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Effects of Dynamic Land Use and Land Cover Variations on hydrological regime of Densu River Basin of Ghana

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ABSTRACT

Persistent variations in land use along with land cover in Densu River basin over time, have contributed significantly to climatic situations in the basin. This phenomenon has impacted the hydrological parameters of the catchment. Therefore, it is essential to analyse the repercussions of dynamic changes in land use, anthropogenic activities and climate variability on hydrologic regimes of the Densu River basin. The dynamic land-use-change modeller, Soil Water Assessment Tool (SWAT) besides Geographic Information System were applied in this research. The land use change from 1986 to 2005 recorded a decline in dense forest cover from 69% to around 26% whilst open forest increased from around 16% to approximately 52%. The results depicted those major hydrological processes in the Densu basin were significantly influenced by curve-number (CN_2), groundwater-delay-time (GW_Delay) and baseflow-alpha-factor (Alpha_BF). Based on recommended performance statistics for model timesteps, Nash-Sutcliffe-Efficiency results for calibration and validation of the simulations were above 0.80 and classified as good. The P_{BIAS} results were classified as good. The spatial dispersion of the basin's evapotranspiration and groundwater recharge zones for the basin were identified. This research provides a foundation for developing strategies for monitoring groundwater recharge zones and other hydrological processes in river basins.

Keywords – Climate, Hydrological, streamflow, Modelling, Water

INTRODUCTION

The rise in population and growing anthropogenic activities, in recent years, have culminated in the wanton degradation of environmental resources especially water in developing countries (Welde and Gebremariam,2017). Ecological resources including land and water, play momentous roles in the socio-economic advancement of economies around the globe. Therefore their preservation must be the top priority of every country to realise their optimum utilization (Thakur et al., 2018).

Climate variations as well as Land Use and Land Cover Changes (LULCC) remain critical determinants linked with fluctuations in hydrological processes for watersheds (Kumar et al., 2018; Welde & Gebremariam, 2017). Variations in climatic conditions have been predicted to have considerable consequences on the hydrological system of river basins globally (Hermassi and Khadhraoui, 2017; Hlásny et al., 2015). Analysis of climate variability and LULCC have unveiled a great range of consequences on development including socio-economic, ecological, government policies and operations of intergovernmental entities (Dos Santos et al., 2014).

The precariousness associated with the availability, coupled with the accessibility of water resources, has been touted to have significant distress on agronomic activities, straining socio-economic systems and posing threats to environmental sustainability (Golmohammadi et al., 2011). The implications linked with climate variations might be critical mainly in countries whose economic activities are intensely reliant on agribusiness productions and related activities (Anand et al., 2018; Daggupati et al., 2018).

Numerous hydrological simulations or models have been applied in determining hydrological processes in addition to regimes of river basins (Zhang et al., 2017). Notwithstanding the successes of these techniques in determining the hydrological regimes of river basins, the models however associated with limitations attributed to the calibration and validation of parameters (Mekonnen et al., 2017; Zhang et al., 2017) alongside the availability of adequate datasets. These limitations are key constraints hampering the reliability of these models particularly those that apply to developing countries (Bouslihim et al., 2016).

Several hydrological models such as MIKE-SHE, WATFLOOD, TOPMODEL, HEC, HEC-RAS, VIC and SWAT (Guzha et al., 2018) are proficient in analysing the spatiotemporal variabilities in the hydrological patterns of a catchment and also supporting the consideration of the mechanisms that impact land use transformations (Mekonnen et al., 2017; Amisigo et al., 2015).

By exploiting these hydrological simulations, some studies have endeavoured to examine the hydrological repercussions of various watersheds to the LULCC and climate variability at varied spatiotemporal scales (Hlásny et al., 2015). Long-term hydrological records can display temporal variations in streamflow that may be influenced by climate variations along with land use and land cover vicissitudes (Xue et al., 2017). Investigating such identified changes from the hydrological records could recognize not only changes in streamflow or runoff in the basin but may also help decipher the critical impressions of anthropogenic deeds and climate change (Guzha et al., 2018).

A seamless amalgamation of LULCC with any hydrologic model offers a generally representative picture of the temporal consequences of land use fluctuations (Worqlul et al.,2017; Woldesenbet et al., 2017). Integration of human-induced activities and land use with a given hydrologic model has the capacity to improve the temporal extrapolative capability resulting from the model (Worqlul et al.,2017). Several researchers (Castillo et al., 2014; Hermassi & Khadhraoui, 2017) have acknowledged the fact that a close-fitting temporal integration of LULCC and hydrologic regimes are required to precisely characterize the connections between climate change, land use transformation and hydrologic patterns. Although the consequences associated with dynamic illustration of changes in land use have been documented (Yu et al., 2014; Ashiagbor et al., 2013), a dynamic incorporation of LUC into hydrologic models are seldom cited in previous studies (Aladejana et al., 2018; Ejieji et al., 2016). LULCC and climate changes might have both short-term and long-term insinuations on the hydrological patterns of river basins, shifting the equilibrium between rainfall and evapotranspiration in addition to the resulting streamflow (Sisay et al., 2017). Fluctuations in the hydrological variables could have several inferences on localized climatic features and also basin-wide characteristics (Guzha et al., 2018).

The Densu River basin in Ghana has been undergoing various levels of LULCC and some levels of variations in the climatic conditions (Aduah et al., 2017). There have been significant observations of increasing rainfall patterns in parts of the Densu Basin (Ansa-Asare & Gordon, 2012; Schep et al., 2016). The watershed has also witnessed variations in temperature over time (Hagan et al., 2011; Osei et al., 2016). These observed LULCC and climate variabilities provide the necessity to investigate their combined consequences on the hydrologic system of the Densu River basin. The objective of this work is to analyse the effects of LULCC and variability in climate on the hydrologic regime of Densu River basin through hydrological modelling.

MATERIALS AND METHODS

Hydrologic modelling using SWAT

Soil and Water Assessment Tool (SWAT) was designed mainly to forecast implications regarding various ecological along anthropogenic activities relating to sediment yield, groundwater recharge, streamflow regime and agrochemical yields in river basins (gauged and ungauged) (Arnold et al., 2012). Hydrologic modelling in the Densu Basin entails a model that can handle the challenge of limited data availability. The Penman-Monteith model for calculating Potential Evapotranspiration (PET) was adopted for this study in consonance with an earlier study in Africa (Aladejana et al., 2018; Ejieji et al., 2016). The water balance for every hydrological response unit (HRU) was determined using Equation 1.

$$S_{W.f} = S_{W.i} + \sum_{i=1}^{f}\left(P_i - Q_{su} - Q_{lat} - ET_i - Q_{sub} - Q_{seep}\right) \quad \ldots\ldots (1)$$

where:

$S_{W.f}$: the final soil-water-content (mm); $S_{W.i}$ -the initial-soil-water (mm); P_i- precipitation (mm); Q_{sub} -the groundwater-flow (mm); Q_{la} -the lateral-flow (mm); Q_{seep} – percolation (mm); Q_{su} -the overland-runoff (mm) and ET_i - evapotranspiration (mm)

In the SWAT model, for a specified time step, the overland runoff of the basin was calculated by using the Curve-Number (CN) method developed as part of Soil Conservation Service (USDA-SCS, 1972 cited by (Hermassi & Khadhraoui, 2017). The surface runoff for an HRU was calculated using Equation 2

$$Q_{surf} = \frac{\left(R_{day} - 0.2S\right)^2}{\left(R_{day} + 0.8S\right)}; R > 0.2S \quad \ldots\ldots\ldots(2)$$

where:

Q_{surf} -the surface run-off (mm); R_{day} - rainfall for a specific day (mm) and S – soil water retention parameter (mm).

The retention parameter was calculated using Equation 3

$$S = 25.4\left(\frac{1000}{CN} - 10\right) \quad \ldots\ldots\ldots\ldots (3)$$

The CN-value may be classified into three situations namely: wet, mean moist and dry. The result of the SWAT model covers surface runoff, evapotranspiration, sediment yield, reservoir water balance and groundwater recharge characteristics (Puno et al., 2019).

SWAT Input Dataset for Hydrological Simulation

To smooth the use of SWAT, the model was set up with ArcGIS 10.3 software with the ArcSWAT extension for ArcGIS. Fig 1 shows the conceptual framework for the modelling of the hydrologic regime of the Densu Basin outlet using SWAT is represented in the flow chart.

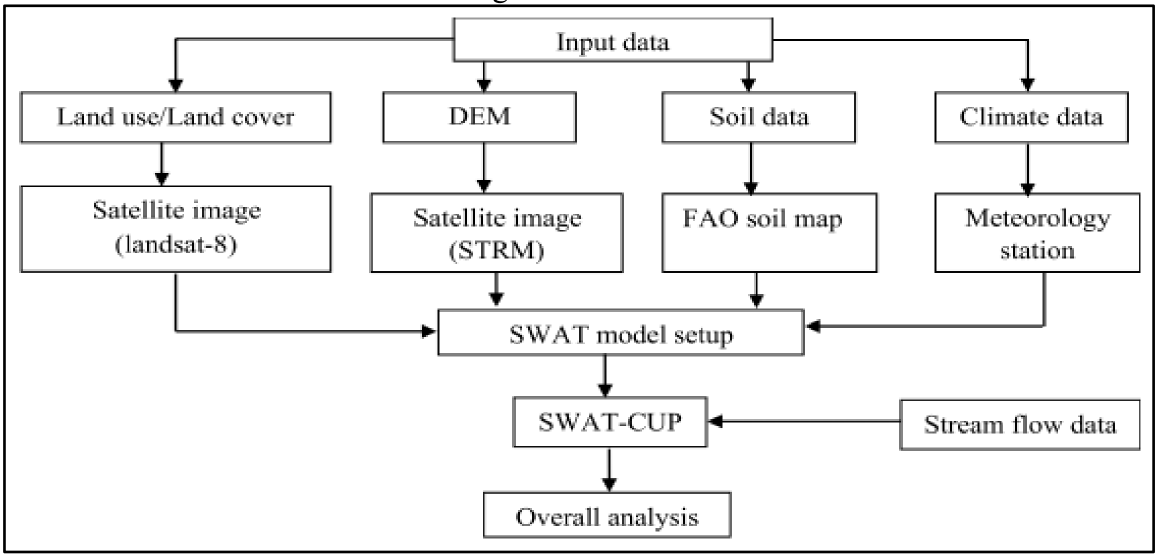


Fig 1: Conceptual framework for SWAT Modelling (Sisay et al., 2017)

The spatial dataset (GIS input) vital for modelling in ArcSWAT interface comprises the Digital Elevation Model (DEM), land use and land cover (LULC) information, climate and soil dataset. The calibration and validation stages of the SWAT model for the watershed used stream discharge data in addition to climate data.

Digital Elevation Model (DEM)

This refers to raster data encompassing an array of pixels that define or entail the elevation of an area at a definite spatial resolution (Sisay et al., 2017). A 30 m x 30 m resolution ASTER DEM (Advanced Spaceborne Thermal Emission and Reflection Radiometer digital elevation model) of the Densu basin was used for the delineation of the study area. The DEM aided the further demarcation of sub-basins, the flow direction of streams and the HRUs.

Weather Data

The smooth processing of SWAT necessitates meteorological data on a daily timescale, that could be generated from a field-measured dataset or by adopting data from the weather generator model. Daily weather datasets comprise wind velocity, precipitation, minimum and maximum temperature as well as relative humidity. The Densu Basin, rainfall and temperature (maximum and minimum) data were acquired from the Ghana Meteorological Agency (GMET) for the period 1976–2015. The other parameters were simulated from the weather generator model. Fig 2 illustrates the position of weather stations located in the Densu River basin.

Land Use and Land Cover

Land use and land cover (LULC) is deemed a very significant feature that influences surface runoff, erosion and evapotranspiration in river basins. The

LULC data of the river basin under consideration is needed for HRU characterisation and then for determination of the Curve Numbers (CN) of the land areas for surface runoff calculations as well as hydrological analysis. The LULC map used for the hydrologic model was obtained by processing Landsat satellite imageries of 1986, 1991 and 2005.

The maximum likelihood algorithm (MLA) in ArcGIS 10.3 was adopted for this study. The MLA remains the most widely utilized procedure in land use classification (Appiah Mensah et al., 2019; Nath et al., 2018). The supervised classification of the study area shown in Fig 3 was done to reclassify the LULC. The Cellular-Automata Markov chain algorithm in IDRISI Selva V17 was used for the projection of the LULC from 2017 to 2027 (Liping et al., 2018; Silva et al., 2020).

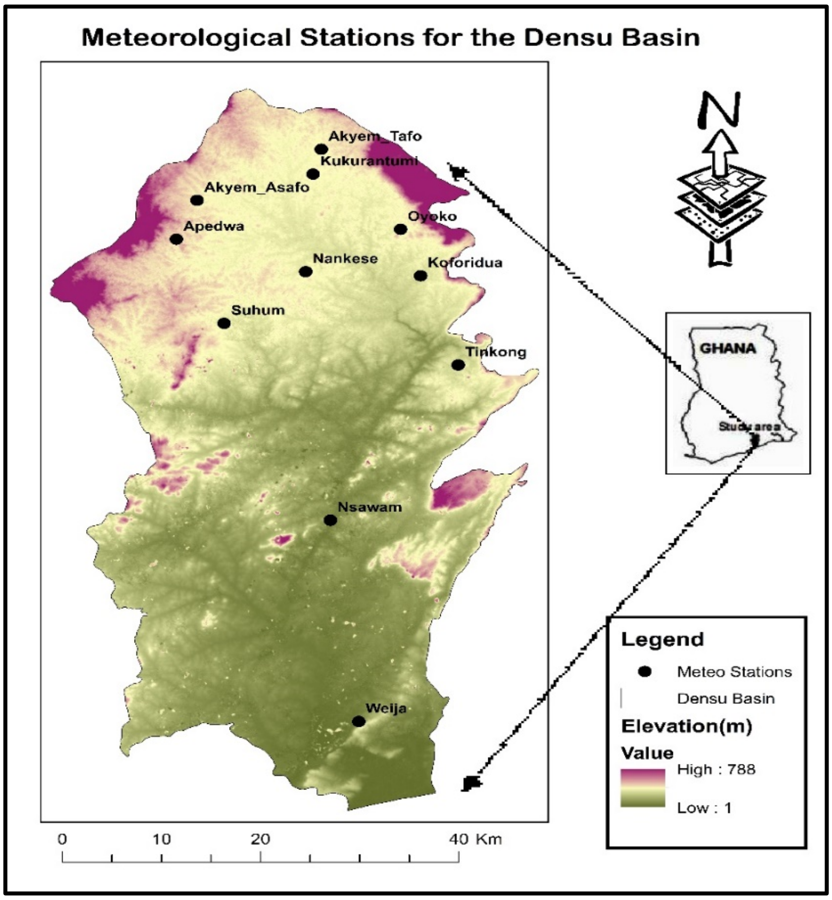


Fig 2: Location of Weather stations in the Densu River Basin

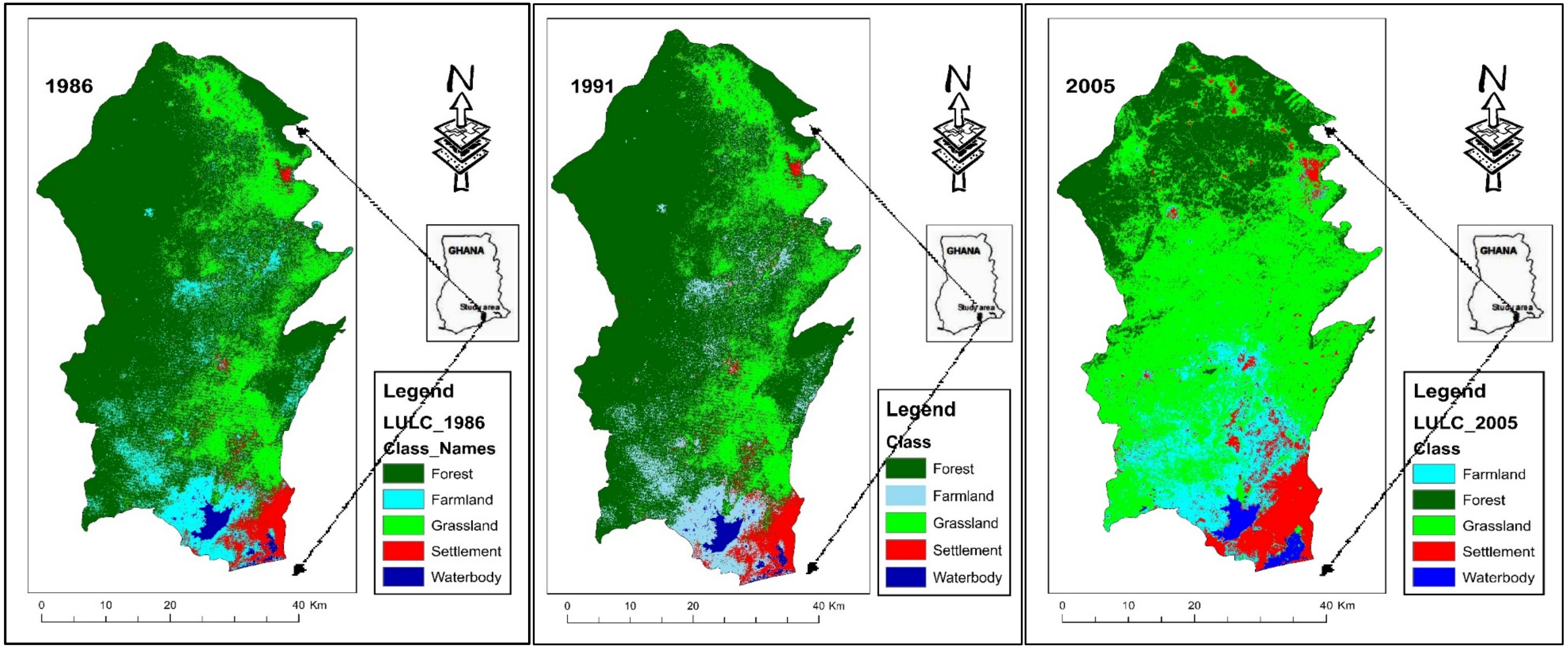
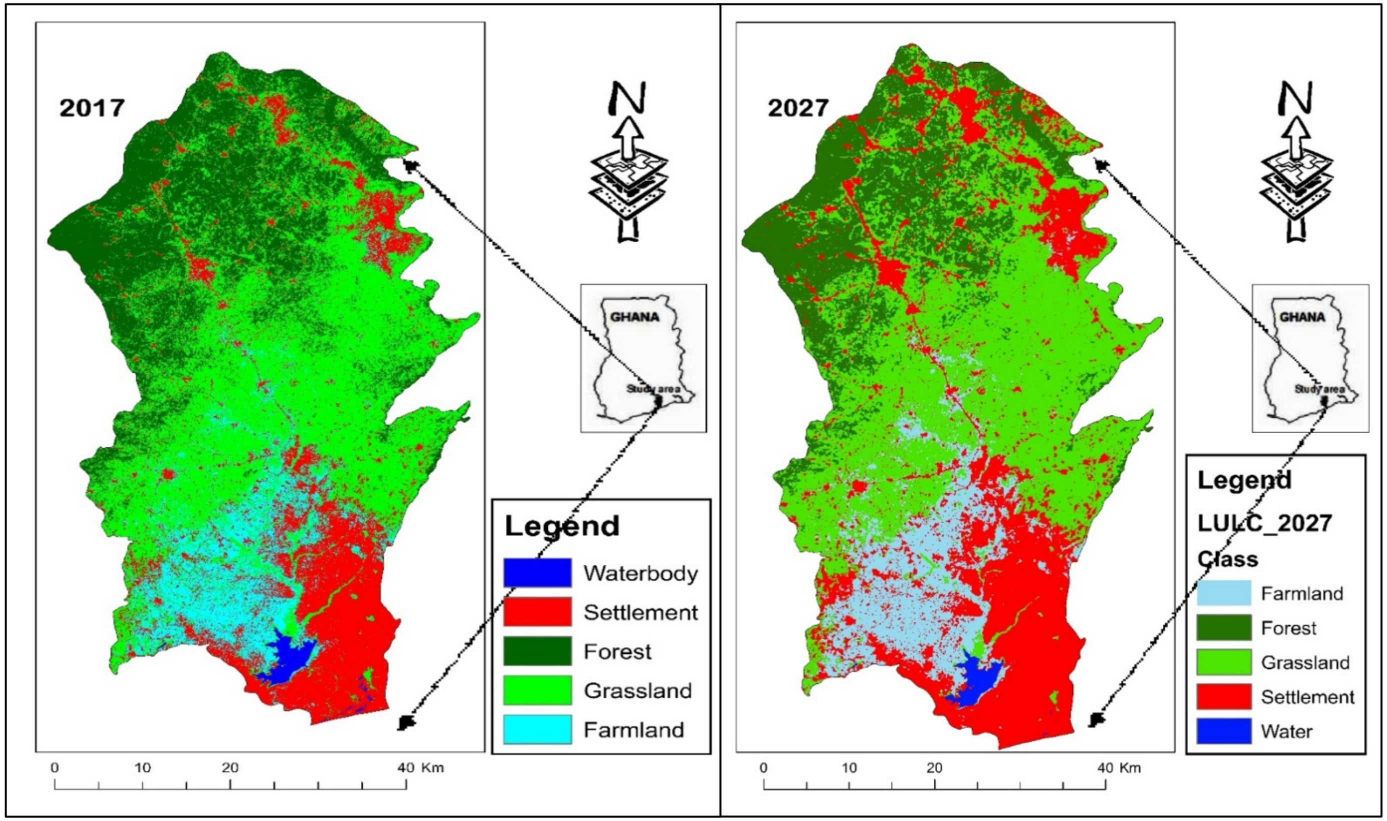


Fig 3a: Land use and land cover Map of Study Area (a-1986, b-1991 and c-2005)



The map representing the LULC characteristics (Fig 3) associated with the study area was fashioned to derive the highly substantial land use categories in the Densu basin. Reliant on the supervised classifications performed, five major land use categories were observed. It can be deduced from Table 1 that Dense Forest has been declining over the years whilst settlements have been experiencing increases in land area.

Fig 3b: Land use and land cover Map of Study Area (2017 and 2027)

Table 1: Land use land cover for 1986-2027

	1986	1991	2005	2017	2027
Land Use Classification	**Percentage**	**Percentage**	**Percentage**	**Percentage**	**Percentage**
Waterbody	1.05	1.05	1.56	1.07	0.93
Settlement	3.83	3.82	7.79	18.90	24.98
Dense Forest	68.86	68.84	26.07	26.69	19.15
Open Forest	16.64	16.66	52.12	41.75	42.79
Cropland	9.62	9.63	12.46	11.58	12.16
Total	**100**	**100**	**100**	**100**	100

Table 2: Soil Types in the Densu Basin

S/N	Soil Type	Percentage (%)
1	Acrisols	9.25
2	Arenosols	0.11
3	Fluvisols	4.45
4	Leptosols	14.57
5	Lixisols	58.50
6	Luvisols	11.88
7	Plinthosols	0.62
8	Solonetz	0.44
9	Waterbody	0.18
	Total	100

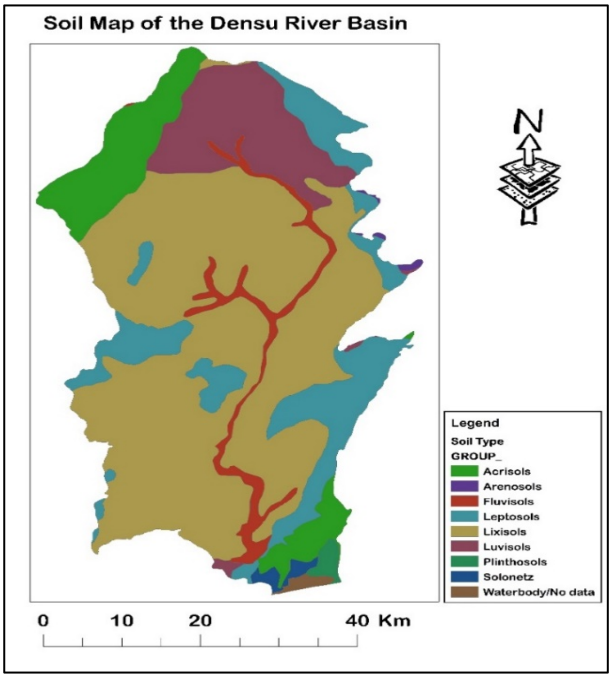


Fig 4: Types of Soil in the Densu River Basin

Fig 4 displays the categories of soil classes existing in the study area. The percentage coverage of each soil class is illustrated in Table 2.

Soil Data

The digital soil information for the Densu basin was extracted from the Harmonized World Soil Database (HWSD V1.2). The HWSD was generated by the Food and Agriculture Organization (FAO) of the United Nations and its partner institutions (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009, 2012).

Lixisols (58.50 %) are the predominant soil type in the Densu River basin, followed by Leptosols (14.57 %) and Luvisols (11.88 %). These soils, according to (Ashiagbor et al., 2013), have high sand content compared to clay and silt.

Hydrological Data

Hydrological Services Department of Ghana, provided the daily streamflow data for the Densu River. The streamflow data ranged from 1976 to 2013. Due to the higher degree of missing data and some inconsistencies, the Nsawam dataset was adopted for both calibration and validation of the hydrological model developed. The missing data were estimated based on the multi-year mean monthly flow observations for hydrological stations in the Densu Basin (Napoli et al., 2017).

SWAT Model Setup

Watershed delineation

The initial stage in producing SWAT model input involves the demarcation of the catchment from a projected DEM of the study area. The data inputs used for the SWAT model were then prepared and arranged based on their spatial and temporal characteristics. Fig 5 illustrates the sub-basins in the study area.

Hydrological Response Units (HRUs)

The land size for each of the sub-basins was segregated into HRUs which facilitated the loading of input data such as LULC, soil type and the generation of slope map of the model. The LULC, soil types and the slope of the Densu River basin were reclassified to match the parameters set out SWAT database.

Hydrologic Analysis of Dynamic Land Use

To incorporate the dynamic land use changes (Zarezadeh and Giacomoni, 2017) into the hydrologic regime of the Densu basin, a modified version of an R-script (Nguyen, 2012) for simulating variations in land use was applied. Fig 6 depicts the framework for dynamic land use change analysis adopted for this study. The HRU for hydrologic models developed for 1986, 1991 and 2005 were used to create an amalgamated HRU. The result generated by the model was calibrated and validated.

Calibration and Validation of Model

Calibration and validation of the model were implemented by comparison of the simulated and measured streamflow data. Statistical and graphical techniques were applied to evaluate the performance of the SWAT model. Monthly streamflow data for the period 1986 to 1995 was used for calibration and 1996 to 2007 were used for validation of the surface runoff. A simulation warm-up period of five years (1981-1985) was utilized. Semi-automated Sequential Uncertainty Fitting (SUFI-2) calibration and validation system implemented in SWAT - Calibration and Uncertainty Procedures (SWAT-CUP) was adopted for the model's calibration and validation (Abbaspour, 2015).

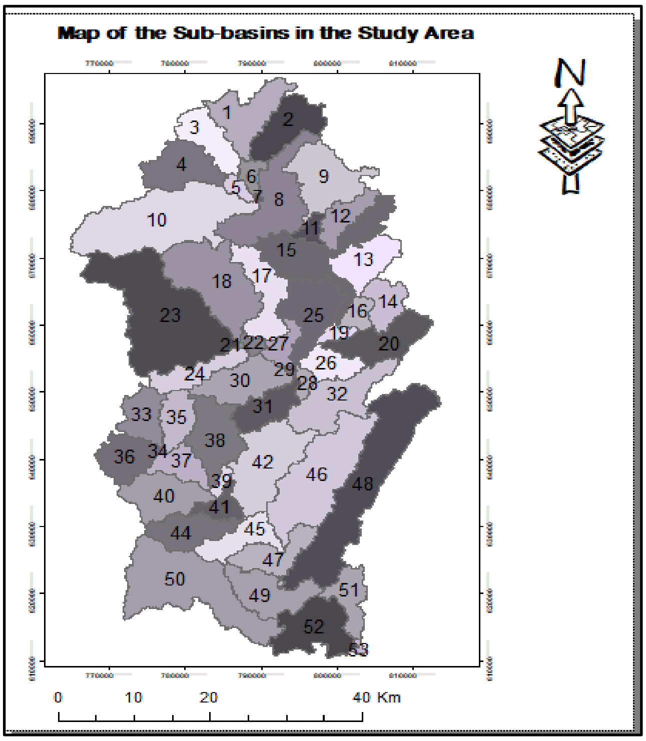


Fig 5: Sub-basins of the study area

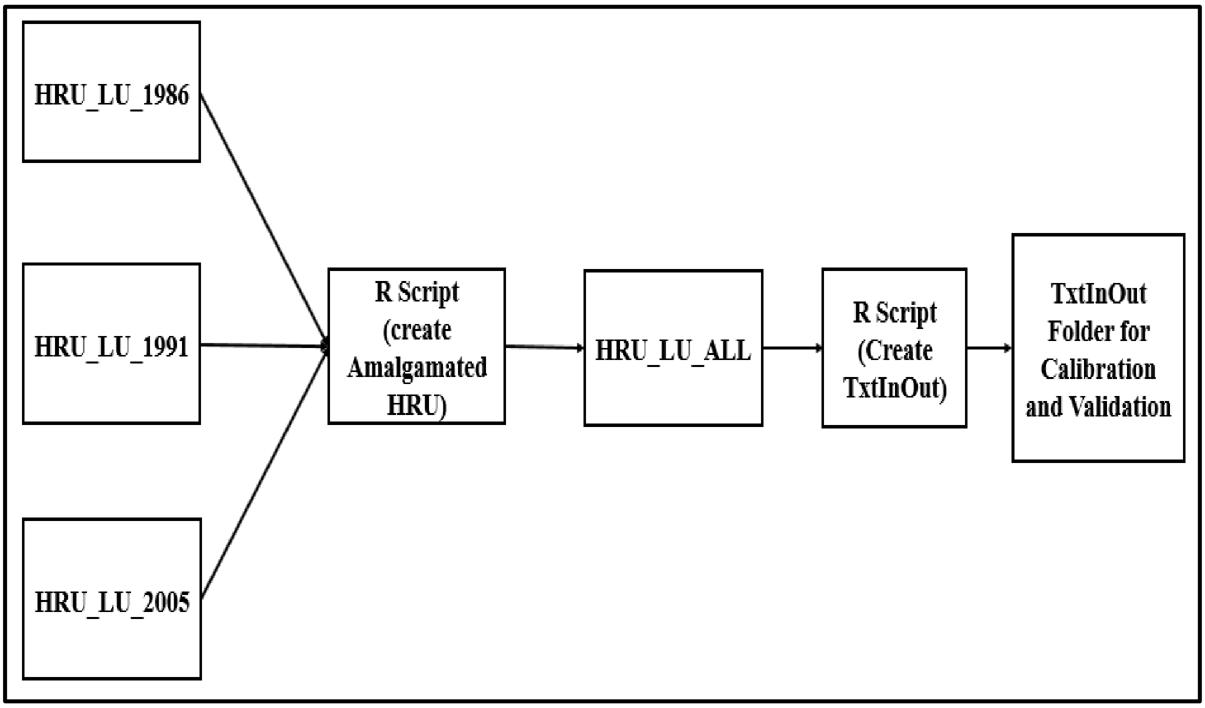


Fig 6: Framework for Dynamic Land Use Analysis

Model Performance Evaluation

The hydrological model performance was assessed using both statistical and graphical methods. The hydrological characteristics or streamflow behaviour of the basin was evaluated. Statistical parameters such as the Nash–Sutcliffe-Efficiency (NSE), coefficient of determination (R^2), Percentage Bias (P_{BIAS}) and root mean square error to the standard deviation ratio (RSR) with the representative hydrographs were chosen as recommended (Gyamfi, 2016; Welde and Gebremaria et al., 2017).

Nash-Sutcliff-Efficiency (NSE)

The NSE values determine the comparative extent of residual variance of simulated discharge relative to the discrepancy of measured or observed data (Nash & Sutcliffe, 1970). NSE is estimated using Equation 4. The NSE values range from $-\infty$ to 1, where 1 signifies a perfect correlation between simulated and measured variables.

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n} \left(Q_{sim} - Q_{obs} \right)^2}{\sum_{i=1}^{n} \left(Q_{obs} - \overline{Q_{obs}} \right)^2} \right] \ldots\ldots\ldots\ldots (4)$$

The Coefficient of Determination (R^2)

This indicator determines the proportional variation in the observed variable and the simulated variable. R^2 is calculated by using Equation 5. The results of the coefficient of determination vary between 0 to 1. The results of r^2 determine the level of predictability of the dependent variable. High values of r^2 indicate a good correlation between the dependent and independent variables and vice versa.

$$R^2 = \left[\frac{\sum_{i=1}^{n} \left(Q_{obs} - \overline{Q_{obs}} \right)\left(Q_{sim} - \overline{Q_{sim}} \right)}{\sqrt{\sum_{i=1}^{n} \left(Q_{obs} - \overline{Q_{obs}} \right)^2} \times \sqrt{\sum_{i=1}^{n} \left(Q_{sim} - \overline{Q_{sim}} \right)^2}} \right]^2 ; 0 \le R^2 \le 1 \ldots\ldots \ (5)$$

Per cent Bias (PBIAS)

The best value of P_{BIAS} is 0.0, whilst low values are indicative of correct model simulation. Positive values of Pbias show underestimation by the model and negative values of Pbias signify model over-valuation of bias (Bouslihim et al.,2016). It is evaluated using Equation 6 and measured in percentage.

$$PBIAS = \left[\frac{\sum_{i=1}^{n} \left(Q_{sim} - Q_{obs} \right)}{\sum_{i=1}^{n} Q_{obs}} \times 100 \right] \ldots\ldots\ldots (4)$$

RMSE-observations standard deviation ratio (RSR)

The RSR was calculated using Equation 7.

$$RSR = \frac{\sqrt{\sum_{i=1}^{n}\left(Q_{sim}-Q_{obs}\right)^2}}{\sqrt{\sum_{i=1}^{n}\left(Q_{obs}-\overline{Q_{obs}}\right)^2}} \quad \ldots\ldots\ldots (5)$$

Where:

Q_{obs}-observed data; Q_{sim} - simulated data;

$\overline{Q}_{obs}$ − Mean Observed data $\overline{Q}_{sim}$ − Mean simulated data

Sensitivity Analysis of the SWAT Model

Sensitivity analysis helped to indicate the utmost flow parameters (Anaba et al., 2017; Kouchi et al., 2017), that impact the basin modelled by SWAT for calibration (Anaba et al., 2017). This was accomplished by applying the semi-automated Sequential Uncertainty Fitting (SUFI2) algorithm, which uses the global sensitivity evaluation technique (Abbaspour, 2015; Marhaento et al., 2017; Kumar et al., 2018).

Table 3: Parameters for Sensitivity Analysis

S/N	Parameter Name	Description
1.	CN2	SCS runoff curve number
2.	ESCO	Soil evaporation compensation factor
3.	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O)
4.	SOL_AWC	Soil available water storage capacity (mm H2O/mm soil)
5.	GW_REVAP	Groundwater revap coefficient
6.	RCHRG_DP	Deep aquifer percolation function
7.	SOL_Z	Soil depth (mm)
8.	SURLAG	Surface runoff lag coefficient (day)
9.	SOL_K	Soil hydraulic conductivity (mm h^{-1})
10.	CH_K2	Effective hydraulic conductivity in the main channel (mm h^{-1})
11.	ALPHA_BF	Baseflow alpha factor (day)
12.	GW_DELAY	Groundwater delay (day)
13.	ALPHA_BNK	The baseflow alpha factor for bank storage (day)
14.	REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)

(source: (Kiros et al., 2015))

The sensitivity parameters (Table 3) are necessary for estimating the quantity of flow a watershed generates. The p-values and t-statistics displayed in Table 3 help to rate the numerous parameters thought to determine the stream flow. The final range and sorting of parameters were made concerning the statistical significance of the ranked parameters (Anaba et al., 2017).

RESULTS AND DISCUSSION

Sensitivity Trends of Streamflow

Global sensitivity analysis relating flow parameters designated that streamflow for the Densu basin was highly sensitive to three parameters (Table 4), the groundwater-delay period (GW_Delay), the baseflow-alpha parameter (Alpha_BF) and curve number (CN2). The sensitivity of threshold water level in shallow aquifers for baseflow (GWQMN) was statistically not significant.

These results are reinforced by the conclusions of other researchers (Gyamfi et al., 2016; Castillo et al., 2014; Chu et al., 2010), which advocate that curve number (CN2), groundwater-delay-time (GW_Delay) and baseflow-alpha-factor (Alpha_BF) are sensitive streamflow parameter. Even though streamflow was deemed to be less sensitive to the other parameters in the basin (the less sensitive parameters had p-values that were bigger than 5%), there are other studies (Demirel et al., 2018; Dwarakish and Ganasri, 2015) with similar sensitivity levels of these parameters in their research work.

According to a study by Anaba et al., (2017), because of the vicissitudes in the geographic location of basins, soil types, geology, LULCC and climatic factors, variations and deviation of sensitivity parameters do not greatly influence the models. Results from the calibration and validation of sensitive streamflow parameters (Table 5) indicated the influence of sensitive parameters.

Table 1: Ranking of Sensitivity parameters

Parameter Name	P-value	t-stat	Ranking
V__GW_DELAY.gw	0.00	7.63	1
V__ALPHA_BF.gw	0.00	4.00	2
R__CN2.mgt	0.04	1.88	3
V__GWQMN.gw	0.46	-0.74	4

where,
V__ specifies that the value of the parameter is replaced by the derived value;
R__ specifies the value of the parameter is multiplied by (1 + the given value)

Table 2: Calibrated values of sensitive streamflow parameters

Parameter Name	Min_value	Max_value	Fitted Value
R__CN2.mgt	-0.200	0.200	-0.135
V__ALPHA_BF.gw	0.000	1.000	0.103
V__GW_DELAY.gw	30.000	450.000	39.45
V__GWQMN.gw	0.000	2.000	1.045

Where:
Prefix v__ specifies that the value of the parameter is replaced by the derived value;
Prefix r__ specifies the value of the parameter is multiplied by (1 + the given value)

SWAT Model Results

The observed and simulated streamflow results for both calibration (January 1981 to December 1995) and validation (January 1996 to December 2007) periods are correlated based on statistical parameters. Graphical presentation of results for calibration together with validation of the models are displayed in Fig 7 and Fig 8.

The coefficient of determination of the calibration (Fig 9) as well as the validation cycles (Fig 10) were 0.94 and 0.92 respectively. These results illustrate a greater correlation between the simulated and observed data for calibration timesteps compared with the validation period.

Statistical SWAT model's performance for streamflow outputs or outcomes during the calibration and validation timesteps are displayed in (Table 5). Based on the recommended performance statistics for monthly timestep (Daggupati et al., 2018; Demirel et al., 2018), NSE and R^2 results for both calibration and validation of the model were greater than 0.6 and could be deemed good (Table 6). The P_{BIAS} results could be classified as good. The RSR results can also be said to be very good. All these results indicate a good model performance.

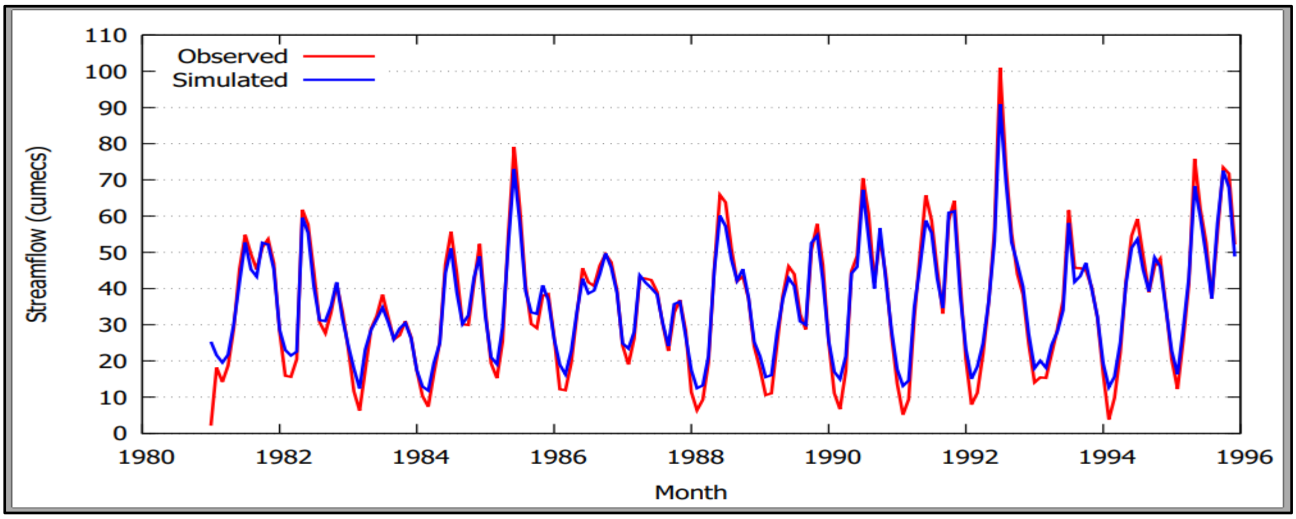


Fig 7: Monthly streamflow for Nsawam gauge station during calibration (1981-1995)

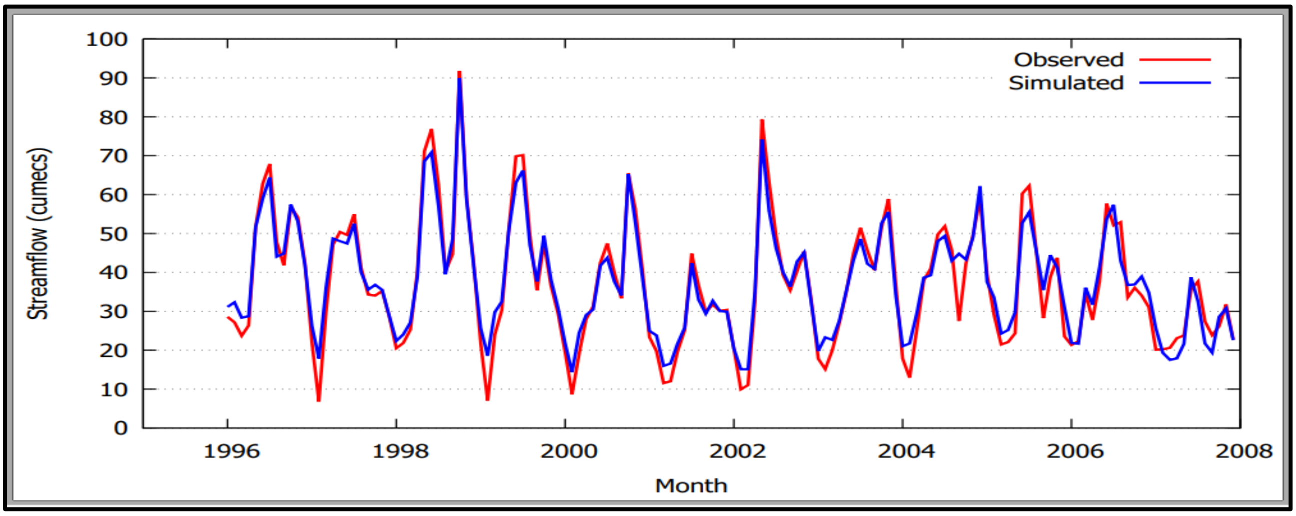


Fig 8: Monthly streamflow for Nsawam gauge station during validation (1996 – 2007)

Table 3: Model performance statistics

Statistical parameter	Model Stage	
	Calibration	Validation
R^2	0.94	0.92
NSE	0.88	0.83
RSR	0.22	0.25
PBIAS (%)	1.3	1.8

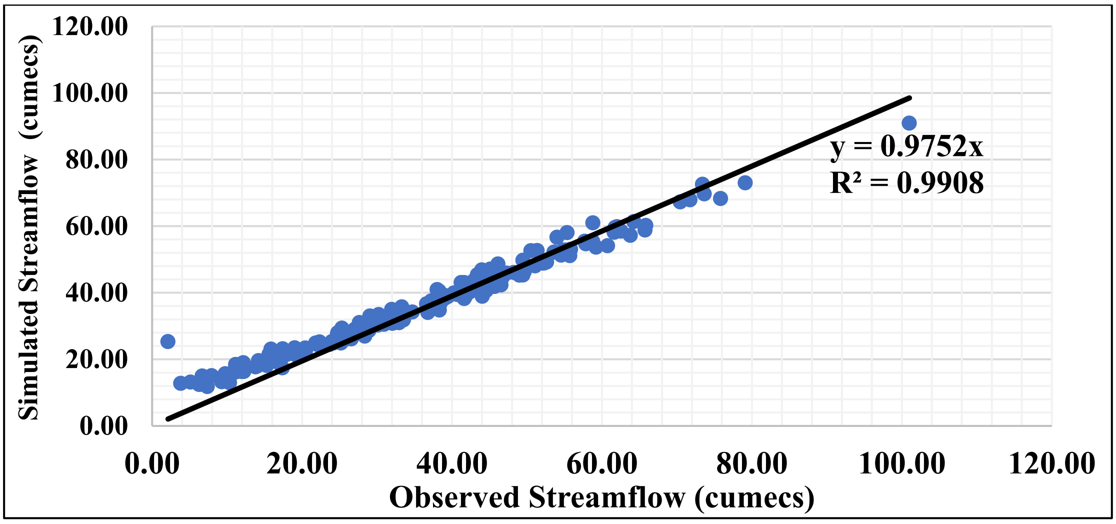


Fig 9: Simulated and observed discharge for the calibration period (1981-1995)

where –
x represents the observed streamflow
y represents the simulated streamflow

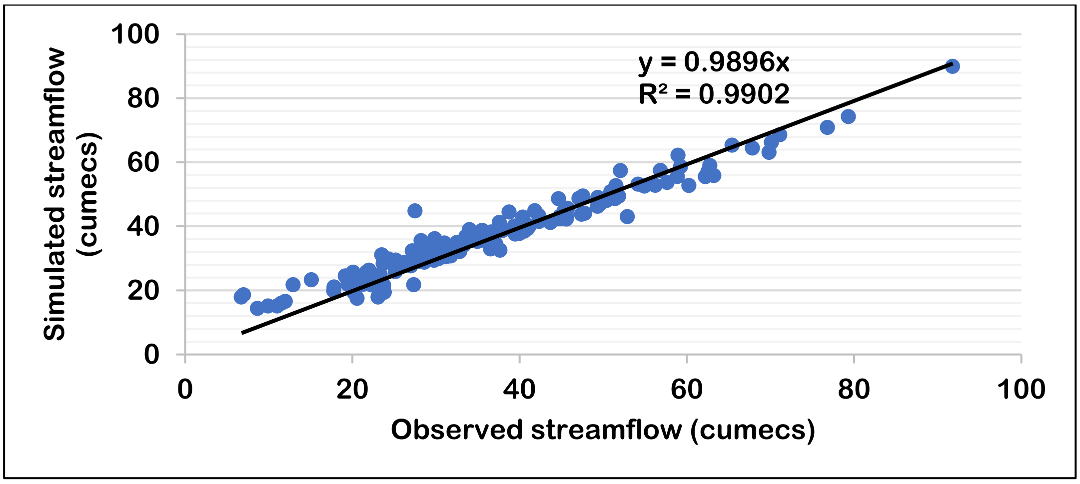


Fig 10: Simulated and observed discharge for the validation period (1996-2007)

where –
x represents observed streamflow
y represents simulated streamflow

Land Use and Land Cover Dynamics and Streamflow

It can be deduced from Fig 11 that the flow pattern, compared to preceding periods, shows some consistent behaviours. Another critical reason that accounts for streamflow may be the influence of rainfall alongside temperature changes in the Densu Basin (Abeysingha et al., 2016; Cancelliere 2019; Jajarmizadeh et al., 2017). Streamflow variability has been observed to be greatly influenced by climate forcing and groundwater flow characteristics.

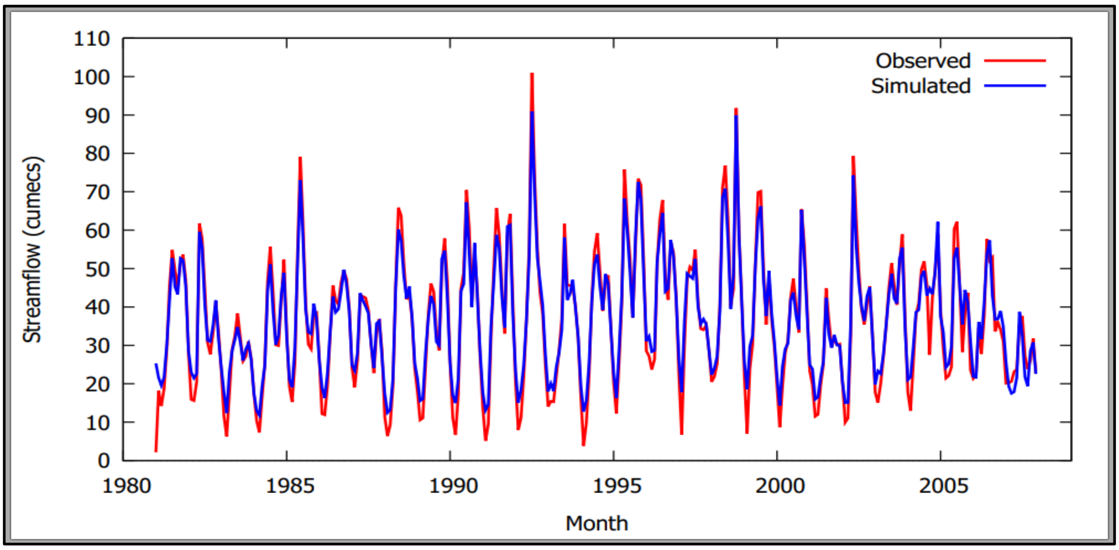


Fig 11: Observed and Simulated Streamflow (1981-2007)

The land use conversions were mainly from dense forests and open forests to other land classes such as bareland, cropland and settlements. The hydrological balance in a watershed is inveigled greatly by alterations of the LULC (Dos Santos, et al., 2018).

Results from the study (Fig 12) depict that the mean annual evapotranspiration for the Densu basin was high for upstream areas of the basin. These areas have dense forests and sparse forests as dominant land cover (Woldesenbet et al., 2017). The dense forest areas had average ET values ranging between 700 and 900 mm. The downstream areas also recorded moderately high evapotranspiration. The land use classes for the downstream areas were predominantly settlement and some agricultural fields (Kouchi et al., 2017). The downstream values ranged between 500mm and 700mm. The barelands, paved areas and built-up conditions downstream contributed significantly to high temperatures which serve as a trigger for evapotranspiration (Liu et al., 2019).

The mid-stream portions of the basin recorded relatively low ET values ranging between 419 to 425 mm. The mid-stream areas of the basin have mixed land use classes – dense and sparse forests, settlements, Cropland and water bodies. The low ET values may be attributed to the tendency for precipitation to be converted to surface runoff hence reducing the quantum available for ET (Jajarmizadeh et al.,2017).

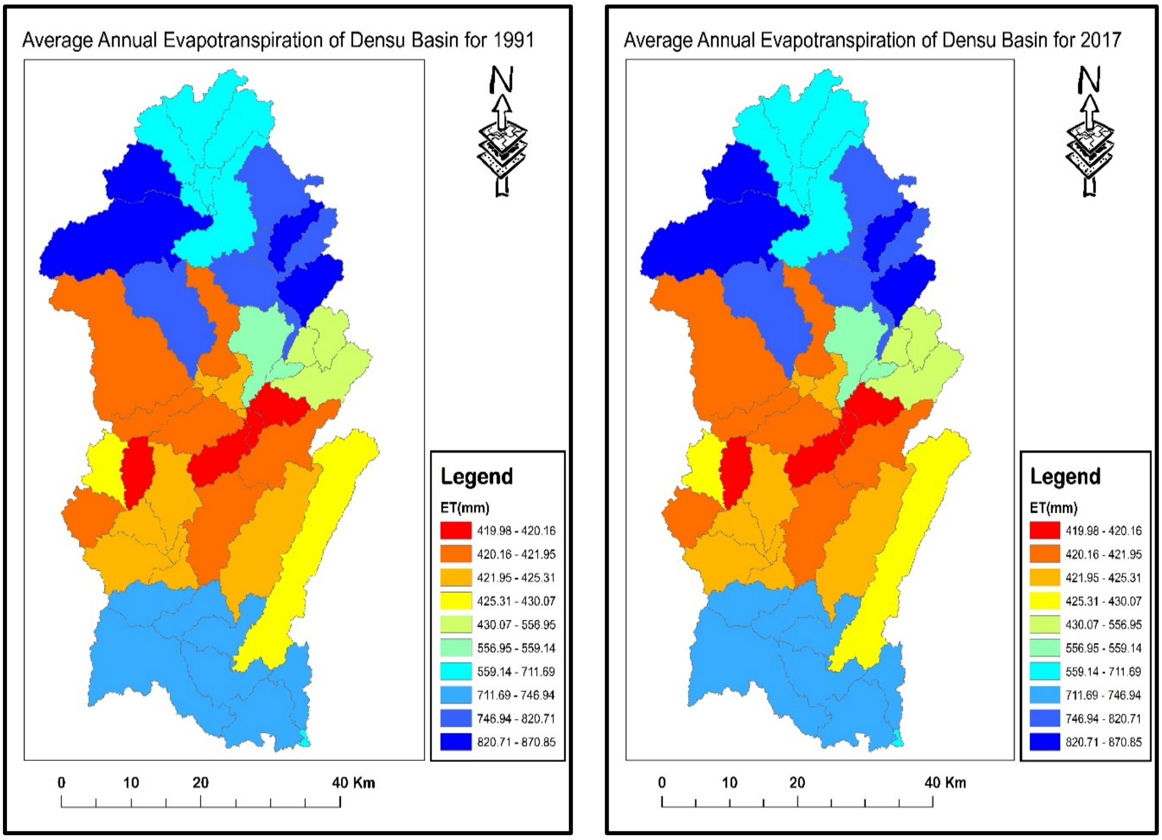
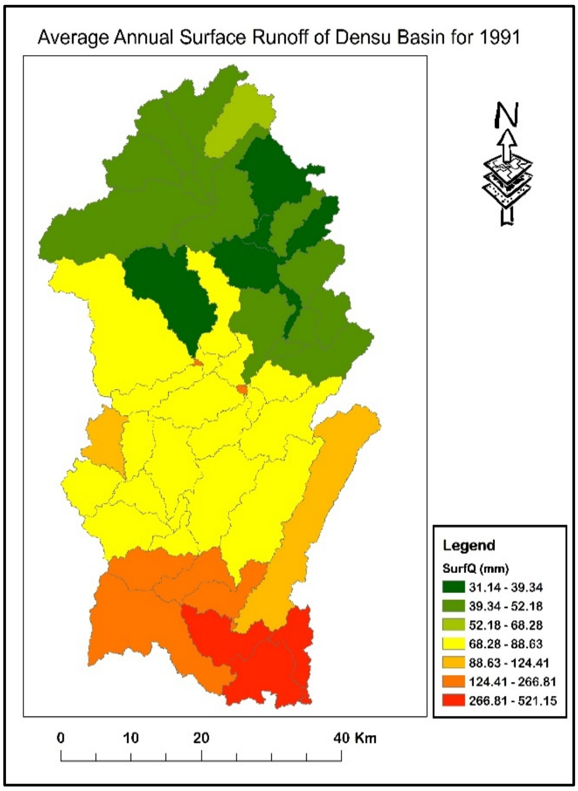


Fig 12: Average Annual Evapotranspiration for Densu Basin

The surface runoff of the basin for the upstream area was lower (31.14 - 52.18 mm). The mid-stream portions had moderate surface runoff values (52.18- 88.63 mm) while the downstream recorded high surface runoff values (88.63-521.20 mm). These results indicate an inverse connection between the intensity of forest cover and surface runoff. The results (Fig 13) depict that a decline in forest cover results in an upsurge in surface runoff. Outcomes from other investigations related to forest cover situations demonstrated that surface runoff declined when forest cover made gains (Guzha et al., 2018). Therefore, the results from the LULC for 2017 and 2027 bring out the fact that the forest cover of the basin is declining at an alarming rate and hence may result in flash floods especially in built-up areas. This assertion is clearly depicted in Fig 13.

The study identified potential groundwater recharge zones in the basin. The areas that were identified to have high percolation (Fig 14) coincided with the high-elevation zones in the basin. Some of the areas (Kuano, Osiem and Akyem-Asafo) are notable farming areas. The identification of these areas as high percolation areas requires the education of the communities on agronomic practices that would curtail the pollution of groundwater. The basin is underlain by a granitoid and hence groundwater recharge in the mid-stream could be relatively low compared to the upstream.



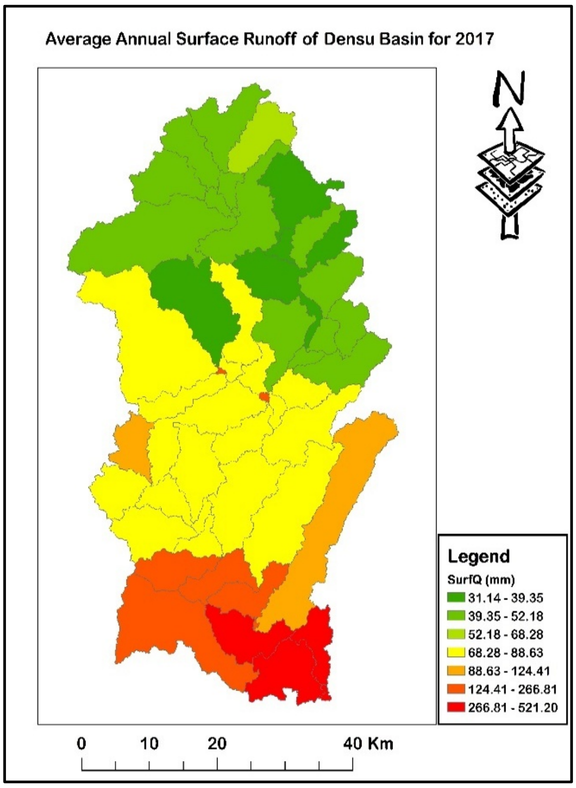
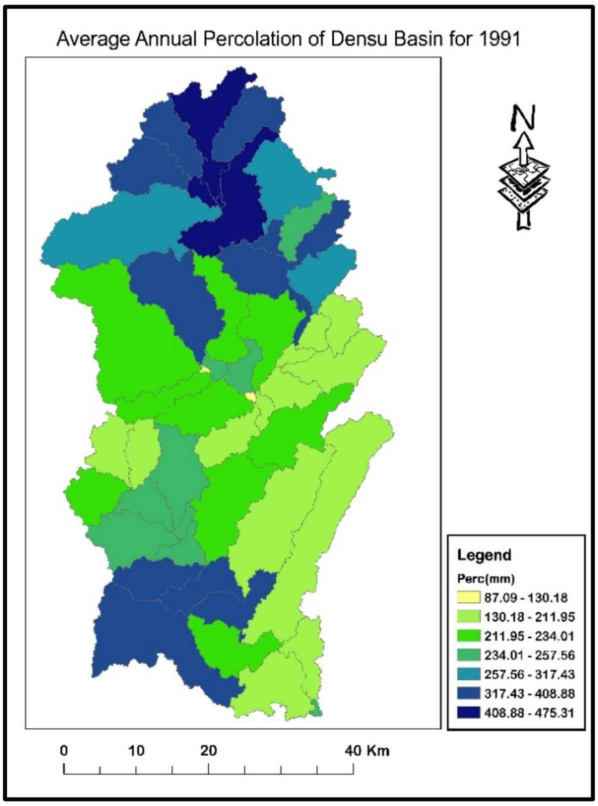


Fig 13: Average Annual Surface Runoff for the Densu Basin



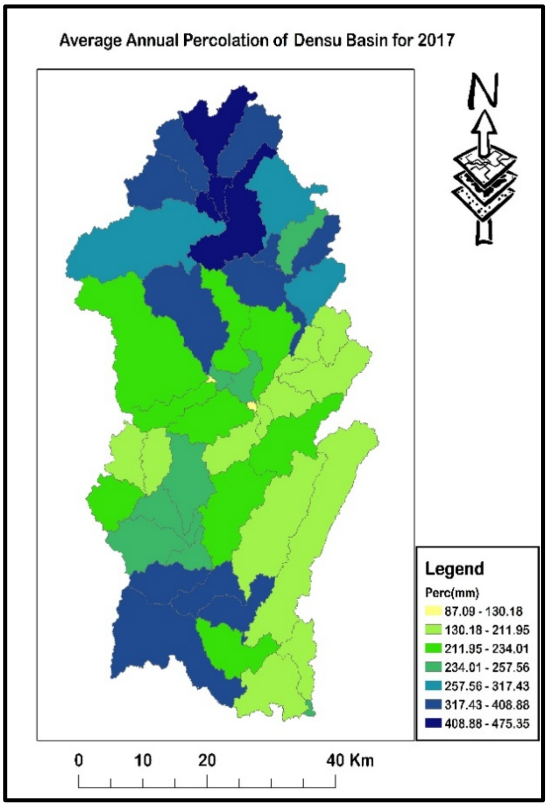


Fig 14: Average Annual Percolation of the Densu Basin

CONCLUSION

For this research, the SWAT model was utilized in the examination of the hydrologic feedback of the Densu River basin resulting from dynamic LUC. The sensitive parameters of streamflow were curve-number (CN2), groundwater-delay (GW_DELAY), baseflow-alpha-factor (ALPHA_BF) and threshold depth of water in shallow aquifer required for return flow (GWQMN). The most statistically significant parameters were CN2, ALPHA_BF and GW_DELAY. Thus, these factors could be applied during future hydrological and ecological research for Densu basin. The pertinency of the SWAT model in modelling stream flow dynamics of the Densu River basin has been validated by the satisfactory results of the model and simulation statistics. The changing LULC as well as variability in climate was observed to influence evapotranspiration, groundwater recharge and surface runoff.

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