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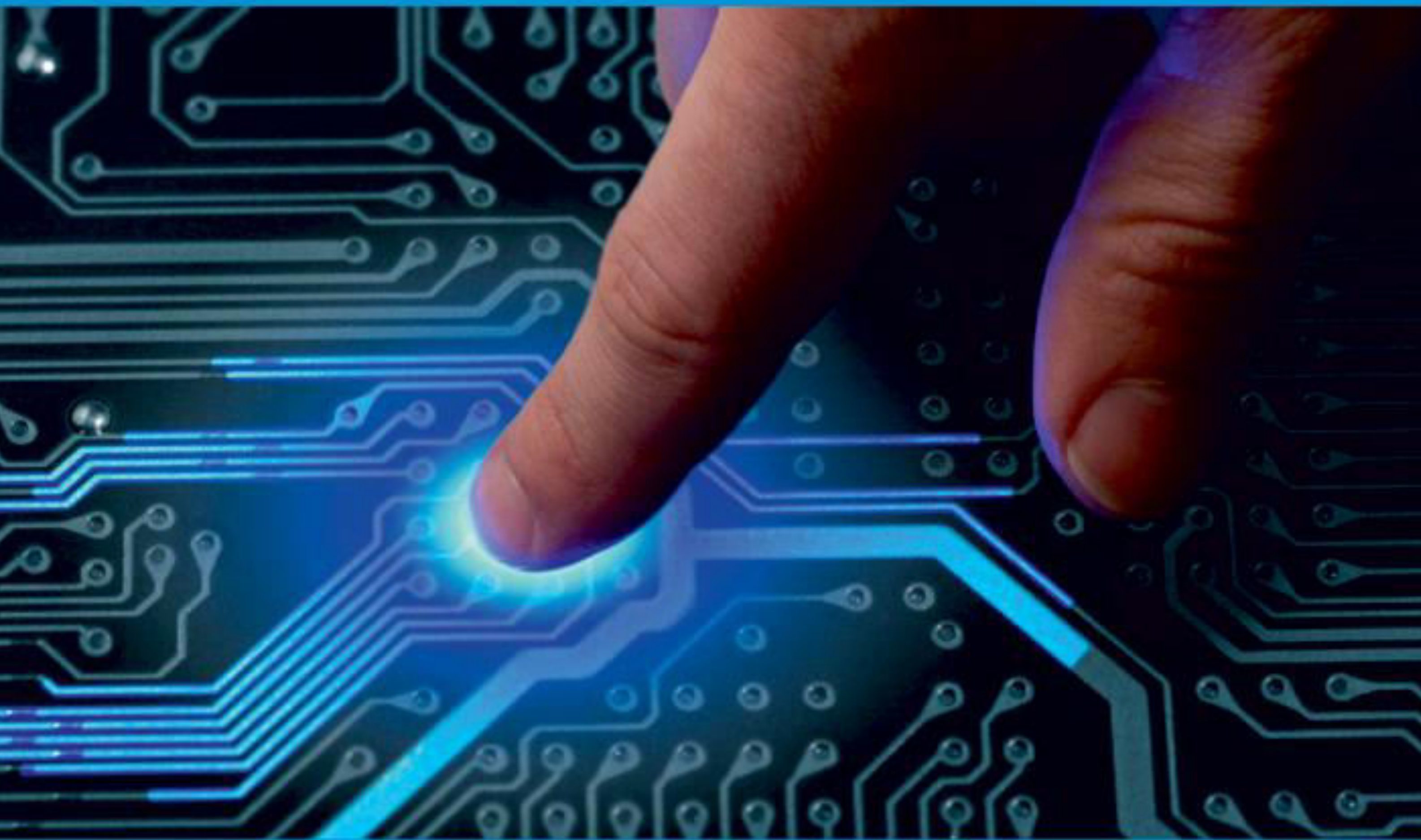

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Design and Implementation of a Privatisation-based Flood Predictive Model: A Morphological and GIS-based Approach for Sub-Watershed Analysis

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ABSTRACT: In order to lessen the negative impact that flooding has on people and infrastructure, it is essential to improve flood prediction and management technologies. The purpose of this research is to investigate a unique method to flood prediction by means of the design and implementation of a privatization-based flood predictive model. The model focuses on sub-watershed analysis by utilizing morphological factors and Geographic Information System (GIS) technology. The concept incorporates ideas of privatization, which encourages engagement from the private sector in flood risk management. This, in turn, improves the allocation of resources and the efficiency of operations. Using geographic information system (GIS) techniques, key morphological features, such as the shape of the watershed, the slope, the drainage pattern, and the qualities of the soil, are examined in order to determine the sub-watershed level of flood vulnerability. The model makes use of a multi-criteria decision-making framework in order to prioritize sub-watersheds according to the risk of flooding they pose. This makes it easier to implement focused interventions and properly distribute resources. Validation of the model's forecasting ability is accomplished by the utilization of historical flood data, hydrological statistics, and inputs from remote sensing. It is demonstrated via the use of the case study that the privatization-based strategy considerably enhances the accuracy and responsiveness of flood predictions. Morphological analysis may be integrated with geographic information systems (GIS) to provide thorough spatial evaluation, which in turn provides insights that can be put into action for flood risk management. The findings illustrate the potential advantages that may be gained from the engagement of the private sector in the improvement of flood prediction models and bring to light the significance of conducting comprehensive sub-watershed analyses in flood control plans. This paper provides a complete framework for the development of successful flood forecasting models, advocating for a collaborative approach that makes use of the experience and resources available in the private sector. In order to promote a proactive and resilient approach to flood risk management, the model that has been suggested serves as a significant tool for urban planners, legislators, and professionals working in disaster management.

KEYWORDS: Privatisation-Based, Morphological, Gis, Flood, Humidity, LSTM Model, Coefficients

I. INTRODUCTION

When it comes to successful flood risk management methods, the development and deployment of flood prediction models are crucial components. This is especially true in locations that are highly prone to flooding. For the purpose of sub-watershed analysis, this work focuses on the construction of a flood forecasting model that is based on privatization and employs a morphological and geographic information system-based methodology. This model integrates the participation of the private sector and makes use of modern geographic information systems (GIS) technology with the purpose of improving both accuracy and efficiency. This is in contrast to traditional techniques, which frequently depend primarily on data that is generally accessible to the public and on government organizations for flood prediction. As a means of supplementing the efforts of the government in the areas of flood risk assessment and mitigation, flood prediction models that are based on privatization make use of the knowledge and resources of private firms. The integration of private data sources, including as satellite images, aerial surveys, and proprietary hydrological models, which may not be easily available to public agencies, is made possible through the use of this collaborative method. In order to improve emergency response planning and infrastructure resilience, privatization-based models can

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give flood forecasts that are more complete and timely. This is accomplished by using the talents of both the public and private sectors.

In order to determine the degree to which sub-watersheds are susceptible to floods, the morphological component of the model focuses on examining the physical features of sub-watersheds. These factors include the slope of the terrain, the land use or land cover, the type of soil, and the drainage patterns. In the process of assessing the hydrological behavior of watersheds, morphological factors play a significant role and can be of assistance in locating places that are at a high risk of flooding. Through the use of morphological data and geographic information system (GIS) technology, the model is able to create comprehensive flood risk maps and pinpoint susceptible locations with increased accuracy. The geographic information system (GIS)-based technique is a useful supplement to the morphological study since it offers capabilities for spatial data processing and display. The technology known as geographic information systems (GIS) makes it possible to include several data layers into a single geographic information system. These data layers include topographic maps, satellite images, and hydrological models. The ability to do spatial analysis, identify sub-watersheds, compute morphological characteristics, and develop flood risk maps is made possible as a result of this. The use of geographic information system technology also makes it easier for stakeholders to share data and work together, which improves communication and coordination in the context of flood risk management initiatives.

In order to successfully apply the privatization-based flood forecasting model, there are numerous essential measures that must be taken. In the first step of the process, data collection is carried out in order to acquire pertinent morphological and hydrological data. This includes the collecting of topographic maps, data on land use and land cover, soil maps, data on precipitation, and streamflow data. This information is then processed and analyzed with geographic information system (GIS) software in order to create flood risk maps, designate sub-watersheds, and compute morphological parameters. The next step is to verify the model by utilizing historical flood data and actual flood occurrences that have been observed in order to evaluate its accuracy and dependability. After it has been verified, the model may be utilized for the purpose of flood prediction and risk assessment in situations that occur in real time or near real time. The prediction capabilities of the model may be improved and the model can be adapted to changing environmental conditions if stakeholders continually update the data that is input into the model and refine the algorithms that are used in the model. Furthermore, the method that is based on privatization makes it possible for governmental agencies, private firms, and research institutes to work together on a continuous basis in order to improve flood risk management techniques and come up with novel solutions. There is a viable strategy for enhancing flood risk management that involves the creation and deployment of a flood forecasting model that is based on privatization and uses a morphological and geographic information system-based approach. This model is able to produce flood predictions that are more complete and precise because it makes use of the experience and resources of both the public and commercial sectors. As a result, it improves both disaster preparedness and the resilience of infrastructure. Further, the use of geographic information system (GIS) technology enables spatial analysis, data visualization, and cooperation among stakeholders, which makes the model an invaluable instrument for decision-makers in areas that are prone to flooding events. Flood forecasting models that are based on privatization have the potential to drastically lessen the damage that floods has on communities and infrastructure if they are continuously refined and collaborated on.

II. MATERIALS AND METHODS

Zaria, which is located in Kaduna State, Nigeria, includes the study area. There are around 670 meters of elevation above mean sea level in Zaria, which is one of the provinces that are included in the Central High Plains of Northern Nigeria regions. It is situated around 950 kilometers distant from Lagos, and it encompasses a total surface of approximately 61 kilometers squared. As a result of its locational features, it assumes the role of a nodal point in terms of road and rail transportation.

This study's data, as well as the sources from which they were obtained, are presented in Table 1. The data on the channel cross-section was gathered by means of a topographical survey that was produced with the assistance of Total Station (Tables S1 and S2). For the purpose of driving the HEC-HMS and HEC-RAS models, climate and geographical data were collected and exploited. The United States Geological Survey (USGS) Global Visualization Viewer GLOVIS was used to acquire the Landsat 8 Operational Land Imager (OLI), which has a spatial resolution of thirty meters. The

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supervised classification approach was utilized in order to accomplish the land use classification, and the onsite data was utilized in order to assess the classification. Both ground truthing and a comparison of the data collected in the field were utilized in order to evaluate the correctness of the LULC map. In order to determine the accuracy of the producer, the user, and the kappa (with a kappa index of 96%), a confusion matrix was built. Data for the digital elevation model (DEM) of the Shuttle Radar Topography Mission (SRTM) were obtained from GLOVIS and had a spatial resolution of 30 meters. The Food and Agricultural Organization (FOA) was the source of the data for the soil map. A time series of the climatic data, which included rainfall data from the Zaria station of the Nigerian College of Aviation Technology, was received from the Nigerian Meteorological Agency (NiMet). This time series spanned the period from 1967 to 2017 (that is, fifty years of data).

Table 1. Data type and sources of the data.

S/N	Data Category	Data Type	Data Source
1	Satellite imagery(Landsat8OLI)	Land use data(30m)	United State Geological Survey (USGS)
2	GIS data	SRTMDEM(30m)	United State Geological Survey (USGS)
		Slope	
3	Meteorological data	Rainfall data	Nigerian Meteorological Agency(NiMet)
		Observed discharge data	
4	Geomorphological data	Soil data(10m)	Digital World Soil Map(FAO)
5	Ancillary data	Channel cross-section and elevation data	Field(Topographical survey)

III. INTENSITY DURATION FREQUENCY CURVE IDF

The production of an intensity duration frequency curve, also known as an IDF, is the initial stage in the HEC-HMS hydrologic modeling process when the frequency storm approach is utilized. The maximum discharges, denoted by the symbol Qmax, were calculated for a variety of return durations. The method that was proposed by the Indian Meteorological Department was used to lower the maximum daily (24-hour) precipitation data for Samaru from 1968 to 2017. The data was then reduced to a shorter time scale of 10, 20, 30, 60, 120, 360, 720, and 1440 minutes. The formula has reached widespread acceptability and has been utilized by a large number of people.

Equation (1) provides the result of the needed precipitation depth, which is less than twenty-four hours.

$$P_t = P_{24}\left[\frac{t}{24}\right]^{\left(\frac{1}{3}\right)}, \quad (1)$$

In this equation, Pt represents the needed precipitation depth for a period of fewer than 24 hours in millimeters, P24 represents the daily precipitation depth in millimeters, and t represents the required time length in hours. For the purpose of determining the intensity, duration, and frequency curves of the Samaru stream watershed, crucial input data for the HEC-HMS simulation and Gumbel's statistical distribution for frequency analysis were relied upon. Frequently, this technique is utilized for the purpose of forecasting extreme hydrological occurrences, such as floods. The following is the formula that represents the cumulative distribution function (cdf) of the Gumbel extreme value distribution (maximum):

$$F(X) = exp[-exp(-y)] = e^{-e^{-y}}, \quad (2)$$

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In this equation, the probability distribution function of a random variable x is denoted by F(X), and the reduced variate is identified by y. There is a correlation between the return period (T) and the chance of exceeding the mark. Therefore, the likelihood of exceeding the occurrences that are excluded is as follows:

$$F_1(X) = 1 - F(X) = \frac{1}{T}, \qquad (3)$$

where F1(X) = the probability of exceedance at a return period (T), and T = the return period.

IV. MODEL SETUP AND EVALUATION

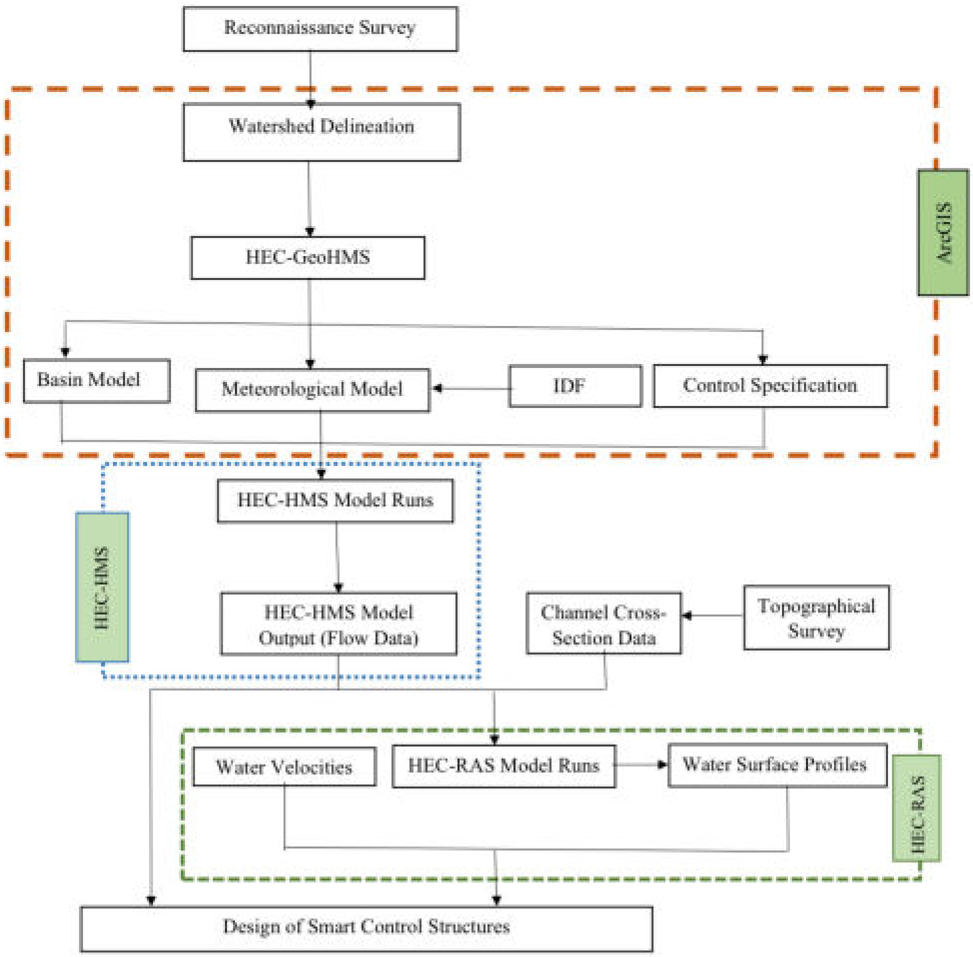

Figure 1. A flowchart depicting the methodology:

HEC-HMS Model

Information that is pertinent to the physical characteristics of a watershed is included in the HEC-HMS basin model. This information includes the basin area, river reach connectivity, and reservoir statistics, among other things. Four of these components are included in the model of the Samaru basin, which was created in Arc-GIS with the help of the HEC-GeoHMS extension. There are a total of 18 hydrologic elements that were developed for the Samaru model. This model is comprised of nine sub-basins, four river reaches, four junctions, and one outlet (which is located at the

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location where the Samaru stream empties into the Malmo River). Despite the fact that the meteorological model was constructed on the basis of the climatic data of the geographic region under investigation, the control parameters were subsequently established. Hourly time intervals were chosen in this investigation, and the simulation was only carried out for a period of two days. The temporal magnitude of the streamflow that was observed was taken into consideration while selecting this time. In order to calibrate and validate the HEC-HMS model for the Samaru watershed, the daily discharge data from August and September 2014 were utilized. These data were gathered from a gauge station that was situated at the outflow of the watershed. We chose the data from August and September because we are interested in peak discharge, and during those months of the year, the watershed often sees flood events. This is the reason why we chose those months. During the process of calibrating the model parameters, an auto-optimization procedure and the peak weighted root mean square error (PWRMSE) were used to make up the objective functions in the HEC-HMS model. This method was chosen because of its ease of implementation and its very high level of performance. In order to conduct a sensitivity analysis of the model parameter, the values of the different model parameters were varied by a margin of error of twenty percent at intervals of five percent. The curve number, the lag time, the % imperviousness, and Muskingum K were the characteristics that were determined to be accurate. A graph was created to illustrate the percentage change in the simulated peak flow and volume that occurred as a consequence of changes in the parameters of the corresponding models. The performance of the model was evaluated by utilizing statistical hydrologic indicators that measured the degree of agreement between the runoff values that were observed and those that were simulated. The root mean square error (RMSE), the Nash–Sutcliffe efficiency (NSE), and the percentage bias (PBIAS) were the indices that were utilized.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(Q_{obs} - Q_{comp}\right)_i^2}$$

$$NSE = 100\left[1 - \frac{\sum_{i=1}^{n}\left(Q_{obs} - Q_{comp}\right)_i^2}{\sum_{i=1}^{n}\left(Q_{obs} - \overline{Q_{obs}}\right)_i^2}\right]$$

$$PBIAS = 100\left[\frac{\sum_{i=1}^{n}\left(Q_{obs} - Q_{comp}\right)}{\sum_{i=1}^{n} Q_{obs}}\right],$$

in where Qobs represents the observed storm runoff in millimeters, Qcomp represents the computed runoff in millimeters, Qabs represents the mean observed storm runoff in millimeters, N represents the total number of rainfall runoff events, and i represents an integer that can range from one to N.

HEC-RAS Model

Geometric data, flow data, and plan data are the three primary components that were required for the construction of the HEC-RAS model, which was a procedure that was carried out in two stages. The conversion of flow values into water surface elevation along the stream was the goal of the hydraulic modeling process. The HEC RAS solves the energy equation by employing the conventional step-backwater approach to compute the water surface profiles of consecutive channel cross-sections. This allows the problem to be solved. It is the energy equation that is shown in Equation (16). The construction of a river system schematic, which includes the connectedness of the river system, is a part of the geometric data. By entering cross-section data, which required defining all of the essential junction information, adding hydraulic structures, and interpolating cross-sections, it was possible to accomplish this goal. Following the completion of the river schematic procedure, the data for the cross-section were input. A geometric boundary was established for the stream based on the cross-sectional data. From Ganga Uku to the ABU detention basin, the cross-sections were measured at a variety of typical places at various points. The selection of the roughness coefficient offered by Manning requires judgment, skills, and subjectivity for the user. provided in-depth images of natural streams and rivers, along with the roughness levels that corresponded to each of these characteristics. An evaluation of the Samaru stream main channel and the Barnes standard pictures was used to determine the "n" value that was assigned by Manning. This evaluation was based on field observations. Following the outcome of the comparison, the roughness value was determined to fall somewhere in the range of 0.035 to 0.03, and it was chosen for

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the main channel of the Samaru stream. It was necessary to manually insert the expansion and contraction coefficients into the HEC RAS cross-section data editor. The United States Army Corps of Engineers provides typical values for expansion and contraction coefficient-based flow transition types. It was determined that the transition was gradual, and default values of 0.3 and 0.1 were assigned for the expansion and contraction coefficients, respectively, based on the knowledge of the physical features of the stream. Seven different sets of discharge data were input for the return periods of two years, five years, ten years, twenty-five years, fifty years, one hundred years, and two hundred years. These data were collected from the outputs of the HEC HMS model. It was decided that the critical depth would serve as the upstream boundary condition, and the channel slope would serve as the downstream boundary condition. Following this decision, a steady flow study was carried out.

$$y_2 + Z_2 + \frac{\alpha_2 v_2^2}{2g} = y_1 + Z_1 + \frac{\alpha_1 v_1^2}{2g} + h_e,$$

In this equation, the variables y1 and y2 represent the water depths in the two cross sections, Z1 and Z2 represent the heights of the main channel above the datum, v1 and v2 represent the average speeds, α1 and α2 represent the velocity weighting coefficients, g represents the acceleration due to gravity, and he represents the head loss of energy to the level of the head.

Hydraulic Evaluation

The floods that were simulated by the HEC-HMS program for a variety of return durations were used as flow data in the HEC-RAS for surface water profiles and velocity computations. In addition, fundamental parameters were required for hydraulic assessment. Through the utilization of the HEC-HMS and HC-RAS outputs, the Samaru stream was specifically constructed to have the most cost-effective channel segment. The part of the channel that Chow considers to be the most economically viable is the one in which the most discharge results in the least amount of wetted perimeter. In order to compute the channel dimension, the equation developed by Manning was utilized, and a free board that was twenty percent of the usual flow depth was taken into consideration. It was determined whether or not the channel was stable by following the process that Muhammad et al. suggested performing. It was first determined how to compute the mean velocity and the tractive stress. Following that, an evaluation of the current stability was accomplished by contrasting the estimations of the local and instantaneous shear velocities with the values of the velocity. If it was determined that the current circumstances were stable and that they were in conformity with the other project objectives, then the channel was declared stable, and it was not necessary to do any more investigation.

V. RESULTS AND DISCUSSION

The IDF for the Samaru watershed was built by utilizing daily rainfall data for a period of fifty years. Small time increments were used to discretize the data on the highest daily rainfall that occurred during each year. With regard to the analysis of flood frequency, the Gumbel distribution was utilized. Table 2 provides information on the amount of rainfall that occurred during various return periods at various time steps, whereas Figure 4 illustrates the IDF curve of the Samaru stream watershed. A correlation was found between the return period and the rainfall depth, as seen in both Table 2 and Figure 4. The rainfall depth rose as the return period increased. For the purpose of peak flow simulation at a variety of return periods, the IDF and the return period were utilized as inputs in the meteorological model of HEC-HMS.

Table 2. Values for intensity, frequency, and duration for occurrences that last for twenty-four hours.

Estimated Rainfall Intensity (mm/h) for Different Return Periods									
Duration (Minutes)	2Years	5Years	10Years	25Years	50Years	100Years	200Years	400Years	1000Years
5	129	222	283	361	419	476	533	589	665
10	82	140	179	227	264	300	336	371	419

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15	62	107	136	174	201	229	256	283	319
30	39	67	86	109	127	144	161	179	201
60	25	42	54	69	80	91	102	112	127
120	16	27	34	43	50	57	64	71	80
180	12	20	26	33	38	44	49	54	61

Table 3. Cont.

Estimated Rainfall Intensity (mm/h) for Different Return Periods									
Duration (Minutes)	2Years	5Years	10Years	25Years	50Years	100Years	200Years	400Years	1000Years
300	8	14	19	24	27	31	35	38	43
360	7	13	16	21	24	27	31	34	38
720	5	8	10	13	15	17	19	21	24
1440	3	5	7	8	10	11	12	14	15

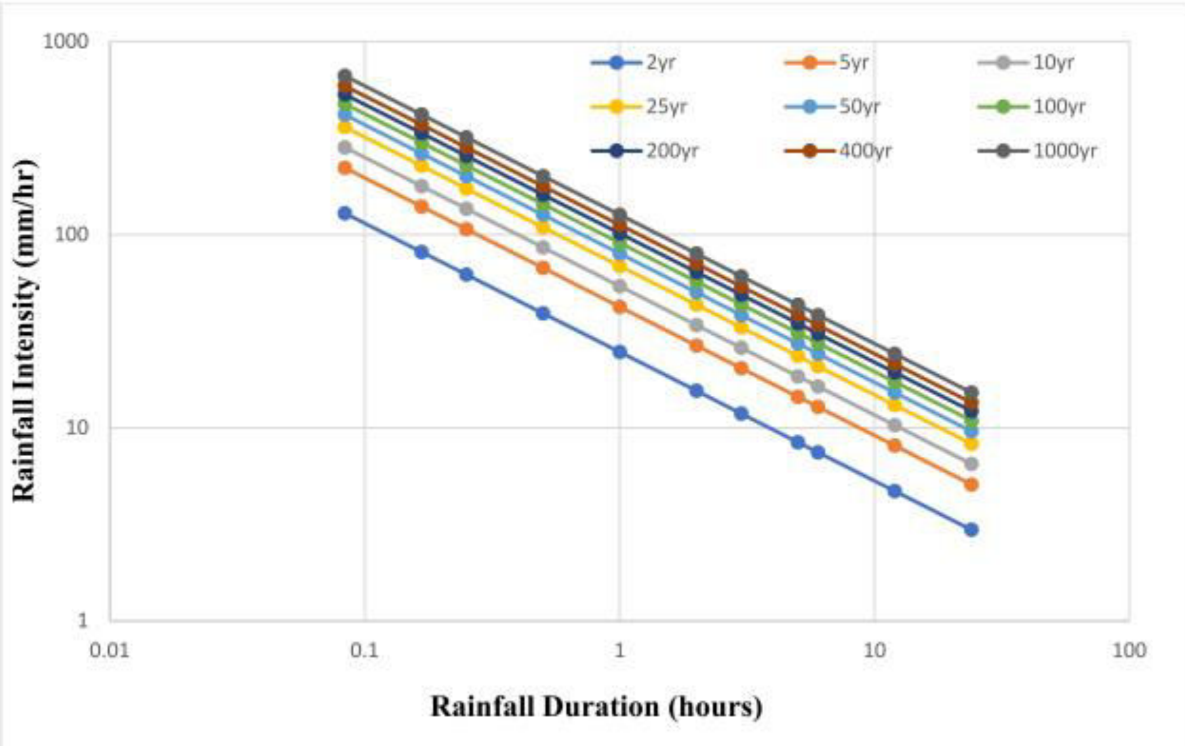

Figure 2. A curve representing the IDF of the Samaru watershed.

HEC-HMS Parameters Sensitivity Analysis

A sensitivity analysis of the model was carried out in order to ascertain which of the model's parameters had a substantial impact on the results produced by the model. With the use of sensitivity analysis, a ranking was established for the number of model parameters that contributed to an overall inaccuracy in the predictions made by the model. For the purpose of conducting sensitivity analysis, the model's four (4) parameters were examined. A check was performed on the curve number, impervious area, lag duration, and Muskingum K at intervals of 5% and a ±20% increment. As

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can be seen in Figure 5, the curve number was located to be the parameter that exhibited the highest degree of sensitivity. A twenty percent rise in the curve number resulted in a thirteen percent increase in the peak discharge, while a twenty percent drop in the curve number resulted in a twelve point one percent decrease in the peak discharge. It is the most sensitive parameter because it is dependent on land use, hydrological soil types, and antecedent moisture conditions, which are recognized to be the most significant elements in runoff generation. This is the reason why it is the most sensitive parameter. Additionally, it was discovered that lag time is sensitive, as it has a tendency to raise the peak discharge by 7.2% when it is extended by 20%, and it has a tendency to lower the peak discharge by 6.8% when it is shortened by 20%. The deviation of these parameters from the starting point is seen in Figure 6.

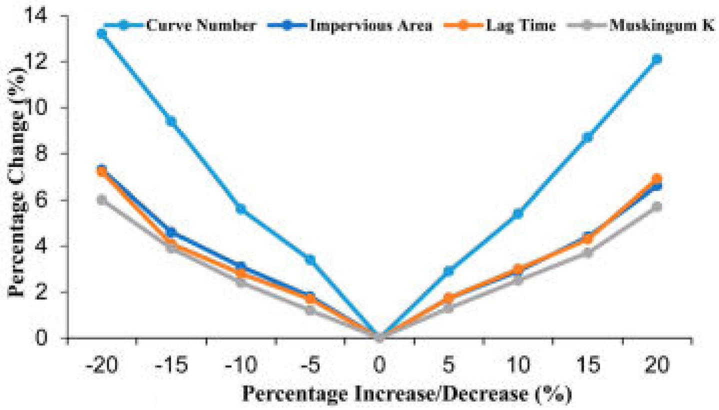
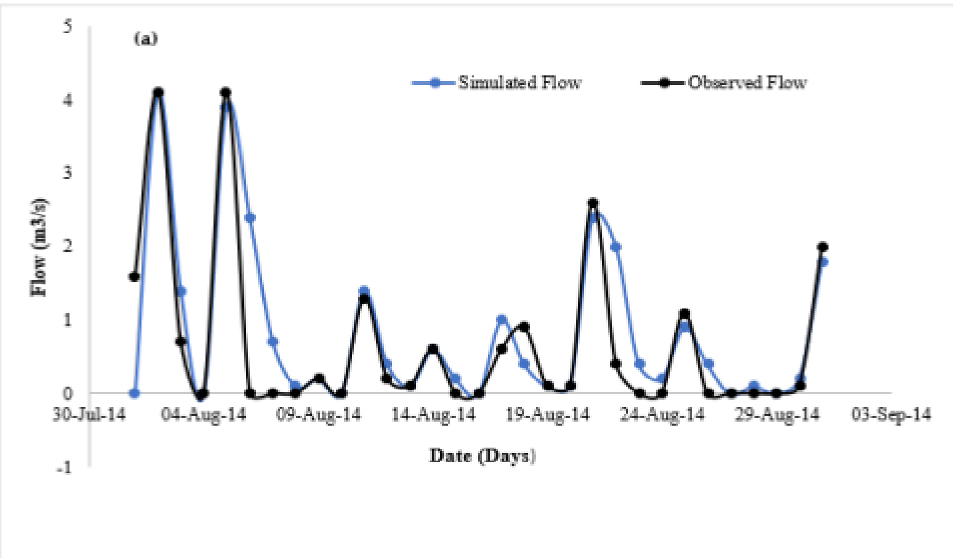


Figure 3. A sensitivity analysis was performed on a simulation with a return period of one hundred years.



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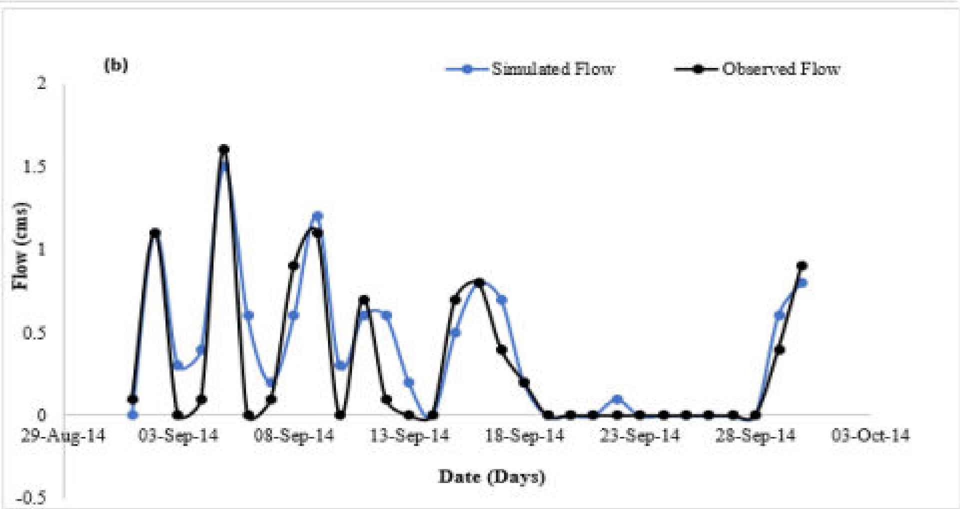

Figure 4. There are two parts to hydrographs, the first being the calibration and the second being the validation.

HEC-HMS Model Calibration, Validation, and Performance Evaluation

It was discovered that the model was sensitive to the curve number (CN), the lag period, and the Muskingum K measure. Through the process of auto-optimization of the model's sensitive parameter, the HEC-HMS model calibration was successfully accomplished. Three of the parameters that were optimized were the Muskingum K, the lag time, and the curve number. In order to optimize the model output, the optimization procedure was carried out on parameters that were sensitive as well. The starting values of the sensitive parameters of the model are presented in Table 3, along with their optimized values.

Table 4. For the HEC-HMS model, the initial and optimized parameters are as follows:.

Element	Parameter	Units	InitialValue	OptimizedValue
AllSub-basins	SCS Curve Number—Initial Abstraction Scale Factor		1	1.1603
AllSub-basins	SCS Curve Number—CurveNumberScaleFactor		1	0.98729
W120	SCS Curve Number—CurveNumber		92.66304	75.453
W110	SCSCurveNumber—CurveNumber		88.41209	56.694
W100	SCSCurveNumber—CurveNumber		89.13062	41.733
W180	SCSCurveNumber—CurveNumber		84.12308	84.421
W170	SCSCurveNumber—CurveNumber		80.13656	73.511
W160	SCSCurveNumber—CurveNumber		91.75	70.627
W150	SCSCurveNumber—CurveNumber		90.01976	63.081
W140	SCSCurveNumber—CurveNumber		81.43609	52.916
W130	SCSCurveNumber—CurveNumber		83.84741	55.924
W120	SCSUnitHydrograph—LagTime	MIN	16.66416	13.776
W110	SCSUnitHydrograph—LagTime	MIN	163.1303	156.74
W100	SCSUnitHydrograph—LagTime	MIN	76.08306	81.507
W180	SCSUnitHydrograph—LagTime	MIN	141.1654	163.75

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W170	SCSUnitHydrograph—LagTime	MIN	79.06074	88.216
W160	SCSUnitHydrograph—LagTime	MIN	4.1292	4.8915
W150	SCSUnitHydrograph—LagTime	MIN	81.23118	100.31
W140	SCSUnitHydrograph—Lag Time	MIN	62.38896	79.1
W130	SCS Unit Hydrograph—Lag Time	MIN	67.54464	84.897
R90	Muskingum—K	HR	0.1	0.35946
R80	Muskingum—K	HR	0.11	0.34604
R50	Muskingum—K	HR	0.11	0.2658
R40	Muskingum—K	HR	0.1	0.16622

The discharge data from August 2014 were utilized for the calibration, which comprised the period beginning on August 1 and ending on August 31, 2014. The calibration demonstrated a high degree of concordance between the simulated outflows at all junctions, including the outlet. The hydrograph patterns that were formed by the observed outflows and the time it took for them to reach their peak were quite similar, as can be seen in Figure 6. A comparison of the root mean square error standard deviation (RMSE), the Nash–Sutcliffe coefficient (NSE), and the percentage bias (PBIAS) before and after optimization is shown in Table 4. Additionally, the simulated peak discharge and the total volume at the outlet were 5.3 m3/s and 583.1 mm before optimization, and they were 4.1 m3/s and 401.7 mm after optimization. On the other hand, when the root mean square error (RMSE), Nash–Sutcliffe coefficient, and percentage biases were all under the acceptable threshold limit, the performance of the model dramatically increased.

Table 5. indications of performance throughout the verification process.

Performance		Calibration			Validation
Indices	Before Optimization	Remark After Optimization	Remark		Remark
RMSE	0.9	Unsatisfactory 0.6	Good	0.5	Good
NSE	0.27	Poor 0.67	Very Good	0.78	Very Good
PBIAS	50.6%	Very Poor 20.5%	Satisfactory	20.8%	Good

By using the daily discharge data for the month of September 2014, which covered the period from September 1 to September 30, the model was determined to be accurate. Through the process of running the calibrated model with the events that occurred in September 2014 (Figure 6), the validation was accomplished. The validation reveals that the observed and simulated outflows at the watershed exit are quite similar to one another; nonetheless, it failed to account for the peak discharge to the same extent as it should have. On the basis of the model performance indicators, the result was quite comparable to the result that was produced during the calibration session. Table 4 displays the results of the validation, which showed that the RMSE, NSE, and PBIAS were respectively 0.50, 0.78, and 20.8%, suggesting that the performance was extremely excellent. Using the HEC-HMS model, our findings are in good agreement with those obtained by Derdour et al. [51], who modeled the Boukhalef watershed in Morocco. They worked on the Ain Sefra watershed and the Ksour Mountains (SW Algeria), and they modeled the Boukhalef watershed. Additionally, other researchers utilized the SCS-CN approach for the purpose of simulating rainfall runoff, and the findings of their model performance were comparable to the results achieved in this research.

Simulation of Peak Runoff

Table 5 displays the simulation results of the HEC-HMS model when the frequency storm method is used for periods of two years, five years, ten years, twenty-five years, fifty years, one hundred years, and two hundred years at the upstream (Ganga Uku culvert), the NUGA gate culvert, towards the outlet (Dan Fodio culvert), and the watershed outlet in cubic meters per second. when a consequence of the findings, it was discovered that the discharge rises when the flow length is increased. Specifically, this is due to the contributions that the river gets from subbasins that are next

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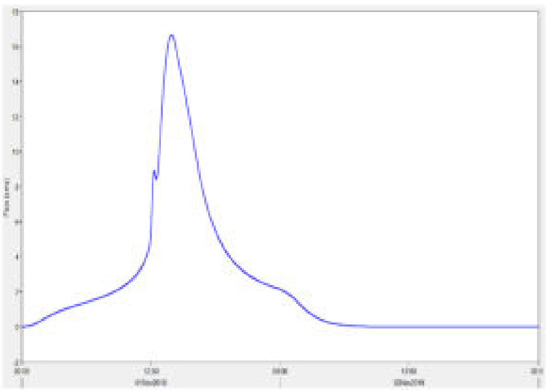
to it. To give an example, the highest flow at the NUGA gate culvert for a return period of fifty years was 14.3 m3/s. This is lower than the peak discharge of 27.3 m3/s at the Dan Fodio culvert, which is located downstream of the NUGA gate culvert. The reason for this is because the stream is able to take runoff from the impervious surfaces of Dan Fodio by way of the tributary that is located upstream of the Dan Fodio culvert. Since the peak discharge was found to increase with an increase in the return time, the result also follows a normal pattern of hydrological analysis. This is because the return period was observed to increase.

Table 6. The maximum discharges measured in cubic meters per second at a particular place of interest.

Location	2-Year	5-Year	10-Year	25-Year	50-Year	100-Year	200-Year
Ganga Uku(upstream)	2.9	5.4	7.1	9.4	11.1	12.8	14.6
NUG Agate culvert	3.7	6.8	9.1	12.1	14.3	16.6	19
Mid-section	5.7	11	14.9	20	23.9	27.8	31.8
Dan Fodio culvert (Towardstheoutlet)	6.3	12.4	16.9	22.8	27.3	31.8	36.4
Outlet	7.5	14.9	20.3	27.3	32.6	38	43.5

Figure 7 depicts the flood hydrograph for the 100-year Tr at the NUGA gate culvert and the watershed outflow. This hydrograph was taken at the watershed outlet. The form of the flood hydrographs is comparable to the shape of the ones that were acquired, as can be seen in the image.


(a)

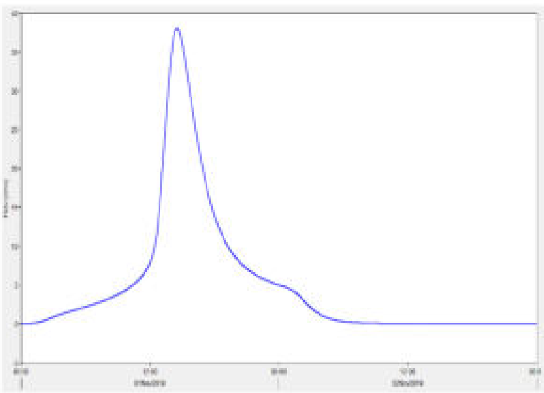

(b)

Figure 5. The flood hydrograph of the 100-year Tr is obtained at two locations: (a) the NUGA gate culvert and (b) the watershed outflow.

VI. CONCLUSION

A significant step forward in flood risk management techniques is represented by the creation and execution of a flood forecasting model that is based on privatization and makes use of a morphological and geographic information system-based approach. This model makes use of the knowledge and resources of both the public and commercial sectors in order to generate flood forecasts that are more accurate, comprehensive, and timely. As a result, it improves both disaster preparedness and the resilience of infrastructure. With the incorporation of private data sources and cutting-edge GIS technology, the privatization-based approach provides enhanced capabilities for spatial analysis, which in turn enables the identification of sensitive regions with a higher degree of precision. As a result of this improved predictive capabilities, stakeholders are able to more efficiently allocate resources, prioritize mitigation initiatives, and design emergency response plans that are specifically targeted. Because of the collaborative character of the

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privatization-based strategy, it encourages continual innovation and the sharing of information between research institutions, private firms, and public bodies. This partnership not only improves the forecasting capacities of the model, but it also encourages the creation of creative solutions for the control of flood risk. Continued improvement and validation of the flood predicting model that is based on privatization are important in order to guarantee the model's accuracy and dependability in situations that occur in the real world. A further enhancement of the model's efficiency and scalability will be achieved by the implementation of initiatives that encourage the sharing of data, the standardization of procedures, and the interoperability of GIS systems. The flood prediction model that is based on privatization is an encouraging instrument that has the potential to handle the issues of flood risk management in areas that are prone to flooding. This strategy has the ability to drastically lessen the damage that flooding has on communities, infrastructure, and the environment. It does this by utilizing the capabilities of both the public and private sectors, as well as by harnessing the power of sophisticated geographic information system technologies.

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