A participatory multi-criteria approach for flood vulnerability assessment

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Preface

This thesis is submitted in partial fulfilment of the requirements for obtaining the Ph.D. degree in Natural Sciences (*Doctor rerum naturalium*) at the University of Bonn. The work described herein was conducted at the Department of Geography between March 2015 and April 2018 under the supervision of Professor Dr. Mariele Evers. This research was funded by the Brazilian Coordination for the Improvement of Higher-Education Personnel (CAPES) in cooperation with the German Academic Exchange Service (DAAD) through the grant 13669-13-3.

The thesis follows a paper-based approach in accordance with the guidelines of the University of Bonn and includes the following articles:

[1] **de Brito, M.M**., Evers, M. (2016) Multi-criteria decision-making for flood risk management: a survey of the current state-of-the-art. Natural Hazards and Earth System Sciences, 16, 1019-1033, doi:10.5194/nhess-16-1019-2016.

[2] **de Brito, M.M.**, Evers, M., Höllermann, B. (2017) Prioritization of flood vulnerability, coping capacity and exposure indicators through the Delphi technique: a case study in Taquari-Antas basin, Brazil. International Journal of Disaster Risk Reduction, 24, 119-128, doi:10.1016/j.ijdrr.2017.05.027.

[3] **de Brito, M.M.**, Evers, M., Almoradie, A. (2018) Participatory flood vulnerability assessment: a multi-criteria approach. Hydrology and Earth System Sciences, 22, 373-390, doi:10.5194/hess-22-373-2018.

[4] **de Brito, M.M.**, Almoradie, A., Evers, M. (2018) Spatially-explicit sensitivity and uncertainty analysis in a MCDA-based flood vulnerability model. (Manuscript).

The following conference abstracts, conference papers, and book chapter were also written during the Ph.D. period, and deal with the general topic of the thesis:

[5] Evers, M., Almoradie, A., **de Brito, M.M.** (2018) Enhancing flood resilience through collaborative modelling and MCDA. In: Fekete, A., Fiedrich, F. (eds.) Urban disaster resilience and security - novel approaches for dealing with risks in societies. The Urban Book Series. Springer, Cham, doi: 10.1007/978-3-319-68606-6_14.

[6] Evers, M, **de Brito, M.M.** (2018) Multi-criteria and participatory vulnerability analysis – a transdisciplinary approach to flood risk management In: Proceedings of the 20th Tag der Hydrologie, Dresden, Germany.

[7] **de Brito, M. M.**, Almoradie, A., Evers, M. (2018) Spatially-explicit sensitivity analysis of criteria weights in GIS-based flood vulnerability assessment In: Proceedings of the 20th Tag der Hydrologie, Dresden, Germany.

[8] **de Brito, M. M.**, Evers, M. (2018) Incorporating stakeholders' knowledge into flood vulnerability assessment: a multi-criteria approach. In: EGU General Assembly, Vienna. Geophysical Research Abstracts, v. 20.

[9] **de Brito, M. M.**, Evers, M. (2017) A participatory spatial multi-criteria approach for flood vulnerability assessment In: Proceedings of AGILE conference, Wageningen, Netherlands.

[10] **de Brito, M. M.**, (2017) A participatory multi-criteria approach for flood vulnerability assessment: a case study in Taquari-Antas Basin, southern Brazil In: Dangerous Landscapes: re-thinking environmental risk in low-income communities, Hannover, Germany. Volkswagen Stiftung.

[11] **de Brito, M. M.**, Evers, M. (2017) Assessing flood vulnerability: a participatory multi-criteria approach. Proceedings of the 19th Tag der Hydrologie 2017.

[12] **de Brito, M. M.**, Evers, M., Passuello, A. (2016) Selection of flood vulnerability indicators based on the Delphi technique. Proceedings of the 1st Brazilian Congress on Disaster Risk Reduction.

[13] **de Brito, M. M.**, Evers, M. (2016) Multi-criteria decision making in flood risk management: research progress and the challenge of handling uncertainty and stakeholder participation. In: EGU General Assembly, Vienna. Geophysical Research Abstracts, v. 18.

Mariana Madruga de Brito

Bonn, April 2018

This work is dedicated to the memory of my
mother Maria Elena Madruga de Brito,
whose example will always inspire me

"On a given day, a given circumstance, you think you have a limit. And you then go for this limit and you touch this limit, and you think, 'Okay, this is the limit'. And so you touch this limit, something happens and you suddenly can go a little bit further. With your mind power, your determination, your instinct, and the experience as well, you can fly very high." **Ayrton Senna**

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Abstract

The management of flood risk calls for a better understanding of vulnerability, as hazards only become disasters if they impact a system that is vulnerable to their effects. Although different frameworks have been proposed to assess vulnerability, they often focus on the physical vulnerability of structures, assuming a homogeneous social vulnerability and coping capacity for the entire population. Furthermore, the multiple relationships between input criteria are often neglected and the role of stakeholder participation in the modeling process has received little attention.

To tackle these issues and increase the model transparency, this thesis addresses the design and deployment of a participatory approach for flood vulnerability assessment. More specifically, it focuses on how multi-criteria tools can be combined with participatory methods to overcome common issues in the development of indexes and to open up the "black-box" nature of vulnerability models. The main argument which is pursued throughout the thesis is that participation and collaboration are key aspects for bridging the gap between modelers and end users.

The applicability of the proposed transdisciplinary framework is demonstrated in the municipalities of Lajeado and Estrela, Brazil. The model was co-constructed by 101 expert stakeholders from governmental organizations, universities, research institutes, NGOs, and private companies. Participatory methods such as the Delphi survey, focus groups, questionnaires and workshops were applied. A participatory problem structuration, in which the modelers work closely with stakeholders, was used to establish the structure of the vulnerability index. The preferences of each participant regarding the criteria importance were spatially modeled through the analytic hierarchy process (AHP) and analytic network process (ANP) multi-criteria methods. Experts were also involved at the end of the modeling exercise for validation. The robustness of the model was investigated by employing a one-at-a-time sensitivity and uncertainty analysis.

Both AHP and ANP proved to be effective for flood vulnerability assessment; however, ANP is preferred by participants as it leads to more robust results.

The results of the spatially-explicit sensitivity analysis helped to identify highly vulnerable areas that are burdened by high uncertainty and to investigate which criteria contribute to this uncertainty. The validation questionnaire indicated that the participants found the results clear, trustworthy, and valuable, suggesting that participatory modeling exercises like the one proposed here are worthwhile. These findings highlight that the use of a transdisciplinary approach to acknowledge and integrate multiple viewpoints without forcing consensus improved the results acceptance. In summary, the combination of qualitative and quantitative methods for flood vulnerability assessment led to an increased, shared understanding of the problem by avoiding the limited perspective of a single expert.

The approach proposed herein is particularly novel in the context of vulnerability assessment in the respect that stakeholders were actively involved in all steps of the vulnerability modeling process and that the relationship between criteria was considered. The use of participatory tools in combination with multi-criteria methods can support social learning processes and enhance the credibility and deployment of vulnerability indicators, as stakeholders' opinion, expert judgment, and local knowledge are taken into consideration throughout the entire modeling process. From a practical standpoint, the outcomes of this Ph.D. thesis can support local authorities to understand the vulnerability patterns in the region, its associated uncertainty, and the criteria contributing to this uncertainty.

Key-words: MCDM, vulnerability, participation, transdisciplinary, ANP, AHP

Zusammenfassung

Das Management von Hochwasserrisiken erfordert ein besseres Verständnis der Vulnerabilität, da Gefahren nur dann zu Katastrophen werden, wenn sie sich auf ein System auswirken, das für ihre Auswirkungen anfällig ist. Obwohl bereits verschiedene Frameworks zur Bewertung der Vulnerabilität vorgeschlagen wurden, konzentrieren sich diese oft auf die physische Vulnerabilität von Strukturen unter der Annahme einer homogenen sozialen Vulnerabilität und Bewältigungskapazität für die gesamte Bevölkerung. Darüber hinaus werden oftmals die vielfältigen Beziehungen zwischen den Eingabekriterien vernachlässigt und auch die Rolle der Beteiligung von Stakeholdern am Modellierungsprozess findet wenig Beachtung.

Um diese Probleme anzugehen und die Modelltransparenz zu erhöhen, befasst sich diese Arbeit mit der Gestaltung und dem Einsatz eines partizipativen Ansatzes für die Bewertung von Vulnerablität bei Hochwasserereignissen. Im Speziellen fokussiert sich die Arbeit darauf, inwiefern Multi-Kriterien-Tools mit partizipativen Methoden kombiniert werden können, um häufige Probleme bei der Entwicklung von Indizes zu überwinden, und die natürliche „black-box" von Vulnerabilitätsmodellen zu öffnen. Das Hauptargument, das in dieser Dissertation verfolgt wird ist, dass Partizipation und Kollaboration Schlüsselaspekte sind, um die Lücke zwischen ModelliererInnen und EndnutzerInnen zu schließen.

Die Anwendbarkeit des vorgeschlagenen transdisziplinären Frameworks wird anhand der Gemeinden Lajedo und Estrela in Brasilien verdeutlicht. Das Modell wurde von 101 beteiligten ExpertInnen aus Regierungsorganisationen, Universitäten, Forschungsinstituten, Nichtregierungsorganisationen und privaten Firmen mitentwickelt. Dabei wurden partizipative Methoden, wie die Delphi-Umfragen, Fokusgruppen, Fragebögen und Workshops angewendet. Eine partizipative Problemstrukturierung, bei der ModelliererInnen eng mit Stakeholdern zusammenarbeiten, wurde verwendet, um die Struktur des Vulnerabilitätsindexes zu entwickeln. Die individuellen Präferenzen der verschiedenen Beteiligten bezüglich der Bedeutung der Kriterien wurden räumlich durch Analytische Hierarchieprozess (AHP) und Analytischen Netzwerkprozess (ANP) -Methoden modelliert. Zur Validierung am Ende des

Modellierungsprozesses waren ebenfalls Experten beteiligt. Die Robustheit des Modells wurde durch eine Sensitivitäts- und eine Unsicherheitsanalyse untersucht.

Sowohl AHP als auch ANP erwiesen sich als wirksam für die Bewertung von Hochwasservulnerabilitäten. Aufgrund der robusteren Ergebnisse wird der ANP jedoch bevorzugt. Die Ergebnisse der räumlich-expliziten Sensitivitätsanalyse haben dazu beigetragen, hochsensible Bereiche mit hoher Unsicherheit zu identifizieren und zu untersuchen, welche Kriterien zu dieser Unsicherheit beitragen. Der Validierungsfragebogen zeigte, dass die Teilnehmer die Ergebnisse als klar, vertrauenswürdig und wertvoll empfanden, was darauf hindeutet, dass partizipative Modellierung, wie die hier vorgeschlagene, lohnenswert sind. Die Ergebnisse zeigen, dass die Verwendung eines transdisziplinären Ansatzes zur Anerkennung und Integration verschiedener Sichtweisen ohne erzwungene Konsense die Akzeptanz der Ergebnisse verbesserte. Zusammenfassend führte die Kombination von qualitativen und quantitativen Methoden zur Bewertung von Hochwasservulnerabilität zu einem größeren, gemeinsamen Problemverständnis, da die eingeschränkte Perspektive eines einzelnen Experten vermieden wurde.

Im Kontext der Vulnerabilitätsbewertung ist der in dieser Arbeit vorgeschlagene Ansatz besonders innovativ, durch die aktive Beteiligung der Stakeholder in allen Schritten des Vulnerabilitätsmodellierungsprozesses und die Berücksichtigung der Beziehungen zwischen den relevanten Kriterien. Die Verwendung partizipativer Instrumente in Kombination mit Multi-Kriterien-Tools kann soziale Lernprozesse unterstützen sowie die Glaubwürdigkeit und die Verwendung von Vulnerabilitätsindikatoren verbessern, da die Meinung von Stakeholdern und ExpertInnen als auch lokales Wissen während des gesamten Modellierungsprozesses berücksichtigt werden. Aus praktischer Perspektive können die Ergebnisse dieser Dissertation lokale Behörden dabei unterstützen, die Verwundbarkeitsmuster in der Region, die damit verbundene Unsicherheit und die Faktoren, die zu dieser Unsicherheit beitragen, zu verstehen.

Schlüsselwörter: MCDM, Vulnerabilität, Partizipation, Transdisziplinarität, ANP, AHP

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List of Abbreviations

AHP	Analytic hierarchy process
ANP	Analytic network process
AVG	Average
CEMADEN	Centro nacional de monitoramento e alertas de desastres naturais
CI	Consistency index
CI	Confidence intervals
CP	Compromise programming
CR	Consistency ratio
CV	Coefficient of variation
DRI	Disaster risk index
ELECTRE	Elimination et choix traduisant la realité
EM-DAT	Emergency events database
FAST	Fourier amplitude sensitivity test
FVI	Flood vulnerability index
GDAL	Geospatial data abstraction library
GIS	Geographic information system
GSA	Global sensitivity analysis
IBGE	Instituto Brasileiro de geografia e estatística
IPC	Increment of percent change
IQR	Interquartile range
MACBETH	Measuring attractiveness by a categorical based evaluation technique
MAUT	Multi-attribute utility theory
MAVT	Multi-attribute value theory

MCA	Multi-criteria analysis
MCDA	Multiple-criteria decision-analysis
MCDM	Multi-criteria decision-making
MCE	Multi-criteria evaluation
NGT	Nominal group technique
OECD	Organisation for economic co-operation and development
ORESTE	Organization, rangement et synthese de donnes relationnelles
PCA	Principal component analysis
PROMETHEE	Preference ranking organization method for enrichment of evaluations
PVI	Prevalent vulnerability index
RPC	Range of percent change
SA	Sensitivity analysis
SD	Standard deviation
SAW	Simple additive weighting
SPSS	Statistical package for the social sciences
SoVI	Social vulnerability index
TOPSIS	Technique for order preference by similarity to an ideal solution
UA	Uncertainty analysis
UNDP	United Nations development programme
UNISDR	United Nations office for disaster risk reduction
VIKOR	Vlsekriterijumska optimizacija i kompromisno resenje

CHAPTER 1

Introduction

1.1 Background

The rapid urbanization in developing countries without proper spatial planning has often led to the occupation of unsuitable areas such as floodplains and river banks (Saghafian et al., 2008; Suriya and Mudgal, 2012). The expansion of human settlements and accompanying activities in these places without considering the fragility of the environment exposes people and buildings to floods, leading to injury and loss of lives, disturbing social, economic and ecological systems, and destroying properties (Bakkensen et al., 2017; Prior et al., 2017).

In Brazil, due to their frequency and damage, floods represent the most deathly and costly types of disaster. According to the Brazilian National Atlas of Disasters, about 2,455 people died due to extreme floods between 1991 and 2012. In the same period, approximately 54 million people were affected in some way by these disasters (i.e. injured, displaced, evacuated or requiring immediate assistance) (UFSC and CEPED, 2013). Apart from the loss of lives, floods also cause great economic losses. For instance, the flash flood that occurred in 2008 in the Itajaí-Açú River, southern Brazil, caused an estimated US$ 2.1 billion in damage (World Bank, 2012a).

In order to mitigate the negative impacts of floods, the Sendai framework for disaster risk reduction recommends that the design and implementation of risk management strategies should be based on a comprehensive understanding of risk in all its dimensions, including the hazard characteristics, the vulnerability, the coping capacity, and the exposure of persons and assets (UNISDR, 2015b). The assessment of risk, when carried out holistically, can provide floodplain managers better tools to make informed decisions for flood mitigation at various levels. It can assist decision makers to elaborate land use planning policies and to identify areas where preventive and corrective measures are needed, and, if so, which option is most suitable. Additionally, it can help to raise public awareness by providing an understandable visualization of the flooding risks.

In recent decades, several hydrological and hydrodynamic studies have been carried out to estimate flood hazard characteristics, such as the inundation depth, peak discharge, and flow velocity (e.g. Ballesteros-Cánovas et al., 2013; Sampson et al., 2015; Suriya and Mudgal, 2012). Nevertheless, while the practical analysis of hazard and exposure has significantly improved, the assessment of vulnerability remains one of the biggest hurdles in flood risk assessment (Jongman et al., 2015; Koks et al., 2015; Prior et al., 2017; Sorg et al., 2018). Even when vulnerability is considered, its analysis focuses on the physical resistance of buildings and infrastructure (Prior et al., 2017). In such studies, vulnerability is often represented using damage functions, which show the relationship between potential losses (people and other exposed elements) and flood hazard (for example, flood depth).

However, the usage of a single average-vulnerability curve representing only the relation between flood depth and damage does not address the entire range of human behavioral responses (Aerts et al., 2018). The extent of disaster damages depends drastically on human behavior patterns and choices, which are intrinsically related to the coping capacity and social vulnerability of the exposed people (Müller et al., 2011). Indeed, floods do not necessarily cause extreme impacts and major harm, as hazards only become disasters if they impact a community that is vulnerable to their effects (Cardona et al., 2012; Reilly, 2009). Nevertheless, current vulnerability-curve approaches largely neglect the social vulnerability (Aerts et al., 2018). Therefore, it is timely and necessary to develop risk maps that incorporate not only the hazard characteristics but also the exposure and the multi-dimensions of vulnerability (Gain et al., 2015), since if any of these elements increases or decreases, then the risk increases or decreases, respectively.

Part of the complexity of incorporating vulnerability in risk analysis arises from the fact that vulnerability is multifaceted and determined by a number of physical, economic, social, political and environmental root causes which make the exposed elements susceptible to the impacts of a hazard (Willis and Fitton, 2016). These various dimensions are sometimes hard to capture and to describe precisely and even harder to measure and evaluate (Müller et al., 2011). They form a complex subject for quantitative risk scientists to understand and integrate into their methodologies. Consequently, vulnerability is considered to be an ill-structured problem as its analysis possesses multiple solutions paths and experts often disagree regarding whether a particular choice is appropriate (Rashed and Weeks, 2003).

A variety of approaches have been proposed to estimate vulnerability, including: (1) vulnerability or damage curves (Ozturk et al., 2015; Tsubaki et al., 2016; Ward et al., 2011); (2) damage matrices (Bründl et al., 2009; Papathoma-Köhle et al., 2017); and (3) vulnerability indicators, indices or indexes (Cutter et al., 2003; Roy and Blaschke, 2015). Both vulnerability curves and damage matrices are building type-specific and focus on the physical vulnerability of structures to a certain hazard, neglecting the social vulnerability and coping capacity of the inhabitants (Koks et al., 2015). Nevertheless, the ability of a society to anticipate, cope with, and recover from disasters is equally important to assess flood potential impacts. Consequently, several authors emphasize the need for a holistic understanding of vulnerability by integrating its different dimensions and key factors in an overarching framework through the use of indicators (Birkmann et al., 2013; Fuchs et al., 2011; Godfrey et al., 2015a).

The importance of indicators is also stressed in the key activities of the Hyogo Framework for Action (UNISDR, 2005) and reiterated in the Sendai Framework for disaster risk reduction (UNISDR, 2015b), which underlines the necessity of developing vulnerability indicators to assess the social, economic and environmental impacts of disasters. Indicator-based methods allow summarizing complex and multi-dimensional problems in a simple and easy to understand way (Ciurean et al., 2013). Besides, they do not require detailed empirical data as damage matrices and curves, being useful in data-scarce environments.

The development of indicators is frequently aided by the use of multi-criteria decision-making (MCDM) tools. MCDM is a generic term used to describe a set of methods which help individuals or groups to solve problems that involve multiple and conflicting criteria. One of the strengths of MCDM is that it allows considering both qualitative criteria (e.g. high risk perception), as well as quantitative ones (e.g. monthly income). MCDM facilitates compromise and collective decisions and provides a good platform for stakeholders to communicate their personal preferences. Furthermore, it makes the criteria evaluation process more explicit and rational, by making subjective judgments visible in a transparent and fair way (Mateo, 2012b).

Examples of studies that applied MCDM tools to overcome some of the shortcomings of assessing vulnerability using damage curves and matrices include the application of AHP (analytic hierarch process) (e.g. Godfrey et al., 2015b; Roy and Blaschke, 2013), TOPSIS (technique for order performance by similarity to ideal solution) (e.g. Chung et al., 2014; Jun et al., 2013), ELECTRE (elimination and choice translating reality) (e.g. Chung and Lee, 2009), and SAW (simple additive weighting) (e.g. Johnston et al., 2014; Scheuer et al., 2011; Sowmya et al., 2015).

For instance, Kienberger et al. (2009) used AHP to assess the socio-economic vulnerability in the Salzach catchment, Austria. A rather similar approach, termed fuzzy AHP, was used by Wang et al. (2011) to integrate all relevant dimensions of vulnerability without measuring them on monetary terms. Chung and Lee (2009) compared five different MCDM methods in the assessment of potential flood damages. The authors concluded that there was not a clear preference for any of MCDM tools investigated as the results were similar. More recently, Yang et al. (2018) developed an integrated flood vulnerability index based on TOPSIS and the Shannon entropy method to describe the uncertainty of the exposure, sensitivity, and adaptive capacity indicators.

1.2 Motivation

Even though flood vulnerability indicators have been extensively elaborated with the support of MCDM tools and statistical methods, their construction is not a straightforward process as modelers are faced with multiple and legitimate choices, thus introducing subjectivity into the modeling process. This raises a series of technical issues that, if not addressed adequately, can lead to indicators being misinterpreted or manipulated. Based on recent systematic reviews, a number of challenges in the development of vulnerability indicators have been identified, including: (1) selection of the input criteria; (2) data standardization; (3) determination of criteria weights; (4) consideration of relationships between them; (5) criteria aggregation; (6) results validation; and (7) conduction of sensitivity and uncertainty analysis (Beccari, 2016; Fekete, 2012; Müller et al., 2011; Rufat et al., 2015; Tate, 2012).

The main issue is that the methodologies applied to develop vulnerability indicators are often not presented transparently (Hinkel, 2011). The bulk of vulnerability studies neglects to explain why a particular design was used in the index construction and, more importantly, how the design choices affect the output index (Tate, 2012). However, the structural design of the indicators is a critical step as it establishes the framework for all other stages to follow. Typically, the rationale for decisions regarding criteria selection, weighting and aggregation is either justified based on choices made in previous studies or unstated. In several cases, no justification is provided at all and the decisions are restricted to project members (Rufat et al., 2015).

Notwithstanding the different levels of importance of the criteria, surprisingly, the majority of vulnerability indicators employs an equal weighting, i.e. all variables are given the same weight (Fekete, 2012). According to Tate (2012), the use of equal weights is applied as a default option due to a lack of understanding of the relationship between criteria. Nevertheless, even though it is difficult to find an acceptable weighting scheme, an unweighted index is still subjective rather than objective, as it implies that all criteria are "worth" the same (Oulahen et al., 2015). Moreover, if variables are grouped into dimensions and those are further aggregated into a composite index, then applying equal weighting may imply an unequal weighting of the dimension (the dimension with more criteria will have a higher weight). This can result in an unbalanced structure in the composite index (OECD, 2008).

Regarding the aggregation of criteria, the arithmetic mean or additive aggregation is nearly universally applied (Tate, 2012). Only a small minority of indices combine the criteria using the geometric mean or other aggregation techniques. However, additive aggregation implies that a low weight of one criterion can be compensated by a large weight of another criterion. This is problematic as it assumes that one factor or indicator such as persons with disabilities can be evened out by another criterion. In addition, it assumes relatively strong independence conditions (Schuwirth et al., 2012), which is not the case of vulnerability. Indeed, the dimensions of vulnerability have diverse and complex linkages among each other (Fuchs, 2009). For instance, disabled people are disproportionately likely to be poor, as are members of minorities such as ethnic groups and older people. Yet, the relationships between vulnerability criteria are often neglected (Chang and Huang, 2015; Rufat et al., 2015).

A further problem is that the validation of vulnerability indicators is seldom conducted (Fekete, 2009). Still, this is a crucial step, as it allows evaluating whether a model performs well in different situations and whether it can thus be used for predictions (Merz et al., 2010). Since vulnerability is not a directly observable phenomenon, the validation requires the use of proxies such as mortality and build environment damage (Schneiderbauer and Ehrlich, 2006). Alternatively, the reliability of the model can be tested based on sensitivity analysis (SA) and uncertainty analysis (UA). However, neither sensitivity nor uncertainty analysis are common practice in the field of spatial MCDM regardless of the application area (Chen et al., 2010; Xu and Zhang, 2013). This occurs due to the technical complexity of doing SA and UA in a spatial context, in comparison with the well-established tools for non-spatial MCDM, due to (1) the large number of pixels in a map; (2) the heterogeneity of input data and the variety of parameters involved; (3) the uncertainty range that might be associated with each raster cell, which increases the computation time; and (4) the lack of pre-built tools in existing GIS software (Delgado and Sendra, 2004; Ferretti and Montibeller, 2016; Ghorbanzadeh et al., 2018).

In addition to the methodological issues raised above, no attention has been paid to the participation of multiple stakeholders in the index construction. Even when several actors are considered, their involvement is usually fragmented and limited to consultation at specific stages. None of the vulnerability indicators reviewed by de Brito and Evers (2016) systematically promoted an active participation throughout the entire vulnerability modeling process. Critical modeling choices concerning any assumptions regarding the selection of the input criteria, data standardization, and calibration were normally constrained to researchers conducting the study.

Nevertheless, participation and cooperation are key aspects for bridging the gap between modelers and end users and eventually between science and policy (Barthel et al., 2016; Voinov and Bousquet, 2010). If practitioners are involved in creating an index that they find useful, it is more likely they will incorporate it into policy decisions (Oulahen et al., 2015). Furthermore, better insights can be gained since knowledge beyond the boundaries of single expert or organization is considered. Thus, a broader and systematic understanding of the problem can be reached, which, in turn, allows for the designing of more effective vulnerability models (Müller et al., 2012). The inclusion of stakeholder perspectives is, therefore, crucial for model improvement and to broaden the system understanding. In addition, it can help to democratize the modeling process and open up the “black-box” nature of many vulnerability models.

To address the above concerns, this thesis presents a participatory MCDM approach to assess flood vulnerability while considering the interdependence between criteria. The approach was conceptualized to be applied in data-scarce environments at a municipal level. In order to bring credibility to vulnerability indicators, participant satisfaction, and mutual learning, stakeholders with sufficient technical knowledge were engaged in all key milestones of the index development. Also, to improve the transparency and analytic rigor of the model, the rationale for model decisions such as the choices of input criteria, data standardization, and weighting, were explicitly expressed, leading to justifiable decisions and reproducible results. The robustness of the model was tested by conducting SA and UA of the input criteria weights. The applicability of the proposed approach was demonstrated in two municipalities located in the Taquari-Antas River basin, southern Brazil. They were chosen based on their representativeness in terms of susceptibility to flooding as well as the high exposure of the population.

1.3 Research questions

The overall aim of this thesis is to design and implement a participatory MCDM methodology for flood vulnerability assessment that will be reflective of the local context and trusted by those involved in policymaking. The proposed transdisciplinary framework aims to integrate contrasting opinions towards social learning. The main hypothesis is that participation and collaboration are key aspects for bridging the gap between modelers and end users. In order to enhance the quality and acceptance of vulnerability model results, eight subsidiary research questions have been formulated:

Question 1: Which MCDM methods are most commonly applied for flood vulnerability assessment?

Question 2: What are the main trends and research gaps in MCDM applied to flood-related problems regarding stakeholder participation?

Question 3: Which criteria should be incorporated in the vulnerability model developed for the study area and how should they be structured?

Question 4: Do experts with different backgrounds and levels of knowledge rely on divergent rationalities regarding the importance of vulnerability criteria?

Question 5: What do the participants perceive about the effectiveness of the developed collaborative approach for flood vulnerability assessment?

Question 6: What are the differences in model results between MCDM methods that consider the interrelationship between the vulnerability criteria and the ones that consider the variables to be independent?

Question 7: Which vulnerability criteria are most and least sensitive to weight changes?

Question 8: How does the uncertainty of model results vary in space?

A brief summary of how these research questions are addressed in the published and submitted papers is outlined in Table 1.

Table 1. Overview of research questions, methods, and research highlights of the published and submitted papers

	Research question	Methods	Research highlights	Paper status
Paper 1	Which MCDM methods are most commonly applied for flood vulnerability assessment? What are the main trends and research gaps in MCDM applications to flood-related problems regarding stakeholder participation?	Systematic literature review of 128 papers indexed in six research databases (e.g. ProQuest, Scopus, Web of Science, SpringerLink)	• AHP was the most used MCDM tool, indicating that other methods may be overlooked • None of the reviewed vulnerability studies used MCDM tools that consider the interdependence between criteria • Participation was fragmented and focused on particular stages of the decision-making process • Agreement between participants about criteria importance was rarely sought • Only 2 out of the 27 reviewed papers that assessed flood vulnerability conducted some sort of sensitivity analysis	Published in "Natural Hazards and Earth System Sciences". doi:10.5194/nhess-16-1019-2016
Paper 2	Which criteria should be incorporated in the vulnerability model developed for study area and how should they be structured? Do experts with different backgrounds and levels of knowledge rely on divergent rationalities regarding the importance of vulnerability criteria?	Snowball sampling; two-round Delphi survey; inferential statistics; bootstrap analysis; and focus group discussion	• Participants agreed on a set of 12 criteria that should be incorporated in the model. These were organized in 3 clusters: social vulnerability, coping capacity and infrastructure vulnerability • Neither profession nor affiliation institution affected the experts´ perception of the vulnerability criteria importance, showing that they do not rely on divergent rationalities • Differences were found regarding the experts level of knowledge. Participants with less expertise tended to modify more their answers in the direction of the group median	Published in "International Journal of Disaster Risk Reduction" doi:10.1016/j.ijdrr.2017.05.027

Paper 3	What do the participants perceive about the effectiveness of the developed collaborative approach for flood vulnerability assessment? What are the differences in model results between MCDM methods that consider the interrelationship between the vulnerability criteria and the ones that consider the variables to be independent?	Workshops; focus group discussion; AHP and ANP MCDM methods; web-based GIS platform; and online feedback questionnaires	• All respondents agreed that the developed approach provides a promising framework for integrating interdisciplinary knowledge in the effort to bring credibility to vulnerability indices • The deliberative feedback throughout the process positively impacted the participants' perception of transparency of the results • Overall, the results of both MCDM methods were similar. However, the ANP tool was preferred by experts given that it was easier to understand and it provided a way to make all the relationships among variables explicit	Published in "Hydrology and Earth System Sciences" doi:10.5194/hess-22-373-2018.
Paper 4	Which vulnerability criteria are most and least sensitive to weight changes? How does the uncertainty of model results vary in space?	One-at-a-time sensitivity and uncertainty analysis developed in Python using a geospatial data abstraction library	• The criterion "households with improper building material" has the highest sensitivity, while the criteria "persons under 12 years" and "persons over 60 years" appear to be least sensitive to weight changes • There are almost no cell shifts between classes in the 550 runs. Indeed, 93.41% of the pixels remained in the same vulnerability class they were in the base run • SA and UA helped to identify highly vulnerable areas that are burdened by high uncertainty and to investigate which specific criteria contribute to the uncertainty. Robust areas with low standard deviation scores and very high or high vulnerability are located in the northwest of the study area	Manuscript in preparation

1.4 Outline of the thesis

This thesis has been organized into six chapters as shown in Figure 1.

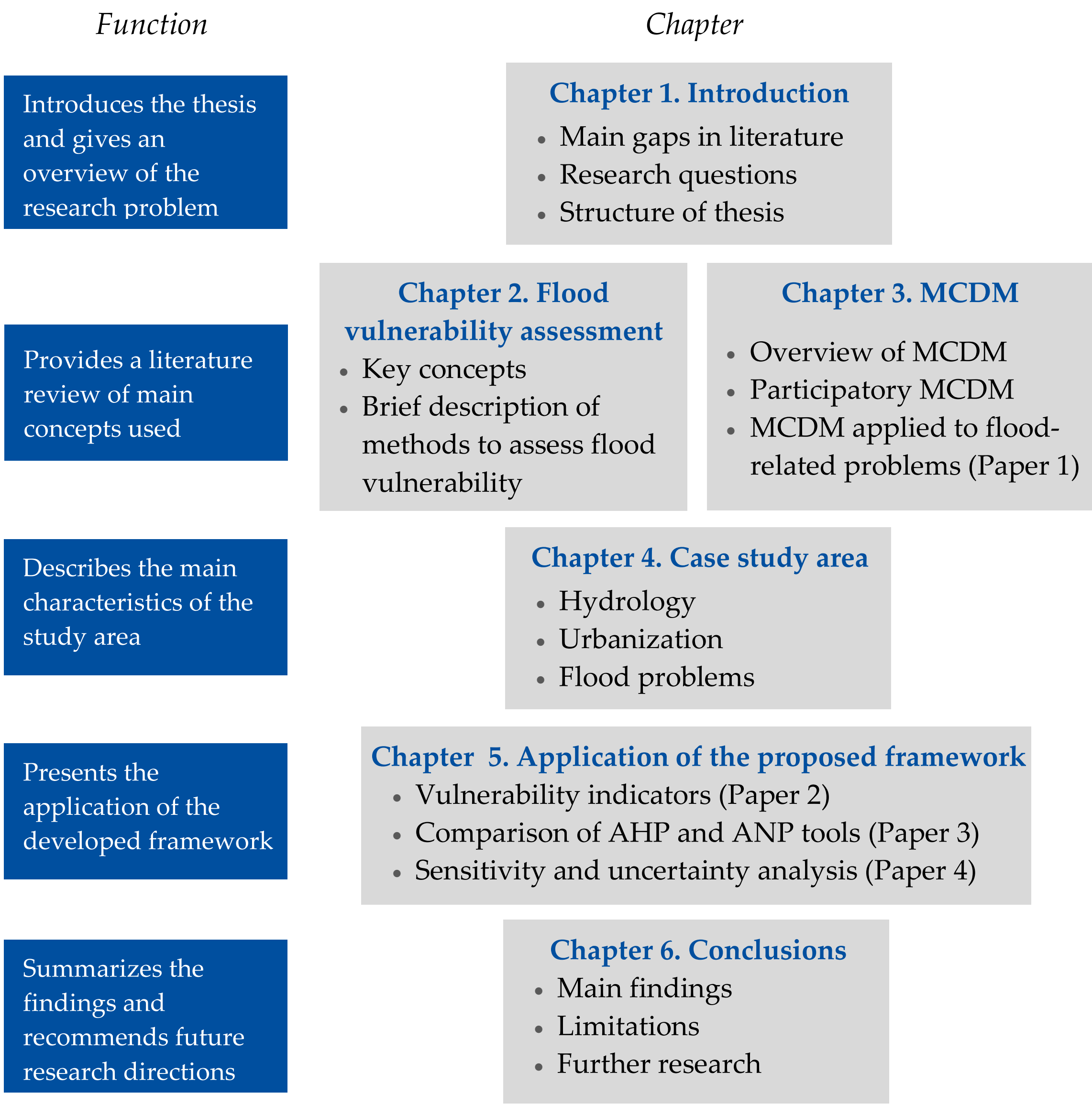

Figure 1. Overview of the chapters of this thesis

Chapter 1 outlines the relevance of vulnerability assessment for flood risk management. Furthermore, it provides a general overview of the research questions that guided the thesis and a summary of how these questions were addressed in each paper.

Chapter 2 introduces the main concepts used in the thesis and gives the theoretical background necessary to understand flood risk. The review covers the concepts of risk, vulnerability, exposure, and coping and adaptive capacity. Also, it explores a selection of existing approaches to assess flood vulnerability.

Chapter 3 discusses the several steps of the MCDM process, from identifying a decision problem to presenting a solution. It also provides an up-to-date systematic literature review of MCDM applied to flood risk management problems (Paper 1).

Chapter 4 provides a brief description of the Taquari-Antas River Basin, southern Brazil, and describes why the municipalities of Lajeado and Estrela were chosen as case studies. It includes the geographical setting of the study area, as well as hydrology, flooding problems and urbanization aspects.

Chapter 5 describes the design and deployment of the proposed framework for flood vulnerability assessment in the study area. It includes three research papers. Paper 2 describes in detail how the relevant expert stakeholders were identified. The two-round Delphi process used to prioritize the vulnerability criteria is discussed and the differences between the participant's perspectives are explored. Paper 3 focuses on a comparison of two MCDM tools to assess flood vulnerability in the study area: AHP, which considers the input criteria to be independent; and ANP, which allows capturing the complex relationships among vulnerability drivers. The paper investigates how MCDM tools can be used to integrate interdisciplinary knowledge to guarantee not only a useful model according to the needs of the end users but also to increase the acceptance of the vulnerability maps. Paper 4 presents a methodology for conducting a spatially-explicit SA and UA of the developed vulnerability model. It explores the model uncertainties and investigates which specific criteria contribute to the uncertainty in model outcomes.

Chapter 6 summarizes the study findings and draws conclusions about the value of the work presented in the thesis. Limitations and possible further research directions are also given.

CHAPTER 2

Flood vulnerability assessment

Before examining vulnerability in detail, it is necessary to clarify the connections between vulnerability and related concepts. This chapter describes the key terms used in the field of flood risk assessment and underlines the importance of measuring vulnerability. Different approaches used to assess flood vulnerability are also discussed, with a focus on vulnerability indicators.

2.1 Conceptualization of flood vulnerability and risk

The literature on flood risk contains an array of concepts, including vulnerability, coping capacity, adaptive capacity, resilience, hazard, and risk. The relationships between these terms are often unclear, and the same term may have different meanings when used in different contexts and by researchers with different backgrounds (Bharwani et al., 2008). Hence, a clear understanding of the peculiarity of each concept is essential.

In this study, flood risk is considered as a function of the severity and frequency of the hazard, of the number of people and assets exposed, and of their vulnerability to damage (Equation 1) (Koks et al., 2015; UNISDR, 2015a; Welle and Birkmann, 2015). From this perspective, risk is the area where vulnerability, exposure, and hazard interact. Though this is a very conceptual equation, it suggests what should be considered in flood risk assessment.

$$\text{Risk} = f\,(\text{hazard, exposure, vulnerability}) \qquad \text{Eq. 1}$$

Within this framework, a **hazard** is a dangerous phenomenon of a given magnitude and frequency that occurs in a specific area (Thouret et al., 2013). A flood itself is a hazard which is usually represented in the form of maps that show flood characteristics such as inundation depth, flow velocity and inundation duration (Ward et al., 2011). The estimation of the flood hazard is usually performed using hydrologic and hydraulic-hydrodynamic models that allow assessing the flood peak and the propagation in time and space of the flood wave (Sampson et al., 2015).

The hazard event is not the sole driver of risk. Indeed, the adverse effects of disasters are mainly determined by the vulnerability and exposure of societies and social-ecological systems (Cardona et al., 2012). Hence, people and other assets must be exposed to hazards for these events to become disasters, otherwise, the risk will be zero (Takara, 2013). The term **exposure** refers to the elements located in an area in which a natural phenomenon may occur (UNISDR, 2009). These include, for example, people, their livelihoods, properties, economic activities, physical infrastructures, and environmental services and resources. Furthermore, exposure can also be differentiated into a temporal and spatial component, since communities might be exposed spatially to a certain degree and/or over a specific time period, due to their workplace or place of residence (Welle and Birkmann, 2015). The metrics used to analyze the exposure usually comprise the number of people or assets located in potentially hazard-prone areas.

Like the hazard, exposure is a necessary, but not a sufficient determinant of risk. Therefore, it is possible to be exposed to a hazard but not be vulnerable. For example, a person can live in a floodplain but have sufficient means to modify the building structure to mitigate potential losses (Cardona et al., 2012). Thus, the management of flood risk calls for a better understanding of vulnerability. The term **vulnerability** refers to the propensity of exposed elements such as human beings, their livelihoods, and assets to suffer adverse effects when impacted by hazards. It is often determined by the physical, social, economic, environmental conditions and circumstances of a community or system that make them susceptible to the damaging effects of a hazard (UNISDR, 2009). Therefore, everyone may be exposed to a hazard in a certain area, but some social groups may respond better to emergencies (Steinführer et al., 2008).

Some frameworks consider that vulnerability is composed by the exposure (how exposed people are to disasters) and susceptibility (how likely it is that they get harmed) (UNDP, 2014). However, in this study vulnerability is regarded as an intrinsic characteristic of an asset and, thus, independent of the magnitude of a specific hazard but dependent on the context in which it occurs (Rashed and Weeks, 2003; Thywissen, 2006). Consequently, the vulnerability does not change if the hazard is more intense or not – it is the exposure that might change and that influences the degree of risk (Fuchs, 2009). The advantage of hazard-independent vulnerability assessment is that it can be applied to any flood hazard, be it from small or large rivers, or be extended to coastal floods or flash floods (Fekete, 2012).

A leading component of vulnerability is the **coping capacity**, which refers to the positive features of a system that may reduce the risk posed by a certain hazard. Within the context of this study, coping capacity is defined as the ability of people, organizations, and systems, using available skills and resources, to face and manage adverse conditions, emergencies or disasters (UNISDR, 2009). These capacities can be associated with existing resources that help to face and manage emergencies, such as relevant institutions, early warning systems, medical care, and hospital capacities. Conversely, the lack of these capacities can also be taken into account, for example, regarding the provision of an effective civil protection system or the option to purchase an insurance against natural hazards (Welle and Birkmann, 2015).

The positive side of vulnerability can also incorporate the **adaptive capacity**. In contrast to the coping capacity which is primarily short-term oriented, adaptation is defined as a long-term structured strategy that aims to reduce the impacts of a hazard (Cardona et al., 2012; O'Brien and Vogel, 2003). It encompasses measures and strategies that enable communities to change and to transform in order to deal with expected negative consequences of natural hazards. Hence, these capacities focus on resources that allow changing structures within a society (Welle and Birkmann, 2015).

Although some frameworks (e.g. Scheuer et al., 2011) do not consider the coping and adaptive capacities to be part of the vulnerability, these are not independent concepts. Indeed, as stated by Billing (2005), the vulnerability is the opposite reverse of coping and adaptive capacities. For instance, a community that is unorganized for disaster response has an inadequate civil protection system (low capacity) and therefore is likely to suffer more from the impacts of a disaster (high vulnerability).

The term **resilience** expands on vulnerability and may be viewed as the qualities the ability of a system, community or society exposed to hazards to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management (UNISDR, 2009). The current literature reveals different interpretations of the term resilience, especially concerning the question of whether it should be incorporated into the concept of vulnerability (Birkmann, 2006). Indeed, according to some researchers, resilience is an integral part of vulnerability (Figure 2a), while others often embed adaptive capacity within resilience (Figure 2b). A third perspective sees resilience and vulnerability as separate but often linked concepts (Figure 2c) (Cutter et al., 2008). Regardless of the framework adopted, Gall (2013) points out that while vulnerability can be seen as a fairly static concept, resilience is dynamic in nature. It contains uncertain feedback loops and interaction effects, changing with internal conditions, external forces, and with the community's ability to respond to floods. Hence, considering the seemingly insurmountable conceptual as well as methodological challenges in resilience assessment, this study does not attempt to measure it.

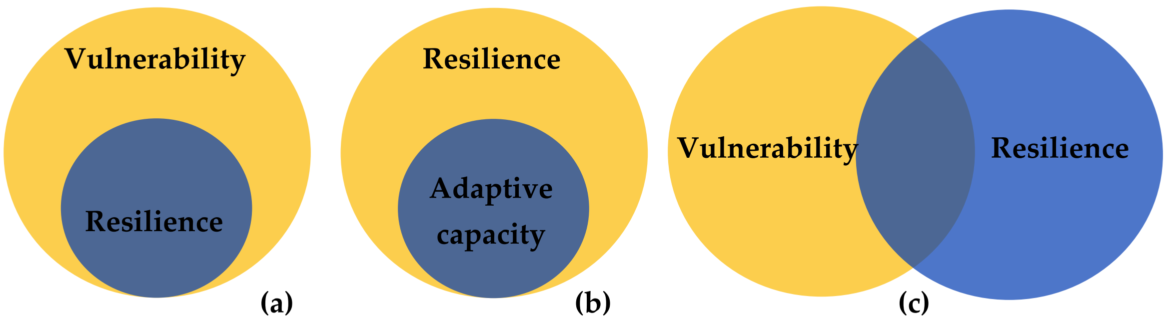

Figure 2. Conceptual linkages between vulnerability, resilience, and adaptive capacity according to different perspectives (Redrawn from Cutter et al., 2008)

For a detailed discussion on existing frameworks for risk assessment and the different definitions of the term vulnerability, the reader is referred to Birkmann (2006), Birkmann and Wisner (2006), Cardona et al. (2012), Thywissen (2006), UNDRO (1980), UNISDR (2009).

2.2 Methods to assess flood vulnerability

The assessment of vulnerability provides valuable information for all phases of the risk management cycle. Before the occurrence of a flood, information regarding the vulnerability of the elements at risk may guide the establishment of emergency plans and resource allocation. During the occurrence of floods, rescue crews may use vulnerability maps to determine where to respond first to save people that need assistance. After the disaster, the results of vulnerability analysis can be compared with the actual damage to improve the accuracy of risk maps (Edwards et al., 2007).

Although vulnerability is a key issue in understanding disaster risk, its assessment is as a complex task since it is not possible to directly measure it (Jongman et al., 2015; Koks et al., 2015). As a consequence, there remains little consensus on the best way to assess vulnerability. There are even those who argue that vulnerability as a concept cannot be adequately quantified (Hinkel et al., 2012) and hence is "unmeasurable" (Birkmann and Wisner, 2006).

Recently, the number of publications related to the measurement of risk and vulnerability has increased. Birkmann (2006) provides an extensive compilation of methodologies for different scales and levels. In general, the approaches used to estimate vulnerability can be classified into: (1) vulnerability curves (Papathoma-Köhle et al., 2012; Tsubaki et al., 2016; Ward et al., 2011); (2) damage matrices (Bründl et al., 2009; Papathoma-Köhle et al., 2017); and (3) vulnerability indicators (Cutter et al., 2003; Roy and Blaschke, 2015). Each method is designed for different data requirements, levels of complexity, types of application and spatial scales (Godfrey et al., 2015a).

Vulnerability curves, also referred to as damage curves, state-damage curves or functions, relate the expected damage of an individual element at risk with the hazard intensity. Usually, the flood depth is used as a measure of the intensity (i.e. relatively high damage percentages for a given inundation depth). Nevertheless, other hazard parameters such as velocity and duration are occasionally used (Jongman et al., 2012; Merz et al., 2010). The curves can be derived using empirical, expert judgment, analytical, and hybrid approaches (Godfrey et al., 2015a). Also, they can be expressed both in qualitative (e.g. high damage) or quantitative terms (e.g. Euros). They are defined for a specific type of asset and area. For this reason, a curve designed for one region is usually not applicable to other contexts. Figure 3 shows damage curves of different land use classes in the Netherlands, where it is possible to see that each element at risk has a different level of damage even though the hazard intensity is the same. Although vulnerability curves offer a great advantage in terms of quantitative estimation of the damages, they require a significant amount of input data and computation capabilities.

A somewhat simpler approach is given by the use of **vulnerability matrices**, which are based on the assumption that a given element at risk will display the same level of damage when submitted to a hazard with similar intensity (Godfrey et al., 2015a). The matrices are developed based on empirical data, statistical analysis or expert judgment. Buildings that have not been damaged by the event are given a lower vulnerability score and the ones that are totally damaged receive a higher value. This approach makes the relationship between hazard and impacts clear and easy to understand by non-experts. However, the method is subjective as the qualitative description of the damage levels may differ among experts. For this reason, transferability and comparison possibilities are limited (Papathoma-Köhle et al., 2017). Table 2 shows an example of a vulnerability matrix developed for different types of structures under varying flood intensities.

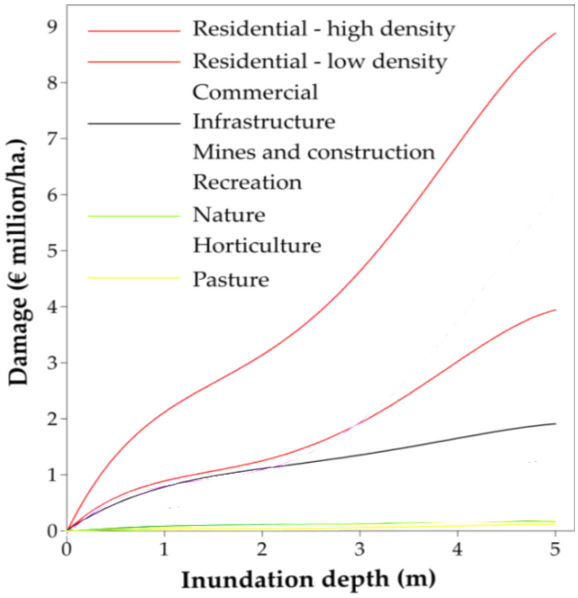

Figure 3. Vulnerability curves derived for different land use classes in the Netherlands (Redrawn from Ward et al., 2011)

A limitation of both vulnerability matrices and curves is that they are building type-specific and focus on the physical vulnerability of structures (Kappes et al., 2012). Although this captures the susceptibility of assets to a certain flood hazard, it neglects the social vulnerability of their inhabitants (Koks et al., 2015), assuming a homogeneous coping and adaptive capacity of the entire population. However, the capacity of households to cope, adapt and respond to hazards is equally important to assess the potential impacts of floods.

An alternative to overcome this problem is to use **vulnerability indicators**, which allow integrating several dimensions of vulnerability (e.g. physical, social, economic, and coping capacity) in an overarching framework. Indicator-based methods allow the aggregation of complex information into intuitively conceivable numbers, which are easy to understand (Ciurean et al., 2013). Furthermore, they are particularly useful in areas where limited or no information on past damage events exist (Godfrey et al., 2015a).

Table 2. Vulnerability matrix for different flood intensities. The values were determined based on experiences from comparable, past events. 0 denotes no vulnerability while 1 means total destruction (Bründl et al., 2009)

Type of structure	Vulnerability values		
	Weak flood	Middle flood	Strong flood
Residential buildings	0.02	0.20	0.30
Agricultural buildings	0.05	0.30	0.40
Restaurants	0.02	0.20	0.30
Roads	0.00	0.01	0.10
Railways	0.50	0.80	1.00

Since indicator-based approaches do not require detailed data as damage curves, they have been extensively deployed to assess the social vulnerability to floods (Fekete, 2009; Frigerio and de Amicis, 2016). Indicator-based methods are also popular in assessing the socioeconomic vulnerability (Kienberger et al., 2009), physical vulnerability (Godfrey et al., 2015a) as well as to combine multiple dimensions of vulnerability (Roy and Blaschke, 2015; Vojinovic et al., 2016) or conduct multi-hazard vulnerability analysis (Kappes et al., 2012).

Despite the popularity of vulnerability indicators, the major limitation of this approach is the subjectivity in weighting, aggregation, normalization, and selection of criteria (Beccari, 2016; Müller et al., 2011; Rufat et al., 2015). According to Birkmann (2006), it is difficult – and perhaps even impossible - to reduce the concept of vulnerability to a single equation. If the construction of the composite indicator is not transparent and/or lacks sound statistical or conceptual principles, it may be misused, e.g. to support a desired policy (OECD, 2008). Thus, explicitly showing the rationale for model decisions could benefit the development of vulnerability indices.

A brief description of the advantages and shortcomings of each one of the methods discussed in this section is presented in Table 3. No methodological approach may be considered better than the others. On the contrary, they may complement each other and, if possible, they should be used in combination to capture the full complexity and the various tangible and intangible aspects of vulnerability (Cardona et al., 2012; Papathoma-Köhle et al., 2017). Regardless of the method used it crucial to stress the existing shortcomings to avoid a reckless use of model outcomes. This is especially relevant an interdisciplinary field, where some scientists want to measure vulnerability with precision, while others believe in the impossibility of quantifying vulnerability (Fekete, 2012).

Table 3. Overview of existing methods for the assessment of vulnerability (Elaborated based on Papathoma-Köhle et al., 2017)

Method	Advantages	Shortcomings
Curves	• May translate a hazard into a monetary cost • May be used for the assessment of costs for future scenarios	• Data demanding • Cannot be transferred to areas with different housing types • Consider only the physical vulnerability
Matrices	• No need for ex-ante data or detailed information • Easy to understand • Clear relationship between hazard and impacts	• Results are normally not translated into monetary loss • Transferability and comparison possibilities are limited • Consider only the physical vulnerability
Indicators	• Allows considering multiple dimensions of vulnerability • Easy to understand • Summarize complex issues • Good basis for discussing risk reduction measures	• High subjectivity • Are subject to misuse and at disposal of politics • Results are not expressed in monetary terms making the method less attractive for practitioners • Usually provide a static description of vulnerability

2.3 Vulnerability indicators

In order to translate the abstract concept of vulnerability into a measurement, several composite indicators have been developed in the last decades. In general, they can be classified according to their unit of analysis, ranging from individual and household level to sub-national, national and global level. Table 4 presents an overview of existing methods according to the unit of analysis, the hazard type, and assessment methodologies. For a comprehensive outlook of existing vulnerability indicators, the reader is referred to the following papers (Balica, 2012; Beccari, 2016; Birkmann et al., 2012; Khazai et al., 2014; Prior et al., 2017; Schauser et al., 2010).

Well-known composite indicators that use the **country** as the smallest unit of analysis include the Disaster Risk Index (DRI) (UNDP, 2004), the World Risk Index (Garschagen et al., 2016; Welle and Birkmann, 2015), and the Prevalent Vulnerability Index (PVI) (Cardona and Carreño, 2011). The World Risk Index, which is recalculated annually, combines 28 indicators regarding exposure and vulnerability (susceptibility, coping and adaptive capacities) to compare risk values from 173 countries. The Risk Index of each country is reported as an overall value, as well as by their sub-indexes. Even though the indicators included in the index have different levels of importance, equal weighting is applied. Conversely, the PVI by the Inter-American Development Bank uses the AHP multi-criteria tool to calculate the weight of each one of its 24 indicators. The PVI depicts predominant vulnerability conditions across countries in Central and South America by measuring exposure, socioeconomic fragility and lack of social resilience. This index is calculated using available national data, allowing countries and regions to be ranked relative to each other (Parsons et al., 2016).

Another common measurement of vulnerability uses a **sub-national region** - a community - as the smallest unit of analysis. Sub-nation measurements usually take three forms: (1) using political boundaries (e.g. municipality, district); (2) distinguishing between urban and rural zones; (3) defining a geographic area with similar characteristics (UNDP, 2014). Among existing indicators, the Social Vulnerability Index (SoVI) is arguably the most well-established and widely-used methodology (Cutter et al., 2003; Oulahen et al., 2015). It is constructed using principal component analysis (PCA) to reduce the number of explanatory factors representing wealth, age, economic dependence, housing, race, ethnicity, and infrastructure characteristics. Other important indicators include the Flood Vulnerability Index (FVI) (Connor and Hiroki, 2005), the Social Susceptibility Index (SSI) (Fekete, 2010), the MOVE Framework (Birkmann et al., 2013), and the PEARL vulnerability framework (PeVI) (Sorg et al., 2018). Of these, both the SSI and the PeVI consider an equal weighting scheme. In contrast, the weights of criterion in the MOVE framework index are elicited based on expert judgments while the weights in the SoVI are derived through regression analysis.

The smallest unit of analysis is the **household or the individual** (UNDP, 2014). Examples of measurement frameworks that collect data on the household or individual are the Community-based Social Vulnerability Index (De Marchi and Scolobig, 2012) and the Evaluation Resilience Framework (DRLA and UEH, 2012). Both approaches are based on a mix of qualitative methods, such as household survey, key informant surveys and focus group discussions. However, neither of them quantifies measures of vulnerability spatially.

Table 4. Overview of existing composite-indicators for vulnerability assessment

Vulnerability indicator	Reference	Unit of analysis	Type of hazard	Methodology
Disaster Risk Index (DRI)	UNDP (2004)	Country	Earthquakes, tropical cyclones and floods	Mixed approach: statistical analysis using a multiple logarithmic regression model and expert opinion
World Risk Index	Garschagen et al. (2016)	Country	Multi-hazard	Mixed approach: factor analysis, questionnaires and expert opinion
Prevalent Vulnerability Index (PVI)	Cardona and Carreño (2011)	Country	Multi-hazard	Quantitative approach: AHP
Social Vulnerability Index (SoVI®)	Cutter et al. (2003)	Sub-national	Multi-hazard	Quantitative approach: principal component analysis
Flood Vulnerability Index (FVI)	Connor and Hiroki (2005)	Sub-national	Floods	Quantitative approach: multiple linear regression analysis
Social Susceptibility Index (SSI)	Fekete (2010)	Sub-national	Floods	Quantitative approach: factor analysis
PEARL vulnerability framework (PeVI)	Sorg et al. (2018)	Sub-national	Floods	Quantitative approach: equal weighting, based on the World Risk Index variables
MOVE Framework	Welle et al. (2014)	Sub-national	Heat waves, floods, and earthquakes	Mixed approach: expert workshops, stakeholder interviews
Community-based Social Vulnerability Index	De Marchi and Scolobig (2012)	Household or the individual	Floods	Qualitative approach: participant observation, key informants interview, household survey, focus groups
Evaluation Resilience Framework	DRLA and UEH (2012)	Household or the individual	Multi-hazard	Qualitative approach: workshops, focus groups, key informants interview, household survey

CHAPTER 3

Multi-criteria decision-making (MCDM)

Due to the fuzzy and multi-dimensional nature of vulnerability, the creation of flood vulnerability indicators is often assisted by MCDM tools, which can consider several criteria and different stakeholder's perspectives. This chapter explores the application of MCDM to flood-related problems. First, the main steps of the spatial MCDM process and some aspects of participatory decision-making are described. Then, the first paper of this Ph.D. thesis is provided (de Brito and Evers 2016). It consists of a systematic literature review of MCDM applications to flood risk management, seeking to highlight trends and research gaps.

3.1 An overview of MCDM

Multiple-criteria decision-making (MCDM), also termed multi-criteria evaluation (MCE), multi-criteria analysis (MCA), or multiple-criteria decision-analysis (MDCA) is a family of tools that aid individuals in formally structuring multi-faceted problems. The aim of MCDM is not to find a final and "best" solution, but to deliver a set of alternatives to better inform decision makers (Roy, 1985). MCDM is suitable for addressing complex problems featuring high uncertainty, multiple criteria, conflicting objectives, different forms of data, and the accounting for different interests and perspectives (Mateo, 2012b).

One of the main advantages of MCDM is that it allows integrating the interests and objectives of multiple stakeholders since the preferences from every actor can be taken into account in form of criteria weights (Tsoutsos et al., 2009). Furthermore, MCDM can improve the transparency and analytic rigor when solving ill-structured problems since the choices of input criteria, data standardization, criteria weighting, and aggregation are explicitly expressed, leading to justifiable decisions and reproducible results.

Nevertheless, as with any other method, MCDM tools also convey a number of shortcomings that are mostly related to their subjectivity, in particular in the choice of criteria on which to base the decision and the relative weights of importance given to those criteria (Tsoutsos et al., 2009). In this regard, Belton and Stewart (2002) points out that subjectivity is inherent in decision-making. MCDM does not dispel that subjectivity; it simply seeks to make the need for subjective judgments explicit and the process by which they are taken into account transparent.

3.2 Phases of the spatial MCDM process

MCDM tools are often combined with geographic information systems (GIS) to analyze spatial problems such as flood vulnerability, susceptibility and risk assessment (e.g. Roy and Blaschke, 2015b; Stefanidis and Stathis, 2013). GIS-based MCDM transforms and combines several criteria represented in form of input maps and the individuals' preferences into a decision map according to a specified aggregation rule (Malczewski and Rinner, 2015).

Figure 4 illustrates the key steps of spatial MCDM. During the **initial phase** the problem is defined and structured into several components that include: (1) a goal; (2) a group of stakeholders and their preferences with respect to the importance of the evaluation criteria; (3) a set of evaluation criteria which is preferentially independent, complete, concise, and operationally meaningful; (4) a set of alternatives which are represented in GIS-MCDM by raster cells or polygons that correspond to a geographic entity (e.g. town or region); and (5) an appreciation of the uncertainties that are critical to the problem at hand (Belton and Stewart, 2010; Malczewski, 1999). This is considered to be the most important phase of the MCDM process as improved decision structuring increases the quality of the results (Corner et al., 2001).

The **second phase** of the MCDM process comprises criteria standardization, weighting, and combination, which are the building blocks of spatial MCDM (Malczewski and Rinner, 2015). Before being integrated into a GIS environment the criteria need to be rescaled to common dimensionless scale as they are represented by different measurement units (e.g. meters, density/km^2). For this purpose, standardization or normalization methods are used. Also, in this phase, decision makers' judgments about the criteria importance are elicited. Dozens of MCDM techniques exist to weight criteria in GIScience context.

Malczewski and Rinner (2015) provide a review of the most common methods (e.g. AHP, ANP, CAR, SMART). The final step is the combination of the individual criteria maps into one map. The ways in which the individual criteria are aggregated in GIS depend on the MCDM method used, but the most common approaches are the weighted linear combination and ordered weighted average (Malczewski and Rinner, 2005).

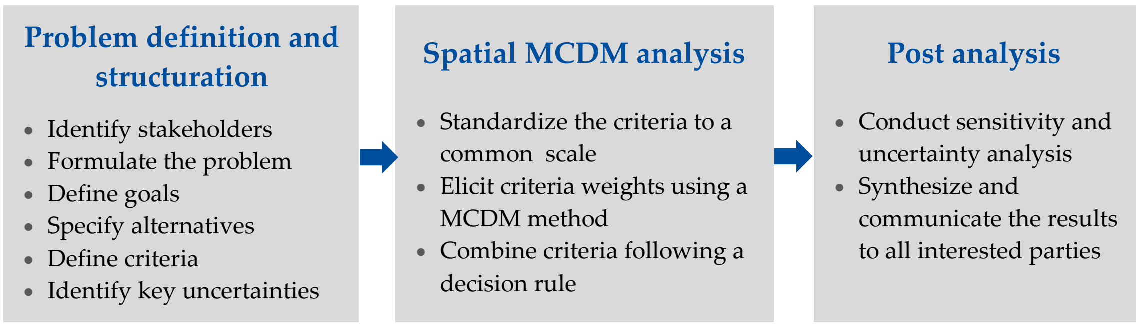

Figure 4. Phases of the GIS-based MCDM process (Adapted from Belton and Stewart, 2010)

The **final phase** consists of a post analysis study to check for model inaccuracies. Uncertainty analysis (UA) investigates how uncertainty in model inputs translates into uncertainty in model outputs (Tate, 2012). Similarly, sensitivity analysis (SA) investigates how the results vary when the criteria are changed. This helps to identify crucial variables in the model and allows disagreements between individuals to be examined to see if they make a difference in the final results. At the end of the process, the outcomes of the MCDM analysis should be made available to all interested parties through reports and other channels of communication.

Although the MCDM phases are presented here as a logical sequence of steps Lawrence et al. (2001) emphasizes that, in reality, the decision-making process may be far from sequential and continuous. In practice, the whole process is iterative, possibly having internal conflicts that require an on-going review of the problem structure to ensure an agreed set of goals. It is, therefore, necessary to adjust the decision model as the process evolves.

3.3 Participatory MCDM

Several authors state that decisions made collectively tend to be more effective and sustainable than decisions made by an individual decision maker (Jankowski, 2009; Oulahen et al., 2015; Simão et al., 2009). Indeed, people are much more likely to accept and implement a decision if they feel that their opinion was fairly considered (Hyde, 2006).

Among the benefits of participation, Evers (2012) highlights that it: (1) increases the transparency of decision-making; (2) empowers the participants as they can express their interests and influence the decisions; (3) facilitates social learning since the parties involved can learn from each other through constructive dialogues; (4) supports a common discourse, providing a basis for long-term perspectives; (5) results in more effective implementation and monitoring of the adopted solutions; (6) increases public awareness and acceptance, legitimizing the decisions taken; and (7) allows considering different kinds of knowledge from both experts and non-experts.

Thus, it is suggested that MCDM should be applied in a participatory and collaborative setting, where a group of individuals with different backgrounds can be brought together to explore, understand, and solve the problem at hand (Jelokhani-Niaraki, 2013; Paneque Salgado et al., 2009). Participatory MCDM provides a flexible platform for structuring a decision problem and organizing communication in a group setting. Furthermore, the integration of participatory methods and MCDM tools may facilitate the achievement of consensus, which is essential for finding solutions that reconcile conflicting interests and can be accepted by the majority (de Brito and Evers, 2016; Malczewski, 2006; Simão et al., 2009).

However, it must be recognized that simply conducting participatory activities will not automatically achieve these benefits. Participation also has the ability to create several problems if implemented poorly. As Mostert (2003) notes, participation can be constrained as decision makers are often unwilling to listen to some stakeholders, resulting in disappointment and reduced acceptance. Similarly, if mediation activities are not handled properly, conflicts can exacerbate. In addition, participatory modeling can be resource intensive, which can mean that cheaper, less-participatory methods are often implemented instead (Warren, 2016).

Despite the advantages of integrating participatory methods and MCDM tools, several reviews show that MCDM is commonly applied by an individual expert (Estévez and Gelcich, 2015; Malczewski, 2006; Mendoza and Martins, 2006; Mosadeghi et al., 2013). For instance, a review of 341 papers that use GIS-MCDM revealed that in 79.47% of the studies the MCDM model was constructed by a single modeler (Malczewski, 2006). Likewise, results of a systematic literature review made by Estévez and Gelcich (2015) showed that participation in MCDM has been generally fragmented. The authors found out that participation occurred only on particular steps of the MCDM process such as the definition of criteria and elicitation of weights. Conversely, other important stages such as standardizing the data, estimating consequences and prioritizing management alternatives, exhibited low levels of participation. However, meaningful collaboration requires direct involvement of the interested parties in all phases of the decision process (Marttunen et al., 2013).

As shown in Table 5, the use of MCDM tools works best when participants are engaged in as many steps and as early as possible. Early participation improves the value of the results in terms of its usefulness to decision makers, its educational potential for the public, and its credibility (Voinov and Bousquet, 2010). Nevertheless, this is not always possible since intensive participation usually requires more resources and time (Marttunen et al., 2013). Thus, trade-offs have to be made between the available resources and the quality and effectiveness of the expected outcomes.

Table 5. Levels of integration and participation in MCDM (Marttunen et al., 2013)

Level	Integration of MCDM results in planning and decision-making	Stakeholders participation
Low	MCDM is realized as a separate process. It is unclear how its results are used	MCDM is realized by experts. Stakeholders do not know what is happening
Moderate	MCDM has some links/impacts on planning or decision-making	Stakeholders are consulted (one way flow of information), but their participation is limited to certain steps. Weight elicitation is realized without personal support using e.g., questionnaires
High	MCDM brings structure to the planning. The phases of planning and MCDM are well synchronized	Stakeholders collaborate in some phases of the process (two way flow of information). There are personal interaction e.g., group discussion, in weight elicitation and results analysis
Very high	MCDM provides a roadmap for planning or decision-making. MCDM's principles and practices are largely used when structuring the decision problem	Stakeholders are actively involved in different phases and feel a sense of ownership. There are face-to-face personal interviews and group discussions

In order to investigate how multiple stakeholders were considered when solving flood risk management problems in a MCDM context, a systematic literature review was conducted (de Brito and Evers, 2016). The methods used and main results found are provided in Section 3.4.

3.4 Multi-criteria decision-making for flood risk management: a survey of the current state of the art (Paper 1)

This paper was originally published as: de Brito, M.M.; Evers, M. (2016) Multi-criteria decision-making for flood risk management: a survey of the current state-of-the-art. Natural Hazards and Earth System Sciences, 16, 1019-1033, doi:10.5194/nhess-16-1019-2016.

3.4.1 Abstract

This paper provides a review of Multi-Criteria Decision-Making (MCDM) applications to flood risk management, seeking to highlight trends and identify research gaps. A total of 128 peer-reviewed papers published from 1995 to June 2015 were systematically analysed. Results showed that the number of flood MCDM publications has exponentially grown during this period, with over 82% of all papers published since 2009. A wide range of applications were identified, with most papers focusing on ranking alternatives for flood mitigation, followed by risk, hazard and vulnerability assessment. The Analytic Hierarchy Process (AHP) was the most popular method, followed by Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), and Simple Additive Weighting (SAW). Although there is greater interest in MCDM, uncertainty analysis remains an issue and was seldom applied in flood-related studies. In addition, participation of multiple stakeholders has been generally fragmented, focusing on particular stages of the decision-making process, especially on the definition of criteria weights. Therefore, addressing the uncertainties around stakeholders' judgments and endorsing an active participation in all steps of the decision-making process should be explored in future applications. This could

help to increase the quality of decisions and the implementation of chosen measures.

3.4.2 Introduction

Floods can be regarded as one of the most costly natural hazard both in developing and developed countries all over the world (Balica et al., 2013; Uddin et al., 2013). According to the Emergency Events Database (EM-DAT), these processes were the most frequent natural disaster worldwide between 2000 and 2014, causing at least 85,000 fatalities and affecting about 1.4 billion people. Apart from the loss of lives and physical damage, floods have resulted in approximately US$ 400 billion in damage since 2000 (CRED and OFDA, 2015).

In order to mitigate these impacts, a set of flood reduction measures need to be taken. The decision-making process related to flood risk management, especially in the prevention and emergency phases, tends to be rather complex and uncertain (Akter and Simonovic, 2005; Kenyon, 2007). Part of this complexity arises from the involvement of multiple stakeholders, each one with different views, background knowledge, interests, and frequently with competing objectives (Evers, 2008). In addition, the exact flood magnitude and damage are generally unknown and surrounded by considerable uncertainties (de Kort and Booij, 2007). As a consequence, making these decisions can rarely be solved with intuition alone. Thus, flood risk management requires the use of decision support tools, which can consider multiple stakeholders' views, objectives, trade-offs, feasible alternatives and evaluation criteria.

Flood risk management can benefit from the use of multi-criteria decision-making (MCDM) tools. MCDM is an umbrella term used to describe a set of methods for structuring and evaluating alternatives on the basis of multiple criteria and objectives (Voogd, 1983). These methods provide targeted decisions, as they can handle the inherent complexity and uncertainty of such problems as well as the knowledge arising from the participation of several actors (Yan et al., 2011; Zagonari and Rossi, 2013).

MCDM can enhance the quality of decisions, by making the process more explicit, rational and efficient, leading to justifiable and explainable choices (Mateo, 2012a). Furthermore, MCDM promotes the role of participants in the decision process, facilitates compromise and group decisions, and provides an adequate platform for stakeholders to communicate their personal preferences

(Pohekar and Ramachandran, 2004). The combination of these characteristics enables the development of real participatory processes, which are crucial for the implementation of successful and long-lasting flood management programs (Affeletranger, 2001).

Therefore, MCDM provides a powerful tool for flood management and has received a great deal of attention in solving such problems, not only from researchers but also decision makers and practitioners outside the scientific community. Since the mid-90s, MCDM has been successfully applied to select the best strategies for flood risk mitigation, helping to optimize the allocation of available resources (e.g. Tkach and Simonovic, 1997; Ghanbarpour et al., 2013; Malekian and Azarnivand, 2015). In recent years, MCDM has also been used to access the flood risk and coping capacity (e.g. Guo et al., 2014; Roy and Blaschke, 2015; Yang et al., 2013).

Several authors have reviewed MCDM techniques in various fields of study. For example, Stewart (1992) conducted a theoretical review by identifying potential advantages and pitfalls in the usage of various MCDM methods. Hajkowicz and Collins (2007) analysed over 134 papers in the field of water resource planning and management, focusing on problems such as water policy evaluation, strategic planning, and infrastructure selection. More recently, Estévez and Gelcich (2015) presented a concise literature survey, exploring the challenges behind participatory MCDM in marine conservation. However, despite practical experiences and methodological advances, there is no comprehensive literature review that explores the use of MCDM for flood risk management.

Hence, we believe that there is a need for a systematic survey to consolidate and synthesize recent research conducted in this area. Therefore, this paper aims to provide a literature review of the state-of-the-art regarding the application of MCDM as a decision support tool for flood risk management, seeking to assess emerging trends and identify issues for future investigation. In addition, it attempts to provide a better understanding of the current status of how participatory MCDM is being conducted and the way uncertainties are considered in the decision-making process. With this review, we attempt to answer the following questions:

1. Which flood risk management problem has used MCDM approaches further?
2. Where was the research undertaken?

3. Which MCDM method was most commonly applied?
4. Were multiple stakeholders explicitly included in the decision-making process?
5. To which extent did these studies apply uncertainty and sensitivity analysis?

For reader's convenience, the remainder of this paper is structured as follows. In Sect. 2, the basic features of the MCDM methods are briefly described. Section 3 outlines the search strategy and the procedure used to classify the literature. Section 4 covers the discussion of the outcomes and provides answers to the research questions. In Sect. 5, limitations of this study and recommendations for further research are provided. Finally, Sect. 6 presents concluding remarks. We hope that this review will serve as a useful and ready source of information for scholars and practitioners working with MCDM and flood risk management.

3.4.3 Overview of multi-criteria decision-making methods

MCDM is a broad term used to describe a set of methods that can be applied to support the decision-making process by taking into account multiple and often conflicting criteria through a structured framework (Cinelli et al., 2014). Since the 1960s, dozens of MCDM techniques have been developed (Mendoza and Martins 2006). Generally, they can be classified into the following groups (Hajkowicz and Collins, 2007):

1. Multi-attribute utility and value functions: the goal of these methods is to define an expression for the decision maker's preferences through the use of utility/value functions. Based on this, all criteria are transformed into a common dimensionless scale (Linkov et al., 2004). Popular methods include MAUT (multi-attribute utility theory) and MAVT (multi-attribute value theory), which have a compensatory nature. This implies that the poor performance of one criterion (e.g. high loss of lives) can be compensated by the better performance of another (e.g. financial cost). Although MAUT and MAVT have well-established theoretical foundations, the preference elicitation can be cognitively challenging and time-consuming (Schuwirth et al., 2012);

2. Pairwise comparisons: this approach involves comparing pairs of criteria by asking how much more important one is than the other according to a predefined scale. Pairwise comparisons are particularly useful when it is not possible to define utility functions, otherwise MAUT is

recommended (Ishizaka and Nemery, 2013). Common techniques include AHP (analytic hierarchy process), ANP (analytic network process) and MACBETH (measuring attractiveness by a categorical based evaluation technique). Due to its simplicity and flexibility, AHP is the most applied MCDM tool. Nevertheless, AHP has a limitation when dealing with interdependence among the criteria as it assumes that they are independent (Li et al., 2011). In addition, only a limited number of alternatives can be considered at the same time;

3. Outranking approaches: unlike MAUT, MAVT and AHP, outranking methods are based on the principle that one alternative may have a degree of dominance over another (Kangas et al., 2001), rather than assuming that a single optimal solution exists. Common methods include ELECTRE (elimination et choix traduisant la realité), PROMETHEE (Preference ranking organization method for enrichment of evaluations) and ORESTE (organization, rangement et synthese de donnes relationnelles). An advantage of outranking approaches is that they avoid compensation between criteria and any normalization process, which alters the original data (Ishizaka and Nemery, 2013). Therefore, they are appropriate when criteria metrics are not easily aggregated, measurement scales vary over wide ranges, and units are incommensurate or incomparable (Linkov et al., 2004);

4. Distance to ideal point methods: the alternatives are evaluated and ordered based on their distance from the ideal point, which represents a hypothetical alternative that best suits the decision makers' goals. Hence, the alternative that is closest to the ideal point is the best solution (Malczewski, 1999). Well-known methods include TOPSIS (technique for order preference by similarity to an ideal solution), CP (compromise programming) and VIKOR (vlsekriterijumska optimizacija i kompromisno resenje). The main characteristic and advantage of this family of approaches is the ability to consider a non-limited number of alternatives and criteria;

5. Other methods: there are a large number of miscellaneous techniques that cannot be placed under any of the described categories. These include, for example, tailored methods which usually extend or adapt a fundamental method to a particular application, as well as fuzzy and hybrid approaches.

Despite the large number of MCDM methods, none is perfect and applicable to all decision problems. Therefore, the selection of an appropriate tool will depend on the problem type and decision makers' objectives. Guidelines such as the one proposed by Guitouni and Martel (1998) can be followed to choose from available MCDM techniques. Table 6 provides an outline of the fundamental properties of the MCDM methods that have been cited throughout the paper. A comprehensive and detailed description of the theoretical foundations of these techniques alongside with their main strengths and weaknesses can be found in Triantaphyllou (2000), Tzeng and Huang (2011) and Ishizaka and Nemery (2013).

3.4.4 Framework for systematic literature review

3.4.4.1 Search strategy

A comprehensive literature review was undertaken, aiming to identify peer-reviewed papers that apply MCDM to flood-related problems. With this scope in mind, the systematic quantitative approach outlined in Pickering and Byrne (2014) was used since this method is explicit, reproducible and has fewer biases when compared to traditional narrative reviews. To ensure that potentially relevant papers were not missed, six databases were systematically searched, including Scopus, ProQuest, Science Direct, SpringerLink, Emerald Insight, and Web of Science. Publications such as doctoral dissertations, book chapters, reports, and conference proceedings were not considered. Furthermore, only papers written in English were included. To find eligible papers in the mentioned databases, Boolean functions were applied to combine the following keywords:

> Keywords (Multi-criteria OR MCDM OR multi-criteria decision-making OR MCDA OR MCA OR AHP OR analytic hierarchy process OR ANP OR analytic network process OR MAUT OR multi-attribute utility theory OR MAVT OR multi-attribute value theory OR ELECTRE OR TOPSIS OR MACBETH OR PROMETHEE OR NAIADE OR VIKOR OR weighted sum method OR simple additive weighting OR DSRA OR ORESTE OR DEMATEL OR goal programming) AND (flood OR floods)

Table 6. Description of the MCDM methods cited in the reviewed papers

Abbr.	Method	Description	Reference
AHP	Analytic hierarchy process	Structured technique for analysing MCDM problems according to a pairwise comparison scale, where the criteria are compared to each other	Vaidya and Kumar (2006)
ANP	Analytic network process	Generalization of the AHP method which enables the existence of interdependences among criteria	Saaty (2004)
CP	Compromise programming	Method based on the use of different distance measures to select the most suitable solution	Ballestero and Bernabeu (2015)
ELEC-TRE	Elimination et choix traduisant la realité	Group of techniques addressed to outrank a set of alternatives by determining their concordance and discordance indexes	Figueira et al. (2013)
MAUT	Multi-attribute utility theory	Method in which decisions are made by comparing the utility values of a series of attributes in terms of risk and uncertainty	Wallenius et al. (2008)
MAVT	Multi-attribute value theory	Simplification of MAUT that does not seek to model the decision makers' attitude to risk	Belton (1999)
PROME-THEE	Preference ranking organization method for enrichment of evaluations	Family of outranking methods based on positive and negative preference flows for each alternative that is used to rank them according to defined weights	Behzadian et al. (2010)
TOPSIS	Technique for order preference by similarity to an ideal solution	Technique based on the concept that the best alternative is the one which is closest to its ideal solution and farthest from the negative ideal solution	Behzadian et al. (2012)
VIKOR	Vlsekriterijumska optimizacija i kompromisno resenje	Method that uses aggregating functions and focuses on determining compromising solutions for a prioritization problem with conflicting criteria	Mateo (2012b)
SAW*	Simple Additive Weighting	Tool that aims to determine a weighted score for the alternatives by adding each attribute multiplied by their weights	Abdullah and Adawiyah (2014)

* Other terms such as weighted linear combination (WLC), weighted summation, weighted linear average, and weighted overlay are also used to describe SAW

Distinct combinations of these terms were used, taking into consideration the syntax requirements of each search engine. When possible, only the abstract, title, and keywords were searched. This narrowed the search space substantially and enabled to exclude papers that mention the keywords only in the references or literature review sections.

These queries elicited over 1,350 references published between September 1989 and June 2015. In order to have a two decades review, which is considered to be long enough to arrive at consistent conclusions (Jato-Espino et al., 2014), 1995 was chosen as a starting date for this survey. At first, the title, abstract, and keywords were screened manually to exclude irrelevant references. After this preselection, the full-text of 207 selected papers was revised in detail. Of this total, 74 papers were found to be beyond the scope of the inquiry and five were not available through the library system. In the end, 128 papers met all inclusion criteria and were included in the analysis.

The review covers articles published in 72 different journals, in several areas of knowledge, suggesting that a diversity of publishers share an interest in flood risk management. Journals with the most papers were Natural Hazards, followed by Natural Hazards and Earth System Sciences, Water Resources Management, and Stochastic Environmental Research and Risk Assessment, with 16, 11, 10, and 6 articles, respectively. The remaining journals account mainly for one or two papers each.

3.4.4.2 Classification scheme

Following the selection, all included papers were classified according to some key domains: publication year; area of application; country of application; MCDM method; whether or not it was carried out in a participatory process; participatory techniques applied; and if uncertainty and sensitivity analysis were performed. With regard to the MCDM method, only techniques that were used thrice or more have their own category, whilst the rest were grouped in “others”. In terms of research area, the papers were classified based on the overall emphasis of the application discussed. A total of eight types of MCDM applications were identified as follows.

1. Ranking of alternatives for flood mitigation: comprises the selection of the best combination of structural and/or non-structural mitigation solutions from a set of potential alternatives to reduce flood impacts and magnitude;

2. Reservoir flood control: consists in selecting operational options among a range of alternatives to ensure safe operation of reservoirs during high inflow events, aiming to reduce the floods intensity to acceptable levels;
3. Susceptibility assessment: expresses the likelihood that a flood will occur in an area on the basis of local terrain conditions (e.g. slope, elevation, lithology). It does not consider the flood temporal probability or return period (i.e. when or how frequently floods may occur) (Santangelo et al., 2011);
4. Hazard assessment: comprehends a qualitative or quantitative assessment of the spatial and temporal probability of the occurrence of potentially damaging floods of a certain magnitude in a given area within a specific period of time (Dang et al., 2011);
5. Coping capacity assessment: comprises the evaluation of the ability of people, organizations and systems, using available skills and resources, to face and manage adverse conditions and emergencies resulting from floods (UNISDR, 2009);
6. Vulnerability assessment: refers to articles that assess the propensity of exposed elements such as human beings, their livelihoods, and assets to suffer adverse effects when impacted by floods (UNISDR, 2009);
7. Risk assessment: consists in analysing potential flood hazards combined with existing conditions of vulnerability that together could potentially harm exposed people, property, services, livelihoods and the environment (UNISDR, 2009);
8. Emergency management: the papers in this class are concerned with the organization and management of resources and responsibilities for addressing all aspects of emergencies, in particular, preparedness and response steps (UNISDR, 2009).

3.4.5 Results and discussion

This section presents a systematic analysis of 128 peer-reviewed papers published between 1995 and June 2015. To help readers extract quick and meaningful information, the results are summarized in various charts and tables. A complete list of the reviewed papers, including their classification scheme, is provided in the Supplementary Table S1.

3.4.5.1 Trends by year of publication

In an attempt to model the evolution of MCDM in time, the data gathered were organized by year of publication. As can be seen from Figure 5, there has been a continuing growth in the number of flood MCDM studies from 1995 to June 2015. In fact, over 82% of the compiled papers have been published since 2009. Until 2004, the number of publications was equal to or less than one per year. Surprisingly, from 2010 to 2013, the use of MCDM dramatically increased, from 5 to 22 papers. Accordingly, it can be estimated that in the coming years, these numbers will keep growing. This indicates that MCDM has a good vitality and acceptance for flood risk management.

A reason for the increasing number of publications could be a reflection of a growing awareness of natural disaster prevention and reduction policies. Secondly, the availability of easy-to-use and inexpensive MCDM software packages may also be an influencing factor. Alternatively, this increase may just match a general rise in published papers related to floods as a whole.

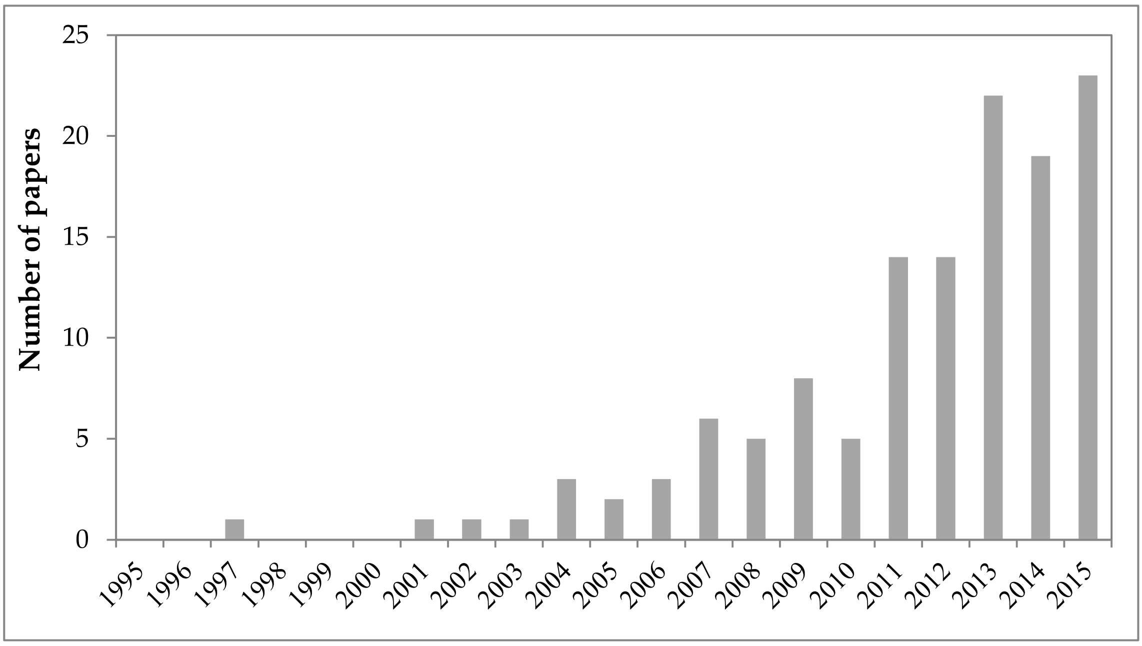

Figure 5. Number of MCDM flood papers published between 1995 and June 2015

To correctly measure the interest in MCDM for flood risk management, an increase of MCDM papers in relative terms needs to be calculated. Thus, a normalization was made according to the number of flood publications in the Web of Science and Science Direct databases, found through searches using only "flood" as keyword. Figure 6 shows that the increase of flood MCDM publications is significantly greater than the increase of flood publications, especially after 2011. This confirms the hypothesis that the use of MCDM to solve flood-related problems has been growing considerably since 1995.

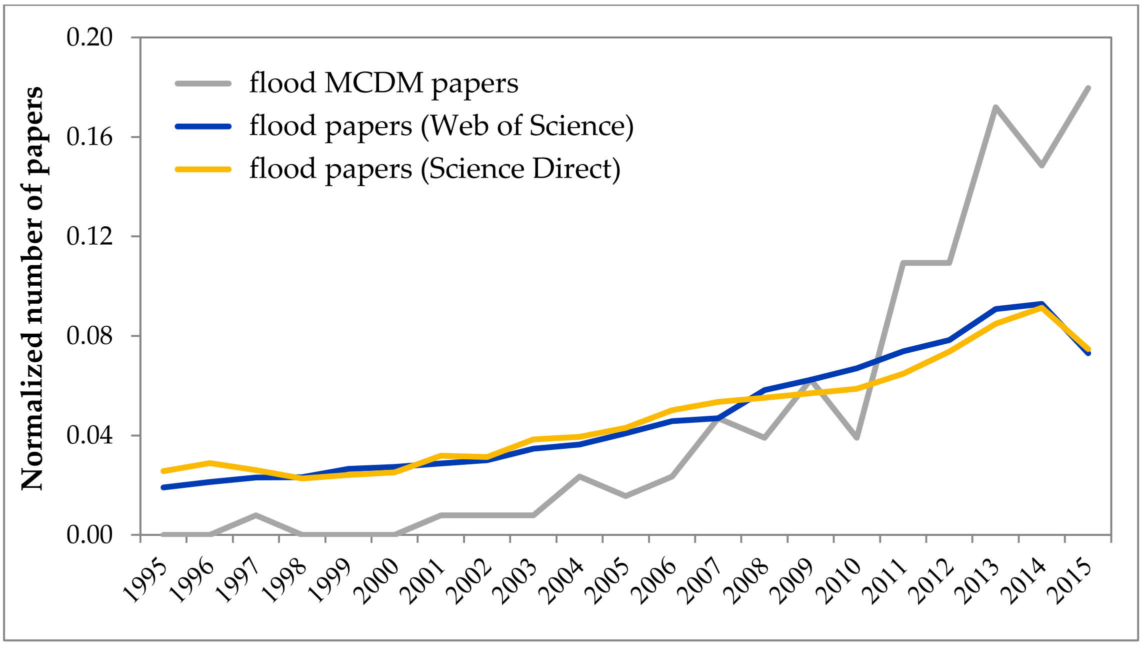

Figure 6. Normalized number of MCDM and flood papers published between 1995 - June 2015, based on data from the Web of Science and Science Direct

3.4.5.2 Trends by area of application

During the last two decades, ranking alternatives for flood mitigation was the most widespread flood management topic, with more than 22% of all applications (Table 7). These studies focus mainly on selecting traditional engineering measures to reduce flood risk (e.g. Azibi and Vanderpooten, 2003; Tkach and Simonovic, 1997). Nevertheless, in recent years, they emphasize not only the so-called structural measures, which are still relevant, but also incorporate a wide range of non-structural options such as the development of evacuation plans, enforcement of building codes and insurance schemes.

The second most common theme was risk assessment (21.11%), followed by vulnerability and hazard analysis, both with 15.00% of all applications. In this regard, it is worth noting that several papers evaluate the vulnerability, hazard and risk simultaneously (e.g. Lee and Chung, 2007; Zou et al., 2013; Wu et al., 2015). Few papers used MCDM as a decision support tool in reservoir flood control and emergency management problems. This is probably because managing emergencies, both in rivers and reservoirs, is a complex task, requiring effective coordination and communication among teams involved as well as reliable information regarding the current situation of emergency (Shan et al., 2012).

Table 7. Distribution of applications by flood risk management topic

Area of application	N	%
Ranking of alternatives for flood mitigation	41	22.78
Risk assessment	38	21.11
Vulnerability assessment	27	15.00
Hazard assessment	27	15.00
Susceptibility assessment	21	11.67
Coping capacity	11	6.11
Reservoir flood control	8	4.44
Emergency management	7	3.89
Total	**180**	**100**

In order to have a complete overview of works published through time, Figure 7 presents a temporal breakdown of the different flood topics. As can be seen, flood risk management has recently shifted its main focus from ranking alternatives for flood mitigation towards a risk-based perspective, which includes the assessment of risk and its components. This finding is in agreement with a worldwide trend, where disaster prevention is emphasized over assistance or relief, and evaluating the risk becomes a key element (World Bank, 2006).

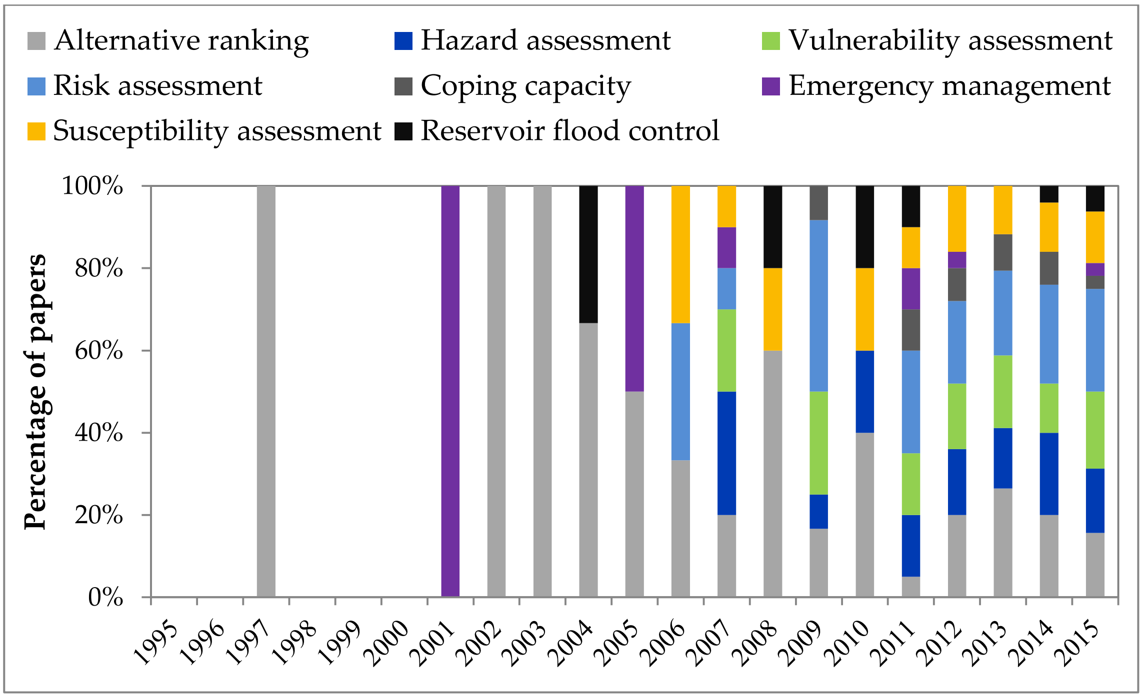

Figure 7. Distribution of MCDM papers by application area between 1995 - June 2015

Another interesting result is that coping capacity studies are quite new in comparison to other topics, with the first paper published in 2009. In addition, the graph reveals that since 2010, the trend in the other flood problems has remained fairly stable. This diversity of applications shows MCDM flexibility to support decision-making in all stages of the flood management cycle.

3.4.5.3 Trends by country of application

A total of 37 countries on all populated continents have contributed to this survey (Table 8), showing that the spread of MCDM is truly global. China accounts for 19.40% of all applications, which is not too surprising. Indeed, similar results were obtained by other MCDM review papers (e.g. Jato-Espino et al., 2014). In contrast to previous surveys (e.g. Govindan and Jepsen, 2015), Germany and South Korea were found to be prolific users of MCDM tools.

Surprisingly, South American countries such as Brazil, Colombia, and Venezuela, which are severely affected by floods (CRED and OFDA, 2015), were not represented in the literature. The limited use of MCDM in these countries could be explained by restrictions, such as lack of expertise, resources and technology. On the other hand, it could be that the existing studies are published in non-English journals (e.g. Drozino et al., 2015; Magalhães et al., 2011). Unlike other MCDM review papers (e.g. Behzadian et al., 2010; Mosadeghi et al., 2013), MCDM tolos were rarely applied to solve flood-related problems in Australia. The reason could be that potentially relevant studies are published in conference papers, government reports, non-indexed journals or in other grey literature.

Half of the MCDM studies were conducted in Asia, followed by Europe (35.07%), North America (8.21%), Africa (3.73%) and finally by Australia and South America, each with 1.49% of all applications. Therefore, it is clear that when we analyse the findings of the present study, we are providing a predominantly Asiatic and European view of flood risk management.

Furthermore, only three papers report cross-country investigations (e.g. Ceccato et al., 2011; Evers et al., 2012; Almoradie et al., 2015). For example, Ceccato et al. (2011) analysed five case studies in Austria, Germany, India, Bhutan, and China. The authors found out that although the studied watersheds were characterized by distinct ecological, social and economic dimensions, the criteria selected by the stakeholders were rather similar. In this regard, multiple-case studies allow findings to be compared, parallels to be drawn, and differences across diverse cultural, environmental and governmental contexts to be examined.

Table 8. Distribution of applications by country of application

Country	N	%	Country	N	%
China	26	19.40	Netherlands	2	1.49
Germany	13	9.70	Finland	2	1.49
South Korea	10	7.46	Italy	2	1.49
Iran	7	5.22	Kenya	1	0.75
Greece	6	4.48	Kuwait	1	0.75
India	6	4.48	Vietnam	1	0.75
Canada	6	4.48	Taiwan	1	0.75
Malaysia	5	3.73	Bhutan	1	0.75
Bangladesh	5	3.73	Switzerland	1	0.75
USA	5	3.73	South Africa	1	0.75
UK	5	3.73	Poland	1	0.75
France	4	2.99	Spain	1	0.75
Slovakia	3	2.24	Portugal	1	0.75
Egypt	2	1.49	Serbia	1	0.75
Turkey	2	1.49	Nigeria	1	0.75
Japan	2	1.49	Chile	1	0.75
Australia	2	1.49	Argentina	1	0.75
Croatia	2	1.49	Romania	1	0.75
Austria	2	1.49	**Total**	**134**	**100.00**

3.4.5.4 Trends by MCDM method

Results showed that AHP and its family of methods were by far the most used MCDM approach (Table 9). One reason for this might be that its structure is straightforward, flexible and easily understandable (Cinelli et al., 2014). Thanks to these characteristics, it can be adapted to different problems without requiring previous knowledge from the analyst. Moreover, several software packages incorporate AHP (e.g. DECERNS, ExpertChoice, MakeItRational, EasyMind and Super decisions), including GIS (Geographic Information System) software (e.g. ArcGIS, Idrisi, and ILWIS). The second most employed method was TOPSIS, closely followed by SAW. These results, with a few differences and similarities, were confirmed by other MCDM review papers such as Jato-Espino et al. (2014) and Broekhuizen et al. (2015) that ranked AHP as the first and TOPSIS as the second method with more applications.

Table 9. Distribution of applications by MCDM method

MCDM method	N	%
AHP, fuzzy AHP, trapezoidal fuzzy AHP and ANP	70	42.42
TOPSIS, fuzzy TOPSIS and modified TOPSIS	22	13.33
SAW	21	12.73
Others (MACBETH, NAIADE, goal programming, etc.)	20	12.12
CP, spatial CP and fuzzy CP	10	6.06
ELECTRE I, II, III and TRI	7	4.24
MAUT and MAVT	7	4.24
PROMETHEE I and II	5	3.03
VIKOR and fuzzy VIKOR	3	1.82
Total	**165**	**100**

Note that the sum of the applications (165 items) in Table 9 does not match the number of papers (128 items) since some articles used several MCDM techniques to analyse differences in scoring and ranking. For example, Chitsaz and Banihabib (2015) compared seven MCDM tools and concluded that ELECTRE III stood superior to select flood management options. On the other hand, Chung and Lee (2009) employed five methods and found out that there is no clear methodological advantage to any of the considered techniques. Apart from comparative studies, several researchers have combined two MCDM approaches to complement each other (e.g. Margeta and Knezic, 2002; Lee and Chung, 2007; Zhou et al., 2014). For instance, Zhou et al. (2014) applied AHP to assign relative weights to each criterion and TOPSIS to rank the risk. Overall, 106 out of 128 papers (82.81%) used one MCDM method while 12.50% used two, 3.13% used three and 1.56% applied more than three.

The survey also showed that MCDM techniques are not used only in a stand-alone mode, but are commonly extended and combined with soft computing technologies, including fuzzy set theory (e.g. Chen and Hou, 2004; Guo et al., 2014), artificial neural network (e.g. Radmehr and Araghinejad, 2014; Liu et al., 2014), and tools such as SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis (e.g. Vafaei and Harati, 2010; Miyamoto et al., 2014). Furthermore, there are also numerous hybrid methods, developed to address gaps in classical techniques (e.g. Yang et al., 2013; Shams et al., 2014). This suggests that MCDM is versatile, enabling researchers to combine it effectively with different tools according to the requirements of the decision to be taken.

Overall, AHP is the most prominent MCDM method in all application areas, except for reservoir flood control (Table 10). The primary reason for the popularity of AHP for mapping the risk and its components is that the implementation of this technique within the GIS environment is straightforward, enabling the users to quickly derive the weights associated with criteria map layers (Malczewski, 2006). For reservoir flood control, miscellaneous methods such as fuzzy hybrid approaches were the preferred techniques. This is probably because reservoir operations involve a large number of uncertain factors that can be properly addressed by fuzzy set theory. Additionally, TOPSIS is highly popular for ranking alternatives for flood mitigation, which emphasizes the effectiveness of this technique to deal simultaneously with conflicting objectives.

Table 10. Distribution of applications by MCDM method and area of application

Area of application / Number of applications	**AHP**	**TOPSIS**	**SAW**	**Others**	**CP**	**ELECTRE**	**MAUT**	**PROMETHEE**	**VIKOR**
Ranking of alternatives for flood mitigation	14	10	9	8	9	5	2	3	1
Risk assessment	27	10	5	6	1	1	3	1	2
Vulnerability assessment	21	3	5	4	1	1	2	0	0
Hazard assessment	25	3	2	5	1	1	0	0	0
Susceptibility assessment	18	0	4	0	0	0	0	0	0
Coping capacity	8	4	2	0	0	0	1	0	0
Emergency management	5	0	1	0	0	0	0	1	0
Reservoir flood control	1	1	0	5	0	1	0	0	0
Total*	**119**	**31**	**28**	**28**	**12**	**9**	**8**	**5**	**3**

* Some papers analysed two or more flood problems simultaneously by using the same MCDM method. Thus, the number of applications in Table 10 is higher than in Table 9.

Although the most widespread MCDM methods were used at least once, no study has used DEMATEL (decision-making trial and evaluation laboratory) or ORESTE (organization, rangement et synthese de donnes relationnelles). A likely explanation is that these methods are cognitively demanding when compared to classical approaches, especially when numerous criteria are involved (Dou et al., 2014b; Moffett and Sarkar, 2006). For instance, DEMATEL needs to be coupled with other MCDM tools, such as ANP to generate criteria weights, which makes its application difficult. In addition, there is a limited amount of software available, and most of it is paid (e.g. Decision Era). However, DEMATEL was specifically developed to address limitations of traditional techniques regarding interdependence between criteria. Likewise, ORESTE is suitable for problems with limited information and with incommensurable criteria (Moffett and Sarkar, 2006).

3.4.5.5 Trends regarding stakeholders' involvement

Flood risk management decisions may be designed without the direct participation of multiple stakeholders. However, they cannot be implemented without them (Affeletranger, 2001). Therefore, flood management decision-making should be ideally carried out in a participatory process, where the knowledge and preferences of interested actors are integrated into the process from the beginning. According to Evers et al. (2014), this creates trust among decision makers and stakeholders, which often lead to a successful implementation of the chosen measures.

The survey revealed that 65 (50.78%) studies have explicitly acknowledged the involvement of multiple actors in the decision-making process. Policy makers and experts were the stakeholders that participated most. This was expected since they are often responsible for the selection and implementation of chosen measures and have a broad knowledge of the problem of interest. Additionally, some papers mentioned the involvement of local community members (e.g. Kandilioti and Makropoulos, 2012; Sahin et al., 2013; Roy and Blaschke, 2015). According to Affeletranger (2001), the consideration of community members' opinion may improve their resilience as well as their response capacity when confronting natural disasters.

Nevertheless, participation was generally fragmented and restricted to consultation at specific stages, such as the selection of evaluation criteria (e.g. Haque et al., 2012) and the definition of criteria weights (e.g. Kienberger et al., 2009; Sahin et al., 2013). This segmentation may be related to methodological and time constraints since participatory decision-making is time-consuming and costly, particularly when the decisions are made in a group where proper facilitation is required.

Crucial aspects of the decision-making process like the definition of objectives, identification of the alternatives, and estimation of its consequences were usually constrained to analysts and experts, which inhibit the achievement of genuine participation. Only in exceptional cases, was the input from the stakeholders a critical element in the entire process (e.g. Ceccato et al., 2011; Evers et al., 2012). For example, Ceccato et al. (2011) developed a methodological proposal aimed at strengthening the communication and collaboration within the scientific community and local actors for flood management decision-making. The authors applied the NetSyMoD (Network Analysis – Creative System Modelling) framework (Giupponi et al., 2008), where the identification of relevant stakeholders, definition of the problem, establishment of objectives and criteria, and the selection of alternatives are conducted in a participatory process.

Another interesting result is that only four studies sought to obtain consensus (e.g. Haque et al., 2012; Lee et al., 2013; Lee et al., 2014; Lee et al., 2015), in which participants make decisions by agreement rather than by majority vote or averaging approaches. Nevertheless, enhancing mutual understanding for consensus building is essential for a long-lasting and successful flood management program, especially for selecting alternatives for flood mitigation and emergency management. It allows decision makers to derive meaningful solutions that fulfil their own needs while at the same time satisfying the requirements of other actors, legitimating the participation as a learning process to solve complex problems.

A total of 43 out of 65 studies provided unambiguous descriptions of the participatory decision-making techniques applied. Figure 8 shows that questionnaires (e.g. Giupponi et al., 2013; Taib et al., 2015) and face-to-face interviews (e.g. Deshmukh et al., 2011; Jun et al., 2011) were the most applied tools. These methods allow for opinions to be conveyed without influence from dominant participants and are simple and fast to realize. On the other hand, the participants are not able to share and hear different perspectives through open dialogue, which is essential for achieving common agreement.

In this sense, Mendoza and Martins (2006) argue that group elicitation methods involving open discussion offer several advantages, including the consistency in the information obtained, and a better definition of the preferences. On the other hand, the results can be influenced by dominant stakeholders and noises in the responses (Hsu and Sandford, 2007). Group elicitation methods such as workshops (e.g. Kenyon, 2007; Porthin et al., 2013), group meetings (e.g. Azibi and Vanderpooten 2003; Marttunen et al. 2013) and focus group discussions (e.g. Rahman and Saha, 2007; Haque et al., 2012) were less applied in the reviewed papers.

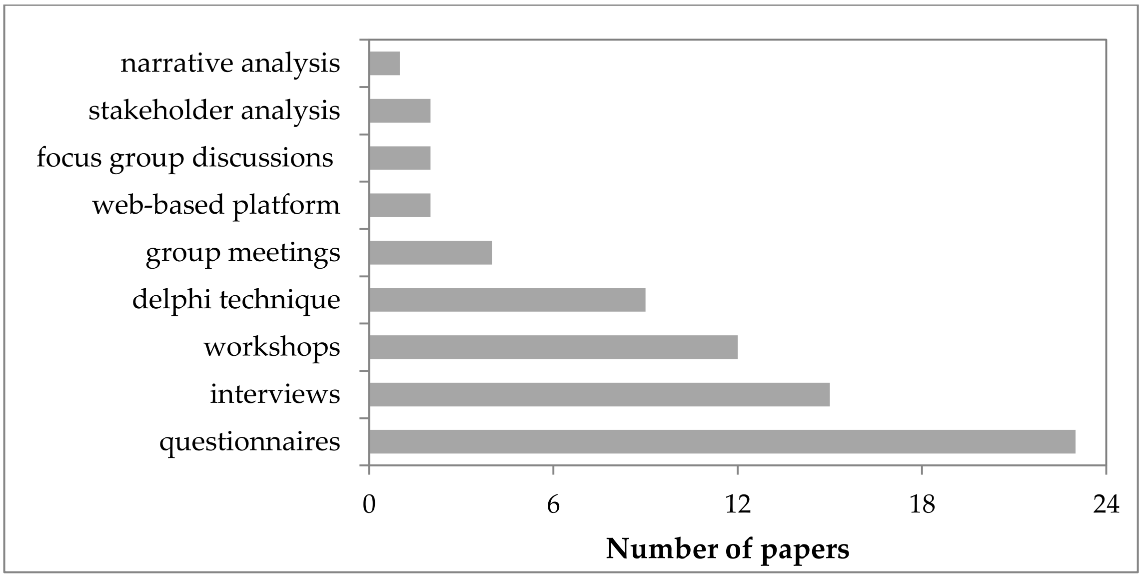

Figure 8. Methods used to incorporate multiple stakeholders' views in the decision-making process

Recently, researchers have used the Delphi technique to overcome shortcomings of conventional group elicitation methods regarding dominant individuals and time constraints (e.g. Chung et al., 2014; Lee et al., 2014). This method provides anonymity to respondents, a structured feedback process, and is suited for consensus building (Hsu and Sandford, 2007). Additionally, it is advantageous when the stakeholders live some distance apart, and it is prohibitive to bring them together for a workshop or group meeting (Lee et al., 2013).

It is interesting to highlight that two studies reported the use of collaborative web-based platforms in which stakeholders select and rank alternatives interactively (e.g. Evers et al., 2012; Almoradie et al., 2015). These platforms have the potential to overcome hindrances in participatory MCDM such as the limitation of financial resources and stakeholders' spatial distribution, providing full transparency of information and results. By taking this approach, the confidence in the decision-making process is increased as well as the level of acceptance of negotiated measures, which are crucial conditions for successful participatory flood risk management.

3.4.5.6 Trends regarding sensitivity and uncertainty analysis

Flood decision-making is subjected to multiple sources of uncertainty, including the assessment of criteria weights, the parameters' uncertainties, and structural uncertainty (Broekhuizen et al., 2015). In addition, there are uncertainties associated with the inherent randomness of flood events (Von Merz et al., 2008), which, in principle, cannot be reduced. Thus, in order to improve the quality of decisions and verify the robustness of the model outputs, flood risk management should be based on a comprehensive assessment of the sensitivity combined with a thorough investigation of the uncertainties involved.

In this review, 93 (72.65%) papers do not report any kind of sensitivity analysis, thereby ignoring the impact of changes in input weights on model results. The remaining articles (35 or 27.34%) applied mainly one-way sensitivity analysis, where one criteria weight or performance score is modified at a time and the variation of the alternatives' ranking is observed. If the induced variation does not change the rank order of alternatives, the decision is considered robust. This technique is intuitively appealing and requires little time, making it a practical way to assess the sensitivity. Even though this method is sufficient for most flood applications, the range over which weights are varied is normally arbitrarily defined, and the commutative impact of uncertainty is not considered. Hence, these drawbacks may lead to a biased view of the influence of uncertainty on the final decision (Broekhuizen et al., 2015).

Two papers performed global sensitivity analysis (GSA) by applying the FAST (Fourier amplitude sensitivity test) procedure, where two or more evaluation criteria are varied at the same time (e.g. Fernández and Lutz, 2010; Chen et al., 2015). Although GSA allows for the full uncertainty range of the criteria to be explored and analysed, it can become an extremely time-consuming task, as a large number of criteria are included in the analysis. Additionally, four papers elaborated best- and worst-case scenarios to incorporate decision makers' attitude to risk (e.g. Kandilioti and Makropoulos, 2012; Penning-Rowsell et al., 2013; Ghanbarpour et al., 2013; Alipour, 2015). Finally, two studies used a probabilistic approach (e.g. Yazdandoost and Bozorgy, 2008; Fernández and Lutz, 2010), which is the most rigorous form of sensitivity analysis. This approach requires the estimation of a maximum percentage that the actual criteria weight may differ from the estimated value.

Several authors have listed the uncertainty as a major drawback (e.g.; Bana e Costa et al., 2004; Edjossan-Sossou et al., 2014; Godfrey et al., 2015; Almoradie et al., 2015). However, only eight papers (6.25%) perform uncertainty analysis, in an attempt to describe the entire set of possible outcomes, together with their associated probabilities of occurrence. In situations where uncertainty is mainly due to randomness, the methods used were probability-based. This is the case of Qi et al. (2013) and Li (2013) who used Monte Carlo simulation to convert uncertainties in input criteria into probability distributions. Another approach applied was the Taylor's series error propagation method (e.g. Fernández and Lutz, 2010), which analyses how the uncertainty in input data propagates through the model and affects its outputs. In addition, three papers assessed the uncertainty qualitatively, by describing its main sources (e.g. Cozannet et al., 2013) or by analysing the degree of confidence related to stakeholders' opinion (e.g. Ceccato et al., 2011; Penning-Rowsell et al., 2013).

Apart from uncertainty and sensitivity analysis, fuzzy set theory is widely combined with AHP, TOPSIS, and CP to handle uncertainty and incomplete information about the decision situation. For instance, Lee et al. (2013) integrated TOPSIS and fuzzy set theory to fuzzify the weighting values and all criteria maps. In the same sense, the approach proposed by Yang et al. (2012) combines AHP and triangular fuzzy number to assess the flood risk and its components. Fuzzy set theory is widespread in MCDM due to its intuitiveness and computational requirements. Nevertheless, some studies have shown that fuzzy AHP do not provide better results than regular AHP since the judgments in AHP are already fuzzy (Saaty, 2006). Therefore, the additional complexity of utilizing fuzzy numbers may be unnecessary in some cases.

Finally, it is relevant to note that some MCDM methods explicitly account for uncertain input criteria scores. For instance, ELECTRE and PROMETHEE adopt the pseudo-criterion model that introduces indifference and preference thresholds. Likewise, MAUT considers imprecise data input with probabilistic approaches (Cinelli et al., 2014). Also, AHP allows the generation of an inconsistency index, which can be considered as an indirect measure of the uncertainty in the criteria weighting step.

3.4.6 Research limitations and recommendations for future research

3.4.6.1 Limitations

There are some caveats that should be considered when interpreting the results obtained in this review. One of the main shortcomings is that the papers' quality was not evaluated since they were all published in peer-reviewed journals. Thus, some applications were superficial, while others were detailed, including intensive stakeholder participation, validation of results, and probabilistic-based uncertainty and sensitivity analysis. Some studies were carried out with real data, involving real decision makers and stakeholders, while others discussed hypothetical applications or were secondary studies that re-examined empirical work. A future review paper can address this limitation by applying heuristic checklists (e.g. Beecham et al., 2008) to assess the overall quality of the study.

In addition, defining the flood application area turned out to be a subjective process, especially when it came to distinguishing between susceptibility, hazard, and risk assessment. There is a misunderstanding about these terms in the literature, which are used in slightly different ways by researchers with different backgrounds. Thus, in some cases, it was difficult to define a clear line for when it was susceptibility, hazard or risk. Whenever possible, the term used by the authors was respected.

The exclusion of non-English literature can also be understood as a limitation (Behzadian et al., 2010). The results of our preliminary searches showed that several MCDM French school authors have published in French language journals. Furthermore, there are a significant number of research papers published in German, Chinese and Korean. Thus, it should be emphasized that, when feasible, searches using multiple languages are advantageous (Pickering and Byrne, 2014).

Nevertheless, despite these potential limitations, this paper is the first to present a literature review of the state-of-the-art of the use of MCDM for flood-related problems. The sample of papers analysed provides sufficient information to stimulate discussion and research that addresses challenges in this area of knowledge.

3.4.6.2 Recommendations for future research

This review enabled us to identify gaps in the knowledge of MCDM for flood risk management regarding several aspects. First, classical MCDM methods such as MAUT, MAVT, PROMETHEE, and DEMATEL were overlooked. Almost half of reviewed applications used AHP to elicit criteria weights, which is a relatively easy and flexible method, requiring fewer skills than other tools. In this sense, exploring the implications of methodological differences in existing MCDM methods for flood risk management is an interesting research challenge. Similarly, future research can focus on understanding advantages and limitations of each method for handling different sources of uncertainty.

Secondly, there were surprisingly few studies that effectively considered stakeholders' participation throughout the entire decision-making process. Therefore, greater rigour in endorsing an active participation in all stages of the decision-making process should be undertaken, in order to increase the feasibility and subsequent implementation of chosen measures. Future research could be directed towards developing web platforms to elicit stakeholders' preferences, aiming to reach consensus in a simpler and easily accessible way. In addition, this course of action can be combined with other participatory techniques such as cognitive mapping, Delphi technique, and voting theory. Conversely, it should be noted that intensive participation is time-consuming. Thus, in real-life applications, trade-offs have to be made between the available resources and the expected outcomes of the MCDM process.

The third challenge, and perhaps the most relevant research gap, refers to fully considering the uncertainties around decision makers' judgments. Although uncertainty in MCDM is not a new problem and significant improvements have been made over the last decades, it remains a major open issue. Previous studies suggest that properly addressing the uncertainties can substantially improve MCDM applications, assisting stakeholders to make better decisions. Potential exists to apply Bayesian framework methods (e.g. Bayesian networks and Dempster–Shafers' theory), possibility theory, and evidence theory. Regardless of the uncertainty method applied, considering all sources of uncertainty in the decision-making process might not be a feasible task (Mowrer, 2000). Nevertheless, it is essential to identify as many sources of uncertainty as possible, and attempt to reduce or handle them.

Lastly, a significant gain can be made if flood MCDM applications are able to consider climate and socioeconomical changes, which have potential to aggravate existing risks. This has been tackled in a recent study by Giupponi et al. (2013) that assessed the flood vulnerability within the broad context of climate change adaptation.

3.4.7 Conclusions

This study has presented a systematic review of 128 papers that apply MCDM to flood-related problems, aiming to provide an overall picture of what has motivated researchers and practitioners in 37 different countries over the past two decades. Our findings suggest an increasing interest in flood MCDM since 2009, as compared to the previous 14 years. A wide range of applications were identified, with most papers focusing on ranking alternatives for flood mitigation, followed by risk, hazard, and vulnerability assessment. This highlights the utility of MCDM as a decision support tool in all stages of the flood management process.

Nearly 85% of the applications were conducted in Asian and European countries, mainly in China, Germany and South Korea. Hence, potential exists to develop cross-country investigations, especially in South America and Australia. Overall, AHP was the most widespread method, indicating that other methods may be overlooked. The review also shows that fuzzy and hybrid approaches (e.g. triangular fuzzy AHP, hybrid fuzzy AHP-TOPSIS, AHP-SWOT, modified TOPSIS) are being increasingly applied to overcome limitations of classical methods.

About half of the studies have acknowledged the involvement of multiple stakeholders. However, participation was fragmented and focused on particular stages of the decision-making process. Most of the reviewed studies rely on the use of questionnaires and interviews to capture stakeholders' perspectives, with few applications seeking to obtain consensus. In addition, shortcomings remain in handling the uncertainty. Thus, greater rigour in considering the uncertainties around stakeholders' preferences and endorsing an active participation are important research gaps. Additionally, sensitivity analysis should be conducted as a primary method to check the stability of the results and identify the most critical criteria. This could help to increase the quality of decisions as well as the transparency and credibility of the MCDM outcomes.

It is clear from the literature that the challenge for further research is to foster the development of true collaborative MCDM applications that take the uncertainty around stakeholders' judgments into account. We believe that this paper can provide valuable information for guiding future research and that it can serve as a ready reference for researchers and practitioners working with flood risk management and MCDM.

CHAPTER 4

Case study area

4.1 Geographical setting

Given that flood vulnerability is site specific (Cardona et al., 2012; Cutter et al., 2003), the municipalities of Lajeado and Estrela (274.79 km²) were used as a case study. These municipalities are situated on opposite sides of the Taquari River, Taquari-Antas River Basin, southern Brazil (Figure 9). They were chosen based on their representativeness in terms of susceptibility to flooding as well as the high exposure of the population, which will be discussed in detail in the following sections.

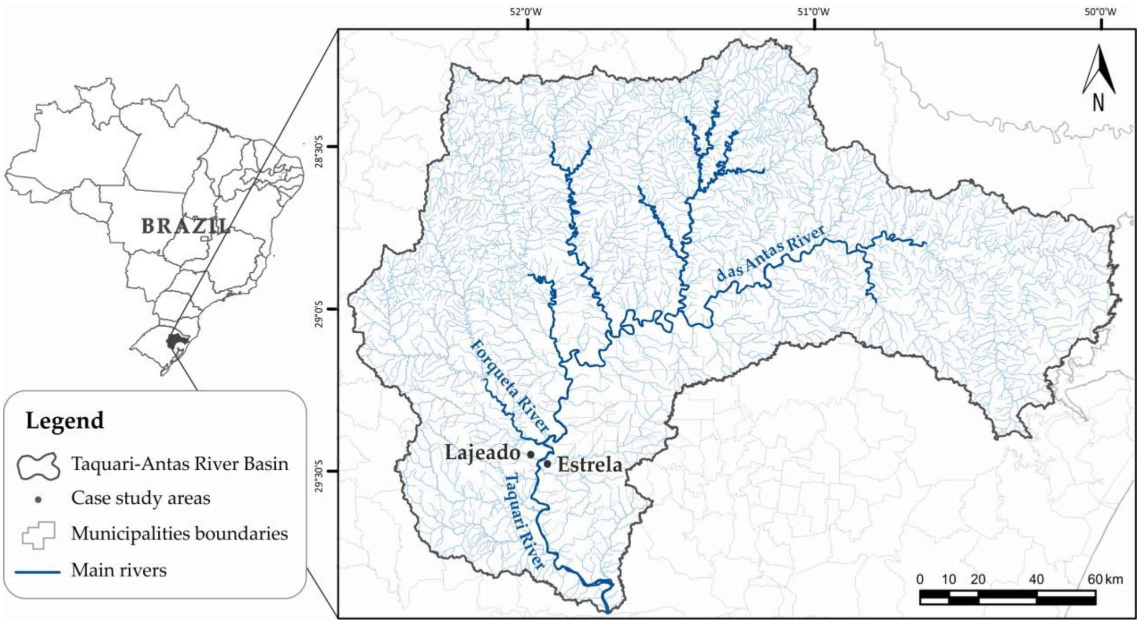

Figure 9. Location of the municipalities of Lajeado and Estrela within the Taquari-Antas River Basin, state of Rio Grande do Sul, southern Brazil

According to the Brazilian National Atlas of Flood Susceptibility, elaborated by the National Water Agency (ANA, 2013), the stretches of the Taquari River and Forqueta River are highly susceptible to flooding. Hence, the municipalities of Lajeado and Estrela, which are located on the confluence of those rivers, are considered by the Federal Government of Brazil as a priority for disaster risk reduction, being part of the National Plan of Risk Management and Response to Natural Disasters (CEMADEN, 2017).

4.2 Climate

The regional climate is classified by the Köppen-Geiger system as humid subtropical (Cfa) (Peel et al., 2007), with mean temperatures of 25°C in January and 15°C in June (Figure 10). The precipitation is uniformly distributed throughout the year, without a dry season. Rainfall ranges between 1,600 and 1,800 mm per year, with a maximum 24 hour precipitation of 179 mm in 14th April 2011 (Climate Data, 2017). Regional climate models indicate that, in the future 10-70 years, the annual precipitation will increase in the Taquari-Antas River Basin (Bork, 2015). Thus, negative impacts of floods might increase, especially in the lower portion of the basin. This escalates the challenges for the disaster risk managers in the area as they lack monetary resources to tackle local vulnerability.

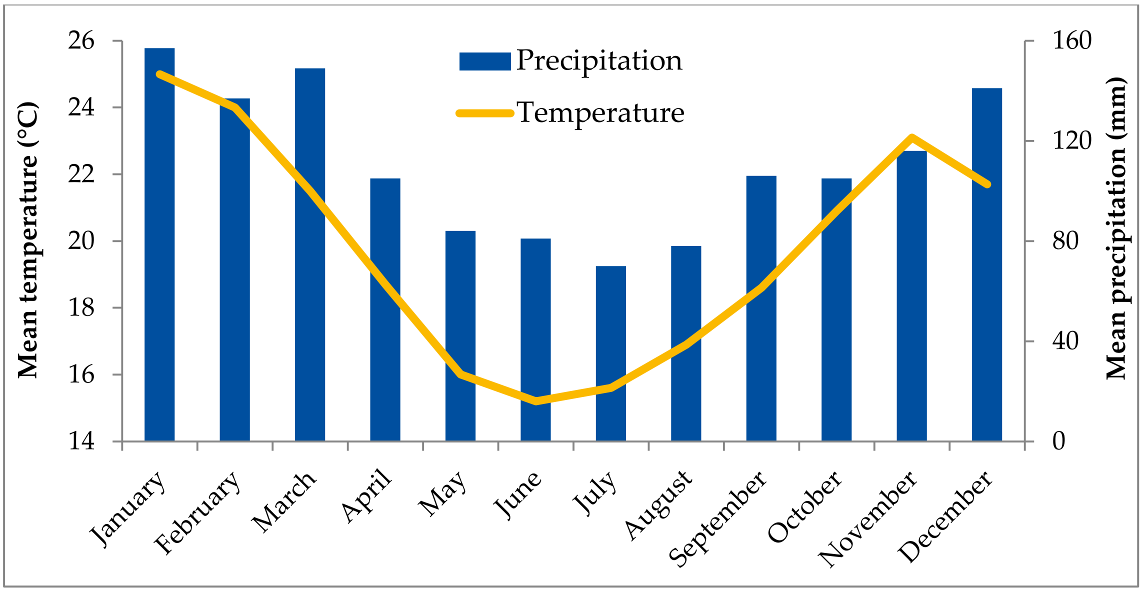

Figure 10. Monthly mean temperature and precipitation in Lajeado municipality (Climate Data, 2017)

4.3 Hydrology

The main river of the Taquari-Antas River Basin is 530 km long and flows from a high basaltic plateau (ca. 800 to 1200 m) through deeply incised valleys until the lowlands, where it is known as Taquari River (Figure 9). The lowlands (ca. 20 to 100 m) are formed by alluvial deposits with low permeability (Becker et al., 2013).

The average discharge of the Taquari River is 321 m³/s. Nevertheless, due to the dense and radial drainage pattern, low soil permeability, and high mean slope there are abrupt flow variations (Siqueira et al., 2016). Hence, in critical situations it can reach over 10,000 m^3/s and water level can rise in relative high rates considering the basin drainage area, with variations of 1 meter per hour (FEPAM, 2010; Siqueira et al., 2016). As a consequence, floods occur almost annually, albeit sometimes twice in a year.

Floods in this area are usually associated to frontal systems, especially stationary fronts (Wollmann, 2014), and lag time between the peak of rainfall in basin headwaters and flood peak is generally 2 to 3 days (Bombassaro and Robaina, 2010). However, in saturated soil conditions, extreme rainfall events can cause the rise of the Taquari River in approximately 1 day. Table 11 shows the peak discharges, flood depths and extent of flooded areas according to different return periods in Lajeado and Estrela.

Table 11. Extension of floods with different return periods in Lajeado and Estrela (Fadel, 2015)

Return period (years)	Discharge (m^3/s)	Flood depth (m)	Flooded area (km^2)
2	7,982	22.75	30.20
5	9,369	25.15	37.80
10	10,188	26.58	41.68
25	11,142	28.28	47.52
50	11,604	29.17	50.58
100	12,438	30.62	55.05
200	13,046	31.74	57.92

4.4 Socio-economic aspects and urbanization

The first settlements along the Taquari River were established with the arrival of German immigrants in the 1850s. The municipalities of Estrela and Lajeado were officially created in 1876 and 1891, respectively. Since the 1960s, the region has become heavily urbanized, causing dramatic changes in the environment, including the deforestation of the riparian forest and unplanned occupation of river banks. In 2010, the urbanization rate was 99.6% in Lajeado and 86.0% in Estrela, which is above the regional (84.0%) and national rates (84.5%) (IBGE, 2017). Currently, main socio-economic activities include the food industry, agriculture, and livestock production.

In 2016, the total population was approximately 112,000 and the GDP per capita was about US$12,800, with nearly 20% of households living below the poverty line (IBGE, 2017). The impoverished families are concentrated in floodplains and in hilly slopes as these areas are typically undesirable and thus affordable (World Bank, 2012b). Besides being susceptible to flooding, the informal settlements located in floodplains have poor basic infrastructure in terms of sanitation and waste management (Figure 11). As a consequence, they are more vulnerable to the negative impacts of these events.

Figure 11. Informal settlements located in floodplains in (a) Estrela; and (b) Lajeado

4.5 Spatio-temporal characteristics of floods

In order to understand the flood patterns in the Taquari-Antas River Basin and identify how these processes evolved over time, an analysis of historical floods was conducted. Based on the intensive data compilation (Bombassaro and Robaina, 2010; de Brito et al., 2011; MI, 2017), 610 flood registers were identified between 1980 and 2016 (Figure 12). Totally 103 out of the 119 municipalities within the basin were affected by floods at least one time during this period. The area with highest susceptibility to is the lower part of the basin, a region which is named Taquari-Valley. Estrela and Lajeado were the most affected municipalities, with 34 and 32 events respectively.

An analysis of the annual distribution of floods reveals that no obvious trends exist and that flooding is not a new problem in the region (Figure 13). In fact, floods have been documented since the establishment of the first settlements in Lajeado and Estrela (Figure 14). Nevertheless, while the hazard may not have changed, the transformation of the environment increased the exposure and vulnerability of the population and, consequently, the negative impacts of such events. During this period, floods were more recurrent during winter, especially in June and July. Nevertheless, due to a low seasonality (Siqueira et al., 2016), there are records of floods in all months of the year.

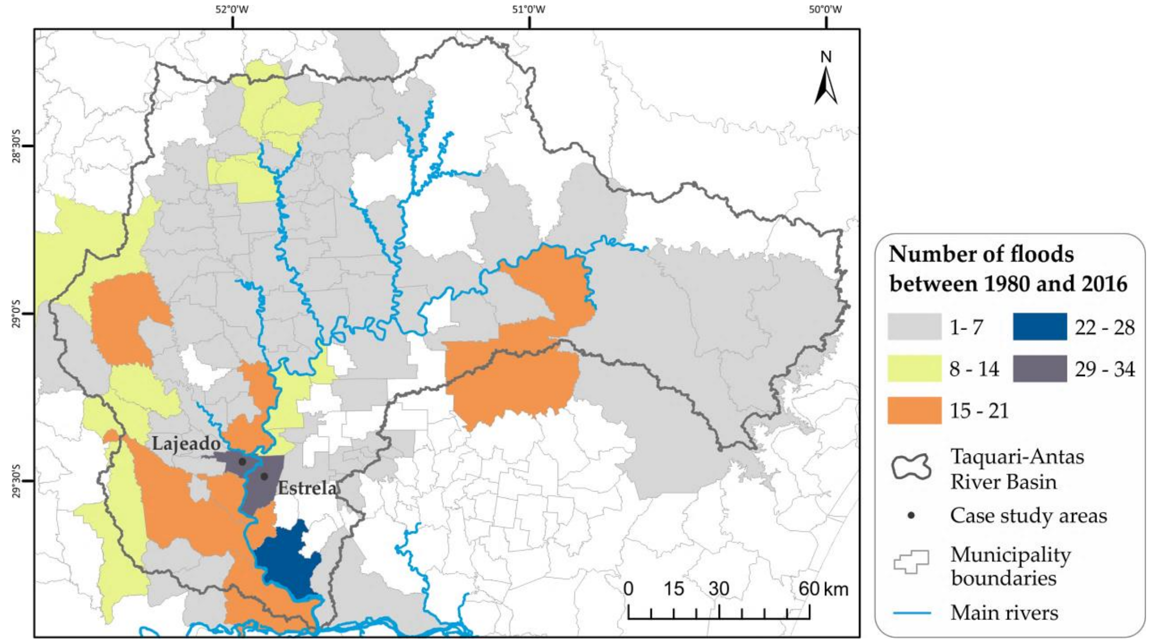

Figure 12. Number of recorded flood events in each municipality between 1980 and 2016 in the Taquari-Antas Basin

Table 12 presents an overview of the main impacts caused by floods between 2002 and 2016. Besides displacing many people, floods in the region pose damages to standing crops, livestock and houses as well as loss of cultivable land due to erosion.

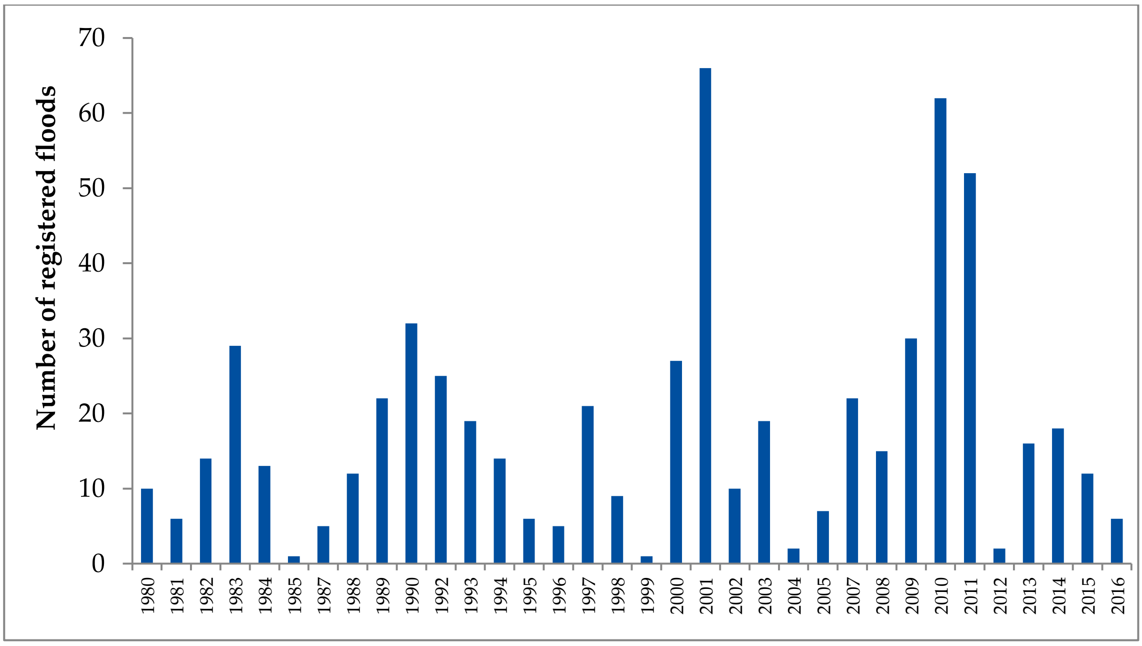

Figure 13. Temporal distribution of floods between 1980 and 2016

Table 12. Overview of the damages caused by floods in Lajeado and Estrela, Brazil*

Year	Municipality	N. of affected persons	N. of damaged buildings	Damage (R$)
2002	Estrela	5,654	42	706,401
2002	Lajeado	1,550	150	-
2003	Estrela	162	12	156,500
2003	Lajeado	573	-	-
2008	Estrela	7,000	2550	4,481,110
2008	Lajeado	530	32	411,640
2009	Estrela	1,338	3	4,000
2009	Lajeado	440	-	-
2011	Estrela	13,725	117	3,243,852
2011	Lajeado	720	182	913,000
2013	Estrela	414	11	310,854

* Data compiled from state of emergency and public calamity declarations published between 2002 and 2015 (MI, 2017). Only events that affected more than 100 people are shown here.

Since Lajeado and Estrela are a priority municipalities for disaster risk reduction they were included in the emergency action conducted by the Geological Survey of Brazil to delimit areas prone to floods (CPRM, 2012, 2013). A total of 12 and 6 polygons were identified in Estrela and Lajeado, respectively (Figure 15). It is important to highlight that only highly populated areas were considered. Thus, the south of Estrela and north of Lajeado, which are regularly affected by floods, were not considered in this study as they are sparsely populated. According to the results of this investigation, at least 8,000 persons live in high risk areas in these municipalities (CPRM, 2012, 2013).

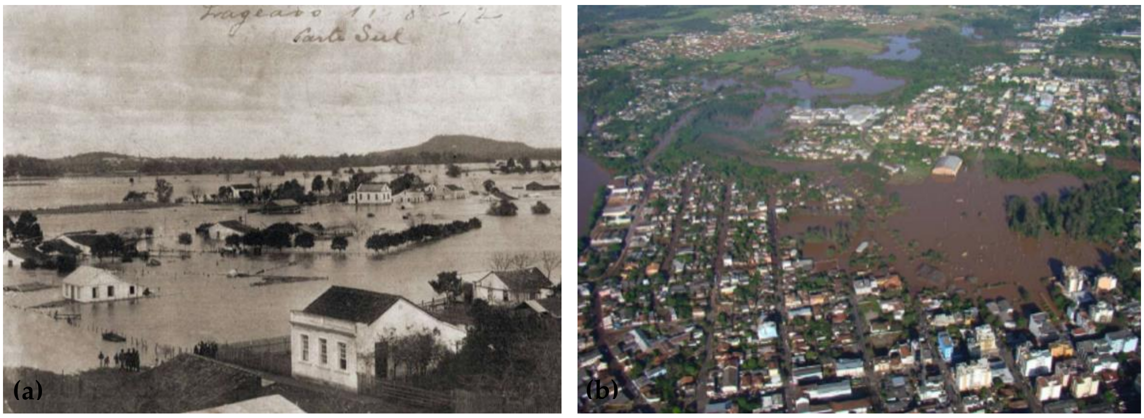

Figure 14. Historic floods in the study area: (a) Lajeado in 1911; (b) Lajeado in 2012 (AEPAN, 2011; Fotos Aéreas RS, 2008; Palagi et al., 2014)

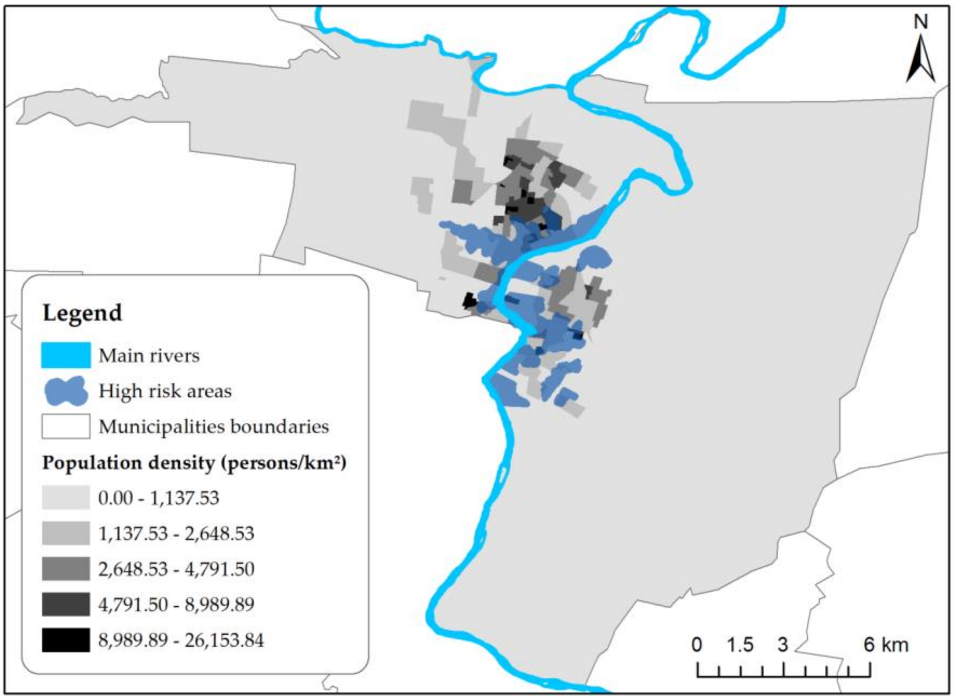

Figure 15. High risk areas in Lajeado and Estrela. Redrawn from CPRM (2012, 2013)

CHAPTER 5

Application of the proposed framework for flood vulnerability assessment

In the following sections, the application of the proposed methodology for flood vulnerability assessment is described in detail. To overcome some of the gaps identified by de Brito and Evers (2016) regarding vulnerability assessment, the framework goes beyond the limited perspective of a single expert by acknowledging multiple standpoints and explicitly showing the rationale for model decisions. For this purpose, participation of key expert stakeholders is considered throughout the entire modeling process, including criteria selection, standardization, weighting, as well as model validation.

5.1 Prioritization of flood vulnerability, coping capacity and exposure indicators through the Delphi technique: a case study in Taquari-Antas basin, Brazil (Paper 2)

This paper was originally published as: de Brito, M.M., Evers, M., Höllermann, B. (2017) Prioritization of flood vulnerability, coping capacity and exposure indicators through the Delphi technique: a case study in Taquari-Antas basin, Brazil. International Journal of Disaster Risk Reduction, 24, 119-128, doi:10.1016/j.ijdrr.2017.05.027.

5.1.1 Abstract

This paper presents the outcomes of a participatory study that aimed to reach agreement among experts about flood vulnerability, coping capacity and

exposure indicators through a Delphi survey. The objective was to collaboratively develop an index for the Taquari-Antas basin, Brazil, using the available data. A total of 117 scientists, policy makers, and practitioners were invited to prioritize 26 indicators, focusing on the pre-disaster phase. This survey was followed by a final selection in a focus group. The sensitivity of the ratings was analyzed by bootstrapping the original sample. The response rate was 86.32% and 79.20% in the first and second round, respectively. Overall, the highest rated items were related to coping capacity aspects of vulnerability and human and infrastructure exposure. The answers' deviation was reduced between rounds, thereby enabling the achievement of consensus on 21 indicators. The results revealed similarities in how vulnerability and exposure are perceived across the different professions and sectors investigated. The Delphi process allowed the collaboration of professionals with opposing views to prioritize a common set of indicators in a systematic and transparent way. Hence, this study is timely in describing a feasible alternative to reach agreement among stakeholders to build flood-related indices. From a practical standpoint, this research provides decision makers with a core list of indicators to better understand the impacts of floods in the basin. We expect that incorporating input from end users in the creation of the index will enable it to reflect the local context and gain legitimacy.

5.1.2 Introduction

According to the Sendai Framework for disaster risk reduction the design and implementation of risk management strategies should be based on a holistic understanding of risk in all its dimensions, including vulnerability, coping capacity, exposure of persons and assets, hazard characteristics, and the environment (UNISDR, 2015b). While the understanding of hazard and exposure has significantly improved over the last decades, the analysis of vulnerability remains one of the biggest hindrances in flood risk assessment (Jongman et al., 2015; Koks et al., 2015).

Part of this complexity arises from the fact that there is no consensus on the definition of vulnerability or on what should be included in its assessment. According to UNISDR (2009), vulnerability is the physical, social, economic and environmental aspects, which make the exposed elements susceptible to the impacts of a hazard. A leading component of vulnerability is the coping capacity, which refers to the ability of people, organizations, and systems, using available skills and resources, to face and manage adverse conditions, emergencies or disasters.

Vulnerability reduction is critical to risk mitigation since hazards only become disasters if they impact a society that is vulnerable to their effects (Reilly, 2009). In other words, risk is only present if there is a vulnerable community or system. Therefore, a proper understanding of vulnerability is crucial to promote disaster-resilient societies, leading to more effective mitigation and preparedness strategies. For this reason, there is a need to consider not only the physical aspects of vulnerability, but to integrate all vulnerability dimensions (e.g. physical, social, economic) in an overarching framework by using indicators (Birkmann, 2006). Indicator-based methods are flexible, transparent and easy to use and understand by decision makers (Ciurean et al., 2013). Nevertheless, a major limitation is that it is difficult to choose the variables that contribute to vulnerability since their exclusion or inclusion can significantly influence the results (Lee et al., 2013; Müller et al., 2011). Hence, the main challenge is to select a set of indicators which is, on the one hand, minimal and applicable, and on the other hand, explains the phenomenon as clearly as possible in a specific area (Fekete, 2012).

Numerous flood vulnerability, coping capacity and exposure indicators can be found in the literature (e.g. Kandilioti and Makropoulos, 2012; Roy and Blaschke, 2015; Scheuer et al., 2011; Solín, 2012). Yet, a meta-analysis of 67 flood vulnerability studies conducted by Rufat et al. (2015) found out that the selection of input variables is usually based on choices made in previous studies, disregarding the local conditions that influence the vulnerability. In several cases, no justification is provided at all.

In addition to this issue, a review by Brito and Evers (2016) highlights that insufficient attention has been given to the participation of multiple stakeholders in the construction of flood vulnerability indicators. Crucial aspects, such as the structuration of the index into sub-indices and selection of the indicators were usually constrained to researchers conducting the study. However, there is considerable agreement that the collaboration of researchers with non-academic stakeholders may yield better results in terms of results' acceptance. If practitioners are involved in creating an index that they find accurate and useful, it is more likely they will incorporate the index findings in local policy decisions (Oulahen et al., 2015).

Even when multiple stakeholders are involved, most studies have not tried to achieve consensus (de Brito and Evers, 2016). Nevertheless, consensus building is essential to derive meaningful outcomes that can be accepted by the majority, legitimizing participation as a learning process to solve complex problems. Therefore, using participatory and transdisciplinary methods in which stakeholders work together to prioritize vulnerability indicators and try to achieve consensus could foster such actions while assuring local context.

In light of these issues, this study aims to achieve agreement among expert stakeholders about a set of indicators to assess flood vulnerability, coping capacity and exposure in data-scarce areas, focusing on the pre-disaster phase. In addition, the study aims to investigate whether or not participants with different backgrounds and levels of knowledge rely on divergent rationalities. For this purpose, the participatory Delphi technique was applied given that it is a widely accepted approach for achieving convergence of opinion on complex problems in a systematic and transparent way. The applicability of this method is demonstrated in Taquari-Antas River Basin, Brazil, where limited information about the resistance of the elements at risk is available.

5.1.3 Vulnerability within the framework of disaster risk

Flood risk and its associated components have been studied from a variety of perspectives by researchers with different scientific backgrounds, leading to conflicting views and interpretations on how to assess it. In this study, we consider risk as the product of hazard, exposure, and vulnerability (Figure 16). According to UNISDR (2009), hazard is the probability of occurrence of a dangerous phenomenon (e.g., flood, drought, fire) while exposure consists of the presence of people, property, and assets in hazardous areas.

Within this framework, vulnerability is one of the most ambiguous concepts, being used differently. Due to this plurality of meanings, there is no unique understanding of the definition of this term or of what should be included in its assessment. A common definition of vulnerability, introduced by UNDRO (1980), is the degree of loss of a given element, resulting from the occurrence of a natural hazard and expressed on a scale from 0 (no damage) to 1 (total loss). Here vulnerability is mostly related to the likelihood of buildings collapsing and infrastructure being damaged due to hazardous events. Nevertheless, several researchers (Birkmann, 2006; Kappes et al., 2012) argue that vulnerability should not be reduced to its physical component, but it should consider the social, political, economic and environmental susceptibility of the exposed elements to damages.

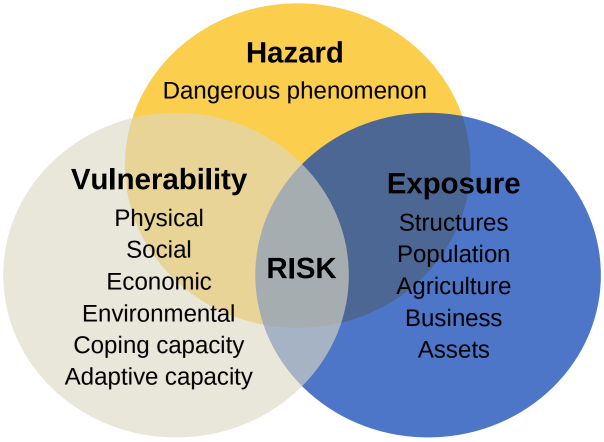

Figure 16. Conceptual framework for disaster risk assessment (adapted from Spalding et al., 2014)

In this sense, it is important to emphasize that some communities, social groups, and ecological systems may cope better with the impact of disasters due to its inherent characteristics (e.g. age, disability, resilience, risk perception). This underlines the fact that vulnerability can also take into account the coping capacity of the potentially affected society (Birkmann, 2006). Hence, in this paper, we will use a more integrative definition of vulnerability, which considers it as the physical, social, economic, environmental, coping and adaptive conditions and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard (UNISDR, 2009).

5.1.4 Method

5.1.4.1 Study area

Given that vulnerability is site specific (Cardona et al., 2012), the Taquari-Antas River Basin was chosen to demonstrate the applicability of the Delphi technique to prioritize indicators. The basin is located in southern Brazil, (Figure 17), with an area of 26,470 km^2.

The main river flows from a high basaltic plateau (ca. 800 to 1200 m) through deeply incised valleys until the lowlands, formed by alluvial deposits, with elevations ranging between 20 and 100 m (Becker et al., 2013). The basin is characterized by torrential regimes of rapid runoff, which cause frequent floods in the lowlands. Due to its high susceptibility, 6 municipalities located within the basin are considered by the Brazilian Federal Government as a priority for disaster risk reduction (CEMADEN, 2017).

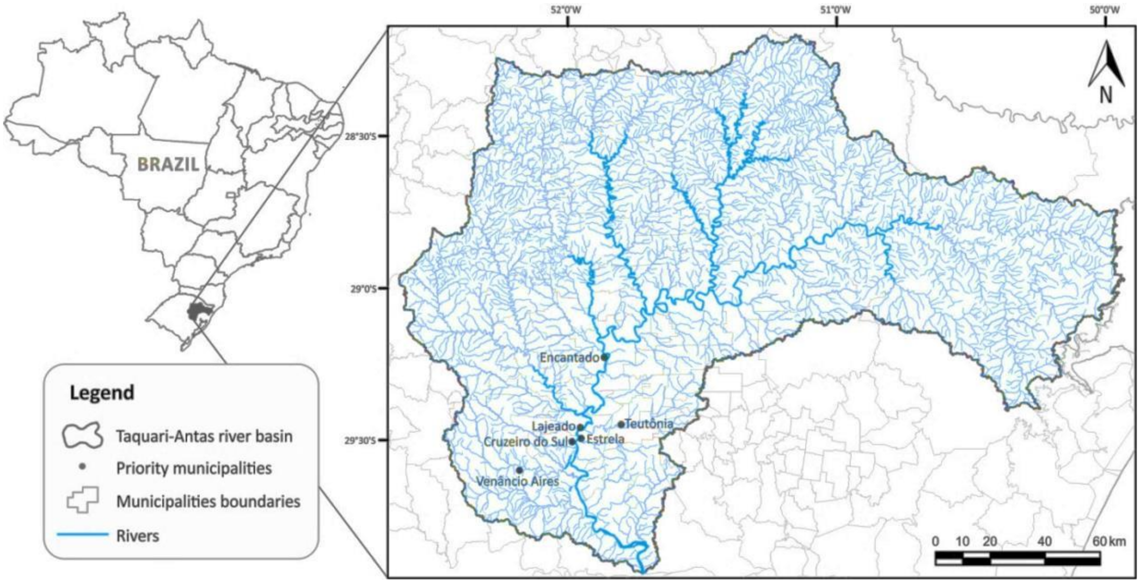

Figure 17. Location of the Taquari-Antas River Basin, RS, southern Brazil

Despite the significance of flood events in this area, limited information about hazard impacts and the resistance of the elements at risk is available. In some cases, the existing data are difficult to access as the information is not coordinated or some agencies are reluctant to release them. This restricts the applicability of quantitative approaches to measuring the vulnerability such as damage matrices and curves (Kappes et al., 2012). Hence, an alternative is to use indicator-based methods, which are flexible and feasible to apply in developing countries.

5.1.4.2 List of potential indicators

A list of potential indicators was created based on a recent systematic review conducted by Brito and Evers (de Brito and Evers, 2016). This was further supplemented with the outcomes of a meta-analysis of 67 flood vulnerability studies made by Rufat et al. (Rufat et al., 2015) and a literature review of 106 vulnerability composite indicators by Beccari (2016). According to these studies, the most commonly used indicators are related with demographic and socioeconomic aspects of vulnerability, including variables such as the population density, elderly and children, gender, unemployment rate and GDP per capita. Due to data availability limitations and to allow comparisons over time and space, only indicators that could be obtained from the Brazilian National Census and other governmental agencies were considered. Based on this, 26 indicators encompassing demographic, socioeconomic, environmental and structural aspects were preselected and included in the Delphi questionnaire.

5.1.4.3 Identification of relevant experts

In this study, an expert is anyone with extensive and in-depth knowledge of flood vulnerability, acquired through practice or education (Krueger et al., 2012). In order to identify nationwide qualified experts, the snowball sampling technique was applied. During this process, initially sampled experts indicated other specialists, which in turn lead to other prospective participants and so on. A total of 49 people were contacted, of which 34 (69.38%) replied and indicated 94 persons. To overcome limitations regarding the potential exclusion of uncited experts, the snowball sampling was supplemented with an extensive search in the Lattes CV platform[1]. In the end, 117 experts were selected and approached by telephone or email to ask whether they would be willing to participate in the survey. The experts who accepted the invitation were ensured with a comprehensive description of the research objectives and were informed about their right to withdraw at any time.

Figure 18 depicts a sociogram organized by the in-degree centrality (Musiał et al., 2009), in which the experts with more connections are located in the center of the graph. The in-degree centrality considers not only the presence or absence of links, but also the importance of such connections. Thus, an actor who is recommended by experts with many connections can be regarded to be more important. Since they play a central role within the formed network in terms of their connectedness, they were invited to take part in a focus group in a further step of the study.

5.1.4.4 Prioritization of indicators using the Delphi technique

The Delphi survey is a systematic and interactive technique, where the knowledge from a panel of experts is collected through a series of questionnaires interspersed by controlled feedback (Chu and Hwang, 2008). After each round, the participants can revise their judgments based on the opinions of their anonymous colleagues. The aim is to decrease the answers'

[1] Lattes CV platform (http://lattes.cnpq.br/) is a curriculum database maintained by the Brazilian Government, which provides information about researchers, professionals, and institutions involved in science and technology.

variation, enabling the achievement of group consensus. From a practical perspective, Delphi is very effective, allowing experts who are geographically dispersed to contribute. Moreover, it avoids the influence of dominant individuals as the respondents remain anonymous throughout the process.

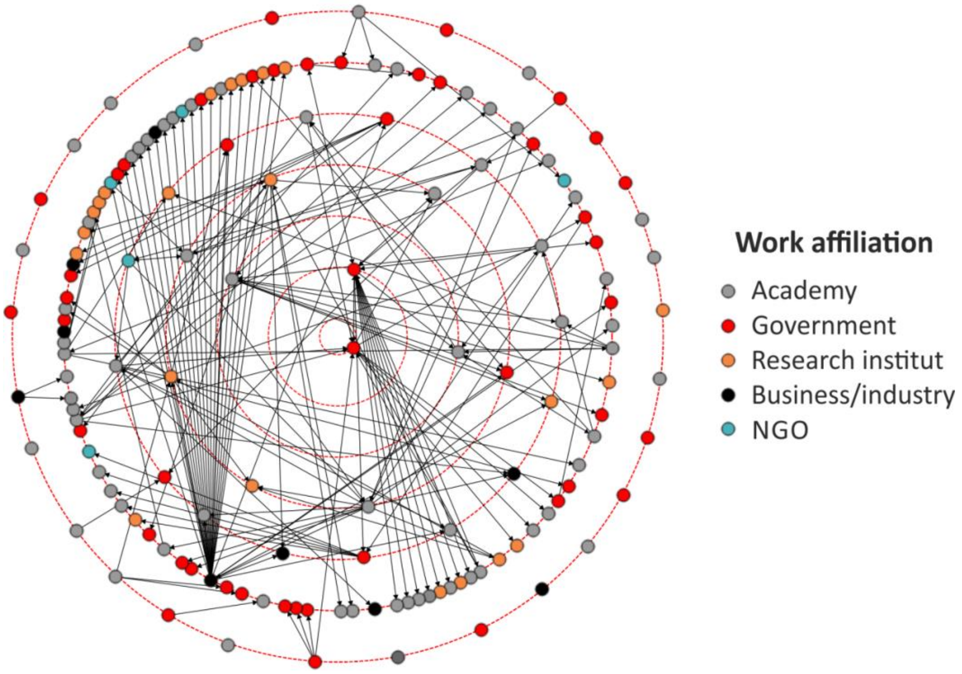

Figure 18. Social network diagram depicting the linkages between the selected experts. Each node represents an actor, and its proximity to the center depends on their connectedness. The arrow direction indicates who cited whom, while the circles collect all experts with the same degree of centrality

In this study, the web-based questionnaires were conducted using the Survey Monkey® tool. In order to analyze the ease of taking the survey, identify ambiguities and explore potential reactions, the questionnaire was pre-tested with 7 individuals. Based on this, the list of indicators and the wording were fine-tuned to improve the feasibility of administration. Then, the survey was sent to 117 panelists, who were invited to rate the importance of 26 indicators for flood vulnerability assessment in the pre-disaster phase on a 5-point Likert scale (1 = not important, 5 = very important). Participants could justify their score and suggest adding extra items they felt deserved evaluation in subsequent rounds. In this case, they had to consider the relevance and availability of the proposed indicator. The items that were mentioned by 4 or more experts were included in the second questionnaire. Conversely, the ones considered to be redundant by at least 10 panelists were excluded.

Besides the indicators' rating, demographic information of the respondents was also collected, including education level, profession, work affiliation, gender identity, and self-reported degree of knowledge of flood vulnerability analysis. A 'very good' knowledge implies that the expert currently works on this topic and has a prolonged and in-depth experience in this field. A 'reasonable' knowledge indicates that the expert devoted himself in the past to this issue or closely related subjects and continues to follow the work of others. A 'limited' knowledge suggests that the participant is not informed in the field.

After the first questionnaire, a report with the results was sent to respondents. To that end, a statistical summary, including measures of central tendency (median and mean), dispersion (interquartile range, standard deviation, and coefficient of variation), and frequency distribution (histograms) was provided. In addition, all comments made by panel members were sent together with an individual feedback. This enabled participants to see where their response stood in relation to the group. Based on this, the experts who completed the first questionnaire were given the opportunity to alter prior estimates. The goal was to allow them to consider the reasoning behind outlying opinions to decrease the response variability. When a panelist's estimation strongly deviated from the group response, they were asked to justify why their assessment is correct in contrast to the majority opinion. This assured that only thoughtful statements were given.

5.1.4.5 Consensus and stability measurement

A general procedure for determining consensus in Delphi studies does not yet exist. As a result, several authors leave the interpretation of consensus entirely to the reader (Powell, 2003). In this study, consensus was defined a priori as an interquartile range (IQR) of 1 or less. The IQR is the absolute value of the difference between the 75th and 25th percentiles, with smaller values indicating higher degrees of agreement. This measure is commonly accepted as an objective and rigorous way to measure consensus in Delphi surveys (Alshehri et al., 2015; Giannarou and Zervas, 2014).

Since the measurement of consensus alone is not sufficient to ascertain if additional rounds are required, the stability of responses between Delphi rounds was also considered. To this end, the Wilcoxon signed-ranks test was performed. This test assesses whether or not there is a difference in expert responses between rounds. A p-value of < 0.05 was considered to be statistically significant.

In addition, the coefficient of variation (CV) difference was determined for each indicator aiming to provide a normalized measure of dispersion. The CV is a dimensionless number and is calculated as the standard deviation divided by the mean. The difference was obtained by subtracting the CV from round 2 from that obtained in round 1. According to Shah and Kalaian (Shah and Kalaian, 2009), a CV difference smaller than 0.2 or 20% indicates that stability was reached, and no further Delphi rounds are required.

5.1.4.6 Statistical analyses

In order to investigate whether or not participants with different professions, work affiliations and levels of knowledge rely on divergent rationalities, the non-parametric Mann-Whitney U and Kruskal-Wallis H tests were conducted. These statistical tests were performed using SPSS Statistics 22, considering a significance level of $p < 0.05$.

Additionally, bootstrap analysis was carried out to assess the reliability and stability of expert's answers. This approach is a Monte Carlo-type data augmentation method, which replaces the original values and generates multiple samples as a proxy to the real sample (Akins et al., 2005). This strategy is robust in estimating statistics such as means and their confidence intervals (Akins et al., 2005; Wakai et al., 2013). In this study, 1000 samples were generated from the first round original results, which contain the largest diversity of responses. If the group judgments fell within the 95% confidence interval of the resampled data, its performance is assumed to be reliable.

5.1.4.7 Index structuration in a focus group

As an extension of the Delphi technique, a focus group (Gibbs, 2012) was conducted to structure the indicators with a mean superior to 3.5 into sub-indexes. The meeting also aimed at discussing the items for which consensus has not been reached and clarify reasons for disagreements. To this end, the most cited experts within the network (Figure 18) were invited to participate. The Mann-Whitney U test was applied to assess the non-participation bias as only 15 were invited to the meeting. For this purpose, the round 2 ratings of the focus group participants were compared with the answers of non-attenders.

During the focus group, the research objectives and results of the Delphi survey were briefly presented. Then, the participants were asked to organize the selected indicators into a hierarchy with sub-indexes of their choice (e.g. social, economic, environmental vulnerability). First, they sorted the indicators individually on a sheet of paper. By soliciting individual sorting schemes, we aimed to avoid the potential bias of experts' responses being influenced by the opinions of others as well as by the pre-existing relationships between them (Frey and Fontana, 1991). Afterwards, the participants verbally put forward their ideas, and when everyone agreed with the sorting scheme, the moderator recorded those on a whiteboard with the support of flash cards. When consensus was not met for a specific decision, the participants were asked to vote by show of hands. All participants were encouraged to contribute to the discussion, which was conducted with minimal intrusion from the researcher.

5.1.5 Results

5.1.5.1 Response rate and experts' characteristics

The response rate was 86.32% and 79.20% in the first and second round, respectively. There was a considerable multidisciplinary among participants' background, which is essential to stimulate discussions, resulting in high quality and highly acceptable solutions than homogeneous groups (Delbecq et al., 1975). Out of the 101 participants, 26.5% are geographers, 24.5% engineers, 19.6% geologists, and the remaining 29.3% have miscellaneous professions (Table 13). Most (56.4%) work at universities, followed by government organizations (31.7%) and research institutes (20.1%). In addition, the vast majority (94.1%) has acquired post-graduate degrees. As expected, no one claimed to have a limited knowledge of flood vulnerability analysis.

No significant differences were found between the characteristics of respondents and non-respondents. Nevertheless, lawyers and social scientists were more likely to drop out of the Delphi process than those from engineering and earth sciences. As expected, participants with reasonable knowledge were more prone to withdraw from the study than the ones with very good knowledge ($U = 732$, $p = .041$).

A total of 9 out of 15 invited experts attended the focus group meeting. To assess bias caused by the limited number or participants, the round 2 ratings of attenders and non-attenders were compared. No statistically significant differences were found for any indicator. However, as the expert connectedness was the criterion for invitation, there is a bias towards participants with 'other' professions ($U = 245$, $p = .026$).

Table 13. Experts' characteristics in the Delphi questionnaire and focus group meeting

Characteristic	1st round n (%)	2nd round n (%)	Drop-out rate n (%)	Focus group n (%)
*Work affiliation**				
Academy	57 (56.4)	43 (44.3)	14 (24.6)	6 (60.0)
Government organizations	32 (31.7)	27 (27.8)	5 (15.6)	1 (10.0)
Research institutes	21 (20.8)	19 (19.6)	2 (9.5)	2 (20.0)
Business/industry	9 (8.9)	6 (6.2)	3 (33.3)	0 (0.0)
NGO	3 (3.0)	2 (2.1)	1 (33.3)	1 (10.0)
Gender identity				
Male	54 (53.6)	44 (55.0)	10 (47.6)	2 (22.3)
Female	47 (46.5)	36 (45.0)	11 (52.4)	7 (77.7)
Education level				
Ph.D.	56 (55.4)	44 (55.0)	12 (21.4)	3 (20.0)
Master	35 (34.6)	28 (35.0)	7 (20.0)	4 (26.7)
Bachelor	4 (4.0)	3 (3.7)	1 (25.0)	1 (6.7)
Lato sensu post-graduation	4 (4.0)	4 (5.0)	0 (0.0)	0 (0.0)
High school	2 (2.0)	1 (1.3)	1 (50.0)	1 (6.7)
*Profession**				
Geography	27 (26.5)	21 (25.9)	6 (22.2)	0 (0.0)
Engineering	25 (24.5)	20 (24.7)	5 (20.0)	3 (18.8)
Geology	20 (19.6)	16 (19.8)	4 (20.0)	0 (0.0)
Others	8 (7.8)	8 (9.9)	0 (0.0)	3 (18.8)
Architecture	5 (4.9)	4 (4.9)	1 (20.0)	2 (12.5)
Law	5 (4.9)	2 (2.5)	3 (60.0)	0 (0.0)
Social sciences and service	4 (3.9)	2 (2.5)	2 (50.0)	1 (6.3)
Biology	3 (2.9)	3 (3.7)	0 (0.0)	0 (0.0)
Economy	3 (2.9)	3 (3.7)	0 (0.0)	0 (0.0)
Meteorology	2 (2.0)	2 (2.5)	0 (0.0)	0 (0.0)
Self-reported knowledge of flood vulnerability analysis				
Limited	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)
Reasonable	43 (42.6)	31 (38.8)	12 (27.9)	3 (33.3)
Very good	58 (57.4)	49 (61.3)	9 (15.5)	6 (66.7)

* Participants could select more than one work affiliation and profession. Only the professions that were mentioned twice are shown here. The remaining was grouped in the 'others' category.

5.1.5.2 Delphi questionnaires

In the first round, the participants suggested the inclusion of 67 indicators in addition to the initial 26. Some items, although pertinent, are difficult to measure meaningfully such as ‘risk perception’ and ‘effectiveness of disaster prevention agencies’, limiting their use in data-scarce environments. Moreover, 43 indicators were mentioned only once and were related to hazard aspects (e.g. proximity to a river, intensity of floods) or were too generic (e.g. political-institutional vulnerability). Thus, to keep the resulting list manageable and avoid introducing bias, only the items that were cited by at least 4 experts were included in the second round. Hence, the indicators ‘escape routes’ and ‘evacuation drills and training’ were added to the questionnaire. Furthermore, the items ‘overpopulation’ and ‘education level’ were excluded since, according to more than 10 experts, they are redundant.

Overall, the highest rated items were ‘social hot spots’, ‘disaster prevention institutions’ and ‘population density’ (Table 14). Both indicators added to the second survey were deemed to be important by the majority of experts. Interestingly, variables that are rarely considered in vulnerability studies, such as households with open sewage and without garbage collection, were regarded as relevant. Conversely, the education level and illiterate adults, considered in other indexes (e.g. Guo et al., 2014; Plattner et al., 2006), obtained low mean values. Participants argued that, in some cases, illiterate persons have a better perception of risk than others with formal education. Likewise, the property value received one of the lowest ratings. In Brazil, the floodplain is occupied mainly by impoverished families as these areas are typically undesirable and thus affordable (World Bank, 2012b). Therefore, considering monetary terms can mask the real vulnerability.

There was a decrease in the standard deviation of answers between the 2 rounds for 21 indicators, showing a high congruence between experts. Nevertheless, consensus was not reached for 5 indicators (IQR = 2) (Table 14). This was expected given the wide range of participants and their varying backgrounds. Interestingly, the items in disagreement achieved the lowest scores and were mostly related to social aspects of vulnerability. In some cases, the lack of consensus was due to minor differences in ratings. In others, there were wide disparities in judgments, especially for the indicators gender, environmentally protected areas, and monthly income. In the case of gender, there were divergences even among the experts who rated it as important. For example, the rationale for considering gender as crucial was explained by a participant who wrote: "women are more fragile and linked to their children, requiring assistance in emergencies". Conversely, another panelist mentioned that "women are less vulnerable as they are more cautious and avoid risky situations".

Even though there was a change in panelists' judgments between rounds, the CV difference was still less than 0.2 or 20% for all items (Table 14), indicating that stability of responses was achieved and no further Delphi rounds are required. In addition, the p-values obtained from Wilcoxon signed-rank were higher than 0.05 for 23 out of 26 indicators. This shows that there was no statistically significant difference in expert responses between rounds for the majority of indicators. Therefore, we decided to terminate the Delphi survey and clarify the disagreements in a focus group meeting given that a large number of rounds may cause participant fatigue with steep dropout rates (Schmidt, 1997).

A comparison of the opinion shift between rounds according to the declared knowledge of vulnerability analysis revealed that respondents with less knowledge modified their judgments more towards the group median. Indeed, only 10% of the opinions given by experts with good knowledge were modified, against 15% of the responses provided by participants with reasonable knowledge. Regarding the indicators' ratings, no significant differences by level of knowledge were found, except for 2 items in round 1, and 5 items in round 2 (Figure 19). In general, experts with reasonable knowledge tended to emphasize the importance of those items. Furthermore, the deviation of their answers was lower (mean SD = 0.82) when compared to the participants with very good knowledge (mean SD = 0.94).

Table 14. Results of the Delphi survey for prioritizing vulnerability, coping capacity and exposure indicators

Indicator	Round 1 (n = 101)				Round 2 (n = 80)				CV	p-value*	Outcome
	Mean	95% CI	SD	IQR	Mean	95% CI	SD	IQR			
Social hot spots	4.66	4.54-4.78	0.61	1	4.79	4.68-4.90	0.50	0	-0.03	.008	selected
Disaster prevention institutions	4.62	4.47-4.77	0.75	1	4.70	4.54-4.86	0.70	0	-0.01	.206	selected
Population density	4.70	4.57-4.84	0.69	0	4.65	4.48-4.82	0.76	0	0.01	.414	selected
Building material	4.56	4.43-4.70	0.67	1	4.63	4.50-4.76	0.58	1	-0.02	.112	selected
Persons with disabilities	4.49	4.35-4.64	0.73	1	4.57	4.40-4.74	0.76	1	-0.01	.083	selected
Age (children and elderly)	4.47	4.32-4.62	0.76	1	4.56	4.39-4.72	0.75	1	0.00	.166	selected
Escape routes**	-	-	-	-	4.56	4.38-4.74	0.80	1	-	-	selected
Critical infrastructure	4.41	4.24-4.58	0.87	1	4.55	4.37-4.73	0.83	1	-0.03	.016	selected
Evacuation drills and training**	-	-	-	-	4.54	4.38-4.70	0.70	1	-	-	selected
Density of buildings	4.43	4.25-4.61	0.90	1	4.44	4.21-4.66	1.01	1	0.01	.885	selected
Cost of flood damage	4.29	4.08-4.50	1.05	1	4.37	4.14-4.60	1.03	1	0.00	1.00	selected
Distance to shelters	4.29	4.12-4.46	0.85	1	4.34	4.16-4.52	0.81	1	-0.01	.458	selected
Economic activities	4.24	4.07-4.43	0.90	1	4.20	3.99-4.42	0.95	1	0.01	.159	selected
Health care facilities	4.15	3.98-4.33	0.87	1	4.20	4.01-4.39	0.83	1	-0.02	.297	selected
Households with open sewage	4.12	3.92-4.32	0.99	1	4.14	3.92-4.36	0.98	1	-0.01	.206	selected
Households with accumulated garbage	4.05	3.84-4.26	1.04	2	4.01	3.78-4.24	1.04	1	-0.01	.480	selected
Environmentally protected areas	3.91	3.69-4.12	1.07	2	3.83	3.60-4.07	1.03	2	-0.01	.260	selected
Monthly per capita income	3.71	3.49-3.94	1.13	2	3.73	3.48-3.97	1.08	2	-0.03	.809	selected
Illiterate adults	3.49	3.30-3.68	0.97	1	3.44	3.23-3.64	0.91	1	-0.01	.685	excluded
Households without electric power	3.56	3.35-3.77	1.04	1	3.43	3.22-3.63	0.94	1	-0.01	.124	excluded
Cultural heritage	3.28	3.04-3.53	1.21	2	3.18	2.90-3.47	1.23	2	0.00	.068	excluded
Recent immigrants	3.01	2.78-3.24	1.16	2	3.09	2.83-3.34	1.14	2	-0.02	.100	excluded
Unemployment	3.10	2.87-3.33	1.18	2	2.99	2.72-3.25	1.17	2	0.00	.033	excluded
Gender	2.76	2.52-3.01	1.24	2	2.64	2.39-2.89	1.13	1	-0.03	.164	excluded
Property value	2.68	2.46-2.90	1.08	2	2.60	2.35-2.85	1.09	1	-0.01	.480	excluded
Race	2.01	1.78-2.24	1.15	2	1.81	1.59-2.04	1.02	1	-0.01	.107	excluded
Overpopulation***	4.32	4.14-4.50	0.90	1	-	-	-	-	-	-	excluded
Education level***	3.54	3.34-3.75	1.02	1	-	-	-	-	-	-	excluded

*p-value obtained through the Wilcoxon signed-rank test; **Indicators included in the 2nd round; ***Indicators excluded in the 2nd

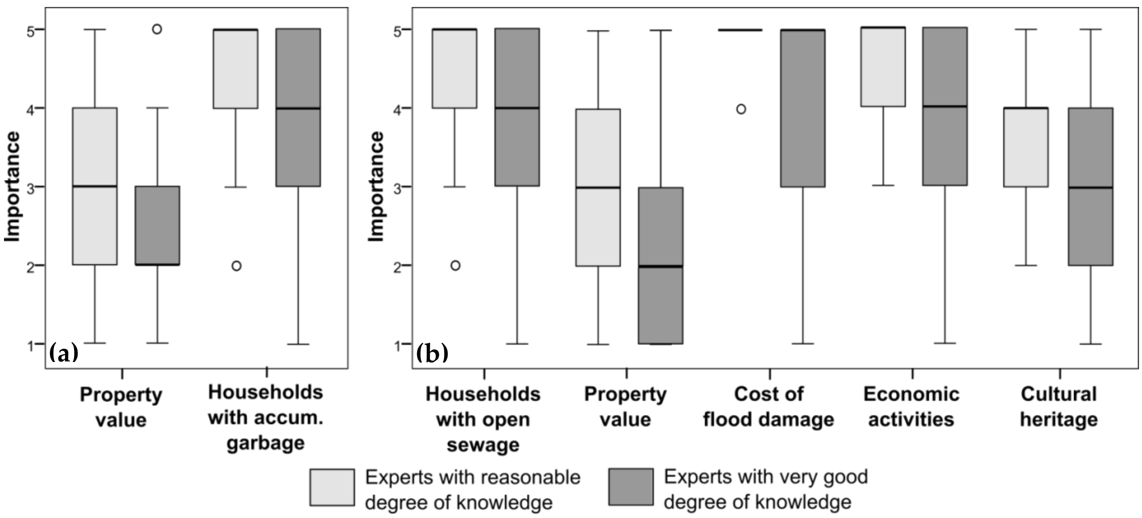

Figure 19. Indicators for which there is a difference in ratings according to the experts' degree of knowledge of flood vulnerability analysis. (a) round 1: property value (U = 770.50, p = .014); and households with accumulated garbage (U = 964, p = .039); (b) round 2: households with open sewage (U = 553, p = .029); cost of flood damage (U = 452.5, p = .022); property value (U = 459, p = .016); economic activities (U = 513.5, p = .012); and cultural heritage (U = 658, p = .395)

Although flood vulnerability assessments are used differently according to the work purpose (e.g., civil defense, insurance companies, and academy), there were no differences between the ratings of participants with distinct work affiliations in both rounds. Likewise, no statistically significant associations were found according to the experts' profession, except for 3 indicators in round 1. In general, geographers tend to think that the income is more important than engineers (p = .013). Moreover, experts from social sciences seemed more concerned about the item social hot spots than participants with miscellaneous professions (p = .020). Regarding the building material, both geologists and experts from social sciences agreed that the material used has a high influence in the physical vulnerability when compared with engineers (p = .017).

Bootstrap analysis was performed to derive estimates of mean and confidence intervals (CI) in a computer-generated sample of 1000 responses. As shown in Table 15, the Delphi results remained stable after resampling the round 1 original data. In general, the generated 95% CI overlapped with the initial values (Table 14), with the CI in the augmented sample being more compact. The mean and standard deviation exhibited stability, which indicates that the results are plausible approximations of what might be found if a sample of 1000 experts was used. Based on this, it is reasonable to assume that the 101 participant's opinions are representative of that of their colleagues.

Table 15. Descriptive statistics of the computer-generated sample (n = 1000) obtained by bootstrapping the round 1 results. The mean and CI intervals that do not overlap with the original data are highlighted

Indicator	Mean	95% CI	SD
Population density	4.70	**4.55** - 4.82	0.69
Social hot spots	4.66	4.55 - 4.77	0.61
Disaster prevention institutions	4.62	**4.45** - 4.75	0.75
Building material	4.56	4.43 - 4.69	0.67
Persons with disabilities	4.49	4.35 - 4.63	0.73
Age (children and elderly)	4.47	**4.32** - 4.61	0.76
Density of buildings	4.43	**4.24** - 4.61	0.90
Critical infrastructure	4.41	4.24 - 4.55	0.87
Overpopulation	4.32	4.15 - 4.49	0.90
Cost of flood damage	4.29	4.08 - 4.49	1.05
Distance to shelters	4.29	**4.10** - 4.45	0.85
Economic activities	**4.25**	**4.04** - 4.42	0.90
Health care facilities	4.15	**3.96** - 4.31	0.87
Households with open sewage	4.12	3.92 - 4.32	0.99
Households with accumulated garbage	4.05	**3.83** - 4.24	1.04
Environmentally protected areas	3.91	3.69 - 4.11	1.07
Monthly per capita income	3.71	3.49 - 3.94	1.13
Households without electric power	3.56	3.36 - 3.75	1.04
Education level	3.55	3.34 - 3.75	1.02
Illiterate adults	3.49	3.30 - 3.66	0.97
Cultural heritage	3.28	3.05 - **3.54**	1.21
Unemployment	3.10	**2.84** - **3.31**	1.18
Recent immigrants	3.01	**2.77** - 3.23	1.16
Gender	2.76	**2.50** - 3.00	1.24
Property value	2.68	2.46 - 2.88	1.08
Race	2.01	1.80 - 2.23	1.15

5.1.5.3 Focus group

After the Delphi survey, a focus group was conducted, aiming to distribute the selected indicators into sub-indexes. Based on the discussions, the indicators were organized into a framework with 7 sub-indexes and 2 main indexes, one encompassing the vulnerability and the other the exposure (Table 16). In addition, the indicator 'age' was split into 2 items, one focusing on elderly and the other on children. Based on the suggestions, the wording of some indicators was fine-tuned.

Table 16. Organization of the indicators into sub and main indexes and metrics used to measure them

	Sub-index	Mean	Indicator	Metric
Vulnerability	Social vulnerability	4.35	Persons under 12 years	persons/km²
			Persons over 60 years	persons/km²
			Persons with disabilities	persons/km²
			Monthly per capita income	R$
	Physical/ infrastructure vulnerability	4.26	Households with improper building material	percentage
			Households with accumulated garbage	percentage
			Households with open sewage	percentage
	Coping capacity	4.47	Disaster prevention institutions	inst. /km²
			Evacuation drills and training	drills./km²
			Distance to shelters	meters
			Existence of marked escape routes	location
			Health care facilities	facilities/km²
Exposure	Human exposure	4.65	Population density	persons/km²
	Environmental exposure	3.83	Environmentally protected areas	location
	Socioeconomic exposure	4.28	Economic activities	location
			Cost of flood damage	R$
	Infrastructure exposure	4.59	Critical infrastructure (water and sewage treatment plants, power plants, hospitals, roads, bridges)	location
			Social hotspots (hospitals, schools, daycare centers, retirement homes)	location
			Density of buildings	build./km²

As the focus group participants share a similar background and expertise (Table 13), there was agreement for most decisions taken. Nevertheless, some experts argued that the item 'population density' could also be included in the social vulnerability sub-index. However, the majority agreed that the population density is an indicator of exposure, which is consistent with other studies (e.g. Li et al., 2013; Zou et al., 2013).

The coping capacity was included in the vulnerability index since according to the participants vulnerability is, among other things, the result of a lack of capacity. Within this context, the coping capacity was regarded as the most important sub-index of vulnerability, which reflects its significance to reduce flood damages. Regarding the exposure, the participants prioritized the human and infrastructure aspects over the environmental exposure. According to them, risk management should focus on the potentially affected population as human lives are the most important goods to protect.

Table 16 also shows the metrics for measuring the indicators based on the outcomes of the focus group. The spatial data needed to represent these variables can be obtained mainly through the Brazilian National Census (IBGE, 2010). The remaining can be acquired in other national databases (e.g. S2ID DATASUS) or can be mapped based on reports from municipal, regional or state Civil Defenses.

5.1.6 Discussion

The main goal of this study was to incorporate the knowledge from scientists, policy makers and practitioners in the prioritization of a set of indicators to analyze flood vulnerability, coping capacity and exposure in the Taquari-Antas river basin. Given that selecting indicators in a systematic, interdisciplinary, and transparent way was central to this study, the Delphi technique was used. This method is a widely accepted approach for achieving convergence of opinions when consensus is lacking and when the only alternative available is an anecdotal approach (Linstone and Turoff, 2002).

Based on extensive stakeholder engagement, 19 indicators that are regularly measured in the study area were selected. The spatial data needed to represent them can be obtained through the Brazilian National Census and other databases. Thus, in contrast to quantitative methods such as curves and damage matrixes, composite indicators are fairly flexible. They can be adapted to use only the existing information, which is appealing to data-scarce environments (Nasiri et al., 2016). In addition, they are easy to interpret and use by stakeholders. This may help to optimize the allocation of limited financial resources, enabling the decision maker to prioritize detailed quantitative assessments for critical areas.

The focus group contributed to the organization of the indicators into a framework with 7 sub-indexes and 2 main indexes. Within the vulnerability index, the coping capacity sub-index was given the highest importance, which reflects the growing tendency to widen up the concept of vulnerability to incorporate the ability of systems to face disasters (Birkmann, 2006). According to Cardona and van Aalst (Cardona et al., 2012) until recently, vulnerability studies tended to ignore the coping capacity, focusing too much on the negative aspects of vulnerability. Nevertheless, recent papers recognize the ability of organizations and people to reduce the risk (Parsons et al., 2016; Roy and Blaschke, 2015), acknowledging that people are not 'helpless victims'. Local citizens and organizations can act as important agents to reduce the adverse consequences of floods, thus diminishing their passive dependency from the relief offered by outsiders.

Regarding the exposure index, there was an agreement among the panel that humans and infrastructure are the most important elements at risk. Special attention was given to social hotspots, which comprehends hospitals, schools, daycare centers, and retirement homes. These facilities, if affected by floods, would have a high impact on the community as they provide a variety of services. Also, they concentrate vulnerable persons such as children, elderly, or chronically ill people (Meyer et al., 2009).

Interestingly, the items 'households with open sewage' and 'households with accumulated garbage', deemed to be important in this study, have not been reported as relevant in previous vulnerability indexes. Nevertheless, 54.3% of the sewage is not piped in Brazil (IBGE, 2011), and the solid waste is commonly accumulated on the street in poor neighborhoods. As a result, outbreaks of water-related diseases such as leptospirosis are common after floods (Barcellos and Sabroza, 2001). The uncollected waste not only causes damage through the spread of diseases, but it is also a key contributor to localized urban flooding due to the obstruction of culverts and drains (Douglas et al., 2008). Thus, these variables play a crucial role in vulnerability assessment in the study area.

In contrast with previous studies, commonly used indicators were regarded as trivial, including property value (e.g. Kubal et al., 2009; Lee et al., 2015; Scheuer et al., 2011), education level (e.g. Guo et al., 2014; Kandilioti and Makropoulos, 2012; Kienberger et al., 2009; Plattner et al., 2006), illiterate adults (e.g. Roy and Blaschke, 2015; Saxena et al., 2013), and gender (e.g. Guo et al., 2014; Sowmya et al., 2015). These findings are consistent with those of Wachinger et al. (2013), which emphasize that formal education and gender do not play such an important role as a primary predictor of disaster preparedness. The role of gender in short-term flood vulnerability spawns controversy. In this sense, Cutter et al. (2006) highlight that there is no empirical evidence to support or reject the hypothesis that gender affects the risk perception significantly, and in that case, towards which direction. Indeed, historical data on flood fatalities reveal that men are also vulnerable (Ashley and Ashley, 2008; Fitzgerald et al., 2010) due to risk-taking behavior and a higher proportion of males who work for the emergency services (Jonkman and Kelman, 2005). This controversy was also observed in the questionnaire results. While some participants argued that women are more concerned about the risk and thus are more cautious than man, others claimed that women are more exposed to floods as many of them stay at home with their children and elderly relatives. Nevertheless, several participants pointed that there is no statistical data available regarding gender of the flood victims in Brazil to support their claims.

Regarding the property value, several experts argued that it can mask the real vulnerability in developing countries. Also, according to their experience, citizens without formal education may have a qualified perception of risk through previous experience with floods and participation in community training (Muttarak and Pothisiri, 2013). We believe experts gave an unimportant score to education level and illiteracy because in Brazil risk is commonly mapped using collaborative and participatory approaches (e.g. de Brito et al., 2014; Favero et al., 2016; Hirata et al., 2013). In such studies, indigenous and scientific knowledge are integrated to assess the risk. This intense contact with the affected communities may have changed the participants' perception of the relevance of formal education to reduce the vulnerability and the ability of people to cope with floods.

The Delphi process allowed participants to change their views in a non-threatening, anonymous manner, which led to a decrease in the standard deviation of answers between rounds for 21 indicators. This demonstrates that a change in the understanding of vulnerability has taken place. Among our sample, interesting distinctions were noted when opinion shifts between groups with different levels of knowledge were compared. Participants with less expertise tended to modify more their answers in the direction of the group median. Likewise, experts with very good knowledge were not willing to adjust their ratings, thus enhancing their influence in the final results. This is in agreement with the findings of Elmer et al. (2010), who states that experts tend to be based on solid experience and therefore, may be reluctant to change their views.

Several authors claim that the interpretation of vulnerability varies across disciplines (Fuchs et al., 2012; Godfrey et al., 2015a). In this sense, Fuchs (2009) argues that social scientists tend to view vulnerability as a set of socio-economic factors that determine people's ability to cope with disasters. Conversely, engineers often view vulnerability in terms of the likelihood of occurrence of specific hazards, and its associated impacts on the built environment. Nevertheless, neither profession nor affiliation institution seemed to affect experts´ perception of flood vulnerability, showing that they do not rely on divergent rationalities. Only punctual differences were identified in the first round of the questionnaire. Hence, even though the members of the expert panel have diverse backgrounds, it is reasonable to assume that they are part of the same group. The differences between the ratings depend more on the internal mental states of the respondents, such as their experiences and beliefs (Wedgwood, 2002), than their working field or profession.

A mutual understanding between participants was achieved on 21 indicators, lending legitimacy and credibility to the index. Nevertheless, due to the diversity of viewpoints and schools of thought, the experts disagreed on 5 items. There were multiple understandings underpinning the indicators 'monthly income', 'recent immigrants' and 'unemployment'. However, the divergence among participants should not be mistaken for lack of robustness. The tendency in conventional studies is to omit or even deny differences (Stirling and Mayer, 2001). Still, we believe that documenting contrasting views and systematically showing underlying reasons for different interpretations is a more transparent approach.

The stability and reliability of the findings were investigated by examining the sensitivity of the ratings by resampling the original data. Bootstrap analysis showed that the participant's opinions are representative of that of their colleagues. This, combined with the high response rate, makes the Delphi results particularly robust, decreasing the likelihood that the findings are compromised by nonresponse error. Furthermore, the investigation of the non-respondents characteristics showed that there was no bias concerning work affiliation, profession or education level.

A major criticism of the developed index is that, in its current state, the interconnectedness of the indicators is neglected. As highlighted by Fuchs (2009) the dimensions of vulnerability have diverse and complex linkages among each other. For instance, the monthly per capita income affects the percentage of households with improper building material, which in turn influences the existence of open sewage. Therefore, multi-criteria decision-making (MCDM) tools which consider the interdependence between variables such as the DEMATEL (decision-making trial and evaluation laboratory) and ANP (analytic network process) should be used to aggregate the individual indicators into a composite index. The use of these tools allows capturing the complex relationships among vulnerability drivers in a transparent way.

Another limitation is that since the developed framework has not yet been formally implemented in a real case study, it is difficult to assess its practical suitability. Thus, in later stages of this research, potential redundancies will be evaluated by measuring the indicators at several locations and subsequently applying principal component analysis (Abdi and Williams, 2010). The indicators layers will then be combined into a single composite index in a GIS environment, which will enable the generation of flood vulnerability and exposure maps. In the end, expert and end user validation will be carried out to evaluate the model's usefulness.

Regarding the external validity, the final index can be easily implemented in other Brazilian watersheds with similar conditions. However, as it represents the perspective of experts working in Brazil, the findings cannot be generalized to other countries without adaptations. Additionally, the outcomes of any consensus process may differ with a distinct panel of experts. Therefore, further studies are needed to create generalizable and universally applicable vulnerability and exposure indexes. Such studies could benefit from the use of group decision-making tools such as the real-time Delphi survey (Gnatzy et al., 2011), nominal group technique (Maynard and Jacobson, 2017), and multi-voting approaches (Bens, 2005), in which stakeholders work together to consider and evaluate alternative courses of action.

Even though the Delphi technique is a widely used and accepted method, it is important to emphasize that its results represent a group of experts' opinions rather than unquestionable facts. Thus, the results obtained are only valid as the judgments of the participants who made up the panel (Yousuf, 2007). A further drawback of using a questionnaire approach is that it may slow the prioritization of indicators in contrast to commonly used practices. Nevertheless, as argued by Krueger et al. (Krueger et al., 2012), participation makes the results more salient, reliable and better understood by decision makers and practitioners. Moreover, participatory approaches play a heuristic role in enabling wider social learning (Ravera et al., 2011), giving legitimacy and credibility to the final index.

5.1.7 Conclusions

While there has been much discussion on the development of flood vulnerability, coping capacity, and exposure indicators, the selection of input criteria has largely been based on personal experience and anecdotal evidence. Even when participation of multiple stakeholders is undertaken, the consensus between them is rarely considered. Nevertheless, in order to assess flood risk, it is essential to understand what vulnerability entails according to those who are involved in disaster risk management. Hence, this study is timely in describing a feasible and systematic method to reach agreement about relevant indicators by soliciting the perspectives of local practitioners, policymakers, and scientists. The participatory Delphi survey combined with the in-person focus group proved to be an effective way of stimulating and facilitating the interaction of experts. This approach seems viable for creating flood-related indexes for other areas as well as for other types of hazards. Its main advantage refers to the capacity to bring together different perspectives towards social learning and, therefore, to ensure that the final set of indicators fulfills the requirements of the involved actors.

As a result of the interactive and participatory Delphi process, an understanding of 19 indicators that can influence the vulnerability and exposure was developed among the stakeholders. The agreed indicator set comprises 12 vulnerability and 7 exposure indicators. In general, the results confirm that coping capacity is a key determining aspect of vulnerability since, contrary to the hazard, it can often be influenced by policy and practice. As such, more emphasis should be placed on assessing the capacity of people to face disasters as its improvement will eventually lead to a reduced risk. Regarding the exposure, there was a strong consensus among the panel that besides the human exposure it is particularly important to consider the infrastructure exposure, especially the location of social hot spots.

The second aim of this study was to test whether experts with different backgrounds and levels of knowledge rely on divergent rationalities. Despite the fact that some researchers found evidence of contrasting views according to different professional groups, we did not identify a clear link between the indicators ratings and professions, work affiliation, and level of knowledge. Hence, it is reasonable to assume that the participants belong to a common group or population. Nevertheless, experts with a higher degree of self-reported knowledge were more persistent in their opinions, thus having a stronger influence on the final results compared to experts with reasonable knowledge.

The innovation stemming from this study lies in the combination of the Delphi technique with bootstrap analysis, and an in-person focus group for developing indicators in a more transparent way. From a practical standpoint, this research provides decision makers with an initial set of indicators to better understand the flood impacts in the Taquari-Antas river basin. The develop index will serve as a foundation for the development of vulnerability, coping capacity, and exposure maps, which will help contextualize flood risk in the study area. We expect that incorporating the knowledge from practitioners, scientists and decision makers in the creation of the index will enable it to reflect the local context properly and gain legitimacy among end users.

5.2 Participatory flood vulnerability assessment: a multi-criteria approach (Paper 3)

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5.2.1 Abstract

This paper presents a participatory multi-criteria decision-making (MCDM) approach for flood vulnerability assessment while considering the relationships between vulnerability criteria. The applicability of the proposed framework is

demonstrated in the municipalities of Lajeado and Estrela, Brazil. The model was co-constructed by 101 experts from governmental organizations, universities, research institutes, NGOs, and private companies. Participatory methods such as the Delphi survey, focus groups, and workshops were applied. A participatory problem structuration, in which the modellers work closely with end users, was used to establish the structure of the vulnerability index. The preferences of each participant regarding the criteria importance were spatially modelled through the analytic hierarchy process (AHP) and analytic network process (ANP) multi-criteria methods. Experts were also involved at the end of the modelling exercise for validation. The final product is a set of individual and group flood vulnerability maps. Both AHP and ANP proved to be effective for flood vulnerability assessment; however, ANP is preferred as it considers the dependences among criteria. The participatory approach enabled experts to learn from each other and acknowledge different perspectives towards social learning. The findings highlight that to enhance the credibility and deployment of model results, multiple viewpoints should be integrated without forcing consensus.

5.2.2 Introduction

The management of flood risk calls for a better understanding of vulnerability, as hazards only become disasters if they impact a community or system that is vulnerable to their effects (Reilly, 2009). In other words, the vulnerability of the exposed elements will determine whether the hazard will translate into a disaster (Birkmann et al., 2014). Nevertheless, while the understanding of flood hazard has greatly improved over the last decades, the knowledge of vulnerability remains one of the biggest hurdles in risk analysis and improving its assessment is seen as the “missing link” for enhancing our understanding of risk (Jongman et al., 2015; Koks et al., 2015).

In general, vulnerability refers to the physical, social, economic, and environmental conditions, which increase the susceptibility of the exposed elements to the impact of hazards (UNISDR, 2009). Since vulnerability is not directly measurable, several methods have been proposed to estimate it including damage curves (Merz et al., 2010; Papathoma-Köhle, 2016), fragility curves (Ozturk et al., 2015; Tsubaki et al., 2016), and vulnerability indicators (Cutter et al., 2003; Roy and Blaschke, 2015). Both damage and fragility curves are building type-specific and focus on the physical vulnerability of structures to a certain hazard, neglecting the social vulnerability and coping capacity of the inhabitants (Koks et al., 2015). Nevertheless, the ability of a society to anticipate, cope with, and recover from disasters is equally important to assess floods potential impacts. Consequently, several authors emphasize the need for a holistic understanding of vulnerability by integrating its different dimensions in an overarching framework through the use of indicators (Birkmann et al., 2013; Fuchs et al., 2011; Godfrey et al., 2015b).

Indicator-based methods are transparent and easy to use and understand (Ciurean et al., 2013). Since they do not require detailed data as damage and fragility curves, flood vulnerability indicators have been extensively deployed to assess the social vulnerability (Fekete, 2009; Frigerio and de Amicis, 2016), socioeconomic vulnerability (Kienberger et al., 2009), and physical vulnerability (Godfrey et al., 2015b; Kappes et al., 2012), as well as to combine multiple dimensions of vulnerability (Roy and Blaschke, 2015; Vojinovic et al., 2016).

Despite the broad variety of motivation and practice, a number of challenges remain in the development of vulnerability indices as modellers are faced with multiple legitimate choices, thus introducing subjectivity into the modelling process. Key challenges include (1) selection of the input criteria, (2) data standardization, (3) determination of criteria importance, (4) consideration of relationships between them, and (5) results validation (Beccari, 2016; Müller et al., 2011; Rufat et al., 2015). Typically, the rationale for decisions regarding criteria selection, weighting, and aggregation is either unstated or justified based on choices made in previous studies. In several cases, no justification is provided at all and the decisions are restricted to project members (Rufat et al., 2015). Surprisingly, notwithstanding the different levels of importance of the criteria, the vast majority of vulnerability indices employ an equal weighting (Tate, 2012). Also, even though the dimensions of vulnerability have diverse and complex linkages among each other (Fuchs, 2009), the relationships between criteria are often neglected and they are assumed to be independent (Chang and Huang, 2015; Rufat et al., 2015). Thus, considering the relationships between vulnerability criteria, their importance weights, and explicitly showing the rationale for model decisions could benefit the development of vulnerability indices.

In addition to these issues, the participation of multiple stakeholders in the index construction is usually fragmented and limited to consultation at specific stages. None of the vulnerability indicators reviewed by de Brito and Evers

(2016) systematically promoted an active participation throughout the entire vulnerability modelling process. Typically, key expert stakeholders were consulted only in the weight assessment step. Critical aspects, such as the selection of the input criteria and data standardization, were usually constrained to researchers conducting the study. However, participation and cooperation are key aspects for bridging the gap between modellers and end users and eventually between science and policy (Barthel et al., 2016; Voinov and Bousquet, 2010). If practitioners are involved in creating an index that they find useful, it is more likely they will incorporate it into policy decisions (Oulahen et al., 2015). Furthermore, better insights can be gained since knowledge beyond the boundaries of an organization is considered. Therefore, a broader and systematic understanding of the problem can be reached, which, in turn, allows for the designing of more effective vulnerability models (Müller et al., 2012).

To tackle these issues, the development of vulnerability indicators could be aided by the use of participatory multi-criteria decision-making (MCDM) tools (Kowalski et al., 2009; Paneque Salgado et al., 2009). MCDM is an umbrella term to describe a set of techniques that can consider multiple criteria to help individuals explore decisions (Belton and Stewart, 2002). The aim of MCDM is not to find a final and optimal solution (Kowalski et al., 2009; Roy, 1985), but to deliver a set of alternatives to better inform decision makers by making subjective judgments explicit in a transparent way. Participatory MCDM refers to a process in which a multi-criteria tool is used within participatory settings, where a group of key experts and stakeholders is actively involved (Paneque Salgado et al., 2009). Participatory MCDM provides a promising and structured framework for integrating interdisciplinary knowledge in an effort to bring credibility to vulnerability indicators, participant satisfaction, and some degree of mutual learning (Sheppard and Meitner, 2005). It can improve the transparency and analytic rigour of flood vulnerability assessment since the choices of input criteria, data standardization, weighting, and aggregation are explicitly expressed, leading to justifiable decisions and reproducible results.

Considering these challenges, we present a participatory approach for assessing the vulnerability to floods by comparing two MCDM methods: the analytic hierarchy process (AHP) and the analytic network process (ANP). We investigate how MCDM tools can be combined with participatory methods to develop vulnerability maps that will be reflective of the local context and trusted by those involved in policymaking. The goal is not to derive a single solution with the "best" flood vulnerability model; instead, our aim is to propose a framework that promotes transparency and integrates contrasting opinions towards social learning. The approach responds to many of the identified challenges, and, to the best of our knowledge, represents one of the first attempts to apply such a systematic and participatory approach for vulnerability assessment while considering the interdependence among the criteria.

5.2.3 Study area

Since vulnerability is site specific (Cardona et al., 2012), the municipalities of Lajeado and Estrela (274.79 km²), southern Brazil, were used as a case study (Figure 20). In 2016, the total population was approximately 112,000 and the GDP per capita was about USD 12,800, with nearly 20% of households living below the poverty line (IBGE, 2017). The regional climate is humid subtropical (Köppen Cfa) and the precipitation is uniformly distributed throughout the year, without a dry season. Rainfall ranges between 1,400 and 1,800 mm per year, with a maximum 24 hours precipitation of 179 mm in 14th April 2011.

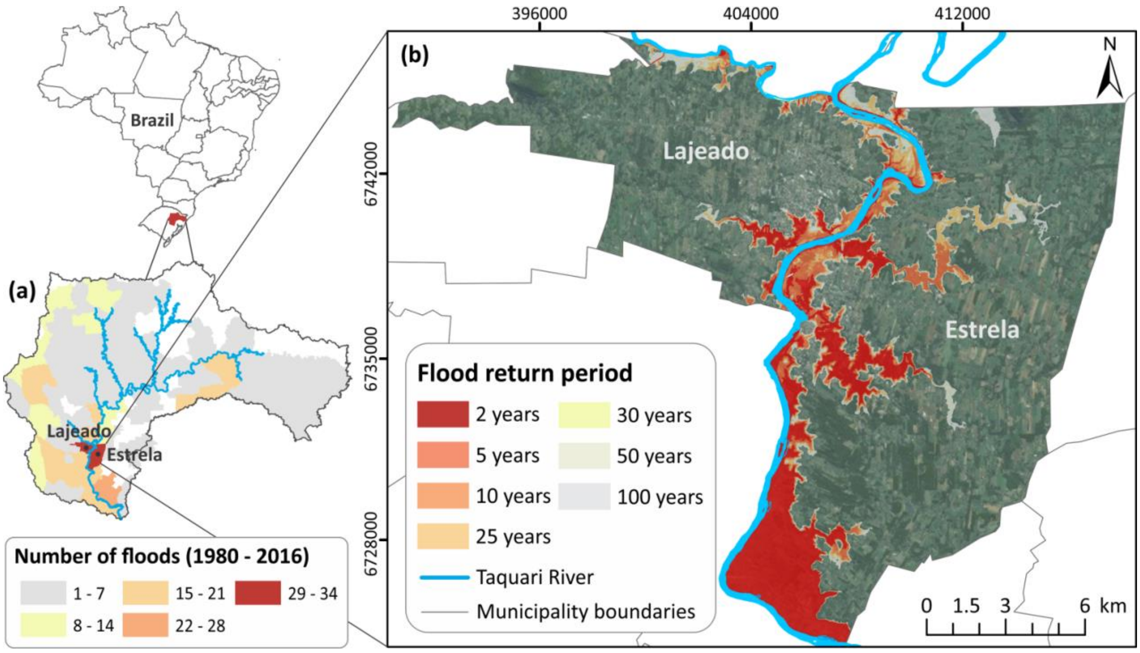

Figure 20. Location of the study area, southern Brazil: (a) number of floods between 1980 and 2016 in the Taquari-Antas River Basin (elaborated based on Bombassaro and Robaina, 2010; MI, 2017); (b) extent of floods with different return periods in the municipalities of Lajeado and Estrela (Fadel, 2015)

The discharge of the Taquari River is characterized by abrupt flow variations, with an average flow of 321 m^3/s and peaks of 10.300 m^3/s (FEPAM, 2010). These fluctuations are caused by the dense and radial drainage pattern, high mean slope and low soil permeability (Siqueira et al., 2016). As a consequence of the torrential regimes of rapid runoff, floods occur almost annually, albeit sometimes twice in a year. Between 1980 and 2016, 32 and 34 flood events were reported in Lajeado and Estrela, respectively (Figure 20a).

Figure 20b shows the extent of floods with different return periods, which correspond to the average period of time that it takes for a flood to recur at a given location. Currently, it is estimated that at least 8,000 persons live in areas with a flood return period of 2 years (CPRM, 2012, 2013). In these areas, floods have a probability of occurrence of 1/2 or 50% in any year. Due to this high susceptibility, the municipalities of Lajeado and Estrela are considered by the Brazilian Government as a priority for disaster risk reduction (CEMADEN, 2017).

5.2.4 Framework for flood vulnerability assessment

The proposed participatory approach for flood vulnerability modelling is summarized in Figure 21. Experts from governmental organizations, universities, NGOs, and private companies were engaged in all key milestones of the index development. In addition, the partial results of the research were iteratively fed back to participants throughout the entire process to serve as a social learning tool. Participatory techniques which encourage open dialogue, such as focus groups and workshops, were used to enable experts to exchange knowledge, and to understand and acknowledge each other's positions. A detailed description of the methodological steps will be provided in the following sections.

5.2.4.1 Identification of relevant experts

In this study, we consider an expert as anyone with an in-depth knowledge of flood vulnerability analysis, acquired through experience or education (Krueger et al., 2012). Based on the snowball sampling technique (Wright and Stein, 2005), 117 Brazilian experts that have extensive practical experience in the field of vulnerability analysis were selected. The actors who were cited by more persons were invited to take part in workshops and focus groups in further steps of the study as they play a central role in terms of their reputation and connectedness.

A social network analysis depicting the linkages between the selected experts is provided by de Brito et al. (2017).

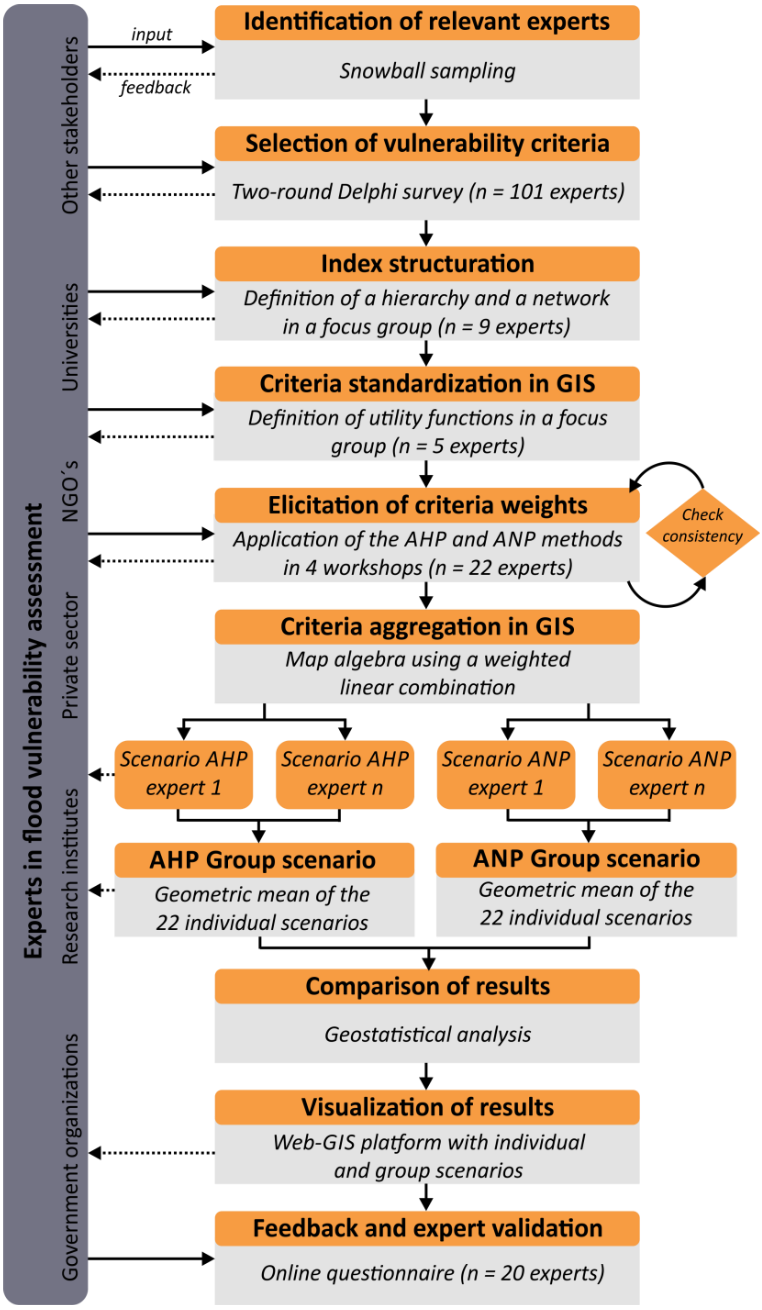

Figure 21. Methodological framework for flood vulnerability assessment. The solid horizontal arrows denote the input given by experts while the dashed arrows indicate the feedback provided to them in the form of partial reports. The number of participants in each step of the index development process is shown in parentheses

5.2.4.2 Selection of vulnerability criteria using the Delphi technique

A two-round Delphi survey was employed to select the input criteria in a systematic and transparent way. The Delphi technique is a structured process for collecting knowledge from a panel of experts using a series of questionnaires interspersed by controlled feedback, seeking to obtain an agreement among the anonymous participants (Linstone and Turoff, 2002). A detailed description of the methods used to prioritize the vulnerability criteria as well as discussion of the results obtained can be found in de Brito et al. (2017).

Based on the Delphi survey, 11 input criteria[2] were selected to be included in the vulnerability index (Table 17). Consensus among participants regarding the relevance of the criteria was reached on all selected criteria, except monthly income. The response rate was 86.32% (n = 101) and 79.20% (n = 80) in the first and second questionnaire, respectively. A description of participants' background, work affiliation and education level can be found in Supplementary Table S2.

Table 17. Selected criteria, their respective data source and metrics used to measure them

Criteria	Consensus*	Metric	Data source
Persons under 12 years	Yes	persons/km²	IBGE (2010)
Persons over 60 years	Yes	persons/km²	IBGE (2010)
Persons with disabilities	Yes	persons/km²	MS (2016)
Monthly per capita income	No	R$	IBGE (2010)
Households with improper building material	Yes	percentage	IBGE (2010)
Households with accumulated garbage	Yes	percentage	IBGE (2010)
Households with open sewage	Yes	percentage	IBGE (2010)
Disaster prevention institutions	Yes	inst. /km²	interviews
Evacuation drills and training	Yes	drills./km²	interviews
Distance to shelters	Yes	metrers	interviews
Health care facilities	Yes	facilities/km²	MS (2016)

*Consensus was defined as an interquartile range of 1 or less. For details see de Brito et al. (2017)

The datasets used to represent the selected criteria were obtained mainly from the Brazilian 2010 Census (IBGE, 2010). Information on the location of persons with disabilities and health care facilities was retrieved from DATASUS (MS, 2016). In addition, interviews were carried out with local civil defence representatives to obtain information on the location of shelters and disaster prevention institutions as well as the number of evacuation drills and training.

[2] Originally, 12 criteria were selected (de Brito et al., 2017). However, the criterion "existence of clearly marked escape routes" was not included in the final model as there are no escape routes in the study area.

All datasets were transformed into 20 m resolution raster files by using the cell centre method (ESRI, 2017).

5.2.4.3 Structuration of the flood vulnerability index

To proceed with the application of the MCDM tools, a conceptual model with the relationships between the selected criteria needs to be created. The AHP method requires the decomposition of the decision problem into a hierarchy with sub-indices (e.g. social, economic). The ANP, on the other hand, uses a network to represent the interaction between criteria and sub-indices. The elements in this network can be related in any possible way as ANP can incorporate feedback and interdependence relationships.

In this study, a focus group discussion (Morgan, 2005) was conducted to build the AHP and ANP conceptual models. In order to allow all participants to contribute equally to the discussion and avoid the disintegration of the group into smaller sub-groups, the participation in the focus group was limited to nine persons. The experts were chosen based on their degree of connectedness, which indicates their perceived level of prestige (see de Brito et al. 2017).

During the meeting, the research objectives and results of the Delphi survey were briefly presented. Then, participants were asked to individually identify the interactions between criteria and organize them into a hierarchy and a network. By soliciting individual schemes, we aimed to avoid the potential bias of experts' responses being influenced by the opinions of dominant persons as well as by the pre-existing relationships between them (Frey and Fontana, 1991). Afterwards, the participants verbally put forward their ideas, and when all agreed with a decision, a moderator recorded those on a whiteboard with the support of flash cards. The use of flash cards, rather than writing directly on the whiteboard, allowed for the criteria to be moved around. When there was no broad consensus among experts for a specific decision, they were asked to vote by show of hands. All participants were encouraged to contribute to the discussion, which was conducted with minimal intrusion from the researcher. The discussion lasted about 4 hours.

5.2.4.4 Criteria standardization

Before aggregating the criterion maps into a GIS environment, they need to be transformed into common units as they are represented by different measurement scales (e.g. metres, density/km^2). As the selected criteria do not have a linear behaviour and since the definition of crisp classes was not desired, we used value functions to standardize the data in a continuous scale. Value functions, also referred to as fuzzy membership functions in the GIS literature (Malczewski and Rinner, 2015), avoid setting hard thresholds by recasting the criterion values into a gradual membership of vulnerability ranging from 0 (no vulnerability) to 1 (full vulnerability).

The value function type and the control points that govern their shape were defined in a focus group with five experts. The original criteria maps were printed to provide a visual representation of the criteria spatial distribution as well as their minimum and maximum values. Based on that, participants were asked to determine the function type (e.g. sigmoidal, J-shaped, linear, or user-defined) and to define wheter the function was increasing, decreasing or if it was symmetric (Smith et al., 2008). Then, the experts had to determine the function control points: a = membership rises above 0; b = membership becomes 1 (full vulnerability); c = membership falls below 1: and d = membership becomes 0 (no vulnerability). Similarly to the first focus group, the experts' preferences were recorded on a whiteboard. When participants disagreed on a particular choice, they were asked to vote by hand. The collaborative group discussion lasted about 2 h.

5.2.4.5 Assigning criteria weights using AHP and ANP

It is widely recognized that vulnerability criteria have different levels of importance (Fekete, 2012; Tate, 2012), but it is difficult to find an acceptable weighting scheme. Indeed, assessing the criteria weights is seen as a sensitive and controversial step in the development of indices. According to Oulahen et al. (2015), an unweighted index is still subjective rather than objective, as it treats all criteria as being equally important. Usually, weights are directly assigned by modellers using implicit judgments. In this study, we used the AHP (analytic hierarchy process) and ANP (analytic network process) multi-criteria methods to elicit experts' preferences about criteria weights. The advantage of using structured techniques refers to transparency and results' reproducibility.

In AHP, a reciprocal pairwise matrix is constructed by comparing the criteria and assigning a relative importance value to its relation according to a nine-point scale (Table 18). This reduces the problem complexity as only two criteria are compared at a time. Once these comparisons are done, the criteria weights are obtained by the principal eigenvector of the matrix (Saaty, 1980).

Table 18. Scale of relative importance used to compare criteria in AHP and ANP (Saaty, 1980)

Numerical rating	Verbal judgment of preferences
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance

AHP is conceptually easy to use; however, one of its underlying assumptions is that the evaluation criteria are independent. This is a rather strong assumption, especially in the context of spatial problems where interactions among criteria exist (Malczewski and Rinner, 2015). As a solution, Saaty (1999) proposed the ANP, which represents the problem as a network of criteria, grouped into clusters. This provides a more accurate modelling of complex settings by considering inner and outer dependences of the criteria. In ANP, similarly to AHP, pairwise comparisons are used to generate matrices of dependent clusters and criteria. The final weights are obtained by using a supermatrix approach. A detailed description of mathematical foundations of ANP and AHP can be found in Saaty (1980, 1999, 2004).

In this study, the hierarchical and network conceptual models were constructed in Super Decisions 2.6.0 software, which automatically created a list with 40 pairwise comparisons needed to run the AHP and ANP evaluations. The AHP comparisons were carried out by asking "which of the two criteria is more important for vulnerability assessment?" while the guiding question in ANP was "which of the two criteria influences a third criterion more with respect to vulnerability assessment?". A questionnaire with these comparisons was prepared in an electronic spreadsheet, and the experts with more connectedness (de Brito et al., 2017) were invited to take part in four workshops to complete the survey. The workshops started with a presentation of the study objectives, methodology, and preliminary findings. Then, each participant was requested to complete the questionnaire with the 40 comparisons using either the verbal or numeric nine-point scale (Table 18). In the case of the ANP method, the participants could remove any connection between criteria they thought to be unnecessary. Once the comparisons were done, the weights were automatically displayed in the spreadsheet together with the consistency ratio (CR). The CR measures the probability that the matrix ratings were randomly generated. If the inconsistency was higher than 10%, the experts were asked to revise their judgments. The workshops lasted about 3 hours each and involved a total of 22 participants.

5.2.4.6 Aggregation of criteria to create flood vulnerability maps

In order to generate the flood vulnerability maps, the standardized criteria were multiplied by the derived weights and subsequently summed. Two scenarios were created for each expert: one with the AHP and the other with the ANP method. In addition, a group scenario was generated by aggregating individual priorities (AIP) using the geometric mean (Ossadnik et al., 2016). The resultant maps were classified into five categories of vulnerability to facilitate their interpretation and comparison: very low (0.00 – 0.20), low (0.20 – 0.40), medium (0.40 – 0.60), high (0.60 – 0.80), and very high (0.80 – 1.00).

5.2.4.7 Comparison of AHP and ANP results

The individual AHP and ANP weights were analysed to investigate whether the experts' preferences were substantially different from each other and the spatial implications of these differences. The interquartile range (IQR), which is commonly accepted as a rigorous way to measure consensus (Giannarou and Zervas, 2014), was used to quantify the degree of conflict between participants regarding the criteria prioritization. The similarities between the individuals were further investigated using cluster analysis with Ward's method (Brusco et al., 2017). In addition, cross-tabulation analysis was conducted to compare the spatial distribution of the AHP and ANP vulnerability maps.

5.2.4.8 Validation

To validate the proposed methodological approach, the opinions of the 22 experts that participated actively in the entire process were collected through a feedback questionnaire. For this purpose, each participant received a report with their own results together with the cluster analysis results. In addition, a Web GIS platform with the 22 individual and group vulnerability scenarios, flood hazard maps, and historical floods was developed. This platform allowed participants to have a comprehensive and synthetic view of their results through a customizable user-friendly graphical interface.

Based on the provided feedback, experts were asked about their satisfaction with: (1) the selected criteria; (2) how the criteria were grouped; (3) the weights obtained through the AHP and ANP techniques; (4) the usefulness of the generated vulnerability maps for their professional activities; (5) the quality of the focus group and workshop discussions (6) the feedback received; (7) the transparency of the process; (8) the participatory process as a whole; and (9) the use of the MCDM approach for integrating interdisciplinary knowledge. A 4-point Likert scale (i.e. very unsatisfied, unsatisfied, satisfied and very satisfied) was used to avoid neutral responses as this scale forces the users to form an opinion (Croasmun and Ostrom, 2011). Participants were also asked to comment on the difficulty of the MCDM tools and what could be improved in future applications.

5.2.5 Results

5.2.5.1 Definition of the structure of the flood vulnerability index

In the first focus group, nine experts (Supplementary Table S2) co-developed the AHP and ANP conceptual models with the relationships between the selected criteria. A three-level hierarchical tree was built for AHP (Figure 22a), where the first layer corresponds to the goal, and the second and third levels correspond to the sub-indices and criteria. Conversely, a network with bilateral relationships was established for the ANP method (Figure 22b), which enables interactions between criteria situated in different clusters and dependences between elements in the same cluster to be considered.

No fundamental disagreements in the organization of the sub-indices were evident during the focus group. Nevertheless, minor divergences occurred in the definition of linkages between criteria on the ANP approach. Despite these challenges, the group succeeded in reaching workable compromises about generic conceptual models that could be used.

The findings of criteria grouping are well aligned with current guidance on vulnerability (Beccari, 2016; Cardona et al., 2012), highlighting the importance of coping capacity, as vulnerability is, among other things, the result of a lack of capacity. An emphasis was given to infrastructure aspects which are rarely considered in vulnerability indices such as the existence of open sewage and accumulated garbage on the street. These criteria play a crucial role in vulnerability assessment in the study area as 54% of the sewage is not piped in Brazil (IBGE, 2011), and the solid waste is commonly disposed in the open environment in poor neighbourhoods. This causes not only the spread of diseases after floods but is also a key contributor to localized flooding.

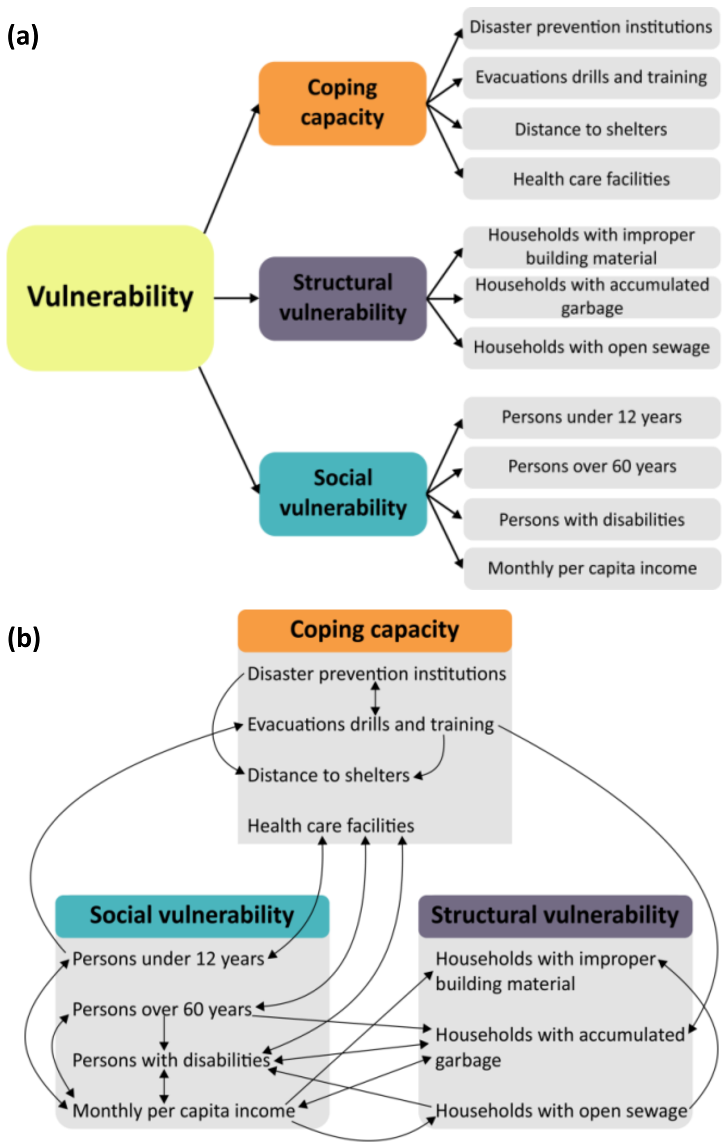

Figure 22. Conceptual models of the flood vulnerability index: (a) AHP hierarchical tree; (b) ANP network, where the arrow direction indicates the interdependence relationships between criteria. A single-direction arrow shows the dominance of one criterion by another. A double-direction arrow shows the mutual influence between them

5.2.5.2 Data standardization

A shared understanding of the value functions and control points used to standardize the criteria was achieved via a focus group with five experts. Due to the small number of participants and since they share a similar background and expertise (Supplementary Table S2), there was an agreement for most decisions taken. Increasing value functions were selected for all social and structural vulnerability criteria, except for the monthly income (Figure 23). Conversely, as a higher coping capacity leads to a reduced vulnerability, decreasing functions were used for coping capacity criteria.

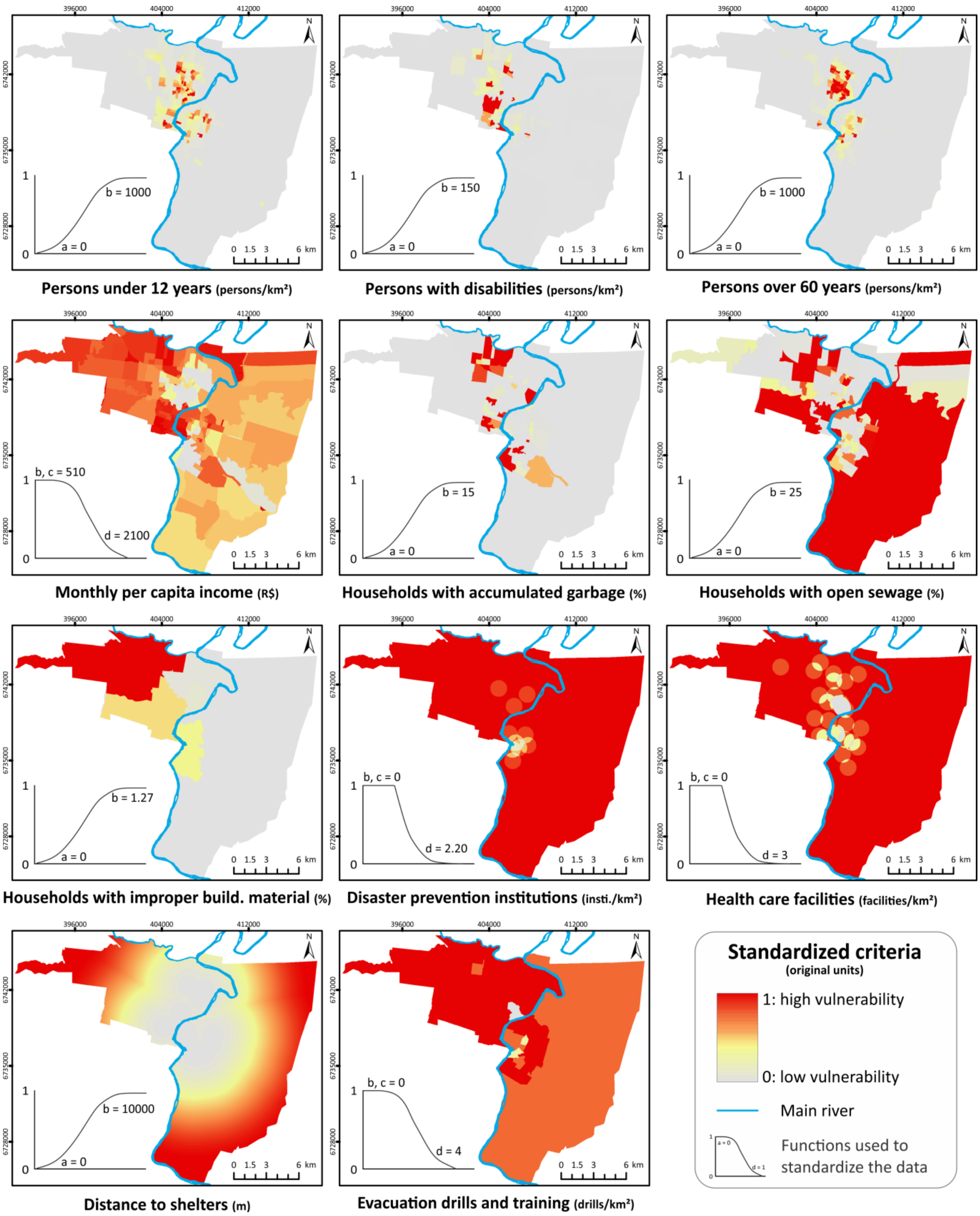

Figure 23. Standardized criteria maps, utility functions and control points that govern their shape (a = membership rises above 0; b = membership becomes 1; c = membership becomes 0). The original units used to represent the criteria are shown in parentheses

5.2.5.3 Comparison of AHP and ANP group results

A total of 22 experts attended the workshops designed to complete the AHP and ANP questionnaires (Supplementary Table S2). Overall, the participants had no problems completing the survey. However, due to the large number of pairwise comparisons, some answers needed to be revised as they were contradictory, especially in relation to the AHP technique as the comparison matrices had more elements.

The weights derived from the two techniques were similar, except for the monthly per capita income (Table 19). In both methods, the percentage of households with improper building material was the most relevant criterion, closely followed by the number of evacuation drills and other types of training. This importance is partly explained by the high weights attributed to the coping capacity sub-index, which reflects the tendency to widen up the concept of vulnerability to incorporate the ability of the society to face disasters (Birkmann, 2006), acknowledging that people are not 'helpless victims'.

Agreement among experts about criteria weights, measured as an IQR of 20% or less, was achieved only for a few variables. In general, the IQR values were lower in the ANP model, indicating higher levels of consensus. The monthly per capita income was the most controversial criterion in the AHP technique and there was a significant divergence among experts about the building material criterion in the ANP model.

Table 19. Group criteria weights and their respective standard deviation (SD) and interquartile range (IQR). An IQR of 20% or less indicates consensus; 20-30% indicates moderate divergence; 30-40% significant divergence; and >40% strong divergence

Sub-index	AHP weight	Criteria	AHP results			ANP results		
			weight	SD	IQR	weight	SD	IQR
Social vulne-rability	30.64	Persons under 12 years	6.80	4.47	10.20	4.37	4.01	8.26
		Persons over 60 years	6.64	4.17	17.68	3.96	2.70	6.30
		Persons with disabilities	9.39	9.97	23.03	8.84	7.51	19.30
		Monthly per capita income	7.81	10.69	52.87	13.49	8.05	13.90
Structural vulne-rability	28.68	Households with improper building material	14.61	9.54	34.39	15.06	10.15	28.66
		Households with accumulated garbage	6.97	7.17	28.01	7.20	7.92	23.83
		Households with open sewage	7.10	9.40	22.48	6.41	7.42	20.94
Coping capacity	40.67	Disaster prevention institutions	10.80	9.91	25.52	9.36	9.59	24.90
		Evacuation drills and training	14.17	11.87	36.79	14.54	9.98	23.96
		Distance to shelters	6.42	5.23	7.32	7.26	5.56	19.64
		Health care facilities	9.28	7.63	19.10	9.51	7.64	14.56

A visual comparison of the AHP and ANP output maps shows that they a similar pattern with minor discrepancies in the northwest of Lajeado (Figure 24). This difference can be attributed to the lower monthly income in this region. The vulnerability scores from the two models have a linear relationship with a strong correlation (R^2 = 0.97) (Figure 25). Indeed, cross-tabulation analysis showed that 83.11% or 228.39 km² of the study area received the same classification by the two models (diagonal values in Table 20). The main difference was observed in the medium-vulnerability class of the AHP model, of which 22.73 km² was classified as of high vulnerability in the ANP method.

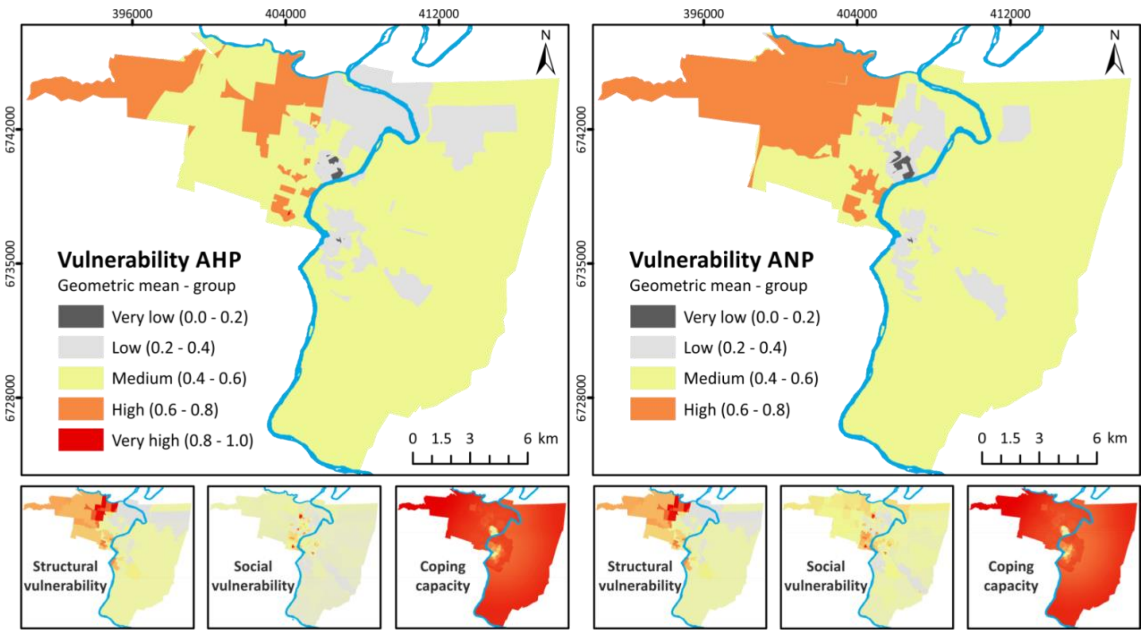

Figure 24. Spatial distribution of flood vulnerability in the study area

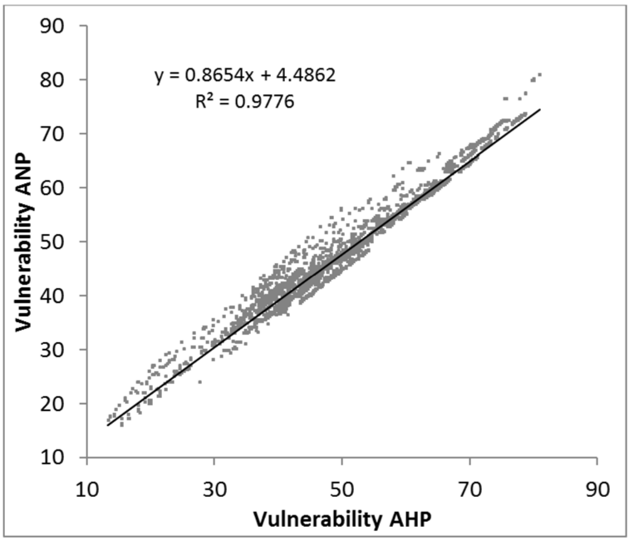

Figure 25. Correlation of the ANP and AHP flood vulnerability maps scores

Table 20. Comparison of vulnerability classes according to the AHP and ANP models. Diagonal values correspond to areas that were classified equally by both models. The column sum shows the area that is occupied by the respective class of vulnerability in the ANP technique while the line sum shows the area in the AHP technique

Area AHP (km^2)		Area ANP (km^2)					
	Vulnerability	Very low	Low	Medium	High	Very high	Total AHP
	Very low	**0.43**					0.43
	Low	0.39	**18.40**	20.90			39.69
	Medium		2.25	**181.82**	22.73		206.80
	High			0.13	**27.74**		27.87
	Very high				0.01	**0.00**	0.01
	Total ANP	0.82	20.65	202.85	50.48	0.00	**274.79**

5.2.5.4 Comparison of individual weights and scenarios

The dispersion of individual weights is illustrated in Figure 26, where each point represents the weight given to a criterion by one participant. As hinted before by the high IQR and SD values (Table 19), the weights varied significantly across experts, with the greatest differences in the monthly per capita income and households with improper building material items. Given this high degree of disagreement, the aggregation of the individual weights by their geometric mean resulted in a loss of information. The points of agreement are criteria that were given a low priority, such as the density of children and elderly.

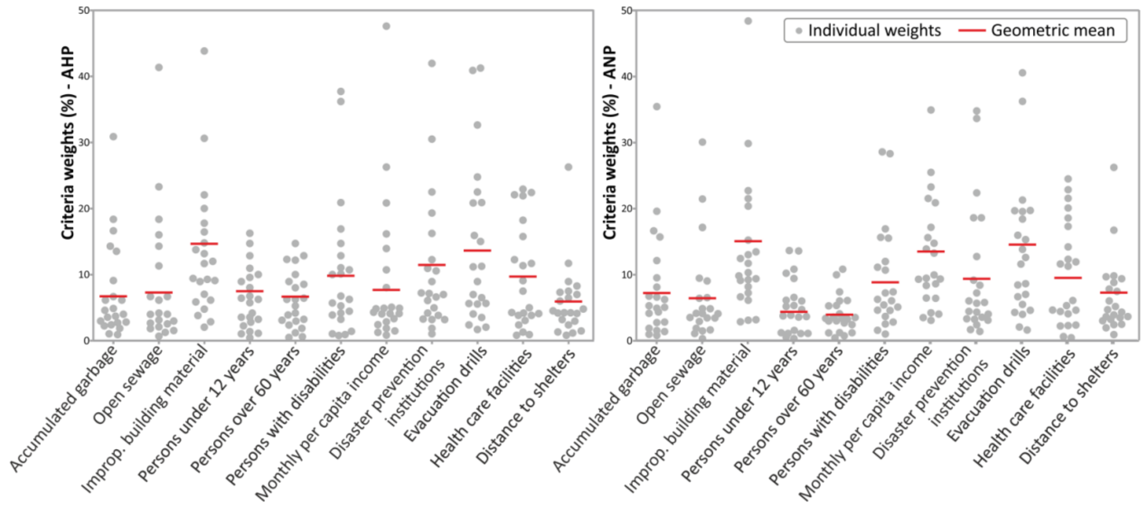

Figure 26. Diagram of dispersion of individual weight. Each point represents an expert and the red line delineates the mean

To identify similarities across participants' opinions, we conducted a cluster analysis. The heat map in Figure 27 shows the similarities between the experts' priorities. No trends were identified based on their background and work affiliation. Nevertheless, even though individuals hold different viewpoints, there is a lot of common ground where the importance between criteria is similar, as shown in red colours.

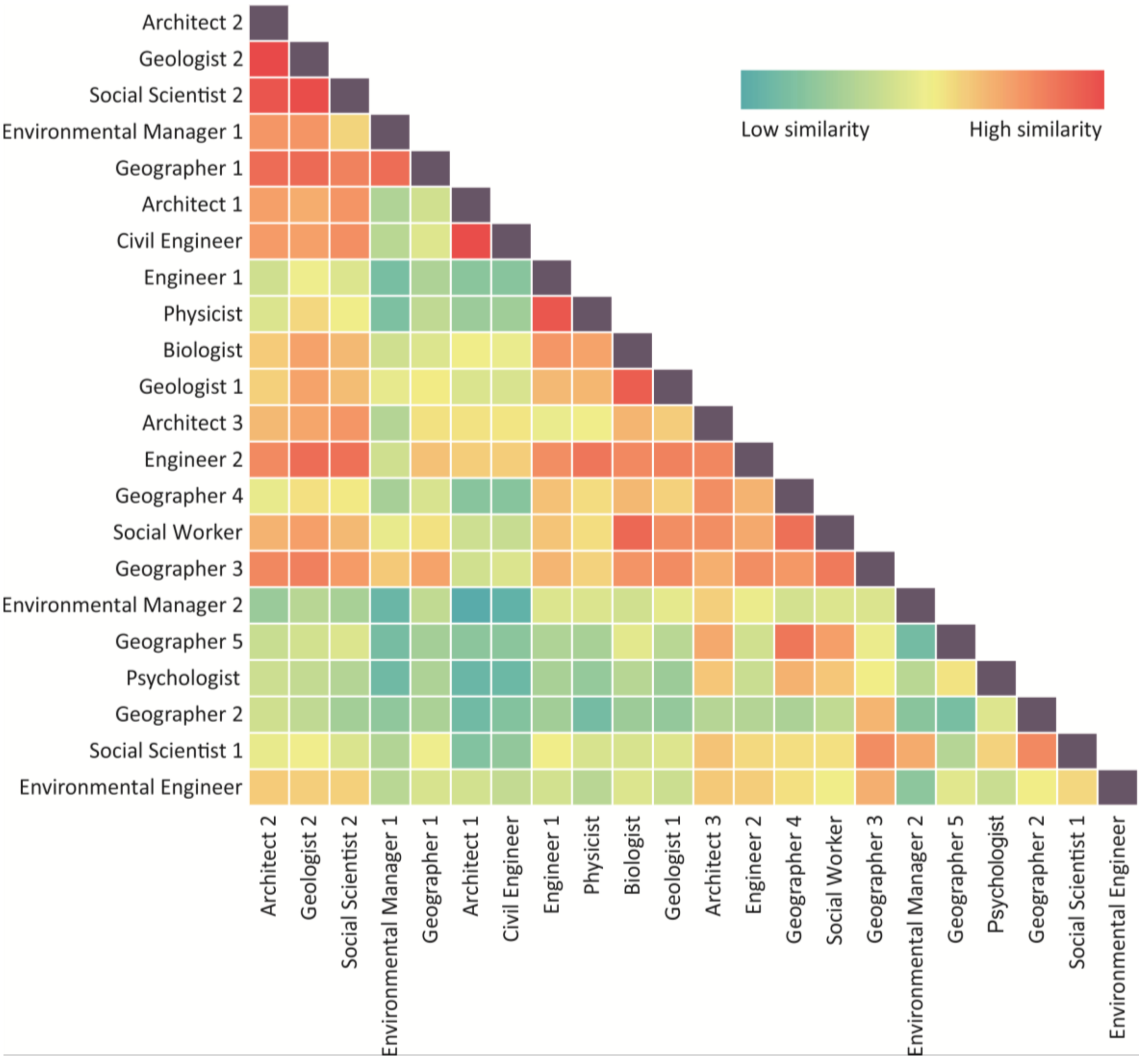

Figure 27. Heat map of similarities between experts' weights. The colour gradient from green to red indicates increasing similarity

To investigate the spatial implications of the different criteria weights, individual vulnerability scenarios were created for each expert (Supplementary Figure S1). The results demonstrate how different perspectives on criteria weights applied to the same data lead to differences in vulnerability classification. Nevertheless, the trend was similar for both methods, with higher vulnerability values in the northwest of the study area.

A Web GIS platform was set up to allow experts, end users and the public view the model results in form of thematic layers set in a geographical context and overlaid on background data. In this platform (Figure 28), participants could select their scenarios and compare them with the other participants' results, bringing their positions closer. Also, it was possible to visualize the hazard zones with different return periods, aiming to identify risk areas.

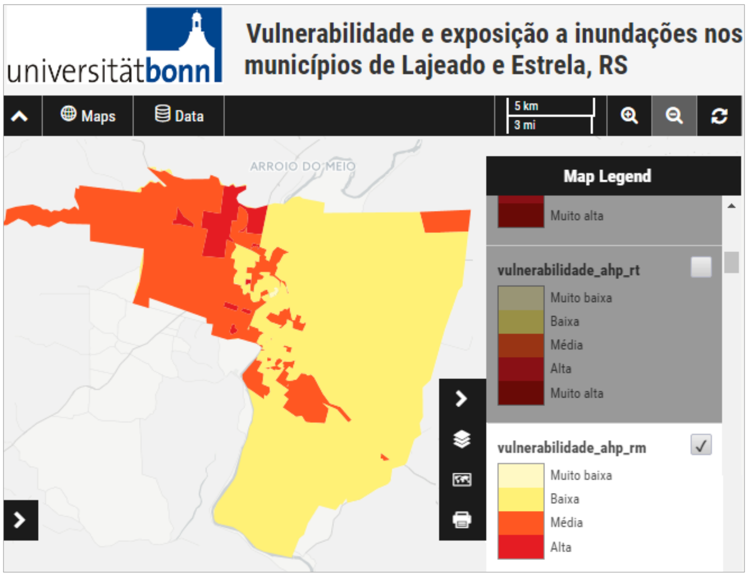

Figure 28. Web GIS platform with the 22 vulnerability scenarios

5.2.5.5 Feedback from participants about the proposed participatory MCDM approach

A total of 20 out of 22 invited experts answered the feedback questionnaire. All respondents agreed that the participatory MCDM approach provides a promising framework for integrating interdisciplinary knowledge in the effort to bring credibility to vulnerability indices. Most of them were very satisfied (89%) or satisfied (11%) with the transparency of the process and with the feedback received. Evaluations of the individual components of the MCDM approach were also generally positive. All respondents were satisfied or very satisfied with the ANP weights and only one (5%) was unsatisfied with the AHP results. A total of 50% and 45% of experts were very satisfied and satisfied with the indicators that were selected, suggesting that the Delphi results were representative. Nevertheless, one expert (5%) was unsatisfied with how the criteria were grouped. Finally, over 53% and 47% respondents indicated that the developed maps are very useful or useful for their professional activities, respectively. Figure 29 shows the mean ratings given by participants in each item of the feedback questionnaire.

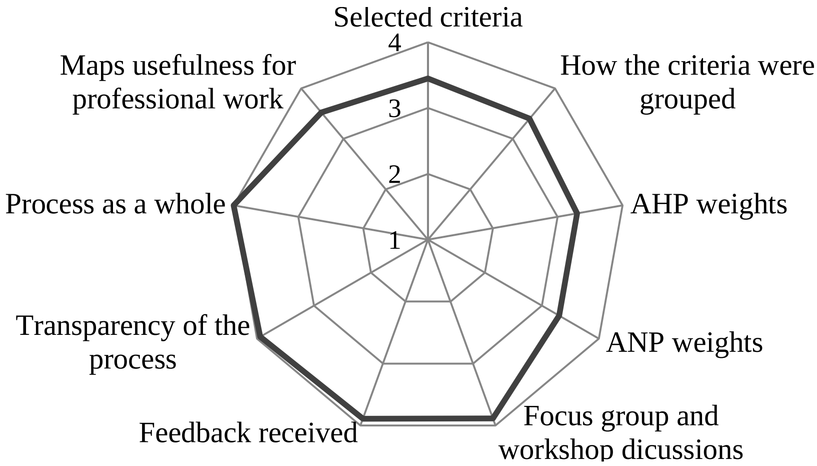

Figure 29. Participants satisfaction with the participatory process (1 = very unsatisfied; 2 = unsatisfied; 3 = satisfied; 4 = very satisfied)

Some participants stated that bringing together individuals with different viewpoints resulted in a more comprehensive and complete view of vulnerability. Quoting a statement from an expert: "the participatory approach allowed a greater dialogue among stakeholders and encouraged mutual learning, improving the knowledge about multifaceted problems like flood vulnerability". Several respondents mentioned that the feedback received in the form of the Web GIS platform and partial reports enabled them to see where their response stood in relation to the group. According to them, this interaction with other experts allowed them to expand their knowledge and led, in some cases, to a change in opinion based on the information received.

Regarding the difficulty of the MCDM methods used, there was a slight preference for the ANP method. 25% and 20% of the respondents felt that it was difficult or very difficult to complete the AHP and ANP questionnaires, respectively. In this regard, one participant stated that the MCDM tools are not applicable to persons with low education levels due to its complexity. Despite this, experts found it easy to grasp the fundamental concepts of AHP and ANP during the workshops, showing enthusiasm about the methodological approach. This was confirmed in the feedback survey, in which the majority (85%) showed interest in applying parts of the proposed method in their future work.

5.2.6 Discussion

5.2.6.1 Reflections on the participatory process

This study aimed at developing a participatory MCDM approach to assess the vulnerability to floods in an effort to enhance the credibility and deployment of the model outputs. To this purpose, experts were actively involved in all steps of the vulnerability modelling process, thus, having a great influence over the final index. The choices of input criteria, model schematization, data standardization and criteria weighting were done collectively, acknowledging multiple perspectives in a transparent way. By doing so, we avoided that the resulting vulnerability maps were perceived as black boxes by participants since the rationale for key decisions was explicitly expressed, leading to reproducible results. This fostered a sense of ownership among participants which, according to Voinov and Bousquet (2010), brings legitimacy to the model results.

The selection of input criteria using the Delphi technique allowed experts to reframe their personal opinions and reflect on their underlying assumptions through the exchange of information based on the feedback provided and social learning. Further, it gave participants an equal opportunity to contribute without the influence of dominant individuals as all participants remained anonymous. The majority of respondents (95%) were satisfied or very satisfied with the selected criteria, except for one participant. However, as highlighted by Oulahen et al. (2015), the construction of any index is likely to exclude variables considered relevant by some stakeholders.

The two focus groups stimulated in-depth discussions about the structuration of the vulnerability index into sub-indices and encouraged participants to think about how each criterion contributes to vulnerability. The elicitation methods used made it possible to transform tacit and implicit knowledge into information useful for vulnerability modelling. Despite some punctual divergences, participants showed a flexible attitude towards accepting other experts' opinions and succeeded in reaching workable compromises about generic conceptual models and value functions that were satisfactory to all participants. Given the complexity of the elicitation activities, involvement in the focus groups was restricted to a few participants to enable them to contribute equally to the discussions. Nevertheless, the results were representative of the experts' sample as 95% of respondents were satisfied or very satisfied with the developed conceptual models. In this regard, Howarth and Wilson (2006) argue that deliberative processes that are designed to achieve a mutual agreement rather than averaging individual results can enhance the acceptance and quality of the decisions.

Overall, the four workshops used to assign the criteria weights worked well, as supported by participants' enthusiasm and feedback. The AHP and ANP tools allowed the documentation of different viewpoints about the criteria importance without suppressing dissenting voices, enabling divergent framing assumptions to become explicit. This was central to this study, as vulnerability remains an ill-structured problem (Müller, 2011), where there are multiple solution paths and uncertainty about the input criteria and their importance. Therefore, we believe that systematically showing contrasting views and the underlying reasons for different interpretations is a more transparent approach than deriving a single solution. As shown in Figure 26, the aggregation of weights through the geometric mean resulted in a loss of information as several prioritizations were reduced to a single vector. Hence, participants whose values are very different from the calculated average may feel that they are not properly represented (Garmendia and Gamboa, 2012). In this regard, van den Hove (2006) argues that forcing consensus by averaging results in a search for a unique weighting scheme can decrease the legitimacy and effectiveness of participation as a learning process to solve complex problems. Thus, different preferences and conflicts must be recognized and all feasible outcomes should be considered in the decision-making process.

The deliberative feedback throughout the entire process positively impacted the participants' perception of the results' transparency, resulting in improved credibility. Consequently, all respondents were very satisfied or satisfied with the transparency of the methodology and with the feedback received. According to Ledwith and Springett (2009), communication and continuous feedback are essential to the success of any participatory approach as it encourages participants' commitment and interest and may motivate individuals with opposing views to engage in change. In this study, the partial reports, Web GIS platform, and the final report with cluster analysis results, made explicit potential coalitions, enabling participants to see that they are closer to other professionals than previously perceived.

The validation questionnaire indicated that participants were somewhat likely to agree that the models were clear, trustworthy, and valuable, suggesting that participatory modelling activities like the one proposed here are worthwhile. All respondents answered that the resulting maps are very useful or useful for their professional activities. Although this does not mean that the maps are being used in reality, it indicates their willingness to use the results. This finding becomes even more relevant when considering that several respondents work for the local Civil Defences and the National Centre for Monitoring and

Early Warning of Natural Disasters (CEMADEN) thus, having great influence over decisions related to flood risk management in the region. These results reinforce the findings of other participatory modelling exercises (Falconi and Palmer, 2017; Kissinger et al., 2017; Maskrey et al., 2016; Oulahen et al., 2015; Voinov and Bousquet, 2010) that state that end users find it more accurate and useful when the model is created based on their perspectives.

Nevertheless, a couple of risks of participation also have to be considered when developing participatory MCDM studies such as potential costs, time consumption, domination of the process by strong leading voices, and exclusion of important stakeholders (Evers, 2012). Thus, the degree of participation in certain stages of the modelling process needs to be based on a proper balance between conducting a time-efficient process and ensuring that results are representative of local conditions, and trusted by stakeholders (Andersson et al., 2008). In other words, trade-offs have to be made between the available resources and the expected quality of the MCDM outcomes. Participation in vulnerability assessment, though, is crucial for enhancing the results acceptance.

5.2.6.2 Reflections on the AHP and ANP model results

To analyse the effects of considering the interdependence between criteria in model outputs, two MCDM tools were used to elicit experts' preferences about criteria weights. AHP is the most common MCDM method in flood-related studies (de Brito and Evers, 2016). Despite its simplicity, it considers that the criteria are independent of each other, which can be an issue in vulnerability analysis since the magnitude of some vulnerability criteria can vary according to inhabitants coping capacity and socioeconomic status (Rufat et al., 2015). For example, the elderly can either be highly vulnerable or less vulnerable depending on their income. To overcome this problem, we used the ANP method, which has a network structure with bilateral relationships, enabling inner and outer dependences between criteria to be considered (Azizi et al., 2014).

Overall, the criteria weights and ranking were similar in both methods, with the exception of the monthly income. The controversy around the income had already been noticed in the Delphi survey, with this criterion having the lowest degree of consensus among experts. This discrepancy can be explained by the fact that some participants rated it as irrelevant when using the AHP technique. However, when completing the ANP questionnaire, they answered that the income plays a leading role in determining the vulnerability as it influences other criteria such as the building material and households with accumulated garbage or open sewage. Hence, ANP provides a more accurate approach for modelling problems where interrelationships between criteria exist (Saaty, 2004).

Several authors argue that to be accepted and used by stakeholders, models should be simple and easy to use, as complexity can obscure transparency and limit model accessibility (Falconi and Palmer, 2017; Horlitz, 2007). During the workshops, it became clear that the elicitation of criteria weights demands a significant cognitive effort from participants due to the inconsistency in the matrices, especially in the AHP technique. Some experts misunderstood the nine-point scale (Table 18) and overused large scores by ranking the criteria they felt more important with 9, regardless of the criteria with which it was being compared. Despite this issue, participants quickly grasped the concepts of the scale and succeed in arriving at consistent judgmeents. As a result, the majority of them (75% in AHP and 80% in ANP) found it easy or very easy to complete the questionnaires.

The investigation of the spatial implications of the criteria weights showed that the vulnerability scores from the two models are strongly correlated ($R^2 = 0.97$), with 83.11% of the pixels receiving the same classification. Nevertheless, both ANP and AHP models are sensitive to the individual weighting schemes, leading to the creation of different, but equally plausible flood vulnerability maps (Supplementary Figure S1). Even though the general pattern of vulnerability is stable in the study area, a natural question arises given the variability of the vulnerability maps: "which scenario is the best one?" This is still an open question, as all scenarios are equally legitimate. As argued by Strager and Rosenberger (2006), MCDM should be used to gain a better insight into the decision-making problem and not as the only or final approach. MCDM makes models more explicit by opening up appraisal inputs to a wider diversity of framings, avoiding simplistic and often misleading one-track solutions (Bellamy et al., 2013; Stirling, 2008).

Experts were, in general, very satisfied with the AHP and ANP results, showing that both methods are effective in solving the ill-structured and interdisciplinary problem of vulnerability. There was a slight preference for the ANP model as participants thought it was easier to understand its logic and no one was unsatisfied with the results. In addition, the agreement among participants about the criteria importance, measured by the standard deviation and IQR, was higher in the ANP model. Hence, ANP should be adopted whenever possible, given that it provides a way to make explicit all the relationships among variables. Nevertheless, it should be noted that while AHP can be easily implemented without the need for complex software, ANP requires the use of more sophisticated tools to construct and solve the supermatrix.

5.2.6.3 Limitations and future research

Although efforts were made to mitigate the risk of bias, some caveats must be acknowledged when interpreting the results obtained. First, the small number of participants in the focus groups and workshops poses the risk of unrepresentativeness. This limitation is, according to Garmendia and Stagl (2010), inherent in the nature of participatory modelling processes as they involve normally few participants. To reach a broader audience, it would be necessary to use online tools such as questionnaires or web platforms. Nevertheless, these alternatives also present a number of drawbacks since the participants would not be able to share and hear different perspectives through open dialogue, which is essential for achieving common agreement. Hence, given the complexity of the tasks at hand and considering that face-to-face discussions can help clarifying controversial issues (Orsi et al., 2011), we opted to conduct small focus groups to standardize the criteria and build the conceptual models. Despite the reduced number of participants, the results were representative of the experts' sample as 95% of them were satisfied or very satisfied with how the criteria were grouped.

A second issue is that, even though the majority of experts found it easy to complete the AHP and ANP questionnaires, the elicitation of criteria weights using pairwise comparisons is cognitively demanding (Cinelli et al., 2014). This might restrict the number of criteria to fewer than desired due to the high number of comparisons needed. Thus, in future applications, simpler MCDM methods such as the SMART, CAR, and SWING tools could be tested. Empirical evidence shows that centroid weighting methods such as CAR and SMART provide almost the same accuracy as AHP while requiring less input and mental effort from decision makers (Alfares and Duffuaa, 2008; Riabacke et al., 2012). Hence, the use of these tools might help to reach a broader number of participants since they can be easily implemented in online questionnaires.

Nevertheless, it is important to emphasize that SMART, CAR and SWING do not consider the multiple interactions between the criteria.

A third issue refers to the lack of validation with past flood damages. The absence of a systematic approach to record the impacts caused by disasters in the study area makes it difficult, if not unrealistic, to perform validation based on actual flood outcomes. This is a recurrent problem in flood vulnerability studies, as mentioned by several authors (Bakkensen et al., 2017; Beccari, 2016; Fekete, 2009, 2012). Indeed, in a review of 106 vulnerability indicators, Beccari (2016) found out that only three models were validated against recorded flood impacts. The problem is that independent second data source to validate vulnerability indicators is rarely available (Fekete, 2009). Even when there is enough information, the direct comparison of the damage from historical events with the present situation is problematic, because in between the two dates there may have been substantial changes in the land use (Chen et al., 2016). This reinforces the need for developing new approaches for validating flood vulnerability models.

The final criticism is that only a basic approach was used to document the sensitivity of the criteria weights. Further research includes conducting one-at-a-time and global sensitivity analyses to assess the effects of design choices (e.g. standardization, weighting, criteria aggregation) in model outputs. This could be achieved by repeatedly running the model in a Monte Carlo approach (Lilburne and Tarantola, 2009). Alternatively, since global sensitivity analysis is computationally expensive when spatially distributed inputs are considered, simpler approaches such as the procedure described by Chen et al. (2010) could be used as a starting point. Such analyses would be useful in evaluating the effects of epistemic uncertainty (Walker et al., 2003), helping to understand which choices contribute most to possible variances in the index scores.

Further improvements of the methodology include the conduction of a final workshop to create a vulnerability map by mutual consent. In this setting, the group of participants would determine a weighting scheme that all participants can support. This was suggested in the feedback questionnaire but was not implemented due to time and budget constraints. It would also be interesting to carry out a survey at the beginning and the end of the participatory process to investigate how the preferences of participants have evolved over time. This would allow assessing the extent to which social learning occurred. For this purpose, the methods outlined in Garmendia and Gamboa (2012) and Maskrey et al. (2016) could be used. Also, even though the developed approach was applied to flood hazards, the methodology could be used for other types of hazards or even for multi-hazard analysis.

It is believed that the proposed vulnerability index can be applied to other Brazilian watersheds with similar conditions. The development of more case studies, as well as the consideration of the opinion of persons who live in flood-prone areas and non-expert stakeholders, could allow the creation of generalizable models to assess vulnerability. However, as the selected indicators and weights represent the perspective of experts working in Brazil, the findings cannot be generalized to other countries without adaptations.

5.2.7 Conclusions

This study demonstrates how MCDM tools can be used to integrate interdisciplinary knowledge to not only guarantee a useful model according to the needs of the end users but also to increase the acceptance of the vulnerability maps. The approach proposed herein is particularly novel in the context of vulnerability assessment in the respect that participants were actively involved in all steps of the vulnerability modelling process. This led to (1) an increased, shared understanding of the problem by avoiding the limited perspective of a single expert, (2) an ability to transform implicit and tacit knowledge into information useful for vulnerability modelling, and (3) an enhanced credibility and deployment of the final results when compared to studies conducted without any kind of participation or collaboration.

To the best of our knowledge, this is the first time that the interdependence among criteria was considered to assess the vulnerability to floods. Both AHP and ANP techniques proved to be effective for assessing the vulnerability to floods. Nevertheless, ANP should be used whenever possible as it allows for the capturing of the complex relationships among vulnerability criteria in a transparent way.

Based on the lessons learned during this participatory process, we can draw some important conclusions. First, if modellers expect the vulnerability model outputs to be used in decision-making, end users should be actively involved in designing it. Second, the search for sound modelling choices should not impose an artificial consensus by averaging individual results. This is crucial to ensure that the model is legitimized and accepted. Third, MCDM methods which consider interdependence between criteria are preferred for vulnerability assessment given that interrelationships between criteria exist.

From a practical standpoint, the maps created may support local authorities to understand the spatial distribution of vulnerability to floods in the region. The results can also be useful to identify places for site specific risk assessment, enabling the prioritization of human, technological, and financial resources, and thereby improving risk mitigation.

5.3 Spatially-explicit sensitivity and uncertainty analysis in a MCDA-based flood vulnerability model (Paper 4)

This manuscript has not yet been submitted: **de Brito, M.M.**, Almoradie, A., Evers, M. (2018) Spatially-explicit sensitivity and uncertainty analysis of in a MCDA-based flood vulnerability model.

5.3.1 Abstract

This study presents a methodology for conducting sensitivity and uncertainty analysis of a GIS-based multi-criteria model used to assess flood vulnerability. The paper explores the robustness of model outcomes against slight changes in criteria weights, identifying input criteria that are particularly sensitive. The applicability of the proposed approach is illustrated in a case study in the municipalities of Lajeado and Estrela, southern Brazil. One criterion was varied at-a-time, while others were fixed to their baseline values. An algorithm was developed using the Python scripting language and a geospatial data abstraction library (GDAL) to automate the variation of weights, implement the ANP (analytic network process), reclassify the raster results, compute the class switches, and generate an uncertainty surface. Results helped to identify highly vulnerable areas that are burdened by high uncertainty and to investigate which criteria contribute to this uncertainty. Overall, the criteria “houses with improper building material” and “evacuation drills and training” are the most sensitive ones, thus, requiring more accurate measurement. The sensitivity of these criteria is explained by (1) their weight values in the base run, (2) their

spatial distribution, and (3) the resolution of the spatial data. These findings can support decision makers for characterizing, reporting, and mitigating uncertainty in vulnerability assessment. The case study results demonstrate that the developed approach is simple, flexible, transparent, and may be applied to other complex spatial problems.

5.3.2 Introduction

In general, GIS-based multi-criteria decision-analysis (MCDA) can be thought of as a collection of methods for transforming and combining geographic data and users' preferences to assist decision-making (Malczewski and Rinner, 2005). Well-known methods include, for example, the analytic hierarchy process (AHP), analytic network process (ANP), and technique for order preference by similarity to ideal solution (TOPSIS). Given its flexible capabilities for analyzing spatial problems with multiple and incommensurate criteria, MCDA tools have been extensively applied to assess flood vulnerability (de Brito and Evers, 2016; Feizizadeh and Kienberger, 2017; Giupponi et al., 2013). They can increase the transparency and analytic rigor of vulnerability modeling since the choices of input criteria, data standardization, criteria weighting, and aggregation are explicitly expressed, leading to justifiable decisions and reproducible results (Mateo, 2012b). Furthermore, MCDA allows integrating the interests of multiple stakeholders by considering the preferences from each actor in form of criteria weights (Tsoutsos et al., 2009).

Notwithstanding its benefits, the outcomes of GIS-based MCDA are prone to uncertainties (Ghorbanzadeh et al., 2018), which are mainly related to model assumptions, criteria weighting, quality and availability of data, natural variability, and human judgment (Chen et al., 2011; Crosetto et al., 2000; Ligmann-Zielinska and Jankowski, 2014; Malczewski, 2006). Of these, criteria weights are often recognized as the main contributors to controversy and uncertainty (Chen et al., 2013; Dhami et al., 2017; Ghorbanzadeh et al., 2018; Xu and Zhang, 2013) since even small changes in weights may have a significant impact on model results, leading to inaccurate outcomes (Feizizadeh and Blaschke, 2014).

To better understand the uncertainties raised by MCDA and assess the stability of model outputs under a wide range of possible conditions, sensitivity analysis (SA) and uncertainty analysis (UA) of criteria weights have been widely recommended (Chen et al., 2013; Dhami et al., 2017; Feizizadeh et al., 2014). This is especially relevant when the MCDA outcomes aim at supporting decision-making. UA quantifies the variability of model outcomes, while SA helps to identify key criteria that are responsible for the variability in model outputs (Percival and Tsutsumida, 2017). Even though these two terms refer to different concepts, the same set of model runs can be used for conducting both UA and SA (Loucks and van Beek, 2017). A well-structured SA and UA can lead to the identification of criteria which require further refinement and can guide model simplification by discarding criteria that have little or no impact on the outcome uncertainty (Ligmann-Zielinska and Jankowski, 2014; Saltelli and Annoni, 2010). Furthermore, they can help end-users understand the consequences of setting up different priorities (Geneletti and van Duren, 2008).

Despite their importance, both SA and UA are not a common practice in the field of spatial MCDA regardless of the application area (Chen et al., 2010; Ligmann-Zielinska and Jankowski, 2006; Xu and Zhang, 2013). This occurs due to the technical complexity of doing SA and UA in a spatial context, in comparison with the well-established tools for non-spatial SA and UA, due to (1) the large number of pixels in a map, (2) the heterogeneity of input data and the variety of parameters involved, (3) the uncertainty range that might be associated with each raster cell, which increases the computation time, and (4) the lack of pre-built tools in existing GIS software (Delgado and Sendra, 2004; Feizizadeh and Blaschke, 2013; Ferretti and Montibeller, 2016; Ghorbanzadeh et al., 2018). Hence, performing SA and UA in the context of GIS-based MCDA may enhance the understanding of the spatial implications of model variations.

In recent years, an increasing number of studies have conducted SA and UA of criteria weights in spatial MCDA applications (e.g. Chen et al., 2013; Moreau et al., 2013; Paul et al., 2016; Şalap-Ayça and Jankowski, 2016; Xu and Zhang, 2013). For instance, Romano et al. (2015) used the one-at-a-time (OAT) SA approach to investigate the sensitivity of a model used for land suitability mapping. Feizizadeh and Blaschke (2014) examined the robustness of a spatial MCDA-based evaluation for landslide susceptibility assessment with the help of Monte Carlo simulations and variance-based global sensitivity analysis (GSA). More recently, Tang et al. (2018) used Monte Carlo simulations to analyze the uncertainty of criteria weights in a model used to delineate flood susceptible areas.

In the context of flood vulnerability, integrated SA and UA of GIS-based MCDA models are still scarce (e.g. Feizizadeh and Kienberger, 2017) and the model uncertainties are often ignored. According to Tate (2012) we know remarkably little about the robustness of vulnerability indices. Indeed, a systematic literature review by de Brito and Evers (2016) showed that the investigation of the spatial variability of criteria weights in vulnerability assessment is still largely absent or rudimentary, which can result in flawed results regarding hazard mitigation strategies. Only 2 out of the 27 reviewed papers conducted some sort of partial SA by creating different scenarios (Giupponi et al., 2013; Kandilioti and Makropoulos, 2012). None of the vulnerability studies reviewed by de Brito and Evers (2016) has performed UA. Furthermore, to the best of our knowledge, only few studies have conducted spatially-explicit SA and UA of MCDA methods that consider the interrelationship between the criteria, such as the ANP approach (e.g. Dou et al., 2014; Ferretti, 2011; Ghorbanzadeh et al., 2018). Hence, enhancing flood vulnerability models with SA and UA is crucial, as it will enable to better understand the dynamics of spatial change (Chen et al., 2010), and improve the model transparency (Ferretti and Montibeller, 2016).

The aim of this study is, thus, to understand the behavior of an ANP-based MCDA model used to assess flood vulnerability by conducting a spatially-explicit SA and UA. The paper addresses the following questions: (1) What are the vulnerability criteria that are most sensitive to weight changes? (2) Is there a criterion that does not impact the final results? (3) What are the limits of variation of the criteria weights for stable results? (4) How does the uncertainty of the vulnerability maps vary in space? We discuss these questions through a complete case study on a flood vulnerability model developed by de Brito et al. (2017, 2018). The goal is to provide end-users crucial information for decision-making by identifying the uncertainties associated with the ANP MCDA model.

5.3.3 Material and methods

5.3.3.1 Participatory flood vulnerability modeling

The effectiveness of the proposed approach for spatially-explicit SA and UA was evaluated using data and criteria weights from a study in which ANP was applied to assess flood vulnerability (de Brito et al., 2017; 2018). The study area comprehends the municipalities of Lajeado and Estrela Brazil, which are severely affected by floods, with more than 32 flood records between 1980 and 2016. The area encompasses 274.79 km^2, with an estimated population of 112,000 (IBGE, 2017). For detailed information regarding the physical characteristics of the studied basin, the reader is referred to Bombassaro and Robaina (2010), Chagas et al. (2014), and Siqueira et al. (2016).

The model used to estimate flood vulnerability was constructed in a participatory setting, with the collaboration of 101 expert stakeholders from governmental organizations, universities, research institutes, NGOs, and private companies. The selection of the model input criteria was done through the use of the Delphi technique (Hasson et al., 2000). After the second round of the survey, participants agreed on a set of 11 criteria related to social, structural and coping capacity aspects that should be incorporated into the vulnerability model (Table 21).

Table 21. Input criteria, metrics used to measure them, their spatial data source, and the ANP weights used in the base run (based on de Brito et al., 2018)

Cluster	Abbr.	Criteria	Metric	Weight	Data source
Social vulnerability	V01	Persons under 12 years	persons . km^{-2}	4.37	IBGE (2010)
	V02	Persons over 60 years	persons . km^{-2}	3.96	IBGE (2010)
	V03	Persons with disabilities	persons . km^{-2}	8.84	MS (2016)
	V04	Monthly per capita income	USD	13.49	IBGE (2010)
Structural vulnerability	V05	Households with improper building material	percentage	15.06	IBGE (2010)
	V06	Households with accumulated garbage	percentage	7.20	IBGE (2010)
	V07	Households with open sewage	percentage	6.41	IBGE (2010)
Coping capacity	V08	Disaster prevention institutions	institut . km^{-2}	9.36	interviews
	V09	Evacuation drills and training	drills . km^{-2}	15.54	interviews
	V10	Distance to shelters	meters	7.26	interviews
	V11	Health care facilities	facilities . km^{-2}	9.51	MS (2016)

The preferences of each participant regarding the criteria weights were estimated through the ANP tool (Saaty, 2004; Saaty and Vargas, 2013). In this MCDA method, the decision problem is broken down into a nonlinear network structure with bilateral relationships, which allows considering feedback and interdependence connections within and between criteria and clusters (Saaty, 1999). The relationships between the criteria and clusters were defined based on a focus group discussion with 9 participants. Then, the developed conceptual models were introduced in Super Decisions 2.6.0 software, which generated a list with 40 pairwise comparisons required to run the ANP model. Based on that, a questionnaire was prepared and applied in four workshops with a total of 22 participants. Stakeholders were also engaged at the end of the modeling exercise for results validation. Table 21 shows the model input criteria and their weights, which were derived based on the opinion of the stakeholders who participated in the workshops. A detailed description of the methods used to prioritize the vulnerability criteria, as well as discussion of the results obtained, can be found in de Brito et al. (2017; 2018).

Spatial data were converted into raster format with 50 m resolution, resulting in 255,663 pixels (557 columns and 459 rows). Then, the resulting maps were standardized to a scale of 0 (no vulnerability) to 1 (full vulnerability) using fuzzy membership functions which were defined by 5 experts that participated in a focus group (de Brito et al., 2018).

5.3.3.2 Spatial sensitivity and uncertainty analysis

Various local and global SA approaches have been developed to determine how sensitive model outputs are to changes in model inputs. Local SA methods such as the one-at-a-time (OAT) technique, examine the effects of changes in a single input criterion assuming no changes in all the other inputs (Loucks and van Beek, 2017). In contrast, global sensitivity analysis (GSA) approaches such as Monte Carlo simulations, and variance-based SA, investigate how output variations can be attributed to multiple sources of uncertainty in the model input assumptions (Saisana and Saltelli, 2008). Given that OAT is methodologically simple, computationally cheap, and easy to implement (Chen et al. 2013), we opted to use it to investigate the sensitivity of criteria weights and determine critical weights for which a slight modification causes the reversal of the vulnerability classes.

The use of the OAT method requires the setting of two parameters, i.e., the range and the step size of the particular weight changes. Following similar SA studies (Ilia and Tsangaratos, 2016; Mosadeghi et al., 2015; Xu and Zhang, 2013), we assigned a step size or increment of percent change (IPC) of ±4% and a range of percent change (RPC) of ±100%. Hence, the simulation consists of a total of 550 evaluation runs (50 runs x 11 criteria), where each run results in a single new vulnerability map. To ensure that all criteria weights sum to one, we adjusted the other criteria weights proportionally using Equation 2 (Chen et al., 2010).

$$W_{c_i,ss} = (1 - W(c_m, ss)) \times \frac{W(c_i,0)}{(1-W(c_i,0)}\qquad i \neq m, 1 \leq i \leq n \qquad \text{Eq. 2}$$

Where $W_{c_i,ss}$ is the weight of the i-criterion c_i at a certain step size ss; $W_{c_i,0}$is the weight of the i-criterion at the base run; c_m is the main changing criterion; n is the total number of criteria.

The software bundle Anaconda and PyCharm IDE GUI were used to set-up the Python libraries and GDAL, and to develop the algorithm. The algorithm (1) first reads and adjust the base weights in a RPC of ±100% with a step size of 4%, producing 50 RPC maps for each criterion, (2) reclassifies the RPC map scores into 5 vulnerability classes (very low, low, medium, high and very high) by applying the equal interval method, (3) counts the number of cells in each vulnerability class for each RPC map, and (4) computes the changes in the number of cells in each vulnerability class when compared to the base run (Figure 30). Tables of summary statistics were automatically computed to summarize the results of each step. ArcGIS was used to visualize the SA and UA results.

Additionally, an algorithm was developed to compute other spatial statistical parameters by employing local map algebra operations (average, sum, variance and standard deviation) for all RPC maps. The standard deviation (SD) map, which corresponds to the uncertainty surface, was combined with the average (AVG) map to visualize the spatial distribution of uncertainty according to the degree of vulnerability. Following the recommendations of Dhami et al. (2017), we assumed that the raster cells with 25% of the highest SD scores (the 75th percentile) indicate highly uncertain areas. The remaining cells are considered to be robust, where robustness is defined as the capacity of the model outcomes to remain unaffected by small, but deliberately introduced variations in the model inputs (Heyden et al., 1999).

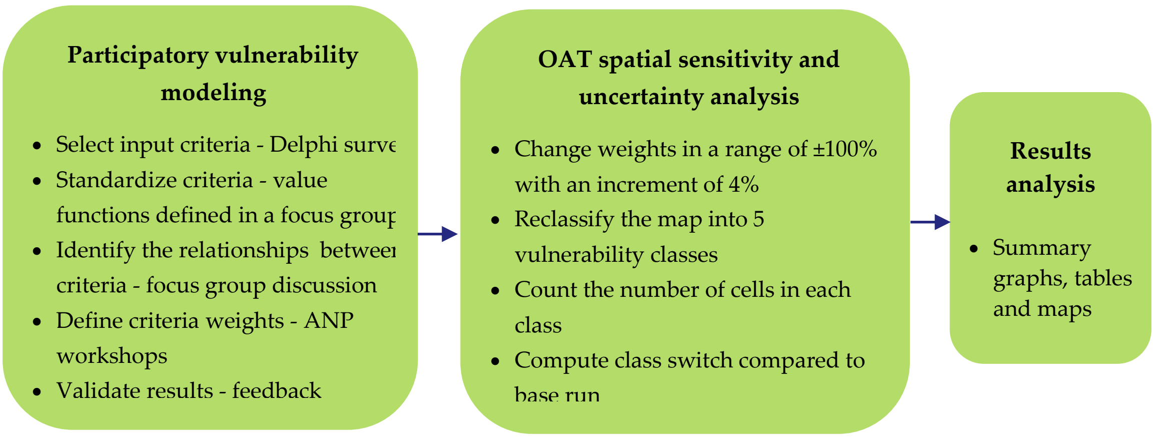

Figure 30. Flowchart of the adopted procedure

5.3.4 Results

Based on the OAT method, 550 unique RPC vulnerability maps were generated. The summary of the results (Figure 31) shows that the number of pixels classified with very low, very high, and high vulnerability remained relatively stable. Major changes occurred in the low and medium classes, especially for the criteria "households with improper building material", "evacuation drills and training", "health care facilities" and "disaster prevention institutions".

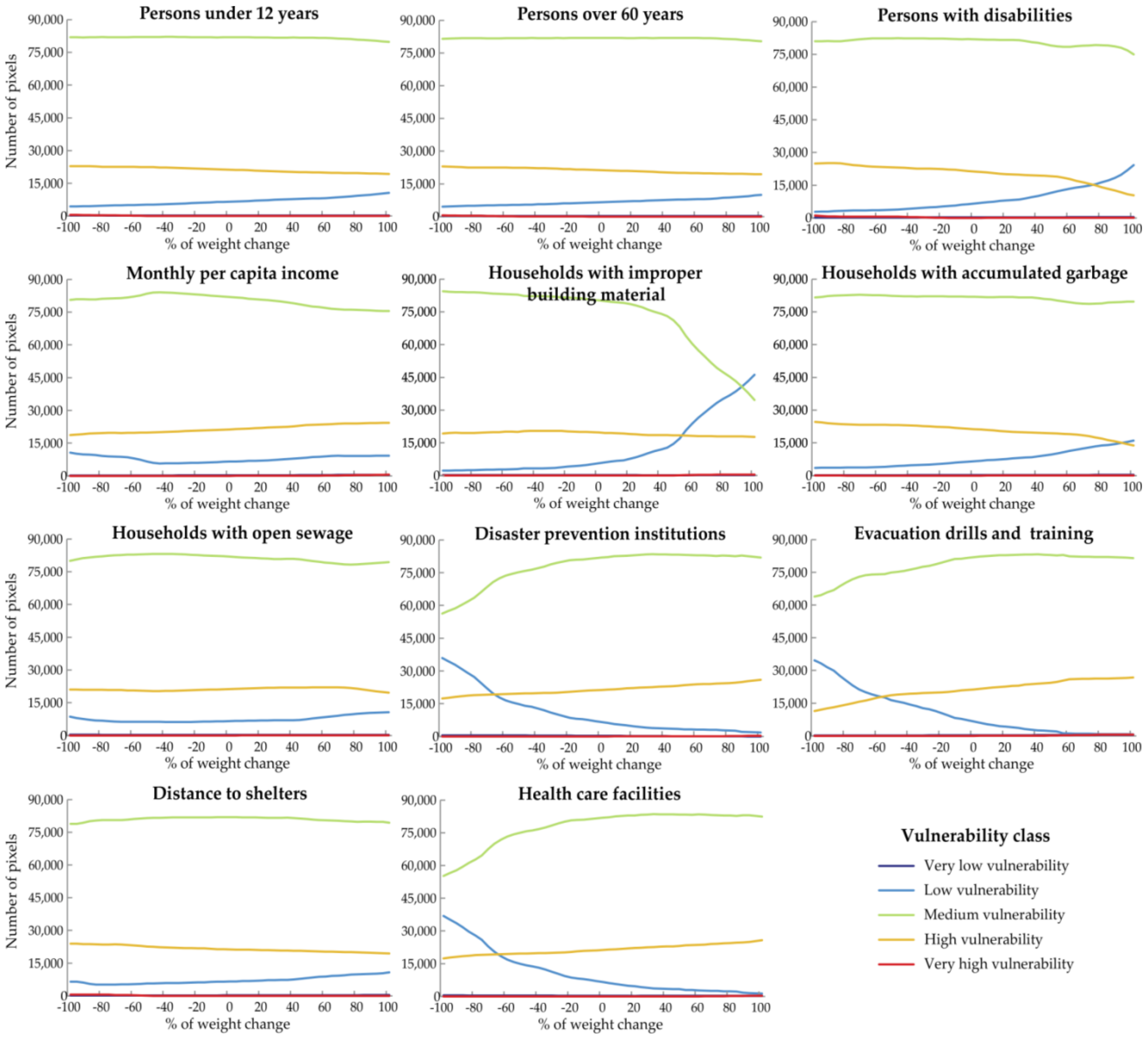

Figure 31. Counting of pixels in each vulnerability class from the 50 runs for each criterion

The class switches or the number of pixels that changed from one vulnerability class to another is given in Figure 32 for all simulation runs. Most of the changes correspond to medium to low (31.59%) and low to medium (10.81%). In order to analyze the limits of variation of the criteria weights for stable classification results, Table 22 shows the percentage of pixels that remained in the same vulnerability class in each run. It can be observed that the model results are relatively robust despite a certain degree of variability. Overall, in 506 out of the 550 runs (92.00%) there is no change in the classification for more than 90% of the study area. The runs where class switch is higher than 10% are highlighted with red colors in Table 22. For instance, for the criterion "evacuation drills and training", the model results vary more than 20% when the weight is changed - 76%.

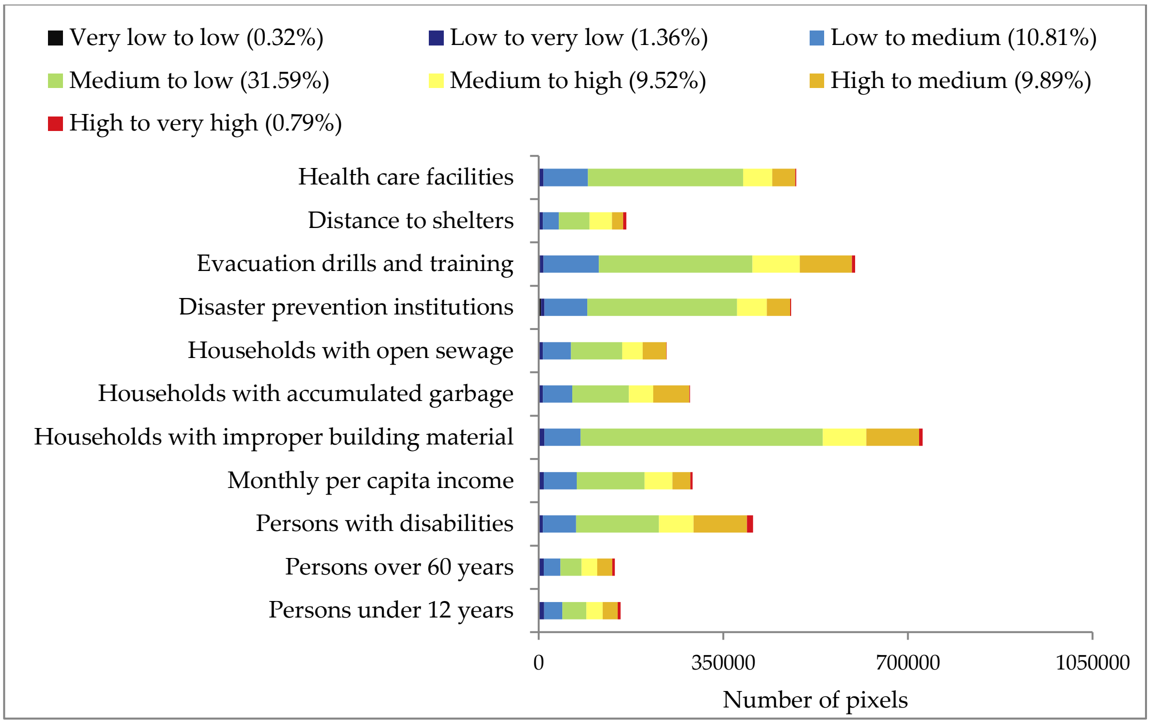

Figure 32. Counting of pixels in each vulnerability class from the 50 runs for each criterion

To provide insights into the spatial patterns of the SA and analyze how similar the results are across simulation runs, maps with the class switch were generated. The maps in Figure 33 show where the flood vulnerability classification changes took place according to each simulation run for the criterion "households with improper building material". In the northeast of the study area, the vulnerability class changed from high to medium when the importance of this criterion was diminished. Conversely, the higher the weight, the lower was the vulnerability in the west of the study area. This is because the buildings in this area have better building standards when compared to the other portion of the region (de Brito et al., 2017).

Table 22. Percentage of pixels that remained with the same vulnerability classification in each of the 550 runs. Green colors stand for stable runs while red colors indicate that the variability was high

IPC	V01	V02	V03	V04	V05	V06	V07	V08	V09	V10	V11
-100	95.33	95.26	91.09	88.58	80.19	93.79	92.78	69.27	65.30	92.53	68.47
-96	95.41	95.54	91.31	89.35	81.42	94.08	93.36	71.00	67.03	92.59	70.25
-92	95.55	95.90	91.61	89.98	82.45	94.46	93.86	72.77	69.30	93.28	72.05
-88	95.73	96.12	91.83	90.59	83.62	94.65	94.24	74.70	71.24	94.15	74.01
-84	95.97	96.32	92.18	91.14	84.85	94.83	94.62	76.65	73.95	94.56	76.16
-80	96.17	96.41	92.67	91.63	85.91	95.00	94.80	78.54	76.58	94.83	77.91
-76	96.29	96.55	93.07	91.85	87.11	95.14	95.18	80.97	79.12	94.97	79.88
-72	96.43	96.73	93.34	92.19	88.35	95.25	95.40	83.47	81.42	95.28	82.74
-68	96.57	96.88	93.68	92.58	89.29	95.36	95.54	85.86	82.99	95.63	85.16
-64	96.76	97.03	93.87	92.93	90.18	95.49	95.86	87.56	84.58	95.88	87.06
-60	96.91	97.20	94.05	93.61	91.11	95.58	96.09	88.81	85.89	96.42	88.52
-56	97.11	97.32	94.24	94.25	92.37	95.69	96.42	89.82	87.00	96.96	89.69
-52	97.30	97.49	94.47	94.95	93.68	95.86	96.67	90.57	88.56	97.53	90.41
-48	97.51	97.61	94.77	95.63	94.41	96.10	96.87	91.35	89.43	97.82	91.12
-44	97.78	97.80	95.06	96.15	94.82	96.33	97.09	91.87	90.13	98.10	91.67
-40	97.95	97.98	95.61	96.30	95.13	96.58	97.35	92.67	91.03	98.25	92.35
-36	98.12	98.14	96.05	96.78	95.36	96.80	97.60	93.48	91.81	98.37	93.14
-32	98.28	98.39	96.41	96.92	95.67	97.13	97.84	94.52	92.86	98.54	94.17
-28	98.50	98.60	96.80	97.47	96.01	97.43	98.01	95.38	93.45	98.72	95.11
-24	98.76	98.83	97.22	97.77	96.58	97.70	98.23	96.22	94.30	98.83	96.15
-20	98.95	99.00	97.66	97.92	97.32	97.98	98.50	97.12	95.28	98.99	97.03
-16	99.16	99.19	98.01	98.24	97.86	98.29	98.74	97.68	96.38	99.13	97.67
-12	99.38	99.34	98.43	98.90	98.33	98.82	99.02	98.18	97.66	99.44	98.09
-8	99.57	99.59	99.09	99.27	98.81	99.25	99.23	98.68	98.45	99.68	98.65
-4	99.75	99.76	99.47	99.64	99.39	99.56	99.46	99.23	99.21	99.75	99.18
0	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
4	99.54	99.56	99.29	99.40	99.23	99.40	99.64	99.43	98.93	99.64	99.38
8	99.36	99.38	98.82	99.01	98.72	99.01	99.31	98.80	98.16	99.48	98.78
12	99.13	99.17	98.33	98.60	98.28	98.68	99.00	98.31	97.42	99.39	98.28
16	98.85	98.98	97.73	98.37	97.85	98.24	98.63	97.73	96.76	99.20	97.73
20	98.62	98.78	97.25	98.07	96.95	97.83	98.17	97.24	96.35	99.04	97.25
24	98.43	98.64	96.98	97.73	96.10	97.43	97.72	96.74	95.91	98.85	96.75
28	98.16	98.37	96.70	97.13	94.96	97.10	97.31	96.33	95.44	98.71	96.32
32	97.87	98.11	96.13	96.87	93.79	96.88	97.02	96.02	94.57	98.61	95.95
36	97.64	97.79	95.52	96.40	92.85	96.62	96.74	95.74	94.07	98.53	95.66
40	97.47	97.57	94.83	95.92	92.06	96.14	96.46	95.50	93.69	98.33	95.48
44	97.28	97.42	94.05	95.38	91.07	95.68	96.02	95.35	93.27	98.00	95.38
48	97.17	97.20	93.29	94.85	89.29	95.14	95.48	95.01	92.83	97.62	95.16
52	97.05	97.12	92.40	94.22	86.54	94.54	94.97	94.51	92.21	97.17	94.63
56	96.94	96.99	91.42	93.95	82.56	93.92	94.49	94.31	90.87	96.88	94.47
60	96.79	96.91	90.29	93.46	79.16	93.22	93.98	94.01	90.14	96.64	94.18
64	96.59	96.79	89.01	93.02	76.23	92.48	93.57	93.87	89.80	96.37	93.98
68	96.31	96.64	88.01	92.68	73.74	91.63	93.16	93.73	89.56	96.12	93.63
72	96.07	96.41	86.95	92.40	71.17	90.77	92.65	93.47	89.51	95.87	93.47
76	95.88	96.18	85.63	92.27	68.88	89.68	92.10	93.13	89.35	95.62	93.09
80	95.56	95.98	84.07	92.17	66.88	88.84	91.47	92.83	89.13	95.42	92.84
84	95.28	95.80	82.65	91.96	65.19	87.89	90.78	92.59	89.03	95.08	92.57
88	94.97	95.50	80.95	91.88	63.23	87.03	90.24	91.81	88.97	94.90	91.90
92	94.69	95.25	78.86	91.72	60.82	85.89	89.74	91.22	88.82	94.71	91.44
96	94.30	94.88	76.06	91.54	58.20	84.80	89.27	90.77	88.74	94.48	90.92
100	93.98	94.59	73.49	91.48	55.04	83.56	88.81	90.30	88.51	94.02	90.43

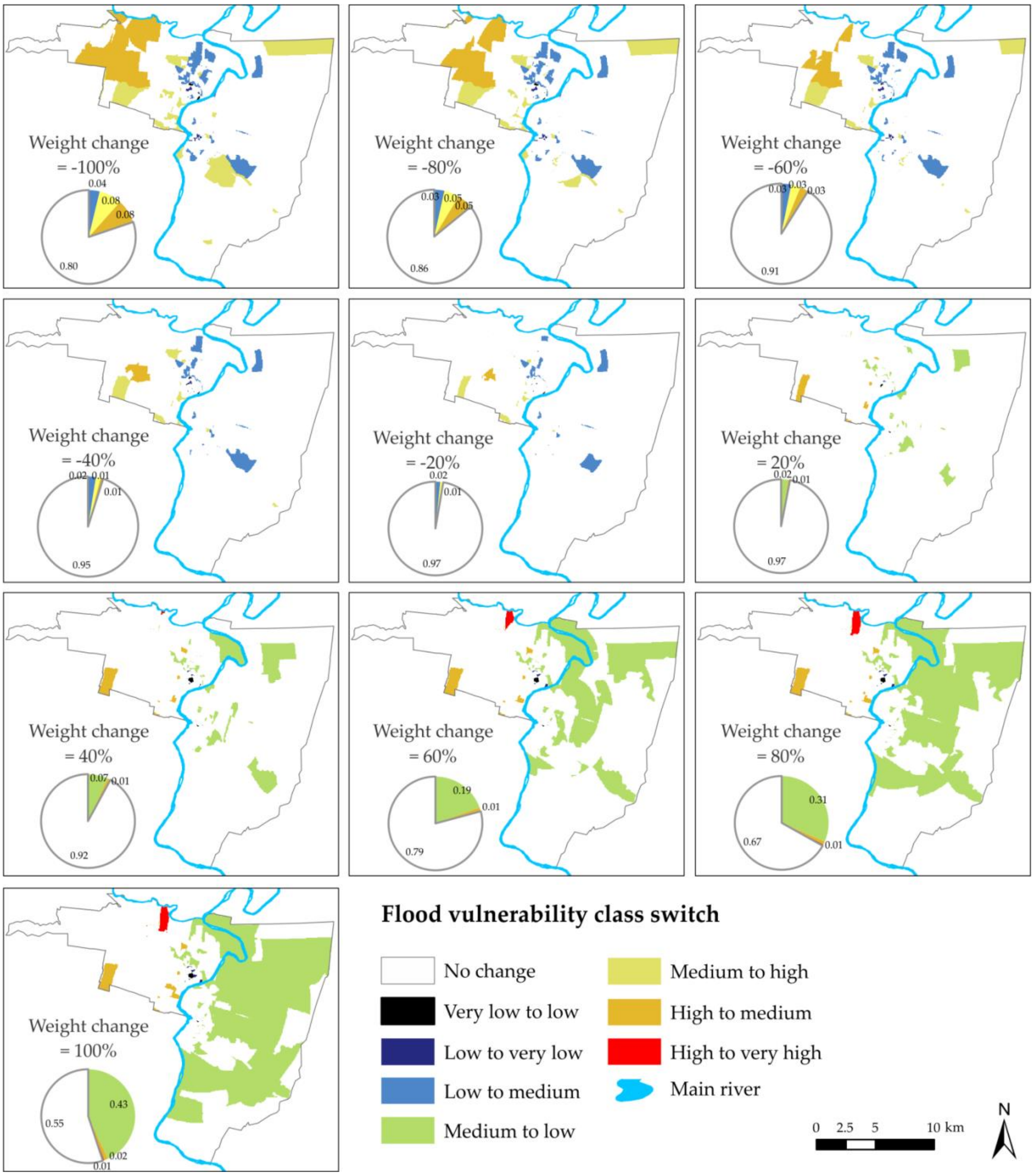

Figure 33. Class switches for different weights of the criteria "households with improper building material". The percentage of area occupied by each class is shown in the graphs

When analyzed conjunctively, the uncertainty maps for each criterion are quantitatively very different (Figure 34). Overall, the criterion "evacuation drills and training" has the highest SD values, whereas the criteria "persons over 60 years" and "persons under 12 years" have the lowest scores.

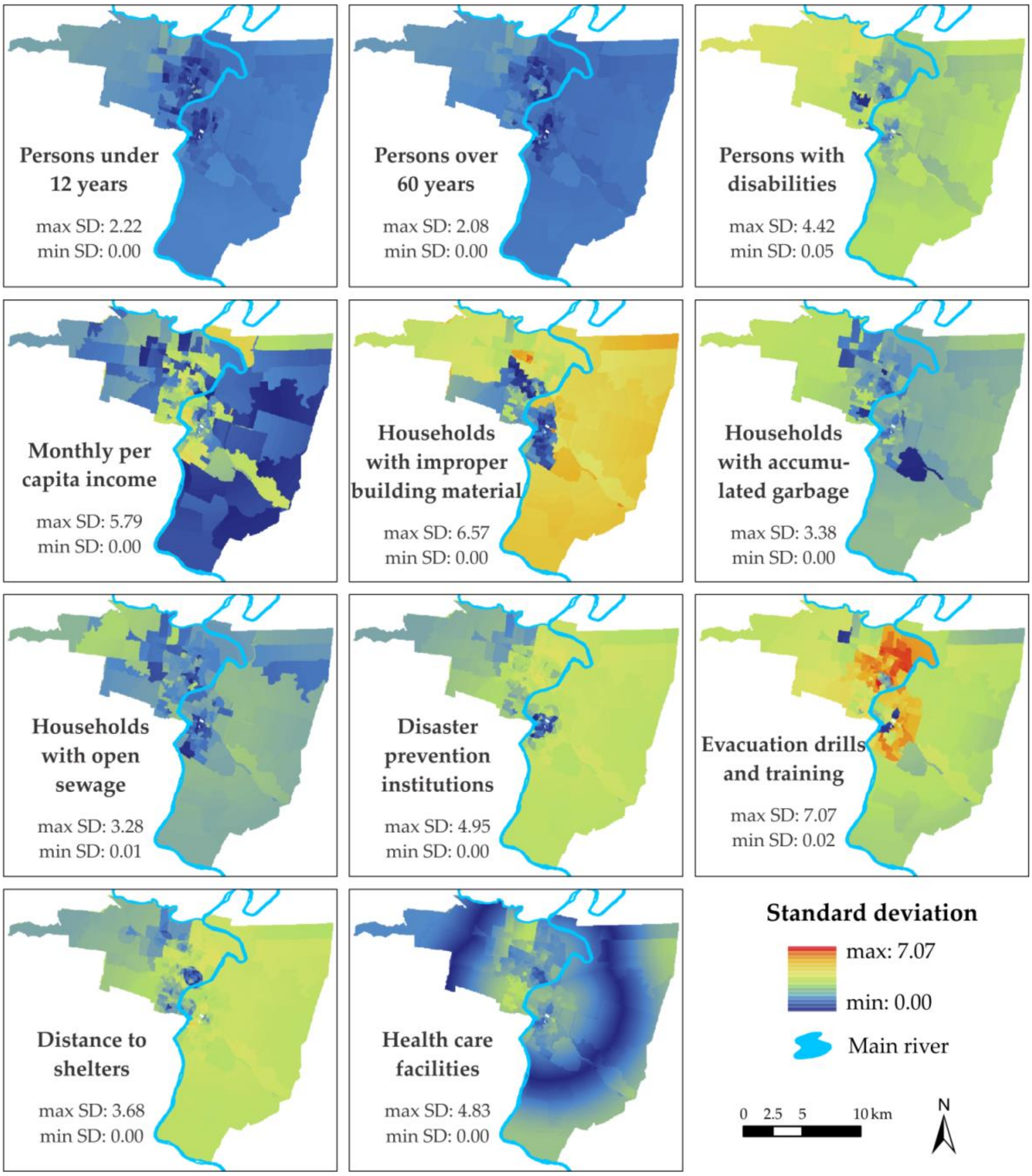

Figure 34. Uncertainty maps derived based on the 50 runs for each criterion

To further explore the uncertainty and identify critical regions, a map with the average SD of all 550 runs was created (Figure 35a). Results indicate that despite the spatial heterogeneity in uncertainty, the predicted vulnerable areas are robust, meaning that the spatial pattern remains stable when vulnerability criteria weights are varied, with a maximum SD value of 3.28. The computed AVG vulnerability scores (Figure 35b) fall within the 13-81% interval of the normalized score range (0-100%), which implies that there are no raster cells with minimum and maximum flood vulnerability. The surface was partitioned according to their AVG vulnerability and average SD (Figure 35c). The resulting map shows that 18.86% of the study area is of high vulnerability with a low uncertainty and 0.48% of high vulnerability and high uncertainty. The less robust pixels correspond to areas with medium vulnerability (21.90% of the study area).

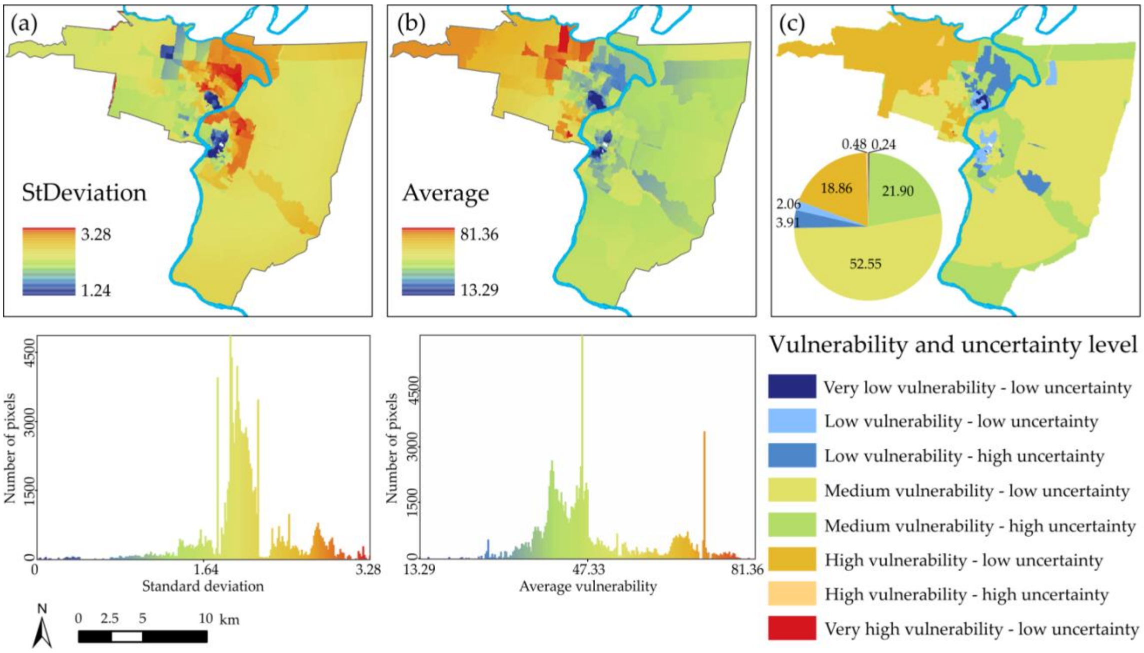

Figure 35. (a) Uncertainty map derived based on the standard deviation scores of all 550 runs with its histogram; (b) AVG vulnerability scores with its histogram; (c) vulnerability classes according to different uncertainty levels. The percentage of area occupied by each class is shown in a graph

5.3.5 Discussion

This study introduces an approach for conducting spatially-explicit SA and UA of an ANP-based vulnerability model. With the aid of summary tables and graphs generated, we can derive the following general summary regarding the reliability of the model, its behavior and limitations: (1) for all 11 criteria, there are no raster cells that either increased or decreased more than one vulnerability level when compared with their original class in the base run; (2) the vulnerability class switches for all 550 runs are relatively low. Indeed, 93.71% of the raster cells remained in the same class they had in the base run; (3) most of the variation in model outputs arise from the criteria "households with improper building material" and "evacuation drills and training"; (4) the criteria "persons under 12 years" and "persons over 60 years" appear to be least sensitive to weight changes; (5) robust areas with very high or high vulnerability correspond to 51.85 km² (18.87% of the total area) and should be the focus for the establishment of flood risk reduction measures; (6) areas with high uncertainty constitute about 72.21 km² (26.28% of the study area).

In comparison to other MCDA models with high uncertainty (e.g. Ligmann-Zielinska and Jankowski, 2014; Şalap-Ayça and Jankowski, 2016; Tang et al., 2018), the developed model is relatively robust for the study area, with a maximum SD of 3.28%. Indeed, Şalap-Ayça and Jankowski (2016) encountered SD values higher than 7%. Similarly, Ligmann-Zielinska and Jankowski (2014) obtained a maximum SD of 11% in a model used for land suitability evaluation. The relatively low SD scores in our study can be partly attributed to the use of the ANP tool, which is often considered to be more robust and reliable than other common MCDA approaches such as the AHP method (Dou et al., 2014a; Ghorbanzadeh et al., 2018). In this regard, a comparative analysis of the performance of vulnerability indicators conducted by Tate (2012) found out that models with hierarchical structures are more sensitive to change in criteria weights than other structural designs.

The low uncertainty of the developed model can also be attributed to the use of participatory modeling techniques to select the input criteria and determine their weights. According to Chen et al. (2011), the uncertainty of weights in MCDA models lies in the subjective expert or stakeholder judgment regarding the relative importance of each criterion. Hence, the co-construction of the vulnerability model with the support of 101 expert stakeholders may have helped to eliminate unnecessary variables and define a more accurate set of weights, thus, reducing the uncertainty. As argued by Voinov and Bousquet (2010), when stakeholders with expertise are involved in the modeling process and are able to achieve a certain degree of consensus, the reliability of results tends to be higher.

Despite the relative robustness, model outcomes are locally sensitive to weight changes, especially in the center of the study area, which has the highest urbanization rates. Hence, end-users should take into consideration that the criteria "households with improper building material" and "evacuation drills and training" require better calibration and careful measurement as they have the highest impact on results. This information can be used by end-users to conduct further studies aiming to refine the role of these two criteria in flood vulnerability assessment in the case study area. For example, the analyst could use data with a finer resolution to determine the vulnerability in the less robust regions (Figure 35c), aiming to reduce the uncertainty.

The criteria "persons under 12 years" and "persons over 60 years", which have received the lowest weights, have almost no impact on model outcomes. Indeed, even when these criteria are removed from the analysis, around 95% of the pixels remain in the same class they had in the base-run (Table 21). Nevertheless, this does not mean that these criteria should be ignored as their lower sensitivity is partially explained by their spatial distribution in the study area. Given that the rural and peri-urban regions in Estrela and Lajeado have a low population density, most of the study area was classified with low vulnerability for these two criteria (Figure 36a). Therefore, the impact of these criteria is restricted to regions with higher urbanization rates. The sensitivity of the criteria in MCDA models is also explained by their weights values in the base run. As already observed in other studies (Xu and Zhang, 2013), the additive nature of the aggregation technique employed influences the SA results. Consequently, criteria with higher weights tend to be more sensitive. Another factor that influences the sensitivity is the spatial resolution of the data. In this regard, criteria with a coarser spatial resolution such as "households with improper building material" (Figure 36b) have a higher sensitivity than the criterion "monthly per capita income", which has a similar weight (Table 21) but a finer resolution (Figure 36c).

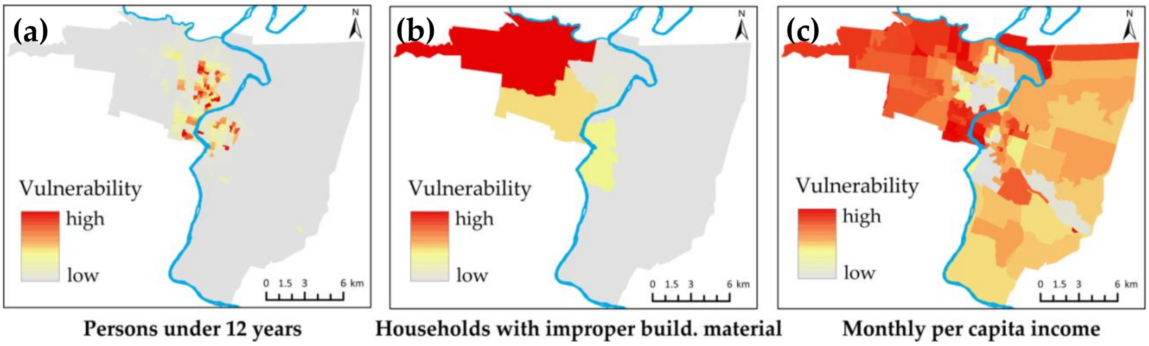

Figure 36. Spatial distribution and resolution of standardized criteria maps: (a) persons under 12 years; (b) households with improper building material; (c) monthly per capita income

Even though this study advanced towards a better understanding of uncertainty in flood vulnerability modeling, it only focused on the SA and UA of weights, as they have been often criticized as the main subjective component of MCDA (Ligmann-Zielinska and Jankowski, 2006). Nevertheless, other sources of uncertainty in GIS-based MCDA models should also be addressed, including the inclusion or exclusion of variables, scale of the analysis, as well as the transformation, standardization, aggregation and MCDA methods used

(Ligmann-Zielinska and Jankowski, 2014; Percival and Tsutsumida, 2017; Tate, 2012; Zhou and Ang, 2009). In this regard, Joerin et al., (2001) point out that the choice of the MCDA technique has a significant effect on model outcomes. To analyze the effects of using other MCDA tools, we also applied the AHP technique to derive criteria weights in a previous step of this study (de Brito et al., 2018). Results showed that the final vulnerability map was not significantly affected by the choice of the MCDA and that the differences were negligible. Nevertheless, the uncertainty of vulnerability map can be further evaluated by comparing the effects of using MCDA tools that do not rely on the use of pairwise comparisons, such as outranking (e.g. ELECTRE and PROMETHEE), ranking (e.g. CAR and SMART), and distance to ideal point methods (e.g. TOPSIS and VIKOR).

The standardization method used to convert the criteria into a common scale has also been shown to affect the model outcomes due to the different assumptions of each technique (e.g. linear scaling, ordinal, z-scores, fuzzy membership functions), as well as due the modeler subjectivity regarding how the criterion contributes to the problem at hand (Ligmann-Zielinska and Jankowski, 2006; Zhou and Ang, 2009). For example, a stakeholder may think that elderly are more vulnerable, as they require assistance during an emergency evacuation. Another person may consider that elderly have more experience in dealing with floods, and hence have a higher coping capacity. Even though this study has not evaluated this type of uncertainty, a focus group with multiple expert stakeholders was used to derive the functions used to standardize the criteria (de Brito et al., 2018). Hence, it is expected that the subjectivity was reduced and that a better picture of different concerns and values was achieved (Ferretti and Montibeller, 2016) as consensus regarding the type and the control points that govern the shape of the function was reached. Moreover, fuzzy membership functions (Malczewski and Rinner, 2015) were used instead of a linear standardization approach. Thus, we prevented making an unrealistic assumption that vulnerability criteria have a linear decay (Ferretti and Montibeller, 2016) and avoided setting hard thresholds by recasting the criterion values into a gradual membership of vulnerability.

Regarding the SA and UA method, limitations also need to be considered. Even though OAT is an intuitive and efficient approach to SA, it ignores the interactions caused by modifying the weights of multiple criteria simultaneously (Butler et al., 1997). This can be especially problematic when dealing with spatial problems, where model inputs can be spatially auto-correlated or can locally co-vary (Ligmann-Zielinska and Jankowski, 2014). Therefore, changing criteria simultaneously can enrich the SA and UA results. In this context, GSA approaches such as Monte Carlo simulations and variance-based SA should be used whenever possible, since they allow assessing the multiple sources of variation in the input assumptions. Nevertheless, GSA approaches also have some drawbacks that should be taken into account. First, GSA has a high computational cost as it requires a large number of model executions (Ligmann-Zielinska and Jankowski, 2014). Second, the subjective assumptions for the parameters of the probability distributions and the normality of the distribution are often subject to bias (Crosetto et al., 2000). Hence, trade-offs between available computational resources and accuracy requirements should be considered when selecting the SA and UA tool to be used.

In future applications, stakeholders could also be engaged in the SA and UA. As suggested by Ferretti and Montibeller (2016), simple methods such as the OAT could be conducted interactively with the decision makers and end-users, with real-time visualization techniques (e.g. using online tools). According to Ligmann-Zielinska and Jankowski (2006), group SA has the potential to bridge quantitative and qualitative approaches in decision-making. It can provide opportunities for group discussions and some degree of social learning among participants (Garmendia and Stagl, 2010). Furthermore, interactive group SA can help to generate more awareness regarding the uncertainties inherent in any MCDA model, allowing participants to achieve a deeper understanding of the structure of the problem (Ferretti, 2011).

5.3.6 Conclusions

This study has employed the OAT method to examine criteria weight sensitivity in an ANP-based vulnerability model aiming to provide information for its effective implementation in flood risk management. The key functionalities of the developed approach are demonstrated using a case study in the municipalities of Lajeado and Estrela, Brazil. SA and UA results provided information on regions with high vulnerability, the spatial distribution of the uncertainty, and the criteria contributing to this uncertainty.

Overall, the sensitivity of the criteria is explained by (1) the weight values in the base run, i.e., criteria with higher weights tend to be more sensitive due to the aggregation technique, (2) the spatial distribution of the standardized criteria. In this regard, criteria related with the population density (e.g. elderly, and children) have a lower sensitivity as their values are concentrated in the center of the study area; and (3) the resolution of the data, i.e., criteria with a coarser spatial resolution have a higher sensitivity than criteria with a similar weight but a finer resolution.

Based on the SA and UA results, end-users can guide their efforts to reduce the uncertainty, enabling to prioritize human, technological and financial resources. Focus should be given to areas classified with high AVG vulnerability and high SD, which are potentially vulnerable but need to be further examined due to a significant degree of uncertainty associated with the vulnerability scores. Regarding the establishment of risk reduction measures, decision makers should emphasize the regions with high and very high vulnerability and low SD depicted in Figure 35c.

Even though the developed approach was applied to a vulnerability model, its flexibility does not limit its use, and it can be applied to other spatial complex problems. Hence, we suggest that SA methods such as the one employed in this study should be regarded as an essential part of any GIS-based MCDA model. The advantages of spatially-explicit OAT consist in its cost-effectiveness, and transparency. Furthermore, it provides easy information for non-experts to explore and visualize how changes in weights affect the model outcomes.

CHAPTER 6

Conclusions and recommendations

This chapter begins with an overview of the key findings drawn from this research. It highlights the significant theoretical, practical, and empirical contributions of this thesis, as well as the implications of the overall findings. Next, a number of limitations and unanswered questions are also discussed. Finally, the chapter gives some suggestions for future research.

6.1 Main findings

In order to recapitulate and summarize the key findings, these will be placed in the context of the research questions formulated in **Section 1.3**. Detailed answers to each of these questions are provided in the corresponding research papers (**Sections 3.4, 5.1, 5.2** and **5.3**).

Question 1: Which MCDM methods are most commonly applied for flood vulnerability assessment?

Overall, the AHP technique was the most used MCDM method, with 21 applications in a total of 27 studies that assessed flood vulnerability (Table 10). One reason for this might be that its structure is straightforward, flexible, and easily understandable (Cinelli et al., 2014). Thanks to these characteristics, it can be adapted to different problems without requiring previous knowledge from the analyst. Moreover, several software packages incorporate AHP (e.g. ExpertChoice, and Super decisions), including GIS software (e.g. Idrisi, and ILWIS). The second most employed method was the simple additive weighting (SAW), with 5 applications. Similarly to AHP, SAW is intuitively appealing to decision makers and it can easily be implemented in GIS environment using map algebra operations (Malczewski and Rinner, 2015).

It should be pointed out that both AHP and SAW assume that the criteria are independent of each other. Arguably, this assumption is difficult to apply in real-world problems, as they typically involve a complex pattern of interactions and dependences among elements (Malczewski and Rinner, 2015). Nevertheless, none of the reviewed vulnerability studies used MCDM tools that consider the interdependence between criteria, such as the ANP and DEMATEL. In addition, classical MCDM methods such as MAUT, MAVT, and PROMETHEE were overlooked.

Question 2: What are the main trends and research gaps in MCDM applied to flood-related problems regarding stakeholder participation?

The systematic literature review revealed that 65 (50.78%) studies have explicitly acknowledged the involvement of multiple actors in the MCDM process. Still, participation was generally fragmented and restricted to consultation at specific stages, especially the elicitation of criteria weights (e.g. Kienberger et al., 2009; Sahin et al., 2013). Crucial aspects of the modeling process like the selection of criteria, data standardization, and model validation were usually constrained to analysts and team members, which inhibit the achievement of genuine participation. The input from stakeholders was a critical element in the entire process only in few studies (e.g. Evers et al., 2012).

Regarding the participatory techniques used, questionnaires, and face-to-face interviews were the most common tools (Figure 8). These methods allow for opinions to be conveyed without influence from dominant individuals. However, by using these methods, participants are not able to share and hear different perspectives through open dialogue. In this regard, Mendoza and Martins (2006) argue that group elicitation methods involving open discussion allow for clarification and often promotes more accurate conceptualizations. Yet, group elicitation methods such as workshops, meetings and focus group discussions were less applied.

Interestingly, only four studies sought to obtain consensus (e.g. Haque et al., 2012; Lee et al., 2013; Lee et al., 2014; Lee et al., 2015), in which participants make decisions by agreement rather than by averaging individual responses. Nevertheless, enhancing mutual understanding for consensus building allows decision makers to derive solutions that fulfil their own needs while at the same time satisfying the requirements of other actors, legitimating participation as a learning process to solve complex problems.

Question 3: Which criteria should be incorporated in the vulnerability model developed for the study area and how should they be structured?

Based on the two-round Delphi survey, 12 criteria were selected: (1) persons under 12 years; (2) persons over 60 years; (3) persons with disabilities; (4) monthly per capita income; (5) households with improper building material; (6) households with accumulated garbage; (7) households with open sewage; (8) disaster prevention institutions; (9) distance to shelters; (10) existence of clearly marked escape routes; (11) health care facilities; and (12) evacuation drills and training (Table 16). Consensus among participants regarding the criteria relevance was reached on all selected items, except monthly income.

Interestingly, the criteria "households with open sewage" and "households with accumulated garbage" have not been reported as relevant in previous vulnerability indexes. Conversely, commonly used indicators were regarded as trivial, including education level, illiterate adults, and gender. These findings are consistent with those of Cutter et al. (2006), which highlight that there is no empirical evidence to support or reject the hypothesis that gender affects the risk perception significantly, and in that case, towards which direction. Regarding the education, citizens without formal education may have a qualified perception of risk through previous experiences and community trainings (Muttarak and Pothisiri, 2013).

The selected indicators were distributed into three clusters based on a focus group discussion: (1) social vulnerability; (2) coping capacity; and (3) infrastructure vulnerability. These where then organized in a hierarchical and in a network structure (Figure 22). Despite some punctual divergences, participants had a flexible attitude towards accepting other experts' opinions and succeeded in reaching workable compromises about generic conceptual models that were satisfactory to all participants.

Question 4: Do experts with different backgrounds and levels of knowledge rely on divergent rationalities regarding the importance of vulnerability criteria?

Neither profession nor affiliation institution affected experts´ perception of flood vulnerability, showing that they do not rely on divergent rationalities. Only punctual differences were identified in 3 criteria (Figure 19). In general, geographers tend to think that the income is more important than engineers. Moreover, experts from social sciences were more concerned about the item social hot spots than participants with miscellaneous professions. Regarding the criterion households with improper building material, both geologists and social scientists agreed that this criterion has a higher importance when compared with engineers.

Some distinctions were noted when opinion shifts between persons with different levels of knowledge were compared. Participants with less expertise tended to modify more their answers in the direction of the group median. Likewise, experts with a higher degree of self-reported knowledge were more persistent in their opinions, thus enhancing their influence on final results. This is in agreement with the findings of Elmer et al. (2010), who states that experts tend to be based on solid experience and therefore, may be reluctant to change their views.

Question 5: What do the participants perceive about the effectiveness of the developed collaborative approach for flood vulnerability assessment?

The validation questionnaire indicated that the participants perceive the developed collaborative approach as a success given that almost all indicated that they would use model results in their future work. All respondents (n = 20) agreed that the participatory MCDM approach provides a promising framework for integrating interdisciplinary knowledge in the effort to bring credibility to vulnerability indexes. Evaluations of the individual components of the methodology were generally positive (Figure 29). All respondents were satisfied or very satisfied with the ANP weights and only one was unsatisfied with the AHP results. Furthermore, 95% of respondents were satisfied or very satisfied with the selected criteria.

The deliberative feedback throughout the entire process positively impacted the participants' perception of the results transparency, resulting in improved credibility. Consequently, all respondents were very satisfied (89%) or satisfied (11%) with the transparency of the methodology. Finally, over 53% and 47% respondents indicated that the developed maps are very useful or useful for their professional activities, respectively. Although this does not mean that the maps will be used in reality, it indicates their willingness to make use of the results. This finding becomes even more relevant when considering that several respondents work for the local Civil Defenses and the National Center for Monitoring and Early Warning of Natural Disasters (CEMADEN) thus having a great influence over decisions related to flood risk management.

Some participants stated that bringing together individuals with different viewpoints resulted in a more comprehensive view of vulnerability. They felt that combining the knowledge of many professionals helped to create a better model schematization. Quoting a statement from an expert, "the participatory approach allowed a greater dialogue among stakeholders and encouraged mutual learning, improving the knowledge about multifaceted problems like flood vulnerability". According to some participants, the interaction with other experts allowed them to expand their knowledge and led, in some cases, to a change in opinion.

Question 6: What are the differences in model results between MCDM methods that consider the interrelationship between the vulnerability criteria and the ones that consider the variables to be independent?

Overall, the weights of the vulnerability criteria were similar in both methods, with the exception of the criterion monthly income. This discrepancy can be explained by the fact that some participants rated it as irrelevant when using the AHP technique. However, when filling the ANP questionnaire, they answered that the income plays a leading role in determining the vulnerability as it influences other criteria such as the building material. Hence, ANP provides a more accurate modeling of complex settings by considering inner and outer dependences among criteria.

The investigation of the spatial implications of the criteria weights showed that the vulnerability scores from the two models are strongly correlated ($R^2 = 0.97$), with 83.11% of the pixels receiving the same classification (Figure 25). Nevertheless, both ANP and AHP models are sensitive to the individual weighting schemes, leading to the creation of different maps.

Participants were, in general, very satisfied with the AHP and ANP results, showing that both methods are effective in solving the ill-structured and interdisciplinary problem of vulnerability. There was a slight preference for the ANP model as participants thought it was easier to understand its logic and no one was unsatisfied with the results (Figure 29). In addition, the agreement among participants about the criteria importance was higher in the ANP model.

Question 7: Which vulnerability criteria are most and least sensitive to weight changes?

Sensitivity analysis results showed that most of the variation in model outputs arises from the criteria “households with improper building material” and “evacuation drills and training”. Hence, end users should consider that these criteria require better calibration and careful measurement as they have the highest impact on results. The criteria “persons under 12 years” and “persons over 60 years”, which have received the lowest weights, have almost no impact on model outcomes. Indeed, even when these criteria are removed from the analysis, around 95% of the pixels remain in the same class they had in the base-run.

The sensitivity of the criteria is explained by: (1) the weight values in the base run, i.e., criteria with higher weights tend to be more sensitive due to the aggregation technique (Xu and Zhang, 2013); (2) the spatial distribution of the standardized criteria. In this regard, criteria related with the population density (e.g. elderly, and children) have a lower sensitivity as their values are concentrated in the center of the study area; and (3) the resolution of the data. Criteria with a coarser spatial resolution such as “households with improper building material” have a higher sensitivity than the criterion “monthly per capita income”, which has a similar weight but a finer resolution.

Question 8: How does the uncertainty of the vulnerability maps vary in space?

Results of the spatially-explicit sensitivity and uncertainty analysis indicate that despite the spatial heterogeneity in uncertainty, the predicted vulnerable areas are robust, meaning that the spatial pattern remains stable when vulnerability criteria weights change. In comparison to other MCDM models with high uncertainty (e.g. Ligmann-Zielinska and Jankowski, 2014; Şalap-Ayça and Jankowski, 2016; Tang et al., 2018), the developed model has low uncertainty values, with a maximum SD of 3.28%. The relatively low SD scores in our study can be partly attributed to the use of the ANP, which is considered to be more reliable than other common MCDM approaches (Dou et al., 2014a; Ghorbanzadeh et al., 2018).

The low uncertainty can also be attributed to the use of participatory modeling techniques to select the criteria and determine their weights. According to Chen et al. (2011), the uncertainty of weights in MCDM models lies in the subjective expert or stakeholder judgment regarding the relative importance of each criterion. Hence, the co-construction of the vulnerability model may have helped to eliminate unnecessary variables and define a more accurate set of weights, thus, reducing the uncertainty.

The final vulnerability map shows that 18.86% of the study area is of high vulnerability with a low uncertainty, and 0.48% of high vulnerability and high uncertainty. These are located mainly at the northeast of the municipality of Lajeado. The less robust pixels correspond to areas with medium vulnerability (21.90% of the study area).

6.2 Concluding remarks

The main purpose of this study was to present a framework for flood vulnerability modeling that relies upon the co-design and cooperation between 101 local practitioners, policy-makers, and scientists. Specifically, this thesis investigated how MCDM tools can be combined with participatory methods to improve not only the assessment of flood vulnerability, but also to democratize the modeling process and open the "black-box" nature of vulnerability models.

The findings demonstrate the merits and feasibility of carrying vulnerability assessments by engaging expert stakeholders in crucial aspects of the MCDM modeling process, including criteria selection, standardization, and weighting. Results show that if modelers expect the vulnerability outputs to be used in decision-making, it is imperative to include end users in the model design. It was found that an active participation led to: (1) an increased shared understanding of the problem by avoiding the limited perspective of a single expert; (2) an ability to transform implicit and tacit knowledge into information useful for vulnerability assessment; (3) a heightened perception of the model being unbiased, fair and inclusive of diverse perspectives; (4) an increased sense of ownership given that participants had a greater ability to effectively influence the direction of the model; and (5) an enhanced credibility and deployment of the final results.

The case study demonstrated that, when sufficiently motivated, stakeholders are prepared to invest the required amount of effort to achieve project objectives. Even though the model development activities were time consuming, the response rate of the questionnaires and the levels of cooperation during the workshops and focus groups were both high and constructive. To achieve this, relevant stakeholders must be introduced as early as possible in the process, when none of the model assumptions are set. Only then can one ensure that their interests will be attended. Particular attention must also be paid to feedback provided. The information delivered must be relevant and should be provided in a way that is readily accessible and understandable. This helps to generate and maintain the necessary commitment and respect for the approach.

In light of the preceding findings, it is important to highlight that participatory modeling exercises such as the one proposed in this thesis can provide benefits that go beyond the production of the final model (Warren, 2016). Indeed, this thesis aimed not at deriving a "single metric" with the "best" flood vulnerability map; instead, it aimed at proposing a framework to estimate vulnerability that promotes transparency and integrates contrasting opinions towards social learning and participants' empowerment. To achieve this, the plurality of views was considered by opening up appraisal inputs to a wider diversity of framings and forms of knowledge (Stirling, 2008). In this regard, the approach exceeds a solely technical view on vulnerability by bridging the gap between different disciplines and viewpoints.

In broad terms, the main scientific outcome of this research is an improved MCDM-based methodology for flood vulnerability analysis that enables considering the stakeholder's different perspectives. The developed transdisciplinary methodology can lead to significant advancements in traditional vulnerability mapping since it provides a platform to enable a truly collaborative, transparent and inclusive process that rightfully empowers participants. The main advantage of using MCDM tools compared to an only verbal discursive approach is to provide tangible information and concrete ideas to act in the respective geographic and societal context, showing cause-effect relationships and illustrating the individual and group-based scenarios.

This study provides a solid contribution to vulnerability and risk analysis research as currently there is no method to evaluate the vulnerability while considering the interrelationship between criteria. The use of the ANP to consider the inner and outer dependences between criteria proved to be effective. Hence, MCDM methods that take interdependencies into account should be used whenever possible as they allow capturing the complex relationships among vulnerability criteria in a transparent way.

This research also generated new intellectual property in the field of spatially-explicit SA and UA analysis of vulnerability models. According to Tate (2012), there is remarkably little knowledge about the robustness of vulnerability indices. Indeed, the systematic literature review conducted showed that the investigation of the spatial variability of criteria weights in vulnerability assessment is still largely absent or rudimentary. Only 2 out of the 27 reviewed papers conducted some sort of partial SA by creating different scenarios and none of them has performed UA (de Brito and Evers, 2016). Hence, this study is timely in describing a feasible method to identify areas that are burdened by high uncertainty and to investigate which criteria contribute to this uncertainty.

The research is also significant from a practical perspective, as there has been limited research on vulnerability in Brazil (e.g. de Almeida et al., 2016; Cançado et al., 2008). Despite the frequency of floods with damaging effects, most studies concentrate on flood descriptions (e.g. Deus et al. 2013; Stevaux et al. 2009), and hazard assessment (e.g. Campana and Tucci 2001; Martinez and Le Toan 2007; Mendes and Chaffe 2014), neglecting the social vulnerability and coping capacity of the exposed elements. Hence, this research can contribute to reduce the lack of knowledge about flood vulnerability in Brazil by providing a manageable approach that can be used in data-scarce environments. The implementation of the results can enable improved planning of flood risk management measures. This can enhance the allocation of financial, technological, and human resources. Furthermore, the set of indicators can be used to create vulnerability indicators in other Brazilian watersheds with similar conditions.

To summarize, this study contributes to recent research activities regarding flood vulnerability analysis and participatory modeling in five aspects. First, it provides an overview of research gaps in the field of flood MCDM and points out future research directions. Second, it contributes to the overall goal of the Sendai Framework for disaster risk reduction by advancing the understanding of disaster risk. Third, it proposes a novel participatory approach for flood vulnerability assessment while considering the interdependence between criteria. Fourth, it presents a simple methodology for conducting sensitivity and uncertainty analysis of GIS-based MCDM models. Finally, it increases information about flood vulnerability in the studied area.

6.3 Limitations of the study

Notwithstanding the efforts made to minimize biases, shortcomings must be acknowledged to avoid uncritical application of this study's findings. First, the small number of participants in the two focus groups limits the generalization of the model conceptualization and data standardization results to other stakeholders, countries, and study areas. This limitation is inherent in participatory modeling processes as they involve normally few participants (Garmendia and Stagl, 2010). To reach a broader audience, it would be necessary to use tools such as questionnaires or web platforms. However, these alternatives also present drawbacks since the participants would not be able to share and hear different perspectives through open dialogue, which is essential for clarifying controversial issues (Orsi et al., 2011). Therefore, we opted to conduct focus group discussions to standardize the criteria and build the conceptual models. Despite this drawback, the results were representative of the experts' sample as 95% of them were satisfied or very satisfied with the conceptual models.

A further methodological caveat was the lack of validation with past flood damages. The absence of a systematic approach to record impacts caused by disasters in the study area makes it difficult, if not unrealistic, to perform validation based on actual flood outcomes. This is a recurrent issue in vulnerability analysis as few indices are empirically validated (Bakkensen et al., 2017; Beccari, 2016; Fekete, 2009, 2012). Indeed, in a review of 106 vulnerability indicators, Beccari (2016) found out that only 3 models were validated against recorded flood impacts. The problem is that since vulnerability does not denote an observable phenomenon (Hinkel et al., 2012), independent data source to validate indicators is seldom available (Fekete, 2009). Even when there is enough information, the direct comparison of the damage from historical floods with the present situation is problematic, because in between the two dates there may have been changes in the land use (Chen et al., 2016). Furthermore, there are many other unobserved and potentially confounding variables. This reinforces the need for developing new approaches to validate vulnerability models. Despite the absence of formal validation, the results of a feedback questionnaire showed that participants have enough confidence in the results to actually use it in their decision-making, which proves the model´s reliability.

Another methodological limitation is that only a basic approach was used to document the sensitivity of the criteria weights. Even though OAT is an intuitive and efficient approach to SA, it ignores the interactions caused by modifying the weights of multiple criteria simultaneously (Butler et al., 1997). This can be especially problematic when dealing with spatial problems, where model inputs can be spatially auto-correlated or can locally co-vary (Ligmann-Zielinska and Jankowski, 2014). Furthermore, other sources of uncertainty were ignored, including the scale of the analysis, the transformation, standardization, and aggregation techniques, and the MCDM method used. Although these uncertainties are not negligible, this study focused only on the UA and SA of weights, as they have been often criticized as the main subjective component of MCDM (Ligmann-Zielinska and Jankowski, 2006).

The developed model does not claim completeness. In this regard, another area which needs to be addressed is the consideration of different temporal effects in vulnerability assessment. The developed composite-indicator is static, providing an estimate of vulnerability for a discrete moment in time and space. Still, vulnerability is embedded in social dynamics and can vary considerably with the stage of disaster and according to the behavior and risk perception of individuals (Aerts et al., 2018; Prior et al., 2017). The same group may be vulnerable in certain phases of a disaster and not vulnerable in others. For instance, children are usually more vulnerable before the flood due to lack of awareness and preparedness (Rufat et al., 2015). During the disaster, men and middle-aged populations are at a higher danger due to risk-taking behavior and involvement in rescue and emergency operations (Jonkman and Kelman, 2005). After floods, minorities and low-income households are more vulnerable due to resource availability (Green et al., 2007). Hence, the maps developed can serve as a baseline scenario to monitor and evaluate future assessments of vulnerability. In this regard, an advantage of MCDM is that, once data becomes available, new scenarios can be easily developed to account for temporal effects.

The final criticism is that while the vulnerability maps produced may help decision makers to identify target areas to reduce flood vulnerability, more detailed information is necessary to determine what measures are necessary. The question remains on how to stimulate coping and adaptive strategies that improve the resilience of exposed communities. Thus, even though composite-indicators such as the one elaborated in this study may be a useful starting point for setting priorities, they are not a replacement for detailed field-based vulnerability and risk analysis. For this purpose, the assessment of vulnerability at a household level in the critical areas is crucial to deepen the understanding of the possible impacts of floods on exposed elements.

6.4 Recommendations for further research

Further improvements of the methodology include conducting a final workshop to create a vulnerability map by mutual consent. In this setting, the participants would determine a weighting scheme that all agree. This would likely improve the stakeholders' sense of ownership, thus, increasing the likelihood that the results will be used. Such studies could benefit from the use of consensus decision-making tools such as the nominal group technique (NGT), which helps to engage stakeholders to share and discuss ideas, considering an equal representation of all members. The NGT allows disparate ideas on matters of shared interest to be expressed and compared, with a view to identifying areas of consensus (Harvey and Holmes, 2012). Alternatively, the dotmocracy (Bowles et al., 2016), fall-back methods (Heitzig and Simmons, 2012), and multi-voting tools (Bens, 2005) could be used.

In order to derive a group set of weights, simpler weighting techniques such as SMART, CAR, and SWING could be tested. Empirical evidence shows that centroid weighting methods (e.g. CAR and SMART) provide almost the same accuracy as AHP while requiring less input and mental effort from respondents (Alfares and Duffuaa, 2008; Riabacke et al., 2012). Hence, it would be easier to use it in a group setting when compared to AHP and ANP, which demand a significant cognitive effort from participants due to the inconsistency in the matrices. These techniques could also be implemented in questionnaires in order to reach a broader number of participants. Nevertheless, none of these tools consider the interactions between the criteria. In this regard, potential exists to combine the above-mentioned methods with the DEMATEL technique. Unlike traditional MCDM methods, DEMATEL identifies the interdependence among the elements. It is based on graph theory, allowing to visualize the relations between relevant criteria (Chung-Wei and Gwo-Hshiung, 2009).

Regarding the sensitivity and uncertainty analysis, further research includes conducting GSA to assess the effects of design choices (e.g. scale of analysis, data transformation, MCDM method, and criteria standardization and aggregation) in model outputs. This could be achieved by repeatedly running the model in a Monte Carlo approach (Lilburne and Tarantola, 2009) or using variance-based SA (Saint-Geours et al., 2014). Such analyses would be useful in evaluating the effects of epistemic uncertainty (Walker et al., 2003), helping to understand which choices contribute most to possible variances in the index scores. Additionally, innovative approaches may be required to improve the computationally intensive calculations required for performing spatially-explicit UA and SA (Percival and Tsutsumida, 2017).

In future applications, stakeholders could also be engaged in the SA and UA. As suggested by Ferretti and Montibeller (2016), the OAT method could be conducted interactively with the decision makers and end users, using real-time visualization techniques (e.g. online platform). Interactive group SA can help to generate more awareness regarding the uncertainties inherent in any MCDM model, allowing participants to achieve a deeper understanding of the problem structure (Ferretti, 2011). Furthermore, it can provide opportunities for group discussions and some degree of social learning (Garmendia and Stagl, 2010).

Concerning social learning processes, it would be interesting to carry out a survey at the beginning and at the end of the participatory modeling process to investigate how the preferences of participants have evolved over time. This would allow assessing whether social and shared learning have occurred, and if so, to what extent, and between whom, when, and how. For this purpose, a similar questionnaire as the ones outlined in Garmendia and Gamboa (2012) and Maskrey et al. (2016) could be used. Alternatively, interviews could also be conducted to assess social learning at the individual and community level (Benson et al., 2016).

Lastly, a significant gain can be made if vulnerability models are able to incorporate human behavior and risk perception in a dynamic way. Currently, most assessments assume that vulnerability remains constant across time and space. This assumption implies that individuals do not adapt, learn from experience, or prepare for an event based on risk information or early warning (Aerts et al., 2018). Thus, static quantifications of vulnerability may overestimate future losses by assuming constant vulnerability in a changing climate (Mechler and Bouwer, 2015). Given these challenges, an appropriate way forward is to adopt an interdisciplinary approach to measure risk at a local level by integrating behavioral assessments dynamically. This promises to enhance flood risk assessment in accordance with the priorities of the Sendai Framework for disaster risk reduction.

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Supplementary material

Figure S1. Individual vulnerability maps

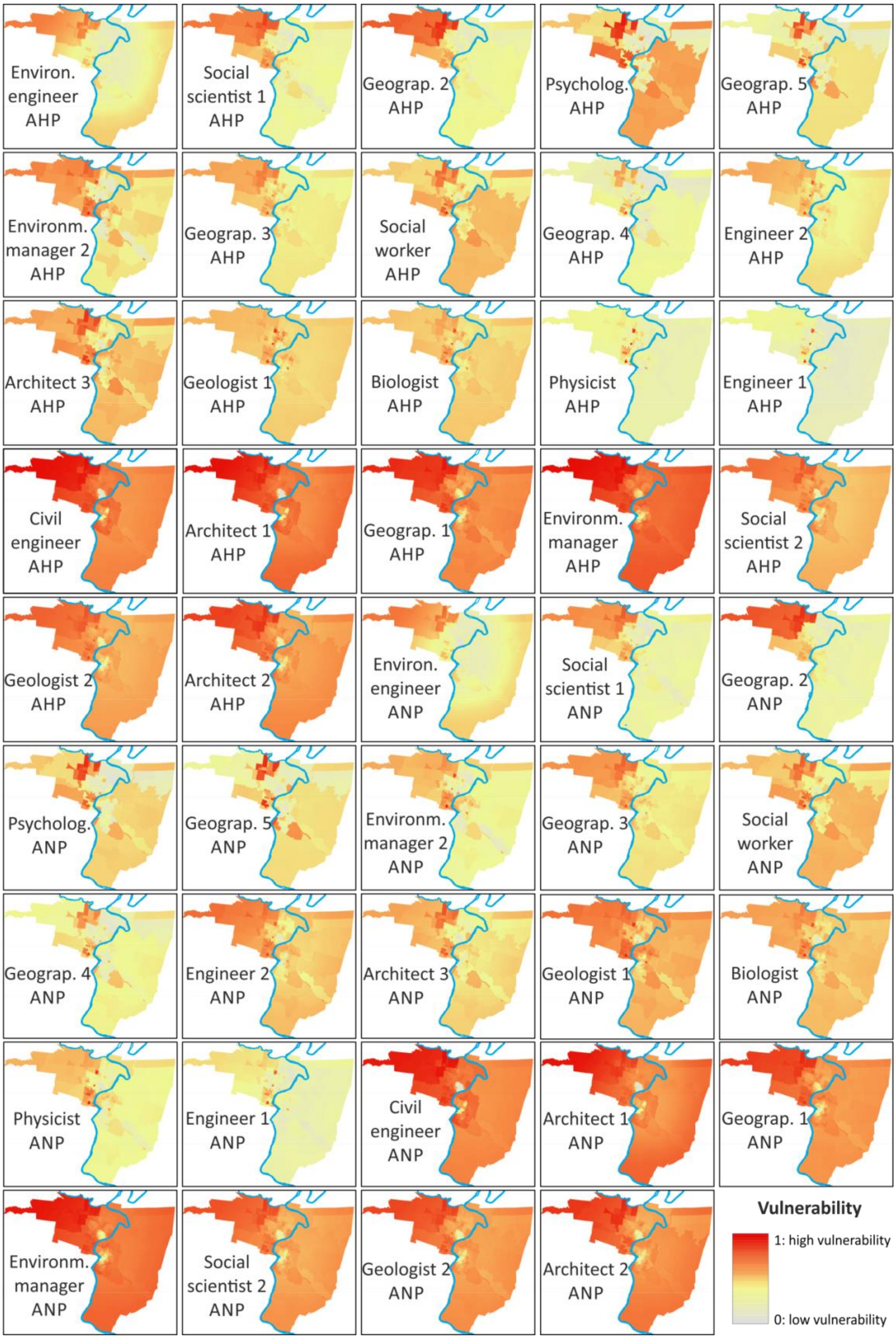

Table S1. Overview of the papers included in the literature review

Author(s)	Year	Title of the publication	Journal	Country(ies) of application	Area(s) of application	MCDM method(s)	Stakehol-ders invol-vement	Participatory technique(s) applied*	SA	SA method	UA	UA method
Tkach and Somonovic	1997	A new approach to multi-criteria decision making in water resources	Journal of Geographic Information and Decision Analysis	Canada	alternative ranking	SCP, CP	No		No		No	
Buzolic et al.	2001	Decision support system for disaster communications in Dalmatia	International Journal of Emergency Management	Croatia	emergency management	PROMETHEE	No		No		No	
Margeta and Knezic	2002	Selection of the flood management solution of Karstic Field	Water International	Croatia	alternative ranking	AHP, PROMETHEE I, PROMETHEE II	Yes	does not mention	No		No	
Azibi and Vanderpooten	2003	Aggregation of dispersed consequences for constructing criteria: the evaluation of flood risk reduction strategies	European Journal of Operational Research	France	alternative ranking	WSM	Yes	group meeting	No		No	
Bana e Costa et al.	2004	Multicriteria evaluation of flood control measures: the case of Ribeira do Livramento	Water Resources Management	Portugal	alternative ranking	MACBETH	Yes	interviews	Yes	one-way SA	No	
Brouwer and van Ek	2004	Integrated ecological, economic and social impact assessment of alternative flood control policies in the Netherlands	Ecological Economics	Netherlands	alternative ranking	WSM	Yes	stakeholder analysis	Yes	does not mention	No	
Chen and Hou	2004	Multicriterion decision making for flood control operations: theory and applications	Journal of the American Water Resources Association	China	reservoir flood control	fuzzy recognition model	No		No		No	
Levy	2005	Multiple criteria decision making and decision support systems for flood risk management	Stochastic Environmental Research and Risk Assessment	China	emergency management	ANP	Yes	workshops	No		No	
Simonovic and Niruoama	2005	A spatial multi-objective decision-making under uncertainty for water resources management	Journal of Hydroinformatics	Canada	alternative ranking	spatial fuzzy CP	No		No		No	
Al-Awadhi and Hersi	2006	Surface runoff hazard map distribution in Kuwait	Management of Environmental Quality: An International Journal	Kuwait	susceptibility	AHP	Yes	delphi technique	No		No	
Plattner et al.	2006	Integrating public risk perception into formal natural hazard risk assessment	Natural Hazards and Earth System Sciences	Germany	risk	AHP	Yes	delphi technique, workshops, questionnaires	No		No	
Simonovic and Akter	2006	Participatory floodplain management in the Red River Basin, Canada	Annual Reviews in Control	Canada	alternative ranking	fuzzy CP	Yes	interviews, questionnaires, workshops	No		No	
Gao et al.	2007	An assessment of flood hazard vulnerability in the Dongting Lake Region of China	Lakes & Reservoirs: Research and Management	China	susceptibility, hazard, vulnerability	AHP	Yes	does not mention	No		No	

Kenyon	2007	Evaluating flood risk management options in Scotland: a participant-led multi-criteria approach	Ecological Economics	Scotland	alternative ranking	rank sum method, rank order centroid	Yes	workshops	No		No
Lee and Chung	2007	Development of integrated watershed management schemes for an intensively urbanized region in Korea	Journal of Hydro-environment Research	South Korea	hazard, vulnerability, risk	composite programming, AHP	Yes	does not mention	No		No
Levy et al.	2007	Multi-criteria decision support systems for flood hazard mitigation and emergency response in urban watersheds	Journal of the American Water Resources Association	Japan	emergency management	ANP	Yes	interviews	No		No
Martin et al.	2007	Urban stormwater drainage management: the development of a multicriteria decision aid approach for best management practices	European Journal of Operational Research	France	alternative ranking	ELECTRE III	Yes	questionnaires	Yes	one-way SA	No
Rahman and Saha	2007	Flood hazard zonation - a GIS aided Multi Criteria Evaluation (MCE) approach with remotely sensed data	International Journal of Geoinformatics	Bangladesh	hazard	AHP	Yes	focus group discussions	No		No
Fu	2008	A fuzzy optimization method for multicriteria decision making: an application to reservoir flood control operation	Expert Systems with Applications	China	reservoir flood control	extended fuzzy TOPSIS	No		No		No
Raaijmakers et al.	2008	Flood risk perceptions and spatial multi-criteria analysis: an exploratory research for hazard mitigation	Natural Hazards	Spain	alternative ranking	WSM	Yes	questionnaires, interviews	No		No
Scolobig et al.	2008	Integrating multiple perspectives in social mu lticriteria evaluation of flood-mitigation alternatives: the case of Malborghetto-Valbruna	Environment and Planning C - Government and Policy	Italy	alternative ranking	NAIADE	Yes	interviews, questionnaires, narrative analysis	No		No
Sinha et al.	2008	Flood risk analysis in the Kosi river basin, north Bihar using multi-parametric approach of AHP	Journal of the Indian Society of Remote Sensing	India	susceptibility	AHP	No		No		No
Yazdandoost and Bozorgy	2008	Flood risk management strategies using multi-criteria analysis	Proceedings of the Institution of Civil Engineers: Water Management	Germany	alternative ranking	WSM, evamix	No		Yes	probabilis tic SA	No
Chung and Lee	2009	Identification of spatial ranking of hydrological vulnerability using multicriteria decision making techniques: Case study of Korea	Water Resources Management	South Korea	hazard, vulnerability, risk	AHP, Composite programming, CP, ELECTRE II, evamix, Regime	Yes	questionnaires	No		No
Jiang et al.	2009	Risk assessment and validation of flood disaster based on fuzzy mathematics	Progress in Natural Science	Malaysia	risk	AHP	No		No		No
Kienberger et al.	2009	Spatial vulnerability units – expert-based spatial modelling of socio-economic vulnerability in the Salzach catchment, Austria	Natural Hazards and Earth System Sciences	Austria	vulnerability, coping capacity	AHP	Yes	questionnaires	No		No
Kubal et al.	2009	Integrated urban flood risk assessment – adapting a multicriteria approach to a city	Natural Hazards and Earth System Sciences	Germany	vulnerability, risk	WSM	No		No		No

Lim and Lee	2009	The spatial MCDA approach for evaluating flood damage reduction alternatives	KSCE Journal of Civil Engineering	South Korea	alternative ranking	CP, SPC	No		No		No	
Meyer et al.	2009	Flood risk assessment in European river basins - concept, methods, and challenges exemplified at the Mulde River	Integrated Environmental Assessment and Management	Germany	risk	WSM	No		Yes	one-way SA	No	
Meyer et al.	2009	A multicriteria approach for flood risk mapping exemplified at the Mulde river, Germany	Natural Hazards	Germany	risk	MAUT, Disjunctive approach	No		Yes	one-way SA	No	
Nijssen et al.	2009	Planning of technical flood retention measures in large river basins under consideration of imprecise probabilities of multivariate hydrological loads	Natural Hazards and Earth System Sciences	Germany	alternative ranking	fuzzy AHP	No		No		No	
Choudhury	2010	Reservoir flood control operation model incorporating multiple uncontrolled water flows	Lakes & Reservoirs: Research and Management	India	reservoir flood control	goal programming	No		No		No	
Fernández and Lutz	2010	Urban flood hazard zoning in Tucumán Province, Argentina, using GIS and multicriteria decision analysis	Engineering Geology	Argentina	susceptibility	AHP	No		Yes	GSA (FAST), Monte Carlo	Yes	Taylor's series error
Schumann	2010	Handling uncertainties of hydrological loads in flood retention planning	International Journal of River Basin Management	Germany	alternative ranking	TOPSIS, fuzzy AHP	No		No		No	
Vafaei and Harati	2010	Strategic management in decision support system for coastal flood management	International Journal of Environmental Research	Iran	alternative ranking	AHP	No		No		No	
Yahaya et al.	2010	Multicriteria analysis for flood vulnerable areas in Hadejia-Jama'are River Basin, Nigeria	European Journal of Scientific Research	Nigeria	hazard	AHP	No		Yes	one-way SA	No	
Ceccato et al.	2011	Participatory assessment of adaptation strategies to flood risk in the Upper Brahmaputra and Danube river basins	Environmental Science & Policy	Germany, Austria, India, Bhutan, China	alternative ranking	ELECTRE III	Yes	Delphi technique, workshops	Yes	one-way SA	Yes	qualitative UA
Chen et al.	2011	Integrated application of the analytic hierarchy process and the geographic information system for flood risk assessment and flood plain management in Taiwan	Natural Hazards	Taiwan	risk	AHP	Yes	questionnaires	No		No	
Dang et al.	2011	Evaluation of flood risk parameters in the Day River flood diversion area, Red River Delta, Vietnam	Natural Hazards	Vietnam	hazard, vulnerability, risk	AHP	Yes	workshops, interviews	No		No	
Das et al.	2011	An aggregative fuzzy risk analysis for flood incident management	International Journal of System Assurance Engineering and Management	Canada	emergency management	fuzzy AHP	No		No		No	
Deshmukh et al	2011	Impact of flood damaged critical infrastructure on communities and industries	Built Environment Project and Asset	USA	emergency management	AHP	Yes	questionnaires, interviews	No		No	

			Management								
Jun et al.	2011	Development of spatial water resources vulnerability index considering climate change impacts	Science of The Total Environment	China	risk	TOPSIS	Yes	questionnaires, interviews	Yes	one-way SA	No
Kourgialas and Karatzas	2011	Flood management and a GIS modelling method to assess flood-hazard areas—a case study	Hydrological Sciences Journal	Greece	hazard	WSM	No		No		No
Liu et al.	2011	Assessment of capacity of flood disaster prevention and reduction with 2-tuple linguistic information	Journal of Convergence Information Technology	China	coping capacity	TOPSIS	No		No		No
Malekmohammadi et al.	2011	Ranking solutions of multi-objective reservoir operation optimization models using multi-criteria decision analysis	Expert Systems with Applications	Iran	reservoir flood control	ELECTRE-TRI	No		Yes	does not mention	No
Ozturk and Batuk	2011	Implementation of GIS-based multicriteria decision analysis with VB in ArcGIS	International Journal of Information Technology & Decision Making	Turkey	susceptibility	AHP	No		Yes	one-way SA	No
Sarker et al.	2011	GIS and RS combined analysis for flood prediction mapping - a case study of Dhaka City corporation, Bangladesh	International Journal of Environmental Protection	Bangladesh	susceptibility	AHP	No		No		No
Scheuer et al.	2011	Exploring multicriteria flood vulnerability by integrating economic, social and ecological dimensions of flood risk and coping capacity - from a starting point view towards an end point view of vulnerability	Natural Hazards	Germany	vulnerability , coping capacity, risk	WSM	No		No		No
Wang et al.	2011	Flood control operations based on the theory of variable fuzzy sets	Water Resources Management	China	reservoir flood control	variable fuzzy sets	No		No		No
Wang et al.	2011	A GIS-based spatial multi-criteria approach for flood risk assessment in the Dongting Lake Region, Hunan, Central China	Water Resources Management	China	hazard, vulnerability, risk	fuzzy AHP	Yes	delphi technique, questionnaires	No		No
Adiat et al.	2012	Integration of geographic information system and 2D imaging to investigate the effects of subsurface conditions on flood occurrence	Modern Applied Science	Malaysia	hazard	AHP	No		No		No
Ball et al.	2012	A new methodology to assess the benefits of flood warning	Journal of Flood Risk Management	UK	emergency management, alternative ranking	WSM	Yes	workshops, interviews, questionnaires	Yes	one-way SA	No
Chen and Chen	2012	Spatio-temporal variation of flood vulnerability at the Poyang Lake Ecological Economic Zone, Jiangxi Province, China	Water Science & Technology	China	hazard, coping capacity, vulnerability, risk	AHP	No		No		No
Chen et al.	2012	Losses assessment for region flood disasters based on entropy weight TOPSIS model	Advances in Information Sciences and Service Sciences	China	risk	TOPSIS	No		No		No
Elmoustafa	2012	Weighted normalized risk factor for floods risk assessment	Ain Shams Engineering Journal	Egypt	susceptibility	WSM	No		No		No
Evers et al.	2012	Collaborative modelling for active	Natural Hazards and	Germany	alternative ranking	fuzzy TOPSIS	Yes	stakeholder	No		No

		involvement of stakeholders in urban flood risk management	Earth System Sciences	and UK				analysis, interviews, workshops, web-based platform				
Haque et al.	2012	Participatory integrated assessment of flood protection measures for climate adaptation in Dhaka	Environment and Urbanization	Bangladesh	alternative ranking	WSM	Yes	focus group discussions	Yes	one-way SA	No	
Irvem et al.	2012	Identification of flood risk area in the Orontes river basin, Turkey, using multi-criteria decision analyses	Journal of Food, Agriculture & Environment	Turkey	hazard	AHP	No		No		No	
Kandilioti and Makropoulos	2012	Preliminary flood risk assessment: the case of Athens	Natural Hazards	Greece	susceptibility, vulnerability, risk	AHP	Yes	questionnaires	Yes	best and worst case scenarios	No	
Li et al.	2012	Research on flood risk analysis and evaluation method based on variable fuzzy sets and information diffusion	Safety Science	China	risk	AHP	No		No		No	
Majlingová et al.	2012	An assessment of hucava mountain stream catchment susceptibility to flooding	Journal of Forest Science	Slovakia	susceptibility	WSM	No		No		No	
Markovic	2012	Multi criteria analysis of hydraulic structures for river training works	Water Resources Management	Serbia	alternative ranking	ELECTRE	No		No		No	
Musungo et al.	2012	Using multi-criteria evaluation and GIS for flood risk analysis in informal settlements of Cape Town: the case of Graveyard Pond	South African Journal of Geomatics	South Africa	vulnerability	AHP	Yes	questionnaires	No		No	
Yang et al.	2012	A fuzzy AHP-TFN based evaluation model of flood risk analysis	Journal of Computational Information Systems	China	susceptibility, hazard, risk, vulnerability, coping capacity, alternative ranking	fuzzy AHP-TFN	No		No		No	
Elmoustafa et al.	2013	Flash flood risk assessment using morphological parameters in Sinai peninsula	Open Journal of Modern Hydrology	Egypt	susceptibility	WSM	No		Yes	does not mention	No	
Gaňová et al.	2013	A rainfall distribution and their influence on flood generation in the eastern Slovakia	Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis	Slovakia	hazard	rank sum method	No		No		No	
Ghanbarpour et al.	2013	A comparative evaluation of flood mitigation alternatives using GIS-based river hydraulics modelling and multicriteria decision analysis	Journal of Flood Risk Management	Iran	alternative ranking	TOPSIS	No		Yes	best and worst case scenarios	No	
Giupponi et al.	2013	A dynamic assessment tool for exploring and communicating vulnerability to floods and climate change	Environmental Modelling & Software	India	vulnerability, coping capacity	MAVT	Yes	workshops, questionnaires	Yes	one-way SA	Yes	does not mention
Jun et al.	2013	A fuzzy multi-criteria approach to flood risk vulnerability in South Korea by considering climate change impacts	Expert Systems with Applications	South Korea	hazard, coping capacity, vulnerability, risk	WSM, TOPSIS, fuzzy TOPSIS	Yes	Delphi technique	No		No	

Kang et al.	2013	A sensitivity analysis approach of multi-attribute decision making technique to rank flood mitigation projects	KSCE Journal of Civil Engineering	South Korea	alternative ranking	WSM	No		Yes	one-way SA	No	
Le Cozannet et al.	2013	An AHP-derived method for mapping the physical vulnerability of coastal areas at regional scales	Natural Hazards and Earth System Sciences	France	susceptibility	AHP	Yes	does not mention	Yes	one-way SA	Yes	qualitative UA
Lee et al.	2013	Integrated multi-criteria flood vulnerability approach using fuzzy TOPSIS and Delphi technique	Natural Hazards and Earth System Sciences	South Korea	risk	fuzzy TOPSIS	Yes	Delphi technique	No		No	
Li	2013	Fuzzy approach to analysis of flood risk based on variable fuzzy sets and improved information diffusion methods	Natural Hazards and Earth System Sciences	China	risk	AHP	No		No		Yes	Monte Carlo
Li et al.	2013	Impact assessment of urbanization on flood risk in the Yangtze River Delta	Stochastic Environmental Research and Risk Assessment	China	hazard, vulnerability, risk	AHP	No		No		No	
Marttunen et al.	2013	How to design and realize participation of stakeholders in MCDA processes? A framework for selecting an appropriate approach	EURO Journal on Decision Processes	Finland	alternative ranking	MAVT	Yes	interviews, group meetings, questionnaires	No		No	
Penning-Rowsell et al.	2013	A threatened world city: the benefits of protecting London from the sea	Natural Hazards	UK	alternative ranking	weighted average	Yes	does not mention	Yes	one-way SA, best and worst case scenarios	Yes	qualitative UA
Porthin et al.	2013	Multi-criteria decision analysis in adaptation decision-making: a flood case study in Finland	Regional Environmental Change	Finland	alternative ranking	MAVT	Yes	workshops	Yes	one-way SA	No	
Qi et al.	2013	GIS-based spatial Monte Carlo analysis for integrated flood management with two dimensional flood simulation	Water Resources Management	USA	alternative ranking	SCP	Yes	questionnaires	Yes	does not mention	Yes	Monte Carlo
Sahin et al.	2013	Assessment of sea-level rise adaptation options: multiple-criteria decision-making approach involving stakeholders	Structural Survey	Australia	alternative ranking	AHP	Yes	questionnaires	Yes	one-way SA	No	
Salehi et al.	2013	Urban flood hazard zonation using GIS and fuzzy-AHP analysis (Case study: Tehran city)	Journal of Environmental Studies	Iran	susceptibility	fuzzy AHP	No		No		No	
Saxena et al.	2013	Development of habitation vulnerability assessment framework for coastal hazards: Cuddalore coast in Tamil Nadu, India—A case study	Weather and Climate Extremes	India	risk	AHP	Yes	interviews, questionnaires	No		No	
Solín	2013	Spatial variability in the flood vulnerability of urban areas in the headwater basins of Slovakia	Journal of Flood Risk Management	Slovakia	vulnerability	MAUT	No		No		No	
Stefanidis and Stathis	2013	Assessment of flood hazard based on natural and anthropogenic factors using analytic	Natural Hazards	Greece	susceptibility	AHP	No		No		No	

		hierarchy process (AHP)									
Yang et al.	2013	Application of a triangular fuzzy AHP approach for flood risk evaluation and response measures analysis	Natural Hazards	China	hazard, vulnerability, coping capacity, risk, alternative ranking	fuzzy AHP, trapezoidal fuzzy AHP, hybrid fuzzy AHP-TFN	No		No		No
Zagonari and Rossi	2013	A heterogeneous multi-criteria multi-expert decision-support system for scoring combinations of flood mitigation and recovery options	Environmental Modelling & Software	Italy	alternative ranking	fuzzy TOPSIS	Yes	does not mention	Yes	does not mention	No
Zou et al.	2013	Comprehensive flood risk assessment based on set pair analysis-variable fuzzy sets model and fuzzy AHP	Stochastic Environmental Research and Risk Assessment	China	hazard, vulnerability, risk	trapezoidal fuzzy AHP	Yes	does not mention	No		No
Anacona et al.	2014	Moraine-dammed lake failures in Patagonia and assessment of outburst susceptibility in the Baker Basin	Natural Hazards and Earth System Sciences	Chile	susceptibility	AHP	No		No		No
Chung et al.	2014	Water resource vulnerability characteristics by district's population size in a changing climate using subjective and objective weights	Sustaintability	South Korea	hazard, coping capacity, vulnerability, risk	TOPSIS	Yes	Delphi technique	No		No
Edjossan-Sossou et al.	2014	A decision-support methodology for assessing the sustainability of natural risk management strategies in urban areas	Natural Hazards and Earth System Sciences	France	alternative ranking	weighted arithmetic mean	No		Yes	one-way SA	No
Ghasemi et al.	2014	Investigation of flooding and causative factors in Balegli Chay Watershed by GIS, RS, and AHP techniques	Journal of Environmental Studies	Iran	hazard	AHP	No		No		No
Guo et al.	2014	Integrated risk assessment of flood disaster based on improved set pair analysis and the variable fuzzy set theory in central Liaoning Province, China	Natural Hazards	China	hazard, coping capacity, vulnerability, risk	hybrid AHP entropy weight	No		No		No
Hashemi et al.	2014	An extended compromise ratio model with an application to reservoir flood control operation under an interval-valued intuitionistic fuzzy environment	Applied Mathematical Modelling	China	reservoir flood control	fuzzy compromise ratio method	Yes	does not mention	Yes	one-way SA	No
Johnston et al.	2014	Assessing the vulnerability of coastal infrastructure to sea level rise using multi-criteria analysis in Scarborough, Maine (USA)	Ocean & Coastal Management	USA	vulnerability	WSM	No		No		No
Lawal et al.	2014	Group-based decision support for flood hazard forecasting: a geospatial technology-based group analytic hierarchy process approach	Research Journal of Applied Sciences, Engineering and Technology	Malaysia	hazard	AHP	Yes	does not mention	No		No
Lee et al.	2014	Robust spatial flood vulnerability assessment for Han River using fuzzy TOPSIS with α-cut level set	Expert Systems with Applications	South Korea	risk	fuzzy TOPSIS, α-level based fuzzy TOPSIS	Yes	Delphi technique	No		No
Liu et al.	2014	Rapid assessment of flood loss based on neural network ensemble	Transactions of Nonferrous Metals	China	risk	AHP	No		No		No

			Society of China									
Miyamoto et al.	2014	Development of an integrated decision-making method for effective flood early warning system	Journal of Disaster Research	Bangladesh	alternative ranking	AHP-SWOT, fuzzy AHP	Yes	questionnaires, workshops	No		No	
Ouma and Tateishi	2014	Urban flood vulnerability and risk mapping using integrated multi-parametric AHP and GIS: methodological overview and case study assessment	Water	Kenya	hazard	AHP	Yes	does not mention	No		No	
Radmehr and Araghinejad	2014	Developing strategies for urban flood management of Tehran City using SMCDM and ANN	Journal of Computing in Civil Engineering	Iran	susceptibility	AHP	No		No		No	
Shams et al.	2014	Improving consistency evaluation in fuzzy multi-attribute pairwise comparison-based decision-making methods	Asia-Pacific Journal of Operational Research	Australia	alternative ranking	hybrid fuzzy AHP TOPSIS	Yes	interviews, questionnaires	No		No	
Su and Tung	2014	Multi-criteria decision making under uncertainty for flood mitigation	Stochastic Environmental Research and Risk Assessment	Greece	alternative ranking	PROMETHEE II	Yes	does not mention	Yes	one-way SA	Yes	probabilistic
van Loon-Steensma et al.	2014	Green adaptation by innovative dike concepts along the Dutch Wadden Sea coast	Environmental Science & Policy	Netherlands	alternative ranking	WSM	Yes	does not mention	No		No	
Yeganeh and Sabri	2014	Flood vulnerability assessment in Iskandar Malaysia using multi-criteria evaluation and fuzzy logic	Research Journal of Applied Sciences, Engineering and Technology	Malaysia	susceptibility	WSM	No		Yes	one-way SA	No	
Zhao et al.	2014	Dynamic risk assessment model for flood disaster on a projection pursuit cluster and its application	Stochastic Environmental Research and Risk Assessment	China	risk	fuzzy AHP	Yes	does not mention	No		No	
Zhou et al.	2014	Study of the comprehensive risk analysis of dam-break flooding based on the numerical simulation of flood routing. Part II: model application and results	Natural Hazards	China	risk	AHP, TOPSIS	No		Yes	one-way SA	No	
Ahmadisharaf et al.	2015	Evaluating the effects of inundation duration and velocity on selection of flood management alternatives using multi-criteria decision making	Water Resources Management	USA	alternative ranking	SCP	No		Yes	does not mention	No	
Alipour	2015	Risk-informed decision making framework for operating a multi-purpose hydropower reservoir during flooding and high inflow events, case study: Cheakamus River System	Water Resources Management	Canada	reservoir flood control	AHP	No		Yes	best and worst case scenarios	No	
Almoradie et al.	2015	Web-based stakeholder collaboration in flood risk management	Journal of Flood Risk Management	Germany, UK	alternative ranking	TOPSIS	Yes	web-based platform, workshops	No		No	
Berry and BenDor	2015	Integrating sea level rise into development suitability analysis	Computers, Environments and Urban Systems	USA	susceptibility	AHP	No		No		No	

Chen et al.	2015	Flood hazard assessment in the Kujukuri Plain of Chiba Prefecture, Japan, based on GIS and multicriteria decision analysis	Natural Hazards	Japan	hazard	AHP	No		Yes	global SA (FAST)	No
Chitsaz et al.	2015	Comparison of different multi criteria decision-making models in prioritizing flood management alternatives	Water Resources Management	Iran	alternative ranking	WSM, CP, VIKOR, TOPSIS, M-TOPSIS, AHP ELECTRE I, ELECTRE III	Yes	does not mention	Yes	one-way SA	No
Dassanayake et al.	2015	Methods for the evaluation of intangible flood losses and their integration in flood risk analysis	Coastal Engineering Journal	Germany	risk	MAUT, AHP	No		No		No
Gao et al.	2015	Research on meteorological thresholds of drought and flood disaster: a case study in the Huai River Basin, China	Stochastic Environmental Research and Risk Assessment	China	hazard	AHP	No		No		No
Godfrey et al.	2015	Assessing vulnerability of buildings to hydro-meteorological hazards using an expert based approach – An application in Nehoiu Valley, Romania	International Journal of Disaster Risk Reduction	Romania	vulnerability	AHP	Yes	does not mention	No		No
Lai et al.	2015	A fuzzy comprehensive evaluation model for flood risk based on the combination weight of game theory	Natural Hazards	China	susceptibility, hazard, vulnerability, risk	AHP	Yes	does not mention	No		No
Lee et al.	2015	Group decision-making approach for flood vulnerability identification with the fuzzy VIKOR method	Natural Hazards and Earth System Sciences	South Korea	risk	group fuzzy VIKOR, fuzzy VIKOR, fuzzy TOPSIS	Yes	Delphi technique, questionnaires, interviews	No		No
Mamun et al.	2015	Application of a goal programming algorithm to incorporate environmental requirements in a multi-objective Columbia River Treaty Reservoir optimization model	Canadian Water Resources Journal	Canada	reservoir flood control	goal programming	No		No		No
Nivolianitou et al.	2015	Flood disaster management with the use of AHP	International Journal of Multicriteria Decision Making	Greece	emergency management	AHP	Yes	interviews	No		No
Oumeraci et al.	2015	XtremRisK — Integrated flood risk analysis for extreme storm surges at open coasts and in estuaries: methodology, key results and lessons learned	Coastal Engineering Journal	Germany	risk	MAUT, AHP	No		No		No
Ou-Yang et al.	2015	Highway flood disaster risk evaluation and management in China	Natural Hazards	China	susceptibility, hazard, vulnerability, risk	AHP	Yes	does not mention	No		No
Papaioannou et al.	2015	Multi-criteria analysis framework for potential flood prone areas mapping	Water Resources Management	Greece	susceptibility	fuzzy AHP, AHP	Yes	does not mention	No		No
Ronco et al.	2015	KULTURisk regional risk assessment methodology for water-related natural hazards - Part 2: Application to the Zurich	Hydrology and Earth System Sciences	Switzerland	risk	weighted average	Yes	group meetings	No		No

		case study									
Roy and Blaschke	2015	Spatial vulnerability assessment of floods in the coastal regions of Bangladesh	Geomatics, Natural Hazards and Risk	Bangladesh	vulnerability, coping capacity	AHP	Yes	does not mention	No		No
Seo et al.	2015	Development of priority setting process for the small stream restoration projects using multi criteria decision analysis	Journal of Hydroinformatics	South Korea	risk	PROMETHEE, WSM	Yes	does not mention	No		No
Sowmya et al.	2015	Urban flood vulnerability zoning of Cochin City, southwest coast of India, using remote sensing and GIS	Natural Hazards	India	vulnerability	WSM	No		No		No
Taib et al.	2015	Conflicting bifuzzy multi-attribute group decision making model with application to flood control project	Group Decision and Negotiation	Malaysia	alternative ranking	fuzzy TOPSIS, fuzzy AHP	Yes	questionnaires	Yes	one-way SA	No
Walczykiewicz	2015	Multi-criteria analysis for selection of activity options limiting flood risk	Water Resources	Poland	alternative ranking	TOPSIS, sum of the weighted mean	Yes	does not mention	No		No
Wu et al.	2015	Integrated flood risk assessment and zonation method: a case study in Huaihe River basin, China	Natural Hazards	China	hazard, vulnerability, risk	AHP	Yes	does not mention	No		No

* "Does not mention" means that multiple stakeholders were considered in the analysis, but the authors did not specify the technique applied to capture the stakeholders´ opinion. In the case where multiple stakeholders were not considered, this column was left empty

Table S2. Characteristics of the expert stakeholders

Characteristic	Delphi 1st round n (%)	Delphi 2nd round n (%)	1st focus group n (%)	2nd focus group n (%)	Workshops n (%)
*Work affiliation**					
Academy	57 (56.4)	43 (44.3)	6 (60.0)	4 (66.7)	13 (48.1)
Government organizations	32 (31.7)	27 (27.8)	1 (10.0)	0 (0.0)	8 (29.6)
Research institutes	21 (20.8)	19 (19.6)	1 (10.0)	1 (16.7)	4 (14.8)
Business/industry	9 (8.9)	6 (6.2)	1 (10.0)	0 (0.0)	1 (3.7)
NGO	3 (3.0)	2 (2.1)	1 (10.0)	1 (16.7)	1 (3.7)
Gender identity					
Male	54 (53.6)	44 (55.0)	2 (22.3)	2 (40.0)	8 (36.4)
Female	47 (46.5)	36 (45.0)	7 (77.7)	3 (60.0)	14 (63.6)
Education level					
Ph.D.	56 (55.4)	44 (55.0)	3 (20.0)	4 (80.0)	11 (50.0)
Master	35 (34.6)	28 (35.0)	4 (26.7)	1 (20.0)	8 (36.4)
Bachelor	4 (4.0)	3 (3.7)	1 (6.7)	0 (0.0)	2 (9.1)
M.B.A.	4 (4.0)	4 (5.0)	0 (0.0)	0 (0.0)	0 (0.0)
High school	2 (2.0)	1 (1.3)	1 (6.7)	0 (0.0)	1 (4.5)
*Profession**					
Geography	27 (26.5)	21 (25.9)	0 (0.0)	0 (0.0)	5 (21.7)
Engineering	25 (24.5)	20 (24.7)	3 (18.8)	4 (66.7)	5 (21.7)
Geology	20 (19.6)	16 (19.8)	0 (0.0)	0 (0.0)	2 (8.7)
Others	8 (7.8)	8 (9.9)	3 (18.8)	0 (0.0)	5 (21.7)
Architecture	5 (4.9)	4 (4.9)	2 (12.5)	1 (16.7)	3 (13.0)
Law	5 (4.9)	2 (2.5)	0 (0.0)	0 (0.0)	0 (0.0)
Social sciences and service	4 (3.9)	2 (2.5)	1 (6.3)	1 (16.7)	3 (13.0)
Biology	3 (2.9)	3 (3.7)	0 (0.0)	0 (0.0)	0 (0.0)
Economy	3 (2.9)	3 (3.7)	0 (0.0)	0 (0.0)	0 (0.0)
Meteorology	2 (2.0)	2 (2.5)	0 (0.0)	0 (0.0)	0 (0.0)
Self-reported knowledge of flood vulnerability analysis					
Limited	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)
Reasonable	43 (42.6)	31 (38.8)	3 (33.3)	2 (40.0)	11 (50.0)
Very good	58 (57.4)	49 (61.3)	6 (66.7)	3 (60.0)	11 (50.0)
Total n. of participants	**101**	**80**	**9**	**5**	**22**

*The participants could select more than one work affiliation and profession. Only the professions that were mentioned twice are shown here. The remaining was grouped in the 'others' category

Publications

Journal publications

[1] **de Brito, M.M.**, Evers, M., Almoradie, A. (2018) Participatory flood vulnerability assessment: a multi-criteria approach. Hydrology and Earth System Sciences, 22, 373-390, doi:10.5194/hess-22-373-2018.

[2] García-Santos, G., **de Brito, M.M.**, Höllermann, B., Taft, L., Almoradie, A., Evers, M. (2018) Methodology to explore emergent behaviours of the interactions between water resources and ecosystem under a pluralistic approach. Proceedings of the International Association of Hydrological Sciences, 95, 1-5, doi:10.5194/piahs-95-1-2018.

[3] **de Brito, M. M.**, Evers, M., Höllermann, B. (2017) Prioritization of flood vulnerability, coping capacity and exposure indicators through the Delphi technique: A case study in Taquari-Antas basin, Brazil. International Journal of Disaster Risk Reduction, 24, 119-128, doi:10.1016/j.ijdrr.2017.05.027.

[4] **de Brito, M.M.**, Weber, E.J., Silva Filho, L.C.P. (2017) Multi-criteria analysis applied to landslide susceptibility mapping. Revista Brasileira de Geomorfologia, 17(4), 719-735, doi:10.20502/rbg.v18i4.1117.

[5] **de Brito, M.M.**, Weber, E.J., Krigger, V.S., Leitzke, F.P. (2017) Analysis of landslide conditioning factors in Porto Alegre municipality based on historical data. Brazilian Journal of Cartography, 68(1), 1853-1872.

[6] **de Brito, M.M.**, Weber, E.J., Passuello, A. (2017) Multicriteria analysis applied to landslide susceptibility mapping: a case study in Cascata District, Porto Alegre, RS. Revista Brasileira de Geografia Física, 10(3), 12-24, doi: 10.5935/1984-2295.20170048.

[7] **de Brito, M.M.**, Evers, M. (2016) Multi-criteria decision making for flood risk management: a survey of the current state-of-the-art. Natural Hazards and Earth System Sciences, 16, 1019-1033, doi:10.5194/nhess-16-1019-2016.

[8] **de Brito, M.M.** (2015) Identification of landslides scars in the Eastern Edge of the Paraná Basin based on Landsat 5-TM images. Revista Brasileira de Geografia Física, 8(1), 56-70.

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[9] Evers, M., Almoradie, A., **de Brito, M.M.** (2018) Enhancing flood resilience through collaborative modelling and MCDA. In: Fekete, A., Fiedrich, F. (eds.) Urban disaster resilience and security - novel approaches for dealing with risks in societies. The Urban Book Series. Springer, Cham, doi: 10.1007/978-3-319-68606-6_14.

[10] Passuello, A., **de Brito, M.M.**, Giazzon, E., Foresti, A., Pauletti, C., Favero, E., Bresolin, J., Silva Filho, L.C.P. (2017) Tecnologia social como ferramenta para a redução de vulnerabilidade a riscos. In: Marchezini, V., Saito, S., Londe, L., Trajber, R., Iwama, A.Y., Furtado, J.R. (Eds.) Redução de vulnerabilidade a desastres: em busca de rotas para prevenção. RiMA editor.

[11] Silva Filho, L.C.P., Pauletti, C., Passuello, A., Bussular, C.Z., Korzenowski, C., Rocha, C. S., Giazzon, E.M.A., Costa, E.A., Favero, E., Bresolin, J.T., Fin, J., Guasselli, L.A.; Souza, L. P., Bressani, L.A., Fonseca, M.R., **de Brito, M.M.**, Assis, M., Schavinski, M., Fontes, P.W., Alves, R.C.M., Lucena, R. B., Saito, S.M., Marchezini, V. (2015) Capacitação em gestão de riscos. 2nd ed. Porto Alegre: Universidade Federal do Rio Grande do Sul. 214p.

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[12] Evers, M, **de Brito, M.M.** (2018) Multi-criteria and participatory vulnerability analysis – a transdisciplinary approach to flood risk management In: Proceedings of the 20th Tag der Hydrologie, Dresden, Germany.

[13] **de Brito, M. M.**, Evers, M. (2017) A participatory spatial multi-criteria approach for flood vulnerability assessment In: Proceedings of AGILE conference, Netherlands.

[14] **de Brito, M.M.**, Giazzon, E.M.A., Korzenowski, C., Araújo, S.F., Alves, A.L., Passuello, A., Pauletti, C., Silva Filho, L.C.P. (2014) A participatory and integrated flood risk management experience: Belo Horizonte, Brazil. Proceedings of the 6th International Conference on Flood Management, Sao Paulo, Brazil.

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[16] **de Brito, M.M.**, Farias, A. (2013) Spectroradiometry of fruit trees and the effect of moisture on the spectral response of leafs. Proceedings of the 16th Brazilian Remote Sensing Symposium. Foz do Iguaçu: INPE, p. 3245-3252, Foz do Iguacu, Brazil.

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[22] **de Brito, M.M.**, Evers, M. (2017) Assessing flood vulnerability: a participatory multi-criteria approach. Proceedings of the Tag der Hydrologie 2017.

[23] **de Brito, M.M.**, Evers, M. (2016) Multi-criteria decision making in flood risk management: research progress and the challenge of handling uncertainty and stakeholder participation. In: EGU General Assembly, Vienna. Geophysical Research Abstracts, v. 18.

[24] **de Brito, M.M.**, Weber, E.J., Silva Filho, L.C.P. (2015) GIS-based landside susceptibility mapping using the analytic hierarchy process: a case study in Porto Alegre municipality, Brazil. Proceedings of the 23th International Conference on Multiple Criteria Decision Making, Hamburg, Germany.