EMPLOYING THE GENERALIZED LASSO MODEL TO EVALUATE KEY DETERMINANTS OF LIVELIHOOD VULNERABILITY IN THE SOUTHWESTERN COASTAL BANGLADESH

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ABSTRACT

Bangladesh is a disaster-prone country due to its geographical location, flat topography, and monsoon climate. The coastal zone is the most vulnerable part of Bangladesh due to the regular occurrence of natural disasters such cyclones, storm surges, floods, salinity, erosion, and waterlogging. This study employed the generalized Least Absolute Shrinkage and Selection Operator (LASSO) machine learning model to find out the key influential factors that make people vulnerable regarding their livelihoods. The study was carried out in Gabua Union, a remote region along the southwest coast. Initially, twenty-five livelihood vulnerability factors were chosen based on expert comments, field observations, and extensive literature review. Data collection involved field surveys with questionnaires, focus groups (FGD), and key informant interviews (KII), along with the utilization of satellite images and a digital elevation model (DEM). Various regularization techniques were tested, including Compact (0.0), LASSO (1.0), Ridge LASSO (1.1), and Ridge (2.0). Among these, Ridge (2.0) emerged as the top performer with the highest receiver operating characteristic (ROC) value of 0.9493, utilizing 25 coefficients effectively. The high ROC value, 0.9493 and a classification accuracy, 87% additionally, the high precision (0.93), recall (0.87), F1 score (0.89), and specificity (0.87) together show that the model is good at its classification task and indicate the effectiveness of the generalized LASSO model in ranking key influential factors. Conversely, the models exhibited lower values for the overall misclassification rate (0.27791), the balance error rate (0.09467), and negative average log likelihood. These findings reinforce the superior performance of the models. The study identified the most crucial factors among the 25 influential livelihood vulnerability factors as proximity to the river, slope, distance from Kheya Ghat, height of rainfed water inundation, livelihood dependency on natural resources, normalized difference vegetation index (NVDI), distance from a potable water source, having a bank account, gardening at home, and dependency ratio are the most important ones. The study's outcomes can assist decision-makers in formulating more contextually effective initiatives and strategies. It may also contribute to national risk reduction policies and, in the same way, attain the objectives of the Sendai Framework and Sustainable Development Goals (SDG).

Keywords: *Coastal zone, Disaster risk reduction, Generalized LASSO model, Livelihood Vulnerability*

1. INTRODUCTION

Globally, the consequences of hazards are rising unexpectedly because of climate change and the increasing exposure of communities and individuals (UNDRR, 2022). Rising temperatures, shifting precipitation patterns, sea-level rise, and the overall increasing trend of frequency and intensity of extreme weather events adversely affect agricultural output, quality and quantity of potable water, human well-being, and the environment, as indicated by Keutgen 2023; Yadava et al., 2023; Wheeler and Von Braun, 2013. Bangladesh is a disaster-prone country because of its geographical location, topography, multiplicity of rivers, and monsoon climate (Rahaman, 2023). The coastal area of Bangladesh is remarkably vulnerable, experiencing frequent climate-related disasters such as cyclones, storms, floods, salinity, erosion, and waterlogging (Asma and Kotani, 2021; Bari and Sayeed, 2023). The coastal communities confront several challenges, including poverty, drinking water crisis, poor sanitation, roads, and health problems (Tasnuva et al., 2022). Additionally, the southwestern coast of Bangladesh has extreme livelihood vulnerability, with limited physical resources, inadequate access to fresh water, few livelihood strategies, a limited variety of crops, and poor health conditions (Brojen et. al.23; Brojen & Bari 2023; Nasreen et al., 2023).

Vulnerability is defined as the conditions influenced by social, physical, financial, and environmental factors or processes that intensify the susceptibility of individuals, communities, assets, or systems to the consequences of hazards (UNDRR,2022). Vulnerability assessments play a vital role in disaster risk reduction by recognizing and assessing the weaknesses and exposures of communities, infrastructure, and ecosystems to potential hazards. By understanding and concentrating on vulnerabilities, communities can proactively reduce risks and build more robust systems to withstand and recover from disasters. Key factors contributing to vulnerability must be identified to build a more resilient society that can face and overcome issues associated with climate change (Aksha et al., 2019).

Livelihood vulnerability pertains to the susceptibility of households or communities to diversified hazards that can disrupt their capacity to sustain their livelihoods and realize their critical requirements (Venus et al., 2022). People with limited resources and lower income levels are more susceptible to livelihood vulnerability (Mudasser et al., 2020). Livelihood vulnerability assessment is an effective and efficient tool for identifying the impact of climate change on coastal areas in terms of adaptation. In the process, certain aspects of different societal strata become evident in explaining the idea of livelihood vulnerability. There is a scarcity of studies on vulnerability assessments at the individual household level in developing countries (Debesai, 2020). However, research focused on determining the top influential determinants contributing to livelihood vulnerability still significantly less.

Acknowledging these challenges, the aim of this research is to use machine learning (ML) techniques to determine the factors that influence livelihood vulnerability. The current study intends to combine all indicators correlated to exposure, sensitivity, and adaptive capacity. Machine learning (ML) techniques can accomplish interactions between variables. By identifying these key determinants of livelihood vulnerability and their interrelationship, it can be possible to enhance the ability of disaster risk reduction at the local level through the implementation of targeted strategies and specific initiatives. Therefore, the suggested approach considers interactions between determinants to capture the multidimensional and complex aspects of livelihood vulnerability in the coastal area.

Findings from the research can offer an effective approach that can be applied across the coastal areas of different geographical settings to understand better the determinants influencing livelihood vulnerability. Instantaneously, it also seeks to determine the relative importance of the determinants contributing to the vulnerability of coastal households' livelihoods by utilizing a more extensive sample size at the micro-level (ward level). The main novelty of the study lies in emphasizing the transition from traditional methodologies to illustrating the application of advanced tools for identifying most influential determinants for livelihood vulnerability in coastal area Bangladesh.

Subsequently, the paper offers a unique way for utilizing a machine learning model to identify the most relevant factors of livelihood vulnerability, which adds lots of value to the field of disaster management. This approach is versatile enough to be used in different coastal regions throughout the world. Furthermore, the majority of current studies evaluate livelihood vulnerability at the macro-level and there are relatively few that do so at the household level in coastal areas, this study will significantly contribute to the field of disaster management because micro-level studies are more useful in developing effective policies for area-oriented contextual disaster risk reduction (Badawy et al., 2022).

2. METHODOLOGY

2.1 Study area selection

The study was conducted in Gabura,a coastal island union. Gabura is situated in the Satkhira district's Shyamnagar Upazila in southwest Bangladesh's coastline region. The Kholpetua and Kopothakho rivers flow along the union's western and eastern borders, thus dividing it from the mainland. Gabura was selected as the research site because of its high catastrophe risk.

2.2 Selection of livelihood vulnerability determinants

There was a total of 25 determinants, each with its implication concerning the study's objectives, as outlined below in Table 1.

Table 1: Selected determinants for livelihood vulnerability assessment

Vulnerability domains	**Determinants**
Exposure	Elevation, river proximity, drainage density, slope, rainfed water inundation depth, riverbank erosion area, storm surge inundation area
Sensitivity	Distance from kheya ghat, economic vulnerability, unhygienic latrine, livelihood dependency on natural resources, distance from potable water source, educational status, dependency ratio
Adaptive Capacity	Household having bank account, Household migration status, Distance from market, Distance from health center, Household with electric facilities, NDVI, Household gardening status, household livestock status, household involved with improved agricultural activities, household communication status, women involvement in household income

2.3 Sample size calculation and sampling methods

Based on data provided by the Gabura union parishad in 2023, there are a total of 8,237 households distributed among these nine wards. Among 8237 households, we randomly chose 1014 households (approximately 12% of total households). Though the study primarily employed quantitative methodology, it also incorporated qualitative components. This method involved applying a questionnaire survey as the primary data collection method, supplemented by qualitative methods like focus group discussions (FGDs) and key informant interviews (KIIs).

2.4 Method for LVI modelling approaches

The generalized LASSO machine learning model has been used in this study to evaluate the top influential determinants of livelihood vulnerability. The generalized LASSO is an accessible and effective machine learning and statistics regularization method. It simplifies the LASSO method. It expands on the theory of LASSO (L1 regularization) and Ridge (L2 regularization) to develop a more comprehensive outline that supports a wide range of optimization challenges and permits combining several regularization techniques. The generalized LASSO methodology is applied to multitasking tasks such as variable selection, model regularization, regulating a predictive model's complexity, and assessing linear and non-linear models (Xi et al., 2023).

2.4.1 Equation of generalized LASSO model

The generalized LASSO model's primary equation combines a loss function and several regularization terms to solve an optimization problem.

$$\frac{1}{2n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 + \lambda_1 \sum_{j=1}^{p}|w_j| + \lambda_2 \sum_{j=1}^{p} w_j^2 + \lambda_3 \sum_{j=1}^{p}|w_j|^q$$

Where n denotes the number of data points

P, denotes the number of features (model coefficients)

y_i denotes the observed target value for the *i*-th data point

$\hat{y}_i$ denotes the predicted target value for the *i*-th data point

w_j denotes the *j*-th model coefficient

λ_1, λ_2, and λ_3 indicates hyperparameters that control the strength of the regularization terms.

The first term denotes the standard loss function, often the mean squared error (MSE) for regression.

The second term ($\lambda_1 \sum_{j=1}^{p}|w_j|$) associates with L1 (LASSO) regularization, promoting sparsity by penalizing the absolute values of coefficients.

The third term ($\lambda_2 \sum_{j=1}^{p} w_j^2$) corresponds to L2 (Ridge) regularization, discouraging large coefficient magnitudes.

The fourth term ($\lambda_3 \sum_{j=1}^{p}|w_j|^q$) confirms a more general compact regularization term that can include several norms, like L∞, depending on the specific problem.

The objective of the optimization problem is to discover the value of model coefficients (w_j) that result in the minimization of this objective function. The selection of hyperparameters (λ_1, λ_2, and λ_3) and the specific regularization terms employed (such as L1, L2, or others) is subject to the specific needs of the problem and the desired balance between sparsity and magnitude of coefficients.

2.4.2 Regularization techniques of generalized LASSO model

The generalized LASSO model is a flexible strategy that unifies several regularization techniques, such as LASSO, Ridge, Ridge LASSO, and others, under the general heading of compact regularization. Compact, LASSO, Ridge LASSO, and Ridge with specific values, such as 0.0 or 2.0, are used in a generalized LASSO model to denote several penalty structures and the regularization level employed in the model.

When the term is described as "compact", it usually means that no regularization is applied, with a value of 0.0. In this instance, the model is effectively doing ordinary least squares (OLS) regression, and the regression coefficients are not penalized. A value of 0.0 for "LASSO" denotes strengthless L1 regularization ($\lambda = 0$) and indicates that no regression coefficients are penalized or shrunk by the model, and thus, the L1 penalty term is essentially disabled. The term "Ridge LASSO" is not commonly used while discussing regularization. The model keeps all its properties and operates similarly to Ordinary Least Squares (OLS) regression. A value of 2.0 for "Ridge" denotes a positive L2 regularization strength ($\lambda = 2.0$) in the Ridge regression. The L2 penalty used in ridge regression encourages regression coefficients to be small but does not set them to preciously zero. The greater the λ value, the stronger the penalty, resulting in a more significant coefficient shrinkage toward zero. L2 regularization with a λ value of 2.0 indicates a relatively robust application. All analysis of generalized LASSO model were performed in Salford Predictive Modeler (Machine Learning and Predictive Analytics Software) 8.3.2 version.

3. RESULTS AND DISCUSSION

3.1 Application of Generalized LASSO in Modeling Livelihood Vulnerability

Generalized LASSO expands on the concept of traditional LASSO (L1 regularization) by adding extra penalty terms, such as the Elastic Net (a combination of L1 and L2 regularization). It is employed to perform feature selection and shrink coefficients in linear regression models, targeting to indicate a limited set of coefficients that play the most crucial role in predicting the target variable. Table 1 briefly explains how generalized LASSO relates to elasticity, the solution, the number of coefficients, average likelihood (Negative log-likelihood), misclassification rate, overall lift, and ROC for modeling livelihood vulnerability with 25 indicators.

Table 2: Solution By elasticity

Elasticity	Sol.	N Cef.	Learn Ave. L.L (Neg)	Learn Mc.R. Overall (Raw)	Learn ROC	Learn Lift	Test Ave. L.L (Neg.)	Test Mc.R. Overall (Raw)	Test ROC	Test Lift
Compact (0.0)	107	1	0.5431	0.1677	0.8355	1.4169	0.5448	0.2396	0.8212	1.3442
Compact (0.0)	112	1	0.5376	0.1677	0.8355	1.4169	0.5393	0.1677	0.8209	1.3442
Compact (0.0)	197	2	0.4431	0.1677	0.8737	1.5647	0.4476	0.1677	0.8255	1.3878
Compact (0.0)	200	2	0.4398	0.1677	0.8737	1.5647	0.4432	0.1677	0.8439	1.4462
LASSO (1.0)	121	5	0.4141	0.1677	0.9077	1.5654	0.4161	0.1637	0.9033	1.5953
LASSO (1.0)	150	12	0.3544	0.1371	0.9256	1.5811	0.3611	0.1400	0.9209	1.5654
LASSO (1.0)	199	23	0.2536	0.0828	0.9558	1.5811	0.2730	0.0927	0.9489	1.5811
LASSO (1.0)	200	23	0.2516	0.0809	0.9560	1.5811	0.2720	0.0937	0.9491	1.5811
Ridged LASSO (1.1)	116	5	0.4244	0.1677	0.9074	1.5654	0.4260	0.1667	0.9025	1.5969
Ridged LASSO (1.1)	150	12	0.3545	0.1351	0.9265	1.5811	0.3614	0.1400	0.9216	1.5654
Ridged LASSO (1.1)	198	23	0.2558	0.0868	0.9555	1.5811	0.2740	0.0917	0.9487	1.5811
Ridged LASSO (1.1)	200	23	0.2517	0.0799	0.9561	1.5811	0.2721	0.0937	0.9491	1.5811
Ridge (2.0)	4	10	0.6549	0.3738	0.8955	1.5969	0.6554	0.3738	0.7867	1.5496
Ridge (2.0)	5	13	0.6529	0.3738	0.9104	1.5969	0.6535	0.3738	0.8244	1.5811
Ridge (2.0)	199	25	0.2622	0.0868	0.9551	1.5811	0.2779	0.0947	0.9493	1.5811
Ridge (2.0)	200	25	0.2601	0.0838	0.9554	1.5811	0.2765	0.0957	0.9492	1.5811

*Sol. =Solution; N. Cef. =No of Coefficient; Ave. LL.(Neg.) = Average LogLikelihood (Negative); Mc. R= Misclass Rate

This table illustrates that having only two coefficients compact (0.0) results in the highest optimal ROC values in training (0.8737) and testing (0.8438). For LASSO (1.0), the highest optimal ROC is achieved at 0.9560 in training and 0.9491 in testing with 23 coefficients. The Ridged LASSO (1.1) with 23 coefficients exhibits the highest optimal ROC 0.9561 in training and 0.9491 in testing. In the case of Ridge (2.0), the highest optimal ROC is seen 0.9554 in training and 0.9493 in testing with 25 coefficients. So, among all these regularization techniques of generalized LASSO model Ridge (2.0) showed the highest ROC value and indicated the effectiveness of the generalized LASSO model.

Table 2 summarizes the model's performance metrics for training and testing. These metrics are essential for evaluating the model's efficiency in predicting livelihood vulnerability.

Table 2: A well-structured and informative summary of the best model

Name	**Learn**	**Test**
Average LogLikelihood (Negative)	0.26215	0.27791
ROC	0.95510	0.94928
Variance of ROC	0.00005	0.00005
Lower Confidence Limit ROC	0.94163	0.93496
Upper Confidence Limit ROC	0.96858	0.96360
Lift	1.58110	1.58110
Kolmogorov-Smirnov (K-S) statistic	0.82236	0.79972
Misclass Rate Overall (Raw)	0.08679	0.09467
Balanced Error Rate (Simple Average over classes)	0.10576	0.12366
Class. Accuracy (Baseline threshold)	0.89152	0.87377

This table shows the lower value (0.27791) of average negative log-likelihood and the higher value of ROC (0.94928) of the test dataset, which indicates better model performance. On the other hand, a low variance of ROC (0.00005) suggests that the model performance is consistent. Lift greater than 1 indicates improved model performance. In livelihood vulnerability assessment, both learn and test datasets have a lift of 1.58110, suggesting an improvement over random guessing. K-S statistic indicates how well the model separates positive and negative cases. A higher K-S state value (0.79972) in the test data set suggests better model performance. Otherwise, the misclass Rate is lower (0.09467) in the test dataset, which indicates a lower proportion of incorrect prediction. In the same way, a lower balanced error rate (0.12366 in the test dataset) indicates better performance in correctly classifying vulnerable and nonvulnerable classes. Moreover, finally, a higher classification accuracy shows how well the model performs in correctly classifying vulnerable and nonvulnerable households regarding livelihood vulnerability.

3.3 Model validation by confusion matrix

A confusion matrix is a tabular tool applied in machine learning and statistics to evaluate a classification model's performance. It displays the numbers of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) to provide a clear picture of classification results. These numbers help determine a model's recall, accuracy, precision, and F1-score—all necessary measures for assessing how well the model divides data into distinct classes. Figure 1 highlights all these values for the generalized LASSO model for analysing the key influential factors that make people vulnerable regarding their livelihoods.

3.4 Measuring model performance by roc curve, lift chart, cumulative lift chart, and gain chart

In data analytics, model validation approaches like ROC, Lift, Cumulative Lift, and Gain are frequently employed, especially when assessing the effectiveness of prediction models like classification models. Figure 2 shows their interpretation, which provides valuable insights into model effectiveness in assessing livelihood vulnerability.

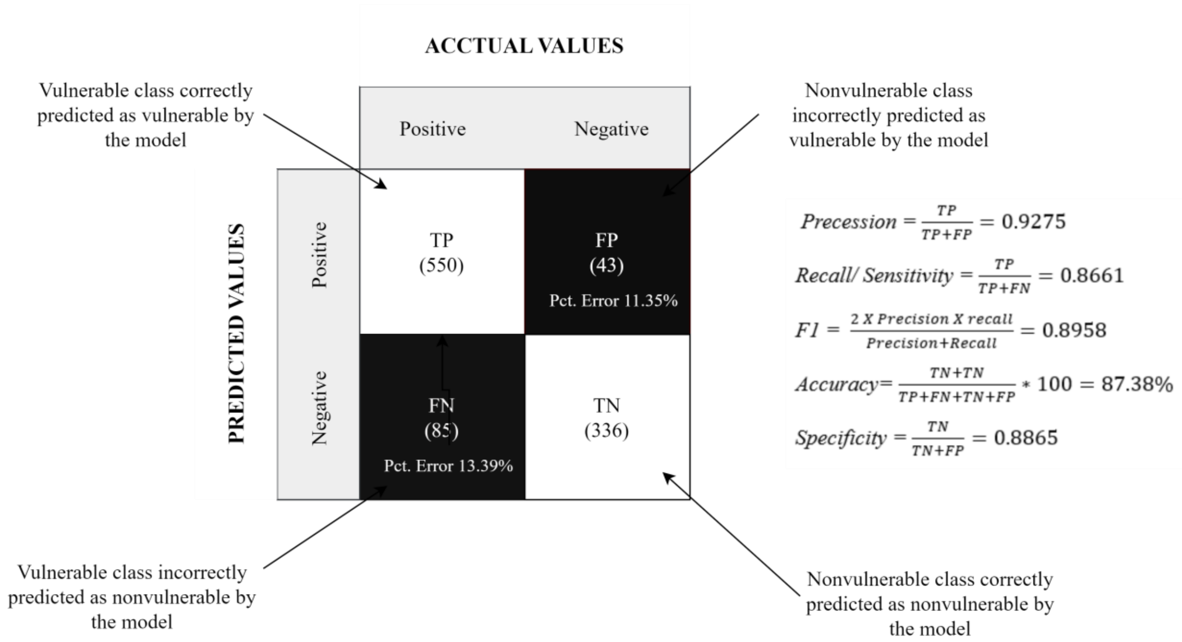

Figure 1: Confusion matrix of vulnerable and nonvulnerable classes in the generalized LASSO model

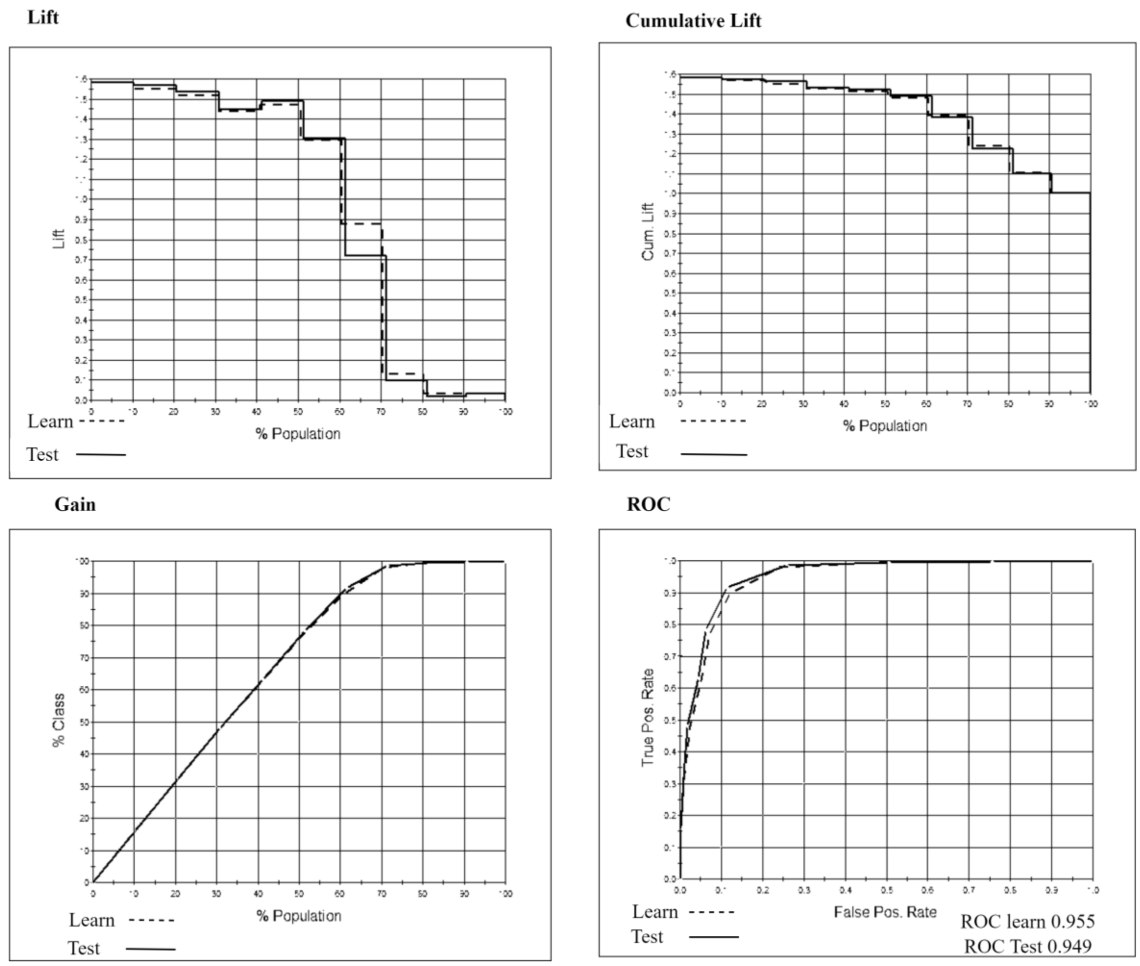

Figure 2: Lift chart, Cumulative Lift chart, Gain chart, and ROC curve for the generalized LASSO model

3.5 Relative importance of the detriments of livelihood vulnerability

Figure 3 highlights the relative importance of the 25 determinants in assessing livelihood vulnerability, revealing the varying degrees to which each element contributes to household vulnerability. This allows for the identification of key factors and their respective impacts on the outcome of interest. A higher score implies a more significant contribution to livelihood vulnerability, while a lower score reveals a lesser contribution.

Illustratively, the determinant "proximity to the river" holds the highest score at 100%, emphasizing its paramount importance. Following closely are "slope" at 76%, "distance from Kheya Ghat" at 59%, "rainfed water inundation height" at 51%, and "livelihood dependency on natural resources" at 48%, underscoring their significant roles in determining livelihood vulnerability. In contrast, the household's livestock status (2%) receives the lowest score, representing its relatively minor impact on livelihood vulnerability.

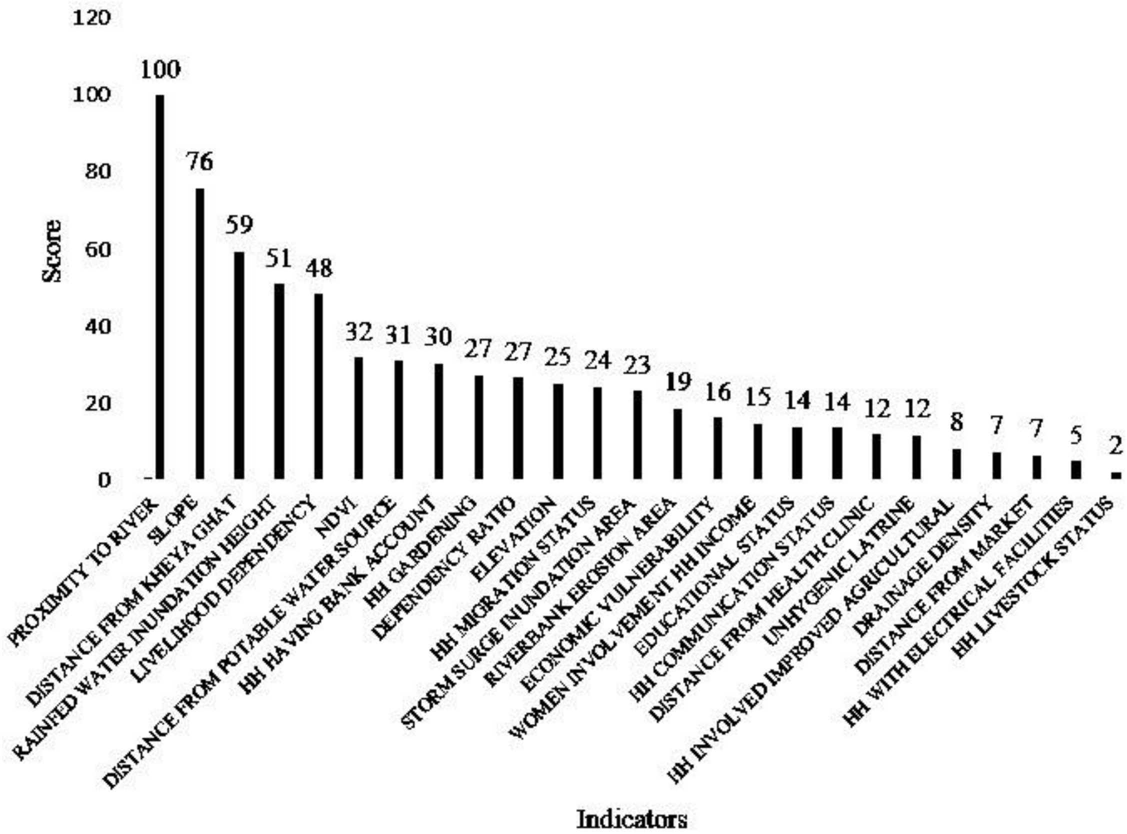

Figure 3: Determinants of livelihood vulnerability with score

Residents living alongside the river face significant challenges, including riverbank erosion and storm surge inundation issues. The slope of the land is a crucial factor, as areas with a gentle slope can be more susceptible to prolonged inundation. Likewise, a gentle offshore slope contributes to the spread of storm surges over a larger area, potentially mitigating their height but posing challenges for those residing in low-lying regions. As the study union is encircled by river, there are no direct land connections with the mainland of upazila except the waterway and the inhabitants of the area suffered most, due to their communication with the towns. Significant amount of precipitation coupled with poor drainage system are responsible for high rainfed water inundation height. With the limited livelihoods opportunities, many people in study union fully dependent on forest and river for their basic needs and income generation. People who are completely dependent on these natural resources are more vulnerable than others because, in a certain month of the year access to mangrove forests for resource collection is totally prohibited.

The severity of human vulnerability to natural disasters depends on geographical location, including physical attributes and socioeconomic factors (Hansuwa et al., 2022; Sheehan et al., 2023). Proximity to the coast, rivers, and local terrain is crucial for hazard exposure (Hossain, 2015). In this water encircled union, residences face significant threats from heightened tides, cyclonic surges appearing at elevations surpassing one meter above sea level, and riverbank erosion owing to their proximity to the river. Proximity to the coastline, rivers, and the nearby topography plays a fundamental role in influencing vulnerability to hazards, as emphasized by Hossain (2015).

During the Focus Group Discussions (FGD) and Key Informant Interviews (KII), participants from Gabura consistently highlighted that the absence of regular maintenance has resulted in a gradual accumulation of sediment in the riverbed. Consequently, the width of the embankment is shrinking, and its condition is weakening over time. Five consecutive cyclones, storm surges, and coastal floods severely impacted people's economic activity and their ability to maintain basic living standards. The residents in this union experience a multitude of vulnerabilities that significantly impact their livelihoods.

4. CONCLUSIONS

This research introduces a novel and alternative approach for stakeholders and policymakers to explain effective strategies for addressing the top determinants of livelihood vulnerability. To address the most influential determinants in livelihood vulnerability, we employed the generalized LASSO model, which is appropriate for binary classification, even when dealing with imbalanced class variables. Our demonstration revealed that the generalized LASSO model performed very well in evaluating the most significant determinants, as evidenced by the optimal ROC curve, confusion matrix value, and other pertinent performance metrics. The findings regarding the relative importance of determinants indicated that the proximity of households to the river is the leading contributor to livelihood vulnerability in the study union. We emphasize the significance of our research outcomes and the demonstration of applying machine learning with extensive household-level data, as they have the potential to assist decision-makers in formulating more contextually effective initiatives and policies. The study's findings also contribute to national risk reduction policies, supporting the Sendai Framework and Sustainable Development Goals (SDG) objectives. Subsequently, the local authorities, particularly Gabura union Parishad, can benefit from the study's outcomes. Despite its numerous practical contributions, the study does have certain limitations. Firstly, it relies solely on the generalized LASSO machine learning model for evaluating the primary determinants of livelihood vulnerability. Secondly, the study concentrates on Bangladesh's lowest administrative level (i.e., the union), which may need to incorporate the broader institutional dynamics fully. This paper recommends that future research investigate the determinants of livelihood vulnerability at higher administrative levels to reduce the vulnerability.

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