Evaluate the Impacts of Land Use/Land Cover Dynamics on Stream Flow of Gelda Watershed, Upper Blue Nile Basin, Ethiopia

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Abstract: This study evaluates the impact of land use/land cover change dynamics on Gelda stream using SWAT and SWAT-CUP models in Gelda watershed. Environment for visualizing images (ENVI) and Arc GIS were used to generate land use land cover maps from Landsat TM, ETM+, and OLI/TIRS developed in 1984, 2000, and 2016, respectively. The land cover maps were generated using the Maximum Likelihood Algorithm of Supervised Classification. Change detection was done by using ENVI 5.1 software. During this study, most parts of the grazing land and vegetative covers were changed to agricultural land (14.32%). An increase of agricultural land by 32.23 % from 1984- 2016 resulted in a change of stream flow. In the change detection analysis from this study between 1984 and 2016, the sum of forest, bush, and grazing lands were significantly changed to agricultural land by 32.77% whereas the sum of the forest, bush, and grazing lands were changed to built-up area by 1.14 %. The Model calibration and validation for stream flow were done for 20 (1987-2006) and 10 (2007-2016) years without warm up period respectively. The monthly calibration and validation results showed that a very good agreement between measured and simulated flow with R2 of 0.86, NSE of 0.81 and PBIAS of 0.08 for calibration, and R2 of 0.88, NSE of 0.78, and PBIAS of 0.11 for validation. The analysis indicated that, the stream flow during the wet months has increased, while the flow during the dry months has decreased. The surface runoff increased, while groundwater flow de-creased from the year 1984-2016. The model results showed that the stream flow characteristics was changed due to the land use land cover change during the study periods from1984-2016.
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Key words: CFSR data, SWAT, SWAT-CUP, LULCC, Calibration, and validation

1 Introduction

Land use /land cover change is straightforwardly linked to the dynamics of human activities. Land use/land cover dynamics modify the availability of different resources including vegetation, soil, water (Ahmadizadeh, 2014). Changes in land use/land cover alter both runoff behaviour and the balance that exists between evapotranspiration, groundwater recharge and stream discharge in specific areas and in entire watersheds, with considerable consequence for all water users. The LULC during the past three decades are mostly linked to agricultural development attributed to population pressure and environmental changes (Akpoti et al., 2016).

The current trends in land use land cover must be improved, toward the resource management and conservation of the existing vegetation and other natural resources. These should be done in teamwork with all stakeholders for effective management of natural resources (Asres et al., 2016). This type of study aimed to evaluate the impact of land use land cover on the hydrologic features of a watershed (Briones et al., 2016). Real change and final change were analysed to determine the values of LU changes and their hydrological consequences on watershed (Zhang et al., 2014).

The main objective of this study is to evaluate the effect of land use-land cover dynamics on the Hydrology of Gelda watershed. Therefore, this paper attempts to assess land use and land cover changes, quantify the major land use-land cover changes and assess the effect of land use land cover change on the hydrology of Gelda watershed in the past 33 years (1984-2016).

2. Methodology

2.1 Study Area Description

Gelda watershed is one of the sub basins in the Lake Tana basin and far from Bahir Dar town by 36 km in the east direction and it is located at Latitude 11.64°N and 11.71°N, and longitude 37.69°E and 37.61°E (Figure 1). The study area covers approximately 4,479.43 ha (44.8 km^2) and the elevation of this watershed ranges from 2005m to 2478m above mean sea level. Based on observed data, the average annual minimum and maximum temperatures of the study area are 7.80°C and 29.79°C respectively whereas the average annual rainfall ranges from 1201-1497 mm. This study area has three major soil types namely; Nitosols (7.5%), Luvisols (25.5%) and Vertisols (67.0%) with their physical and chemical properties.

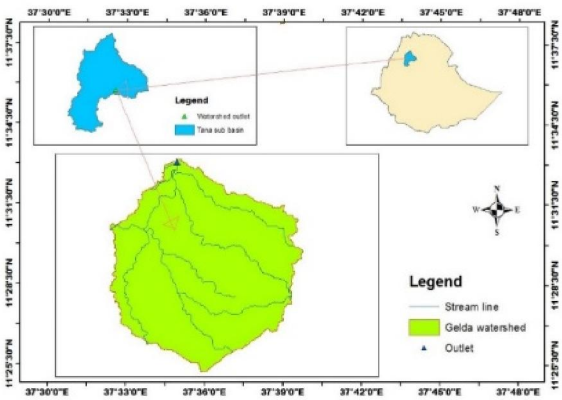

Fig. 1. Location of the study area map

2.2 Image preprocessing and Classification

Cloud-free Landsat images were selected to classify the study area. The images were Landsat-5 TM image for 1984, Landsat-7 ETM+image for 2000 and Landsat-7 OLI/TIRS image for 2016. All images were rectified to UTM Zone 37N, WGS1984 using well distributed ground control points. The satellite images pre-processing before any analysis is very important in order to establish more direct relationship between the acquired data and biophysical phenomena (Hassan et al., 2016). Radiometric calibration and Atmospheric correction were done to avoid radiometric errors and avoid absorption and scattering of solar radiation from an object respectively.

The land use land cover classification was done using Environment for Visualizing images (ENVI5.1) integrating with Arc GIS 10.4.1 under supervised classification, Maximum Likelihood is more preferable and used in this study. The supervised classification involved the selection of a number of known sites for each image.

2.3 Images Classification Accuracy Assessment

The objective of Accuracy Assessment for Classified Images is to determine quantitatively how pixels were grouped successfully in to the correct feature classes (Manandhar et al., 2009). To assess the classification accuracy, confusion matrix was used including (91, 107, and 115) ground control points and used to validate the classified image for each image and checked by Google earth. From this error matrix, a number of accuracy measures; overall accuracy, user's accuracy, and producer's accuracy were determined (Valiquette et al., 1994). In addition, the kappa statistics is used for the accuracy assessment. The Kappa statistic incorporates the diagonal elements of the error matrices (i.e., classification errors) and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance. Kappa value lies between -1 and 1, where -1 represents no agreement at all whereas 1 indicates a perfect agreement. $K = (P_o - P_e)/(1 - P_e)$, where; P_o proportion of correct agreements and Pe proportion of expected agreement.

2.4 Change detection analysis

Next to the, the post-classification, change detection statistics were computed by comparing values of area of one data set with the corresponding value of the second data set in each period. The method used for LULC change detection in this study is the comparison statistics. Percentage area for each land cover classes were derived from the classified images for each year (1984, 2000, and 2016) separately using ENVI 5.1. The change detection between 1984 and 2000, 2000 and 2016, and finally 1984 and 2016 images were done. But in order to get a significant change, the time between 1984 and 2016 was selected in 33 years.

2.5 Climate Forecast System Reanalysis (CFSR) Data

Correctly representing weather data is critical to hydrological modeling, but poor quality observations can often compromise model accuracy (Zhang et al., 2012). CFSR datasets help to address this basic challenge. The CFSR dataset provides continuous, globally available records. However, the use of CFSR data for hydrological modeling in tropical and semi-tropical basins has not been adequately evaluated (Fuka et al., 2014). In this study, some techniques were used to use CFSR data as follows.

1. Adding both local and CFSR data on the GIS interface using their longitude, latitude, and elevation. In this step we can identify which CFSR rainfall stations are near to or far from the study area.
2. making a linear relationship between each local station with respect to coefficient of determination (R^2) between CFSR and observed RF data and developing correlation equations for each station like $Y=\alpha x \pm b$ where y is observed rainfall data, α is coefficient of CFSR rainfall data, x is CFSR data and b is the intercept. Finally converting the CFSR data into observed data by using the developed correlation equation.
3. Making Thiessen polygon on the GIS interface to select the most dominant RF stations to the watershed. This polygon defines an area of influence around its sample point, and any location inside the polygon is closer to the other sample points.

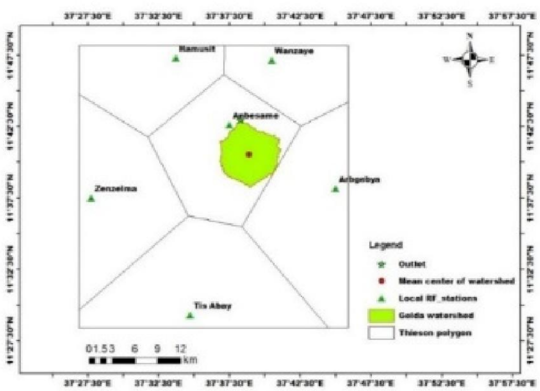

Fig. 2. Thiessen polygons of rain fall stations

4. Measuring the Arial distances starting from the mean center of the watershed. In this step, Anbesame and Arbgebeya are better (nearer) than the others to the watershed. Due to this topographical location, Arbgebeya station has its own influence on the stream flow on the watershed.

5. Taking the selected nearest stations depend on their distance from the mean center of the watershed and topographic conditions of the watershed.

6. Making long term annual mean rainfall for both selected stations from 2008-2014 based on observed and CFSR Rainfall data and then developing conversion factor (c). Arbgebeya Rainfall station is far from the watershed but located in the upper part of the watershed and this influence on stream flow of Gelda River (Table 2).

Table 1. Distances of each Rainfall station from the center of Gelda watershed

Station Name	Distance (km) from the centre	Remark
Anbesame	4.48	Selected
Arbgebeya	12.04	Selected
Wanzaye	12.50	Not Selected
Hamusit	15.50	Not Selected
Zenzelma	21.40	Not Selected
Tis Abay	22.30	Not Selected

Table 2. Long term annual mean rainfall values from 2008-2014 for both observed & CFSR data

Station	Mean Annual Observed data	Mean Annual CFSR data	$C=\frac{\text{Observed data}}{\text{CFSR data}}$
Anbesame	1396.25	1478.48	0.9444
Arbgebeya	1437.50	1536.85	0.9354

7. In order to characterize the Gelda watershed in rainfall, an average value of the two nearest stations to the watershed have to be calculated because their Conversion factors are almost close to each other (Table 2) that means, Gelda watershed daily rainfall value = ((Anbesame RF+Arbgebeya RF))/2. For this study, applying the averaged values of the two rainfall stations to the watershed and preparing this averaged daily RF data for SWAT model as an input in the form of data base form (dbf). Then run the model (simulation) using this converted CFSR rainfall data followed by calibration and validation on SWAT and SWAT-CUP models respectively.

2.6 Consistency checking using Double Mass curve

Double Mass Curve (DMC) analysis is the method that used to check consistency of rainfall as well as flow for adjustment of inconsistent data. The inconsistency data series must be adjusted to consistent values using proportionality equation:

$$\text{Proportionality} = \frac{\text{slope of orginal line}}{\text{slope of deviated line}}$$

The DMC plot shows (Figure 3) two of stations that found around the Gelda watershed has better correlation because plot of cumulative annual rainfall of neighbouring versus each station are align on a single straight line.

2.7 Homogeneity checking using Rainbow software

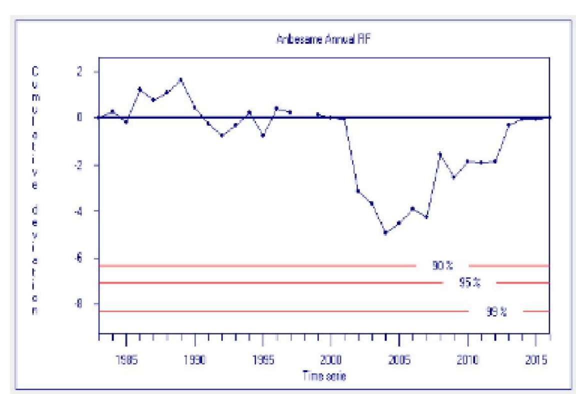

Fig. 3. Anbesame homogeneity test

The homogeneity of the data of a time series was tested by evaluating the maximum and the range of the cumulative deviations from the mean. In this study, Anbesame RF station, Arbgebeya RF station and Gelda stream flow gauge were homogeneous at 90%, 95% and 99% probability, respectively (Figure 4,5, and 6).

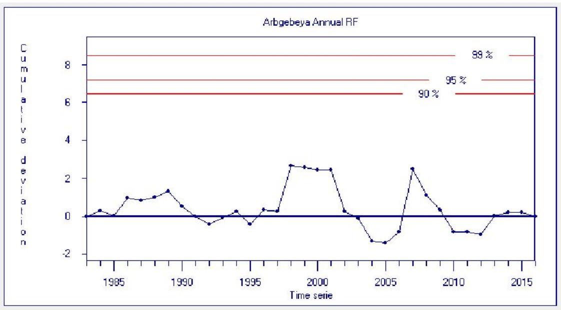

Fig. 4. Arbgebeya RF homogeneity test

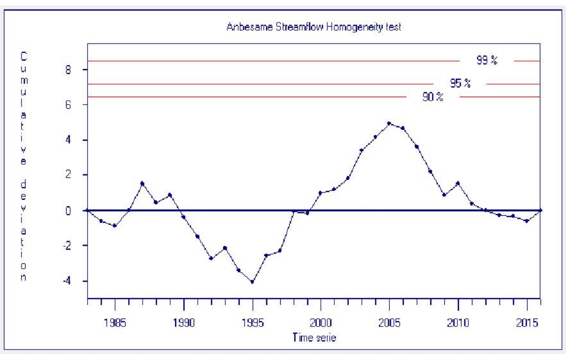

Fig. 5. stream flow homogeneity test

2.8 Soil and Water Assessment Tool Model

In the SWAT model, there are two options in defining HRU definition: assign a single HRU to each sub watershed or assign multiple HRUs to each sub watershed based on a certain threshold value. The SWAT user's manual Winchell et al. (2007) suggests that a 20 % land use threshold, 10 % soil threshold and 20 % slope threshold are adequate for most modeling application. Therefore, for this study, HRU definition with multiple options that accounts for 20% land use, 10% soil and 20% slope threshold combination was used. These threshold values indicate that land uses which form at least 20% of the sub watershed area and soils which form at least 10% of the area within each of the selected land uses were considered in Hydrologic Response Units.

SWAT requires daily precipitation, air temperature, solar radiation, wind speed, and relative humidity. These data will be generated in two cases: when the user specifies that simulated weather will be used or when measured data is missing (Rajawatta et al., 2014). In this study area, there is a lack of full and realistic long period of climatic data. The daily values of all climatic variables from CFSR data were used instead of measured data. This study used these CFSR data for all climatic variables obtained from https://globalweather.tamu.edu/ for the stations around Gelda watershed. For weather generator data definition, the weather generator data file in data base form (dbf) was selected first. Then, rainfall, temperature, relative humidity, solar radiation and wind speed data were selected and added to the model respectively.

2.9 Sensitivity analysis, calibration and validation in the SWAT-CUP model

A sensitivity analysis is needed to determine the most sensitive parameters in the basin for the calibration and validation process and also helps to understand the model's behavior and the predominant processes (Narsimlu et al., 2015).

The calibration was performed based on the parameters and the following objectives: a good agreement between the averages simulated and observed catchment runoff volume, a good overall agreement of shape of the hydrograph, and a good agreement for peak flow and low flow with respect to timing, rate and volume. To fulfil these objectives, the Sequential Uncertainty Fitting (SUFI-2) model for optimization and uncertainties analysis was used in the SWAT-CUP for calibration and validation. The Nash-Sutcliff (NS) coefficient was assigned as the objective function. In SUFI-2, a parameter uncertainty was propagated as uniform distribution through a statistical method for generating a sample of reasonable collections of parameter values from sampling. It is referred to as the 95% representing prediction uncertainty (95PPU) (known as P-factor) calculated at 2.5% and 97.5% levels for each parameter. The 95PPU is the degree to which all uncertainties are accounted.

2.10 Model Performance Evaluation

Calibration and validation results indicate that SWAT model is an effective watershed management tool that can be run with available data. For this study three objective functions have been used to measure the overall fit between the observed and predicted stream flow by SWAT model as described below.

Percent of Bias (PBIAS): - As a general rule given by Moriasi et al. (2007), a PBIAS of 10% or less is considered very good, between ±10% and ±15% is good, and between ±15 and ±25% is satisfactory whereas values greater than 25% indicate an" unsatisfactory" model simulation. The optimal value of PBIAS is zero. A positive PBIAS value indicates the model is under-predicting whereas negative values indicate over-predicting using the equation:

$$\text{PBIAS}=\frac{\sum_{i=1}^{n}(Q_{obs}-Q_{sim})}{\sum_{i=1}^{n}(Q_{obs})}*100$$

Where; "Qsim" is the simulated flow and "Qobs" is the observed flow.

Coefficient of Determination (R^2):- R^2 ranges from 0 (indicates the model is poor) to 1 (indicates the model is good), with higher values indicating less error variance, and typical values greater than 0.6 are considered acceptable (Bonumá et al., 2015). The R^2 is calculated as using the equation:

$$R^2 = \frac{\left(\sum(X_i - X_{av})(Y_i - Y_{av})\right)^2}{\sum(X_i - X_{av})^2 \sum(Y_i - Y_{av})^2}$$

Where, Xi-measured value, Xav- average measured value, Yi- simulated value and Yav- average simulated value in (m^3/s).

Nash-Sutcliffe Efficiency (NSE): - The value of NSE ranges from negative infinity to 1 (best) i.e., (-∞, 1]. NSE value < 0.5 indicates the mean observed value is better predictor than the simulated value, which indicates unacceptable performance while NSE values greater than 0.5, the simulated value is better predictor than mean measured value and generally viewed as acceptable performance. The NSE indicates that how well the plots of observed versus simulated data fits the 1:1 line and computed using the equation:

$$NSE = 1 - \frac{\sum(\text{observed value} - \text{simulated value})^2}{\sum(\text{observed value} - \text{average observed value})^2}$$

2.11 Evaluation of Stream Flow due to Land Use Land Cover Change

Simulation of the impacts of land use/land cover change on Gelda stream flow was one of the most significant parts of this study. There was a high expansion of cultivated lands in the expenses of forest, bush, and grazing lands during the study periods considered. To evaluate the variability of stream flow due to land use/land cover change from 1984 to 2016, three independent simulation runs were conducted on a yearly basis using all land use/land cover maps for the period of 1984-2016 keeping other input parameters unchanged. Seasonal stream flow variability of 1984, 2000 and 2016 due to the land use/land cover change was assessed and comparison were made on stream flow contributions based on observed stream flow data, and surface runoff & ground water flow contributions to stream flow based on the simulation outputs using SWAT Viewer.

3. Results And Discussion

3.1 Accuracy Assessment Using Confusion matrixes

To assess the classification accuracy, confusion matrix was used including overall, user's and producer's accuracies. A classification is not complete until its accuracy is assessed using the known Kappa statistics (Forkuor and Cofie, 2011). In this study, the confusion matrix was used ground control points (91,107,115 for 1984, 2000 and 2016 images, respectively) to validate the classified images in each period in addition to unchanged ground control points from1984 to 2016.

The overall accuracies for 1984, 2000, and 2016 were, 81.3%, 83.2%, and 90.4%, with Kappa statistics of 73.0%, 76.1%, and 87.2% and User's and producer's accuracies of individual classes were also consistently high, ranging from 66.7% to 92.9% and 75.0% to 96.0%, respectively (Table 3).

Table 3. Accuracy assessment from 1984 to 2016

Year	O.A Accuracy	User's Accuracy	Producer's Accuracy	Kappa coefficient
1984	81.3%	66.7-92.9%	75.0-92.9%	73.0%
2000	83.2%	76.5-95.5%	76.5-88.9%	76.1%
2016	90.4%	83.3-96.4%	84.2-96.0%	87.2%

3.2 Land Use and Land Cover Maps

Based on the information from field survey; Forest land, bush land, grazing land, agricultural land and built up were the major land use land cover classes of Gelda watershed. Land-cover conversions are measured by a shift from one land-cover category to another, as it is the case in agricultural expansion, deforestation, or change in urban extent. After relevant bands selected, falls color composite were considered for layer stacking, Red, Green and Blue (RGB) bands 3, 2, 1 for both 1984 and 2000 images and 4, 3, 2 for 2016 images were combined to make conventional color composite images before any classification is done each year as follows.

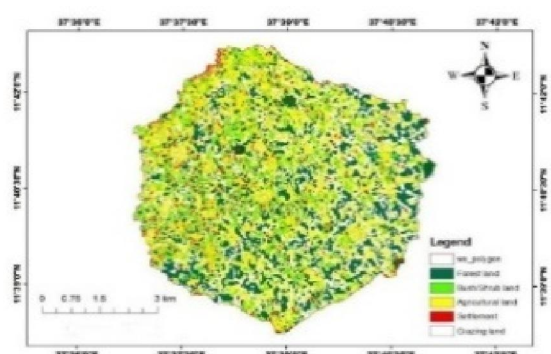

Fig. 6. Gelda Land cover map of 1984

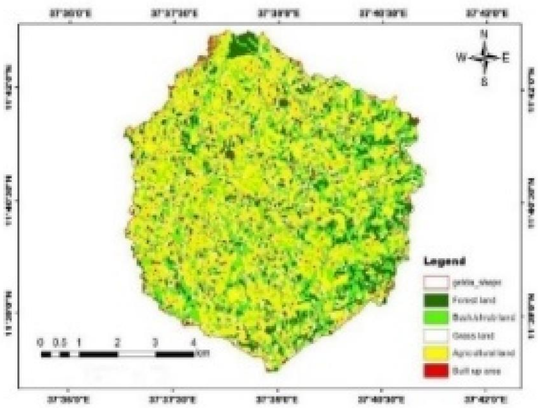

Fig. 7. Gelda Land cover map of 2000

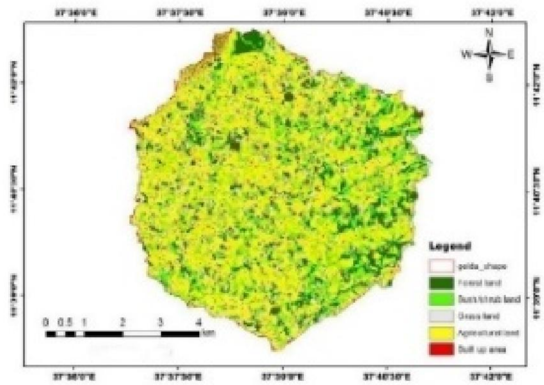

Fig. 8. Gelda Land cover map of 2016

Table 4. Summaries of land cover classes fromb1984 -2016

	1984		2000		2016	
LU classes	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Forest land	738.83	16.49	612.32	13.67	376.16	8.40
Bush/shrub land	1020.42	22.78	693.78	15.49	548.64	12.25
Grazing land	1064.62	23.77	752.64	16.80	397.42	8.87
Agricultural land	1640.84	36.63	2384.43	53.23	3084.49	68.86
Built up Area	14.72	0.33	36.26	0.81	72.72	1.62
Total	4479.43	100.00	4479.43	100.00	4479.43	100.00

From this study, there has been a significant land use/land cover change in the watershed where the agricultural land increased from 36.63-68.86 % (1984-2016) and the built-up area also increased from 0.33-1.62 % (1984-2016) in 33 years at the expense of forest, bush, and grazing lands. This could be attributed to the increase in population that has increased the demand for agriculture. The forest land was decreased from 16.49%-8.40 % (1984-2016). The bush land was decreased from 22.78 %-12.25 % (1984-2016) and the Grazing land was decreased from 23.77-8.87 % (1984-2016). This land use/land cover change may have effect on the hydrology of the Gelda catchment.

3.3 Rate of land use/land cover change

The magnitude of change is the degree of expansion or reduction in the land use/land cover changes size. A negative value represents a decreasing land use/land cover sizes/values while a positive value indicates an increasing land use/land cover sizes/values (Mahmud and Achide, 2012). The percentage change values between 1984-2000, 2000-2016, and 1984-2016 from their initial (original) value and final value were calculated and described in Table 7 using the following equation: R=(FV-IV) *100/FV. Where; R is the percentage rate (change) value between the two years, IV is the initial (referenced) year (1984 and 2000) value and FV is the final years (2000 and 2016) and/ (1984 and 2016) values.

Table 5. Summary of LULC class rates from their original size

LULC type	Rate (1984-2000)		Rate (2000-2016)		Rate (1984-2016)	
	area	%	area	%	area	%
Forest land	-126.51	-17.12	-236.16	-38.57	-362.67	-49.09
Bush/shrub land	-326.64	-32.01	-145.14	-20.92	-471.78	-46.23
Grazing land	-311.98	-29.30	-355.22	-47.20	-667.20	-62.67
Agricultural land	743.59	31.19	700.06	22.70	1443.65	46.80
Built up area	21.54	59.40	36.46	50.14	58.00	79.76

From this study, the agricultural land rated by 46.8 % from 36.63 % in 1984 to 68.86 % in 2016 and the built up area also rated by 79.8 % from 0.33 % in 1984 to 1.62 % in 2016 in 33 years at the expense of forest, bush, and grazing land whereas the forest land was adversely rated by 49.1 % from 16.49 % in 1984 to 8.40 % in 2016, the Grazing land was also adversely rated by 62.7 % from 23.77 % in 1984 to 8.87 % in 2016, and the bush land was adversely rated at the same time by 46.2 % from 22.78 % in 1984 to 12.25 % in 2016 from their original size in 1984 and final size in 2016 (Table 4 and Table 5). This land use and land cover change may have effect on the hydrology of the catchment (Gelda watershed at Gelda River).

3.4 Change Detection Analysis

In order to determine the quantity of conversions from a particular land cover to another land cover category and their corresponding area over the evaluated period, the land use/land cover change detection based on remote sensing images have been widely applied in this research for LU/LC change, natural resource management and environment monitoring & protection (Zhang et al., 2014). In this study, the land use/land cover change detection statistics was done using ENVI 5.1 software. In order to get and show a significant change, the time between 1984 and 2016 was done in 33 years (Figure 10 and Table 6).

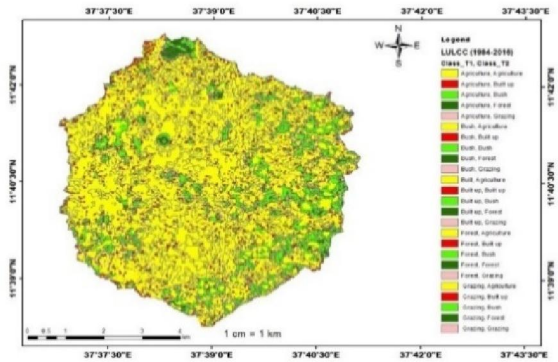

Fig. 9. Change detection analyses between 1984 and 2016

Table 6. Change detection analyses between 1984 and 2016

Class_1984	Class_2016	Area (Ha)	(%)	Class_1984	Class_2016	Area (Ha)	(%)
Agriculture	Agriculture	1613.84	36.03	Built up	Forest	0.64	0.01
Agriculture	Built up	11.81	0.26	Built up	Grazing	0.62	0.01
Agriculture	Bush	4.63	0.10	Forest	Agriculture	346.59	7.74
Agriculture	Forest	3.58	0.08	Forest	Built up	4.85	0.11
Agriculture	Grazing	5.72	0.13	Forest	Bush	18.86	0.42
Bush	Agriculture	479.76	10.71	Forest	Forest	359.67	8.03
Bush	Built up	18.92	0.42	Forest	Grazing	7.66	0.17
Bush	Bush	510.78	11.40	Grazing	Agriculture	641.67	14.32
Bush	Forest	7.84	0.18	Grazing	Built up	27.42	0.61
Bush	Grazing	3.84	0.09	Grazing	Bush	13.46	0.30
Built up	Agriculture	2.62	0.06	Grazing	Forest	4.52	0.10
Built up	Built up	9.72	0.22	Grazing	Grazing	379.20	8.47
Built up	Bush	1.17	0.03				
Total						4479.43	100.00

From this study in the selected period 1984 to 2016, the sum of forest land (7.74%), bush land (10.71%), and grazing land (14.32%) were significantly changed to agricultural land by 32.8 % whereas the sum of the forest land (0.11 %), bush land (0.42 %), and grazing land (0.61 %) were changed slightly to built-up area by 1.14 % due to increase in population size and expansion of their demands on relevant infrastructures and others and also the Built-up area slightly changed to forest land (0.01%), bush land (0.03%), grazing land (0.01%) and Agricultural land (0.06%) due to dynamic human activities like shifting of settlement area from their original piece of land to another one. In general; this result due to land use/land cover change may have effect on the hydrology of the catchment and alarming to the society that they are living in and around the watershed (Fig. 10 and Table 6).

3.5 Sensitivity Analysis, Calibration and Validation

3.5.1. Sensitivity Analysis

The sensitivity analysis was needed to determine the most sensitive parameters in the Gelda watershed for the calibration process using simultaneous analysis method. In this analysis for this study, varying and adjusting all parameter minimum and maximum values at the same time before running. After 50 to 1000 iterations were done, ten most sensitive parameters were selected and used during the calibration as well as validation process including Parameter sensitivity ranks (Table 7).

Table 7. Final Parameter sensitivity analyses and their rank

Parameter Name	t-Stat	P-Value	Fitted Value	Min. value	Max. value	Sensi. rank
R__CN2.mgt	-5.35	0.00	0.05	-0.20	0.20	1
V__GW_DELAY.gw	-1.89	0.06	158.10	30.00	450.00	2
R__SOL_AWC (1).sol	1.88	0.07	-0.54	-1.00	1.00	3
V__ALPHA_BF.gw	-1.80	0.07	0.11	0.00	1.00	4
V__ESCO.hru	1.09	0.28	58.29	-1.00	100.00	5
V__REVAPMN.gw	0.93	0.35	4545.00	0.00	5000.00	6
V__RCHRG_DP.gw	-0.82	0.41	76.33	10.00	100.00	7
V__GWQMN.gw	-0.70	0.49	0.66	0.00	2.00	8
V__GW_REVAP.gw	-0.63	0.53	82.09	10.00	100.00	9
V__CH_K2.rte	-0.25	0.80	8.32	1.00	20.00	10

r_, means the existing parameter value which is multiplied by (1+a given value), v_, means the default parameter value which is replaced by a given value, a_, means a given quantity that is added to the default value (Sellami et al., 2014). Table 7 gave the summary of the most sensitive parameters; their final range given by the last iteration in SUFI-2, the fitted values and the sensitivity rank. Parameter ranking is based on the t-stat and the p-value in the SUFI-2 program. T-test gave a measure of the sensitivity that means the larger the t-stat in absolute value, the more sensitive the parameter is while the p-value determined the significance of the sensitivity and P-values closed to zero are more sensitive that means the smaller the p-value, the more sensitive the parameter is (Abbaspour, 2013).

3.5.2. Calibration and Validation

Next to sensitivity analysis, model calibration was done by adjusting minimum and maximum values of each parameter, more iteration was done to fit good simulation. Calibration covers two third of the total sample data. In this study, there was 33 stream flow sample data (1984-2016) then the calibration covers 20 years starting from the year 1987-2006. Validation was also done without adjusting the minimum and maximum value of each parameter and covers one third of the total sample data. In this study, the validation covers 10 years from the year 2007-2016.

3.5.2.1. Average Monthly Calibration and Validation

Average Monthly Calibration: the average monthly calibration (Figure 11) showed that, the percentage bias is 0.08, the objective function which is the Nash-Sutcliffe coefficient (NSE) is 0.81 and the goodness of fit between the measured and the simulated coefficient of determination (R2) is also 0.86. The result of calibration for monthly stream flow showed that, there is a good agreement between the measured and simulated average monthly flows.

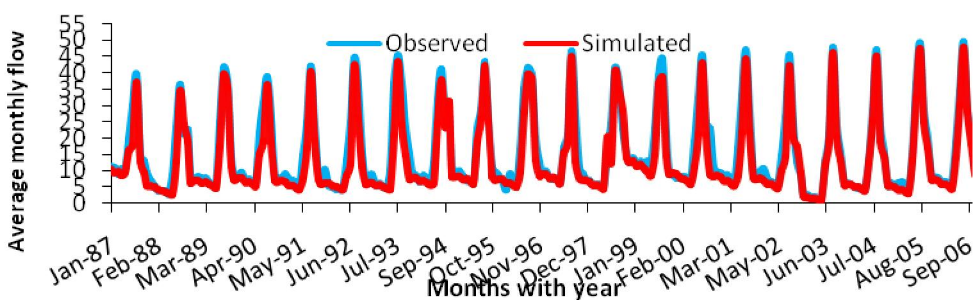

Fig. 10. The result of calibration for average monthly stream flows

Average Monthly Validation: The average monthly Validation (Figure 12) showed that, the percentage bias is 0.11, the Nash-Sutcliffe coefficient (NSE) is 0.78 while the goodness of fit between the measured and the simulated coefficient of determination (R2) is also 0.88. The result showed the good agreement of simulated and observed Average monthly flow.

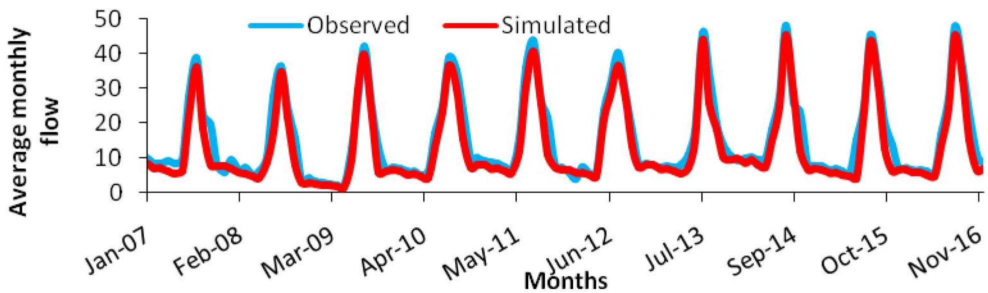

Fig. 11. Average monthly validations for stream flows

The above hydrographs (figures 11 and figure 12), showed the under prediction of the model (because observed stream flow values are greater than simulated one) and the difference between observed. This could be due to the missing data technique that was nearby station method on flow data type.

Table 8. Summary of Calibrated and validated values

Model Evaluator	Calibration		Validation	
	Daily	Monthly	Daily	Monthly
PBIAS	12%	8%	14%	11%
NSE	75%	81%	72%	78%
R^2	79%	86%	76%	88%

3.6 Evaluation of Stream Flow due to LU/LC Change dynamics (1984-2016)

After calibration and validation of the model, evaluation of stream flow was done to quantify the variability of stream flow due to the change of land use/land covers. There was high expansion of cultivated land in the expenses of forest; bush and grazing lands during the study periods were considered. The evaluation was done in terms of the impact of land use and land cover changes on the seasonal stream flow and variations on the major components of stream flow including surface runoff, and groundwater flow during from1984 to 2016. Land use/land cover has a great influence on the rainfall-runoff process due to forest and bush land covers reduction followed by infiltration and percolation reduction. This influence causes raise of run off in wet season and reduces stream flow in dry seasons.

To evaluate the variability of stream flow due to land use/land cover change from 1984 to 2016, three independent simulation runs were conducted on a yearly basis keeping the most sensitive input parameters unchanged. Seasonal stream flow variability of 1984, 2000 and 2016 due to the land use/land cover change was assessed and comparison were made on stream flow based on observed data, and both surface runoff and ground water flow contributions to stream flow were based on SWAT output data after simulation using SWAT viewer. An observed inputs and outputs were compared and the flow was changed during the wettest months of stream flow taken as (June-September) and the driest stream flow were considered in the months of (January-April) were calculated and used as indicators to estimate the effect of land use/land cover change on Gelda stream flow. This evaluation was mainly done on seasonal stream flow, annual surface runoff (SURQ), and annual ground water flow (GWQ) independently.

3.6.1. Change evaluation in Seasonal Stream flow

Table 9. Mean seasonal wet and dry stream flow and their variability

Different years of LU	Mean Seasonal flow (m^3/s)		Changes (m^3/s)			
	Wet months (Jun-Sept)	Dry months (Jan- Apr)	Wet	Percent	Dry	Percent
LULC map of 1984	64.36	3.18	-	-	-	-
LULC map of 2000	92.42	2.23	28.06	43.6%	-0.95	-29.87%
LULC map of 2016	128.68	1.07	36.26	39.23%	-1.16	-52.02%

*The negative (-) sign indicates the decreased values

Based on the observed data, the mean seasonal stream flow for wet months had increased from 64.36 to 92.42 m3/s by 43.6% from 1984 to 2000 and from 92.42 to 128.68 m3/s by 39.2 % from 2000 to 2016 due to reduction of forest and bush covers on the watershed and this allows high runoff in wet season whereas the mean seasonal stream flow for dry season had decreased from 3.18 to 2.23 m3/s by 29.9 % from 1984 to 2000 and 2.23 to 1.07 m3/s by 52.0% from 2000 to 2016 during the 1984 to 2016 periods due to increase in temperature and evapotranspiration related with forest and bush cover reduction on and around the watershed. This may have adversely resulted on stream flow reduction in dry months. Generally; the rate of stream flow has increased in wet season from 1984 to 2016 by 64.32m3/s (50 %) while the rate of stream flow has reduced in dry season from the period 1984 to 2016 by 2.11m3/s (66.4%). These two results may have alarm to all stockholders in the study area (Table 9).

3.6. 2. Change evaluation in annual Surface Runoff and ground water flow

Change evaluation analysis was made on the surface runoff (SURQ) and ground water flow (GWQ). Table 12 describes the SURQ and GWQ of the stream simulated using 1984, 2000 and 2016 land use/land cover maps for each period annually. These values were calculated from the SWAT outputs (simulations) using SWAT Viewer software on annual basis for the selected years 1984, 2000, and 2016, respectively.

Table 10**.** Annual SURQ and GWQ of the stream from simulated values

D/t years of LU	SURQ (mm)	GWQ (mm)	Change			
			SURQ (mm)	Percent	GWQ (mm)	Percent
LULC map of 1984	241.54	68.47	-	-	-	-
LULC map of 2000	318.12	51.21	76.58	24.10%	-17.26	-25.2%
LULC map of 2016	436.89	30.58	118.77	27.20%	-21.63	-40.3%

*The negative (-) sign indicates the decreased values

The SWAT output shows that, the contribution of surface runoff has increased from 241.54 to 318.12 mm from 1984 to 2000 by 24.1 %, and from 318.12 to 436.89 mm by 27.2 % from 2000 to 2016 due to expansion of deforestation, expansion of built up area, and increase in soil compactness whereas the ground water flow has decreased from 68.47 to 51.21 mm by 25.2 % from 1984 to 2000 and from 51.21 to 30.58 mm by 40.3 % from 2000 to 2016. These results were created due to decrease in infiltration followed by percolation, increase in surface runoff, increase in legal/illegal abstraction of ground water, and others gradually occurred in the year between 1984 and 2016. The rate of groundwater flow has decreased from 1984 to 2016 by 37.89 mm (55.3%) whereas the surface runoff has increased by 195.35mm (44.7%). These results may have alarm to all stakeholders in and around the Gelda watershed.

Generally, the hydrological investigation with respect to the land use/land cover change within Gelda watershed showed that the flow characteristics have changed significantly, with increase in surface flow (during wet season) and reduce base flow (in dry season) during this study period from 1984 to 2016 over 33 years.

4. Conclusions

This study has addressed the impact of LULC change on Gelda watershed over 33 years using Landsat images. The classification of LULC were performed and also the stream flow calibration and validation were done This study showed that LULC change in Gelda watershed from the period1984 to 2016 were identified from satellite images. The LULC maps of the year 1984, 2000 and 2016 were prepared and the accuracy assessments of these three maps were checked using the confusion matrix. On the other hand, sensitivity analysis, calibration, validation and evaluation of model performance were performed on the selected models (Arc SWAT and SWAT-CUP).

From the LULC change analysis, it can be concluded that the LULC of the Gelda watershed for the period of 1984 to 2016 showed significantly changed. Agricultural land was extremely changed from 36.63 % to 68.86 % (1984-2016). The expansion of agricultural land and small town have an impact on the reductions of forest and bush lands. Thus, the forest land decreased from 16.49 % to 8.40 % (1984-2016). Cultivated and built up areas increased from 36.63 % to 68.86% and 0.33% to 1.62% (1984-2016), respectively in the last 33 years.

In the change detection analysis from this study between 1984 and 2016, the sum of forest, bush, and grazing lands were significantly changed to agricultural land by 32.77% whereas the sum of the forest, bush, and grazing lands were changed slightly to built-up area by 1.14 % due to increase in population size and expansion of their demands on relevant infrastructures and others. This result due to LULC change may have effect on the hydrology of the Gelda catchment and alarming to all stakeholders.

The sensitivity analysis using SWAT-CUP model was identified ten most sensitive parameters that control the stream flow of the studied watershed. The daily model performance was done with PBIAS, NSE, and R2 of 0.12, 0.75, and 0.79 values for calibration, respectively and 0.14, 0.72, and 0.76 for validation, respectively. Monthly model Performance for both calibration and validation were done with objective functions of PBIAS, NSE, and the coefficient of R2 values of 0.08, 0.81, and 0.86 for calibration, and 0.11, 0.78, and 0.88 for validation, respectively.

LULC changes recognized to have major impacts on hydrological processes, such as stream flow, surface runoff, and groundwater flow. The result of the model for all land use/land covers (1984, 2000 and 2016) indicated that:

- The mean seasonal stream flow for all LULC maps were rated by 50.4% in wet seasons whereas in dry seasons, rated by 65.6% from 1984 to 2016.
- The annual surface runoff for all LULC maps was rated by 44.6% whereas the annual ground water flow was rated by55.1% from 1984 to 2016.

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References

1. Ahmadizadeh, S., Land use change detection using remote sensing and artificial neural network: Application to Birjand, Iran. Computational Ecology and Software, 2014. 4(4): p. 276.
2. Akpoti, K., E.O. Antwi, and A.T. Kabo-bah, Impacts of rainfall variability, land use and land cover change on stream flow of the black Volta Basin, West Africa. Hydrology, 2016. 3(3): p. 26.
3. Asres, R.S., et al., Analyses of land use/land cover change dynamics in the upland watersheds of Upper Blue Nile Basin, in Landscape Dynamics, Soils and Hydrological Processes in Varied Climates. 2016, Springer. p. 73-91.
4. Briones, R.U., V.B. Ella, and N.C. Bantayan, Hydrologic impact evaluation of land use and land cover change in Palico watershed, Batangas, Philippines using the SWAT model. Journal of Environmental Science and Management, 2016. 19(1).
5. Zhang, T., et al., An analysis of land use change dynamics and its impacts on hydrological processes in the Jialing River Basin. Water, 2014. 6(12): p. 3758-3782.
6. Hassan, Z., et al., Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan. SpringerPlus, 2016. 5(1): p. 812.
7. Manandhar, R., I.O. Odeh, and T. Ancev, Improving the accuracy of land use and land cover classification of Landsat data using post-classification enhancement. Remote Sensing, 2009. 1(3): p. 330-344.
8. Valiquette, C.A., et al., Computing Cohen's kappa coefficients using SPSS MATRIX. Behavior Research Methods, Instruments, & Computers, 1994. 26(1): p. 60-61.
9. Zhang, L., A. Kumar, and W. Wang, Influence of changes in observations on precipitation: A case study for the Climate Forecast System Reanalysis (CFSR). Journal of Geophysical Research: Atmospheres, 2012. 117(D8).
10. Fuka, D.R., et al., Using the Climate Forecast System Reanalysis as weather input data for watershed models. Hydrological Processes, 2014. 28(22): p. 5613-5623.
11. Winchell, M., et al., ArcSWAT interface for SWAT 2005. User'sGuide, Blackland Research Center, Texas Agricultural Experiment Station, Temple, 2007.
12. Rajawatta, K., D. He, and P. MKDK, CMWSim: development and evaluation of probability-based weather generating software for crop growth simulation. Italian Journal Of Agrometeorology-Rivista Italiana Di Agrometeorologia, 2014. 19(3): p. 5-14.
13. Narsimlu, B., et al., SWAT model calibration and uncertainty analysis for streamflow prediction in the Kunwari River Basin, India, using sequential uncertainty fitting. Environmental Processes, 2015. 2(1): p. 79-95.

14. Moriasi, D.N., et al., Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the ASABE, 2007. 50(3): p. 885-900.
15. Bonumá, N.B., et al., Modeling surface hydrology, soil erosion, nutrient transport, and future scenarios with the ecohydrological SWAT model in brazilian watersheds and river basins. Tópicos Ci. Solo, 2015. 9: p. 241-290.
16. Forkuor, G. and O. Cofie, Dynamics of land-use and land-cover change in Freetown, Sierra Leone and its effects on urban and peri-urban agriculture–a remote sensing approach. International Journal of Remote Sensing, 2011. 32(4): p. 1017-1037.
17. Mahmud, A. and A.S. Achide, Analysis of Land Use/Land Cover Changes to Monitor Urban Sprawl in Keffi-Nigeria. Environmental Research Journal, 2012. 6(2): p. 129-134.
18. Sellami, H., et al., Uncertainty analysis in model parameters regionalization: a case study involving the SWAT model in Mediterranean catchments (Southern France). Hydrology and Earth System Sciences, 2014(18): p. p. 2393-p. 2413.
19. Abbaspour, K.C., SWAT-CUP 2012: SWAT calibration and uncertainty programs–a user manual. Eawag: Dübendorf, Switzerland, 2013. 103.

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