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Assessment of Socioeconomic Vulnerability in Selected Villages of Gosaba Block, Sundarban, India Using an Artificial Neural Network

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Authors' contributions

This work was carried out in collaboration between both authors. Author SD conceptualization, author CSD writing review and editing of this study. Author SD wrote the original draft preparation of the manuscript. Author SD, Author CSD visualization and supervision of the study. Both authors read and approved the final manuscript.

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ABSTRACT

The Indian Sundarban represent an endangered ecosystem with a distinct biogeographical composition. It is susceptible to natural disasters like storms, floods, and cyclones, hence jeopardizing its socioeconomic systems due to environmental stresses. This study aimed to

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evaluate the present socioeconomic vulnerability, identify key factors that exacerbate this vulnerability, and validate these factors using an Artificial Neural Network (ANN) prediction model. Researchers also wanted to validate this evaluation with ANN to promote substantive discussions between researchers, local authorities, and stakeholders. Comprehensive reviews and successful adaption plans will improve. The study conducted in selected villages with 160 households in the Gosaba Block, located on the periphery of the Sundarban. The present study employed an integrated vulnerability approach, calculating the exposure, adaptive capacity, and sensitivity index by weighting the initial eigenvalues of each indicator with a variance percentage through principal components analysis (PCA). Based on this criterion, 156 households (97.5%) exhibited an extremely high vulnerability score, while 4 households (2.5%) displayed a moderate vulnerability grade. The villages of Pakhiralay and Lahiripur exhibit significant vulnerability, with a markedly deficient adaptive capacity. The villages of Mathurakhand, Kumirmari, and Satjelia exhibit vulnerability alongside moderate adaptation capacity. All are priority villages, however, Villages with moderate adaptive capacity may become less vulnerable with adequate interventions Proximity to market strongly affects MLP neural networks' assessment of environmental, economic, and social variables' effects on exposure, sensitivity, and adaptive capacity. Respondent age, family size, social network, storm surges, supplementary sources of household income Dwelling years, temperature, embankment failure, and income greatly affect model performance. A policy initiative should prioritize the enhancement existing social and financial capital, facilitate access to local government, and promote community-oriented activities. National disaster, social welfare, and resource management strategies need separate action plans. The national government is also encouraged to decentralize governance to enable local governments to achieve their goals.

Keywords: Vulnerability index; exposure; adaptive capacity; sensitivity; Artificial Neural Network (ANN).

1. INTRODUCTION

The expected consequences of climate change are forecasted to have substantial impacts on both societies and economies (Ajani, et al., 2013). The vulnerability of households, particularly in rural areas, is profoundly influenced by prevailing climate shocks and stresses (Manandhar et al., 2011, Shah et al., 2013, Sujakhu, 2018). Vulnerability results from the interaction of biophysical factors, such as climatic exposure, along with the system's sensitivity and adaptive capacity (Shah et al., 2013).The vulnerability of rural households is ascribed to a combination of economic, environmental, and social factors, together with their exposure to climatic extremes and gradual climatic changes (Nelson, 2011, Goodrich et al., 2017).Vulnerability can be assessed by analyzing the interaction between physical and social systems through diverse approaches. The identification of suitable site-specific indicators is essential for addressing intricate issues in vulnerability assessment (Hahn et al., 2009). Numerous researchers have employed various methodologies to assess vulnerability, including the gap method (Sullivan et al., 2002) the human development index (Bray et al., 2012), the composite vulnerability index (Rygel et al., 2006) the sustainable livelihood security index (Sajjad and Nasreen, 2016) and fuzzy logic (Ahmed et al., 2018). Index-based vulnerability analysis enables explicit vulnerability assessment through the integration of several indicators that signify different vulnerability scenarios. These indicators have been widely employed by researchers as effective tools for policymaking (Kelkar et al., 2011, Malakar & Mishra, 2017). The social and economic conditions of a region determine its vulnerability to hazards (Malakar & Mishra, 2017). The scientific community has begun to develop concepts on vulnerability assessment and adaptation to climate change (Tian and Lemos, 2018). In the 1970s, scientific engineering and technical methodologies predominated in vulnerability assessment, whereas the 1980s saw a shift towards social science-oriented approaches for the same purpose. The prior method was employed to examine vulnerability in part; however, it was ultimately replaced by a human-centric approach that considered institutional, social, cultural, environmental, and economic aspects (Blaikie et al., 2005, Ciurean et al., 2013). A considerable quantity of research on social vulnerability assessment employed a semi-quantitative approach grounded in spatial, socioeconomic, demographic, and field-derived factors (Fekete, 2019). The index-based disaster resilience assessment is an essential component of natural hazard management and planning.

Indices facilitate the assessment of changes induced by hazards and the identification of priority areas of concern through inductive, deductive, qualitative, and quantitative techniques (Ogie and Pradhan, 2019). Acknowledging that the susceptibility of a specific location or system is determined by both exterior physical parameters and internal socio-economic factors, we choose to develop a vulnerability index. This index is derived from the vulnerability criteria established by the IPCC and use an indicators-based methodology to assess the socio-economic and physical determinants of vulnerability. The IPCC characterizes vulnerability to climate change and variability as consisting of three essential components: exposure, sensitivity, and adaptive capacity. Artificial neural networks (ANNs) are capable of identifying intricate patterns in data sets that computational formulas cannot discern (Vicente et al., 2011, Aradag et al., 2017, Taormina et al., 2015, Hajihassani et al., 2015, Chau, 2007). Moreover, it generates dependable predictions in the presence of noisy and ambiguous data (Taormina et al. 2015, Hajihassani et al., 2015). Consequently, ANN may provide highly precise classified vulnerability maps derived from intricate interactions. To create an ANN structure based on specific research indicators, it must be trained. Training ANN requires a suitable selection of training parameters (Chau, 2007, Gordan, 2016, Hinton, 1992). The primary restriction of an ANN is its efficiency, which is significantly influenced by the training method and network architecture. Regrettably, there are yet no standards established to delineate both network characteristics. The ideal and optimal network can be ascertained using a trial and error methodology (Jensen 1994, Bishop 1995, Liang et al., 2017, Islam et al., 2017, Sharma et al., 2018). While the fundamental groundwork for developing the required abilities and policies for climate-resilient development has been established at the national level, there is still a lack of comprehensive studies and scientific input on the impacts and vulnerability of climate change, particularly at the local level. Local governments and communities play a crucial role in adapting to climate change by organizing strategies to address local effects, facilitating communication between individual and communal efforts to reduce susceptibility, and overseeing the distribution of resources to support adaptation (Agrawal 2010) Conducting a spatial vulnerability assessment at a local level might be a valuable tool for researchers and local stakeholders to communicate with each other. This evaluation involves visualizing climate vulnerability and integrating both its physical and socio-economic factors (Preston et al. 2009). Therefore, the main aim of this paper is to elucidate the principal elements that exacerbate vulnerability using an Artificial Neural Network (ANN) prediction model. Furthermore, we aimed to authenticate this evaluation utilizing ANN, which will facilitate productive discussions among researchers, local authorities, and stakeholders. This will ultimately enhance comprehensive evaluations and the formulation of successful adaption plans.

2. MATERIALS AND METHODS

2.1 Study Area

The Indian Sundarban are situated in the state of West Bengal on the eastern coast of India. The Indian Sundarban refers to the 19-block region including the two districts of West Bengal: North 24 Parganas (6 blocks) and South 24 Parganas (13 blocks). The terrain is located inside the recently established delta system formed by the Ganga, Brahmaputra, and Meghna rivers. The region's average elevation is significantly low, with the islands generally ranging from 3 to 8 meters in height and being entirely inundated during tidal surges (Hazra et al. 2002). We selected the villages of Gosaba Block as our study region because of their favorable geographical position. In the Indian portion, the villages are situated adjacent to the Sundarban Reserve Forest (SRF) and in the midst of an interconnected system of creeks and intermittent rivers. (Fig. 1). The region is delineated to the west by the River Bidya and to the east by the Rivers Gomar and Raimangal (Ghosh and Mistri 2020). The 2011 Census data reveals that the villages of Mathurakhand, Pakhiralay, Satjelia, Lahiripur, and Kumirmari, situated within the Bali I, Rangabelia, Satjelia, Lahiripur, and Kumirmari Gram Panchayats, cover areas of 7.85, 4.79, 9.65, 8.51, and 20.20 square kilometers, respectively, serving populations of 3,826, 3,946, 8,757, 6,851, and 17,451 individuals. A considerable number of settlements in the study region are located near both the Sundarban Reserve Forest (SRF) and the Sundarban Mangrove Forest (SMF).

2.2 Methodology

The present study employs a descriptive-analytic method and uses survey data obtained from households in the selected study area. In the very initial phase of village selection in the Gosaba Block, multistage cluster sampling was implemented. Initially, the Block's GPs were divided into two strata: adjacent to the forest edge and connected to the mainland. Villages have been selected from each tier using a simple random sampling lottery method. Our sample households (n=160) came from the villages of Mathurakhand (22), Pakhiralay (39), Satjelia (38), Lahiripur (28), and Kumirmari (33).The sampled households were chosen based on a 95% confidence level that the true value is within ±5% of the measured/surveyed value. Households were sampled in proportion to their population size. The demographic data of the respondents show that the average age is 45 years. The survey results demonstrate that 85.62% of individuals identified as male, while 14.38% identified as female. The average household size indicated by respondents was 4.26 members, with 49% of the households being below the poverty line (BPL).

2.2.1 The overall vulnerability index

Scholars have employed a range of indicators to quantify the extent of vulnerability and vulnerability necessitates evaluation and policy implementation (Abuodha and Woodroffe, 2010, Hahn et al., 2009, Luers et al., 2003, Orencio 2014, Sam et al., 2017; Szlafsztein and Sterr, 2007). Vulnerability is a key aspect in determining whether individuals face livelihood risks. IPPC (2007) defines vulnerability assessment as a measure of a community's ability to respond to hazards and safeguard its livelihood. The index serves as a comparative tool among communities. The vulnerability index (LVI) was established by Hahn et al.2009, Riederer, and Foster 2009, Madhuri, Thewari, and Bhowmick, 2014, Simane et al.2016, and Richardson et al., 2018. This study examined socioeconomic vulnerability in selected villages of Gosaba Block by employing its main elements and site-specific sub-indicators. Key variables, including environmental, economic, and social factors, were utilized to assess the levels of exposure, adaptive ability, and sensitivity. Exposure was evaluated by indicators including the nature and magnitude of local environmental change concerning possible threats (frequent cyclones, storm surges, severe rainfall, coastal erosion, riverbank erosion, embankment failure, and rising temperatures) within our community. Adaptive capacity was evaluated through indicators including primary household income sources, income derived from remittances, agricultural and livestock profit generation, absolute distance to markets, household earning status, the establishment of social networks to sustain social safety nets against environmental challenges, and the nature of trust among neighbours. Sensitivity was evaluated through the indicators of sex, respondent age, duration of residence in the region, family composition (both male and female), number of dependent members on earning members, as well as electricity, water security, stability, and cleanliness within the locality. Age, gender, class, and economic status are more important when considering disaster risk reduction (Ayeb-Karlsson et al., 2019). Social variables such as education level, income, and the disabled population are important indicators for risk mitigation (Papathoma-Köhle, et al. 2019). Principal components analysis (PCA) is a statistical method used to determine the optimum linear combinations that accurately represent the data found in a wide variety of variables. Kaiser 1960) proposed the "eigenvalue-greater-than-one" criteria as a method for creating composite indices with PCA. This rule specifies that the number of reliable factors is equal to the number of eigenvalues that are greater than one. Exposure, Adaptive capacity, Sensitivity Index were formulated by weightage of each indicator initial eigenvalues with percentage of variance. This research implements an integrated vulnerability method, as proposed by Madu (2012) and used by Tesso et al., (2012) in Ethiopia, that combines socio-economic and biophysical aspects to create vulnerability indices for each household. Households with more adaptation capacity are deemed less susceptible to the effects of climate-induced pressures, sustaining a uniform level of exposure in this study. The integrated assessment methodology employs socioeconomic and biophysical methods to determine vulnerability. The Intergovernmental Panel on Climate Change (IPCC 2012) established the vulnerability index, defined as the aggregate of adaptive capacity (socio-economic) and sensitivity/exposure (biophysical):

Vulnerability = (Adaptive capacity) – (Sensitivity+ Exposure) Equation (1)

A household is less vulnerable to the consequences of climate change when its adaptation capacity exceeds its sensitivity and exposure, and vice versa. Exposure and sensitivity were both assigned negative values for establishing the direction of association, or sign, of vulnerability indicators. The reasoning is that, assuming ongoing adaptive capacity, households with high exposure to climate shocks are more susceptible to damage. As a result, lower vulnerability lower vulnerability is indicated by a greater net value and vice versa. On the other hand, the scale of analysis plays a crucial role in the index creation. Vulnerability analysis can be done at the local, household, or global levels, as Tesso et al., 2012 pointed out based on Deressa et al., 2008 and Brooks et al. 2005. Scale selection is determined by the goals, procedures, and accessibility of the data. Based on the value of their vulnerability index, the households in this study were divided into three categories: highly vulnerable, vulnerable, and less susceptible. On the other hand, the calculated index does not have an absolute value or rely on thresholds. It is a relative metric that expresses the households' own assessment of their prior level of adjustment in relation to other households. Each household in this case was assigned a category: (1) highly vulnerable, signifying a substantial negative difference between sensitivity/exposure and adaptive capacity; (2) moderately vulnerable, indicating that the difference between sensitivity/exposure and adaptive capacity is almost negligible.

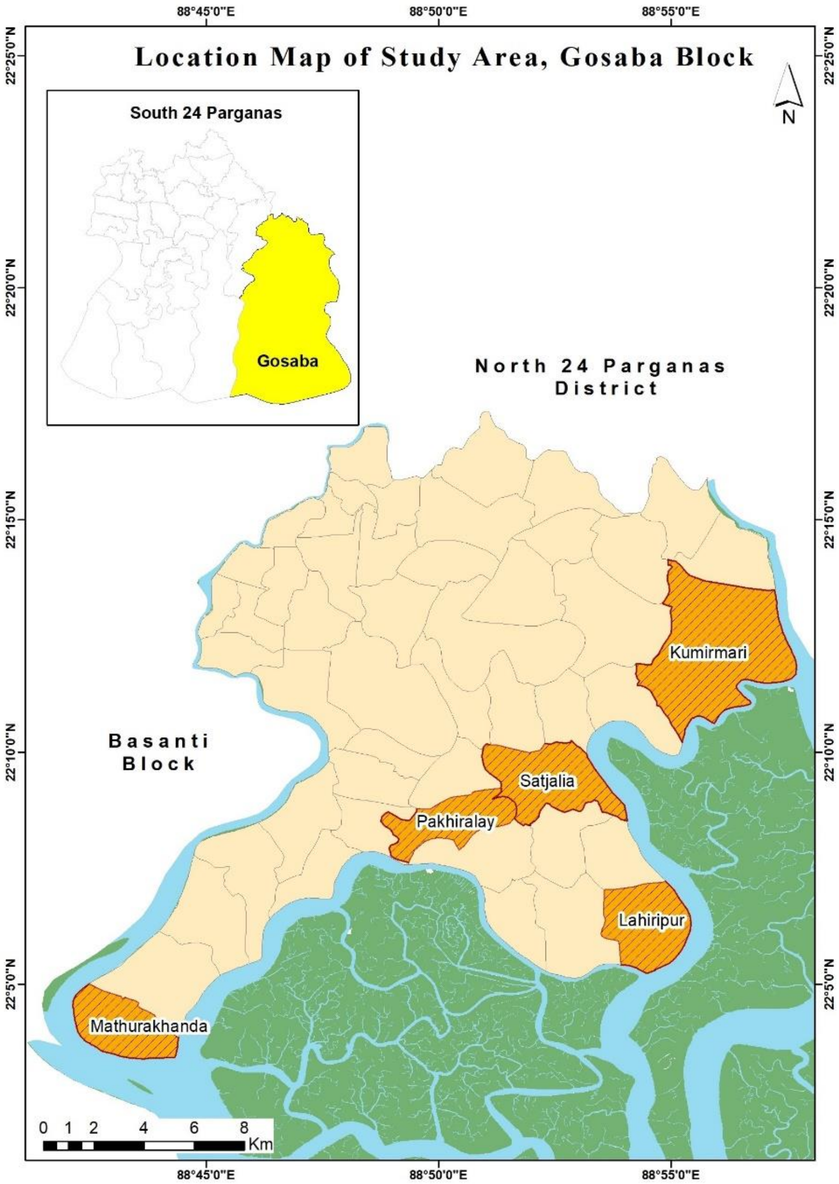

Fig. 1. Location Map of Study Area, Gosaba Block

Table 1. Variables used for Computing Vulnerability Index and ANN

Variable's code	Description of Measurement
Exposure component Variable Environment	Nature and extent of local environmental change for the last 10 to 20 years, nature and extent of local environmental change for the last 10 to 20 years affecting livelihoods (measured on a scale of 1-7), potential environmental threats (frequent cyclones, storm surges, heavy rainfall, coastal erosion, riverbank erosion, embankment breaching, and increased temperature) in our community (1 as the least serious threat to 6 as the most serious threat).
Adaptive capacity Component Variable Economic	Main and Subsidiary sources of household income, distance to markets (absolute distance), income generation from remittances, profit generation from agriculture and livestock (on a scale of 1-7 building a social network to maintain the social safety net to fight against the environment, the nature of trust in neighbours (on a scale of 1-7).
Sensitivity Component Variable Social	Sex, age of the respondent, experiences of living in the area, number of family members (male and female), number of dependent members on earning members, power, water security and stability and sanitation in the locality(on a scale of 1-7).

2.2.2 Artificial Neural Network (ANN)

The accuracy of the multilayer perceptron (MLP) neural network functions was tested using IBM SPSS 26. Artificial Neural Networks are computing algorithms that can tackle complex problems by simulating simplified animal brain processes (McClelland et al. 1986). Three layers make up the neural network architecture used in this study. These layers are commonly referred to as an input layer, a hidden layer that describes the hidden neurons and covers radially symmetric functions and unsupervised learning, and an output layer with a categorical node that enables computation of the index class for the input pattern and the weighted sum from the hidden layer outputs. Data from various sources, including thematic sources, are fed into the input layer, which contains the neurons. The neurons rely on the number of input data sources. This input data is thoroughly processed in the hidden layers, initial output layers, and so on. Trial and error determines the number of hidden layers and the number of neurons in each one (Hagan et al. 1996, Paola and Schowengerdt 1995, Atkinson and Tatnall 1997 Gong 1996, Abraham 2005).The number of output layer neurons is determined by the application and indicated by the type of class analysis. Each hidden neuron interacts with the weighted inputs obtained from the connected neurons of the preceding input layers. Upon calculating the weighted total of inputs for each hidden neuron, a transfer function is employed to ascertain the activation of the respective neuron (Abraham 2005).

In order to develop a model and determine which weight training dataset was utilized, the experiment involved randomly assigning the dataset's various partition rates—ANN1 = 70%–30%–0%, ANN2 = 80%–20%–0%, and ANN3 = 60%–40%–0%—for training, testing, and holdout. Testing data is used to find errors and prevent overtraining in training mode. The holdout data is used to validate the model. Only data from the training set was used, and all covariates were normalized using the formula (xmin)/(maxmin), whose values should be between 0 and 1. Variables used to build the ANN are based on exposure, adaptive capacity and sensitivity components along with associated variables of Gosaba block (Table 1).

3. RESULTS AND DISCUSSION

3.1 The Overall Vulnerability Index

The aggregate vulnerability index was calculated by adding the composite vulnerability sub-indices for exposure, sensitivity, and adaptive capacity (Equation 1). Based on this methodology, 156 households (97.5%) exhibited an extremely high vulnerability index, whereas 4(2.5%) households demonstrated a moderate vulnerability index. After the calculation of aggregate components value in exposure, sensitivity and adaptive capacity and composite vulnerability index for the200,240,160 and160 units of study for the Sagar, Kultali, Gosaba and Hingalganj Block respectively, the units were again categorised into four groups using Standard Deviation (SD) as an interval from 'mean' score. Therefore, further categorization of Household based on Vulnerability Index are Very High, High, Moderate, Low.70.63%, 25%, 3.13%,1.25% households exhibited the above mentioned vulnerability Index respectively (Fig. 2).

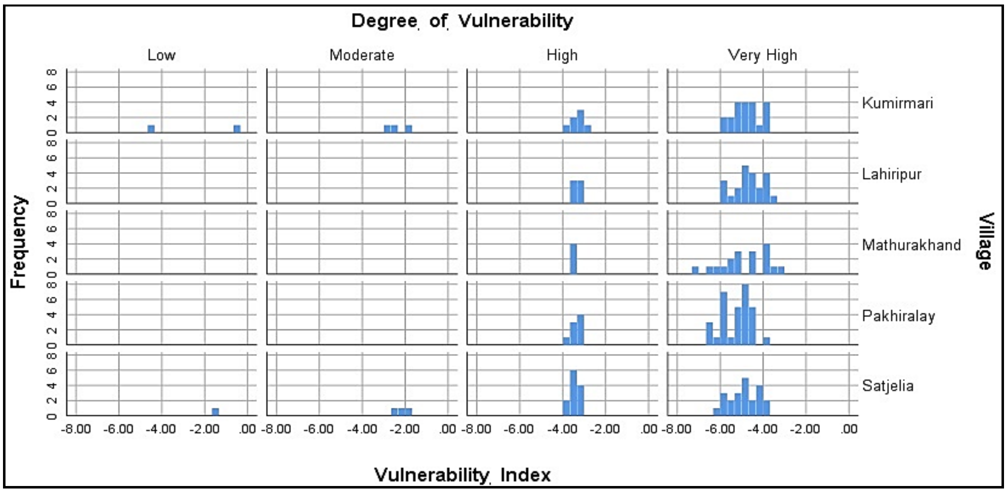

Fig. 2. Village wise Degree of Vulnerability of Gosaba Block

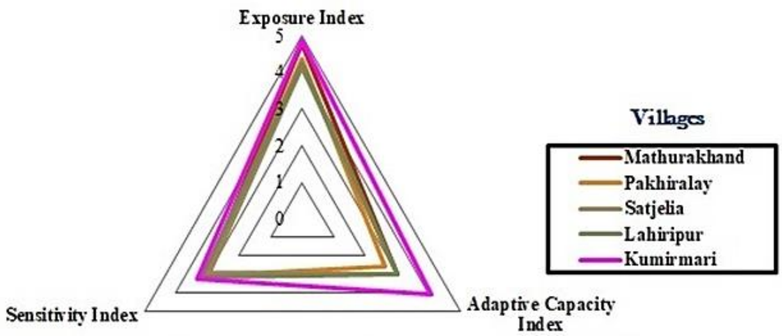

Fig. 3. Schematic Representation of Exposure, Sensitivity and Adaptive Capacity of Gosaba Block

The vulnerability analysis methods suggested by the Intergovernmental Panel on Climate Change (IPCC,2012) identified Mathurakhand, Pakhiralay, Satjelia, Lahiripur, and Kumirmari villages in Gosaba block as needing urgent attention to reduce vulnerability levels. These villages have shown a significant level of vulnerability and sensitivity with minimal adaptability. The priority villages situated at the forest fringe and are facing significant destruction from disasters. Nevertheless, the villages of Kumirmari, Mathurakhand, and Satjelia require appropriate intervention due to their higher adaptive capacity compared to other communities (Fig. 3).

The proximity to markets, Dwelling years, Environmental changes impacting livelihood. Storm surges, Income generated from remittances, Water and sanitation security. Relying on neighbours, Age, Riverbank erosion. Primary source of household revenue, Income generated from agriculture and livestock. Family size and the establishment of social networks are some of the Environmental Risk Variables and variables related to Livelihood conditions make Gosaba Block vulnerable. Adaptive capacity and vulnerability have an inverse relationship. Therefore, a village with a greater adaptation ability is more resilient to environmental pressures. Income and social security are factors that might be seen as variables affecting adaptive capacity. Increased income correlates with an increased likelihood that a family will be able to handle difficult circumstances. Efforts should focus on enhancing the adaptive ability in these areas by upgrading basic infrastructure, providing improved facilities, and enhancing transportation and communication.

The present research attempted to assess socioeconomic vulnerability in five villages in Gosaba Block. A field-based micro-level study helps us better comprehend the complexities of socioeconomic vulnerability. Data availability for a certain variable becomes a difficulty when undertaking a meso- or macro-level investigation using secondary data. The combination of local factors and family questionnaires allows researchers to investigate many facets of socioeconomic vulnerability (Fekete et al. 2010). While studies at the meso or regional level (Bahinipati 2014, Ahammed and Pandey 2019) and macro- or national level (Cutter et al. 2003, Boruff et al. 2005, Boateng 2012) assist in identifying regions of importance within a country, a village-level vulnerability assessment also provides the local government with information about place-based needs and priorities, allowing them to make location-specific decisions. Several studies have used the combination of exposure, sensitivity, and adaptive capability to estimate vulnerability (Cutter et al. 2008, Torresan et al. 2012, Ahsan and Warner 2014, Le 2019).The framework has been changed and adopted in accordance with the current study. Overall, settlements in the Indian Sundarban remain vulnerable in terms of basic infrastructure. In this circumstance, any climate extremes will increase their susceptibility, perhaps resulting in the loss of livelihoods, properties, and even lives. To increase resilience, individuals should implement various tactics. To increase people's adaption, the welfare of the residents should be prioritized (Biswas and Nautiyal 2020). Social capital has been shown to play a crucial role in adaptation (Le 2019). The current study found that persons who had higher access to social and financial capital recovered faster.

3.2 Artificial Neural Network (ANN)

The primary objective of this study was to assess the predictive capabilities of a Multi-Layer Perceptron (MLP) neural network in determining the influence of environmental, economic and social variables of the components exposure, sensitivity and adaptive capacity on the degree of vulnerability. ANN displays the number of neurons in each layer as well as the 23 parameters. Automatic architecture selection assigned 209 nodes to the input layer, 10 nodes to the concealed layer, and 4 nodes to the output layer for coding the dependent variable degree of vulnerability. The activation function for the hidden layer was the hyperbolic tangent, while the output layer utilized the softmax function. Cross entropy was utilized as the error function due to the softmax function.

As shown in, the summary for the designed models provides information regarding the training (and testing) and holdout samples. During the training phase, the neural network minimizes its error function. The ANN1 model was found to have the lowest cross-entropy error (.008), indicating the model's ability to predict the influence of exposure, sensitivity and adaptive capacity on the degree of vulnerability. According to the research findings, the ANN1 model generated 3.2% and 7.1% of erroneous forecasts on the training and testing samples, respectively. The training procedure was carried out until one consecutive step occurred in which the error function did not decrease (Das et al. 2022).

Table 2 displays a classification table (i.e. confusion matrix) for categorical dependent variable degree of vulnerability, by partition and overall. The predicted outcome by the ANN3 model for each case was defined as correct if the predicted probability was bigger than 0.5. The ANN1 network correctly classified 98.9%,96.6% of Predicted Very high, High,33.3% Moderate and 100% Low Degree of vulnerability measured by the four categories in the training data sample and 100%,87.5%,0%,0% Predicted Very high, High, 33.3% Moderate and 100% Low Degree of vulnerability in the testing sample. Overall, the designed model ANN1 properly classified 96.8% of the training cases and 92.9% of testing cases.

The ANN1 model was validated by the ROC curve, which illustrated classification performance for all possible cut-offs in terms of sensitivity and specificity. The measures of Sensitivity and specificity for the designed ANN1, ANN2, and ANN3 were represented by Area under the curve (AUC), which displays the complete position of the ROC curve according to the two categories of the degree of vulnerability as the ANN study variable. The maximum AUC =.999, .992, .975 and 1.000 (ANN1) for very high,high,moderate and low degree of vulnerability indicates that if the Predicted degree of vulnerability are selected at random, there is a 999, .992, .975 and 1.000 chance that the model-predicted pseudo-probability for very high, high, moderate and low degree of vulnerability degree of vulnerability.

Based on the training and testing illustrations of the ANN1 model (Fig. 4), the sensitivity and specificity diagram was constructed. The 45-degree line from the upper right angle of the chart to the lower left characterizes the situation of arbitrarily guessing the category. The greater the deviation of the curve from the 45-degree reference line, the more precise the classification will be.

Table 2. Survey sample classification of the ANN model

		Predicted				
Sample	**Observed**	**Low**	**Moderate**	**High**	**Very High**	**Percent Correct**
Training	Low	3	0	0	0	100.0%
	Moderate	0	1	1	1	33.3%
	High	1	0	28	0	96.6%
	Very High	0	0	1	90	98.9%
	Overall Percent	3.2%	0.8%	23.8%	72.2%	96.8%
Testing	Low	0	0	0	0	0.0%
	Moderate	0	0	1	0	0.0%
	High	0	0	7	1	87.5%
	Very High	0	0	0	19	100.0%
	Overall Percent	0.0%	0.0%	28.6%	71.4%	92.9%

Dependent Variable: Degree of vulnerability,
Source: Computed by Authors

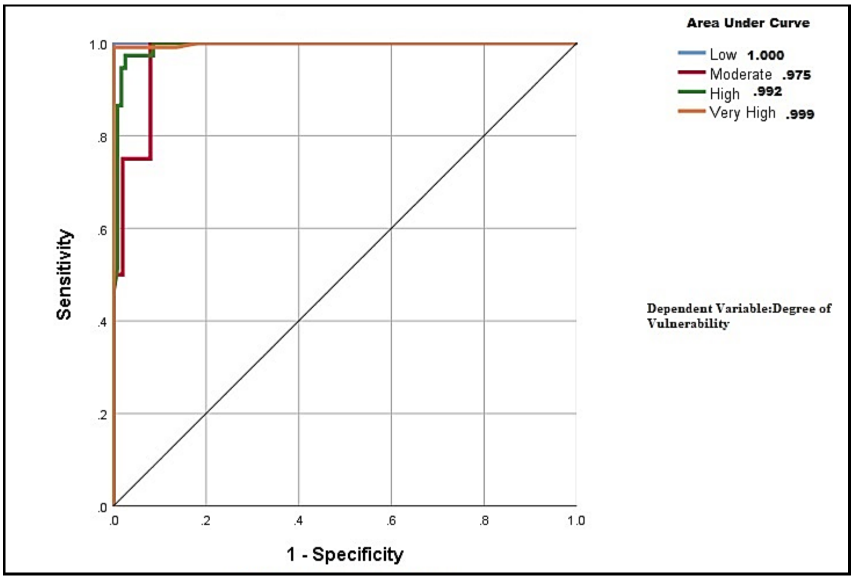

Fig. 4 Area Under Curve

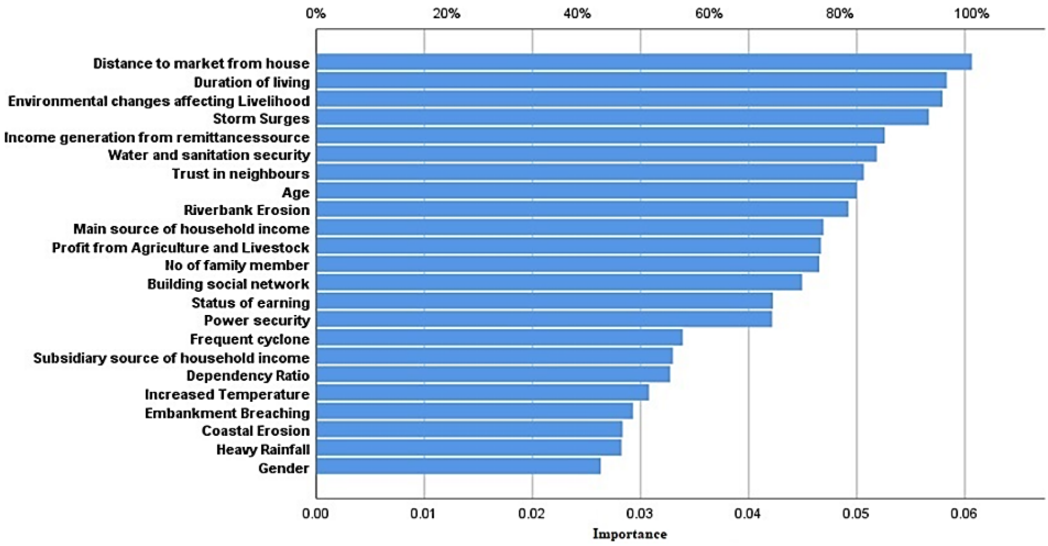

Fig. 5. Normalised Importance of ANN Study Variables of Gosaba Block

Fig. 5 demonstrates the normalized significance of the independent variables as determined by the ANN1 model, highlighting the importance of each variable and the model's sensitivity to variations in the input variables. The proximity of the market significantly impacts the ability of MLP neural networks to forecast the effects of environmental, economic, and social variables on the components of exposure, sensitivity, and adaptive capacity regarding susceptibility levels. Dwelling years, Environmental changes affecting livelihood. Storm surges, Income generated from remittances, Water and sanitation security. Relying on neighbours, Age, Riverbank erosion are significant factors influencing the predicted accuracy of the model.

3.3 Policy Recommendations

Micro-level assessments seek to ascertain the fundamental causes and factors that contribute to vulnerability. Villages are vulnerable due to inadequate socioeconomic and environmental conditions. The settlements in the Indian Sundarban have persistently increased vulnerability index scores, indicating a necessity for policymakers to promote socio-economic advancement. Alongside social and economic factors, social capital, especially trust, can act as an important source of assistance during calamities. The concept of 'community' ought to be promoted among residents. The authors produced substantial policy recommendations based on the findings. A village-level vulnerability assessment distinctly underscores the socio-economic challenges and necessities. Vulnerability assessment must be implemented across the entire Indian Sundarban region. Local authorities ought to target villages exhibiting higher vulnerability scores. It is essential to acknowledge the distinct needs of the complex socio-ecological system of the Indian Sundarban at the national level. Distinct action plans are essential for various regions when developing national policies concerning a disaster management, social welfare, or resource management. The national government must facilitate effective decentralization of governance to enable local governments to pursue their specific agendas. Further investigation is required to attain a comprehensive understanding of the measures undertaken and to provide more sustainable options. Vulnerability levels vary across time (McLaughlin et al. 2002, Blaikie et al. 2005). Consequently, it is essential to undertake extensive long-term research on a specific location to ascertain its vulnerability with more precision.

4. CONCLUSION

This paper examined the degree of household vulnerability and validated it through an Artificial Neural Network (ANN) prediction model in selected villages within the Gosaba Block of Sundarban, adjacent to both the Sundarban Reserve Forest (SRF) and the Sundarban Mangrove Forest (SMF). This study examined socioeconomic vulnerability in selected villages of Gosaba Block, utilizing its principal components and site-specific sub-indicators. The extent of exposure, adaptive capacity, and sensitivity were examined through three primary variables: environment, economics, and society. The integrated assessment methodology employs socioeconomic and biophysical approaches to ascertain vulnerability. The IPCC's (2012) vulnerability assessment techniques identified the villages of Mathurakhand, Pakhiralay, Satjelia, Lahiripur, and Kumirmari in the Gosaba block as need urgent action to mitigate risk levels. These settlements exhibit considerable vulnerability and sensitivity, with restricted adaptability. Priority villages are situated on the forest periphery and are vulnerable to significant disaster-related damage. The Multi-Layer Perceptron (MLP) neural network illustrates the normalized significance of independent variables using the artificial neural network utilizing the ANN1 model. Proximity to market significantly influences MLP neural networks' assessment of the impact of environmental, economic, and social variables on the susceptibility of components, including exposure, sensitivity, and adaptive capacity. Age of respondent, family size establishing a social network, Storm surges, Supplementary sources of household income Dwelling years, Increased temperature, embankment failure, and earning status substantially influence model predicting efficacy. It is essential to analyze the progression of social and economic aspects related to exposure, sensitivity, and adaptation capacity, focusing specifically on marginalized segments of society. The results offer a comprehensive understanding of the conditions in the Indian Sundarban and may serve as a model for the rest of the region. National disaster management, social welfare, and resource management strategies must each include distinct action plans. The national Government is also encouraged to facilitate sufficient decentralization of governance to enable local governments to address their own objectives.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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SUPPLEMENTARY

Table A1. Computation of Vulnerability Index

Name of the village	Exposure Index	Adaptive Capacity Index	Sensitivity Index	VI(AI-(SI+EI)
Mathurakhand	4.981	2.174	4.2	-7.007
Mathurakhand	4.511	2.003	3.67	-6.178
Mathurakhand	2.963	2.676	3.08	-3.367
Mathurakhand	4.962	2.748	3.43	-5.644
Mathurakhand	5.254	2.497	3.58	-3.51
Mathurakhand	4.366	2.926	2.07	-3.51
Mathurakhand	4.657	3.775	3.1	-3.982
Mathurakhand	4.546	3.232	2.09	-3.404
Mathurakhand	3.79	3.282	4.05	-4.558
Mathurakhand	4.558	2.996	2.42	-3.982
Mathurakhand	4.527	2.893	2.81	-4.444
Mathurakhand	4.431	3.32	2.73	-3.841
Mathurakhand	4.296	3.714	2.7	-3.282
Mathurakhand	4.962	2.748	3.43	-5.644
Mathurakhand	4.882	2.731	2.86	-5.011
Mathurakhand	5.013	3.576	3	-4.437
Mathurakhand	5.685	2.893	3.16	-5.952
Mathurakhand	5.656	2.947	2.61	-5.319
Mathurakhand	5.27	4.48	3.19	-3.98
Mathurakhand	5.708	3.2	2.61	-5.118
Mathurakhand	4.482	3.072	2.02	-3.43
Mathurakhand	5.254	2.497	3.58	-6.337
Pakhiralay	5.282	2.355	3.62	-6.547
Pakhiralay	5.289	2.898	2.18	-4.571
Pakhiralay	4.827	2.625	3.51	-5.712
Pakhiralay	4.855	2.323	2.45	-4.982
Pakhiralay	4.203	3.107	2.69	-3.786
Pakhiralay	4.299	1.684	3.07	-5.685
Pakhiralay	5.015	2.663	3.45	-5.802
Pakhiralay	3.771	1.944	3.39	-5.217
Pakhiralay	4.851	2.506	2.82	-5.165
Pakhiralay	3.249	2.354	3.55	-4.445
Pakhiralay	3.908	2.268	3.09	-4.73
Pakhiralay	3.57	3.184	3.22	-3.606
Pakhiralay	4.905	3.819	1.95	-3.036
Pakhiralay	3.367	3.012	5.4	-5.755
Pakhiralay	4.34	2.316	2.97	-4.994
Pakhiralay	2.356	2.224	3.03	-3.162
Pakhiralay	4.818	2.513	2.43	-4.735
Pakhiralay	4.482	2.173	2.34	-4.649
Pakhiralay	5.015	2.663	3.45	-5.802
Pakhiralay	3.771	1.753	3.39	-5.408
Pakhiralay	4.851	2.506	2.82	-5.165
Pakhiralay	3.249	2.354	3.55	-4.445
Pakhiralay	3.908	2.268	3.09	-4.73
Pakhiralay	3.57	3.184	3.22	-3.606
Pakhiralay	4.905	3.819	1.95	-3.036
Pakhiralay	3.367	3.012	5.4	-5.755
Pakhiralay	4.34	2.316	2.97	-4.994
Pakhiralay	2.356	2.224	3.03	-3.162
Pakhiralay	4.818	2.513	2.43	-4.735
Pakhiralay	5.708	3.314	2.61	-5.004
Pakhiralay	4.482	3.072	2.02	-3.43
Pakhiralay	5.254	2.497	3.58	-6.337
Pakhiralay	5.282	2.355	3.62	-6.547

Name of the village	Exposure Index	Adaptive Capacity Index	Sensitivity Index	VI(AI-(SI+EI)
Pakhiralay	5.289	2.898	2.18	-4.571
Pakhiralay	4.827	2.625	3.51	-5.712
Pakhiralay	4.948	2.425	2.48	-5.003
Pakhiralay	3.863	2.782	2.64	-3.721
Pakhiralay	4.698	2.808	2.89	-4.78
Pakhiralay	4.764	2.541	3.8	-6.023
Satjelia	4.416	2.861	3.81	-5.365
Satjelia	5.159	2.558	3.11	-5.711
Satjelia	5.159	2.079	3.05	-6.13
Satjelia	4.894	3.824	4.02	-5.09
Satjelia	3.959	3.629	2.82	-3.15
Satjelia	4.905	4.394	1.95	-2.461
Satjelia	3.367	3.012	5.4	-5.755
Satjelia	4.34	2.316	2.97	-4.994
Satjelia	2.356	2.224	3.03	-3.162
Satjelia	4.818	2.513	2.43	-4.735
Satjelia	4.482	2.173	2.34	-4.649
Satjelia	1.881	2.241	3.46	-3.1
Satjelia	4.488	2.695	2.56	-4.353
Satjelia	4.363	2.591	1.89	-3.662
Satjelia	4.063	2.019	2.9	-4.944
Satjelia	3.367	2.655	4.02	-4.732
Satjelia	3.367	2.823	3.4	-3.944
Satjelia	3.657	2.555	2.64	-3.742
Satjelia	3.367	2.494	3.35	-4.223
Satjelia	3.29	2.353	2.82	-3.757
Satjelia	4.851	3.575	2.82	-4.096
Satjelia	3.249	3.21	3.55	-3.589
Satjelia	3.908	3.124	2.79	-3.574
Satjelia	3.57	4.788	3.22	-2.002
Satjelia	4.905	5.316	1.95	-1.539
Satjelia	4.63	4.427	3.35	-3.553
Satjelia	3.841	4.388	2.27	-1.723
Satjelia	4.277	3.531	2.7	-3.446
Satjelia	4.551	2.747	2.45	-4.254
Satjelia	4.966	2.748	2.69	-4.908
Satjelia	3.92	3.067	2.3	-3.153
Satjelia	5.194	3.335	3.17	-5.029
Satjelia	5.078	2.555	2.99	-5.513
Satjelia	4.642	3.356	2.74	-4.026
Satjelia	3.084	2.347	2.67	-3.407
Satjelia	4.855	2.131	2.45	-5.174
Satjelia	4.203	3.107	2.69	-3.786
Satjelia	4.299	1.684	3.07	-5.685
Lahiripur	4.366	2.926	2.07	-3.51
Lahiripur	4.657	3.775	3.1	-3.982
Lahiripur	4.546	3.232	2.09	-3.404
Lahiripur	3.79	3.282	4.05	-4.558
Lahiripur	4.558	2.996	2.42	-3.982
Lahiripur	4.527	2.893	2.51	-4.144
Lahiripur	4.431	3.32	2.73	-3.841
Lahiripur	4.296	3.714	2.7	-3.282
Lahiripur	4.962	2.748	3.43	-5.644
Lahiripur	5.015	3.733	3.45	-4.732
Lahiripur	3.771	2.822	3.39	-4.339
Lahiripur	4.851	3.575	2.82	-4.096
Lahiripur	3.249	3.21	3.55	-3.589
Lahiripur	4.363	2.591	1.89	-3.662
Lahiripur	4.063	2.019	2.9	-4.944

Name of the village	Exposure Index	Adaptive Capacity Index	Sensitivity Index	VI(AI-(SI+EI)
Lahiripur	3.367	2.976	4.02	-4.411
Lahiripur	5.485	3.18	3.61	-5.915
Lahiripur	4.81	3.093	3.31	-5.027
Lahiripur	4.674	3.148	4.35	-5.876
Lahiripur	3.185	3.255	4.86	-4.79
Lahiripur	2.832	2.98	4.01	-3.862
Lahiripur	4.294	1.999	2.97	-5.265
Lahiripur	4.905	3.819	1.95	-3.036
Lahiripur	3.367	3.012	5.4	-5.755
Lahiripur	4.34	2.316	2.97	-4.994
Lahiripur	2.356	2.224	3.03	-3.162
Lahiripur	4.818	2.513	2.43	-4.735
Lahiripur	4.482	2.173	2.34	-4.649
Kumirmari	1.881	2.241	3.46	-3.1
Kumirmari	4.488	2.695	2.56	-4.353
Kumirmari	4.855	2.131	2.45	-5.174
Kumirmari	5.159	3.413	2.81	-4.556
Kumirmari	5.159	3.255	3.05	-4.954
Kumirmari	4.894	5.321	4.02	-3.593
Kumirmari	3.959	4.912	2.82	-1.867
Kumirmari	5.054	4.284	3.84	-4.61
Kumirmari	4.722	4.245	3.21	-3.687
Kumirmari	4.728	4.609	2.8	-2.919
Kumirmari	4.687	6.923	2.72	-0.484
Kumirmari	4.728	5.103	5.71	-5.335
Kumirmari	5.668	5.717	2.84	-2.791
Kumirmari	4.661	4.643	3.06	-3.078
Kumirmari	5.666	4.39	3.25	-4.526
Kumirmari	4.253	5.395	3.76	-2.618
Kumirmari	5.606	3.216	3.4	-5.79
Kumirmari	5.188	5.249	3.68	-3.619
Kumirmari	5.606	3.506	3.39	-5.49
Kumirmari	5.668	4.789	4.11	-4.989
Kumirmari	5.668	3.806	3.27	-5.132
Kumirmari	5.606	3.773	3.46	-5.293
Kumirmari	5.604	5.875	4.27	-3.999
Kumirmari	3.79	3.603	3.75	-3.937
Kumirmari	4.558	2.996	2.42	-3.982
Kumirmari	4.527	3.321	2.81	-4.016
Kumirmari	4.431	3.32	2.73	-3.841
Kumirmari	4.296	3.714	2.7	-3.282
Kumirmari	4.962	3.283	3.43	-5.109
Kumirmari	5.015	3.733	3.45	-4.732
Kumirmari	3.771	2.822	3.39	-4.339
Kumirmari	6.241	3.894	3.6	-5.947
Kumirmari	6.05	3.985	2.77	-4.835

Source: Computed by Authors

Table A2. Network information for case processing

Layer	Partition	Number of Units	Activation Function
ANN1 8-2-0			
Input	80(81.8%)	209	-
Hidden	20(13.2%)	10	Hyperbolic tangent
Output	0	4	Softmax
ANN2 7-3-0			
Input	70(77.6%)	204	-
Hidden	30(22.4%)	13	Hyperbolic tangent
Output	0	4	Softmax
ANN3 6-4-0			
Input	60(67.8%)	201	-
Hidden	40(32.2%)	11	Hyperbolic tangent
Output	0	4	Softmax

Notes: N= number of cases divided for calculations. Standardized rescaling method for covariates; Error Function = cross-entropy. Dependent variable Degree of vulnerability
Source: Computed by Authors

Table A3. Summary for designed models

	Layer Description	ANN1	ANN 2	ANN 3
[1]Training	Cross Entropy Error	**15.447**	31.668	20.706
	Percent Incorrect Predictions	**3.2%**	8.5%	5.9%
	Training Time	**0:00:01.17**	0:00:00.89	0:00:00.70
Testing	Cross Entropy Error	**4.830**	15.984	17.544
	Percent Incorrect Predictions	**7.1%**	14.7%	16.7%

1 Notes: Stopping rule used = 1 consecutive step(s) with no decrease in error. Error computations are based on the testing sample.
Source: Computed by Authors

Table A4. Area under the curve

		ANN1	ANN2	ANN3
		80%-20%-0%	70%-30%-0%	60%-40%-0%
Degree of vulnerability	Very High	**.999**	.977	.991
	High	**.992**	.957	.975
	Moderate	**.975**	.961	.951
	Low	**1.000**	.924	.997

Source: Computed by Authors

Table A5. Independent variable importance

Variables	ANN1 70%-30%-0%		ANN2 80%-20%-0%		ANN3 60%-40%-0%	
	Importance	Normalized Importance	Importance	Normalized Importance	Importance	Normalized Importance
Income from remittances	0.037	63.0%	0.064	100.0%	**0.063**	**100.0%**
Proximity to markets	0.040	68.2%	0.061	95.2%	**0.056**	**89.4%**
Age	0.051	86.6%	0.055	86.1%	**0.055**	**87.1%**
Family size	0.040	67.8%	0.048	75.9%	**0.052**	**83.4%**
Building social network	0.042	70.6%	0.042	67.2%	**0.052**	**83.3%**
Storm surges	0.050	83.9%	0.045	71.4%	**0.051**	**80.5%**
Subsidiary sources of household income	0.036	60.4%	0.030	47.3%	**0.050**	**80.0%**
Dwelling years	0.059	100%	0.057	89.7%	**0.049**	**78.3%**
Increased Temperature	0.047	79.4%	0.035	54.5%	**0.049**	**77.8%**
Embankment breaching	0.046	78.2%	0.048	76.2%	**0.048**	**75.9%**
Status of Earning	0.050	84.7%	0.040	62.9%	**0.044**	**70.8%**
Heavy Rainfall	0.045	76.2%	0.032	50.3%	**0.040**	**63.8%**
Environmental changes affecting livelihoods	0.046	77.1%	0.040	63.0%	**0.040**	**63.0%**
Frequent cyclone	0.046	78.2%	0.038	60.4%	**0.038**	**61.1%**
Profit from Agriculture and Livestock	0.039	66.5%	0.034	53.3%	**0.038**	**60.6%**
Trust in Neighbours	0.040	67.3%	0.044	68.7%	**0.037**	**59.2%**
Local environmental Change	0.033	55.5%	0.029	45.5%	**0.037**	**58.4%**
Water and sanitation security	0.044	73.6%	0.050	78.8%	**0.034**	**54.6%**
Electric/Power security	0.047	78.6%	0.043	67.3%	**0.034**	**54.0%**
Main source of household income	0.052	87.0%	0.040	63.4%	**0.033**	**52.2%**
Riverbank erosion	0.042	70.9%	0.037	57.9%	**0.029**	**46.1%**
Number of dependent members on earning members	0.027	45.1%	0.037	58.6%	**0.028**	**44.0%**
Coastal erosion	0.029	49.4%	0.036	57.2%	**0.025**	**40.1%**
Gender/Sex	0.011	19.2%	0.014	22.1%	**0.019**	**29.5%**

Source: Computed by Authors

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