Detection and prediction of land use change impact on stream flow regime in Sahelian river basin, northwestern Nigeria

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Abstract

Detecting and predicting the impact of land use/land cover (LULC) changes on streamflow are crucial sources of information for the effective management and protection of land and water resources in Sahelian ecosystems such as the Hadejia river basin. In this study, LULC change detection was performed using ENVI, while the LULC modeling was conducted using the cellular automata (CA)–Markov in the IDRISI environment. However, the streamflow trend and variation were assessed using the Mann–Kendall (MK) trend test and the inverse distance weightage (IDW). Before the LULC modeling and projection (2030), the LULC was classified for 1990, 2000, and 2010 using supervise classification. Model output revealed a strong relationship between LULC and streamflow trend, thus, the decade 1990–2000, was the decade with high forest clearance and streamflow output, consequently severe floods. However, the decade 2000–2010 witnessed land use expansion mainly via construction (3.4%). Meanwhile, the scenario will slightly change in the future as agriculture is projected to expand by about 9.3% from 2010 to 2030 due to the increased human population. Thus, food insecurity aggravated by climate change should be anticipated, and measures to avert/reduce their effects must be initiated.

Key words: cellular automata, inverse distance weightage, land use, northwestern Nigeria, streamflow

Highlights

- The pattern of land use change was detected and predicted in Hadejia river basin.
- Agriculture was and is still the dominant land use type in the basin area.
- The construction land use and related here referred to as ‘others’ is the most expanding land use type.
- Both temporal and spatial analysis shows that land use changes exact certain influence on stream flow in the basin.

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INTRODUCTION

Modification of the land and its related resources has gradually become one of the critical and topical issues currently attracting global attention and is now at the heart of sustainability and environmental conservation (Bock et al. 2018). This is perhaps due to increasing manifestation of land use and climate change repercussions (Jiang et al. 2019; John & John 2019). These repercussions have been further accentuated by increased land use/land cover (LULC) modifications as a consequence of rapid population growth and the accompanied socio-economic development from various facets (Guan et al. 2011; Halmy et al. 2015; Zheng et al. 2015). West Africa’s gradual integration into a global market economy, for instance, has led to the acceleration of foreign investment in the Guinean forest countries in mining and timber industries, which momentously increases the rate of forest loss. Similarly, the increasing prosperity of nations stimulated by the growing population has changed the consumption patterns of many individuals, thus, the growing demand by wealthy urban populations for processed food, meat, and dairy, is gradually yielding untold repercussions on land and other natural resources (Sedano et al. 2019).

Besides the anthropogenic explanations, changes have also been brought to the land and its uses by the natural conditions, and, of significant concern, are those brought by climate change. Therefore, the influence of climate on land cover transformation has complicated the human-induced causes and can be seen and measured on different timescales (Sedano et al. 2019). Part of the climate challenges aggravating the problem of land use changes are the concerning recurrence and persistent drought and its worst repercussions, especially in the Sahelian and semi-arid strips of West Africa where Hadejia river basin (HRB) is located. These effects of climate change on land cover can be visualized via dwindling water bodies, soil desiccation which is undermining the vegetation’s profusion and diversity, thus increasing the vulnerability of the soil to erosion. Ultimately, this is jeopardizing the talent of the inhabitants to utilize the land for the supposed different purposes such as irrigation and rain-fed farming, pushing these people to find other means of accessing their livelihoods. Subsequently, the land use and climate change repercussions breed environmental and security challenges posing additional problems to both the inhabitants and authorities of the region.

The drought threat to agriculture in Nigeria’s Sudano-Sahelian region, for instance, has forced farmers and herdsmen to migrate from the arid terrain to wetter areas of the country or to major cities in search of jobs, eventually worsening the security complications and uncalled congestions in the host areas. In other scenarios, the combined burden of drought and population pressure has triggered huge investments in soil and water resources and in the intensification of agriculture in northern Nigeria, hence most of these environmental resources are overstretched (Sedano et al. 2019). Although it is a well-known fact that LULC driving factors work in complicated ways, the most recognized and discussed drivers of this change are: (a) population, which dictates the nature and magnitude of land resources demands and (b) climate, which influences the availability of such land resources (Nerantzaki & Papalexiou 2019; Valipour et al. 2020).
Due to climate change and rising population, the transformation of LULC into agricultural land and metropolitan regions, has steadily become detrimental to multiple environmental processes, especially the environmental flow processes (Kreuter et al. 2001; Bock et al. 2018; Leach & Coulibaly 2019). The effects of these modifications have led to the degradation of the general working mechanism of the environment, slowing down the effectiveness of the ecosystem services, thus hijacking the full attainment of the maximum benefits derivable from the ecosystem (Portela & Rademacher 2001; Temesgen et al. 2013; Wang et al. 2014). Considering these realities, the detection and quantification of land use dynamics and its effects on environmental flow becomes essential and this will provide information crucial for managing the land and water resources within the basin’s vicinity (Szumacher & Pabjanek 2017). This will serve as a background for future prediction to support the development of realistic strategies that will guide the workable utilization of both land and water resources (Li & Yeh 2004; Long et al. 2007; Wei et al. 2017).

In recent years, scientists in different academic fields from those who are mainly concerned about modeling to those who are more inclined towards the reasons for and implications of LULC dynamics (Gautam et al. 2003; Porter-Bolland et al. 2007) have been significantly drawn to the problems of the LULC changes and the complexities of the processes. The groups studying LULC have generated a large number of working models to mimic the likely LULC modifications in the future. Many models, such as cellular automata (CA) (Verburg et al. 2006; Anand et al. 2018), Markov chain (Guan et al. 2014), agent-based (Xie et al. 2007), and CLUE (Han et al. 2015), have been created to predict the change in LULC. Even though it was advocated that a multidisciplinary model combination might be highly crucial in designing future LULC change projections (Guan et al. 2011), the CA model is recognized as the most efficient and reliable model frequently used in spatial and temporal simulation research (Guan et al. 2014; Anand et al. 2018). Flexibility, intuition, and the capacity to integrate the spatial and temporal characteristics of the procedures, as well as the capacity to model complicated dynamic systems, are significant reasons why the CA model has been widely used to boost urban growth trends and future changes in land use in the latest years (Wu et al. 2016; Mosammam et al. 2017; Yirsaw et al. 2017).

The Mann–Kendall (MK) test, a rank-based nonparametric trend detector (Chatfield 2018), has been applied in the current study for a widely used technique to assess the significance of monotonic trends in hydro-meteorological time series (Umar et al. 2018). This trend test technique has also been recommended by the World Meteorological Organization (WMO 1988) for trend detection in meteorological data. Its wide application in trend assessment was informed by the numerous advantages over other techniques which include (1) the ability to accommodate data from non-normal distribution, data with outliers and missing values and (2) its high asymptotic efficiency (Fu et al. 2017). Meanwhile, the Sen’s, also a non-parametric method, known for its robustness, has been commonly adopted to assess the real path of the current trend (Yadav et al. 2016; Panwar et al. 2018).

Geostatistical technique has similarly been incorporated into this study, and of all the spatial interpolation techniques currently in use, kriging and inverse distance weightage (IDW) are the most commonly used (Zhao et al. 2016; Qiao et al. 2018). However, the IDW method has been acknowledged as the best over the rest of spatial interpolation techniques. It is less complex and straightforward, speedy in calculation and it gives more appreciable results than other techniques (Qu et al. 2017; Shahid et al. 2017). The underlying mechanism of IDW is based on the assumption that the attribute value of the unmeasured station is the weighted average of the measured values within the area and inversely proportional to the distances between the predicted and the measured points (Qu et al. 2017).

The HRB is characterized by persistent LULC change which is typical and symbolic due to a rapid increase in human and livestock population resulting in urban expansion and increased economic activities. For these reasons, prevalent LULC alteration and the shrinking of the environment and its associated values have been observed (Long et al. 2009).
Despite this obvious reality the impact of land use change on streamflow regime has not been fully investigated in HRB, thus this provides a research vacuum which the current study seeks to fill. These gross inadequacies of research endeavors to detect the current and future modifications of LULC and the corresponding hazard to the environmental services, such as the streamflow services, requires urgent consideration in a semi-arid river catchment that is also under the tyranny of climate fluctuations.

Therefore, it is imperative to conduct a research of this nature to detect the trends, magnitude, and frequency of LULC change and to predict the change into the future. Equally important is also the effects of the LULC changes on streamflow of this important river catchment that support not less than 15 million people for their livelihood. The outcome of this study will guide the sustainable land resources utilization and control, bearing in mind that unwise use of the land resources will translate into many effects, among which, include the distortion of the natural environmental flow which also has its cost. In view of this, the current study is intended to: (i) detect trends and variations of land use and streamflow in the HRB; (ii) simulate and model the future distribution of LULC types based on a CA–Markov model and discovering the transformation procedures; and (iii) predict the frequency and magnitude of the transformations into the future (2030). This will provide vital information for future planning and policy formulation that will seek to regulate excesses in land use utilization and its effects on especially the environmental flow, which will in turn, help to maintain the distinctive natural features and environmental standards of the regional ecosystem.

MATERIALS AND METHODS

The study area

The HRB is an inter-state basin with most of the basin falling within Kano and Jigawa, with only a small proportion of it spread into Katsina, Kaduna, and Bauchi states (Figure 1). It covers an area of about 24,687 km². The basin has its origin in the northern uplands of Bauchi and Kano states.
Olofin (1993) described the basin as belonging to the area referred to as the northern plains, which are characterized largely by extensive flat to gently undulating plains sloping gradually from over 600 m above sea level south and west of Kano to less than 300 m towards Hadejia-Nguru wetland downstream of the basin. The main features of the central area of the basin are the extensive longitudinal dunes and the extensive alluvial flats existing in the inter-dune areas. The river systems in the basin provide extensive floodplains that are used for livelihood (Sobowale et al. 2010).

The HRB is a sub-catchment of the Hadejia-Jama'are-Komudugu-Yobe Basin (HJKYB). This sub-catchment has an area of 24,680 km² (Adakayi 2012). The basin is controlled by two air masses, one from the southwestern part, and the other from the northeastern part of the country. The southwest wind is rainfall-bearing from the Gulf of Genue, thus, precipitation over the given location is dictated by the coverage of the southwest air masses (Ebele & Emodi 2016).

Climate

The climate of the HRB is controlled by the seasonal movement of two air masses (maritime and dry continental air masses) separated by the Intertropical Convergence Zone (ITCZ) (Abrate et al. 2013). The climate of the basin varies considerably according to the month and season: there is a cool dry season from November to February, a hot dry season from March to May, and a warm wet season from June to September. However, two distinct seasons, a rainy and dry season usually prevail. The basin is within the region of great weather extremes in the country. Mean annual rainfall varies from over 1,100 mm in the south of the basin to less than 300 mm in the extreme northeast.

Precipitation

There is strong inter-annual rainfall variability in the area. During the wet decade, rainfall ranged from 400 to 1,344 mm/year as against 250–750 mm/year in the dry decades (Dammo et al. 2015). Beside the temporal variations, rainfall in the basin is characterized by spatial dissimilarities which is further accentuated by the effect of topographical differences particularly between the upstream and downstream of the basin.

Temperature

Temperatures reach as high as 45 °C before the onset of the rains (April/May) and drop as low as 16 °C in December/January. The maximum temperature in the basin can be as high as 45 °C in the northern Sahelian and sub-arid desert region, the annual averages range between 20 and 30 °C, while the minimum is about 10 °C (Amodu & Ejieji 2017). The basin is characterized by strong evaporation ranging from 2,000 to 2,500 mm/year, particularly at the northeastern part of the basin (Amodu & Ejieji 2017). Relative humidity can be less than 20%.

Soils

Due to the low weathering and low leaching prevalent under the dry climate, the development of the soils is minimal. Generally, the HRB is dominated by arenosols soils. However, there is a small percentage of fluvisols, mostly in the valley of the river basin. Similarly, there is also a mix of leptosols and lixisols soils in the northeastern part of the basin (Abdul et al. 2018). Thus, most of the soils are sandy in nature and are therefore most vulnerable to drought and wind erosion. Generally, the soils are well-drained with low water-holding capacity, organic matter content, and fertility. The exceptions are the soils in the wetlands (mostly found in the river valleys) which are characterized by finer textures, a higher level of organic matter, and greater water-holding capacity (Ndabula...
et al. 2018). Therefore, these are the most important soils in the basin. The floodplains have extensive thick sealing clays which prohibit seepage (Tukur et al. 2018).

Hydrology and drainage basin

The drainage and hydrology of the area are influenced by the climate, rock structure, and human activities. The Hadejia River dominates the drainage of the area and drains essentially northeastwards into Lake Chad (Olofin 1993). The area lies in an inland drainage system of the Lake Chad basin with the Hadejia River meandering for about 828 km across the area with a lot of braiding. The Hadejia River is an example of a principal through-flow system with the Kano, Challawa, and Gaya rivers as the important headstreams (Olofin 1993). Like all streams flowing in the savannah, the study area is characterized by large variations of flow between the wet and dry seasons.

Relief

The relief of the study area is greatly influenced by the geology. The Chad Formation is the lowest relief unit of the Kano region (Goes 2001). This unit essentially consists of plains developed on the sedimentary structure. Towards the immediate west of the hydrogeological divide are the transitional plains, which although developed on rocks of the basement complex, are lower than 450 m above sea level and are covered by sands of the Chad Formation. The mean elevation of the relief units in the area ranges from about 1,577 m southwest of the basin and about 324 m in the extreme northeast.

Geology

The basin is geologically underlain by the basement complex upstream and the Chad Formation to the middle and downstream. While the upstream part is characterized by mainly impermeable basement complex rocks covered by permeable Quaternary sediments which consist of fine to coarse-grained sand, with intercalation of sandy clay, clay, and diatomite, the dunes in the middle part of the basin and alluvial deposits along the river systems are superficial deposits lying on the Chad Formation (Arabi et al. 2018). The longitudinal dunes occur as parallel ridges extending northeast–southwest for several kilometers without interruption and as high as 15–20 m. The river alluvium deposits consist of sands, silts, and clays with the occasional existence of coarse sands and gravel along younger river channels (Abdul et al. 2018).

Vegetation and land use

The HRB spans three vegetation zones of Nigeria. The southern parts are in the Guinea Savannah which is characterized by shrubs and dense grasses with a few trees. Much of the natural cover, however, has been tampered with by human activities. The western parts of the basin fall in the Sudan Savannah that sustains fewer trees and shorter grasses (Arowolo & Deng 2018). The northeastern parts fall in the Sahel Savannah which is characterized by short grasses, and few and scattered acacia species. In the extreme northeast of the basin, desert conditions characterized by sand dunes and scattered oases prevail (Arowolo & Deng 2018). The combined action of climate and physiography influences the pattern of land use in the basin. This, of course, determines the soil type, availability of water, vegetation, etc. all of which determines what use the land can be put to.

Socio-economic characteristics

The population of the basin (estimated at over 15 million) is basically rural and is classified into farmers, fishermen, pastoralists, and a few that are engaged in commercial and petty trading
activities (Sobowale et al. 2010). The HRB provides means for various socio-economic activities. The upland has soils that are suitable for various crop production, each providing a means of livelihood for millions of people. Thus, more than 90% of the population depends on agriculture (rainfed and irrigation agriculture) for their livelihoods, which are supported by the basin river water resources. The main occupation in the basin includes upland crop production, fishing, irrigated crop production, and livestock production. Main agricultural outputs produced in the basin include onion, sugar cane, tomato, carrot and pepper, garden egg, wheat and rice in the dry season; while in the wet season sorghum, millet cowpea, groundnuts, and cassava are the main products.

**LULC data acquisition and processing**

The data (satellite imageries) for the LULC change detection in this study were basically from Landsat TM (Thematic Mapper) acquired from the United States Geological Survey (www.earthexplorer.usgs.gov). The images with 30 m spatial resolution were for 1980, 1990, 2000, and 2010. The choice of the dataset was guided by seasonal consideration of the climate, thus images taken during the summer season when the sky is clearer were prioritized. This is to minimize the effect of cloud cover and associated reflectance. The choice of Landsat data for this study was informed by the freeness of the data for public accessibility and the consistency of its global coverage. Moreover, the medium resolution spatial (30 m) of the Landsat data makes it suitable for a study of this nature, and thus Landsat data were and still are the most frequently used data in land use change detection studies (Roy et al. 2014; Wang et al. 2019). The study also used other supplementary data sources such as topographic and LULC maps obtained from the Federal Ministry of Land and Survey Nigeria as well as Google Earth images. Prior to the analysis and interpretations of the images, atmospheric correction was conducted with geometric rectification. The maps were first geo-referenced in the UTM Zone 50 projection and then projected with the WGS84 datum into UTM Zone 50 to match the satellite image datum. The image classification method used to identify LULC modifications in this research was the supervised image classification with the maximum likelihood classification (MLC) algorithm using Terrset software (Ayele et al. 2019; Biswas et al. 2019).

The MLC was selected for this study, being the most popular, tested, and recognized as the best technique with higher accuracy in land use classification and change detection task (Bureau 2014; Chim et al. 2019; Pokhrel et al. 2019). It is also operationally simple, easily applicable, and robust in performance. Additionally, the researcher has prior knowledge of the region which is immensely crucial for the successful generation of the final LULC classes using this image classification technique (Bureau 2014; Ayele et al. 2019).

After successfully classifying the LULC classes of the basin area into agriculture, forest, water body, and others (which consist of all the construction land uses, gullies, and rock outcrop) (Table 1) for the four time slices, the classified images were vectorized using the ERDAS Imagine 9.1 image analysis software in the ArcMap 10.4 within the GIS environment. The temporal changes

| LULC classes | General description |
|---------------|---------------------|
| Agriculture   | Arable land, stable crops, and mixed agricultural areas |
| Forest        | Natural vegetated areas and plantations |
| Water body    | Permanent open water, lakes, ponds, and reservoirs |
| Others        | All types of construction land uses, eroded sites, gullies, and rock outcrops |
in the LULC between the time periods were quantified to enable comparison in the changes that occur between the time series. Furthermore, the net changes of a given LULC type as well as the net changes to persistence ratio was computed and shown via the transition probability matrixes of each LULC type. The map was also verified compared to an independent dataset of 150 ground points distributed across the study area. Verification points were recognized by a mixture of very high-resolution image visual interpretation for 2010 (Google Earth) and known locations in true color Landsat images (Yirsaw et al. 2017). The evaluation was done per scene. Consequently, results from each scene were mosaics in a final map at 30 m scale wrapping the entire study location.

Classification accuracy assessment

The overall accuracy of a specific map or classified image is achieved by computing its overall classification accuracy, the producer and user accuracy as well as the Cohen’s Kappa coefficient of agreement (Costa et al. 2018). This overall accuracy denotes the percent of correctly classified sample points, as matched to their corresponding reference data in all the categories. The omission errors shown by the producer accuracy is determined by dividing the total number of correctly classified samples in a given category by the total number of samples in that category. However, the commission error, which is a product of the user accuracy, is determined by dividing the number of correctly classified samples in a given category by the number of samples in all categories (Maktav et al. 2005; Yang et al. 2014). Meanwhile, the most widely used index in the accuracy assessment, the Kappa index, is used to accommodate the effects of change agreement in the accuracy; although it has been variously criticized, it is the most reliable index in accuracy indexing and the value must not go below 0.85 (Shamsudheen et al. 2005; Yan et al. 2015):

$$\text{User accuracy} = \frac{\text{Number of Correctly Classified Pixles in a class}}{\text{Total Number of Pixles in a class}}$$  

(1)

$$\text{Producer's accuracy} = \frac{\text{Number of Correctly Classified Pixles in a class}}{\text{Total Number of Pixles in all classes}}$$  

(2)

$$\text{Overall accuracy} = \frac{\text{Total Number of all Correctly Classified Pixles}}{\text{Total Number of Pixles in all classes}}$$  

(3)

$$\text{Kappa Index of Agreement (K)} = \frac{N \sum_{i=1}^{n} m_{ii} - \sum_{i=1}^{n} (G_{i}C_{i})}{N^2 - \sum_{i=1}^{n} (G_{i}C_{i})}$$  

(4)

where, $i =$ class number, $N =$ total number of classified values compared to truth values, $m_{ii} =$ number of values belonging to the truth class $i$ that have also been classified as class $i$ (i.e., values found along the diagonal of the confusion matrix), $C_{i} =$ total number of predicted values belonging to class $i$, and $G_{i} =$ total number of truth values belonging to class $i$.

METHODS

LULC change modeling

The CA–Markov model has been ubiquitously cited as the most powerful technique for modeling the likelihood of spatial and temporal shift in LULC in combination with the GIS technique (Yu 2009;
A Markov chain is constructed in the CA–Markov model, based on the potential of the change matrices, connected with the temporal adjustment that occurs among the various types of LULC (Subedi et al. 2013). The CA model is employed to project the spatiotemporal changes, taking into account neighborhood set-up and the alteration map of the LULC (Kityuttachai et al. 2013). The CA–Markov model can achieve better simulation of LULC inequalities via the hybridization of these two approaches (White & Engelen 1994; Yang et al. 2014). This characteristic makes the model a solid simulation study of LULC change (Kityuttachai et al. 2013; Subedi et al. 2013).

In this study, a paired CA–Markov model was used to perform the LULC change modeling processes. The concept of combining CA–Markov model reflects advances in spatio-temporal dynamics in modeling and forecasting attempts to achieve a better simulation of LULC fluctuations for quantitative assessment on the temporal scale (Sang et al. 2011; Yang et al. 2019). The whole process was achieved using the built-in algorithms in the IDRISI Andes that integrates the CA filter and Markov functions and processes, which is based on the transition tables and probability conditionality from the transition map used in the simulation and forecasting of the states of LULC changes. Thus, in the present study, the simulation of LULC changes into the future via CA–Markov model was based on the following procedures:

1. The graded LULC maps for the years 1980, 1990, 2000, and 2010 were used after the conversion processes (vector data to raster data) to acquire the transition matrices for the land use/cover classes from 1980 to 1990, 1990 to 2000, and from 2000 to 2010 on the basis of the Markov first-order model (Wang & Kalin 2018).

2. The transition maps used to project the LULC in 2030 and to replicate the distributions in 2030 were developed on the basis of major transitions between the LULC classes from 2000 to 2010 (Long et al. 2014), using the study area’s first-hand understanding to explain the conversion rules and define factors and limitations. In addition, the regular 5 × 5 contiguity filter was used as the neighborhood characterization to determine CA filters.

3. The strategy used in the modeling process in the CA–Markov model is such that the LULC for 2000 was modeled on the transformation likelihoods from 1980 to 1990 and that of 2010 was modeled on the basis of the transformation likelihoods from 1990 to 2000 with the LULC base map from 2010. Kappa statistic assesses the reliability and consistency between the projected maps and the actual LULC maps.

4. Finally, following a similar procedure, the LULC was projected on the basis of the transition probabilities from 2000 to 2010 (with a Kappa index of more than 0.85) and the LULC base map from 2016 with the CA–Markov model in IDRISI.

Streamflow data collection and processing

The streamflow data collation at the HRB started in 1963 after the Government of Northern Nigeria established streamflow stations under the oversight of the irrigation department of the Ministry of Agriculture (Goes 2002). These stations were institutionalized and expanded with the aid of the United States Geological Survey (USGS) office based in Nigeria in 1964 to the Systematic Survey of Surface Water Resources (Medugu et al. 2011). For the purposes of the current study, however, 36-year (1980–2015) monthly river discharge information from six streamflow stations collected from the HJRBDA and the JSMWR have been used for trend detection.

Data analysis

Prior to the implementation of suitable statistics, the data were exposed to quality assurance (QA)/quality control (QC) evaluation (Duhan & Pandey 2015). Data abnormalities such as the outliers...
and missing records have been verified. The QA/QC screening disclosed that the data were acceptable statistically with the exception of a little missing information, accounting for only a small proportion (10%) of the entire dataset. These missing data have been filled by the averages of the two observations that bind the observed missing data (Brockwell & Davis 2002). The trend in river discharge was evaluated using the MK trend test and Sen’s slope estimator. MK test is applied when the data values $X$ of a time series are assumed to obey the model derivations:

$$X = f(t) + \sum t$$  

(5)

where $f(t)$ is a continuous monotonic increasing or decreasing function of time and the residual $\sum t$ can be assumed to be from the same distribution with zero mean. The MK test statistic $S$ is given as:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \text{sgn}(x_j - x_k)$$  

(6)

where $r$ is the length of the time series $x_1 \cdots x_n$, $\text{sgn}()$ is a sign function, $x_j$ and $x_k$ are values in years $j$ and $k$, respectively. The expected value of $S$ equals zero ($E[S] = 0$) for series without trend and the variance is computed as:

$$(S) = \frac{1}{18} \left[ n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p-1)(2t_p+5) \right]$$  

(7)

Here $q$ is the number of tied groups and $t_p$ is the number of data values in $p^{th}$ group. The test statistic $Z$ is then given as:

$$z = \begin{cases} 
\frac{s - 1}{\sqrt{\sigma^2(s)}} & \text{if } s > 0 \\
0 & \text{if } s = 0 \\
\frac{s + 1}{\sqrt{\sigma^2(s)}} & \text{if } s < 0 
\end{cases}$$  

(8)

Increasing trends are indicated by positive values while negative values demonstrate declining patterns. The Sen’s non-parametric method, known for its robustness, is used to assess the real path of the current trend (Yadav et al. 2016; Panwar et al. 2018) proposed by Sen (1968). It is computed as:

$$Q_i = \frac{x_j - x_k}{j - k} \text{ for } i = 1, \ldots N,$$  

(9)

where $Q_i$ is the trend slope, $x_j$ and $x_k$ are the data values at times in years $j$ and $k$ ($j > k$), respectively.

The spatial analysis of the data were conducted with the aid of spatial interpolation method, the inverse distance weightage (Rimal et al. 2018). IDW was employed being less complex and straightforward, speedy in calculations and it gives more appreciable results than other techniques (Qu et al. 2017; Shahid et al. 2017). Thus, the purpose of spatial interpolation in this study IDW was to estimate and interpolate the values between the measured points. This is because the underlying mechanism of IDW is based on the assumption that the attribute value of the unmeasured station is the weighted average of the measured values within the area and inversely proportional to the distances between the predicted and the measured points (Qu et al. 2017).
RESULTS

LULC change detection and prediction

In consideration of the LULC change characteristics of the study area, four major LULC types were identified, including agriculture, forest, water bodies, and other (which comprises all types of construction land uses, gullies, and eroded lands) (Table 1). The land use change matrix as well as the produced land use maps are presented in Figures 2(a)–2(d) and 3(a)–3(d).

Based on the Kappa statistic (Table 2), it is obvious that the actual LULC map for the years 1990, 2000, and 2010 stands agreeably comparable with the CA–Markov-simulated maps. With the Kappa statistical values (0.85) and overall accuracy of more than 91% (Table 2), the predicted and the actual results showed good promise between the values of the LULC types. Thus, for predicting future LULC change, the model is considered reliable with the confidence that a consistent rate of change will occur in the future (Alkan et al. 2013).

The degree of LULC change is illustrated by the percent changes between different time slices as shown in Table 3 and Figure 4. The Kappa coefficients of accuracy classification for all the time series (1980, 1990, 2000, and 2010) were greater than 0.80 (Table 3). This ascertained the validity of the interpreted results and its reliability for future projection. Thus, considering the result of the accuracy assessment that indicates good promise between the simulated and the actual result the future LULC map was predicted to 2030.

With the Kappa statistical values (0.85) and a general precision of more than 91% (Table 3), it is shown that there is strong promise between the expected result and the real value of the LULC types (Sedano et al. 2019). Thus, for predicting future LULC change, the model is considered reliable with the confidence that a consistent rate of change will occur in the future.

The dominant land use types of the HRB were agricultural and forest land uses (Table 3), which accounted for about 80% of the entire area. There were two main trends of land use changes

![Figure 2](http://iwaponline.com/h2open/article-pdf/doi/10.2166/h2oj.2021.065/884970/h2oj2021065.pdf)
during the four decades (1980–1990, 1990–2000, 2000–2010), including also the projected period (2010–2030): the decrease of forest and the increase of agricultural and construction land use. Compared with 1990, forest and the water body of 2000 decreased by 10.61 and 0.16%, respectively, while agriculture and construction land of 2000 increased by 1.4 and 1.45%, respectively. However, from 2000 to 2010 the trend was that agricultural land, forest, and water bodies decrease by 2.0, 0.4, and 0.32%, respectively. Thus, only construction land uses increases by 3.36%. Meanwhile, for the projected time period 2010 to 2030, the percentage gain was in favor of agricultural and construction land uses, which is 9.34 and 2.53%, respectively, where the percentage loss was against the forest (4.77%) and water bodies (0.00%) (Figure 4). Compared to their baselines of 1980, the existing surface water bodies will likely disappear from the 2030s onward, and the process which will perhaps be aggravated by the effects of changing climate.

### Table 2 | Error matrices of the accuracy assessment

| S/N | Land use/land cover | 1980 | 1990 | 2000 | 2010 |
|-----|---------------------|------|------|------|------|
|     |                     | UA   | PA   | UA   | PA   | UA   | PA   |
| 1   | Agriculture         | 94.8 | 91.3 | 94.4 | 93.2 | 94.4 | 89.6 | 93.6 | 94.4 |
| 2   | Forest              | 93.7 | 91.5 | 96.9 | 94.3 | 89.3 | 92.4 | 89.4 | 93.4 |
| 3   | Water body          | 47.5 | 95.3 | 69.8 | 86.4 | 86.4 | 98.4 | 74.1 | 100 |
| 4   | Others              | 94.4 | 93.7 | 89.4 | 95.2 | 95.8 | 88.7 | 94.9 | 89.6 |
|     | Overall accuracy    | 91.5 | 92.1 | 91.6 | 90.5 |      |      |      |
|     | Overall Kappa       | 0.92 | 0.93 | 0.92 | 0.91 |      |      |      |

UA, user accuracy; PA, producer accuracy (Others = construction land use, gullies and eroded lands).
On the whole, the percentage change in land use in the HRB was found to be less noticeable from 1980 to 1990, while it was so obvious during the 2000–2010 period with three (agriculture, forest, and water body) out of the four major land uses suffering losses of different magnitudes. Meanwhile, the decrease in the forest was more severe during the 1990–2000 period (10.99%). However, the gain was highest in the projected time period (2010–2030) in agriculture (9.3%), corroborating the projected increase in population which will necessitate opening up more land for farming to feed the growing population. Thus, the changing pattern of increased agricultural and construction land use at the

| Table 3 | Summary of percentage changes of LULC |
|---------|---------------------------------------------------------------|
| **Land use types** | **Agriculture** | **Forest** | **Others** | **Water bodies** |
| 1980–1990 | | | | |
| Agriculture | 69.15 | 2.68 | 0.47 | 0.08 |
| Forest | 6.27 | **16.33** | 0.23 | 0.00 |
| Others | 2.98 | 0.58 | **0.50** | 0.01 |
| Water bodies | 0.15 | 0.01 | 0.00 | **0.48** |
| Kappa index = 0.90 | | | | |
| 1990–2000 | | | | |
| Agriculture | **70.55** | 3.53 | 0.34 | 0.01 |
| Forest | 15.05 | **5.72** | 0.26 | 0.00 |
| Others | 0.90 | 0.58 | **1.95** | 0.02 |
| Water bodies | 0.12 | 0.03 | 0.62 | **0.32** |
| Kappa index = 0.91 | | | | |
| 2000–2010 | | | | |
| Agriculture | 68.55 | 11.05 | 1.19 | 0.01 |
| Forest | 8.24 | **5.32** | 0.60 | 0.01 |
| Others | 1.75 | 1.64 | **5.31** | 0.17 |
| Water bodies | 0.01 | 0.01 | 0.91 | 0.00 |
| Kappa index = 0.86 | | | | |
| 2010–2030 (projected) | | | | |
| Agriculture | 77.8 | 0.01 | 2.92 | 0.1 |
| Forest | 4.0 | **0.55** | 0.06 | 0.8 |
| Others | 0.5 | 0.5 | 7.8 | 0.0 |
| Water bodies | 0.1 | 0.8 | 0.0 | 0.0 |

Others = construction land use, gullies and eroded lands.

![Figure 4](chart.png) | Percentage gains/losses from 1980 to 2010. (Other = construction land uses, gullies and eroded lands.).
detriment of forest and water bodies should be anticipated in the same manner in the foreseeable future (Figure 2). The changes were viewed as two clusters: one was the mutual conversion of forest to agriculture, the other was the conversion of farmland to other land use, particularly to the construction land use. Unlike in the historical years where the percentage gain is higher in the construction land use, in the future, the percentage gain will be higher in the agricultural land use, likely due to increased population and influx of immigrants from neighboring areas (e.g., Yobe and Borno states, Figure 5) where insurgency is still bedeviling the inhabitants.

Individually, the percent changes of one land use to another indicate that in 1980–1990 and 1990–2000 the changes from forest to agricultural land use was the highest (6.27% and 15.5%) and forest to water bodies was the least (0.00% for both time slices). Meanwhile, in 2000–2010, changes from agriculture to the forest was the highest (11.05%) and agriculture to water bodies was the lowest (0.01%). For the projected time period, forest to agriculture was the highest change (4.02%), and the changes from construction land use to water bodies was the least (0.00%).

Thus, agriculture and construction land uses were the most hastily increasing land use categories in both historical and projected analysis. However, agricultural land use will be the most intensifying land use type in the future. For the construction land use, the expansion will mainly be as a result of the urban growth and other infrastructural development and the direction of the expansion will maintain the historical pattern that is primarily around Kano–Wudil axis (Figure 2) and, along the linear profile of Hadejia River. Thus, the areas with rapid urban development were found to have higher runoff mean due to the effect of urbanization (Figure 5(a) and 5(b)).

Additionally, there are also spatial disparities between the upstream and downstream areas in terms of runoff generation and streamflow, believed to be influenced by land use changes as the former area is more urbanized than the latter. Thus, this will be one of the reasons for high mean discharge around Wudil station (Figure 6(b)) even though it is a confluence station where two river streams merged.

**Streamflow trends and variations**

The 36-year (1980–2015) trend of streamflow information in the HRB was evaluated via the MK trend test. The annual trend output disclosed a statistical insignificant trend in the upstream stations

![Figure 5](http://iwaponline.com/h2open/article-pdf/doi/10.2166/h2oj.2021.065/884970/h2oj2021065.pdf)
(Chiromawa, Challawa, and Wudil stations) (P values range 0.91–0.39 MK) (Table 4) as well as statistically significant decreasing trends in both downstream locations (Kafin Hausa and Hadejia) (Table 4).

However, blended outcomes of positive and negative trends were indicated by the monthly trend results. The monthly trends have usually increased in the upstream parts of the basin in all months except in May; However, a significant declining trend was shown at Hadejia and Kafin Hausa station in the downstream part of the basin (Figure 7).

Generally, the annual trend for the individual stations shows significant decreasing trend only at Kafin Hausa and Hadejia stations. However, the monthly trend showed significant declining trend in September at Chai-Chai, in November at Kafin Hausa, and in May, June, and August at Hadejia station (Figure 4). River discharge time series plots of annual and decadal averages showed that 1982 and 2001 were the low and high discharge years, meanwhile, the 1980 and 1990 s were the lowest and the highest river discharge decades, respectively (Figure 8(c) and 8(d)).

**Table 4** | Summary of annual streamflow trend in Hadejia river basin (1980–2015)

| Stations        | Slope | MK  | Trend |
|-----------------|-------|-----|-------|
| Chiromawa       | 0.13  | 0.61| ↑     |
| Challawa        | 0.04  | 0.39| ↑     |
| Wudil           | 0.02  | 0.91| ↑     |
| Chai-Chai       | −0.20 | 0.12| ↓     |
| Kafin Hausa     | −0.35 | 0.02| ↓     |
| Hadejia         | −0.59 | 0.02| ↓     |
| Basin           | −0.95 | 2.07| ↓     |

Increasing trend ↑, Decreasing trend ↓.

**DISCUSSION**

This research detects the pattern of LULC change in northwestern Nigeria in the HRB, climatically classified as a semi-arid region. The LULC change was simulated and predicted using the Markov and CA–Markov model in the GIS environment and assessed the connections between the LULC...
Figure 7 | (a)–(m): annual and monthly river discharge trends in HRB.
change's temporal and spatial relationship with the streamflow fluctuations in the basin. The model has been validated with the base year's real data and demonstrates a satisfactory general outcome, showing that CA–Markov is a credible and suitable model for predicting future LULC change. The findings of the projected changes in the LULC revealed declines in forest and water bodies with an increase in construction and agricultural land use.

The spatial scope of the current study is largely within Kano and Jigawa states (Figure 3), which are relatively peaceful and dominantly agricultural; hence people from neighboring states, particularly

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**Table 5 | MK trend test results for river discharge in Hadejia River basin**

| Stations | Chiromawa | Challawa | Wudil | Chai-Chai | Kafin Hausa | Hadejia |
|----------|-----------|----------|-------|-----------|-------------|---------|
| Months   | Slope     | MK       | Slope | MK        | Slope       | MK      |
| Jan      | −0.04     | 0.56     | 0.00  | 1.00      | 0.14        | 0.10    |
| Feb      | 0.00      | 0.91     | 0.00  | 1.00      | 0.00        | 0.86    |
| Mar      | −0.01     | 0.71     | 0.00  | 1.00      | 0.07        | 0.23    |
| Apr      | −0.03     | 0.78     | 0.02  | 0.14      | −0.05       | 0.77    |
| May      | −0.03     | 0.75     | −0.23 | 0.22      | −0.69       | 0.06    |
| Jun      | 0.05      | 0.49     | 0.00  | 0.88      | 1.23        | 0.12    |
| Jul      | −0.14     | 0.57     | 0.70  | 0.01      | −0.42       | 0.74    |
| Aug      | 0.28      | 0.70     | −0.47 | 0.16      | −0.05       | 0.91    |
| Sep      | 0.65      | 0.67     | 0.64  | 0.13      | −1.46       | 0.38    |
| Oct      | 0.52      | 0.29     | −0.01 | 0.65      | 0.61        | 0.53    |
| Nov      | 0.08      | 0.39     | 0.00  | 0.19      | 0.00        | 1.00    |
| Dec      | −0.02     | 0.74     | 0.00  | 1.00      | 0.08        | 0.53    |
| Annual   | 0.13      | 0.61     | 0.04  | 0.39      | 0.02        | 0.91    |

Bold font is significant at 95%.

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**Figure 8 | Decadal percentage changes in LULC: (a) gain/loss in LULC over the decades, (b) decadal and annual river discharge mean (c) and (d).**
Yobe and Borno states, flee to any peaceful nearby state for safety and livelihoods. The percentage domination of a specific land use in a certain region partly determined the percentage of runoff generation and flows. Thus, the conversion of forest land use to agricultural land use does affect the volume and percentage of runoff generation (Zhao et al. 2016). Likewise, forest transformation to construction land use (urbanization) can increase the volume and the percentage of runoff, often significantly (Zhao et al. 2016). Previous studies (Sobowale et al. 2010; Kazaure 2013; Umar et al. 2018) have reported flood incidences to this effect, and more flood challenges, particularly the recurrent and flash floods, should be anticipated with their related consequences, provided the land use change pattern carries on in the same manner into the future as projected.

The shrinking of the agricultural land use in the 2000–2016 time period is largely attributed to the insurgency activities (Boko Haram) that displace many people, particularly the youth (the agricultural working force) that either joint the Boko Haram movement or flee for safety elsewhere (Oyewole 2015). Meanwhile, the apparent expansion of construction land use throughout the study period is directly connected to the consequences of the population explosion of 4.3% annually, necessitating fresh demand for more land for both agriculture and settlements (Sang et al. 2011). A similar result was reported by Yirsaw et al. (2017) where urbanization resulted in LULC instability in the Su Xi-Chang region of China.

Based on the temporal pattern of the change, the period between 2000 and 2010 indicates the highest percentage changes, and agriculture is also top in terms of rapid change pattern in all the land use types of the area. On the whole, the percentage change in land use in the HRB was found to be less noticeable from 1980 to 1990, while the changes were obvious between the 2000 and 2010 period with three (agriculture, forest, and water body) out of the four major land uses decreasing at different magnitudes. Meanwhile, the decrease in the forest was more severe during the 1990–2000 period (10.99%). However, agriculture will have the highest gain (9.3%) during the projected time period (2010–2030) base on the predicted LULC changes. This corroborates the projected increase in population which will necessitate opening up more land for farming to feed the growing population.

Thus, the historical changing pattern of agriculture and construction land use at the detriment of forest and water bodies should be anticipated in the same manner in the future. The temporal assessment of the streamflow indicates the 1990s as the decade with highest streamflow in all the decades considered; this corresponds to the decade (1990–2000) with severe forest removal as shown by the LULC change detection results. Similarly, the spatial synthesis of the LULC change revealed that areas experiencing rapid urban development, such as around Kano and Wudil axis, generate high surface runoff due to surface concretization that reduces the rate of infiltration around cities, and the same behavior should be anticipated. Other factors that affect the LULC change and streamflow relationship are rainfall amount, soil and geology, temperature and rate of evaporation, and also the river regulations. Thus, considering the intricacies and complexities of the major driving factors affecting the hydrology and water resources of the basin, of which LULC change is only one, comprehensive and broad basin land and water resources studies that will consider a range of other factors are highly recommended, particularly using climate and hydrological modeling.

**CONCLUSION**

A combination of multivariate and geostatistical modeling approaches were used to detect and predict the spatio-temporal trend of the impact of land use change on stream flow regime in the Sahelian river basin of Nigeria. From the spatial and temporal analysis of the synergy between LULC changes and the environmental flow fluctuations, it is revealed that besides rainfall pattern, LULC changes are the major influencing factor explaining the spatial and temporal behavior of the environmental flow in the basin sphere. This was corroborated by the apparent disparity in flow generation between the
upstream and downstream areas of the basin that cannot be equated in terms of LULC composition, change pattern and processes. Similarly, the decadal synthesis and the percentage gain/loss has indicated that the decade with high environmental flow corresponded with the decade of severe forest removal and vice versa.

The study as it is will assist in the land and urban management as well as in evaluating the impact of land use changes on hydrology and water resources of the basin. The rapid decrease in the forest land use and the expansion of the agricultural and construction land use is a potential signal for high environmental flow in one end and increased water demand in the other end. Thus, the additional surface runoff anticipated will likely cause floods, and yet it is feared that the extra surface flow will be counterbalanced by increased temperature and infiltration before contributing to the total discharge which may result in water deficit downstream. Moreover, the population growth scenario of about 4.5% is expected to pose additional land and water demand challenges in response to the increasing population and urbanization. It is recommended that future studies should integrate geological, climatic as well as socio-economic factors to unveil the congregational effects/contributions of individual factors to the generation and behavior of environmental flow and processes.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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