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A Machine Learning Framework for Assessing Systemic Societal Vulnerability to Coastal Flooding

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ABSTRACT

Vulnerability indices are increasingly used to understand why coastal urban communities experience differential flood impacts. However, they are criticised for subjective indicator selection, weighting and aggregation, which rely on researcher judgement and rarely integrate uncertainty. This study develops a machine-learning framework for comparing and ranking household-level vulnerability to coastal flooding in the Lekki Peninsula, Nigeria. The research employed a multi-source dataset, including household surveys, key informant interviews, field observations and secondary data. The expectation-maximisation (EM) algorithm identifies latent vulnerability clusters, while support vector machines (SVMs) model nonlinear relationships to predict household membership. A probability-weighted index and confidence threshold are integrated to quantify classification reliability. The EM-SVM model achieved 98% accuracy on the test dataset, with near-perfect separability, as indicated by an area under the curve of 0.99. Spatial analysis showed that 7.4% of households were highly vulnerable, 68.9% moderately vulnerable and 23.5% had low vulnerability. Five vulnerability profiles emerged; two exhibited relatively high education and, in one case, higher income, but remained moderately vulnerable due to dependence on flood-exposed healthcare and water infrastructure and housing types susceptible to flooding. One profile showed low vulnerability due to lower exposure of healthcare infrastructure and higher self-perceived coping capacity, indicating the role of critical infrastructure reliability and psychological preparedness. The findings reinforce the understanding that vulnerability is systemic and intersectional rather than determined by independent socio-economic attributes. Through this framework, the vulnerability approach reduces bias and offers a transparent, data-driven alternative to conventional approaches, thereby reinforcing the evidence base for equitable flood-risk planning and more targeted adaptation interventions.

1 | Introduction

Flood risk management begins with an in-depth understanding of who is vulnerable, as well as clarity regarding how and why that vulnerability arises (de Bruijn et al. 2022). Without such insight, flood risk policies cannot be effectively implemented to account for the different social dynamics within a community. This clarity forms the critical basis for developing inclusive interventions, enabling policymakers to protect communities more equitably from flood hazards

(Birkmann 2006c; Ziga-Abortta and Kruse 2023). This understanding is important in how vulnerability is defined. In this study, vulnerability is referred to as the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards (UNDRR 2017b). This implies that vulnerabilities are pre-existing underlying conditions, characteristics and qualities of the system that occur independently of the hazard (Cumberbatch et al. 2020). Vulnerability is viewed as systemic

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because it arises from interactions and interdependencies among components within the system, resulting in direct and indirect connections that produce cascading and mutually reinforcing effects on how people are impacted by flooding. In contrast, hazards are physical processes or phenomena that may result in loss of life, injury, other health impacts, property damage, social and economic disruption or environmental degradation (UNDRR 2017a). A disaster, therefore, emerges when these pre-existing conditions intersect with a hazardous event, producing varying degrees of impact across different vulnerability profiles (Cutter 2003; Wisner and Wisner 2004; Ziga-Abortta and Kruse 2023).

Arguably, the concept of vulnerability has undergone a significant transformation in recent years, with research drifting towards a re-evaluation of how vulnerability is framed and measured (Bakkensen et al. 2017). In this, vulnerability may be characterised by three distinct paradigms that began in the 1990s Blaikie et al. (1994) and Cutter (1996), where the focus was on identifying who was vulnerable. By the 2000s, attention shifted towards where vulnerability occurs, emphasising spatial patterns through vulnerability mapping (Bankoff et al. 2013; Percival et al. 2019; Weis et al. 2016). More recent work has moved further, examining how different social groups experience disaster impacts and developing vulnerability profiles that capture recurring patterns of vulnerability within communities (Lapietra et al. 2024; Tate et al. 2025). These profiles group shared characteristics into identifiable archetypes, helping to reveal underlying vulnerability processes and informing strategies for disaster risk reduction (Akindejoye et al. 2025; Carolle Da et al. 2022; Tate et al. 2025). Different social profiles may have distinct lived realities of flood impacts, influenced by their pre-existing conditions, which may either amplify or reduce their vulnerability to hazards (Bullard 2008; Finch et al. 2010).

1.1 | Case Study

Lekki Peninsula lies along the Atlantic coast of Lagos and has gradually become one of the city's main growth corridors, linking Victoria Island with newer industrial areas (Fasona et al. 2023; Obiefuna et al. 2021). As shown in Figure 1, the peninsula is approximately 10km wide and about 80km long (Obiefuna et al. 2021). Despite high-end real estate growth, the area contains socioeconomic inequalities, with pockets of low-income settlements where residents often work as service providers for wealthier households (Olajide 2015). In some cases, some of these settlements have been demolished for redevelopment, like the Makoko community (Adegbola et al. 2016; Olajide 2015). These socioeconomic disparities influence differential flood exposure and recovery, producing a recovery gap between social groups (Ajaero 2024; Houston et al. 2021).

The Lekki Peninsula has a long history of coastal flooding, with events recorded since the 1940s (Adelekan and Fregene 2015). Between 1986 and 2020, 33 floods, including 10 ocean surges, were documented across communities such as Okun Alfa, Okun Ajah and Lafiaji (Zhou et al. 2021), indicating an average of at least one flood per year. Hazard maps consistently identify Igbon-Efon, Osapa and Ajah as highly flood-prone (Alfieri et al. 2013; Climate Central 2023), with recent events in July

2021 and July 2024 which flooded multiple wards. Flooding in Lekki arises from interacting meteorological, geomorphological and urbanisation-related drivers (Atufu and Holt 2018; Obiefuna et al. 2021). The wet season, which runs from April to October, brings intense rainfall that coincides with rapid land-use change and reduced natural drainage (Obiefuna et al. 2021; Ogolo et al. 2024). All year round, the Lekki coastline is exposed to oblique long swells generated in the southern Atlantic Ocean, which propagate towards Lagos and produce a characteristic wavelength of approximately 1.36m, contributing to a persistent and complex coastal-flooding regime (Almar et al. 2015).

Flood impacts in Lekki have been severe: the 2012 flood affected about 5000 residents and the 2021 compound event caused roughly 100 fatalities and US\$320 million in losses (Ndimele and Emmanuel Ojewole 2024). Later, floods displaced hundreds more (NEMA 2022), with floodwaters often remaining stagnant for up to 4 days before receding (Adelekan 2010). Recovery support is offered by self-help groups, community networks and charities (Adegun 2023; Chigozi Igwe et al. 2016; Soneye 2014). Although government agencies provide occasional technical and humanitarian support through temporary shelter, dredging or public-health services, such support is often limited (Abubakar and Shafii 2025). Although private flood insurance exists, uptake is low due to affordability constraints, optimism bias and distrust of claims processes, with coverage mainly among larger firms and developers (Adelekan 2014; Nkwunonwo et al. 2016; Ogbonna and Umeh 2023).

2 | Systemic Societal Vulnerability

Vulnerability is conceptualised as systemic societal vulnerability (SSV), which encompasses the vulnerability of social, biophysical and critical infrastructures (Figure 2). SSV adopts a holistic perspective, recognising that no element functions in isolation; they form a complex web of interconnected systems. The SSV framework is informed by the political ecology approach (Oliver-Smith 2013; Wescoat 2015) and the Pressure and Release (PAR) model (Awal 2015; Blaikie et al. 1994; Frantzova et al. 2008; Marchezini et al. 2017). Both schools of thought associate the root cause of vulnerability with political, social and economic structures. They argue that marginalisation, historical processes, discrimination, inequality and systemic pressures influence the conditions that make communities vulnerable to hazards. Further to this, the Hazard-of-Place (HOP) model (Cutter 1996) is integrated to capture how vulnerability developed spatially through the intersection of biophysical risk and social characteristics such as socioeconomic status. This perspective positions the SSV as a multifaceted framework and reveals how vulnerabilities can cascade through a system, resulting in disproportionate impacts on different profiles within a community.

The systemic societal vulnerability profile (SSVP) refers to the classification of households based on shared pre-existing and inherent characteristics that influence their susceptibility to harm (Akindejoye et al. 2025). Rather than aggregating indicators into a single index, the SSVP approach groups entities according to recurring patterns or archetypes (Merino et al. 2018). These classifications form context-specific typologies that indicate the probability

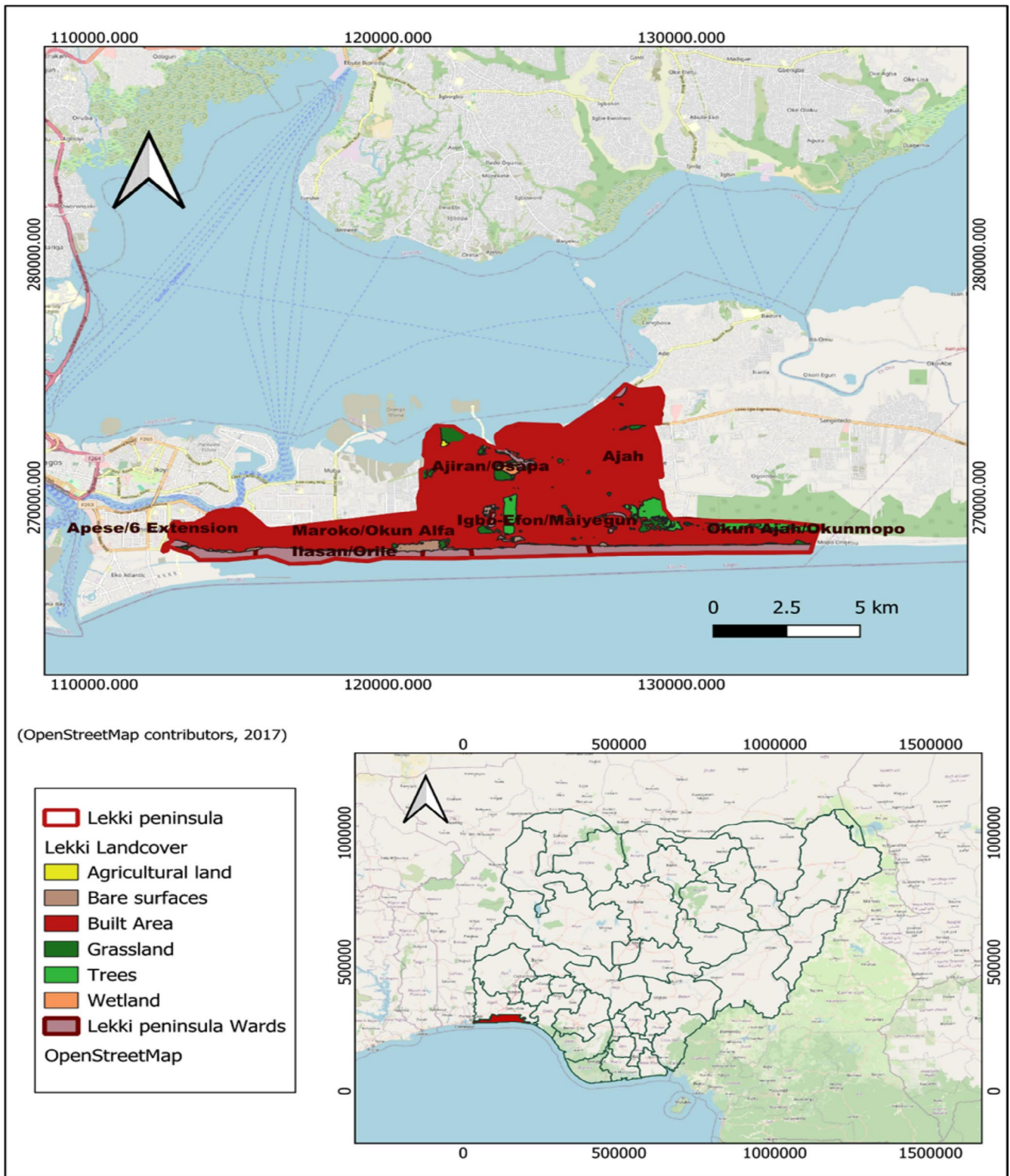


FIGURE 1 | Map showing the Lekki peninsula in Lagos, Nigeria.

of households belonging to vulnerability groups. Indicators may converge based on their interactions, creating trends not necessarily restricted by geographical boundaries (Tate et al. 2025).

The SSVP approach serves two main purposes. It serves as an explanatory tool for identifying the root causes of vulnerability and showing how different social profiles interact

with hazards to produce unequal impacts (Di Baldassarre et al. 2026). This clarifies why some groups face greater risk within interconnected systems (Di Baldassarre et al. 2026; Sietz et al. 2011; Singh 2014). It also guides strategic planning by informing targeted mitigation and system-level governance responses (Danaa and Thorlund 2022; Schweizer and Juhola 2024; Tate et al. 2021). SSVPs show intersectionality

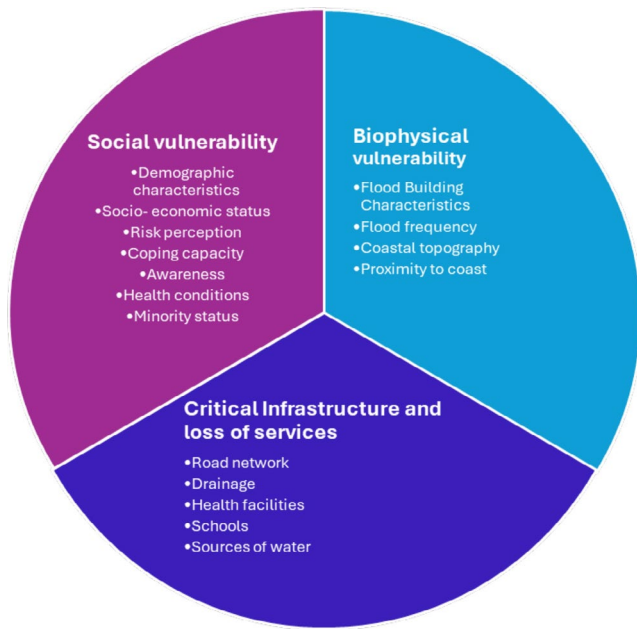


FIGURE 2 | Systemic societal vulnerability framework.

by indicating how overlapping disadvantages such as low income, unemployment, disability, mobility constraints and marginalised ethnic status, as well as biophysical risk and disrupted access to critical infrastructure, interact to amplify systemic risk (Kuran, et al. 2020). These compounded disadvantages often result in more severe and differential impacts than if each factor were experienced independently (Emrich et al. 2020). Through multidimensional typologies, this SSV approach preserves the specificity and integrity of each indicator, thereby mitigating the information loss and statistical uncertainty inherent in aggregate quantitative indices (Spielman et al. 2020; Tate 2012).

In contrast, index-based methods reduce complex systems into single measurable metrics, which often fail to capture non-linearity or critical thresholds (Akindejoye et al. 2025; de Ruiter and Van Loon 2022; Tate 2012). Their construction requires several methodological choices, such as indicator weighting, aggregation rules and model validation, each introducing potential subjectivity and bias (Joakim et al. 2016). Another limitation is the inadequate treatment of uncertainty, as these approaches typically assume equal confidence across classifications despite varying reliability (Chen et al. 2019; Maranzoni et al. 2023; Zahmatkesh and Karamouz 2017). Also, indicator selection and aggregation are often justified through precedent rather than contextual relevance, or not explained at all (Anderson et al. 2019; De Brito et al. 2018; Fekete 2019; Moreira et al. 2021). Applying a single index to heterogeneous populations with varying socioeconomic conditions and risk perceptions may produce inaccurate interpretations (Tate et al. 2025). It may also obscure intra-community differences by imposing homogeneous criteria on groups whose lived experiences and exposure contexts differ significantly.

Machine learning (ML) presents a feasible pathway to resolve the limitations of the index-based approach by identifying and retaining features based on their objective contribution to model performance and interpretation (Jiang et al. 2024). ML can

model complex, multidimensional and nonlinear relationships among vulnerability indicators, identify latent vulnerability patterns and produce precise vulnerability predictions (Akindejoye et al. 2025; Kyriazos et al. 2024). It performs well with high-dimensional data without restrictive statistical assumptions, preserving data validity even in complex datasets (Maturo et al. 2025; Mire et al. 2021). Through feature-importance and selection techniques, ML can prioritise the most influential determinants of vulnerability (Kalaycoglu et al. 2023). Thus, reducing noise and producing structured vulnerability profiles that reflect intersectional realities and inform flood risk reduction and adaptation strategies.

Recent studies have shown the efficacy of artificial intelligence (AI) and ML in flood risk management. Wang and Wu (2025) found that AI improves flood prediction and early response by providing accurate real-time assessments using diverse data sources such as satellite imagery and hydrological reports. In another study (Nhangumbe et al. 2023) showed that supervised and unsupervised ML methods applied through Google Earth Engine provide efficient and low-cost approaches for flood mapping in data-limited regions. Asitatie et al. (2025) further demonstrated that random forest models integrating Sentinel-2 imagery and geospatial datasets can produce high-resolution flood susceptibility maps, which is a significant advantage over traditional hydrological models. Despite this advancement, most ML approaches on flood risk applications predominantly focus on flood susceptibility (Kaur et al. 2025; Pourzangbar et al. 2025; Waleed and Sajjad 2025), flood risk mapping (Deroliya et al. 2022; Rahimi et al. 2026) and the physical dimensions of vulnerability (Asitatie et al. 2025; Parvin et al. 2022). More efforts are required to transition towards evaluating how these computational tools can integrate multiple dimensions of vulnerability to gain insight into diverse profiles through the lived experiences of affected populations. Also, research must evaluate the efficacy of these models in measuring the reliability of classification outcomes and the degree of confidence associated with each identified profile.

Therefore, this study aims to develop a new approach for comparing and ranking SSVs to coastal flooding by embedding it in a machine-learning framework informed by the lived experiences of households in the Lekki Peninsula, Nigeria. The analysis is guided by three major research questions: How can the machine learning model be implemented and validated to identify systemic societal vulnerability profiles? How are machine learning derived probability scores integrated to quantify the vulnerability assessment's uncertainty? How does this new approach enhance the accuracy of a vulnerability assessment compared to existing methods?

The paper is organised as follows: Section 3 outlines the methodology; Section 4 presents the vulnerability profiles and spatial patterns; Section 5 discusses methodological implications; Section 6 details the study's limitations; and Section 7 concludes with insights for flood-risk planning and coastal adaptation.

3 | Materials and Methods

The integrated machine-learning framework for assessing SSV consists of three components: (a) indicator selection and

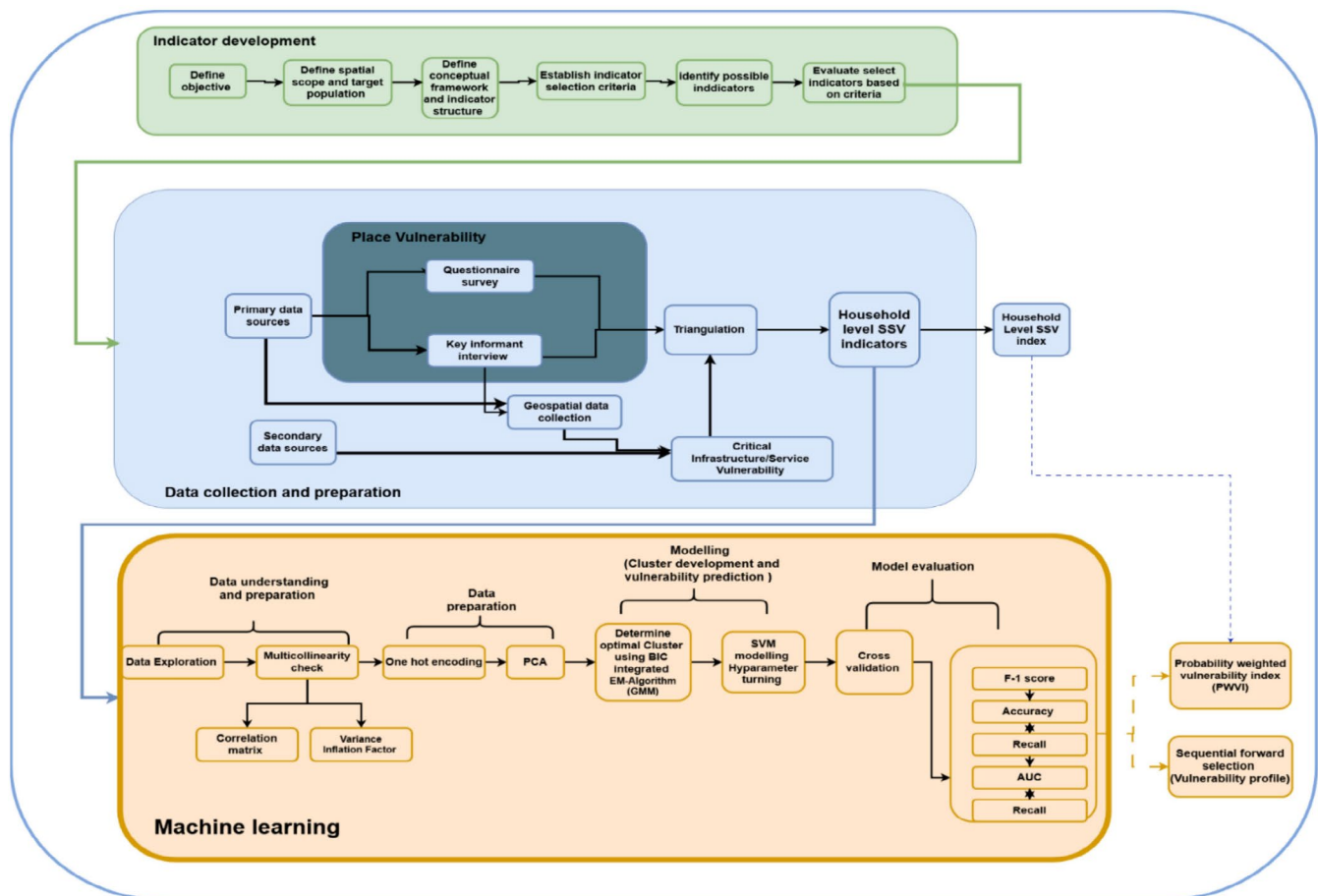


FIGURE 3 | A machine learning framework for systemic societal vulnerability assessment.

construction, (b) data collection and preparation and (c) the machine-learning pipeline (Figure 3). Indicators representing social, biophysical, infrastructural and service-related dimensions were defined and contextualised using primary and secondary datasets. These indicators were then operationalised within a machine-learning workflow combining unsupervised clustering and supervised classification to derive vulnerability profiles and quantify the degree of confidence.

3.1 | Indicator Selection and Construction

This study applies a structured, context-driven selection process informed by Birkmann (2006b) and Niemeijer and De Groot (2008). The process began with a systematic literature review to clarify the study objectives and identify potential indicators. The spatial scope, population and infrastructure networks were defined and vulnerability was conceptualised using the UNDRR definition with modifications for coastal infrastructure. Indicators reflect underlying ontological and epistemological assumptions and were operationalised through household characteristics, exposure to infrastructure and services, adaptive capacity and risk perception, consistent with political ecology and the HOP model. Although Figure 2 presents a broad systemic vulnerability framework, only indicators with reliable and spatially consistent data for Lekki could be implemented. Some indicators, such as flood

frequency, infrastructure reliability, health data and longitudinal recovery information, were unavailable, limiting the representation of some biophysical components. Table 1, therefore, presents indicators adopted in this study; the justification is provided in the Appendix S1.

3.2 | Data Collection and Quantification

A mixed-methods approach was used to contextualise indicators for the case study, including secondary datasets capturing biophysical and infrastructural dimensions. Flood hazard data (100-year return period) were obtained from the Global Flood Awareness System and combined with a 1 km shoreline buffer. Data on schools, healthcare facilities, water supply and road networks were sourced from the Humanitarian Data Exchange and OpenStreetMap. Due to the absence of geospatial data on storm drainage, 340 observation points were generated using spatially proportional random sampling in QGIS. Drain types and conditions were classified using Google Street View and verified through fieldwork. To analyse critical infrastructure and services at high resolution, the seven political wards were subdivided into 20 blocks (B1–B20) based on the Lekki master plan and road network (Figure 4). This scale captured the area's socio-economic heterogeneity more effectively than larger administrative units. Social vulnerability data were collected through a household survey of 1334 respondents using purposive

TABLE 1 | Systemic societal vulnerability dimensions, components and indicators.

Vulnerability dimension	Vulnerability component	Vulnerability indicators
Social dimension	Demographic	Number of children per HH (< 14 years)
		Number of aged parents per HH (> 65 years)
		Gender Female-led HH
		HHs who are lone parents with children
		HHs who are single parents with children and grandparents
		Friends living together
		Single-person HH
	Socio-economic component	HH heads who are unemployed
		HHs who are marginalised workers
		HH heads who are retired
		Student HHs
		Financially unstable HHs
	HHs earning less than 90,000 naira	
	Minority status	HHs who are Non-native speakers
		HHs who are immigrants
	Health characteristics	HH with People with long-term sickness
		HH with an individual Mobility problem
		HH with an individual mental health problem
Adaptive capacity	HH with a short length of residences	
	HH without any form of insurance	
	HH without a history of post-flood assistance	
	HH without social network	
	HH who did not coping despite previous flood experiences	
Risk perception	HH without someone who participates in a flood risk awareness programme	
	HH, who did not cope despite previous flood experiences	
	HH without a recovery plan	
Biophysical dimension	Dwelling characteristics	HH living in a mobile or temporary structure.
		HH whose dwelling unit are bungalow.
	Physical characteristic	HH living hazard zone and 1 km from the shoreline
Critical infrastructure and services dimension	Access to critical services and infrastructure	HHs who live in neighbourhoods with disrupted access to quality water
		HH who live neighbourhood with poor drainage management
		HHs who live in a neighbourhood with a potential loss of access to the road network connecting critical utilities
		HH residing in a neighbourhood where the healthcare facility is exposed to flooding
		HH who live in the neighbourhood where the educational facility is exposed to flooding

sampling, which was guided by the need to include households with direct flood experience, ensuring that the sample captured those most affected by past flood events and therefore most relevant to the study objectives. Fourteen key informant interviews provided contextual insights. Interview data were thematically analysed and indicators were finalised through triangulation of qualitative and quantitative evidence. A full description of the data collection and indicator-development process is detailed in (Akindejoye et al. 2025).

3.3 | Machine Learning Approaches to Systemic Societal Vulnerability

The triangulated dataset was imported into Google Colab, a cloud-based environment, where the analysis was conducted in Python. Preliminary checks assessed missing values, outliers, distributions and multicollinearity. Variance inflation factor values for all 23 predictors were below 5 (maximum 1.83), indicating no multicollinearity. Categorical variables

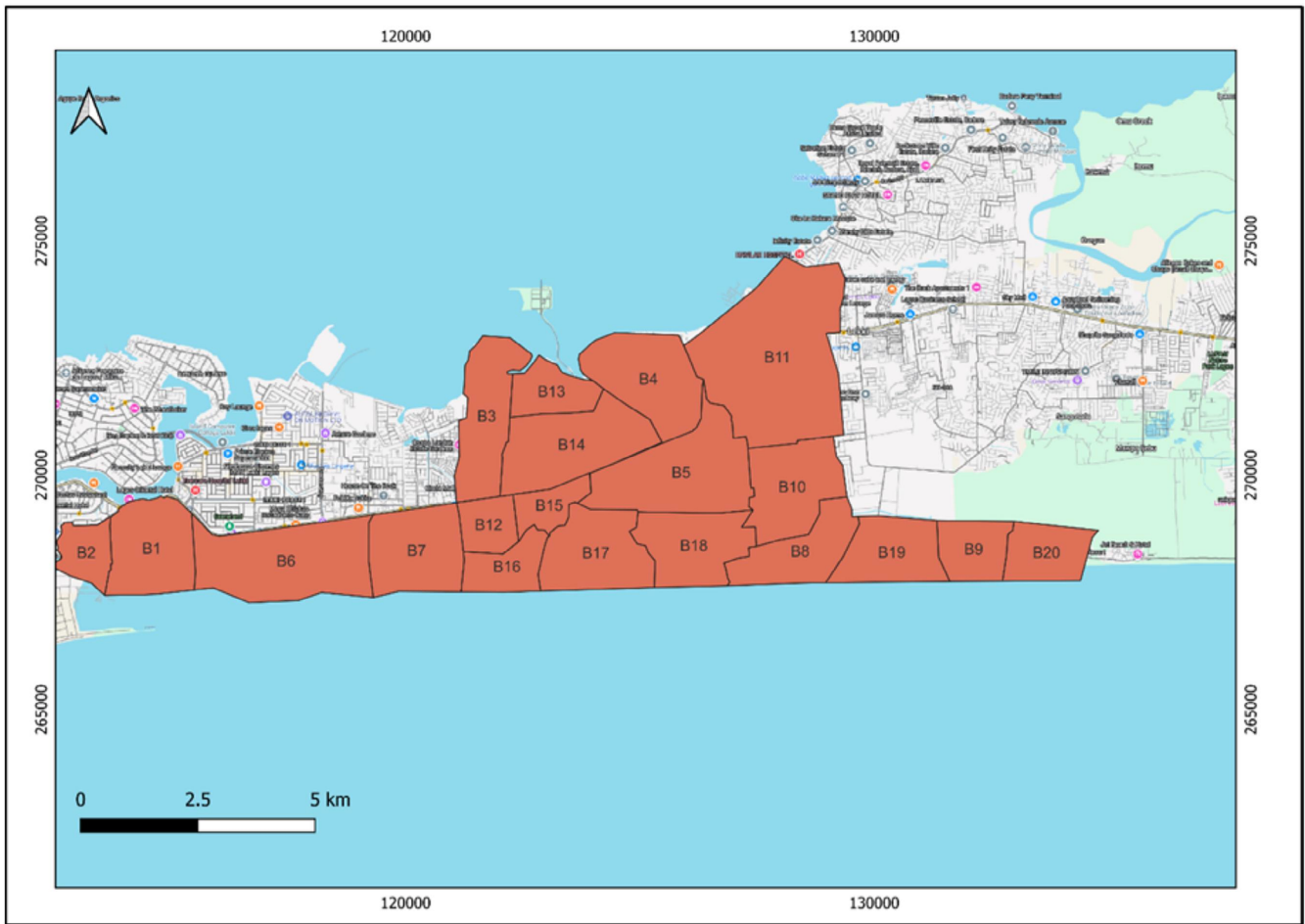


FIGURE 4 | Lekki Peninsula division by blocks.

were converted into a numerical format using one-hot encoding (Okada et al. 2019). The one-hot encoding is a prevalent method of accessing multiple-class classification tasks (Rodríguez et al. 2018), by creating binary variables for each unique category within a feature, assigning a value of 1 if an observation belonged to that specific group and 0 otherwise (Seger 2018). It was applied to indicators such as gender, education, flood awareness, financial stability, housing characteristics and coping capacity. Variables with numerous unique values, including age and two infrastructure indicators, were retained in their original form to avoid excessive dimensionality. This encoding process increased the dataset's dimensionality, expanding the number of features from an initial 23–79, as shown in Table 2. While this transformation allowed for more flexible modelling, it also introduced challenges such as higher computational complexity and the potential for increased noise. To address this expanded feature space and reduce redundancy, Principal Component Analysis (PCA) was applied. The PCA was set up to retain 95% of the cumulative explained variance (Jolliffe and Cadima 2016). This process transformed the 79 encoded features into 47 orthogonal principal components, preserving 95% of the total variance in the dataset. The cumulative explained variance is illustrated in Figure 5. The 47 principal components at the household level were passed on within the pipeline for clustering.

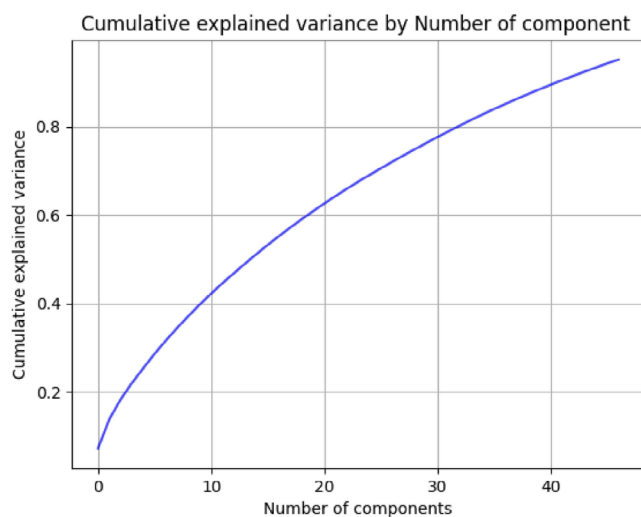
3.3.1 | Expectation-Maximisation Algorithm (EM)

The study adopted an EM algorithm for the clustering of household vulnerability and the identification of latent patterns. This approach is suitable for datasets with uncertainty and incomplete information, which commonly occur in self-reported survey data. The EM algorithm is a tool frequently employed for tasks involving latent variables, such as mixture estimation. It provides an iterative solution for finding maximum likelihood estimates of parameters (Sammaknejad et al. 2019; Xu and Jordan 1996). The algorithm consists of two steps: Expectation (E) and Maximisation (M). In the E-step, the conditional expectation of the log-likelihood is estimated with respect to the current model parameters. Whereas the M-step calculates new parameter values that maximise this expected log-likelihood, often referred to as the Q-function (Fadali 2024; Moon 1996). These steps are iterated until the parameters converge. The specific mathematical implementation of the EM algorithm in this research follows the framework of Kasim et al. (2021).

In this study, EM was implemented using a Gaussian mixture model (GMM) and tested for one to seven clusters. The Bayesian Information Criterion (BIC) was used to identify the optimal model, with the lowest BIC indicating the best fit. The results showed that five clusters ($K=5$) provided the optimal grouping.

TABLE 2 | Indicator transformation and feature expansion.

Indicator	Initial format	Transformation	Number of features
Coping capacity	Categorical	One-hot encoding	5
Education	Categorical	One-hot encoding	4
Employment	Categorical	One-hot encoding	5
Financial stability	Categorical	One-hot encoding	2
Flood awareness	Categorical	One-hot encoding	4
Flood recovery plans	Categorical	One-hot encoding	2
Gender	Categorical	One-hot encoding	3
Health conditions	Categorical	One-hot encoding	2
Health infrastructure	Categorical	One-hot encoding	6
House composition	Categorical	One-hot encoding	3
Housing characteristic	Categorical	One-hot encoding	6
Immigrant status	Categorical	One-hot encoding	2
Income	Categorical	One-hot encoding	4
Insurance	Categorical	One-hot encoding	2
Language	Categorical	One-hot encoding	3
Length of residence	Categorical	One-hot encoding	3
Post-flood support	Categorical	One-hot encoding	4
School infrastructure	Categorical	One-hot encoding	5
Social network	Categorical	One-hot encoding	2
Water infrastructure	Categorical	One-hot encoding	9
Age	Continuous	Retained	1
Drainage infrastructure	Continuous	Retained	1
Loss of access (roads)	Continuous	Retained	1

**FIGURE 5** | PCA cumulative explained variance.

These five clusters were subsequently used as target classes for the SVM in the supervised learning stage and would be referred to as classes within the SVM.

3.3.2 | Support Vector Machine (SVM)

SVMs are ML algorithms capable of modelling complex relationships and non-linear decision boundaries (Howley and Madden 2005). SVMs are a discriminative approach that consistently yields optimal hyperplane parameters by solving a convex optimisation problem through quadratic programming (Sahana et al. 2024). Compared to the multi-layer perceptron and genetic algorithm classifiers, which vary with each training initialisation because they attempt to minimise training error, which can lead to multiple hyperplanes satisfying this requirement (Awad and Khanna 2015). For a given kernel function that maps input data to a higher-dimensional feature space, training an SVM model yields distinct features for each dataset. SVMs aim to find the ideal decision boundaries that best separate different classes (Cortes and Vapnik 1995; Pal and Mather 2005). For linearly separable, two-class problems, SVMs select the linear decision boundary that minimises generalisation error by maximising the margin (Cortes and Vapnik 1995). The margin is described as the summation of the distances from the hyperplane to the closest points of the two classes (Pal and Mather 2005). These critical points, known as support vectors, are the elements of the dataset that define the margin and make subsequent predictions. By maximising this margin,

TABLE 3 | Hyperparameter tuning for SVM.

Hyperparameter	Range of values	Best value
Regularization	0.001, 0.01, 0.1, 1, 0.1, 1, 10, 100	100
Kernel	Poly, RBF, Sigmoid	RBF
Class weight	Balance accuracy and none	None
Gamma	1, 0.1, 0.01, 0.001, 0.0001	0.001

TABLE 4 | The evaluation of the radial basis function, polynomial and sigmoid function.

Kernel	Accuracy	ROC AUC	Macro F1-score
Radial basis function	0.98	0.99	0.94
Sigmoid	0.95	0.99	0.90
Polynomial	0.95	0.99	0.90

SVMs aim to make their predictions more reliable and less prone to errors on new, unseen data.

To handle such complex and nonlinear relationships, the SVM adopts a kernel trick (Che and Wang 2014). By transforming the input dataset into a higher-dimensional space where linear regression can be applied to construct a separate hyperplane with maximum margin, capturing complex patterns (Demidova et al. 2018). The commonly used SVM kernel functions include linear, polynomial, radial basis function (RBF) kernel and sigmoid kernel (Prajapati and Patle 2010). Model performance was optimised through hyperparameter tuning using GridSearchCV, as shown in Table 3, which systematically evaluates combinations of parameters to identify the best configuration (Verma and Yadav 2024). The dataset was divided into training and test sets (80/20) and models were evaluated using 10-fold cross-validation to maximise balanced accuracy. The predicted vulnerability classes were then developed for each household. Different kernel functions were tested and the RBF kernel achieved the highest evaluation scores (Table 4). This kernel is widely recognised for its ability to model non-linear relationships and maintain strong generalisation performance (Debnath and Takahashi 2002; Ding et al. 2021). The mathematical formulation presented by (Nariswari and Pudjihastuti 2023) is adopted for this study.

Model performance was evaluated using the area under the curve (AUC), accuracy, precision, recall and F1-score. A confusion matrix was used to compare predicted and observed vulnerability classes and assess classification performance (Saeed et al. 2022). The sequential forward selection method was employed to identify the five most influential indicators per class based on the EM-SVM model. Each class represents a specific combination of inherent characteristics influencing flood vulnerability.

3.4 | Probability Weighted Vulnerability Index

To quantify household flood vulnerability, the Probability Weighted Vulnerability Index (PWVI) was developed. This index integrates two main components: the class mean probability prediction derived from the SVM model, and the class household mean of vulnerability indicators. In practice, this means households are not treated as equally representative of their assigned class; instead, their contribution is adjusted based on how confidently the model classifies them. This approach helps reduce the influence of borderline cases that sit near decision boundaries, which might otherwise distort the results. A probability threshold of 0.7 was applied, so households falling below this level were excluded from the class average to improve reliability. Six households were removed in total across Classes 0, 1 and 4. The resulting PWVI values range from 1.0 to 5.0, with scores between 1.0 and 2.33 indicating low vulnerability, 2.34–3.66 representing moderate vulnerability and 3.67 to 5.0 reflecting high vulnerability. The equations used to compute the class average and PWVI are presented in Equations (1) and (2).

$$\mu_c = \frac{1}{n_c} \sum_{h \in H_c}^n \text{SSV}_h \quad (1)$$

where μ_c is the arithmetic mean vulnerability score for class C , H_c set of households assigned to class C , n_c is the number of households in class C and SSV_i is the systemic societal vulnerability index for household h .

$$\text{PWVI}_c = \frac{1}{n} \sum_{i=1}^n (\mu_c \times P_c) \quad (2)$$

where PWVI is the probability weighted vulnerability index for class c , n = number of households in class, μ_c is the mean class SSV vulnerability index and P_c is the mean class SVM probability.

4 | Result

4.1 | EM-SVM-Derived Vulnerability Profiles and PWVI

The EM results, visualised using the first two principal components (Figure 6), indicate that vulnerability in the study area is characterised by a continuous feature space, as observed particularly among Classes 0 and 1. Most households are within transitional zones with overlapping characteristics, supporting the notion that vulnerability is multidimensional. The first vulnerability profile from the model is the educated with a mixed service profile (Class 0), which is characterised by households with education above a bachelor's degree but living in areas where healthcare and water infrastructure are moderately exposed to floods. Most reside in bungalows, which increases flood susceptibility. The class shows an average vulnerability score of 2.92, PWVI 2.88 and a prediction probability of 0.99, indicating moderate vulnerability despite strong human capital.

Affluent households with a mixed service profile are categorised as moderate vulnerability (Class 1). Like Class 0, this

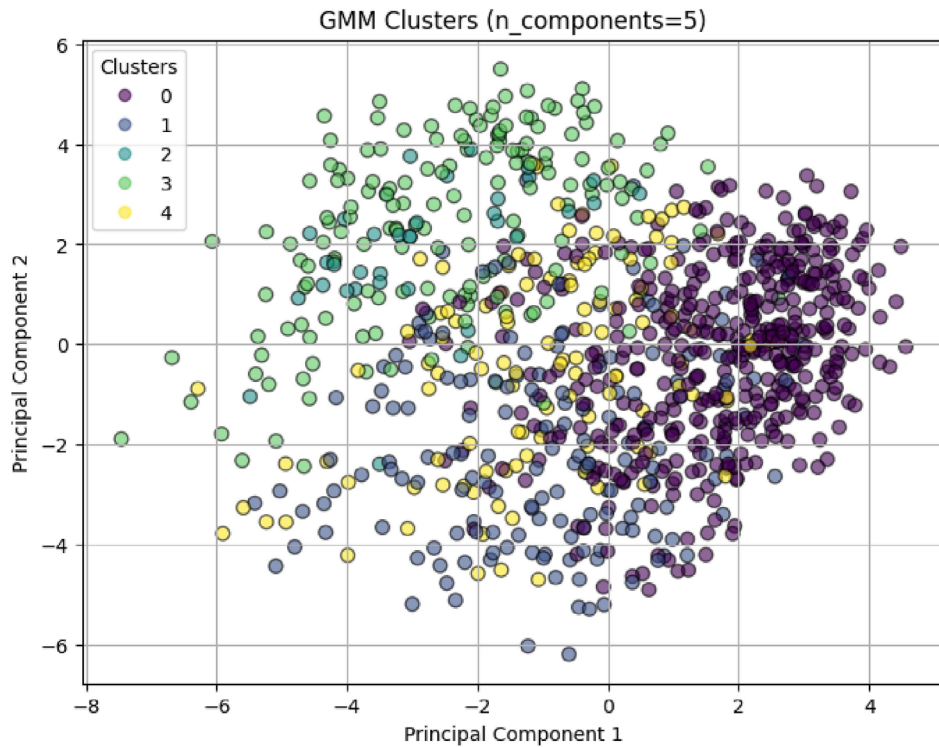


FIGURE 6 | EM clusters (classes) visualised in PCA feature space.

group includes households where the head has an education above a bachelor's degree and earns between ₦150,001 and ₦180,000, indicating a relatively affluent segment of the community. They experience similar infrastructural exposure to Class 0, including moderately vulnerable healthcare and water systems and bungalow housing. The class has an average vulnerability score of 2.73, PWVI 2.67 and prediction probability 0.97, indicating moderate vulnerability despite greater financial capacity. Resilient households with low service exposure (Class 2) are classified as low vulnerability. This class is distinctively defined by households' self-perceived coping capacity: they strongly agree, agree or neither agree nor disagree that they cope with past floods. More importantly, they reside in blocks where the healthcare facility is less exposed to flood hazards. This household profile shows the lowest class average household vulnerability (2.48) and PWVI (2.34). The slightly lower probability of 0.93 is not surprising; as the confusion matrix analysis in Figure 2 shows, this class had more false positives than any other.

Class 3 is the unaware and mixed infrastructure quality profiles. A critical characteristic of this class is that households are not aware of flooding in their neighbourhood, stressing the critical gap in local knowledge or perception. Despite residing in multi-storey buildings constructed with concrete materials that enhance structural integrity, resident still face multiple infrastructural challenges: healthcare facilities are moderately exposed to flood hazards, the connecting road to school is exposed and water distribution pathways are moderately susceptible. With a class average HH vulnerability of 2.76 and a PWVI of 2.68, this class is moderately vulnerable. The last group of households, the uncertain coping capacity with high health risk (Class 4), is ranked as moderate vulnerability. This class

is characterised by households that express uncertainty about coping with floods and reside in blocks where healthcare infrastructure is highly exposed to flooding. Additional pressures include vulnerable water distribution systems and moderately exposed school access routes. The class records an average vulnerability of 2.77, PWVI 2.65 and prediction probability 0.96, indicating moderate vulnerability, largely driven by infrastructural exposure. In addition, the result reveals that 48% of the population belongs to Class 0, while Class 2 has the lowest population distribution. PWVI results were aggregated at the block level to assess spatial distributions (see Figure 7). The results reveal that few blocks had a homogeneous vulnerability distribution. For instance, B1 and B7 are comprised almost entirely of Class 1, while B11 is uniquely dominated by Class 2. Most of the blocks displayed complex mixed class memberships; B10, B12, B13, B15 and B20 show significant internal diversity, with multiple vulnerability profiles overlapping within the same geographic boundary.

4.2 | Evaluation Results of the EM-SVM Model for Vulnerability Classification

The EM-SVM model was evaluated using AUC, precision, recall, F1-score and accuracy, showing strong performance across most classes. Classes 0 and 1 achieved near-perfect results, with training scores close to 1.0 and test scores around 0.99. Class 3 also performed well, though recall dropped slightly to 0.92. Class 4 remained consistent, with precision, recall and F1-scores between 0.96 and 0.97. Class 2 presented a notable challenge, although recall was high (1.0); test precision dropped to 0.64, producing a lower F1-score of 0.78 and indicating poor generalisation for this group, as shown in Table 5. SSV overall accuracy

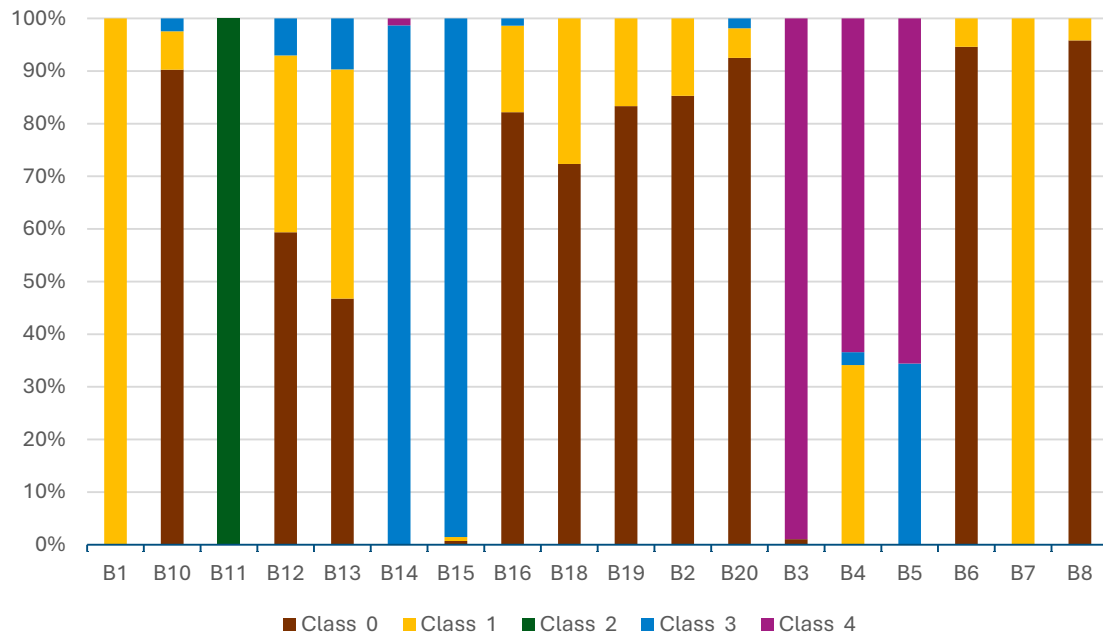


FIGURE 7 | Probability weighted vulnerability index by block.

TABLE 5 | Classification performance metrics: Precision, Recall and F1-score per class.

Class	Precision (train)	Precision (test)	Recall (train)	Recall (test)	F1-score (train)	F1-score (test)
0	1	0.99	1	1	1	0.99
1	0.98	0.99	0.99	0.99	0.98	0.99
2	1	0.64	1	1	1	0.78
3	0.99	0.99	0.98	0.92	0.98	0.96
4	0.97	0.96	0.96	0.96	0.96	0.96

remained high (Figure 8), 99% for training and 98% for testing, suggest strong generalisation, with a similarly strong macro F1-score (0.99 training, 0.98 test) despite the poor precision for Class 2.

The confusion matrix provides a detailed summary of the model's classification performance across each class. As shown in Figure 9, Classes 0 and 1 were classified perfectly with no misclassifications. Classes 3 and 4 showed only minor errors. Whereas Class 2 had the lowest classification accuracy, with 7 samples correctly predicted and 4 misclassified as Class 3, indicating overlap between these vulnerability profiles.

The result from the receiver operating curve, as shown in Figure 10 reveals that the tuned EM-SVM achieves near-perfect separability, and both the micro and macro average AUCs are 0.999. This shows that there is an equally strong performance across the dataset. Class-level curves reveal perfect AUC = 1.000 for Classes 0 and 1 and still an exceptional AUC almost equal to 0.997 for Classes 2 and 4, with all curves rising to a true positive rate of 1.0 at a false positive rate below 1%. In practical terms, the model can capture nearly every positive instance for each profile while committing almost no false positives.

5 | Discussion

5.1 | Implementation of Machine Learning Models for Vulnerability Profiles

The findings on the EM-SVM pipeline in the SSV model open an important discussion in disaster literature about vulnerability assessment. Earlier research, particularly within the political ecology school of thought, argued that vulnerability is not a natural condition but is socially constructed (Oliver-Smith 2013). It rarely follows a linear pattern, which makes quantification complex (Balica et al. 2011; Vatenmacher et al. 2022). Critics like Ranci and Migliavacca (2010) and Rana and Routray (2018) have emphasised that traditional approaches often impose multidimensional realities into static categories. The clustering results from the EM analysis reinforce this argument that households with similar income brackets or education levels were placed in different vulnerability groups when exposure, adaptive capacity, risk perception, minority status, socioeconomic status and access to critical services were considered together. This suggests that vulnerability is better understood as an interaction of systems rather than an isolated component. This supports the views of scholars in socio-ecological Modica and Zoboli (2016) and systems-based approaches (Beevers et al. 2016). In this

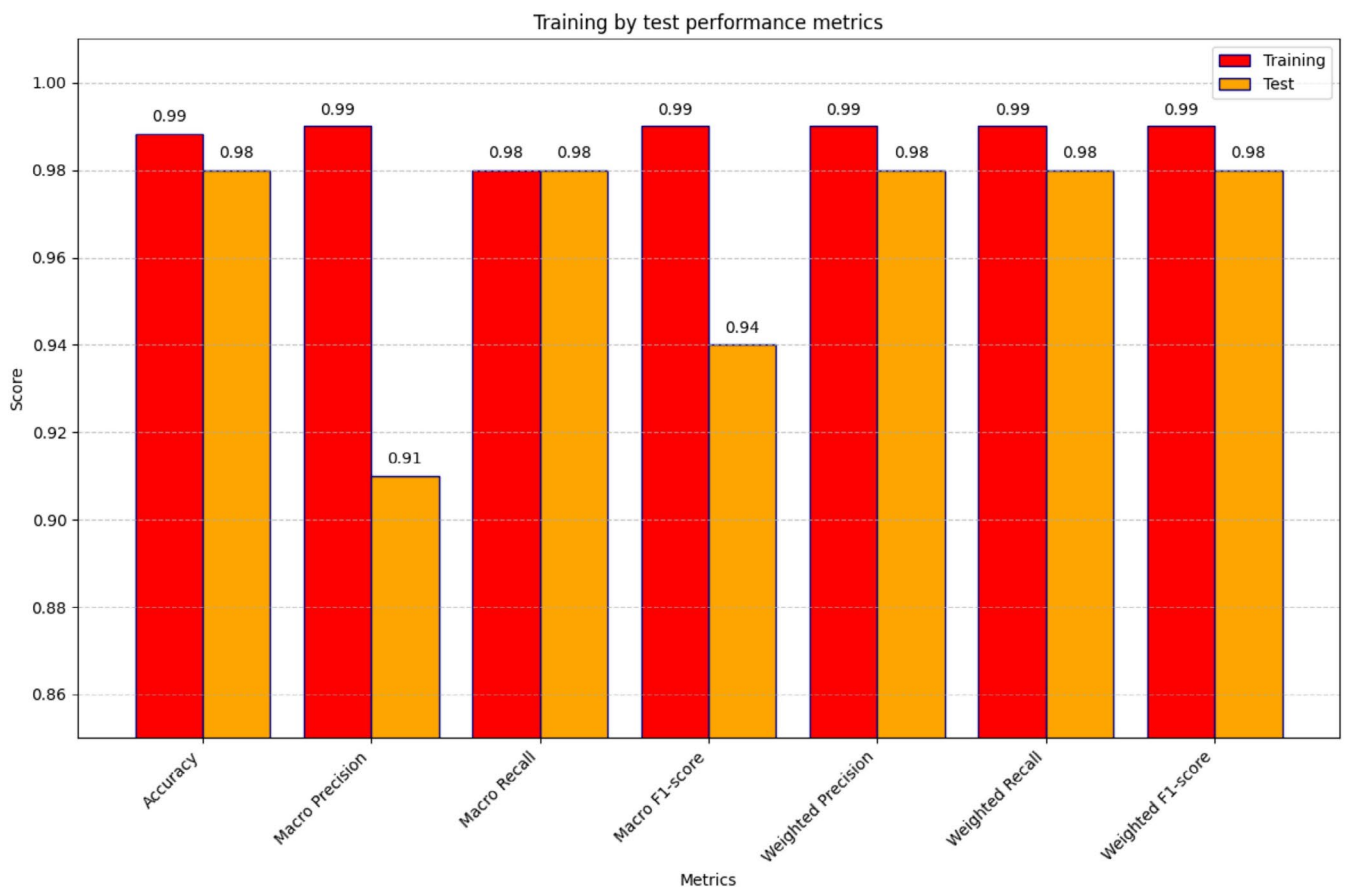


FIGURE 8 | EM-SVM model evaluation result of the overall training and test.

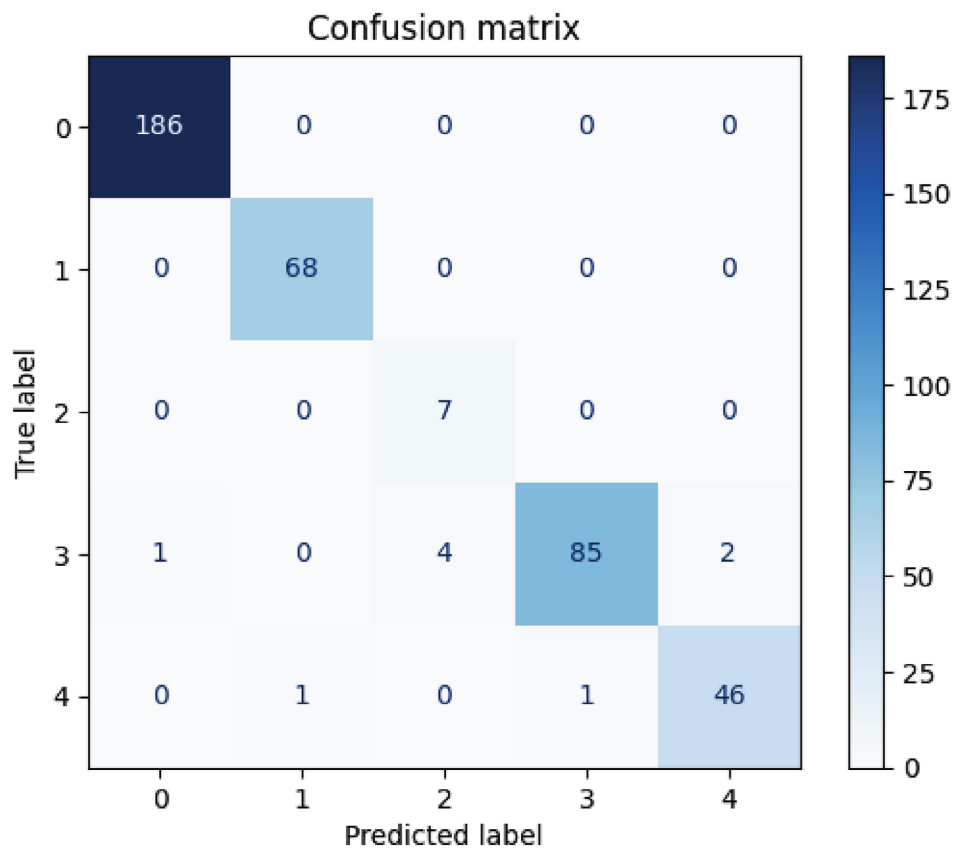


FIGURE 9 | EM-SVM confusion matrix.

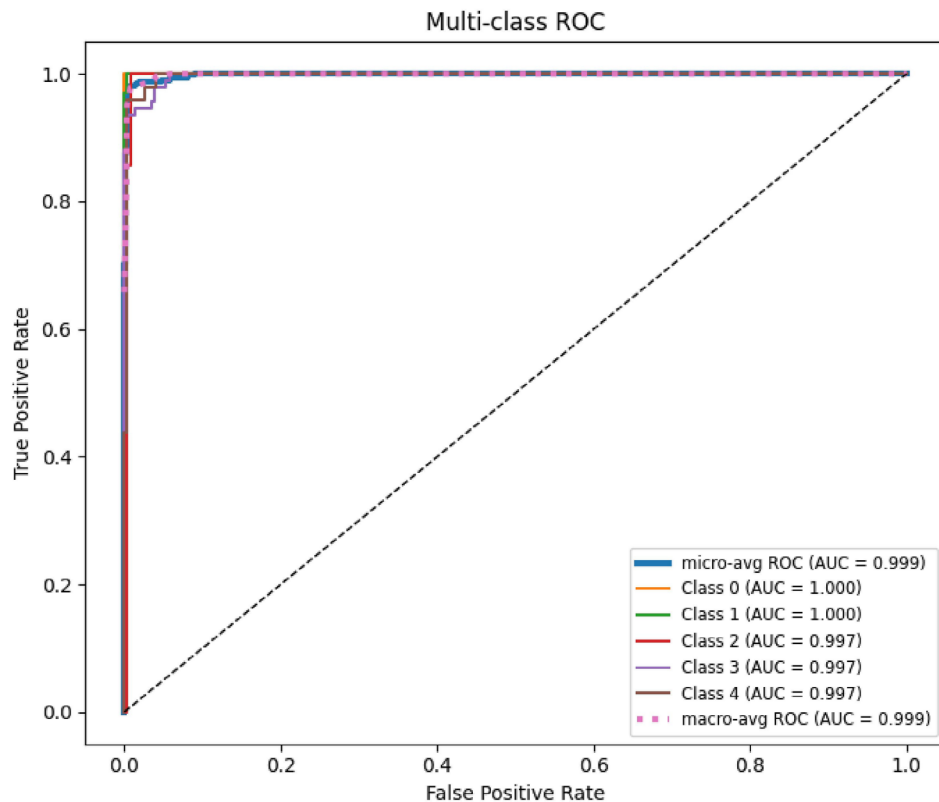


FIGURE 10 | EM-SVM receiver operating curve showing area under the curve.

context, the use of the EM algorithm and Gaussian mixture modelling was relevant because it allowed the clustering of households using inherent characteristics. Rather than assigning households to predefined low, medium and high categories, the EM method allowed patterns to surface by themselves without labels. This resolves one of the recurring criticisms of the vulnerability indicator approach, that predefined classes may mask underlying differences. Studies such as these raise similar concerns, warning that index-based assessments can overlook non-linear relationships or threshold effects (El-Zein and Tonmoy 2017). The five clusters identified in this research indicate that vulnerability categories may be less uniform and even more context-dependent than what is assumed in policy documents.

The study reinforces earlier evidence that Lekki is among Lagos's most flood-vulnerable coastal zones, driven by rapid urbanisation, wetland loss, low-lying terrain and poor drainage (Adegun 2023; Obiefuna et al. 2021). Compared to previous GIS, hydrodynamic or index-based assessments (Dossa et al. 2025; Nkwunonwo 2017; Obiefuna et al. 2021). The EM-SVM framework uncovers heterogeneous household vulnerability profiles within the same hazard environment. Traditional methods show where risk is high (Adegun 2023; Obiefuna et al. 2021), but not why households facing similar exposure experience different outcomes. The present study demonstrates that differences in adaptive capacity, socioeconomic conditions, infrastructure reliability and access to essential services may produce substantial differences in vulnerability under comparable hazards. By deriving groups directly from household characteristics and capturing non-linear interactions, the framework complements spatial hazard mapping and clarifies divergent household impacts.

The SSVP also have operational value: councils, emergency units and infrastructure managers can identify households likely to face evacuation, recovery or service-access barriers. Groups marked by mobility constraints, limited coping capacity or reliance on flood-exposed infrastructure indicate where targeted support, early-warning communication or reinforcement would be most effective.

Kernelized SVMs help capture complex, non-linear boundaries between vulnerability groups. This aligns with recent disaster studies, where scholars such as Ghosh et al. (2019) and Du et al. (2024) stated that social and infrastructural vulnerabilities interact in ways that cannot be separated by simple linear models or additive indices. The F1-scores findings across most classes indicate these non-linear interactions are present and are key to vulnerability formulation in urban coastal environments. Moreover, the debate over weighting schemes also corroborates these findings. Assigning weights to indicators has long been debated, with scholars such as Drakes and Tate (2022), Moreira et al. (2021) and Rufat et al. (2015) questioning why an indicator should carry more influence than another (particularly in unequal weighing methods). Many weighting systems rely on expert judgement, which may not translate across different socio-cultural contexts. This study's use of one-hot encoding offers a more data-driven alternative, though not without limitations. While PWVI improves transparency by linking weights to modelled probability, it still depends on how accurately the classifier captures underlying relationships. This raises some important questions as to whether model-based weighting replaces expert-based weighting, what new assumptions are introduced and how these influence the certainty in the construction of indicator-based vulnerability assessment. This might not

necessarily be a limitation, but it indicates the need to keep questioning the foundational understanding of data-driven assessment methods.

Critiques of composite indices such as Hinkel (2011), Saisana and Tarantola (2002), Wehbe and Baroud (2024) remain relevant. They caution that summing up multiple dimensions to a single index can hide the structural drivers of vulnerability. The EM-SVM framework addresses this by retaining five group-specific profiles, showing how different priority pathways, such as access to infrastructure and services, socio-economic, demographic, adaptive capacity and health-related, intersect to influence vulnerability. This approach is consistent with systemic and intersectional views of vulnerability that are gradually more important to climate adaptation and resilience theory (Chisty et al. 2021; Kuran, et al. 2020; Penny et al. 2018). The interpretation of clusters also relates closely to existing theoretical positions. The higher-income or well-educated groups (Clusters 0 and 1) still experience moderate vulnerability because of systemic exposure, similar to arguments such as P. Blaikie et al. (2014), which reveal that socio-economic advantage does not automatically translate into safety if critical infrastructure is unreliable. In a different view, Cluster 2 presents a relatively low vulnerability, partially determined by good coping capacity and reliable healthcare access, corroborating the views that vulnerability is not solely experienced or personal perception but psychological.

5.2 | Enhancing Accuracy in Vulnerability Assessment

As discussed earlier, traditional vulnerability methods face challenges and criticisms. Most existing methods begin with predefined categories of vulnerability (i.e., low, medium, high) and impose expert-defined thresholds. This has been criticised for reinforcing researcher assumptions rather than revealing how vulnerability manifests in the population (Tate et al. 2025). The EM algorithm addresses this limitation by identifying inherent clusters in the data without predefined categories. This matches with socio-ecological theories that argue vulnerability arises from emergent interactions rather than fixed boundaries (Adger 2006; Birkmann 2006a). EM cluster structure, therefore, reflects observed patterns rather than assumed ones, which enhances the accuracy and validity of interpretation.

Traditional indices rely on linear combinations of indicators, even though vulnerability theory emphasises non-linear feedback and threshold effects (Adger 2006; Fussler and Klein 2006; Rehman et al. 2019; Wisner 2004). For example, being poor does not necessarily mean that a household has low coping capacity (as seen in Class 2), because coping capacity depends on many factors (UNDRR 2017c) and is influenced by more than income. Likewise, having a good education doesn't guarantee awareness (as seen in Class 3) and infrastructure exposure can undermine the socioeconomic advantage a household may present (as seen in Classes 0 and 1). The RBF kernel used with the SVMs captures these nonlinear and intersecting relationships, which are key to producing more accurate classification of households whose vulnerability is influenced by multiple overlapping factors.

Another critique of many vulnerability methods is the arbitrary weighting of indicators (Moreira et al. 2021; Rufat et al. 2015). Although the indicator was associated with values during the computation of the SSV index in this study, these weightings were rendered invalid within the machine-learning pipeline. Once the categorical indicators were transformed using one-hot encoding, each category was represented as a binary variable (0 or 1), making any externally assigned weight irrelevant to model behaviour (neutralised prior weighting). Instead of relying on assumed hierarchical importance, the machine-learning model identifies relationships directly from the data, allowing its internal optimisation process to determine which indicators meaningfully contribute to classification outcomes using sequential feature selection. Sequential feature selection responds directly to this critique by identifying the most influential indicators for each cluster, reducing noise from weak predictors and basing the assessment on observed patterns. This approach advances vulnerability assessment from assumed theoretical weightings to proven empirical relevance.

6 | Limitation

This study used ML to identify five vulnerability profiles, but these profiles are not tied to specific locations. The clustering was non-spatial, grouping households by attributes rather than geography. A block is assigned its dominant vulnerability type even though it may contain mixed household classes. Thus, the analysis highlights areas with high concentrations of vulnerable households but does not claim that any block belongs exclusively to one class. The spatial interpretation of systemic vulnerability is indicative rather than definitive, representing overall block-level vulnerability. Also, a key limitation appears in the classification of Class 2. Its lower precision (0.64) and F1-score (0.78) likely reflect the small sample size and overlap with Class 3, driven by self-perceived coping capacity. As such, distinctions between these two profiles are less reliable, and related policy use should be used cautiously. The EM-SVM framework captures long-term structural vulnerability, rather than short-term or rapidly changing conditions. Event-specific disruptions blocking drainage, restricting road access or temporary loss of healthcare services can severely increase vulnerability but are not represented in these indicators. While some effects may appear indirectly, the model cannot detect severe changes. Findings should therefore be interpreted as underlying systemic vulnerability rather than real-time changes.

7 | Conclusion

We have challenged the existing vulnerability methods using single composite indices and predefined vulnerability categories. It has been observed that vulnerability is non-linear and arises from distinct patterns and complex interactions, rather than fitting rankings. Multiple factors interact through feedback loops; high income does not imply resilience and higher education does not always translate into flood awareness, while infrastructure exposure can amplify vulnerability even among more affluent groups. It means there is a need for policy interventions for flood disasters that ought not be restricted to demographic and socioeconomic assumptions. They must

address systemic and structural drivers such as inequality, governance failures, spatial segregation, poor land-use planning and inadequate infrastructure. The framework also shows that reducing vulnerability requires more than short-term flood response. Therefore, effective interventions must include broader systemic reforms to strengthen resilience across identified profiles.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Questionnaire survey on social vulnerability to floods in Lekki Peninsula. **Appendix S1:** Systemic societal vulnerability dimensions, components, indicators and justification for inclusion. Adapted from Akindejoye et al. (2025).