

A systematic framework for assessing social vulnerability to flood for integrated flood risk management: A case study in Metro Manila, Philippines

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ABSTRACT

Assessing social vulnerability to floods (SVF) is a crucial component of integrated flood risk management, especially in flood-prone regions such as Metro Manila in the Philippines. This study presents a holistic framework to assess SVF, based on susceptibility, exposure, and resilience factors while recognizing its multi-dimensional, multi-attribute, and context-dependent nature. The assessment was applied to three cities of Metro Manila: Marikina, Parañaque, and Manila. Indicators were systematically identified using deductive and hierarchical approaches, and factor indices were derived using a combined Simple Additive Weighting and Analytic Hierarchy Process, while the SVF index was estimated using the vulnerability relationship of the factors. The results exhibit a strong positive correlation with historical social flood damages and robustness across weight and normalization variations, with Marikina being the most vulnerable, followed by Parañaque and Manila. The city-level vulnerability profiles highlight salient determinants such as high population exposure in Parañaque, a relatively high population of susceptible social groups in Marikina, and significant disparity in flood control projects among the cities. Scenario analyses underscore the efficacy of flood countermeasures that reduce exposure and increase resilience. This study offers valuable insights and practical guidance for developing effective disaster reduction plans and policies in the study areas and similar regions by identifying disparities in vulnerability and understanding local conditions and drivers.

1. Introduction

Urban communities are suffering from the devastating impacts of floods, highlighting the need for robust assessments of social vulnerability to floods (SVF). Disastrous floods often occur when a large volume of water brought by heavy rainfall or overflow from waterways temporarily inundates normally dry areas, negatively affecting residing communities. Considering rapid urbanization and the projected increase in flood frequency, more people are expected to be at risk of floods [1].

Flood risk arises from the interaction between hazard (the probability of a flood happening) and vulnerability of the people (the potential to be harmed from the negative consequences of the hazard) [2–4]. Vulnerability is a complex component of risk that

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describes the social dimension of risk yet there is no universally accepted working definition and standard assessment method. Despite this, there is a shared understanding that it is a multi-disciplinary, multi-dimensional, and multi-attribute construct that depends on the conditions of the study area [5]. It is associated with terms such as susceptibility, sensitivity, coping capacity, adaptive capacity, resistance, and resilience when exposed to a hazard. It comes from the Latin word *vulnerare* meaning “to wound” which means “the capacity to be wounded” [6]. In terms of flood risk management, vulnerability analysis requires the indicators of elements-at-risk, exposure, and susceptibility, considering that communities, in general, have a higher potential to be harmed when they are exposed and susceptible to the impacts of hazards [7]. Meanwhile, drawing from the context of climate change adaptation and disaster management, the MOVE Framework expresses vulnerability as having three core factors: exposure (the geographical or spatial component), susceptibility (the social characteristics contributing to potential harm), and resilience (the capacities to reduce negative impacts and maintain the system) [8]. These frameworks consider exposure as a component of vulnerability and have been used in recent studies [9–11]. In contrast, a recent review study [12] found that some studies consider exposure as a separate component; thus, highlighting the complexity and challenges of vulnerability analysis. Focusing on the social dimension of flood risk while considering the three factors, this study describes SVF as the potential of households and communities to be harmed by flood considering their state or characteristics of exposure, susceptibility, and resilience [3–5]. Despite variations in frameworks, SVF is a significant component representing the social construct of risk. Therefore, integrating SVF into flood risk assessments is crucial for comprehensive analysis.

Traditional disaster risk analyses were focused on hazard analysis which prompted global initiatives such as the Sendai Framework for Disaster Risk Reduction stressing the significance of understanding not only hazards but also vulnerability to efficiently mitigate disasters [13]. SVF assessment provides planners and decision-makers with critical insight into the drivers of vulnerability, which helps in developing plans and policies targeted to the identified vulnerable zones to efficiently address the critical issues [5]. Consequently, incorporating this into integrated flood risk management allows for a comprehensive understanding of flood risks in the area. The first step of vulnerability assessment is to determine the guiding conceptual framework [14]. However, the lack of a universal working definition of vulnerability from different frameworks and fields of study has led to various methods of analysis, measurement, and terms used [5,8] such as clustering indicators into sub-indices using factor analysis [10,15,16], semantics [9,17] and systems approach [18,19] to identify indicators in clusters or thematic groups before generating a composite index or no clustering is specified to generate the composite index [20]. In disaster management, it is imperative to identify the critical determinants of social vulnerability. Thus, clustering the indicators into sub-indices is beneficial to have an overview of the factors and easily distinguish the critical factors of vulnerability.

Although there is no standard method of indicator aggregation, previous studies aggregated indicators by summation of the principal components of factored indicators [15,21,22], using the vulnerability equation [18,19] or a similar form such as the fraction of negative and positive contributors to vulnerability [17], a weighted median of the normalized indicators [23], and multiple-criteria-decision-making (MCDM) or multiple-attribute-decision-making (MADM) method [6,11,24] (though not always explicitly stated). MADM method is an umbrella term for multiple tools of decision-making which include the Analytic Hierarchy Process (AHP) and Simple Additive Weight (SAW) or weighted sum which are two of the most used methods for vulnerability and hazard analysis, owing to their practicality and flexibility [25]. Considering the multiple attribute property of vulnerability represented by several indicators, it is beneficial to use a systematic and explicit approach such as the multi-attribute-decision-making (MADM) methods to aggregate the indicators for holistic and realistic vulnerability assessment and risk management planning [5]. Thus, for this study, this approach is employed coupling the AHP and SAW methods.

In terms of presenting results, researchers often used maps [22,26,28] and composite indices [17,20,29] to reflect the relative so between areas of a specified spatial scale. Maps are generated from composite indices and provide a visual aid for planners and decision-makers in formulating risk management plans. Although very helpful in identifying the critical areas, a composite index and map are not enough to present the contributors or critical determinants of vulnerability. Thus, a profile analysis of the vulnerability should also be provided as support in developing programs to reduce vulnerability.

Validation of social vulnerability indices is also a challenge due to the complexity and lack of available data. Thus, this part of the analysis is often not performed in previous studies [12]. Moreover, Tate et al. [26] highlight that neglecting the validation and robustness of methods used might present weak indices for disaster planning. Thus, the vulnerability analysis should include validation of results and/or robustness tests to check variations of results due to changes in methods used to present more reliable outputs.

Vulnerability is affected by the demographic characteristics (such as age, sex and persons with special needs) as well as socio-economic conditions (such as poverty and unemployment) of a particular area [12,16,27]; thus, it varies per community, region and nation [28]. Secondary data from census and official sources are commonly used to measure indicators. The advantage of using such data is that they are readily available and can provide insight into the SVF in the study area. However, there are unobtainable sets of information from these sources, such as the perspectives of individuals on floods, their experiences, and access to information. Such information can only be gathered from a social survey, which also provides more ground information, allowing for a better understanding of the conditions in the study area. Thus, SVF assessment should not only rely on secondary data but also conduct social surveys to gain more insight into the status of the area and validate the information obtained from secondary data.

In Metro Manila, the capital and most densely populated region of the Philippines, floods are frequent, so much so that they appear normal, and often expected when there is heavy downpour, typhoons, or monsoon rains. Since the catastrophic event of 2009, flood disasters have continued in the region. According to the National Disaster Risk Reduction Council (NDRRMC), 13,132 families were affected by the November 2020 flood associated with Typhoon Vamco, 6405 families by the 2021 flood during Typhoon In-fa, and 8867 families in 2022 during Typhoon Nalgae. To mitigate the negative impact of recurring floods, the government has developed and implemented several flood control projects, mostly based on hazard assessment using flood simulations and structural measures. For example, dikes and floodwalls have been constructed along major rivers (e.g., the Pasig River) and their tributaries. In addition, pumps

with floodgates were installed, particularly downstream of the Pasig River and near Manila Bay. Flood early warning systems have complemented these structures but need to broaden coverage and ensure effectiveness [29]. Despite these countermeasures, the current situation indicates that existing practices and plans are inadequate and underscore the prevalent vulnerability of the population to floods. Therefore, there is a need to assess social vulnerability to flood (SVF) and incorporate it into integrated flood risk management.

Despite the persistent floods, comprehensive studies on SVF for integrated flood risk management in Metro Manila and the Philippines are limited. This can be attributed to the challenges in obtaining data and conducting the study. Moreover, the approval and implementation of government plans rely on tangible quantitative data for them to be accepted and funded. Among the early studies related to SVF in Metro Manila, Zoleta-Nantes [30] highlighted that not only poverty but also social isolation and lack of representation in decision-making affect the vulnerability of the community. Applying principal component analysis and using census data to evaluate the social vulnerability index, Porio and See Ref. [15], found that social vulnerability in the region varies per social scale, i.e. household, barangay, and city. Using a similar approach, Ignacio [22] expanded the analysis to a nationwide scale which was updated and validated by Ref. [21]. These studies gave valuable insight into the determinants and spatial differences of social vulnerability in Metro Manila and the Philippines. However, noting that the indicators were clustered into thematic groups and presented in a single composite index, there was no explicit distinction to which vulnerability core factor the themes and indicators are associated with, and the critical determinants are difficult to identify. Factors and indicators contributing to the degree of SVF vary per spatial scale and study area [15,31]; thus, efforts to reduce SVF need to be tailored to the specific conditions of the study area. For planning and policymaking, it is useful to assess SVF by considering the key factors and applying a systematic and explicit approach that reflects the transparency of the indicators and their contribution to vulnerability. To effectively assess the SVF in Metro Manila, there is a need to provide a comprehensive, updated, and practical assessment of SVF applicable to the context of Metro Manila.

Building upon the identified limitations in existing vulnerability assessment for integrated flood risk management this study proposes a comprehensive framework for assessing SVF in Metro, Manila Philippines. This framework integrates the key vulnerability factors of susceptibility, resilience, and exposure. It leverages primary data obtained from social surveys to capture the local experiences of residents. Additionally, we employed a systematic and practical approach based on the MADM method to quantify these factors. This approach provides a better understanding for decision-makers and planners [25] and enhances transparency and replicability for future SVF assessments. Furthermore, the framework incorporates validation and robustness tests using historical flood damage data and alternative MADM approaches to ensure the reliability of results. Finally, scenario analysis explores the effectiveness of potential vulnerability countermeasures, informing the development of targeted interventions that aim to decrease vulnerability to flood. Overall, the study aims to (1) develop a practical and replicable framework for assessing SVF applicable to the context of Metro Manila and similar urban regions, (2) provide a methodology that can be used for future SVF analysis and improvement, and (3) identify critical determinants of vulnerability in flood-prone areas of Metro Manila, informing the development of targeted countermeasures to minimize vulnerability. This comprehensive approach addresses the need for robust, data-driven SVF assessments in Metro Manila, contributing to the development of more effective flood risk management strategies in urban settings facing similar challenges.

The following sections describe the proposed method, including an overview of the study area, present and discuss the calculated factor and SVF indices, show the results of the validation and consistency tests, and culminate with the study conclusions and limitations.

2. Materials and methods

The flow diagram of the methods used in this study is shown in Fig. 1. The first step is to define the conceptual framework to provide a clear understanding of the vulnerability dimensions and factors involved, especially when there is still a large discussion of the concepts and definitions applicable to all fields. The second step is specifying the study area because identifying indicators of each factor, which is the third step, depends on the vulnerability of the area. The fourth step is the aggregation of the indicators to determine the factor values, which are then used to estimate the SVF indices. The fifth step involves the validation of the results and testing of robustness by considering variations in the methods. The last step involves the analysis of a set of scenarios to present changes in the SVF index when the conditions are improved.

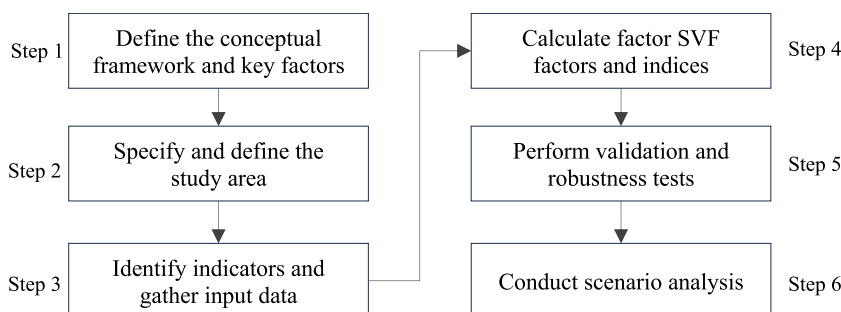


Fig. 1. Methods flow diagram.

2.1. SVF conceptual framework and factors

This study adopted the MOVE framework [8] and the vulnerability-risk relationship [7] wherein the key factors of vulnerability are susceptibility, exposure and resilience. The derived framework shows SVF as the interaction of the natural environment, the socioeconomic dimension, and the institutional dimension, which affect their exposure, susceptibility, and resilience factors (Fig. 2). These dimensions reflect the main group of actors whose interplay affects the living conditions of the people or community, as expressed through the factors and SVF indices.

The natural environment refers to the geographic or spatial aspects of the flood event. The socioeconomic dimension involves individuals, households, and communities, whose interactions affect their social and economic living conditions. The institutional dimension covers government offices and non-governmental organizations involved in planning, policymaking, and implementing risk-mitigating plans and programs.

The exposure factor is described in the MOVE Framework [8] as the “extent to which a unit of assessment falls within the geographical range of a hazard event”. This definition is similar to the definition of exposure by IPCC [3] which is “The presence of people ... in places and settings that could be adversely affected” despite it being considered as a separate component of risk. Adopting these contexts for this study, the exposure factor is described by the population that will be exposed to flood considering their proximity to the pathways and the characteristics of the flood [7,8,28]. To describe and quantify the factor, it answers the question, “How many people are exposed to a flood of this characteristic?”. In line with this concept, theoretically, exposure increases SVF. In the literature, variables used to measure exposure include population density, population in flood-prone areas, and population growth rate [8,9,18]. Considering the framework, exposure is quantified by the intersection of affected households and flood. In terms of dimension, it is the interplay of the natural environment and socioeconomic dimension, while it is controlled by the institutional dimension.

Meanwhile, susceptibility in the MOVE Framework “describes the predisposition of elements at risk (social and ecological) to suffer harm” whereas in the vulnerability analysis for risk management [7] “indicates the process of damage” and that its indicators “measure how sensitively an element at risk behaves when it is confronted with some kind of hazard.” Adopting these concepts for this study, the susceptibility factor describes the characteristics or predisposition of households in an urban community when in contact with a flood [7,8]. This is the most common factor included in social vulnerability studies, covering demographic and socioeconomic characteristics based on census data. Similar to exposure, the more susceptible a community is, the more vulnerable it becomes. The indicators of social flood susceptibility are associated with demographic, socioeconomic, and living conditions [12,27,32]. Referring to this framework, susceptibility is affected by the interaction of the socioeconomic dimension with both the natural environment and institutional dimensions.

Resilience refers to the capacity of the community to cope with damages incurred during a flood and to adapt and recover after the event [7,8,28,33]. It is associated with initiatives and actions by the government to reduce damage and improve the lives of the community. This includes flood protection measures, mandating flood insurance, improving early information dissemination through flood early warning systems (FEWS), and the capacity of institutions to manage disasters. Unlike exposure and susceptibility, the more resilient a community is, the lower its SVF. In most social vulnerability studies, this factor is not explicit but implied by economic conditions and rarely expounded [12]. Other indicators include social cohesion, availability and access to early warnings or information, and availability of plans and policies. Concerning the dimensions, resilience is acted upon by the institutional and

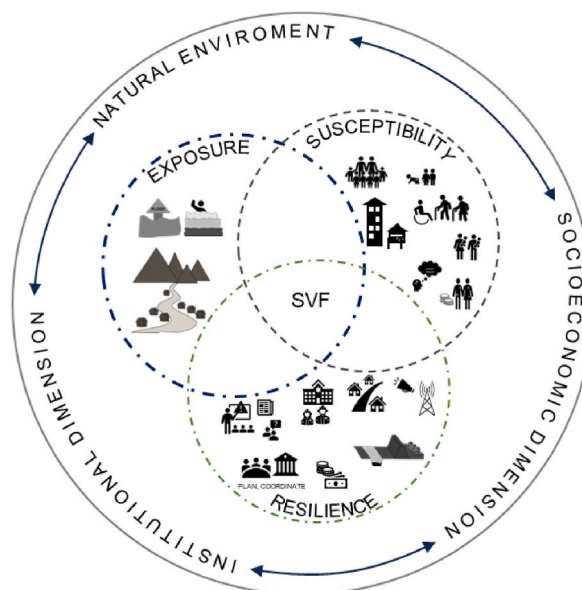


Fig. 2. Conceptual framework of social vulnerability to flood.

socioeconomic systems, depending on the natural environment.

The indicators or attributes of each key factor were deduced using a hierarchical approach [26] while considering the guiding frameworks [7,8], related studies [12,15,16,18,21,30,32] and disaster reports from research [20,34] and local reports that reflect the context of vulnerability in the study area. Various datasets were used to quantify these indicators, including social survey data, census data, and public information from government offices and other official sources.

2.2. Study area

As the capital region where most businesses are situated, individuals and families migrate to Metro Manila to find jobs in the hope of improving their economic conditions despite recurring floods. In 2020, 5.47 million lifetime migrants were recorded by the Philippine Statistics Authority (PSA). The regional population, as of the May 2020 PSA census, is 13.48 million, distributed across sixteen cities and one municipality (Fig. 3).

From these highly urbanized areas, this study focuses on three target cities (Fig. 3) chosen for their historical flood events and damages, population density, and hydrological representation. These criteria were established in a prior study [35] to ensure a broad representation of the case study while acknowledging limitations in resources and time in conducting social surveys. Table 1 shows the non-normalized data used in selecting the cities for the case study.

From the mentioned criteria, the top- and bottom-ranked cities were chosen to reflect the most and least flood-affected cities, respectively (Table 2). The first two cities selected are Marikina and Parañaque.

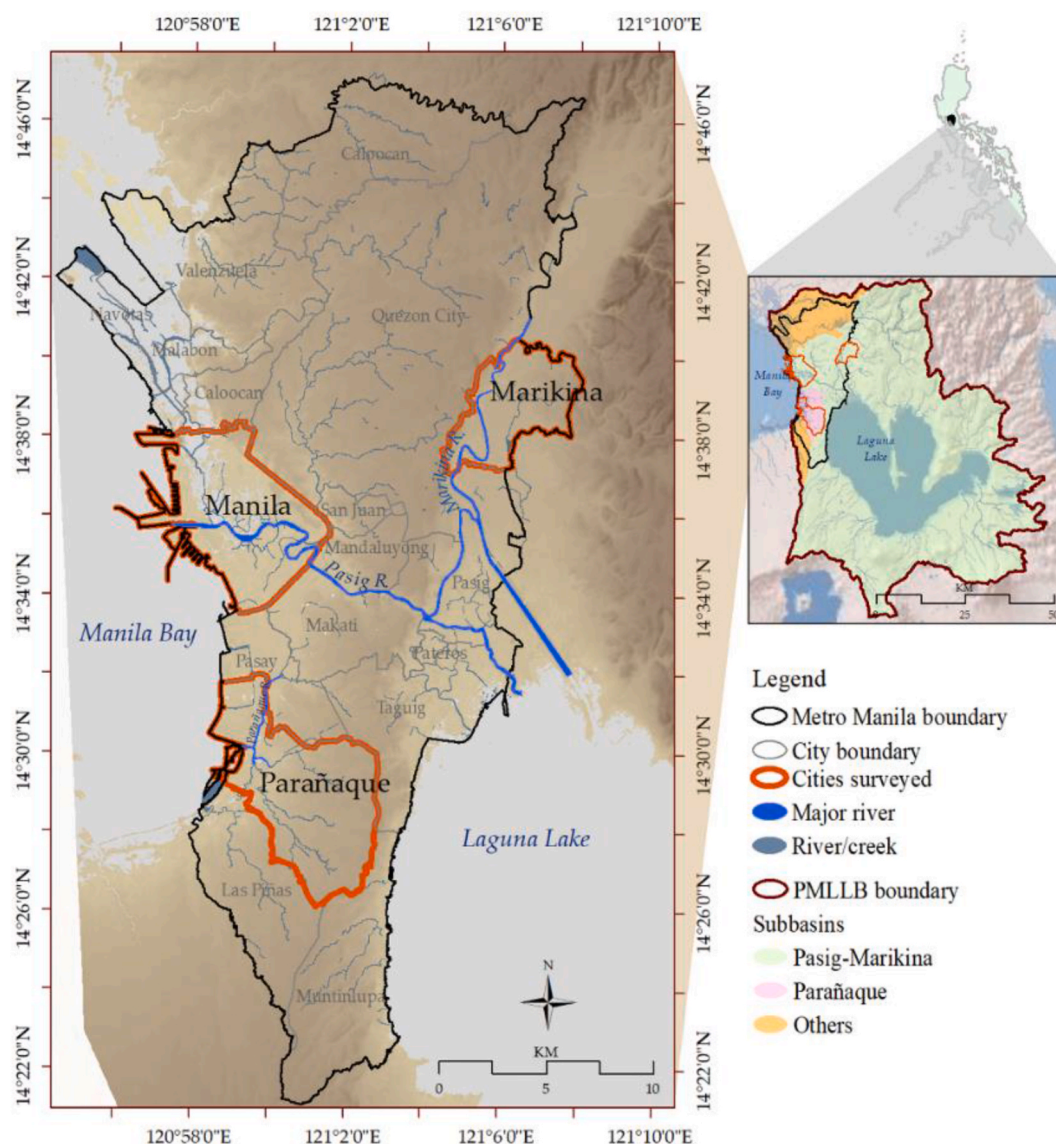


Fig. 3. Location of the three target cities in Metro Manila.

Table 1

Data used to select target cities.

City/Municipality	Non-normalized Data					
	c_1 [count]	c_2 [pop/km ²]	c_{31} [count]	c_{32} [count]	c_{41} [km ²]	c_{42} [km ²]
Caloocan	12	31,204	89,450	926	5	22
Las Piñas	15	18,511	26,330	259	6	41
Makati	11	25,213	3395	260	5	43
Malabon	20	24,125	9851	763	20	76
Mandaluyong	19	37,620	19,660	1232	7	34
Manila	25	43,987	5790	4887	12	76
Marikina	19	19,883	178,985	21,149	48	68
Muntinlupa	18	13,869	11,850	6377	3	25
Navotas	17	23,487	194	2974	2	71
Parañaque	14	15,387	2250	1290	9	44
Pasay	18	24,628	8537	365	5	57
Pasig	20	25,650	127,110	3350	27	71
Pateros	11	40,520	32,320	439	2	66
Quezon City	27	18,217	113,420	3600	13	33
San Juan	11	21,859	2234	427	15	38
Taguig	16	24,879	132,630	3070	4	43
Valenzuela	21	15,353	8091	2827	8	31

Note.

 c_1 = number of flood events from 2009 to 2020 based on 33 NDRRMC disaster reports. c_2 = population density. It was derived from the May 2020 PSA census data and the administrative data obtained from UN-OCHA whose sources are the National Mapping Resources Information Agency (NAMRIA) and the PSA. c_{31} = number of persons affected by the 2009 flood during Typhoon Ondoy. c_{32} = Number of persons affected by the 2020 flood during Typhoon Ulysses. c_{41} = probable affected area considering a 100-yr flood with high flood depth based on Project NOAH. c_{42} = probable affected area considering a 100-yr flood and all flood depths based on Project NOAH.

Marikina City is located upstream of the Pasig-Marikina River and is part of the Pasig-Marikina-Laguna Lake basin (PMLLB) which has a catchment area of 4522 km² [36]. It lies near the foot of a mountainous region and has hilly terrain. Running across it is the Marikina River, which is susceptible to flood overflows associated with heavy rainfall during typhoons or monsoon season. Owing to the city's topography and urban drainage problems, Marikina is often affected by fluvial, pluvial and flash floods. Historically, Marikina has often been the most affected city because of the high discharge along the Marikina River. In the 2009 and 2020 disastrous floods, Marikina had the highest number of affected persons in the region, according to the NDRRMC disaster reports. Improper and unorganized urban planning has also allowed the proliferation of residential settlements and commercial establishments along the river, subjecting these areas to high exposure to floods.

Parañaque City, on the other hand, is located south of Metro Manila characterized by hilly and low-lying flat terrain with several creeks passing through its area. The upstream areas are affected by fluvial and pluvial floods whereas the low-lying areas located near Manila Bay are affected by tidal floods, which occur whenever there is high tide causing backwater effects to nearby creeks and canals flooding adjacent houses. Aligning the downstream of the Paranaque River are informal settlements that are often affected by floods.

The third city is Manila, owing to its political, economic, and social significance as well as its hydrological characteristics concerning its river basin. As the capital city of the Philippines, Manila has become the administrative and economic center of the country. Urban development in the area has contributed to it being the most densely populated city in the region. Manila is located downstream of PMLLB, where flooding can be due to fluvial, pluvial, and coastal floods. Fluvial floods occur due to the overflow of the tributaries of the Pasig River, whereas pluvial floods are associated with inadequate drainage network capacity. Along the west side of Manila is Manila Bay, where storm surges and high tides affect nearby and low-lying areas, respectively.

In terms of socio-economic conditions, in 2021, poverty statistics by the PSA found that Parañaque was in the top half of the cities in Metro Manila with a relatively high percentage of poverty incidence. Accordingly, 4.34 % of the families in the city have insufficient income to meet basic food and non-food needs. On the other hand, Marikina and Manila were in the bottom half, with poverty

Table 2

Rank of cities and municipality based on the selection criteria.

City/Municipality	Rank	City/Municipality	Rank
Marikina	1	Pasay	10
Manila	2	Caloocan	11
Pasig	3	Valenzuela	12
Quezon City	4	Las Piñas	13
Malabon	5	Muntinlupa	14
Mandaluyong	6	Makati	15
Taguig	7	San Juan	16
Pateros*	8	Parañaque	17
Navotas	9		

* Lone municipality of Metro Manila.

incidences of 2.55 % and 1.69 %, respectively. Although Manila had the lowest poverty incidence among the three cities, it had the highest unemployment rate of 12.5 % (third in the region), while Parañaque and Marikina had unemployment rates of 10.2 % and 10.0 %, respectively.

2.3. Selecting indicators and sources of datasets

2.3.1. Identifying indicators

The indicators used in this study were selected considering the guiding frameworks, the contextual relevance of the indicators and their variables used in literature, and data availability. In vulnerability analysis, there is no universally accepted set of indicators owing to the heterogeneity and unique characteristics of social groups and communities across different regions or nations. Moreover, the choice of indicators and variables used to measure them depends on the availability and format of data [27]. Adding to the challenge is the difference in terms and concepts used as the basis for the analysis leading to variations in the indicators employed by empirical studies. Furthermore, indicators can vary even within the same region, such as between household and city levels [15].

In this study, we adopted a deductive and hierarchical approach to select indicators that are contextually relevant to Metro Manila. This approach acknowledges that some indicators used in other areas may not be appropriate or applicable to the study area. For example, flood insurance is a common indicator of vulnerability especially in developed countries such as the U.S.A [16], and Germany [37]. However, for developing countries such as the Philippines, flood insurance is still a non-existent concept in the study area, rendering it an unsuitable indicator.

The selection process involved identifying indicators for each SVF factor (exposure, susceptibility, and resilience) through deductive reasoning. This process considered the indicators used in the literature, their applicability to the context of Metro Manila, the guiding frameworks, and local disaster reports. When an indicator was broad, it was further described in detail by more specific variables. This hierarchical clustering approach allowed for a systematic and comprehensive assessment of SVF. Variables used to quantify the indicators were adjusted considering the data provided by recognized government agencies (e.g. NDRRMC, PSA, Local Government Units (LGUs)). Data limitations and inconsistencies were addressed through data cleaning and harmonization processes.

By considering the contextual relevance, data availability, and established frameworks, we aimed to select a comprehensive set of indicators that provide a robust foundation for assessing SVF in Metro Manila. However, we acknowledge the dynamic nature of vulnerability assessments and the potential need to incorporate additional indicators as data availability and understanding of social vulnerability evolve.

Fig. 4 shows the schematic diagram of the hierarchical clustering of the indicators and sub-indicators. Each key factor is described by its multiple attributes or indicators. The indicators are further described in detail by sub-indicators. In turn, the indicators are quantified by their respective sub-indicators using specified variables. After which the indicators are used to quantify the factors. Thus, the identification of the indicators starts from the top of the hierarchy, but the quantification starts from the bottom. This procedure presents decision-makers with an explicit and rational procedure to systematically analyze SVF [25] and easily identify and trace the indicators or critical determinants of SVF.

2.3.2. Datasets to calculate indicators

Two sets of data were used in this. The primary dataset was collected through a social survey whereas the secondary data was gathered from government offices. These datasets were integrated into the calculation of the SVF index as fractions of the total sample size, population or spatial coverage depending on the data type. The succeeding sections describe the indicators for each vulnerability factor.

2.3.2.1. Primary dataset. For this data, a door-to-door household survey was conducted in the three cities from February to March 2023 with the assistance of local officers or residents of the area. The point location of the surveyed households is illustrated in Fig. 5. The collected data include household conditions, socioeconomic status, sources of information for disaster warnings, and flood experience.

Before conducting the survey, the flooding condition, location, general housing, and economic conditions were considered to obtain a better representation of the household population. The survey was carried out in flood-prone areas with the aid of the local officers and residents. In addition, permissions from local government units were also secured. For every survey, the participants were notified of the purpose of the survey, that their personal information would not be published, and that their input would only be used

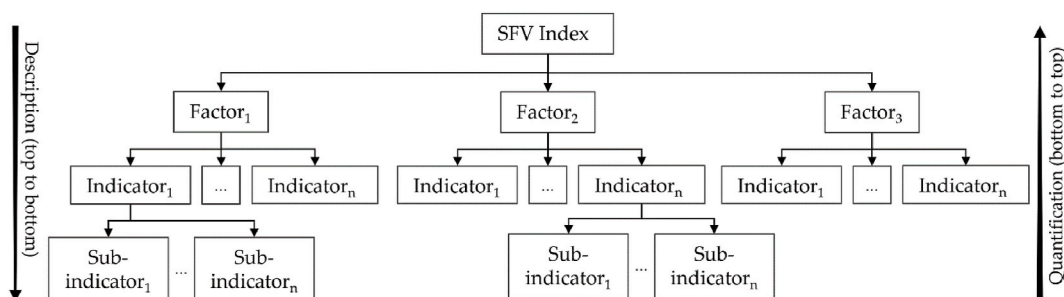


Fig. 4. Schematic diagram of the hierarchical clustering of indicators and sub-indicators.

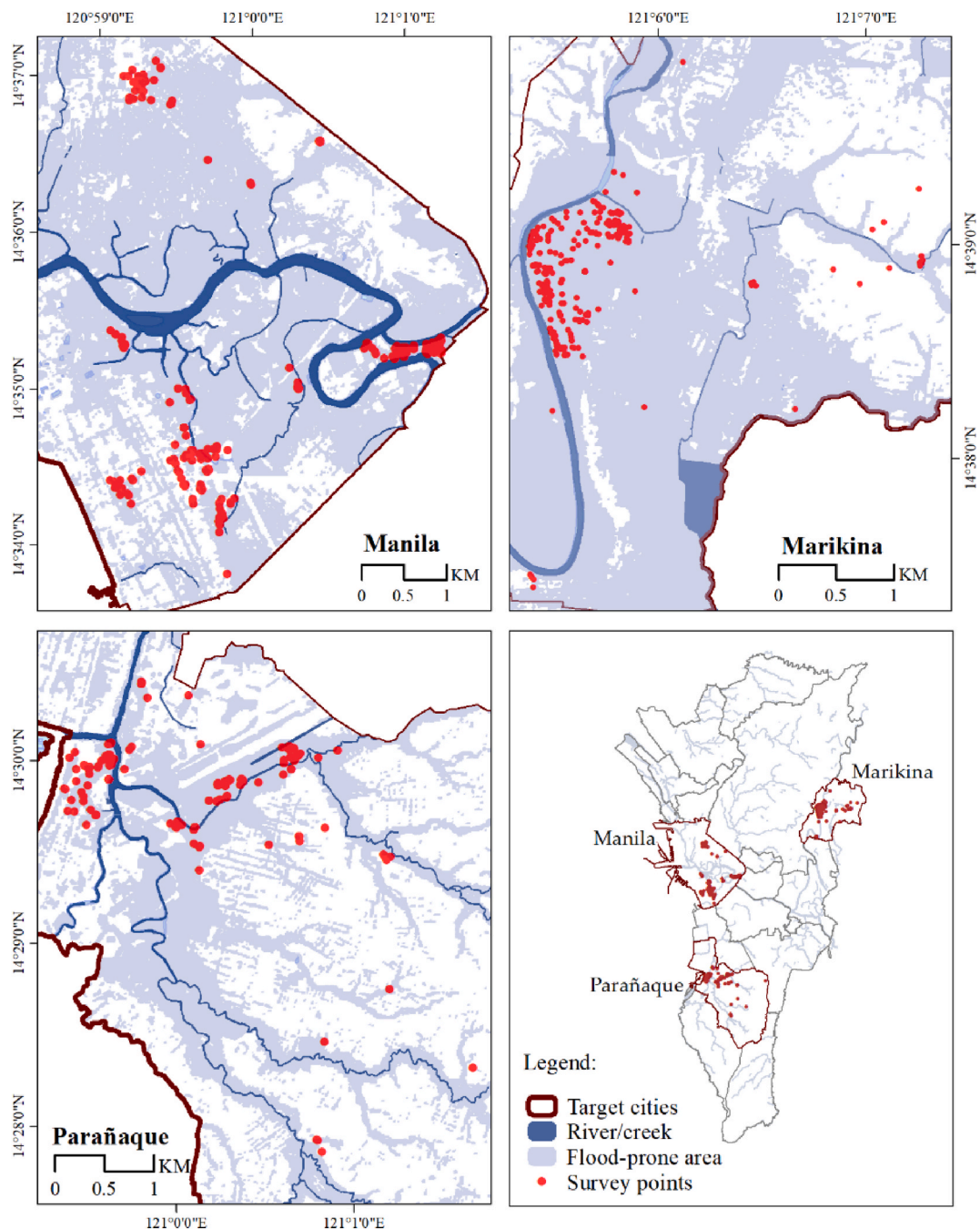


Fig. 5. Point location of surveyed households per city.

for research purposes. Despite this, there were instances when potential participants declined, for which we respected their wishes to ensure voluntary participation and consent.

Each household was randomly selected wherein the household head, or the breadwinner of the family, was interviewed. They were chosen to represent their household because they have detailed knowledge of their household conditions and flood experiences. A total of 1169 households (i.e., Manila = 385, Marikina = 394, and Parañaque = 390) were interviewed in the three cities (see [Appendix A](#) for a summary of interviewed households). These numbers comply with the minimum sample size (i.e., Manila = 385, Marikina and Parañaque = 384) based on the Cochran formula [38,39], with 95 % confidence interval and 0.05 margin of error.

2.3.2.2. Secondary dataset. The secondary dataset was collected from the government offices of each city or downloaded from an official website. The data collected includes government information regarding flood control projects, available funds during emergencies or disasters, development plans, and available forest and open areas that help mitigate floods. For this dataset, not all data are

available online, such as the comprehensive land use plans and local disaster risk reduction and management plans; thus, some data had to be collected in-person after submitting necessary documents to the head of the respective government agency or administrative head and in some instances meeting the community leader.

2.3.3. Exposure indicators

Two indicators were used to quantify exposure: flood characteristics and proximity to a pathway (Table 3). In this case, flood characteristics refer to the number of households exposed to a specific flood characteristic, which is classified into three namely (1) flood in the neighborhood, FA; (2) flood inside their house, FH, and (3) flood while going to/from work or while doing their job, FW. Proximity to the river or creek refers to households living within a certain distance from the river or creek, which is classified into four categories based on distance from the riverbank: A $\leq$ 5m from the bank, B = 5m–10m from the bank, C > 10m from the bank, and D = no river/creek nearby. For this factor, the indicators were quantified using the social survey data.

2.3.4. Susceptibility indicators

In this study, there are 11 indicators and 15 sub-indicators for the susceptibility factor (Table 4). The indicators were selected based on the consensus of published related studies, locally and internationally, local disaster reports, and their applicability to the context of the study area. These indicators are grouped into five themes and were quantified based on their respective variables using census and survey data, as shown in Table 4 (see Appendix A for details on the calculation).

The first theme describes the social structure (SS). In terms of social structure, children, the elderly, and persons with special needs are among the vulnerable groups because they need more assistance during calamities [30,40,41]. In terms of sex, not only females but also male working groups (ages 15 to 65) are susceptible based on reviews of historical flood mortality reports [32,42] and NDRRMC reports. For example, after the 2009 extreme flood in Metro Manila, NDRRMC reported that 64 % of the mortality counts were male, excluding 31 % unspecified, due to drowning and leptospirosis. According to the findings of the social survey, able males stay behind to guard their residences in case of theft. They are typically and tacitly assigned to physical tasks, particularly during rescue operations, which consequently increase their exposure and potentially affect their susceptibility to floodwaters.

The second theme reflects household structure (HHS). Single parents and households with large family members are more sensitive to flood damage because of difficulties in managing tasks to care for the family as well as finding financial resources to support the family [16,21,32].

The third describes the existing socioeconomic conditions of the household (SEC). The poor and unemployed describe the vulnerable group of the community because they tend to stay in high-risk areas and have limited income to have access to basic needs and live in better housing conditions [15,30]. Although these indicators intersect with resilience indicators, they are classified under susceptibility because they describe the internal pre-conditions of households and the community.

The fourth theme describes the housing conditions (HC) of the residents. Those who are renting, including transient residents [16], are considered susceptible. They have less control to reinforce their house because they are not owners, and in cases of damage due to floods, the responsibility for repairs is not clear. The quality of house material also affects the susceptibility of the household to floods [15]. Those living in dilapidated houses are most susceptible because the walls may not withstand the flood and may affect the family living inside. In Metro Manila, dilapidated houses are mostly located along flood pathways, which increases their possibility of being affected.

The fifth theme reflects low-risk perception (LRP). It is a cognitive and intuitive behavioral response of individuals to possible risk based on information received, flood experience, and protection measures [7,43,44]. It is a significant indicator of social vulnerability [12] but is more difficult to assess because it involves the intuition of individuals, unlike other indicators that can be quantified using tangible and non-intuitive information such as census data. In related studies, the inclusion of risk perception in the analysis of social vulnerability is limited due to its contextual definition; thus, no standard framework has yet been established and indicators vary [45–47]. In this study, two indicators are used to quantify low-risk perception: flood frequency in linguistic terms and decisions made after receiving news of a possible flood. For the linguistic terms, respondents were asked to describe how many times their neighborhood is flooded using the following terms: (1) always flooded, (2) often flooded, (3) sometimes flooded, (4) rarely flooded and (5) never flooded. Respondents who never or rarely experience flooding are assumed to have low-risk perceptions when they hear possible flooding in their area due to the belief that because their area is never or rarely flooded, they will not be affected, thus creating a false sense of safety [48,49]. The second indicator, the decisions made due to perceived risk, are based on the decisions of the household in preparation for a possible disaster. Residents who decide to prepare ahead of possible floods and pre-emptively evacuate have a high-risk perception, thus making them less susceptible to the adverse impacts of a flood. Respondents who decide to go to work at risk

Table 3
Exposure indicators and variables of measurement.

^{a)} Indicator	^{b)} Variables and Measurements	Input source	ID	Relationship with vulnerability
Flood characteristics	Percentage of households exposed to a specified flood category annually	Survey data	E1. FC	↑ exposure, ↑ vulnerability
Proximity to the pathway	Percentage of households living at a specified distance from the riverbank	Survey data	E2. PP	↑ proximity, ↑ vulnerability

^{a)} References: [7,8,18].

^{b)} See Appendix A for the equations used to quantify indicators/attributes.

Table 4
Susceptibility indicators and variables of measurement.

Theme	^{a)} Indicator	Variables and Measurements	Input Source	ID	Relationship with vulnerability
Social structure (SS)	Age	Percentage of children population	^{b)} Census data	S1. Child	<i>for all SS variables:</i> ↑ population, ↑vulnerability
		Percentage of elderly population	^{b)} Census data	S2.Elder	
	Sex	Percentage of male working group (15–65yrs old)	^{b)} Census data	S3.Mwg	
		Percentage of females (≥15yrs old)	^{b)} Census data	S4.Fem	
	Functional Difficulty	Percentage of households with persons with disability (PWD)	Survey data	S5.FD	
Household structure (HHS)	Household size	average number of household members	Survey data	S6. HH _{size}	↑HH size, ↑vulnerability
	Household head	Percentage of single-headed and solo household	Survey data	S7. HH _{head}	↑HH size, ↑vulnerability
Socioeconomic condition (SEC)	Poverty	Percentage of poor households	Survey data	S8.Poor	↑poor HH, ↑vulnerability
	Unemployment status	Percentage of unemployed household head	Survey data	S9. uEmp	↑unemployed, ↑vulnerability
Housing condition (HC)	Rent	Percentage of households renting	Survey data	S10. Hrent	↑renting HH, ↑vulnerability
	House: wall material	Percentage of houses made of dilapidated wall	Survey data	S11. Hmd	<i>for all materials:</i> ↓quality material, ↑vulnerability
		Percentage of houses made of wood wall	Survey data	S12. Hmw	
		Percentage of houses made of mixed wood and concrete wall	Survey data	S13. Hmm	
		Percentage of houses made of galvanized sheet walls	Survey data	S14. Hmg	
Low-risk perception (LRP)	Flood experience	Linguistic description of the number of times an area is flooded	^{c)} Survey data	S15.LRP	↓frequent flooding, ↓RP, ↑vulnerability
	Decisions made based on perceived risk	Willingness to prepare food anticipating flood & water	^{c)} Survey data		↓willingness to prepare, ↓RP, ↑vulnerability
		Willingness to evacuate to evacuation center when advised by local authority	^{c)} Survey data		↓willingness to evacuate, ↓RP, ↑vulnerability
		Voluntary use of basic protective gear when wading in low flood	^{c)} Survey data		↓use protection, ↓RP, ↑vulnerability
		Percentage of households who conduct other protective and preparedness actions	^{c)} Survey data		↓preventive plan, ↓RP, ↑vulnerability
		HH head works even if the neighborhood has low flood	^{c)} Survey data		↑willingness to work, ↓RP, ↑vulnerability
		HH head works even if the neighborhood has a high flood	^{c)} Survey data		↑willingness to work, ↓RP, ↑vulnerability

^{a)} References: [5,12,16–18,22,30,46].

^{b)} Census data from the Philippine Statistics Authority (PSA) May 2020 census.

^{c)} See [Appendix A](#) for the equations used.

of wading through high and low floods have a low-risk perception.

2.3.5. Resilience indicators

For the resilience factor, seven indicators were used in this study which make use of the social survey data and government-obtained data, as shown in [Table 5](#). The indicators are quantified using the variables indicated (see [Appendix A](#) for details on the calculation).

The first indicator is access to information. Communities that are provided an early warning and information about impending floods will be more prepared to avoid possible damage. This indicator was measured by the proportion of households that received information through the flood early warning system (FEWS), social media, their neighbors, and local government officers. Respondents were asked to list their sources of information to determine access to information.

Education is associated with coping capacity such that higher education is linked to better income and access to information, which help in a better understanding of information and faster recovery [21]. This second indicator is expressed as the percentage of household heads who at least graduated from high school. Respondents were asked to state the highest educational attainment of the household head or breadwinner of the family.

The third indicator, social cohesion, is described by the active coordination between the local government and the residents as well as the closeness of residents to their neighbors [31,45,50]. In this study, it was measured by the percentage of the population who received help from nearby relatives, their neighbors, and the local authorities before, during, and after a flood event. Closed-type questions with responses of yes, no, and sometimes, asked the respondents if they were able to get help from relatives, neighbors,

Table 5
Resilience indicators and variables of measurement.

^{a)} Indicator	^{b)} Variable	Input Source	ID	Relationship with vulnerability
Access to information	Proportion of households receiving information via (a)FEWS, (b)media/ neighbors, and/or (c)local gov't officers.	Survey data	R1. AccInfo	↑information access, ↑resilience, ↓vulnerability
Educational attainment	Highest educational attainment of the household head.	Survey data	R2.Educ	↑education, ↑resilience, ↓vulnerability
Social cohesion	Proportion of households receiving help from (a) nearby relatives, (b) neighbors, and/or (c) local government before/during/after a flood event.	Survey data	R3.SC	↑cohesion, ↑resilience, ↓vulnerability
Government flood control projects	Available flood control projects	^{c)} Government data	R4.FCP	↑projects, ↑resilience, ↓vulnerability
Development plans	Existing and updated land use and disaster management plans for the city	^{d)} Government data	R5.DP	↑plans, ↑resilience, ↓vulnerability
Land cover	Area of open space and forest in the city	^{e)} Government data	R6.LC	↑green-open space, ↑resilience, ↓vulnerability
Local revenue per capita	City revenue per total population	^{f)} Government data	R7.LR	↑local fund, ↑resilience, ↓vulnerability

^{a)} References: [5,8,16,21,31,45,50].

^{b)} See [Appendix A](#) for the equations used to quantify the indicators.

^{c)} Flood control project by the Metropolitan Manila Development Authority (MMDA) and the Department of Public Works and Highways (DPWH) from the General Appropriations Act FY2021 by the Department of Budget and Management.

^{d)} from government office - city hall and interview of officers.

^{e)} 2020 landcover of NCR, Region 3, and Region 4A from the Geoportal Philippines website.

^{f)} 2021 Annual Financial Report for the Local Government, Volume I by the Commission on Audit.

and local government.

The succeeding indicators are secondary data obtained from government offices and official reports. The fourth indicator, flood control projects, is described by the availability of flood protection measures that reduce vulnerability, expressed by the appropriated funds for the execution of the flood control projects. The fifth indicator is described as the status of the comprehensive land use plan (CLUP) and the local disaster risk reduction and management plan (LDRRMP) if they exist and if updated. The existence of updated development plans provides a reference for effective disaster mitigation policies and projects, thus reducing vulnerability. The sixth indicator is land cover, which describes the available space, such as open space, grassland, and forest land, which can attenuate or decrease surface runoff within the city. The land cover map was downloaded from the Philippine Geoportal by the National Mapping and Resources Information Agency (NAMRIA). The seventh indicator is local revenue, which reflects the available funds for disaster reduction management. This is measured by the ratio of the city revenue to the total city population.

2.4. Calculating SVF factors and index

This section details the procedures involved in calculating the Social Vulnerability to Floods (SVF) index, as illustrated in the flow diagram of [Fig. 6](#). The calculation process involves four main steps, utilizing a MADM approach and the vulnerability relationship of the three factors. It starts by normalizing the data to ensure all variables are on a common scale for aggregation. Next, the relative importance of each variable is determined using the AHP method, assigning weights to reflect their influence on vulnerability. These weights are then incorporated into a weighted sum or SAW method to estimate the index for each SVF factor. Finally, the individual factor indices are combined to calculate the overall SVF index. The following subsections describe these steps in detail.

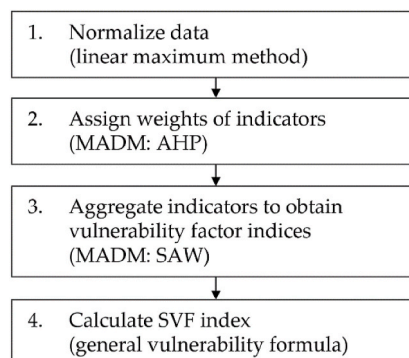


Fig. 6. Steps in calculating the SVF index.

2.4.1. Data normalization

Considering that the indicators or attributes have different units, the values were normalized so that they have a common scale [dimensionless] which allows them to be used for aggregation. There are several normalization methods but for deductive and hierarchical approaches, the linear maximum is often used [9]. In this study, the values were normalized using the linear sum (N1) method (1) considering that non-zero values still have a value compared to actual zero values [18]:

$$I_{Ni} = \frac{I_i}{\text{maximum}_{i,n}(I_i)} \quad (1)$$

where I_{Ni} = normalized value of the indicator, I_i = raw value of the indicator, and $\text{max}_{i,n}(I_i)$ = maximum value of the set of indicators I , and n = the total count of indicators considering a specified spatial scale.

2.4.2. Weight assignment

Assigning weights to indicators reflecting vulnerability is challenging due to the subjectivity involved. While assigning equal weights is common, AHP allows for incorporating expert judgment regarding the relative importance of various indicators [12,25]. Different indicators likely contribute to overall vulnerability to varying degrees. For example, among vulnerable groups, the impact of a flood event may be more critical to persons with functional disability compared to children or elderly groups.

In line with this, while noting the multidisciplinary nature of SVF, this study solicited the participation of nine experts involved in flood risk management, but from different fields such as flood management planning and decision-making, water resources engineering and economics, climate change, and environmental and health sciences, to determine the weights of the indicators using AHP. Weights assigned through AHP help quantify these relative differences in importance, allowing researchers to prioritize factors with a greater influence on vulnerability. This weighted approach leads to a more nuanced understanding of vulnerability compared to assigning equal weight to all indicators.

AHP is a commonly used MADM or MCDM method developed by Saaty [51]. In this method, the weights are determined by performing a series of pairwise comparisons of the attributes or indicators using a standard scale from 1 to 9 as presented in Table 6.

In this method, the consistency of the set of comparisons of the attributes is checked by using the consistency ratio, CR , expressed by equation (2).

$$CR = \frac{CI}{RI} \leq 0.10 \quad (2)$$

where CI is the consistency index and RI is the random index based on a [52] as shown in Table 7.

CI is calculated using equation (3) where a is the number of attributes and λ_{max} is the largest eigenvalue from the comparison matrix (which is made up of the group of attributes compared). As per Saaty [51], and in previous studies [53–55], the judged weight is consistent if $CR \leq 0.10$, otherwise, the comparisons have to be modified.

$$CI = \frac{\lambda_{max} - a}{a - 1} \quad (3)$$

For multiple participants, the weight of an attribute is obtained by calculating the geometric mean of the set of weights from all participants [24,56]; then the adjusted weight of each attribute is normalized using linear sum so that the sum of the weights is 1.0.

In this study, the participants were asked via an online questionnaire to compare the importance (i.e., which determinant is more vulnerable, based on their judgment) of the sub-indicators of an indicator and the indicators of a factor using Table 6 as reference. The comparison was done in a pairwise manner and repeated for all sets of sub-indicators and indicators. Next, the judged weights by each participant were tested for consistency to ensure they passed the criteria (i.e. CR is less than or equal to 0.10). Then, the weights from all participants were aggregated using the geometric mean and were normalized so that the sum of all sets of weights was 1.0.

In the case of the risk perception indicator, the sub-indicators of the indicators were also compared. However, noting that risk perception is formed from intuition and is highly variable, its attributes are given equal weights.

2.4.3. Aggregation of indicators to estimate SVF factor index

The SVF factors (E, S and R), V_f , were calculated using the simple additive weighting (SAW) [57]:

$$V_f = \sum_{i=1}^n w_i I_{Ni} \quad (4)$$

Table 6

Scale of importance by Saaty [51].

Intensity of importance	Definition (A vs. B)	Rate of importance
1	Equal influence	Both criteria contribute equally
3	Moderate influence	Experience and judgment slightly favor one criterion over the other
5	Strong influence	Experience and judgment strongly favor one criterion over the other
7	Very strong influence	Experience and judgment very strongly favor one criterion over the other
9	Extreme influence	Evidence favoring one criterion over the other is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values	

Table 7
Random Consistency Index [52].

α	1	2	3	4	5	6	7	8	9	10
R.I	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

where V_f is the SVF factor index (E, S and R), w_i is the weight of the indicator obtained through the AHP method, and n is the total number of indicators. SAW, sometimes referred to as weighted sum, is one of the most commonly used MADM method owing to its ease of use [25]. Previous studies (such as [9,17]) have also used this method to aggregate indicators but have not explicitly mentioned the name.

2.4.4. Estimation of SVF index

After determining the factors, the SVF index was estimated using the flood vulnerability equation adopted from Balica et al. [18] wherein, it is expressed by the following equation:

$$SVF = \frac{E \bullet S}{R} \quad (5)$$

where E = exposure, S = susceptibility, and R = resilience. The equation describes the influence of the factors on vulnerability such that the factors that increase vulnerability are directly proportional to SVF while the factors that decrease it are indirectly proportional. Exposure and susceptibility are directly proportional to social vulnerability, whereas resilience is indirectly proportional to vulnerability because it reduces SVF as its value increases. This fractional expression aligns with previous studies such as Villordon [19] for Dumaguete, Philippines, and Tascon-Gonzales et al. [17] for Ponferrada, Spain, although the latter used different terms such as “resistance” instead of “resilience”.

2.5. Validation and robustness tests

2.5.1. Validation of SVF index

Validation of social vulnerability indices presents distinct challenges compared to their physical counterparts. Social vulnerability is a latent construct which means it is not directly observable and has no single definitive tool to directly measure it [16]. For example, Burton et al. [14] used disaster outcomes (e.g. applications for flood compensation and affected uninsured renters) of Hurricane Sandy to validate social vulnerability. Consequently, studies have employed observable, independent and quantifiable data as proxies for validation [26].

Common approaches involve comparing [26] vulnerability indices to flood damage through techniques such as regression analysis [21,22] or correlation analysis [56,58].

This study adopted a similar validation approach, employing Spearman’s rank correlation analysis to compare the SVF index rankings for each city with historical social (human-related) flood damages. Considering the multi-dimensionality and non-linearity of social vulnerability [26,59], coupled with the ordinal nature of the ranking data, Spearman’s correlation analysis was employed as a suitable method. Two validation tests were performed. Data on the number of affected and displaced families per flood event, obtained from the NDRRMC disaster reports (SitReps), served as proxies for social flood damage. To account for population shifts, the figures were transformed into proportions relative to the total number of households during the closest census year (NB: “families” in disaster reports align with “households” in PSA census data wherein it defined the latter as “a group of persons usually living together and composed of the head and other persons related to the head by blood, marriage or adoption. It includes both the nuclear and extended family”). Thus, the employed social damage metrics were: (1) the proportion of affected families and (2) the proportion of displaced families.

For this test, despite the frequent flood events in the region, only 11 disaster reports were used considering the completeness of records in the published disaster reports. Tables 8 and 9 list the flood records considered for affected and displaced families,

Table 8
Count of affected families based on the NDRRMC Report.

Related Event	Count of Affected Families		
	Manila	Marikina	Parañaque
1. 2009 TS Ondoy	1158	35,789	450
2. 2013 TS Maring & SWM	4103	7784	2506
3. 2014 TY Glenda	1156	114	260
4. 2014 TS Mario	981	8254	
5. 2014 TY Ruby	1607	1189	433
6. 2018 SWM	53	3368	18
7. 2018 TS Karding	220	5451	
8. 2020 STY Rolly	1017	102	375
9. 2020 TY Ulysses	1205	4678	304
10. 2021 TY Fabian	411	3521	184
11. 2022 STS Paeng	1080	2401	328

Note: Blank spaces are unclear if no person was affected or no data was submitted by the local government.

respectively. In the first validation procedure, the correlation of the set of SVF indices and the 11 sets of the proportion of flood-affected families was evaluated. However, for the second validation, only eight flood records were used because three did not have data on displaced families.

2.5.2. Robustness testing of SVF index rankings

While validation assesses the relationship between the SVF index and established data on social vulnerability, robustness testing examines the consistency and sensitivity of the index rankings when different methods or variables are used. In social vulnerability analysis, several methods and approaches were applied to estimate the vulnerability index due to the lack of a standard method which can result in changes in rankings of vulnerability [26]. Considering this and acknowledging the existence of other normalization tools for MADM, this study performs a robustness test to examine the consistency of the rankings of the SVF index of each city.

In this study, the robustness testing involved three scenarios as follows: (T1) using two other normalization methods; (T2) using another MADM method; and (T3) applying equal weights to attributes.

- T1: Impact of normalization methods

This scenario investigates the influence of alternative normalization techniques on the relative SVF index rankings of each city. In MADM, normalizing the attribute scores ensures they operate on a common scale, facilitating their aggregation. While the MADM method is a recognized method, there is no established normalization method applicable to all MADM methods [60]. Consequently, the chosen method can influence the final rankings. Therefore, testing alternative normalization methods strengthens the basis for decision-making. The specific normalization methods employed in this study are:

$$\text{Linear max} - \text{min (N2)} : a_{Ni} = \frac{a_i - \text{minimum}_{i,n}(a_i)}{\text{maximum}_{i,n}(a_i) - \text{minimum}_{i,n}(a_i)} \quad (6)$$

$$\text{Linear sum (N3)} : a_{Ni} = \frac{a_i}{\text{sum}_{i,n}(a_i)} \quad (7)$$

- T2: Impact of alternative MADM method

This scenario evaluates how the rankings change when a different MADM method is utilized. In this case, each key factor was calculated using the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) without changing the normalization method used (N1 in equation (1)). TOPSIS is one of the widely used MADM methods that evaluates solutions based on their distance to the ideal best and worst solutions [61].

- T3: Impact of weighing scheme

This scenario examines the consistency of the rankings if all indicators and sub-indicators have equal weights, a practice mostly applied in previous studies [15,18,21,22]. In this case, the normalization method was maintained (i.e., N1).

2.6. Performing scenario analysis

A scenario analysis was conducted to evaluate the reduction of the SVF index when factor indices are improved. This method involves a set of tests that assess the performance of SVF under different hypothetical situations ("scenarios"). The specific details of the scenarios considered are presented in Table 10.

For each scenario, the analysis focused on changing the attributes of a single factor (exposure, susceptibility, or resilience) by 10 %, 20 %, 30 %, and 50 %, while holding the attributes of the other two factors constant. In the case of exposure and resilience, all attributes were modified uniformly. However, for susceptibility, only the population of poor (S8) and unemployed (S9) were adjusted, as these factors are considered more directly controllable by government and resident actions.

The primary objective of this analysis was to identify the critical factor that mitigation plans and programs could target to

Table 9
Count of displaced families based on the NDRRMC Report.

Related Event	Number of Displaced Families		
	Manila	Marikina	Parañaque
2009 TS Ondoy	0	20,034	0
2013 TS Maring & SWM	4103	7784	2506
2014 TY Glenda	1156	114	260
2014 TS Mario	290	1047	0
2014 TY Ruby	0	0	0
2018 SWM	56	2103	0
2018 TS Karding	0	10	
2020 STY Rolly	0	0	0
2020 TY Ulysses	0	0	0
2021 TY Fabian	419	3521	184
2022 STS Paeng	1080	2401	328

Note: Blank spaces are unclear if no person was affected or no data was submitted by the local government.

Table 10
Considered scenarios for testing.

Scenario ID	Description	% Changes
Sc1	Decreasing susceptibility attributes: poor and unemployed households	10, 20, 30, 50
Sc2	Increasing resilience attributes	10, 20, 30, 50
Sc3	Decreasing exposure attributes	10, 20, 30, 50

efficiently decrease the SVF. The analysis employed identical attribute changes across scenarios to facilitate this comparison.

- Scenario 1 (Sc1) simulates a situation where programs and aid are provided to communities to reduce the population of poor and unemployed residents. This scenario reflects a decrease in attributes S8 (poor) and S9 (unemployed) by 10 %, 20 %, 30 %, and 50 %, while all other attributes remain unchanged.
- Scenario 2 (Sc2) represents a situation where community resilience is increased through the implementation of flood mitigation plans and programs.
- Scenario 3 (Sc3) reflects a scenario where the number of households exposed to floods is reduced through structural and non-structural plans.

3. Results and discussion

3.1. Factor and indicator weights

Fig. 7 presents the local weights of the SVF factors and their corresponding indicators, as determined by the expert participants through AHP-based weighting. The results reveal a clear prioritization of resilience compared to exposure and susceptibility. The local weight for resilience is at least 36 % higher than exposure and nearly double that of susceptibility, signifying its greater importance in determining overall social vulnerability to floods. This finding aligns with the growing interest in improving resilience as a strategy to mitigate disasters brought by natural hazards. A review study by Wang et al. [62] highlights the shift from traditional flood control to flood resilience studies to manage flood disasters and achieve sustainability in communities. The recently revised National Disaster Risk Reduction and Management Plan (NDRRMP) of the Philippines also recognizes the need to strengthen resilience in the country, acknowledging the changing climate and urban conditions.

The local weights were subsequently employed to derive the global weights presented in Table 11. Between the exposure indicators, proximity to the flood pathway (e.g. river) is the more influential factor contributing to SVF. This finding aligns with the intuitive understanding that the closer a residence is situated to a flood pathway, the greater the likelihood of experiencing flood exposure. In contrast, the characteristics of the flood itself (e.g., depth, velocity) were assigned a lower weight, suggesting that even residences situated near pathways might experience varying degrees of exposure depending on the specific flood event.

The indicators for susceptibility reflect the inherent characteristics of a population that influence their vulnerability to floods. The

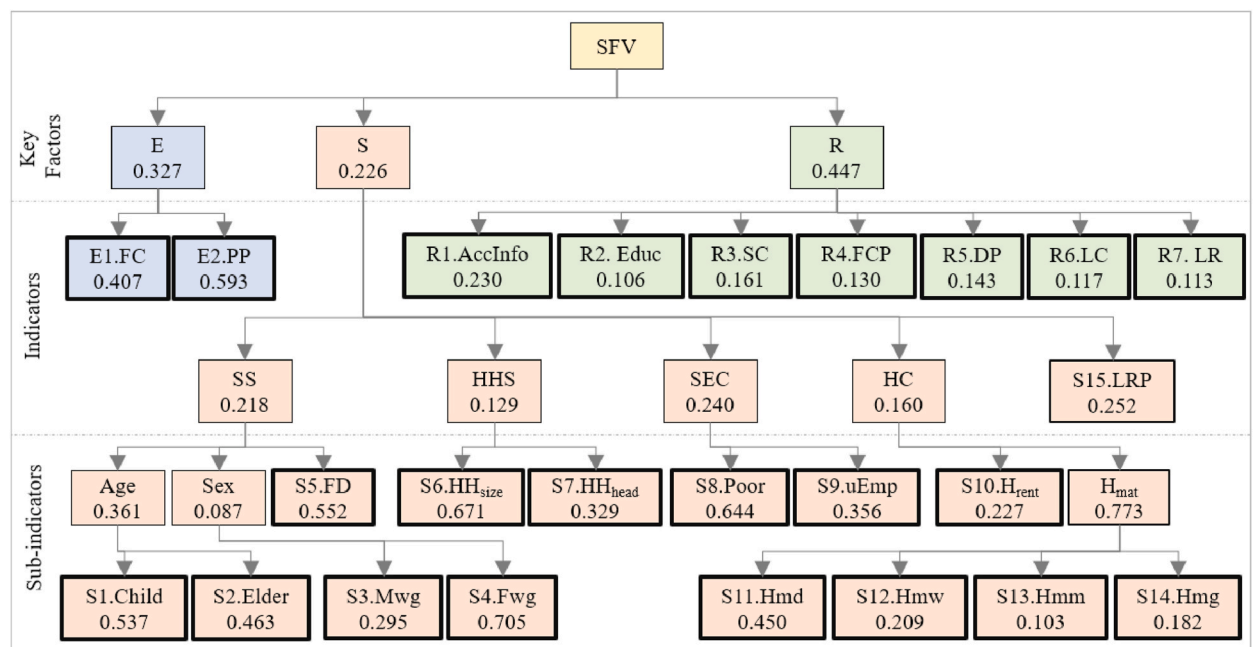


Fig. 7. Local weighting of factors and indicators from AHP.

Table 11
Global attribute weight.

Exposure Attribute	Weight	Susceptibility Attribute	Weight	Resilience Attribute	Weight
E1. FC	0.133	S1. Child	0.010	R1. AccInfo	0.103
E2. PP	0.194	S2. Elder	0.008	R2. Educ	0.072
		S3. Mwg	0.001	R3. SC	0.050
		S4. Fem	0.003	R4. FCP	0.048
		S5. FD	0.027	R5. DP	0.058
		S6. HHsize	0.020	R6. LC	0.064
		S7. HHhead	0.010	R7. LR	0.052
		S8. Poor	0.035		
		S9. uEmp	0.019		
		S10. Hrent	0.008		
		S11. Hmd	0.014		
		S12. Hmw	0.006		
		S13. Hmm	0.003		
		S14. Hmg	0.005		
		S15. LRP	0.057		

analysis identified low-risk perception as the most influential indicator, closely followed by socioeconomic conditions (i.e., poverty and unemployment). This result underscores the critical importance of assessing risk perception during evaluations of social vulnerability to floods and other natural hazards. Individuals with a low perception of risk are less likely to undertake precautionary measures, potentially exacerbating their vulnerability during flood events.

The indicators for resilience capture the capacity of a population to withstand and recover from flood events. The analysis indicates that the existence of flood control projects holds the greatest influence on resilience, closely followed by the availability of local funds. The presence of robust flood control measures (e.g., levees and dikes) can significantly reduce the impact of floods on communities. Similarly, access to local funds enables communities to invest in preparedness measures and facilitates faster post-flood recovery efforts.

Overall, the findings from the AHP analysis emphasize the significance of prioritizing strategies that build community resilience to reduce social vulnerability to floods. Investing in flood control projects, enhancing risk awareness, and strengthening the social capital of communities are key contributors. Through collaboration with residents, policymakers can develop a more resilient society better equipped to cope with future flood events.

3.2. SVF index and profile

Fig. 8 illustrates the SVF index and rank of each city. The results show that Marikina is the most vulnerable with an index of 0.15, followed by Paranaque with an index of 0.14, then Manila at 0.11. In the pyramid chart, the closer the point to the edge, the more they are likely to be vulnerable.

Comparing the factor indices of each city, Marikina ranked first owing to it having the highest susceptibility index, second-highest exposure index and second-lowest resilience index. Even though Paranaque has the highest exposure and lowest resilience, the difference between these indices compared to Marikina's is minimal, unlike the difference between their susceptibility indices. Hence, the

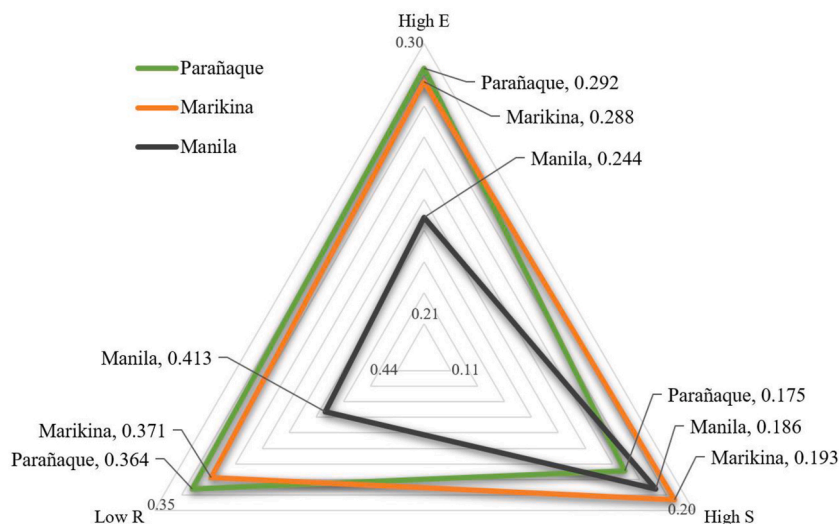


Fig. 8. Estimated index of factors and SVF.

degree of variation between cities influences the resulting SVF index. Consequently, it has a direct impact on the prioritization of projects towards the identified vulnerable zones.

In contrast, Manila is the least vulnerable owing to it having the highest resilience index as well as having the lowest exposure and second-lowest susceptibility indices. Thus, resilience plays a significant role in reducing relative SVF.

Fig. 9 shows the SVF profile which illustrates the relative score of the indicators of each city. This chart helps in identifying the critical indicators of vulnerability to provide targeted solutions. It can provide answers as to why a certain area (city) is vulnerable compared to another.

Parañaque has the highest proportion of the population that experiences floods due to its low-lying areas near Manila Bay combined with informal settlements along the riverbanks. Overflowing canals flood arterial streets and adjacent neighborhoods during high tides, causing a backwater effect that hinders water discharge. Marikina, however, has the highest population density near the flood pathway – in this case, the Marikina River and its tributaries, increasing their exposure to floods.

In terms of the susceptibility index, Parañaque exhibits the lowest score owing to a relatively low population classified as needing assistance during disasters and generally better household conditions. Conversely, Marikina has the highest susceptibility due to consistently higher values in its susceptibility indicators compared to the other cities. This highlights the importance of considering the composition of the population and their socioeconomic characteristics when assessing vulnerability.

Regarding resilience, Marikina exhibits the lowest literacy rates, which could potentially hinder community preparedness efforts. Additionally, Marikina has the least allocated budget for flood control projects and the lowest level of local revenue. This financial constraint may limit their ability to invest in preventative measures and rapid response strategies. Notably, Manila possesses the least amount of open/green space, which can exacerbate flooding by limiting natural water absorption. Furthermore, the significant disparity in allocated flood control projects between Manila and the other cities suggests potential inequities in resource allocation.

The analysis underscores the need for targeted flood mitigation strategies. In Parañaque, given its high exposure and frequent inundation events, upgrading drainage systems and integrated flood mitigation strategy can mitigate frequent flooding [63]. For Marikina, targeted programs aimed at reducing the susceptibility of the people to flood are necessary. This could involve initiatives that provide sustainable aid to vulnerable groups and households such as livelihood and housing programs [64], and investment in disaster preparedness education that are accessible and cater to diverse literacy levels [65]. As for Manila, the local government can invest in the creation and expansion of green spaces to improve natural water absorption capacity and provide incentives for the development of green infrastructure projects such as rain gardens and green buildings [66]. Finally, the significant disparity in allocated flood control projects indicates a need for a more equitable distribution of resources.

3.3. SVF index validation

Table 12 presents the results of the Spearman correlation analysis between the SVF and social damages, specifically, the number of affected families and displaced families. Data from Typhoon (TY) Ruby, TY Rolly, and TY Ulysses for displaced families were excluded due to the absence of recorded data.

The SVF index generally exhibits a strong positive correlation with the number of affected families across typhoon events. However, TY Glenda and TY Rolly stand as exceptions, demonstrating a negative correlation. This can be attributed to the specific typhoon tracks. Both events traveled south of Metro Manila, prompting warnings of storm surges for coastal residents. Consequently, a larger number of evacuations occurred in Manila and Parañaque, cities bordering Manila Bay, compared to Marikina.

Similarly, the SVF indices have a strong positive correlation with the number of displaced families, excluding TY-Glenda.

These findings, supported by a strong positive correlation between the SVF index and social damages, suggest the effectiveness of the index in identifying socially vulnerable areas during typhoons in Metro Manila.

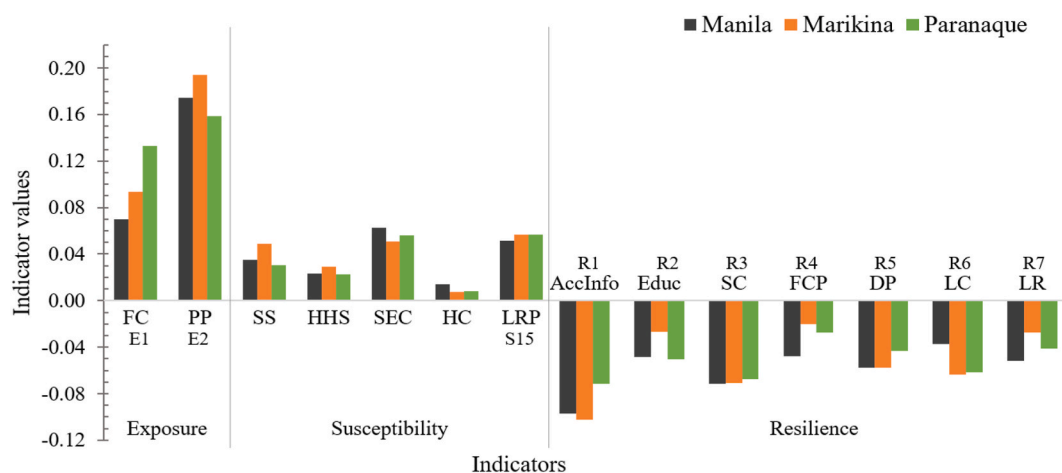


Fig. 9. SVF profile.

Table 12
Correlation between SVF and social flood damage.

Event	Correlation coefficient
2009 TY Ondoy	1.0
2013 TS Maring	1.0
2014 TY Glenda	-1.0
2014 TS Mario	0.5
2014 TY Ruby	0.5
2018 SWM	0.5
2018 TS Karding	0.5
2020 TY Rolly	-1.0
2020 TY Ulysses	0.5
2021 TY Fabian	1.0
2022 STS Paeng	0.5
Event ^a	Correlation coefficient
2009 TY Ondoy	0.9
2013 TS Maring	1.0
2014 TY Glenda	-1.0
2014 TS Mario	0.5
2018 SWM	0.5
2018 TS Karding	0.9
2021 TY Fabian	1.0
2022 STS Paeng	0.5

a) Correlation of affected families.

b) Correlation with displaced families.

a\ Events without displaced families, marked with “*” on the left table, were removed from the list.

3.4. SVF index robustness

Table 13 presents the result of the robustness tests T1 (varying normalization method) and T2 (changing SAW to TOPSIS), and Table 14 shows the relative ratio of the indices to the least vulnerable index (i.e., ranked 3rd) to show how the values change per method.

In T1, the ranks did not change despite the varying normalization method and even though the ratio or relative difference between indices varied greatly, particularly when N2 was used. Similarly, the ranks did not change when TOPSIS was used to calculate the SFV factor indices instead of SAW. Thus, the ranks are robust such that they are not sensitive to changes in the normalization method and when TOPSIS is used.

Table 15 shows the results of the robustness test, T3 (equal weighting of indicators). Similar to T1 and T2, the ranking of the SVF indices did not change. Moreover, the multiplicative factor based on the least vulnerable city is similar in both cases (see the last two columns of Table 15). Thus, the weights have a small impact on the difference between the SVF indices of the cities. The result indicates that the indicators and methods used are not sensitive to weights.

3.5. Scenario analysis

Fig. 10 summarizes the results of the scenario analysis which demonstrate that vulnerability reduction measures focused on decreasing exposure to floods (Sc3) yielded the greatest reduction in the SVF index across all three cities. Conversely, programs solely targeting susceptibility reduction (Sc1) resulted in the least significant change in the SVF index.

Sc1 considered a situation where susceptibility is decreased. Under this scenario, the SVF index in the cities can be decreased by at least 2.4 % and at most 14.6 %. Potential countermeasures include government-provided employment opportunities to reduce unemployment and investments in education to improve future employment prospects for the poor. While these measures can enhance overall well-being, their impact on immediate flood risk reduction is relatively limited.

Sc2 considered a scenario where resilience is increased. It presented a reduction in the SVF index ranging from 9.1 % to 33.3 % across the cities. Example measures include implementing structural countermeasures and ensuring clear communication of early warnings. Integrating disaster preparedness education into the curriculum is another approach to enhance resilience.

Finally, Sc3 focused on decreasing exposure. This condition showed the most significant reduction in the SVF index, ranging from 10 % to 50 % across the cities. Possible countermeasures include relocating residents from high-risk areas and enforcing regulations on construction near waterways.

The findings from the scenario analysis underscore the importance of addressing both exposure and resilience when aiming to reduce the social vulnerability of communities to floods. In this study, the changes per city are similar. Specifically, the changes in the SVF indices are the same for Sc2 and Sc3, whereas only slight differences between cities are observed for Sc1. Comparing the three scenarios, Sc3 reduced the SVF index of each city the most, closely followed by Sc2. Overall, these results emphasize the need for comprehensive flood risk management strategies that combine structural and non-structural measures tailored to the specific vulnerabilities of each city.

Table 13

Result of robustness tests, T1 and T2.

City	SVF Index Ranking (T1)			SVF Index Ranking (T2)	
	SAW-N1	SAW-N2	SAW-N3	SAW-N1	TOPSIS
Manila	3	3	3	3	3
Marikina	1	1	1	1	1
Parañaque	2	2	2	2	2

Table 14

Ratio from least vulnerable city (T1 and T2).

City	Method			
	SAW-N1	SAW-N2	SAW-N3	TOPSIS
Manila	1.00	1.00	1.00	1.00
Marikina	1.36	5.21	1.42	7.72
Parañaque	1.28	3.97	1.28	3.16

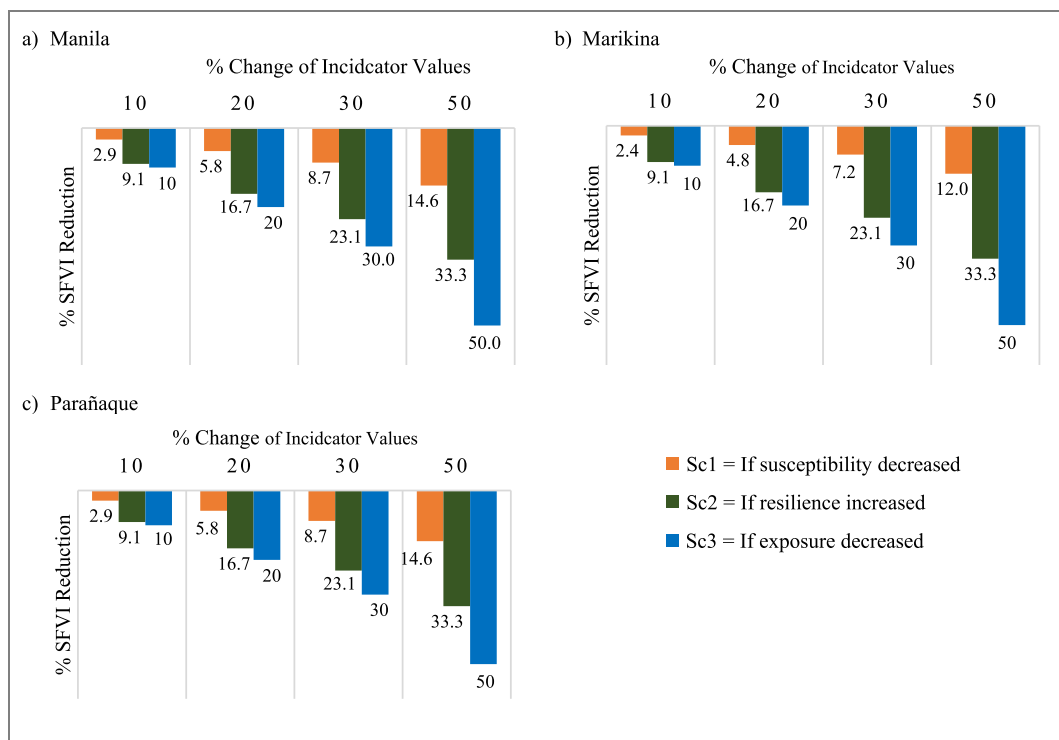
Table 15

Result of robustness test, T3.

City	a) Sc0		T3		Rank changed?	b) Factor	
	SVFI	Rank	SVFI	Rank		Sc0	T3
Manila	0.11	3	2.81	3	No	1.00	1.00
Marikina	0.15	1	3.66	1	No	1.36	1.30
Parañaque	0.14	2	3.54	2	No	1.28	1.26

a) Sc0 = original case, SAW-N1 with different weights.

b) Multiplicative factor based on the lowest SVF.

**Fig. 10.** Scenario analysis of SVFI per city.

3.6. Limitations of the study and recommendations for future research

3.6.1. Weight selection

While the AHP method with expert input ($n = 9$) provided robust weightings for the SVF factors, the study may benefit from a broader and more diverse participant pool in future research. Although there is no standard set to determine the sufficient number of participants, including residents alongside experts from various flood risk management fields would enhance stakeholder representation and potentially lead to a richer understanding of how weighting choices affect the SVF index. This may increase the applicability of the results for local planners and policymakers working to reduce vulnerability within the study area due to the inclusion of local participants [24,67]. In line with this, it is recommended for future studies to investigate how the different numbers of participants will affect the result.

3.6.2. Spatial scale

This research assessed SVF and its components at the city level in Metro Manila. However, social vulnerability is inherently multifaceted and can vary within a city. A finer-grained analysis at the barangay, community, or even household level would provide a more nuanced understanding of the specific vulnerabilities and needs of different social strata within these urban areas. This detailed vulnerability profiling could inform the development of targeted countermeasures that address the unique challenges faced by these diverse populations.

4. Conclusion

This study presented a comprehensive framework for assessing SVF using a MADM approach. The framework integrates exposure, susceptibility, and resilience, encompassing natural environment, socioeconomic, and institutional dimensions. Weights for each factor were determined through AHP with expert input. These weights were then used to estimate factor values using SAW. Then, the SVF index was determined considering the relationship of these factors expressed by the vulnerability formula.

The practicality of the framework was demonstrated in a case study in Metro Manila, Philippines focusing on the cities of Manila, Marikina, and Parañaque. Social survey data, along with census and development plan information, quantified factor indicators. The results indicated that Marikina is relatively the most vulnerable, followed by Parañaque and then Manila, aligning with historical social flood damages. The methods employed exhibited robustness through their low sensitivity to variations in weights and normalization techniques.

The findings reveal that the relative rank of a city by its SVF index is influenced by the degree of disparity between its susceptibility, exposure, and resilience indices. In this case, susceptibility differences significantly influenced vulnerability rankings. This underscores the importance of identifying vulnerability hotspots to tailor appropriate countermeasures. Effective risk management necessitates that planners and policymakers critically examine the key contributors to SVF to inform targeted interventions that address the critical needs of affected communities.

Scenario analysis revealed that interventions reducing exposure and enhancing resilience have a greater impact on lowering SVF compared to those solely targeting susceptibility. Prioritizing plans and actions aimed at reducing the number of households exposed to floods is crucial in mitigating disasters. Additionally, programs supporting the poor and providing employment opportunities can reduce susceptibility, and government initiatives to mitigate disaster coordinated with the constituents can increase resilience. The significant decrease in the SVF index through exposure reduction and resilience improvement underscores the importance of these two factors in SVF assessment.

While this study employed expert input for weight determination, future research could involve a larger and more diverse group, including residents, to enhance stakeholder representation and strengthen the credibility of results. Additionally, future studies could evaluate SVF at a finer scale (barangay/community level) to provide a more nuanced understanding of vulnerability across different social strata.

The framework and findings offer valuable guidance for planners and policymakers engaged in integrated flood risk management, particularly in Metro Manila and similar settings. In any setting, however, careful consideration should be given to adapting indicators and variables for application in contexts with distinct social, economic, and cultural characteristics. Vulnerability is inherently context-dependent, necessitating future studies to account for the specific human systems within new areas of investigation. Finally, this study emphasizes the utility of vulnerability profiling and scenario analysis in informing the development of targeted and effective countermeasures.

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CRedit authorship contribution statement

Judy Marie T. Dulawan: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Yoshiyuki Imamura:** Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing, Methodology. **Toru Konishi:** Methodology, Supervision, Writing – review & editing. **Hideo Amaguchi:** Supervision, Writing – review & editing. **Miho Ohara:** Conceptualization, Formal analysis, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Due to the sensitive nature of the data employed in this research, certain datasets will be accessible upon request following confidentiality protocols.

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Appendix A. Supplementary data

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