Urban Climate 48 (2023) 101426

Contents lists available at ScienceDirect

Urban Climate

journal homepage: www.elsevier.com/locate/uclim

An integrated indicator-based approach for constructing an urban flood vulnerability index as an urban decision-making tool using the PCA and AHP techniques: A case study of Alexandria, Egypt

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ARTICLE INFO

Keywords:
Climate change
Urban areas
Flood vulnerability
Vulnerability index
PCA
AHP
Decision support
MOVE framework

ABSTRACT

Several cities are exceptionally vulnerable to flood impacts due to increasing urbanization, population growth, and climate change. Quantifying flood vulnerability is useful for identifying the system's weakness, monitoring its evolution, and supporting targeted flood risk adaptation policies. One of the vital aims of assessing urban flood vulnerability is to create an understandable link between flood vulnerability conceptual theories and the daily decision-making process through an easily accessible tool. Although several studies have described the development of an integrated flood vulnerability index (FVI) combining physical, social, and economic dimensions in urban areas, this index has not been assessed in developing countries. Therefore, this study focuses on an integrated indicator-based approach to develop an urban FVI based on exposure, susceptibility, and resilience to urban flooding at the neighbourhood scale. To evaluate the flood vulnerability of the population, we used the Improvement of Vulnerability Assessment in Europe (MOVE) framework. Accordingly, the vulnerability indices cover exposure, susceptibility and resilience aspects. The index is applied to Alexandria, one of the most important coastal cities of Egypt, which is highly vulnerable due to its dense population, low adaptive capacity, flat topography, and exposure to various water-related disasters, such as cyclones, storm surges, bank erosion, sea-level rise, tidal floods, and frequent urban floods. In this study, we use inductive principal component analysis (PCA) to develop a composite indicator for the FVI and to evaluate the vulnerability of 101 census administrative units (sheyakhahs) in Alexandria. We apply the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity to assess sample adequacy and perform data standardization for all indicators. Furthermore, the analytic hierarchy process (AHP) is adopted for simplicity and comparison with the PCA results to assess their robustness. We clustered 58 and 13 flood vulnerability-related indicators into three major dimensions, i.e., physical, social, and economic, through PCA and the AHP, respectively. Official collected data are analysed using combined methods using advanced statistical analysis (SPSS) software and a

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https://doi.org/10.1016/j.uclim.2023.101426
Received 31 August 2022; Received in revised form 19 December 2022; Accepted 15 January 2023
Available online 20 January 2023
2212-0955/

geographic information system (GIS). The findings highlight the variability in flood vulnerability across highly urbanized and suburban areas. Based on the PCA, 38 indicators were defined as the most comprehensive flood vulnerability assessment (FVA) used in Egyptian cities. Additionally, due to reliability of the approach to indicator selection and the weighting process, the chosen 13 indicators for the AHP analysis yielded similar results. This research provides spatial planners and decision-makers with an integrated, comprehensive, and unified urban FVI to assess vulnerability and, thus, improve flood resilience in Egypt and countries in similar situations.

1. Introduction

Water- and weather-related disasters are expected to affect more cities worldwide with greater strength, frequency and unpredictability due to various drivers (Abdrabo et al., 2022a; Abdrabo et al., 2022b; Osman et al., 2021). Among them are global warming, increased runoff flow due to the extension of impervious surfaces in urbanized areas, unplanned growth in urbanization, severe changes in land use patterns, human interference, and socioeconomic factors (Saber et al., 2021a). In this context, the importance of flood vulnerability assessment has been emphasized by international programmes such as the Sendai Framework for Disaster Risk Reduction 2015–2030 (Ouma and Tateishi, 2014; UNISDR, 2015). Due to differences in the views and ideas of scholars, various definitions and conceptual frameworks to assess vulnerability have been proposed: individual, economic, ecological, physical, social and urban vulnerability (Adger, 2006; Jamshed et al., 2017). Vulnerability has been defined as the propensity of exposed elements, such as physical or capital assets and human beings and their livelihoods, to experience harm and suffer damage and loss when impacted by single or compound hazard events (Cutter and Finch, 2008). (Wisner et al., 2014) defined vulnerability as the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist and recover from the impact of a natural hazard (an extreme natural event or process). The Intergovernmental Panel on Climate Change (IPCC) described vulnerability as the degree to which a system is susceptible to and unable to cope with the adverse effects of climate change, including climate variability and extremes (Field and Barros, 2014). This definition includes the characteristics and situations of a person or group that affect its ability to anticipate, endure, deal with, and recover from the adverse effects of physical events (Cardona et al., 2012). Though many definitions exist, the concept of vulnerability adopted in this study follows the approach introduced by (Welle et al., 2014); they defined vulnerability as the likelihood of injury, loss and disruption of livelihood caused by an extreme event and/or by obstacles in recovering from the disturbance that a system can potentially cause. Based on this conceptualization, vulnerability has specific spatial, socioeconomic–demographic, cultural and institutional contexts that can be expected under certain conditions of exposure, susceptibility and resilience that pose challenges to research on vulnerability to flooding (Kuhlicke et al., 2011). Thus, in the current study, these three factors (exposure, susceptibility, and resilience) are considered to assess flood vulnerability; this approach is supported by (Birkmann et al., 2013; Hamidi et al., 2020; Jamshed et al., 2020; Jamshed et al., 2019).

Urban areas generally suffer from comparatively high flood vulnerability due to the high exposure of people and assets (Abdrabo et al., 2021; Abdrabo et al., 2020). In this regard, flood vulnerability assessment (FVA) is a vital planning tool that supports planners and decision-makers in detecting highly vulnerable areas, determining system weaknesses, observing changes in vulnerability, allocating adaptation and mitigation resources, and justifying policy to the public (Eriksen and Kelly, 2007). However, FVA at the urban level has many deficiencies. The most critical deficiency is the lack of understanding of its importance, its mechanism, and its implications for the main task of policymakers and city authorities in flood-prone areas (Abdrabo et al., 2020; Esmaiel et al., 2022; Saber et al., 2020; Esmaiel et al., 2022). Consequently, a holistic assessment approach is required to understand the complexity of processes generating vulnerability and to achieve sustainable development and urban resilience goals.

Developing vulnerability assessment approaches can support stakeholders in reducing human and property losses, while enhancing our understanding of flood risk vulnerability. Over the last two decades, various methods for the assessment of flood vulnerability have been developed. Some of these methods focus on quantifying the hazard values and their distribution and deriving vulnerability. These methods use detailed input data related to the digital elevation model (DEM) and hydrological factors. However, information on economic losses and various inaccuracies regarding model validation and calibration are not considered. Other approaches use damage curve functions, damage matrices, and an indicator-based approach (Kappes et al., 2012; Papathoma-Köhle et al., 2017; Tarbotton et al., 2015; Papathoma-Köhle et al., 2017; Abdrabo et al., 2020; Elboshy et al., 2019; Moreira et al., 2021). Both damage functions and matrices assess physical vulnerability, neglecting the socioeconomic vulnerability of the inhabitants (Koks et al., 2015). Most current FVA studies are often indicator based and are meant to be precursors for impact analyses of vulnerable regions (Kotzee and Reyers, 2016). Indices play a vital role in summarizing complex and multidimensional issues to assist decision-makers, facilitate the interpretation of a phenomenon, and increase public interest through an overview of the results. A flood vulnerability index (FVI) is a tool for measuring the degree of vulnerability by aggregating several indicators (Moreira et al., 2021). The indicator-based approach is suitable for FVA due to its ability to incorporate multiple physical, economic, social, environmental, cultural, and institutional characteristics that influence the exposed elements' susceptibility to hazards (Eriksen et al., 2020). The FVI can be used to communicate multidisciplinary topics in a relatively straightforward manner due to the large number of components that provide a good overview of flood vulnerability on different scales. It also provides the user with a value that can be relatively simply communicated to other stakeholders, and therefore, it should raise awareness of vulnerability.

There are two main methods for indicator selection and weighting: inductive and deductive. The inductive method has been used to conduct indicator-based vulnerability assessments (Rana and Routray, 2018; Reckien, 2018) because the deductive method suffers from many limitations, such as the utilization of a limited number of indicators and the dependence on expert (subjective) knowledge of related theories, literature, and local context, as in the analytical hierarchy process (AHP) (Yoon, 2012). On the other hand, the inductive method uses a broader range of indicators; the set of indicators can be reduced to smaller numbers of variables (components) by merging highly correlated indicators into one component. Thus, principal component analysis (PCA) is typically used as a method of reduction (Cutter et al., 2003; Reckien, 2018; Yoon, 2012). Although indicators are drawn from the literature, the assessment includes all relevant indicators (Yoon, 2012). This approach is suitable for utilizing a rich data source such as the census (Cutter et al., 2003; Reckien, 2018). However, the PCA technique can be complex due to the time required for collecting data and the need for technical experience with statistical methods. In this study, we focused on AHP and PCA, rather than other index-based vulnerability assessment methods, for the following reasons: (1) Their ability to deliver comparable and reliable results has been proven (Kurek et al., 2022); (2) They have also been widely used to compare deductive and inductive methods and form the basis for other methods, such as Fuzzy AHP (Feng and Wen, 2011).

These different dimensions have been considered in various attempts to develop an FVI on different scales (local or regional), as well as for both qualitative and quantitative data (Fernandez et al., 2016). Researchers such as Balica and others have developed FVIs based on social, economic, and physical components using 71 indicators (Balica et al., 2009; Balica and Wright, 2010). However, there is redundancy in some of these indicators and some of them do not influence the results. Salazar-Briones et al. attempted to construct an integrated FVI for developing countries; however, the physical component depended mainly on the results from hydraulic and hydrological modelling rather than the actual characteristics of buildings and infrastructure. Additionally, the selection of indicators was subjective. For assessing the urban areas of developing countries, an integrated FVI combining physical, social, and economic dimensions with accessible indicators has not been introduced (Salazar-Briones et al., 2020).

In Egypt, there are several research gaps in FVA: (1) Most previous studies were performed based on minimal indicators, ignoring the various dimensions of FVA and considering only the regional scale; (2) FVA in Egypt follows the indicator-based approach guided by a subjectively based selection of indicators and weights, and FVA based on PCA has not been conducted in any study, despite the fact that almost 58 articles discuss FVA; (3) There is no integrated vulnerability index for use in the urban areas of Egypt (Abdrabo et al., 2022a, 2022b; Abdrabo et al., 2020). For a comprehensive and integrated FVI, the relevance and importance indicators must be analysed in depth to effectively portray the reality of pluvial floods.

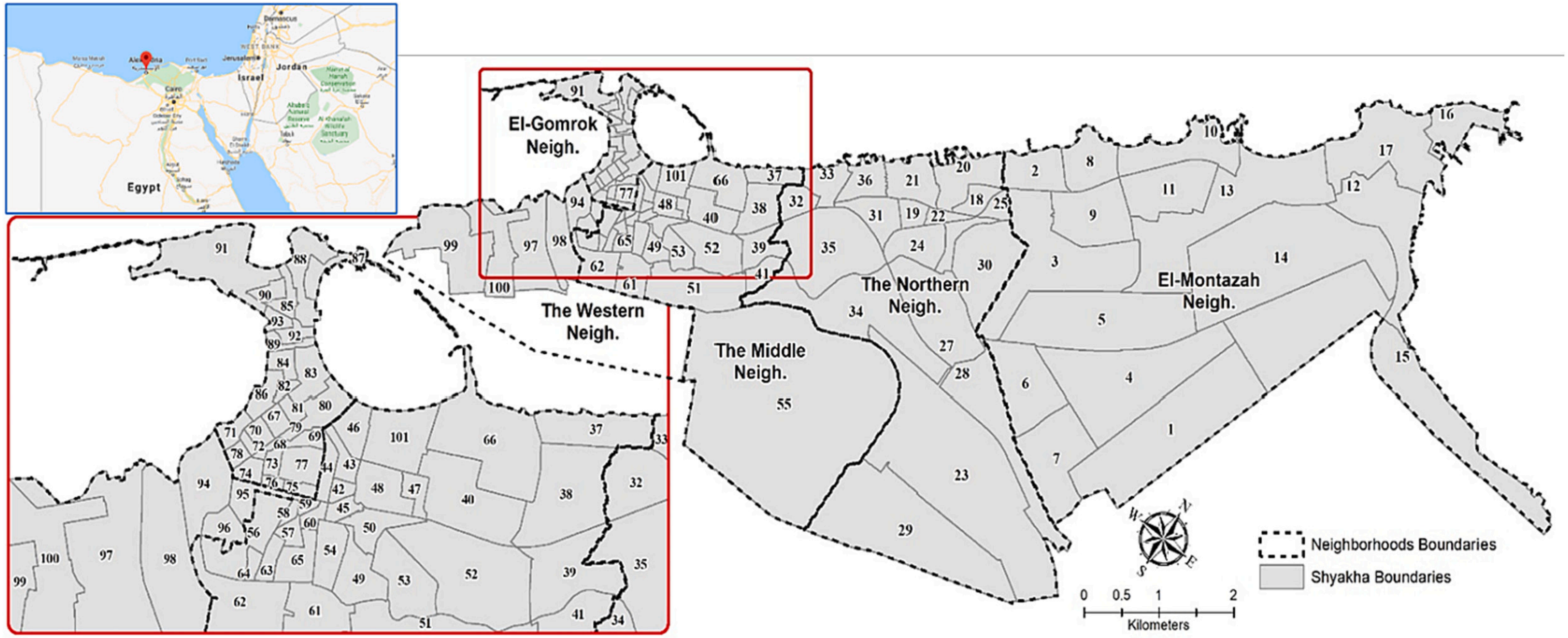
Accordingly, this work focuses on an integrated indicator-based methodology for generating a unified and comprehensive urban FVI on the neighbourhood level utilizing all possible indicators that cover social, economic, and physical aspects. Additionally, we investigate the performance of the AHP compared to PCA.

2. A theoretical and conceptual framework for vulnerability

The following section describes a framework for multidimensional, comprehensive vulnerability assessment as part of risk appraisal and risk management in the context of Disaster Risk Management (DRM) and Climate Change Adaptation (CCA). A framework is a heuristic tool that may direct systematic evaluations of vulnerability and offer a foundation for comparing indicators and criteria produced to analyse important elements and different aspects of vulnerability. There are four main methods for analysing vulnerability and risk. The four methods are not conflicting, but rather each approaches risk from a distinct perspective and with unique goals in mind, ranging from uncovering global-to-local system links to the hunt for measurable risk metrics. The four approaches are as follows: (1) political economics; (2) social ecology; (3) vulnerability and catastrophe risk assessment from a holistic perspective; and (4) climate change systems science. The political economy approach ties susceptibility to dangerous circumstances and discrete risk on a vulnerability continuum that connects local risk to larger national and global developments in the political economy of resources and political power.

In contrast to political economics, social ecology emphasizes society's transformational capabilities concerning nature and the consequences of environmental changes on social and economic systems. It contends that understanding a system's exposure and susceptibility requires addressing these coupling mechanisms and interactions. Comprehensive viewpoints on vulnerability and catastrophe risk assessment have attempted to establish an integrated explanation of risk. These methods distinguish between exposure, susceptibility, social reaction capacity, and a lack of resilience. Within the framework of Climate Change Adaptation, the fourth school of thought formed. However, this does not imply that all DRR and CCA techniques or ideas can be harmonized since they often reflect two distinct interpretations of vulnerability and hence are complementary approaches, such as (Field et al., 2012; O'brien et al., 2007).

According to the vulnerability paradigm proposed by (Turner et al., 2003), individuals, communities, and whole ecosystems may all be assessed for their susceptibility to the negative effects of global environmental change. According to the Bogardi, Birkmann, and Cardona Framework (BBC), vulnerabilities should be seen as continuous occurrences that may be quantified on ecological, social, and economic scales (Birkmann, 2006; Bogardi and Birkmann, 2004). For example, (Schröter et al., 2005) proposed an eight-step method for assessing vulnerability. By including several dimensions (physical, social, economic, institutional, and environmental) in the vulnerability theory, (Birkmann, 2006) greatly expanded its applicability. The use of a vulnerability scope diagram has also been suggested(Polsky et al., 2007). In the context of disaster risk management and climate change adaptation, the IPCC's Special Report on Managing the Risks of Extreme Events and Disasters to Advance Adaptation explains vulnerability as a secondary component of disaster risk and its effect on development (Field et al., 2012). MOVE (Methods for the Improvement of Vulnerability Assessment in Europe) is a new framework proposed to enhance vulnerability assessment in Europe (Birkmann et al., 2014). All these models have shown that vulnerability and its evaluation are multifaceted. All these frameworks demonstrated that vulnerability assessments in the context of natural disasters and climate change might be based on some degree of agreement among various techniques. That is, vulnerability analysis in both DRM and CCA often takes four crucial elements into account: (a) exposure to a hazard or stressor; (b)



1	El Tawfiqeya	18	El Qasai Bahri	35	Ezbat Saad	52	Ambrooz and Moharam Bek	69	El Genena El Kabira and Souq El Maeez	86	El Belkatria
2	El Seyouf Bahri	19	Zarabanah	36	Mostafa Kamel and Bolokly	53	Bualino and El Eskandrani	70	El Hara El Wasah and El Takhsheba	87	El Sayala Shark and includes - El Sayala 3
3	El Seyouf Qebli and Derbala	20	San Stephano	37	El Ibrahimeya Bahri	54	Ragheb Pasha	71	El Seka El Gidida and El Tartoshi	88	El Sayala Gharb and includes - El Sayala 4
4	El Kerdahi	21	Fleming	38	El Ibrahimeya Qebli and El Hadra Bahri	55	Abis 7-8-12	72	El Saboura	89	El Madoura
5	El Mansheya El Bahria	22	Bakoos	39	El Hadra Qebli	56	El Kara,El Tobgeya and Kafr El Ghates	73	El Naga El Gidid	90	El-Sayadeen
6	El Mohagreen	23	Abis EL Thania	40	Bab Sharki and Waboor El Myah	57	Bab Sedra El Barani Shark	74	El Naga El Qidim	91	Raas El Teen
7	Khurshid El Bahria	24	El Zaheria	41	Ezbat El Gamea	58	Bab Sedra El Barani Gharb	75	Bab Sidra El Jouanny and Genena	92	El Shamoli
8	Sidi Bishr Bahri	25	El Qasai Qebli	42	El Suri	59	Bab Sedra Bahri includes Souq El Ghanam	76	El Ayoni and El Sconia	93	Safr
9	Sidi Bishr Qebli	26	El Mahrosa	43	El Atarin Shark	60	Gamea Sultan	77	Haret El Farahda	94	El Borsa and includes - Kafr Ashri
10	El Mandara Bahri	27	Hagar El Nawateya	44	El Atarin Gharb	61	Gheat El Enab Shark	78	Souq El Gomaa and El Mounir	95	El Amood - Amood El Sawari
11	El Mandara Qebli	28	Khurshid	45	El Marghani	62	Gheat El Enab Gharb	79	Mashmes El Basal	96	Kom El Shaqafa
12	El Maamora	29	Abis EL Owla	46	El Masala Gharb and Sherif Pasha	63	Karmouz Shark	80	El Mansheya El Kobra	97	El Mafroza
13	El Amrawi	30	Dana	47	Koom El Deka Shark	64	Karmouz Gharb	81	El Hamamil	98	El Qabari Gharb and El Qabari Shark
14	El Nasiriya	31	Abou El Nawateer	48	Koom El Deka Gharb	65	Nobar	82	Souq El Barseem	99	Om kebeba - El Metras
15	Tolmbat El Tabiah	32	El Reyada	49	El Bab El Gidid Sharki	66	El Azareta and El Shatbi	83	El Magharba and Souq El Tourk	100	El Wardian
16	Abou Qir El Sharkia	33	Sidi Gaber	50	El Bab El Gidid Gharb and Monsha	67	El Godod and El Laban	84	Abou Shosha	101	El Masala Shark
17	Abou Qir El Gharbia	34	Ezbat El Nozha	51	El Sobheya,Ezbat Sharkas and Ezbat Raafat	68	El Genena El Saghira and Koom Bakeer	85	El Baraka and includes - El Baraka and El Hegazy		

Fig. 1. Alexandria city location, its administrative units (sheyakhahs), and the divisions of the district.

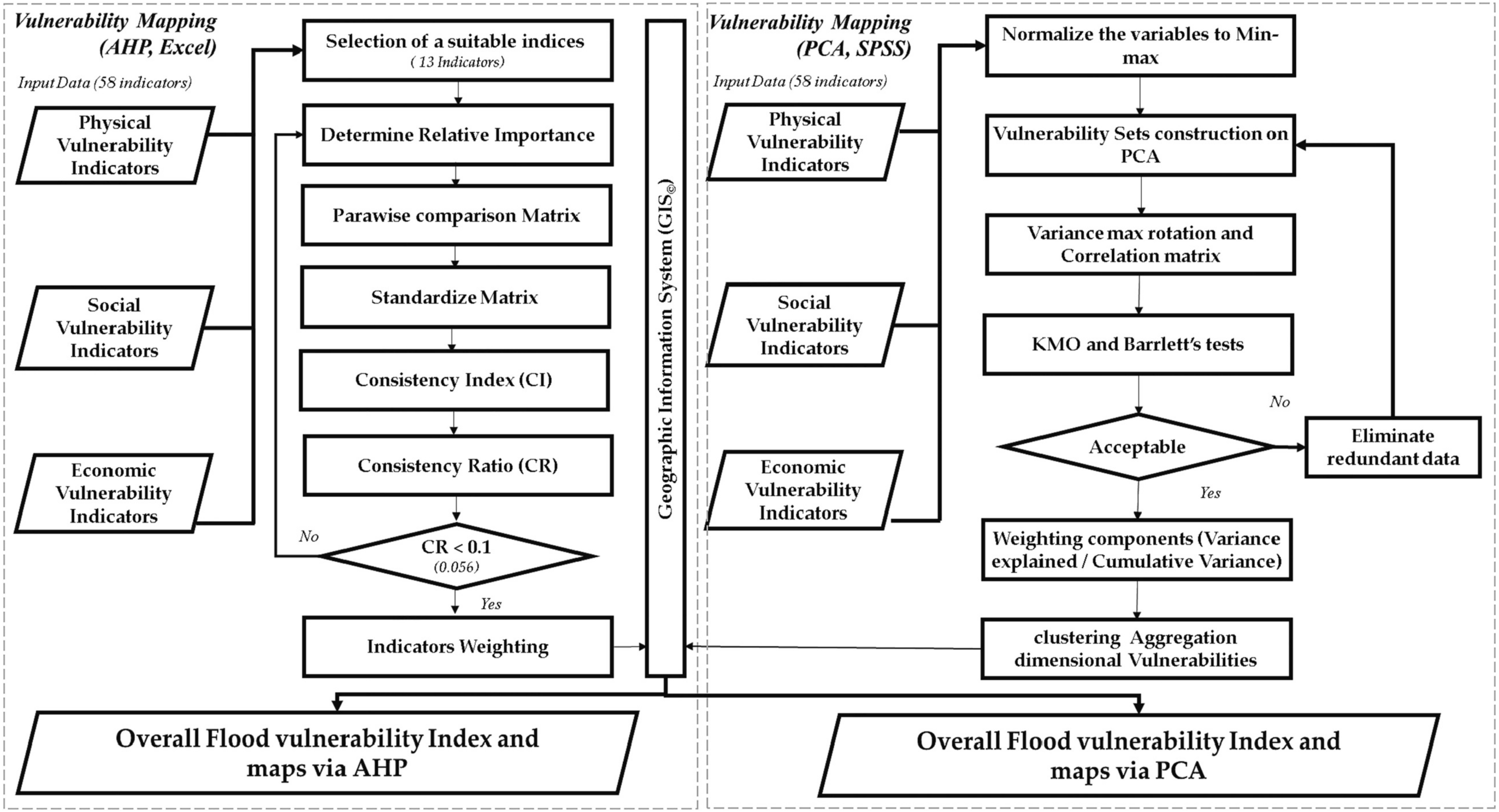


Fig. 2. Flow diagram of the FVA process using PCA and the AHP.

susceptibility (or fragility); (c) societal response capabilities or lack of resilience; and (d) adaptive skills. Some methods, however, regard exposure as a component in addition to vulnerability (see Field et al., 2012) or as a mixture of vulnerability and natural hazard or physical event. There are important indicators for measuring exposure, susceptibility, and response capabilities in terms of resilience (lack of coping or recovery skills) as well as adaptive processes. All these models have confirmed the multidimensional characteristics of vulnerability and its assessment (Rana and Routray, 2018). Therefore, we adopted the MOVE framework in this study as in many other studies, even after the IPCC 2012 (Hamidi et al., 2020; Lianxiao Morimoto, 2019; Matusin et al., 2019; Rainer and Wood, 2011; Robielos et al., 2020).

3. Study area

Over the last 15 years, Egypt's flood risk has significantly increased due to urbanization, population growth, and economic development. In Egypt, floods frequently cause severe financial losses and casualties, accounting for 45%, 45.1%, and 46.5% of the frequency, mortality, and contribution to the average annual loss, respectively, of hazards that confront Egypt. It was estimated that from 1980 to 2010, approximately 262,864 people in the country were affected by floods, and 1527 people were killed, with a total annual loss due to flooding of 1.342 billion USD (CRED EM-DAT: The OFDA/CRED - International Disaster Database, 2015). Egypt is exposed mainly to flash and pluvial floods (surface floods occurring in urban areas) (Abdrabo et al., 2022a, 2022b; Abdrabo et al., 2020; Saber et al., 2021b; Saber et al., 2020).

Alexandria is the second largest metropolitan city and a major coastal city in Egypt, located on the Mediterranean (GOPP, 2008; World Bank, 2011). The city's area is approximately 2818 km^2. In 2017, its population was 5.1 million and was projected to range between 6.5 and 6.8 million by 2030 (Central Agency for Public Mobilization and Statistics, 2017; World Bank, 2011). The city is highly exposed to storm surges and urban floods due to climate change and its impacts, such as extreme rainfall events, in addition to the city's low elevation and complex topographic features (El-Boshy et al., 2019; World Bank, 2011; Zevenbergen et al., 2017). Floods in Alexandria have claimed the lives of 119 people and wounded >26 others since 1991 (El-Boshy et al., 2019; Zevenbergen et al., 2017).

Alexandria has exhibited a lack of resilience in facing several events. The city experienced its worst flooding events on 25 October and 4 November 2015; nearly 60% of the city was flooded. The flood inundation ranged from 0.5 m to 2.3 m, and lowland areas remained affected for 15 days. Alexandria has five districts with a high population density and urban sprawl areas: El-Montazah, the Northern District, the Middle District, the Western District, and El-Gomrok (Alexandria Governorate, 2019). This study was conducted on a local city scale, covering five districts, including 101 neighbourhoods/sheyakhahs. Fig. 1 shows the city's location, administrative units and districts, and inundated parts due to flood events.

The physical indicators significantly change based on a study's scale; this study was carried out on an urban scale, rather than the sub-basin level (Abdrabo et al., 2020). For instance, most studies on the regional scale are based on physical indicators that are more related to natural land, not the urbanized area (Salazar-Briones et al., 2020). Slope, proximity to streams, land cover and soil type, topography, and stream flow are the most common parameters on the regional scale. The local scale requires much more detailed information to determine physical vulnerability, such as the urban context, health and emergency services availability, infrastructure connectivity, urban density, and the construction, material, structure, and height of buildings (Aroca-Jimenez et al., 2017).

4. Methodology

This research comprehensively establishes an FVI using PCA and includes most of the social, economic, and physical components most likely to be affected by a flood disaster (58 indicators). The proposed FVI methodology begins with assessing the vulnerability levels for each factor (exposure, susceptibility, and resilience) on the neighbourhood and district scales. Then, a quantitative evaluation is made by aggregating indicators. The AHP is conducted for simplicity using 13 indicators, and its results are compared with the PCA results to assess its performance.

The developed integrated methodology of the FVI is depicted in Fig. 2, and detailed over-stepwise procedures are explained in the following sub-sections.

4.1. Indicator selection

Flood vulnerability is a multidimensional issue influenced by the characteristics of a person or group and situations that affect the ability to anticipate, endure, deal with, and recover from the adverse effects of physical events. The most challenging task in constructing an FVI is the choice of the primary indicators, since the selection depends on the quality of available variables and the subjectivity of decisions (Nardo et al., 2005). The indicators utilized in this study are selected based on sub-systems of physical, social and demographic, and economic systems (Annex A.1). The chosen indices cover the exposure, sensitivity, and adaptive capacity aspects of vulnerability analysis (Wu, 2021) and are highly related to flood issues. For PCA, 58 indicators are calculated at the scale of primary administrative units (101 sheyakhahs) and the scale of five districts. The indicators selected in this study can be considered a detailed description of different sheyakhahs' physical (15 indicators), economic (20 indicators), and social (23 indicators) contexts. For the AHP, 13 of the 58 indicators are chosen for FVA, including six indicators for the physical dimension, 4 for the social dimension, and 3 for the economic dimension (Annex A.2). The selected indicators provide a broad qualification of physical traits and the observed socioeconomic situation in Egypt.

4.2. Data and materials

Census data on Alexandria and the physical features of a geodatabase constituted the core of the vulnerability and risk assessments. The data required for the vulnerability and risk assessments were obtained by direct contact with the relevant authorities, mainly the Central Agency for Public Mobilization and Statistics (CAPMAS) and the General Organization of Physical Planning (GOPP). The CAPMAS is the national body that collects, processes, analyses, and disseminates statistical data and conducts the census. Additionally, it is responsible for correctly cross-referencing the statistical information of the surveys with the corresponding geographical locations. The primary geostatistical data source (census) was used due to the availability of economic and social data and some physical data on Egypt. Table 1 summarizes the collected data and their metadata. The census of 2017 was obtained in Excel from the CAPMAS. Since the data on the population's economic conditions are not yet available, a geodatabase for the census of 2006 was used to complete the missing information.

The GOPP provided a detailed geodatabase. It contained the physical features of Alexandria city, including buildings, roads, and public infrastructure. Additionally, other data sources were utilized to obtain data with potential usefulness. These data included the locations of schools, hospitals, and historical sites.

4.3. PCA method

PCA has been utilized as an inductive approach to minimize the number of potential variables associated with vulnerability. PCA has a high potential for using rich data sources in conducting vulnerability assessments (Reckien, 2018). Thus, a dataset that includes all potential variables (58) was prepared for 101 sheyakhahs (Annex A.2). The variables were constructed based on census data, a physical geodatabase, and the previously mentioned data sources. PCA was used to combine partly correlated variables with smaller uncorrelated components (Reckien, 2018; Török, 2018). Several software packages can be used to implement PCA. Specifically, SPSS was used in this study. This method is based on the work undertaken by Cutter et al. (Cutter et al., 2003) and was followed by many other researchers interested in assessing social vulnerability (Frigerio and De Amicis, 2016; Reckien, 2018). The FVA process using PCA is described as follows:

1- Data processing and normalization: A recent study by Reckien (Reckien, 2018) revealed that area-based metrics are preferable to percentage-based metrics (Cutter et al., 2003). Accordingly, all potential variables were normalized as an area-based metric for normalizing the indicators (number of assets per sq. km). Several normalization methods were discussed by Yoon (Moreira et al., 2021; Tate, 2012; Yoon, 2012). However, the min-max method yielded results comparable to those of the AHP. This normalization method rescales all variables to values between 0 (worst rank) and 1 (best rank) (Eq. 1). Data normalization was performed for all indicators, and IBM SPSS Statistics was used to carry out all statistical procedures.

$$Min - max = \frac{X_{in} - min(X_{in})}{Max(X_{in}) - min(X_{in})} \tag{1}$$

2- Vulnerability set construction based on PCA: PCA is a data analysis tool used to reduce the dimensionality (number of variables) in the context of many interrelated variables while retaining as much information as possible. In this study, we implemented PCA with a data matrix of 58 variables and 101 tracts to summarize the latent factors describing the physical-natural and socioeconomic context observed in the five districts. The selected variables were grouped into three sets representing vulnerability dimensions: physical, social, and economic vulnerability (Annex A.2). PCA was conducted separately for each dimension's set of variables to detect the vulnerability type to support decision-makers in the mitigation process. Consequently, three different groups of components were extracted, one set for each dimension (physical, social, and economic) (Török, 2018).

Table 1
Data for the vulnerability assessment.

Data	Information	Source	Format	Scale
Census 2017	Buildings and units' physical conditions Population social conditions	Central Agency for Public Mobilization and Statistics (CAPMAS)	Excel	Sheyakhah administrative units
Census 2006	Population economic conditions		Geodatabase	
The city's physical geodatabase	Building information (use, heights, conditions, structure) Infrastructure (i.e., roads, public networks)	General Organization of Physical Planning (GOPP)	Geodatabase	
Schools	Location, type, and number of students	General Authority for Educational Buildings (GAEB)		Building level
Hospitals	Location	Ministry of Health	Shapefiles	
Historical sites	Location and area	Atlas of Antiquities from Ministry of State of Antiquities		

3- Varimax rotation and correlation matrix: Highly correlated indicators were grouped based on the correlation matrix resulting from using the varimax rotation tool in SPSS. The exclusion of highly correlated variables (correlation coefficient > 0.80) was investigated (after retaining the dominant factor) to eliminate data redundancy (Abson et al., 2012; Field, 2013; Török, 2018). In this study, the number of significant axes (or dimensions) was chosen by retaining the components with eigenvalues >1 (de Sherbinin and Bardy, 2015; Török, 2018; University of South Carolina HaVRI, 2011; Wood et al., 2010).
4- The Kaiser–Meyer–Olkin (KMO) test and Bartlett's test: The KMO test and Bartlett's test of sphericity for sampling adequacy were implemented to check model robustness. The KMO index varies from 0 to 1, and to perform the factor or component analysis, categories can be defined based on the following thresholds: 0.90 (marvellous), 0.80 (meritorious), 0.70 (middling), 0.60 (mediocre), 0.50 (miserable), and below 0.50 (unacceptable). Bartlett's test of sphericity checks if redundancy exists in variables and if the utilized variables are suitable for PCA when $p < 0.01$ (Field, 2013; Török, 2018; Wood et al., 2010; Wu, 2021).
   In this study, datasets with a KMO index greater than or equal to 0.70 and a p-value for Bartlett's test of sphericity <0.01 were considered suitable for PCA.
5- Weighting components (variance explained/cumulative variance): Eleven principal components that explained 71.3% of the total variance were retained. To better understand these components, rotated factor loadings of the indicators were analysed, and the significant values are highlighted in Annex A.2 (Field, 2013; Török, 2018; Wood et al., 2010). Components with absolute loading values below 0.4 were excluded. Following the factor rotation stage, a directional adjustment process was applied to the entire factor to ensure that the individual component variables act in the same direction, increasing or decreasing vulnerability. Thus, components enhancing vulnerability were considered positive, while those that reduced vulnerability were deemed negative. Consequently, we assigned a positive score when the resulting factor increased the total vulnerability and a negative score when it decreased total vulnerability. We applied PCA separately to the physical, social, and economic dimensions to obtain a more comprehensive picture.
6- For FVI calculation of each administrative unit, the resulting factor scores for each component were weighted by the ratio of the component's variance explained to the cumulative variance explained by the dimension's components. The components were mapped separately using the resulting weighted factor scores. The summation of the weighted components resulted in a cumulative vulnerability score for each dimension. Additionally, the cumulative vulnerability score was used to map its spatial distribution, as shown in (Eq. (2) (Abdrabo et al., 2020; Abson et al., 2012; Reckien, 2018; Tate, 2012).

$$Vulnerability = \sum_{f=1}^{n} w_f * s_f \tag{2}$$

where f is the vulnerability indicator, n is the total number of indicators, w_f is the relative weight assigned to the indicators, and s_f represents the indicator score. The weights wf are obtained from the factor loadings matrix mentioned above based on (Eq. 3:

$$w_{fj} = \frac{\left(factor - loading_{fj}\right)^2}{eigenvalue_j} \tag{3}$$

where factor loading kj is the value of the factor loading of indicator f in principal component j and eigenvalue j is the eigenvalue of the jth principal component. Finally, the FVI can be calculated as a weighted aggregation of the intermediate sustainability indicators, as shown in (Eq. 4:

$$FVI_i = \sum_{j=1}^{j=11} \alpha_j IVI_{ji} \tag{4}$$

where FVIi is the value of the composite indicator for tract i and αj is the weight applied to intermediate vulnerability indicator j. These weights are calculated as shown in (Eq. 5:

$$\alpha_j = \frac{eigenvalue_j}{\sum_{j=1}^{j=11} eigenvalue_j} \tag{5}$$

The cumulative vulnerability scores for the three dimensions were summed to calculate the overall vulnerability and map it. This aggregation method is commonly implemented in vulnerability assessment studies (Frigerio and De Amicis, 2016; Tate, 2012). The map was classified using normalization classes to represent the score variations (Török, 2018; Wood et al., 2010).

4.4. AHP method

The AHP was developed by Saaty (Saaty, 1988) as an essential tool for decision-makers or groups of decision-makers, enabling their preferences to be analysed and discussed (Saaty, 2000). The AHP constructs a pairwise comparison matrix (PCM) to compare the criteria. The AHP is used to estimate the weighting of each criterion, which describes its importance. Saaty suggested a scale of 1 to 9 for PCM elements, where 1 indicates that the criteria are equally important. A value of 9 indicates that the criterion under consideration is essential in relation to the other criterion with which the comparison is made. The relative weights of the indicators are computed using the AHP. The AHP is implemented using six steps, as discussed and depicted below.

1. The relative importance of each parameter pair is determined based on the pairwise comparison importance scale; this step is called prioritization (Table 2)

2. Pairwise comparison for a matrix of 13 × 13 cells is created for the 13 vulnerability indicators (Table 4). The elements in row i and column j of the matrix are labelled I and J. The matrix has the property of reciprocity (aij = 1/aij) and is shown (Table A.2) in the Appendices
3. The matrix is standardized using the mathematical expression $aij/\sum_{i,\ j=1}^{n} aij$.
4. The normalized value for each parameter from pairwise comparisons is used with the weighted values in the last column of the standardized matrix to obtain the eigenvector, representing the consistency index (CI) matrix.
5. The CI is applied to check the pairwise comparison matrix using (Eq. 6:

$$\mathrm{CI} = \frac{(\lambda\ max - n)}{n - 1} \tag{6}$$

CI is the consistency index, n is the number of vulnerability indicators being compared, and λ max is the most significant value of the eigenvector matrix.

6. The consistency ratio (C.R.) is the ratio of the CI and the random index (R.I.) shown in Table 3 and is expressed mathematically using (Eq. 7

$$CR = \frac{CI}{RI} \tag{7}$$

Saaty developed the C.R. to check the consistency of the pairwise comparisons (Samela et al., 2016). The C.R. was calculated, and the value was 0.057, which is <10% (0.1), indicating that the pairwise matrix is consistent. The final vulnerability map was obtained using equal dimension weighing, and it was ranked into four low- to very high-vulnerability classes.

The vulnerability mapping method combines multiple physical, economic, and social indicators (Table 4). The six physical vulnerability indicators are the ratio of the green space area, the number of low-rise buildings (two floors or less per sq. km), the number of low-quality buildings per sq. km, the number of buildings not connected to sanitation per sq. km, the number of makeshift buildings per sq. km and the average distance to the nearest hospital in km. The economic vulnerability has three indicators: the dependency ratio, the industrial and commercial land use ratio, and the ratio of the service land use area. Social vulnerability's four indicators are population density per sq. km, the elderly population above 65 years old, the population of children below five years of age, and the disabled population per sq. km.

All 13 selected indicators were normalized (Eq. 1). The AHP approach was used to determine the relative weights of each vulnerability indicator (Table 4) following the steps above. The flood vulnerability maps were calculated (Eq. 2). The final values of each dimension were multiplied by 0.33 to maintain equal weighting of each vulnerability dimension. Based on the literature, the resulting vulnerability maps were categorized based on their min-max value into five categories distributed equally from 0 to 1: very low (0–0.201), low (0.0202–0.401), moderate (0.402–0.600), high (0.601–0.800), and very high (0.801–1.0) (Abdrabo et al., 2020). The vulnerability maps were calculated based on (Aroca-Jimenez et al., 2017; Frazier et al., 2014).

5. Results

5.1. PCA flood vulnerability maps

The PCA flood vulnerability maps were divided into the main dimensions of vulnerability (physical, social, and economic), as shown in Fig. 3. Eleven principal components (3 physical, 4 social, and 4 economic) that explained 71.3% of the total variance were retained. All pairwise correlation coefficients among the 58 indicators were calculated in SPSS Statistics 26. Accordingly, 20 indicators were excluded due to their high correlation, and 38 were used for FVA with PCA (9 physical, 13 social, and 16 economic), as shown in Annex A.3.

5.1.1. PCA physical vulnerability

A set of three components was used to calculate physical vulnerability: (1) a building's connectivity to infrastructure, (2) a building's structure, and (3) residential built-up area density. The most effective indicator in each of the previously mentioned components was the number of buildings not connected to sanitation, bearing walls, and residential buildings. The cumulative variance explained by the components was nearly 62%, with a middling value (approximately 0.7) in the KMO test and Bartlett's test of sphericity was significant with $p < 0.001$. Annex A.2 summarizes the physical vulnerability results, including the variance explained by the physical components and the loading scores of their contributing variables (9 variables). The cumulative physical vulnerability was

Table 3
RI based on the order of the pairwise matrix.

No. of indicators	1	2	3	4	5	6	7	8	9	10	11	12	13
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56

Table 2
Pairwise comparison importance scale (Saaty, 1988).

Scale	Description	Reciprocals*
1	Elements i and j have equal importance	1
3	Element i is slightly more important than element j	1/3
5	Element i is more important than element j	1/5
7	Element i is strongly more important than element j	1/7
9	Element i is very strongly more important than element j	1/9

* Reciprocals are used if element i has a lower value than j.

Table 4
Scoring criteria for the vulnerability indicators.

No.	Category	Indicators	Relation	Score/wt%
1	Physical	The ratio of the green space area	−	8.7
2		The number of low-rise buildings (two floors and less per sq. km)	+	12.3
3		The number of low-quality buildings per sq. km	+	16.1
4		The number of buildings not connected to sanitation per sq. km	+	4.4
5		The number of makeshift buildings per sq. km	+	9.3
6		The average distance to the nearest hospital in km	+	7.3
7	Social	Population density per sq. km	+	11
8		The number of elderly people above 65 years old per sq. km	+	5.5
9		The number of children below five years old per sq. km	+	3.8
10		The number of disabled people per sq. km	+	6.4
11	Economic	Dependency ratio	+	5.2
12		The ratio of industrial and commercial land uses	+	3.8
13		The ratio of the service area	+	4

estimated by summing these three components' weighted factor scores and is illustrated in Annex. A.2. The units with high to very high physical vulnerability accounted for 17 out of 101 administrative units with 2.54% of the total population and 1.43% of the total area, concentrated in El-Gomrok and the Western District. Several administrative units had medium to high vulnerability categories in El-Montazah, the Northern District, and the Middle District. However, in terms of area, El-Gomrok and the Western District were relatively small compared with El-Montazah and the Northern District (Fig. 3.a).

5.1.2. PCA social vulnerability

A set of four components identified social vulnerability: (1) the population structure, (2) the population social status, (3) the population with poor mobility, and (4) overcrowding. The most effective indicator in each of the previously mentioned components was the number of children under five years, the widowed population, the number of students in primary schools, and the overcrowding rate. The cumulative variance explained by the component was nearly 77.5%, with a value of 0.75 in the KMO test and $p < 0.001$ in Bartlett's test. Annex A.3 summarizes the social vulnerability results, including the variance explained by the social components and the loading scores of their contributing variables (13 variables). The cumulative social vulnerability was estimated by summing the weighted factor scores of these four components and is illustrated in Annex A.3. The units with high to very high social vulnerability accounted for 10 out of 101 administrative units with 5.41% of the total population and 0.86% of the total area, concentrated in El-Gomrok, the Northern District and El-Montazah. Several administrative units had medium to high vulnerability categories in the Middle and Western Districts (Fig. 3.b).

5.1.3. PCA economic vulnerability

A set of four components identified economic vulnerability: (1) population work activities, (2) service activities, (3) poverty, and (4) dependency. The most effective indicator in each of the previously mentioned components was the number of people working in transportation and communication activities, the ratio of services, the extreme poverty ratio, and the dependency ratio. The cumulative variance explained by the component was nearly 74.3%, with an excellent value (approximately 0.81) from the KMO test and $p < 0.001$ in Bartlett's test. Annex A.3 summarizes the social vulnerability results, including the variance explained by the social components and the loading scores of their contributing variables (16 variables). The cumulative physical vulnerability was estimated by summing the weighted factor scores of these three components; it is illustrated in Annex. A.3. The units with high to very high physical vulnerability accounted for 18 out of 101 administrative units with 20.32% of the total population and 4.45% of the total area, concentrated in El-Gomrok, the Northern District, and the Middle District. Several administrative units had medium to high vulnerability categories in El-Montazah and the Western District (Fig. 3.c).

5.1.4. PCA overall vulnerability

The very high and high scoring units were distributed across the study area. El-Gomrok had the highest vulnerability values, followed in order by the Middle District, the Western District, the Northern District, and El-Montazah (Fig. 4).

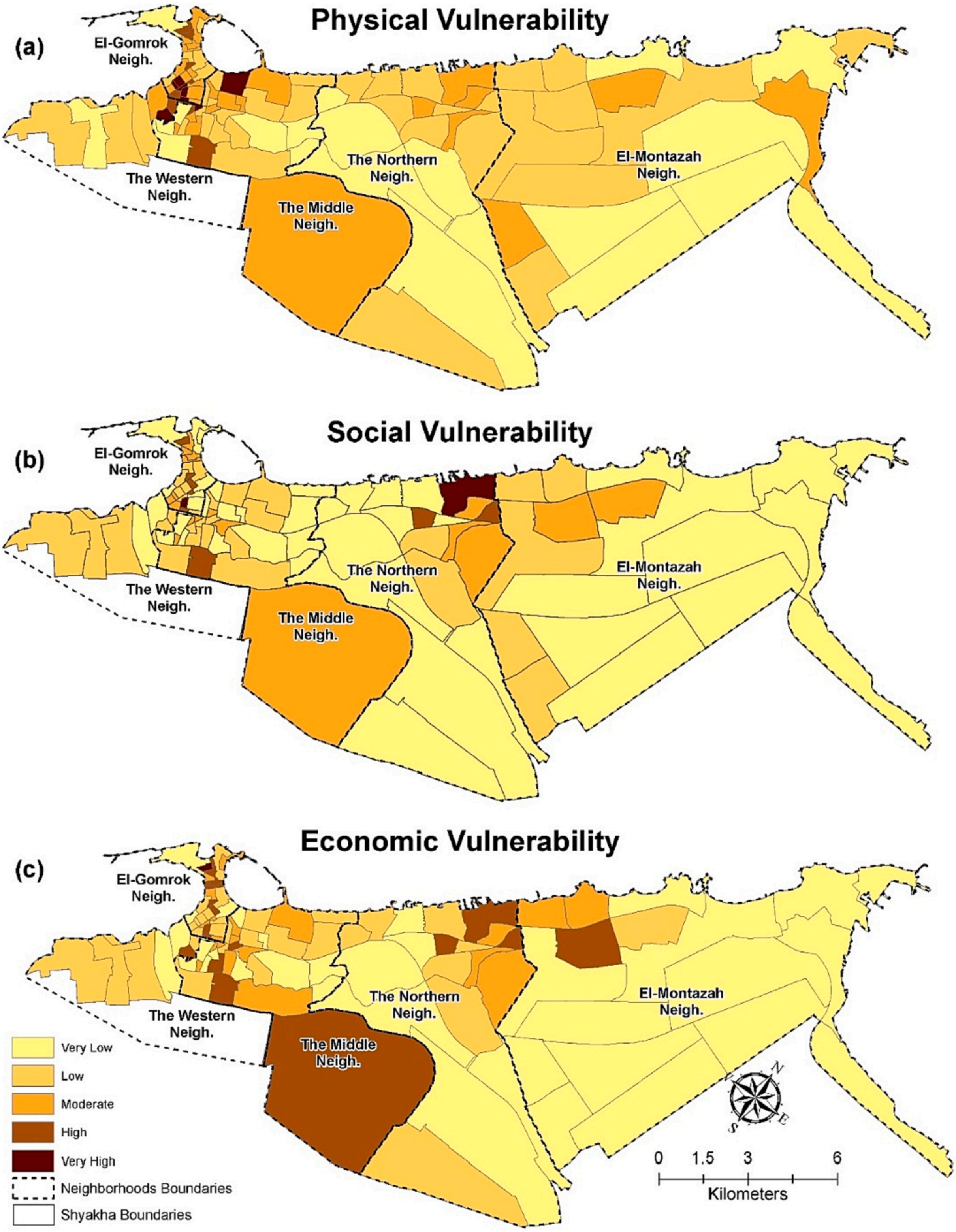


Fig. 3. a. Physical, b. social, and c. economic flood vulnerability results using PCA.

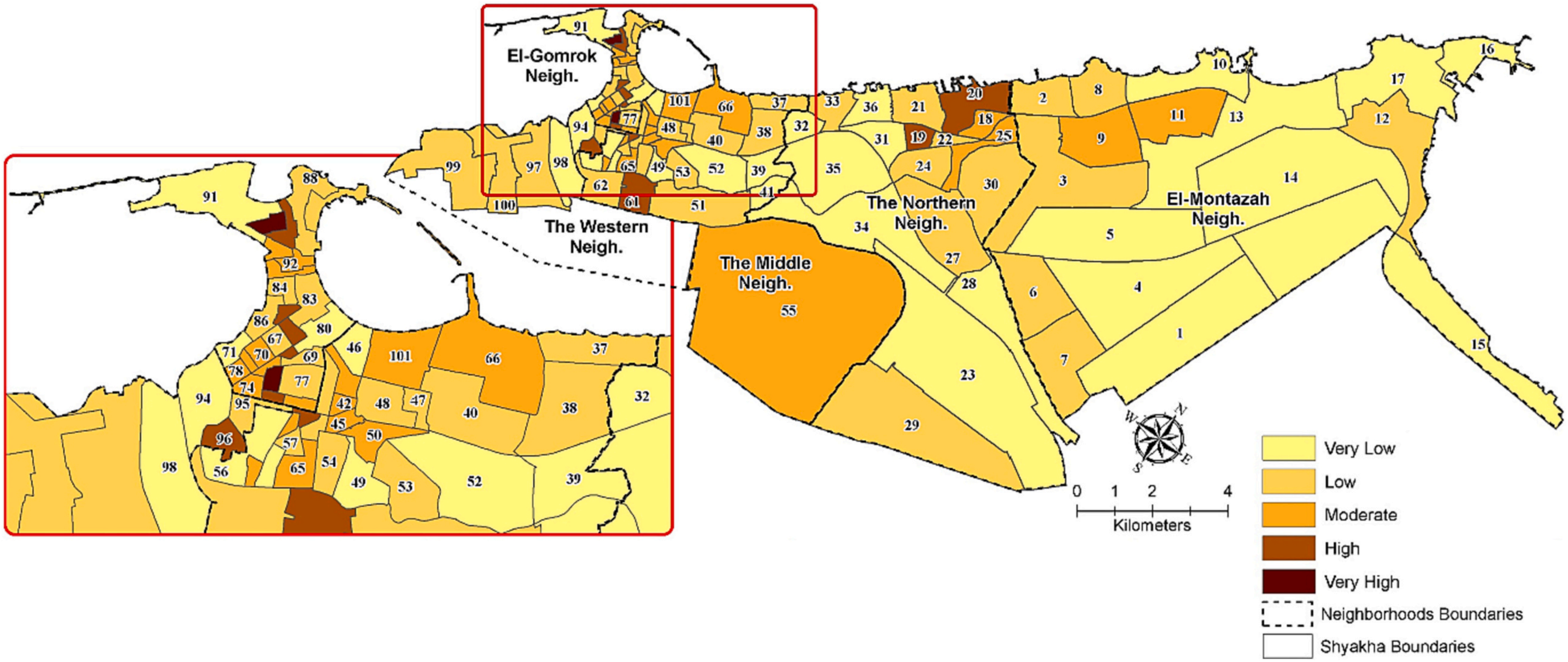


Fig. 4. Overall flood vulnerability using PCA.

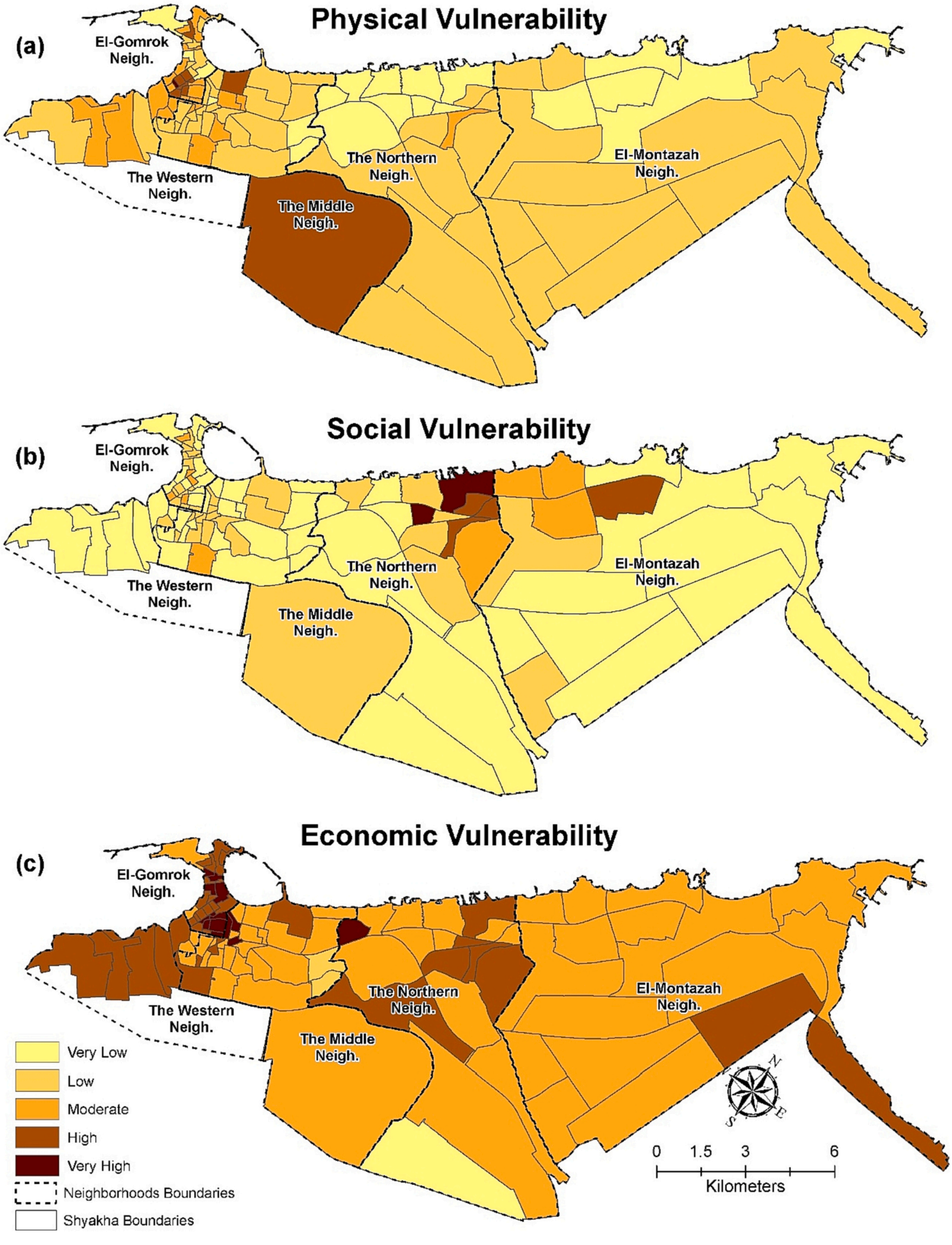


Fig. 5. a. Physical, b. social, and c. economic flood vulnerability results using the AHP.

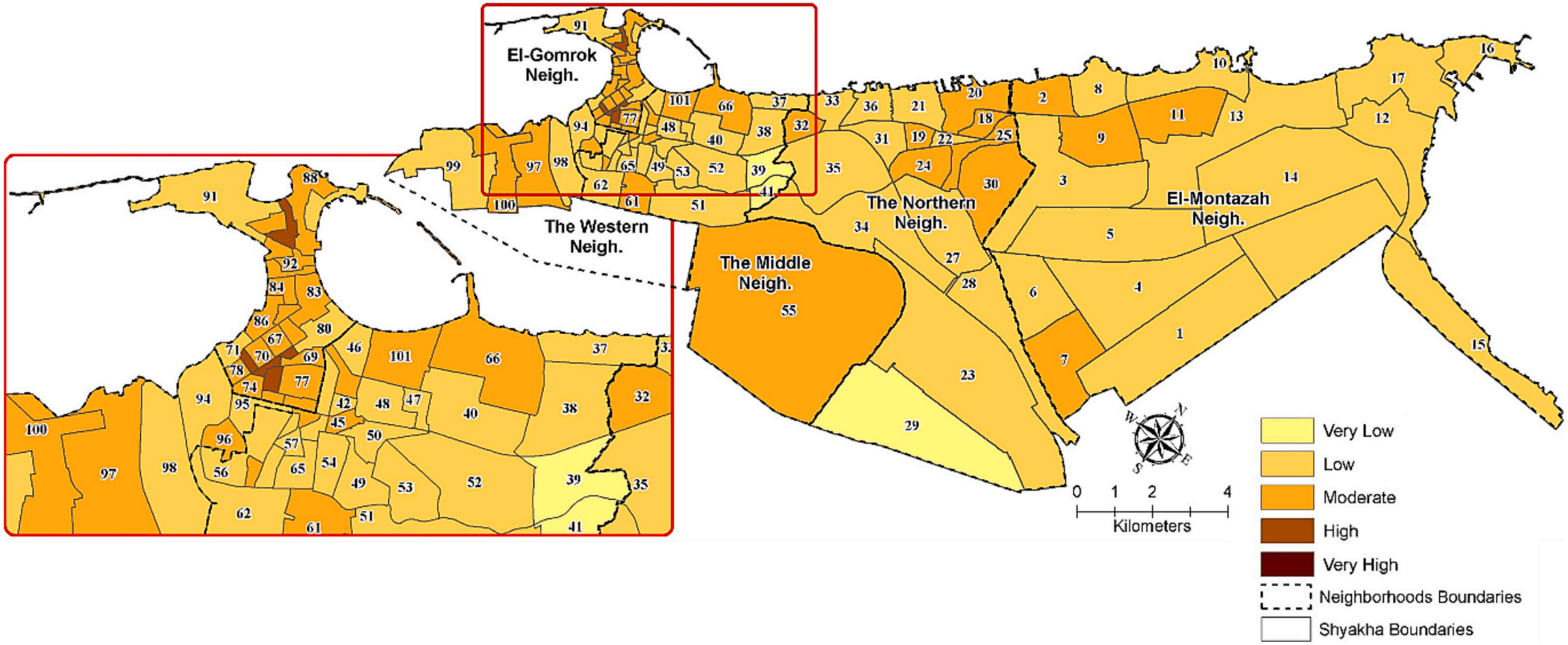


Fig. 6. Overall flood vulnerability using the AHP.

5.2. AHP flood vulnerability maps

The AHP flood vulnerability maps were divided into the main dimensions of vulnerability: physical, social, and economic. Thirteen indicators were chosen, categorized, and weighted by experts (Table 4). All 13 selected indicators were normalized (Eq. 1), and the physical, economic, social (Fig. 5), and overall vulnerability (Fig. 6) maps were calculated (Eq. 2).

5.2.1. AHP physical vulnerability

Table 4 summarizes the physical vulnerability indicators and weighting. The units with high to very high physical vulnerability accounted for 10 out of 101 administrative units with 1% of the total population and 0.52% of the whole area. Similar to the results of physical vulnerability using PCA, the administrative units with high and very high vulnerability were concentrated in El-Gomrok and the Western District, and several administrative units had medium to high vulnerability categories in El-Montazah, the Middle District, and the Northern District (Fig. 5.a).

5.2.2. AHP social vulnerability

Table 4 summarizes the social vulnerability indicators and weighting. The units with high to very high social vulnerability accounted for 6 out of 101 administrative units, with 15.11% of the total population and 2.74% of the entire area. In agreement with the results of social vulnerability using PCA, the administrative units with high and very high vulnerability were concentrated in El-Gomrok, the Northern District and El-Montazah. Several administrative units had medium to high vulnerability categories in the Middle and Western Districts (Fig. 5.b).

5.2.3. AHP economic vulnerability

Table 4 summarizes the economic vulnerability indicators and weighting. The units with high to very high economic vulnerability accounted for 47 out of 101 administrative units, with 25.35% of the total population and 21.89% of the entire area. In contrast to the results of economic vulnerability using PCA, all five districts showed high vulnerability, especially El-Gomrok, the Northern District, and the Western District with several administrative units, and there were medium to high vulnerability categories in El-Montazah and the Middle District (Fig. 5.c).

5.2.4. AHP overall vulnerability

The units with very high and high scores were distributed across the study area. Similar to the results obtained from the PCA, El-Gomrok had the highest vulnerability values, followed in order by the Middle District, the Western District, the Northern District, and El-Montazah (Fig. 6).

6. Discussion

Addressing flood vulnerability for risk reduction purposes requires understanding that the most effective vulnerability dimensions (physical, social, and economic) must be covered (Mavhura et al., 2017). An integrated approach and unified FVI for urban areas in developing countries is necessary as a tool to enable urban planners and stakeholders to transition from a disciplinary approach to a holistic approach that integrally solves urban planning processes and reduces the risk of floods. Stakeholders and experts usually prefer the deductive approach due to its simplicity when the drivers of vulnerability are clear. In this case, an assessment can be implemented based on a small number of indicators, incorporating the relative importance of each indicator by using weights as in the AHP (Arabameri et al., 2020). This approach is useful in practice because of its results can be clearly communicated to stakeholders (Reckien, 2018; Yoon, 2012). However, scholars often avoid using weights because there is a lack of appropriate determination.

The influence of individual indicators is not specified since the final vulnerability index is a sum; this can be overcome by mapping individual indicators (Reckien, 2018; Török, 2018). The inductive approach is described as a complex practice, challenging to communicate to stakeholders; nevertheless, it is the most commonly used approach owing to its relative simple approach to considering all possible indicators (Reckien, 2018; Yoon, 2012). Abson et al. (Abson et al., 2012) argued that PCA has the advantage of information richness that makes it possible to understand the multi-variance drivers of vulnerability provided by mapping each component individually (Reckien, 2018; Yoon, 2012).

Accordingly, modelling a unified FVI based on the objective tool PCA is vital for urban development and flood risk management. In this study, like a few articles that introduced an FVI, the economic, physical, and social dimensions were given the same weight to bridge the different approaches and make it easier for stakeholders and the community to make accurate decisions (Balica and Wright, 2010; Salazar-Briones et al., 2020; Wu, 2021). In contrast to other methods, the level of analysis was on an urban scale and not at the sub-basin level. Additionally, unlike in other studies, we utilized a physical vulnerability index that combines the intrinsic vulnerability of buildings and flash flood intensity to evaluate the propensity to suffer damage resulting from indicators related to building properties. The physical indicators related to flow parameters were neglected to avoid redundancy since they will be used in hydrological models to obtain hazard maps as a part of the flood risk assessment process. The most common indicators among the previous articles and this research in the social dimension were population density, education level, gender, and the underage and elderly population (Cutter et al., 2003; El-Boshy et al., 2019; Rufat et al., 2015). At the same time, this study considered other indicators, such as the illiteracy rate, household connectivity to infrastructure, disabilities, and the tenure type (owned, rented, etc.). For the economic dimension, the most common indicators were employment status, occupation, and the poverty ratio (Müller et al., 2011). Indicators related to the land-use type, land, or property value were also considered in this study.

The comparison of the AHP and the PCA techniques demonstrated good agreement between both sets of results in both the physical and social vulnerability maps. However, there was a noticeable difference in economic vulnerability. To explain these results, we must mention that they mainly depend on indicator selection, weighting, and aggregations. Notably, 10 out of 13 indicators used in the AHP were already included in the PCA indicator set. Four out of 6 indicators were used in the AHP physical indicators (makeshift buildings, low-quality buildings, the number of buildings not connected to sanitation, and the average distance to the nearest hospital). The other 2 (low-rise buildings (2 floors and less) and the ratio of the green space area) were replaced by similar indicators in PCA (bearing wall buildings and built-up area density). Accordingly, the results for physical vulnerability matched between PCA and the AHP in terms of both their values and spatial distribution (Figs. 3.a and 5.a).

Similar results for social vulnerability were obtained by AHP and PCA. Three of four AHP social indicators were included in the PCA indicator set (children below five years old, population density, and the number of disabled people) (Figs. 3.b and 5.b). All the economic indicators in the AHP were represented in the PCA indicator sets. However, there were 16 indicators for economic vulnerability in PCA and 3 in the AHP. All three indicators were found to have a negative impact on economic vulnerability and to have high values, which led to the differences mentioned above (Figs. 3.c and 5.c).

Both the AHP and PCA in the overall vulnerability maps agreed that El-Gomrok had the highest vulnerability values, followed in order by the Middle District, the Western District, the Northern District, and El-Montazah. The high vulnerability values in El-Gomrok were explained by the fact that it is the oldest part of the city (Abdel-Salam, 1995) (Figs. 4 and 6).

The AHP tended to have higher values than PCA, but the minor differences showed a similar trend (Fig. 7). The AHP tended to have higher values than the PCA values regarding the total area and population under higher flood vulnerability categories, except for the high and very high classes (Fig. 8). However, it exhibited the same trend. The average overall flood vulnerability value using the AHP was 0.398; using PCA, the value was 0.34.

7. Conclusion

This study was conducted to fill global and local gaps in FVA. This study is one of a few studies to introduce an integrated FVI for urban areas in developing countries. It is also one of four studies to compare both deductive and inductive methods for indicator-based approaches regarding their implementation requirements and options regarding indicator selection, metrics, transformation, and weighting, as well as the difference in their results. Additionally, this study is the first attempt to use PCA in FVA in Egypt to provide spatial planners and stakeholders with a unified FVI that utilizes an objective approach for selecting and weighting the indicators (Reckien, 2018; Yoon, 2012). In this study, the total number of indicators was reduced from the 58 indicators to 38 indicators. A further reduction in the number of indicators will be considered in future work to simplify the decision-making process and the effort involved in data collection. Appropriate mathematical methods (a derivative and correlation) were applied to identify the essential critical indicators for a simpler, easier, and low-cost application. Highly correlated variables (correlation coefficient > 0.80) were excluded to eliminate data redundancy (Abson et al., 2012; Field, 2013; Török, 2018). The utilized approach can be used to construct an FVI locally, nationally, and internationally. The proposed FVI overcomes the drawbacks of obtaining flood vulnerability data by utilizing all the available local indicators, resulting in a quality index used as a planning tool in urban areas with similar characteristics. In this study, we also constructed a unified FVI for flood projects in the Egyptian context, avoiding the variability in results due to dependence on expert opinions. In this study, an integrated FVI for urban flooding was developed using local indicators to generate a localized flood vulnerability for more realistic results of vulnerability and resilience indices. The resulting FVI, including the most effective indicators without redundancy, can be easily used as an educational tool to improve flood risk reduction decision-making.

Based on a comparison of the results of the PCA and AHP methods, we found that the AHP tended to yield higher values than PCA, but the differences were minor and exhibited a similar trend. Accordingly, for the FVI in arid urban areas (especially Egypt), the results indicated that the 38 indicators obtained from PCA are the best to use in Egyptian city FVA (if available); otherwise, using the 13 indicators resulting from the AHP analysis can lead to similar results.

We recommend retaining both the physical and social vulnerability indicators for the AHP since they were very closely matched with the PCA results. Regarding the economic vulnerability indicators for the AHP, we recommend using more indicators to reduce the differences between its results and those obtained from PCA. Additionally, a validation process for the FVA results should be carried

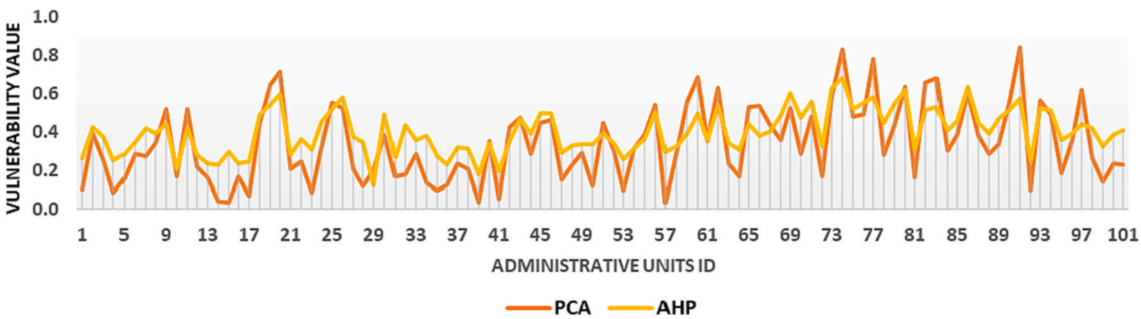


Fig. 7. Overall flood vulnerability using the AHP.

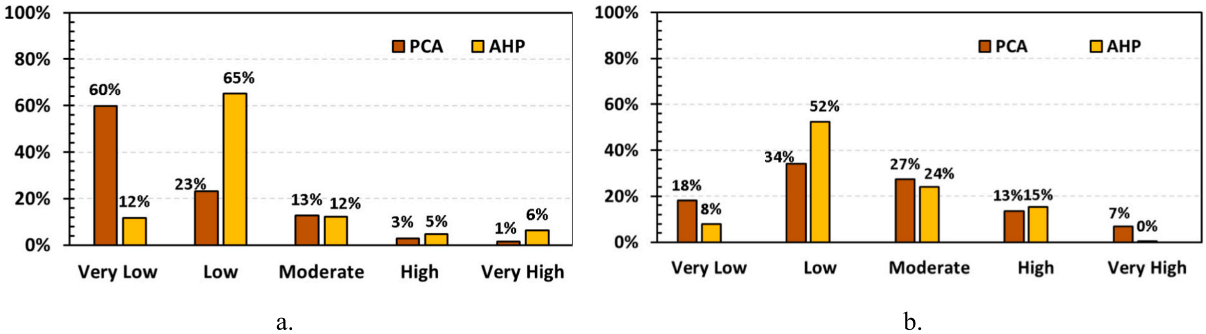


Fig. 8. PCA and AHP vulnerability comparison regarding a. total area and b. total population.

out with real-world, observed impacts accompanied by statistical or expert-based analysis, highlighting the factors most relevant to vulnerability (Reckien, 2018; Yoon, 2012). Moreover, other cities should be investigated using the same indicators and methods to generalize the results of the study. Additionally, when implementing the methods used in this study on different scales, attention should be paid to the scale's effect on data collection and subsequent analysis (Tate, 2012; Yoon, 2012).

This study faced several challenges, and the most crucial challenge was obtaining the data from different agencies, as mentioned in Section 3.2, which took more than six months.

Decision-makers should be provided with vulnerability assessments using different approaches to decide based on their preferences (Yoon, 2012); in this study methods that utilize both subjective and objective approaches for selecting and weighting vulnerability indicators were presented (Reckien, 2018; Yoon, 2012). The results of this study can be used as a reference to guide and assist planners and officials in FRA and mitigation measures. The provided FVI can be used as a tool for decision-making to direct investments in the appropriate sectors and to help develop flood defence, policies, measures, and activities.

CRediT authorship contribution statement

Karim I. Abdrabo: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Sameh A. Kantoush:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Aly Esmaiel:** Conceptualization, Software, Formal analysis, Data curation. **Mohamed Saber:** Supervision, Project administration. **Tetsuya Sumi:** Supervision, Project administration, Funding acquisition. **Mahmood Almamari:** Writing – review & editing. **Bahaa Elboshy:** Writing – review & editing. **Safaa Ghoniem:** Supervision.

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

Data will be made available on request.

Acknowledgements

Funding: KA is funded by a full scholarship from the Ministry of Higher Education of the Arab Republic of Egypt, core-to-core program, the Japan Society for the Promotion of Science (JSPS), grant number JPJSCCB20220004

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.uclim.2023.101426.

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