWAT model.

---

*Corresponding author
Peer review under the responsibility of University of Baghdad.
https://doi.org/10.31026/j.eng.2025.02.10

Article received: 01/07/2024
Article revised: 14/11/2024
Article accepted: 21/11/2024
Article published: 01/02/2025

1. INTRODUCTION

In water resources field, the hydrological studies dealing with surface runoff due to rainfall in the rainy season represent an important in various topics related to controlling flood hazards, design of the hydraulic structure, agricultural uses, etc**. (Doost et al., 2024)**, and determination quantity of surface water supplied into river is very crucial in water resources management. In arid regions, the climatic changes which are represented by changes in air temperature, sudden rainfall, and terrain diversity make the surface runoff occur randomly **(Saleh et al., 2024)**. Also, the soil properties heterogeneity has a considerable effect on the surface runoff in various areas of basins, therefore, it's important to study the hydrological cycle and its phenomena to recognize these effects on the watershed. A hydrologic unit is called a watershed, which is a catchment basin bound within topographic features in which water drains toward the lowest ground surface that is produced through the interaction of the land surface with precipitation **(Winkler et al., 2010)**.
In modeling watersheds, the GIS technique is an important program working as a tool in watershed modeling as remote sensing the information that can be merged with the ordinary database to determine the amount of runoff which can help in the planning of water conservation measures **(Farhan and Abed, 2022)**. Total precipitation that falls within the catchment area is divided into two parts, the first part remains on the soil surface called runoff, and the other part moves within the soil to reach groundwater. Both two parts were used for different purposes such as irrigation, domestic, and industrial **(McGlynn and McDonnell, 2003)**. For sustainable development, it is crucial to model the surface runoff and quantify a hydrological parameter from all the parts of the watershed using modern mathematical models **(Oleiw et al., 2023)**. in the past time, several models developed to simulate the effect of soil properties and the climate change on the hydrological cycle. These models require in their software operation different types of data such as precipitation, temperature, soil properties, characteristics of topography, hydrological parameters, etc. **(Pandi et al., 2021)**. Estimation or prediction of the future surface runoff due to rainfall is important in determining the amount of water that will reach the river or stream as surface flow. In the Iraqi western, there are many valleys in different size areas **(Al-Ansari et al., 2019; Al-Ansari, 2021)**, and in rainy seasons, the rainwater falling in these valleys forms temporary torrents that move as surface water toward the nearest river according to the topography.
This study was undertaken by applying the hydrological model (SWAT) which integrates the GIS information with an attribute database with the weather generation model (LARSWG) to estimate the predicted future surface runoff (for the next ten years) reaching the Euphrates River from Alhegia Valley located in the Iraqi western desert.

2. METHODOLOGY

2.1 The Study Area

The study area represents Sahiliya Valley, one of the valleys that lies in the Iraqi western desert in Alanbar Governorate. Area of this valley (5585.3) km². Maxi. Elevation (787) m amsl and Min. Elevation (86) m amsl. In rainy seasons, Sahiliya Valley discharges the surface runoff collected in its watershed to the Euphrates River at an outflow point located in Heet City at a distance (101) km from Haditha Dam D/S in coordinate (42.723°) E Longitude and (33.719°) N Latitude, the location of this valley is shown in **Fig. 1 (Urutseg, 2021).**

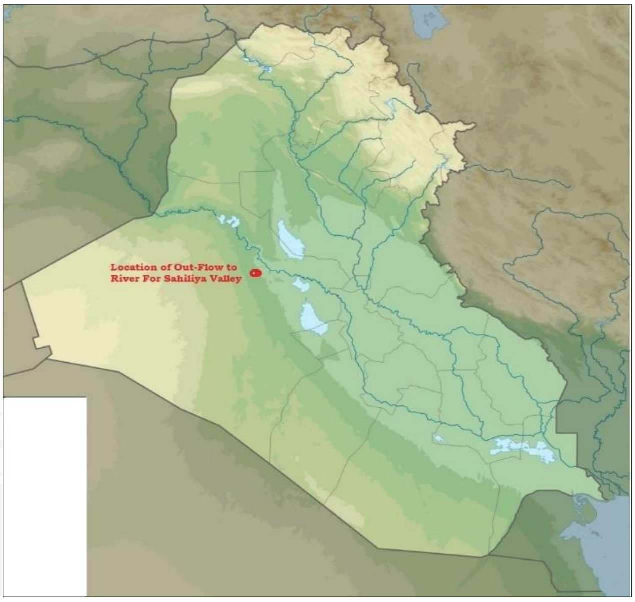

Figure 1. Location of Sahiliya Valley Out-Flow within Iraqi map **(Urutseg, 2021)**.

2.2 Models Application

2.2.1 LARSWG Model

Model LARS-WG, (Long Ashton Research Station Weather Generator) is a (stochastic weather generator) which widely used in climate research and hydrological modeling. **Fig. 2**. shows the model program interface **(Semenov, 2021)**. This model is a tool that is used to simulate synthetic climate data with one site under both historical and future conditions, that provides a stochastic and allows the users to generate a long time series of daily and monthly weather variables **(Zubaidi et al., 2019; Karimi et al., 2015)** and make a correlation between them for approximation of probability distributions of wet and dry series of daily. This model can be describe with the following key Feature: 1. The stochastic nature: Model LARS-WG operates on the stochastic basis and using randomness for the generation weather data **(Zakaria et al., 2013)**. 2. The Variable Outputs: Model can generate and simulate a range of weather Parameters data that including but not limited to precipitation, temperature, etc., these parameters are the important inputs for different hydrological and environmental models **(Dibike and Coulibaly, 2005)**.

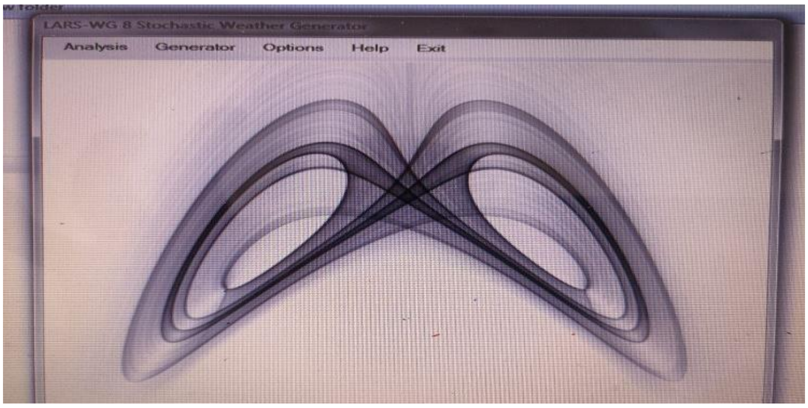

Figure 2. LARS WG Program Interface **(Semenov, 2021)**.

2.2.2 SWAT Model

The Hydrological Model "SWAT" Soil and Water Assessment Tool, is a watershed, basin or scale-model and a physically model which developed by the Agricultural Research Servicers (USDA-ARS) **(Neitsch et al., 2011)**. For the swat simulating process, the entire could be divided into two parts (the land surface and the water surface). Specific inputs data required in swat model about topography, weather, soil properties, vegetation, land cover changes that occurs in the watersheds, digital elevation model and the land use map **(Farhan and Al Thamiry, 2020; Farhan and Abed, 2021)**. Using this model for predicting the effect of the land practices management on the surface water , sediment, and the agricultural chemical yields for long-term period within a wide ungauged watersheds **(Ang and Oeurng, 2018)**. Sub-watersheds are divided into several hydrological response units (HRU) to improve the simulation accuracy **(Gassman et al., 2007)**. The SWAT model has emerged as one of the most popular models for basin studies and has been widely used in dealing with many hydrological and/or environmental problems **(Gassman et al., 2014)**, this model can be used to predict and simulate the runoff volume, and the water quantity. **Fig. 3**. Shows the the main parameters that required being as input and outing put of SWAT model.

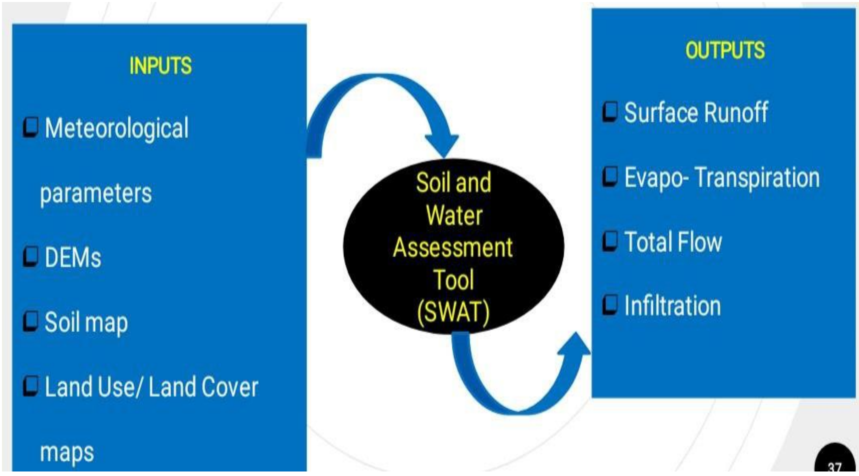

Figure 3. Input and output parameters for SWAT model.

The following key features represent the Model Description: 1. Climate Input: Climate inputs, including precipitation, temperature, and solar radiation **(Gassman et al., 2014)** are critical for driving the model. These input parameters can be historical or represent future climate scenarios. For the users integrating LARS-WG with hydrological models, the synthetic weather data may be used as inputs for hydrological simulations. These models would then simulate the impacts of the synthetic climate scenarios on water resources, runoff, etc. that divided into HRUs. 2. Watershed Scale: SWAT model is typically applied at the river basin or watershed scale, which allowing for the assessment of hydrological processes across a defined geographical area. 3. Soil Properties: SWAT model considers the soil properties such as texture, depth, and water retention characteristics to simulate the soil-water interactions. 4. The Land Use and Land Cover (LULC) : SWAT model incorporates both land cover and land use data for representing the distribution of different land uses within watershed **(Ware et al., 2024)**. Also, simulate changes in the Land use and management practices. 5. Sediment Transport and Nutrient: SWAT model used to accounts transport of sediment and nutrients such as (phosphorus and nitrogen) within the watershed, helping in the assessment of water quality impacts. 6. The sub-basin and reach representation: SWAT model divides the watershed into sub basins, each with its own set of parameters. River reaches, are also represented, that allowing the modelling of channel processes and streamflow. 7. Predicting Surface Runoff Volume: SWAT model can simulate and predict the surface runoff volume and the water discharge out from the catchment basin (valley) throw outflow point to nearest stream **(Ali et al., 2011)**.

3. INPUT DATA

3.1 Lars Data (Climate Model Data Input):

Weather data such as (rainfall, maximum and minimum temperature , solar radiation) and weather station information about longitude, latitude and altitude) for previous or current years which are listed in **Tables 1-4** were used by a stochastic weather generator "LARS WG model" to generate the future weather data. These previous weather data were collected from Ramai Weather Station, latitude (33.42° N), longitude (43.3° E) and altitude (53 m a.s.l).

Table 1. Monthly Precipitation (mm) for the period (2014-2023) **(IMOS, 2024)**

Month / Year	Jan	Fab	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2014	48.5	9.2	19.2	8.5	0.6	0	0	0	0	1.7	7.3	5.4
2015	8.6	10.1	11.9	4.5	0	0	0	0	0	5.9	39.8	19.9
2016	0.6	30.7	18.5	7.9	0	1.2	0	0	0	0	0.4	31.4
2017	3.7	9.3	31.6	16.3	4.2	0	0	0	0	0	0.6	8.5
2018	0	50.8	1.3	55.4	7.9	0	0	0	0	2.5	61.7	28.9
2019	30	5.5	69.2	28.1	10.8	0	0	0	0	2.2	2.4	21.5
2020	10.7	7.6	32.3	0	0	0	0	0	0	0	6.8	0.8
2021	9.8	17.7	4.2	0	0	1.7	0	0	0	1.1	1.8	1.8
2022	10.5	14.5	5.7	0	3.3	0	0	0	0	1.2	14.1	12.7
2023	22.9	0	24.5	12.4	2.6	0	0	0	0	1.5	15.5	13.6

Table 2. Average Maximum Monthly Temperature (°C) - period (2014-2023) **(IMOS, 2024)**

Month / Year	Jan	Fab	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2014	13	16	21	26	30	33	35	36	32	25	18	15
2015	13	16	20	23	30	33	37	36	34	27	18	13.
2016	13	17	21	26	30	34	36	37	32	28	20	12
2017	12	14	19	24	30	34	38	38	34	27	20	16
2018	15	17	23	24	29	34	35	35	34	26	17	14
2019	13	15	18	21	30	35	34	35	32	27	20	14
2020	14	15	19	24	37	36	36	35	33	27	19	14
2021	15	17	20	27	32	33	36	35	31	27	19	14
2022	14	16	18	25	28	34	36	35	32	28	19	15
2023	13	16	20	25	30	33	34	36	34	30	21	15

Table 3. Average Minimum Monthly Temperature (°C) - period (2014-2023) **(IMOS, 2024)**

Month / Year	Jan	Fab	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2014	6	5	14	18	25	29	32	31	27	20	10	9
2015	4	8	10	17	25	28	33	32	30	22	13	5
2016	5	9	13	18	25	30	33	33	26	19	9	3
2017	3	2	12	17	24	29	34	33	28	19	13	6
2018	5	9	15	15	25	29	32	32	28	21	13	8
2019	4	7	9	16	22	28	29	31	25	22	10	9
2020	4	6	13	18	22	28	30	31	26	21	12	7
2021	4	10	10	16	22	24	29	27	22	16	11	8
2022	4	6	9	17	22	26	29	29	24	20	14	10
2023	5	8	12	16	23	27	32	30	29	18	11	5

Table 4. Average Monthly Solar Radiation (MJ/m^2/day)- period (2014-2023) **(IMOS, 2024)**

Month / Year	Jan	Fab	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2014	11	15	14	17	15	16	18	18	16	13	13	11
2015	11	15	16	19	16	16	18	18	14	12	12	13
2016	13	14	14	17	16	17	18	17	15	13	12	10
2017	12	14	14	15	16	17	18	18	15	14	11	12
2018	11	12	15	15	14	16	18	18	15	12	10	9
2019	11	13	14	16	15	17	18	16	14	12	11	8
2020	13	13	13	15	16	17	17	17	14	12	10	9
2021	11	12	16	18	16	17	17	16	15	14	10	8
2022	12	12	13	12	14	17	17	16	15	13	13	11
2023	12	14	14	16	16	16	17	17	13	12	11	10

These weather data were uesd to generate the future weather data which is used as input data to operate and run the hydrological model (SWAT) to simulat and predict the future surface runoff for Sahiliya Valley due to falling rainfall in Iraqi western, which directly reaches the Euphrates River.

3.2 SWAT Software Data

To simulate the swat model, several input data are required in this section for run the model software in the purpose of estimating the quantity of surface runoff, such as the digital elevation model (DEM), land use map, soil map, and the weather data.

3.2.1 The Digital Elevation Model (DEM)

The topography for the study area that included the Sahiliya Valley was represented using the available Digital Elevation Model DEM with spatial resolution of 30 m, by satellite imagery that is loaded from the Website of Landsat 8, which provided by "global Shuttle Radar Terrain Mission" (SRTM) from the (USGS) (www.usgs.glovis.com). **Fig. 4**. Illustrates the DEM of this valley within study area.

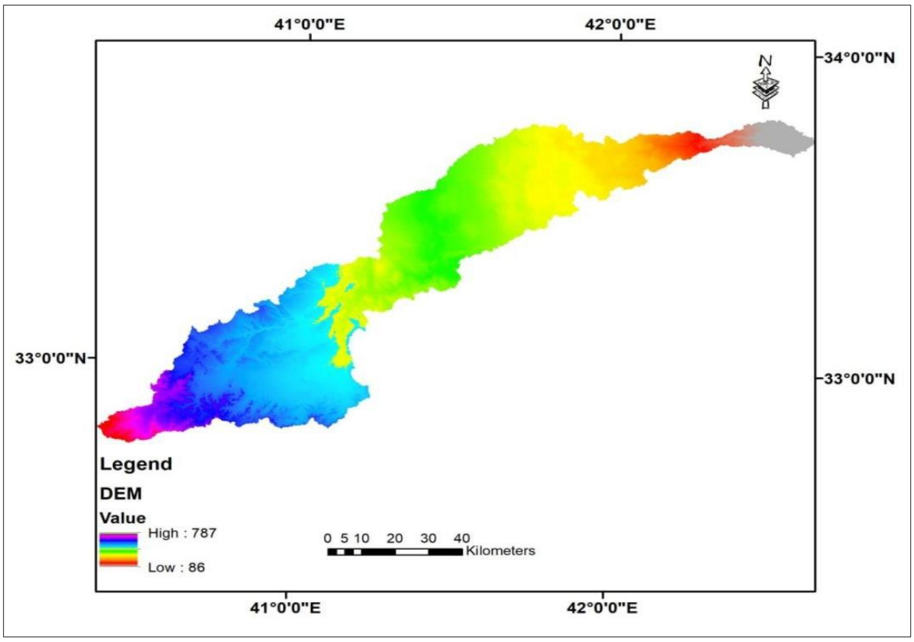

Figure 4. The DEM for Sahiliya Valley within study area.

3.2.2. The Land-Use Map

Both land use - land cover (LULC) satellite images were obtained from Website (http://seamless.usgs gov/website/seamless/view) which has three bands with a spatial resolution of 30 m. The GIS software is used to geometrically, digitize, and atmospherically correct **(Khalaf et al., 2016; Kadhim, 2018)**. In the study area, the vegetation cover has a low effect on the water surface runoff by considering it is in a low density compared with the whole. **Fig. 5**. Illustrates the land use land cover (LULC) for the study area which is classified into two Plants Agricultural Land-Row Crops, Corn, and Orchard.

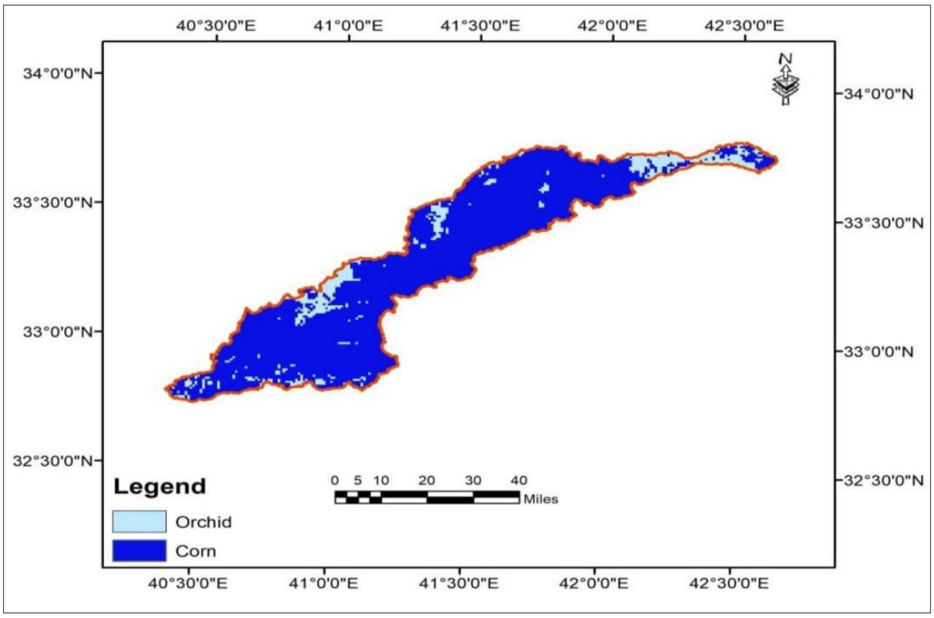

Figure 5. The land use and land cover (LULC) for Sahiliya Valley.

3.2.3. The Soil Map

Surface runoff is influenced by the soil composition of the watershed area represented by soil texture in terms of porosity and permeability **(Fu et al., 2011)**. Valley soil in the study area, which represents the source of surface runoff result from rainfall that reaches the Euphrates River. The desert soils are unsuitable for purposes of agriculture because it has a low quantity of organic materials except the alluvial soils and which that nearest streamflow and adjacent to the Euphrates River which has an acceptable quantity of organic materials. Registration of area in this study be done by Arc GIS and digitized the soil hydrologic group through assistant of Soil Plant Assistant Water Model, using textural data and the organic matter data obtained from the Food and Agriculture Organization "FAO were classification into four types (clay, sandy loam, loam sand, and sand). **Fig. 6.** Illustrates the soil map of area of case study.

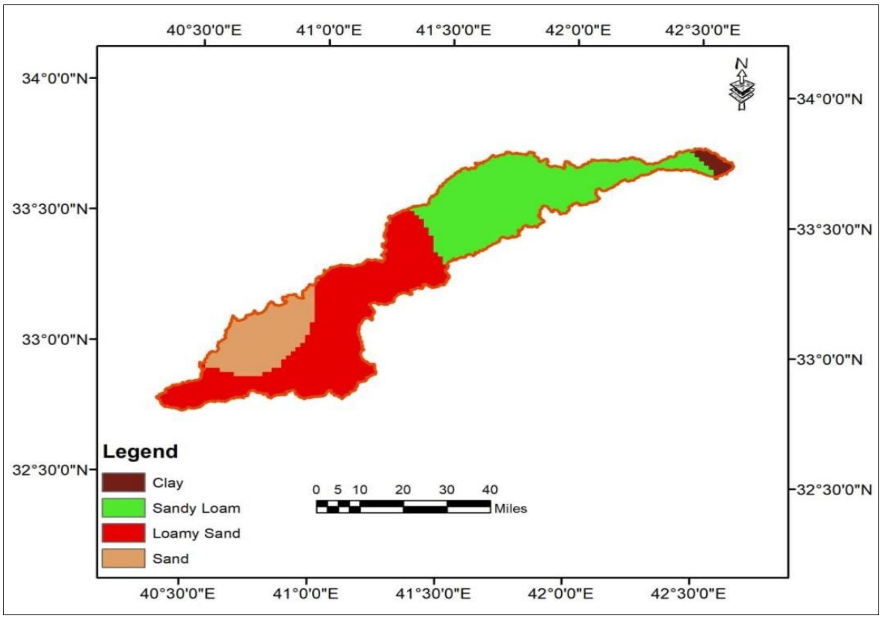

Figure 6. The soil map for Sahiliya Valley.

3.2.4. Swat Modeling

For Sahiliyavalley, the SWAT model has been chosen and operated through the interface Arc SWAT for predicting and estimating future surface runoff. The SWAT model can divide the watershed into units which have similar characteristics in both soil and land cover, then they are placed in the similar subbasin, which is called as a Hydrologic Response Unit (HRU) **(Kalcic et al., 2015)**. This model depends on several parameters for representation of different weather, soil, plant and hydrological progressions within a watershed. The map of both land use and hydrologic soil in the subbasin (subunits) interior borders were used to make a unique incorporation, and can be assume that all incorporation as identical in physical properties.

1. Delineation of Watershed

Digital Elevation Model (DEM) with 30m resolution was used for watershed delineation by SWA **(Ali, et al., 2008)**. the delineation of the watershed performed with the aid of the Arc

Geographic Information System with a spatial analysis **(Mustafa et al., 2016)**. One of the important steps that have been needed to operate the model is describing the topography related to characterization such as elevation above sea level, slope, aspect, a network of stream flow, creating streamlines, outlets of watersheds, selecting outlets of a watershed for both definition and calculation of sub-basin parameters and then dividing the basin into several sub-catchments. In the processes of watershed delineation, the number of Sub-basins for this valley equal to (14)were controlled by the number of hydrologic response unit equal to (59) HRU, which depends on the nature of the illustrated situation and the value of the suitable threshold. For the topography of Sahiliyavalley, the Max. Elevation (787 m), Min. Elevation (86m), Mean (461.7) and the Std. Deviation (116.4). The watershed delineation for this valley as shown in **Fig. 7**.

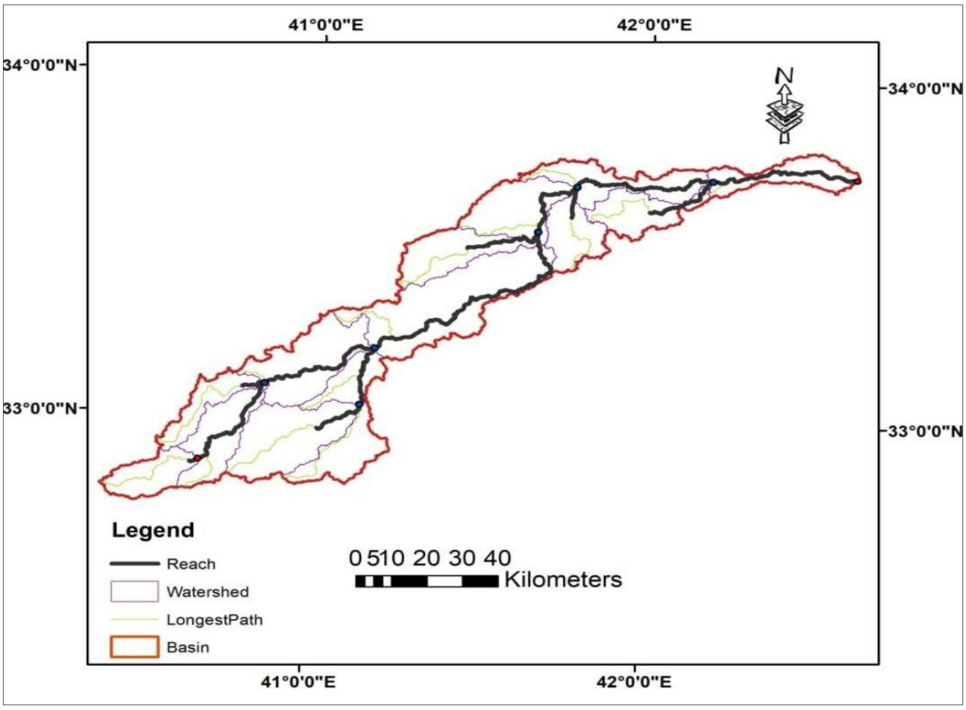

Figure 7. The watershed delineated for Sahiliya Valley.

2. Analysis of Hydrological Response Unit (HRU)

The term "HRUs" means the smallest segments of subbasin that be specified by the changes in soil, slope, and classification of the LULC. **(Winchell et al., 2015)**. In the processes of the HRU Analysis, several steps were down. The first step in the HRU formation was inserting the LULC map containing classes for the land uses in the basin, these classes were matched with the classes in the database of Arc SWAT to reclassify the land use map. Using high-resolution images was important for the validation of land use. Also, the soil map was added, and then matching FAO soil map with the SWAT default soil database to make the same soil classes of soil map. Also, the slope of the land was included in the model, which is based on the DEM elevations. This model gave the user two options, either a single slope or multiple slopes, in this study, the multiple slopes were chosen. For the last step, overlaying was done for the land use, soil, and slope layers. In this point, the land use, soil, and slope classes were taken into account in the processes of simulation.

3. Land Use Reclasses

One of the important performances of the SWAT model was a reclassification of land use types which done to load data that corresponding SWAT model information by overlapping the satellite image of land use with the area of the Sahiliyavalley, as shown in **Fig. 8**.

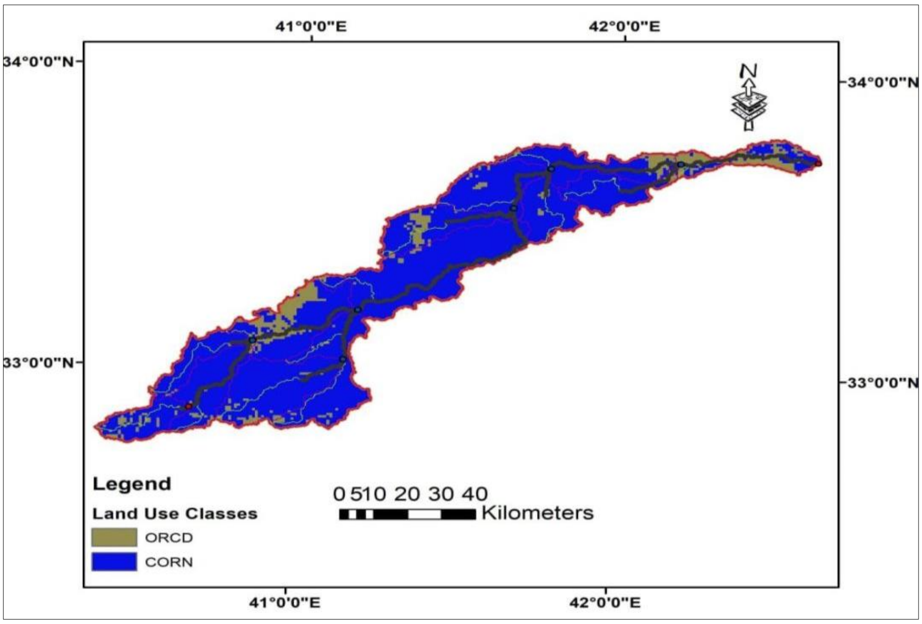

Figure 8. Land use Reclassified by Swat model for Sahiliya Valley.

4. Soil Reclasses

Also, for the performance of Swat model, the reclassification of soil types was done to load data that corresponding SWAT model information by overlapping the satellite image of soil with the area of the Sahiliyavalley as shown in **Fig. 9**.

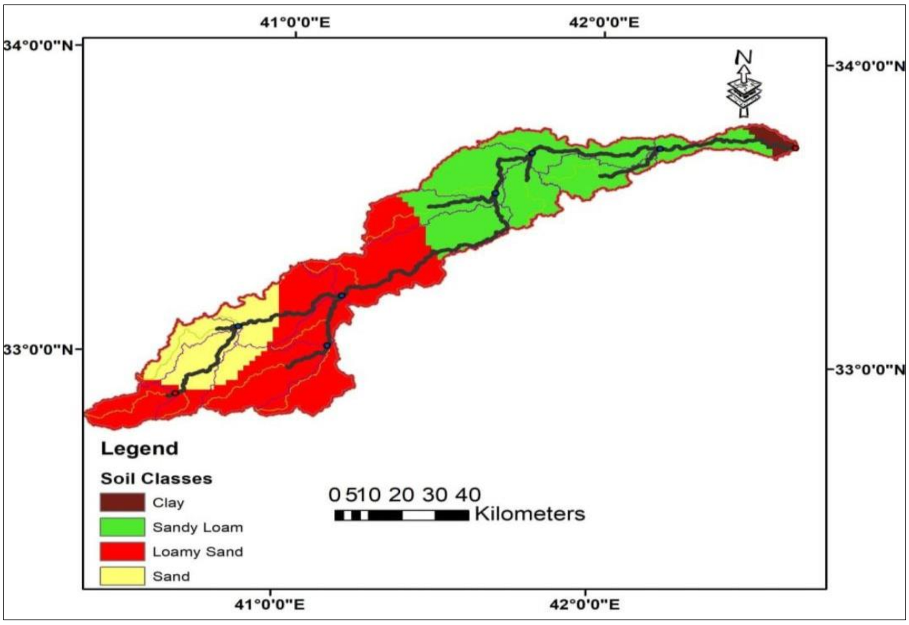

Figure 9. Soil reclassified by Swat model for Sahiliya Valley.

5. Slope Reclassified

The reclassification of land slope types was done to load data that corresponding SWAT model information by overlapping the satellite image of the slope with the area of the Al-Khabazvalley, as shown in **Fig.10**. The Hydrological Response Unit (HRU) for this valley summarized in **Table 5**.

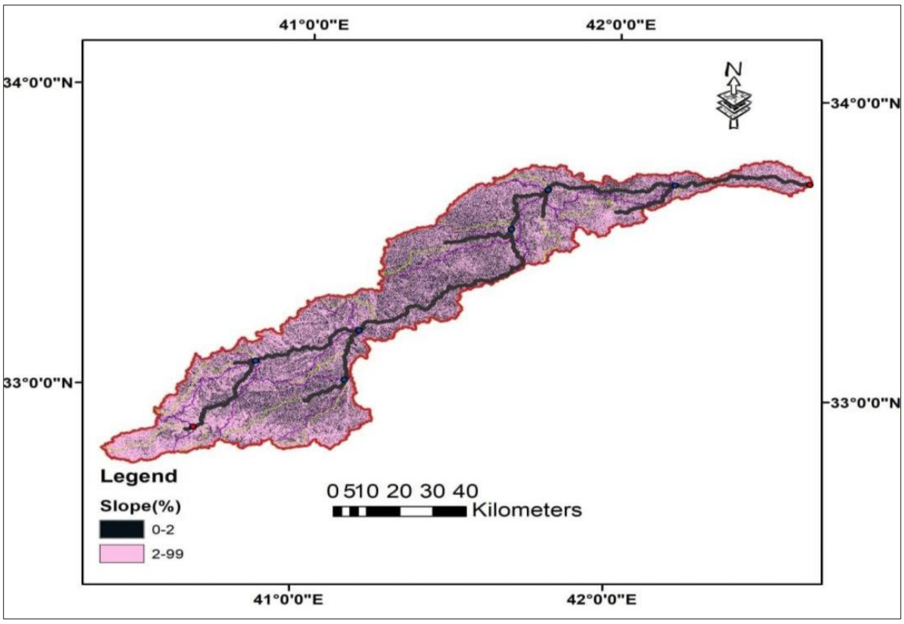

Figure 10. Slope Reclassified by Swat model for Sahiliya Valley.

Table 5. The analysis of HRU for Sahiliya Valley.

Soil Reclassification		**Land Reclassification**	
Soil Type	**Model Area %**	**Land Type**	**Model Area %**
Clay	3	ORCD	12
Sandy Loam	38	CORN	88
Loamy Sand	44		
Sand	15		

4. RESULTS AND ANALYSIS

4.1 Weather Data Generation Model (LARSWG)

4.1.1 The Suitability and Acceptibilty of Model

To test the suitability of applying the LARAWG model in the generation of weather data for future periods under climate change, and to be used as input data in the application of the SWAT model, statistical test was done, such as (k-S) test (P–value) test to performed for equality testing of the seasonal distributions of both wet and dry series (WD Series) for the distributions of Rain, (min.–max.) Temperature daily distribution is estimated from both downscaled and observed data. Both (K-S) and (p-value) tests were used to make decisions about accepting or rejecting the hypotheses for two groups of data **(Sarkar et al., 2015; Khosravanian et al., 2015)**. **Table 6**. shows the results of the statistical analyses for the model's performance in generating data and simulating seasonal observed data,

Table 7 shows the model perfect in the simulation of the daily rain in each month and **Tables 8 and 9** show the performance of the model in simulating of daily "min.–max." temperature in each month. The assessment of LARS-WG model performance in generating and simulation seasonal weather in Anbar City was inserted in the last column in **Table 6.** For precipitation values. From the statistical results, which can be observed from the assessment that the model performance is perfect in Autumn (SON) and (v. good fit) in the winter (DJF), the rain as fitting of the dry and wet spells series distributions in the two seasons are perfect or v. good. For the performance of the model in fitting in both wet and dry spells series distributions in (MAM)spring season it is also assessed to be (v. good fit) for the distribution of both wet and dry spells respectively. In the summer season (JJA), there Poor fit performance in the distributions of both wet and dry series, it performs is poorly in fitting in this season, the reason for the poor performance in the summer season which is dry, or there is no rainfall data recorded in this season.

Table 6. K-S-test and P-value for seasonal (wet-dry) series distributions.

Season	Wet - Dry	N	K-S	P-Value	Assessment
DJF (Winter)	Wet	12	0.138	0.971	V. good fit
	Dry	12	0.153	0.93	V. good fit
MAM (Spring)	Wet	12	0.107	0.999	V. good fit
	Dry	12	0.146	0.952	V. good fit
JJA (Summer)	Wet	12	1	0	Poor fit
	Dry	12	0.49	0	Poor fit
SON (Autumn)	Wet	12	0.069	1	Perfect
	Dry	12	0.053	1	Perfect

Table 7. K-S test and P-value test for distributions of daily RAIN.

Month	N	K-S	P-Value	Assessment
January	12	0.132	0.891	Perfect
February	12	0.062	1	Perfect
March	12	0.251	0.953	Perfect
April	12	0.201	0.691	Good fit
May	12	0.261	0.359	Moderate fit
June	12	NO Precipitation		
July	12	NO Precipitation		
August	12	NO Precipitation		
September	12	NO Precipitation		
October	12	0.226	0.992	Perfect
November	12	0.168	0.87	Perfect
December	12	0.242	0.965	Perfect

In **Table 7**, the assessment of statistical parameters resulted shows that the LARS-WG8 model perfect in the generation and simulation of the daily rainfall distributions in all months is (Perfect) except in May shows (Moderate fit) and no precipitation in the summer season for both observed and generated data. In assessment, the statistical parameters resulted in **Tables 8 and 9**. The LARS-WG8 model performance in generating and simulating the distributions of the daily (Min.-Max.) temperature distribution in all months lie between Perfect and very good fit. The results in **Tables 6 to 9**, show that the LARS-WG8 model is more capable and suitable in generating and simulation of the seasonal distributions for both (dry - wet) spells and the daily weather data distributions for each month. The two statistical tests are critical when using the results of the model in the impact studies. Finally, the LARS-WG8 model is suitable, thus it is used to predict future changes in precipitation and other weather parameters under conditions of climate change and used to generate weather data for next years with the input of the daily weather parameters for past or current periods in the western region of Iraq.

Table 8. K-S-test and P-value for daily (Min. Temperature) distributions.

Month	N	K-S	P-Value	Assessment
January	12	0.053	0.978	Perfect
February	12	0.093	0.893	Perfect
March	12	0.140	1	V. good fit
April	12	0.039	0.996	Perfect
May	12	0.094	0.932	Perfect
June	12	0.018	1	Perfect
July	12	0.106	0.999	V. good fit
August	12	0.158	0.913	V. good fit
September	12	0.044	0.966	Perfect
October	12	0.087	0.929	Perfect
November	12	0.017	1	Perfect
December	12	0.048	1	Perfect

Table 9. K-S-test and P-value” for daily (Max. Temperature) distributions.

Month	N	K-S	P-Value	Assessment
January	12	0.106	0.999	Perfect
February	12	0.053	1	Perfect
March	12	0.012	0.965	Perfect
April	12	0.045	0.989	Perfect
May	12	0.093	1	Perfect
June	12	0.106	0.922	V. good fit
July	12	0.136	0.954	V. good fit
August	12	0.114	0.831	good fit
September	12	0.033	1	Perfect
October	12	0.106	0.963	V. good fit
November	12	0.105	0.948	V. good fit
December	12	0.044	1	Perfect

4.1.2 Data Generation

In this study, the LARS-WG8 model used the historical weather data for (10) years, period (2014 – 2023) to generate weather data for the next (10) years, period (2025 – 2034) as shown in **Fig. 11** to generate the precipitation and **Figs. 12 and 13** to generate the Max. and Min. Temperature respectively.

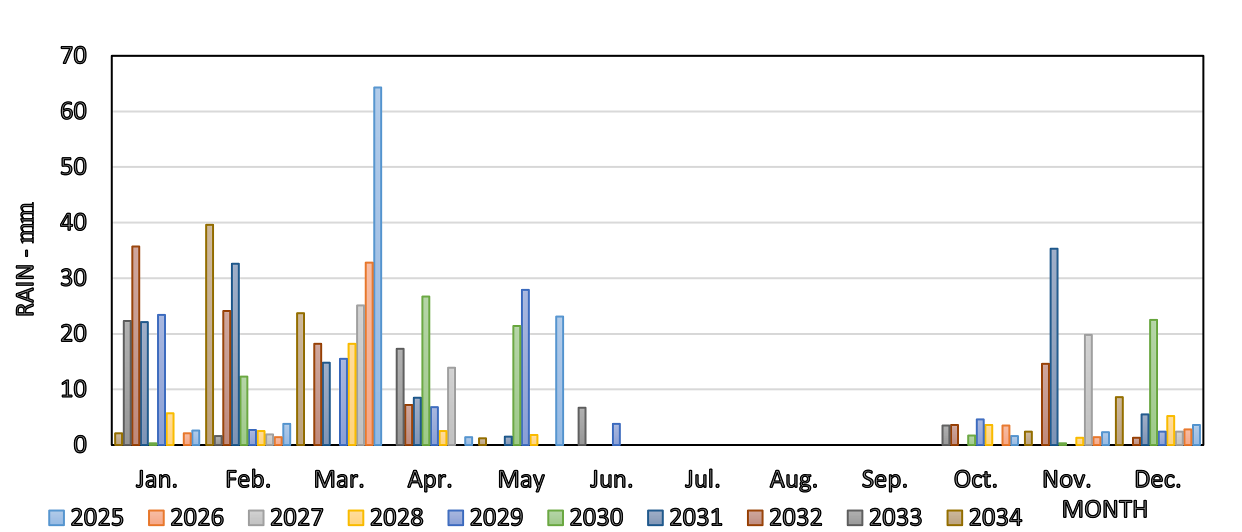

Figure 11. Monthly precipitation (mm) within study area for period (2025 - 2034).

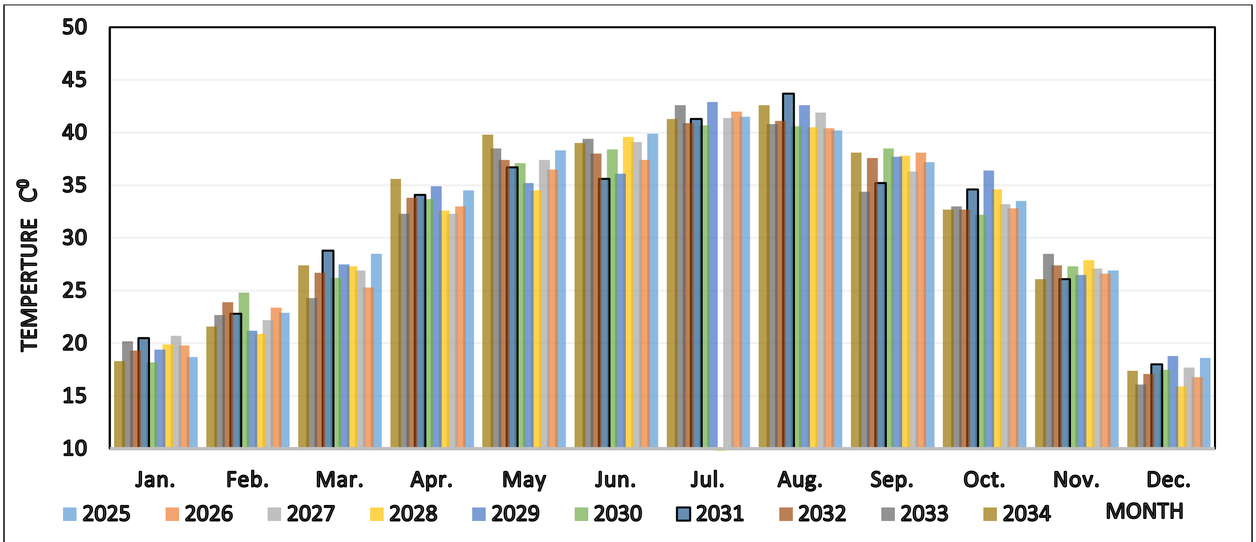

Figure 12. Average maximum monthly temperature (C^0) for period (2025 - 2034).

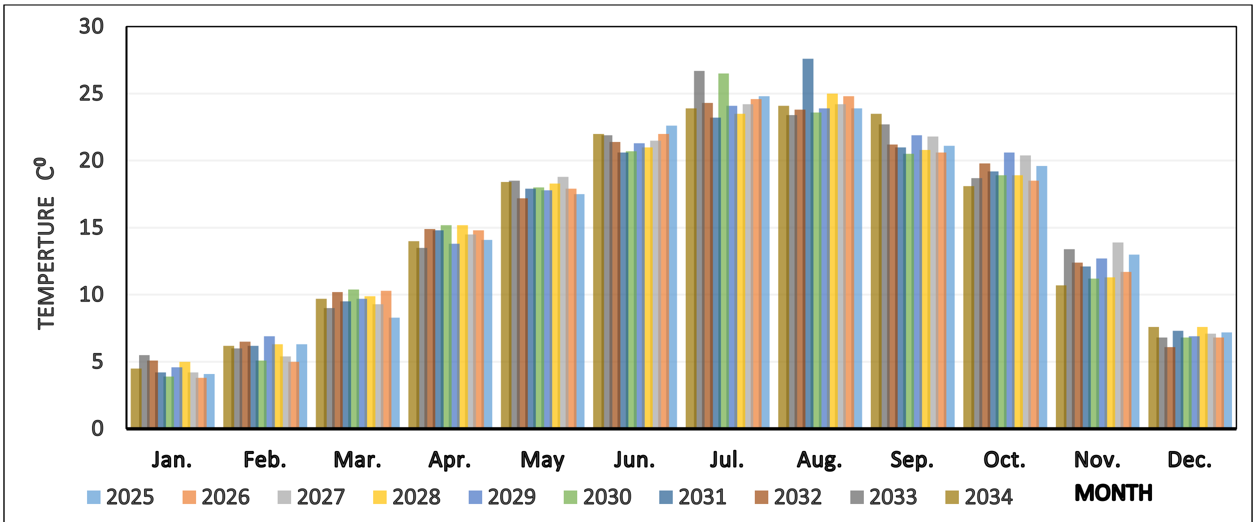

Figure 13. Average minimum monthly temperature (C^0) for period (2025 - 2034).

4.2 SWAT Model Resultes

SWAT model operated to estimate and predict the future surface runoff for SahiliyaValley located in the Iraqi western desert.

4.2.1 Suitability of Applying SWAT Model

Many researchers have used the SWAT model to estimate surface runoff in the Iraqi western desert. **(Farhan, 2020; Sulaiman et al., 2021)** demonstrated the suitability of applying this model, the reliability of its results, and the potential for adopting it in simulating and estimating the amount of surface runoff. Because of the unavailability of observed field data about the surface runoff for Sahiliya Valley, the observed rainfall data for the period (2014-2023) was used to calculate the field surface runoff for this valley, as listed in **Table 10**.

Table 10. Annual S. R. O. (Calculated from field data – simulated from the model) for Sahiliya Valley - period (2014-2023).

Year	Calibration Period						Validation Period			
	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Calculated S. R. O. (mm)	19.9	8.3	11.7	16.2	5.5	14.4	8.1	9.8	6.4	11.3
Simulated S. R. O. (mm)	27.9	14.7	16.8	24.3	13.6	21.1	13.4	15.6	9.3	18.5

4.2.2 The Statistical Test Analysis:

Statistical analysis done to test the goodness and suitability of applying the model for Sahiliya Valley with its simulated data and calculated (from field data) as listed in **Table 10** for the period (2014-2023). The Calibration for six years (2014- 2019) and Validation for four years (2020-2023) were conducted. Two Statistical tests (Nash-Sutcliffe - NS) test, Eq.(1), and Coefficient of determination-R^2 test, Eq. (2), were applied for the two sets of data on Surface Runoff in both periods.

$$NS = 1 - \left[\frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{mean})^2}\right] \tag{1}$$

Where: NS is the Nash-Sutcliffe coefficient, (Y) is and variable, (obs.) is observed data, (sim.) is simulated data by model.

$$R^2 = \frac{[\sum_i(Q_{m,i} - \bar{Q_m})(Q_{s,i} - \bar{Q_s})]^2}{\sum_i(Q_{m,i} - \bar{Q_m})^2 \sum_i(Q_{s,i} - \bar{Q_s})^2} \tag{2}$$

Where: R^2 is the Coefficient of determination, (Q) is any variable, (m) is measured data, (s) is simulated data by model. The results of these tests are listed in **Table 11**

Table 11. Statistical testing for Sahiliya Valley of the model calibration – validation.

Evaluation of Model	NS	R^2
Calibration - (2014-2019)	0.72	0.78
Validation - (2020-2023)	0.64	0.67

From these results, the values of the (NS) test for both simulated and calculated data in the calibration and validation periods are somewhat similar. Also, the same goodness of results in the (R^2) test.

4.2.3 Surface Runoff Predicting for Sahiliya Valley - future period (2025-2034)

The ability of SWAT model in predictions of surface runoff for the future period based on the availability of input data such as future weather data (precipitation, temperature), DEM, land cover maps and all other data required in model prediction. Therefore, the stochastic weather generator model "Lars WG" was used to generate weather data for the period (2025 – 2034) under the effect of climate change in the study area as shown in **Figs. 11-13**. After using all data that were required to run SWAT software, the results (output data) represent the predicted Surface Runoff in the next (10) years for SahiliyaValley as shown in **Figs. 14 and 15** for annual surface runoff as depth in (mm) and as volume in (mm^3).

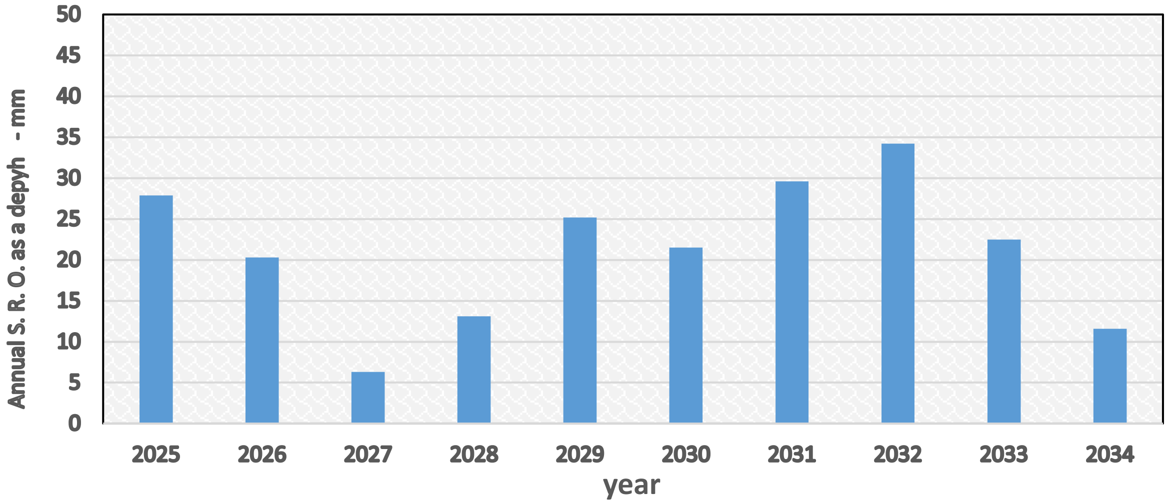

Figure 14. Annual Surface Runoff as depth for Sahiliya Valley –Period (2025-2034).

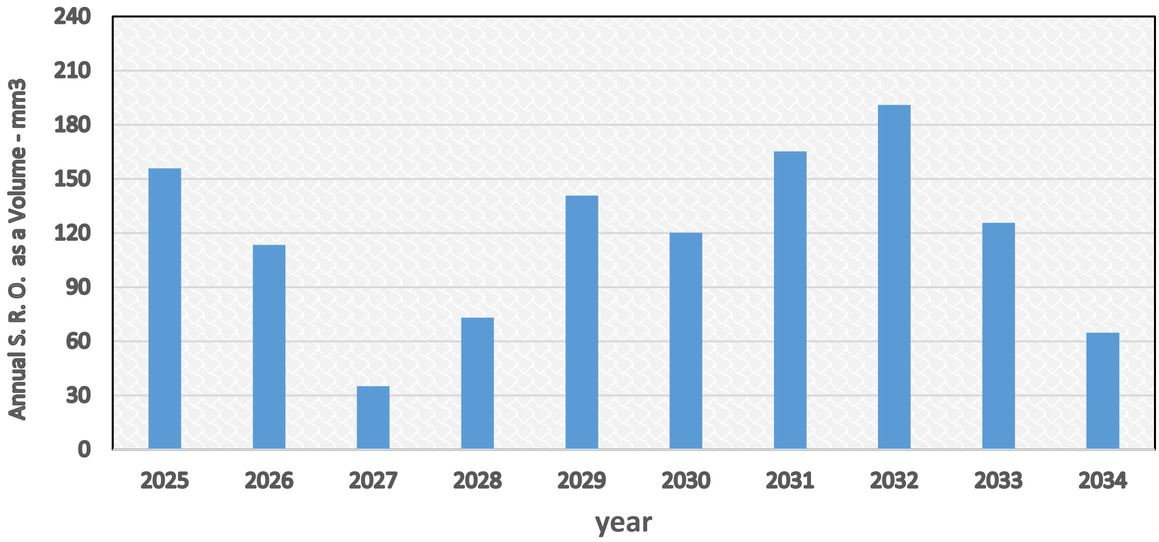

Figure 15. Annual Surface Runoff as Volume for Sahiliya Valley - (2025-2034).

In additional, **Fig. 16** shows results for expected future monthly surface runoff as depth in (mm).

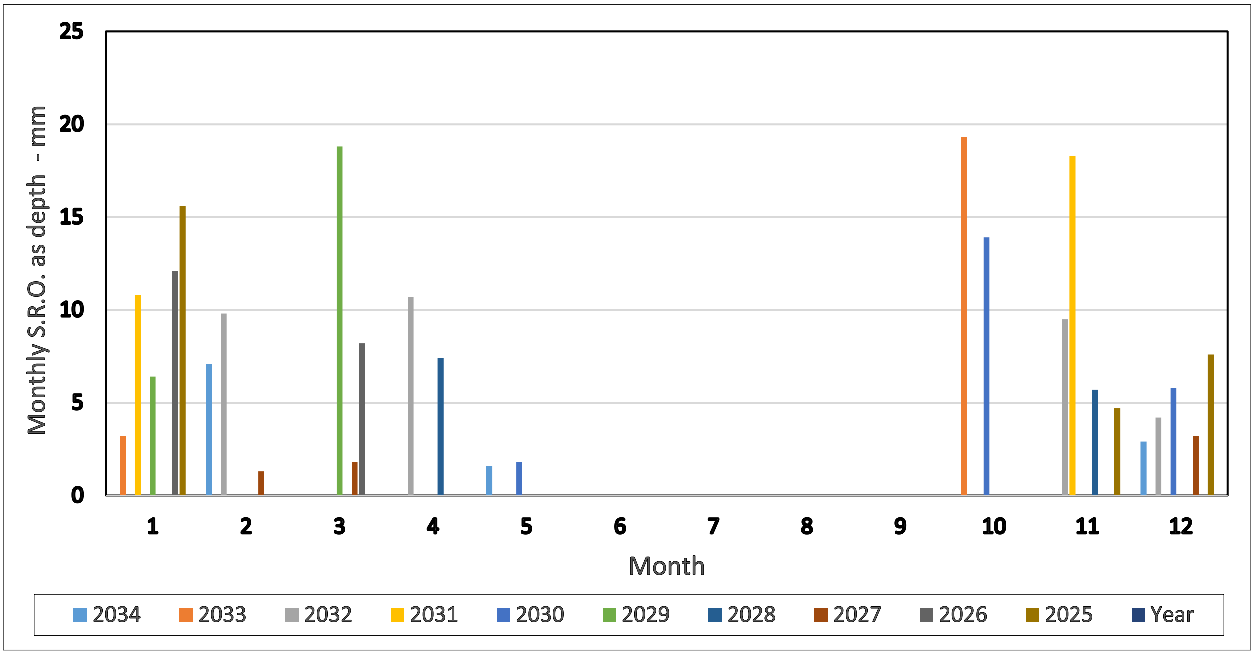

Figure 16. Expected future monthly surface runoff as depth in (mm) that are - predicted by SWAT Model for Sahiliya Valley - period (2025-2034).

The results in **Fig.16** show that the expected future monthly runoff as a depth is equal to zero in several months for each year, except for a few months in the winter season (rainy season) from October to February, and in the Spring season from March to May with different values of runoff quantity. These data are very useful in knowing the quantities of water for the next periods that are expected to come from the Sahiliya watershed area, which is delivered directly to the Euphrates River. These data are considered important information in the water resources management plans for the Euphrates River Basin since this river suffers from a severe shortage and lack of water supplies coming from the Syrian border.

5. CONCLUSIONS

From the analysis of results, the following conclusions were gained for this study:

1. Analysis of statistical tests for the weather generation model (LARSWG) shows that K-S test values were close to zero, and p- test value is somewhat close to one, which means that the model is very good or perfect in the generation of future weather data.
2. Predicating of future Surface Runoff can be obtained by simulating the SWAT model after entering the future weather data from the LARSWG model. The results of these predicted data show that maximum runoff occurs in October and November in the winter season, and March in the spring season in each year.
3. By predicting the quantities of future monthly surface runoff by SWAT model, it becomes clear that the runoff occurs at a rate of one to four times (1-4) annually, and in some years twice only, which indicates the limited amount of surface runoff water added to the Euphrates River from this valley.

Acknowledgements

This work was supported by the University of Baghdad, College of Engineering, Department of Water Resources Engineering.

Credit Authorship Contribution Statement

Wisam Abdulabbas Abidalla: Investigation, Formal analysis, Writing–original draft. Prof. Dr. Basim Sh. Abed: Supervision, Writing –review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCE

Al-ansari, N., 2021. Water resources of Iraq. *Journal of Earth Sciences and Geotechnical Engineering*, 11(2), pp.15-34. https://doi.org/10.47260/jesge/1122.

Al-ansari, N., Adamo, N. and Sissakian, V., 2019. Hydrological characteristics of the Euphrates rivers. *Journal of earth sciences and geotechnical engineering*, 9(4), pp.1-26. https://www.researchgate.net/publication/337172113.

Ali, A.A., Al-Thamiry, H.A., and Alazawi, S.Q., 2011. Estimation of runoff for Goizha-Dabashan Watershed with aid of remote sensing techniques. *Journal of Engineering*, 17(02), pp.306-320. https://doi.org/10.31026/j.eng.2011.02.08.

Ali, H.Z., Abbas, B.S., and Daham, M.A.M., 2008. Evaluation of mathematical techniques used for producing digital elevation model (DEM). *Journal of Engineering*, 14(02), pp.2443-2465. https://doi.org/10.31026/j.eng.2008.02.10.

Ang, R., Oeurng, C., 2018. Simulating streamflow in an ungauged catchment of Tonlesap Lake Basin in Cambodia using Soil and Water Assessment Tool (SWAT) model. *Water Science*, 32(1), pp.89-101. https://doi.org/10.1016/j.wsj.2017.12.002.

Dibike, Y.B., Coulibaly, P., 2005. Hydrologic impact of climate change in the saguenay watershed: Comparison of downscaling methods and hydrologic models. *Journal of hydrology*, 307(1-4), pp.145-163. https://doi.org/10.1016/j.jhydrol.2004.10.012.

Doost, Z.H., Alsuwaiyan, M., and Yaseen, Z.M., 2024. Runoff management based water harvesting for better water resources sustainability: a comprehensive. *Knowledge-Based Engineering and Sciences* 5(1), pp.1-45. https://doi.org/10.51526/kbes.2024.5.1.1-45.

Farhan, A. M., 2020. Estimation of Surface Runoff in Arid Regions by using Soil and Water Assessment Tool (SWAT), M.Sc Thesis, Department of water resources engineering, University of baghdad, Iraq.

Farhan, A.A., Abed, B.S., 2021. Estimation of surface runoff to Bahr Al-Najaf. *Journal of Engineering,* 27(9), pp.51-63. https://doi.org/10.31026/j.eng.2021.09.05.

Farhan, A.M., Al Thamiry, H.A., 2020. Estimation of the surface runoff volume of Al-Mohammedi valley for long-term period using SWAT model. *Iraqi Journal of Civil Engineering*, 14(1), pp.8-12.

Farhan, A.A. and Abed, B.S., 2022. Numerical modelling of surface runoff in watershed areas related to Bahr AL-Najaf. In Geotechnical Engineering and Sustainable Construction. *Sustainable Geotechnical Engineering* (pp.241-251). https://doi.org/10.1007/978-981-16-6277-5_20.

Fu, Z., Li, Z., Cai, C., Shi, Z., Xu, Q. and Wang, X., 2011. Soil thickness effect on hydrological and erosion characteristics under sloping lands: A hydropedological perspective. *Geoderma*, 16, pp.41-53. https://doi.org/10.1016/j.geoderma.2011.08.013.

Gassman, P.W., Reyes, M.R., Green, C.H. and Arnold, J.G., 2007. The soil and water assessment tool: historical development, applications, and future research directions. *Transactions of the ASABE*, 50(4), pp.1211-1250. https://doi.org/10.13031/2013.23637.

Gassman, P.W., Sadeghi, A.M. and Srinivasan, R., 2014. Applications of the SWAT model special section: overview and insights. *Journal of Environmental Quality*, 43(1), pp.1-8. https://doi.org/10.2134/jeq2013.11.0466.

Kadhim, M.M., 2018. Monitoring land cover change using remote sensing and GIS techniques: a case study of Al-Dalmaj marsh, Iraq. *Journal of Engineering*, 24(9), pp.96-108. https://doi.org/10.31026/j.eng.2018.09.07.

Kalcic, M.M., Chaubey, I., and Frankenberger, J., 2015. Defining soil and water assessment tool (SWAT) hydrologic response units (HRUs) by field boundaries. *International Journal of Agricultural and Biological Engineering*, 8(3), pp.69-80.

Karimi, S., Karimi, S., Yavari, A.R., and Niksokhan, M.H., 2015. Prediction of temperature and precipitation in Damavand catchment in Iran by using LARS–WG in future. *Earth Sciences*, 4(3), pp.95-100. https://doi.org/10.11648/j.earth.20150403.12.

Khalaf, A.G., Mohammed, G.H., and Jaseem, A.A., 2016. Monitoring change of marshes in South of Iraq by using image processing techniques for landsat images through period from 1990 to 2015. *Journal of Engineering Technology,* 34, pp.261-274.

Khosravanian, J., Onagh, M., Goudarzi, M., and Hejazi, S.A., 2015. Prediction of climatic parameters using LARS-WG model in Ghare-su Basin. *Journal Of Geography And Planning*, 19(53),pp. 93-115. https://www.sid.ir/paper/203661/en.

McGlynn, B.L., McDonnell, J., 2003. Quantifying the relative contributions of riparian and hillslope zones to catchment runoff. *Water Resources Research*, 39(11). https://doi.org/10.1029/2003WR002091.

Ministry of Transport, General Authority for Meteorology and Seismic Monitoring/Climate and Scientific Research Center. http://meteoseism.gov.iq/.

Mustafa, A.S., Sulaiman, S.O., and Hussein, O.M., 2016. Application of swat model for sediment loads from valleys transmitted to Haditha reservoir. *Journal of Engineering,* 22(1), pp.184-197. https://doi.org/10.31026/j.eng.2016.01.12.

Neitsch, S.L., Arnold, J.G., Kiniry, J.R., and Williams, J.R., 2011. Soil and water assessment tool theoretical documentation version 2009. *Texas Water Resources Institute*, 8(3),pp.23-39.

Oleiwi, A.S., Abed, B.S. and Hasan, B.F., 2023. Rainfall prediction and runoff modelling under climate change scenarios for Tigris River from Mosul to Baghdad cities.*International Journal of Design and Nature and Ecodynamics*, Vol.18, No.3, 537-546. https://doi.org/10.18280/ijdne.180305.

Pandi, D., Kothandaraman, S., and Kuppusamy, M., 2021. Hydrological models: A review. *International Journal of Hydrology Science and Technology*, 12(3), pp.223-242. http://dx.doi.org/10.1504/IJHST.2021.117540.

Saleh, R.A.Q., Oleiwi, A.S. and Lateef, Z.Q., 2024. The impact of climate change on water quality and consumption in the Tigris River Basin (Mosul-Baghdad). In IOP Conference Series*: Earth and Environmental Science* (Vol. 1374, No. 1, p. 012048). IOP Publishing. https://doi.org/10.1088/1755-1315/1374/1/012048.

Sarkar, J., Chicholikar, J.R., and Rathore, L.S., 2015. Predicting future changes in temperature and precipitation in arid climate of Kutch, *Gujarat*: Analyses based on LARS-WG model. Current science, pp.2084-2093.

Semenov, M.A., 2021. LARS-WG stochastic weather generator (LARS-WG 6.0). Zenodo. https://doi.org/10.5281/zenodo.4572752.

Sulaiman, S.O., Mahmood, N.S., Kamel, A.H., and Al-Ansari, N., 2021. The evaluation of the SWAT model performance to predict the runoff values in the Iraqi western desert. *Environment and Ecology Research*, 9(6), pp.330-339. https://doi.org/10.13189/eer.2021.090602.

Urutseg, 2021. Iraq location map. *Retrieved from*: https://commons.wikimedia.org/wiki/User:Urutseg/gallery.

Ware, H.H., Chang, S.W., Lee, J.E., and Chung, I.M., 2024. Assessment of hydrological responses to land use and land cover changes in forest-dominated watershed using SWAT model. *Water*, 16(4), p.528. https://doi.org/10.3390/w16040528.

Winchell, M.F., Folle, S., Meals, D., Moore, J., Srinivasan, R. and Howe, E.A., 2015. Using SWAT for sub-field identification of phosphorus critical source areas in a saturation excess runoff region. *Hydrological Sciences Journal*, 60(5), pp.844-862. https://doi.org/10.1080/02626667.2014.980262.

Winkler, R.D., Moore, R.D., Redding, T.E., Spittlehouse, D.L., Carlyle-Moses, D.E., and Smerdon, B.D., 2010. Hydrologic processes and watershed. *Compendium of forest hydrology and geomorphology in British Columbia*. BC Min. For. Range, 66, p.133.

Zakaria, S., Al-Ansari, N., and Knutsson, S., 2013. Historical and future climatic change scenarios for temperature and rainfall for Iraq. *Journal of Civil Engineering and Architecture*, 7(12), pp.1574-159. https://doi.org/10.17265/1934-7359/2013.12.012.

Zubaidi, S.L., Kot, P., Hashim, K., Alkhaddar, R., Abdellatif, M., and Muhsin, Y.R., 2019. Using LARS–WG model for prediction of temperature in Columbia City, USA. In *IOP Conference Series: Materials Science and Engineering (Vol. 584, No. 1, p. 012026)*. IOP Publishing. https://doi.org/10.1088/1757-899X/584/1/012026.

التنبؤ بالجريان السطحي المستقبلي الواصل إلى نهر الفرات باستخدام موديل لارس المناخي وموديل سوات (وادي سهيلة في صحراء غرب العراق، حالة دراسية).

وسام عبد العباس عبد الله ، باسم شبع عبد*

قسم هندسة الموارد المائية، كلية الهندسة، جامعة بغداد، بغداد، مجمع الجادرية، 10071، العراق

الخلاصة

تم استخدام موديل توليد البيانات المناخية "لارس" والموديل الهيدرولوجي "سوات" في هذه الدراسة للتنبؤ بالسيح السطحي المستقبلي لوادي سهيلة، أحد اودية الصحراء الغربية العراقية. تم استخدام بيانات الطقس للسنوات العشرة الماضية كبيانات مدخلة في موديل لارس لتوليد بيانات مناخية مستقبلية تحت تأثير التغيرات المناخية. في هذا الموديل، يتم اجراء التحليل الاحصائي تلقائيا، ولدالتين احصائيتين. قيم نتائج الاختبار الاحصائي الأول كانت قريبة من الصفر، بينما كانت للاختبار الاحصائي الثاني قريبة من الواحد، مما يعني ان الموديل مثالي وملائم في توليد القيم المطرية ودرجات الحرارة واكثر قدرة وملائمة في محاكاة التوزيعات الموسمية. تم استخدام نتائج موديل لارس المناخي كبيانات مناخية مدخلة في الموديل الهيدرولوجي سوات، والذي يتطلب لغرض تشغيله بيانات مختلفة مثل نموذج الارتفاع الرقمي، خارطة استخدام الأراضي والغطاء الأرضي، وخريطة تصنيف التربة وبيانات المناخ. تم تشغيل هذا الموديل، حيث أظهرت المحاكاة مستجمعات المياه للوادي موضوع الدراسة انشاء 14 حوضا فرعيا، و59 وحدة استجابة هيدرولوجية. ولاختبار مدى ملاءمة تطبيق هذا النموذج، تم تطبيق اختبارين إحصائيين (Nash-Sutcliffe - NS وR^2) لمجموعتي البيانات المحسوبة من القيم الحقلية والمحاكاة من الموديل للجريان السطحي في كل من فترتي المعايرة والتحقق، وكانت نتائج هذه الاختبارات (0.72) (0.78) للمعايرة، و(0.64) (0.67) للتحقق على التوالي، حيث ظهرت كل من البيانات المحاكاة والمحسوبة في فترتي المعايرة والتحقق تقاربا إلى حد ما في اختبار (NS)، وأيضًا نفس جودة النتائج في اختبار (R^2) مما يعني ملائمة استخدام هذا الموديل. تشير نتائج البيانات من نمذجة SWAT للسنوات العشرة القادمة بان اعلى سيح سطحي يحدث عند شهري أكتوبر ونوفمبر من موسم الشتاء، وشهر مارس من موسم الربيع في كل سنة، وان السيح السطحي يحدث بمعدل مرة واحدة الى أربعة مرات سنويا، وبعض السنوات يحدث مرتين. ذلك يعني ان كمية السيح السطحي التي ستضاف الى مياه نهر الفرات من وادي سهيلة محدودة وغير مستمرة.

الكلمات المفتاحية: نظم المعلومات الجغرافية، اودية العراق، موديل لارس للمناخ، الجريان السطحي، موديل سوات.