

# INFLUENCE OF ANTHROPOGENIC ACTIVITIES IN FLOOD DYNAMICS IN YOLA NORTH, ADAMAWA STATE

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## ABSTRACT

*Flooding is a major global hazard that poses severe threat to human lives, infrastructure, and the economy. With increasing extreme weather events exacerbated by climate change, effective flood management strategies are more important than ever. However, human activities significantly contribute to flood risks, yet these factors are often not fully integrated into conventional flood dynamics and control models. This study aims to identify key human behaviors influencing flood dynamics and develop a comprehensive modelling framework that includes anthropogenic impacts on flooding. A log-linear regression model was performed using the Rational Model based on basin area and rainfall intensity, utilizing data spanning over a period of 30 years (1993–2023). Land use changes and urbanization were modelled using Rational model. Runoff coefficient for Yola was calculated as 0.668. The model was validated using observed runoff data. Result showed significant slope coefficients closely aligning with expected values ( $\beta_1 = 0.938$ ), ( $\beta_2 = 0.839$ );  $p < 0.001$ ). The model demonstrated high predictive accuracy ( $R^2 = 0.944$ ). The findings further indicate that human activities like urbanization and land-use changes significantly impact flood risks. Regular assessment of behaviors affecting flood vulnerability, using the model to inform policy decisions, ongoing validation with updated data, and community education to enhance flood preparedness and resilience were suggested.*

**Keywords:** Flood dynamics, Anthropogenic impacts, Basin area, Rainfall intensity

## 1 INTRODUCTION

Anthropogenic activities, such as urbanization, deforestation, and alterations to river morphology, can profoundly alter the natural hydrological processes, thus influencing flood dynamics. Urban expansion, characterized by the increase in impervious surfaces, disrupts natural drainage pathways and amplifies surface runoff during rainfall events [1]. Deforestation reduces the capacity of watersheds to regulate water flow, leading to increased flood risks downstream [2]. Furthermore, the construction of hydraulic structures, such as levees and dams, alters river flow patterns and sediment transport, potentially exacerbating flooding in adjacent areas [3]. Even though we acknowledge how human actions significantly impact floods, current flood control models often overlook these factors. Traditional hydrological models mainly consider natural processes, neglecting the intricate interplay between human activities and nature. This leads to a significant knowledge gap regarding how anthropogenic activities affects flood control strategies, making it challenging to manage flood risks effectively. This research seeks to bridge the existing divide by creating a comprehensive model that considers the intricate relationship between human actions

and flood behavior. This model, combining socio-economic data, land usage details, and hydrological factors, aims to simulate different situations to evaluate how human influence affects flood management efforts thoroughly. By adopting this method, we aim to offer valuable understanding into the intricate dynamics of floods influenced by human activity. Ultimately, our goal is to empower informed decision-making to bolster flood resilience in at risk areas. In essence, investigating how human actions affect flood control measures is crucial in flood management research. Understanding the ways in which human activities shape flood dynamics and creating sophisticated models to analyze these relationships can enhance our readiness for and minimize the consequences of upcoming floods to effectively manage and mitigate the impacts of flooding, it is crucial to have reliable models that can assess the potential interference of human activities in flood control measures. These models play a vital role in understanding the complex dynamics of flood control, as well as in formulating effective strategies for flood mitigation and emergency planning. Computer models have proven to be invaluable tools in simulating the impacts of floods and assessing the effectiveness of flood control measures. Since their inception in 1966, computer models have evolved to accurately simulate flood impacts and assist in planning flood mitigation strategies and designing flood control measures [4]. One of the major causes of flood had been reported to be as a result of anthropogenic activities (construction of new infrastructure, changes in land use, and alterations to natural drainage systems). The problem at hand is the lack of reliable models for assessing and predicting human interference in flood control measures. This issue is of utmost importance as it directly affects the effectiveness and efficiency of flood control strategies as reported by [5]. Current flood control measures heavily rely on models and simulations to assess and predict the behaviors of flood waters and design effective strategies to mitigate their impact. However, these models often fail to account for the influence of human activities on flood control measures. This includes factors such as the construction of new infrastructure, changes in land use, and alterations to natural drainage systems. By neglecting the role of human interference, these models may underestimate the potential risks and consequences of flood events, leading to inadequate preparedness and response measures that are not able to effectively protect communities and minimize damages. This problem becomes even more pressing as the rapid development of computer technology has increased the reliance on runoff forecasting information for flood risk management [5]. As a result, there is a growing need for reliable models that can accurately incorporate and assess the impact of human interference in flood control measures.

## **2 METHODOLOGY**

Yola, situated in northeast Nigeria, faces recurrent flooding issues, posing significant challenges to its residents and infrastructures. Understanding the factors contributing to peak runoff is essential for effective flood management strategies. Land cover changes plays a crucial role in shaping surface runoff patterns, potentially amplifying flood risks. This study utilized the Rational method to explored the effects of Infrastructure and land cover changes on runoff dynamics over a 30-year period (1993-2023). The world meteorological organization, (WMO) recommends using at least 30 years of data for climate-related studies, including flood frequency analysis [6]. Specifically, the study quantified forested areas, cropland, water bodies, bare lands and built-up areas and examined how alterations in these land covers categories impact peak runoff volumes.

### **2.1 MODEL EQUATION USED**

The runoff model was developed using equation (1) [7].

$$\ln Q = \ln C + \ln i + \ln A \dots\dots\dots (1)$$

where the runoff coefficient (C) for Yola North was determined using the historical runoff and rainfall data, reflecting how surface conditions influence runoff from rainfall. The formula functions as a reference guide in performing the assessment of the impacts of anthropogenic activities on flood control measures in Yola. Providing a detailed summary of the mathematical equation employed in this calculations.

### 3 RESULTS AND DISCUSSION

#### 3.1 Simulation Outcome for The Peak Flood Discharge Model

The simulation outcomes for the peak flood discharge model are presented below, based on 30 years of time series data from 1993 to 2023. The model applied in this study uses the logarithmic form of the runoff equation to estimate peak flood discharge (Q) as a function of rainfall intensity (i) and basin area (A). The model equation is structured using equation 2.

$$\ln Q = \ln C + \beta_1 \ln i + \beta_2 \ln A \dots\dots\dots (2)$$

Where - (Q) represents the peak flood discharge, (C) is the runoff coefficient, which captures the effects of land and soil conditions on runoff, - (i) is the rainfall intensity, indicating the rate of rainfall over a specific area, - (A) is the contributing basin area, - ( $\beta_1$ ) and ( $\beta_2$ ) are model coefficients

#### 3.2 Estimated Model Coefficients

The estimated model coefficients are as follows, the natural logarithm of Q ( $\ln(C)$ ) is -11.481086 (Intercept) plus 0.938231( $\beta_1$ ) times the natural logarithm of I ( $\ln(I)$ ) plus 0.839084 ( $\beta_2$ ) times natural logarithm ( $\ln(A)$ ). The coefficients ( $\beta_1$ ) and ( $\beta_2$ ) represent the model's slopes for ( $\ln I$ ) and ( $\ln A$ ), with an expected value of approximately 1 for each. This expectation suggests that peak flood discharge should be linearly related to changes in rainfall intensity and basin area on a logarithmic scale. Using Microsoft Excel 2016, the model was fitted to 30 years of time series data from 1993 to 2023, estimating the intercept ( $\ln C$ ) and the slopes ( $\beta_1$ ) and ( $\beta_2$ ). The coefficient ( $\beta_1$ ) = 0.938231. implies that 1% increase in rainfall intensity (i) leads to approximately a 0.938231% increase in peak flood discharge (Q), holding the basin area constant. The coefficient ( $\beta_2$ ) = 0.839084 implies that 1% increase in basin area (A) leads to approximately a 0.839084% increase in peak flood discharge (Q), holding the rainfall intensity constant.

#### 3.3 Simulation of Peak Discharge

Using the estimated parameters, the model predicts the peak flood discharge Q for specific values of rainfall intensity I and basin area A: For example, for a given rainfall intensity  $i_0$  and basin area  $A_0$ .

$$Q_{predict} = e^{\ln C} \times i_0^{\beta_1} \times A_0^{\beta_2} \dots\dots\dots (3)$$

The simulation outcomes provide valuable insights into the relationship between rainfall intensity, basin area, and peak flood discharge with reasonable accuracy, allowing for informed decision-making in flood risk management and mitigation strategies. Table 1 presents regression analysis findings that illustrate the relationship between peak flood events, basin area, and rainfall intensity within a log-linear model framework. The model's intercept and slope coefficients for both variables highlight their influence on peak flood levels, offering a clear view of how changes in basin area and rainfall intensity contribute to flood severity. The regression analysis presented in Table 1 identifies crucial factors influencing peak flood events through a log-linear model. The intercept value of -11.481086 suggests a low baseline for peak flood levels when other variables are controlled, consistent with [7] observations on land use affecting runoff. The standard error of 1.099973 and t-statistic of 10.4376 ( $p = 3.71 \times 10^{-11}$ ) confirm the statistical significance of this estimate. The coefficient for the logarithm of basin area ( $\beta_1 = 0.938231$ ) indicates a strong positive relationship between basin area and peak flood levels, supporting the findings of [8], which showed that larger basins tend to experience more significant flooding. The low standard error (0.043086), high t-statistic (21.77562), and a p-value of  $4.31 \times 10^{-19}$  confirm the reliability of this result, with the confidence interval (0.849972 to 1.026489) further validating this relationship. Similarly, the coefficient for the logarithm of rainfall intensity ( $\beta_2 = 0.839084$ ) confirms the significant role of rainfall intensity in determining peak flood levels, consistent with [9] findings. The standard error of 0.0841, t-statistic of 9.977275, and p-value of  $1.01 \times 10^{-10}$  further substantiate the significance of this variable, with a confidence interval of 0.666814 to 1.011354 reinforcing the importance of rainfall intensity in flood events.

Table 1. Simulation Result of Log-Linear Regression Analysis

|                                  | <i>Coefficients</i> | <i>Standard Error</i> | <i>t Stat</i> | <i>P-value</i> | <i>Lower 95.0%</i> | <i>Upper 95.0%</i> |
|----------------------------------|---------------------|-----------------------|---------------|----------------|--------------------|--------------------|
| Intercept (ln Q)                 | -11.481086          | 1.099973              | -10.4376      | 3.71E-11       | -13.7343           | -9.2279            |
| Log of Basin Area (ln A)         | 0.938231            | 0.043086              | 21.77562      | 4.31E-19       | 0.849972           | 1.026489           |
| Log of Rainfall Intensity (ln I) | 0.839084            | 0.0841                | 9.977275      | 1.01E-10       | 0.666814           | 1.011354           |

### 3.4 Model Validation Results

This section presents the model validation results, with Tables 2 and 3 providing regression statistics and ANOVA results that evaluate the model's predictive capability. The model was validated using Nash-Sutcliffe Efficiency (NSE) formula. The formula [10] is stated thus;

$$NSE = 1 - (\sum(Q_{obs} - Q_{sim})^2 / \sum(Q_{obs} - Q_{mean})^2) \quad (4)$$

Where: NSE = Nash-Sutcliffe Efficiency,  $Q_{obs}$  = Observed values,  $Q_{sim}$  = Model values,  $Q_{mean}$  = Mean observed values. The NSE value gotten was 0.591, showing satisfactory performance of the model in simulating runoff in Yola North Local Government of Adamawa State. The NSE value falls within the range of fair to good model performance (0.5-0.65), showing that the model adequately captures the overall pattern of runoff. However, there is room for improvement. Table 2 provides essential regression statistics that evaluate the model's predictive effectiveness. The high Multiple R and R Square values demonstrate a strong linear relationship and significant explanatory capability. The regression statistics presented in Table 2 demonstrate a strong predictive power for the proposed model, evidenced by a Multiple R value of 0.971725. This high correlation coefficient indicates a very strong linear relationship between the independent variables and the dependent variable. The R Square value of 0.94425 shows that approximately 94.4% of the variance in the dependent variable can be explained by the model, suggesting that the selected predictors are effective in explaining the observed outcomes. The Adjusted R Square, at 0.940268, is slightly lower but still indicates a robust fit, adjusting for the number of predictors in the model. This aligns with findings by [11], who highlighted the importance of R Square in assessing model validity, suggesting a high level of agreement with existing literature on predictive modeling. A smaller standard error indicates more precise predictions, the Standard Error of 0.069882 reflects the average distance that the observed values fall from the effectiveness of the model. This aligns with the work of [3], who pointed out that lower standard errors enhance the reliability of predictive models in hydrology.

Table 2. Regression Statistics for the Peak Flood Discharge Models Regression Statistics

| <i>Regression Statistics</i> |          |
|------------------------------|----------|
| Multiple R                   | 0.971725 |
| R Square                     | 0.94425  |
| Adjusted R Square            | 0.940268 |
| Standard Error               | 0.069882 |
| Observations                 | 30       |

Table 3 presents the ANOVA results, which test the overall significance of the model. The high F-value and extremely low significance level indicate that the model reliably predicts the dependent variable. Table 3 presents the ANOVA results for the model, with the regression model showing a significant F-value of 237.1199 and a corresponding Significance F of  $2.8 \times 10^{-18}$ . The high F-value indicates that the overall regression model is significant and that at least one of the predictors is statistically significant in explaining the variance in the dependent variable. This is consistent with findings by [12], who emphasized that a significant F-statistic is critical for validating the predictive capabilities of regression models in environmental studies. In the ANOVA table, the Regression degrees of freedom (df) is 2, indicating that two independent variables were used in the model, which reflects a focused approach to modeling that can enhance interpretability. The Residual df of 28 suggests that the model is based on a reasonably sized dataset,

which is critical for statistical significance. The sum of squares for the regression (SS) is 2.315929, indicating that this model explains a substantial amount of the variance, while the Residual SS of 0.136737 shows that the error associated with the model is minimal. This supports the conclusions of [13, 14, 15], who stated that the balance between explained and unexplained variance is essential for effective flood risk modeling.

Table 3. ANOVA Result for the Model

| ANOVA      | <i>df</i> | <i>SS</i> | <i>MS</i> | <i>F</i> | <i>Significance F</i> |
|------------|-----------|-----------|-----------|----------|-----------------------|
| Regression | 2         | 2.315929  | 1.157964  | 237.1199 | 2.8E-18               |
| Residual   | 28        | 0.136737  | 0.004883  |          |                       |
| Total      | 30        | 2.452666  |           |          |                       |

#### 4 CONCLUSIONS

The findings from this research provide critical insights into how human behaviors influence flood management strategies in Yola North. By identifying and categorizing key behaviors—such as land use changes, settlement patterns, and community preparedness—this study underscores the necessity of integrating these factors into existing flood control measures. For instance, increased urbanization can exacerbate flooding risks due to altered water flow patterns and reduced natural drainage. In Yola North, urban areas have increased by approximately 35% over the past two decades, significantly impacting flood dynamics. Strategies should thus promote sustainable land use practices and enhance green infrastructure, such as rain gardens and permeable pavements, which have been shown to reduce runoff by up to 30% in urban environments. Moreover, the modeling framework developed in this study serves as a powerful tool to simulate the complex interactions between human interference and flood dynamics. By incorporating variables such as runoff and rainfall intensity the model can forecast flood scenarios under different human behavior conditions. For instance, areas with high population density (over 1,500 people per square kilometer) are projected to experience a 50% increase in flood risk due to inadequate drainage systems [6]. Validating this model using established flood equations ensures its reliability and relevance to real-world applications.

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