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Hydrological Characterization of a Watershed for Streamflow Prediction

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***Abstract*—**In this paper, we extend the versatility and usefulness of GIS as a methodology for any river basin hydrologic characteristics analysis (HCA). The Gurara River basin located in North-Central Nigeria is presented in this study. It is an on-going research using spatial Digital Elevation Model (DEM) and Arc-Hydro tools to take inventory of the basin characteristics in order to predict water abstraction quantification on streamflow regime. One of the main concerns of hydrological modelling is the quantification of runoff from rainstorm events. In practice, the soil conservation service curve (SCS) method and the Conventional procedure called rational technique are still generally used these traditional hydrological lumped models convert statistical properties of rainfall in river basin to observed runoff and hydrograph. However, the models give little or no information about spatially dispersed information on rainfall and basin physical characteristics. Therefore, this paper synthesizes morphometric parameters in generating runoff. The expected results of the basin characteristics such as size, area, shape, slope of the watershed and stream distribution network analysis could be useful in estimating streamflow discharge. Water resources managers and irrigation farmers could utilize the tool for determining net return from available scarce water resources, where past data records are sparse for the aspect of land and climate.

***Keywords*—**Hydrological characteristic, land and climate, runoff discharge, streamflow.

I. Introduction

STREAMFLOW forecasting plays a pivotal role in water resources planning and management. Forecasting of streamflow has proved useful in flood caution, reservoir operation, quantification and assessment of water for hydropower generation, domestic and irrigation water scheduling among other uses [1]. The importance of accurate and reliable streamflow forecasts also helps decision makers in creating water allocation policies for sustainable economic development of an area.

Streamflow is a spatio-temporal interval representation of runoff over a basin [2], and thus, can exhibit strong nonlinear dependency on hydro-meteorological and anthropogenic factors [3].

Watershed characteristic factors that could potentially affect basin streamflow predictability have been the subject of immense interest in recent years: [4]-[6], as well as the impact of climate change on streamflow [7]-[9]. Thus, the flow of any stream has been influenced by climatic factors of precipitation and the physical characteristics of the drainage basin. For most rivers basin, the physical characteristics include: topographic terrain characteristic, type of drainage network, basin orientation, extent of artificial and indirect drainage, land use, soil type and vegetation cover [10], [11]. These hydrologic characteristics of a watershed reveal the volume of discharge hydrograph produced by a specific rainfall hyetograph [12]. However, the influence of land and soil cover on storm water runoff generation has been interwovenly complicated. This has an effect on rainfall interception, surface retention, evapotranspiration, and resistance to overland flow.

Tropical regions like the Guinean forest-savanna mosaic in the ecoregion of Nigeria, the study area (Gurara Basin) (see Fig. 1), have been susceptible to climate change and large water withdrawals stress [13].

Recent rapid agricultural and economic development has occurred in the Gurara basin following the inter-basin water transfer to supply Abuja, the Federal Capital Territory (FCT) municipality and to augment the lower Usama-Shiroro hydropower generation plant [14]. The water transfer infrastructures have led to increasing competition among the riparian communities for the Gurara waters. As the watershed becomes more developed, it is witnessing more geomorphological active terrain reflecting streamflow entrance and exit. Thus, constitutes unexpected hydraulic discharge rate and the expected flood volume. This development calls for a modern scientific approach to investigate the basin characteristics to predict water abstraction on streamflow regime quantification. This will support efficient, equitable, and environmentally sustainable water uses for socio-economic development in the basin. Changes in sectoral water availability have affected many aspects of human society. These impacts vary from agricultural productivity to flood control, municipal and industrial water supply to fisheries and wildlife management [15], [16].

The present study acknowledges the work of Alexander, Dingbao [17] upon which some review sections of this work were built. Works by Wang and Hejazi [8] strengthen the idea that streamflow prediction is a function of spatial rainfall distribution and basin characterization. This research tends to improve the previous conventional method of SCS in forecasting streamflow from rainfall-runoff studies. The studies highlight a novel way on the usage of Arc Hydro tools for integrated land and water resources management. They depict modern methods in water management, especially in semi-arid Africa, where its majority rural dwellers depend on

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the available scare water resources to feed their irrigated farmland from streamflow diversion. New methods are needed to safeguard against the compounded problem of climate variability and its impact on watershed or basin predictor variables; notwithstanding, the supportive managerial role of inclusive policy and institutional reform that support the ever-growing population is required, despite the daunting economic decline and paucity scarcity of water in many regions. The rest of the paper is organised thus: Section I introduces the main objective of this work, which is in twofold. Firstly, to conduct critical review and analysis of the existing streamflow forecasting methods and secondly to demonstrate a GIS Muskingum River routing with modified SCS methods as a versatile streamflow prediction model.

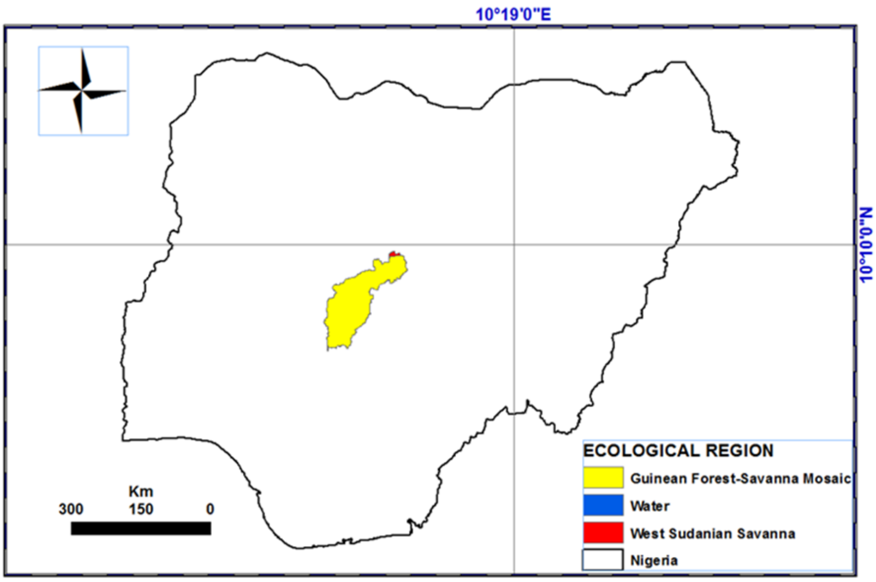

Fig. 1 Gurara located in Central Nigeria

Section II examines the utilization and comparison of synthesis convoluted SCS method with spatially distributed basin characteristics, in which all hydrologic processes are simulated within a GIS framework. Section III presents the results and discussion of watershed characteristic factors that could potentially affect basin streamflow predictability. Finally, Section IV summarizes the main findings and provides a concise usage of slope, shape factor and stream length synthesis from GIS hydrologic similarity and prediction in ungauged basins.

A. Review of Existing Method for Streamflow Prediction

Streamflow forecasting has been broadly categorised into three: physics-based methods, time series methods, and machine learning methods [18]. Physics-based models are mathematical abstractions of physical processes that govern the water movement and storage in watersheds [19]. These models suffer from uncertain physical parameters input and equifinality challenges [19]. Aside from that, most have been built on small scale physics, and application to large watersheds have been difficult due to "the effects of spatial heterogeneity in landscape properties, integral complexity of hydrological processes and interactions at that scales" [20], [21].

Traditional time series methods are linear regression models that are most suited for short-term forecasting based on daily or weekly timescales. They are found wanting in the long-term, particularly in annual and seasonal timescales, where they cannot handle the non-linearity exhibited by rainfall-runoff models [22]-[25]. These challenges and others explain the hydrologic community interest in machine learning methods.

Machine learning methods and supervised learning methods refer broadly to statistical techniques for developing predictive models using training data. Unlike physics-based models, machine learning methods are data-driven and rely almost exclusively on information embedded in training datasets. Artificial neural network (ANN) is one of the earliest machine learning methods adopted by the hydrologic community. Despite its popularity in streamflow forecasting [22], [25]-[27], main issues of ANN include its tendency to over fit training data and instability with short training data records [28]. Poor generalization may result from either over fitting or under fitting. Recent years have seen a surge of interest in the development of machine learning methods, and in particular, the support vector machine (SVM) algorithm [29] was introduced to address two challenges alluded in the above, namely, (a) how to establish a relationship between the training data size and the generalization performance of the trained model, and (b) how to incorporate such knowledge gain during training process in overcoming over fitting challenge. SVM projects the input data such that the projected training data exhibit linearity and linear regression methods can be applied.

Both the SVM and ANN are deterministic algorithms per se and do not provide a direct quantification of uncertainty prediction. Ensembling of SVM or ANN models through uncertain resampling and cross validation has improved quantify prediction performance [30], [31]. Notable work done on relevance vector machine (RVM) was designed to improve the original SVM deficiencies, which have been well documented in [32]. A main limitation of the use of RVM is that it can produce unreliable results when a tested data point is located far from the relevance cluster vectors. The projected distribution will be a Gaussian with mean and variance tending to zero [33].

To mitigate the issue of RVM, the Gaussian Process Regression (GPR) was introduced. The GPR is a full Bayesian learning algorithm that has received significant attention in the machine learning community for applications such as model approximation, multivariate regression, and experiment design [33]-[35].

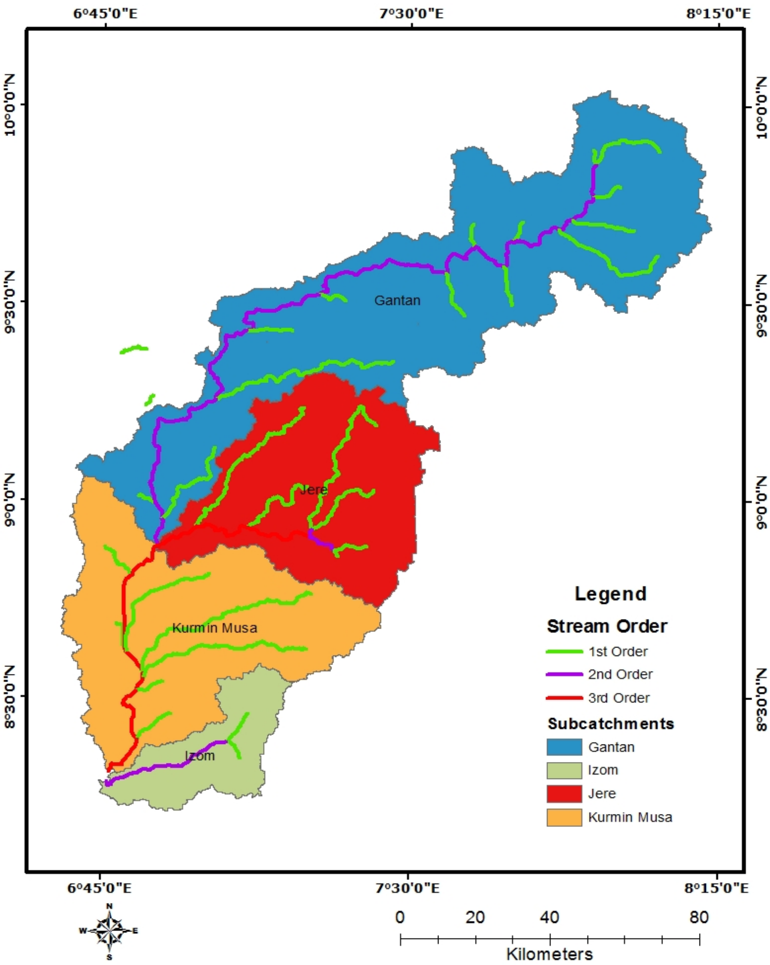

Fig. 2 Gurara hydrological sub-basin stations

GPR capability in lowering the regression processes and easy results interpretation has offered superior benefits over other machine learning approaches. Value added include its all-in -one integration of tasks [37], parameters assessment [38] and uncertainty estimation [39]; notwithstanding, it is available in the public domain for various hydrological applications [36].

In comparison to the above mentioned methods, GPR can be considered a type of multivariate regression technique that is closely related to the generalized least squares method, and has enjoyed wide populace in regional regression analysis [24], [37]. However, the application of GPR in streamflow forecasting has been rather limited [17].

Recent advances in hydrological modelling seek to investigate the effects of land-use and land-cover changes on water resources, and their contributions to storm runoff generation [4]. A drainage basin has been acclaimed as the fundamental unit for the collection and distribution of water, solutes, and sediment in fluvial landscapes studies [40], as against previous traditional conceptual rainfall-runoff models that consider the entire catchment or sub-catchment as one unit, and illustrate the conversion of rainfall to runoff with simple concepts. These limitations in model conceptualizations brought the development of lumped catchment models which carefully imbibed predicting the impacts of land-use change on catchment runoff [41].

Among the many methods used in the estimation of storm flow, among them is the rational method and SCS. The SCS runoff method can evolve storm flow at every location using different antecedent moisture conditions (AMC) to generate the runoff potential and compute the peak runoff rate. The streamflow dynamic forecasting distribution varies both in spatial and temporal entity. This physiographic terrain configuration (morphometric analysis) provides a quantitative description of the drainage system, which is an important aspect of the characterization of watersheds [42].

B. Description of the Study Area

The Gurara River basin is situated in Northern Nigeria, between latitudes 8°15' and 10°05' N and longitudes 6°30' and 8°30' E. It has a total catchment area of 15,402 km^2. Between 1961 and 1981, four hydrological sub-basin stations namely: Gurara at Gantan, Gurara at Jere, Gurara at Kurmin Musa and Gurara at Izom were established on the River Gurara and its major tributaries for monitoring the streamflow [43]. Fig. 2 depicts the sub catchment location.

However, the availability of in-situ gauge data have not been forthcoming owning to a variety of many factors, among which are paucity of funds in carrying out the task as at when due, human laxity, and inadequate employment and trained handling personnel, as well as natural factors such as death, sickness, heavy storm, and lack of storage facilities. This hinders proper information documentation of both real-time and historical data. Obsolete staff scale equipment in gauge height readings and current meter discharge readings are still used [43]. These measuring instruments are not automated but are manually placed and read within a specified time. The Niger and Kaduna State Water Board reads and records gauge and discharge data [44], which has resulted in the paucity of relevant and accurate data required for hydrological modelling.

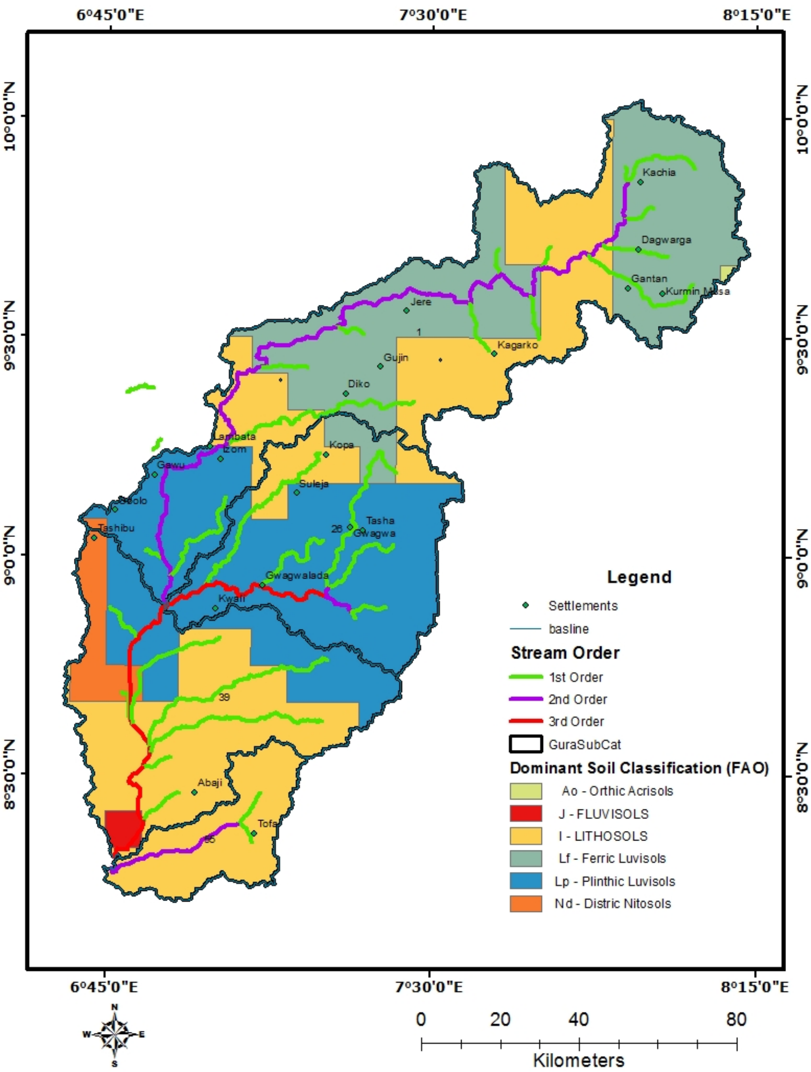

Fig. 4 Gurara dominant soil classification bases on FAO

Undulating surfaces and dissected terrain characterize the study area. The dominant underlying rock structure shows conformity undifferentiated basement complex [45].

Its geology is predominantly Precambrian (Archean + Proterozoic). Savannah grassland interspersed with tropical forest remnants characterizes the vegetation type with shrubs and coarse tall grasses [45]. The mean annual rainfall varies from 1,100 mm-1,600 mm and the mean monthly maximum and minimum temperature is in the range of 37.3°C and 19.7°C, respectively, mostly occurring in the months of February, March and April. [45]. Prolonged human activities and animal grazing coupled with seasonal variation have caused a degrading of land and dry areas. The watercourses are forested with large trees [46]. Fig. 4 illustrates the six dominant soil classification based on the Food Agricultural Organisation (FAO).

II. Materials and Methods

Rainfall-runoff computation by distributed hydrological models and the use of GIS methods have become progressively possible, popular and practical, despite the adjourn weakness that most GIS and simulation software customization processes are time consuming, requiring technical expertise in many languages [47]. These models are becoming more prominent in geospatial representation for predicting streamflow and aiding decision-making towards integrated watershed management. Most of the river basins in sub-Sahara Africa are ungauged, lacking modern stream discharge measurement. The physically employed on-site manual method requires much effort and time, and the lack of relevant and accurate data for design purposes has been a major challenge.

Grid-based GIS appears to be a very suitable tool for spatially distributed hydrologic modelling using a DEM, and soil and land raster format maps. Geographic information systems (GIS) allows for merging vector-based soil map units with the raster-based land use and land cover (LULC) map into a delineated hydrologic response unit (HRU). The flow movement is then routed through the grid network cell [47]. Fig. 3 depicts the research methodology flowchart adapted after Arun [48].

A. Data Collection and Processing

The spatial pattern of the seasonality of rainfall in the study area was determined by analysing mean daily rainfall data and the available streamflow discharge data collected at NIMET and Niger State Water Board/Kaduna River Basin Development Authority (KRBDA) for Gurara gauging station spanning 30 years (1970-2003) with some missing data for four years.

The scant streamflow data (1980-1989) were used for channel outflow for Gurara channel routing. The study made use of spatially distributed satellite imagery such as digital the elevation model (DEM) acquired from ASTER (Advanced Space-borne Thermal Emission and Reflection Radiometer), and land use, and soil information as inputs for processes using spatial analysis tool box in ESRI ArcGIS. These data were processed to determine natural channel storage estimation to compute the water surface profile for each possible condition of flow in the channel. The routing analysis was carried out in the GISJ algorithm to determine the volume of water to be expected at downstream of Gurara River during any month of the year. Fig. 4 is the soil routing and dominant FAO base classification, while Fig. 5 shows the DEM of the basin.

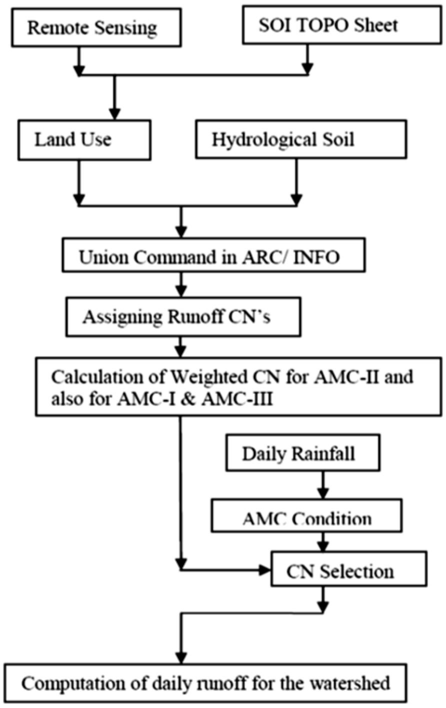

Fig. 3 Research methodology flowchart

B. Watershed Delineation/Clipping in GIS for Channel Routing Development

The Gurara River Basin was delineated from the main data set of Nigeria hydrological watershed boundaries and stream networks DEM image, using Arc Hydro tool in GIS. This selected boundary serves as one of the basic inputs to ArcInfo for further analysis. Using the SHAPEARC command in the spatial tool box converts the shape file into a cover. Both these files were further converted into grid form using the POLYGRID command. Otherwise, the given data itself can be saved in raster/grid (Gurara DEM) form. The grid file can directly be accessed and processed using spatial tools in GIS once the file is saved in the working directory.

The ''lateral flow procedure'' using the DEM steepest method allows for a raster-based drainage network to be implemented to build a digital river flow routing model from the external upstream node to the internal downstream junction node. At each junction, the discharge is then routed to the next grid junction until the river flow is routed to the outlet of the catchment. This routing phenomenon is modelled after the Muskingum method, refer to (1)-(3),

$$S = K\{XI + (1-X)Q\} \quad (1)$$

where S= storage (cumulative channel storage); I = inflow (volume/time); Q = Outflow (volume/time); and K = Proportionality coefficient indicative of residence time, while X = weighting factor.

$$Q^{J+1} = C_1 * I^{J+1} + C_2 * I^J + C_3 * Q^J \quad (2)$$

where

$$C_1 = \frac{\Delta t - 2*K*X}{2*K(1-X)+\Delta t},\ C_2 = \frac{\Delta t + 2*K*X}{2*K(1-X)+\Delta t}\ C_3 = \frac{2*K(1-X)-\Delta t}{2*K(1-X)+\Delta t} \quad (3)$$

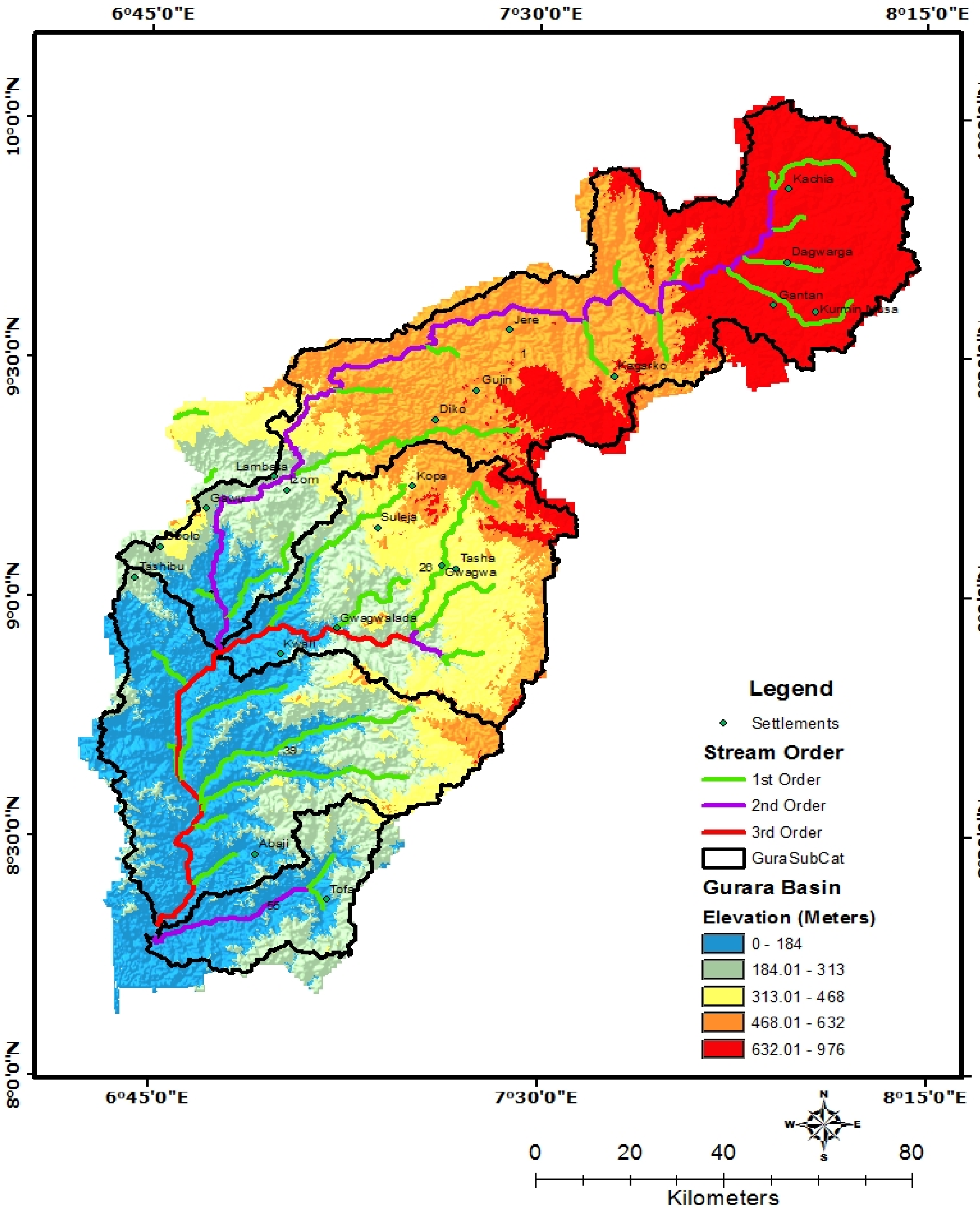

Fig. 5 Gurara Elevation model

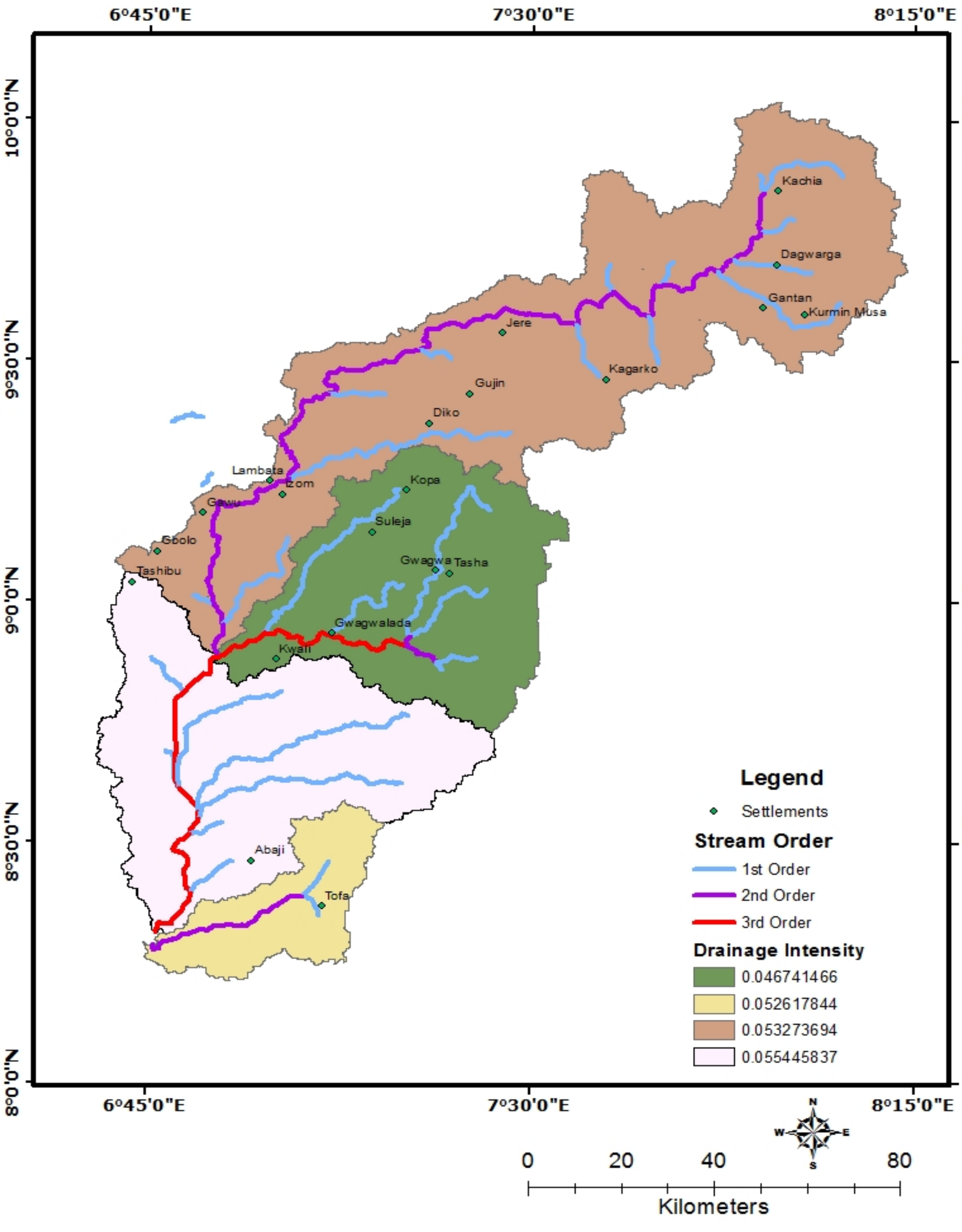

Fig. 6 Drainage intensity

The routing coefficients C_1 C_2 $C_3$are required in the Muskingum routing techniques to generate the outflow (Q) hydrographs where: Δt = routing period, days; Q^{J+1}= outflow of the first day, I^{J+1}= inflow of the first day, I^{J}= Inflow of the previous day, Q^{J}= Outflow of the previous day, J and J + 1 denote the times separated by the interval Δt^{J}.

The dimensional weighting factor X and the corresponding channel constant K was obtained from (1) through Grid base analysis. $C_1, C_2, and\ C_3$ are computed from (3), Figs. 6 and 7 depict the drainage intensity and drainage density aspect to the discharge prediction.

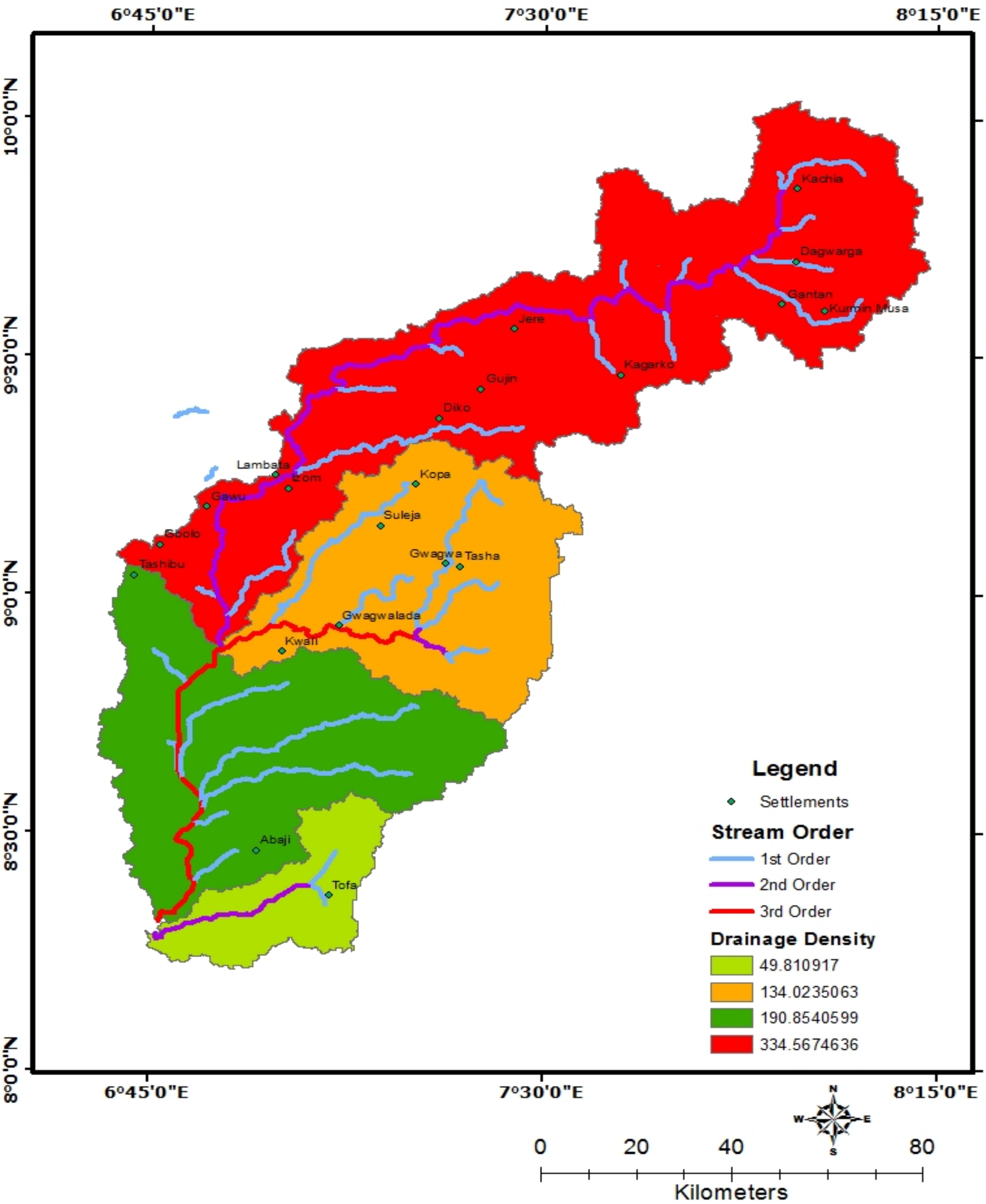

Fig. 7 Illustration of the drainage density

C. Flow Direction Conversion into Flow Accumulation

The spatial tools for slope and aspect were executed using commands slope and aspect, respectively. The output network of aspect was used as the input grid for the flow direction calculation, which was further converted into flow accumulation through the flow accumulation command [51].

The default approach for estimating overland velocity from land cover uses Manning's equation with values of hydraulic radius assigned to each cell based on drainage area by user is also supported by using the different AML programme and tools in ArcGIS. This is further processed to compute important morphological parameters which can be determined for different aspects of the basin. Fig. 8-10 show the overland, slope and land use/land cover maps.

D. Calculation of Runoff from the Basin

For runoff quantification, modified SCS-CN method is used. The SCN method is referred to (4)-(7) [52].

$$S = \frac{1000}{CN} - 10 \quad (4)$$

where S = potential maximum retention after runoff begins.

For a given precipitation event, the CN method partitions a given uniform depth of precipitation into infiltration abstraction and a runoff component generated refer to (8), (9), [50].

$$Q = \frac{(P-I_a)^2}{(P-I_a)+S} \tag{5}$$

where Q= runoff (m^3/s); P = rainfall (mm); S= potential maximum retention after runoff begins; I_a= Initial abstraction, represents that portion of retention associated with interception, ponding, and wetting of soil and vegetation surfaces.

$$I_a = 0.2S \tag{6}$$

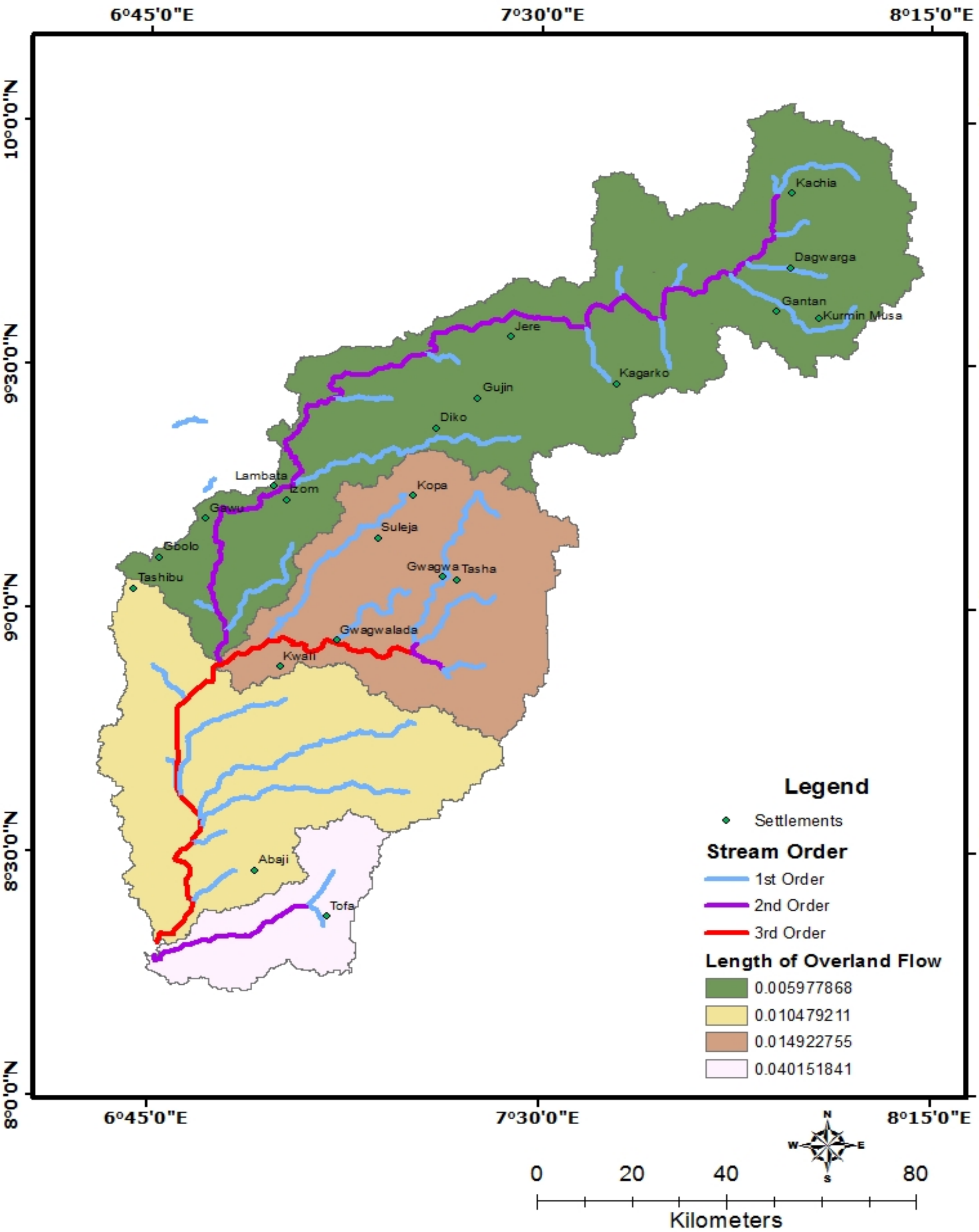

Fig. 8 Maps of overland routed flow along the grid

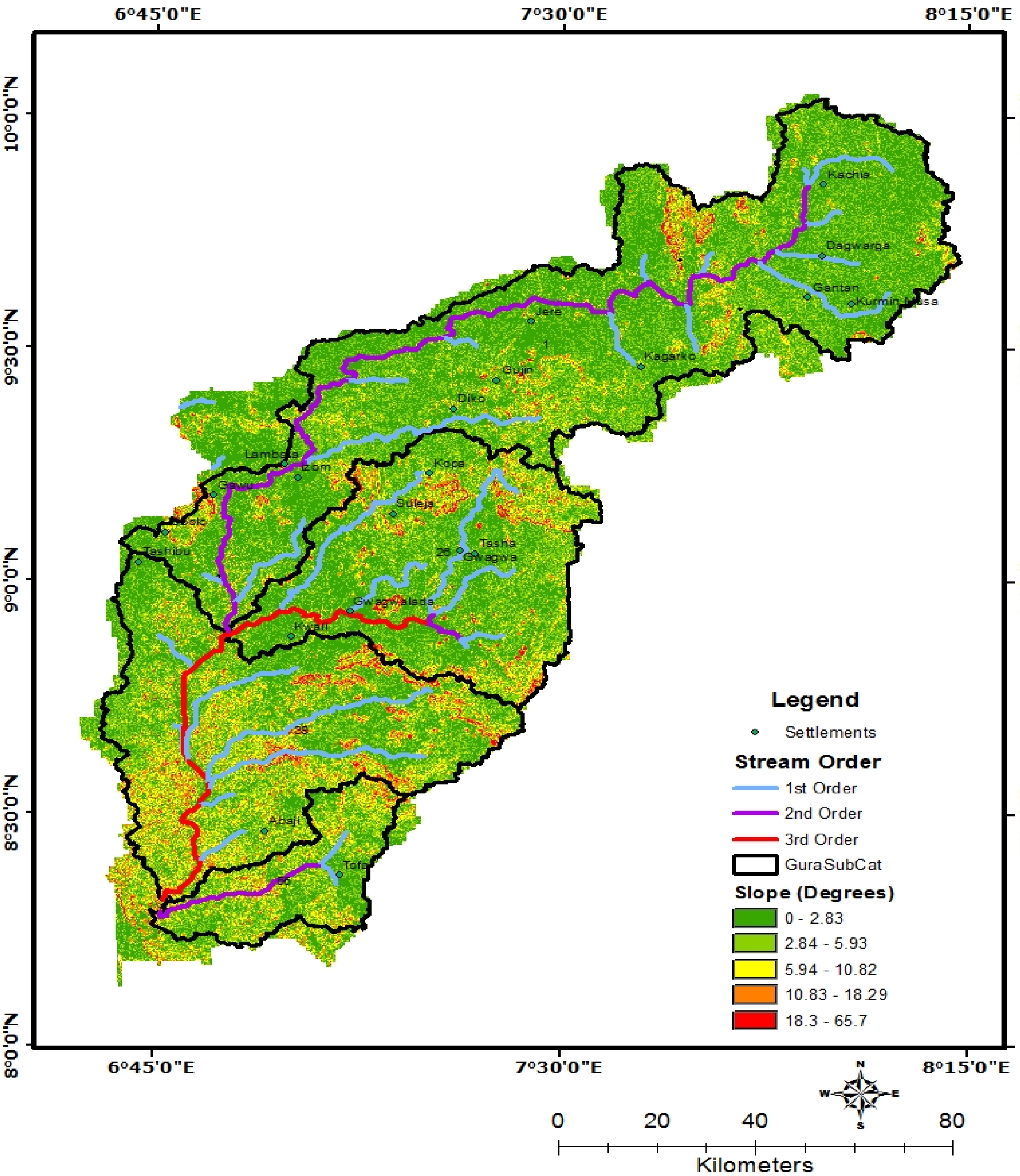

Fig. 9 GIS Slope image for the area

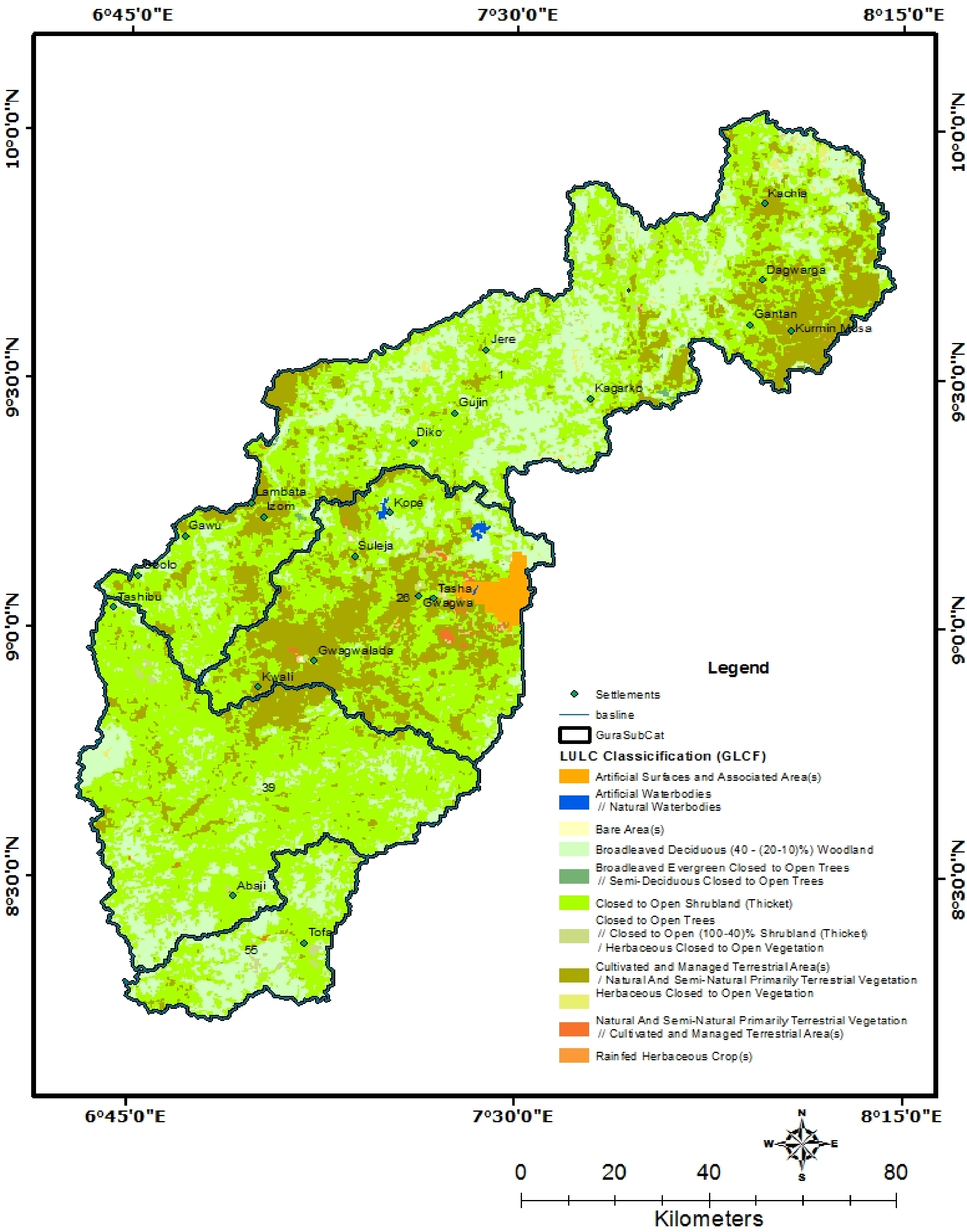

Fig. 10 Map of the land use land cover classification for the area

Substituting (9) in (8) gives:

$$Q_{m^3s^{-1}} = \frac{(P-0.2SI_a)^2}{(P+0.8I_a)+S} \tag{7}$$

For a given uniform depth precipitation event (P), Q, the uniform depth of runoff (in mm) is then determined. Effective rainfall and direct runoff can then be derived by the convolute formula for the unit hydrograph model, refer to (8),

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$$R.U = Q \quad (8)$$

where

$$R=\begin{bmatrix} R_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & R_m \end{bmatrix} \; U = \begin{bmatrix} U_1 \\ U_2 \\ U_{N-M} \end{bmatrix} \text{ and } Q = \begin{bmatrix} Q_1 \\ Q_m \\ Q_N \end{bmatrix}$$

Therefore,

$$Q_i = \sum_{M-1}^{N \le M} R_M U_{i-M+1} \quad (9)$$

where R_m is effective rainfall, U_i is the unit hydrograph ordinate, Q_i is direct runoff, M is the number of rainfall values. Solving the linear system, refer to (10), can be tedious, but with MATLAB, the equation can be solved with one command line: >> % solve the linear equation by QR decomposition.

$$U = \frac{R}{Q} \quad (10)$$

E. Estimating Peak Discharge

The peak discharge can be obtained refer to (10)-(15) [49].

$$q_p = \frac{2.08A}{t_p} \quad (11)$$

where q_p = Peak discharge (m^3/s), A = watershed area (km^2), T_p = time to peak (hr), Time to peak and lag time

$$t_p = \frac{t_r}{2} + t_L \quad (12)$$

or

$$t_p = \frac{t_c + 0.133t_c}{1.7} \quad (13)$$

where t_c = time of concentration (hr), t_r = storm duration (hr), t_L = lag time (hr), t_c = time of concentration (hr) (Kirpich's equation)

$$t_c = 0.06628\left[\frac{L^{0.77}}{S^{0.395}}\right] \quad (14)$$

where L = length of channel (stream) in km, S = Slope of channel (m/m), t_L= Lag time equivalent to

$$t_L = 0.6t_c \quad (15)$$

Measured and derived data for time to peak and peak runoff forecasting refer to (11)-(15), and see Tables I and II.

TABLE I
GURARA STATIONS DERIVED DATA FROM SPATIAL IMAGE ANALYSIS

Basin ID	*L(km)*	*A(Km)^2*	*t_c(hr)*	*Slope*	*t_L(hr)*	*t_r(hr)*	*t_p(hr)*	*q_p (km^3/hr)*
Gantan	506.86	6064.39	7.48	4.73	4.49	0.82	4.98	7077.93
Jere	256.73	4108.04	4.61	4.73	2.76	0.50	3.07	2331.84
Kurmin-Musa	306.61	5016.91	3.87	4.73	2.32	0.42	2.58	4724.08
Izom	57.02	536.12	2.74	4.73	1.65	0.30	1.83	3231.60

TABLE II
ANALYSIS OF SUB BASIN (IZOM) UNIT HYDROGRAPH FOR PEAK RUNOFF FORECASTING

t/tp	*Tp*	*t(hr)*	*q/qp*	*Qp*	*q(km^3/hr*
0.00	3.07	0.00	0.00	2336.84	0.00
0.20	3.07	0.61	0.08	2336.84	1748.76
0.40	3.07	1.23	0.28	2336.84	6528.72
0.60	3.07	1.84	0.60	2336.84	1399.11
0.80	3.07	2.46	0.89	2336.84	2075.99
1.00	3.07	3.07	1.00	2316.84	2336.84
1.20	3.07	3.68	0.92	2336.84	21451.5
1.40	3.07	4.30	0.75	2336.84	1747.63
1.60	3.07	4.91	0.56	2336.84	1307.43
1.8	3.07	5.52	0.42	2336.84	979.07
2.00	3.07	6.14	0.32	2336.84	7461.39
2.20	3.07	6.75	0.24	2336.84	5596.04
2.40	3.07	7.37	0.18	2336.84	4197.03
2.60	3.07	7.98	0.13	2336.84	3031.19
2.80	3.07	8.59	0.098	2316.84	2285.05
3.00	3.07	9.21	0.075	2336.84	1748.76
3.50	3.07	10.74	0.036	2336.84	839.41
4.00	3.07	12.28	0.018	2336.84	419.70
4.50	3.07	13.81	0.009	2336.84	209.85
5.00	3.07	15.35	0.004	2336.84	93.27

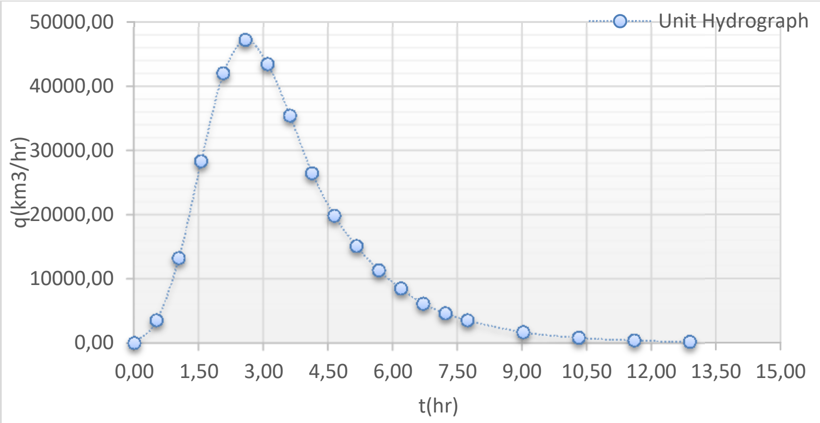

Fig. 11 The hydrograph for Izom sub-catchment area

TABLE III
ANNUAL RAINFALL FOR PERIOD OF SELECTED 11 YEARS

YEAR	RAINFALL(MM)	RANK-M	FREQUENCY(%)(M/N+1)
2002	647.50	1	8.33
2001	547.45	2	16.67
1993	511.28	3	25.00
1981	423.49	4	33.33
1986	416.38	5	41.67
1983	369.04	6	50.00
1982	350.51	7	58.33
1985	342.53	8	66.67
1984	340.81	9	75.00
1978	268.89	10	83.33
1977	45.60	11	91.67

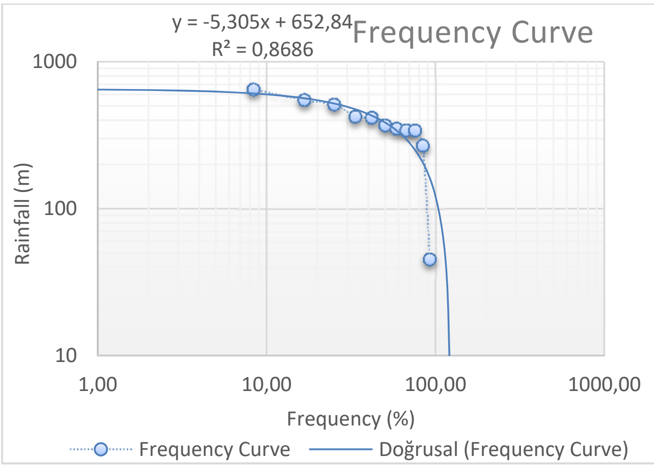

Fig. 12 The graph of rainfall against percentage frequency

The unit-hydrograph response estimation routine computes the distribution of flow at the sub-basin catchment outlet. The following instantaneous input event and the resulting Izom unit hydrograph, is represented in Fig. 11.

The frequency recurrence intervals curve can be used to derived the required rainfall at probable time interval is analyzed in Table III, while the graph of ('P vs. F') on a semi-log paper (Fig. 12) gives the frequency recurrence intervals curve.

III. RESULTS AND DISCUSSION

Based on the obtained results from the Arc Hydro morphometric analysis and SCS-CN validation of the stream-flow discharge, a good knowledge of the catchment dynamic and watershed characteristic factors that can potentially affect basin streamflow predictability represent a key step in developing spatial data driven streamflow forecasting models. The cumulative discharge is often calculated as the runoff coefficient which depends upon the influence of catchment slope, land use, and soil type multiplied by net precipitation. This represents the aggregation of topographical and geological features upon which rainfall intensity and soil moisture depend. The result of the downstream unit hydrology indicates streamflows from high altitude, lithological variation and moderately steep slopes. Other catchment factors affecting the distribution of runoff are:

A. Elevation

The heterogeneous elevation nature of the area range from 0 m to 184 m above mean sea level (Fig. 5); part of the basin lies in the intermediate zone of the Sahara North and the sub-humid climate in the South. On the contrary, flatland and gentle slopes characterize the southern and central parts of the study area.

B. Drainage

The drainage pattern of the area derived from soil and land-use accumulation flow depicts a dendritic varying pattern which indicates the homogeneity in texture and lack of structural control (Fig. 8). The drainage density index gives a good idea of the complexity and development degree of the watershed's drainage system [52]. A rich drainage system has a greater water concentration capacity because water runs through less distance to the streams. Likewise, a poorer system gives place to higher infiltration values, and therefore, lower and delayed flow peaks are expected. It indicates the closeness of spacing of the channels. The calculated value for the drainage intensity using a network shapefile in ArcGIS was 0.822 km/km^2. The Elongation ratio (0.44) helps to give an idea about the hydrological character of a drainage basin. The area of dense drainage work was found to have a high runoff volume.

C. Slope

For this basin, the observed slope has been group into classes (Fig. 9). A higher slope produces higher and faster runoff peaks. It determines the concentration time. It expresses the time elapsed since the beginning of the precipitation until the moment in which the total area of the watershed contributes to the runoff at the outlet.

D. Land Use/Soil Type

The soil profile characteristics are important in relation to their effects upon infiltration and generation of interflow (Fig. 4). Open texture sandy soils will tend to be associated with high infiltration volumes than fine grained closely compacted clay soil. The extracted drainage network from the DEM land use shows that the basin LULC base on the Global Land Cover Characterization (GLCC) database is characterized majorly by cultivated and managed Terrestrial Bar Areas - woodland; Sparse Terrestrial vegetation to rainfed - Herbaceous crops in the South (Fig. 10). The soils types have different distributions ranging from light silt loam and dark to dark red clay soils.

E. Vegetation and Drainage Network

The effect of vegetation and drainage network influence of river discharge; its morphology characterization depicts the streamflow in time variation (Fig. 7). The Gurara basin is highly undulating with various inconsistent vegetation, shrubs, isolated hills, and ridges. Some prominent hills are Zuma rock, at the North-eastern boundary with FCT, Abuja, and Kusheriki ridge in the North Central part of the country.

IV. CONCLUSION

In this paper, a GIS and Muskingum River Routing (MRR) hydrologic approach was adopted for the assessment of land-use change on streamflow prediction processes. This study advances the GIS underlying processes of catchment modelling. The applied methodology considers the spatial heterogeneity of the basin parameters, especially for an ungauged watershed, to predict discharge hydrographs. Given the satisfactory AMC of soil parameter determination, the effect of land use change on streamflows prediction has been easier. Also, manual derivation of CN's for large drainage basins can be time consuming and labour intensive, thus making raster data structure and processing in GIS environment an appropriate tool for use.

The improved SCS Method to estimate flow parameters found usefulness in reconnaissance investigations, and can be used to extend quantification of streamflow for farm irrigation purposes, where past records are sparse or unavailable.

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