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Machine Learning Enhances Flood Resilience Measurement in a Coastal Area – Case Study of Morocco

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ABSTRACT. Understanding the characteristics contributing to enhancing flood resilience is a matter of urgency in managing urban areas, especially for developing countries, given the challenges imposed by climate change, social growth and urbanization. Identifying resilience metrics remains challenging, mainly because the concept is relatively new, methodological approaches are almost absent, and many types of resilience-related data are still unavailable. A number of indices for flood resilience have been introduced in the literature, typically based on clustering algorithms that allow complex behaviors to be mapped to specific levels of resilience. Consequently, the qualitative aspects of such indices are highly sensitive to the availability, quality and heterogeneity of data. Historically, this assessment has often been performed using rather simple algorithms such as Principal Components Analysis (PCA). Whilst they allow reliable resilience metrics in some areas, their use in a complex urban system such as the northern coastal area in Morocco is arguable. In the present study, we introduce an advanced Machine Learning (ML) method, namely the Self-Organizing Map (SOM), to build a Flood Resilience Index (FRI). Compared to classical methodologies, this present technique allows an improved assimilation of the complex relationship between data representing the social, economic and physical status of the area and resilience level. The success of this approach is mainly due to the ability of SOM to deal with complex, heterogeneous and sparse datasets. The results demonstrate great potential for such algorithms to shed light on systems that are too complex for classical techniques.

Keywords: resilience, flooding, composite indicators, machine learning, flood resilience index

1. Introduction

Adaptation to climate change is a significant challenge that local governments and communities need to address to achieve local and regional development goals (Schipper and Pelling, 2006). According to the Intergovernmental Panel on Climate Change (IPCC), the risks associated with global warming are going to increase during the future (IPCC, 2022). Therefore, greater populations will be affected by water and climate-related disasters. Indeed, several studies have shown that these events are more likely to increase in the future under the impact of climate change (Krausmann et al., 2008; Kellens et al., 2013; Qasim et al., 2016), which is predicted to lead to considerable economic losses and tremendous social stress (Masozera et al., 2007).

As reported by Centre for Research on the Epidemiology of Disasters (CRED, 2022), floods dominated 375 annual catastrophic event for 2001 ~ 2020, with 223 occurrences. Because of the resulting impact of extreme weather events and rapid urbanization, floods remain one of the most devastating natural hazards worldwide (Lamond et al., 2015; Kotzee and Reyers, 2016), affecting a greater proportion of the population than any other type of climate disaster, particularly in Africa (Keating et al., 2014). In addition, population growth is likely to put more stress on urban cities (DESA, 2014). Consequently, communities, stakeholders and urban decision-makers need to review their management to cope with different challenges resulting from the combined impacts of climate change, social growth and urbanization.

Historically, the management of climate-driven hazards has mainly focused on standard mitigation measures through excessive construction such as physical barriers, retention basins, early warning systems (Alfieri et al., 2016), and the retreat or relocation of settlements (Macintosh, 2013). Previous work has considered those measures as traditional resistant strategies, responsive with a short-term focus to make the community reactive to a natural disaster so that the losses are kept to a minimum (De Bruijn, 2004; Papadopoulos et al., 2017). Whilst being necessary for adaptation purposes, they remain insufficient to reduce losses. Resilience to climate-related disasters can also be improved through the adaptation of policies and

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laws, public awareness raising, training and education (IPCC, 2012). The ideas mentioned above have led to rising practitioners and researcher's interest in investigating how to improve urban resilience (Rus et al., 2018). Therefore, the resilience concept has gained a broad interest as the primary goal of adaptation plans and policies.

Several previous works have been dedicated to defining resilience and measurement processes (Carpenter, 2002; Folke et al., 2002; Klein et al., 2003; Walker et al., 2004; Brand and Jax, 2007; Marshall and Marshall, 2007; Norris et al., 2008; Cutter et al., 2010; Hung et al., 2016; Sharifi and Yamagata, 2016a; Asadzadeh et al., 2017). Generally, these studies demonstrate that resilience should be addressed based on two different perspectives: socio-environmental and engineering (Rus et al., 2018). Resilience metrics should, therefore, incorporate both these approaches. In the first approach, resilience is identified as the needed actions allowing the urban system to recover from a disaster in a small fraction of time. While from an engineering perspective, resilience is mainly based on the needed infrastructures to be settled before a hazardous event.

Generally, when quantifying the resilience of an urban complex system, numerous data are used. Most of the time, these data are sparse and heterogeneous, which means that the available data are neither of the same type (numerical, categorical) nor the same nature. In fact, they are very dependent on the nature of the socio-economical activities happening in the region. Composite indicators are often used to quantify resilience towards a specific disaster (Cutter et al., 2014). During the last few years, many indicators have been constructed to assess resilience and compare their levels within a particular geographical area (Sharifi and Yamagata, 2016b; Asadzadeh et al., 2017).

For example, Cutter et al. (2010) defined a community resilience index based on indicators that act as a baseline. Establishing the baseline allows monitoring resilience in time and space. Magis (2010) has shown that such indicators are particularly useful to assess the social sustainability of a complex urban system. However, a method's ability to provide an accurate insight into the resilience level towards a specific disaster relies on the accuracy of the data obtained (Sherrieb et al., 2010). In addition, Joerin et al. (2014) introduced a climate disaster resilience index, which allows the assessment of an urban system's sensitivity towards climate disasters from different perspectives (economical, institutional, natural, physical, and social). This index has been further adapted for communities (Peacock et al., 2010) and localities (Hung et al., 2016). Particular indicators have also been developed in the specific case of flood resilience, such as the Integrated Flood Resilience Index (FResI) (Bertilsson et al., 2019), Composite Resilience Indices (CRI) (Qasim et al., 2016), and Flood Resilience Index (FRI) (Kotzee and Reyers, 2016; Chen and Leandro, 2019). The Composite indicator approach has proven to be tangible, providing a synthetic measurement of a complex, multi-dimensional, and meaningful phenomena through the aggregation of multiple individual indicators (Marana et al., 2019).

Despite these advances, previous studies have also highlighted the challenges associated with data quality and availability constraints (Cai et al., 2018; Moghadas et al., 2019). The computation of these composites requires the aggregation of several heterogeneous data. Calculating resilience metrics means mapping non-linear behaviour between observed phenomenon (social, physical, and economical) measured by data and a resilience level. This is mainly achieved using clustering algorithms. To date, only the classical Principal Component Analysis (PCA) method has been used in the literature (Kotzee and Reyers, 2016). Advanced Machine Learning (ML) techniques are still lacking to enhance the complex relationship between the FRI and the different data, although a few studies have highlighted the opportunity behind machine learning applications to identify better predictors of resilience (Knippenberg et al., 2019; Soden et al., 2019).

Moreover, there is a lack of resilience measurement tools developed by local authorities and organizations in developing countries (Sharifi, 2016), and very few of these tools have been implemented in an operational context. Cutter (2019) has identified a gap in studies comparing the measurement tools and indices developed to operationalize the resilience.

This study represents one of the first attempts to introduce an advanced ML method to estimate the FRI. Here, the Self Organizing Map (SOM) is used to measure the resilience to floods in the spatialized form. A comparison between this method and the classical (PCA) is also be presented.

The Kohonen SOM is a special kind of artificial neural network (ANN) based on competitive learning, and it has not been used in the field of disaster risk management. Moreover, SOM has been introduced as a computational data analysis method that produces nonlinear mappings of data to lower dimensions (Kohonen et al., 1997). In this study, the SOM method is used as a clustering algorithm, producing clusters of selected variables that are aggregated into a composite index.

The present study focuses on a site in Morocco, and thus regards the different challenges towards regional development. Previous work in Morocco has identified this Mediterranean country as a hotspot for climate change (Born et al., 2008; Driouech et al., 2009; Ouhamdouch and Bahir, 2017). Although there is evident variability in the different simulations of Regional Climate Models (RCM) over this area to assess the intensity of the impact, all simulations predict that Morocco will experience an increase in temperature and a decrease in precipitation (Driouech et al., 2010). Thus, the region is very vulnerable to climate change impacts (Schilling et al., 2012), such as severe impacts on agriculture (Rochdane et al., 2014), water resources (Bahir et al., 2020), and natural hazards (Satta et al., 2016; Satour et al., 2021). Because of the ubiquitous uncertainties in future climate scenarios, quantifying this impact remains a challenging issue.

For example, Tramblay et al. (2012) studied the impact of climate change on extreme precipitation. The authors highlighted that assessing the expected occurrence of such an event is challenging in northern Morocco. Consequently, it is difficult to accurately predict the impacts on future flood events in this area (Fink and Knippertz, 2003).

Increasing resilience against flooding is of utmost importance to achieve sustainability of urban systems (Snoussi et al.,

Table 1. Indicators Set for the Measurement of Resilience to Floods

Variables	Description, effect on resilience & justification
Children under 14 years of age Elderly Special needs	% Population: Elder, children and population with physical or mental disability, have constraints of mobility during floods and evacuation process (Qasim et al., 2016; kotzee and Reyers, 2016; Hung et al., 2016).
Illiteracy	% Person who has never learned to read: can make the emergency and public awareness processes challenging.
Schooling age	% School age Population (7~12 years): Children are vulnerable individuals. The access to education increases understanding of skills to prepare and protect from floods (Brilly and Polic, 2005).
Unemployment	% Population with employment It reduces poverty and increases economic capacity Qasim et al., 2016; Cutter et al., 2010). However, an unemployed citizen is in front with his disability to recover or rebuild their damage. Balica, 2012).
Houshold density	The proportion of household members per the total sector surface. It expresses the exposure of the population to floods and negatively influences the resilience (Balica and Wright, 2010).
Wall materials Flooring material Roofing materials	Numbers of houses made of reinforced concrete, bricks with mortar will be more resilient to floods than mud houses (Qasim et al., 2016).
Housing age	% of housing units built before 50 years or under than ten years (Cutter et al., 2010). It is an indice of place attachment (kotzee and Reyers, 2016).
House state: ownership House state: co-owner House state: tenancy	% of houses ownership statute (revealing the economic stability of the population).
Electricity accessibility Water infrastructure	% of Population connected to public distribution network: Public infrastructure (Hung et al., 2016).
Television Mobile phoe Internet	% of Population having communication capacity (kotzee and Reyers, 2016).
Elevation	Averaged elevation (m) (Hung et al., 2016).

Table 2. Principal Components Extracted to Build FRI

Components	Extraction sum of squared loadings			Rotation sum of squared loadings		
	Total (*eigenvalue*)	*% of variance*	*Cumulative %*	*Total* (*eigenvalue*)	*% of variance*	*Cumulative %*
1	5.903	28.111	28.111	4.663	22.206	22.206
2	3.598	17.132	45.243	3.366	16.030	38.236
3	2.533	12.061	57.304	3.149	14.995	53.231
4	1.628	7.753	65.057	2.220	10.571	63.802
5	1.148	5.468	70.526	1.298	6.183	69.985
6	1.052	5.011	75.536	1.166	5.551	75.536
Kaiser-Meyer-Olkin measure of sampling adequacy				*0.795*		
Bartlett's test of sphericity			$\chi^2 = 1819.319$	d.l.l = 210	$p < 0.0001$	

2008). Morocco has engaged in several projects to mitigate climate change, especially impacts from flooding. For example, a current project aims to decrease the impact of flooding in the northern Moroccan region by transferring the excess water to the arid southern region. While this project may help to reduce the negative impact of climate change (flooding in the North and water stress in the South), its viability remains unclear regarding climate change (El Moçayd et al., 2020).

Furthermore, the increase in urban population is another key-challenge that the communities need to tackle to meet the region's development goals. Furthermore, the increase in urban population is another key challenge to tackle in order to meet region's development goals. In Morocco, urban population is expected to increase in the coming few years (HCP, 2018), urban population is expected to increase in the coming few years. Therefore, it is now critical to evaluate FRI's in the Moroccan region that could be implemented in the operational context. These algorithms need to consider the complex nature of the available data and examine the spatial distribution of the resilience index, regarding their importance (Satour et al., 2021).

The study makes a comparative analysis of PCA and SOM methods highlighting the differences between them, in the Flood Resilience measurement process, while showing the usefulness of these procedures for identifying recommendations revealed from identifying flood resilience determinants in the study area.

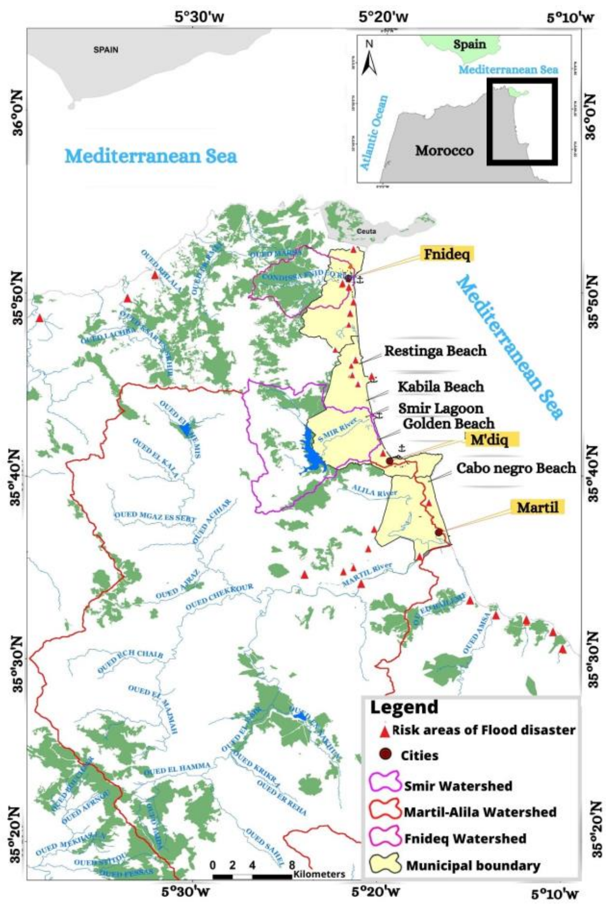

Figure 1. Map of the study area showing its location in North of Morocco, and three municipalities of Fnideq, M'diq and Martil.

2. Overview of the Study Area

Fnideq, M'diq and Martil (FMM) municipalities are located within the metropolitan area of Tangier-Tetouan. Over a length of 44 km extending on the coastal edge, FMM municipalities are situated in two low sandy regions separated by the rocky cape of Capo Negro (Niazi, 2007), and are downstream from three watersheds: Fnideq, Smir and Martil-Alila (Figure 1). The urban coastal area is highly developed, putting pressure on the ecosystems (Snoussi et al., 2010). The socio-economic activities are mainly driven by seasonal tourism, whilst the industrial sector remains minor. The area has faced many hazardous floods since 1980 (ABHL, 2016), where14-flooded areas are localized at FMM. From 2000 until 2010, historical records show that floods have occurred in the area almost annually (Pateau, 2014). For example, in December 2000, Martil municipality experienced the most intense flood in the last 60 years (3500 m^3/s, 150 Mm^3), causing eight deaths and injuries and considerable material damage (Ministry of Equipment, Transport, Logistics and Water, 2017). The frequency of hazardous event in this area is likely to increase in the future (Satta et al., 2016).

3. Data

Data were collected at the local level from the last 2014 Census of Morocco (RGPH, 2014) as well as government publications, municipal planning documents and an online RGPH 2014 database. Table 1 summarizes the available data and describes the continuous variables used in this study. Classification and Visualization were undertaken using Geographic Information System (GIS) tools. Our Maps were created using the Free and Open Source QGIS.

4. Methodology: Resilience Assessment Based on PCA and SOM

4.1. Construction of the Index Composite: FRI

A useful tool for policymaking and public communication is the composite indicator, which has increasingly been used to convey information (Gallopin, 1996; Cutter et al., 2010). Nevertheless, the use of this indicator to measure resilience is relatively recent (Prior and Hagmann, 2014). The application of a weighting system through a set of selected variables has been suggested to construct composite indices using data collected from surveys and databases (Vyas and Kumaranayake, 2006). In this study, among the existing weighting techniques, we investigate the use of two methods: PCA and SOM.

4.2. Flood Resilience Assessment Based on Principal Component Analysis

PCA is a statistical technique employed to cluster the variables according to their correlation. It can be used to encompass a high number of variables highly correlated into new, statistically independent components that best explain the variation in the data (Kaźmierczak and Cavan, 2011). Basically, PCA uses the correlation matrix to transform sequentially the original variables into latent variables (components). The new variables are achieved by maximizing the variance of a linear combination of the original variables. For this purpose, a certain number of latent components with maximum variability are retained to represent the data. The obtained components are aggregated to compute the composite index (Nardo et al., 2005).

Furthermore, the new axes are ordered in terms of the percent of the amount of variation from the total they account for (Table 2). The Kaiser's varimax rotation method is used for the computation of the eigenvalue decomposition of a data covariance matrix.

A study by Gómez-Limón and Riesgo (2008) shows that the process to calculate the index FRI is based on the extracted principal components. The authors suggest using a weighted aggregation of indicators w_{kj} and I_{ki} (the normalized indicator k achieved by ward i) for $k = 1, \ldots, n$, to determine the components IRI_{ji} of the intermediate resilience indicator IRI_j that correspond to each principal component. The same formulations were also employed in this study to calculate IRI_{ji} and W. The components IRI_i of the index composite FRI can then be calculated as a weighted aggregation of the intermediate resilience indicators:

$$FRI_i = \sum_{j=1}^{j=6} \alpha_j IRI_{ji} \tag{1}$$

where FRI_i is the value of the composite indicator for the ward i and α_j is the weight applied to the intermediate sustainability indicator IRI_{ji}. These weights are calculated as follows:

$$\alpha_j = \frac{eignvalue_j}{\sum_{j=1}^{j=6} eignvalue_j} \tag{2}$$

The result corresponding to the index scores shows that obtained values can be negative or positive. The normalization using min-max is used to standardize the index scores.

4.3. Flood Resilience Assessement Based on Self-Orgnizing Map

The SOM (Kohonen neural network) is the closest of all artificial neural network architectures and learning schemes to the biological neuronal network (Kohonen et al., 1997). The self-organizing map has one single layer of neurons usually arranged in a two-dimensional plane, and the number of neurons in the input layer is equal to the dimension of the input space (En-Naimani et al., 2016). A defined architecture means that each neuron has a finite number of neurons as nearest neighbours and are usually arranged in squares, which means that each neuron has four nearest neighbours (Joudar et al., 2019).

Generally, there are two major classes of learning: supervised learning and unsupervised learning. In our case, the model falls within the unsupervised learning class. The input data is a dimensional vector $\mathbf{X} = \{x^1, x^2, \ldots, x^n\}$, with $x^i = \{x_1{}^i, x_2{}^i, \ldots, x_3{}^i\}$, where n is the sample size and d is the input dimension.

As a first step, each neuron is associated with a reference vector $w^j = (w_1{}^j, w_2{}^j, \ldots, w_3{}^j)$, $j = 1, \ldots, N$, belongs to input space. The goal is to find the best weights W^* that represent the training data X.

The second step, each x^i at a time t is compared with all w^j to find the reference vector $\mathbf{w}^k$ that satisfies a minimum distance or maximum similarity criterion. Although several measures are possible, the Euclidean distance is the most commonly used:

$$k = \arg\min_{j=1}^{N} \| x^i - w^j \| \tag{3}$$

The best-matching unit (BMU = k) and neurons within its neighborhood are then activated and modified:

$$w^j(t+1) = w^j(t) + \beta_{k,j}(t) \| x^i - w^j \| \tag{4}$$

One of the main parameters influencing the training process is the neighborhood function ($\beta_{k,j}(t)$), which defines a distance-weighted model for adjusting neuron vectors. It is defined by the following relation:

$$\beta_{k,j}(t) = \exp\left(\frac{-d_{k,j}}{2\sigma_k^2(t)}\right) \tag{5}$$

This latter is dependent on both the distance ($d_{k,j}$) between the BMU and the respective neuron j, and on the time step reached in the overall training process (t). Using a Gaussian model, this function involves a kernel width (σ) which is not a fixed parameter.

The correlations are first estimated using SOM between the considered variables, in order to compare the FRIs. For this purpose, the data X are considered as realizations d times of each variable $X_1, \ldots, X_n$, i.e., $X = \{x_q{}^j\}$, $i = 1, \ldots, n$; $q = 1, \ldots, d$. Moreover, we consider the set of weights associated to map as: $W = \{w_q{}^j\}$, $i = 1, \ldots, N$; $q = 1, \ldots, d$. With $N << n$, meaning that the number of neurons considered in the map is very small compared to the number of elements in the database.

Moreover, the SOM algorithm can be used to calculate FRI based on the optimal weights $W^{1*} = (w^{1*}, w^{2*}, \ldots, w^{N*})$ associated to N neurons. Each neuron corresponds to an intermediate resilience indicator (IRI_j), computed iteratively using the following formula:

$$IRI^j(t+1) = IRI^j(t) + \beta_{k,j}(t) \| I^i - IRI^j(t) \| \tag{6}$$

As a result, after the convergence of the algorithm the vector $IRI_j^* = \left(IRI_1^{j*}, IRI_2^{j*}, \ldots, IRI_d^{j*}\right)$ represents the intermediate resilience indicator values ($IRI_j{}^*$). Where $w_q{}^{j*}$ is the intermediate resilience indicator for the neuron j and the ward i. The weights $w_i{}^j$ of each associated vector $\mathbf{w}^j$ are normalized:

$$FRI_i = \sum_{k=1}^{k=N} \beta_j IRI_{ji} \tag{7}$$

where FRI_i is the value of the composite indicator for the ward i and β_j is the weight applied to the intermediate sustainability indicator j. These weights are calculated and normalized as follows:

$$\beta_j = \frac{total\ number\ of\ associated\ variables\ winning\ by\ neurone_j}{total\ number\ of\ variables} \tag{8}$$

5. Results and Discussion

5.1. Principal Component Scores and Clustering with SOM

Six principal components explain 75% of the total variance. Table 2 provides the factor loadings for the linear transformation of the original variables to the components. The rotated factor loading can be used to analyze the components'

Table 3. Rotated Components Matrix from PCA (Factor Loadings)

	Components					
	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6
Illiteracy	–0.825					
Schooling age 7 ~ 12 years old	0.567					
Flooring materials	–0.792					
Electricity	0.603					
Television	0.826					
Mobile Phone	0.733					
Internet	0.794					
Walling materials bricks with mortar		0.905				
Flooring materials		–0.887				
Roofing materials		0.865				
Children under 14 years of age			–0.654			
Elderly			0.744			
Special need			0.622			
Unemployment			0.662			
House Age > 10 years			–0.829			
House Age < 50 years			0.638			
Owner, co-owner				–0.917		
Tenant				0.850		
Water accessibility				0.462		
Household density					0.878	
Elevation						0.861

Extraction method: Principal Component Analysis.
Rotation method: Varimax with kaiser normalization.

meaning and specify the variables that affect them.

From these results, only four principal components were retained, explaining 75% of the total variation in the data (Figure 2). These components correspond to the eigenvalues of PCA. The variance accounting for each of these six components are respectively 28.11, 17.13, 12.06, 7.75, 5.46 and 5.05% (Figure 2).

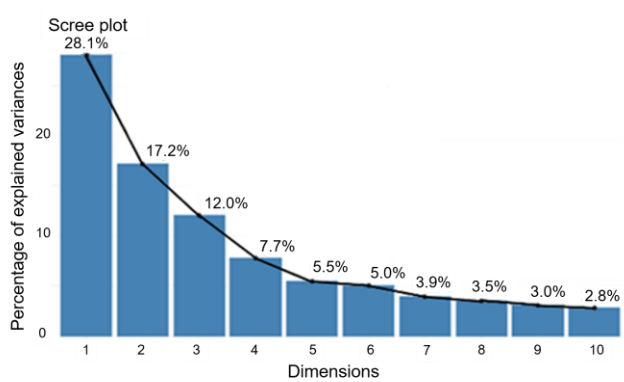

Figure 2. Scree plot of percentage of explained components.

Most of the PCA variables contribute highly to the construction of the first and the second components. They also contribute lightly to construct components 3 and 4 (Table 3). Variables of illiteracy, flooring materials, electricity and communication devices (television, mobile phone, and internet) scored highly in component 1 (Table 3). Based on the predominance of public services variables in component 1, this was classified as an economic resilience component. Variables loaded highly in component 2 include walling materials (A) and (B), and roofing materials. Component 2 was classified as the building materials component (Table 3).

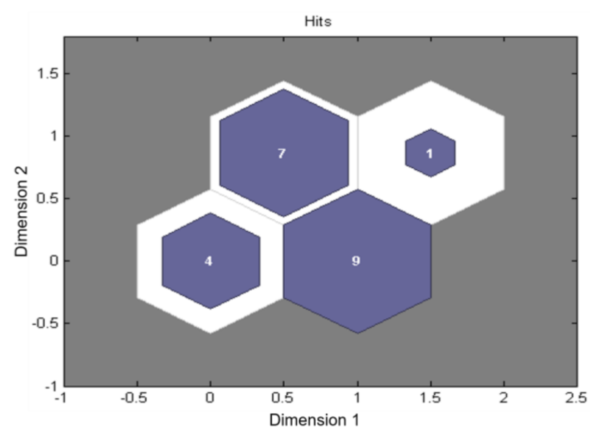

Figure 3. A representation of the 4 clusters with the number of variables contained in each cluster.

The elderly population, a person with a particular need, house age 10 years and 50 years, loaded highly in component 3. With a high negative loading of house age 10 years and children under 14 years. Based on these variables, component 3 was classified as social. Component 4 had only three variables: owner and co-owner, tenant statutes, and water accessibility. The household density and the elevation are loading respecttively to components 5 and 6.

The SOM will project the original data points into a hexagonal topology "output space". The SOM divided data from 21 different sectors into four clusters (Figure 3).

Variables of illiteracy, unemployment, child under 14 years and roofing materials scored on the first neuron. Based on the predominance of social variables in component 1, it was classified as a social neuron.

Variables loaded highly in neuron 2 include the Elderly population, people with special needs, building density, roofing and flooring materials, house ages, internet and elevation. Neuron 2 was classified as the physical resilience neuron (Figure 3).

The third neuron included scho0ling 7 ~ 12 years, walling materials, electricity, water, television and mobile phone. Based on these variables, neuron 3 was classified as economic resilience neuron. Neuron 4 had only the tenancy variable (Figure 3).

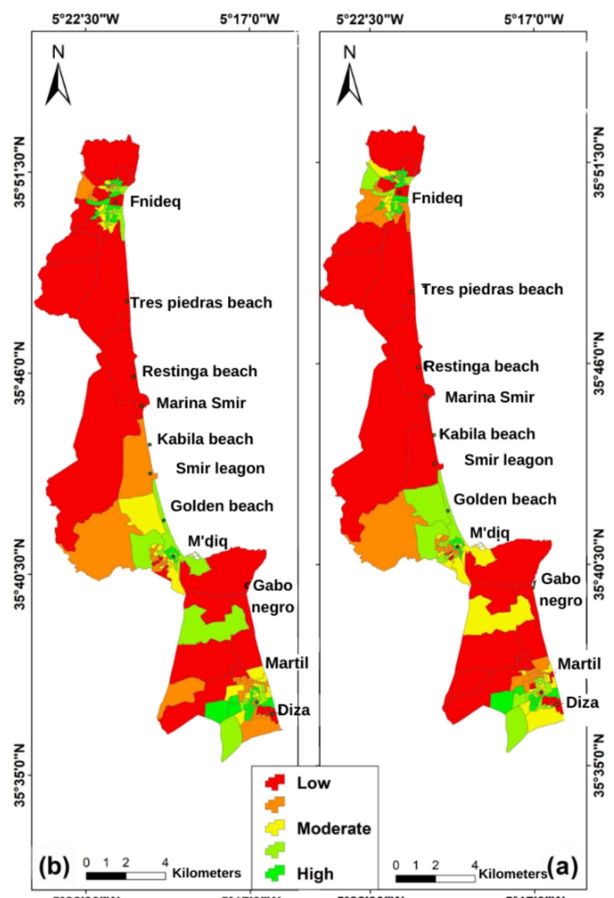

Figure 4. Spatial distribution of flood resilience index (FRI) values and their related ward ranking for the Martil, M'diq and Fnide municipalities. a): FRI calculated using PCA, and b) FRI calculated using SOM approach.

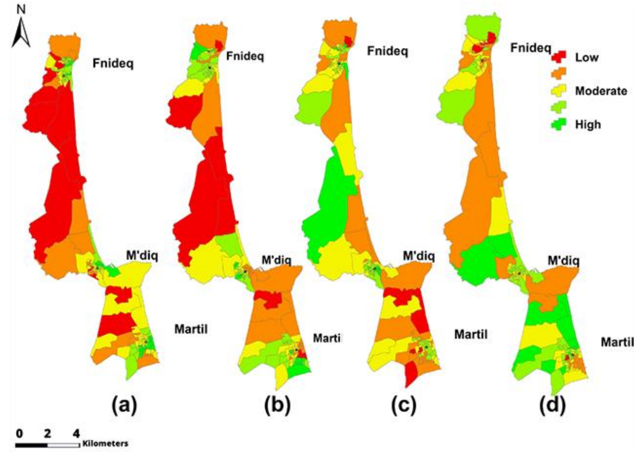

Figure 5. Spatial distribution of disaggregated components of the flood resilience index calculated using PCA: showing (a) economic resilience, (b) physical resilience, and (c) social resilience.

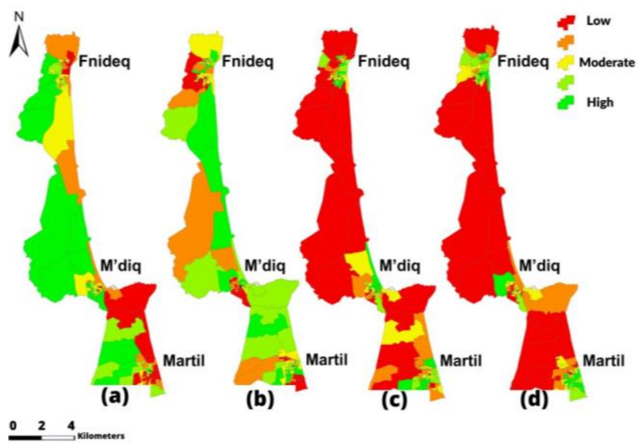

Figure 6. Spatial distribution of disaggregated neurons of the flood resilience index calculated using SOM: Neuron1 (a): social; Neuron 2, (b): physical; Neuron 3, (c): economic; Neuron 4, and (d): Tenancy variable.

5.2. Comparative Analysis of PCA and SOM to Build FRIs

The composite index and spatial analysis have proven to help summarize and present a complex array of variables linked to resilience. The two different flood resilience mapping, PCA and SOM, are presented in Figures 4a and 4b.

The estimated FRI values were classified into different resilience classes using the quantiles classification method. Using the two methods (PCA and SOM), the FRI scores are represented with their spatial distribution using Geographic Information Systems (GIS). The two FRI estimated were superimposed of 126 RGHP 2014 sector of control boundaries throughout the study area. The estimated values were classified into five levels (from very low to very high; at 20% intervals) and then compared in

Table 4. *t*-tests for Global Comparison between FRI-PCA and FRI-SOM

PCA – SOM Comparison	Paired differences					
	Mean	Std. deviation	Std. error mean	*t*	d.f	*p*-value
FRI_PCA - FRI_SOM	0.010	0.018	0.002	6.569	124	0.000

Figure 4.

The flood resilience index distribution demonstrates the large variability across the study area (Figure 4). FRI mapping results show a similarity in the two FRI assessment schemes (PCA and SOM) (Figures 4a and 4b), with slight differences observed for the means and standard deviations calculated in the two cases (PCA approach: mean 1 = 0.491 and sdv 1 = 0.034; SOM approach with a mean 2 = 0.501 and sdv 2 = 0.043). Moreover, SOM and PCA do not lead to the same clustering structure in the final results. SOM affected the two isolated variables with PCA: "elevation" and "household density" to the second cluster. These differences illustrate the possible presence of non-linearity in the data, which is not captured by PCA. Thus, SOM is suitable to detect the non-linearity between variables. A general overview of the graphical results (Figures 4a and 4b) over the whole region shows that the high flood resilience scores were found in the three municipalities' central urban zone: Martil, M'diq and Fnideq. The moderate flood resilience was observed in the outer sectors. In contrast, the lesser levels were observed in the peri-urban areas. They were seemingly localized in the same sectors. There are some exceptions highlighted, in the west of Fnideq, Kabila beach, Smir lagoon, M'diq center, sector surrounding Alia River and Diza district. Theses sectors could be the possible outliers in the dataset.

To further the comparison, a disaggregation into PCA components and neurons for SOM allows the determination of the major flood resilience drivers (Kotzee and Reyers, 2016) (Figures 5 and 6).

5.3. FRI Desegregated into Its PCA Components

When the index FRI is disaggregated into its six components, the significant determinant parameters of flood resilience become clear (Kotzee and Reyers, 2016) (Figure 5).

For PCA, to further explore the geographic trends in the data, the intermediate resilience indicator (IRI) scores for the four retained components are displayed using a GIS tool. Based on standard deviations from the mean value, those components helped emphasize sectors that rank high or low in terms of their flood resilience.

Using GIS, we seek here to represent the spatial distribution of the four disaggregated components of the index across the study area are represented.

The distribution of economic resilience (Figure 5a) shows the highest scores are only in some sectors in the main towns of the three municipalities: Martil, M'diq and Fnideq. Average scores were found in sectors adjoining the central urban sectors. The lowest was found in the central area and developing sectors in term of economic resilience (Figure 5a).

The distribution of physical resilience (Figure 5b) shows few highest scores are within the wards, including the main cities of the respective municipalities. The moderate scores were found in the outer sectors bordering the municipalities of Martil, M'diq and Fnideq. The low scores were found in the outer sectors and developing areas as in the west of Fnideq.

In term of social resilience (Figure 5c), highest scores were measured within and around city centres. The lowest scores were highlighted around Martil city centre, with average scores on the whole surface of M'diq and Fnideq cities.

Component 4 (Figure 5d) had only three variables: owner and co-owner, tenant statutes, and water accessibility. The distribution of component 4 shows relatively high scores predominant in the three municipalities and low scores in Diza district in Martil, and the less developing sectors in the central area.

5.4. FRI Desegregated into Its Neurons

Following the same process of desegregation, to explore flood resilience using SOM, FRI is disaggregated into the four neurons. Into the first neuron (Figure 6a), the highest scores were found over large surfaces of the whole study area. However, Fnideq and M'diq centres have moderate scores. Lowest flood resilience was found in urban sectors situated on Martil coastal area.

Figure 6b shows that the lowest FRI scores are within urban wards of the three municipalities, while the highest scores were found within Martil centre and in the outer sectors bordering M'diq and Fnideq city centres.

In terms of the third and the last neuron, the highest scores were found within the center urban wards, while the lowest scores were prevailing at large surfaces of the whole study area (Figure 6c).

The disaggregation step revealed many differences between the results of FRI calculated through PCA, FRI and SOM. Therefore, a *t*-test (Table 4) is calculated to highlight significant differences between the means in the output of the two methods: PCA and SOM.

5.5. Paired Sample *t*-test (PCA-FRI, SOM-FRI) and Robustness Check

Both methods have confirmed their applicability in evaluating and measuring flood resilience. To test and assess the reli- ability of PCA and SOM method taking into account the results of the FRI_PCA and FRI_SOM obtained over the whole study area (126 sectors), a comparison analysis is established be- tween the proposed methods using paired sample *t*-tests for equality of means. Table 4 shows the results of these tests. There is a significant difference (p-value = 0.0000 < 0.05 and t = 6.569) between two FRI measurements calculated by the two methods. The *t*-test justifies the main differences already highlighted in the same sectors in term of economic, physical and social resilience.

In order to assess the PCA or SOM methods' accuracy in making relevant results, an examination of the results reliability is developed based on the validation step. The external validity is applied since the risk and vulnerability oriented studies (Niazi, 2007; Snoussi et al., 2010; Nejjari, 2014; Satta et al., 2016) are available in the study area, analyzing the strongly related phenomenon, external validity is applied.

The FRI-SOM method findings mention that central wards of urban cities (Diza sector, Martil Alila, central wards in Fnideq and M'diq) requires high-level attention in terms of physical and social resilience, which is not the case with the FRI-PCA method suggesting moderate attention.

The FRI calculated with SOM provides consistent results visualizing, much more easily, the sectors presenting the outliers in the dataset: the low flood resilience scores in Diza district in Martil. This was expected as it located in a highly hazardous flooded area and locked between the riverbed and a dead-arm. This ward contains informal settlements, characterized by illiteracy, unemployment, and insalubrious houses (Le Tellier, 2006). These characteristics contribute to their low flood resilience level.

Nevertheless, the highest similarities revealed between the two FRI calculated are valid. The lowest resilient sites calculated with SOM and PCA (Martil-Alila plain, Smir Lagoon and Restinga beach) are notably highly vulnerable to flash floods and sea-level rise impacts (Niazi, 2007; Snoussi et al., 2010; Satta et al., 2016).

Nevertheless, the two indices support the idea that areas with higher vulnerability levels examined have lower resilience levels (Hung et al., 2016; Scherzer et al., 2019).

6. Conclusion

In the present study, the potential of Machine Learning tools to evaluate resilience in a complex urban system has been highlighted. The two clustering methods used in this study (PCA and SOM) enabled the examination of the critical factors that drive flood resilience. This information was essential in understanding the resilience level to floods in the whole area and its spatial distribution. Both methods provided insights on the geographic distribution of FRI across Fnideq, M'diq and Martil municipalities. Both PCA and SOM have proven to be simple to apply. However, the *t*-test and a robustness check showed that only SOM was able to provide tangible recommendations reliably. PCA may provide some less irrelevant information, with 6 principal components retained, in our case, explaining less than 80% of the total variance.

The ability of SOM to reduce the dimensionality of data, to deal with non-linear and heterogeneous data were the main determining factors for this performance. Therefore, SOM is an efficient neural network method to deal with the resilience assessment based on information from high dimensional data.

These results highlighted the importance of the robustness check step, to be sure if the composite index calculated reflects the reality. In addition, such algorithms are highly dependable on the used data. The most significant challenge in this study was related to the accessibility and quality of data. In conclusion, integrating climatic data (flood data or flood simulation data) are suggested for future improvements. Moreover, using an index-based resilience measurement requires the intervention of a time dimension because of the dynamism of our urban systems. Another challenge was the external validation step based on the opposite relationship between risk and resilience. Resilience is locational and context-specific. Thus, the local stockholders can clearly benefit from using Machine Learning techniques to inform their development decisions.

References

ABHL (2016). Typology and inventory of sites at risk of flooding. Flood protection project. http://ww.abhloukkos.ma/abhl/index.php/fr/ (accessed March 8, 2023) (in French)

Alfieri, L., Feyen, L., and Di Baldassarre, G. (2016). Increasing flood risk under climate change: a pan-European assessment of the benefits of four adaptation strategies. *Clim. Change*, 136(3-4), 507-521. https://doi.org/101007/s10584-016-1641-1

Asadzadeh, A., Kötter, T., Salehi, P., and Birkmann, J. (2017). Operationalizing a concept: the systematic review of composite indicator building for measuring community disaster resilience. *Int. J. Disaster Risk Reduct*, 25, 147-162. https://doi.org/10.1016/j.ijdrr.2017.09.015

Balica, S. and Wright, N.G. (2010). Reducing the complexity of the flood vulnerability index. *Environ. Hazards*, 9(4), 321-339. https://d oi.org/10.3763/ehaz.2010.0043

Balica, S.F. (2012). *Applying the Flood Vulnerability Index as a Knowledge Base for Flood Risk Assessment.* Delft University of Technology and Academic Board of the UNESCO-IHE, Delft, Netherlands, pp 152. ISBN 978-0-415-64157-9

Bahir, M., Ouhamdouch, S., Ouazar, D., and El Moçayd, N. (2020). Climate change effect on groundwater characteristics within semi-arid zones from western Morocco. *Groundw. Sustain. Dev.*, 11, 100380. https://doi.org/10.1016/j.gsd.2020.100380

Bertilsson, L., Wiklund, K., de Moura Tebaldi, I., Rezende, O.M., Veról, A.P., and Miguez, M.G. (2019). Urban flood resilience – A multi-criteria index to integrate flood resilience into urban planning. *J. Hydrol.*, 573, 970-982. https://doi.org/10.1016/j.jhydrol.2018.06.052

Born, K., Christoph, M., Fink, A.H., Knippertz, P., Paeth, H., and Speth, P. (2008). *Moroccan climate in the present and future: combined view from observational data and regional climate scenarios*. In Climatic changes and water resources in the Middle East and North Africa. Springer, Berlin, Heidelberg, pp 29-45. https://doi.org /10.1007/978-3-540-85047-2_4

Brand, F.S. and Jax, K. (2007). Focusing the meaning(s) of resilience: resilience as a descriptive concept and a boundary object. *Ecol. Soc.*, 12(1), 23. http://www.ecologyandsociety.org/vol12/iss1/art23/

Brilly, M. and Polic, M. (2005). Public perception of flood risks, flood forecasting and mitigation. *Nat. Hazards Earth Syst. Sci.*, 5(3), 345-355. https://doi.org/10.5194/nhess-5-345-2005, 2005

Cai, H., Lam, N., Qiang, Y., Zou, L., Correll, R.M. and Mihunov, V. (2018). A synthesis of disaster resilience measurement methods and indices. *Int. J. Disaster Risk Reduct.*, 31, 844-855. https://doi.org/10.1016/j.ijdrr.2018.07.015

Carpenter, M.A. (2002). The implications of strategy and social context for the relationship between top management team heterogeneity and firm performance. *Strat. Mgmt. J.*, 23: 275-284. https://doi.org/10.1002/smj.226

Chen, K.F. and Leandro, J. (2019). A conceptual time-varying flood resilience index for urban areas: Munich city. *Water*, 11(4), 830. https://doi.org/10.3390/w11040830

CRED (2022). 2021 Disasters in numbers, Brussels. Centre for Research on the Epidemiology of Disasters – CRED. https://cred.be/sites/default/files/2021_EMDAT_report.pdf (assessed March 8, 2023)

Cutter, S.L., Burton, C.G. and Emrich, C.T. (2010). Disaster resilience indicators for benchmarking baseline conditions. *J. Homel. Secur. Emerg. Manag.*, 7(1), Article 51. https://doi.org/10.2202/1547-7355.1732

Cutter, S.L., Ash, K.D. and Emrich, C.T. (2014). The geographies of community disaster resilience. *Glob. Environ. Change*, 29, 65-77. https://doi.org/10.1016/j.gloenvcha.2014.08.005

Cutter, S.L. (2019). Community resilience, natural hazards, and climate change: Is the present a prologue to the future? *Nor. Geogr. Tidsskr. Norwegian J. Geography*, 74(3), 200-208. https://doi.org/10.1080/00291951.2019.1692066

De Bruijn, K.M. (2004). Resilience and flood risk management. *Water Policy*, 6(1), 53-66. https://doi.org/10.2166/wp.2004.0004

DESA (2014). UN. World urbanization prospects: The 2014 revision highlights. United Nations, Department of Economic and Social Affairs (UN/DESA), Population Division. United Nations publication. https://esa.un.org/unpd/wup/Publications/Files/WUP2014-Highlights.pdf (accessed December 20, 2022).

Driouech, F., Déqué, M. and Mokssit, A. (2009). Numerical simulation of the probability distribution function of precipitation over Morocco. *Clim. Dyn.*, 32(7), 1055-1063. https://doi.org/10.1007/s00382-008-0430-6

Driouech, F., Déqué, M. and Sánchez-Gómez, E. (2010). Weather regimes – Moroccan precipitation link in a regional climate change simulation. *Glob. Planet. Change*, 72(1-2), 1-10. https://doi.org/10.1016/j.gloplacha.2010.03.004

En-Naimani, Z., Lazaar, M. and Ettaouil, M. (2016). Architecture Optimization Model for the Probabilistic Self-Organizing Maps and Speech Compression. *Int. J. Computat. Intell. Appl.*, 15(2), 1650007. https://doi.org/10.1142/S1469026816500073

El Moçayd, N., Kang, S. and Eltahir, E.A.B. (2020). Climate change impacts on the Water Highway project in Morocco. *Hydrol. Earth Syst. Sci.*, 24(3), 1467-1483. https://doi.org/10.5194/hess-24-1467-2020

Fink, A.H. and Knippertz, P. (2003). An extreme precipitation event in southern Morocco in spring 2002 and some hydrological implications. *Weather*, 58(10), 377-387. https://doi.org/10.1256/wea.256.02

Folke, C., Carpenter, S., Elmqvist, T., Gunderson, L., Holling, C.S. and Walker, B. (2002). Resilience and sustainable development: building adaptive capacity in a world of transformations. *AMBIO*, 31(5), 437-441. https://doi.org/10.1579/0044-7447-31.5.437

Gallopin, G.C. (1996). Environmental and sustainability indicators and the concept of situational indicators. A systems approach. *Environ. Model. Assess.*, 1(3), 101-117. https://doi.org/10.1007/BF01874899

Gómez-Limón, A., and Riesgo, L. (2008). Alternative approaches on constructing a composite indicator to measure agricultural sustainability. *Proc. of the 107th EAAE Seminar "Modelling of Agricultural and Rural Development Policies"*, Sevilla, Spain.

HCP (2018). Projections de la population des provinces et préfectures de la région Tanger-Tétouan-Al Hoceima 2014-2030 [Population projections for the provinces and prefectures of the Tangier-Tetouan-Al hoceima region 2014-2030], *Tanger*. Haut-Commissariat au Plan.

Hung, H.C., Yang, C.Y., Chien, C.Y. and Liu, Y.C. (2016). Building resilience: Mainstreaming community participation into integrated assessment of resilience to climatic hazards in metropolitan land use management. *Land Use Policy*, 50, 48-58. https://doi.org/10.1016/j.landusepol.2015.08.029

IPCC (2012). Managing the risks of extreme events and disasters to advance climate change adaptation. *A special report of Working Groups I and II of the Intergovernmental Panel on Climate Change.* Cambridge University Press, Cambridge, UK, and New York, NY, USA, 30(11), 7575-7613.

IPCC (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [H.O. Pörtner, D.C. Roberts, M. Tignor, E.S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, B. Rama (eds.)]. Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA, 3056, doi:10.1017/9781009325844.

Joerin, J., Shaw, R., Takeuchi, Y. and Krishnamurthy, R. (2014). The adoption of a climate disaster resilience index in Chennai, India. *Disasters*, 38(3), 540-561. https://doi.org/10.1111/disa.12058

Joudar, N., En-naimani, Z. and Ettaouil, M. (2019). Using continuous Hopfield neural network for solving a new optimization architectture model of probabilistic self-organizing map. *Neurocomputing*, 344(7), 82-91. https://doi.org/10.1016/j.neucom.2018.09.095

Kaźmierczak, A. and Cavan, G. (2011). Surface water flooding risk to urban communities: Analysis of vulnerability, hazard and exposure. *Landsc. Urban Plan.*, 103(2), 185-197. https://doi.org/10.1016/j.lan durbplan.2011.07.008

Keating, A., Campbell, K.A., Mechler, R., Michel-Kerjan, E.O., Mochizuki, J., Kunreuther, K., Bayer, J.L., Hanger, S., Mccallum, I., See, L.M., Williges, K., Atreya, A., Botzen, W.J., Collier, B.L., Czajkowski, J., Hochrainer, S. and Egan, C. (2014). Operationalizing resilience against natural disaster risk: opportunities, barriers, and a way forward. http://opim.wharton.upenn.edu/risk/library/zurichf

Kellens, W., Terpstra, T. and De Maeyer, P. (2013). Perception and communication of flood risks: a systematic review of empirical research. *Risk Anal.: An Int. J.*, 33(1), 24-49. https://doi.org/10.1111/j. 1539-6924.2012.01844.x

Klein, R.J.T., Nicholls, R.J. and Thomalla, F. (2003). Resilience to natural hazards: How useful is this concept? *Glob. Environ. Change Part B: Environ. Hazards*, 5(1), 35-45. https://doi.org/10.1016/j.hazards.2004.02.001

Knippenberg, E., Jensen, N. and Constas, M. (2019). Quantifying household resilience with high frequency data: Temporal dynamics and methodological options. *World Dev.*, 121, 1-15. https://doi.org/10.1016/j.worlddev.2019.04.010.

Kohonen, T., Kaski, S. and Lappalainen, H. (1997). Self-organized formation of various invariant feature lters in the adaptive-subspace SOM. *Neural Comput.*, 9(6), 1321-1344. https://doi.org/10.1162/ne co.1997.9.6.1321

Kotzee, I. and Reyers, B. (2016). Piloting a social-ecological index for measuring flood resilience: A composite index approach. *Ecol. Indic.*, 60, 45-53. https://doi.org/10.1016/j.ecolind.2015.06.018

Krausmann, F., Fischer-Kowalski, M., Schandl, H. and Eisenmenger, N. (2008). The global sociometabolic transition: past and present metabolic profiles and their future trajectories. *J. Ind. Ecol.*, 12 (5-6), 637-656. https://doi.org/10.1111/j.1530-9290.2008.00065.x

Magis, K. (2010). Community Resilience: An Indicator of Social Sustainability. *Soc. Nat. Resour.*, 23(5), 401-416. https://doi.org/10.1080/08941920903305674

Le Tellier, J. (2006). *Territorial evolution in Northern Morocco. Urban dynamics in the Tingitane peninsula and governance of public utilities in Tangier and Tétouan (Morocco). The inclusion of poor districts through access to transport and drinking water*. Ph.D. Dissertation, U.F.R of Geographical Sciences and Planning, University of Provence Aix-Marseille I, Marseille, France. (in French)

Lamond, J.E., Rose, C.B. and Booth, C.A. (2015). Evidence for improved urban flood resilience by sustainable drainage retrofit. *Proc. ICE: Urban Des. Plan.*, 168(2), 101-111. https://doi.org/10.1680/udap.13.00022

Macintosh, A. (2013). Coastal climate hazards and urban planning: how planning responses can lead to maladaptation. *Mitig. Adapt. Strateg. Glob. Chang.*, 18(7), 1035-1055. https://doi.org/10.1007/s11027-012-9406-2

Marshall, N.A. and Marshall, P.A. (2007). Conceptualizing and operationalizing social resilience within commercial fisheries in northern Australia. *Ecol. Soc.*, 12(1), 1. https://www.jstor.org/stable/26267830

Marana, P., Eden, C., Eriksson, H., Grimes, C., Hernantes, J., Howick, S., Labaka, L., Latinos, V., Lindner, R., Majchrzak, T., Pyrko, I., Radianti, J., Rankin, A., Sakurai, M., Sarriegi, J.M. and Serrano, N. (2019). Towards a resilience management guideline – Cities as a starting point for societal resilience. *Sustain. Cities Soc.*, 48, 101531. https://doi.org/10.1016/j.scs.2019.101531

Masozera, M., Bailey, M. and Kerchner, C. (2007). Distribution of impacts of natural disasters across income groups: A case study of New Orleans. *Ecol. Econ.*, 63(2-3), 299-306. https://doi.org/10.1016/j.ecolecon.2006.06.013

Moghadas, M., Asadzadeh, A., Vafeidis, A., Fekete, A. and Kötter, T. (2019). A multi-criteria approach for assessing urban flood resilience in Tehran, Iran. *Int. J. Disaster Risk Reduct.*, 35, 101069. https://doi.org/10.1016/j.ijdrr.2019.101069

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A. and Giovannini, E. (eds.) (2005). *Handbook on constructing composite indicators: methodology and user guide*. OECD Statistics Working Paper. OECD, Paris

Nejjari, A., (2014). Environmental vulnerability and urban planning: the case of M'diq coastline (Tangier-Tetiouan region), *Review AFN Morocco*, 12-14, 2014 June. https://revue-afnm.org/Numéro%2012-14/4%20RAFNM.pdf (accessed December 20, 2022) (in French)

Niazi, S. (2007). *Climate change and sea level rise impacts on the coastal area of Tetouan (Western Mediteranean, Morocco): vulnerability and adaptation*. Ph.D. Dissertation, Faculty of Sciences, Mohamed V University, Rabat, Morocco (in French)

Norris, F.H., Stevens, S.P., Pfefferbaum, B., Wyche, K.F. and Pfefferbaum, R.L. (2008). Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *Am. J. Community Psychol.*, 41(1), 127-150. https://doi.org/10.1007/s10464-007-9156-6

Ouhamdouch, S. and Bahir, M. (2017). Climate change impact on future rainfall and temperature in semi-arid areas (Essaouira Basin, Morocco). *Environ. Process.*, 4(4), 975-990. https://doi.org/10.1007/s40710-017-0265-4

Papadopoulos, T., Gunasekaran, A., Dubey, R., Altay, N., Childe, S.J. and Fosso-Wamba, S. (2017). The role of Big Data in explaining disaster resilience in supply chains for sustainability. *J. Clean. Prod.*, 142, 1108-1118. https://doi.org/10.1016/j.jclepro.2016.03.059

Peacock, W.G., Brody, S.D., Seitz, W.A., Merrell, W.J., Vedlitz, A., Zahran, S., Hariss, R.C. and Stickney, R. (2010). *Advancing Resilience of Coastal Localities: Developing, Implementing, and Sustaining the Use of Coastal Resilience Indicators: A Final Report*. Hazard Reduction and Recovery Center, College of Architecture, Texas A&M University, TAMU 3731.

Pateau, M. (2014). *Surface dynamics and risk management in the hinterland of the Tangier-Med port complex (Rif septentrional, Morocco)*. Ph.D. Dissertation, Paris Diderot University, Paris, France. (in French)

Prior, T. and Hagmann, J. (2014). Measuring resilience: methodological and political challenges of a trend security concept. *J. Risk Res.*, 17(3), 281-298. https://doi.org/10.1080/13669877.2013.808686

Qasim, S., Qasim, M., Shrestha, R.P., Khan, A.N., Tun, K. and Ashraf, M. (2016). Community resilience to flood hazards in Khyber Pukhthunkhwa Province of Pakistan. *Int. J. Disaster Risk Reduct.*, 18, 100-106. https://doi.org/10.1016/j.ijdrr.2016.03.009

QGIS.org, %Y. QGIS Geographic Information System. QGIS Association. http://www.qgis.org (accessed November 22, 2019)

RGPH (2014). Institutional site of General Census (Morroco). https://www.hcp.ma/downloads/?tag=Annuaires+statistiques+du+Maroc (accessed March 9, 2023) (in French)

Rochdane, S., Bounoua, L., Zhang, P., Imhoff, M.L., Messouli, M. and Yacoubi-Khebiza, M. (2014). Combining satellite data and models to assess vulnerability to climate change and its impact on food security in Morocco. *Sustain.*, 6(4), 1729-1746. https://doi.org/10.3390/su6041729

Rus, K., Kilar, V. and Koren, D. (2018). Resilience assessment of complex urban systems to natural disasters: a new literature review. *Int. J. Disaster Risk Reduct.*, 31, 311-330. https://doi.org/10.1016/j.ijdr r.2018.05.015

Satour, N., Raji, O., El Mocayd, N., Kacimi, I., and Kassou, N. (2021). Spatialised flood resilience measurement in rapidly urbanized coastal areas with complex semi-arid environment in Northern Morocco. *Nat. Hazards Earth Syst. Sci. Discuss.*, 21(3), 1101-1118. https://doi.org/10.5194/nhess-21-1101-2021

Satta, A., Snoussi, M., Puddu, M., Flayou, L. and Hout, R. (2016). An index-based method to assess risks of climate-related hazards in coastal zones: The case of Tetouan. *Estuar. Coast. Shelf Sci.*, 175, 93-105. https://doi.org/10.1016/j.ecss.2016.03.021

Scherzer, S., Lujala, P. and Rød, J.K. (2019). A community resilience index for Norway: An adaptation of the Baseline Resilience Indicators for Communities (BRIC). *Int. J. Disast. Risk Re.*, 36, 101107. https://doi.org/10.1016/j.ijdrr.2019.101107

Sharifi Ayyoob (2016), A critical review of selected tools for assessing community resilience, *Ecol. Indic.*, 69, 629-647. https://doi.org/10.1016/j.ecolind.2016.05.023.

Sharifi, A. and Yamagata, Y. (2016a). Urban Resilience Assessment: Multiple Dimensions, Criteria, and Indicators. In: Yamagata, Y., Maruyama, H. (eds) Urban Resilience. Advanced Sciences and Technologies for Security Applications. Springer, Cham. https://doi.org/10.1007/978-3-319-39812-9_13

Sharifi, A. and Yamagata, Y. (2016b). On the suitability of assessment tools for guiding communities towards disaster resilience. *Int. J. Disaster Risk Reduct*, 18, 115-124. https://doi.org/10.1016/j.ijdrr.2016.06.006

Sherrieb, K., Norris, F.H. and Galea, S. (2010). Measuring capacities for community resilience. *Soc. Indic. Res.*, 99(2), 227-247. https://d oi.org/10.1007/s11205-010-9576-9

Schipper, L. and Pelling, M. (2006). Disaster risk, climate change and international development: scope for, and challenges to, integration. *Disasters*, 30(1), 19-38. https://doi.org/10.1111/j.1467-9523.2006.0 0304.x

Schilling, J., Freier, K.P., Hertig, E. and Scheffran, J. (2012). Climate change, vulnerability and adaptation in North Africa with focus on Morocco. *Agric. Ecosyst. Environ.*, 156, 12-26. https://doi.org/10.1016/j.agee.2012.04.021

Snoussi, M., Ouchani, T. and Niazi, S. (2008). Vulnerability assessment of the impact of sea-level rise and flooding on the Moroccan coast: the case of the Mediterranean eastern zone. *Estuar. Coast. Shelf Sci.*, 77(2), 206-213. https://doi.org/10.1016/j.ecss.2007.09.024

Snoussi, M., Niazi, S., Khouakhi, A. and Raji, O. (2010). Climate change and sea-level rise: a GIS-based vulnerability and impact assessment, the case of the Moroccan coast. *Geomatic Solutions for Coastal Environments Book.* Nova Publishers, pp 275-310. ISBN: 978-1-61668-140-1

Soden, R., Wageanar, D., Luo, D. and Tijssen, A. (2019). Taking Ethics, Fairness, and Bias Seriously in Machine Learning for Disaster Risk Management. *arXiv preprint*, arXiv:1912.05538. https://doi.or g/10.48550/arXiv.1912.05538

Ministry of Equipment, Transport, Logistics and Water (2017). Presentation: Disaster risk management in the metle (Morocco). https://www.gestionrisques.ma/presentation-atelier_marrakech/Table-ro nde_2/taleb_hassaGestion_des_risques_de_catastrophes-au-sein_du_METLE.pdf (accessed March 9, 2023) (in French)

Tramblay, Y., Badi, W., Driouech, F., El Adlouni, S., Neppel, L. and Servat, E. (2012). Climate change impacts on extreme precipitation in Morocco. *Glob. Planet. Change,* 82-83, 104-114. https://doi.org/10.1016/j.gloplacha.2011.12.002

Vyas, S. and Kumaranayake, L. (2006). Constructing socio-economic status indices: how to use principal components analysis. *Health Policy Plan*., 21(6), 459-468. https://doi.org/10.1093/heapol/czl029

Walker, B., Holling, C.S., Carpenter, S.R. and Kinzig, A. (2004). Resilience, adaptability and transformability in social–ecological systems. *Ecol. Soc.*, 9(2), 5. https://www.jstor.org/stable/26267673