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Modelling the Impact of Land Use Change on Hydrological Processes in the Katsina-Ala Basin Using SWAT

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Abstract

The hydrology of the Katsina-Ala Basin is increasingly influenced by climate change and land-use/land-cover (LULC) changes, raising concerns about the sustainability of water resources. This study utilized the Soil and Water Assessment Tool (SWAT) to simulate hydrological processes and assess the impacts of LULC changes over a 20-year period (2000-2020). Sensitivity analysis identified CN2.mgt, SURAG.hru, and ESCO.hru as the most influential parameters. The model calibration (2012-2015) and validation (2016-2019) demonstrated high performance, with Nash-Sutcliffe Efficiency (NSE) of 0.987 and 0.986, Coefficient of Determination (R^2) of 0.990 and 0.995, and Percent Bias (PBIAS) of 0.014 and 0.013, respectively. The P-factor values were 0.81 (calibration) and 0.94 (validation), while the R-factor values were 2.82 and 2.0, respectively, indicating the model's reliability in capturing observed hydrological processes. The calibrated model revealed significant LULC changes indicating an 11% increase in cultivated land, an 8.19% decline in forest cover due to logging and agricultural expansion, a 3.22% net gain in grassland, and a slight increase in artificial surfaces (0.34%). These changes resulted in increased surface runoff (7.79%) due to reduced infiltration, decreased evapotranspiration (1.58%), lateral flow (1.49%), and groundwater recharge (0.66%)—largely attributed to deforestation and land management practices. A slight increase in water yield (1.05%) was observed as a cumulative effect of these changes. The findings underscore the importance of adopting sustainable land-use practices to mitigate hydrological imbalances and ensure the long-term sustainability of water resources in the Katsina-Ala Basin.

Keywords

Water Resources Management, Land Use and Land Cover Change, SWAT Model, Surface Runoff, Hydrological Modeling

1. Introduction

Land use and land cover changes have had a substantial impact on regional hydrological processes, ranging from small to large scales. In the context of the current global water crisis, assessing land use change is crucial (Rolando et al., 2017; Loveland et al., 2000). Water, as a vital and indispensable natural resource, exerts a pivotal influence on societal dynamics and its scarcity imposes significant risks and strains on human communities. Factors such as prolonged and severe droughts, seasonal fluctuations in precipitation, and resource degradation exacerbate this challenge (Adejuwon & Adeleke, 2012). Anthropogenic activities in the Katsina-Ala Basin in north-central Nigeria have an impact on LULC and water resource availability. Research indicates that changes in watershed hydrology are primarily caused by changes in interception, infiltration, evapotranspiration, and groundwater recharge, all associated to LULC variations (Baker & Miller, 2013). The Katsina-Ala River in Nigeria is a tributary of the Benue River, it features numerous populated floodplains that support a rich ecosystem ideal for agriculture and is seldom prone to flooding (Akinyede et al., 2012). Monitoring the surrounding watershed is crucial for optimizing water resources and determining the impact of Land Use/Land Cover (LU/LC) changes on its hydrological cycle. Quantifying the impact of LULC on large watersheds is challenging because of the complicated relationship between LULC, climate, and hydrology (Uhlenbrook et al., 2003). Watershed assessment of hydrological responses to LULC changes can be done using hydrological modeling (Wang et al., 2008). There are many significant advantages of using the hydrological model like Soil and Water Assessment Tool (SWAT) (Tuo et al., 2016; Niraula et al., 2015) which includes spatially mapping the patterns of hydrological consequences resulting from LULC changes, comparison of basin changes in hydrological components with basin scale changes in LULC. The SWAT model is primarily used in precipitation runoff analysis (Arnold et al., 1993) climate change effect on water cycle (Eckhardt & Ulbrich, 2003; Muttiah & Wurbs, 2002) and land-use change effect on the water cycle (Fohrer et al., 2005; Tripathi et al., 2005). Land-use change impacts land-cover type, surface runoff generation, and the catchment hydrological process. Research on the impact of land-use change on the water cycle mostly focuses on annual runoff (Brown et al., 2005). Studies on the hydrological processes of watersheds based on LULC change demonstrate a significant rise in rainy season flow and surface runoff potential, which correlates with the growth of agricultural land, urban areas and the reduction of forest cover (Gashaw et al., 2018; Kebede et al., 2014; Khadr, 2016). The goal of this study is to maximize water resource management in response to the basin's increasing environmental concerns, with a particular emphasis on ensuring food security and mitigating the consequences of hydrological extremes such as droughts and flooding. While numerous studies have utilized the SWAT model to assess the impact of LULC changes on hydrology, this study stands out by integrating high-resolution satellite imagery with the model. This approach allows for more precise mapping of LULC changes and enhances hydrological predictions, providing a detailed understanding of land cover dynamics over the 20-year period studied. Using the SWAT model, we simulated the *** and then evaluated how land use changes affected the basin's hydrological processes. The impacts of different climate scenarios on runoff were also simulated. These data are designed to help manage and monitor land practices and active water management strategies in basins that are vulnerable to agricultural growth.

2. Data and Methods

2.1. Study Area

Covering over 22,920 km^2, the Katsina-Ala basin is located between 9˚15' and 9 56' East and 6˚55' and 7˚36' North, its landscape is shaped by diverse factors including relief, climate, and human activities. With an average elevation of 1537 m and significant annual rainfall of 1787.9 mm and temperature of 29.34˚C. Primarily characterized by crystalline basement complex rocks of the middle Benue Trough like quartzite and siliferous rocks (Offodile, 2002), the basin boasts fertile soils conducive to agriculture and supports various crops, with maize, rice, and yam being prominent. This agricultural activity coexists with other uses like fishing and transportation along the riverbanks. **Figure 1** shows the location of the study area.

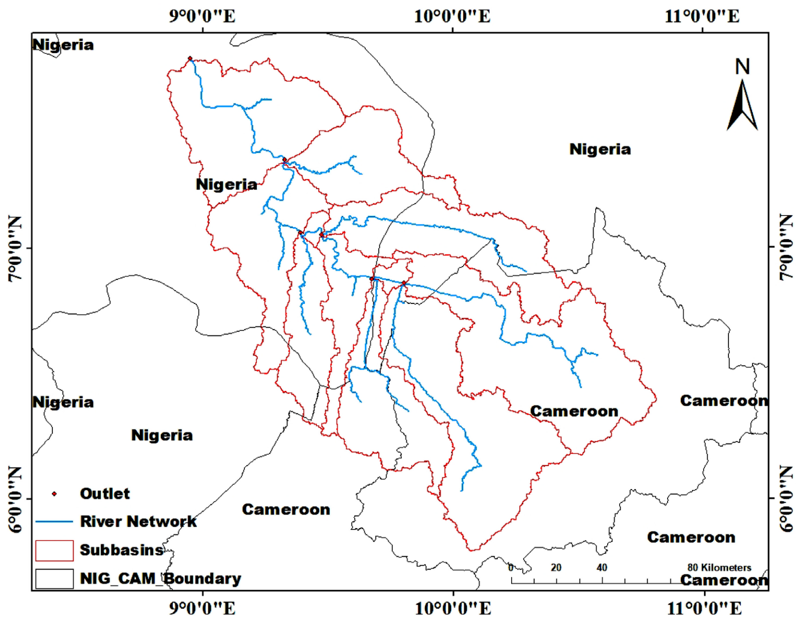


Figure 1. Location of the Katsina-Ala river basin covering some parts of Nigeria and Cameroon.

2.2. SWAT Model

High-resolution satellite data were utilized to derive detailed LULC maps for the study period. These maps were integrated into the SWAT model to enhance the spatial accuracy of land cover representation and improve the model's ability to simulate hydrological responses. This methodological advancement ensures more reliable predictions of the hydrological impacts of LULC changes, distinguishing this study from prior research.

The Hydrological SWAT model was developed to investigate the impact of land use and land cover on streamflow in the Katsina-Ala Watershed. The SWAT model with geographically and temporally dispersed parameters was used to calculate the LULC change effect on hydrological responses when soils, LULC, and slope were changed (Gumindoga et al., 2014). The SWAT simulation includes two primary hydrologic cycle phases: land and routing (channel-based). The land phase simulates the amount of water, nutrients, sediment, and pesticides transported to the associated major channel by surface runoff from each sub-basin. The land phase's hydrologic cycle is simulated using the water balance equation in each hydrological response unit (Equation (1)).

$$SW_f = SW + R_{day} - \left(Q_{surface} + ET + W + Q_{ground}\right) \tag{1}$$

SW_f is final soil water content in day (mm); SW is initial soil water content in day (mm); t is time (days); R_{day} is daily precipitation (mm); $Q_{surface}$ is daily surface run-off (mm); ET is daily evapotranspiration (mm); W is daily percolation (mm) and Q_{ground} is daily groundwater flow (mm). The water balance is the foundation and driving force for all hydrological processes in the SWAT model (Devia et al., 2015)

The routing phase manages stream processes like water movement, sediment transport, and nutrient loading. SWAT uses the Soil Conservation Service Curve number approach, kinematic storage routine method, Penman-Monteith equation, and modified rational method to calculate runoff volumes, lateral flow, potential evapotranspiration, and peak runoff rate, based on soil type, land use, and management measures. The principle of runoff simulation of the SWAT model is as follows: when the rainfall reaches the ground, the water infiltration rate is larger due to the dryness of the surface soil. The continuous rainfall process causes the soil moisture to increase, which leads to the decrease of water infiltration rate. When the rainfall intensity is greater than the infiltration rate, the filling begins. Once the surface is filled, the surface runoff will be generated. The SWAT model is a hydrological simulation method that uses the water balance equation to predict surface runoff in watersheds. It divides a watershed into sub-basins, which are further divided into smaller sections called Hydrological Response Unit (HRU). These HRUs are based on land use, soil, slope, and management features (Kushwaha & Jain, 2013). The model predicts the impacts of LULC changes on hydrological parameters in the watershed. In the Katsina-Ala watershed, 11 sub-watersheds were divided into 105 HRUs for the year 2000 and 97 HRUs, for the year 2020 using a multiple land use/soil/slope technique

2.3. Model Input Data

The SWAT model requires various input data to simulate hydrological processes accurately. The 30 m resolution Digital Elevation Model (DEM) used was sourced from SRTM, 30 m resolution LULC data was derived from Global landcover data sourced maps, soil data was obtained from the FAO/UNESCO Digital Soil Map of the World. Daily weather data spanning 20 years, including rainfall, solar radiation, temperature, humidity, and wind were downloaded from NASA POWER Data Access Viewer at $1/2 \times 5/8$ latitude/longitude grid , filling missing weather variables was achieved using R-studio. LULC maps classify the watershed's surface into categories like cultivated land (AGRL), forest (FRST), grassland (RNGE), water bodies (WATR), Artificial surfaces (URBN), and bare land (BARR), impacting hydrological responses. **Figure 2** shows the LULC maps used for the years 2000, 2010, 2020. The DEM is crucial for computing hydrological parameters such as flow direction, accumulation, and stream network creation, while also determining slope gradient and terrain characteristics as shown in **Figure 3(a)**. To analyze the change dynamics, pre-classified satellite imagery from Global land cover platform was reclassified and utilized. The study period covers a span of 20 years, allowing for a comprehensive evaluation of the transitions in land use and land cover. Soil data, categorizes soil types such as sandy-clay-loam, clay, and sandy loam, with the primary soil type in the Katsina-Ala watershed being sandy-clay-loam (**Figure 3(b)**). Additionally, checks for data consistency and homogeneity are conducted using methods such as the double mass curve. This comprehensive approach ensures the SWAT model's accuracy in simulating watershed hydrology.

2.4. SWAT Calibration and Performance Analysis

The SWAT model was simulated on a daily time step for the period 1984-2022, with 1984-1986 designated as the warm-up period to allow the model to stabilize before generating reliable outputs. Observed discharge data for 2012-2015 were used for model calibration, while data for 2016-2019 were applied for validation. A total of eight hydrological parameters were selected for sensitivity analysis based on insights from previous SWAT studies (Nguyen et al., 2022; Abbaspour et al., 2015; de Oliveira Serrão et al., 2022) and a review of literature for the study region. These parameters were analyzed using the R-SWAT interface, employing the Sequential Uncertainty Fitting Version 2 (SUFI-2) algorithm. The Nash-Sutcliffe Efficiency (NSE) coefficient was chosen as the objective function to assess model performance. The SUFI-2 algorithm iteratively adjusts parameter ranges, simulating data within the 95% prediction uncertainty (95 PPU) interval, which is defined by the 2.5% and 97.5% levels of the cumulative distribution of output variables (e.g., discharge, evapotranspiration, and sediment) (Abbaspour et al., 2015). A global sensitivity analysis was conducted using 50 iterations of five parallel runs to identify the most influential parameters. The Dotty plots,

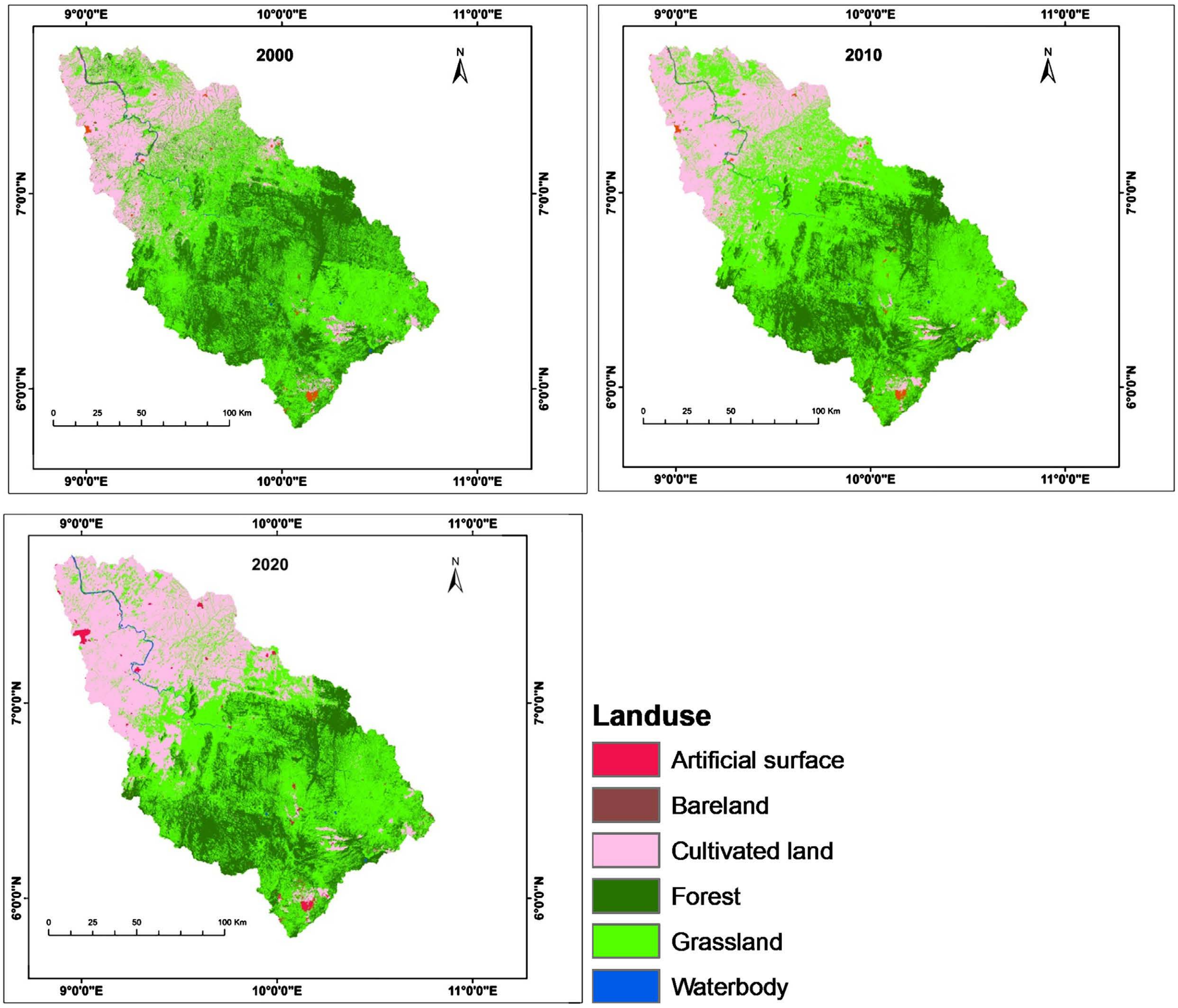
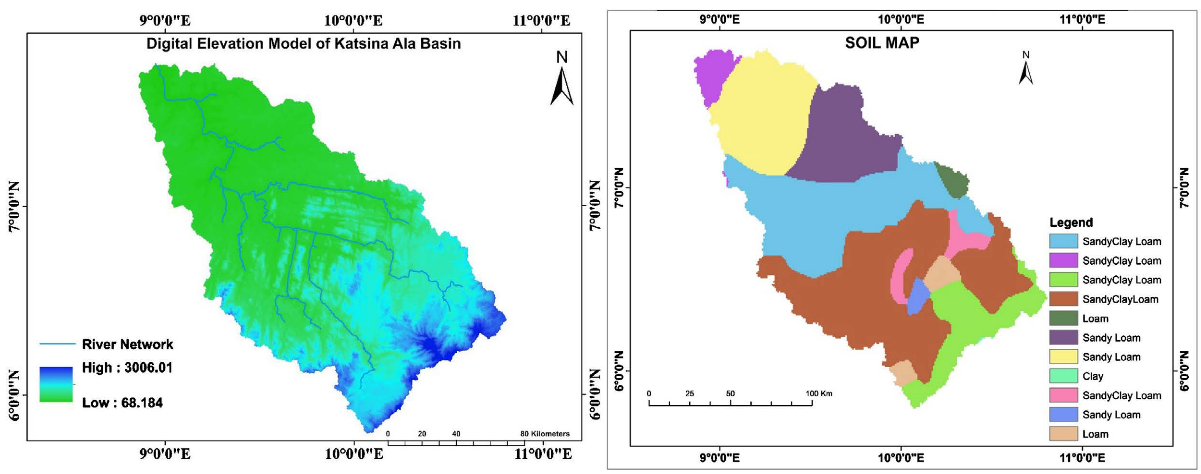


Figure 2. Shows land use land cover map of the study area for the years 2000, 2010 and 2020.



(a) (b)

Figure 3. (a) DEM map; (b) Soil map of the Katsina-Ala watershed.

visualizing the relationship between the NSE coefficient and each parameter, revealed progressively refined parameter ranges after each iteration. This iterative process was repeated until the third iteration, which showed significant improvement in model performance. The t-test was used during sensitivity analysis to measure the significance of each parameter, with higher absolute t-stat values indicating greater sensitivity. The calibration results demonstrated a strong agreement between simulated and observed monthly flow values, confirming the robustness of the model. This calibration process optimized the SWAT model for evaluating the hydrological impacts of land-use and land-cover changes in the study area.

2.5. Performance Evaluation of the SWAT Model

The SWAT model's performance was evaluated using key statistical indicators recommended by the International Precipitation Working Group (IPWG) and detailed in studies by Abbaspour et al. (2018), Nguyen et al. (2022), and de Oliveira Serrão et al. (2022). The Nash-Sutcliffe efficiency (NSE) (Equation (2)), percentage bias (PBIAS) (Equation (3)), and coefficient of determination (R2) (Equation (4)), were employed to assess model accuracy. R^2 measures the correlation between observed and simulated values, NSE evaluates predictive accuracy by comparing the variance of errors to observed data, and PBIAS quantifies bias, with positive values indicating underestimation and negative values indicating overestimation. Model uncertainty was assessed using the P-factor, which represents the percentage of observed data within the model's prediction uncertainty range, and the R-factor, which measures the relative width of this range. Ideally, a P-factor of 1 and an R-factor of 0 indicate perfect model performance. These metrics collectively validated the SWAT model's ability to simulate hydrological processes accurately and reliably.

$$NSE = \frac{\left(\sum_{i=1}^{N}\left(O_i - O_{avg}\right)^2\right) - \left(\sum_{i=1}^{N}\left(S_i - S_{avg}\right)^2\right)}{\left(\sum_{i=1}^{N}\left(O_i - O_{avg}\right)^2\right)} \tag{2}$$

$$PBIAS = \frac{\sum_{i=1}^{n}\left(O_i - S_i\right)}{\sum_{i=1}^{n}\left(O_i\right)} \times 100\% \tag{3}$$

$$R^2 = \frac{\sum_{i=1}^{N}\left(O_i - O_{avg}\right)\left(S_i - S_{avg}\right)}{\sum_{i=1}^{N}\left(O_i - O_{avg}\right)^2\left(S_i - S_{avg}\right)^2} \tag{4}$$

where n is the total number of records, O_i is the observed value, O_{avg} is the mean of the observed values, S_i is the simulated value, and S_{avg} is the mean of the simulated values.

3. Result and Discussion

The study examined land use and land cover changes over two decades, revealing both continuities and concerning trends as shown in **Figure 4**. Agriculture remains a central feature, with cultivated land for food crops increasing by 11% since 2020. However, some cultivated areas face challenges like water management. Forest cover has seen a significant decline of 8.19%, likely due to logging and agricultural expansion. This highlights the need for conservation efforts to protect the remaining forested areas. Grassland areas have fluctuated over the study period, increasing from 45.7% in 2000 to 42.49% in 2020. Table 1 shows these variations despite the overall grassland area having exhibited a relatively stable pattern with net gains and losses totaling only 3.22% over the entire period. Waterbodies, vital for the local hydrological cycle and water quality, have also experienced some fluctuations. While the area covered by waterbodies shrunk from 0.3% of the landscape in 2000 to 0.24% in 2010, it has since rebounded to 0.44% in 2020, resulting in a small net gain of 0.12% over the study period.

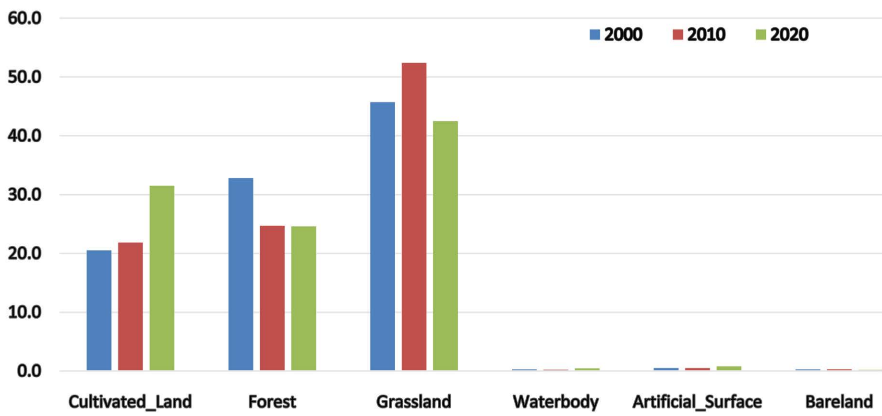


Figure 4. Graphical representation of land use land cover changes from 2000-2020.

Table 1. LULC proportion in km² and percentages from 2000-2020.

	2000		2010		2020		
	km²	%	km²	%	km²	%	%Change 2020-2000
Cultivated Land	4689.74	20.5	5012.22	21.87	7220.64	31.50	11.04
Forest	7509.36	32.8	5662.48	24.71	632.84	4.58	8.19
Grassland	10476.12	45.7	12005.31	52.38	9738.73	42.49	3.22
Waterbody	73.10	0.3	55.61	0.24	99.74	0.44	0.12
Artificial surfaces	106.85	0.5	114.67	0.50	183.90	0.80	0.34
Bareland	65.19	0.3	70.08	0.31	44.51	0.19	0.09

3.1. Change Detection Analysis

Using the Idrisi Land Change Model tool, it becomes feasible to identify the primary contributors to land cover change, which in this case include grassland, cultivated land, and forest. Additionally, the tool enables the prediction of potential future changes and land cover utilization under different scenarios. From the land use conversion graph Figure 5(a) the most dramatic shift was grassland converting to cultivated land, covering a massive 34.5% of the total area and this indicates a major boom in agriculture in the area. Over the observed period there was a huge conversion from forest to grassland, accounting for 33.8% of the area. While logging intensified in areas losing forest cover, about 4.8% area was converted from grassland to forests. These changes are visually represented on the conversion map from 2000-2020 in Figure 5(b). The gain and loss graph and map in Figure 5(c) show a significant loss in grassland and forest and gain for cultivated land. Overall, Katsina-Ala underwent a significant transformation. Cultivated land increased substantially, likely due to improved farming techniques and government initiatives. Forest cover transitioned into grasslands, while some grassland became forests, suggesting some conservation efforts alongside agricultural expansion.

3.2. Sensitivity Analysis, Calibration and Model Performance

Eight parameters were selected to determine the most influential SWAT parameters, as presented in Table 2. The sensitivity of these parameters was assessed using the t-stat and p-value as metrics, where higher absolute t-stat values indicate greater sensitivity and lower p-values (approaching 0) reflect higher significance. The sensitivity rankings were assigned accordingly, with CN2.mgt, SURAG.hru, and ESCO.hru were identified as the most sensitive parameters. These results emphasize the critical influence of these parameters on the hydrological model outputs. The Dotty plots (Figure 6) visualizes the parameter's sensitivity with the objective function of the Nash-Sutcliffe (NS) coefficient, further corroborating the sensitivity ranking.

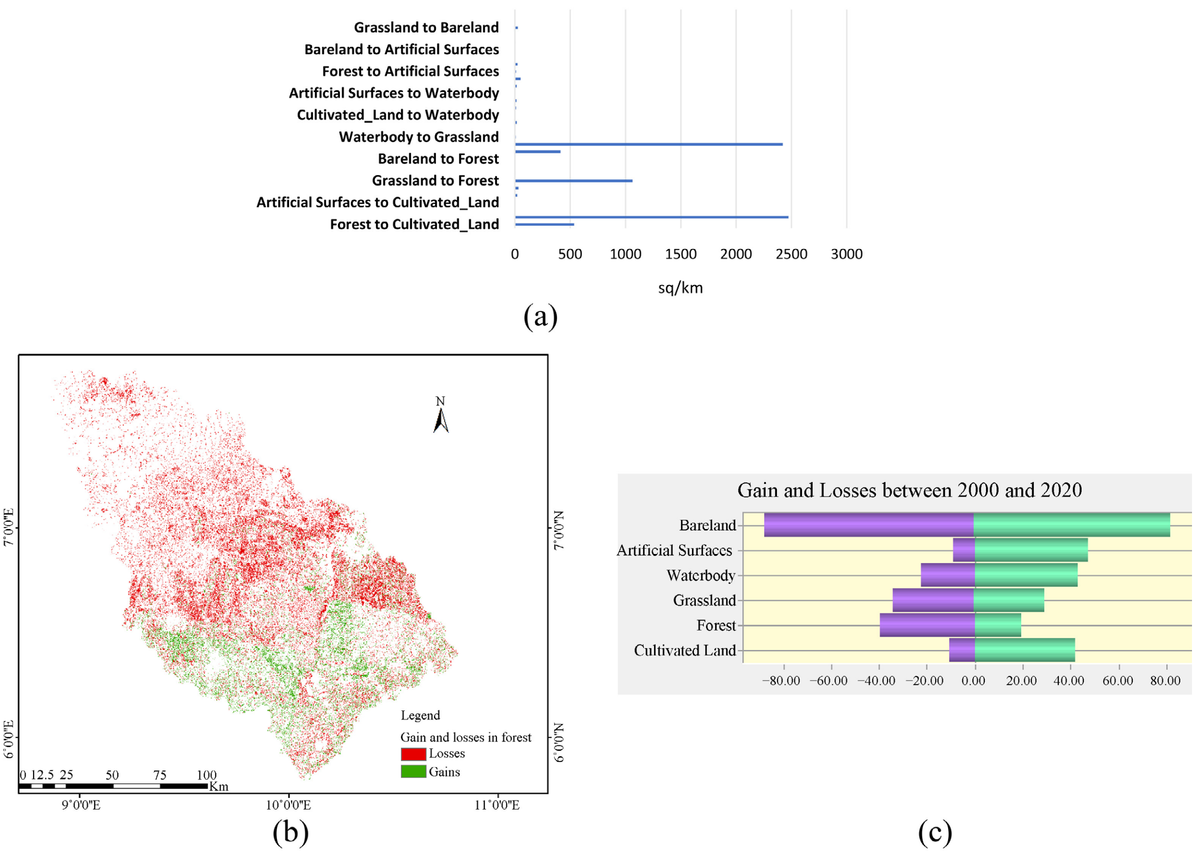


Figure 5. (a) Land use conversion from 2000-2020 (sq/km); (b) The change detention analysis between (c) Gains and losses 2000 and 2020.

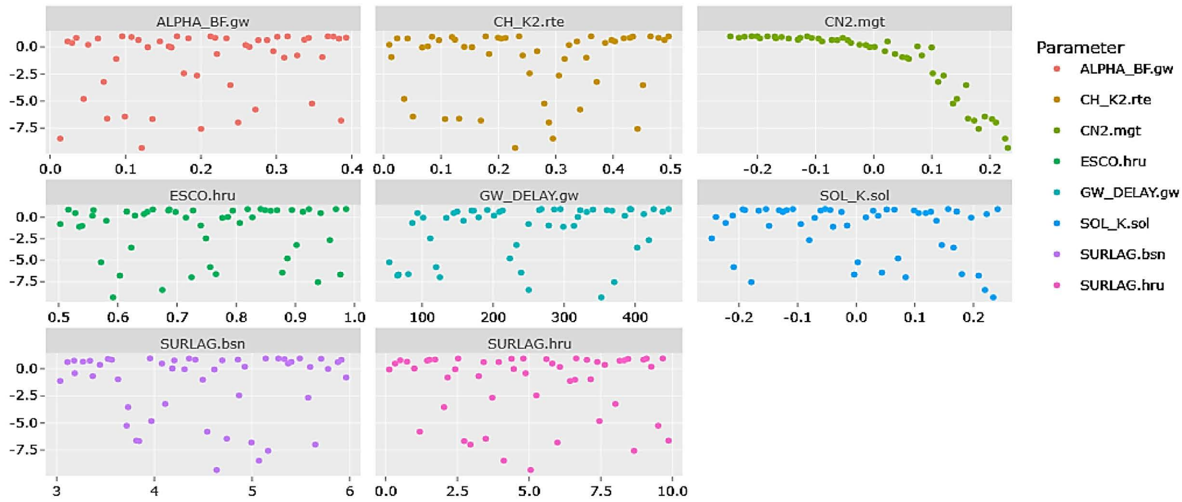


Figure 6. Dotty plots with the objective function of the NS coefficient.

Table 2. The sensitive model parameters with their relative sensitivities and ranking.

Parameter code	Definition	Relative sensitivity (absolute_t_stat)	Rank
r_CN2.mgt	Curve number for moisture condition II.	9.83	1
v_SURLAG.hru	Surface runoff lag coefficient.	1.81	2
v_ESCO.hru	Soil evaporation compensation factor.	1.70	3
a_GW_DELAY.gw	Groundwater delay in days.	1.49	4
v_CH_K2.rte	Effective hydraulic conductivity in the main channel.	0.97	5
v_SURLAG.bsn	Basin surface runoff lag coefficient.	0.96	6
r_SOL_K.sol	Saturated hydraulic conductivity.	0.83	7
v_ALPHA_BF.gw	Baseflow alpha factor.	0.08	8

v—Replace: replaces the existing value; r—relative: multiplies the existing value; a—absolute: applies value to existing value.

The observed and simulated flows were compared graphically for both the calibration period (2012-2015) and the validation period (2016-2019), as shown in Figure 7. A close match was observed between the simulated and observed discharge values, indicating good model performance. The performance metrics—Coefficient of Determination (R^2), Nash-Sutcliffe Efficiency (NSE), and Percent Bias (PBIAS)—are summarized in Table 3. For calibration, the R-factor and P-factor were 2.82 and 0.81, respectively, while for validation, they were 2.0 and 0.94, respectively. These results confirm the model's reliability during both calibration and validation periods. The optimized parameters obtained during calibration were subsequently used for SWAT model simulations to evaluate the hydrological responses to land-use and land-cover (LULC) changes.

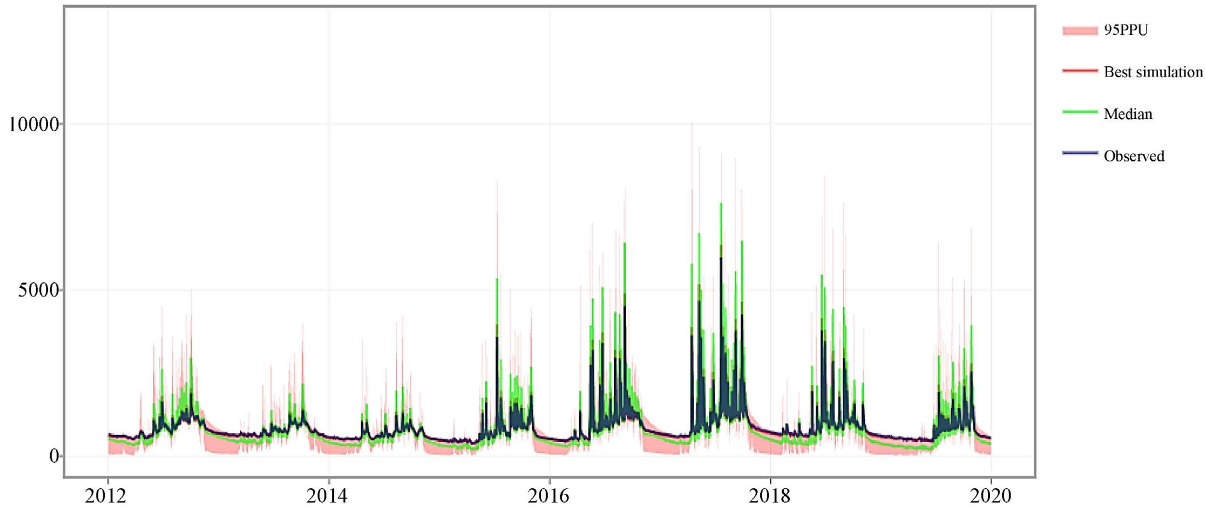


Figure 7. Simulated and observed flows during the calibration and validation period (2012-2019).

Table 3. Model performance statistics for the calibration and validation periods.

	Calibration (2012-2015)	Validation (2016-2019)
Statistics		
Nash-Sutcliffe efficiency (NSE)	0.987	0.986
R^2	0.990	0.995
Percent bias (PBIAS)	0.014	0.013
P-Factor	0.81	0.94
R-Factor	2.82	2.0

3.3. Land-Use and Land-Cover Effects on the Outflow Parameters (Surface Runoff (Surf-Q))

Increased urbanization frequently results in the construction of impermeable surfaces such as highways, parking lots, and buildings. These surfaces keep water from penetrating the earth, increasing surface runoff. Furthermore, forest removal diminishes vegetation cover, which is important for regulating water flow. Rainwater is absorbed and slowed by forests. As a result, deforestation can lead to increased runoff. Table 4 shows that changes in the LULC have a large impact on the outflow parameters, just as they do on the inflow parameters. The outflow parameter here is the Surface runoff (Surf-Q), which increased from 230.88 mm to 248.86 mm over a 20-year period. For the period 2000-2020, the annual water balance components evapotranspiration (ET), groundwater flow (GW-Q), and lateral flow (LAT-Q) all decreased by 1.6%, 0.64%, and 1.49%, respectively. The decrease in ET, GW-Q, and LAT-Q is due to increased agricultural activity, urbanization, and deforestation. Natural vegetation is frequently replaced by impermeable surfaces such as highways and buildings during urban development. As these surfaces heat up, the amount of vegetation available for transpiration decreases, resulting in decreasing evapotranspiration rates. Furthermore, forest clearing reduces the total leaf area available for transpiration. Furthermore, tree loss reduces overall canopy interception of precipitation, resulting in less water evaporated from the ground surface. Changes in agricultural land use, such as the conversion of natural landscapes to farming, can have an impact on evapotranspiration. Agricultural activities may include the removal of natural vegetation as well as the cultivation of crops with varying transpiration rates.

Table 4. Changes occurring in the hydrological components of Katsina-Ala Basin for 2000 and 2020 landuse and landcover.

Hydrological components	LULC Scenarios		% Change
	2000	2020	
Surface runoff (mm) Surf-Q	230.88	248.86	7.79
Lateral flow (mm) Lateral-Q	174.33	171.77	−1.47
Evapotranspiration (mm) ET-Q	703.30	692.20	−1.58
Groundwater (mm) GW-Q	679.72	675.41	−0.66
Total water Yield (mm)	1059.19	1070.29	1.05

The model successfully estimated the effects of land cover changes on surface runoff and volumes in the Katsina-Ala Basin. The results showed that the detected land cover changes enhanced peak discharge and runoff volumes in the sub-basins. This effect is more severe in areas where deforestation and agricultural growth were prevalent. It is clear that the greatest impact of LULC alteration was on the volume of runoff produced. This finding is similar with Ghaffari et al. (2010) who found that among the three hydrologic components evaluated (streamflow, groundwater, and base flow), streamflow was more affected by LULC changes. **Figure 8** shows that average annual values for four hydrological components: surface runoff, water yield, lateral flow, and groundwater. In comparison to the LULC in 2000, the basin's average annual surface runoff is 17.98 mm higher in 2020. The average water yield in 2000 was 1059.19 mm, and it increased to 1070.29 mm with LULC in 2020 (a 1.05% increase). The average lateral flow decreased by 1.46% between 2000 and 2020. Groundwater levels have been found to decline. The drop in average groundwater recharge can be due to increased surface runoff, lower soil infiltration, and higher evapotranspiration. It can also be claimed that groundwater in the basin is used for a variety of purposes, including home water use and irrigation. The reduction in groundwater recharge depicted by the model results is consistent with (Calow et al., 2010) findings, which stated that groundwater is a preferred source of water over surface water due to the high inter-annual variations in precipitation that affect surface water availability. This is especially true in Africa's semi-arid regions, as well as the Katsina-Ala basin. The results of the simulation revealed that urbanization, deforestation and agricultural activities are the strongest contributors to change in surface runoff. The results from the land cover change analysis indicated a remarkable decrease in grassland and forest land and increase in farmland and urbanization. At the same time, **Table 4** shows an increase in the volume of runoff. The result is in line with the study of (Tang et al., 2021) which showed that the increase in urbanization might possibly create impervious layers decreasing the infiltration and percolation of water to the shallow aquifers that leads to increase in surface runoff. When natural surfaces are replaced by more impermeable man-made surfaces such as buildings, paved roads and concrete which have very low infiltration capacities, the hydrological consequences are enormous and often result to increase in peak discharges and total volumes of runoff. The decline in ET coincides with the decrease in forest cover (**Table 4**) over the same time period. This is because forest trees can access soil moisture from greater depths for transpiration and have larger canopy cover for precipitation interception, resulting in higher measured ET (Yan et al., 2017). The area largely impacted by these changes is within sub-basin 1 (Gboko and Buruku towns) which indicates the peak flow within the basin (**Figure 9** and **Figure 10**). It would be seen that there was high increase in deforestation, and also agricultural activities within this sub-basin. Alteration in Water balance ratios give a framework for assessing how rainfall is partitioned into distinct components in response to watershed conditions changes. **Table 5** shows the water balance ratios in the Katsina-Ala Basin under two LULC altering scenarios. The changes observed in the water balance ratios generally follow the trend of the impact of LULC changes on hydrological components already discussed.

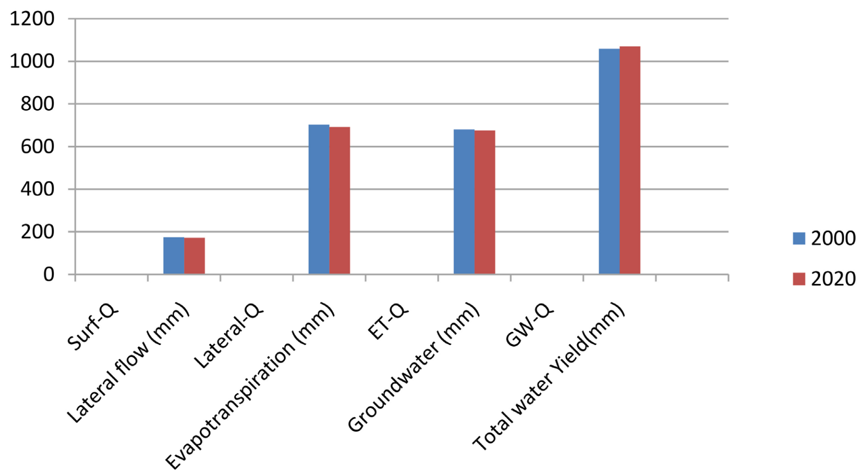


Figure 8. Average annual basin values of surface runoff, water yield, lateral flow and groundwater for two land use and land cover scenarios in the Katsina-Ala Basin.

Table 5. Water balance ratios.

	Water Balance Ratios*					
	SF/P	BF/TF	SR/TF	PC/P	DR/P	ET/P
2000	0.57	0.77	0.23	0.38	0.02	0.39
2020	0.58	0.76	0.24	0.38	0.02	0.39

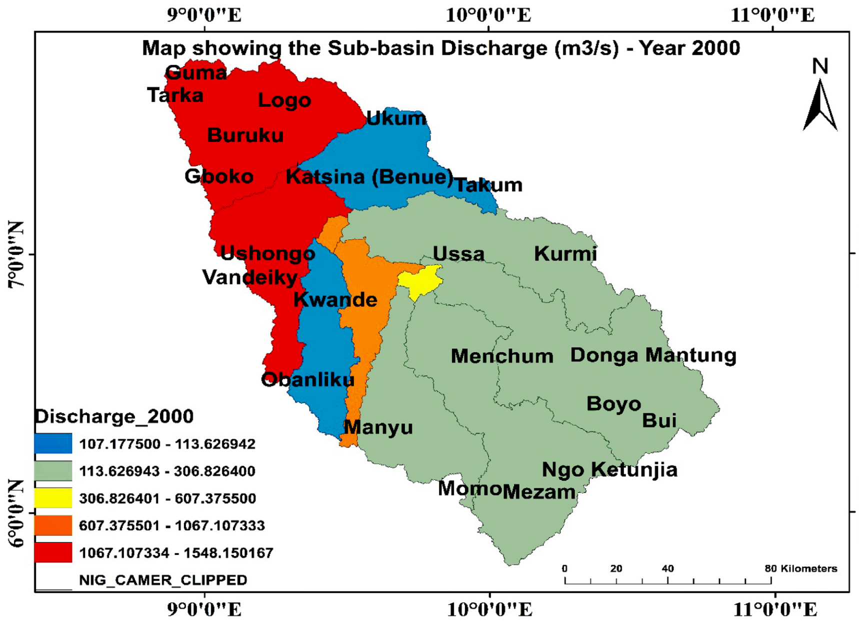


Figure 9. Map showing the sub-basin discharge (m³/s) in 2000.

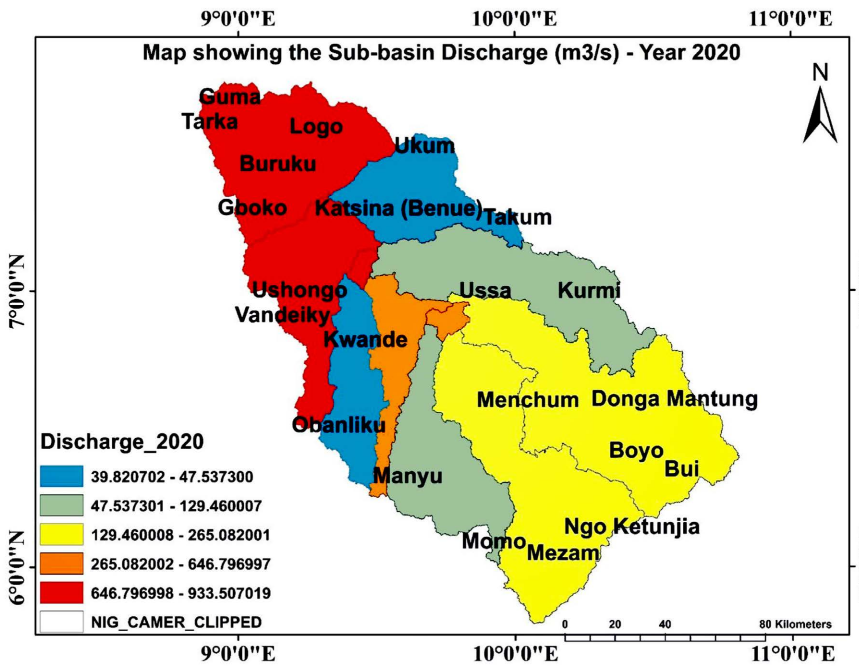


Figure 10. Map showing the sub-basin Discharge (m³/s) in 2020.

4. Conclusion

The SWAT model and satellite data were used to assess the impact of land use and land cover (LULC) changes on the hydrology of Katsina-Ala Basin during a two-decade period. Calibration of the model was conducted to fine-tune parameters, ensuring that simulated results closely matched observed data. Sensitivity analysis identified the most influential factors driving the hydrological changes in the basin, particularly the effects of agricultural expansion and deforestation. Performance evaluation, using statistical metrics such as Nash-Sutcliffe Efficiency (NSE) and R^2, demonstrated the model's satisfactory predictive ability, reinforcing the credibility of the observed hydrological trends. The results show a considerable rise in cultivated land for agriculture, as well as a decline in forest cover, which is most likely caused by logging and agricultural expansion. These alterations resulted in a series of hydrological impacts, including increased surface runoff and decreased evapotranspiration, groundwater recharge, and lateral flow. While the study found a modest increase in overall water yield, this could be a transitory occurrence that masks underlying imbalances. Continued deforestation and agricultural growth are a serious danger to the basin's water security. Increased surface runoff can lead to deadly flash floods, particularly in metropolitan areas, and decreased infiltration. To secure the long-term sustainability of the Katsina-Ala Basin's water supplies, a multifaceted approach is required. Implementing soil conservation strategies and supporting sustainable agriculture practices can help to reduce soil erosion and increase water penetration. Investing in reforestation initiatives, combined with stricter deforestation regulations, can help restore lost forest cover while also facilitating natural water regulation and promoting biodiversity. Furthermore, increasing community awareness and promoting water conservation techniques in both the agricultural and domestic sectors can help to mitigate water scarcity risks. Looking ahead, more research is needed to acquire a complete knowledge of the basin's water system. Analyzing the influence of climate change on the basin's hydrology, as well as designing and analyzing various land-use scenarios, is critical for developing successful long-term water resource management strategies.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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