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The spatial dimension in the assessment of socio-economic vulnerability challenges for an application on an urban scale, a systematic review

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Abstract. The social and economic dimensions are only two of the dimensions of vulnerability. This paper aims to review the various case study areas, hazards, methods, spatial variables/indicators/indexes and tools addressed and used in the spatial assessment of socio-economic vulnerability in the period between 2008 and 2018. This review was conducted in December 2018. For the purposes of this study, Clarivate Analytics was the primary source of information. The gross number of articles reviewed was 235. We found 42 highly relevant articles, 27 articles of medium relevance, 15 of low relevance and 151 of no relevance. However, only 21 articles containing content considered highly relevant were included in the final analysis. The highest numbers of case study areas for the spatial analysis of socio-economic vulnerability are in China, the US, India and Germany. Most of the articles that consider the spatial dimension in the assessment of socio-economic vulnerability are related to floods. The Social Vulnerability Index (SoVI®) remains the benchmark for the assessment of socio-economic vulnerability. In the spatial assessment of socio-economic vulnerability, urban facilities are the most frequent variables, and population density is the most common indicator. The Social Vulnerability (SV) index and Spatial Vulnerability Units (SVU) are benchmarks of what it is a spatial index to evaluate socio-economic vulnerability in the urban context. In summary, we identified 21 spatial variables, 19 spatial indicators and four spatial indexes. Geographic Information Systems (GIS), Remote Sensing (RS), statistical analysis and programming languages are tools used by the scientists for the assessment of socio-economic vulnerability. Nevertheless, after the review, we can conclude that it is not sufficient to only estimate the specific level of vulnerability per unit area; it is also necessary to determine the influence of the spatial component in this degree of socio-economic vulnerability.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

1 Introduction

The social and economic dimensions are only two of the dimensions of vulnerability to multiple stressors and shocks, including disasters, due to the fragility and susceptibility of human well-being, to be damaged by disruption to individual (physical and mental health) and collective (e.g. education, services, health) social systems and their characteristics (e.g. age, ethnicity, disabilities) (Birkmann et al., 2013). Social vulnerability (SV) refers to the inability of people, organisations and societies to cope with negative impacts from different stressors to which they are exposed, due to pre-existing conditions that reduce society's ability to prepare and recover from disasters (Cutter and Finch, 2008; Zhou et al., 2014). Low-income populations, women, pregnant women, children, the elderly (Zhou et al., 2014) and physically and or mentally challenged individuals (Contreras and Kienberger, 2012) are the groups most affected by disasters. These impacts are the consequences of social interactions, institutions and systems of cultural values (Warmer et al., 2007).

This concept of SV represents the multidimensionality of disasters by focusing attention on the totality of relationships in a given social situation, which, in combination with environmental forces, results in a disaster (Oliver-Smith, 2003). Power relationships that exclude certain individuals or groups from benefiting from Disaster Risk Reduction (DRR) or post-disaster recovery efforts are examples of SV. These power relationships manifest between individuals or socio-economic groups in the framework of institutions or culturally determined dialogues about stressors (Warmer et al., 2007). The economic dimension of vulnerability is the predisposition for the loss of economic value from damage to physical assets (Birkmann et al., 2013) and/or business interruption (activities, services or delivery of products). The assessment of SV is orientated to cast the light on the most susceptible groups of a population to be impacted by a disaster, in the spatial and temporal dimensions (Zhou et al., 2014).

Cutter, Boruff and Shirley (2003) have constructed an index of SV called (SoVI®) for environmental hazards in the United States using a factor analytic approach computed in a summary score based on an additive model. In the framework of the Methods for the Improvement of Vulnerability Assessment in Europe (MOVE) project, variables were grouped into single (Vinchon et al., 2011) and composite indicators. In the case study area of Salzburg, an expert-based approach was chosen, and several experts were asked to allocate weights according to the contribution of each variables to the vulnerability of floods (Contreras and Kienberger, 2011). The compilation of all of the SV indicators used through time was undertaken by Fatemi,

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Ardalan, Aguirre, Mansouri and Mohammadfam (2017); however, they did not include the spatial dimension in their overview paper.

Social vulnerability is a multidimensional phenomenon that cannot be represented with a single variable (Cutter and Finch, 2008). The assessment of vulnerability must be done based on indicators to guarantee objectivity and comparability. Indicators and indexes are defined as single qualitative or indirect quantitative measures of a characteristic (Chen, 2016) or a real phenomenon (Fekete, 2009) resulting from systematically observed facts (OECD, 2008). Indicators transform complex data into manageable units of information for performance, change and achievement assessment (Grace and Edwin, 2009). Indicators summarise technical information into indexes, making it simple to comprehend (Simpson and Katirai, 2006). The use of indicators has primarily been applied to the assessment of adaptive capacity and vulnerability (Chen, 2016). These indexes are built up based on indicators and later mapped to display the different categories of vulnerability on each administrative zone, limiting the spatial dimension to this stage.

Nevertheless, quantitative measures to develop indicators can be spatially explicit and based on spatial variables, such as location, area, range, distance, direction, spatial geometries and patterns, spatial connectivity, isolation, diffusion, distribution, spatial association, spatial interaction, spatial evolution, spatial synthesis and scale of the affected area and surroundings (Buzai and Villerías Alarcón, 2018; Contreras et al., 2013; Meentemeyer, 1989). Despite this broad list of spatial variables and indicators, very few authors have elaborated on the spatial dimension for the assessment of social vulnerability. The geographic patterns in vulnerability can increase due to spatial interactions, but additional patterns within these components may be related to the nature of vulnerability stemming from a specific hazard (Amram et al., 2011). The spatial assessment of SV allows visualising the social phenomena in space rather than in graphs and tables. An additional advantage of the spatial assessment of SV is the ability to identify the spatial components that influence the degree of vulnerability of communities that are not visible in other methods of estimating SV.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Spatial vulnerability analyses and interdisciplinary approaches became important after the Indian Ocean tsunami in 2004 and Hurricane Katrina in 2005, which illuminated the problems faced by low-income populations after disasters. These approaches were aligned with the Hyogo Framework for Action (UNISDR, 2007). The use of geographic information systems (GIS) to collect and process data related to hazards and vulnerability was found very suitable (Fekete, 2012).
A spatial indicator of SV is an SV indicator with a physical component (Ebert et al., 2009). Housing structures and the built environment were included by Shuang-Ye, Brent, and Ann (2002) in a GIS-based study of SV. The link between transportation infrastructure and land use was studied by Clark et al. (1998). The physical conditions were considered indicative of the social ones by Rashed and Weeks (2003).

The scale of the spatial level of assessment – namely, global, continental, subcontinental, national, regional, provincial, municipal or local – determines the type of data to be collected and the assessment approaches. Research concentrated on the local level uses primary data collected via questionnaire surveys or focus groups to assess vulnerability (Birkmann, 2006; Sarkar and Vogt, 2015), while for global or regional scales, primary data derived from satellite images or secondary data from the population census is used.

This paper reviews case study areas, data sources, hazards, methods, spatial variables/indicators/indexes and tools used in the spatial assessment of socio-economic vulnerability by different authors in the period between 2008 and 2018. This systematic review aims to evaluate the literature to identify patterns and trends, as well as research gaps, to recommend new research areas through an overview paper. This article aspires to be a guide for those scientists who want to perform a spatial assessment of socio-economic vulnerability. Social vulnerability is dynamic and changes across spatial and temporal scales, depending on demographic, geographic, economic and cultural factors. Hence, no one-size-fits-all approach exists to measure and reduce SV (Zhou et al., 2014).

This paper is divided into six sections. The introduction is the first section and includes a brief literature review. The second section, on methods, elaborates on the criteria for selecting the articles that comprise the literature review. The third section

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Natural Hazards and Earth System Sciences
Open Access
Discussions

focuses on the results. The fourth section focuses on the discussion of the results, the fifth section contains the conclusions and the sixth section proposes a set of recommendations based on the results and conclusions.

2 Methods

This review was conducted in December 2018. For the purposes of this study, Clarivate Analytics was the primary source of information. The terms selected for the query refer to vulnerability in the socio-economic dimension and the spatial variables listed by Meentemeyer (1989), Contreras et al. (2013) and Buzai and Villerías Alarcón (2018). Based on a first screening, to refine the search strategy, we opted to exclude terms related to climate change, health and crime analysis, because they exceed the scope of the present article. The final criterion was to consider those articles published in academic journals between 2008 and 2018.

The abstracts of the articles were read to identify their relevance for the topic of the present review study. Only those articles whose content was considered highly relevant were considered for further analysis. The scheme of the methodology applied is depicted in Figure 1.

Fig. 1 about here

3 Results

The gross number of articles reviewed was 235. After examining each of the articles, I found 42 (18%) highly relevant articles, 27 (11%) articles of medium relevance, 15 (6%) of low relevance and 151 (64%) of no relevance. A total of 84 articles were considered to have some degree of relevance for the purposes of the present paper. These results are illustrated in Figure 2.

Fig. 2 about here

We decided to check the countries in which the case study areas considered in the 84 relevant articles are located. These countries are displayed in Figure 3. The US, with ten case studies, and China, with nine, are the countries where the highest

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

number of socio-economic-vulnerability analyses have been undertaken in the last ten years. These countries are followed by Brazil, with eight cases, Romania and Spain with five, India and Argentina with four, and Germany, Indonesia and Iran with three cases each. Additional information about other case study areas is depicted in Figure 4.

Fig. 3 about here

Fig. 4 about here

Socio-economic vulnerability assessment methods have been applied in 36 developing countries and 16 developed countries in the last ten years. However, broad areas of Asia, Africa, Latin America, Oceania and Europe have not yet been case study subjects for any type of socio-economic vulnerability assessment in the same period.

Based on the highly relevant articles (42), we identified the countries where case study areas for spatial assessment of socio-economic vulnerability between 2008 and 2018 are located. The countries are depicted in Figure 5. Again, the US and China, with five cases each, are the countries in which the highest number of spatial assessments of socio-economic vulnerability analysis have been undertaken in the last ten years. These countries are followed by India, with four cases, Germany with three, and Argentina, France, Italy, Romania and Spain, with three cases each, as presented in Figure 6.

Fig. 5 about here

Fig. 6 about here

Eventually, only 21 (9%) articles were selected for further review from the set of highly relevant. These papers cover all of the hazards and identify case study areas in developing and developed countries. The instances of the highly relevant articles and their characteristics are detailed in Table 1.

Table 1 about here

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

From the set of selected papers, the most common sources of data are the population census, followed by satellite images, surveys and maps. Toké, Boone and Arrowsmith (2014) used air photos; Armaş, Toma-Danila, Ionescu and Gavriş (2017) utilised one orthophoto; Ebert et al. (2009) used lidar data; and Gu et al. (2018) reported to have used multi-source data. Further information is presented in Figure 7 and Table 2.

Fig. 7 about here

Table 2 about here

From the set of highly relevant articles, the hazards or topics that they address are identified. Eight (22%) of the articles that consider the spatial dimension in the assessment of socio-economic vulnerability are related to floods, five (14%) to landslides, four (11%) to earthquakes, three (8%) to cyclones or hurricanes, two to volcanos (5%), two to droughts (5%), two to unspecified hazards (6%), two to wildfires (6%), one to tsunamis (3%), one to epidemics (3%), one to poor walkability (3%), one to thunderstorms (3%), one to heavy rainfall (3%), one to flood and hail (3%), one to snow and freezing (3%) and one to cold or heat waves (3%). These outcomes are depicted in Figure 8.

Fig. 8 about here

Most of the authors built upon the Social Vulnerability Index (SoVI®) developed by Cutter et al. (2003)to quantify SV or to create their own SV indexes, such as Toké et al. (2014) with their Los Angeles Social Vulnerability Index Classification (LA-SoVIC), Ebert et al. (2009) and Fekete (2009) with the Social Vulnerability Index (SVI) and Poudyal, Johnson-Gaither, Goodrick, Bowker and Gan (2012) with the also-named Social Vulnerability Index (SOVUL). These authors also make use of Factor Analysis (FA) and Principal Component Analysis (PCA) to consider interdependency between variables and to reduce their number. Fekete (2009) uses also logistic regression analysis to explain differences between groups for predicting

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

membership in groups. Ebert et al. (2009) also utilise a stepwise regression model to select the best explanatory proxy variables for changes in the SV index applied.

After the SoVI® and its variations, the most common methods for the spatial assessment of SV are all the forms of Spatial Multi-Criteria Evaluation (SMCE) (Armaş et al., 2017), Multi-Criteria Evaluation (MCE) (Walker et al., 2014), Multi-criteria Analysis (Müller et al., 2011) and Decision-Making Trial and Evaluation Laboratory (DEMATEL). The aforementioned analysis includes, in most of the cases, an Analytical Hierarchy Process (AHP) (Armaş et al., 2017; Lin and Hung, 2016; Renard, 2017; Walker et al., 2014).

Gi* de Getis-Ord (1992), a hot spot analysis to determine high or low values of features to cluster them spatially is used by Gu et al. (2018), Renard (2017) and Lin and Hung (2016). The *geon* approach developed by Lang et al. (2014) defines homogeneous spatial units in terms of varying space–time phenomena, semi-automatically delineated with expert knowledge incorporated with uniform response to a phenomenon under policy concert. Another form of regionalisation is the Self-Organising Map (SOM) created by Maharani, Lee and Ki (2016). Lang et al. (2014) and Ebert et al. (2009) applied Object-Based Image Analysis (OBIA) and Object-Orientated Analysis (OOA) methods, respectively, using satellite images for regionalisation applied to the spatial assessment of SV. Poudyal et al. (2012) use an Ordinary Least Square (OLS) model to demonstrate an inverse association between wildfire risk and SV and a Geographically Weighted Regression (GWR) model to test a spatial variation in the association between wildfire risk and SV. Other methods applied to the same purpose are listed in Table 3.

Table 3 about here

We found 21 spatial variables, 19 indicators and four indexes that have been used or can be used for the assessment of socio-economic vulnerability. The spatial variables, indicators and indexes addressed by different authors are listed in Tables 4, 5 and 6, respectively. In principle, the items are organised according to the chronological order of the publications in which they are used, but they are also grouped regarding similarity.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Table 4 about here

Table 5 about here

Table 6 about here

Geospatial information systems are broadly utilised by several authors to collect and process data using different versions of ArcGIS, and QGIS is used by Karmakar, Parthasarathy, Chan and Rau (2015). The IDRISI software is utilised by Alizadeh et al. (2018) to generate an Social Vulnerability Map (SVM). GeoDa, an open source software focused on methods for spatial data, is used by authors who address the topic of spatial association (Gu et al., 2018; Ley-García et al., 2015). Armaş et al., (2017) applied a pairwise comparative method in the AHP implemented in the SMCE module of the Integrated Land and Water Information System (Ilwis) software. The aforementioned is a RS and GIS software, on which the robustness of the results from Armaş et al. (2017) was also tested, with a sensitivity analysis performed in the DEFINITE toolbox implemented in Ilwis. The MATLAB computation environment was used by Maharani et al. (2016) to develop the SOM toolbox. Sherly et al. (2015) also use MATLAB to perform multivariate data analyses, such as PCA and Data Envelopment Analysis (DEA).

Statistical analyses without a spatial component are undertaken in the Statistical Package for Social Science (SPSS). Remote sensing is used by Toké et al. (2014), Müller et al. (2011), Lang et al. (2014) and Ebert et al. (2009). These final two groups of authors processed satellite images to extract data using eCognition. The detailed list of tools used in the spatial assessment of socio-economic vulnerability is provided in Table 7.

Table 7 about here

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Natural Hazards and Earth System Sciences
Discussions

4 Discussion

While is it true that countries such as the US, China and India are challenged every year by natural phenomena, unfortunately, the selection of case study areas for the assessment of socio-economic vulnerability with or without a spatial component does not depend on the perceived degree of exposure. The exception could be China, because it is one of the countries suffering from disasters characterised by a wide distribution of huge losses (Zhou et al., 2014), and it appears in numerous cases of socio-economic vulnerability assessments found in this literature review.

Data sources used in the last ten years include census data, satellite images, surveys, disaster databases, maps and lidar data, amongst others. The criteria for the selection of these sources always depend on the scale to cover and the type of data to collect. Census data usually present national data at the municipal level. Satellite images are useful to collect data from global to local scales. Data sources at a local scale, such as the neighbourhood level, include surveys and focus groups meetings. Lidar data are a proper option for the city scale. However, we can also collect data at the city or regional level using focus group meetings selecting representative members of districts or neighbourhoods.

The use of satellite images as data sources in the spatial assessment of socio-economic vulnerability has been increasing in the last ten years. This fact can be explained because they offer quick, updated and reliable data, making the satellite images the most effective source of information to date. Censuses are usually updated on an average of ten years, depending on the country, and some of the data could be altered by political biases. The surveys require significant manpower and the thematic scope is usually very narrow. Maps, air photos or orthophotos are not frequently updated.

The first attempts to consider the spatial dimension in the vulnerability assessment came from geographers who were interested in estimating environmental vulnerability. This can explain why most of the articles that consider the spatial dimension in the assessment of socio-economic vulnerability are related to floods. The other reason could be that floods are the most frequent natural phenomenon that causes disasters around the world, affecting the most vulnerable populations.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Several authors, such as Gu et al. (2018), Maharani et al. (2016), and Zhou et al. (2014), use the SoVI®, and hence the FA, and in some cases, the PCA to quantify SV in their case study areas. Other authors, such as Toké et al (2014), Ebert et al. (2009), Fekete (2009) and Poudyal et al. (2012) build upon the SoVI® to create their own SV indexes that incorporate the spatial dimension. Fekete (2009) also uses logistic regression. Nevertheless, Cutter & Finch (2008), Gu et al., (2018), Maharani et al. (2016) and Zhou et al. (2014) were also interested in identifying the spatial pattern in the SoVI®; hence, Gu et al (2018) used global Moran's I and local Gi* de Getis-Ord in addition to the SoVI®, while Maharani et al. (2016) utilised the SOM. Buzai and Villerías Alarcón (2018) developed their own SV index and also used global Moran's I, but they elaborated on the spatial patterns of local association using the Local Index of Spatial Association (LISA) to determine hot and cold spots. Lin and Hung (2016) combined Gi* de Getis-Ord to measure the high or low vulnerability association and global Moran's I to determine the homogeneity of the clusters. According to Ley-García et al. (2015), global Moran's I and LISA allow the identification of dependence between attributes and localisations, and then these indicators are useful to determine whether the spatial distribution of elements influences the behaviour of a particular variable. The summary measure of autocorrelation in the territory as a whole is undertaken with global Moran's I, while the autocorrelation of the spatial units included in the territory is measured using LISA. Cutter and Finch (2008) also previously utilised global Moran's I and LISA to identify local variability and cluster similarity of low and social vulnerability. Besides the SoVI® and FA, Zhou et al. (2014) utilise exploratory spatial data analysis (ESDA) to identify the spatio-temporal patterns of SV based on the constructed SoVI® for each county in China. These authors used global and local Moran's I or LISA as ESDA to determine the spatial autocorrelation amongst counties and identify the similarity and/or dissimilarity in the clustering of SV.

The *geon* approach also identifies clusters using semi-automated regionalisation in multispectral image data to represent socio-economic vulnerability in the form of spatial vulnerability units (SVU) (Kienberger et al., 2009) through an advanced mapping scheme of land-use classes (Lang et al., 2010). Poudyal et al. (2012) utilised an OLS model to test an inverse association between wildfire risk and SOVUL and the GWR to identify clusters or sub-regions across six southern states in the US where the relationship between wildfire risk and SOVUL is positive.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Walker et al. (2014) developed an MCE using an AHP to produce a place-specific index of SV to be combined with soil liquefaction, an amplification index and a road network model for access to hospitals and trauma centres. The AHP is used to derive variable weights based on a pairwise comparison and the allocation of weights as model coefficients. The resulting weights are multiplied by the relevant census variables to produce social vulnerability index scores. The MCE is a quantitative method to solve geographic problems and a decision support that integrates multiple spatial datasets with score areas accounting for a predetermined criterion (Malczewski, 1999). To integrate the physical, social and systematic vulnerability components of this MCE, Walker et al. (2014) rescaled each component linearly from 0 to 1 and summed them to produce an equally weighted combined vulnerability score for each census dissemination area.

The spatial variables found are similar to the variables identified by Meentemeyer (1989), Contreras et al. (2013), Buzai and Villerías Alarcón (2018), but we identify other spatial variables used by authors, such as land use and land cover. We also find that urban facilities can be considered spatial variables. We agree with Zeng et al. (2012) that the most frequent spatial indicator in the assessment of socio-economic vulnerability is population density. The reason, according to Gu et al. (2018), is that population density reveals the human resources of a neighbourhood and the relief resources that could be required during a disaster. According to Zhou et al. (2014), indicators such as population change, population density, education level and employment highly influence temporal changes in SV. In the case of China, reduction in SV was associated with the depopulation of some counties.

The global and local Moran's I are listed in Tables 3 and 5, because they are considered by Gu et al. (2018) and Zhou et al. (2014) as methods to identify spatial patterns in the SoVI®, while Buzai & Villerías Alarcón (2018) and Villerías Alarcón (2018) consider them only as an indicator to measure spatial autocorrelation.

Walk Score® is a spatial index originally orientated to measure neighbourhood walkability on a micro scale, but it can be also considered to measure socio-economic vulnerability at the same level, with the advantage that this index includes a 3D component. We decided to include the normalised difference vegetation index as a spatial index of socio-economic

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

vulnerability, because we agree with Toké et al. (2014) that SV be instead tied to a specific hazard related to amenities. Green areas are usually located in areas with lower socio-economic vulnerability (Stow et al., 2007), and it is reported that they are also recognised for their health benefits (Bedimo-Rung et al., 2005). The sector-specific vulnerability index (IVI_S) contains primarily spatial indicators in the economic dimension, such as road freight transport volume, railway freight transport volume and customer proximity (Khazai et al., 2013).

Besides the common spatial variables, indicators and indexes in 2D, there are also spatial indicators and indexes that include the 3D component, such as Walk Score®, neighbourhood walkability (Bereitschaft, 2017a, b), satisfaction with the neighbourhood (Barata et al., 2011) and residential condition (de la Torre and de Riccitelli, 2017). The graph that describes these is presented in Figure 9.

Fig. 9 about here

It has been always difficult to quantify SV; hence, it is absent from post-disaster cost/loss estimation reports (Schmidtlein et al., 2008; Zhou et al., 2014). The use of spatial variables, indicators and indexes will bridge the gap of integrating physical and social vulnerability to achieve a holistic risk assessment. Davidson (1997) provides the first attempt to create an integrated risk assessment framework. Later, Carreño, Cardona, & Barbat, (2007) developed a risk index obtained by multiplying the physical risk index by an impact factor, which is, in fact, an aggravating coefficient consisting of socio-economic variables; nevertheless, in applying this method, the outcome will be similar to the assessment of physical vulnerability, without showing the contribution of SV to the assessment of integrated risk. Schmidtlein, Shafer, Berry and Cutter (2011) tested the link between SV and earthquake losses. The authors found that physical parameters related to hazard, such as distance from the epicentre and peak ground acceleration, were more significant in predicting impacts than was SV. Nevertheless, the same authors established that SV is a significant predictor of earthquake losses in accounting for wealth (dollar losses per average income as the dependent variable). The previous finding reveals that those areas with higher levels of SV experience a greater relative impact than areas with lower degrees of SV.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Natural Hazards and Earth System Sciences
Open Access
Discussions

Another aspect to consider is the relationship between social and economic dimensions, because according to Noy (2009), no evidence exists of a correlation between consequences of disasters, such as the number of fatalities or affected population, and GDP growth. Nevertheless, the same author indicates that the degree of damage due to a disaster will negatively influence GDP growth performance. Then, Noy (2015) proposes to integrate the number of fatalities and injuries with financial damage due to a disaster using a model similar to the estimation of disability adjusted life years (DALYs). His index account for the number of human years lost as a result of the damage.

5 Conclusion

The allocation of funding to projects aiming to assess socio-economic vulnerability, with or without a spatial component, depends on the political willingness and availability of financial resources of development agencies and governmental institutions in charge of addressing this topic.

The lack of data availability hinders the understanding of the concept of vulnerability (Zhou et al., 2014). The most common data sources for the assessment of socio-economic vulnerability are census data and, more recently, satellite images. The more recent use of satellite images has facilitated the inclusion of the spatial component in socio-economic vulnerability assessment. Floods, landslides, earthquakes, tsunamis and hurricanes have motivated the highest number of socio-economic vulnerability assessments due to the extensive damage that these natural phenomena sometimes produce on the national scale.

Each method for the spatial assessment of SV is selected according to its research aim, case study area, data availability or sources, scale to cover, hazard, scope of the study and funding. Some authors are interested in conducting a socio-economic vulnerability assessment using the SoVI® or SMCE, while others wish to identify the association in the spatial patterns of socio-economic vulnerability based on global Moran's I, OLS or GWR or to identify cold and hot spots utilising LISA or Gi* de Getis-Ord. Nevertheless, when the source of information is a satellite image, the spatial pattern of SV requires another approach, such as developing SVU based on the *geon* approach with OBIA or OOA. These methods, rather than being mutually exclusive, are complementary. It is feasible that an author uses any method for the assessment of socio-economic vulnerability,

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

then identify the spatial patterns of association-generating clusters and later determine the hot and cold spots of socio-economic vulnerability.

The most important factor for indicator selection is the availability of data. This factor can lead to reliance on variables that may not be the most accurate indicators of vulnerability (Zhou et al., 2014). Furthermore, considering the method selected for the spatial assessment of socio-economic vulnerability, spatial variables and indicators are selected and indexes are constructed. In the spatial context, we consider the SV index developed by Ebert et al. (2009) and the SVU index developed by Kienberger et al. (2009) et al. as benchmarks of what a spatial index to evaluate socio-economic vulnerability in the urban context should comprise. These indexes could include the Normalised Difference Vegetation Index (NDVI) and spatial indicators, such as road freight transport volume and customer proximity, included in the IVI_S developed by Khazai et al. (2013). The Walk Score®, developed by Bereitschaft (2017a), although originally orientated to measure only neighbourhood walkability, could be adapted as a tool to either complement or validate any spatial index for assessing vulnerability at the local level. The advantage over the SoVI® is that while the SoVI® can be spatialised, the SV index, the SVU index, Walk Score® and the indicators from IVI_S are spatial indexes *per se*.

The presence of urban facilities must be included in the assessment of SV. Walker et al. (2014) suggest developing a weighted 'local resource' index for assessing systemic vulnerability since, for example, the absence of sports facilities is associated by Iguacel et al. (2018), Vandermeerschen, Vos, & Scheerder (2015), and Aguilar-Palacio, Gil-Lacruz and Gil-Lacruz (2013) with high levels of SV. The most frequent spatial indicators in the assessment of socio-economic vulnerability are population density, housing density, spatial association, degree of clustering and hot and cold spots of socio-economic vulnerability.

According to the method, the spatial variables identified, the indicators or indexes selected or developed, the tools to carry out the spatial assessment of socio-economic vulnerability is selected. The primary software used by scientists to collect and process data for the spatial assessment of socio-economic vulnerability are ArcGIS, QGIS and IDRISI. Spatial associations are calculated in GeoDa, and the SMCE in Ilwis. The OBIA and the OOA were undertaken in Definiens eCognition, and non-spatial statistical analysis is usually performed in SPSS.

In the spatial assessment of socio-economic vulnerability, it is necessary to estimate the specific level of vulnerability per unit area as well as to consider the influence of the spatial component represented by physical space in the degree of vulnerability of that specific area, such as the relationship between slums and a low degree of wellness and health (Buzai and Villerías Alarcón, 2018).

The spatial assessment of socio-economic vulnerability in the areas where is it requested will depend not only on the financial resources for research but also on the availability of opensource software with the functionalities of spatial statistics, such as QGIS, GeoDa or Ilwis.

5 Recommendations

The development and yearly updating of a global spatial index of socio-economic vulnerability is an urgent task, with the aim of making informed decisions about priority in funding prevention and mitigation actions. In the meantime, the priority for these types of assessments must be allocated to developing countries with the lowest GDPs and increased levels of SV (Zhou et al., 2014).

The selection of data source depends on the scale of the socio-economic vulnerability assessment. However, it is necessary to also factor in data availability and accessibility (Fekete, 2012) in addition to collection time and the cost and skills required to process the collected data.

Spatial socio-economic vulnerability assessments related to natural phenomena, such as volcanic eruptions, drought, wildfires, tsunami, epidemics, and cold and heat waves, are also requested. An assessment of socio-economic vulnerability is a request for the effective development of emergency management capabilities.

Natural Hazards and Earth System Sciences
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EGU
Discussions

Authors such as Turvey (2007), Walker et al. (2014) et al. and Zhou et al. (2014) highlight the need for place-specific, sub-provincial-level or neighbourhood-scale vulnerability indexes, due to geographic variations in population composition and social structures (Bell N et al., 2007). Macro-scale socio-economic assessment identifies general patterns but fails to capture the detail of the heterogeneity at the micro scale. Thus, assessment at the provincial, county or state level can result in lost information (Zhou et al., 2014) or require tackling issues such as ecological fallacy or the modifiable areal unit problem (MAUP) (Pacione, 2005).

Communities respond differently to vulnerability maps depending on the purpose behind the maps or their cultural backgrounds. On the one hand, some communities reject being mapped as 'victims', but on the other hand, some request being identified as highly vulnerable to gain access to funding opportunities for activities of risk management (Fekete, 2012).
In the assessment of SV, it is necessary to go beyond the administrative boundaries or cartographic variables, as do Renard (2017), who instead used a square mesh, Lin and Hung (2016), who defined pockets, or Lang et al. (2014), who developed the concept of *geon*.

We found interesting spatial indicators of socio-economic vulnerability, such as population density based on land use, as considered by Zeng et al. (2012), which we consider more accurate than population density estimated at an area unit. This indicator can better integrate, through the use of RS, the spatial dimension of the exposure and susceptibility of the population in the assessment of the socio-economic vulnerability of a case study area.

Another aspect to integrate into the spatial assessment of vulnerability is the 3D element, in which the community living in the space is involved in the assessment; this is the added value of the Walk Score® index and neighbourhood walkability (Bereitschaft, 2017a, b). The use of the local scale for the assessment of SV will be more useful for the planning of resilient actions (Lee, 2014; Maharani et al., 2016) than would be vulnerability assessment at a regional scale, which is more orientated to the collection of pathologies in the social dimension. It is necessary to more closely examine so-called 'proxy indicators' to measure SV at micro-local scales or intra-city levels (Gu et al., 2018).

The right management of the spatial component by a community can reduce its economic vulnerability. Groß (2017) presented the case of ski-lift entrepreneurs in Vorarlberg (Austria) who reduced the probability of business interruption by accelerating the uphill and downhill flows of people through manipulating snow and topography.

Regarding tools, it is necessary to take full advantage of the functionalities of spatial statistics in opensource software to conduct a more complete and accurate spatial assessment of socio-economic vulnerability.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Natural Hazards and Earth System Sciences
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Discussions

AUTHOR	YEARS	RESEARCH OBJECTIVE	HAZARD	COUNTRY
Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B.	2018	To reveal the urban social vulnerability at a fine scale in 5,432 neighbourhoods in Shanghai, China and explore its spatial pattern.	Floods	China
Buzai, G., & Villerías Alarcón, I.	2018	To carry out a spatial analysis of the social determinants of the health in the basin of the Lujan River in the province of Buenos Aires, Argentina	epidemics	Argentina
Bereitschaft, B.	2017	To explore inequity in neighbourhood walkability at the micro-scale level related to social vulnerability in terms of imageability, enclosure, human scale, transparency, complexity, tidiness and safety in Pittsburgh Streetscapes.	Not walkability	USA
Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A.	2017	To develop an overall vulnerability index to seismic hazard based on a spatial approach applied to Bucharest, Romania.	Earthquakes	Romania
Renard, F.	2017	To obtain precise spatial knowledge of the territorial vulnerability in the face of floods.	Floods	France
Maharani, Y. N., Lee, S., & Ki, S. J.	2016	To propose the use of Self-Organizing Maps (SOM) approach to conducting the social vulnerability assessment around the Merapi volcano.	Volcanos	Indonesia
Chen, Y.	2016	To develop a set of valid and reliable indicators to evaluate the regional land subsidence disaster vulnerability in the Xixi-Chengnan area, in China.	Landslides	China
Lin, W.-Y., & Hung, C.-T.	2015	To apply spatial autocorrelation statistics to analyze the spatial association of vulnerability among townships in Taiwan.	Not specified	Taiwan
Sarkar, R., & Vogt, J.	2015	To analyze the vulnerability of drinking water management during and after a natural disaster in the rural and coastal areas of Bangladesh.	cyclone	Bangladesh

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

AUTHOR	YEARS	RESEARCH OBJECTIVE	HAZARD	COUNTRY
Ley-García, J., Denegri de Dios, F. M., & Ortega Villa, L. M.	2015	The aim is to identify visibility, invisibility and amplification of hazardscape perception in the city of Mexicali, Baja California, Mexico.	Earthquake Landslide Tsunami Volcano Cyclone Thunderstorm Heavy rainfall Flood hail Snow-freeze Strong wind Drought Cold wave Heat wave	Mexico
Walker, B. B., Taylor-Noonan, C., Tabbernor, A., McKinnon, T. B., Bal, H., Bradley, D., . . . Clague, J. J.	2014	To model geophysical processes and identification of socio-economically disadvantaged populations in Victoria, British Columbia.	Earthquakes	Canada
Toké, N. A., Boone, C. G., & Arrowsmith, J. R.	2014	To construct a relative social vulnerability index classification for Los Angeles to examine the social condition within regions of significant seismic hazard, including areas regulated as Alquist-Priolo (AP) Act earthquake fault zones.	Wildfires Landslides Earthquakes	USA
Lang, S., Kienberger, S., Tiede, D., Hagenlocher, M., & Pernkopf, L.	2014	To elaborate on the components of the *geon* approach, showcasing the transferability of the approach and discussing the approach from an information-based ontology perspective and reflecting on its validation.	Floods drought	Austria

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Natural Hazards and Earth System Sciences
Open Access
Discussions

AUTHOR	YEARS	RESEARCH OBJECTIVE	HAZARD	COUNTRY
Khazai, B., Merz, M., Schulz, C., & Borst, D.	2013	To develop an integrated indicator framework to capture the multi-layered vulnerability drivers in industrial production systems and also accounts for the social fragilities and coping capacities in communities.	Not specified	Germany
Fekete, A.	2012	To summarize the current challenges in conducting spatial vulnerability or risk assessments to open a discussion about opportunities for improvements	Floods	Germany
Poudyal, N. C., Johnson-Gaither, C., Goodrick, S., Bowker, J. M., & Gan, J.	2012	To examine spatial variation in the association between social vulnerability (SOVUL) and wildfire risk using geographically weighted regression.	Wildfires	USA
Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T.	2012	To introduce a new method to assess social vulnerability for county-scale regions using population density, based on land use.	Landslides	China
Müller, A., Reiter, J., & Weiland, U.	2011	To empirically investigate the vulnerability due to floods in Santiago de Chile as a component of flood risk.	Floods	Chile
Pandey et al.	2010	This paper presents a method for spatial assessment of vulnerability and risk due to floods and waterlogging in northern Bihar plains.	Floods	India
Ebert et al.	2008	To test the utility of lidar, optical satellite and GIS data to derive social Vulnerability (SV) relevant information by using physical proxy variables for the assessment of social vulnerability, with better time and cost efficiency and higher temporal resolution compared to the traditional analysis methods.	Hurricane Landslide Floods	Honduras

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

AUTHOR	YEARS	RESEARCH OBJECTIVE	HAZARD	COUNTRY
Fekete	2009	The purpose is the development and the validation of a social vulnerability map of population characteristics towards river-floods covering all counties in Germany.	Floods	Germany

Table 1. Highly relevant articles selected for the systematic review of the literature.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

	DATA SOURCES	AUTHORS
Census data	REDATAM	Buzai, G., & Villerías Alarcón, I. (2018)
	Statistics of Sleman Regency https://slemankab.bps.go.id/	Maharani, Y. N., Lee, S., & Ki, S. J. (2016)
	Xishan and Huishan Statistical Yearbook 2008	Chen, Y. (2016)
	Population and Housing Census 2010	Lin, W.-Y., & Hung, C.-T. (2016).
	2000 U.S. Census Bureau	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
		Poudyal, N. C., Johnson-Gaither, C., Goodrick, S., Bowker, J. M., & Gan, J. (2012)
	Statistical Office of Baden-Wuerttemberg	Khazai, B., Merz, M., Schulz, C., & Borst, D. (2013)
	GENESIS-online Datenbank Federal Statistical Office in Germany (BBR, 2007; Destatis, 2006a)	Fekete, A. (2009)
	INE (2002)	Müller, A., Reiter, J., & Weiland, U. (2011)
	Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A. (2017)	
	Renard, F. (2017)	
	Walker, B. B., Taylor-Noonan, C., Tabbernor, A., McKinnon, T. B., Bal, H., Bradley, D., . . . Clague, J. J. (2014)	
	Pandey, A. C., Singh, S. K., & Nathawat, M. S. (2010)	
Satellite images	SRTM	Buzai, G., & Villerías Alarcón, I. (2018)
	ASTERGDEM	Buzai, G., & Villerías Alarcón, I. (2018)
	CORINE land cover	Fekete, A. (2012)
	Quickbird (December 2006)	Müller, A., Reiter, J., & Weiland, U. (2011)
	Quickbird	Ebert, A., Kerle, N., & Stein, A. (2009)

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Natural Hazards and Earth System Sciences
Discussions

	DATA SOURCES	AUTHORS
	ASTER (February 2005)	Müller, A., Reiter, J., & Weiland, U. (2011)
	IRS-AWIFS (2008) LANDSAT-ETM+ (2001) LANDSAT-MSS (1975)	Pandey, A. C., Singh, S. K., & Nathawat, M. S. (2010)
	LANDSAT	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
	SPOT	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
	RecourseSat-1 (IRS-P6) Digital Terrain Model DTM (based on point data)	Ebert, A., Kerle, N., & Stein, A. (2009)
	Lang, S., Kienberger, S., Tiede, D., Hagenlocher, M., & Pernkopf, L. (2014)	
Surveys	Photographs/HD video	Bereitschaft, Bradley (2017)
	Structured Questionaries'/Interview	Sarkar, R., & Vogt, J. (2015)
		Müller, A., Reiter, J., & Weiland, U. (2011)
Maps	Land use – Land cover maps	Müller, A., Reiter, J., & Weiland, U. (2011)
	Flood hazard maps	Fekete, A. (2012)
		Pandey, A. C., Singh, S. K., & Nathawat, M. S. (2010)
	Thematic city maps	Ebert, A., Kerle, N., & Stein, A. (2009)
Disaster Databases	Indonesian Disaster Data Information (DIBI) http://dibi.bnpb.go.id/dibi/	Maharani, Y. N., Lee, S., & Ki, S. J. (2016)
	Risk Atlas of the Municipality of Mexicali 2011	Ley-García, J., Denegri de Dios, F. M., & Ortega Villa, L. M. (2015)
	Federal Office of Civil Protection and Disaster Assistance (BBK)	Khazai, B., Merz, M., Schulz, C., & Borst, D. (2013)
		Fekete, A. (2012)
Air photos	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)	
Orthophoto	Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A. (2017)	
Gridded Lidar DSM	Ebert, A., Kerle, N., & Stein, A. (2009)	

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

DATA SOURCES	AUTHORS
Multi-source data	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018)

Table 2. Data sources for the spatial assessment of socio-economic vulnerability.

METHODS	AUTHORS
SoVI®	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018)
	Maharani, Y. N., Lee, S., & Ki, S. J. (2016).
LA-SoVIC	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
SVI	Ebert, A., Kerle, N., & Stein, A. (2009)
	Fekete, A. (2009)
SOVUL	Poudyal, N. C., Johnson-Gaither, C., Goodrick, S., Bowker, J. M., & Gan, J. (2012)
FA	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018)
	Maharani, Y. N., Lee, S., & Ki, S. J. (2016)
	Zhou, Y., Li, N., Wu, W., Wu, J., & Shi, P. (2014)
	Fekete, A. (2012)
	Fekete, A. (2009)
PCA	Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A. (2017)
	Maharani, Y. N., Lee, S., & Ki, S. J. (2016)
	Sarkar, R., & Vogt, J. (2015)
	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
	Fekete, A. (2009).
Logistic Regression	Fekete, A. (2012)
	Fekete, A. (2009)
Stepwise regression model	Ebert, A., Kerle, N., & Stein, A. (2009)
SMCE	Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A. (2017)
MCE	Walker, B. B., Taylor-Noonan, C., Tabbernor, A., McKinnon, T. B., Bal, H., Bradley, D., . . . Clague, J. J. (2014)
MCA	Müller, A., Reiter, J., & Weiland, U. (2011)
DEMATEL - MCDA	Khazai, B., Merz, M., Schulz, C., & Borst, D. (2013)
AHP	Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A. (2017).

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

METHODS	AUTHORS
	Renard, F. (2017)
	Lin, W.-Y., & Hung, C.-T. (2016)
	Walker, B. B., Taylor-Noonan, C., Tabbernor, A., McKinnon, T. B., Bal, H., Bradley, D., . . . Clague, J. J. (2014)
Global Moran's I	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018).
	Buzai, G., & Villerías Alarcón, I. (2018)
	Renard, F. (2017)
	Lin, W.-Y., & Hung, C.-T. (2016)
	Ley-García, J., Denegri de Dios, F. M., & Ortega Villa, L. M. (2015)
	Zhou, Y., Li, N., Wu, W., Wu, J., & Shi, P. (2014)
Gi* de Getis-Ord	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018)
	Renard, F. (2017)
	Lin, W.-Y., & Hung, C.-T. (2016)
geon	Lang, S., Kienberger, S., Tiede, D., Hagenlocher, M., & Pernkopf, L. (2014)
SOM	Maharani, Y. N., Lee, S., & Ki, S. J. (2016)
OLS model	Poudyal, N. C., Johnson-Gaither, C., Goodrick, S., Bowker, J. M., & Gan, J. (2012)
GWR	Poudyal, N. C., Johnson-Gaither, C., Goodrick, S., Bowker, J. M., & Gan, J. (2012)
ANN	Alizadeh, M., Alizadeh, E., Kotenaee, S. A., Shahabi, H., Pour, A. B., Panahi, M., . . . Saro, L. (2018)
Distance-based network analysis	Walker, B. B., Taylor-Noonan, C., Tabbernor, A., McKinnon, T. B., Bal, H., Bradley, D., . . . Clague, J. J. (2014)
Participant observation approach	Bereitschaft, B. (2017)
Logical analysis method	Chen, Y. (2016)
Fuzzy Delphi method	Lin, W.-Y., & Hung, C.-T. (2016)
Overlay analysis	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
	Pandey, A. C., Singh, S. K., & Nathawat, M. S. (2010)
ESDA	Zhou, Y., Li, N., Wu, W., Wu, J., & Shi, P. (2014)
OBIA	Lang, S., Kienberger, S., Tiede, D., Hagenlocher, M., & Pernkopf, L. (2014)
OOA	Ebert, A., Kerle, N., & Stein, A. (2009).

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Table 3. Methods applied to the spatial assessment of socio-economic vulnerability.

5

SPATIAL VARIABLES	AUTHORS
Location	Buzai, G., & Villerías Alarcón, I. (2018)
Distribution	Buzai, G., & Villerías Alarcón, I. (2018)
Number of primary schools and kindergarten	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018).
School	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
Industry land	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
Office land	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
Commercial and residential land	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
Hospital	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
Critical facilities	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
Road-network	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012
Park space	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
Distribution of urban greenspace	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
Total area of occupied space in the residences	Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A. (2017)
Spatially varied potable ground water availability	Sarkar, R., & Vogt, J. (2015)
Distant to collect water	Sarkar, R., & Vogt, J. (2015)

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

SPATIAL VARIABLES	AUTHORS
Travel distance to trauma centres	Walker, B. B., Taylor-Noonan, C., Tabbernor, A., McKinnon, T. B., Bal, H., Bradley, D., . . . Clague, J. J. (2014)
Distance to hospital	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
Demand dependency	Khazai, B., Merz, M., Schulz, C., & Borst, D. (2013)
Travel barriers to the trauma centres	Walker, B. B., Taylor-Noonan, C., Tabbernor, A., McKinnon, T. B., Bal, H., Bradley, D., . . . Clague, J. J. (2014)
Land use	Müller, A., Reiter, J., & Weiland, U. (2011)
Land cover	Müller, A., Reiter, J., & Weiland, U. (2011)

Table 4. Spatial variables for socio-economic vulnerability assessments.

SPATIAL INDICATORS	AUTHORS
Population density	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018)
	Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A. (2017) Maharani, Y. N., Lee, S., & Ki, S. J. (2016)
	Chen, Y. (2016)
	Sarkar, R., & Vogt, J. (2015)
	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
	Pandey, A. C., Singh, S. K., & Nathawat, M. S. (2010)
	Fekete, A. (2009)
Population per square mile	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
Housing density	Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A. (2017)
Proportion of households with more than 2.5 people per bedroom per building block	Müller, A., Reiter, J., & Weiland, U. (2011)
Living space pp	Fekete, A. (2009)
Global Moran's I	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018).

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

SPATIAL INDICATORS	AUTHORS
	Buzai, G., & Villerías Alarcón, I. (2018)
	Renard, F. (2017)
	Lin, W.-Y., & Hung, C.-T. (2016)
	Ley-García, J., Denegri de Dios, F. M., & Ortega Villa, L. M. (2015)
	Zhou, Y., Li, N., Wu, W., Wu, J., & Shi, P. (2014).
Local Indicators of Spatial Association (LISA)	Buzai, G., & Villerías Alarcón, I. (2018).
	Lin, W.-Y., & Hung, C.-T. (2016)
	Ley-García, J., Denegri de Dios, F. M., & Ortega Villa, L. M. (2015)
	Zhou, Y., Li, N., Wu, W., Wu, J., & Shi, P. (2014).
Degree of clustering	Renard, F. (2017)
	Lin, W.-Y., & Hung, C.-T. (2016)
	Poudyal, N. C., Johnson-Gaither, C., Goodrick, S., Bowker, J. M., & Gan, J. (2012)
GDP density	Chen, Y. (2016)
Density of industrial production	Chen, Y. (2016)
Density of agricultural production	Chen, Y. (2016)
Investment density of fixed assets	Chen, Y. (2016)
Access to medical facilities	Walker, B. B., Taylor-Noonan, C., Tabbernor, A., McKinnon, T. B., Bal, H., Bradley, D., . . . Clague, J. J. (2014)
Walkability	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
Transport dependency	Khazai, B., Merz, M., Schulz, C., & Borst, D. (2013)
Proportion of green spaces per building block	Müller, A., Reiter, J., & Weiland, U. (2011)
Proportion of people without employment per building block	Müller, A., Reiter, J., & Weiland, U. (2011)
Proportion of people without permanent income per building block	Müller, A., Reiter, J., & Weiland, U. (2011)

Table 5. Spatial indicators for socio-economic vulnerability assessments.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

SPATIAL INDEXES	**AUTHORS**
WalkScore®	Bereitschaft, B. (2017)
Normalized Difference Vegetation Index (NDVI)	Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
SV index	Ebert, A., Kerle, N., & Stein, A. (2009)
Spatial Vulnerability Units (SVU)	Kienberger, S., Lang, S., & Zeil, P. (2009).

Table 6. Spatial indexes for socio-economic vulnerability assessments.

METHOD	**SOFTWARE**	**AUTHORS**
GIS	ArcGIS	Lang, S., Kienberger, S., Tiede, D., Hagenlocher, M., & Pernkopf, L. (2014)
	GeoDa (version 1.8.16)	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018)
	GeoDa (version 16.6)	Ley-García, J., Denegri de Dios, F. M., & Ortega Villa, L. M. (2015)
	GeoDa™ 0.9.5-i	Zhou, Y., Li, N., Wu, W., Wu, J., & Shi, P. (2014)
	GeoDa	Cutter, S. L., & Finch, C. (2008)
	ILWIS	Armaş, I., Toma-Danila, D., Ionescu, R., & Gavriş, A. (2017)
	TerrSet (IDRISI)	Alizadeh, M., Alizadeh, E., Kotenaee, S. A., Shahabi, H., Pour, A. B., Panahi, M., . . . Saro, L. (2018)
	Others	Renard, F. (2017)
		Toké, N. A., Boone, C. G., & Arrowsmith, J. R. (2014)
		Müller, A., Reiter, J., & Weiland, U. (2011)
		Pandey, A. C., Singh, S. K., & Nathawat, M. S. (2010)
		Fekete, A. (2009)
RS	eCognition | Trimble	Lang, S., Kienberger, S., Tiede, D., Hagenlocher, M., & Pernkopf, L. (2014)
		Ebert, A., Kerle, N., & Stein, A. (2009)
	Others	Zeng, J., Zhu, Z. Y., Zhang, J. L., Ouyang, T. P., Qiu, S. F., Zou, Y., & Zeng, T. (2012)
		Müller, A., Reiter, J., & Weiland, U. (2011)

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

METHOD	SOFTWARE	AUTHORS
Statistical Analysis	SPSS 19.0	Gu, H., Du, S., Liao, B., Wen, J., Wang, C., Chen, R., & Chen, B. (2018)
		Maharani, Y. N., Lee, S., & Ki, S. J. (2016)
		Sarkar, R., & Vogt, J. (2015).
	SPSS 14.0	Fekete, A. (2012)
Programming language	MATLAB (SOM)	Maharani, Y. N., Lee, S., & Ki, S. J. (2016).

Table 7. Tools used for socio-economic vulnerability assessments.

https://doi.org/10.5194/nhess-2019-147
Preprint. Discussion started: 11 June 2019

Natural Hazards and Earth System Sciences
Discussions

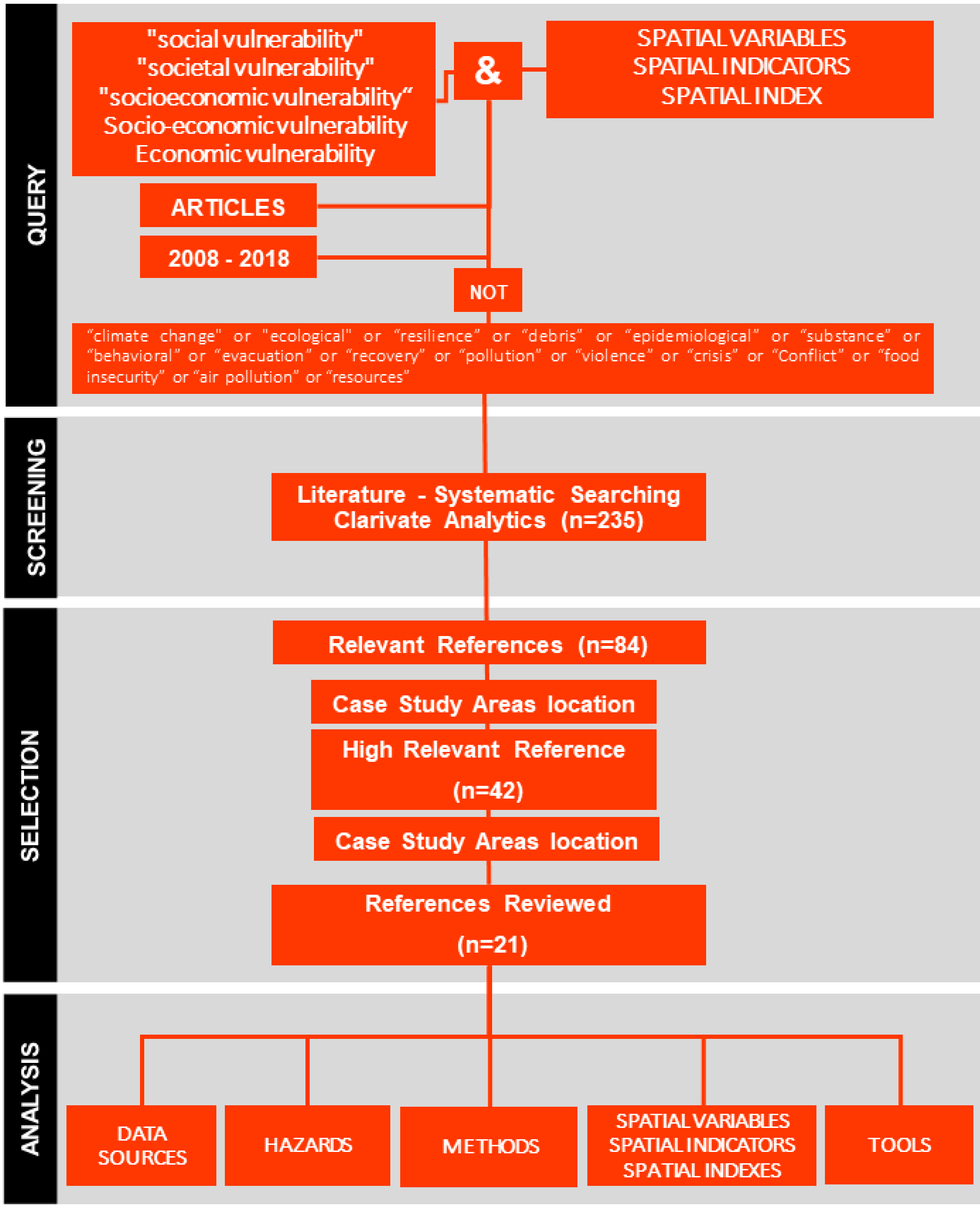

Figure 1: Methodology.

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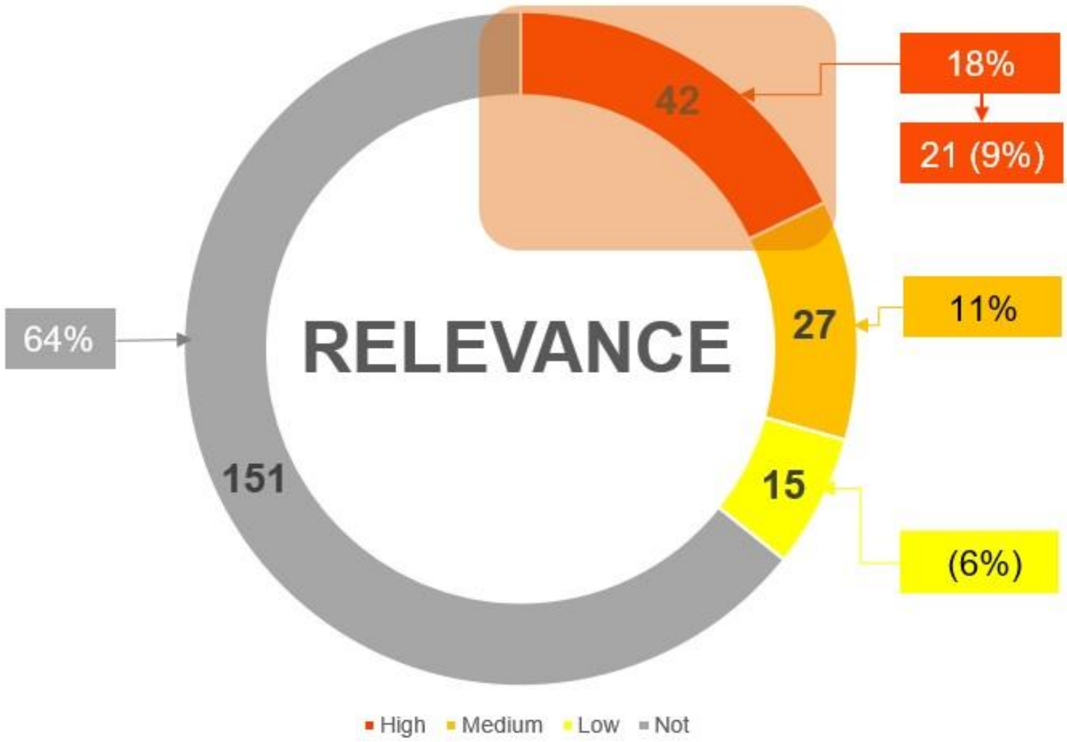

Figure 2: Relevant articles for the literature review.

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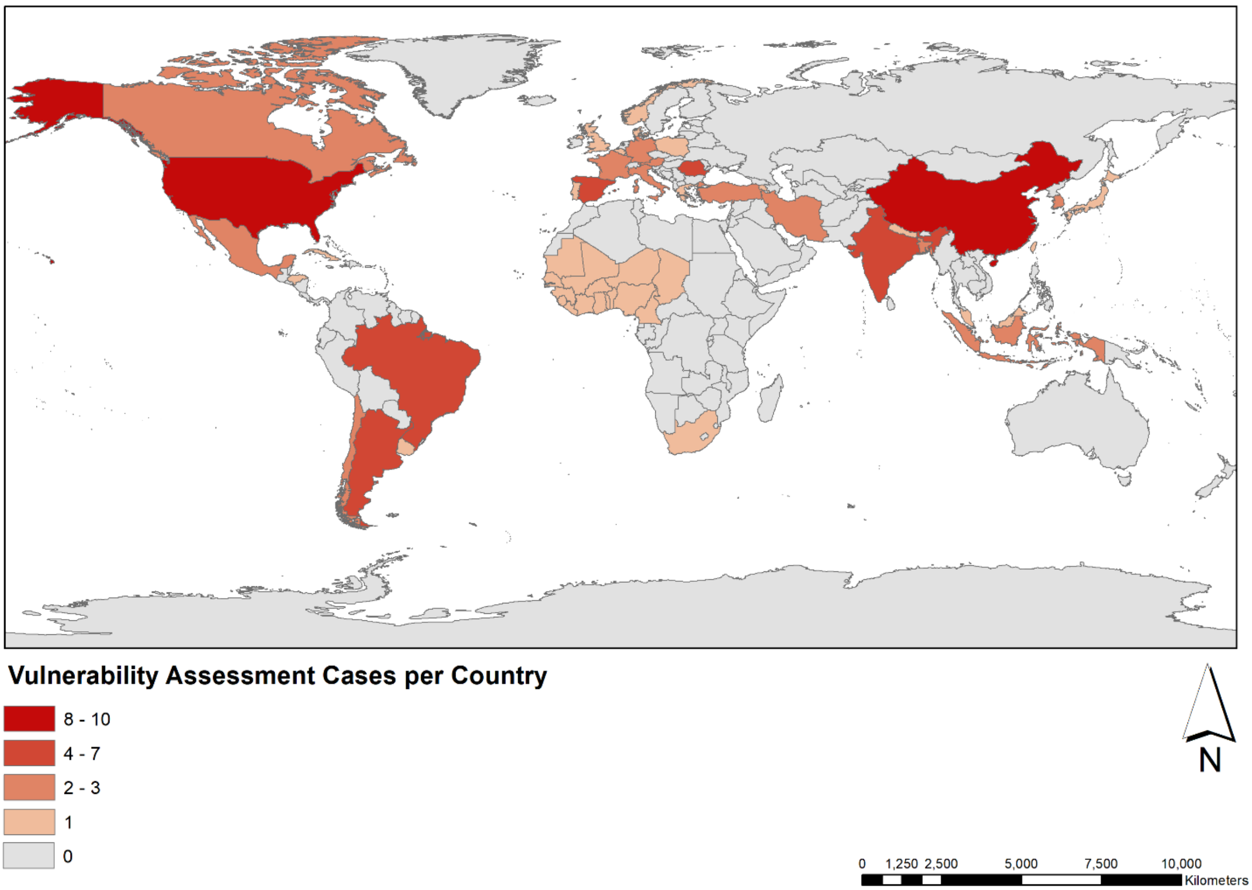

Figure 3: Socio-economic Vulnerability Assessment Cases per Country.

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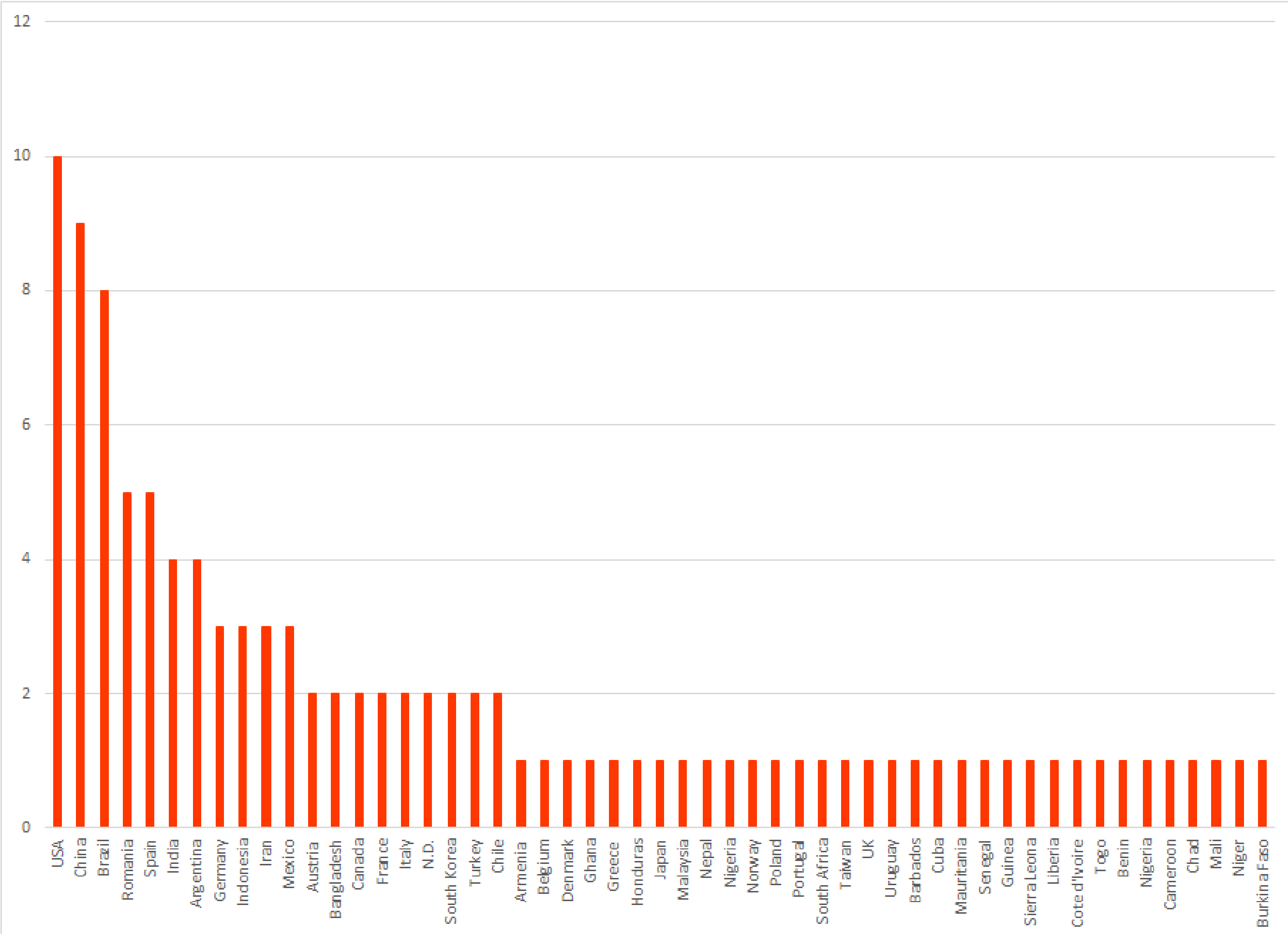

Figure 4: Number of Vulnerability Assessment Cases per Country.

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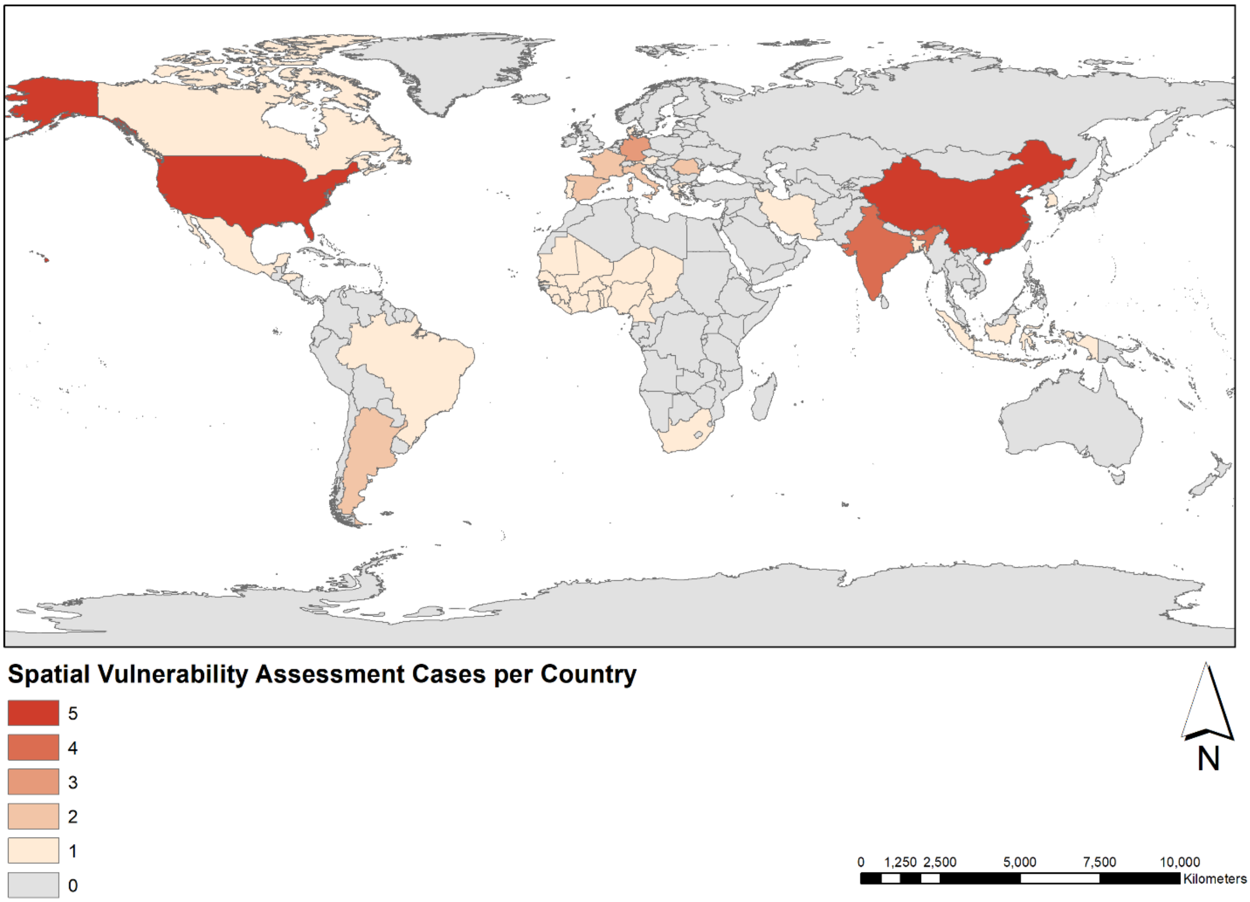

Figure 5: Spatial Socio-economic Vulnerability Assessment Cases per Country.

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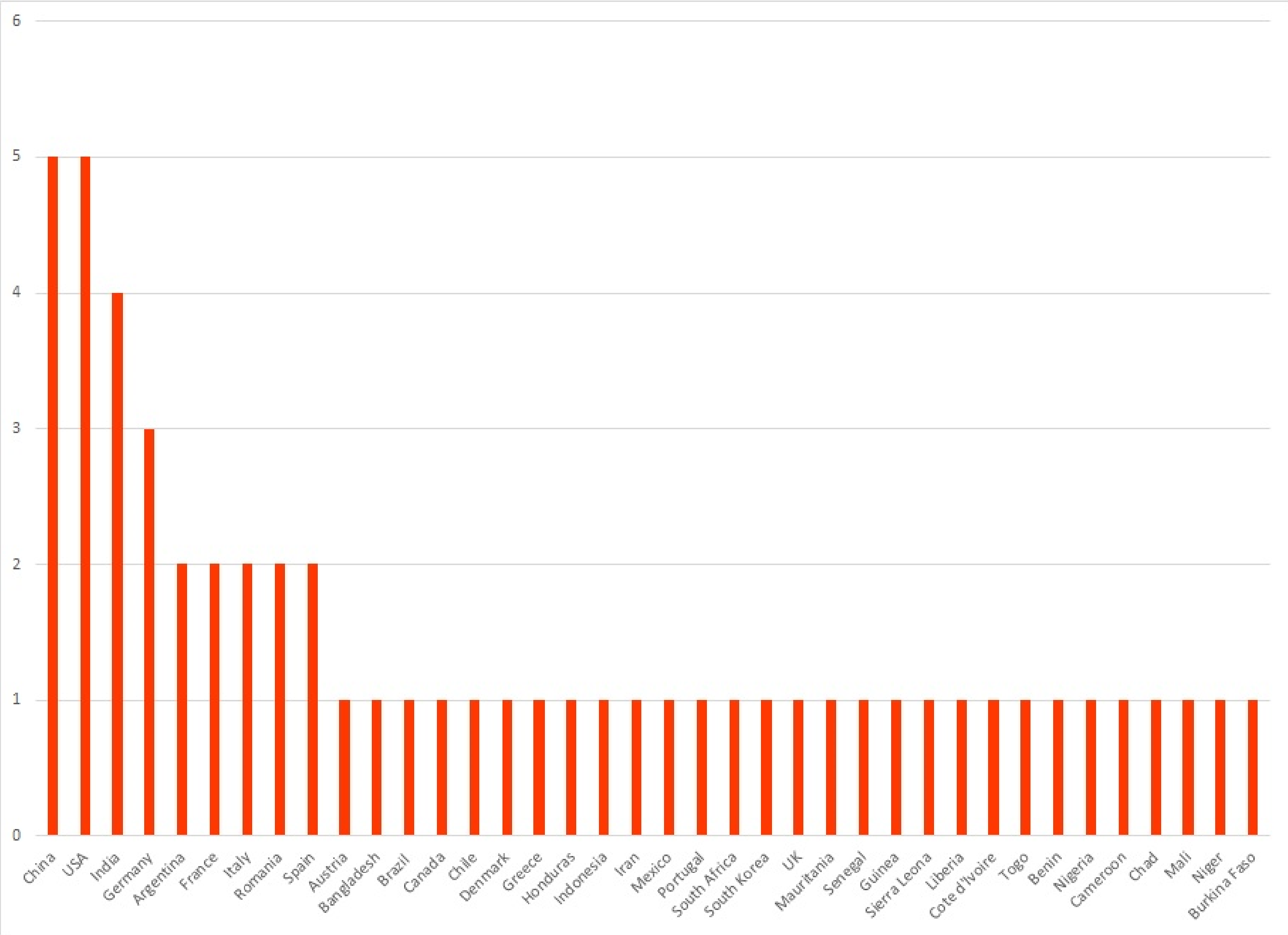

Figure 6: Number of Spatial Vulnerability Assessment Cases per Country.

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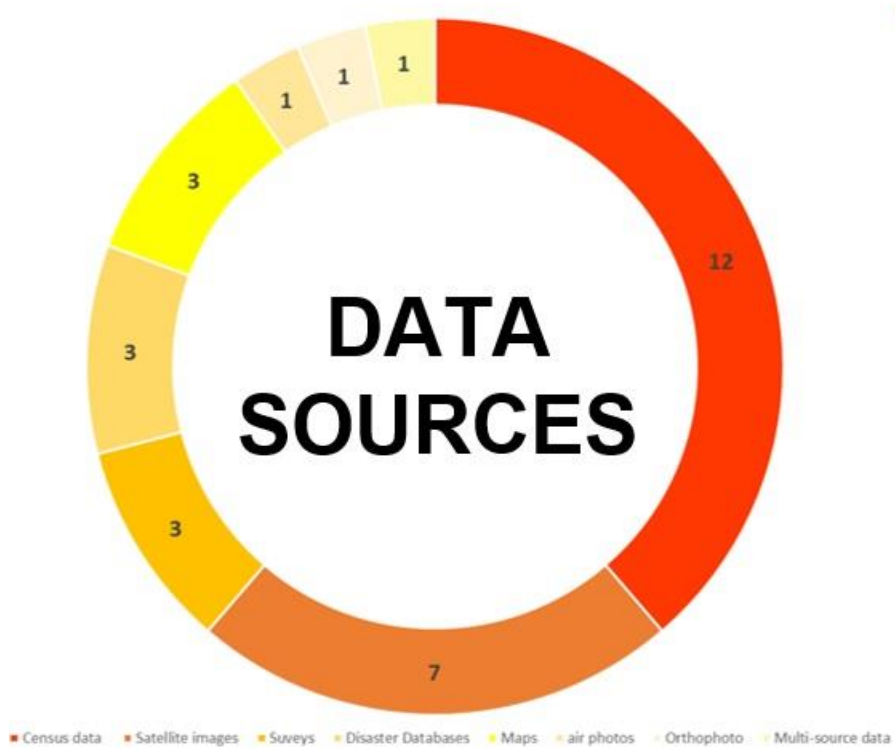

Figure 7: Data sources for spatial vulnerability assessment cases per country.

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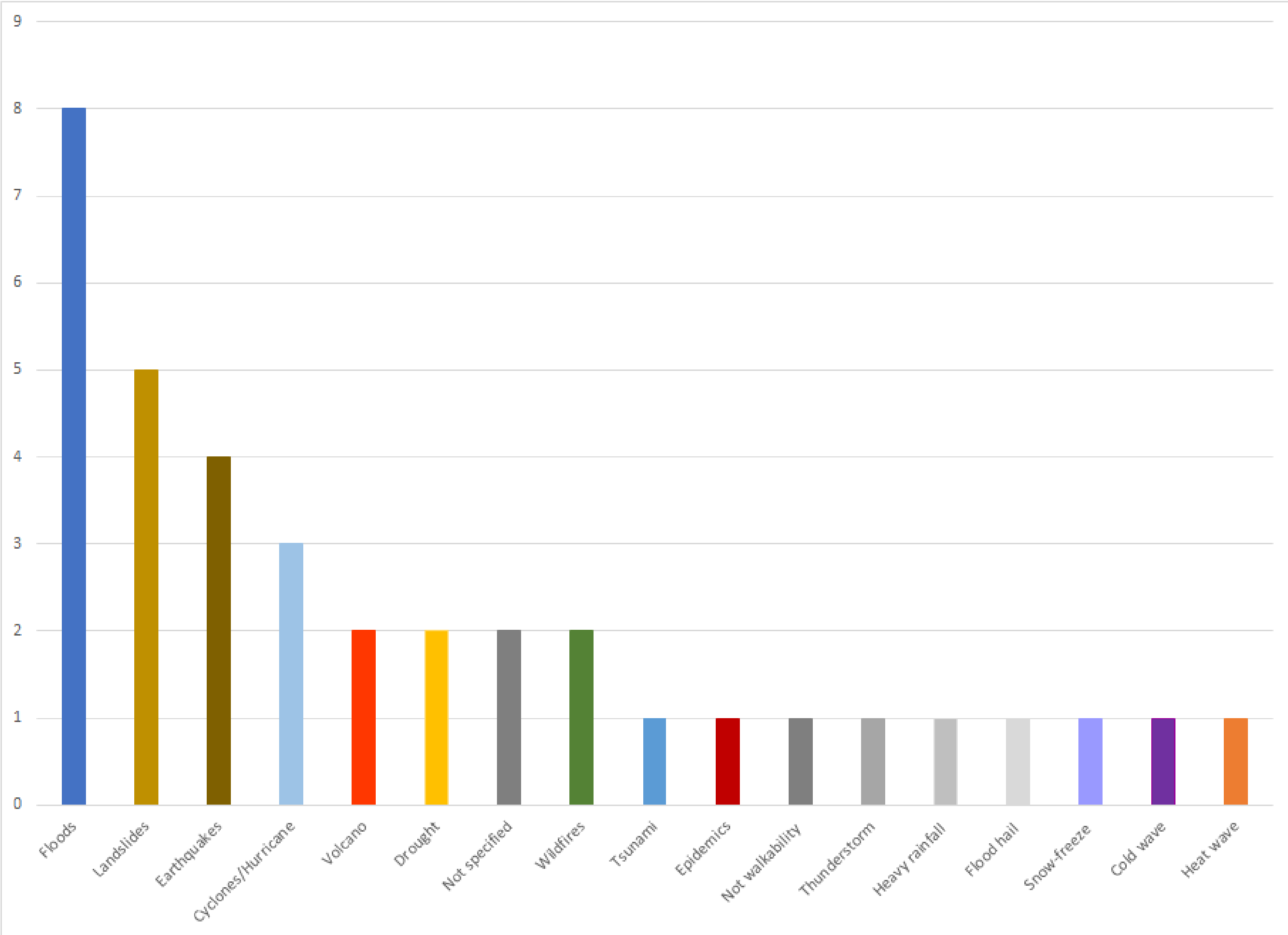

Figure 8: Hazards or topics addressed by the highly relevant articles.

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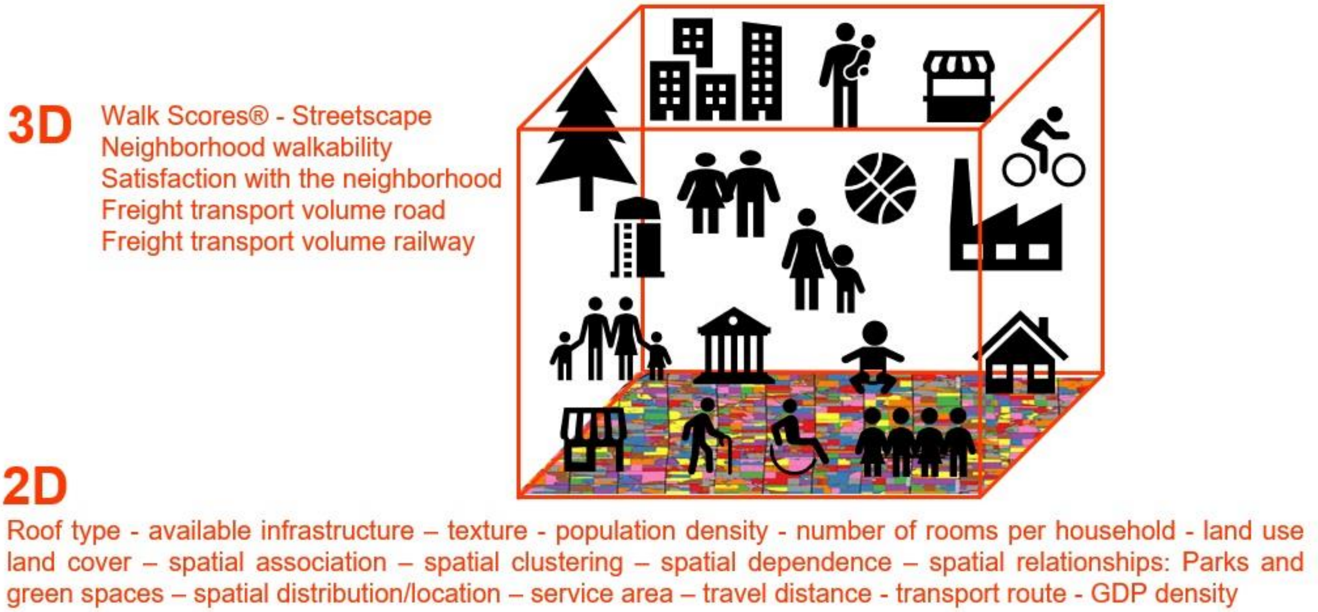

Figure 9: Spatial variables, indicators and indexes used in the socio-economic vulnerability assessment.

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