Quantification of effects of climate change on flood in tropical river basins

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Abstract: Over the past two decades, southeastern Nigeria has witnessed huge economic losses due to severe flooding caused by climate change. Understanding the contribution of climate change to flooding is critical for runoff utilization and control, especially in the tropics. This study is focused on quantifying the amount of flooding contributed by climate change effects in the River Basin of southeastern Nigeria. First, the Climate-Flood model equation was expressed using the Time-Series Autoregressive model technique. Using Minitab software, mean annual values of contributing climate variables from prolonged periods of recorded data were investigated. Runoff predictions made from climate-flood models using only the annual records of climatic variables were filtered from the resultant of the respective annual climatic variables, and mean change in flood due to climate change. The output was analyzed considering geology, infiltration capacity, drainage lines and digital elevation model (DEM) of the area. The result shows the obvious trend in climatic variables consistently generates significant impact on the flood. Owerri had the highest positive change in evaporation of 0.11% with a rainfall of 0.03%. Awka had the highest change in sunshine hours and rainfall of 0.41%. Umuahia had the highest change in solar radiation of 0.08, while Enugu had the highest change in air temperature of 0.12. When the contribution of climate change to runoff variation...
was quantified, Enugu shows highest with 1.68 m$^3$/s while Owerri has 0.04 m$^3$/s. This knowledge is necessary in designing hydrological structures and formulating policies that will help prevent/mitigate flood disasters in the region.

**Keywords:** climate change; model; flood; hydrology; drainage lines; geology

1. **Introduction**

The long-term descriptive character of the atmospheric conditions of a particular place is known as the Climate (Intergovernmental Panel on Climate Change [IPCC], 2014). According to Karl et al. (2009), climate expresses various elements of weather by means of averages and the probabilities of other conditions inclusive of extreme values. According to National Oceanic and Atmospheric Administration [NOAA] (2016) Climate change refers to a statistically significant variation in the mean state of the climate or in its variability persisting over an extended period, normally decades or longer. Therefore, climate change refers to a significant change in the average weather conditions experienced in a particular region or location. The changes could be seen with respect to a significant change in perceived temperature of the region, the amount of rainfall experienced in the region, duration of exposure of the ground to sunlight, etc. The change in water discharge and sediment load of rivers as a response to these climatic changes and human activities became an important topic in hydrological studies (Khan, Daintyari, et al., 2016). The change may occur over periods ranging from decades to millennia (Brikowski, 2008; Huntington et al., 2009; Xie et al., 2010). Many research works (Hall & Crovetti, 2007; Homer et al., 2015; Juckem et al., 2008; Karishma et al., 2016; Ryberg et al., 2015), are suggesting that extreme weather conditions including more high-intensity rainfall events will be witnessed in the future incidences of climate change. There is a likelihood that flood menace will increase, especially in areas where the water channel adjusts to differing flow regimes. Impacts of climate change are broadly classified into environmental, agricultural, economic, health and other socio-economic groups by the United Nations Framework Convention on Climate Change (Poff, 1996). River engineering practices, river training, river management, and the design of water constructions as well as power plant intakes are greatly dependent on river flow variations due to many factors, including climate change etc. (Khan, Hasan, et al., 2016). From the assessment report of the intergovernmental panel on climate change, Africa with an average surface temperature increase of about 3.4°C relative to the period between 1980 and 1990, is probably going to be warmer than the rest of the world by the end of the twenty-first century. As a result of the above, it is therefore imperative to study, analyze and understand the futuristic effect of this climate change on the hydrological cycle.

To quantify the impact of climate change on flood, hydrological model should be developed to help estimate, predict, and analyze the streamflow in the study area. Several hydrological models have been used to estimate stream flows in catchment areas. Popular among them are: (i) The Soil and Water Assessment Tool (SWAT). SWAT as described by Juckem et al. (2008), is the watershed scale model that predicts not only rainfall effects but also the impact of land management practices such as land-use and land cover changes, reservoir management, groundwater withdrawals and water transfers, on complex watersheds over prolonged periods; and (ii) the Time-Series model. Stream flow analysis and estimation using Time-Series, have several methods. First, the State-Space Time-Series (SSTS) method, which is rarely used, is mostly for economic time-series model development and forecasting. The second is the Autoregressive (AR), Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models.

Generally, autoregression focuses on building the most appropriate model to fit observed data. Box et al. (2008) observed that the ARIMA model enhances its accuracy by the use of average estimates of the parameters. This factor corrects the uncertainty of the model and enforcement of stationary autoregressive parameters and inevitable moving average parameters. Based on the pattern recognition concept, most stochastic modeling propositions for generating synthetic stream flows and hydrological time series, recommends AR systems. According to Otache et al.
(2008), several procedures in the time-series modeling approach fall within the framework of multivariate ARMA models. Overall, the performance of AR models and ARIMA models are credible in the analysis of stochastic hydrological data. For a describable short-run issue such as modeling the seasonal variability in a stochastic flow series, AR and ARIMA models are extremely valuable. Partial autocorrelation function (PACF) and autocorrelation function (ACF) can be applied to identify the initial AR model. Reasonably, therefore, in this research work, a Time-Series model using Autoregressive (AR) technique was adopted. Evaluation of the potential impacts of anthropogenic climate change on regional and local water resources relies largely on climate model projections (R. Xu et al., 2019).

Changes in time of precipitation, intensity of rain, sunshine times and other climate parameters impacts significantly on water availability and its management. Empirical modeling and in-depth study of flood at gauging stations in south eastern Nigeria for any change in climate has not been elucidated and is now mostly needed for effective soil and water conservation engineering practices in the region. Necessarily to verify the potential effects of change in climate, several water balance and climate models have been developed. However, according to Elgaali and Garcia (2005), due to their temporal and coarse spatial resolution, many of these models are not precise.

Millions of Nigerians are affected by the adverse effects of the changes in climate conditions. Flooding and droughts are never-ceasing, and traditional farming seasons have been destroyed by unimaginable dry spells and off-season rains, in a country that depends on good weather for agricultural practice. There is evidence of drying-up of lakes and reduced river flows in the arid and semi-arid regions. This has resulted to lower water supplies for hydro power generation, agriculture, and other uses. Climate change is suspected to be the main causative agent. In the 2006 publication of the Federal Ministry of Information and Culture, in southern Nigeria, climate change menace was visible in the massive flood disasters of 2001 and 2002 which swept away farms, buildings, farm produce and even human beings. Similar flooding was witnessed in 2008, 2012, etc. Coastal regions have been seriously threatened by the continuous rise in the sea levels. Due to the low terrain levels and too many river tributaries, the Niger Delta area of Nigeria, which bears the oil formation are extremely exposed to flooding. Landslides caused due to high magnitude rainfall events not only add a tremendous amount of sediment to the river, but also block the river with debris resulting in massive floods when they fail (Singh & Khan, 2020).

Previous researchers have made efforts to study the climate change scenarios in South Eastern Nigeria. Amadi et al. (2019) studied climate change in south-eastern, Nigeria and its implications for agricultural sustainability using data from Enugu as their reference data. Similarly, Odok et al. (2018) studied climatic variability but limited their study area to only Abia. Analysis of 30 years rainfall variability in Imo State of south-eastern Nigeria was carried out by Okorie (2015). Nwajiuba and Onyenekwu (2010) investigated the impact of climate change on food security and agriculture by analysing climatic data from Abia, Imo, Ebonyi and Anambra for a period of 30 years (1978–2007). In all these research works, none has attempted to quantify the impact specifically contributed by change in climate. Quantifying the impact of climate change and dam construction on the flow regime is essential for water resource management and environmental protection (Cui et al., 2020). In southeastern Nigeria, climate change has caused excessive flooding leading to the development of gully erosion. This has devastating effects on many farmland and settlement areas, resulting in poverty in the local populace. There exists now, severe demand competition for water in urban development, agriculture, hydropower, industry, etc., due mostly to the impact of climate change in the region. This research work seeks to quantify the impact of this climate change on flooding, to enable the mitigation and elimination of the water use competition in South Eastern Nigeria's regional river basin.
2. Study area

2.1. Geographical location and hydrological attributes of the study area

The study area (Southeast) is one of the six geopolitical zones in Nigeria. It is under one River Basin known as Anambra-Imo River Basin (Figure 1(a)). It comprises five States (Enugu, Imo, Anambra, Ebonyi and Abia) with a total of 95 Local Government Areas out of 774 in Nigeria. SouthEast (Figure 1(b)) is located on a geographic coordinate of Longitude 6° 30’ –8° 30’E and Latitude 5° 7’ N. It has an annual rainfall range from 2300 to 2800 mm with an estimated area of about 28,658.8 km².
2.1.1. Geology of the study area

Geologic map of the Southeast as shown in Figure 2(a) contains cretaceous to tertiary sequences of Niger Delta basin with 11 different number of formations, namely: Asu river group, Odukpani formation, Eze-Aku Shale, Awgushale, Enugu/Nkporo, Mamu formation, Ajali sandstone, Nsukka formation, Imo shale, Ameki formation and Ogwash-Asaba formation (Onyeogu et al., 2016).

Figure 2. Map of the study area showing (a) the geological characteristics (b) Digital Elevation Model (c) average monthly rainfall (d) average monthly temperature. Map of the study area showing (e) the average monthly sunshine hours (f) average monthly Relative Humidity (g) average monthly wind speed (h) average monthly Atmospheric Pressure. Map of the study area showing (i) the average monthly cloud cover (j) the rivers and drainage line.
2.1.2. South East relief area

Three central landform regions characterize the southeast relief area. **Figure 2(b)** represents the Digital Elevation Model (DEM) map of the study region, where the highland region ranges from 258 m—591 m of elevation occurring in the northern part. This region dominated Enugu state and a minor part of Anambra State. The second is a moderate region with an elevation ranging from 111 m to 258 m, touching every part of the five states but mostly dominated in Enugu and Imo States. The third is the low land region with an elevation of 42 m—111 m, which dominated Ebonyi State, the southern part of Abia State, and the western part of Imo and Anambra States.
2.1.3. Average monthly rainfall amount of the study area
Average monthly rainfall in Southeast Nigeria ranges from 2300 mm—2800 mm. The highest and highest monthly rainfall occurred in the southern part, covering the southern part of Abia State, Imo State, and the eastern part of Ebonyi State. Moderate average rainfall amounts traversed through the central part of Ebonyi, the northern part of Abia, and the central part of Imo State. Low and lowest average monthly rainfall was observed in the northern part of the Southeast, covering significant parts of Enugu and Anambra states. Figure 2(c) displays a map indicating the average monthly rainfall amount.

2.1.4. Average monthly temperature
The average annual temperature of Southeast Nigeria falls between 24°C and 29°C. Figure 2(d) shows the map of the average monthly temperature for Southeast. The northern part of the Southeast, covering majorly Enugu, had the highest temperature (28.3–28.5°C). Moderate temperature (2.7–28°C) occurs in the central part, while the lowest temperature (27.2–27.5°C) occurs in the southern part of the Southeast.

2.1.5. Average monthly sunshine hours
On an average monthly sunshine hour, the lowest sun hours (211.5–224.1 hours) occur within Imo, Abia, and Ebonyi States. Moderate sunshine hours (236.6–249.1 hours) traverse from Anambra to Ebonyi, while the highest sunshine hours (261.6–274.1 hours) traversed between boundaries of Enugu and Ebonyi on the northern part of Southeast (Figure 2(e)).

2.1.6. Average monthly relative humidity
Figure 2(f) presents average monthly humidity reclassified into five in percentages. The highest relative humidity (231.5–238.4%) occurs in the southern part of Southeast dominating Abia State majorly, moderate (217.7–224.6%) occurs in the central part of Southeast covering through the central part of Ebonyi, the northern part of Anambra, and southern part of Enugu. The lowest relative humidity (204–210.8%) happens in the northern part of the Southeast, covering the core north of Enugu and Ebonyi.

2.1.7. Average monthly wind speed
The average monthly wind speed map in southeast Nigeria is shown in Figure 2(g). The highest wind speed (7.9–8.3 kmph) occurs in Enugu and Ebonyi States. Moderate monthly wind speed (7.2–7.6 kmph) is seen in the Anambra, Imo, Abia, and Ebonyi states, while the lowest observed wind speed (6.5–6.9 kmph) occurring in some parts of Abia and Ebonyi, respectively.

2.1.8. Average monthly atmospheric pressure
The average monthly pressure of Southeast is shown in Figure 2(h). The highest (3395.2–3991.1 mb) and moderate (2203.3–2799.2 mb) all happen in the northern part of the Southeast dominated by Enugu state, while the lowest average monthly pressure (1011.4–1607.3 mb) occurs in the southern part of Southeast covering the entire Imo and Abia states.

2.1.9. Average monthly cloud cover
The average monthly cloud cover, as shown in Figure 2(i) in percentages (reclassified into five), reveals that the lowest cloud cover (40.1–45.0%) occurs in the northern part of Southeast, moderate (49.9–54.8%) on the north-central part. In contrast, the highest cloud cover dominated the southern part of the Southeast.

2.1.10. The rivers in the study area with the drainage lines
The main rivers draining in the Southeast are Imo River, River Niger, Ebony River, Urashi River, Adada River, Otamiri River, Oguchie River, Aba River, Ivo River, Afikpo River, and Njaba River, as shown in Figure 2(j).
2.2. The study area sub basins

Eight (8) sub-basins make up the Southeastern Nigeria River basin. They are Imo River, Otanmiri/Oranmiriukwa/Oguchie, Ivo/Ebonyi, Ajali/Niger, Aba/Abia, Njaba/Urashi, Ekpaukwu and Esu. They form the Anambra-Imo-Ebony-Enugu River Basin (Figure 3(a)). Each of the basins is of a different shape and different composition. Table 1 shows the area coverage of the sub-basins. Figure 3(b) represents the map and drainage lines of the Otanmiri subbasin. Figure 3(c) is the map and drainage lines of the Imo River subbasin. Figure 3(d) is the map and drainage lines of the Ivo River subbasin, and Figure 3(e) displays the map and drainage lines of the Ajali/Adada sub-basin.

2.3. Watershed of South Eastern Nigeria

Otanmiri/Oranmiriukwa/Oguchie subbasin (Figure 3(b)) covers 2432.4 Km², representing the fifth-largest drainage basin in southeastern Nigeria. The major rivers in this watershed are Nworie, Otanmiri, Oranmiriukwa, Okitankwo and Oguchie River. It covers Imo State in south-eastern Nigeria. The Imo River Sub Basin (Figure 3(c)) remains the largest river in Abia and Imo States, receiving tributaries from parts of Ideato North and South LGAs moving towards Okigwe Umuahia, Obowo, Mbaise, Ngor-Okpala, and Aba. It forms the boundaries between Imo and Abia States, Abia and River State, Rivers and Imo States, Abia, and Akwa Ibom State. It occupies an area of 1926.7 Km² representing the sixth-largest sub-basin in the Southeast. The gauging station is located at Umuokpara in Umuahia. Ivo/Ebonyi Sub Basin (Figure 3(d)) remains the largest River in Ebonyi state and the second largest sub-drainage basin in Southeast, occupying 7616.2 Km². This basin dominated the majority of Ebonyi State. The Ajali/Adada River Sub Basin (Figure 3(e)) drains from Enugu State, covers Anambra State through a part of the Imo State boundary with different southern Nigerian states emptying into the Atlantic Ocean. The Ajali/Nige subbasin remains the largest drainage basin in the Southeast, with an area of 7639.6 Km² (Table 1).

3. Methodology

3.1. Sources and method of data collection

One river in each of the five states that make up south-eastern Nigeria was selected for the study, viz.: Otanmiri river in Imo State, Ivo (Umuokpara) river in Abia State, Adada River in Enugu State, Ivo River in Ebonyi State, and Ajali river in Anambra State. The recorded annual maximum discharges (runoffs) in the rivers were collected from the Anambra Imo River Basin Development Authority (AIRBDA). Historical hydrological data from the rivers’ gauging stations were collected from Nigerian Meteorological Agency (NIMET). The recorded data collected were air temperature (T), soil temperature (T_s), rainfall (I), evaporation (E), sunshine hours (S), wind speed (W), solar radiation (R), humidity (H), and atmospheric pressure (P). The data collected were 30 years and cover between 1983 and 2004 for all the states. The various average annual values of the collected data were tabulated using Microsoft Excel computer software. Furthermore, the current investigation followed a sequence itemized in a flowchart presented in Figure 4.

| S/N | Name of Subbasin             | Area (Km²)  |
|-----|------------------------------|-------------|
| 1   | Ajali/Niger                  | 7639.56     |
| 2   | Okpaukwu                      | 1399.05     |
| 3   | Esu                          | 1914.89     |
| 4   | Ivo/Ebonyi                   | 7616.15     |
| 5   | Abia                         | 3127.82     |
| 6   | Njaba/Urashi                 | 2602.18     |
| 7   | Imo                          | 1926.72     |
| 8   | Otanmiri/Oranmiriukwa/Oguchie| 2432.42     |
3.2. Average annual hydrological data of the rivers

The average annual hydrological data of the selected rivers are presented in the supplementary pages. Table S1 shows the average annual hydrologic data of the Otamiri river. Table S2 is the average annual hydrological data of the Imo (Umuokpara) River. Table S3 is the average annual hydrological data of the Ivo River. Table S4 is the average annual hydrological data of the Ajali river, and Table S5 is the average annual hydrological data of the Adada river. These are the input variables used for the analysis. Using the Minitab computer software, these variables were subjected to time-series analysis and multiple regression Climate-Flood model statistical investigation to correlate the rivers’ discharge with the climate parameters.

Figure 3. (a) Map of the study area showing the subbasins. Map showing drainage lines of (b) Otamiri River (c) Imo River (d) Ivo River (e) Ajali and Adada Rivers.
3.3. Correlation analysis of climate variables

To illustrate the correlation analysis, two independent variables and a dependent variable \( x_1, x_2, y \), respectively, are used. Means of \( x_1, x_2, y \) were obtained (Agunwamba, 2007) as:

\[
\bar{x}_1 = \frac{\sum x_1}{n} = \frac{\sum x_2}{n} = \frac{\sum y}{n}
\]

(1)

And the variances of \( x_1, x_2, y \) are obtained as:

\[
\sigma^2_{x_1} = \frac{\sum_{i=1}^{n} (x_1 - \bar{x}_1)^2}{n - 1}, \sigma^2_{x_2} = \frac{\sum_{i=1}^{n} (x_2 - \bar{x}_2)^2}{n - 1}, \sigma^2 = \frac{\sum_{i=1}^{n} (y - \bar{y})^2}{n - 1}
\]

(2)

And the correlation coefficients of between \( y \) and \( x_1 \) is

\[
r_{yx_1} = \frac{\sum y x_1 - n \bar{y} \bar{x}_1}{(n - 1)\sigma_y \sigma_{x_1}}
\]

(3)

the correlation coefficients of between \( y \) and \( x_2 \) is

\[
r_{yx_2} = \frac{\sum y x_2 - n \bar{y} \bar{x}_2}{(n - 1)\sigma_y \sigma_{x_2}}
\]

(4)

the correlation coefficients of between \( x_1 \) and \( x_2 \) is

\[
r_{x_1x_2} = \frac{\sum x_1 x_2 - n \bar{x}_1 \bar{x}_2}{(n - 1)\sigma_{x_1} \sigma_{x_2}}
\]

(5)

Partial Correlation Coefficient: By keeping \( x_2 \) constant, the partial coefficient of correlation for \( y \) and \( x_1 \) was computed (Agunwamba, 2007) as:

\[
y_{yx_1 x_2} = \frac{y_{yx_1} - y_{yx_2} y_{x_1 x_2}}{\sqrt{(1 - y_{x_1 x_2}^2) \left(1 - y_{yx_2}^2\right)}}
\]

(6)

The partial correlation coefficient between \( y \) and \( x_2 \) keeping \( x_1 \) constant is computed as

\[
y_{yx_2 x_1} = \frac{y_{yx_2} - y_{yx_1} y_{x_1 x_2}}{\sqrt{(1 - y_{x_1 x_2}^2) \left(1 - y_{yx_1}^2\right)}}
\]

(7)

The partial correlation coefficient between \( x_1 \) and \( x_2 \) keeping \( y \) constant is computed as

\[
y_{x_1 x_2 y} = \frac{y_{x_1 x_2} - y_{x_1 y} y_{x_2}}{\sqrt{(1 - y_{x_1}^2) \left(1 - y_{x_2}^2\right)}}
\]

(8)

The multiple correlation coefficient of \( y \) on \( x_1 \) and \( x_2 \) is

\[
R_{y,x_1x_2} = \sqrt{\frac{y_{x_1}^2 + y_{x_2}^2 + 2y_{x_1 y} y_{x_2 x_1}}{1 - y_{x_1 x_2}^2}}
\]

(9)
The Standard error of estimate is

\[ s_{y|x_1,x_2} = \sigma_y \sqrt{1 - R^2_{y|x_1,x_2}} \]  \hspace{1cm} (10)

The coefficient of correlation calculates the linear magnitude of the relationship between two variables. This always uses a value between \(-1\) and \(+1\), with \(1\) or \(-1\) suggesting a good correlation (most points will indeed lie along its straight line, of zero residual). A near- or equal-zero coefficient of correlation signifies no relationship among variables. A positive correlation coefficient signifies a positive (ascending) correlation, and a negative correlation coefficient signifies a negative (decreasing) correlation. These coefficients of correlation were computed with the aid of Microsoft Excel software.

3.4. The multiple linear regression model

In Montgomery and Runger (2003) a regression model is
\[ Y_i = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k + \epsilon_i \]  

(11)

and imaging that \( n \) observations of the variables \( y, x_1, \ldots, x_k \) are available, which are indices by \( i \) given as \( 1, \ldots, n \). Then, the \( n \) realizations of the interactions can be written as shown in Equation (12).

\[
\begin{bmatrix}
Y_1 \\
Y_2 \\
\vdots \\
Y_n
\end{bmatrix} =
\begin{bmatrix}
1 & x_{11} & \cdots & x_{1k} \\
1 & x_{21} & \cdots & x_{2k} \\
\vdots & \vdots & \ddots & \vdots \\
1 & x_{n1} & \cdots & x_{nk}
\end{bmatrix}
\begin{bmatrix}
\beta_0 \\
\beta_1 \\
\vdots \\
\beta_k
\end{bmatrix}
+ \begin{bmatrix}
\epsilon_1 \\
\epsilon_2 \\
\vdots \\
\epsilon_n
\end{bmatrix}
\]  

(12)

Where, \( \epsilon_i \sim iid N(0, \sigma^2) \), \( \beta_0 \) is the intercept (multi-dimensionally), \( \beta_1, \beta_2, \ldots, \beta_k \) are the regression coefficients for the explanatory variables. \( X_{ik} \) gives the \( k \) th explanatory variable value for the \( i \) th case. In matrix form, the Multiple Linear Regression Model is

\[ Y = X \beta + \epsilon \]  

(13)

\((n \times 1) \ (n \times (k+1))((k+1) \times 1) \ (n \times 1)\)

Design Matrix \( X \): Coefficient matrix \( \beta \):

\[
X =
\begin{bmatrix}
1 & x_{1,1} & x_{1,2} & \cdots & x_{1,k} \\
1 & x_{2,1} & x_{2,2} & \cdots & x_{2,k} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & x_{n,1} & x_{n,2} & \cdots & x_{n,k}
\end{bmatrix}
\begin{bmatrix}
\beta_0 \\
\beta_1 \\
\vdots \\
\beta_k
\end{bmatrix}
\]

considering the case of only two independent variables as it agrees with the nature of the data, Equation (11), reduces to

\[ Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon_i \]  

(14)

The dependent variable is the estimated monthly runoff, \( Y \). According to Montgomery and Runger (2003), \( \beta_0, \beta_1 \text{ and } \beta_2 \) are estimates of the true parameters \( \beta_0, \beta_1 \text{ and } \beta_2 \) of the regression equation. \( \hat{\beta} \) is the mean change for \( Y \) when there is a 1 unit increase in \( X_1 \), while holding the \( X_2 \) constant (partial regression coefficient).

3.5. Least square estimation

Montgomery and Runger (2003) state that the coefficient \( \hat{\beta} \) selected by least-squares factor is termed the least-squares prediction of the correlation variables. The coefficients \( \hat{\beta} \) are comparable in the form that they generate predicted (fitted) average responses, the sum of which would be as low as possible. These vectors are called residuals (Montgomery & Runger, 2003). The derivation sum(s) for the predicted values as well as the measured values were derived as:

The vector \( \hat{\epsilon} = Y - X\hat{\beta} \) are called residuals (Montgomery & Runger, 2003). The sum(s) of derivation for the relationship existing between the measured and the predicted values was obtained as:

\[
S(\hat{\beta}) = \hat{\epsilon}^T \hat{\epsilon} = (Y - X\hat{\beta})^T (Y - X\hat{\beta}) = Y^T Y - Y^T X \hat{\beta} + \hat{\beta}^T X^T Y + \hat{\beta}^T X^T X \hat{\beta}
\]

= \[ Y^T Y - 2Y^T X \hat{\beta} + \hat{\beta}^T X^T X \hat{\beta} \]

(15)
To find estimates of $\beta_0, \beta_1$ and $\beta_2$, the sum(s) of derivation for the relationship existing between the measured and the predicted values were minimized to obtain the least square curve to reach the final expression, the identity $\beta^T X^T Y = Y^T X \beta$ was used, which comes from the fact that the transpose of a scalar which may be constructed as a matrix of order $1 \times 1$ is the scalar itself.

The first-order conditions for optimization are calculated by differentiating the function with respect to the $\beta$ vector and by limiting that outcome to 0, the formulations have an exact solution, and are the vector of ordinary least-square predictions, and it is given by

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$  \hspace{1cm} (16)

Where;

$$X^T X = \begin{bmatrix} n & \sum X_1 & \sum X_2 \\ \sum X_1 & \sum X_1 X_2 & \sum X_1 X_2 \\ \sum X_2 & \sum X_2 X_1 & \sum X_2 X_2 \end{bmatrix}$$  \hspace{1cm} (17)

Thus;

$$\hat{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} = (X^T X)^{-1} X^T Y$$  \hspace{1cm} (18)

Implying:

$$\hat{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} = \left( \begin{bmatrix} n & \sum X_1 & \sum X_2 \\ \sum X_1 & \sum X_1 X_2 & \sum X_1 X_2 \\ \sum X_2 & \sum X_2 X_1 & \sum X_2 X_2 \end{bmatrix} \right)^{-1} \begin{bmatrix} \sum Y \\ \sum X_1 Y \\ \sum X_2 Y \end{bmatrix}$$  \hspace{1cm} (19)

### 3.6. Formulation of climate-flood model

The model was constructed with flood as a function of the climate parameters. The major climate variables, whose average annual measured data at the gauging stations were obtained from NIMET are Rainfall Intensity $I$, (mm), maximum and minimum Air Temperature $T$, (°C), Humidity $H$, duration of Sunlight $S$ (Hrs), Evaporation $E$, Wind Speed $W$, Soil Temperature $T_s$, Solar Radiation $R$, and Atmospheric Pressure, $P$. Average annual runoff, $Q$ were collected from the AIRBDA. Applying the multiple linear regression model as described in Equation (11) gives:

$$Q = a_0 + I^a + S^a + T^b + E^c + H^d + W^e + R^f + T_s^g$$  \hspace{1cm} (20)

Where $a$ is a vector and the regression coefficient, which corresponds to $\beta$ in Equations (11) to (19). According to Montgomery and Montgomery & Runger, 2003), $a$ is the least square prediction of the correlation variables.

### 3.7. Calibration of climate flood model

Taking logarithms to base 10 of all the sides in Equation (20) we will linearize the functions and make feasible the assumptions contained in the construction of the multiple linear regression model. This produced Equation (21) (Montgomery & Runger, 2003) as:
\[
\log_{10} Q = \log_{10} a_0 + a_1 \log_{10} I + a_2 \log_{10} S + a_3 \log_{10} T + a_4 \log_{10} E + a_5 \log_{10} H + a_6 \log_{10} W \\
+ a_7 \log_{10} R + a_8 \log_{10} T_S 
\] (21)

With the aid of the Minitab statistical software, the least square estimate of the regression parameters was computed.

Superimposing \(y, x_1, x_2, x_3, x_4, x_5, x_6, x_7, \) and \(x_8 \) in Equation (21) gives Equation (22)

\[
y = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 + a_5 x_5 + a_6 x_6 + a_7 x_7 + a_8 x_8 
\] (22)

That is

\[
y = a_0 + \sum_{i=1}^{n-8} a_i x_i 
\] (23)

To obtain \(a_i \) \((i = 0–8)\) using least square method (Agunwamba, 2007), the Equation (22) was transformed into the matrix form as in Equation (19). From this matrix format, the least-squares estimates of the regression coefficients, \(a_i \) were calculated. The values of the coefficients after determination were substituted into the original Equation (21). A regression model which is called the climate-flood model was then used to predict the respective annual runoff in each of the catchments under study, using annual records of climatic variables for each of the five states as predictors. It is worth noting that flood caused by climate variables only, and not groundwater, anthropology and/or any other natural sources were deduced from Equation (21).

3.8. Quantification of climate change

The climatic change was calculated as the percentage difference of the mean annual climate for rainfall, evaporation, and humidity. However, for sunshine hour, temperature and wind speed, the climatic change was calculated as the mean of the annual mean change increment. Roy et al. (2001) expressed it as follows.

\[
\Delta I\% = \frac{I_{20th} - I_{19th}}{I_{19th}} \times 100\%
\] (24)

\[
\Delta E\% = \frac{\bar{E}_{20th} - \bar{E}_{19th}}{\bar{E}_{19th}} \times 100\%
\] (25)

\[
\Delta H\% = \frac{\bar{H}_{20th} - \bar{H}_{19th}}{\bar{H}_{19th}} \times 100\%
\] (26)

\[
\Delta S = S_{20th} - S_{19th}
\] (27)

\[
\Delta W = W_{20th} - W_{19th}
\] (28)
\[ \Delta T = T_{20th} - T_{19th} \]  

\[ \Delta R = \bar{R}_{20th} - \bar{R}_{19th} \]  

Where \( \Delta I \) = climatic change for Rainfall Intensity, \( \Delta S \) = climatic change for Sunshine Hours, \( \Delta T \) = climatic change for Air Temperature, \( \Delta T_s \) = climatic change for Soil Temperature, \( \Delta E \) = climatic change for Evaporation, \( \Delta W \) = climatic change for Humidity, \( \Delta W_s \) = climatic change for wind velocity, \( \Delta R \) = climatic change for Solar Radiation

The effect of climatic change on annual runoff was deduced by factoring the climatic change scenario, i.e., the sum of climate change and the climatic variables and yielded the expression:

\[
\Delta Q + Q = 10^{ma} \cdot I \left( \frac{\Delta I \%}{100} + 1 \right)^{\alpha_1} \cdot (S + \Delta S)^{\alpha_2} \cdot (T + \Delta T)^{\alpha_3} \cdot E \left( \frac{\Delta E \%}{100} + 1 \right)^{\alpha_4} \\
\cdot H \left( \frac{\Delta H \%}{100} + 1 \right)^{\alpha_5} \cdot (R + \Delta R)^{\alpha_6} \cdot (T_e + \Delta T_e)^{\alpha_7} \cdot (W + \Delta W)^{\alpha_8}
\]  

(31)

The effect of climatic change on flood was evaluated by substituting the sum of climate change and respective annual records of climatic variables to yield values of \( Q + \Delta Q \). To quantify changes in annual runoff due to climate change, \( \Delta Q \), runoff predictions, \( Q \), obtained from climate-flood models using only the respective annual records of climatic variables were deducted from those obtained from the values of \( Q + \Delta Q \) and mean change in runoff due to climate change.

Therefore, changes in annual runoff due to climate change, \( \Delta Q \), are runoff predictions made from Equation (31) less than those made from Equation (20), which implies that:

\[ \Delta Q = (\Delta Q + Q) - Q \]  

(32)

4. Results and discussion

4.1. Quantified change of climate parameters in South-Eastern Nigeria

The change in climate variables in the study area was computed by applying Equations (24)-(30) to each of the state’s catchment basins. The quantity of change in flood due to climate change in the study area was computed using Equation (32). From Figure 5(a), different levels of evaporation change were observed for the five rivers investigated. Considering the results, it was observed that Owerri had the highest positive change in evaporation of 0.11%, and the lowest positive change in evaporation of 0.06% occurred in Abakaliki. In contrast, other cities had an adverse change in evaporation. Negative evaporation noticed in the other rivers indicate high precipitation. Figure 5(b) displays the change in rainfall intensity as −3.45, −0.55, −0.27, 0.22 and 0 for Owerri, Umuahia, Enugu, Abakaliki, and Awka, respectively. The results further reveal that among the five rivers investigated, Awka had the highest positive change in rainfall of 0.41%, while the lowest positive change in rainfall of 0.13% occurred in Abakaliki. A negative change in rainfall intensity was identified at the rivers Owerri, Enugu, and Umuahia, having −1.68, −0.31, and −0.19, respectively.
In order to understand the relationship of the hydrological characteristics of the river basin, the change in relative humidity was calculated. Figure 5(c), which displays the change in relative humidity, reveals that Awka had the highest positive change in relative humidity of 0.08%. This also corroborates with the change in evaporation within the river basin. Evaporation plays an important role in air cooling, causing a rise in absolute moisture in the atmosphere. The results show a linear relationship between the $X_{20}$ of the change in relative humidity and the $X_{20}$ values of the change in evaporation. In line with this, a rise in evaporation noticeable in the individual rivers results in a rise in relative humidity at the same location. Considering both factors, higher relative humidity and evaporation were observed at Umuahia, while Awka recorded the lowest, as seen in Figure 5(a,c), and this falls in place with the Figure 2(f) where high relative humidity was observed for Abia state and lower values recorded for Anambra state.
Figure 5(d) represents the quantified change in soil temperature, and from the results obtained, Umuahia recorded the highest change in soil temperature of 0.12, while the lowest change in soil temperature of 0.1 occurred in Awka and Abakaliki. Relating the results to the hydrological map in Figure 2(e), it is evident that Anambra and Ebonyi experiences fewer sunshine hours which impacts on the soil temperature. There is a direct link between soil temperature and rainfall in land surface hydrology. From the results obtained, soils of reduced temperature accommodate more moisture, then distributed to the atmosphere. From an energy-balance perspective, the surface albedo of wet soil decreases, allowing the net terrestrial and solar radiation to increase (Zheng & Eltahir, 1998). As a result of the increment in terrestrial and solar radiation levels, moisture convergence rises, thereby increasing precipitation. The results obtained in this study support the findings of Sehler et al. (2019) pointing out that an increase in soil temperature culminates in an increase in evaporation and relative humidity. Figure 5(e) displays the quantified change in sunshine hours within the investigated rivers. The results show that Awka possesses the highest change in sunshine hours of 0.03, while the lowest change in sunshine hours occurred in Owerri and Umuahia.
Furthermore, a quantified change in wind speed, represented by Figure 5(f), was obtained for the different rivers. The report shows that Enugu had the highest change in wind speed of \(-0.08\), while the lowest change in wind speed occurred in Abakaliki, Owerri, and Awka. Solar radiation levels at the individual rivers were obtained (Figure 5(g)), and the results revealed that Umuahia recorded the highest change in solar radiation of 0.08, while the lowest change in radiation of \(-0.01\) occurred in Abakaliki. In relation to the hydrological map, the values obtained satisfies the assertions noticeable within the study region where minimal temperature differentials were observed (see Figure 2(d)). Figure 5(h) displays the change in air temperature, and the plot indicated that Enugu possesses the highest change in air temperature of 0.12. It is also important to note that no significant change in air temperature was observed at Akwa. These results are in tandem with previous research works carried out by Ajiere and Nwarema (2020) in which Enugu had the most significant trend and the highest rate of decrease in air temperature in the southeastern region of Nigeria. The results are also inconsistent with the findings of Amadi et al. (2019) which observed that the highest rate of increase in temperature and wind speed occurred in Enugu.

4.2. Quantified changes in annual flood in South Eastern Nigeria due to climate change

The current investigation documented the changes in annual floods in the south-eastern region (Figure 5 and 6). The results show that the highest mean change of 1.68 m\(^3\)/s in the annual flood in South Eastern climatic Nigeria due to climate change was observed in the Adada river in Enugu state. This implies that variables as well as the long-extended river tributaries were particularly responsible for the significant runoff variations of the river as rightly depicted in Figure 3(e). The mean change of 0.04 m\(^3\)/s observed in Otamiri River was entirely due to climate change even though the climate-flood model of Otamiri river was statistically insignificant. Otamiri river has huge variations arising mainly from non-climatic
factors, as the ever-increasing population of Owerri relies on the river for water supply (Nwajijuba & Onyeneke, 2010). The non-climatic factors (anthropologic) cause losses at the river source and negate the significant increasing trend of rainfall, thus producing a net zero change in the runoff of the river, as seen in Umuahia, Abakaliki, and Awka cities.

It has also been identified that the infiltration number comprising the product of the stream frequency and the drainage density plays a significant role in deriving the infiltration capacity. According to Rai et al. (2014), several components such as vegetation cover, infiltration capacity, runoff, and soil cover permeability, contribute to the infiltration number. Therefore, identifying the infiltration potential of a basin depends on the infiltration number. Furthermore, several researchers have pointed out that a high infiltration number is indicative of a low infiltration capacity, while a low infiltration number represents a high infiltration capacity. Within the study region, the infiltration number recorded was 0.28 (Anambra basin) and 0.09 (Imo basin), and this shows a high filtration rate within the study area. The values obtained in the current study corroborates with a recent study by Ibeje et al. (2018), but are far significantly lower than the infiltration number (1.46–3.40) derived from the Kilange River catchment situated in the northern part of Nigeria (Soyd, 2018).

5. Conclusions
Changes in climate variables caused by climate change were quantified. Trends in climatic parameters consistently generate a corresponding impact of climate change on climatic variables. It is observed that Owerri had the highest positive change in evaporation of 0.11%, while Awka had the highest change in sunshine hours and rainfall of 0.03% and 0.41%, respectively. Umuahia had the highest change in solar radiation of 0.08, while Enugu had the highest change in air temperature of 0.12. These results are also in consonance with the work of Nwajiuba and Onyeneke (2010). Climate-flood models were used to ascertain the impact of climate change on annual runoffs in the selected catchment areas. The highest change of 1.68 m³/s in the annual runoff was observed in the Adada River in Enugu state. The change of 0.04 m³/s observed in the Otanmiri River was entirely due to climate change. River Imo (Umuokpara) has an insignificant change of 10⁻²⁷ m³/s in annual runoff due to climate change because mostly evaporation, solar radiation, and air temperature are significant predictors of a runoff in this river. Considering the outcome of the current investigation, infiltration capacity contributes to the hydrological characteristics of the study area, and it has been shown that the change in relative humidity, rainfall intensity, and evaporation are fundamental components influencing the morphometric attributes within the basin. The similarity of the results from this study with previous research works further indicates that the Climate-Flood model constructed in this work performs credibly in the region. It is recommended that climate variables in flood trends be continuously observed and most frequently analyzed to help form solutions for mitigating annual runoff and global warming in river basins.

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