Journal of Hydrology: Regional Studies 25 (2019) 100621

Contents lists available at ScienceDirect

Journal of Hydrology: Regional Studies

journal homepage: www.elsevier.com/locate/ejrh

Techniques for calibration and validation of SWAT model in data scarce arid and semi-arid catchments in South Africa

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A R T I C L E I N F O

Keywords:
Arid catchments
Calibration
Hydrologic models
Regionalization
SWAT model
South Africa

A B S T R A C T

Study region: This study was conducted in Soutloop River Catchment, Northern Cape, South Africa.

Study focus: Although hydrologic models play a critical role in the management of natural resources in arid areas, their application is challenged by the scarcity of data for calibration and validation. Therefore, this study aimed at to configure, calibrate and validate SWAT model in a data-scarce catchment by using the regionalization with physical similarity approach. This approach uses dual calibration and validation procedure, *i.e.*, one in the donor catchment (by using SWAT-CUP (SWAT Calibration and Uncertainty Programs) and the other on the study catchment (by manual calibration and verification).

New hydrological insights for the region: Based on the sensitivity analysis, sixteen parameters were calibrated by SWAT-CUP. The result from the uncertainty analysis indicated acceptable values of both the R-factor (0.8[**]) and P-factor (0.7**). The model performance evaluation also showed acceptable ranges of values (*e.g.*, NS was 0.76** and R^2 was 0.78**). However, the main calibration and validation process was conducted outside the target catchment, though it was assumed that the donor and target catchments have similar hydrological responses. Therefore, the study suggested further inspection methods to minimize the model uncertainty in the study catchment. This study enables researchers to exploit the river eco-regional classifications of South Africa to apply hydrologic models to estimate the components of water balance in arid/semi-arid catchments.

1. Introduction

Most hydrological systems incorporate extremely complex processes and are not easily understood (Xu, 2002). It is also impractical to measure every data about hydrologic systems and processes due to various reasons. This could be due to higher spatial and temporal heterogeneity of the systems, limitations in measurement methods, and to the fact that measurement methods are usually laborious, time taking and costly to implement. Therefore, hydrological models enable users to manipulate the system's variables/parameters easily and help in understanding the interaction between variables that make up complex systems (Sokolowski and Banks, 2010, 2011). Hydrological models also enable the users to extrapolate both spatial and temporal information on the area of interest (Pechlivanidis et al., 2011). It is assumed that hydrological models are simplified systems that represent the real hydrologic

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** Values are the averages of the calibration and validation procedures.

https://doi.org/10.1016/j.ejrh.2019.100621
Received 17 May 2019; Received in revised form 25 July 2019; Accepted 26 July 2019

processes (Lundin et al., 1999; Tessema, 2011). Hence, Babel and Karssenberg (2013) described hydrologic models are mediators between theory and practice or the real world. Therefore, hydrologic models are important tools in the study of hydrologic processes at catchment, regional and global scales.

Even though it is an essential task, hydrologic modelling is challenging in arid and semi-arid environments because most catchments in this environments are ungauged. It is obvious that the calibration and validation processes are integral part of catchment hydrologic modelling due to the higher spatial and temporal variability of the hydrologic system. This is particularly important for physics-based models. Catchments with available observed data, including but not limited to discharge data, evapotranspiration, profile water content, can be modelled with reasonable accuracies. On the other hand, the unavailability or the presence of limited observed data due to the high cost of spatial hydrological data acquisition makes the use of physics-based models challenging (Ajami et al., 2004; Bekele and Nicklow, 2007; Bárdossy, 2007). Moreover, hydrological modelling in arid and semi-arid catchments is challenging due to the distinctive feature of the hydro-climatological variables in those regions (Pilgrim et al., 1988; Kan et al., 2017). Reports (*e.g.*, Wheater, 2005; Li et al., 2015) indicate that most models are also developed for humid and sub-humid areas where their performance in arid/semi-arid areas vary considerably.

The Soil and Water Assessment Tool (SWAT) is a continuous-time, semi-distributed and processed-based model developed and supported by the USDA Agricultural Research Service (Neitsch et al., 2011; Arnold et al., 2012). The model was originally developed to evaluate the impact of land management practices on water resources, sediment and agricultural chemical yields in large complex catchments with varying soils, land use and management conditions (Neitsch et al., 2011; Daniel et al., 2011). Water balance is the major driving force behind any process in SWAT. Hence, besides the different components of water balance, SWAT is being used to model plant growth and the movement of sediments, nutrients, pesticides and pathogens in a catchment (Neitsch et al., 2011; Arnold et al., 2012; Parajuli and Ouyang, 2013). The model requires several input data to simulate catchment hydrologic processes, and these include a digital elevation model (DEM), land use–land cover data, soil types, and different daily weather data, including details of precipitation, maximum and minimum air temperatures, solar radiation, wind speed, and relative humidity. SWAT has received international acceptance as a robust interdisciplinary catchment-scale modelling tool. However, its application in arid and semi-arid areas is still challenging due to the unavailability of flow data for model calibration and validation procedures.

Even though the calibration of hydrologic models is challenging for data scarce catchments, some methods have been proposed in literature. These include: (i) the regionalization approach, in which a similar, but gauged, catchment will be parametrized and calibrated. The model parameters will then be transferred to the ungauged catchment. It is one of the most widely used method in the prediction of hydrologic variables in ungauged basins (Merz and Blöschl, 2004; Bárdossy, 2007; Bekele and Nicklow, 2007; Reichl et al., 2009; Gitau and Chaubey, 2010; Farsadnia et al., 2014; Swain and Patra, 2017; Emam et al., 2017). (ii) Calibration based on crop yield: this gives confidence on the evapotranspiration and simulates other hydrologic components better. Many researchers (*e.g.*, Nair et al., 2011; Emam et al., 2015; Sinnathamby et al., 2017; Emam et al., 2017) used this method of calibration (calibration based on crop yield). (iii) Calibration based on data retrieved from remote sensing: this method enables the acquisition of important spatio-temporal data like the soil water content and evapotranspiration. Hydrologic models could be calibrated using such data, like the Moderate Resolution Imaging Spectroradiometer (MODIS) and other satellite products (Jajarmizadeh et al., 2012; Zhang et al., 2017; Tobin and Bennett, 2017; Emam et al., 2017; Rajib et al., 2018; Odusanya et al., 2019).

The first and widely implemented method (regionalization approach) has many types. Generally, this approach could be further classified by three. These are regionalization by spatial proximity, physical similarity and regression methods. In the spatial proximity approach, it is usually assumed that neighbouring catchments have homogenous physical and climatic characteristics and hence, have similar hydrological responses (Blöschl et al., 2013; Emam et al., 2017). As a result of this, calibrated parameters could be transferred from gauged to ungauged neighbouring catchments. Calibration with regression methods consist of developing some empirical relationships between catchment descriptors (both physical and climatic) and model parameter values calibrated on gauged catchments (Bastola et al., 2008; Emam et al., 2017). Once these relationships have been established, one determines the parameters of an ungagged basin using its physical and climatic attributes. The regionalization with physical similarity is based on the similarity between an ungagged catchment and one or more gauged donor catchments (Blöschl et al., 2013; Emam et al., 2017).

Focussing on the regionalization by physical similarity approach, catchments are evaluated and grouped based on their similarity in selected physical variables (physiography, geology and soils, climate and potential natural vegetation). In this approach, catchments categorized under similar regions or groups are assumed to have a similar hydrologic response. Hence, during catchment modelling, parameters could be transferred from a gauged and calibrated catchment to ungauged catchments. The regionalization approach has enabled researchers to exploit the potentials of hydrologic models in data scarce catchments. However, it is also believed that the procedure is exposed to higher uncertainity of model outputs since the calibration and validation processes are usually conducted ouside the target catchment. Therefore, the aim of this paper was to calibrate and validate SWAT model in an arid and ungauged catchment by the regionalization with physical similarity approach. Some best practices valuable to minimise model uncertainity in SWAT modelling were also suggested.

2. Materials and methods

2.1. The study area

2.1.1. Location of the study area

The study area is located in the Northern Cape Province of South Africa. It is a catchment that includes Kolomela Mine, with a geographic location of between 22°11′00″ and 23°28″00″ E longitudes and between 28°03′00″ and 29°06′00″ S latitudes. The

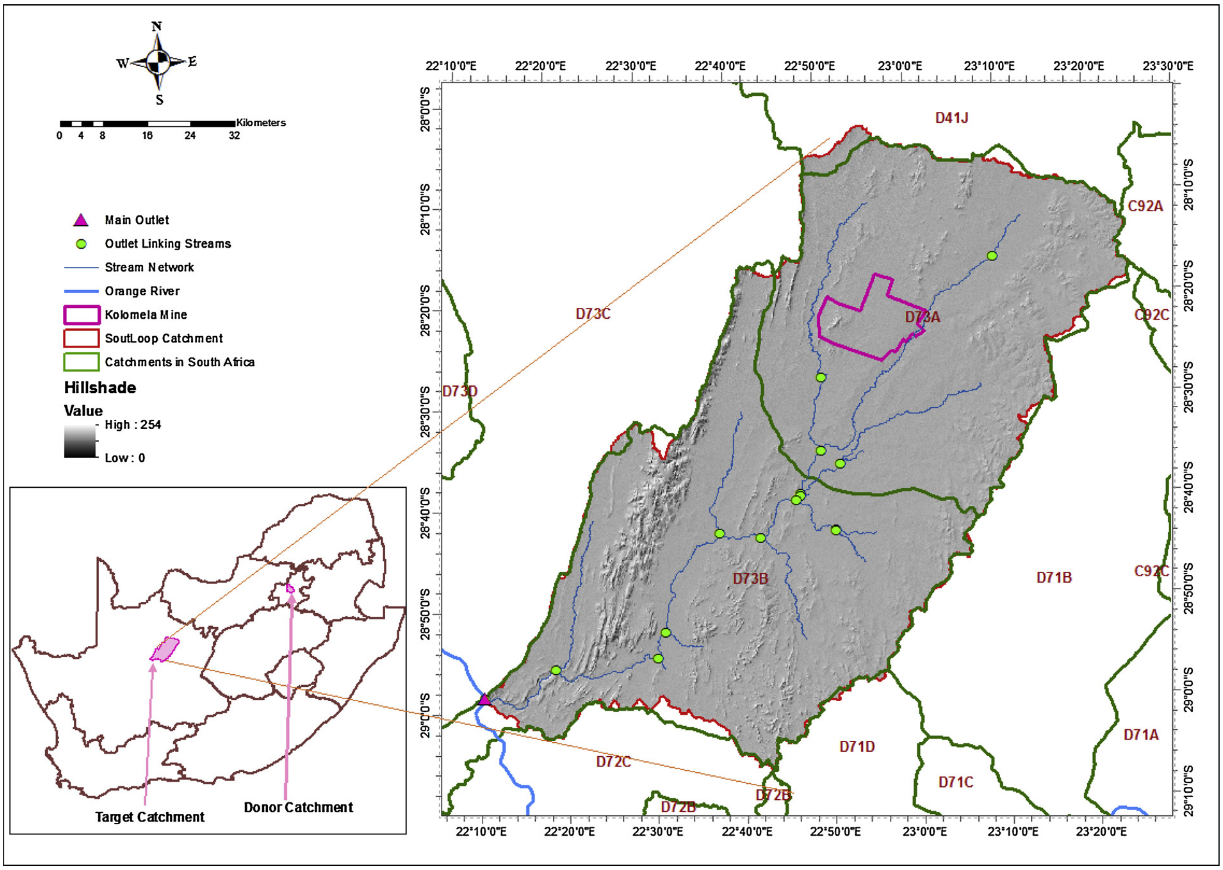

Fig. 1. Location of the donor catchment (A21C Quaternary Catchment) study area (Soutloop Catchment, about 6770 km^2) with its important hydrologic features.

catchment is a combination of two quaternary catchments (D73A and D73B), according to the referencing system of the South African Department of Water and Sanitation Affairs. The location and some hydrologic features of the study catchment (Soutloop Catchment) are depicted in Fig. 1.

2.1.2. Description of the study area

The total area of the study catchment is 6769.7 km^2, with an altitudinal range from 871 up to 1687 masl. Nearly 68% of the catchment has a slope of less than 5%, while the remaining 32% of the area is above a 5% slope. Fig. 2 depicts the spatial distributions of the slope classes in the catchment. The soil type in the area is dominated by Oxidic soils (59%, which includes Hutton and Clovelly soil forms), followed by Lithic origins (21%, including Mispah and rock surfaces). Other soil groups include Calcic (12%, which includes Coega soil form), Duplex soils (6% – Valsrivier soil form), Gleyic groups (1.6% – Katspruit and Kroonstad) and a very small amount of Cumulic soil groups (Dundee and Fernwood). The spatial distribution of the soil groups is shown in Fig. 3. According to the South African LULC classification of 2013/2014 (GEOTERRAIMAGE (South Africa), 2015), land cover within the catchment is dominated by low shrublands (80%), which is classified as range-brush in the SWAT database, followed by gra

ssland (11%, range grass in SWAT), and bushland (7%, classified as forest-mixed), while the remaining 2% of the study area is covered with other land cover classes. Fig. 4 shows the spatial variations of LULC classes in the study catchment. The area is also known for its arid climate. Hence, mean annual precipitation varies from 214 to 365 mm whereas the mean annual air temperature varies from 17.7 °C to 19.7 °C spatially in the study catchment.

2.2. SWAT model inputs

Other than the topographic, soil and LULC data, SWAT requires spatially explicit datasets of climatic data at daily/sub-daily time steps. Major input data for SWAT include DEM, LULC, soil properties, and daily weather data (precipitation, maximum and minimum air temperature, relative humidity, wind speed and solar radiation).

2.2.1. Digital Elevation Model (DEM)

Digital elevation model is an important data, since all the topographic attributes of the catchment, sub-catchment up to the HRUs

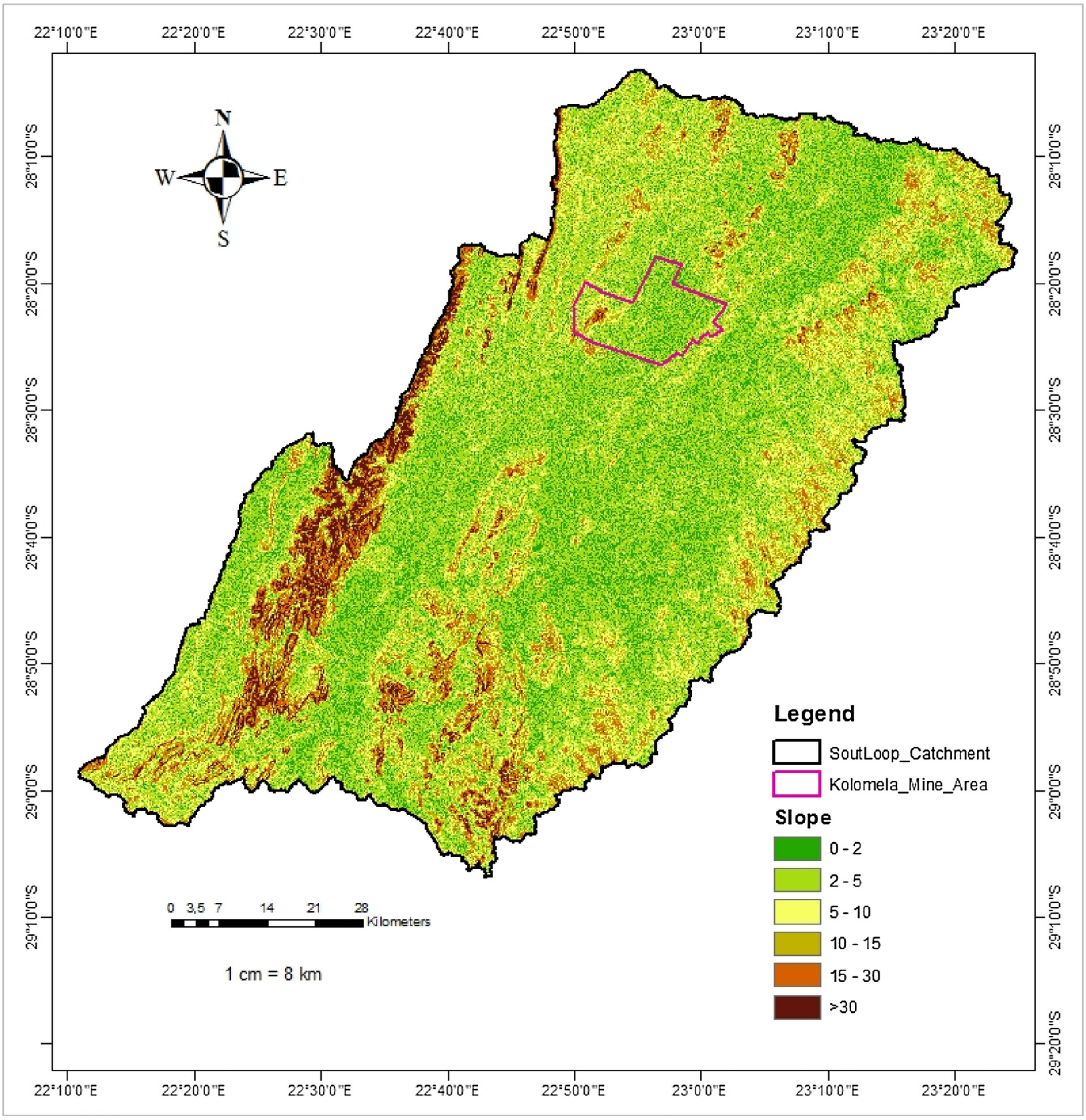

Fig. 2. The spatial variation of the slope classes in the catchment.

level are derived from this dataset. Some of the attributes include area, slope, slope length, channel length, channel slope, channel width, and channel depth. For this study, a 30-metre spatial resolution SRTM (Shuttle Radar Topography Mission) DEM was downloaded from the USGS website (link: https://lpdaac.usgs.gov/data_access/data_pool) and was used as an input dataset.

2.2.2. Land use/land cover data

Details of land use/land cover comprise one of the most determinant datasets required in hydrologic models, like SWAT, when creating the HRUs. For this study, the national land use/land cover layer of South Africa for the 2013/2014 year, with a 30-metre spatial resolution (GEOTERRAIMAGE (South Africa), 2015), was used. It was also modified slightly so that it would be consistent with the plant databases of SWAT.

2.2.3. Soil type and characteristics

Soil is another data that have major influence in catchment hydrology. In this study, the different soil classes were defined based on the Land Type Survey database compiled by the Agricultural Research Institute of South Africa (ARC), Institute of Soil, Climate

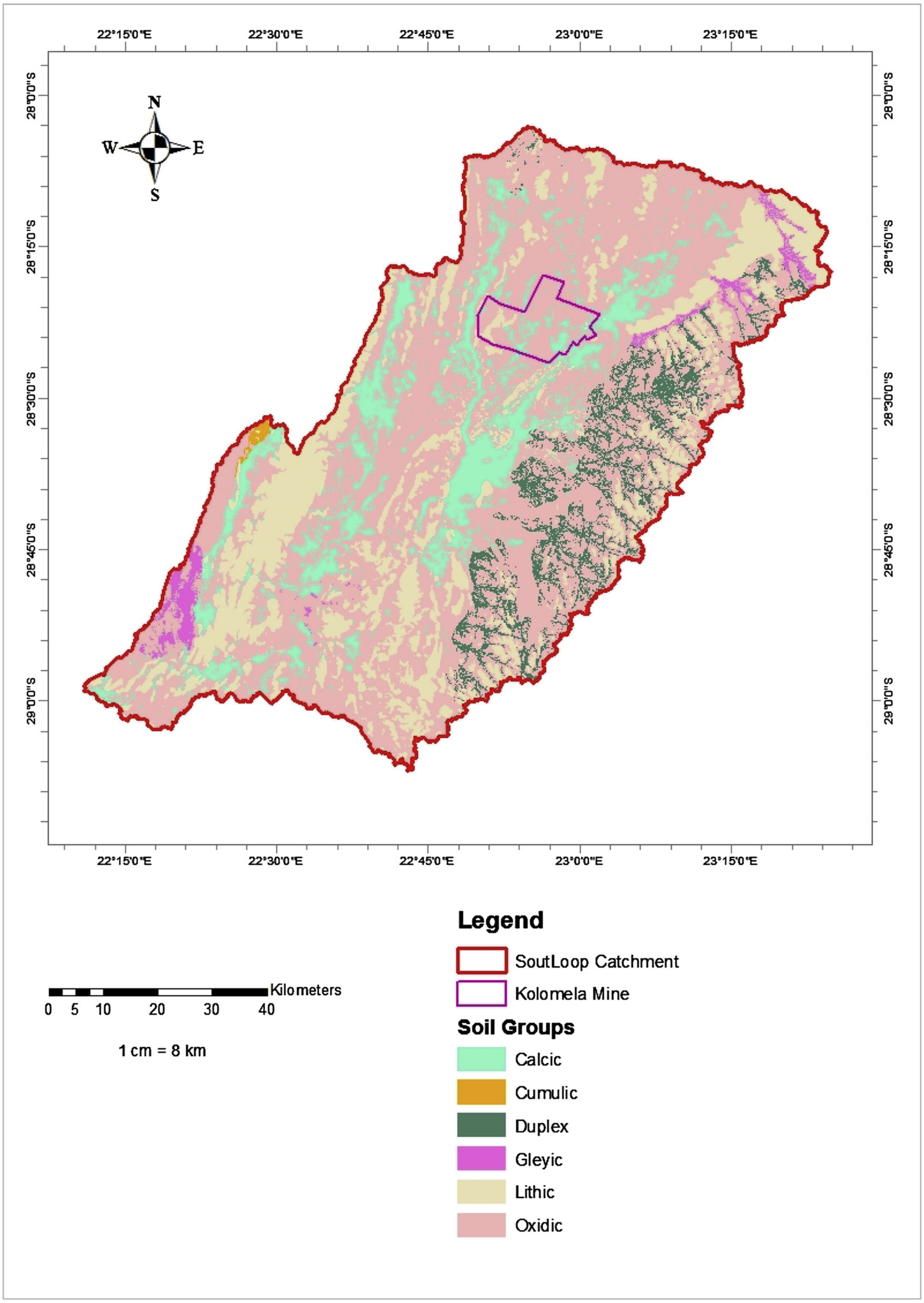

Fig. 3. Major soil groups in the study catchment.

and Water (Land Type Survey Staff, 1972). The Land Type Survey data of South Africa do not consist of soil types only. Rather, it is a combined spatial data that consists of mainly terrain, climate and soil distribution patterns. This Land Type data was also produced at courser scale (1:250,000 scale). Therefore, there was a need to get the actual data of soil types and increase the scale of the data. As a result of this, the soil units were disaggregated from the Land Type Survey data by the use of satellite data (*e.g.*, DEM, Satellite

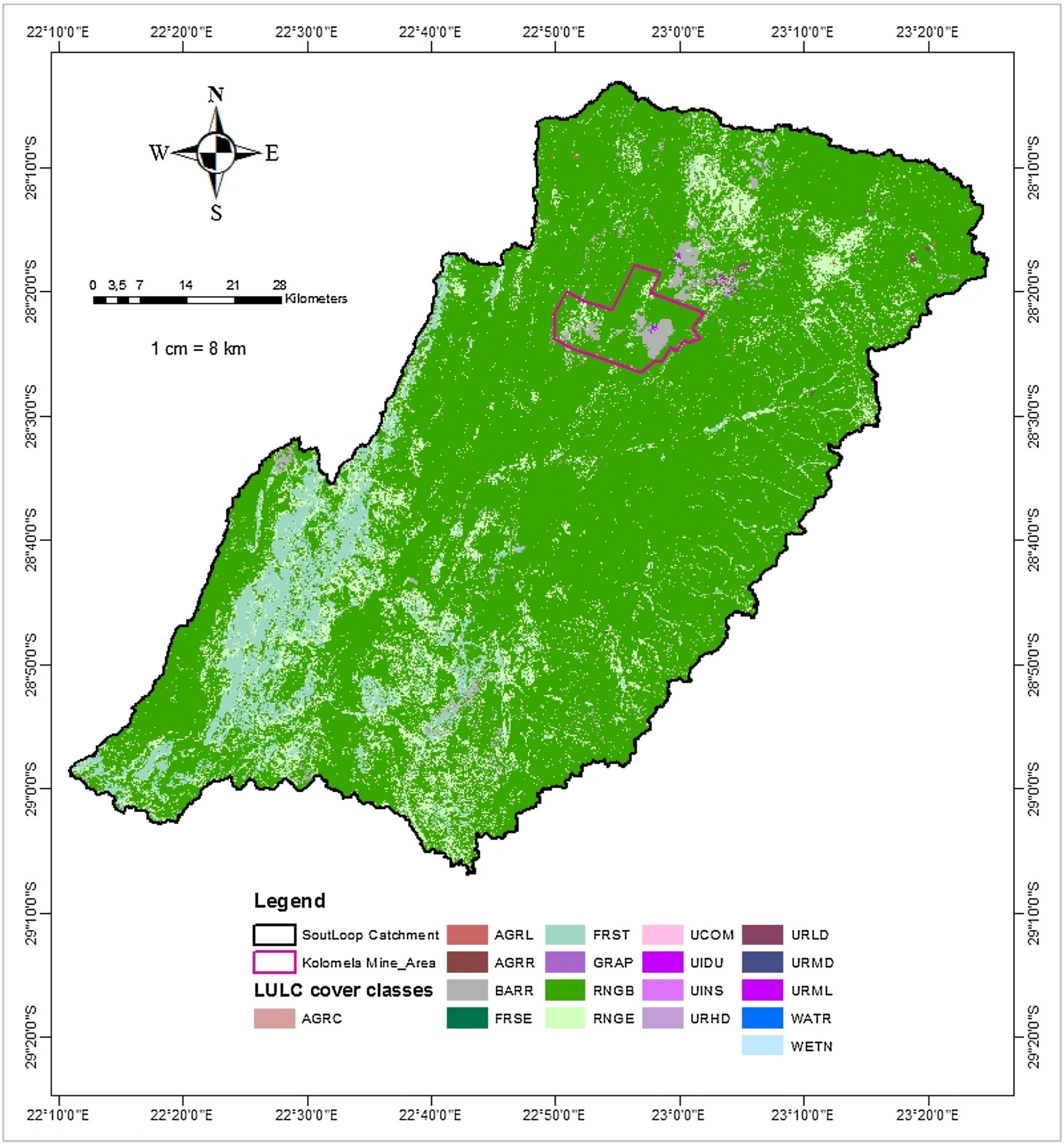

Fig. 4. The spatial variation of land use/land cover classes in the catchment.

Imagery), software programs (ArcGIS, SoLIM-the Soil-Land Inference Model (Zhu, 1997), 3dMapper), field inspections, and expert knowledge. The details of this procedure is explained in detail in Van Zijl et al. (2013).

Finally, ten soil forms were identified in the study catchment. Then, the soil forms were grouped into six soil groups and mapped for the area, based on the criteria of Fey (2010), as shown in Table 1. The spatial variations of the major soil groups of the catchment are also depicted in Fig. 3.

The values of all the soil characteristics required by SWAT were collected by field survey using the soil groups as a base map. As a result, a profile was opened for each soil groups for soil sampling for laboratory and field analysis and also for field verification of the soil groups.

2.2.4. Climatic data

The SWAT2012 model requires daily variables of precipitation, temperature, relative humidity, solar energy, and wind speed. The

Table 1
Keys to the classification of dominant soil forms into soil groups.
(Source: Fey, 2010).

No	Dominant soil forms	Soil group	Major characteristics	Diagnostic horizon/material for classification
1	Coega	Calcic	Presence of carbonate or gypsum enrichment in arid climate	Soft or hardpan carbonate or gypsic B
2	Dundee and Fernwood	Cumulic	Incipient soil formation in colluvial, alluvial or aeolian sediment	Neocutanic or neocarbonate B, regic sand, thick E horizon or stratified alluvium
3	Valsrivier	Duplex	Marked textural contrast through clay enrichment	Pedocutanic or prismacutanic B
4	Katspruit and Kroonstad	Gleyic	Protracted reduction in an aquic subsoil or wetland	G horizon
5	Rocky surfaces and Mispah	Lithic	Incipient soil formation on weathering rock or saprolite	Lithocutanic B or hard rock
6	Hutton and Clovelly	Oxidic	Residual iron enrichment through weathering; uniform colour	Red apedal, yellow-brown apedal or red structured B

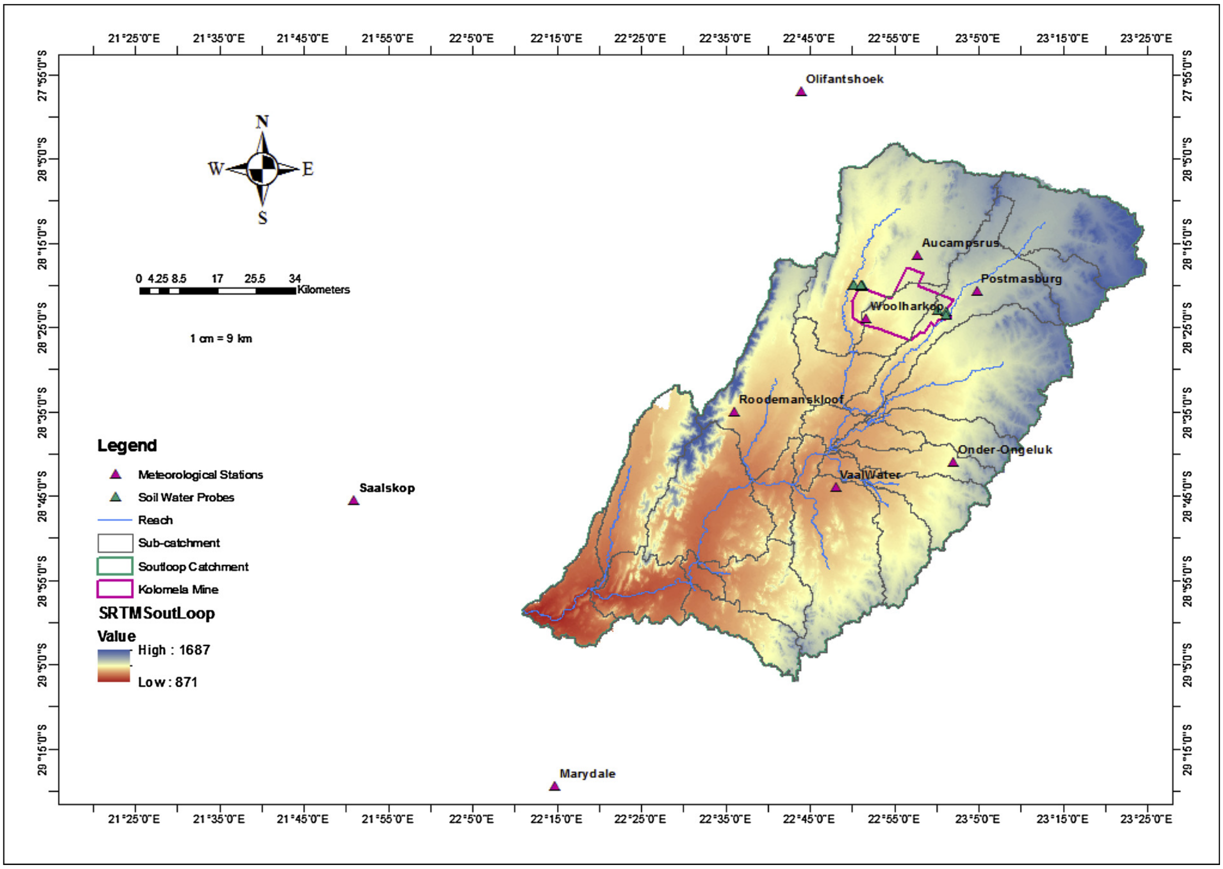

Fig. 5. Some hydrologic features in the study catchment.

SWAT software also has a weather generator tool that assists us to fill in missing data for certain periods of time in the simulation periods. This tool also enables us to generate the relative humidity, solar energy and wind speed, if we can provide it with a long-term daily precipitation rate and maximum and minimum temperatures. This study relies on meteorological stations inside, and in close proximity to, the study catchment, as seen in Fig. 5 and Table 2. The long-term data details were provided by two organizations – the South African Weather Service (SAWS) and the Agricultural Research Centre, Institute for Soil, Climate and Water.

2.2.5. Other data for model calibration and validation

For this study, two datasets were collected for calibration and validation purposes. These are the daily runoff (from the donor catchment, A21C quaternary catchment) and daily soil water content from the target catchment (Soutloop River Catchment). As a result, daily discharge data for the donor catchment were obtained from the Department of Water and Sanitation Affairs of South Africa. Whereas the profile water content was measured *in situ* from the target catchment with DFM capacitance probes (installed in four HRUs). The details for DFM capacitance probes can be referred from Zerizghy et al. (2013) and from the official website of DFM

Table 2
Meteorological stations used for the generation of weather parameters in the study catchment.

No.	Station Name	Longitude	Latitude	Elevation	Owner organization
1	Olifantshoek	−27.950	22.733	1341	ARC_ISCW and SAWS
2	Onder-Ongeluk	−28.683	23.033	1311	ARC_ISCW
3	Roodemanskloof	−28.583	22.600	1204	ARC_ISCW
4	VaalWater	−28.733	22.800	1109	ARC_ISCW
5	Marydale	−29.324	22.246	928	ARC_ISCW
6	Saalskop	−28.760	21.847	861	ARC_ISCW
7	Postmasburg	−28.345	23.079	1321	SAWS
8	Woolharkop	−28.400	22.859	1221	ARC_ISCW and SAWS
9	Aucampsrus	−28.275	22.962	1293	ARC_ISCW and SAWS

ARC_ISCW refers to the Agricultural Research Commission, Institute for Soil, Climate and Water.
SAWS refers to the South African Weather Service.

Technologies at: https://dfmtechnologies.co.za/product/probes.

2.3. Model setup and configuration

In this study, SWAT model was used to estimate all the components of the water balance in the study catchment. In the simulation procedure, catchment delineation was the first procedure. The study catchment was delineated using GIS interface of the Soil and Water Assessment Tool (SWAT2012). An SRTM DEM (digital elevation modelling), with 30-metre spatial resolution, was downloaded from LP DAAC (being one of USGS's data distribution centres, at link https://lpdaac.usgs.gov/data_access/data_pool) and was used for this study. The details of the procedures can be referred to Neitsch et al. (2011) and Arnold et al. (2012).

After the catchment delineation process was completed, the definition of HRUs was continued. The definition of HRUs are also done in the SWAT2012 interface. Three spatial data sets (slope, land use/land cover, and soil maps) are important for the definition of HRUs. Therefore, HRUs are lands with similar topography, land use/land cover and soil types and all the components of the soil water balance could be determined on an HRU basis, with the assumption that similar HRUs would have similar hydrologic characteristics (Neitsch et al., 2011; Arnold et al., 2012; Winchell et al., 2013).

Then, all the required climatic variables were fed to the model, comprising rainfall, minimum and maximum temperature, relative humidity, average wind speed, and solar radiation data. The weather generator tool in the ArcSWAT interface was assigned to fill in the case of unavailability of station data. This tool also enables us to generate the relative humidity, solar energy and wind speed from a long-term daily precipitation and maximum and minimum temperature (Neitsch et al., 2011). The rainfall runoff process was set to be estimated by the curve number (CN-method), the potential evapo-transpiration was estimated by the Penman-Monteith equation, and the channel water routing was simulated by the Variable Storage Routing. After all the above processes were completed, the SWAT simulation was activated. During simulation, a three-year warming-up period was given. Including the three-year warming-up period, the total simulation period (including the warmup periods) was set to run from 1977 to 2018 (*i.e.* 42 years). Hence, a 39-year period of hydrologic variables were simulated for the study catchment (excluding the warmup periods). The framework, showing major procedures in the simulation process, is summarized in Fig. 6.

2.4. Model calibration, validation and sensitivity analysis

2.4.1. The calibration approach

The successful application of hydrologic models is highly dependent on the calibration and sensitivity analysis of the parameters (Abbaspour, 2015; Kouchi et al., 2017). The calibration and validation processes are only employed efficiently with observed data. Particularly discharge data plays a critical role for this procedure. However, the study area does not have a gauging station for stream flow measurement. Therefore, the regionalization with physical similarity approach (Bárdossy, 2007; Wheater et al., 2008; Blöschl et al., 2013) was adopted here for the calibration and validation of the model. The regionalization approach is usually based on the

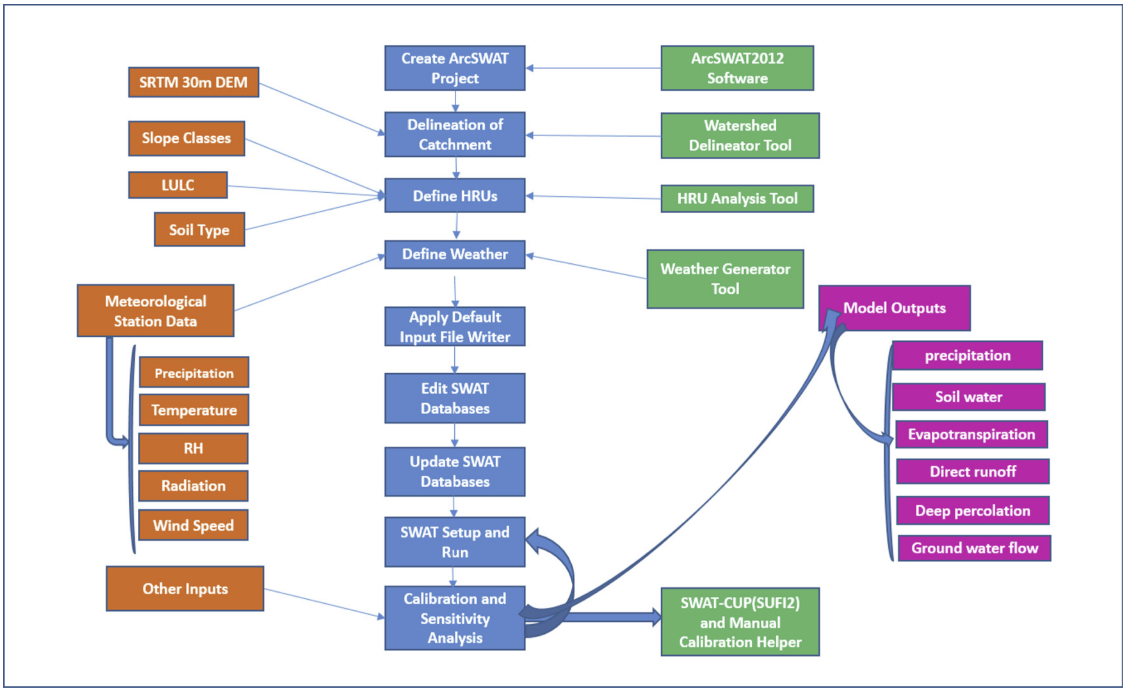

Fig. 6. General framework followed in the modelling process using SWAT2012.

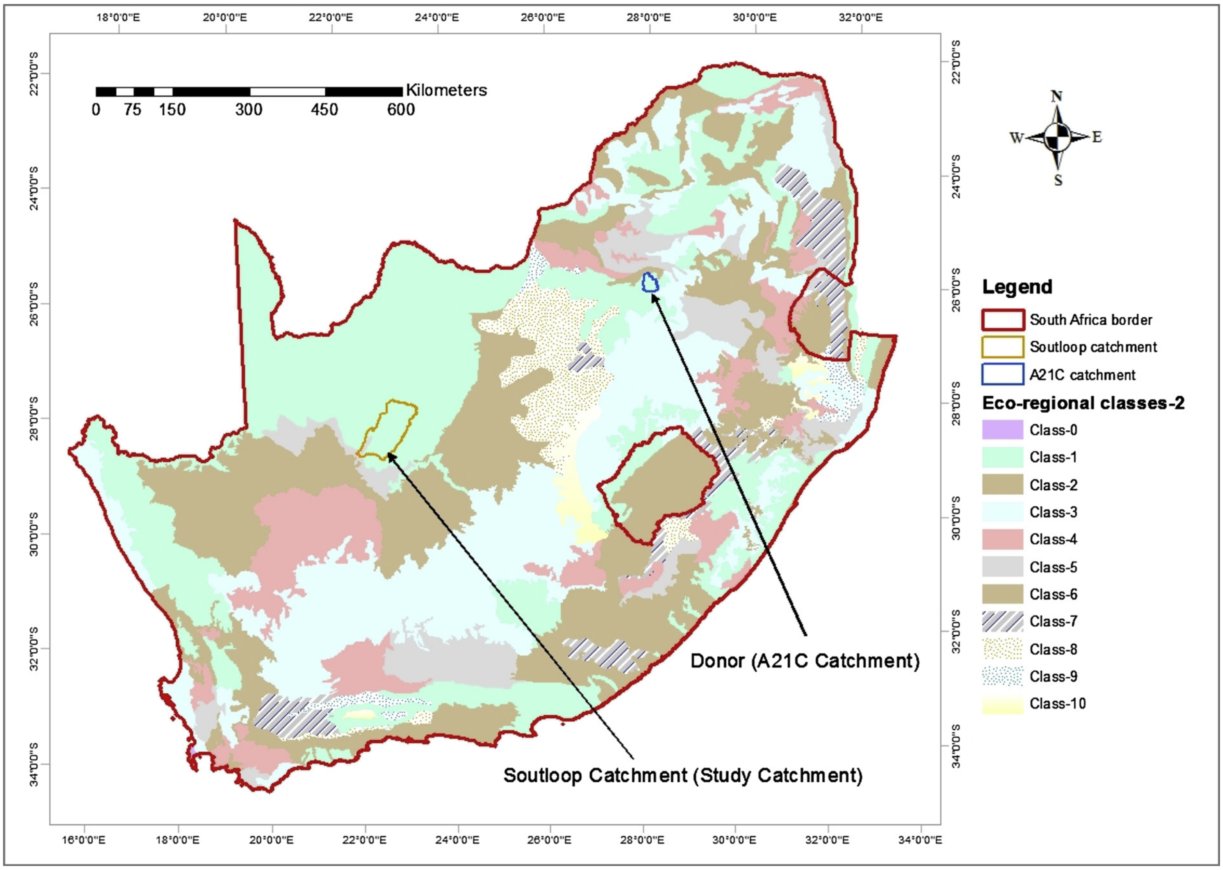

Fig. 7. Location of the study catchment (Soutloop) and the donor catchment (A21C) showing that both are in the same river eco-regional class (Class-1).

assumption that catchments with similar physiographic and climatic attributes would have similar hydrologic responses. As a result, the selection of a catchment that has similar attributes to the catchment of interest and that has a fully functional gauging station is a prerequisite. Therefore, there is a need to characterize, evaluate and categorize catchments for this purpose.

The evaluation and categorization of catchments is based on at least four types of information, *i.e.* soil type, land use, topographic features, and potential natural vegetation (Omernik, 1987; Blöschl et al., 2013). For this study, however, the eco-regional typing and river classification study conducted by the Department of Water Affairs and Forestry (Kleynhans et al., 2005, 2007) was used. This study covers the whole areas of South Africa and grouped rivers based on their similarity. The main aim of the river eco-regional classification was to group areas according to their similarities using a top-down nested hierarchy. The report also indicates that river eco-regional classification helps to extrapolate information from data-rich to data-scarce catchments within the same hierarchical typing concepts. Hence, the quaternary catchment called A21C (Fig. 7) was selected as a donor catchment for the calibration, validation and sensitivity analysis for this study. The details of the river eco-regional classification for South Africa can be referred to in Kleynhans et al. (2005) and Kleynhans et al. (2007). Some of the major attributes used in the classification include terrain morphology, main vegetation types, mean annual precipitation, coefficient of variation of annual precipitation, drainage density, stream frequency, slopes, median annual simulated runoff, and mean annual temperature of catchments. Some of the catchment descriptors used in the evaluation between the donor and study catchments can be seen in Table 3. The comparison table shows that the two catchments are more or less in a physically similar hydro-climatic and physiographic conditions. It is also worthy to note that the two catchments have different sizes that may influence some hydrologic variables. However, the influence of catchment sizes on the uncertainty of model outputs is primarily on sediment, nitrogen and phosphorus loadings (FitzHugh and Mackay, 2000; Jha et al., 2004; Kumar and Merwade, 2009; Wallace et al., 2018). Therefore, the difference in the size of the donor and target catchments have insignificant influences on streamflow estimations. As the focus of this paper is on the calibration of SWAT for estimation of flow in arid and semi-arid catchments, the difference in the size of the donor and target catchments is ignored. However, during the study of point and non-point source pollution, sediment, nitrogen and phosphorus loadings, the influence of catchment sizes could matter on the regionalization process.

2.4.2. Procedures in the regionalization approach

In this study, all the sensitivity, calibration and validation procedures were facilitated by the use of a specialized computer

Table 3
Catchment descriptors used for the evaluation of the similarity between the donor and study catchments.

No.	Catchment descriptors	Donor catchment	Study catchment
1	Annual precipitation (mm)	320-497	214-365
2	Annual PET (mm)	1722-2644	1512.06-2802.07
3	Ratio of Precipitation to PET	0.19	0.13-0.14
4	Ratio of ET to PET	0.15-0.70	0.08-0.70
5	Soil textural class variation	Sandy-loam to Sandy-clay-loam	Clay-Loam to Sandy-loam
6	Dominant LULC	Grasslands, residential with dense trees/bush and mixed forest	Low shrub lands, Grasslands and open bushlands
7	Slope class (percentage)	80% of the catchment is < 10%	86% of the catchment is < 10%
8	Altitudinal range (masl)	1242-1825	871-1687
9	Runoff coefficients	0-0.12	0-0.1
10	Annual ET (mm)	252-1851	118-1961
11	Annual air temp (°C)	17-18.7	17.7-19.7
12	Mean solar radiation (MJ m^{-2})	22.6-21.7	21.2-23.1

PET - potential evapotranspiration ET - evapotranspiration.
LULC - land use and land cover masl - meter above sea level.

program, SWAT-CUP ver-2012 (the SWAT Calibration and Uncertainty Programs), particularly SUFI2 (Sequential Uncertainty Fitting ver. 2). SUFI2 is one of the stochastic calibration programs in SWAT-CUP that was used in this study. The details for the description of SUFI-2 in the whole calibration procedure can be referred to in Abbaspour et al. (2004), (2007), and Abbaspour (2015). First, the calibration, sensitivity analysis and model validation were conducted on the donor catchment (A21C quaternary catchment) and then the model parameters were transferred to the ungauged catchment (Soutloop Catchment), based on the regionalization with physical similarity approach. After the transfer of calibrated parameter values, the model was run, and the major components of the catchment water balance (particularly long-term annual runoff volume and evapotranspiration) were compared with previous studies of the area for simple inspection of model results. Based on this comparison with other similar studies, a manual calibration helper was employed in the ArcSWAT interface for further parameter adjustments.

During calibration of parameters in the donor catchment, only sensitive parameters were calibrated, based on the results of the sensitivity analysis in SWAT-CUP. The soil and some weather parameters were also excluded from the calibration processes since all the soil parameters were measured directly by the field survey. Similarly, the weather parameters were derived from weather station in the study area. To prioritize other sensitive parameters (other than the excluded parameters), a one parameter at a time (OAT) procedure was followed. This was used to select sensitive parameters to stream flow as a first inspection for sensitivity. Then, the sensitivities of all parameters, selected by one-at-a-time option, were further prioritized by the global sensitivity option. This was done by running SUFI2 for one complete iteration (1000 simulations). The global sensitivity uses the p-value and t-stats for

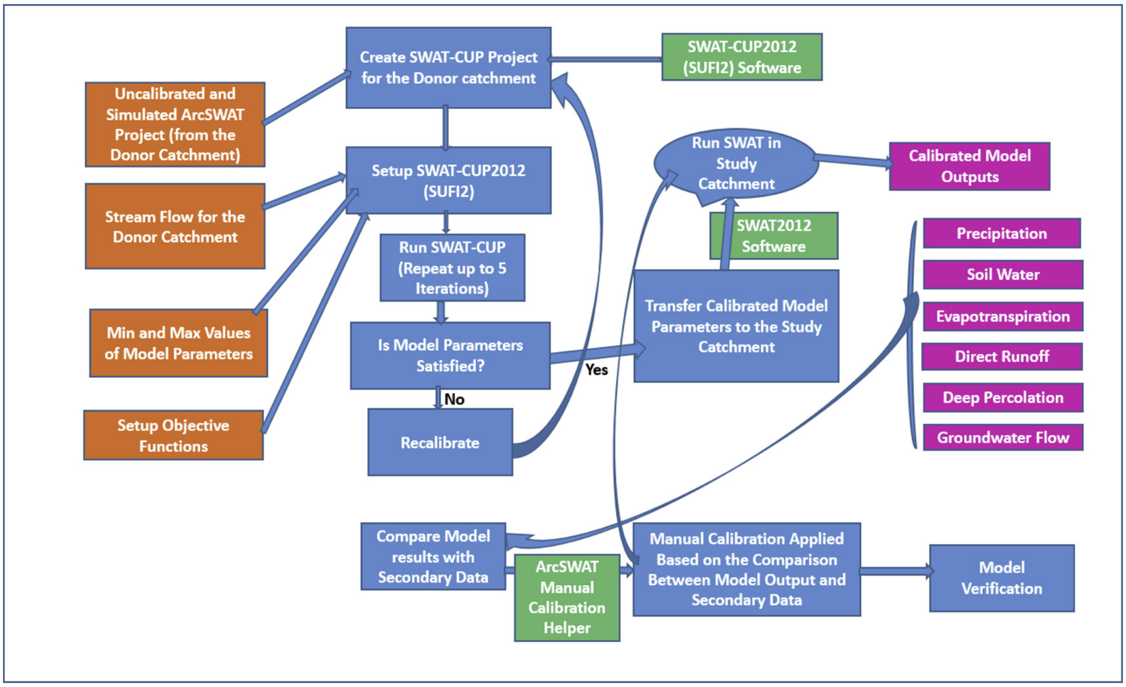

Fig. 8. Workflow for the calibration and sensitivity analysis using SWAT-CUP.

prioritization. The general workflow of the calibration process is depicted in Fig. 8. The flow data from the donor catchment (A21C) were divided into two, one for calibration and the other half for validating the model. Generally, a two-step calibration and validation procedure was employed here; one in the donor catchment and the other in the study catchment. The calibration in the study catchment was assisted by the ArcSWAT manual calibration helper whereas the validation was outside SWAT-CUP, which was in MS excel with simple comparison of simulated *versus in situ* measured soil water content data.

The second model validation that was conducted in the target catchment was actually a simple verification of model results with respect to simulated water content. The SWAT output for soil water content is in millimetre of depths and also excludes the residual water content. Therefore, the observed soil water content at four HRUs measured by DFM capacitance probes (Zerizghy et al., 2013) must also have similar units of depth. The readings from the probes is normally in percentage of total soil volume and it measures at six depths at a time down the soil profile. The average of the six depths was multiplied by the bulk density of the soil profile and this product again multiplied by the soil depth to get the total soil water content in millimetre of depth in the profile at that specific measurement time. The residual water content (permanent wilting point) of the soil (estimated by SWAT model) was subtracted from the observed total soil water content of the profile. Then, the resulting soil water content is the observed one and compared to the output from SWAT model for each of the four HRUs.

2.4.3. Uncertainty and model performance indices

Reports (Blöschl et al., 2013; Abbaspour, 2015) indicate that the sources of model uncertainties could be from driving variables (*e.g.* climate data), the conceptual model itself, measured data, or uncertainty during parametrization. The propagation of all sources of model uncertainties to parameters and model outputs in SWAT-CUP is expressed as the 95% probability distributions, by using the Latin Hypercube Sampling. The 95% probability distributions are calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable and it is called 95% prediction uncertainty (95PPU). SWAT-CUP calculates two statistical indicators to quantify all the sources of uncertainty. These are the P-factor, which is the percentage of observed data enveloped by the modelling result (the 95PPU), and the R-factor, which is the thickness of the 95PPU envelope.

Regarding the model performance indicators, SUFI2 has many options of model performance indicators. For this study, the Nash-Sutcliffe coefficient (NS) was used as a major objective function in the calibration and validation process. The coefficient of determination (R^2), percent bias (PBIAS), and ratio of the root mean squared error to the standard deviation of measured data (RSR) were also additional criteria used for the evaluation. Eqs. (1–4) were used to calculate the performance indices:

$$NS = 1 - \frac{\sum_i (Q_m - Q_s)_i^2}{\sum_i (Q_{m,i} - Q_m)^2} \tag{1}$$

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

$$PBIAS = 100 \times \left[\frac{\sum_{i=1}^{n} (Q_m - Q_s)_i}{\sum_{i=1}^{n} Q_{m,i}}\right] \tag{3}$$

$$RSR = \frac{\sqrt{\sum_{i=1}^{n} (Q_m - Q_s)_i^2}}{\sqrt{\sum_{i=1}^{n} (Q_{m,i} - Q_m)^2}} \tag{4}$$

where *NS* is the Nash-Sutcliffe coefficient, R^2 is the coefficient of determination, *PBIAS* is the percent bias, *RSR* is ratio of the root mean square error to the standard deviation of measured data, Q is a variable (*e.g.*, discharge), m and s stand for measured and simulated variables, and i is the i^{th} measured or simulated data.

3. Results

3.1. Parameterization and parameter sensitivity analysis

As stated earlier, the study area is an ungauged catchment and accordingly all the possibilities of using *in situ* measured data (whether collected by the authors or second party, such as meteorological stations) were given priority. As a result, parameters that were derived from the *in situ* measured data were not considered in the calibration and sensitivity analysis. On the other hand, parameters other than the ones mentioned above and that are highly sensitive were calibrated by the regionalization with physical similarity approach. The list of sensitive parameters is given in Table 4. Parameters are listed based on their sensitivity levels as analysed by SWAT-CUP with the global sensitivity option. It shows that the top sixteen parameters were sensitive and were considered for calibration, from which the first three (the base flow alpha factor, curve number II and initial depth of water in the shallow aquifer) were found to be the top sensitive parameters.

3.2. Model calibration and validation

The lists of calibrated model parameters, methods of change used and the final calibrated values are shown in Table 5. The

Table 4
Parameter sensitivity analysis.

No.	Parameter Name	t-Stat	P-Value	Definitions of abbreviations
1	ALPHA_BF.gw	−9.3448	0.0000	Base flow alpha factor (days).
2	CN2.mgt	−8.3021	0.0000	Curve number for soil water condition 2.
3	SHALLST.gw	−7.9193	0.0000	Initial depth of water in the shallow aquifer (mm).
4	OV_N.hru	−1.4871	0.1381	Manning's "n" value for overland flow.
5	CH_N2.rte	1.3869	0.1666	Manning's "n" value for the main channel.
6	CH_K2.rte	1.2528	0.2113	Effective hydraulic conductivity in main channel alluvium.
7	REVAPMN.gw	−1.2125	0.2264	Threshold depth of water in the shallow aquifer for "revap" to occur (mm).
8	ESCO.bsn	1.06	0.2901	Soil evaporation compensation factor.
9	FFCB.bsn	0.9859	0.3250	Initial soil water storage expressed as a fraction of field capacity water content.
10	GWQMN.gw	0.9019	0.3679	Threshold depth of water in the shallow aquifer required for return flow to occur (mm).
11	GW_DELAY.gw	0.8032	0.4225	Groundwater delay (days).
12	EPCO.hru	−0.67	0.5034	Plant uptake compensation factor.
13	MSK_CO1.bsn	0.6601	0.5097	Calibration coefficient used to control impact of the storage time constant for normal flow.
14	SURLAG.bsn	−0.6265	0.5315	Surface runoff lag time.
15	GW_REVAP.gw	0.5637	0.5734	Groundwater "revap" coefficient.
16	RCHRG_DP.gw	−0.2052	0.8376	Deep aquifer percolation fraction.

Table 5
Methods of a parameter change, initial adjustment intervals, and calibrated values for each parameter.

No.	Parameter Name	Method of change	Min value	Max value	Fitted value one[a]	Fitted value two[b]
1	ALPHA_BF.gw	Replace	0.05	0.65	0.269	0.15
2	CN2.mgt	Relative	−0.15	0.48	−0.434	−0.10
3	SHALLST.gw	Replace	500	10000	2100	1650
4	OV_N.hru	Replace	0.01	0.48	0.435	0.21
5	GW_DELAY.gw	Replace	20	566	496	35
6	EPCO.hru	Replace	0.2993	0.82	0.439	0.67
7	GWQMN.gw	Replace	500	3536	2898	1200
8	FFCB.bsn	Replace	0.12	0.69	0.52	0.52
9	CH_K2.rte	Replace	2.14	185.82	52.93	52.93
10	CH_N2.rte	Replace	0.25	0.76	0.56	0.25
11	MSK_CO1.bsn	Replace	1.33	8.15	5.75	5.75
12	ESCO.bsn	Replace	0.11	0.94	0.201	0.85
13	REVAPMN.gw	Replace	122	3670	285.51	850
14	SURLAG.bsn	Replace	0.98	21.77	6.63	6.61
15	GW_REVAP.gw	Replace	0.014	0.30	0.288	0.033
16	RCHRG_DP.gw	Replace	0.01	0.51	0.367	0.072

[a] Fitted value one-it is the transposed value fitted by the SWAT-CUP program in the donor catchment.
[b] Fitted value two-it is the final fitted value by the manual calibration helper in ArcSWAT2012 software in the study catchment.

graphical comparisons of measured stream flow at the outlet of the donor catchment and its simulated discharge values are depicted in Figs. 9 and 10 for the calibration and validation processes, respectively. Similarly, the performance indices for the calibration and validation processes are given in Table 6.

The performance of the best parameter sets selected in the sensitivity analysis (in Subsection 3.1 above) were evaluated by two major types of statistical evaluations, *i.e.* model prediction uncertainty and model performance evaluation. The prediction uncertainty in SUFI2 (one of the programs in SWAT-CUP) is expressed by the 95PPU (95 percent prediction uncertainty), which is represented by the green-coloured region in Figs. 9 and 10 for the calibration and validation processes, respectively. Two indices are calculated to evaluate the model uncertainty, the P-factor, and the R-factor. Table 6 shows that the P-factor estimated was 0.73 and 0.65 for calibration and validation, respectively. This means that 73% and 65% of the observed discharge is enveloped by the 95PPU during the calibration (1982–1998) and validation periods (2000–2013), respectively. On the other hand, the R-factor, which is the thickness of the 95PPU envelop, was 0.93 for calibration and 0.66 for validation periods, respectively.

Regarding the model performance evaluation, the results of the model performance indicators are shown in Fig. 5. The Nash-Sutcliffe coefficient (NS) was used as the major objective function. Three other performance indices were also selected, namely the coefficient of determination (R^2), the percent bias (PBIAS), and the ratio of the root mean squared error to the standard deviation of measured data (RSR). As the results shows that all the performance indicators for both the calibration and validation periods (R^2 & NS > 0.71, $-9 <$ PBIAS $< +12$, RSR < 0.6) are in fairly acceptable ranges (Moriasi et al., 2007; Abbaspour, 2015; Almeida et al., 2018). In other words, the statistical indices indicate that there is a good agreement between the measured and simulated streamflow. Moreover, the PBIAS (+11.8 and -8.1 for calibration and validation, respectively) indicates that the model over-estimated by 11.8% during calibration, and under-estimated by 8.1% during validation.

It is worthy to note that all the calibration and validation processes with SUFI2 program was completed in the donor catchment. As a result of this, there was no chance of evaluating the model uncertainty in the catchment of interest. Therefore, after the

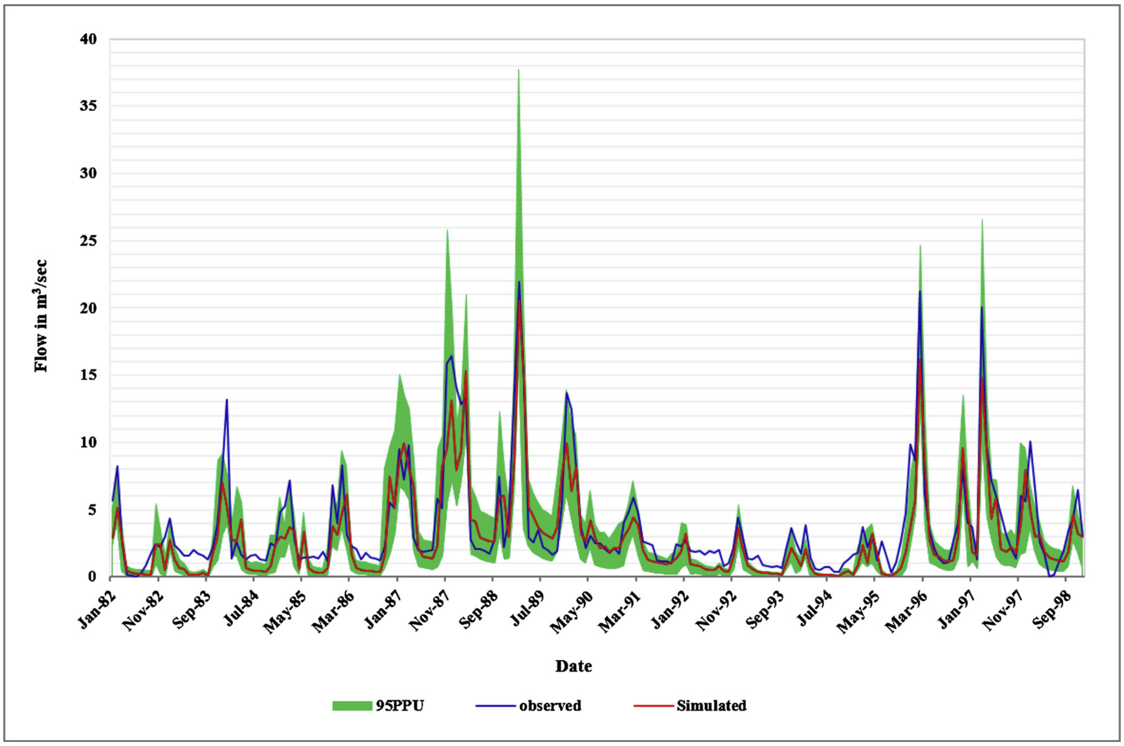

Fig. 9. Comparison of measured and predicted monthly stream flow during the calibration period (1982–1998).

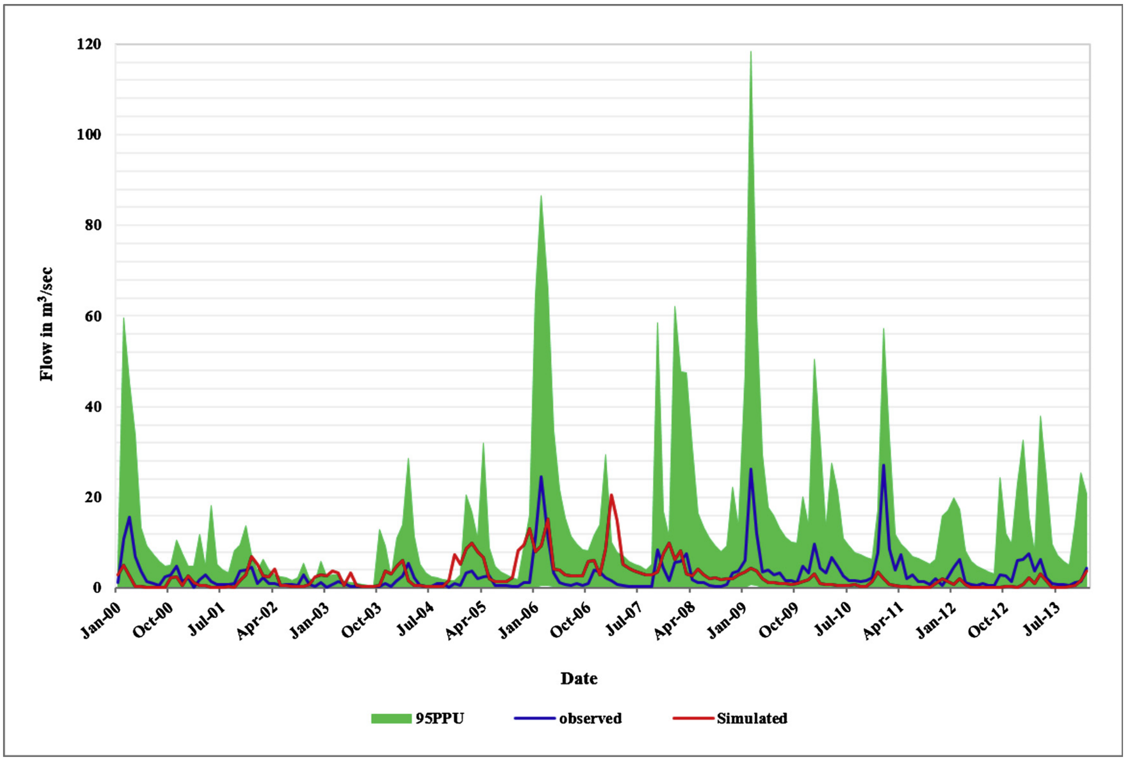

Fig. 10. Comparison of measured and predicted monthly streamflow during the validation period (2000–2013).

Table 6
Summary of statistics for calibration, validation processes with flow data in the outlet of the donor catchment.

Process	P-factor	R-factor	R^2	NS	PBIAS	RSR
Calibration	0.73	0.93	0.83	0.82	11.80	0.43
Validation	0.65	0.66	0.72	0.71	−8.10	0.55

calibrated model parameters were transposed to the catchment of interest, two model outputs (annual runoff volumes and annual evapotranspiration) were compared with results of similar studies in the past. Then, sensitive model parameters were slightly adjusted with a manual calibration helper in ArcSWAT interface so that the simulated values would be closer to the values gained from previous results. The comparison of the model outputs after SWAT-CUP calibration and after SWAT-CUP plus manual calibration is shown in Table 7. The comparison (Table 7) indicated that the manual calibration helped to improve the annual runoff volume and annual evapotranspiration by 23% and 16%, respectively. Finally, the model performance was also verified by the comparison of the *in situ* measured and simulated soil water content, as shown in Fig. 11, panels a–d where the soil water content measurement was taken in selected four HRUs in the study catchment.

4. Discussion

It is obvious that the different types of regionalization approaches play important roles in the hydrological modelling of ungauged catchments in arid and semi-arid environments. However, it is also true that hydrological modelling in ungauged catchments is exposed to significant amounts of model uncertainty due to the unavailability of data for calibration and validation processes. Hence, the regionalization approach needs to be applied cautiously.

In this study, the regionalization with physical similarity approach was employed and some best practices are also recommended to minimize model uncertainties in hydrological models. In hydrological modelling, sensitivity analysis shows the share of all parameters in the uncertainties of the model output. Hence, more sensitive parameters will have a higher share of model uncertainties than less sensitive ones in the model output, if that parameter is left uncalibrated. Therefore, sensitivity analysis is the first step that should be taken into consideration in model calibration. However, not all the sensitive parameters may be calibrated in ungauged catchments. For instance, in this study, all the soil parameters (collected from field or analysed in laboratory) and some weather parameters (derived from available weather stations in the study area) were excluded from the calibration and validation processes. This is because, as stated by (Faramarzi et al., 2015; Kumarasamy and Belmont, 2018; Abbaspour et al., 2018), measured parameters contribute the least sources of uncertainty in hydrologic modelling. As a result of this, it is recommended to use all available data sources of the catchment understudy and exclude those parameters from calibration to avoid unnecessary and arbitrary adjustments of parameters.

Regarding the evaluation of the modelling process in the donor catchment, two types of statistics were used to, *i.e.*, evaluation with respect to model prediction uncertainty and evaluation of the model with performance indicators. The model uncertainty was shown by the P-factor and R-factor. The P-factor was 0.73 and 0.65 for calibration and validation, respectively; whereas the R-factor was 0.93 for calibration and 0.66 for validation periods. Generally, good model uncertainty is expressed by a higher value of the P-factor (towards 100%) and a lower value of R-factor (towards 0). Abbaspour (2015) has recommended that a P-factor of at least 0.7 and an R-factor of around 1 are acceptable for the calibration and validation of a catchment with respect to its discharge. Therefore, the results of this study indicated that 73% and 65% of the observed data from the donor catchment were enveloped with the 95PPU (the region of lower uncertainty) during calibration and validation processes, respectively. Similarly, the smaller thickness of the 95PPU (R-factor of 0.93 and 0.66 for calibration and validation, respectively) also indicate that there was a lower uncertainty of the modelling process in the donor catchment. Moreover, the model performance indicators (NS, R^2, PBIAS and RSR) also indicated the good performance of the model.

However, all the above model uncertainty and performance indicators were conducted outside the target catchment. There was no any chance to statistically evaluate the model's performance and uncertainty in the catchment of interest. As a result, this study suggests some best practices to inspect model results with other sources of data. For instance, the comparison of long-term annual runoff volume and annual evapotranspiration results from the model were compared with previous similar studies. The comparison indicated that the model overestimated the two parameters and the manual calibration improved the model output by 23% and 16% with respect to the previous results for runoff and evapotranspiration components, respectively. After the manual calibration, the profile soil water content from the model was compared with measured soil water content data in the study catchment as means of

Table 7
Summary of statistics for calibration, validation processes with flow data in the outlet of the donor catchment.

Variables compared	Values from previous studies	SWAT-CUP calibration only	SWAT-CUP & manual calibration	Percentage of improvement
Runoff volume[a]	16.5	25.4	21.6	23
Evapotranspiration[b]	188.1	268.3	238.5	16

[a] *Sources for runoff data:* DWAF (2009), Schulze et al. (2007), Kleynhans et al. (2005).
[b] *Sources of evapotranspiration data:* Jovanovic et al. (2015); Bennie and Hensley (2001).

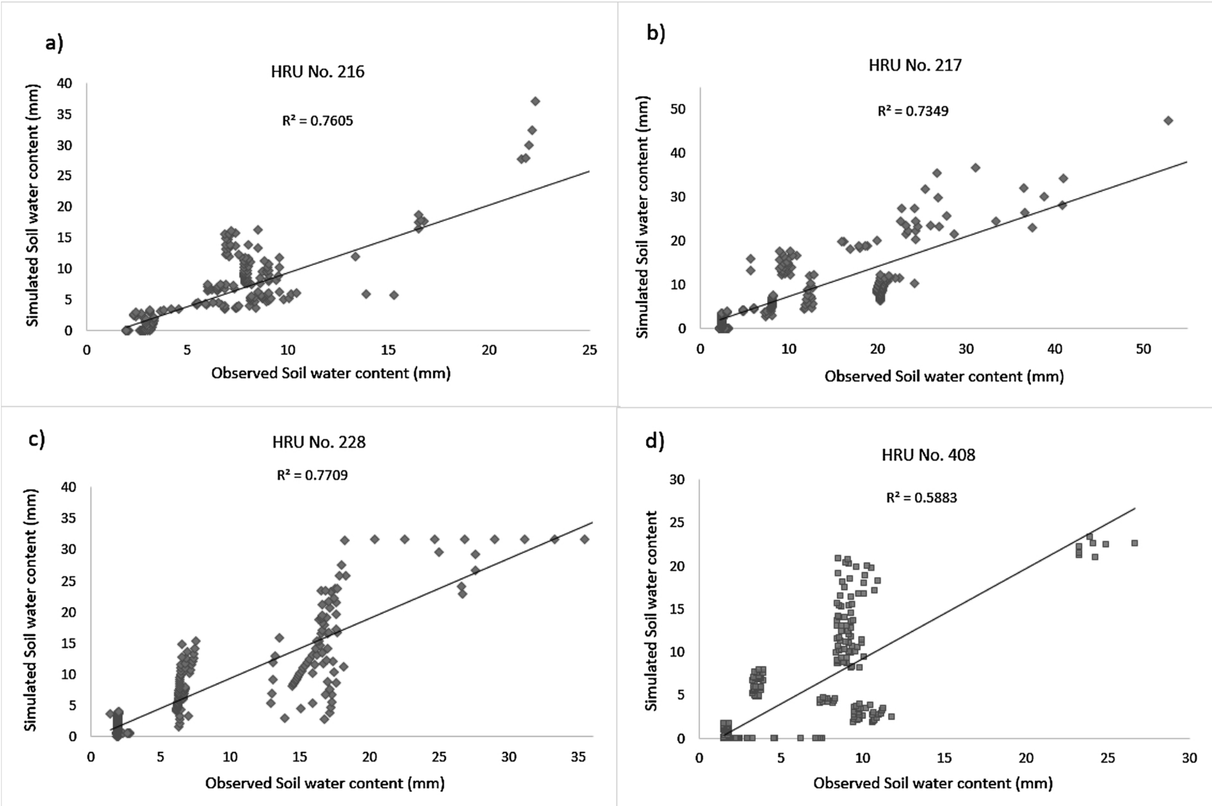

Fig. 11. Comparisons of measured and simulated daily soil water content variations inside Kolomela Mine, measured with DFM probes: (a) at HRU No. 216 from 1/1/2013 to 10/30/2013, (b) at HRU No. 217 from 11/16/2016 to 8/22/2017, (c) at HRU No. 228 from 11/15/2016 to 8/24/2017 and at HRU No. 408 from 01/01/2014 to 12/31/2014.

verification of the model. Hence, model results of four HRUs from the study catchment were selected and it showed a higher value of coefficient of determination (average $R^2 = 0.71$) indicating a good agreement between the observed and simulated profile soil water content in the study catchment.

Generally, the following best practices are suggested here to minimize the model uncertainty of hydrologic models in arid and semi-arid-catchments. (i) excluding some parameters from calibration: parameters that could be derived from data measured *in situ* from the catchment of interest should be excluded from the calibration and validation processes. (ii) regionalize and transpose model parameters from donor (gauged) to study (ungauged) catchment: this is the method that have been already operational and described in the materials and methods section. (iii) comparison of model outputs to previous studies of any of the components of the catchment water balance and identify the gap between the two results. (iv) Manual calibration: if the difference between the result from the model and the previous study is larger, use manual calibration helper to adjust parameter values until the difference between the two results is minimum. (v) conduct an *in situ* measurement: all possibilities of direct measurement of data from the catchment of interest should be given priority. For instance, measurement of soil water content could be relatively easy. The acquisition of satellite soil water content (*e.g.*, Wanders et al. (2014); Alvarez-Garreton et al. (2015) and Rajib et al. (2016)) or evapotranspiration data (*e.g.*, Franco and Bonumá (2017); Emam et al. (2017) and Ha et al. (2017)) are also good alternatives nowadays in arid and semi-arid catchments. This data is important and could be used for the model verification and it gives the modeller a confidence on the model outputs.

5. Conclusion

The aim of this study was to set up, calibrate and validate SWAT model in a data-scarce catchment by using the regionalization with physical similarity approach. A two-way calibration and validation processes were employed, one in the donor catchment (A21C quaternary catchment) with a semi-automatic calibration program, SWAT-CUP, and the second was conducted in the target catchment (Soutloop) with the ArcSWAT interface of manual calibration helper. Generally, many studies have been conducted to simulate the components of a catchment hydrology through utilizing the regionalization approach. However, this study shows that the transfer of calibrated model parameters from a donor catchment to a target catchment, without further inspection of the outputs of the target catchment, would cause a potential uncertainty in the model outputs. The modeller would then finally draw wrong conclusions. There should be a way to conduct at least a simple inspection. In this study, the simulated values were compared with previous and similar local studies, and additional manual calibration was conducted as one alternative for inspecting uncertainity. Moreover, some *in situ* measurements (such as soil water content or evapotranspiration) are also advisable for model verification. The calibration of some of the parameters that are measured *in situ* (for example, soil parameters in this study) could be unnecessary, since the main calibration process is outside the target catchment. The use of weather station data is also advisable for minimizing the uncertainty in model prediction in ungauged catchments. Finally, as the focus of this study was on the regionalization for streamflow estimation, the influence of catchment sizes were ignored during evaluating the similarity between the donor and target catchments. Therefore, during the study of point and non-point source pollution, sediment, nitrogen and phosphorus loadings, the influence of catchment sizes should also be considered in the regionalization process.

Declaration of Competing Interest

None.

Acknowledgements

Thanks to the Kolomela Mine Ore Company (specifically to the Kolomela Mine) for financial assistance for this study. The South African Weather Services and the Agricultural Research Council are also acknowledged for providing us with long-term historic climate data.

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