Simulating Change in Surface Runoff Depth due to LULC Change using Soil and Water Assessment Tool for Flash Floods Prediction

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Abstract

Accurate documentation of land-use/land-cover (LULC) change and evaluating its hydrological impact are of great interest for catchment hydrological management. Jukskei River catchment has undergone a rapid infrastructural and residential development which had an influence on runoff depth. The objective of the study is to integrate Geographical Information System (GIS) and remote sensing (RS) techniques with Soil and Water Assessment Tool (SWAT) model to quantify the spatial and temporal changes in surface runoff depth resulting from LULC change. Landsat images of 1987 MSS, 2001 TM and 2015 OLI were pre-processed and classified using a supervised classification method with maximum likelihood. Results indicated that, there was a significant increase in built-up area from 28700.4ha in 1987 LULC to 36313.6ha in 2001 and 42713.1ha in 2015 at the expense of bare surface, intact vegetation and sparsed vegetation. However, during hydrological modelling, soil, DEM and climatic data were kept constant except LULC images which were interchanged during each simulation phase. Calibrated with observed hydrological data at the catchment outlets, SWAT model was used to evaluate the effect of LULC change on surface runoff depth. The analysis of SWAT model showed increases surface runoff depth from 70.5mm in 1987 LULC to 134.2mm in 2001 and 199.3mm in 2015 LULC. The SWAT model indicated satisfactorily results based on model calibration and validation results. Therefore, this study concluded that, integration of GIS and RS techniques with SWAT model can help in formulating policy guidelines for land-use practices thereby reducing hydrological impacts associated with LULC changes.

Keywords: *Jukskei River catchment, GIS, remote-sensing, SWAT model, surface runoff depth.*

1. Introduction

In flood prediction and rainfall–runoff computation, physically based semi-distributed hydrological models have offered a more feasible approach in recent years (Liu and De Smedt, 2004). Soil, topography and land use/land cover (LULC) are the most important factors that control rainfall–runoff processes following single flood events for a river catchment area (Sanyal *et al.,* 2014). As alterations in soil and topography are insignificant in the short term, changes in LULC are considered to be the key elements in modifying the rainfall-runoff (Miller, 2002). Change in LULC can lead to significant changes in leaf area index, evapotranspiration (Mao and Chekauer, 2009), soil moisture content and infiltration capacity (Costa *et al.,* 2003), surface and subsurface flow regimes including baseflow contributions to streams and recharge (Tu, 2009), surface roughness and runoff (Feddema *et al.* 2005). Within the Jukskei River catchment, there has been a significant change in LULC for the past decades were aerial coverage of natural land cover surfaces decreased tremendously due to increase in residential and infrastructural development which may have a direct impact on the catchment hydrological processes.

According to Shang and Wilson (2009), urban catchments on average lose 90% of storm rainfall to runoff, whereas the non-urban catchments retain 25% of the rainfall, thus only losing 75%. Therefore, in many urbanised catchments, the storm drainage system is usually not designed for a very high surface runoff volume and this results in flash flooding in areas with low elevation. Another problem encountered in urbanised catchments are fast surface runoff caused by large areas of impermeable surfaces such as roofs, streets, and parking lots (Metsäranta *et al,* 2005). Therefore, the determination of surface runoff volume is necessary for designing of dams, reservoir management and prediction of risks and potential losses caused by flooding (Malekani *et al.,* 2014). There is a need for the development of models that can be used to show areas that generate high runoff volume due to LULC change to assists in predicting areas at risk of being affected by flash floods. Additionally, the development of model can also play an important role in adopting the necessary preventative measures, especially in designing hydraulic structures and planning of storm water drainage systems that can sustain a high volume of runoff for flood management within the catchment.

The Soil and Water Assessment Tool (SWAT), a physically distributed model incorporated with Soil Conservation Service (SCS) is being increasingly used to assess the hydrological behaviour of large and complex watersheds (Arnold *et al.,* 1998). For example, Anaba *et al.* (2017) studied the application of SWAT on effects of land use change in the Murchison Bay Catchment in Uganda. The results of runoff and average upland sediment yield estimated from the catchment indicated that both have increased during the study. Gyamfi *et al.* (2016) applied SWAT model to examine hydrological responses to land use or land cover changes in the Olifants Basin, South Africa. The model output results indicated the usefulness of SWAT as a decision support tool in evaluating the impacts of land use changes on water resources. Can *et al.* (2015) assessed the impacts of different land use scenarios on water budget of Fuhe River, China using SWAT model. The results of hypothetical scenario simulations revealed that increasing the forest land, agriculture land and/or grassland areas and decreasing paddy field and urban areas, surface runoff declined whereas groundwater recharge and evapotranspiration increased. Apart from this method, there are also other models used in different studies, such as: Topographically-Based Hydrological Model (TOPMODEL) (Candela *et al.,* 2005), Kinematic Runoff and Erosion Model (KINEROS) (Michaud and Sorooshian, 1994), Hydrologic Engineering Centre-Hydrologic Modeling System (HEC-HMS) (Halwatura and Najim, 2013), Artificial Neural Network (ANN) (Sajikumar and Thandaveswara, 1999), Long-Term Hydrologic Impact Assessment (LTHIA) (Lim *et al.,* 2001) which also use SCS method and offer quantitative simulations of the surface runoff depth based on a certain amount of rainfall.

This study aims to highlight change in the surface runoff depth within Jukskei River catchment during 1987, 2001 and 2015 period and to assess the influence of LULC change on surface runoff depth. To achieve this, specific objectives were outlined (a) historical multi-temporal Landsat images of 1987 MS, 2001 TM and 2015 OLI were classified and analysed; (b) the SWAT model was calibrated and validated, and (c) quantify the spatial and temporal change on the runoff depth due to LULC change overtime. As Jukskei River catchment is frequently affected by hydrological phenomena such as flash floods, mapping the areas that having experienced an increase in surface runoff is very important to better management option for sustainable LULC and water resources development in the Jukskei River catchment.

2. Study area

The Jukskei River catchment is one of the largest catchment areas in Gauteng Province which is largely covered by Cities of Tshwane, Ekurhuleni and Johannesburg Metropolitan Municipality. The catchment area covers an area of approximately 800km2 with the Jukskei River being the longest river among others (Figure 1). The summer season minimum and maximum temperatures range from 14 °C to 25 °C and during winter and during winter season the minimum temperature hovers just below 0 °C with a maximum temperature of 17°C. However, winters months are dry with the annual average rainfall of 713mm, mostly concentrated in the summer months (South African Weather Service-www.weathersa.co.za). The Jukskei River is the largest river within the catchment area with a total length of about 68km and is joined by numerous tributaries

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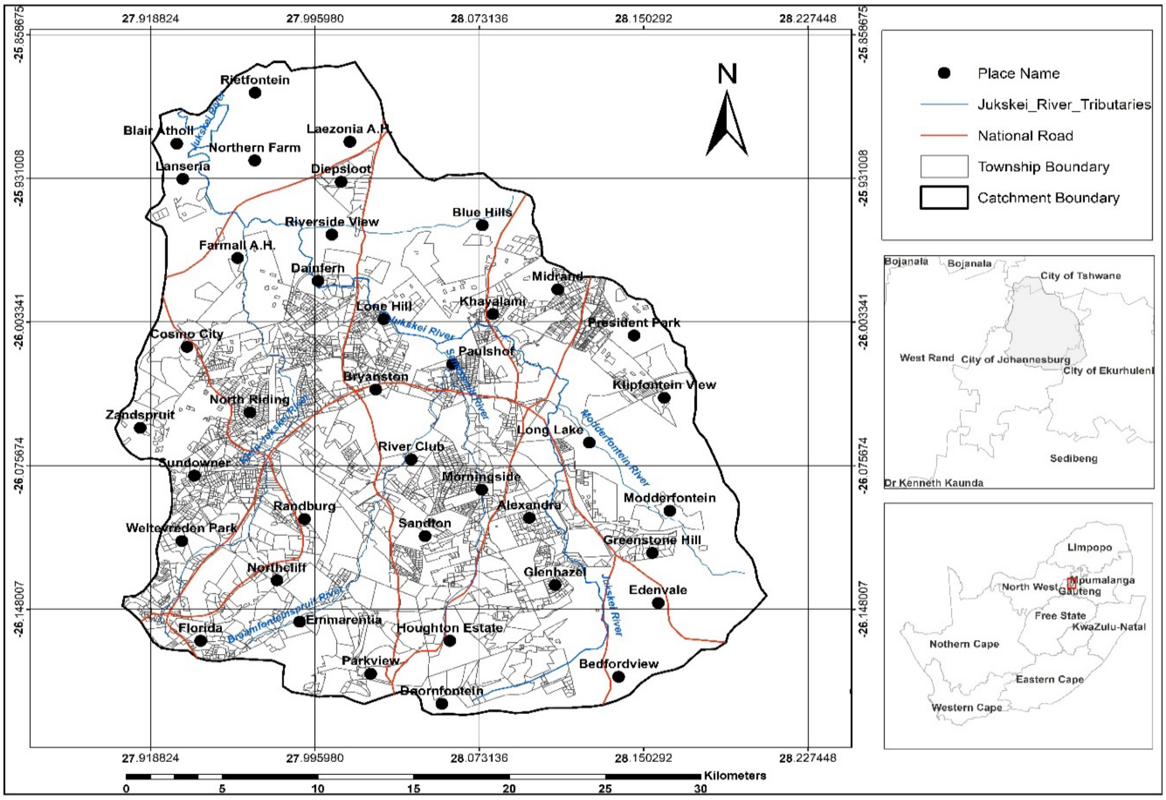

Figure1: Location of the study area

3. Materials and methods

3.1. SWAT Model Data Input

SWAT is a highly data sensitive semi-distributed model that requires specific information about the catchment characteristics such as DEM, LULC, soil data and its properties, climate data and discharge data at the catchment gauging station in a SWAT format. The output results of the SWAT model depend on the quantity and quality of data used. The required SWAT model datasets including LULC, DEM, soil and climate data were integrated and used for model setup (see Table 1). A warm-up period (i.e. years) and simulation periods (i.e. monthly) prior to running the model were also considered. The following sub-sections provide a brief description of the model dataset inputs.

3.1.1. Land Use/Land Cover

Temporal remote sensing datasets available since 1972, provided opportunities for sustainable landscape management (Ramachandra *et al.,* 2014). Landsat images are among the widely used satellite RS data and their spectral, spatial and temporal resolution made them useful inputs for mapping and planning projects (Sadidy *et al.,* 2009). For the purpose of this study, multi-temporal satellite images of Landsat-5 Multispectral Scanner System (MSS) 1987, Landsat-5 Thematic Mapper (TM) 2001 and Landsat-8 Operational Land

Table 1: Description and source of the main input data used

Data type	Data description	Spatial resolution	Period of record	Primary use	Sources
DEM	Digital Elevation Model	20m	Unknown	Model input	SANSA
LULC	Landsat MSS, TM and OLI	60m and 30m	1987-2015	Model input	(https://earthexplorer.usgs.gov)
Weather	Rainfall, minimum and maximum temperature, solar radiation, wind speed, and relative humidity	Daily	1990-2010	Model input	(https://globalweather.tamu.edu)
Soil	Soil properties	1: 5000 000	Unknown	Model input	(http://www.fao.org/soils-portal)
Stream flow	Daily stream data	Daily	1990-2010	Calibration and validation	DWA

Imager (OLI) 2015 were used to detect change in surface runoff depth. These satellite images were downloaded from the United State Geological Survey (USGS) Centre for Earth Resources Observation and Science (EROS) (https://earthexplorer.usgs.gov/). Semi-Automatic Classification plug in Quantum-GIS (QGIS) Version 3.6 was used for image pre-processing of Landsat images by applying DOS1 atmospheric correction. A remote sensing software IDRISI Selva Version 17 was used for image classification of the satellite images into different LULC classes. A supervised maximum likelihood classification technique in IDRISI Selva Version 17 was used to classify LULC classes for 1987, 2001 and 2015. In maximum likelihood classification, the normal probability distributions for each of the spectral classes are demarcated using a covariance matrix by selecting a sufficient number of pixels in each spectral class as training sample for the classification algorithm (Richards and Jia, 2006). Four distinguishable LULC classes were identified in this study as follows: built-up area, bare surface, intact vegetation and sparse vegetation (see Table 2).

Table 2: Description of land-use/land-cover classes in the Jukskei River catchment area

LULC type	Description
1. Built-up Area	This category includes areas with high density of urban settlements, residential, industrial and commercial, roads/pavement and recreational utilities.
2. Bare Surface	This describes the area left without vegetation cover, lands exposed soil, eroded land due to land degradation, and mining areas
3. Intact Vegetation	Area covered with dense vegetation, land allocated for crop cultivation, agricultural lands and natural landscaping
4. Sparsed Vegetation	Areas with very little vegetation cover, it consists of areas with scattered vegetation, areas with a cover of shrubs and short trees mixed with grasses

3.1.2. Digital Elevation Model (DEM)

One of the dominant inputs of the SWAT model is a Digital Elevation Model (DEM) which represents the topography of an area, is recognised as a first-order control on the hydrological response of a basin to rainfall and is a major determinant of flood inundation data (Bates and De Roo, 2000). Gassman *et al.* (2007) noted that the spatial resolution of DEM is the most critical input parameter when developing a SWAT model. For this study, South African Space Agency (SANSA) 20m DEM for the Jukskei River catchment with a spatial resolution of 20 m × 20 m used (Figure 1). This DEM was acquired through ComputaMaps in 2000 and is primarily used as a reference dataset for automated image processing chains (orthorectification), hydrological modelling and defining topographic variables. It was interpolated from 1:50 000 (20cm) contour vector lines and spot heights and patched with a combination of Shuttle Radar Topography Mission (SRTM) 90m (De Lemos, 2014).

3.1.3. Soil Data

The characteristics of soil data are among the fundamental characteristics of a catchment area and they are important input data into hydrological modelling, similarly to DEM and LULC. Unlike LULC features which are constantly changing over time, soil characteristics that are formed by long-term geomorphological processes are relatively stable, and they are not subject to quick variance by human activities (Dessalegn *et al.* 2014). A Digital Global Soil map at a scale of 1:5 000 000 was downloaded from the Food and Agriculture Organisation's (FAO, 2005) website (http://www.fao.org/soils-portal/) and used to derive a soil map of the catchment using ArcMap version 10.7 mapping software (Figure 3b).

3.1.4. Climate and Weather Data

The long-term climate input data are required for SWAT simulation, including daily data of precipitation, maximum and minimum temperatures, relative humidity, wind speed and solar radiation. These parameters were obtained from the National Centres for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) website (http://globalweather.tamu.edu/). When comparing the CFSR dataset to a ground-based climate station, the latter do not always adequately represent the weather occurring over a watershed, since they can be far from the watershed of interest and can have a missing data series, or recent data are not available (Fuka *et al.,* 2014). The CFSR of the NCEP readily provides weather data for any geographic location on earth from 1979 to 2013; hence, this source was considered for this study. However, one CFSR weather station located at 26°04'12.0"S 28°07'48.0"E within the catchment area (see Figure 3c). The climatic data (i.e. precipitation, relative humidity, minimum and maximum temperature, solar radiation, dewpoint and wind speed) which have been used for this study covers a period of 21 years from 01 January 1990 to 31 December 2010.

3.2. SWAT Model Setup

3.2.1. Watershed Delineation

Watershed delineation was performed via a SANSA 20m DEM using the watershed delineation function in ArcSWAT. The initial stage for creating a SWAT model is to set up a SWAT project. The watershed was delineated by following the procedure used by Neitsch *et al*. (2002). A stream gauge A2H044 (see Figure 3c) located at the catchment outlet was selected to be the outlet point of the catchment. The selection of the gauge station was based on the period of operation (i.e. 1971-07-18 to date), availability, accuracy, quality and existence of stream-flow data. Using the ArcSWAT default threshold value of 37630 for stream drainage area, the Jukskei River catchment was delineated into 23 watersheds with the smallest drainage area of 276.6km^2 and the largest with an area of 5840.7km^2 (see Figure 3c). The entire catchment area covers an estimated total area of 752.6km^2 with the Jukskei River covering 68km from upstream to the catchment outlet.

3.2.2. Slope and Hydrological Response Units Definition

The multiple slopes discretization approach in ArcSWAT model was used to create a slope map of the catchment following guidelines by the classification used by Food Agricultural Organisation (2003). The catchment was classified into three slope classes in percentages; namely level to gently undulating (< 8%); rolling to hilly (8% - 30%) and steeply dissected to mountainous (> 30%). Hydrological Response Units (HRUs) are lumped land areas within the watershed that comprise homogeneous LULC, soil, slope and management combinations (Neitsch *et al.,* 2011). According to Setegn *et al.* (2009) the HRUs definition with multiple options that account for a 10% LULC, 20% soil and 10% slope threshold combination, gives a better estimation of runoff and sediment components. HRUs of the catchment were obtained by performing an overlay analysis of LULC, soil and slope datasets. Therefore, in this study, the HRU's definition with multiple HRUs command was adopted to create HRUs that account for 10% for LULC, 20% for soil and subsequently 10% for slope. Hence, within the Jukskei River catchment area, 275 HRUs have been generated across the 23 watersheds, and each has unique LULC, soil and slope combinations.

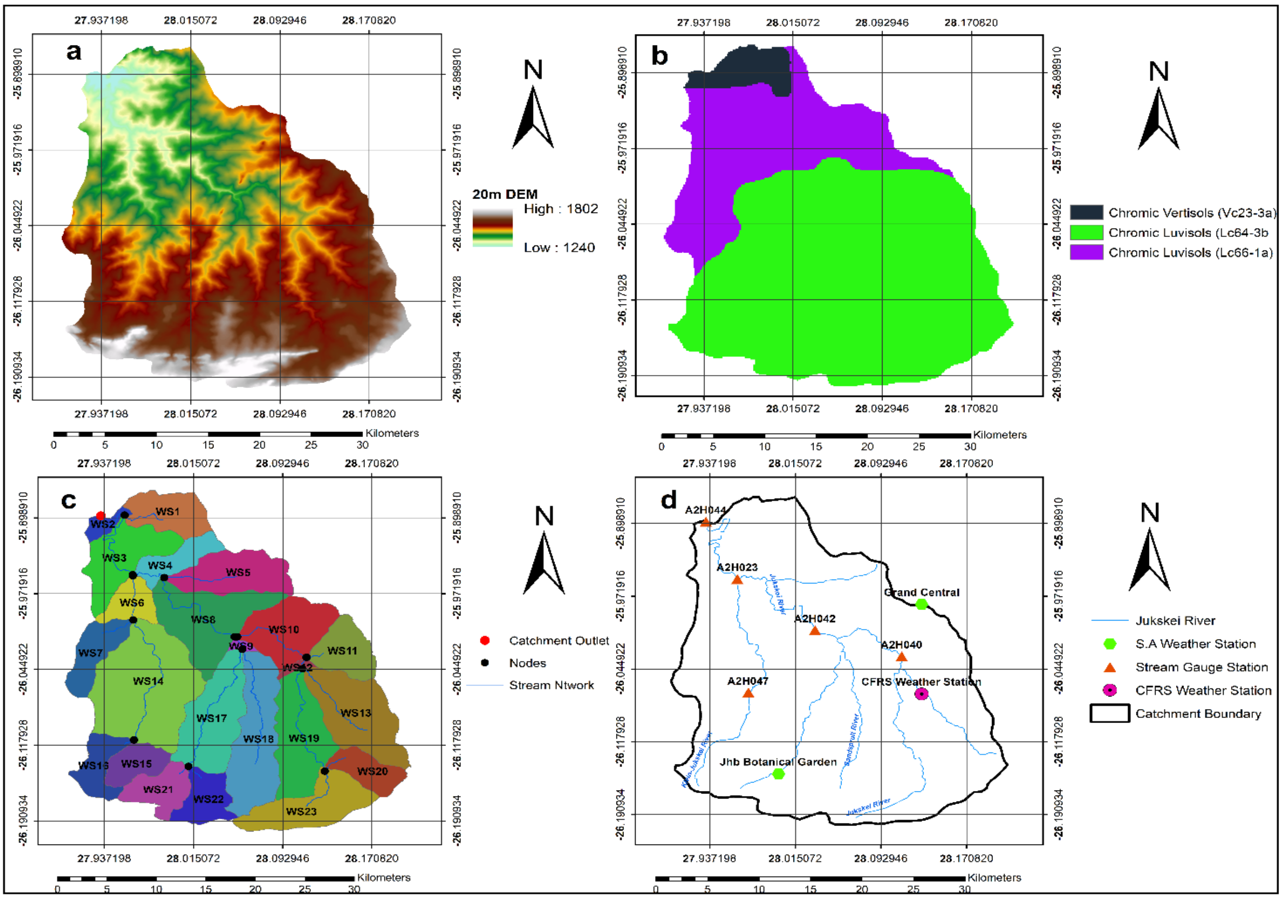

Figure 3: Catchment characteristics (a) DEM; (b) soil types; (c) weather and gauge stations; (d) watersheds

3.3. Sensitive Parameter Analysis, Calibration and Validation

The first step in building any successful and reliable predictive hydrological model is to carry out a sensitivity analysis: this can help in identifying and ranking the parameters that have a significant impact on specific model outputs of interest (Saltelli *et al.,* 2000). For this study, the sensitivity analysis was carried out using SUFI-2 algorithm in the SWAT-CUP to categorise main parameters that have a greater effect on streamflow. Twelve parameters were considered for performing a sensitivity analysis and the sensitivity parameters based on the *p*-value and *t*-test. The *t*-test gives a measure of the sensitivity of a parameter while the *p*-value gives the significance of the sensitivity of that parameter (Gyamfi *et al.,* 2016). Therefore, parameters with high *t*-test values and low *p*-values, show greater sensitivity on the stream flow (Jha, 2011).

The calibration and validation were accomplished by using a SWAT-CUP SUFI-2. The SUFI-2 algorithm which operates based on the Latin Hypercube sampling procedure, was used to calibrate and validate the SWAT model output (Neitsch *et al*., 2002). A split sample procedure using monthly streamflow data (i.e. volume in m^3/s) from gauge station A2H044 (Figure 3d) and all the climatic conditions were therefore satisfied for both calibration and validation. In this study, daily streamflow data (i.e. volume m^3/s) from 1990-2010 were acquired from the A2H044 gauging station and were used to calibrate and validate the SWAT model output. Moreover, for a better parameterisation of the SWAT model and to reduce the model output uncertainty, the SWAT model was warmed up for 3 years (i.e. 1900 to 1992) and a calibration was performed for a period of 10 years (i.e. 1993-2003) while the remaining 7 years (2004-2010) were used to validate the model.

3.4. Statistical Evaluation of the Model Performance

The evaluation of a model's performance with the observed data is important and a statistical evaluation is regarded as the key method in comparing model outputs with the observed data (Yang *et al.,* 2000). In this study, the model's performance during calibration and validation was evaluated by using four statistical criteria, which included Root Mean Square Error-observation Standard Deviation ratio (RSR) (Fallah-Mehdipour *et al.,* 2013), Coefficient of Determination (R^2) (Talei *et al.,* 2013), Nash-Sutcliffe efficiency (E_{NS}) (Tiwari and Chatterjee, 2010), Percent Bias (PBIAS) (Moriasi *et al.,* 2007).

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(Q_{sim} - \overline{Q}_{sim})^2}{\sum_{i=1}^{n}(Q_{obs} - \overline{Q}_{obs})^2} \quad [1]$$

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(Q_{obs} - Q_{sim}) \times 100}{\sum_{i=1}^{n}(Q_{obs})}\right] \quad [2]$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(Q_{obs} - \overline{Q}_{obs})(Q_{sim} - \overline{Q}_{sim})}{\sqrt{\sum_{i=0}^{n}(Q_{obs} - \overline{Q}_{obs})^2(Q_{sim} - \overline{Q}_{sim})^2}}\right] \quad [3]$$

$$RSR = \frac{\mathrm{RMSE}}{\mathrm{STDEV_{obs}}} = \left[\frac{\sum_{i=1}^{n}(\mathrm{Q_{obs}}-\mathrm{Q_{sim}})^2}{\sqrt{\sum_{i=1}^{n}(\mathrm{Q_{obs}}-\bar{\mathrm{Q}}_{\mathrm{obs}})^2}}\right] \quad [4]$$

where Qobs is the observed discharge; Qsim is the simulated discharge; $\bar{Q}$ (obs) and, $\bar{Q}$ (sim) represent mean of observed and simulated discharge respectively; and n is the total number of rainfall-runoff events (months and years).

4. Results and discussion

4.1. Analysis of LULC Change

The analyses of the classified images of 1987, 2001 and 2015 revealed that there were noticeable increases in the built-up area from 28700.4ha (38.1%) in 1987, 36313.6ha (47.8%) in 2001 and 42713.1ha (56.2%) in 2015 compared to other classes within the Jukskei River catchment area for the past 28-year period. A decrease in vegetation cover was also witnessed with the highest being sparse vegetation cover, followed by intact vegetation with varying changes on bare surfaces (see Table 3 and Figure 2). The trends shows that, natural land cover has a slightly potential to recover to its original state as the study area is characterised of urban areas where infrastructural and residential development are increasing at an alarming rates. Additionally, more than half of the total catchment area 42713.1ha (57.4%) was covered by impervious surfaces in 2015 compared to 1987 with 38.1% and 2001 with 48.6%, which has reduced rainfall infiltration, thereby accelerating surface runoff which in turn generates flash flooding.

Table 3: Land-use/land-cover change statistics for the past 28-years

		Aerial Coverage (ha)					
		1987		2001		2015	
Classified Images	**SWAT Code**	**ha**	**%**	**ha**	**%**	**ha**	**%**
Built-up Area	BARR	28700.4	38.1	36313.6	48.6	42713.1	57.4
Bare Surface	URDM	6550.6	8.2	6225.1	7.9	3482.9	4.4
Intact Vegetation	AGRC	18567.3	24.3	16154.1	21.1	7455	9.18
Sparsed Vegetation	PAST	27715.4	36.4	19659.6	25.5	1462.1	18.9

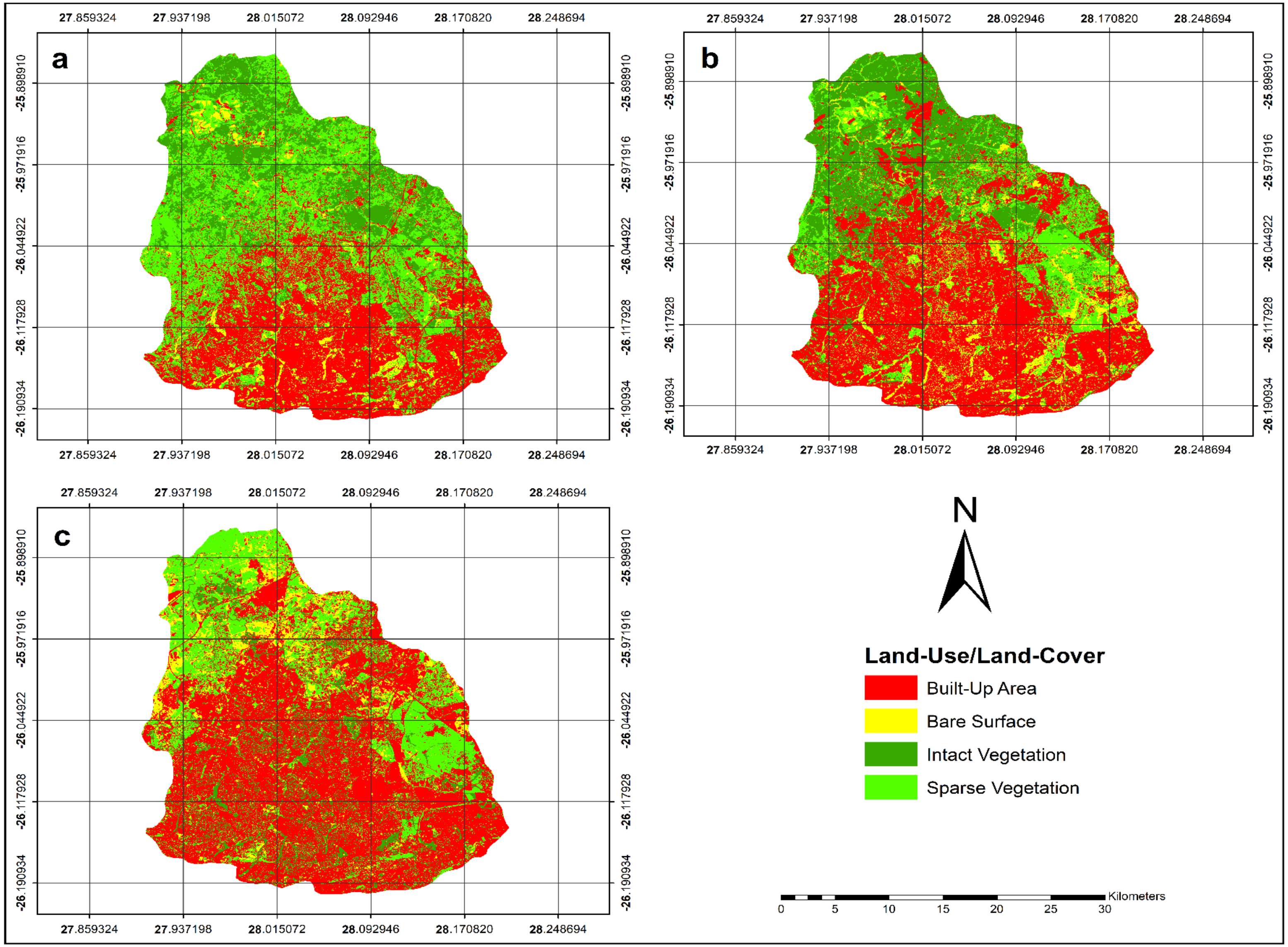

Figure 2: Land use/land cover change maps overtime (a) 1987; (b) 2001; and (c) 2015

5.3 Global Sensitivity Analysis Results Using SUFI-2 Algorithm

Sensitivity analysis was performed using the Soil Water assessment Tool - Sequential Uncertainty Fitting version 2 (SWATCUP - SUFI-2). In this study, twelve parameters which govern the runoff generation process in the basin were selected and grouped under three categories: (1) surface response (2) sub-surface response and (3) basin response (see Table 4). From the initial twelve parameters used in the sensitivity analysis, only eight parameters were considered to be sensitive to streamflow based on *t*-statistics and *p*-value ($p < 0.05$) and were ranked 1 to 8, where 1 indicates the highest and 8 the lowest (CN2, SOL_AWC, SOL_K, and ESCO, (2) sub-surface response (GW_REVAP, REVAPMN, GWQMN, ALPHA_BF, GW_DELAY, ALPHA_BNK) and (3) basin response (SURLAG, CH_K2) (see Table 5). It was found that the remaining parameters (i.e. GW_REVAP, GW_DELAY, GWQMN, and ALPHA_BF) did not have a significant effect on the streamflow simulation in the basin as their *p*-values were greater than 5% (Table 5). However, other studies (Getachew and Melesse, 2012 and Gyamfi *et al.,* 2016) also found these parameters to be sensitive in their studies.

Table 4: List of parameters and their calibrated values (Neitsch *et al.,* 2011)

Parameters	Definition	Range
CN2.mgt	Soil Conservation Service runoff curve number (dimensionless)	35 - 98
ALPHA_BNK.gw	Base-flow alpha factor for bank storage (dimensionless)	0 - 1
SOL_K.sol	Saturated hydraulic conductivity (mm/h)	0 - 2000
ESCO.hru	Soil evaporation compensation factor (dimensionless)	0 - 1
REVAPMN.gw	Threshold depth of water in the shallow aquifer for “revap” to occur (mm)	0 - 500
SOL_AWC.sol	Available water capacity of the soil layer (mm H_2O/mm soil)	0 - 1
SURLAG.bsn	Surface runoff lag time (days)	0.05 - 24
CH_K2.rte	Effective hydraulic conductivity in main channel alluvium (mm/h)	0.05 - 500
ALPHA_BF.gw	Base-flow alpha factor (days)	0 - 1
GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0 - 5000
GW_DELAY.gw	Groundwater delay (days)	0 - 500
GW_REVAP.gw	Groundwater “revap” coefficient (dimensionless)	0.02 - 0.2

Table 5: Sensitive ranking of stream flow parameters in the Jukskei River catchment after first iteration with 500 simulations.

Parameter Name	*t*-Statistics	*p*-Value	Ranking	Fitted Values
1:V__CN2.mgt	-8.91	0.00	1	66.38
12:V__ALPHA_BNK.rte	7.54	0.00	2	0.76
4:V__SOL_K (...).sol	-3.05	0.00	3	456.26
7:V__ESCO.hru	-1.47	0.14	4	0.05
6:V__REVAPMN.gw	-1.30	0.20	5	86.94
3:V__SOL_AWC (...).sol	1.19	0.24	6	0.37
10:V__SURLAG.bsn	1.16	0.25	7	9.25
5:V__CH_K2.rte	-0.68	0.49	8	180.72
11:V__ALPHA_BF.gw	-0.64	0.52	9	0.36
8:V__GWQMN.gw	-0.57	0.57	10	1668.3
2:V__GW_DELAY.gw	-0.45	0.65	11	72.06
9:V__GW_REVAP.gw	0.23	0.82	12	0.05

5. SWAT model calibration and validation results

The split sample method was used in this study with both the dry and wet season being considered during both calibration and validation periods. Figure 7a and Figure 7b show the time series hydrograph of comparison results between observed and simulated runoff for the calibration period (1993-2003) and for the validation period (2004-2010) respectively. The model output results revealed that, there is a slightly overestimations and underestimations of simulated runoff were observed during validation period where the corresponding observed runoff did not match well with the simulated runoff. However, Qiu *et al.* (2012) have suggested that underestimation or overestimation of streamflow discharge by the SWAT model is partly due to the use of curve number which cannot gives an accurate prediction of runoff for days when several storms may occur.

5.1. Model Performance Evaluation Based on Statistical Comparison

In this study, four statistical methods were used to evaluate model performance (i.e. R^2, N_{SE}, PBIAS, and RSR) by comparing observed direct runoff with SWAT simulated runoff. The objective function during calibration was specified as $N_{SE} > 0.5$ in SUFI-2 and this was achieved during model calibration, where N_{SE} was 0.72, while during validation the N_{SE} value obtained was 0.68. The overall simulation shows adequate correlation between observe and corresponding simulated runoff with R^2 value of 0.84 and 0.68 during model calibration

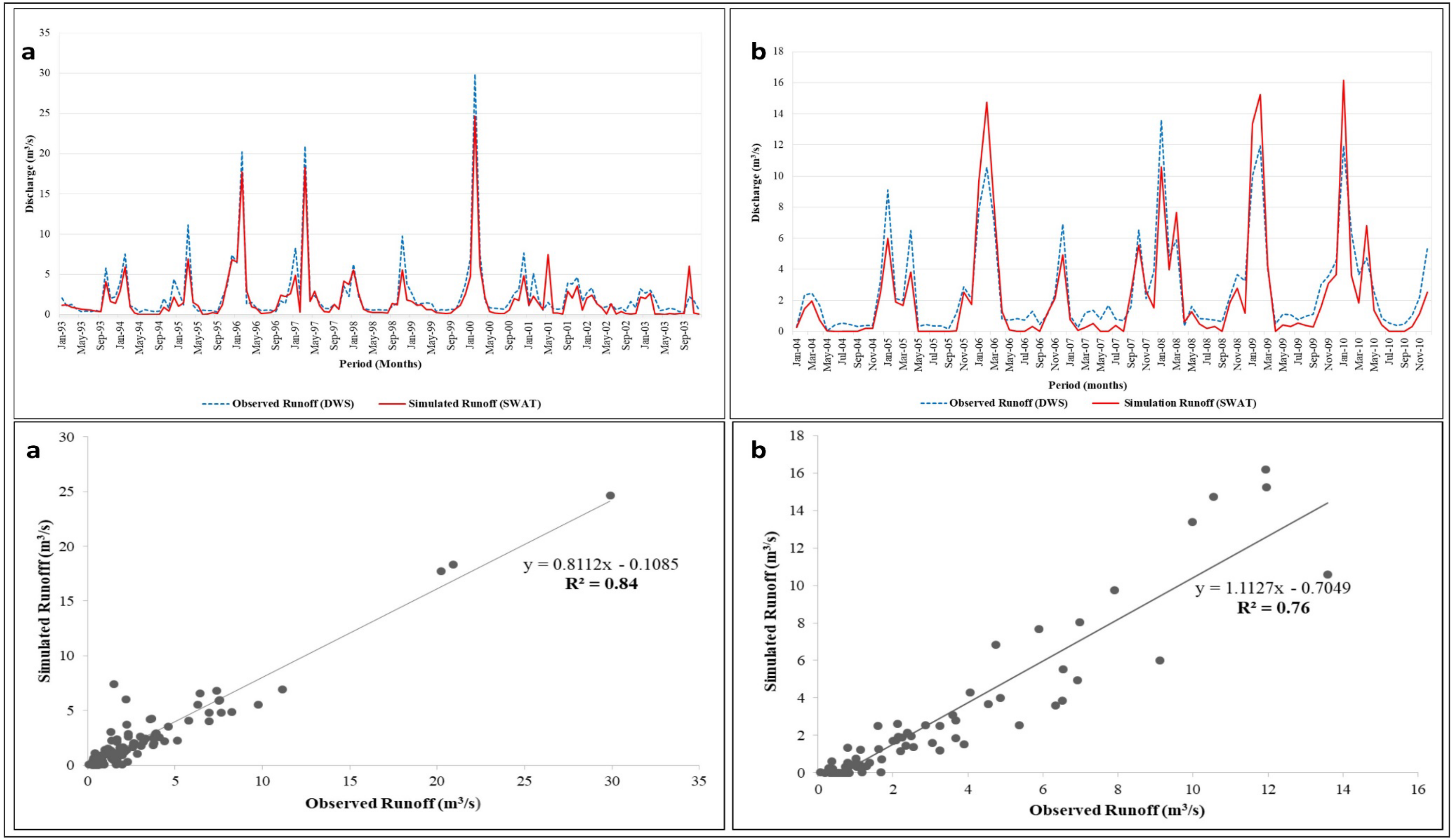

Figure 7: Monthly observed and simulated hydrographs (a) model calibration (1993-2003) and scatter plot at 95% confidence level (b) model validation (2004-2010) and scatter plot at 95% confidence level

and validation, respectively. According to Moriasi *et al.* (2007) if the values of N_{SE} and R^2 are above 0.5, this confirms that the model performs very well. Considering the model performance statistics based on the criteria set out by Moriasi *et al*. (2007), the model performance was rated “good” and “satisfactory” with RSRs of 0.54 and 0.63 for both calibration and validation, respectively. The monthly modelled runoff results showed that the model slightly underestimated runoff during the calibration and validation period with a PBIAS of 16.5 and 20.4 which indicates both satisfactory and unsatisfactory performance of the model, respectively, when based on the criteria set out by Van Liew *et al.* (2007). Moreover, according to Moriasi *et al.* (2007), a PBIAS greater than zero is an indication that the model underestimated runoff flow. Hence, these values indicate that the model had underestimated the observed direct runoff during the validation period and with less accurate model simulation for the calibration period.

5.2. Effect of LULC change to surface runoff change overtime

A “fixing-changing method” was applied in this study where LULC maps were interchanged, while keeping other inputs (i.e. climate data, soil, and DEM) constant when simulating runoff using the SWAT model (Woldesenbet *et al.,* 2017). Figure 8 a-c shows the spatial distribution of the modelled monthly runoff depth in millimetres per watershed: this gives an indication of the percentage of rainfall that was transformed to runoff for the year 1987, 2001 and 2015 LULC respectively. As shown in these figures, there is a correlation between change in LULC and change in runoff depth over time. In highly built-up areas, runoff depth is high compared to areas with bare surfaces, intact vegetation and sparse vegetation. However, the model output results revealed that areas that generates high surface runoff increased from 70.5mm in 1987 LULC to 134.2mm and 199.4mm during the year 2001 and 2015 LULCs condition, respectively. Knebl *et al.* (2005) found that urban areas are prone to flooding due to the large proportion of impermeable surface cover, such as concrete that increases the total volumes of runoff during peak flows. The upstream watersheds which covers areas such as Doornfontein, Bedfordview, Parkview, Edenvale, Greenstone Hill, Alexandra, Sandton, Houghton Estate, Emmarentia, Florida, Randburg and Morningside had more built-up area with less natural land cover areas, whereas areas such as Rietfontein, Laezonia A.H, Monaghan Farm and Lnseria which are located at the downstream toward catchment outlet had more natural land cover than the built-up area.

For the last 28-years surface runoff depth at Modderfontein and Long Lake areas has remained unchanged because a large part of this area is covered by Par-Run Modderfontein Nature Reserve. Additionally, surface runoff depth at the catchment outlet areas such as Lanseria, Vlakfontein and Rietfontein remained unchanged for the past 28 years due to agricultural activities in the area around Northern Farm. According to the results, high surface runoff depth areas were related to impervious surface (i.e. built-up area) whereas low

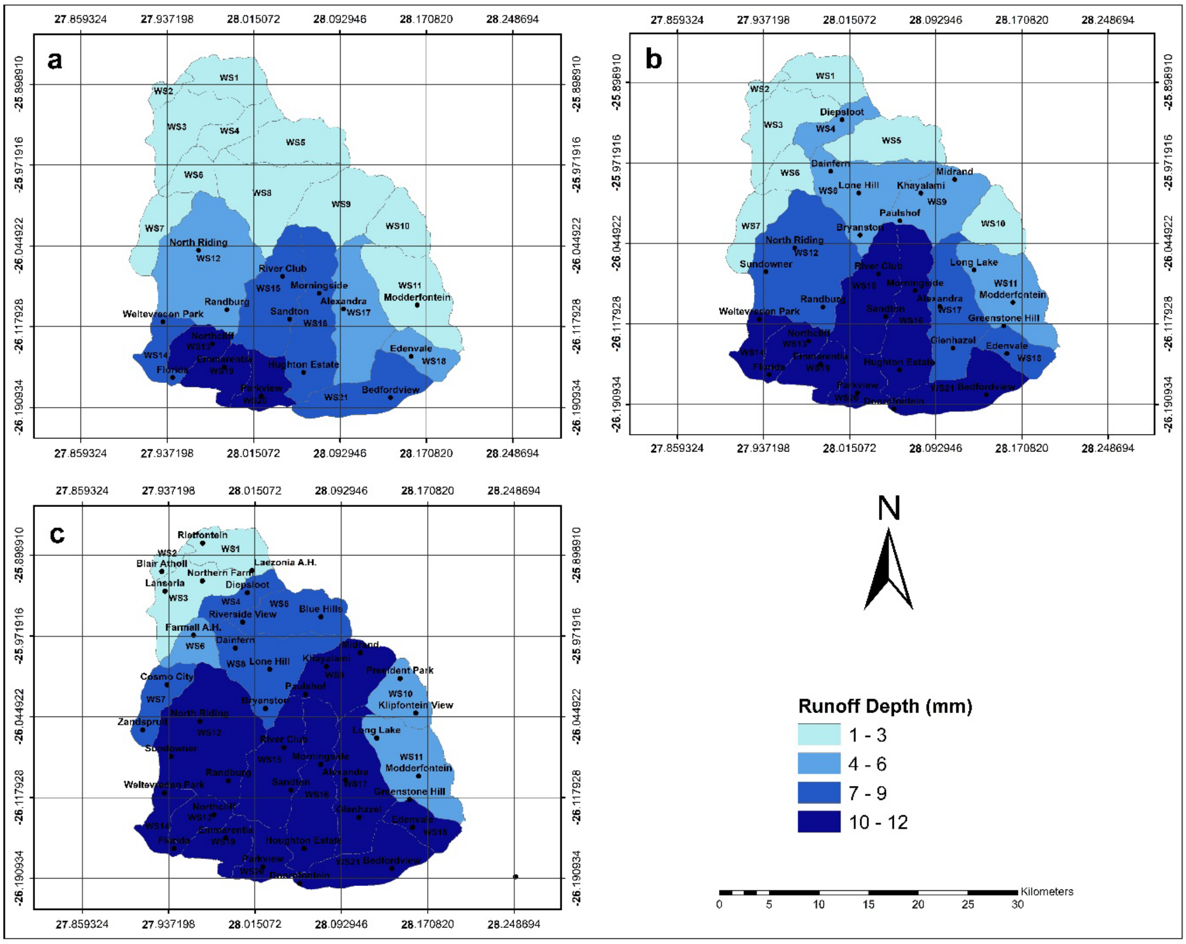

Figure 8: Spatial distribution of the average surface runoff depth over time (a) 1987; (b) 2001 and (c) 2015

surface runoff depth were related to pervious surface (i.e. bare surface, intact vegetation, sparse vegetation). Additionally, these results do not only indicate the amount of increase in surface runoff depth aerial coverage due to LULC change, but also identifies high surface runoff production zones within the catchment area. The surface runoff depth results presented in Figure 8 were also found to be of utmost importance for catchment management specialists, city stormwater managers, property developers or planners, and disaster management personnel for decision making regarding catchment hydrological management.

6. Conclusion

This study adequately demonstrates the usefulness of an integrated RS and GIS techniques with hydrological SWAT model to quantify the spatial and temporal changes in surface runoff depth resulting from LULC change between 1987, 2001 and 2015 in the Jukskei River catchment. The hydrological parameters that were used to quantify change in surface runoff depth includes LULC, soil type, DEM and climatic data. For the last 28-years (i.e. 1987 to 2015), LULC change showed that built-up area had increased drastically from 28700.4ha (38.1%) to 42713.1ha (57.4%) and simultaneously, the natural land cover areas had decreased from 52833.6ha (61.9%) to 12400ha (42.6%) with reference to the total catchment area. In order to simulate change in surface runoff depth due to LULC change, SWAT model was used using LULC scenario of 1987, 2001 and 2015. The correlation between SWAT simulated runoff and observed runoff at the catchment outlet were assessed by using SWAT-CUP-SUFI-2 algorithm to reduce model uncertainty. However, the SWAT model performance with a N_{SE} of 0.72 and 0.68; R^2 of 0.84 and 0.68; RSR of 0.54 and 0.63; PBIAS of 16.5 and 20.4 for both model calibration and validation, respectively represent the acceptable accuracy of the model in simulating runoff depth. The analysis of the results revealed that, conversion of natural land cover to built-up area had increase surface runoff depth from 70.54mm in 1987 LULC to 134.22 and 199.37mm in 2001 and 2015 LULC, respectively. Anaba *et al.* (2017) showed that the increase in urbanization might possibly create impervious layers decreasing the infiltration and percolation of water to the shallow aquifers that lead to increases in surface runoff. Additionally, the integration of GIS and RS techniques with SWAT model were able to quantify the spatial and temporal change of surface runoff depth due to change in LULC overtime. To predict the expected change in runoff depth, the SWAT model can be used for future LULC scenario. Therefore, a better understanding and modelling of areal extent and pattern of LULC changes are vital for the formulation of suitable mitigation measures towards sustainable management of catchment hydrological processes and will support cities administrators in similar projects.

7. References

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