Artvin Çoruh Üniversitesi
Orman Fakültesi Dergisi
ISSN:2146-1880, e-ISSN: 2146-698X
Yıl: 2024, Cilt: 25, Sayı: 1, Sayfa: 111-127

ofd.artvin.edu.tr

Artvin Coruh University
Journal of Forestry Faculty
ISSN:2146-1880, e-ISSN: 2146-698X
Year: 2024, Vol: 25, Issue: 1, Pages:111-127

Evaluation of hydrological parameters and sediment dynamics in the Borçka Dam watershed using the SWAT model

Borçka Barajı havzasında hidrolojik parametrelerin ve sediment dinamiklerinin SWAT modeli ile değerlendirilmesi

Saim YILDIRIMER[1*], Mehmet ÖZALP[2]
[1]Karabük Üniversitesi, Orman Fakültesi, Orman Mühendisliği Bölümü, Havza Yönetimi Anabilim Dalı, Karabük
2Artvin Çoruh Üniversitesi, Orman Fakültesi, Orman Mühendisliği Bölümü, Havza Yönetimi Anabilim Dalı, Artvin

Eser Bilgisi / *Article Info*
Araştırma makalesi / *Research article*
DOI: 10.17474/artvinofd.1426951
Sorumlu yazar / *Corresponding author*
Saim YILDIRIMER
e-mail:saimyildirimer@karabuk.edu.tr
Geliş tarihi / *Received*
28.01.2024
Düzeltme tarihi / *Received in revised form*
24.03.2024
Kabul Tarihi / Accepted
07.04.2024
Elektronik erişim / *Online available*
15.05.2024

Keywords:
Water quality
Streamflow
Sediment yield
SWAT model
Watershed

Anahtar kelimeler:
Su kalitesi
Dere akışı
Sediment verimi
SWAT model
Havza

Abstract
Various human-originating interventions and/or activities have been playing the major role for substantially impacting natural flow regime, water quality, and sediment transport amounts of running waters (streams, creeks etc.) in a negative way. While many studies using in-field measurements of such impacts have proven these changes, applying modeling methods in order to assess such effects are still improving. This study used the SWAT model to assess annual changes in water regime, quality, and sediment yield for Murgul, Hatila, Fabrika, and Godrahav Creeks based on field measurements. The model estimated the highest annual surface flow at Murgul Creek (2.41 m^3/s) and the lowest at Fabrika Creek (0.19 m3/s). Sediment yields were 61855 t/yr at Murgul, 29826 t/yr at Hatila, 3165 t/yr at Fabrika, and 7835 t/yr at Godrahav. The model also provided reliable predictions for most sub-creeks, with R^2 values between 0.85 and 0.91 and NSE values between 0.72 and 0.84. For run-off, Hatila, Fabrika, and Godrahav showed high reliability with R^2 and NSE values around 0.85 and 0.80, respectively, while Murgul had lower scores (R^2: 0.53, NSE: 0.22). Sediment yield was reliable in Hatila and Fabrika with R^2 around 0.82, but less so in Godrahav and Murgul, with NSE values showing significant variability. Water quality predictions for NO_3 were acceptable across all creeks, with R^2 values around 0.82 and varied NSE values, indicating generally reliable outcomes. However, the model predicted less favorable outcomes for Murgul Creek due to significant human-induced alterations. While the SWAT model was generally promising, the study emphasizes the need for detailed, long-term data to improve prediction accuracy.

Özet
İnsan kaynaklı müdahaleler ve/veya faaliyetler akarsuların doğal akış rejimini, su kalitesini ve sediment taşınımını genelde olumsuz etkilemektedir. Bu etkilerin arazi ölçümleriyle kanıtlandığı çalışmalar olmasına rağmen, modelleme yöntemlerinin kullanımı gelişmeye devam etmektedir. Bu çalışma, Murgul, Hatila, Fabrika ve Godrahav Dereleri için yıllık değişiklikleri SWAT modeliyle değerlendirmiştir. Model, Murgul Deresi için en yüksek yüzey akışını (2.41 m^3/s), Fabrika Deresi için ise en düşük akışı (0.19 m^3/s) tahmin etmiştir. Sediment verimi, Murgul'da 61855 t/yıl, Hatila'da 29826 t/yıl, Fabrika'da 3165 t/yıl, Godrahav'da ise 7835 t/yıl olarak hesaplanmıştır. Model, çoğu alt dere için 0.85 ile 0.91 arasında R^2 ve 0.72 ile 0.84 arasında NSE değerleriyle güvenilir tahminler sağlamıştır. Hatila, Fabrika ve Godrahav için yüzey akışı yüksek güvenilirlik göstermişken (R^2 ve NSE değerleri yaklaşık 0.85 ve 0.80), Murgul daha düşük değerler almıştır (R^2: 0.53, NSE: 0.22). Sediment veriminde Hatila ve Fabrika güvenilirken, Godrahav ve Murgul'da NSE değerleri büyük değişkenlik göstermiştir. NO_3 su kalitesi tahminleri tüm dereler için kabul edilebilir olup, R^2 değerleri yaklaşık 0.82 ve NSE değerleri değişkenlik göstermiştir. Ancak, Murgul Deresi için model, ciddi insan kaynaklı değişiklikler nedeniyle daha az olumlu tahminlerle sonuçlanmıştır. SWAT modeli genel olarak umut verici sonuçlar vermiş, ancak çalışma daha doğru sonuçlar için detaylı ve uzun vadeli verilere olan ihtiyacı vurgulamıştır.

INTRODUCTION

Water serves as a fundamental element in Earth's complex ecosystem, sustaining all forms of life and contributing significantly to social and economic development. It is important for various sectors, including agriculture, energy production, industrial processes, and transportation, while also fulfilling the basic daily needs of human populations. Despite the fact that Earth's surface is mostly covered by water, the availability of freshwater that can actually be used is alarmingly limited. The unequal distribution of these resources across different regions makes the global challenge of ensuring water security even more difficult (WWAP 2015, Şahin 2016, USGS 2020).

However, the scarcity of usable water is not the only concern. The increasing contamination of water resources due to domestic, industrial, and agricultural pollution has led to a decline in water quality (Megdal et al. 2017, Loucks 2000, Kükrer and Mutlu 2019, Schilling et al. 2020, Kheirinejad et al. 2022). Addressing this pressing issue and achieving access to clean and fresh water has become an escalating priority, particularly with the changing global conditions and growing human population.

Moreover, climate change has emerged as a critical factor influencing the availability of freshwater resources. Recent years have witnessed growing evidence of its adverse effects on water resources, impacting the hydrological cycle and further exacerbating water scarcity (Frederick and Major 1997, Ertürk 2012, Brosse et al. 2022, Asif et al. 2023). The implications of climate change underscore the urgent need for robust and adaptable water management strategies.

To address these challenges and devise sustainable water management solutions, it is imperative to comprehensively assess the current status of freshwater resources and identify pollution sources and levels accurately, swiftly, and safely. In this context, Remote Sensing (RS) and Geographic Information Systems (GIS) have emerged as indispensable tools, revolutionizing water resource planning and management (Verma et al. 2012, Singh et al. 2014).

Over the years, physically based computer simulation models, integrated with GIS technologies, have been developed to predict various hydrological components, such as surface flow, nutrient transport, and sediment yield from agricultural basins (Dengiz et al. 2014, Gölpınar 2017, Ediş et al. 2021). These sophisticated models leverage the wealth of data obtained through advanced devices and high-speed computers, enabling realistic simulations of complex hydrological processes (Cüceloğlu 2013).

Among the well-regarded hydrological models worldwide, the Soil and Water Assessment Tool (SWAT) Model has gained prominence for estimating water quantity and quality parameters (Güzel 2010, Ezz-Aldeen et al. 2013, Güngör and Göncü 2013, Ghoraba 2015, Ediş 2018, Marahatta et al. 2021). Leveraging the capabilities of GIS software, the SWAT efficiently models hydrological processes, including meteorological data, surface flow, percolation, evapotranspiration, and more (Winchell et al. 2010, Neitsch et al. 2011).

The integration of RS, GIS, the SWAT model offers a powerful approach to uncover the impacts of water, sediment, and pollutant sources, particularly in river systems originating from diverse basins. By simulating these effects, future water resource management decisions can be informed and critical environmental concerns can be addressed proactively.

In light of these capabilities, the Borçka Dam Watershed (BDW), a sub-watershed located within the greater Çoruh River Basin (CRB), was selected as the study area. Lying along the northeastern part of Turkey, the BDW comprises four smaller watersheds, each characterized by distinct land uses and varying degrees of human influence. The primary focus of this study was to explore some characteristics -including the annual changes in flow regime, some water quality parameters, and total suspended sediment (TSS) levels- within the main creeks of the sub-watersheds. To achieve this, a detailed in-field measurements were utilized in order to apply the SWAT model in predicting values of water characteristics for the creeks. The research has dual primary objectives. Firstly, the objective is to employ the SWAT model to calculate essential hydrological parameters in the Borçka Dam Watershed (BDW) with the purpose of gaining valuable understanding of the area's hydrological patterns. Furthermore, the study aims to establish a strong basis for evaluating the amount of sediment that ultimately enters the Borçka Dam reservoir. Understanding sediment levels and patterns is crucial for maintaining the reservoir's storage capacity and ensuring sustainable water resource management practices.

MATERIAL AND METHODS

Description of The Study Area

The Borcka Dam Watershed (BDW) is located in the Eastern Black Sea Region of Turkey. It spans from 41º 03'

99" to 41º 21' 10" Northern Latitudes and from 41º 26' 57" to 41º 55' 26" Eastern Longitudes. The BDW is situated in the lower part of the Coruh River Basin (CRB). Spanning an approximate total area of 867 km^2, the BDW is located within the administrative boundaries of Borcka, Murgul, and the central districts of the city of Artvin.

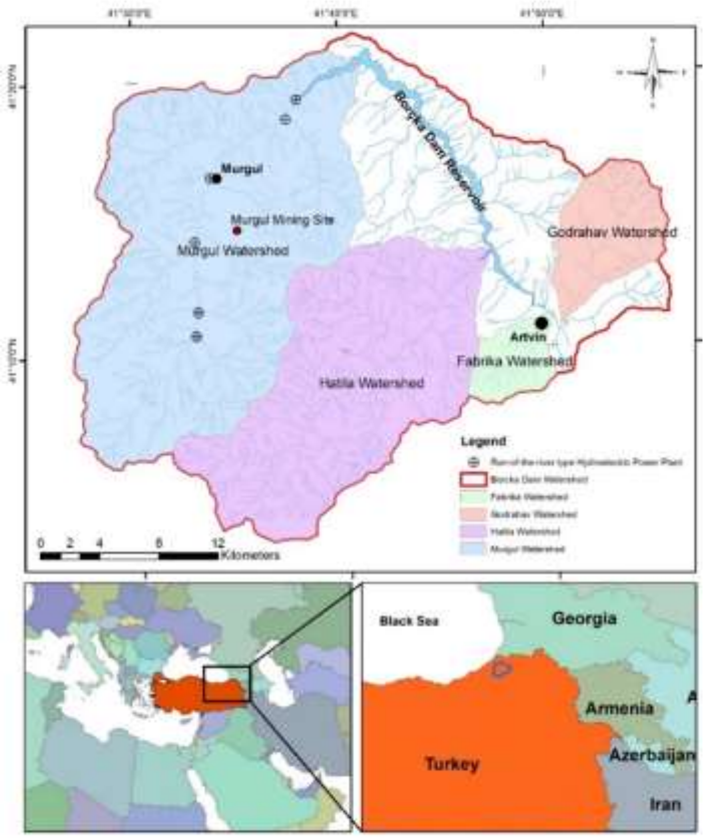

Figure 1. The geographical location of the study area and the borders of the Borcka Dam Watershed

Climatically, the city of Artvin, located within the study area, characterized by an annual average temperature of 12.48 ºC based on observation data collected between 1989 and 2018 from the Meteorological Data Archives of Artvin. The city's climate is characterized by an annual average maximum temperature of 16.75ºC and an average minimum temperature of 8.22ºC. The precipitation data indicates an average annual rainfall of 670.5 mm. Notably, the month with the lowest average annual precipitation is August, recording 27.1 mm, while the month with the highest average precipitation is January, with 87.62 mm (MGM 2018).

The BDW's unique geographical features, climate conditions, and varying land uses make it an ideal study area for investigating water resources and sediment dynamics. Its location within the larger Coruh River Basin contributes to the significance of this study, as the basin plays a pivotal role in supporting local ecosystems and human activities in the Eastern Black Sea Region of Turkey. Understanding the hydrological processes, water quality dynamics, and sediment transport patterns within this basin is essential for developing informed and sustainable water management strategies, crucial to the environmental conservation and socio-economic development of the region.

Overview of SWAT Model

The Soil and Water Assessment Tool (SWAT) is a widely utilized physical model developed by the USDA-ARS (Agricultural Research Services of the United States Department of Agriculture) (Arnold et al. 1998). Renowned for its versatility, the SWAT model is designed to assess the long-term impacts of non-point pollution sources in watersheds, facilitating water budget modeling, water quality assessment, sediment yield estimation, and integrated watershed planning and management. The SWAT model was developed with CREAMS (Chemicals, Surface flow and Erosion from Agricultural Management Systems), GLEAMS (Groundwater Loading Effects of Agricultural Management System), EPIC (Erosion Productivity Impact Calculator), SWRRB (Simulator for Water Resources in Rural Basins), ROTO (Routing Outputs to Outlet), QUAL2E (Enhanced Creek Water Quality Model), which were developed by USDA-ARS (Gassman et al. 2007, Neitsch et al. 2011).

The SWAT program can also be used in modeling hydrological processes such as surface flow, infiltration, percolation, evapotranspiration, lake and reservoir storage, and underground flow as well as plant nutrients and pesticide loads. Daily or longer-term simulations can be performed with this model. The SWAT model, which can work in very large areas, can divide the basin into multiple sub-basins. The model uses various data such as meteorological, topographic, soil, vegetation, and land use data as its input parameters. The modeled basin is divided into hydrological processing units that are called "the smallest HRU" (i.e. Hydrologic Response Units), which differs according to drainage areas and input parameters, and operations are then performed for each HRU (Gassman et al. 2007, Arnold et al. 2012).

One of the distinguishing features of the SWAT model is its ability to partition large basins into multiple sub-watersheds, thereby increasing its applicability in modeling expansive geographic areas. Essential input parameters, such as meteorological, topographical, soil, vegetation, and land use data, are integrated into the model. Within the modeled basin, Hydrologic Response Units (HRUs) are identified; these vary depending on drainage areas and input parameters, and individual operations are conducted for each HRU (Arnold et al. 1998).

Fundamentally, the SWAT model utilizes the water balance equation to meticulously monitor changes in soil water content over specific time intervals. The equation accounts for various components such as daily precipitation (R_day), surface runoff (Q_surf), rates of evapotranspiration (E_a), water percolating into the vadose zone from the soil profile (W_seep), and groundwater return flow (Q_gw) for each time step (Neitsch et al. 2011). In the formulation of the SWAT model, the Penman-Monteith method was utilized to calculate potential evapotranspiration (PET), given its consideration of energy exchange and mass transfer between the vegetation, soil, and atmosphere (Gassman et al. 2007, Neitsch et al. 2011).

The SWAT model executes hydrological processes in accordance with the following water balance equation (Gassman et al. 2007).

$$SW_t = SW_0 + \sum_{i=1}^{t} \left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right)_i$$

Where; SW_t is the final soil water content (mm); SW_0 is the initial water content (mm).; t is the time (days); R_{day} is the amount of precipitation on day i (mm); Q_{surf} is the amount of surface runoff on day i (mm); E_a is the amount of evapotranspiration on day i (mm); W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm); Q_{gw}: the amount of return flow on day i (mm) (Neitsch et al. 2011).

Development of Database

To implement the SWAT model, a comprehensive database comprising mandatory temporal and spatial data is required. This includes but is not limited to a digital elevation model, land use and vegetation cover data, and a soil properties map. Alongside these foundational data sets that are crucial for the model's functioning, additional files are prepared to model water quality parameters. In addition to the essential datasets required for the model to function, a separate data file containing water quality parameters has also been prepared to facilitate the modeling of water quality. The source and procurement of these critical datasets are briefly explained in the following sections, categorized under separate headings for clarity.

Spatial Datasets

The successful implementation of the SWAT model relies on the utilization of crucial spatial datasets, encompassing the digital elevation model (DEM), land use data, and soil properties map.

Digital Elevation Model (DEM)

In the Soil and Water Assessment Tool (SWAT) model, one of the foundational datasets is the Digital Elevation Model (DEM) with a cell size of 15x15 meters. This dataset is used to determine various key parameters, such as watershed and sub-watershed boundaries, flow directions, channel slopes, drainage areas, and the condition of different slopes. Contour data for the study area, sourced from the General Command of Mapping, were employed to create the DEM map using the ArcGIS 10.3.2 software, as illustrated in Figure 2.

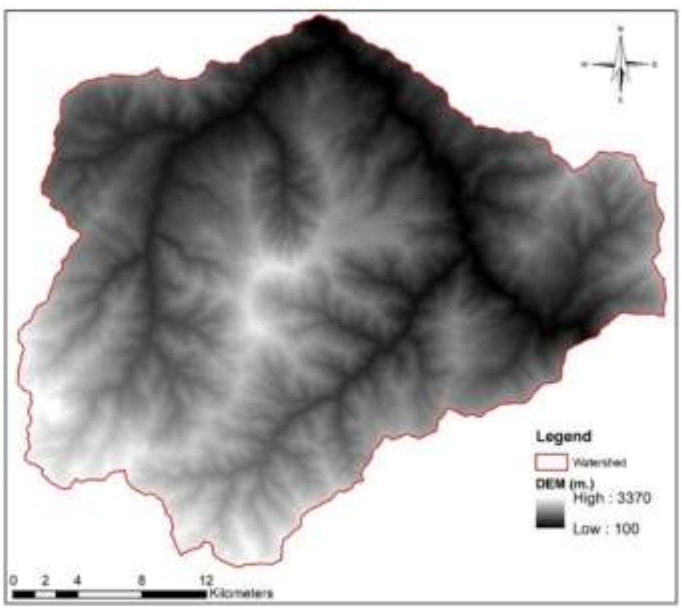

Figure 2. Digital Elevation Map (DEM) of the study area

Land Use

To generate the land use map of the study area, a high-resolution SPOT 7 satellite image with a terrestrial resolution of 1.5 m, acquired in September 2015, was used. Manual digitization and classification of the satellite image resulted in a comprehensive land use map with eight main classes, as listed in Table 1. The land use map (Figure 3) facilitates the assessment of land use patterns and the respective coverage areas within the study area.

Table 1. Land use classes and their match for the SWAT database codes

Rank	Land Use	SWAT Database Codes
1	Forest	FRST
2	Barren forest	BARR
3	Forest gap	RNGE
4	Pasture	PAST
5	Urban	URBN
6	Agriculture	AGRL
7	Mining site	UIDU
8	Water	WATR

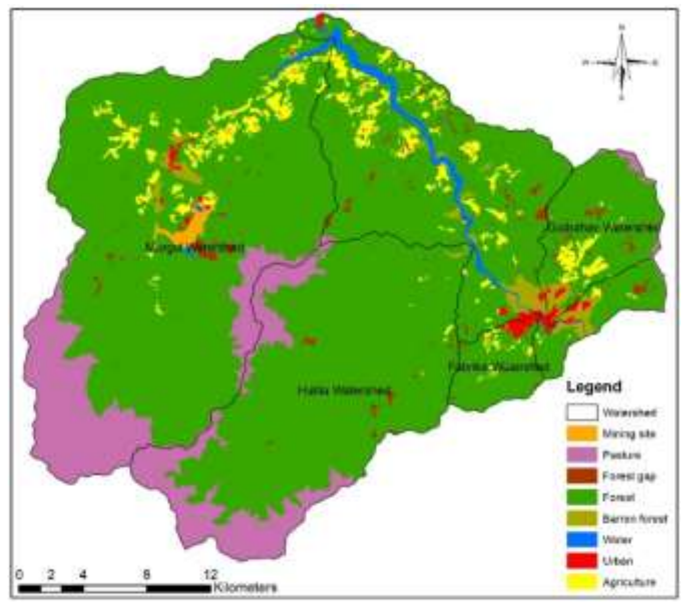

Figure 3. Land use map of the study area

Soil Data

The use of soil samples and some analysis data of a previous study (Erdoğan Yüksel 2015), which was completed in 2015 in the same area and whose author was also a researcher in the scope of the studies, was found to be appropriate, both timely and economically, to create the map of the soil properties of the study area. In this way, the data of 240 soil samples taken in that study were also used in this study. However, 129 more soil samples were taken from the areas that were not sampled in the previous study by considering the land use status in addition to these samples to represent the area better. A total of 369 soil samples (Figure 4) and data from these samples were used to represent the entire watershed, using the Inverse Distance Weighted (IDW) method for soil map creation. The obtained soil characteristics were prepared in line with the data entry format of the model.

Time-Based Datasets

Temporal datasets are equally vital for the proper functioning of the SWAT model. These datasets encompass both meteorological and hydrological data.

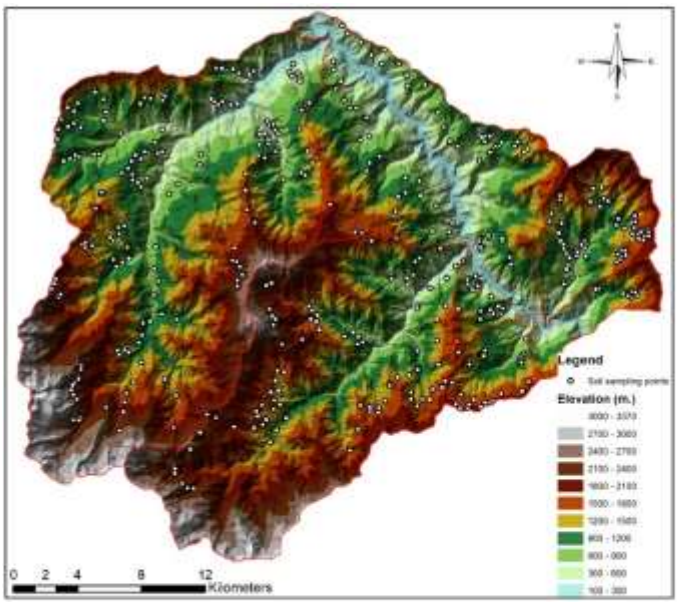

Figure 4. Soil sampling locations in the study area

Meteorological Data

Meteorological data were acquired from the "Artvin 17045" Meteorology Station, located within the working area of the Artvin Meteorology Station Directorate. The dataset spans 30 years, covering the period from 1989 to 2018. Daily recorded meteorological parameters, such as precipitation, wind speed, solar radiation, relative humidity, and temperature, were obtained from this station. These data were prepared as "txt" files in year and month order and used to calculate the statistical values presented in Table 2. Additionally, a "WGEN" file was created, incorporating the meteorological dataset for the SWAT Model.

Hydrological Data

To effectively calculate and model the parameters of water yield, water quality, and sediment yield in the Borcka Dam Watershed, a comprehensive set of hydrological data was collected and analyzed. The data collection process involved monthly measurements over a 12-month period, spanning from July 2016 to June 2017, for calibration at the exit points of the four sub-watersheds, as shown in Figure 1. For the validation process, eight-month datasets were obtained, measured monthly between March 2018 and October 2018. Additionally, the Fabrika and Godrahav Creek Watersheds underwent weekly measurements between March and June 2018, resulting in an augmented dataset for validation purposes.

Table 2. Monthly and annual mean values of meteorological data for Artvin 17045 station

	Monthly averages												
Parameters	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Annual mean**
TMPMX	5.62	7.74	11.96	17.31	21.08	23.56	25.45	26.13	23.51	19.12	12.43	7.07	16.75
TMPMN	-0.26	0.23	2.70	6.73	10.74	14.01	16.71	17.32	13.93	10.27	4.94	1.33	8.22
TMPSTDMX	3.89	5.16	6.06	6.11	5.45	4.24	4.04	3.75	4.75	5.01	4.58	4.14	4.77
TMPSTDMN	2.99	3.52	3.55	3.72	3.24	2.54	2.34	2.31	2.96	3.25	3.43	3.35	3.10
PCPMM	87.62	66.69	57.10	46.79	47.00	46.30	33.62	27.10	33.83	62.86	82.59	79.00	55.88
PCPSTD	7.72	6.18	4.42	3.24	3.30	3.58	3.30	3.10	3.21	5.25	7.67	6.49	4.79
PCPSKW	5.06	4.25	5.10	2.91	3.61	3.50	4.62	7.07	4.21	4.40	4.92	4.03	4.47
PR_W1	0.23	0.24	0.26	0.26	0.26	0.22	0.16	0.15	0.15	0.20	0.18	0.21	0.21
PR_W2	0.53	0.54	0.48	0.49	0.48	0.47	0.40	0.34	0.42	0.51	0.55	0.51	0.48
PCPD	10.31	9.52	10.28	10.07	10.21	8.80	6.38	5.62	6.21	8.86	8.66	9.41	8.69
RAINHHMX	9.14	7.20	5.57	4.22	4.05	4.74	4.06	4.14	4.07	7.13	9.00	8.77	6.01
SOLARAV	4.69	7.76	11.05	14.72	17.70	19.85	19.63	17.91	14.25	8.80	6.15	4.20	12.23
DEWPT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WNDAV	1.08	1.27	1.53	1.48	1.35	1.64	1.80	1.70	1.35	0.92	0.98	1.03	1.34

TMPMX : Average or mean daily maximum air temperature for month (ºC), TMPMN: Average or mean daily minimum air temperature for month (ºC), TMPSTDMX: Standard deviation for daily maximum air temperature in month (ºC), TMPSTDMN: Standard deviation for daily minimum air temperature in month (ºC), PCPMM: Average or mean total monthly precipitation (mm) ,PCPSTD: Standard deviation for daily precipitation in month (mm/day), PCPSKW: Skew coefficient for daily precipitation in month, PR_W1: Probability of a wet day following a dry day in the month, PR_W2: Probability of a wet day following a wet day in the month, PCPD: Average number of days of precipitation in month, RAINHHMX: Maximum 0.5 hour rainfall in entire period of record for month (mm), SOLARAV: Average daily solar radiation for month (MJ/m^2/day), DEWPT: Average daily dew point temperature for each month (ºC) or relative humidity (fraction) can be input, WNDAV: Average daily wind speed in month (m/s)

Flow Rate Measurements

Flow rate measurements were crucial in understanding the dynamics of water movement within the study area. The flow measurements were calculated according to the velocity-area method. According to this method, the velocity is measured at 20% and 80% of the water depth and the average of these measurements is taken to find the average velocity in the cross-sectional area in deep (H>50 cm) rivers. The speed measured at 60% of the water depth from the water surface is accepted as the average speed in shallow waters where the depth is low (H<50 cm) (Genç et al. 2015, Chen et al. 2022).

Determining Total Suspended Solids (TSS)

Sediment dynamics were assessed through the calculation of Total Suspended Solids (TSS) in water samples, collected using the grab sampling method from approximately 30 cm below the water surface. For this quantification, the filtration technique outlined in the "Standard Method for Examination of Water and Wastewater" (Clesceri et al. 1999), specifically method SM2540-D, by the American Public Health Association (APHA) was followed. This method involves filtering the water samples through a pre-weighed filter, drying, and then re-weighing to determine the weight of the suspended solids. Grab samples were collected in 1-liter amber-colored, sunlight-resistant plastic bottles to prevent photodegradation of the samples (Clesceri et al. 1999).

Chemical Water Quality Parameters

Among the chemical water quality parameters measurements of pH, dissolved oxygen (DO), total dissolved solids (TDS), suspended solids (SS), ammonium nitrogen (NH4-N), nitrate nitrogen (NO_3-N), salinity, conductivity, and temperature measurements were conducted on-site using a YSI/Professional-Plus portable water quality device.

In contrast, evaluations of sulfate (SO4), ortho-phosphate (PO4-P), and total nitrogen (TN) were performed in the laboratory using Hach Lange test kits at the Spectroscopy Laboratory of Artvin Coruh University Science-Technology Application and Research Center. Samples for these laboratory analyses were collected using the grab sample method was followed. To maintain sample quality during transportation to the laboratory, samples were kept in a cool transport case and analyzed within 24 hours of collection.

MODEL SIMULATION

Once all the necessary data were successfully entered into the SWAT model, the final settings for simulation were determined to effectively model the hydrological processes in the Borcka Dam Watershed. Considering that the meteorological data started in 1989, the model was initiated from the year 1989. To ensure accurate representation of the watershed's dynamics, the initial 3 years were designated as warm-up years, allowing the model to stabilize before the simulation. Consequently, a 27-year simulation was conducted, spanning from 1989 to 2018.

For the calibration of the model parameters, real measurements obtained from field observations during a full year between 2016 and 2017 were utilized. These measurements were instrumental in fine-tuning the model to closely match the observed data. To validate the calibrated model, monthly measured parameters between March and October 2018 were employed. In particular, the Fabrika and Godrahav Creek Watersheds underwent weekly measurements between May and June, enriching the dataset for validation purposes.

Sensitivity analysis plays a crucial role in assessing the significance of model parameters affecting simulation results. For this study, the SWAT-CUP (SWAT-Calibration and Uncertainty Program) was used in conjunction with the SUFI-2 optimization method for sensitivity analysis. By utilizing SWAT-CUP, the parameters that would undergo sensitivity analysis were manually selected, drawing insights from previous studies that employed similar methodologies (Akhavan et al. 2010, Oeurng et al. 2011, Arnold et al. 2012, Strauch et al. 2012, Güngör and Göncü 2013, Ben Salah and Abida 2016, Gull et al. 2017, Thodsen et al. 2017).

MODEL EFFICIENCY

Performance statistics are used to explain the agreement of the simulated values with the measured observation values in model studies. In the present study, R^2 (specificity coefficient), NSE (Nash-Sutcliffe Efficiency Coefficient), and PBIAS (percent error statistics) were used to test the performance of the model. The criterion value ranges of these performance statistics are given in Table 3.

Table 3. Performance evaluation criteria for model statistics (Moriasi et al. 2007)

Performance rating	Nash-sutcliffe efficiency (NSE)	PBIAS (%)		
		Flow	Sediment	N, P
Very good	0.75 <NSE≤1.0	PBIAS < ±10	PBIAS < ±15	PBIAS < ±25
Good	0.65 <NSE≤0.75	±10 ≤ PBIAS < ±15	±15 ≤ PBIAS < ±30	±25 ≤ PBIAS < ±40
Satisfactory	0.50 <NSE≤0.65	±15 ≤ PBIAS < ±25	±30 ≤ PBIAS < ±55	±40 ≤ PBIAS < ±70
Unsatisfactory	NSE≤0.50	PBIAS ≥ ±25	PBIAS ≥ ±55	PBIAS ≥ ±70

Coefficient of Determination (R^2)

R^2, also known as the specificity coefficient, measures the degree of variation between the simulated and observed values. Ranging between 0 and 1, higher values indicate a stronger agreement between the simulation and observation data (Moriasi et al. 2007).

$$R^2 = \left[\frac{\sum_1^n (Q_{obs} - Q_{obs\_mean})(Q_{sim} - Q_{sim\_mean})}{\sqrt{\sum_1^n (Q_{obs} - Q_{obs\_mean})^2 \sum_1^n (Q_{sim} - Q_{sim\_mean})^2}}\right]^2$$

Where;

n Total sampling number
Q_{obs} Observed value
Q_{obs_mean} Mean observed value
Q_{sim} Simulated value
Q_{sim_mean} Mean of the simulated values

Nash-Sutcliffe Efficiency (NSE)

NSE provides an indicator of the model's predictive ability, with values ranging between -∞ and 1. An NSE value closer to 1 indicates that the model yields accurate estimation results (Moriasi et al. 2007).

$$NSE = 1 - \left[\frac{\sum_1^n (Q_{obs} - Q_{sim})^2}{\sum_1^n (Q_{obs} - Q_{mean})^2}\right]$$

Where;

n Total sampling number
Q_{obs} Observed value
Q_{mean} Mean of the observed values
Q_{sim} Simulated value

Percent Bias (PBIAS)

PBIAS, a percent error statistic, assesses how well the model's simulation values match the observed data, whether overestimating or underestimating. Positive PBIAS values indicate that observed values are greater than simulated values, whereas negative values indicate the opposite (Gupta et al. 1999).

$$PBIAS = \left[\frac{\sum_1^n (Q_{obs} - Q_{sim}) \times 100}{\sum_1^n Q_{obs}}\right]$$

Where;

n Total sampling number
Q_{obs} Observed value
Q_{sim} Simulated value

Model Calibration and Validation

The SWAT model applied to the study area underwent calibration using locally measured data for flow, suspended solids transport, and nitrate nitrogen (NO_3-N). The calibration process was carried out using the SWAT-CUP (SWAT Calibration and Uncertainty Procedures) program, specifically designed for calibrating SWAT model outputs and conducting uncertainty or sensitivity analyses.

For calibration purposes, the SUFI-2 Algorithm, known for its effectiveness, was selected among the optimization methods available in the SWAT-CUP program (Meaurio et al. 2015).

The calibration and validation processes were conducted independently for each of the four sub-watersheds in the study area. Measurements were taken on a monthly basis during the designated period. To ensure a representative monthly average, daily calibration was chosen since single-day measurements may not capture the full variability. The calibration and validation focused on flow, sediment, and nitrate (NO_3) parameters, utilizing measurement data from the exit points of the four sub-watersheds. It is well-established in the literature that the calibration sequence should prioritize flow, followed by sediment, and water quality parameters (Engel et al. 2007, Santhi et al. 2008). Accordingly, the calibration process was carried out in this order for each sub-watershed. The SWAT-CUP Program was executed five times for each sub-watershed, resulting in a total of 1000 simulations (200 simulations in each run).

For validation, eight-month datasets measured monthly from March 2018 to October 2018 were utilized. Additionally, the dataset for Fabrika and Godrahav Creek Watersheds was collected with weekly measurements taken between March and June 2018 to further validate the model.

The calibrated parameters and their corresponding value ranges used in the calibration of surface flow, sediment, and water quality are detailed in Tables 4, 5, and 6, respectively. By calibrating the model with locally measured data, it becomes more capable of representing the specific hydrological processes and water quality dynamics within the Borcka Dam Watershed. The validation process allows for the assessment of the model's performance in capturing real-world conditions, thus providing confidence in its ability to predict and manage water resources effectively.

Table 4. Calibrated parameters and value ranges for calibrating surface flow

Variable name	Definition	Value range	
		min	max
CN2.mgt	Initial SCS runoff curve number for moisture condition II	0	1
ALPHA_BF.gw	Baseflow alpha factor (1/days)	0	1
GW_DELAY.gw	Groundwater delay time	0	500
GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O)	0	5000
GW_REVAP.gw	Groundwater "revap" coefficient	0.02	0.2
SOL_ZMX.sol	Maximum rooting depth of soil profile (mm)	0	3500
SOL_K().sol	Saturated hydraulic conductivity (mm/hr)	0	2000
SOL_AWC().sol	Available water capacity of the soil layer (mm H2O/mm soil)	0	1
SOL_Z().sol	Depth from soil surface to bottom of layer (mm)	0	3500
SOL_BD().sol	Moist bulk density (Mg/m^3 or g/cm^3).	0.9	2.5
EPCO.bsn	Plant uptake compensation factor	0	1
ESCO.bsn	Soil evaporation compensation factor	0	1

Table 5. Calibrated parameters and value ranges used in calibrating TSS

Variable name	Definition	Value range	
		min	max
SPEXP.bsn	Exponent parameter for calculating sediment reentrained in channel sediment routing	1	1.5
SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.001	0.01
CH_ERODMO.rte	CH_ERODMO is set to a value between 0.0 and 1.0. A value of 0.0 indicates a non-erosive channel while a value of 1.0 indicates no resistance to erosion.	0	1
CH_COV1.rte	Channel erodibility factor	-0.05	0.6
C_FACTOR.bsn	Scaling parameter for cover and management factor for overland flow erosion	0.001	0.45
USLE_P.mgt	USLE equation support practice factor	0	1
USLE_K.sol	USLE equation soil erodibility (K) factor	0	0.65
CH_WDR.rte	Channel width-depth ratio (m/m)	-0.1	0.1
CH_BED_KD.rte	Erodibility of channel bed sediment by jet test (cm^3/N-s)	0.001	3.75
CH_BNK_KD.rte	Erodibility of channel bank sediment by jet test (cm^3/N-s)	0.001	3.75
CH_BNK_BD.rte	Bulk density of channel bank sediment (g/cc)	1.1	1.9
CH_BED_BD.rte	Bulk density of channel bed sediment (g/cc)	1.1	1.9

Table 6. Calibrated parameters and value ranges used in calibrating water quality parameters

Variable name	Definition	Value range	
		min	max
SOL_ORGN.chm	Initial organic N concentration in the soil layer (mg N/kg soil or ppm)	0	100
NPERCO.bsn	Nitrate percolation coefficient	0	1
BC1_BSN.bsn	Rate constant for biological oxidation of NH_3 (1/day)	0.1	1
BC2_BSN.bsn	Rate constant for biological oxidation NO_2 to NO_3 (1/day)	0.2	2
BC3_BSN.bsn	Rate constant for hydrolosis of organic nitrogen to ammonia (1/day)	0.2	0.4
CDN.bsn	Denitrification exponential rate coefficient	0	3
SDNCO.bsn	Denitrification threshold water content	0	1
SOL_NO3.chm	Initial NO_3 concentration in the soil layer	0	100
RS4.swq	Rate coefficient for organic N settling in the reach at 20º C	0.001	0.1

RESULTS AND DISCUSSION

Streamflow

The evaluation of the SWAT model's performance in simulating streamflow revealed valuable insights into the hydrological behavior of the study area, particularly regarding the effects of human-induced interventions, such as small hydropower plants (SHPs) (a.k.a. run-of-river hydroelectric power plants)

When analyzing the MCW sub-watershed, the model achieved an acceptable level of performance in predicting streamflow based on the specificity coefficient R^2 (0.53) and the PBIAS coefficient (1.91) according to the model performance statistics criteria (Table 2). However, the NSE coefficient, representing the prediction capacity of the model, fell below the recommended threshold of 0.50 for success (Moriasi et al. 2007), with a value of 0.22. In contrast, the Hatila Creek Watershed, largely situated within the borders of a national park and therefore less affected by human interventions, demonstrated highly successful calibration and validation results (Figure 5). The specificity coefficient R^2 (0.85) and the NSE coefficient (0.84) indicated strong model performance at the calibration point, while the PBIAS coefficient (-4.54) showed minimal error. Similar success was observed in the Fabrika and Godrahav sub-watersheds when compared to the Murgul sub-watershed. The calibration and validation results for these sub-watersheds exhibited high R^2 and NSE coefficients, as well as low PBIAS values (Table 7).

The lower success of estimating streamflow in the MCW sub-watershed compared to others was attributed to the presence of SHPs installed one after the other along the Murgul Creek. It is predicted that these SHPs exerted significant pressure on the model's predictive capacity, particularly during the validation process. Their irregular water release patterns, especially during dry summer months, disrupted the consistency between observed and predicted data. Consequently, the calibration's success was compromised.

Table 7. Performance statistics of calibration and validation outputs for streamflow parameter among all sub-watersheds

			R^2	NSE	PBIAS
Murgul Watershed					
	Sampling Point/Performance Statistics		R^2	NSE	PBIAS
Calibration	M20	Murgul Watershed outlet	0.53	0.22	1.91
Validation	M20	Murgul Watershed outlet	0.86	0.76	-37.1
Hatila Watershed					
	Sampling Point/Performance Statistics		R^2	NSE	PBIAS
Calibration	H3	Hatila Watershed outlet	0.85	0.84	-4.54
Validation	H3	Hatila Watershed outlet	0.85	0.83	-10.66
Fabrika Watershed					
	Sampling Point/Performance Statistics		R^2	NSE	PBIAS
Calibration	F7	Fabrika Watershed outlet	0.85	0.85	0.64
Validation	F7	Fabrika Watershed outlet	0.89	0.88	-4.79
Godrahav Watershed					
	Sampling Point/Performance Statistics		R^2	NSE	PBIAS
Calibration	G5	Godrahav Watershed outlet	0.78	0.72	12.7
Validation	G5	Godrahav Watershed outlet	0.91	0.84	-18.94

Evaluating these results with other similar studies, it can be stated that the performance of the calibrated SWAT model proved to be comparable or even superior. For instance, in the Lower Seyhan Plain study, R^2 and NSE coefficients were 0.73, and the PBIAS value was 2.4, while the validation process yielded 0.58, 0.57, and -5.6, respectively (Gölpınar 2017). In the Mogan Lake Watershed study, the calibration process resulted in R^2 = 0.74, NSE = 0.8, and PBIAS = -19.1, and the validation process yielded R^2 = 0.35, NSE = 0.4, and PBIAS = 62.4 (Özcan 2016). Similarly, in the Lolab Basin study, the calibration process achieved R^2 = 0.74 and NSE = 0.68, and the validation process yielded R^2 = 0.85 and NSE = 0.83 (Gull et al. 2017).

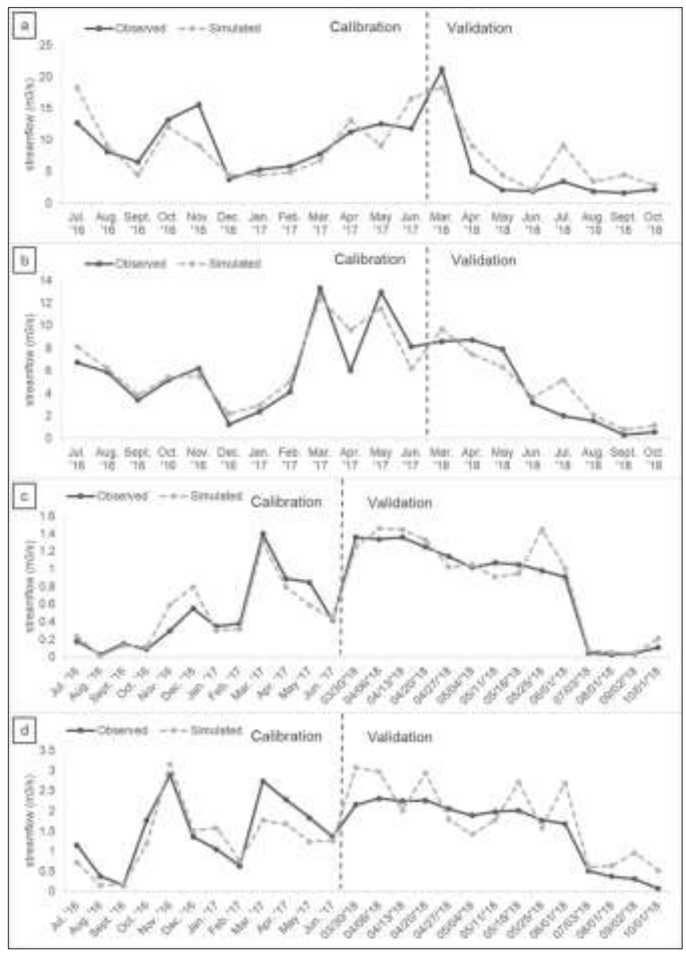

Figure 5. Comparison of the observed and the simulated streamflow patterns during the calibration and validation periods for the waters of Murgul Creek (a), Hatila Creek (b) Fabrika Creek (c), and Godrahav Creek (d).

Overall, the SWAT Model demonstrated promising capabilities in simulating streamflow, providing valuable information about hydrological processes in the study area. Notably, despite the limited data available for calibration and validation, the model achieved performance, underscoring the efficacy and robustness of the simulation under limited data conditions. The model's performance was influenced by human interventions, particularly the presence of SHPs, which affected water flow dynamics. Nevertheless, the model proved successful in sub-watersheds with limited anthropogenic influence, showcasing its potential for water resource management and environmental conservation efforts in the region.

Sediment Yield

The simulation of sediment yield in the selected sub-watersheds using the SWAT Model demonstrated valuable results regarding the dynamics of sediment transport and deposition. The analysis of sediment yield data revealed that the model tended to overestimate the actual observed values in most sub-watersheds. Nevertheless, the model's performance was significant for most sub-watersheds, except for MCW.

Upon examination of the MCW sub-watershed, the calibration indicated a significant R^2 value of 0.85 at the calibration stage. However, no significant results were obtained for the NSE and PBIAS coefficients. During validation, the R^2 remained at 0.84, and the NSE and PBIAS coefficients were again outside the range of significance (

Table **8**). The unfavorable outcomes in the MCW sub-watershed could be attributed to the negative impact of multiple SHPs established along the creek, leading to disturbances in water regime and consequently the distribution and deposition of sediment cycle. The main reason for such disruption is when the creek water is transported through open or closed tunnels on the transmission lines of SHPs, most of the suspended sediment in the water precipitates in the loading pools before released through penstocks. The cumulative effect of multiple SHP facilities along the creek introduces inaccuracies in sample measurements, resulting in higher estimations by the model. The model's predictions suggested an annual average sediment yield of 61855 tons for MCW (Table 9).

In contrast, the HCW sub-watershed, situated mainly within a national park with limited human activities, exhibited promising results in both calibration and validation stages. The model achieved significant R^2 values of 0.82 and 0.94, respectively, indicating good agreement with observed sediment yield. The NSE coefficient, while below the acceptable limit in the calibration period, improved to 0.78 in the validation (

Table **8**). In this sub-watershed, reduced surface erosion and low sediment yield were contributed to by the limited human-induced interventions and significant forest cover, resulting in the success of the model's performance. An annual average sediment yield of 29,826 tons was estimated for HCW (Table 9).

For the FCW sub-watershed, successful calibration was evidenced by significant results obtained for R^2 (0.82), NSE (0.77), and PBIAS coefficient (-17.66). During validation, an R^2 of 0.93, an NSE of 0.82, and a PBIAS coefficient of -33.86 were achieved (Table 8). Despite the presence of different land uses such as urbanization and agriculture, the high rates of calibration and validation suggested that the SWAT model's applicability to FCW is reliable. An annual average sediment yield of 3,165 tons was predicted for FCW (Table 9).

In the GCW sub-watershed, varying results were observed in the model's calibration and validation stages. Significant R^2 values of 0.71 and 0.88 were achieved during the calibration and validation periods, respectively. These results suggest a good agreement between the model's predictions and the observed sediment yield. However, the NSE coefficient remained outside the acceptable range, indicating the model's limitations in accurately estimating sediment yield in this moderately human-impacted watershed. The GCW sub-watershed had intermediate human activities, such as agriculture and settlement, and various creek-side structures, such as retaining walls and detention dams, hindering natural sediment transport and altered sediment dynamics. Consequently, the model estimated an annual average sediment yield of 7.835 tons for GCW (Table 9).

Table 8. Performance statistics of calibration and validation outputs for sediment yield among all Sub-Watersheds

Murgul Watershed					
	Sampling Point/Performance Statistics		**R^2**	**NSE**	**PBIAS**
Calibration	M20	Murgul Watershed outlet	0.85	0.16	-65.82
Validation	M20	Murgul Watershed outlet	0.84	-0.23	-65.53
Hatila Watershed					
	Sampling Point/Performance Statistics		**R^2**	**NSE**	**PBIAS**
Calibration	H3	Hatila Watershed outlet	0.82	-0.33	-33.17
Validation	H3	Hatila Watershed outlet	0.94	0.78	-51.27
Fabrika Watershed					
	Sampling Point/Performance Statistics		**R^2**	**NSE**	**PBIAS**
Calibration	F7	Fabrika Watershed outlet	0.82	0.77	-17.66
Validation	F7	Fabrika Watershed outlet	0.93	0.82	-33.86
Godrahav Watershed					
	Sampling Point/Performance Statistics		**R^2**	**NSE**	**PBIAS**
Calibration	G5	Godrahav Watershed outlet	0.71	0.07	-77.15
Validation	G5	Godrahav Watershed outlet	0.88	-0.89	-124.57

When comparing the estimated sediment yields from the SWAT Model to other studies in the literature, it is evident that the model's performance can be considered as comparable and/or even better in respect to some outcomes. For instance, in the Ankara Creek Basin study, the estimated annual average sediment amount was 0.19 tons/ha/year (Duru et al. 2017). In the Kalaya Basin study in Morocco, the annual average sediment yield was 55 tons/ha/year (Briak et al. 2016). Such studies highlight the importance of effectively utilizing GIS technologies in strategic planning for estimation, prevention, reduction, and protection of soil resources. One of this work evaluated the effectiveness of erosion and flood control measures implemented in the Emine Creek watershed in Osmancık, Turkey, using RUSLE/GIS technologies. The initiatives taken between 1970 and 2020 have reduced soil loss from 417 to 256 metric tons per hectare per year (Ediş et al. 2023).

Table 9. Estimated annual sediment yields based on SWAT model simulation

Sub-Watersheds	Sediment yields	
	tons/year	tons/ha/year
Murgul Watershed	61855	1.77
Hatila Watershed	29826	1.28
Fabrika Watershed	3165	1.32
Godrahav Watershed	7835	1.48

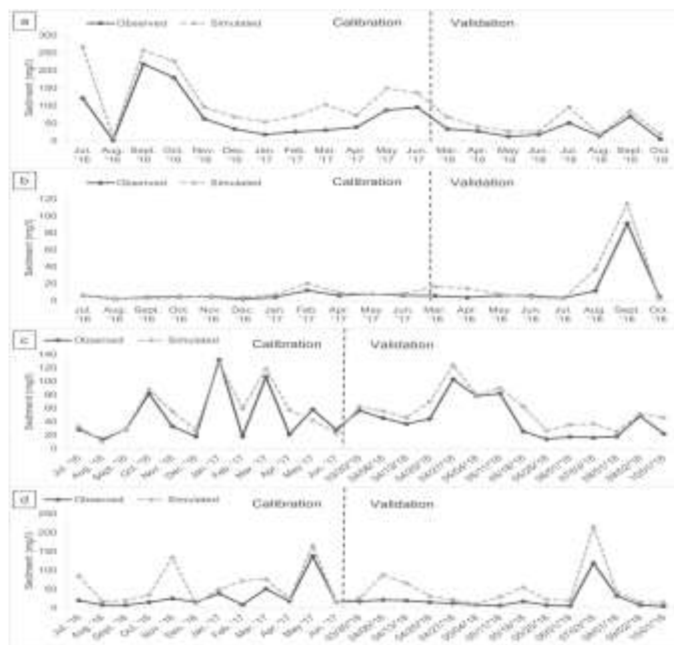

Figure 6. Comparison of observed and simulated TSS yields during the calibration and validation periods for the waters of (a) Murgul Creek (a), Hatila Creek (b), Fabrika Creek (c), and Godrahav Creek (d).

Water Quality Parameters

Among the water quality parameters, only Nitrate (NO_3) values could be simulated in the SWAT Model. The use of 'grab sample' method for collecting water samples, and its successful application in modeling water quality results, particularly NO_3 loads, is a noteworthy achievement. This approach assumes the nitrogen load from instantaneous samples to represent the entire month, a condition under which the model still managed to produce successful outcomes. The measurement period for the analysis of total nitrogen started from December-2016 in the study. For this reason, the dataset remained in a low number, which was the biggest disadvantage in terms of the calibration process, and it affected the applicability of the SWAT Model and, therefore, its reliability directly.

The calibration works for NO_3 were performed with 8 datasets, and validation works were performed with 8 datasets for Murgul and Hatila Creek watersheds, and 14 for Godrahav and Fabrika watersheds (Figure 7).

The results of the model (Table 10) indicated that all watersheds achieved significant levels for the coefficient of specificity (R^2), the NSE coefficient (expressing the prediction capacity of the model), and the PBIAS coefficient (percentage error statistic). Despite the limitations of the dataset, the SWAT Model's ability to provide reliable estimates for NO_3 load in each watershed, given the 'grab sample' data collection method, underlines the model's proficiency and adaptability in handling water quality simulations with limited data. The annual average NO_3 load was estimated to be 1423 kg/year in MCW, 12133 kg/year in HCW and 1747 kg/year in FCW and 3236 kg/year in GCW.

Comparing these results with a similar study conducted in the Mogan Lake Basin in Ankara's Gölbaşı County, it is evident that the small dataset posed similar challenges. In the Mogan Lake Basin study, R^2 could not be calculated due to the limited dataset for NO_3 and TN in calibration, and the NSE and PBIAS coefficients were found to be -0.2 and 37.9 for NO_3, and 0.64 and 11.7 for TN, respectively. Despite the limitations, the study provided valuable insights into specific issues related to the transport of NO_3 and TN from the basin.

Overall, the region encompassed by our study does not engage in intensive agriculture or livestock activities, leading to minimal inputs from point or non-point nitrate sources. Consequently, naturally low nitrate concentrations are anticipated. During periods of increased surface runoff, notably in rainy seasons, the absence of point or diffuse sources further dilutes the existing nitrate concentrations in the creeks, contributing to the observed low and stable nitrate levels. Additionally, the dense vegetation in our study area likely in retaining nitrate before it reaches the streams, even during periods of increased surface runoff, explaining the consistently low and stable nitrate concentrations observed in the creeks.

Table 10. Performance statistics of water quality parameter (NO_3) calibration and validation outputs

			R^2	NSE	PBIAS
Murgul Creek Watershed (NO_3)					
	Sampling Point/Performance Statistics		**R^2**	**NSE**	**PBIAS**
Calibration	M20	Murgul Creek Watershed outlet	0.82	0.65	-16.91
Validation	M20	Murgul Creek Watershed outlet	0.83	0.55	33.68
Hatila Creek Watershed (NO_3)					
	Sampling Point/Performance Statistics		**R^2**	**NSE**	**PBIAS**
Calibration	H3	Hatila Creek Watershed outlet	0.82	0.51	-13.45
Validation	H3	Hatila Creek Watershed outlet	0.79	0.76	-1.22
Fabrika Creek Watershed (NO_3)					
	Sampling Point/Performance Statistics		**R^2**	**NSE**	**PBIAS**
Calibration	F7	Fabrika Creek Watershed outlet	0.82	0.75	-8.93
Validation	F7	Fabrika Creek Watershed outlet	0.88	0.63	-17.31
Godrahav Creek Watershed (NO_3)					
	Sampling Point/Performance Statistics		**R^2**	**NSE**	**PBIAS**
Calibration	G5	Godrahav Creek Watershed outlet	0.83	0.74	-16.76
Validation	G5	Godrahav Creek Watershed outlet	0.83	0.60	-31.95

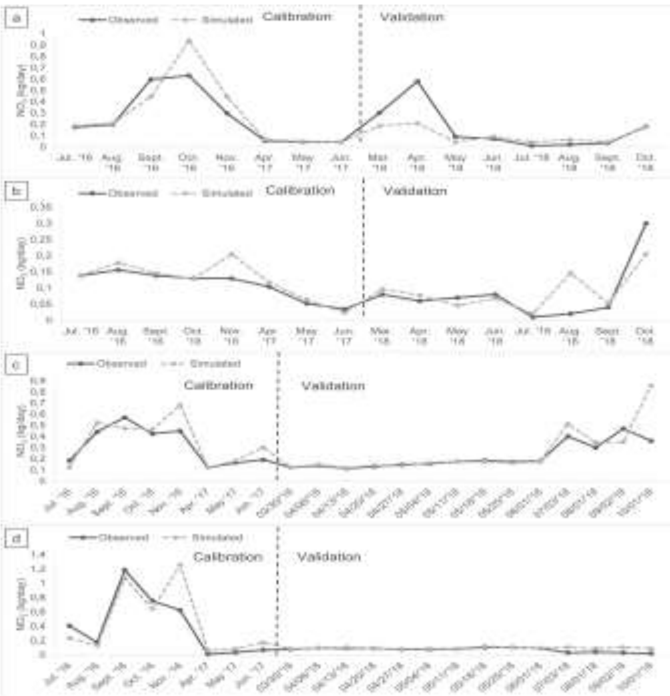

Figure 7. Comparison of observed and simulated nitrate (NO_3) yield during the calibration and validation periods for the waters of MurgulCreek (a), Hatila Creek (b), Fabrika Creek (c), and Godrahav Creek (d).

CONCLUSION

In this study, the SWAT Program (Soil and Water Assessment Tool) was utilized to model four sub-watersheds, namely Murgul, Hatila, Fabrika, and Godrahav, which contribute water and sediment flow to the Borcka Dam reservoir on the Coruh River. The primary objectives were to estimate the water regime (streamflow), water quality (NO_3), and sediment yield (TSS) based on a yearlong in-field measurements with the help of the SWAT Model.

The calibration of the SWAT Model was performed for flow (discharge), total suspended solids (TSS), and nitrate nitrogen (NO_3-N) as water quality parameters. The results demonstrated that the model reliably predicted mean values of all three parameters for the most of the sub-watersheds, with high R^2 values ranging between 0.85 and 0.91, and NSE values ranging between 0.72 and 0.84. However, the MCW sub-watershed, which experienced extensive human-induced alterations among other sub-watersheds, yielded less favorable results mainly due to the negative impacts of multiple SHPs established one-after-another along the Murgul Creek on the natural flow regime.

The model estimated the highest annual average surface flow reaching to the reservoir of Borcka Dam from Murgul Creek with 2.41 m^3/s, while it was predicted the lowest flow occurring from Fabrika Creek with 0.19 m^3/s. Additionally, the annual average sediment yield was calculated to be 61855 tons/yr from MCW, 29826 tons/yr from HCW, 3165 tons/year from FCW, and 7835 tons/year from GCW. The model also predicted the annual average nitrate (NO_3) load to be 1423 kg/yr, 12133 kg/yr, 1747 kg/yr and 3236 kg/yr for the waters of MCW, HCW, FCW and GCW, respectively.

Despite the successful results, it is evident that more detailed and long-term data are needed to enhance the SWAT Model's prediction capacity and achieve more accurate and realistic results. Access to up-to-date maps containing land use, soil, and stand characteristics of the study area is also crucial to improve the spatial resolution of the model. Additionally, the success of modeling studies is closely linked to accurate point-measured data.

In conclusion, the results of this research showed that the SWAT Model provided valuable insights into the water regime, water quality, and sediment yield in the studied sub-watersheds. The main theme from this study is that, despite data limitations, the SWAT Model successfully estimated water quality parameters, demonstrating its potential as a robust tool for environmental management and planning. However, further efforts are required to enhance the model's accuracy and reliability by collecting comprehensive and up-to-date data. Understanding the impact of human activities on water basins is crucial for improving modeling studies and achieving results that better reflect real-world conditions. These findings are valuable for informing water resource management and environmental planning strategies in the study area and serve as a basis for future research and data collection initiatives.

REFERENCES

Akhavan S, Abedi-Koupai J, Mousavi SF, Afyuni M, Eslamian SS, Abbaspour KC (2010) Application of SWAT model to investigate nitrate leaching in Hamadan–Bahar Watershed, Iran. Agriculture Ecosystems & Environment, 139(4): 675-688.

Arnold JG, Moriasi DN, Gassman PW, Abbaspour KC, White MJ, Srinivasan R, Santhi C, Harmel RD, van Griensven A, Van Liew MW, Kannan N, Jha MK (2012) SWAT: model use, calibration, and validation. Transactions of the ASABE, 55(4): 1491-1508.

Arnold JG, Srinivasan R, Muttiah RS, Williams JR (1998) Large area hydrologic modeling and assessment Part I: Model development. Journal of the American Water Resources Association, 34(1):73-89.

Asif Z, Chen Z, Sadiq R, Zhu Y (2023) Climate change impacts on water resources and sustainable water management strategies in North America. Water Resources Management, 37(6-7): 2771-2786.

Ben Salah NC, Abida H (2016) Runoff and sediment yield modeling using SWAT model: case of Wadi Hatab Basin, Central Tunisia. Arabian Journal of Geosciences, 9(11).

Briak H, Moussadek R, Aboumaria K, Mrabet R (2016) Assessing sediment yield in Kalaya gauged watershed (Northern Morocco) using GIS and SWAT model. International Soil and Water Conservation Research, 4(3): 177-185.

Brosse M, Benateau S, Gaudard A, Stamm C, Altermatt F (2022) The importance of indirect effects of climate change adaptations on alpine and pre-alpine freshwater systems. Ecological Solutions and Evidence, 3(1).

Chen Y-C, Hsu Y-C, Zai EO (2022) Streamflow measurement using mean surface velocity. Water, 14(15).

Clesceri LS, Greenberg AE, Eaton AD (1999) Standard methods for the examination of water and wastewater (20th edition). American Public Health Association.

Cüceloğlu G (2013) Darlık Havzasının model destekli hidrolojik analizi. İstanbul Teknik Üniversitesi Yüksek Lisans Tezi, İstanbul.

Dengiz O, İmamoğlu A, Saygin F, Göl C, Ediş S, Doğan A (2014) Soil erosion risk assessment using Icona modelling for Inebolu Watershed. Anadolu Journal of Agricultural Sciences, 29(2).

Duru Ü, Arabi M, Wohl EE (2017) Modeling stream flow and sediment yield using the SWAT model: a case study of Ankara River Basin, Turkey. Physical Geography.

Ediş S (2018) Yarı kurak havzalarda hidrolojik modelleme ile iklim parametrelerinin ve arazi kullanımındaki değişimlerin su kalitesi üzerine etkilerinin analizi: Terme Çayı Havzası Örneği. Çankırı Karatekin Üniversitesi Doktora Tezi, Çankırı.

Ediş S, Aytaş İ, Özcan AU (2021) ICONA modeli kullanarak toprak erozyon riskinin değerlendirilmesi: Meşeli (Çubuk/Ankara) Havzası Örneği. Anadolu Orman Araştırmaları Dergisi, 7(1): 15-22.

Ediş S, Timur ÖB, Tuttu G, Aytaş İ, Göl C, Özcan AU (2023) Assessing the impact of engineering measures and vegetation restoration on soil erosion: a case study in Osmancık, Türkiye. Sustainability, 15(15).

Engel B, Storm D, White M, Arnold J, Arabi M (2007) A hydrologic/water quality model application protocol. Journal of the American Water Resources Association, 43(5): 1223-1236.

Erdoğan Yüksel E (2015) Borçka Barajı Yağış Havzası'nda meydana gelen toprak erozyonu ve sediment veriminin WEPP erozyon tahmin modeli ve CBS Teknikleri kullanılarak belirlenmesi. Artvin Çoruh Üniversitesi Fen Bilimleri Enstitüsü Doktora Tezi, Artvin.

Ertürk A (2012) Managing the effects of the climate change on water resources and watershed ecology. In M. Kumarasamy (Ed.), Studies on Water Management Issues (pp. 259-274). InTech.

Ezz-Aldeen M, Al-Ansari N, Knutsson S (2013) Application of SWAT model to estimate the sediment load from the left bank of Mosul Dam. Journal of Advanced Science and Engineering Research, 3(1): 47-61.

Frederick KD, Major DC (1997) Climate change and water resources. Climatic Change, 37(1): 7-23.

Gassman PW, Reyes MR, Green CH, Arnold JG (2007) The soil and water assessment tool: historical development, applications, and future research directions. Transactions of the ASABE, 50(4): 1211-1250.

Genç O, Ardıçlıoğlu M, Ağıralioğlu N (2015) Calculation of mean velocity and discharge using water surface velocity in small streams. Flow Measurement and Instrumentation, 41: 115-120.

Ghoraba SM (2015) Hydrological modeling of the Simly Dam Watershed (Pakistan) using GIS and SWAT model. Alexandria Engineering Journal, 54(3): 583-594.

Gölpınar MS (2017) Yüzey akışların SWAT Modeli ile belirlenmesi: Akarsu Sulama Birliği Sahası Örneği. Çukurova Üniversitesi Doktora Tezi, Adana.

Gull S, Ma A, Dar AM (2017) Prediction of stream flow and sediment yield of Lolab Watershed using SWAT model. Hydrology: Current Research, 8(1).

Güngör Ö, Göncü S (2013) Application of the soil and water assessment tool model on the Lower Porsuk Stream Watershed. Hydrological Processes, 27(3): 453-466.

Gupta HV, Sorooshian S, Yapo PO (1999) Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. Journal of Hydrologic Engineering, 4(2): 135-143.

Güzel Ç (2010) Application of SWAT Model in a Watershed in Turkey. İstanbul Teknik Üniversitesi Yüksek Lisans Tezi, İstanbul.

Kheirinejad S, Bozorg-Haddad O, Singh VP, Loaiciga HA (2022) The effect of reducing per capita water and energy uses on renewable water resources in the water, food, and energy nexus. Sci Rep, 12(1): 7582.

Kukrer S, Mutlu E (2019) Assessment of surface water quality using water quality index and multivariate statistical analyses in Sarayduzu Dam Lake, Turkey. Environ Monit Assess, 191(2): 71.

Loucks DP (2000) Sustainable water resources management. Water International, 25(1): 3-10.

Marahatta S, Aryal D, Devkota LP, Bhattarai U, Shrestha D (2021) Application of SWAT in hydrological simulation of complex mountainous river basin (Part II: Climate Change Impact Assessment). Water, 13(11).

Meaurio M, Zabaleta A, Uriarte JA, Srinivasan R, Antigüedad I (2015) Evaluation of SWAT models performance to simulate streamflow spatial origin. The case of a small forested watershed. Journal of Hydrology, 525: 326-334.

Megdal S, Eden S, Shamir E (2017) Water governance, stakeholder engagement, and sustainable water resources management. Water, 9(3).

MGM (2018) Tarım ve Orman Bakanlığı Meteoroloji Genel Müdürlüğü, resmi istatistikler.

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the ASABE, 50(3): 885-900.

Neitsch SL, Arnold JG, Kiniry JR, Williams JR (2011) Soil and water assessment tool theoretical documentation version 2009.

Oeurng C, Sauvage S, Sánchez-Pérez J-M (2011) Assessment of hydrology, sediment and particulate organic carbon yield in a large agricultural catchment using the SWAT model. Journal of Hydrology, 401(3-4): 145-153.

Özcan Z (2016) Evaluation of the best management practices to control agricultural diffuse pollution in Lake Mogan Watershed with SWAT Model. Ortadoğu Teknik Üniversitesi Yüksek Lisans Tezi, Ankara.

Şahin B (2016) Küresel bir sorun: Su kıtlığı ve sanal su ticareti. Hitit Üniversitesi Yüksek Lisans Tezi, Çorum.

Santhi C, Kannan N, Arnold JG, Di Luzio M (2008) Spatial calibration and temporal validation of flow for regional scale hydrologic modeling1. JAWRA Journal of the American Water Resources Association, 44(4): 829-846.
Schilling J, Hertig E, Tramblay Y, Scheffran J (2020) Climate change vulnerability, water resources and social implications in North Africa. Regional Environmental Change, 20(1).
Singh P, Gupta A, Singh M (2014) Hydrological inferences from watershed analysis for water resource management using remote sensing and GIS techniques. The Egyptian Journal of Remote Sensing and Space Science, 17(2): 111-121.
Strauch M, Bernhofer C, Koide S, Volk M, Lorz C, Makeschin F (2012) Using precipitation data ensemble for uncertainty analysis in SWAT streamflow simulation. Journal of Hydrology, 414-415: 413-424.
Thodsen H, Farkas C, Chormanski J, Trolle D, Blicher-Mathiesen G, Grant R, Engebretsen A, Kardel I, Andersen H (2017) Modelling nutrient load changes from fertilizer application scenarios in six catchments around the Baltic Sea. Agriculture, 7(5): 41.
USGS (2020) Global water distribution. Retrieved May 4 from
Verma S, Verma RK, Singh A, Naik NS (2012) Web-based GIS and desktop open source GIS software: An emerging innovative approach for water resources management. Advances in Computer Science, Engineering & Applications, Berlin, Heidelberg.
Winchell M, Srinivasan R, Di Luzio J, Arnold J (2010) ArcSWAT interface for SWAT2009 user's guide.
WWAP (2015) The United Nations World Water Development Report 2015: Water for a Sustainable World. UNESCO.