

Full Length Research Paper

Evaluating SWAT model for streamflow estimation in the semi-arid Okavango-Omatako catchment, Namibia

Kaleb Gizaw Negussie^{1,2,5*}, Daniel Wyss², Nichola Knox¹, Miguel Vallejo Orti^{1,4}, Eva Corral-Pazos-de-Provens³, and Martin Kappas²

¹Department of Land and Spatial Sciences, Namibia University of Science and Technology, 13388 Windhoek, Namibia.

²Department of Cartography, GIS and Remote Sensing, Georg-August University Goettingen, 37077 Goettingen, Germany.

³Departamento de Ciencias Agroforestales, Universidad de Huelva, 21819 Huelva, Spain.

⁴Institute of Geography, 3D Geospatial Data Processing Group, Heidelberg University, 69120 Heidelberg, Germany.

⁵Earth Observation and Satellite Application Research and Training Centre (EOSA-RTC), Namibia University of Science and Technology, 13388 Windhoek, Namibia.

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A semi-distributed hydrological model was used for runoff estimation in the Okavango-Omatako catchment in Namibia. The model was configured for a 31-year period from 1985 to 2015. Subsequently, calibration and validation processes followed using the SUFI-2 algorithm. For evaluating catchment simulation, two methods were used: i. model prediction uncertainty measured by *P-factor* and *R-factor* and ii. Model performance indicators, that is, Nash-Sutcliffe Efficiency (NSE), Coefficient of determination (R^2), Percent bias (PBIAS), and Residual variation (RSR). The *P-factor* achieved 0.77 and 0.68 while *R-factor* attained 1.31 and 1.82 for calibration and validation, respectively. The following indicators were used to evaluate the model performance through calibration and validation results respectively; NSE with 0.82 and 0.80, R^2 with 0.84 and 0.89, PBIAS achieving $-20 \leq \text{PBIAS} \leq -1.1$ and RSR performing 0.42 and 0.44. All performance indices achieved very good ratings apart from PBIAS validation which rated as satisfactory. The semi-arid characteristics together with relatively flat terrain features justified the need for the evaluation of model performance using discharge data in our study region. SWAT demonstrated reasonable results in modelling semi-arid streamflow with high and low flows adequately captured. Consequently, this evaluation was necessary for further investigations into impacts of climate change on scarce water resources highlighting the challenges of SWAT model applications in our study area climatic regime and other similar regions globally for further model improvements.

Key words: Stream flow, catchment, semi-arid, SWAT, SUFI-2, calibration, TanDEM-X, Okavango, Namibia.

INTRODUCTION

Hydrological models represent the real-world system in a simplified manner through simulations of water resources (Sood and Smakhtin, 2015). Such models follow complex processes to integrate different spatial and temporal

variables to better understand catchment heterogeneity (Mengistu et al., 2019). However, acquiring data that accurately represents these variables is a major challenge. Field data acquisition methods are expensive,

time-consuming, tedious and error prone, causing limitations in the measurement of hydrological variables (Al-Sabhan et al., 2003). Over the years, traditional techniques for in-situ observations of precipitation, temperature, streamflow, geohydrology, soil moisture, dam levels, etc. have dominantly provided data for catchment monitoring worldwide (Essou et al., 2017). Such ground-based measurements create limitations based on the spatial distribution of the observing stations, which may insufficiently assess catchment evolution over a large area (Lai et al., 2019; Stehr et al., 2008). Considering these constraints, various hydrological investigations around the world explore the integration of satellite-based data and ground measurements to monitor large and complex catchment behavior (Abbaspour et al., 2015; Hashim et al., 2016; Thavhana et al., 2018). A model is a simplified real world representation of a certain phenomenon applied to predict system behavior and understand processes such as stream flow, droughts, floods, vegetation cover, etc. (Devi et al., 2015). The features of models are defined by the parameters used to represent the reality.

In places where natural disasters (e.g. droughts and floods) occur frequently, hydrological models are vital to characterize various processes in sustainable water resource management (Emam et al., 2017). The Soil and Water Assessment Tool (SWAT), is one of such model capable of simulating water balance in large geographical catchments and sub catchments using a time continuous semi-distributed hydrological model, integrating various parameters like land cover/land use, soil types, precipitation, temperature, topography and climate conditions (Arnold et al., 2012).

Namibia is an arid country located in Southwest Africa with regular occurrence of dry periods. Annual rainfall ranges between ~ 50 mm in the west to over 600 mm in the northeast of the country (Mendelsohn et al., 2006). Taking into account the low rainfall and variability of rainfall within the country, water management is vital to conserve the existing water resources (Palmer et al., 2008). According to the Integrated Water Resources Management report, the country is divided into eleven water management areas, each are further sub-divided into water basins (IWRM, 2010). These water management areas are defined by similar drainage systems of rivers, catchment areas, underground water, water supply lines and canals. One such area is the Okavango-Omatako catchment which extends from Central to the Northeastern regions of Namibia. The Okavango-Omatako water management area also referred to as a "catchment" is comprised of the

Omatako-Omuramba and Okavango catchments. The ephemeral Omatako is a tributary to the perennial Okavango. According to IWRM (2010) report, the catchment has indisputable socio-economic importance to activities in proximity to it. Water extracted from the catchment caters to approximately 15% of the Namibian population through livelihood activities such as irrigation, mining, tourism, livestock, etc. Considering this, it is vital to monitor and explore the catchment's behavior to different variables influencing its dynamics. This study emanated from limited comprehensive assessments exploring this catchment (Mendelsohn et al., 2002; Strohbach, 2008), and its dynamic response to different variables.

Several studies have been conducted since the 1990's on catchments in Namibia; from investigations of large ephemeral catchments in Jacobson et al. (1995) to small-scale catchment analysis in O'Connor (2001), as well as more detailed work on various individual catchments (Manning and Seely, 2005; Marsh and Seely, 1992; Mendelsohn et al., 2000). Although considerable studies attempted to map catchments in Namibia, according to Strohbach (2008), many have methodological inaccuracies or non-repeatable methodological descriptions. Further, the coarse resolution from freely available Digital Elevation Models (DEM) supplemented with missing data due to atmospheric interference, shadow effects, etc., has created a challenge to unpack Namibia's hydrological systems and realistically simulate catchment behavior.

To understand streamflow processes, it is essential to evaluate the SWAT model performance (Meaurio et al., 2015), especially when considering large catchments as depicted in this study. To date, no peer reviewed studies have used the SWAT model in the Okavango-Omatako catchment, denoting a general lack of knowledge on hydrological processes in these semi-arid catchments (Strohbach, 2008). To fill the gap, this study evaluated the SWAT model for streamflow estimation using remotely sensed data supplemented by ground observation measurements. It is further imperative to evaluate hydrological models and uncertainty methods in areas with different climatic zones (that is tropical, arid, semi-arid, etc.) (Emam et al., 2018; Rafiei Emam et al., 2015). The semi-arid characteristics of the study site and its relatively flat terrain features justified the need for evaluation of the SWAT model performance using discharge data in an intermediate gauge. Krysanova and White (2015) highlighted the challenges of SWAT model applications in different climatic regimes and specific regions, globally, suggesting the need for several model

*Corresponding author. E-mail: knegussie@nust.na. or kaleb.gizaw@gmail.com.

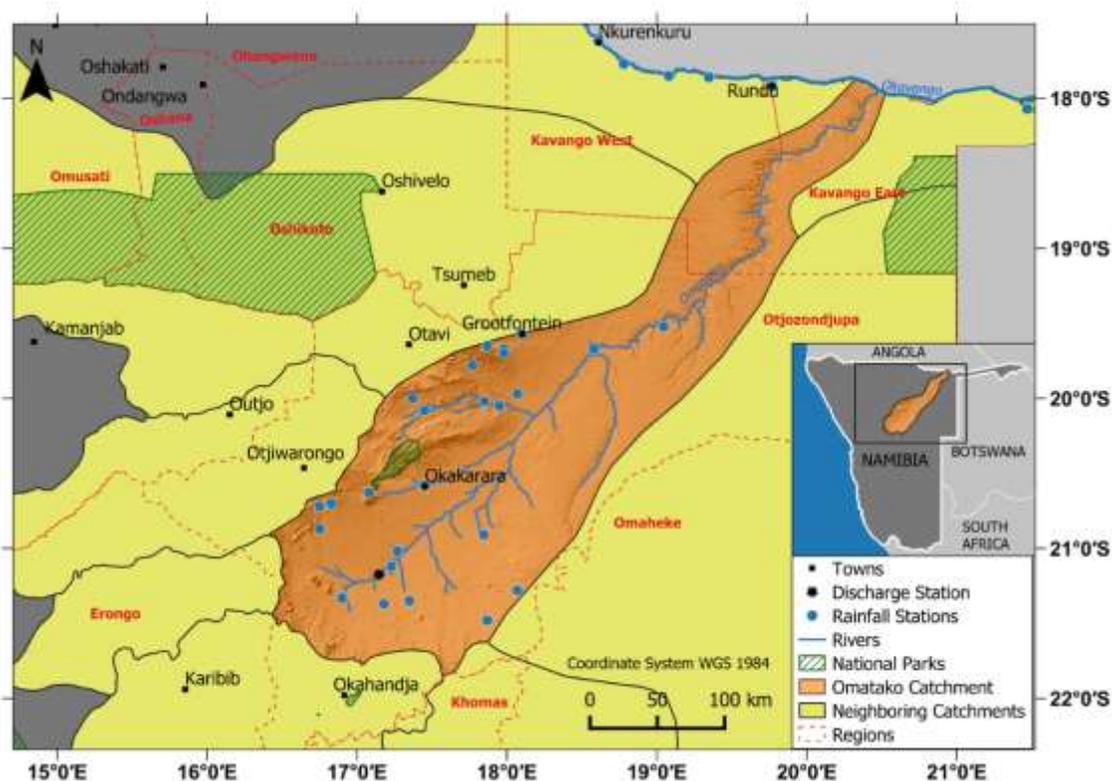


Figure 1. Location of the study area, Okavango-Omatako and neighboring catchments.
Source: Authors

evaluations and improvements. One such area is SWAT applications in regions where water management is crucial due to water scarcity. Estimation of streamflow using historical variables over the semi-arid water scarce environment of the Okavango-Omatako expose catchment behavior, which in turn can be used to prepare short term and long-term water management plans. SWAT depends on the basic units of sub-basins and Hydrological Response Units (HRUs) for streamflow estimation. Due to the study catchment flat terrain, the z-resolution of freely available DEM data is insufficient to generate accurate HRU's, this study therefore used state of the art, high resolution DEM - TanDEM-X (Rizzoli et al., 2017; Wessel et al., 2018). Enhanced knowledge on hydrological processes through modelling improves future investigations on impacts of climate conditions and LULC changes on water resources and management. The study thus supports Namibian National Climate Change Strategies and Action Plan with proposed strategies to counteract impacts of climate change. This includes understanding climate change and its related policy responses, using monitoring and data collection technologies for surface and ground water at the watershed level and promoting conservation and

sustainable utilization of water resources.

Study site

The Okavango-Omatako catchment (Figure 1) extends from central to North-eastern Namibia, bordering Botswana to the east and Angola to the north at approximately 74,700 km² (Strohbach, 2008). According to IWRM (2010), it is one of the eleven water management areas classified along shared drainage systems (that is, aquifers, canals, rivers and pipelines). This catchment is comprised of perennial (Okavango) and ephemeral (Omuramba-Omatako) rivers as well as groundwater. The Omatako dam which has been built on the Omuramba-Omatako ephemeral river and the ground water of Tsumeb, Otavi and Grootfontein Karstveld are major water sources to central Namibia. The main water inflow sources to this catchment are the perennial Cubango and Cuito rivers located in southern Angola. After heavy rains, other ephemeral streams such as Nhoma and Kaudom also join the drainage system of the river basin. The Omatako river is similarly a tributary to the Okavango, however, the contribution is minimal as

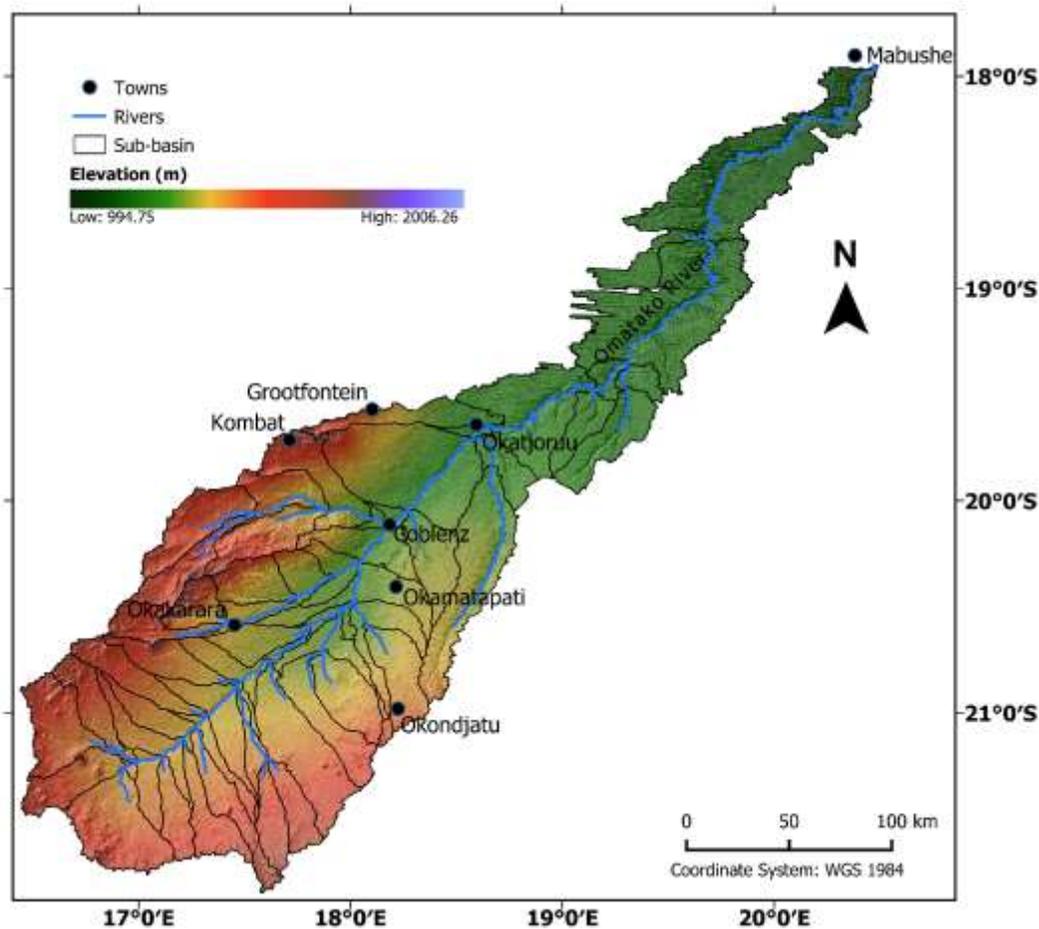


Figure 2. Elevation map showing the 60 sub-basins of the Okavango-Omatako catchment. Source: Authors

the river originates from the dry central plateau of the Kalahari with limited run off either evaporating or draining into the sand along its course (IWRM, 2010). The catchment's average annual rainfall varies between 300 mm in the west to 600 mm in the north-east with an average loss of water through evaporation between 2,600 and 3,200 mm per annum (Mendelsohn et al., 2002).

The Okavango-Omatako catchment is predominantly a flat sandy plateau categorized as the Kalahari Sandveld landscape (Mendelsohn et al., 2002). Although known for its flat terrain, the sandy deposits form dunes in some areas. The landscape near Grootfontein is known as Karstveld and is Namibia's largest underground aquifers, its elevated terrain receives 550 to 600 mm rainfall annually (Mendelsohn et al., 2002). The highest elevation is observed in the south-west of the catchment with a gentle downward slope towards the northeast where it meets the Okavango valley (Figure 2). The vegetation varies from moderate-dense shrubland in the south west, a shrubland-woodland mosaic towards the center of the

basin and a dry woodland-grassland mosaic in the north eastern parts (Mendelsohn et al., 2002).

According to IWRM (2010), the supply of water in Namibia is primarily allocated for domestic use such as livestock farming (communal and commercial). In the Okavango-Omatako catchment, large scale irrigation for, maize, sorghum, cotton and wheat are predominant water consumers, followed by livestock and urban consumption. To a lesser extent, rural domestic consumption, tourism and mining also utilize water from this catchment.

MATERIALS AND METHODS

Data

The data used in this study includes climate data, elevation, soil characteristics, Land Use Land Cover (LULC) and streamflow data (Table 1). Daily in-situ measurements of precipitation and temperature from eight weather stations (Table 1), which cover the

Table 1. Data used and sources.

Data	Sources	Resolution
1. Meteorological Variables: Precipitation(mm), temperature (°C), Solar radiation (MJ/m ²), Relative Humidity (%), and Wind Speed (m/s)	Namibia Meteorological Services (NMS) 1985-2015 and Climate Forecast System Reanalysis (CFSR) (Weather Stations: Awagobibtal, Grootfontein MET, Kalidona, Omambonde Tal, Otjikururume, Otjirukaku, Rundu and Simondeum)	Daily meteorological records
2. Discharge of Omatako Dam (m ³ /s)	Hydrological Services of Namibia	Monthly discharge from 1990 – 2008
3. TanDEM-X Digital Elevation Model (DEM)	German Aerospace Center (DLR)	Relative vertical accuracy of 2 m and a Spatial resolution of 12 m
4. Land use and land cover (LULC)	Sentinel-2 Products from European Space Agency (ESA) and Directorate of Survey and Mapping (DSM), Namibia	Spatial resolution 10 m
5. Soil Information	SOTER (Soil and Terrain Database) (Coetzee 2001, M. Coetzee, personal communication, December 6, 2019, Batjes 2004) Updated Soil Map (from Agro-Ecological Zoning)	Scale 1:250 000

Source: Authors

extent of the study area were identified and prepared for the period 1985-2015. While solar energy, relative humidity, and wind speed data were sourced from the Climate Forecast System Reanalysis (CFSR) of The National Centers for Environmental Prediction (NCEP, 2020). Moreover, the internal “weather generator” from SWAT generated missing weather data to fill the climatic gaps. The soil information over the river basin under study was sourced from an ongoing project to update the Soil Map of Namibia (Coetzee 2001, M. Coetzee, personal communication, December 6, 2019). Land use and land cover (LULC) information was derived from the Copernicus Sentinel-2 mission products supplemented by existing information from the Directorate of Survey and Mapping (DSM) in Namibia. The runoff discharge data measured by the Hydrological Services of Namibia at the Ministry of Agriculture, Water and Forestry was solicited for calibration/validation purposes. The following subsections will further discuss the datasets mentioned above in detail.

Digital elevation model

Stream flow simulation is a complex process with several uncertainties arising from input variables, missing assumptions in the model and lack of knowledge on the catchment being modeled (Abbaspour et al., 2007; Rostamian et al., 2008).

Imperatively, while modeling a large and complex catchment as presented in this study remote sensing plays a major role to successfully model streamflow. This is especially valid in data poor countries where lack of frequent high-resolution data is not accessible. For this reason and due to the flat terrain characteristics of the catchment in this study, a high-resolution TanDEM-X product was sourced to improve simulation capacity as recommended by (Archer et al., 2018). Thus, accurate watershed delineation (stream

slopes and total length of streams) and HRU definition were achieved in this study catchment which were further used to simulate the streamflow effectively as established by Buakhao and Kangrang (2016) and Tan et al. (2015), where the accuracy of the DEM was sensitive to streamflow.

Due to the flat terrain characteristics of the Namibian Northern regions, elevation data of TanDEM-X from the TerraSAR-X DLR mission was used in the study with a relative vertical accuracy of 2 m and a spatial resolution of 12 m sourced from German Aerospace Center (DLR) (Wessel et al., 2018). According to Archer et al. (2018), Maharjan et al. (2013) and Rizzoli et al. (2017), without the High Resolution Terrain Information-3 (HRTI-3) from TanDEM-X, the study area of relatively flat terrain would not define an accurate watershed to create Hydrologic Response Units (HRUs), which are the smallest representation of the basin used in the simulation of streamflow in SWAT. In Figure 2, the elevation map of the river basin derived from TanDEM-X is displayed together with the generated sub-basins of the study area.

Land use land cover mapping

Land use land cover (LULC) is an essential input variable for simulation of streamflow in the SWAT model. An assessment of global LULC products indicated insufficient detail for runoff modelling purpose, therefore a LULC map was generated for the catchment. The LULC was generated using multiple scenes of Sentinel-2-A data of 2017 acquired and mosaicked from Copernicus Sentinel-2 mission (European Space Agency, 2020). This product further attained the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Normalized Difference Built-up Index (NDBI) indices to facilitate the differentiation of vegetation, water and built-up areas. Using high

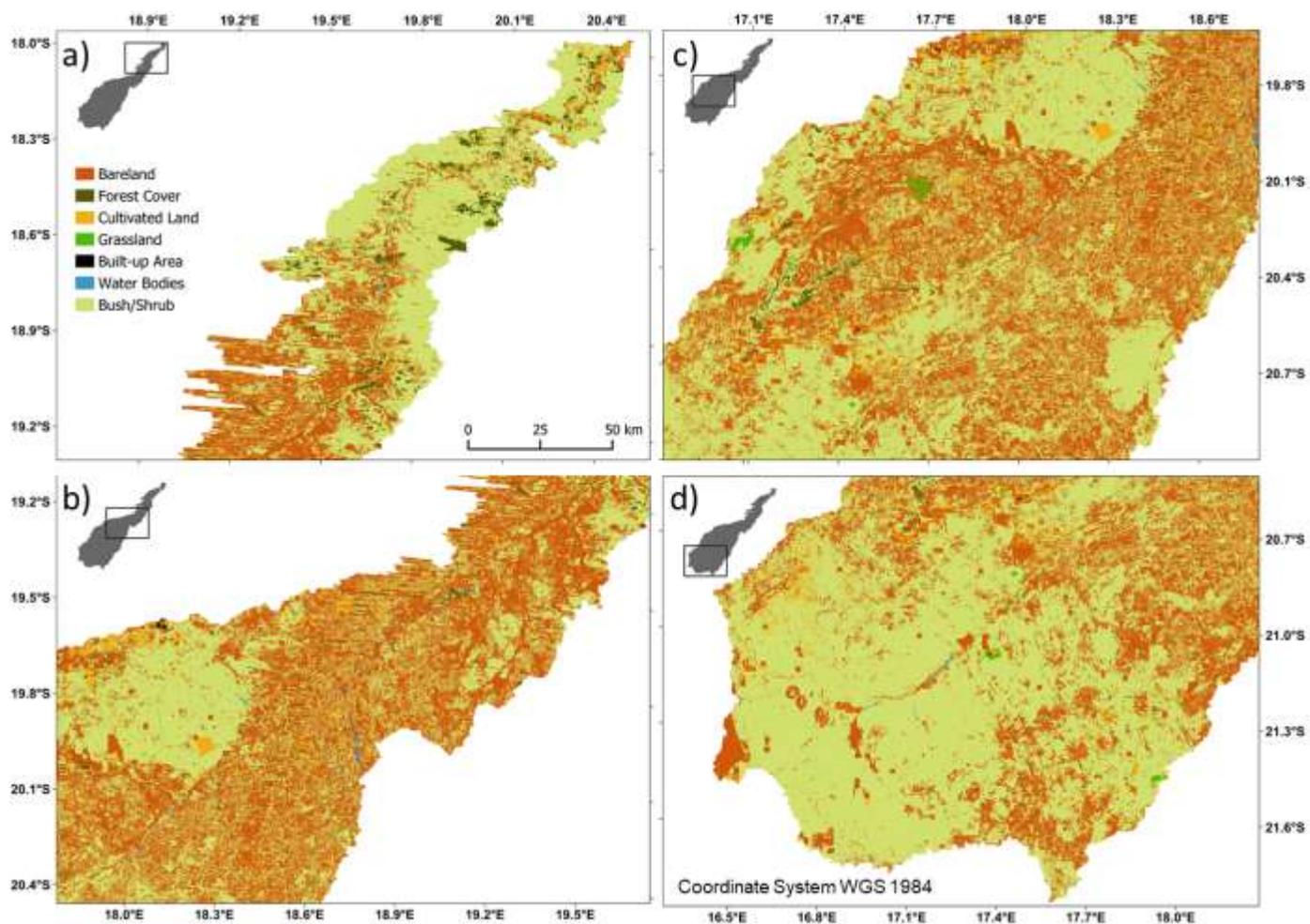


Figure 3. Land Use Land Cover (LULC) map of Okavango-Omatako catchment.
Source: Authors

resolution topographic maps obtained from the Directorate of Survey and Mapping (DSM) for the same timeframe as the Sentinel-2 imagery, seven land cover classes (bare land, forest cover, cultivated land, grassland, built-up area, water bodies and bush/shrub) were visually identified. Using polygons of each landcover classes resultantly, a classification training and validation dataset was derived for these classes. Thanh Noi & Kappas (2017) compared and investigated performances of random forest, k-nearest neighbor, and support vector machine (SVM) classification methods for LULC classification with Sentinel-2 and achieved superior accuracy and consistency in their classification results using SVM. Consequently using ENVI 5.5.1 (Harris Geospatial Solutions Inc, 2020), the SVM algorithm was applied to compute the classification and generate a LULC map (Figure 3) of the interest region. For the independent validation dataset, the classification was validated using a Cohen kappa (K) (Cohen, 1960) and overall accuracy assessment (Congalton, 1991). According to Nyeko et al. (2010) and Rani and Sreekesh (2019), approximately 80% and 0.8 is the overall accuracy and kappa for LULC to be suitable for input into the SWAT model. The classification for the catchment data was performed with an acceptable overall

accuracy of 84% and a kappa coefficient 0.8.

Soil mapping

Soil type information plays a major role in runoff estimation.

According to Yang et al. (2008), model variable inputs such as soil data and its resolution has an effect on modelling streamflow in SWAT. The Soil mapping of the study area was performed at the scale of 1:250 000 while most of the samples for the profile descriptions was taken along the study area as demonstrated in (Coetzee, 2001). In this study, soil profile data for the catchment was acquired and significant information was extracted such as texture classes, profile depth, soil types, etc.

Once the watershed delineation of the study area was completed using the boundary of the delineated basin, sixteen soil classes were identified and further categorized into six dominant groups: Cambisols, Regosols, Arenosols, Calcisols, Leptosols and Fluvisols. The soil type distribution over the catchment was mapped as shown in Figure 4. Based on the available soil properties for different soil classes, all required information for the model input

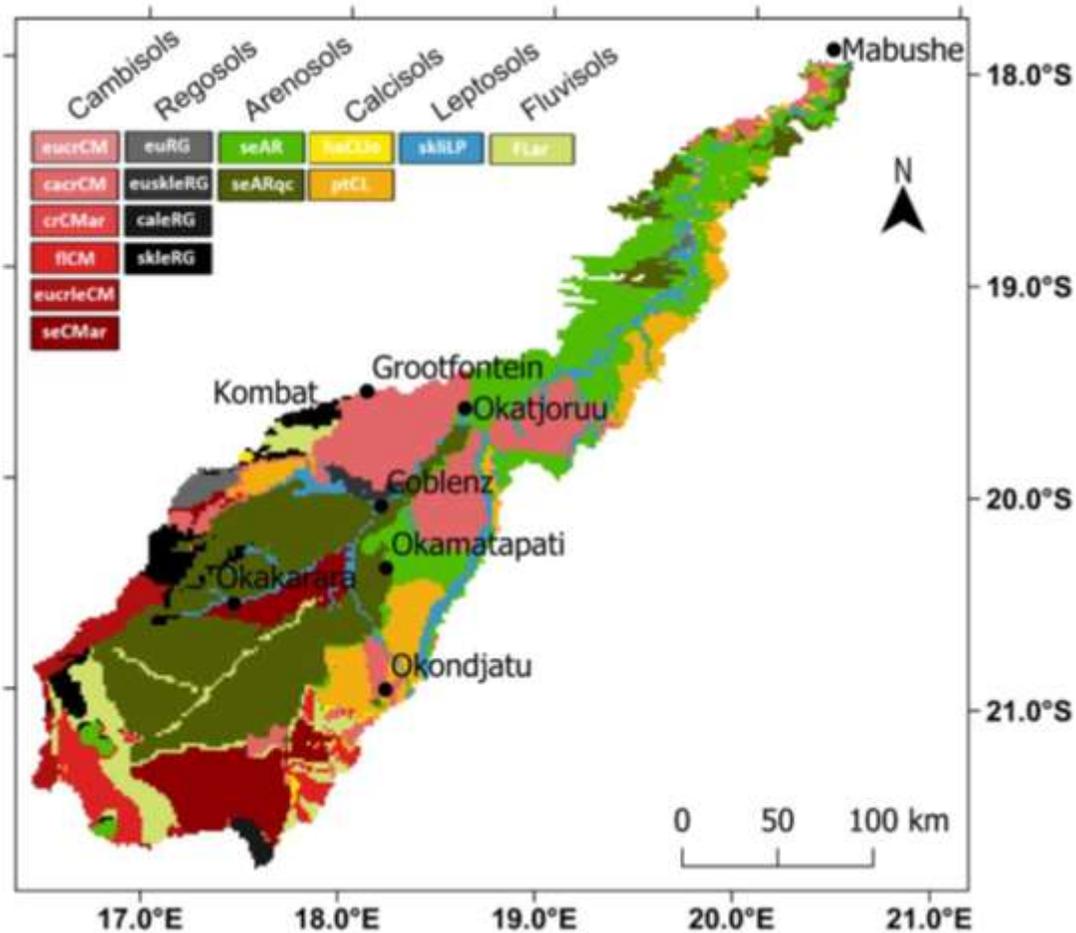


Figure 4. Soil classes of the study catchment. Source: Authors

was calculated.

Catchment modelling

Model setup and configuration

A hydrological SWAT model (Figure 5) was employed to simulate the water balance components of different sub-basins in the catchment under study. To this end, the Okavango-Omatoko catchment was delineated using the SWAT model.

The spatial heterogeneity of the catchment was best modeled through sub-basins and was further divided into HRUs. HRUs represent the smallest spatial units of the catchment with homogenous slope class, soil characteristics and Land use and land cover (LULC) information. HRUs simulated the water balance components with the assumption that different HRUs have different hydrologic characteristics. To execute different SWAT scenarios, the various datasets outlined in Table 1 were utilized. These scenarios were thereafter used to simulate the quantity of water in each sub-basin, computed as the total water departing and arriving into the channel at each time step. Using this model, water balance was computed as shown in Equation (1) (Neitsch et al., 2011):

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

where SW_t refers to the soil water content at time t, the initial soil water content is denoted by SW_0 , R_{day} is the amount of precipitation on day i, Q_{surf} indicates surface runoff on day i, E_a refers to the amount of evapotranspiration on day i, W_{seep} specifies the amount of percolation on day i and Q_{gw} denotes groundwater return flow on day i.

Surface runoff originates when precipitation received on the ground surface surpasses the rate of infiltration. The Soil Conservation Service Curve Number also referred to as SCS-CN is used in this study to simulate the surface runoff (USDA, 1986). To determine surface runoff CN in a specific location of the catchment during a rain event, the method considers the soil hydrologic group, soil moisture conditions and LULC types. The Penman-Monteith approach (Allen et al., 1989; Howell and Evett, 2004) using solar energy, wind speed, humidity and temperature was used to estimate the potential evapotranspiration (PET) for the entire catchment area. Water flowing into the stream network of the basin is simulated using the variable storage routing method developed by (Williams, 1969). The SWAT model setup was adopted to delineate the Okavango-Omatoko catchment into sub-basins using the high-

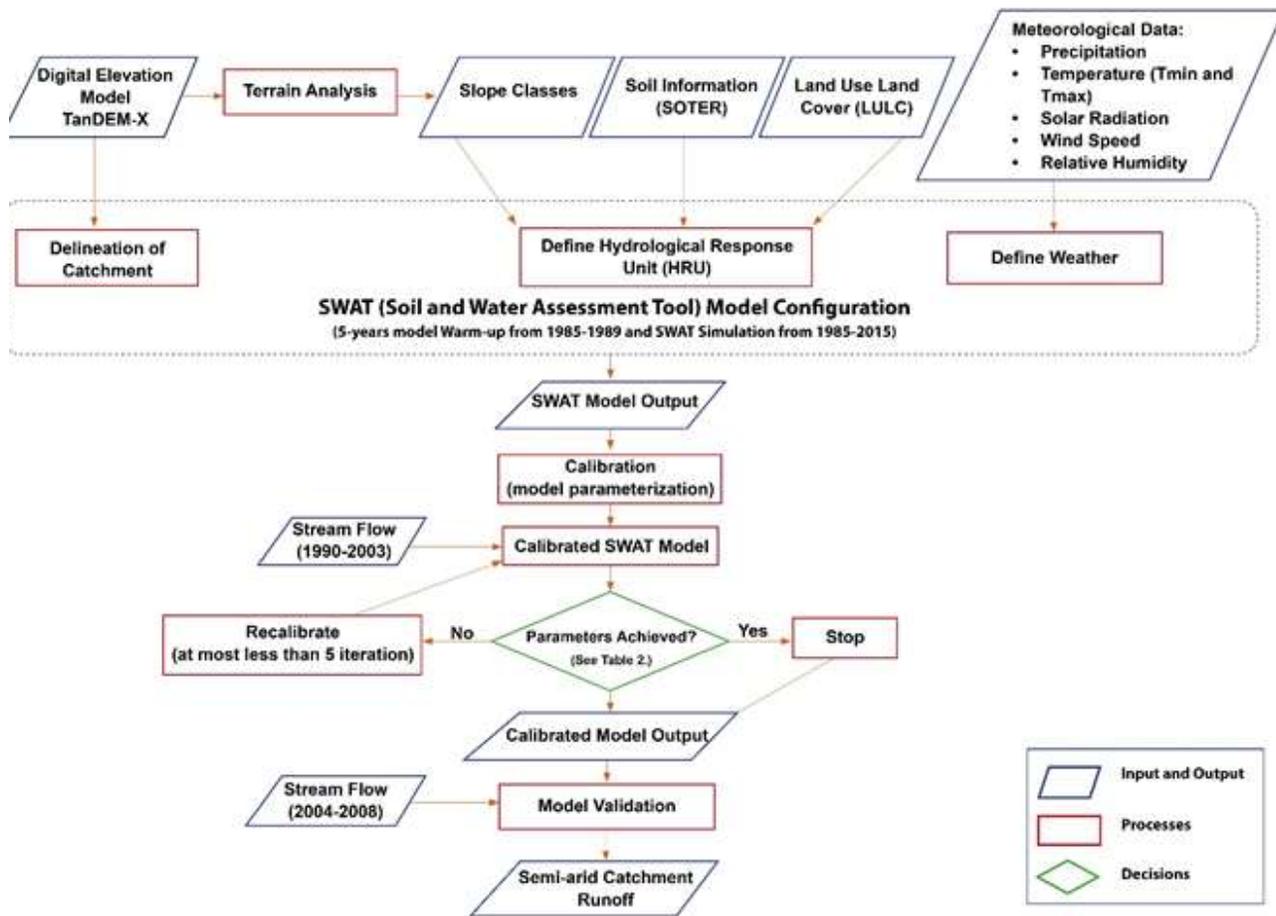


Figure 5. Framework of model setup and configuration using SWAT as well as calibration and validation processes in SUFI-2. Source: Authors

resolution TanDEM-X digital elevation product due to its flat terrain characteristics. These processes were followed to fill DEM depressions, compute flow direction and accumulation, which are further used to apply thresholds for stream definition, subsequently determining stream networks and the number of sub basins. Thereafter, HRUs were created using unique combinations of LULC, Soil and Slope information within each sub basin. As discussed in Table 1, the precipitation and temperature (Tmin and Tmax) data for eight weather stations optimally distributed throughout the study area were defined and SWAT input tables were created. As a final step, the simulation was performed over 31-years (1985-2015), with a five-year warm-up period (1985-1989). The warm-up is an adjustment process used by the model to achieve a stable state (e.g. streamflow values), as initial conditions of a catchment are usually underestimated during simulation in SWAT (Kim et al., 2018). Consequently, the study simulated 26-years (non-inclusive warm-up period) of hydrological parameters of the catchment.

Parameter sensitivity analysis

Sensitivity analysis of parameters is the main driving force for a successful application of streamflow simulation (Mengistu et al.,

2019; Thavhana et al., 2018). Sensitivities of parameters are computed through regression between parameters and the objective function. This process calculates the mean change in the objective function which results from changes in each parameter. Twelve parameters were selected through a careful review of related literatures and considering the semi-arid characteristics of the area under study. The parameters, that is, CN2, OV_N, FFCB, ESCO, EPCO, CH_K2, CH_N2, ALPHA_BF, GW_DELAY, GWQMN, SURLAG and MSK_CO1 (abbreviations are explained in Table 3) were chosen based on their sensitive behavior to streamflow (Aqnouy et al., 2019; Desai et al., 2021; Mengistu et al., 2019). The list of parameters associated with streamflow was applied for further evaluation in a calibration process. Thereafter, a sensitivity analysis was performed by considering the changes in the objective function as a result of the sensitivity of one parameter to other parameters, which determines its influence on streamflow. The t-stat and p-value are used to quantify the sensitivity of a parameter and its significance. A higher t-stat value and a lower p-value demonstrates a more sensitive streamflow in the catchment (Abbaspour, 2015; Arnold et al., 2012).

Calibration, validation, and uncertainty analysis

Evaluation of hydrological models is performed, using performance

criteria through comparison of simulated variables or processes in the basin against measured data. The model calibration and validation are the final vital step to assess the accuracy of the runoff simulation. Once the simulation process is completed in SWAT, the hydrological model undergoes calibration and uncertainty analysis as shown in Figure 5. SWAT Calibration and Uncertainty Procedures (SWAT-CUP) was employed for further processing, which is a program with five different algorithms commonly used in calibration and validation of simulated hydrological models. Large-scale and complex models usually make use of the Sequential Uncertainty Fitting also known as SUFI-2 due to its efficiency and reliability (Yang et al., 2008), especially when compared with deterministic approaches to calibration (Abbaspour, 2015). Given the scale and complexity of our catchment, the study therefore used this stochastic approach. In this algorithm, ranges associated with uncertainty of all variables convey the uncertainty of each parameter by considering the conceptual model, the data measured and its parameters. Uncertainties in parameters lead to uncertainty in model output which is commonly expressed in SUFI-2 by 95% probability distributions which are computed between 2.5 and 97.5% of cumulative distributions for an output variable. This is referred to as 95% prediction uncertainty or a confidence interval (95PPU). This output acquired from the stochastic calibration approach is the most suitable solution at 95% significance level, generated from specified parameter intervals and defined by the modeler.

The calibration and validation process in this study was performed using the split-sample approach with monthly stream flow data from Omatoko gauge station used for the period 1990-2003 (calibration) and 2004-2008 (validation).

This was performed to evaluate the efficiency of streamflow simulation compared to the observed data. The splitting of observed data based on time-period ensures data independence to assess the model performance. Moreover, the selected period for calibration and validation process was due to lack of in-situ data spanning the model duration. During calibration (1990-2003), four iterations each with no less than 500 simulations were executed to refine the model parameters (Abbaspour, 2015; Hajati et al., 2020). With each iteration performed, values of each parameter range become smaller approaching the best solution and achieving better models than previous iterations. According to Abbaspour (2015) the best solution is usually achieved within the above stated iteration. Thereafter, independent observed data can be used to validate the 2004-2008 period. During this process, the exact calibrated parameter ranges and same simulation quantity as defined in the final calibration was repeated, aimed to assess model performance. The calibration and validation results were both quantified using statistics known as P-factor, R-factor, and objective function value (Abbaspour, 2015; Abbaspour et al., 2004). As expressed by Abbaspour (2015), in SUFI-2, a good fit between observation and simulation results is conveyed using two indices 'P-factor' and 'R-factor'. P-factor refers to the observed data enveloped by 95% prediction uncertainty. While the R-factor refers to the thickness of the 95PPU. The P-factor is measured between 0 – 1 with 1 being the perfect result indicating 100 % of the observed data enveloped in the 95PPU, while 0 being the worst with none of the observed data represented within the envelope. In the case of R-factor, possible values range between zero and infinity. The recommended value for R-factor is less than 1.5 for streamflow, (Abbaspour et al., 2004, 2015), whereas P-factor is acceptable with values greater than 0.7. However, the former depends on the project scale, input data, etc. Hence, the above indices can evaluate the goodness of fit between our observed and simulated results in the calibration and validation process. Values slightly outside the acceptable range are still possible, as the recommended values are not necessarily fixed numbers, rather a quest to reach a balance between R factor and P

factor (Abbaspour, 2015).

In this study the good agreement between the observed and simulated streamflow is evaluated through the objective function Nash-Sutcliffe coefficient (NSE) as shown in Equation (2),

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{observed} - Q_{simulated})_i^2}{\sum_{i=1}^n (Q_{observed} - \bar{Q}_{observed})^2} \quad (2)$$

Coefficient of determination (R²) as shown in Equation (3),

$$R^2 = \frac{[\sum_{i=1}^n (Q_{observed,i} - \bar{Q}_{observed})(Q_{simulated,i} - \bar{Q}_{simulated})]^2}{\sum_{i=1}^n (Q_{observed,i} - \bar{Q}_{observed})^2 \sum_{i=1}^n (Q_{simulated,i} - \bar{Q}_{simulated})^2} \quad (3)$$

Percent bias (PBIAS) as shown in Equation (4), and

$$P_{BIAS} = 100 * \frac{\sum_{i=1}^n (Q_{observed} - Q_{simulated})_i}{\sum_{i=1}^n Q_{observed,i}} \quad (4)$$

Ratio of RMSE to the Std. Dev. of observed data (RSR) as shown in Equation (5)

$$RSR = \frac{\sqrt{\sum_{i=1}^n (Q_{observed} - Q_{simulated})_i^2}}{\sqrt{\sum_{i=1}^n (Q_{observed,i} - \bar{Q}_{observed})^2}} \quad (5)$$

Where Q is the variable under observation or simulation, that is discharge, $Q_{observed}$ and $Q_{simulated}$ are discharge data, which have been measured and simulated respectively, while n refers to the number of total records and $\bar{Q}_{observed}$ denotes the average measured data while i is the ith measured or simulated data. Similar to the P-factor and R-factor, there are no specific numbers to achieve, however, the recommended values for watershed scale (Gupta et al., 2009; Hajati et al., 2020; Moriasi et al., 2007, 2015) are as follows; $R^2 > 0.6$, $NSE > 0.5$ and $P_{BIAS} < \pm 25\%$. Hence, the model performance is evaluated as per the performance rating criteria listed in Table 2.

RESULTS AND DISCUSSION

Results of SWAT

In the process of delineation, the catchment was divided into 60 sub-basins and further subdivided into 762 HRUs. The simulation was executed for a 31-year period between 1985 and 2015 with the initial five years from 1985-1989 used as model warm-up. The simulated results showed precipitation in the basin to be low and potential evapotranspiration being expectedly high for simulated timeframe. During the simulation, the ratio of surface runoff to total flow was very low at 0.27, the evapotranspiration to precipitation recorded was 0.57, and the baseflow to total flow ratio was a high 0.73. These results clearly show that the surface runoff was very low and most of the precipitation was lost to the shallow aquifer and the evapotranspiration process.

Sensitivity analysis

Out of the twelve parameters discussed above (that is,

Table 2. Performance Rating for a Monthly Time Step

Model performance rating	RSR	NSE	R^2	PBIAS
Very Good	$0.00 \leq RSR \leq 0.50$	$0.75 < NSE \leq 1.00$	$0.75 < R^2 \leq 1.00$	$PBIAS < \pm 10$
Good	$0.50 < RSR \leq 0.60$	$0.65 < NSE \leq 0.75$	$0.60 < R^2 \leq 0.75$	$\pm 10 \leq PBIAS < \pm 15$
Satisfactory	$0.60 < RSR \leq 0.70$	$0.50 < NSE \leq 0.65$	$0.50 < R^2 \leq 0.60$	$\pm 15 \leq PBIAS < \pm 25$
Unsatisfactory	$RSR > 0.70$	$NSE \leq 0.50$	$R^2 \leq 0.50$	$PBIAS \geq \pm 25$

Source: Koycegiz and Buyukyildiz, 2019; Moriasi et al., 2007

Table 3. Parameters and range of values used in the calibration.

Parameter	Description	Parameter Range	Fitted Value	t-Stat	p-Value
CN2	SCS runoff curve number f	-0.2 – 0.2	-0.1804	-11.6970	0.000
OV_N	Manning's "n" value for overland flow	-1.5 – 1.5	-0.273	1.496	0.135
FFCB	Initial soil water storage expressed as a fraction of field capacity water content	0.12 – 0.69	0.20037	-0.102	0.919
ESCO	Soil evaporation compensation factor	0 – 1	0.269	0.570	0.569
EPCO	Plant uptake compensation factor	0.3 – 1	0.9293	0.496	0.620
CH_K2	Effective hydraulic conductivity in main channel alluvium (mm/h)	2 – 140	82.729996	-1.457	0.146
CH_N2	Manning's "n" value for the main channel	0.25 – 0.76	0.73807	0.453	0.651
ALPHA_BF	Base flow alpha factor (days)	0 – 1	0.135	-6.334	0.000
GW_DELAY	Groundwater delay time (days)	30 – 450	189.179993	7.923	0.000
GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm).	0 – 2	0.142	-0.195	0.845
SURLAG	Surface runoff lag time	0 – 20	13.86	1.349	0.178
MSK_CO1	Calibration coefficient used to control impact of the storage time constant for normal flow	0 – 10	0.43	-0.274	0.785

Source: Authors

parameter sensitivity analysis), three parameters appeared to be highly sensitive to stream flow in the Okavango-Omatako catchment. The most sensitive appeared to be the runoff curve number controlling the surface runoff followed by ground water delay time and baseflow alpha factor influencing the baseflow of the semi-arid catchment during the period 1990 to 2003. Many of the studies performed in arid and semi-arid environments also confirmed these results with Esmali et al. (2021) observing runoff curve number (CN2) ranked the most sensitive in different climatic zones including semi-arid and arid, while ground water delay (GW_DELAY) was found to be most sensitive in arid and baseflow alpha factor (ALPHA_BF) in semi-arid environment. Additionally, Aqnouy et al. (2019) and Desai et al. (2021) noted that out of the three above parameters, two were the most significant in a semi-arid environment in Morocco and India. The sensitivity analysis as indicated by the t-stat and p-value in Table 3 showed CN2, GW_DELAY and ALPHA_BF as the most sensitive parameters in our catchment. The results agree

with similar findings by Thavhana et al. (2018) and Koycegiz and Buyukyildiz (2019), Mengistu et al. (2019) and Leng et al. (2020) on frequently considered parameters which are amongst the most sensitive in the global sensitivity analysis for hydrological processes of semi-arid catchments. The remaining nine parameters were less sensitive with higher p-values and a lower t-stat.

The sensitivity analysis yielded t-stat and p-value for the model parameters as shown in Figure 6. The most dominant significance with the highest t-stat and a low p-value were seen in CN2, GW_DELAY and ALPHA_BF. The parameter CN2 also known as the SCS runoff curve number is used to determine runoff values for the catchment and is found to be the most sensitive parameter with a low p-value ($p < 0.05$) and a high t-stat. According to USDA (1986), this parameter has been used to characterize antecedent runoff conditions in arid and semi-arid watersheds. Following CN2, ALPHA_BF, a parameter affecting base flow, was classed to be sensitive to streamflow in the semi-arid catchment. The

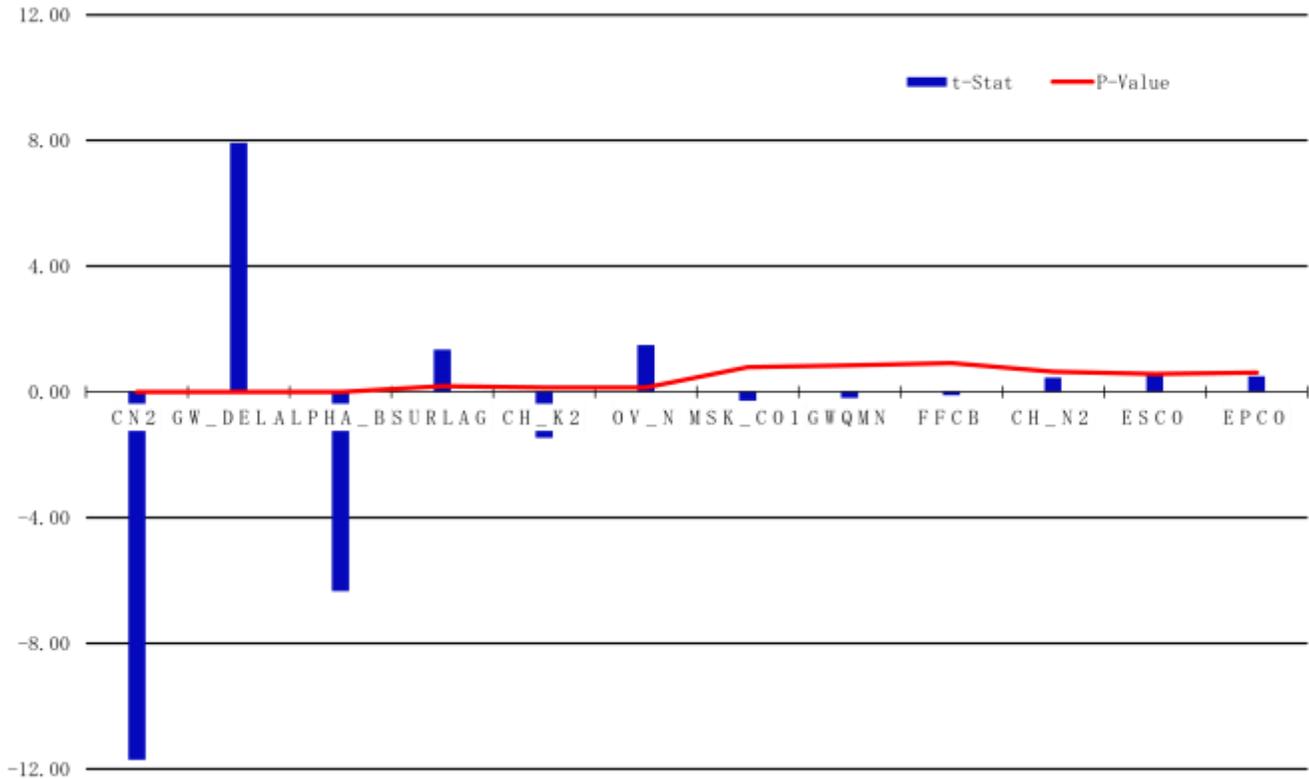


Figure 6. Parameters sensitivity analysis (*t-stat* and *p-value*) of SWAT simulation for the Okavango-Omatoko catchment. Source: Authors

Table 4. Result from calibration and validation.

	Calibration	Validation
P-factor	0.77	0.68
R-factor	1.31	1.82
R^2	0.84	0.89
NSE	0.82	0.80
PBIAS	-1.1	-20.0
RSR	0.42	0.44

Source: Authors

ALPHA_BF fitted value of 0.135 reveals a slow recharge response rate as discussed by Miskewitz (2007), constituting a slow baseflow in the catchment. The next sensitive parameter is GW_DELAY, which is highly influenced by the catchment area size under consideration. The parameter measures the time for water to percolate and reach the water table, being 189 days in this catchment. The remaining nine parameters (OV_N, FFCB, ESCO, EPCO, CH_K2, CH_N2, GMQMN, SURLAG and MSK_CO1) were found to be less sensitive

to streamflow estimation causing increased model uncertainties in the study area. As part of this study, a further in-depth investigation which identifies parameter sensitivity to semi-arid environments similar to this study catchment will be valuable for better model performance in stream flow estimation.

Model calibration

The output of the calibration illustrated the capacity of SWAT to simulate streamflow in this study catchment. The 95PPU illustrated in Figure 7(a), with green in the calibration processes displays the uncertainty of this model through computation of the P-factor, and R-factor indicators. As shown in Table 4, the P-factor estimate was 0.77, thus 77% of the observed discharge lies in the 95PPU bracket for the period of calibration, from 1990-2003. Whereas 95PPU bracket thickness was measured by the R-factor, which was 1.31, resulting in both indicators meeting the optimum value as determined by Abbaspour et al. (2015). During the calibration process, the study achieved the best model between observed and simulated streamflow. It is also apparent

from Figure 7(a) that the observed mainly falls outside the 95PPU during the descent cycle of streamflow, demonstrating the start of the flow modelled very well as opposed to the end of the seasonal flow. In general, the model also performed well in simulating high and low flows between the observed and simulated streamflow.

In addition to the above model performance parameters, all other performance indicators for the model calibration (Table 4) scored between good to very good according to the evaluation criteria outlined in Table 2 (Koycegiz and Buyukyildiz, 2019; Moriasi et al., 2007). The model performance indices evaluated the agreement between simulation and observation of our catchment as presented in Table 4. The objective function used in this study to evaluate the model performance for the period 1990 to 2003 was Nash-Sutcliffe efficiency (NSE) with a calibration of 0.82. These results depict the model simulation success with good results produced according to the model performance evaluation criteria listed in Table 2. Additionally, other performance indicators such as Coefficient of determination (R^2), Percent bias (PBIAS) and residual variation (RSR) were similarly used to evaluate the model. The calibration results as presented in Table 4, with R^2 (0.84) achieved very good performance rating for the recommended statistics on a monthly basis. The PBIAS scored (-1.1), ranking very good on the calibration while the RSR (0.42) also performed very well with values below 0.5 as recommended by (Arnold et al., 2012; Fernandez et al., 2005; Mengistu et al., 2019; Moriasi et al., 2015).

According to Figure 7(b), the scatter plot representing measured vs simulated discharge, visualizes the success of the model performance. Coefficient of determination (R^2) of the scatter plot shows 0.84 for calibration, indicating a higher correlation between observed and simulated data during the calibration period. However, in Figure 7(a) an overestimation during low flow periods were observed. While high flows were simulated satisfactorily, closely matching the observed values, excluding few cases of the peak flow estimations which were slightly underestimated. These findings agree with similar studies by (Koycegiz and Buyukyildiz, 2019; Thavhana et al., 2018; Vilaysane et al., 2015).

Model validation

The validation process compared the simulated discharge of a selected outlet of a sub-basin with observed discharge measured at gauge station nearby, plotted in Figure 8(a) with corresponding precipitation data from the closest meteorological station. As outlined in the methods, the model validation was carried out using in-situ data from 2004 to 2008. The results were a P-factor of 0.68 (that is, 68% of the observed discharge was bracketed by the modeling result of 95PPU), and

R-factor of 1.82 (that is, the 95PPU bracket thickness). In both cases, the results were unable to achieve the recommended values of (Abbaspour, 2015), which were set to be greater than 0.7 for P-factor and less than 1.5 for R-factor. These optimum values as endorsed by Abbaspour et al. (2015) act more of a guide rather than absolute numbers which must be achieved. The values are dependent on project scale and availability of input and calibration data as mentioned in (Abbaspour et al., 2015; Beharry et al., 2021; Musyoka et al., 2021; Pontes et al., 2021). In the validation process the R-factor recorded a value > 1.5, which was found to be satisfactory due to the large size of the study area under consideration and limited calibration data availability. Moreover, the recorded R-factor above the recommended value could be attributed to low flow during the years 2004-2005, especially when compared with peak-flow characteristics during the calibration period. Pontes et al. (2021) also recorded similar results during the evaluation of SWAT model to simulate monthly streamflow in a catchment in Brazil. Nonetheless, the objective function results in the validation process achieved NSE of 0.8, R^2 of 0.89 and RSR of 0.44 with all three scoring in the very good category as stipulated by (Moriasi et al., 2007). While the model indicated a PBIAS of -20.0 falling within a satisfactory range for validation as stated by (Koycegiz and Buyukyildiz, 2019; Moriasi et al., 2007). Similarly, the validation also demonstrated poor performance at the end of a streamflow season, but also at times during low flow by falling outside the 95PPU bracket.

Coefficient of determination (R^2) of the scatter plot in Figure 8(b) attained 0.88 indicating a positive correlation between observed and simulated data during the validation period. This result indicates the success of the model performance.

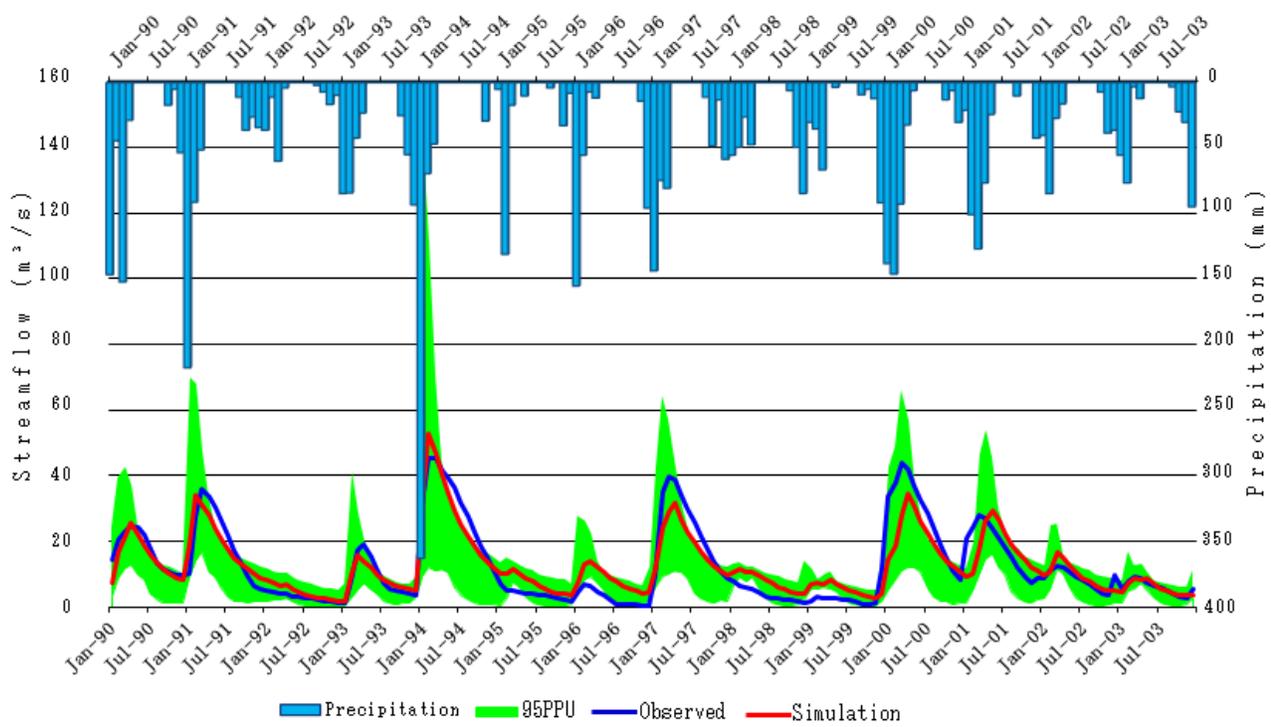
However, in Figure 8(a) a high overestimation during low flow years were seen while closely matched results between simulated and measured streamflow during peak flow years were observed.

Model performance evaluation

A SWAT hydrological model was setup and implemented for a semi-arid catchment in Namibia to evaluate model performance for streamflow estimation. The model was calibrated using the limited available observed river discharge data. Despite the simulation for the study area carried out from 1985 to 2015, the calibration and the validation processes could only be implemented for the periods 1990 to 2008 due to inconsistencies and missing observed discharge data subsequent to this period. Such limitations were also observed by Terskii et al. (2019) in a similar study.

Thus, reliable discharge observation stations collecting

a)



b)

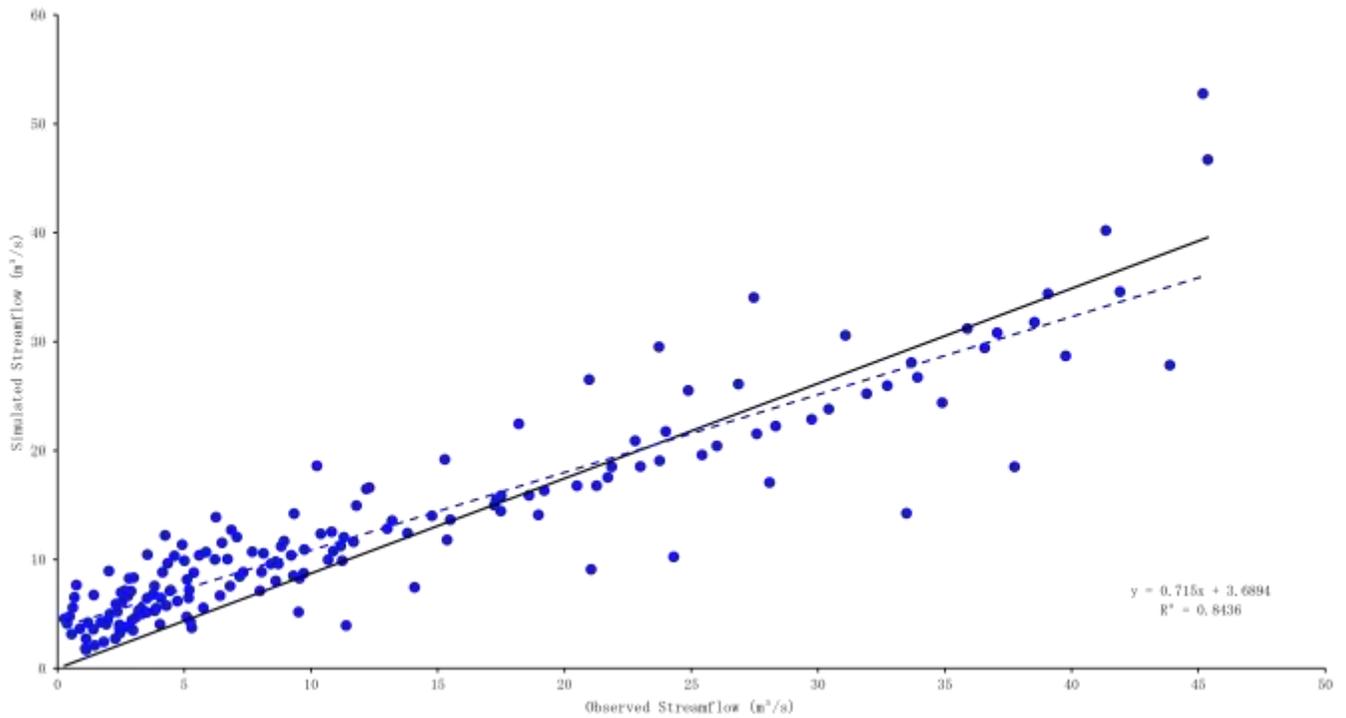
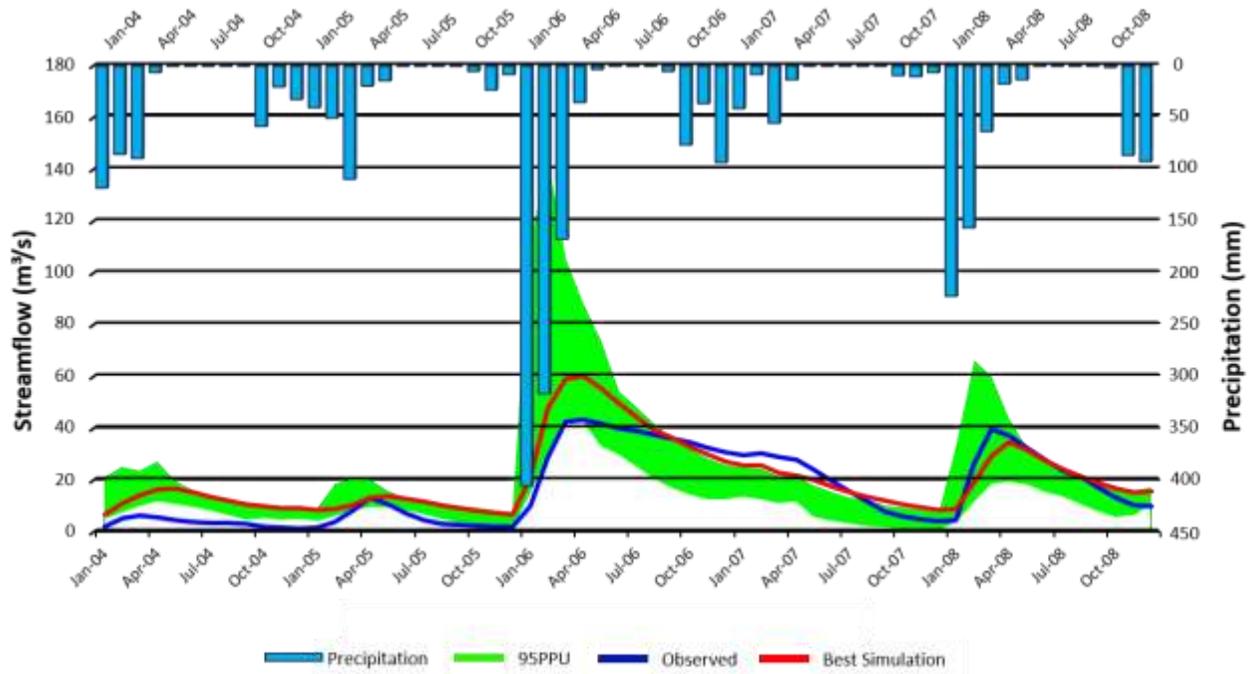


Figure 7. (a) Observed vs simulated monthly stream flow and (b) Scatter plot showing correlation between the observed and simulated for the calibration period (1990 - 2003).
Source: Authors

a)



b)

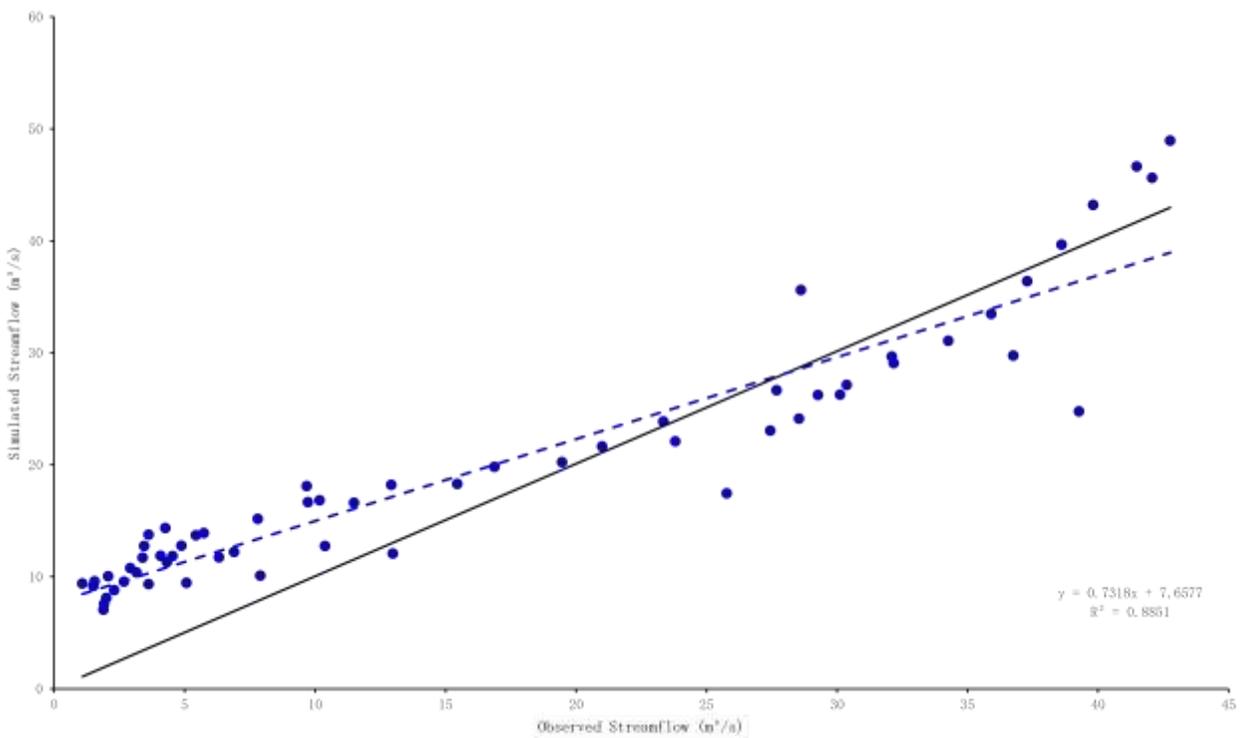


Figure 8. (a) Observed vs simulated monthly stream flow and (b) Scatter plot showing correlation between the observed and simulated for the validation period (2004 - 2008).
Source: Authors

long term flow data could go a long way in modelling catchments similar to the study area.

The general performance of the model as indicated through the values achieved by the different indicators has a good agreement between the observed and simulated streamflow. 95PPU for the calibration and validation processes for the period of study with its corresponding rainfall records are shown in Figure 7(a) and 8(a). It is apparent that after intensive rain occurred, an increased streamflow was observed thereafter. However, this was not the case for all the years of calibration, which could be attributed to climate conditions such as high evapotranspiration, high percolation, abstraction, etc. Despite this, one can still observe the simulated data, predominantly falling within the confidence interval. Similar findings were observed by Koycegiz and Buyukyildiz (2019) and Mengistu et al. (2019), while modelling runoff in a semi-arid catchment, both studies observed an increased flow following a high rainfall event confirming the outcome of simulation in this study.

Prediction uncertainty is used to quantify the agreement between simulated and observed results. The P-factor value for calibration was adequate while the validation value was near the recommended value of 0.7 (Abbaspour et al., 2015). Similarly, the R-factor value of the calibration was within the acceptable range while the validation is slightly on the upper side of the recommended value of 1.5. This could be dependent to and highly attributed to the scale of the project as demonstrated in (Abbaspour et al., 2007, 2015). Hence, the results of this study can be considered to have lower uncertainty in the calibration and slightly higher uncertainty in the validation process. As stated by Abbaspour et al. (2015) while calibrating a continental scale hydrological system, a large-scale catchment as demonstrated in the study could attain slightly higher or lower results than the ranges of the recommended value. Abbaspour et al. (2015) and Beharry et al. (2021), Musyoka et al. (2021) and Pontes et al. (2021) demonstrated that a high R-factor could also occur due to lack of sufficient data for model calibration. To this end, the modelling of the Okavango-Omatako catchment has been challenging due to the quality of input and calibration data with uncertainties leading to a high R-factor.

The model performance indicators used the NSE, R^2 , PBIAS and RSR while results were ranked according to (Koycegiz and Buyukyildiz, 2019; Moriasi et al., 2007). All indicators achieved a very good performance rating with exception of PBIAS validation rated as satisfactory. Similar to Abbaspour et al. (2015), Mengistu et al. (2019) and Moriasi et al. (2007), the results indicate a good overall achievement of model performance within the study area with a good level of agreement between observed and simulated streamflow. Taking a closer look, the PBIAS index reveals that the model underestimated stream flow in the process of simulation by 1.1 and 20%

respectively for calibration and validation, when compared with observed data. Simulated and observed streamflow for both calibration and validation are demonstrated in Figure 7(a) and 8(a), respectively. The model is capable of simulating low and high flows satisfactorily, closely matched to the observed values. However, in some cases the peak flow estimation slightly falls short in the calibration period. These findings are cohesive to similar studies by (Koycegiz and Buyukyildiz, 2019; Thavhana et al., 2018; Vilaysane et al., 2015). Consequently, low flow might have caused an above limit R-factor in our catchment as supported by Musyoka et al. (2021) and Pontes et al. (2021), during the evaluation of SWAT model to estimate monthly streamflow in the dry season of their respective study areas.

After a careful assessment of the simulated versus observed results, the performance of SWAT to effectively model a large complex semi-arid catchment with scarce in-situ data was found to be satisfactory, demonstrating the potential of simulating future streamflow events. This indicates the effectiveness and further exploration of this model to assess impacts of climate change in similar catchments within the region. However, evident limitations are seen in overestimated low flows during calibration and validation timeframes, which are vital for extrapolation to forecast and assess climate change impacts. From a catchment management perspective, the model fairly estimated the peak flow in the calibration period verifying its capacity to be used as a water management tool, except in few cases where underestimations occurred. Further investigations into streamflow intensity and time lag between streamflow events are essential for water resource managers. Another relevant factor which must be considered as a potential impact on catchment flow characteristics is the changes in LULC. In this study, the temporal changes of LULC were not examined.

However, the significance of a time-series analysis of the catchment's LULC cannot be refuted and could go a long way in understanding its impacts on streamflow behavior. This study thus proposes a subsequent investigation on this matter.

One of the limitations in this study is the inadequacy to evaluate parameter sensitivity in the entire catchment. The uncertainty analysis of our model estimation can only be quantified in locations of the sub-basin where calibration was performed. Therefore, results in areas further away from calibrated portions should be examined attentively. One of the reasons for such limitation is the lack of data for use in the calibration process. An alternative, which should be considered to overcome such limitation, is the calibration using other variables such as available remotely sensed evapotranspiration and soil moisture as successfully demonstrated by Emam et al. (2017) and Rajib et al. (2016), respectively. The sensitivity analysis found three parameters to have a dominant influence in the model parameterization for the

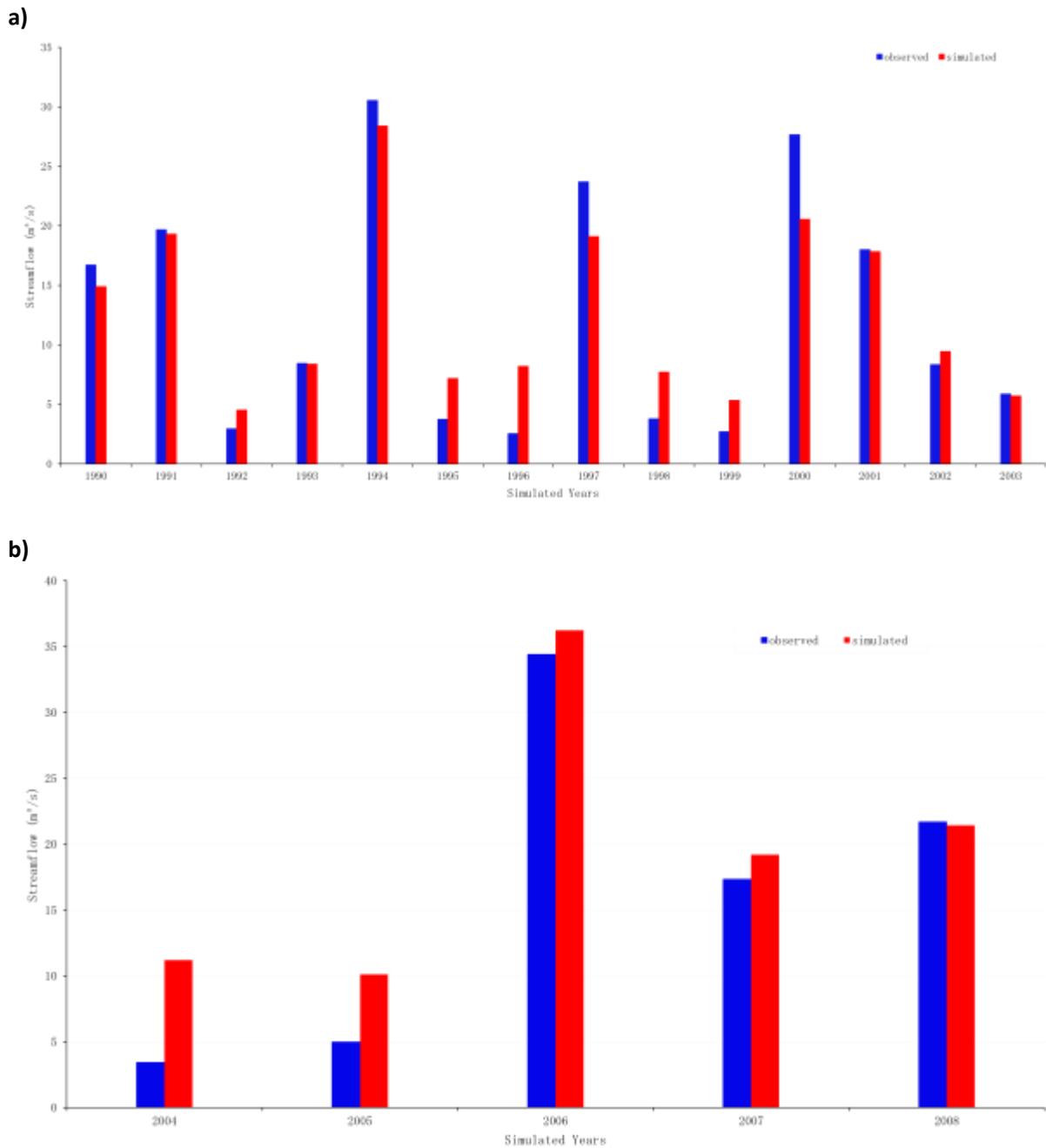


Figure 9. Annual monthly average stream flow of observed and simulated (a) during the calibration period (1990 - 2003) and (b) during the validation period (2004 - 2008). Source: Authors

catchment under investigation. Water resource managers in the area should collect these essential parameters (that is, the runoff curve number, ground water delay time and baseflow alpha factor) to improve model performance.

Annual monthly average stream flow displayed in

Figure 9(a) and 9(b), demonstrates variation of observed and simulated streamflow values with an average overestimation of 1.03 and 16.63% for the calibration and validation periods respectively. The model inclination to overestimate low flows is evident, especially for the periods of 1992, 1995, 1996, 1998, 1999, 2002, 2004 and

2005. The result is confirmed by similar investigations in Tegegne et al. (2017), Thavhana et al. (2018) and Turkmen et al. (2021), and is critical that the model is modified to handle low flows or adjoined with other models for improved estimates. The peak flows were estimated more reasonably and closely matched the observed values with slight underestimations. Bearing the adequate performance of the model estimation and results in mind, hydrological simulation in a semi-arid environment such as Okavango-Omatako catchment can be performed using modified SWAT and/or coupled with other models to manage scarce water resources in the region.

Conclusion

This study evaluated streamflow responses of selected parameters in the Okavango-Omatako catchment and recommends future work to explore the dynamics of the Okavango River basin starting from southern Angola through the northeastern part of Namibia and dissipating in the Okavango delta. Further, to understand the hydrological systems in this area, the link to climate systems such as El Nino/La Nina, Southern Oscillation (ENSO) and Sea Surface Temperature (SST) in the Atlantic and Indian Ocean should be investigated. These links are recommended by Landman and Mason (1999), Namibia Resource Consultants (1999) and Orti and Negussie (2019) to impact the management of water resources in this semi-arid environment, but have not been investigated to date.

It is paramount to understand hydrological systems and their characteristics as well as various parameters which influence these systems. A major part of this process is to recognize the spatial and temporal patterns of precipitation, evapotranspiration, LULC and soil moisture. The varying spatial distribution of these variables in the catchment creates a challenge in simulating streamflow. Serious deficiencies during the modelling process merged from the lack of knowledge on the catchment's physical environment. The need for more comprehensive research to better understand the hydrological processes on catchments in Namibia is obvious. This research is necessary to sustainably use water resources and support water resource managers for efficient planning and management of this scarce resource. This study further recommends the sensitivity of parameters in the catchment under study to be evaluated as familiarities could contribute to a better understanding of streamflow processes.

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CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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