Makerere University Journal of Agricultural and Environmental Sciences
Vol. 14. pp. 42 - 62, 2025

pISSN 1563-3721
eISSN: 2958-4795

https://doi.org/10.70060/mak-jaes-2025-168

Received: *12 April 2025; Accepted*: *28 June 2025*

Application of intensity-duration-frequency curves in flood mitigation for rural communities: A case study of Ibido, Ogun State, Nigeria

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Abstract

Flooding poses significant threats to rural communities in Nigeria, leading to property damage, infrastructure deterioration, and disruptions to livelihoods. This study develops hydrologic parameters for flood risk mitigation in the Ibido community by establishing Intensity-Duration-Frequency (IDF) curves and estimating peak flood discharges for various return periods. Historical rainfall data (1982-2022) were analysed using probability distributions, with the log-normal distribution identified as the best fit based on goodness-of-fit criteria. The study further employed the Rational Method for peak flood estimation and developed design parameters for effective drainage infrastructure. This study found that the predicted design storms for return periods of 5 to 100 years ranged from 136.12 mm to 230.29 mm. The drainage area was 1.0364 km^2, with a time of concentration of 1.35 hours and a runoff coefficient of 0.80, resulting in peak flood discharges ranging from 18.47 m^3/s to 31.25 m^3/s. Future research should incorporate high-resolution terrain data and real-time monitoring for enhanced flood resilience in rural communities like Ibido.

Key words: Flood mitigation, flood-resilient structures, high-resolution elevation data, hydrologic modelling techniques

Introduction

Flooding remains a significant global challenge, disrupting communities and economies while putting pressure on infrastructure and resources. This hydrological hazard results from a combination of factors, including heavy rainfall, storm surges, hurricanes, and rapid snowmelt, which increase the vulnerability of both urban and rural areas (Nasr *et al*., 2021). Data from regional climate studies show that annual maximum daily rainfall in the Ogun-Osun River Basin varies between 150 mm and 250 mm, with extreme events, such as those in 2017 and 2021, surpassing 200 mm within 24 hours (Ogun State Ministry of Environment, 2022). Regional flood frequency analysis, using probability distribution models such as Gumbel and Log-Pearson Type III, indicates that minor floods typically occur at return periods of about 2 to 5 years, while moderate to severe floods have estimated return periods from 10 to 50 years. The 2017 flood, which caused significant agricultural and infrastructural damage, is estimated to have a return period of around 25 years. However, projections of climate change suggest shorter return intervals, meaning events that previously happened once in 50 years could now occur within 30 years or less (IPCC, 2021).

The socio-economic impacts of flooding in Ibido are profound yet underreported, with major flood events estimated to destroy 30%–45% of cultivated farmland. The flood event also disordered 50% of rural access roads and damaged approximately 10 –20 % of residential structures, most of which are constructed from vulnerable mudbrick materials. Direct economic losses are conservatively estimated between ₦ 50 million and ₦100 million per major flood, with individual smallholder farmers reporting seasonal income losses ranging from 20% to 50% (Svetlana *et al*., 2015; NEMA, 2022; Kumar *et al*., 2023).

A rigorous and systematic analysis of rainfall patterns is essential for effective flood mitigation, particularly in the design and construction of hydraulic infrastructure such as drainage systems and culverts. The application of robust statistical and stochastic techniques is fundamental in determining rainfall intensity, a key parameter in hydrological and hydraulic modelling (Ahmed *et al*., 2021). Intensity-Duration-Frequency (IDF) curves serve as indispensable tools in this context, enabling engineers and policymakers to quantify the probability of extreme rainfall events and integrate this knowledge into the design of flood-resilient structures. These curves mathematically express the relationship between rainfall intensity, duration, and recurrence interval, forming a critical component of flood risk management strategies.

One of the recognised approaches for estimating design floods is the flood frequency analysis, as it allows a probabilistic assessment of extreme hydrological events (Chow *et al*., 1988). From this, Intensity-Duration-Frequency (IDF) can be derived by fitting theoretical probability distributions to observed rainfall data, informing the development of sustainable water management infrastructure (Koutsoyiannis, 1998). This procedure is useful in rural communities, where flood vulnerability is exacerbated by inadequate drainage and poorly designed hydraulic structures (Douglas *et al*., 2008). In such rural communities, loss of livelihoods, displacement, and damage to farmland deepen poverty and limit adaptive capacity (Adelekan, 2010; Parvin *et al*., 2016).

Despite the strong need, there is a lack of use and adoption of scientifically developed IDF curves that utilise local climatic and hydrological conditions in many rural communities in Nigeria, including Ibido in Ogun State. The existing infrastructure designs in these rural areas are based on outdated or generalised assumptions without site-specific probabilistic analysis of rainfall extremes. Also, prior studies on IDF development in Nigeria (e.g., Olofintoye & Sule, 2010; Adeboye *et al*., 2016) focused on urban centres, such as Abeokuta or southwestern Nigeria. Thus, a significant gap exists in the use of localised, community-level IDF studies specifically targeting small, vulnerable rural communities like Ibido.

Thus, this study aimed to fill a critical knowledge gap by developing localised IDF curves and estimating design storms and corresponding discharges for the construction of efficient drainage systems in Ibido. By employing the most suitable probability distribution models and flood estimation procedures, this research provides a data-driven, site-specific approach to infrastructure planning. The goal is to ensure that hydraulic conveyance structures in Ibido are robust enough to withstand future extreme rainfall events, thereby enhancing resilience and reducing flood risks in rural Nigeria.

Materials and methods

Description of the study area

The study area is located in Ogun State's Ogun Eastern Senatorial District that neighbours Lagos to the North, and is part of the Odogbolu Local Government Area (Fig. 1). The study region is situated at latitude 6°44'15.01N and longitude 3°54'58.32E. The Dystric Nitosols, the most naturally fertile tropical soil due to high nutrient content and deep porous structure, which are frequently exploited for agricultural purposes, are what distinguishes the Ibido community according to the FAO Geonetwork. Data from NASA Power on the study area's climate characteristics for 38 years (1982 to 2022) showed that temperatures range from 23.72°C to 28.33°C, with the highest annual temperature recorded between November and March; and the average rainfall was about 133.8 mm, that is recorded between June and July as well as September and October, with a minimum of 954.25 mm and a

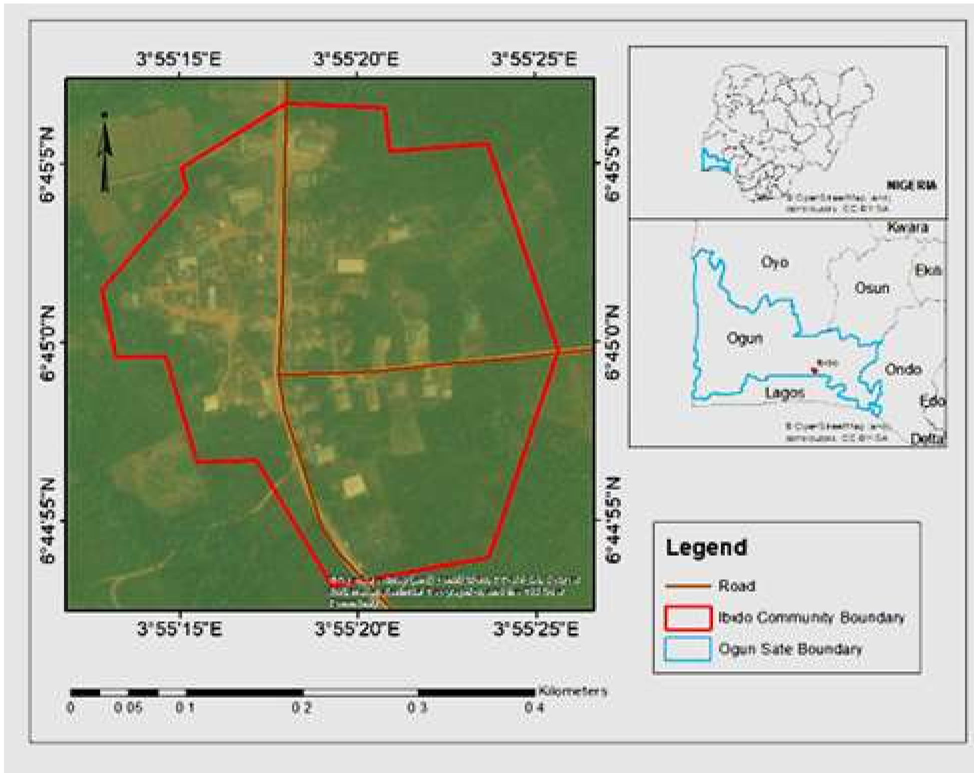

Figure 1. Location map of the study area.

maximum of 2323 mm. Seasonally, the relative humidity varies, reaching its maximum point in September (89.19 %) and its lowest point in January (77.55 %).

Capturing elevation and meteorological data of the area

A 12.5m resolution Digital Elevation Model (DEM) of the study area was obtained from an online repository of the Alaska Satellite Facility. A 41-year (1982-2022) rainfall data for the study area was obtained from the National Aeronautics and Space Administration (NASA) Langley Research Centre (LaRC) Prediction of Worldwide Energy Resource (POWER) Project funded through the NASA Earth Science/Applied Science Program. To create a sequence of 1-day extreme rains, the gathered data was employed. Concise descriptions of the generated series were given using statistical summaries based on mean, standard deviation, skewness, and kurtosis. The generated 1-day extremes were then organised in descending order of magnitude, and Hazen's plotting position was then used to calculate the probabilities that the ranked maxima will be reached or exceeded for any return period as described below:

$$T_r = \frac{(m - 0.5)}{n} \quad \text{......} \quad (1)$$

Where: T_r is the return period, m is the order or rank, and n is the number of years of study.

Probability distributions

Preliminary assessment of the 1-day extreme rainfall series leads to the selection of four probability distributions. These include the two-parameter distributions, such as Weibull, Gamma, Gumbel, Log-normal, and Normal. The probability density functions (PDF) of Weibull, Gamma, Gumbel, Log-normal, and Normal distributions are represented in equations 2, 3, 4, 5, and 6, respectively.

$$f(\mathrm{x};\, \alpha,\, \beta) = \frac{\beta}{\alpha}\left(\frac{\alpha}{x}\right)^{\beta+1} e^{-(\alpha/x)^{\beta}}, \qquad -\infty < \mathrm{x} < \infty,\ \alpha > 0 \quad \text{......} \quad (2)$$

$$f(\mathrm{x},\, \alpha,\, \beta) = \frac{1}{\alpha^{\beta}\Gamma\beta} x^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)}, \qquad \mathrm{x},\, \alpha,\, \beta > 0 \quad \text{......} \quad (3)$$

$$f(\mathrm{x};\alpha,\beta) = \frac{e^{-(x-\beta)/\alpha}\, e^{-e^{-(x-\beta)/\alpha}}}{\alpha}, -\infty < \mathrm{x} < \infty, \alpha > 0 \quad \text{......} \quad (4)$$

$$f(\mathrm{x},\, \mu_{\mathrm{y}},\, \sigma_{\mathrm{y}}) = \frac{1}{\sigma_y x\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln\,(x)-\mu_y}{\sigma_y}\right)^2}, \qquad \mathrm{x},\, \mathrm{y} > 0 \quad \text{......} \quad (5)$$

$$f(\mathrm{x},\, \mu_{\mathrm{x}},\, \sigma_{\mathrm{x}}) = \frac{1}{\sigma_x\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{(x)-\mu_x}{\sigma_x}\right)^2}, \qquad \mathrm{x},\, \mathrm{y} > 0 \quad \text{......} \quad (6)$$

Where: μx and σx are the mean and standard deviation of the series of the annual extreme storm; μy and σy are the mean and standard deviation of the log-transformed series of annual extreme rainfall, α and β are the scale and location parameters, respectively. The Maximum Likelihood Method (MOM) was used to estimate distribution parameters. The theoretical terms and the formulae for parameter estimation using MOM of the selected distributions are given by Hassan *et al*. (2019).

Goodness of fit statistics and criteria

Goodness-of-fit (GOF) statistics were based on the Anderson-Darling (AD) test (Laio, 2004), Kolmogorov–Smirnov (KS) test (Chowdhury, 1991), and Cramer-von Mises (CM) test (Arnold and Emerson, 2011). Goodness-of-fit (GOF) criteria such as Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) were employed to assess the suitability of the selected probability distributions.

The Anderson-Darling (AD) test

The Anderson-Darling (AD) test is used to compare the cumulative distribution function of the empirical and the probability distributions; it is given more attention in outlier detection. AD test (A^2) is represented in equation (7) (Anderson and Darling, 1952):

$$A^2 = -N - \frac{1}{N}\sum_{i=1}^{N}(2i-1) * (lnF_e(Q_i) + (\ln(1 - F_D(Q_i)) \quad \text{.............. (7)}$$

Where: A^2 is the Anderson–Darling test statistic, F_e is the cumulative distribution function of the specified distribution, and Q_i is the ordered observed data.

Kolmogorov–Smirnov (KS) test

Kolmogorov–Smirnov (KS) test is based on the maximum vertical distance between the cumulative distribution functions of the empirical distribution and the theoretical distribution and is represented as:

$$KS = \mathrm{Max}(F(Q_i) - \frac{i-1}{N}, \frac{i}{N} F(Q_i)) \quad \text{.. (8)}$$

Where: is the theoretical cumulative distribution of the distribution being assessed.

Cramer-von Mises (CM) test

Contrasting the first two GOF Statistics, the "CM test considers an observed hydrological time series in an increasing order" (Langat *et al*., 2019), and it's represented in equation 9 (Stephens, 1974):

$$W^2 = \sum_{i=1}^{N}\left(F(Q_i) - \frac{i-0.5}{N}\right)^2 + \frac{1}{12N} \quad \text{... (9)}$$

Akaike information criterion

Concerning the adopted GOF criteria, the Akaike information criterion is widely adopted for selecting suitable stochastic models and is represented in equation 10 (Vrieze, 2012):

$$AIC = n(log\sigma^2 + 1) + 2p \quad \text{.. (10)}$$

Where: σ^2 and p present the variance and the number of parameters of the subset stochastic model. AIC generally give preference to models that minimise equation 10.

Bayesian Information Criterion (BIC)

BIC is closely related to AIC; it is partially based on the likelihood function and is represented by equation 11 (Akaike, 1974).

$$-2 \cdot \ln p(x \mid k) \approx BIC = -2 \cdot \ln L + k \ln(n) \quad \text{.........} \quad (11)$$

Where: x is the observed data, n is the sample size, k is the number of free parameters to be estimated, p(x | k) is the probability likelihood of parameters given the data set, and L is the maximised value of the likelihood function.

In a situation where multiple goodness-of-fit statistics or criteria favour more than one distribution, Stephens (1974) was used for the final selection. Herein, the probability distribution whose cumulative distribution function (CDF) is closest to the empirical distribution, that is, whose AD is lowest. A graphical or qualitative assessment method in the form of CDF plots was further used to affirm the fit of the distributions.

Generation of IDF Curve

Rainfall intensity is defined as the ratio of the total amount of rain (rainfall depth) falling during a given period to the duration of the period. It is expressed in in-depth units per unit of time, usually as mm per hour (mm/hr). The suitable probability distribution for modelling the annual peak flood has been established from the preceding methods. The disaggregated rainfall depth for lower rainfall durations than 24 hours was estimated using the empirical reduction formula given by the Indian Meteorological Department (IMD), reported in the work of Ilaboya and Nwachukwuas (2022), as follows:

$$p_t = P_{24}\left(\frac{t}{24}\right)^{\frac{1}{3}} \quad \text{.........} \quad (12)$$

Where: pt is the required rainfall depth (mm) at t-hr duration, P_{24} is the daily rainfall depth (mm), and t is the duration of rainfall for which the rainfall depth is required in (hr). Rainfall for eight durations namely 5min, 15min, 30min, 60min, 120min, 180min, 360min, 720min, and 1440min were estimated.

Thereafter, rainfall intensities were determined for the calculated rainfall depths at selected durations using the presented equation:

$$I = \frac{R}{T} \quad \text{.........} \quad (13)$$

Where: I is the rainfall intensity (mm/hr), R is the amount of rainfall (mm), and T is the duration of the rainfall (hr).

Hydrological design calculation of the drainage system

The procedure adopted for the hydrologic design calculations is presented in this section. The goal of the hydrological analysis is to forecast the maximum discharges that will be conveyed by drainage systems in the study area.

Catchment characterization

Based on the available satellite images and elevation data, the physiographical characteristics of the upstream catchment were determined to obtain all information concerning areas, altitudes, slopes, and morphometric parameters, along with information concerning principal streams. Based on the above, the limits of the catchment area of the watercourses bordering or crossing the site were delineated. Preliminary investigation shows that the catchment area is about 103.64 ha.

Design storm frequency

The frequency of a storm event is the number of times it occurs during a certain period. The likelihood of flooding is correlated with the number of storm events; a high frequency corresponds to a low danger. The importance of the area that has to be drained and the placement of the drainage system determine the design frequency. The following is the suggested design storm frequency for the various drainage system components as recommended in the Drainage Master Plan of Lagos State (Table 1). To compute the design storms, the Intensity-Duration-Frequency models that were established were adopted.

Table 1. Design return period

Type of system	Design return period
Tertiary drainage network and secondary drainage system	5 years
Primary drainage system	10 years
Box culverts	25 years
River, bridges and detention ponds	100 years

Time of concentration

For a given catchment area, the time of concentration is the time required for rainfall landing on the farthest point of the watershed to reach the catchment's outlet. The time of concentration used in the study was based on the empirical formula given by Kirpich (1940), represented by:

$$t_c = 0.0653(\frac{L^{0.77}}{S^{0.385}}) \quad (14)$$

Where: L is the stream length (m) and S is the slope (m/m).

Peak flood estimation

Design floods may be calculated using a variety of techniques. The use of each technique is influenced by rainfall quantity and type, flow patterns, and catchment area. The Rational Method was adapted for the study because the area contributing to flooding in the project area is less than 500 ha (5km^2) (Argue, 1986). The estimate of peak discharges for different return periods using this method is stated as follows:

$$Q = 0.278 * C * I * A \quad (15)$$

Where: Q: Peak discharge (m3/s); C: Runoff coefficient; A: Catchment area (km^2); I: Rainfall intensity corresponding to the catchment time of concentration (Tc) (mm/hr). The runoff coefficient (C), reflecting the percentage of water flowing on saturated soil, was estimated using information in Table 2.

Results

Statistical description of annual maximum rainfall

Statistical assessment was conducted on annual instantaneous peak rainfall to give a concise understanding of the extreme rainfall for the study period. Table 3 summarises the statistics of the annual maximum rainfall of Ibido from 1982 to 2022. It can be inferred that maximum daily rainfall ranged from 26.03 mm to 139.23 mm. The mean extreme rainfall is slightly above the median, and it is characterised by a standard deviation of 27.37 mm, a positive skewness of 1.16 and a kurtosis value of 4.61 (Table 3).

Frequency analysis of maximum daily rainfall

The return periods were estimated from the Hazen plotting position of each of the peak rainfalls of the ranked years between 1982 and 2022 (Table 4). The highest storm magnitude of 139.23 mm for the study period was estimated to have a return period of forty-one (41) years, with a low probability of being equalled or exceeded by 0.02. It could also be observed that the magnitude of peak rainfall increases as their return period increases, while the probability of exceedance decreases (Fig. 2; Table 4). This goes to show that rainstorms of great magnitude are not frequently experienced in the project area; however, such storms have high risks when they occur. Additionally, the results show that while the plotting position was adequate in fitting the lower left tail of the empirical rainfall distribution, it underperformed in

Table 2. Typical Runoff Coefficient (C) Values (Source: Master Plan Report, 2015)

Types of drainage	Runoff coefficient, C
Business	
Downtown areas	0.70 - 0.95
Neighborhood areas	0.50 - 0.70
Residential	
Single-family areas	0.30 - 0.50
Multi-units, detached	0.40 - 0.60
Multi-unit, attached	0.60 - 0.75
Suburban	0.25 - 0.40
Apartment dwelling areas	0.50 - 0.70
Industrial	
Light areas	0.50 - 0.80
Heavy areas	0.60 - 0.90
Parks, cemeteries	0.10 - 0.25
Playgrounds	0.20 - 0.40
Railroad yard areas	0.20 - 0.40
Unimproved areas	0.10 - 0.30
Lawns	
Sandy soil, flat, 2 per cent	0.05 - 0.10
Sandy soil, average, 2 to 7 per cent	0.10 - 0.15
Sandy soil, steep, 7 per cent	0.15 - 0.20
Heavy soil, flat, 2 per cent	0.13 - 0.17
Heavy soil, average, 2 to 7 per cent	0.18 - 0.22
Heavy soil, steep, 7 per cent	0.25 - 0.35
Streets	
Asphaltic	0.70 - 0.95
Concrete	0.80 - 0.95
Brick	0.70 - 0.85
Roofs	0.75 - 0.95

fitting the far-right tail of the empirical distribution, which is very important in flood risk reduction (Fig. 2). This further validates the need for fitting the empirical distribution into well-established probability distribution models. As presented in the methodology section, five probability distribution models were examined.

Table 3. Statistical summary of the assessed maximum daily rainfall

Statistics	Values (mm)
Min	25.03
Max	139.23
Median	52.68
Mean	59.58
Sd	27.37
Skewness	1.44
Kurtosis	4.61

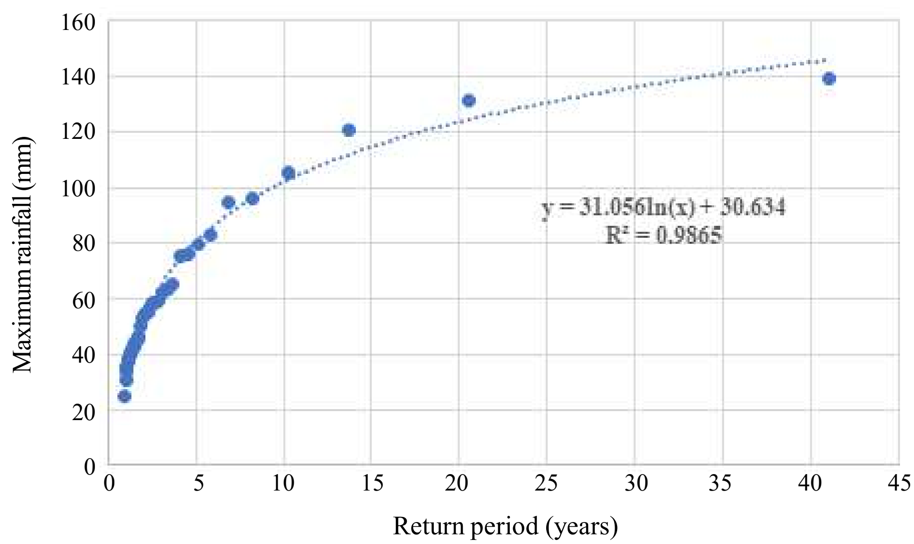

Figure 2. Probability plot of design storm against return period.

Performance of probability distribution models

The five chosen probability distributions were evaluated for suitability using the goodness-of-fit (GOF) statistics based on the Anderson-Darling (AD) test, Kolmogorov-Smirnov (KS) test, and Cramer-von Mises (CM) test, as well as the goodness-of-fit (GOF) criteria such as Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC). The log-normal probability distribution with the lowest value in terms of goodness of fit statistics and criteria was selected and used in predicting the design storms for the project area (Table 5). Design storms for 2 years to 1000 years are presented in Figure 3. Using the established mathematical formula $y = 21.117\text{In}(x)+42.41$, where y is natural log of rainfall, and x represents the actual rainfall depth or storm size, for five return periods of interest, including 5

Table 4. Frequency analysis of maximum daily rainfall (1981-2022)

Annual maximum rainfall	M	Return period(yrs)	Pr. Non-Exceedance
139.23	1	41.0	0.02
131.1	2	20.5	0.05
120.76	3	13.7	0.07
105.56	4	10.3	0.10
96.11	5	8.2	0.12
94.74	6	6.8	0.15
83.25	7	5.9	0.17
79.79	8	5.1	0.20
76.02	9	4.6	0.22
75.1	10	4.1	0.24
65.33	11	3.7	0.27
63.95	12	3.4	0.29
62.53	13	3.2	0.32
59.6	14	2.9	0.34
58.8	15	2.7	0.37
58.44	16	2.6	0.39
56.94	17	2.4	0.41
55.18	18	2.3	0.44
54.85	19	2.2	0.46
54.63	20	2.1	0.49
52.68	21	2.0	0.51
50.1	22	1.9	0.54
46.64	23	1.8	0.56
45.41	24	1.7	0.59
45.29	25	1.6	0.61
44.82	26	1.6	0.63
43.87	27	1.5	0.66
42.97	28	1.5	0.68
42.32	29	1.4	0.71
42.01	30	1.4	0.73
40.93	31	1.3	0.76
40.49	32	1.3	0.78
40.23	33	1.2	0.80
38.7	34	1.2	0.83
38.53	35	1.2	0.85
36.8	36	1.1	0.88
35.67	37	1.1	0.90
34.67	38	1.1	0.93
33.31	39	1.1	0.95
30.66	40	1.0	0.98
25.03	41	1.0	1.00

Table 5. Summary of goodness of fit statistics and criteria

Goodness-of-fit statistics	Fw	Fg	Fgum	Flgn	Fnor
Kolmogorov-Smirnov statistic (KS)	0.156	0.132	0.128	0.118	0.183
Cramer-von Mises statistic (CM)	0.272	0.177	0.118	0.107	0.368
Anderson-Darling statistic (AD)	1.620	1.047	0.792	0.646	2.137
Goodness-of-fit criteria					
Akaike's Information Criterion (AIC)	384.998	377.441	374.576	373.428	390.705
Bayesian Information Criterion (BIC)	388.425	380.868	378.004	376.855	394.132

Fw = Weibull, Fg = Gamma, Fgum = Gumbel, Flgn = Log-normal, Fnor = Normal

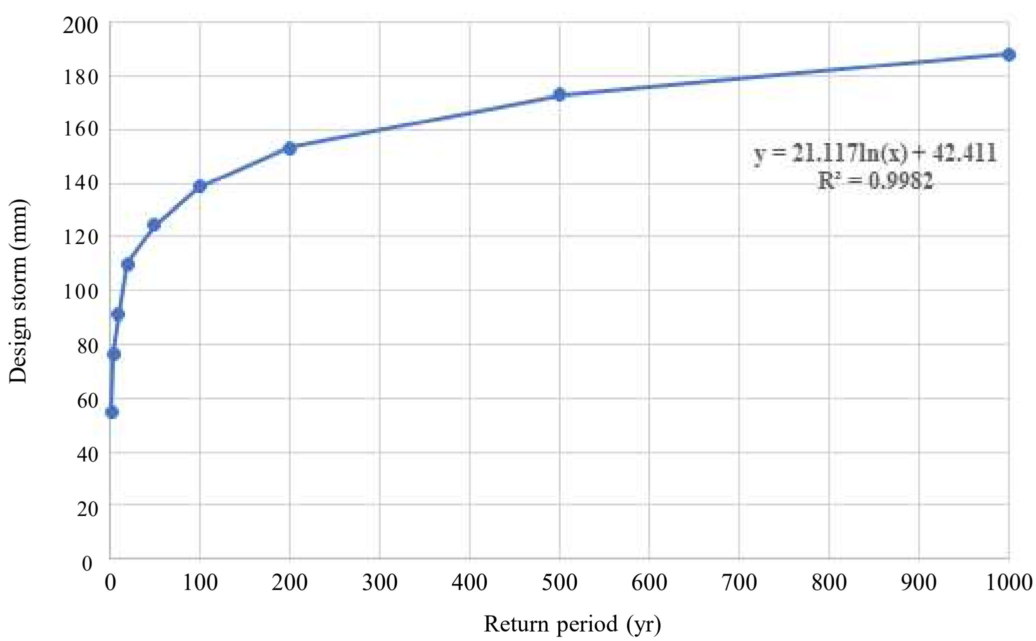

Figure 3. Probability plot of design storm against return period based on Log-Normal Distribution.

years, 10 years, 25 years, 50 years and 100 years, were predicted to be 136.12 mm, 159.07 mm, 186.77 mm, 209.10 mm and 230.29 mm, respectively.

Establishment of rainfall intensity and IDF curve

In order to construct Intensity-Duration-Frequency (IDF) curves, it was necessary to disaggregate the 24-hour maximum daily design storms into shorter rainfall durations. This step is essential because IDF analysis describes the relationship between rainfall intensity, duration, and frequency, and requires data at multiple time intervals. However, in Nigeria, most historical rainfall records are available only as 24-hour cumulative values. To overcome this limitation, empirical reduction techniques were applied to break down the 24-hour rainfall amounts into smaller durations ranging from 5 minutes to 24 hours. The resulting disaggregated rainfall depths are presented in Table 6, while Table 7 shows the corresponding rainfall intensities (in mm/hour) computed for each duration and return period. These values form the basis for establishing site-specific IDF curves for the Ibido catchment.

Table 6. Summary of Disaggregated 24-hour Rainfall for different durations (minutes) and Return Period

Duration	Frequency (return period)				
	5-year	10-year	25-year	50-year	100-year
5 min	11.80	14.08	17.01	19.18	21.39
15 min	16.98	20.26	24.48	27.60	30.78
30 min	21.35	25.46	30.77	34.69	38.69
60 min	26.84	32.01	38.68	43.60	48.63
120 min	33.73	40.23	48.62	54.81	61.13
180 min	38.56	45.99	55.58	62.66	69.88
360 min	48.47	57.81	69.86	78.76	87.84
720 min	60.93	72.67	87.81	99.00	110.42
1440 min	76.59	91.35	110.38	124.45	138.80

Table 7. Summary of disaggregated 24-hour rainfall for different durations (hours) and return period

Duration (hours)	5-year	10-year	25-year	50-year	100-year
0.083333	141.65	168.93	204.14	230.15	256.69
0.25	67.93	81.02	97.91	110.38	123.11
0.5	42.70	50.92	61.54	69.37	77.38
1	26.84	32.01	38.68	43.60	48.63
2	16.87	20.12	24.31	27.40	30.57
3	12.85	15.33	18.53	20.89	23.29
6	8.08	9.64	11.64	13.13	14.64
12	5.08	6.06	7.32	8.25	9.20
24	3.19	3.81	4.60	5.19	5.78

The established IDF curves for the study area are presented in Figure 4. These curves show that shorter storms (like 5–30 minutes) can still drop a lot of rain quickly (e.g., up to 38 mm in 30 minutes). As duration increases, the intensity reduces, but the total volume of water stays significant. For rarer events (e.g., 100-year storms), the intensity is much higher than common storms. For example, a 100-year storm might bring over 39.77 mm of rain per hour, which is almost double the intensity of a common 5-year storm!

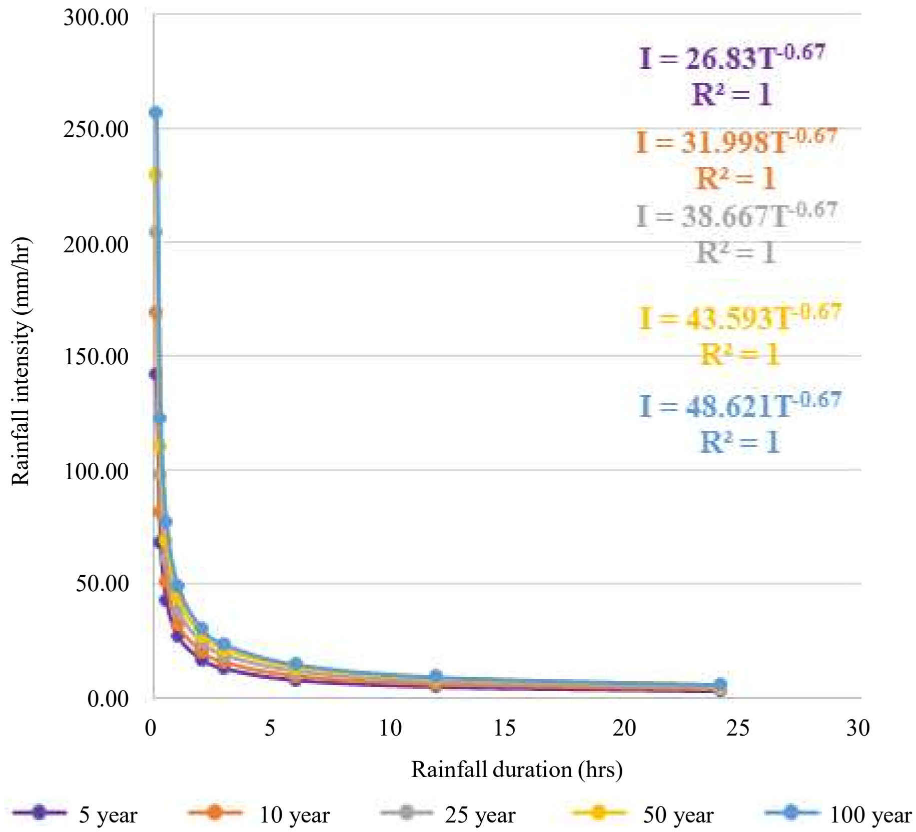

Figure 4. IDF curve and corresponding equations.

Thus, if a drain is sized only for common storms (e.g., 5-year storms), it will fail during bigger storms, leading to flooding. IDF curves help decide how big a drainage channel or culvert should be to survive not just today's storms, but also future extreme events. Communities can use this to plan early warning systems and flood shelters, especially for areas likely to flood every 10 or 25 years. These curves allow rural infrastructure to be built with climate resilience in mind, because extreme storms are becoming more frequent (what used to be a 100-year storm may now happen every 30 years). The established IDF estimates and curves can then be applied in hydrologic and hydraulic modelling, which are useful for drainage and bridge designs to reduce the risk of floods in the study area.

Table 8 shows the summary of the catchment parameters used in the hydrologic design. The length of the longest flow path, 2529.8 meters, shows that the water travels over 2.5 km before reaching the main outlet. The Catchment Area of 1.0364 km^2 represents the total land area that collects rainfall and drains into one point, which is about 100 hectares. A catchment slope of 0.0589 (5.89%) shows that the land is steep, which makes the water run faster, increasing flood risk. The Time of Concentration (Tc) of 1.35 hours explains the time it takes for water from the farthest point in the area to reach the drainage outlet. In this case, flooding can occur very quickly within just over an hour after heavy rain starts. The runoff coefficient (C) of 0.80 implies that 80% of rainfall turns into surface runoff (instead of soaking into the soil), which makes floods more likely. Thus, when it rains heavily, most of the water runs off the land quickly, travels fast due to slope, and reaches roads or homes in about 1–1.5 hours. This is why well-designed drainage systems are urgent.

Table 8. Summary of catchment parameters

Length of the longest flow path (m)	Catchment area (km^2)	Catchment Slop(m/m)	Time of concentration (Tc)	Runoff coefficient
2529.8	1.0364	0.0589	1.35 hrs	0.80

Table 9 shows the summary of the rainfall intensity for different return periods concerning the estimated Tc. The table further presents the design peak discharge at the outlet of the upstream catchment. These parameters are important considerations for the design and construction of flood conveyance structures, such as road drainages, culverts, and channels for natural flow paths in the Ibido rural community.

Table 9. Summary of rainfall intensity and design flood for the corresponding Tc

Parameters	Return period (years)				
	5-year	10-year	25-year	50-year	100-year
Rainfall intensity (mm/h)	21.94	26.17	31.62	35.65	39.77
Peak discharge (m^3/s)	18.47	21.58	25.35	28.37	31.25

Discussion

Floods pose a great risk to the inhabitants of rural communities due to their ability to disrupt household livelihoods. Hydrologic parameters are important for the design and construction of sustainable hydraulic structures, which serve as a conveyance for extreme floods whenever they occur. The Ibido community presently lacks sustainable conveyance structures for draining excess stormwater, resulting in road dilapidation and disruption of economic activities. This study develops an intensity-duration-frequency (IDF) curve and determines design flood estimations for the Ibido community.

This study developed localised Intensity-Duration-Frequency (IDF) curves and estimated peak flood discharges for Ibido, Ogun State, Nigeria, to support flood mitigation efforts. Analysis of 41 years of rainfall data (1982–2022) revealed that maximum daily rainfall ranged from 25.03 mm to 139.23 mm, with an average of 59.58 mm. A positive skewness (1.44) and high kurtosis (4.61) indicated the presence of extreme rainfall events. Using probability distribution modelling, the Log-normal distribution was identified as the best fit based on multiple goodness-of-fit criteria (AD, KS, CM, AIC, and BIC, Table 5). Predicted design storms for return periods of 5, 10, 25, 50, and 100 years were estimated at 136.12 mm, 159.07 mm, 186.77 mm, 209.10 mm, and 230.29 mm, respectively, providing critical data for hydrologic design.

Furthermore, the estimated peak discharges (18.47–31.25 m^3/s) are comparable to those derived by Olofintoye and Sule (2010) for urban drainage design, but when applied to a rural context, they underscore the urgency of tailored drainage systems even in small communities. This validates Koutsoyiannis (1998), who argued that hydrological models and IDF curves must reflect the catchment scale and land-use specifics for effective flood risk planning.

Catchment analysis showed a drainage area of 1.0364 km^2, a time of concentration of 1.35 hours, and a runoff coefficient of 0.80, reflecting high surface runoff potential. Based on these parameters, peak flood discharges were estimated using the Rational Method, yielding 18.47 m^3/s to 31.25 m^3/s across the different return periods. The results from this study align with and extend prior works such as Adeboye *et al*. (2016) and Ahmed *et al*. (2021), which developed IDF curves for cities like Abeokuta and Abuja, respectively. However, this study's emphasis on a rural setting, Ibido in Ogun State, fills a key gap in the literature. Unlike urban-focused models, this research incorporates local catchment parameters, including runoff coefficients and time of concentration, reflective of undeveloped landscapes. The runoff coefficient of 0.80 observed here is higher than what Adeboye *et al*. (2016) recorded for similar return periods in partially urbanised basins, highlighting the rapid overland flow risk in Ibido due to poor soil permeability and compacted surfaces.

This result implies that in heavy rainstorms that occur once every 5 to 100 years, Ibido is likely to receive between 136 mm and 230 mm of rain in a single day. Without proper drainage, the water will move quickly across the land, enough to flood roads, destroy crops, and enter homes. This means that if culverts and road drains are not built with this range in mind, they will be overwhelmed. Community self-help groups and local engineers can use the peak discharge range to plan for infrastructure that matches the maximum volume of water that could flow through any drain.

Furthermore, this research projects hydrologic parameters, including rainfall depths and peak discharge estimates, as a guide for flood mitigation planning and infrastructure development in Ibido. The adoption of the log-normal probability distribution for design storm prediction ensures statistical reliability, while the established IDF curves offer critical input for hydraulic structure design. However, there are limitations of elevation data resolution, which could have introduced minor inaccuracies in catchment characterization.

Conclusion

This study concludes that the Ibido watershed has a catchment area of 1.0364 km^2 with a high runoff coefficient of 0.80, indicating a high flood risk. The log-normal distribution provided the best statistical fit for rainfall extremes over 41 years. The design storms ranged from 136.12 mm (5-year) to 230.29 mm (100-year). Additionally, using the rational method, peak flows ranged from 18.47 m^3/s to 31.25 m^3/s for respective return periods, signifying substantial flows that rural drainage must accommodate. This points to flood risks, warning that the current absence of engineered drainage in Ibido makes it vulnerable to frequent and severe flood events.

Recommendations

The findings are useful for: community planners to estimate the minimum pipe diameter and culvert size needed during road construction to prevent overtopping; agricultural extension officers to use the return period analysis in advising on planting seasons and risk levels for farmland near water paths; disaster risk managers to interpret the return periods (e.g., 5-year flood = 136.12 mm) to update early warning systems and emergency plans.

The developed localised intensity-duration-frequency (IDF) curves and corresponding peak discharge estimates may be used to guide the design of flood-resilient infrastructure in Ibido, a rural community in Ogun State, Nigeria. By using a statistically sound methodology rooted in 41 years of rainfall data, the research provides reliable hydrologic parameters that rural planners and engineers can apply directly to mitigate flood risks. This data-driven approach not only supports current flood adaptation efforts but also establishes a replicable model for other under-served rural areas in Nigeria.

Future research should incorporate high-resolution terrain data, such as LiDAR, to refine hydrologic assessments. Additionally, integrating remote sensing and real-time hydrologic monitoring systems can enhance predictive capabilities and proactive flood management. By leveraging these methodologies, policymakers and engineers can design more effective drainage systems, thereby reducing flood vulnerability in rural communities.

Acknowledgement

The authors appreciate the Technical team that supported the IDF curves establishment and estimated peak flood discharges.

Declaration of conflict of interest

We have no conflict of interest to declare

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