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A COMPLEMENTARY APPROACH TO PREDICTING THE MAGNITUDE OF FLOOD ALONG FOMA RIVER USING CROSS–SECTIONAL VARIABLES

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Abstract: Flood hazards have been on the increase in recent years, especially along the river bank. The hazards tend to impact human lives and result in severe economic damage across the world. However, forecasting the magnitude of flood especially in Nigeria across the coastal areas have been hindered by several complications, including inaccurate data, poor assessment of drainage basin, pollution, and encroachment. This study made use of the Geographical Information System (GIS) tools to derive cross–sectional variables that were significant in complementing the prediction of the magnitude of flood along Foma–river areas. Global Position System (GPS) was used to obtain the coordinate points along the river areas and Google earth imagery and topographical data of the study areas were obtained. The basin areas, streamlines, lengths of the river, and tributaries were also generated. The buffering of the river in 15 and 30 meters exposes the vulnerability status of structures along the river. Out of the 530 structures captured, 49 structures were highly vulnerable, while 105 structures were fairly vulnerable to flood hazards. The predictive accuracy of the ordered logit model approximated 81%. While a 10% error in classification was resulting from the harmonization of the precision value (0.8026) and the recall value (0.6386). The cross–sectional variables that were found to be significant at $\alpha = 0.005\%$ are the river watersheds, the vulnerability status classification of structures across the river areas, the vulnerable structures identified, inadequate bridges and culverts along the river areas, inappropriate size of bridges and culverts, and extreme pollution along the river areas. This study is recommending the use of significant cross–sectional variables to complement the prediction of the magnitude of flood along the river banks.
Keywords: buffering, cross–sectional, georeferenced, magnitude, spatial

INTRODUCTION

Floods are among the most periodic and overwhelming natural hazards, which tend to impact on human lives and result in serious economic damage across the world. Its intensity tends to threaten the entire world due to the underlining effect of climate change (Hasselaar, 2020). However, evaluating the possibility and magnitude of flood has been hindered by several complications including, climate change, inaccurate data, poor assessment of drainage basins, pollution, and encroachment (Ayanshola, et al., 2018). Studies have reported some difficulties in the sampling technique of conventional rain and discharge measurement, which have hindered the accurate evaluation of the magnitude of the flood, especially along the river areas. The work of Nassery, et al., (2017), also established that many existing prediction equations are based on the experimental data having many experimental and constant parameters with an ambiguous estimate often required to be fixed. Such problems from previous predictions are the difficulty in the sampling of conventional rain and discharge measurement networks, which makes it difficult to predict accurately.

The existing assessment of rivers tends to indicate that the level of flood quite differs from one river to the other even despite being in the same geographical location. This can be attributed to both natural and human factors such as, watershed, drainage basin, drainage capacity, level of pollution, encroachment activities, and many others (Du, et al.. 2019). Studies mostly focus on the relationship between the amount of rainfall and the magnitude of floods. This practice cannot be so accurate because, in the actual sense, rainfall is often not evenly distributed along the same geographical location, which may likely have the presence of several streams or rivers with their peculiar factors and determinants (Du et al., 2019).

Studies have established that Geographic Information System (GIS) is a very powerful tool that allows the collection, and processing of geographically related data. The tool has been equally used as an instrument in problem–solving, and decision–making processes, and as a tool for visualizing data in a spatial location (Kraak, & Ormeling, 2020). The tool has several advantages, which include, analyzing geographical data to determine the location of structures and relationships to other landscapes, determination of watershed, and drainage density, what is likely to happen to an area of interest, and particularly, how and in what way an area has changed over time (Picuno, et al., 2019). The realization of data with the use of GIS techniques will give a complementary approach to determining cross–sectional variables, which are significant to predicting the magnitude of flood along the river course. Cross–sectional variables can be observed at the local scale. The procedures involve numerical data about intrusion and runoff dynamics (Rogger, et al., 2017). The variables have some peculiar characteristic that dictates the direction of flow of flood in each river or stream rather than just a prediction through generalization, which may not be so accurate. Figure 1 presents the watersheds of the Foma river areas.

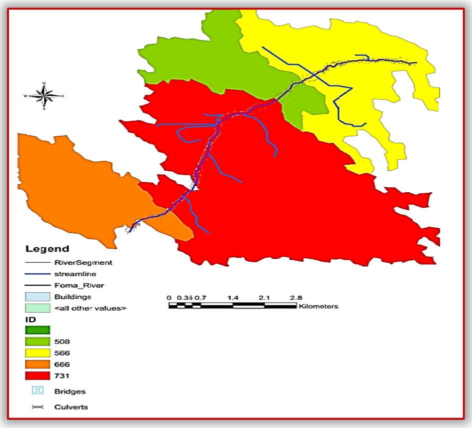

Figure 1. Foma River Watersheds

THE CHALLENGE OF FLOOD FORECASTING AND MITIGATION IN NIGERIA

Nigeria is likely to face the consequences of climate change due to its geographical location. The country is bounded by located along Atlantic Ocean to the south and the Sahara Desert to the north. This, by implication, may lead to an increase in the temperature that influences the rainfall pattern and results in the rise of extreme drought and flood (Ayanshola, et al., 2018). Due to its location, several cases of flooding in Nigeria have been reported in recent times, mostly in Sokoto, Lagos, Ibadan, Abeokuta, Gusau, and Makurdi (Chindo, et al., 2019). No less than 39 people were killed due to flooding in central Nigeria, Plateau State, towards the end of July 2012. The Flamingo dam had an overflow and swept across several localities in Jos, and about 200 houses were inundated or devastated after protracted rain. At least 35 people were reported missing, prompting the head of the Red Cross organization to announce that relief efforts were being initiated (Chindo, et al., 2019). The spatial distribution of areas extremely affected by the flooding in Nigeria is shown in Figure 2.

Similarly, Olorunfemi and Raheem (2013) reported that the major causes of flooding in the Ilorin are building on the floodplain, dumping of refuses in drainages and rivers, farming on the floodplain, all of which cause siltation, blocking off waterways and drainage channels, and inundation. The city of Ilorin is the Kwara State capital, located in the north–central part of Nigeria. The state is found between the latitude 8024'N and 8036'N and between longitude 4010'W and 4036'E, also experiencing flooding in some parts of its metropolis. During the 2017 rainy season, the city of Ilorin experienced a devastating flood hazard. Many residential buildings were reported to have submerged after a protracted rain that lasted for hours. The heavy rain, which was accompanied by flooding, washed away asphalt on some township roads. The ravaging flood also washed away bridges and destroyed valuable properties, as reported in the Nigeria Tribune newspaper (Azeez, 2017). The Alagbado bridge along the Foma river which was washed away during the 2017 heavy raining season is captioned in Figure 3.

Figure 2. Distribution of Areas Affected by Extreme Floods in Nigeria

Figure 3. Alagbado bridge along Foma–river washed away by the flood.

This study aims to develop a supervised model to complement the prediction of the magnitude of floods along the banks of the Foma river. Other sub–objectives are to examine the river buffering in 15 meters and 30 meters across the Foma river floodplain areas, identify the cross–sectional variables in complementing the prediction of the magnitude of flood along the buffering areas of Foma river, determine the significance of the cross–sectional variables in complementing the prediction of the magnitude of flood along Foma river banks using Ordered Logistic Regression (OLR) model, and evaluate the performance of OLR in complementing the prediction of the magnitude of flood along Foma river using performance measurement metrics.

FLOOD EVALUATION USING GIS AND CROSS–SECTIONAL METHODS

A cross–sectional study is an established method to estimate the outcome of interest at a particular time, for a specified location and it is usually applied for health planning, hazard, or risk exposure. In the work of Ezzatvar, et al., (2020), a cross–sectional study reflected a short period of exposition and has some characteristics associated with a specific period. A cross–section design was used to study the mental health status of adults affected by each of the flood–affected households of

Koonimedu village and Tami Nadu. The Study revealed the effects of the flood evidence concerning the standard of living and economy. Similarly, a multidisciplinary evaluation of the effects of green infrastructure and flood administration on physical health, mental health, economy, and flood resilience of individuals, households, and communities was carried out by Venkataramanan, et al., (2019). Among the reasons for carrying out the cross–sectional study is to describe the survey exercise, which usually does not have a hypothesis. The main aim is to describe some groups or sub–groups about the outcome of risk factors. Also, the goal is to elicit the prevalent outcome of interest for a descriptive population or group at a given time (Venkataramanan, et al., 2019).

The GIS application to flood hazard evaluation and management has not been an often–used method until the year 2000. The work of Mejía–Navarro, et al., (1994), initially used the GIS to estimate several risks in many areas of Colorado, to determine the suitability of land. The development of GIS modeling for excess rainfall was the approach adopted by Schumann, et al. (2000). In Nigeria, Isma'il, and Saanyol (2013) observed that the difficulty in the sampling technique of the conventional rain coupled with discharge measurement networks makes it challenging to observe and predict flood accurately. Similarly, Ngene, et al., (2015) elicited some technical deficiencies that have been preventing Nigeria from getting preferred, and accurate, rainfall data. The research enumerated the present capacity of Nigeria's rain gauge network and the need according to the World Meteorological Organization's (WMO) guidelines. Nigeria presently has 87 rain gauges, instead of 1057 (Ngene, et al., 2015). In essence, the country needs extra gauges of 970 to achieve a gauge density of 874 km2 per gauge for the appropriate measurement of rainfall. As a result of this deficiency and based on the current insufficiency of gauges, Nigeria is suffering from a 10% error in design. Because the standard condition to minimize and maximize the effectiveness for areas in the temperate Mediterranean and tropical is a range of 600–900 km2, the inaccurate records of rain data led Nigeria to be hugely affected by the devastating flood of September 2012. This event had negative effects on the economy, roads, ports, rail lines, and most especially the water infrastructures (Ngene, et al., 2015).

METHODOLOGY

This study focused on the assessment of a complementary approach to flood prediction using the GIS software. The software was initiated through Global Positioning System (GPS) to obtain the coordinates of the river channels, while the images of the earth are referenced in eastern (X) and northern (Y) coordinates. The processes elicited some cross–sectional variables from the river areas, which are significant in determining the magnitude of flood along the Foma river channel. Arc GIS 9.3® software was used to analyze high–resolution imagery from Google earth.

— Research Designs

The problem focused upon and addressed in this study is to develop a supervised model of cross–sectional variables to complement the prediction of the magnitude of flood along the Foma river.

This study investigated how GIS–generated variables and direct observation can be utilized to develop a supervised model for predicting the magnitude of the flood (dependent variable) along the Foma river. The GIS application elicited the river buffer to determine the vulnerable areas, generate watersheds, obtain the drainage densities, and determine the vulnerable structures along the buffered areas of the Foma river. Meanwhile, site observations resulted in the location of the bridges and culverts along the river, the size of the bridges and culverts measured, the observation of specific locations along the river, and the pollution rate. The flow chart for the study is shown in Figure 4.

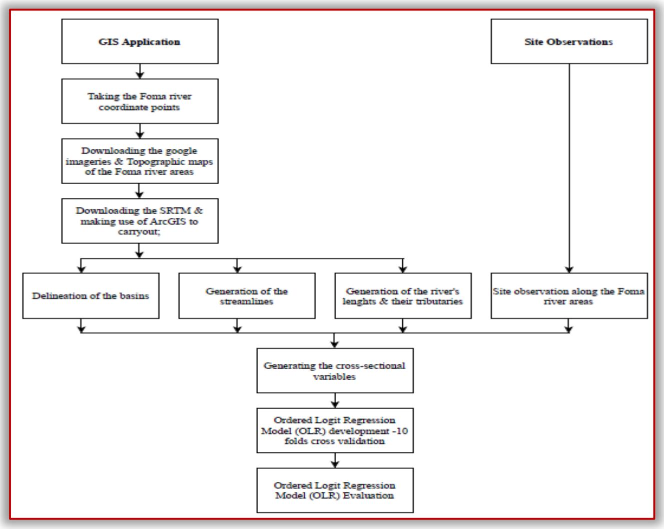

Figure 4. Flow Chart Showing the Research Design

Table 1: Cross–sectional Variables from Foma river Areas

Variable Name	Task	Values	Data Type
River Watershed	Input	Shed1, Shed2, Shed3, Shed4	Nominal
Drainage Density	Input	0.0001, 0.0002, 0.0005, 0.0007	Ordinal
Vulnerable Status of structures	Input	Not Vulnerable, Fairly Vulnerable, Highly Vulnerable	Ordinal
Types of Vulnerable Structures	Input	Hospital, Police post, Fishery ponds, Abattoir, Educational, Commercials, Slum, Agriculture, Residentials	Nominal
Bridges and Culverts	Input	CAIS, Apalara, Oke–foma, Foma–bridge, Ajetunmabi, Oloje–bridge, Abata Baba–oyo, Alagbado Bridge, Sobi–bridge	Nominal
Size of Bridges and Culvert (m)	Input	2.1, 4.5, 7.2, 11.2, 14.9, 15, 19.5, 60.8	Ordinal
River Point	Input	Source, Middle, Extreme, Terminal	Nominal
River Pollution	Input	Fair, High, Severe, Extreme	Ordinal
Magnitude of Flood	Target	Mild, Moderate, Severe, Extreme	Ordinal

Source : Field Work (2019)

The use of GIS tools and methods ensures the generation and observation of some cross–sectional variables that are suspected to be significant in predicting the magnitude of flood along the Foma river. Table 1 presents the cross–section variables that were derived through the application of GIS and site observations.

The study captured the vulnerability status of structures induced by flood activities along the course of the Foma river using remote sensing techniques. This was carried out in flood–prone areas and the buffering was examined using Arc–GIS. Structures located within 15 meters of the river bank were considered highly vulnerable to flood hazards, while those structures within 30 meters of the river were considered fairly vulnerable (The map of Ilorin west was acquired to create a database for the buffering). Also, the Foma river map was extracted, georeferenced, and digitalized into 1:50,000 from the topographical map of Kwara state. The digitalization of the map involves the process of electronic scanning to convert it to points and lines using on–screen digitization. Specifications were then made to identify the objects on the map so that the Arc–GIS was linked using the spatial data with attributes of identified structures.

The buffering of the river revealed the number of structures that were highly vulnerable, fairly vulnerable, and those that cannot be affected by flood hazards. Figure 5 exhibits the status of vulnerable structures along the river areas, while Table 2 reflects the delineation of the vulnerable status and number of structures within each drainage area along the Foma river.

Figure 5. Showing Vulnerable status of structures along Foma river areas

Table 2: Vulnerable Status Classification along the River

ID	Description	Frequency
0	Not Vulnerable	377
1	Fairy Vulnerable	105
2	Highly Vulnerable	49

To carry out the pre–classification exercises, the original sample was split into 90/10 % repeated seed training/ testing sets. A non–exhaustive cross–validation k–fold was used with k=10 so that the original sample be randomly divided into k equal–sized subsamples. Thus, taking out the subsample to be known as validation variables to test the model, where outstanding k–1 subsamples were considered as training data. The process is repeated until every k–fold serves as the test set, such that the average record scores (E) of the 10 folds become the performance metric of the model. Where E as defined in equation 1 is the addition of performance scores in the iteration. The cross–validation technique in the study is demonstrated in Figure 2, where,

$$E = \frac{1}{10}\sum_{i=1}^{10} E_i \qquad (1)$$

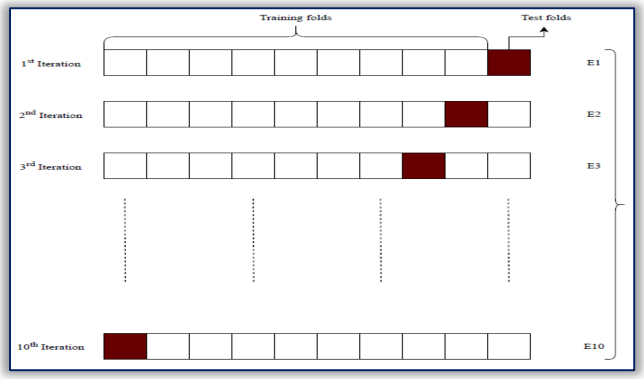

Figure 6. Cross–validation technique in the study

However, the dependent variable (magnitude of the flood) is taking more than two categories. Thus, we employed the use of ordered logit approach due to its capability to predict the presence or absence of a dependent variable. Also, its uniqueness in predicting the probability of each character in the model because the chance is a ratio. The interpretation of results in the odd ratio, parameter estimate, and probability is quite an added advantage in the area of the results' analyses. Since the dependent variable has more than two categories, and the interval between the categories was in the relative sequential order in a way that the value is indeed higher than the previous one, then the ordered logit approach would be deemed applicable.

Ordered response models are usually applied when the dependent variable is discrete and when there is ordered measurement. In general, consider an ordered response variable Y, which can take the value Y+1, 0, 1, 2……j. Such that the general linear function

$$\hat{Y} = X\beta + \varepsilon \qquad (2)$$

The latent variable $\hat{Y}$ is not directly observed, thus, the threshold set by which the observed value change as the predicted, otherwise known as 'CUT POINT'. Cut points establish the relationship between $\hat{Y}$ and Y, let α_i be the threshold. Then:

$$Y = \begin{cases} Y_o & \text{iff} \quad \hat{Y} < \alpha_o \\ Y_1 & \text{iff} \quad \alpha_o \leq \hat{Y} \leq \alpha_1 \\ Y_2 & \text{iff} \quad \alpha_1 \leq \hat{Y} \leq \alpha_2 \\ Y_3 & \text{iff} \quad \hat{Y} \geq \alpha_2 \end{cases} \qquad (3)$$

The response variable Y takes four value categories: 0= mild flood, 1= moderate flood, 2= severe flood, and 3= extreme flood. Therefore, the unknown parameters α_i are estimated jointly with β_s via maximum likelihood. The $\hat{\alpha}_i$ estimates are reported on Gretl as cut_1, cut_2 , and cut_3 in this case. In other to apply the models in Gretl, the dependent variable must either take only non–negative integer values or be explicitly marked.

— Measurement Metrics to Determine the Performance Level of OLR

In multi–class measurement, errors in classification have different implications. Errors in classifying Y as X may likely have different weighted implications than classifying C as D, and many more such errors. The accuracy measure does not take any of such problems into account. The pre–determined assumption was that the sample distribution among classes is balanced. Thus, in the case of imbalanced distribution, the most commonly used classification approach repeatedly produces a disappointing estimate. In this case, the conventional approaches need to be re–examined to address the problem of imbalanced data classification. However, the confusion matrix will create an error table to derive the measurement metrics.

In order to determine the level of accuracy of the significant classifications, the study developed 4 by4–by–4 4 confusion matrices for each of the 10 folds. The matrices enabled the derivation of the measurement metrics (accuracy, F1–Score, precision, and recall). Previous studies have established that accuracy works well in describing balanced data and misleading the performance in imbalanced data. Addition, F1 score–score has proven to be a useful metric when the data is imbalanced.

RESULTS AND DISCUSSION

The 10–folds cross–validation classification accuracy is demonstrated in Table 3.

Table 3: Ordered Logit Classification Performance estimate

Ordered Logit Accuracy For the Folds					
Fold1	Fold2	Fold3	Fold4	Fold5	Fold6
80.7	80.5	80.5	80.5	80.3	81.1
Fold7	Fold8	Fold9	Fold10	Average	
81.3	80.1	81.6	80.3	80.7%	

It was observed that the average number of cases correctly predicted is 80.7%. By this impression, the OLR model is said to be approximately 81% good to predict the magnitude of floods along the Foma river areas. With this classification accuracy, the variables are well fitted to complement the prediction of the magnitude of the Foma river flood. This correct percentage classification is quite high and explains how strongly significant the variables are. Similarly, this study presented eight (8) cross–sectional variables in predicting the magnitude of flood along the Foma river for classification. However, six (6) out of the eight (8) variables' average P–values were less than 0.05. The six variables were found significant and relevant to complement the prediction of the magnitude of flood along the Foma river flood channel. The 6 cross–sectional variables are the river watersheds, vulnerable status, vulnerable structures, bridges and culverts (B & C), size of bridges and culverts, and river pollution. Meanwhile, the 2 other cross–sectional variables were omitted due to exact collinearity, which indicated serial linearity between the two variables; they are the river drainage density and river points along the river channel.

There was an indication of a continuous increase in the probability of the magnitude of flood along the river which was demonstrated by the cut point estimates. The estimates of P–values were highly significant all through the folds, and their coefficients were equally positive. The significance of the P–value is an indication that there is a steady and continuous rise in the level of magnitude of flood across the Foma river areas. Meanwhile, due to the imbalanced data distribution, this study further evaluates the level of significance of the cross–sectional variables using the measurement metrics.

— The Measurement Metrics

The OLR model estimate was quite high which is at 81%, this suggested a high level of classification of the cross–sectional variables in complementing the prediction of the magnitude of flood along Foma river. This study further described the classification performance of OLR using the measurement metrics due to the high disparity in the sampling distribution. Figure 7 demonstrates the level of sampling disparity in the study.

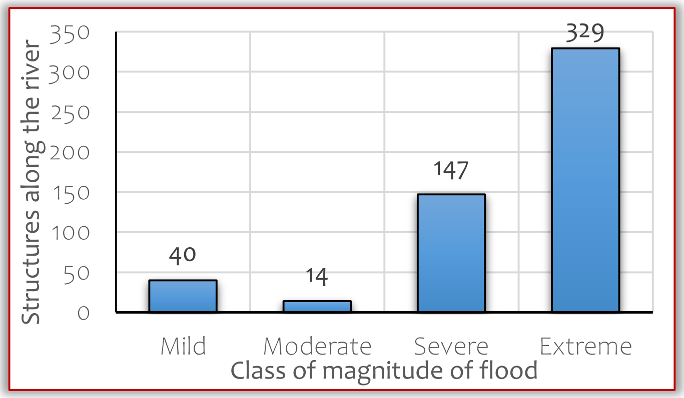

Figure 7. Level of magnitude of flood along Foma river areas

There was an indication of high disparity in the magnitude of flood along the Foma river areas. Thus, the prediction of the magnitude of flood tends to favour the higher categories compared to the lower categories. In order to describe the performance of the OLR model, the F1–score metric was used to measure the OLR performance and minimize the sampling disparities through the use of precision and recall.

Table 4: Values of the Measurement Metrics

Folds	Measurement metrics			
	Accuracy	Precision	Recall	F1–score
Fold – 1	0.8092	0.8778	0.6462	0.7444
Fold –2	0.8050	0.8764	0.6390	0.7390
Fold – 3	0.8050	0.8761	0.6397	0.7394
Fold – 4	0.8050	0.6262	0.6209	0.6236
Fold – 5	0.8029	0.8739	0.6381	0.7376
Fold – 6	0.8113	0.6321	0.6259	0.629
Fold – 7	0.8134	0.8822	0.6681	0.7601
Fold – 8	0.8008	0.6224	0.6221	0.6222
Fold – 9	0.8155	0.8833	0.6463	0.7466
Fold – 10	0.8029	0.8750	0.6396	0.7390
Average	0.8071	0.8026	0.6386	0.7081

The weighted average of precision and recall were used to measure how good the OLR classification is at predicting the magnitude of flood along Foma river. The four–

measurement metrics employed in this study are accuracy, precision, recall, and F1–score to determine the strength of the prediction. The results of the four–measurement metrics for the models are presented in Table 4.

The average values of each of the multi–class metrics derived in Table 4 were directed towards determining the performance of the OLR model in predicting the magnitude of flood along Foma river areas. Figure 8 illustrates the supervised model for complementing the prediction of the magnitude of a flood using cross–sectional variables.

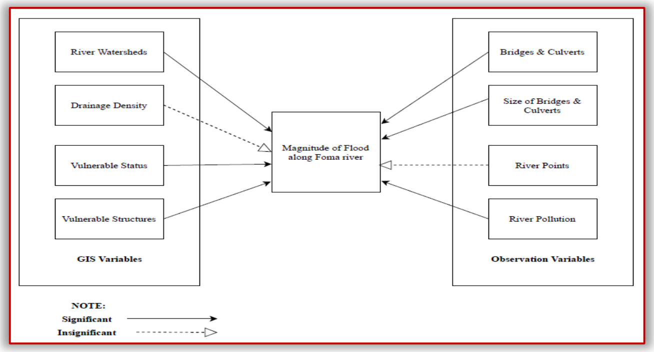

Figure 8. Supervised Model for Complementing the Prediction of Magnitude of Flood along Foma river using Cross–sectional Variables.

CONCLUSION AND RECOMMENDATIONS

This study examined the influences of precision, recall, and F1–score on the process of adjusting the inherent sampling distribution along the course of offering a significant cross–sectional variable in complementing the prediction of the magnitude of flood along Foma river areas. The ordered logit regression average prediction value of 80.71% is vulnerable to error due to the high disparity in the sampling distribution. Consequently, the model was subjected to further evaluation using the F1–score analysis. The F1––score made use of the weighted averages of precision value (0.8026) and recall value (0.6386) to reduce the sampling error by approximately 10%, such that, the model's average capacity to predict the magnitude of flood along Foma river areas is 70.81%. Similarly, the model classification provided six (6) out of the eight (8) cross–sectional variables evaluated to be significant in complementing the prediction of the magnitude of flood along Foma river areas. The average P–values of the six cross–sectional variables are less than 0.05. While the other two variables were considered insignificant due to absolute collinearity.

The river buffer areas within 15 meters and 30 meters established the vulnerability status of structures along the Foma river floodplain. This exercise identified a total number of 154 structures to be vulnerable to flood hazards along the riverbank areas. One hundred and five (105) of the structures were vulnerable, while forty–nine (49) similar structures were at a very high risk of flood hazards along the river areas. In conclusion, this study is recommending the use of significant cross–sectional variables to complement the prediction of the magnitude of flood along the riverbanks.

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