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Evaluation of stream flow under land use land cover change: A case study of Chemoga Catchment, Abay Basin, Ethiopia

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For human beings, land and water are vital. To enhance agricultural productivity and socio-economic development in the agricultural catchment, irrigation development is an important issue. The present study aims to evaluate the stream flow under land use land cover (LULC) change for surface irrigation in Chemoga catchment part of Abay River Basin. To accomplish the objectives of this study, the watershed model SWAT (Soil and Water Assessment Tool) was used based on organization and website data sources. LULC classification was performed using ERDAS imagine 2014 which was used for further analysis of streamflow in SWAT to evaluate surface irrigation. The selected LULC years, 1994 and 2013 were used to assess the impact on streamflow. The result depicts that in wet season streamflow increases and in the dry season the stream flow decreases respectively for the LULC of 1994 and 2013. The performance of the model during calibration and validation period was good. So watershed management approach should be done in the catchment to improve surface irrigation potential.

Key words: Chemoga catchment, streamflow, land use land cover, SWAT model, surface Irrigation.

INTRODUCTION

Land and water are indispensable for the existence of human beings (FAO, 2016). Considering the available water and land resources of the country, Ethiopia has huge potential in expanding irrigated agriculture. The country is gifted with sufficient water resources with an estimated volume of 122 and 2.6 billion m³ of annual surface runoff and groundwater potential respectively (Awulachew et al., 2007); the land irrigation potential is 5.3 million ha (Mha) of which 3.7 Mha can be developed using surface water sources, and 1.6 Mha using groundwater and rainwater management. Belay and Bewket (2013) reported that the current irrigation development in Ethiopia varies between 1.5 to 4.3 Mha, averaged about 3.5 Mha (Makombe et al., 2011). However, the actual and potential irrigated land is not precisely investigated; estimates of irrigable land in
Ethiopia vary from study to study such as Awulachew et al. (2007) 0.16 - 0.2 Mha; Awulachew and Mekonnen (2011) 0.7 Mha; and MoA (2011) reported that 10 - 12% of the total irrigable land that is from 0.53 - 0.64Mha are currently under production using traditional and modern irrigation schemes. This shows that evaluation of the actual potential of stream water flow is not consistent; reliable and well-studied. Appropriate watershed management and selection of the applicable irrigation method is a pre-condition for the utilization of scarce physical resources in terms of land and water. To ensure adequate watershed management and design of a particular irrigation system, a well-developed and suitable database is quite important. Thus, it should be able to deal with spatially and temporally varying stream flows evaluation is important for irrigation potential assessment. Streamflow is an important hydrological variable needed for water resource development, planning and design; this hydrological event has a strong connection with LULC. The trend of deforestation in the Chemoga watershed has been increasing; due to the reason for expansion of residential area and increasing of agricultural land which aggravates the LULC change of the catchment. This continuous of LULC change has influenced the water balance of the catchment by changing the magnitude and pattern of the components of streamflow that are surface runoff, lateral flow and groundwater flow, which results increasing in the extent of the water management problem (Tekleab, 2015). To improve the livelihood of the people irrigation development is essential. However, the water availability of the catchment; irrigable land areas and the water requirement of crops commonly grown in the catchment and also the availability of stream flows under LULC change for surface irrigation development point of view have not been identified so far. LULC change impact on water resource for irrigation point of view is still very much at an early stage throughout the country. Therefore, this present study intended to evaluate the impact of LULC change on streamflow in the context of surface irrigation development in Chemoga Catchment, Abay Basin, Ethiopia. With this respect, the hydrological model which is soil water assessment tool (SWAT) and geographic information system (GIS) facilities were extensively used. The model was used in Ethiopia in the watershed or sub-watershed level (Welde and Gebremariam, 2017; Abebe and Gebremariam, 2019; Setegn et al., 2009; Mengistu and Sorteberg, 2012). The SWAT is a distributed parameter model designed to simulate water, sediment in watersheds and large river basins with varying climatic conditions, soil properties, stream channel characteristics, land use and agricultural management practices (Arnold et al., 1996; 1998). It is a continuous time-scale model, capable of simulating long-term effects of change in land use and land cover; and agricultural management, which uses readily available input data.

**METHODOLOGY**

**Study area**

The Chemoga River catchment (Figure 1) is a tributary of the Abay/Upper Blue Nile basin, located south of Lake Tana, and extended between approximately 10°10’00” to 10°40’00”N latitude and 37° 30’00” to 37°54’00”E longitude. The river flow starts from the Choke Mountain at an elevation of 4000 m above mean sea level (Moriasi et al., 2007).

**Data collection**

To properly accomplish this study, Universal Tranvers Mercator (UTM) converter, Google Earth, geographic information system (GIS), and Soil and Water Assesment Tool (SWAT), ERDAS Imagine 2014 and geographic positioning system (GPS) were used.

**Hydro-meteorological data**

The meteorological data, such as (daily precipitation, maximum and minimum air temperature, sunshine hours, relative humidity and wind speed) were collected from Ethiopian National Meteorological Agency. The hydrological flow data were collected from the Ministry of Water, Irrigation and Electricity of Ethiopia from the hydrology department.

**Spatial (LULC, Soil and DEM) data**

Spatial data were one of the inputs for the SWAT model. These are digital elevation model (DEM) (Figure 2), LULC and soil map. The DEM of the study area was downloaded from Shuttle Radar Topographic Mission (SRTM) which is available at USGS website with the resolution of 30 m which is void filled data and provide open distribution of this high-resolution global data set (https://earthexplorer.usgs.gov). The 1994 and 2013 LULC satellite data were downloaded from the USGS website (https://earthexplorer.usgs.gov). The digital soil map of Chemoga catchment was obtained from the Ministry Agriculture of Ethiopia in the shapefile format.

**Agronomic data**

Irrigation Efficiency, Irrigation Calendar and Dominant Crop were collected from Ethiopian Ministry of Agriculture, Abay basin master plan, East Gojjam zone agriculture office and FAO guideline.

**Data analysis**

The SWAT model requires readymade data and therefore, before using the data for the simulation, the data should be prepared as needed of the model.

**LULC and soil data analysis**

The LULC dataset for the year of 1994 and 2013 consisting of seven and eleven image bands respectively and the Landsat image
provide complete coverage of Chemoga catchment. To represent the LULC conditions in the year of 1994 to 2013, TM and OLI_TIRS of Landsat sensor were selected for mapping of Chemoga catchment. To avoid a seasonal variation in vegetation pattern and distribution throughout the year, the selection of data sets were made as much as possible in the same annual and dry season from the two images of acquired years.

**Image pre-processing**

In order to analyse remotely sensed images, the different images representing different bands must be stacked, that is, band 1 to 7 and band 1 to 11 for LULC 1994 and LULC 2013 satellite images respectively are overlaid using layer stacking syntax in ERDAS imagine 2014.

**Image classification**

The LULC change studies usually need the development and the definition of homogeneous LULC units before the analysis started. It is differentiated using the available data source such as remote sensing, Google earth, ground control points and the previous local
knowledge.

Following this, the tool, ERDAS imagine 2014 software was used for classification of the LULC image of the catchment. Image classification is a difficult and time taking task, and it is the process of assigning pixels of a continuous raster image to the predefined LULC classes. In remote sensing, there are various image classification methods, that is, supervised and unsupervised. For this study, we used the most common type of classification technique, supervised classification type. First, Google earth was taken as a signature for the classification. Second, we performed the classification using the maximum likelihood classifier. Lastly, the accuracy assessment was performed using Google earth image for the LULC 1994 and 193 random points were generated in Arc GIS. Following these procedures, random points were converted to KML (Keyhole Markup Language (Hengl et al., 2015)) in order to display in Google Earth. Whereas, the accuracy assessment of 2013 LULC map was used ground truth points as a reference and 195 points were taken to validate the classification; which was built in 12/05/2016. The analysis result was performed using confusion/error matrix. The physical and chemical properties soil data is one of the major input data for the SWAT model. In SWAT, these properties of the soil govern the movement of water or air through the soil profile and have a major impact on the cycling of water within hydrologic response units (HRU), and used to set initial levels of the different chemicals in the soil respectively.

Hydro-meteorological data analysis

Meteorological data are among the main demanding input data for the SWAT model simulation. The observed meteorological input data required for SWAT simulation includes daily data of precipitation, minimum and maximum air temperature, sunshine hours, wind speed and relative humidity from January 1990 to December 2014. 8 metrological stations in and nearby the watershed is found, due to discontinues of climatic data only five stations in and around the Chemoga catchment selected (Figure 3).

Filling missing precipitation and temperature

There are a number of methods available for estimating missing precipitation data (Chow et al, 1988; Singh, 1994; Lam, 1983 and De Silva, 1997). For this study, we used the normal ratio method; due to the rainfall measured at a different station in the catchment shows greater than 10 % variation (Equation 1).

\[
P_x = \frac{N_x}{n} \left( \frac{P_1}{N_1} + \frac{P_2}{N_2} + \frac{P_3}{N_3} + \cdots + \frac{P_n}{N_n} \right)
\]

Where: \( P_x \) = missing rainfall data at station \( x \), \( N_x \) = missing data station’s normal annual rainfall (\( N_1 \), \( N_2 \), \( N_3 \), ....., \( N_n \) = normal annual rainfall at stations \( i \) and \( n \) is the number of nearby gauges). Moreover, the percent of difference (Equation 2) was used to decide the appropriate methods.

\[
\text{Percent of difference} = \left( \frac{N_x - N_i}{N_x} \right) \times 100
\]

In which \( N_i \) is the normal annual rainfall amount from the missing data station and \( N_x \) is the normal annual rainfall amount from one of the nearby stations (Richards, 1998). The normal ratio method was adopted to fill missing air temperature data.

Homogeneity and consistency

In order to test the rainfall homogeneity, the homogeneity of the stations was made by the rainbow model (Figure 4). In order to check the inconsistency of rainfall, the double mass curve (DMC) technique was used. Therefore, as shown in Figure 5 the computed DMC for the study area, which is a straight slope and R2 is 0.999 for four stations and 0.997 for one station. This indicates that there is no significant change in slope relative to the original slope. There is no data divergence between the meteorological stations, so the recorded data is consistent and there is no need for correction of the original data. The homogeneity test of the streamflow data for Chemoga river at the gauged site was checked by the rainbow model (Figure 6) and has a good quality of streamflow data. Taking the catchment similarities into account (McIntyre et al., 2005 and
Figure 4. Homogeneity test of time series rainfall data for Debre Markos station.

Figure 5. Consistency test for the five stations by DMC.

Oudin et al., 2010), the streamflow data of the gauging site was transformed to the outlet of Chemoga river catchment using catchment area-ratio method. Estimation of streamflow at catchment outlet was developed by a relation provided in Equation 3.

\[ Q_{outlet} = Q_{gauged} \times (\frac{A_{outlet}}{A_{gauge}})^n \]
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Figure 6. Homogeneity test of time series streamflow data of Chemoga catchment.

Where, $A_{\text{outlet}}$ is area upstream of the ungauged site (km$^2$), $A_{\text{gauged}}$ is area upstream of the gauged site, $Q_{\text{outlet}}$ streamflow value at catchment outlet (m$^3$/s) and $Q_{\text{gauged}}$ streamflow value at gauge site (m$^3$/s). The ratio of the ungauged site area to gauged site area is 0.8 to 1.2 or is made so that the exponent of $A_{\text{outlet}}/A_{\text{gauged}}$ is 1 and $n$ is assumed as equal to 1 (Douglas et al., 2005).

Selection of physical catchment characteristics

The physical catchment characteristics (PCCs) used for this study were grouped as physiography, soil and LULC condition. The developed approaches in this study taken into account both the gauged and ungauged catchment PCCs, that is, the relation between the two variables examined using correlation coefficient for developing area-ratio method to transfer the streamflow from gauged to ungauged areas. PCCs were determined using Arc GIS integrating with Arc SWAT for the calibrated and validated streamflow results of 2013 LULC of the catchment. LULCs are cultivated land, forestland, grassland, woodland, water and marshy land, shrub land and urban land.

Soil

There are haplic alisols, eutric cambisols, eutric leptosols, haplic luvisols, eutric vertisols and urban.

Hydrological modeling

Simulation of the hydrological process in SWAT is based on the following water balance Equation 4 (Neitsch et al., 2005).

$$SW_t = SW_0 + \sum_{i=1}^{4} (R_{\text{day}} - Q_{\text{surf}} - E_a - W_{\text{seep}} - Q_{\text{lat}} - Q_{\text{gw}})$$

(4)

Where; $SW_t$ is the final soil water content [mm water], $SW_0$ is the initial soil water content [mm water], $t$ is the time [days], $R_{\text{day}}$ is the amount of precipitation on day $i$ [mm water], $Q_{\text{surf}}$ is the amount of surface runoff on day $i$ [mm water], $E_a$ is the amount of evapotranspiration on day $i$ [mm water], $W_{\text{seep}}$ is the amount of water entering the vadose zone from the soil profile on day $i$ [mm water], $Q_{\text{lat}}$ is lateral flow from soil to channel and $Q_{\text{gw}}$ is the amount of return flow on day $i$ [mm water].

Surface runoff is estimated by using a modified soil conservation service (SCS) curve number method (SCS, 1972), which estimates the amount of runoff based on local LULC, soil type, and antecedent moisture condition (Neitsch et al., 2005). Three methods can be used to estimate potential evapotranspiration (1) the penman-monteith method (Monteith, 1965), (2) the Priestley Taylor method (Priestley and Taylor, 1972), and (3) the Hargreaves method (Hargreaves and Samani, 1985), depending on data availability. In this study, we used the Penman-Monteith method because of the presence of class one station in the centroid of the watershed. Groundwater flow contribution to total streamflow is simulated by routing a shallow aquifer storage component to the stream (Arnold and Allen, 1996). Channel routing is simulated by using the variable storage or Muskingum routing equation (Williams, 1969).

Model setup, calibration and validation

Evaluation of streamflow under LULC change at Chemoga catchment was created in SWAT model using the 1994 and 2013 LULC satellite map, meteorological data, observed monthly streamflow data, soil map and DEM. Potential evapotranspiration (PET), surface runoff, and channel routing were simulated with Penman-Monteith, Curve Number, and Variable Storage methods (Neitsch et al., 2011), respectively. Using the Chemoga catchment DEM, the watershed was first divided into 9 sub-watersheds based on the topographic analysis of flow direction and accumulation; then all sub-watersheds were further subdivided into 139 HRUs for 1994 LULC and 105 HRUs for 2013 LULC using a 5% threshold value.
for land use, 10% threshold value for soil and slope (Figure 7).

The results from simulation cannot be directly used for further analysis but to sufficiently predict the amount of streamflow should be evaluated based on sensitivity analysis, calibration and validation processes. Sensitivity analysis was done prior to the calibration and validation process in order to identify important hydrologic parameters for model calibration. Sensitivity analysis was done prior to the calibration and validation process in order to identify important hydrologic parameters for model calibration. The average monthly streamflow data of 35 years from 1980 to 2014 of the catchment were used to compute the sensitivity of the hydrologic parameters and the first two years of which was used as a warm-up period (Daggupati et al., 2015). Following this, model calibration was done from 1990 to 2004 using automatic calibration. The measured data of average monthly streamflow data of 5 years from 2005 to 2009 were used for the model validation process.

Model performance evaluation

The goodness of fit can be quantified by the coefficient of determination ($R^2$), Nash-Sutcliffe Efficiency (ENS) and relative volume error (RVE) (equations 8-10) respectively. $R^2$ is an indicator of the linear relationship between the observed and simulated values. ENS indicates that how well the plots of observed versus simulated data fit the 1:1 line.

\[
R^2 = \left( \frac{\sum_{i=1}^{n}(Q_{i}^{obs} - Q_{i}^{ave})(Q_{i}^{sim} - Q_{i}^{ave})}{\left(\sum_{i=1}^{n}(Q_{i}^{obs} - Q_{i}^{ave})^2 \sum_{i=1}^{n}(Q_{i}^{sim} - Q_{i}^{ave})^2\right)^{1/2}} \right)^2
\]

\[
NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{i}^{obs} - Q_{i}^{sim})^2}{\sum_{i=1}^{n}(Q_{i}^{obs} - Q_{i}^{ave})^2}
\]

\[
RVE = \frac{\sum_{n=1}^{N}(Q_{obs} - Q_{sim})}{\sum_{n=1}^{N}Q_{obs}} \times 100
\]

Where, $Q_{i}^{obs}$ is the average observed value [m$^3$/s], $Q_{i}^{ave}$ is the average observed value of n value, $Q_{i}^{sim}$ is simulated value [m$^3$/s], $Q_{ave}^{sim}$ is average simulated of n value and $n$ is the number of observations.

LULC change impact on streamflow

The evaluation variability of the streamflow due to LULC changes for the study period, two independent simulation runs were conducted on a monthly basis using both 1994 and 2013 LULC maps, keeping other input parameters unchanged. There was streamflow variability for 1994 and 2013 LULC on seasonal flow and streamflow components (surface runoff, lateral flow and groundwater flow) based on the two simulation outputs due to LULC change assessed (Table 1).

RESULTS AND DISCUSSION

Physical characteristics of the catchment

The physiographic characteristics of the catchment, and the correlation result between gauged and ungauged physical characteristics were greater than 0.9 (Douglas et al., 2005). There is a good correlation between each physical characteristic in the sub-catchment. Based on the result, we can conclude that the gauged and ungauged sub-catchments have similar physiographic...
Table 1. Model parameters performance.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Performance ratings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unsatisfactory</td>
</tr>
<tr>
<td>$R^2$</td>
<td>&lt;0.5</td>
</tr>
<tr>
<td>ENS</td>
<td>&lt;0.5</td>
</tr>
<tr>
<td>$\pm$RVE</td>
<td>&gt;25</td>
</tr>
</tbody>
</table>


Table 2. Confusion matrix for the LULC classification of the 2013 map.

<table>
<thead>
<tr>
<th>Reference/ground data 2013</th>
<th>UB</th>
<th>WL</th>
<th>WB</th>
<th>GL</th>
<th>FL</th>
<th>SL</th>
<th>CL</th>
<th>Total</th>
<th>UA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UB</td>
<td>14</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>16</td>
<td>87.5</td>
</tr>
<tr>
<td>WL</td>
<td>0</td>
<td>17</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>18</td>
<td>94.4</td>
</tr>
<tr>
<td>WB</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>87.5</td>
</tr>
<tr>
<td>GL</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>26</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>31</td>
<td>83.9</td>
</tr>
<tr>
<td>FL</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>1</td>
<td>0</td>
<td>12</td>
<td>83.3</td>
<td></td>
</tr>
<tr>
<td>SL</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>48</td>
<td>2</td>
<td>51</td>
<td>94.1</td>
</tr>
<tr>
<td>CL</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>57</td>
<td>59</td>
<td>60</td>
<td>96.6</td>
</tr>
<tr>
<td>Total</td>
<td>16</td>
<td>19</td>
<td>9</td>
<td>28</td>
<td>12</td>
<td>51</td>
<td>60</td>
<td>195</td>
<td></td>
</tr>
</tbody>
</table>

UA: user accuracy, PA: producer accuracy, OA: over all accuracy.

Table 2 shows the overall accuracy is 91.8% and the kappa index agreement (K) is 0.9023. This implies that the classification process is avoiding 90.23% of the errors that completely random classification generates. This means the results of overall accuracy and kappa index coefficient are within the recommended value range (Jenness and Wynne, 2005).

The map of each LULC type and percentage of area coverage of the Chemoga catchment is presented in Figure 8 and Table 3 for 1994 and 2013. Table 3 depicts that, cultivated land is the maximum area coverage both in 1994 and 2013 LULC and showed expansion for cultivated lands. On the other hand, urban land is increased in the change of LULC in the time trend; but water and marshy land is the least LULC cover in both years of LULC. This is mainly because of the population demand increase for new cultivation land which in turn resulted in shrinking of other types of LULC of the area. This is most probably because of the deforestation activities that have taken place for the purpose of agriculture.

LULC analysis

Accuracy assessment of LULC classification was performed using ground truth points for the LULC map of 2013 as a reference. This is done by confusion/error matrix (Fitzgerald and Lees, 1994 and Lark, 1995) and the analysis result is presented in Table 2. Table 2 shows the overall accuracy is 91.8% and the kappa index agreement (K) is 0.9023. This implies that the classification process is avoiding 90.23% of the errors that completely random classification generates. This means the results of overall accuracy and kappa index coefficient are within the recommended value range (Jenness and Wynne, 2005).

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Hydrological modelling on a monthly timescale

For this analysis, 26 parameters were considered and only 8 more sensitive parameters were identified to have a significant influence in controlling the streamflow in the catchment. Table 4 reveals parameters that result in greater relative mean sensitive values for average monthly streamflow data of the catchment.

Generally, the effects of the sensitive parameters are related to groundwater (Alpha_Bf, Revapmn and Gwqmn), surface runoff (CN2, Esco and Canmx) and soil process (Sol_Z and Sol_Awc) and thus influence on the streamflow of the catchment. From the sensitivity result, curve number (CN2) is identified to be highly sensitive parameters and given to high priority for calibration.
Whereas other parameters such as soil evaporation compensation factor (Esco), total soil depth (Sol_Z), baseflow recession constant (Alpha_Bf), maximum canopy storage (canmx), threshold depth of water in the shallow aquifer for revap to occur (Revapmn), soil available water capacity (Sol_Awc), threshold depth of water in the shallow aquifer required for return flow (Gwqmn) are identified to be medium sensitive parameters. The remaining 18 parameters were not considered during the calibration process because the model simulation result was not sensitive parameters in the catchment.

Calibration and validation of streamflow simulation

The simulation of the model with the default value of parameters in the Chemoga catchment was from 1983-2011. SWAT model calibration was performed for 1994 LULC and 2013 LULC separately. There were two years of the warm-up period, 1983-1984 for 1994 LULC and 2002-2003 for 2013 LULC. The calibration covers 1985-1989 and 2004-2007 for 1994 and 2013 LULC respectively. The validation period covers 1990-1993 and 2008-2011 for 2013 LULC. The calibration result showed relatively weak matching between the simulated and
Table 4. Sensitive parameters for streamflow.

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Relative sensitive values</th>
<th>Sensitivity rank</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cn2</td>
<td>0.253</td>
<td>1</td>
<td>High</td>
</tr>
<tr>
<td>Esco</td>
<td>0.193</td>
<td>2</td>
<td>Medium</td>
</tr>
<tr>
<td>Sol_Z</td>
<td>0.151</td>
<td>3</td>
<td>Medium</td>
</tr>
<tr>
<td>Alpha_Bf</td>
<td>0.125</td>
<td>4</td>
<td>Medium</td>
</tr>
<tr>
<td>Canmx</td>
<td>0.111</td>
<td>5</td>
<td>Medium</td>
</tr>
<tr>
<td>Revapmn</td>
<td>0.0968</td>
<td>6</td>
<td>Medium</td>
</tr>
<tr>
<td>Sol_Awc</td>
<td>0.0653</td>
<td>7</td>
<td>Medium</td>
</tr>
<tr>
<td>Gwqmn</td>
<td>0.0606</td>
<td>8</td>
<td>Medium</td>
</tr>
</tbody>
</table>

Table 5. Default and calibrated value of the sensitive flow parameters.

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Parameter value range</th>
<th>Default value</th>
<th>Fitted value</th>
</tr>
</thead>
<tbody>
<tr>
<td>r_Cn2</td>
<td>±25%</td>
<td>default</td>
<td>+13.98%</td>
</tr>
<tr>
<td>v_Esco</td>
<td>0 - 1</td>
<td>0</td>
<td>0.194</td>
</tr>
<tr>
<td>r_Sol_Z</td>
<td>±25%</td>
<td>default</td>
<td>-24.23%</td>
</tr>
<tr>
<td>v_Alpha_Bf</td>
<td>0 - 10</td>
<td>0.048</td>
<td>0.889</td>
</tr>
<tr>
<td>v_Canmx</td>
<td>0 - 500</td>
<td>1</td>
<td>12.25</td>
</tr>
<tr>
<td>r_Sol_Awc</td>
<td>±25%</td>
<td>default</td>
<td>+2.13%</td>
</tr>
<tr>
<td>v_Gwqmn</td>
<td>0 - 5000</td>
<td>0</td>
<td>37.5</td>
</tr>
</tbody>
</table>

*r_ means the existing parameter value is multiplied by 1 + a given value and v_ means the default parameter is replaced by a given value.

Source: SWAT-CUP manual.

observed streamflow hydrographs. Hence, calibration was done for sensitive flow parameters with observed average monthly streamflow data using table and scatter plots (Figure 9 and Table 5).

The performance of the calibration and validation simulations was checked by R², NSE and RVE. The scatter plot of R² reported in Figure 9 and confirms reasonable streamflow results of the model simulation of calibration and validation period for each LULC. On the other hand, in Table 6, ENS and RVE showed the streamflow simulation was well agreed with the observed value for each LULC. This illustrates that further application of the SWAT model to evaluate streamflow for irrigation and other related waterworks in the catchment could have a minimum bias. The agreement between observed and simulated hydrological components is largely dependent on the meteorological, LULC conditions and soil data in the catchment and model assumptions. After calibration, the agreement between observed and simulated discharges is good, under-estimations and over-estimations are inherent in the simulation (Figures 10 and 11). This is because of the fact that the observed discharge and model-simulated flows during the calibration and validation are biased.

Evaluation of stream flow due to LULC change

The evaluation of surface water availability was done in terms of LULC change impact on seasonal (wet and dry) and the major components of streamflow, that is, surface runoff, groundwater flow and lateral flow; the other input (climate, soil and other) variables are the same during the study period.

Based on the result, the LULC change has an impact on the seasonal streamflow of the catchment. The result has shown that there is an increase of streamflow in the wet season and a decrease in the dry season (Baker and Miller, 2013). The evaluation result of the LULC change impact on the major components of streamflows, surface runoff (SurfQ), groundwater flow (GWQ) and lateral flow (LatQ) is given in Table 7. In the main dry season, the streamflow gets the source from groundwater and lateral flow and in the wet season from surface runoff.

Table 8 depicts the SURQ, GWQ and LATQ components of the streamflow simulated using the 1994 LULC map were 52.52, 24.81 and 22.97% while using the 2013 LULC map were 61.98, 22.95 and 15.06% respectively. The contribution of SURQ has increased by 9.46% while GWQ and LATQ have decreased by 1.86
Figure 9. Scatter plot of the calibration and validation periods respectively.

Table 6. Summary of calibrated and validated performance of ENS and RVE.

<table>
<thead>
<tr>
<th>Performance criteria</th>
<th>Calibration 1994 LULC</th>
<th>Calibration 2013 LULC</th>
<th>Validation 1994 LULC</th>
<th>Validation 2013 LULC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENS</td>
<td>0.84</td>
<td>0.82</td>
<td>0.80</td>
<td>0.84</td>
</tr>
<tr>
<td>RVE</td>
<td>-7.53</td>
<td>-2.75</td>
<td>-9.33</td>
<td>-3.23</td>
</tr>
</tbody>
</table>

Figure 10. Streamflow hydrograph of calibration and validation period for 1994 LULC.
and 7.91% respectively due to LULC change. As seen in the result, the streamflow in the dry season decreases, and the decline of water affects the crop grown in the area. To compromise this shortage, water harvesting structures are needed and in the wet season, the flow increases. The result will be high flooding and erode the land surfaces. In such a condition, it is difficult to practice surface irrigation development in the catchment. From this study, it can be understood that the land surface of the catchment needs soil and water conservation practices. In turn, it helps with surface irrigation development. So, generally to improve the hydrology of the Chemoga catchment different watershed management approaches should be implemented.

### Table 7. Mean monthly seasonal (wet and dry) streamflow variability.

<table>
<thead>
<tr>
<th>Main season</th>
<th>1994</th>
<th>2013</th>
<th>Flux detection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main dry season (Nov-Feb) (m³/sec)</td>
<td>5.57</td>
<td>3.06</td>
<td>-2.51</td>
</tr>
<tr>
<td>Main rainy season (Jun-Sep) (m³/sec)</td>
<td>46.95</td>
<td>58.18</td>
<td>+11.23</td>
</tr>
</tbody>
</table>

### Table 8. Mean annual major components of streamflow due to LULCCs.

<table>
<thead>
<tr>
<th>Item</th>
<th>LULCCs_1994</th>
<th>LULCCs_2013</th>
<th>Flux Detection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface runoff SURQ (mm)</td>
<td>322.78</td>
<td>367.50</td>
<td>+44.72</td>
</tr>
<tr>
<td>Groundwater flow GWQ (mm)</td>
<td>153.35</td>
<td>136.09</td>
<td>-17.26</td>
</tr>
<tr>
<td>Lateral soil flow LATQ (mm)</td>
<td>142.00</td>
<td>89.32</td>
<td>-52.68</td>
</tr>
</tbody>
</table>

### Conclusion

The aim of this study is to evaluate the LULC change impact on catchment hydrology. The LULC data were detected using Landsat images from USGS earth explorer. The classified LULC performed on ERDAS imagine supervised classification was integrated with GIS data. The gauged catchment of Chemoga has similar physical characteristics with the whole ungauged catchment. The correlation results of this PCCs depict a value greater than 0.9. From this result, it can be concluded that regionalization of streamflow at the outlet of the catchment using catchment area-ratio method was acceptable. Streamflow was dependent on LULC changes.
changes; hence in Chemoga River catchment it is shown that the LULC change implied a change in the amount of streamflow in the catchment. The streamflow increased in the wet season but decreased in the dry season during the study period due to conversion of forest lands, shrublands and grasslands to cultivation sites. And also increase in cultivated land in wet season increases surface runoff while in dry season lateral and groundwater flow decreases. During the study period, an increase of the cultivated land by 15.14% (17830.3 ha) resulted in an increase in streamflow by 11.23 m3/s in the wet season and a decrease of 2.51 m3/s in the dry season.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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REFERENCES


