

## RESPONSE TO COMMENTS FROM REFEREE #1

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Authors: We would like to thank Referee #1 for his/her insightful comments. Below, answers to the concerns raised are provided point-by-point.

The paper brings an important contribution to the field of disaster risk reduction and is worth of publication. However, an important effort of synthesis is required. Often the information is repetitive, little elaborated and some other times not relevant enough with respect to the objectives and subject of the paper. This makes difficult to review the paper. For instance, sections 2.1 and 2.2 present many subsections and secondary information which are too general and more relevant for the format of a report than for a scientific article. The authors should make an effort to reduce redundancy and secondary information to streamline the message and render the paper readable by better targeting the specific gap they are addressing.

Authors: Thank you for the comment. Substantial effort has been made to streamline, reorganize and reduce the manuscript (especially in sections 1, 2 and 3). Suggested changes included the following; Section 1 – information is streamlined and reorganized and details provided are now limited to a general overview and the gaps we plan to address, Section 2 – Table 1 has been moved to the appendix, subsections in 2.1.1 – 2.1.6 have been contracted into one paragraph (background). Section 2.2 (application) is reduced to better focus the methodology on expert-based approaches which will be implemented in the conceptual framework, Section 2.3 focuses on current challenges/gaps and specific areas the conceptual framework seeks to address, Section 3 – Information provided is reduced and reorganized into the background (section 3.1), application (section 3.2), and challenges/gaps the conceptual framework seeks to address. Sections 4, 5, 6 – Information is streamlined and reorganized.

Referee #1: Title: if the all method is tailored only to flood perhaps include this in the title. Also, perhaps “adaptive” is little informative and generates confusion with the adaptation component frequently used in the DRR literature. I suggest using the word “generic”: “A generic regional flood vulnerability assessment model: Review and concepts for data-scarce regions”

Authors: Thank you for the suggestion. The title has been modified (also in consideration of comments from reviewer #2). The new title is “A generic physical vulnerability model for floods: Review and concept for data-scarce regions”

Line 13: is this physical vulnerability to floods only? Perhaps add “to floods” after physical vulnerability

Authors: Thank you for your comment. Changes have been made accordingly.

Line 16: not clear what “local protection elements stand for in the context of that sentence.

Authors: Local protection in the context of our study was defined (and now slightly modified) in lines 480-485 as “deliberate or non-deliberate measures that are put in place and can reduce the impact of floods on a building. These measures can be directly included in the building structure e.g. elevation of the entrance door, or measures located in the immediate surrounding of a building. While many local structural protection measures may not be primarily constructed as a protection mechanism against floods, they reduce the impact of floods on a building e.g. fencing wall (Attems et al., 2020; Holub and Fuchs, 2008)”. Due to a suggestion by referee #2, the sentence has been removed from the abstract.

Lines 61-62: insert commas after “e.g.”

Authors: Thank you for the comment. Changes have been made accordingly.

Lines 72-78: perhaps have this paragraph in this format: “...studies earthquakes (cite cite cite), landslides (cite cite cite), tsunamis (cite cite cite)...” and so on.

Authors: Thank you for the comment. Changes have been made accordingly. The sentence was later removed due to the necessary reorganization and streamlining of the manuscript.

Line 80: you mean “physical vulnerability assessment methods”? I’d always add “physical” to “vulnerability” to specify that you look at this type of vulnerability

Authors: Thank you for the comment. The term ‘physical’ is added to vulnerability (also in other parts of the manuscript) to be more specific.

Line 82: “Vulnerability assessment methods are mainly used to estimate damage or loss.” It’s a repetition from line 68

Authors: Thank you for the comment. Changes have been made accordingly.

Lines 82-83: this is a repetition from lines 35-37

Authors: Thank you for the comment. Changes have been made accordingly.

Lines 82-98: perhaps connect this part on models with the previous part in which you also review methods to assess physical vulnerability. Is there any overlap?

Authors: Thank you for the comment. Since the paper focuses on combining the vulnerability indicator method and damage grades, the idea was to introduce them separately. Consequently, we highlight approaches for physical vulnerability assessment (stage damage curves, indicators, matrices, and multivariate methods) at first, and secondly, we report on their application (e.g., monetary loss and damage grade prediction). However, we now combine the parts on commonly applied physical vulnerability assessment methods which are also used for damage grade prediction (stage-damage curves and the multivariate method) and then discuss the vulnerability indicator method separately.

The suggested change in linking the paragraphs (currently in lines 54-56) reads: “Generally, both stage-damage curves and multivariate methods are used to predict flood damage. This ability to predict damage is increasingly seen as an important step towards disaster risk reduction (Merz et al., 2010). Stage-damage curves and multivariate methods used for damage prediction are commonly referred to as flood damage models”.

Lines 121-123: not clear

Authors: We refer to the uncertainties resulting from two factors, (1) the use of stage-damage curves from regions which do not have comparable building or hazard characteristics and (2) from the use of meso-scale aggregated data which can overlook certain characteristics of a community that is only assessable through micro-scale assessment. Thus, lines 121-123 highlights that these two factors can contribute to higher uncertainties. We have streamlined this part in the revised version of the manuscript.

Line 128: what do you mean by “combination of methods” expert based and modeling?

Authors: By a combination of methods, we mean merging (or integrating) approaches or techniques from two different physical vulnerability assessment methods into a new method. For example, combining stage-damage curves (data-driven) with vulnerability indicators (expert-based) as demonstrated in Godfrey et al. (2015). A slightly modified version of the sentence, now in lines 82 – 86, reads “Papathoma-Köhle et al. (2017) recommended a combination of physical vulnerability assessment methods to take advantage of their individual strengths while minimizing their weaknesses. A combination of methods here refers to the integration of approaches (or techniques) from two different physical vulnerability assessment methods into one method (or model). Such a combination of methods that utilize expert-based approaches in place of data-driven methods might provide a desirable compromise for data-scarce regions.”

Section 2: there is overlap and repetition with Lines 64-81. Perhaps reduce section 1 to the main points you want to bring forward in the study and move those lines to section 2.

Authors: Thank you for the comment. Section 1 has been reduced and details on vulnerability indicators have been moved to section 2.

Line 162: you mean” buildings’ vulnerability”?

Authors: Thank you for the comment. We meant the vulnerability of buildings. Necessary changes have been undertaken in the revised version of the manuscript in line 114.

What is it meant by “framing indicator schemes”?

Authors: Framing indicator schemes here means setting the underlying (theoretical) framework for indicators. The phrase will be clarified in the revised version.

Line 165: revise punctuation here.

Authors: Thank you for the comment. Changes have been made accordingly.

Line 170: use Papathoma-Koehle instead of Papathoma

Authors: Thank you for the comment. Changes have been made accordingly.

Line 175-177: this is a repetition from Line 165.

Authors: Thank you for the comment. The repeated part has been deleted in the revised version of the manuscript.

Section 2.2.1 this section might be reduced to a sentence. There seems no need to have a separate section. Also, most of the information contained in this subsection is always consistent with the title of the section. The numbering of the section does not seem to be correct

Authors: Thank you for the comment. In section 2.2.1, it was important to highlight three main issues relating to indicator selection; (1) Recommended criteria for selecting indicators (2) number of indicators, and (3) different approaches and stages used for selecting indicators. The conceptual framework to be introduced in section 5 will require such information as a basis for future studies that implement the framework. Section 2 has been streamlined and details provided have been reduced to focus on deductive methods.

Lines 198-199: the sentence is unclear

Authors: According to Birkmann (2006), the choice of including different dimensions of vulnerability might be related to data availability. For example, in countries where there are regularly-updated and available demographic data (e.g., income level,

gender, age, employment, etc.), it is common to find studies that combine physical and social vulnerability. This sentence has been removed due to the necessary reorganization and streamlining of the manuscript.

Section 2.1.4: Application of what? The title of the section is not informative enough. Overall the section seems to provide redundant information

Authors: Thank you for your comment. We meant ‘Application of the vulnerability index in the risk cycle’. Section 2.1.4 provides information that the vulnerability index can be applied to different stages of the risk cycle. For example, it can be applied for disaster preparedness, disaster response, and disaster mitigation. In addition, it highlights that most studies use developed indices for preparedness and mitigation. Generally, knowledge of the application of the index will guide the selection and weighting of the indicators. Section 2.1.4 has been removed due to the necessary reorganization and streamlining of the manuscript.

Lines 216-218: Perhaps change to “Spatial scales for assessing vulnerability can be micro-, meso- or macro”.

Authors: Thank you for the comment. Changes have been made accordingly.

And you mean indices or indicators?

Authors: Thank you for the comment. “Indicators” is the correct term. Changes have been made accordingly.

Line 223: “smaller” or “bigger”?

Authors: Thank you for the comment. The correct term is ‘bigger’. Changes have been made accordingly.

Section 2.1.5: you use interchangeably micro, small and local. To be consistent please chose one formulation.

Authors: Thank you for the comment. Changes have been made accordingly.

Lines 226-227: not sure about the information provided in this sentence.

Authors: According to Eriksen and Kelly (2007), the basic scale of vulnerability is the micro-(local-) scale since it is at this scale that communities differ (e.g., difference in building material, quality or local protection measures). Consequently, assessing vulnerability at either a regional or national scale leads to information loss due to averaging or aggregation. Consequently, vulnerability assessment at a bigger scale (macro- or meso-) requires careful interpretation. This sentence has been removed due to the necessary reorganization and streamlining of the manuscript.

## RESPONSE TO COMMENTS FROM REFEREE #2

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Authors: We would like to thank Referee #2 for his/her insightful comments. Below, answers to the concerns raised are provided step-by-step.

### "general comments"

The manuscript represents a good contribution to the understanding of natural hazards and their consequences. The presented conceptual framework aims to links vulnerability indicators with damage grades which highlights the value of damage grades in physical vulnerability assessments. A topic which is currently under-investigated. For the reader, it presents a comprehensive review on indicator-based approaches of physical vulnerability and flood damage models. However, I have some major concerns that should be clarified and fixed before the paper can be fully accepted for publication. First, the goals of the study are not always declared clearly. The link between the review part and the conceptual framework could be more streamlined. I suggest condensing the literature review and provide more details how to operationalize the framework including details about developed indicators.

Authors: Thank you for your comment. The manuscript has been streamlined to reduce the review and provide more details on the conceptual framework. Sections 1, 2, and 3 have been streamlined and reduced, and we have taken up the highlighted issues in sections 4 and 5 and provided a more detailed discussion.

Secondly, I am a little bit confused by using the term vulnerability which is usually broader defined and includes social, ecological and economic vulnerability. In Section 2 you mentioned a focus on physical vulnerability to floods with a specific attention to buildings. The term building vulnerability is not properly defined in the paper, and it seems that this specific element of vulnerability is a main research area. Thus, the focus of the paper needs more streamlining (title, review and framework). I doubt that the developed framework is easily transferable to social or ecological vulnerability.

Authors: Thank you for your comment. The manuscript has been streamlined to better adapt the term physical (building) vulnerability in the title and review part. The suggested title now is “A generic physical vulnerability model for floods: Review

and concepts for data-scarce regions". The term building vulnerability was not defined in the earlier sections (section 2, 3) because the reviewed studies used different definitions of vulnerability. A general definition was given for vulnerability in section 1 as the degree of resistance to impacts (line 2 – 3) "Communities with a low resistance to impacts of hazards are often referred to as vulnerable". For our framework, we mention that the focus is on physical vulnerability for buildings. We adopted a specific definition for (building) vulnerability as stated in section 5.1 (lines 466 - 467) "Vulnerability: The degree to which an exposed building will experience damage from flood hazards under certain conditions of exposure, susceptibility and resilience (adapted after Balica et al., 2009)". We have streamlined a revised version of the manuscript so that it becomes clearer.

Thirdly, section 5 needs more attention to explain the operationalization from concept to application. The operationalization of the framework is very conceptual, and in some aspects, it is very vague. It misses the connection to empirical indicators that builds the indices (BII, BRI, etc.) and thus shows that it can actually be applied to empirical case studies. Moreover, there are important aspects in the operationalization of damage grades that need more attention: e.g. judgement biases in the grading process, standardized training of experts and context-specific definitions of the grades etc.

Authors: The proposed indices (BII, BRI) are aggregations of the selected and weighted indicators. Also, as shown in Figure 3 (Phase 3), the BRI and BII form the basis for the proposed synthetic curve(s) used for predicting damage grades. The developed damage grades are meant to offer simplistic comparisons and not precise predictions. Since it is an expert-based approach, judgment biases cannot be completely eliminated. However, in order for the proposed method to capture the actual damage range, we propose the use of the three damage states (most probable, lower probable and higher probable damage). Furthermore, as described in section 5.2.2, based on a recommendation by Grünthal et al. (1998) and Maiwald and Schwarz (2015), the definition of damage grades is not only based on damage patterns but on proportion. This ensures that damage grades are representative of the actual distribution of damage patterns in the region. Since within the scope of this study, we cannot fully address concerns related to judgment biases in the grading process or standardized training of experts, which are common with synthetic methods, we have referred the readers to other studies that have treated these in more details: lines 336 – 337 of the revised manuscript reads "More details on the synthetic what-if analysis are given by Penning-Rowsell et al. (2005), Neubert et al. (2008) and Naumann et al. (2009)". Also, lines 578 – 587 further discuss on context-specific definitions of damage grades. These concerns will be made clearer in the revised manuscript.

Fourthly, the three phases in Section 5.2. could be better embedded in the overall picture of the paper. For example, Table 4 presents a damage grade scheme which is unclear whether the conceptual framework applies the same grading scheme or not. In Section 5.1 and Section 3.1, recommendations for best-practice are mentioned by Blong (2003b). I do not see these recommendations picked up in the framework.

Authors: Thank you for the comment. We have adapted sections 2 and 3 to reflect the methods used in section 5.2; we focused the sections on expert-based methods that can be applied in data-scarce regions. Sections 2 and 3 are streamlined and reorganized into a similar format for vulnerability indicators and damage grades by focusing on (1) background, (2) application, and (3) challenges for data-scarce regions. Further, an extended discussion on identified challenges are presented in section 4.

Table 4 serves to present an example of damage grades developed for Germany by Maiwald and Schwarz (2007). The conceptual framework recommends that damage grades are developed in a regional context. Frequently observed damage patterns within the region are to be used for developing the damage grades. In Section 5.2.2 we outlined that the main aim of this step is to identify commonly-observed damage patterns within a region and categorize them into classes.

The damage grades developed by Maiwald and Schwarz (2007), which our study was based upon, were developed using the recommendations by Grünthal (1993). Consequently, the techniques described in section 5.2.2 systematically integrates the recommendations. We will clarify this in a revised version of the manuscript.

Fifthly, the structure needs attention and the arguments are sometimes not placed in the right sections. In Section 2 you have too many (sub)section, followed by many lists with detailed arguments. Section 4 discusses the need for linking indicator and damage grades but is not clear whether it is linked to the own contributing or written as a conclusion of the literature review. In Section 5, the author's contribution should be in the center. Explanations and smaller reviews should be avoided here. I see Section 5.1. a bit like a repetition of what is explained in section 2, 3 and 4.

Authors: Thank you for the comment. Sub(sections) and details in section 2 have been reduced in the revised manuscript. Section 4 is not a direct conclusion of the reviews presented in sections 2 and 3. Rather, section 4, draws from challenges highlighted in the individual sections and illustrates the added value for combining them in data-scarce regions. This illustration was carried out by using three observed damage cases from a 2017 flood event in Nigeria. For section 5, the information provided has been reduced in the revised manuscript so that the content focuses on our contribution. Section 5.1 was not a repetition but rather background information for terminologies (e.g., vulnerability, exposure, susceptibility, local protection) we adopt in the concept. This information was necessary before introducing section 5.2 "Operationalizing the framework". The information was not provided in sections 2 and 3 (since they are reviews from different studies) or in section 4 (since it focuses on the linkage of vulnerability indicators and damage grades). We will make necessary adjustments on the revised version of the manuscript, see also comments to referee #1.

Sixthly, the main contribution of the conceptual framework, which I think is the applicability in data-scarce regions is not sufficiently discussed in section 2 and 3. It should be more on the point. Also, the term ‘adaptability’ of physical vulnerability assessments to other regions could be better picked up in the review. Are all physical vulnerability assessments adaptive regional models? Which are regional adaptive? Why? I also suggest providing more information about the specific requirements and capacity for applying them across different regions. Your tables should reflect this by focusing on these aspects.

Authors: Thank you for your comment. We will streamline the contents of sections 2 and 3 to better address applications of each method for data-scarce regions. The suggested modification includes introducing challenges (for data-scarce regions) in both sections 2.3 and 3.3. These will serve as a background for research gaps that will be taken up and addressed in the framework. Another suggested change is to focus the review in section 2 on the deductive and normative methods since they are more suitable for data-scarce areas. Based on recommendations from referee #1, we will change the term ‘adaptable’ to ‘generic’ in the title. This was to avoid confusion with the adaption component of the Disaster Risk Reduction (DRR) literature. We will further address the need for making the indicators and damage grades context-based.

#### **“specific comments”**

Paper is too long and own contribution is relatively short.

Authors: Thank you for your comment. Substantial effort has been made to streamline and reduce the contents in sections 1-5 of the manuscript. Our contributions are also more highlighted in the revised manuscript.

Title: “adaptive” and “regional” are not well addressed in the paper.

Authors: Based on a recommendation from Referee #1, we have replaced the term ‘adaptive’ with the word ‘generic’ in order to avoid confusion with the adaptation component frequently used in the DRR literature. We will better address adaptability to the regional situation in the revised version of the manuscript.

Abstract: When reading the abstract the conceptual framework is in the center, however, this is not reflected by the paper which focuses more on the literature review.

Authors: Thank you for your comment. The abstract has now been reformulated to balance both the review and conceptual framework. The revised abstract now reads “The use of different methods for physical flood vulnerability assessment has evolved over time, from traditional single-parameter stage-damage curves to multi-parameter approaches such as multivariate or indicator-based models. However, despite the extensive implementation of these models in flood risk assessment globally, a considerable gap remains in their applicability to data-scarce regions. Considering that these regions are mostly areas with limited capacity to cope with disasters, there is an essential need for assessing the physical vulnerability of the built environment and contributing to an improvement of flood risk reduction. To close this gap we propose to link approaches with reduced data-requirements such as vulnerability indicators (integrating major damage drivers) and damage grades (integrating frequently observed damage patterns). First, we present a review of current studies on physical vulnerability indicators and flood damage models comprising stage-damage curves and the multivariate methods, which have been applied to predict damage grades. Second, we propose a new conceptual framework for assessing the physical vulnerability of buildings exposed to flood hazards specifically tailored to use in data-scarce regions. This framework is operationalized in three steps, (i) developing a vulnerability index, (ii) identifying regional damage grades, and (iii) linking resulting index classes with damage patterns utilizing a synthetic what-if analysis. The new framework is a first step for enhancing flood damage prediction to support risk reduction in data-scarce regions. It addresses selected gaps in literature by extending the application of the vulnerability index for damage grade prediction through the use of a synthetic multi-parameter approach. The framework can be adapted to different data-scarce regions and allows integrating possible modifications of damage drivers and damage grades”.

Introduction: too long and broad

Authors: Thank you for your comment. The introduction has been streamlined and reduced in the revised version of the manuscript.

Line 81: Unclear how social loss is defined. I do not agree that building damages are the only or one of the most important factors for social loss. In particular, if you consider that not all affected people own a building.

Authors: Thank you for your comment. In the revised manuscript, we have excluded this part in order to streamline and reduce the manuscript. The introduction is now strongly focused on physical vulnerability.

Line 83: There is a critical difference between social and physical vulnerability assessment. You need to make clearer.

Authors: Thank you for your comment. In the revised manuscript, we have excluded this part in order to streamline and reduce the manuscript. The introduction is now strongly focused on physical vulnerability.



Line 143: more references.

Authors: Thank you for your comment. Changes have been made accordingly.

Line 149: the term ‘holistic’ needs a proper definition.

Authors: Thank you for the comment. The term ‘comprehensive’ will be used to denote an assessment that considers all possible influencing parameters.

Line 256: difference between indicator and index is not defined.

Authors: Thank you for your comment. Suggested modification in the revised manuscript, line 117 – 119, reads “A vulnerability index is obtained by selecting, weighting and aggregating vulnerability indicators. A vulnerability indicator is a parameter (or variable) that can influence and(or) communicate the vulnerability of a system (e.g., building). Generally, the aim of the indicator approach is to simplify a concept through the use of an index (Heink and Kowarik, 2010; Hinkel, 2011)”.

Line 264: it is not objectivity what you mean it is comprehensiveness. Objectivity is needed for every selected indicator.

Authors: Thank you for your comment. Changes have been made accordingly.

Line 222ff. Indicator weighting: statistical weighting based on data can explain the consistency and inference of indicators but cannot be used for an appropriate weighting of importance or measurability of the indicators. This should be mentioned at the beginning.

Authors: Comment is not very clear. We will add an explanation of the indicator weighting in the revised version of the manuscript.

Line 571: unclear if this is part of the framework or part of literature review.

Authors: Section 4 focuses mainly on the added value for linking vulnerability indicators and damage grades for data-scarce regions. It is not meant to be part of the review or the new conceptual framework, rather, it is the authors' contribution to illustrate the added value of combining different physical vulnerability assessment methods. This was demonstrated by using a hypothetically developed vulnerability index for two regions in combination with three building damage data from Nigeria. This section uses practical examples to bridge the gap between identified challenges/gaps presented in the reviews (sections 2 and 3) and the new conceptual framework (section 5).

Line 701: Do you applied field surveys or remote sensing? When discussion about different option should be mentioned in the review section.

Authors: Carrying out a field survey to determine building typology and characteristics will be the most preferred option for such data collection because experts can have a first-hand impression of the local situation and can identify, in detail, construction features or qualities, which will determine how building representatives are selected. However, due to time and financial constraints, field surveys are not always feasible. Hence, we suggest the use of remote sensing as an option, especially in a meso-(or macro-) scale studies. The authors recommended the study by Blanco-Vogt and Schanze (2014) which focus on extracting building representatives for meso-(or macro-) scale assessment.

Conclusion: Be more precise about the key messages both from the review and from the conceptual framework. An outlook of how the framework will be applied is also helpful for presenting the relevance. Please elaborate on the link between the relevance for risk reduction methods in developing countries and the data scarcity and barriers in collecting data in most of the developing countries?

Authors: Thank you for your comment. In the revised manuscript, more details on challenges for data-scarce regions are now given in sections 2.3 and 3.3. The relevance of the linkage is also elaborated in section 4 of the revised manuscript (see also suggestions of referee #1). The conclusion is streamlined to be more precise. A short outlook for the model has been added in lines 648 – 650, which reads “Its applicability for predominant building types, such as the sandcrete block and clay buildings in Africa, has the potential to promote disaster mitigation in such regions. The application of the new framework to evaluate and compare model performance with a data-driven model is also encouraged. Such an analysis will communicate the success of the framework and also allow for further improvement.”

#### **“technical corrections”**

Line 249: this sentence needs a reference

Authors: Thank you for your comment. Changes have been made accordingly.

Line 322: acronyms are not defined in table figure caption.

Authors: Thank you for your comment. Changes have been made accordingly

Line 329f. Sentence is unclear also the example does not seem to make sense.

Authors: Thank you for your comment. The example has been rephrased in the revised manuscript in order to better capture the intended purpose. The suggested change, now contained in line 211 – 217, is “For example, if we assume the same hazard level affecting both reinforced concrete and clay building, it is most likely that the clay building will incur higher damage (see Maiwald and Schwarz, 2012). Therefore, based on such data, experts may weight a reinforced concrete building as less vulnerable than the clay building. However, assigning a value that qualifies the extent to which the reinforced concrete building is less vulnerable than clay building (e.g., moderate, high, very high) requires expert knowledge. Such expert knowledge will likely come from information on the quality of regional construction types, material or local protection”.

Line 443: reference missing

Authors: Thank you for your comment. Changes have been made accordingly.

Linen 415f:

Authors: The comment is not clear.

Line 650, 661 and 680: fourth level of headline should be avoided.

Authors: Thank you for your comment. Changes have been made accordingly.

# A generic physical~~An adaptive regional~~ vulnerability assessment model for floods: Review and concept~~concepts~~ for data-scarce regions

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## 10 Abstract

~~The use of different methods for physical flood~~ Although the vulnerability assessment has evolved over time, from traditional single-parameter stage-damage curves to multi-parameter approaches such as multivariate or indicator-based models. However, despite the extensive implementation of these models in flood risk assessment globally, a considerable gap remains in their applicability to ~~method has been applied to several~~ data-scarce regions. Considering that these regions are mostly

15 ~~areas, a missing linkage with limited capacity to cope with disasters, there is an essential need for assessing the physical vulnerability of the built environment and contributing to an improvement of flood risk reduction. To close this gap we propose to link approaches with reduced data-requirements such as vulnerability indicators (integrating major damage drivers) and damage grades (integrating frequently observed damage patterns). First~~ damage grades had hindered its application for loss evaluation to complement disaster risk reduction efforts. To address this gap, we present a review of current studies physical

20 ~~vulnerability indicators and flood damage models to gain insights on physical best practice. Thereafter, we present a conceptual framework for linking the vulnerability indicators and flood damage models comprising stage-damage curves and the multivariate methods, which have been applied to predict damage grades. Second, we propose a new conceptual framework for assessing the physical vulnerability of buildings exposed to flood hazards specifically tailored to use in data-scarce regions. This framework is operationalized in~~ damage grades using three steps, phases (i) developing a vulnerability index, (ii)

25 identifying regional damage grades, and (iii) linking resulting vulnerability index classes with damage patterns utilizing a grades. The vulnerability index comprehensively integrates elements of the hazard using a Building Impact Index (BI) on one hand, and exposure, susceptibility and local protection elements using a Building Resistance Index (BRI) on the other hand. For the damage grades, local expert assessments are used for identifying and categorizing frequently observed regional damage patterns. Finally, by means of synthetic what-if analysis. The new framework is a first step, experts are asked to estimate

30 damage grades for enhancing flood damage prediction to support risk reduction in data-scarce regions. It addresses selected gaps in literature by extending each interval of the application BI and class of the BRI to develop a vulnerability index for damage grade prediction through the use of a synthetic multi-parameter approach. curve. The proposed conceptual framework can be adapted to different used for damage prediction in data-scarce regions to support loss assessment and allows integrating possible modifications of damage drivers and damage grades, to provide guidance for disaster risk reduction.

35 **Keywords:** Data-scarce regions, vulnerability indicator, damage grade, flood~~floods~~, building, disaster risk reduction



## 1 Introduction

The magnitude and frequency of floods and their impact on elements at risk ~~have~~<sup>has</sup> increased globally (Quevauviller, 2014). Risks associated with floods are especially high for communities with limited capacity to resist impacts. Communities with a low resistance to impacts of hazards are often referred to as vulnerable. Although the definition of vulnerability varies in different fields of study, efforts ~~to understand~~<sup>aimed at understanding</sup> and ~~reducing~~<sup>reducing</sup> vulnerability are regarded as important steps for disaster risk reduction (UNISDR, 2015). UNISDR (2009) defined vulnerability as the conditions that make communities susceptible to the impact of hazards. These conditions may be linked to limited access to resources, to missing risk transfer mechanisms, and ~~to~~ poor housing quality if elements at risk are considered. Focusing on the latter, poor housing ~~conditions have~~<sup>quality has</sup> been shown to be a key factor if different regions exposed to the same hazard level are compared (Papathoma et al., 2003; Keiler et al., 2006). Although the vulnerability of a community has social, economic, physical, environmental, institutional and cultural dimensions (Birkmann et al., 2013), these dimensions are connected (Mazzorana et al., 2014). Fuchs (2009) and Papathoma-Köhle et al. (2011) identified physical vulnerability as a ~~primer for~~<sup>prior state that</sup> ~~impacts~~ other ~~dimensions of~~ vulnerability ~~dimensions~~. WHO (2009) ~~also highlighted that there is a strong connection between physical vulnerability and other vulnerability dimensions, pointing out that the disruption of physical elements directly affects social and economic activities within a society.~~ highlighted that there is a strong connection between physical flood vulnerability with social and economic vulnerability dimensions, pointing out that the disruption of physical elements directly affects social and economic activities within a society. Additionally, Blanco-Vogt and Schanze (2014) ~~reported that the impacts of floods on the built environment may trigger migration of people from areas at high risk to low-risk areas. As a result, an increasing number of studies focus on the understanding of physical vulnerability since it directly influences social and economic dimensions.~~ Physical vulnerability assessment supports evaluation of economic losses (Blanco-Vogt and Schanze, 2014), analysis of physical resilience (Papathoma-Köhle et al., 2011), cost-benefit ~~analysis~~<sup>evaluation</sup> (Holub and Fuchs, 2008), risk assessment for future system scenarios (Mazzorana et al., 2012), and decision-making by stakeholders responsible for hazard protection through e.g., resource allocation (Fuchs, 2009).

Common approaches used for assessing physical vulnerability to flood hazards include ~~stage-damage curves (vulnerability functions or curves), vulnerability, matrices, vulnerability indicators (Papathoma-Köhle et al., 2017), and more recently, multivariate methods.~~ Stage-damage curves show the relationship between flood depths and the degree of impact (e.g., damage grades, relative or absolute monetary loss). These curves are developed using empirical data or expert knowledge (Merz et al., 2010). The empirical method requires data on flood depths and related building damage patterns or monetary losses after a flood event (Totschnig and Fuchs, 2013). These data allow searching for suitable curves to correlate flood depths to damage or losses. Synthetic methods are based on a what-if analysis derived from expert knowledge to determine expected damage for selected intervals of flood depths (Naumann et al., 2009; Merz et al., 2010; Romali et al., 2015). Multivariate methods ~~deduce relationships between empirical building damage or loss data and multiple damage-influencing parameters statistically.~~

Generally, both stage-damage curves and multivariate methods are used to predict flood damage. This ability to predict damage is increasingly seen as an important step towards disaster risk reduction (Merz et al., 2010). Stage-damage curves and multivariate methods used for damage prediction are commonly referred to as flood damage models. Most flood damage models are based on empirical damage or monetary loss data (see reviews by Merz et al. (2010), Jongman et al. (2012), Hammond and Chen (2015), Gerl et al. (2016)). However, due to the scarcity of such data in data-scarce regions, limitations exist in developing these models and consequently hindering the efforts to reduce disaster risk (Niang et al. 2015). More recently, Englhardt et al. (2019) reemphasized data-scarcity as the limiting factor in physical vulnerability assessment in developing countries. Few flood damage models have been developed using a synthetic and expert-based what-if analysis

(e.g., Penning-Rowsell et al., 2005; Neubert et al., 2008; Naumann et al., 2009) aiming to reduce the dependency on empirical damage and loss data. However, synthetic approaches often use flood depth as the only damage-influencing parameter, leading to increased uncertainty in damage prediction (Pistrika et al., 2014; Schröter et al., 2014).

Flood damage models have been applied to predict damage grades (e.g., and more recently multivariate methods. Vulnerability curves, often also called stage damage curves, show the relationship between flood depth and the degree of impact (e.g., damage grades, relative or absolute loss). These curves are developed using empirical data or expert knowledge. The empirical method requires data on flood depths and related building damage or losses after a flood event. These data allow to search for suitable curves to correlate flood depths to damage or losses. Synthetic methods utilize a what-if analysis based on expert knowledge to determine expected damage for selected intervals of flood depths. Generally, vulnerability curves use flood depths as the only damage-influencing variable. This has been identified as a major limitation for these curves since flood damage is also influenced by several other parameters relating to both, the hazard and building characteristics (Thieken et al., 2005; Schwarz and Maiwald, 2007). Vulnerability matrices are based on qualitative descriptions to relate a hazard magnitude to an impact pattern. Multivariate methods deduce relationships between empirical building damage or loss data and multiple damage-influencing parameters by means of statistical techniques. Thus, including several damage-influencing parameters relating to building and hazard characteristics is a major advantage of the multivariate method compared to vulnerability curves. However, due to underlying data requirements, difficulties exist in applying the multivariate method in data scarce regions. Such data scarcity has been identified to hinder risk assessment which consequently restricts disaster risk reduction efforts (Niang et al., 2015; Enghardt et al., 2019). Vulnerability indicators are based on aggregated variables to communicate the state of a system (e.g. the resistance of a building) and to provide insights in the level to which this system will be impacted by a certain hazard level (Birkmann, 2006). A vulnerability index is obtained using deductive (e.g. expert knowledge), inductive (e.g. data) or normative (e.g., interview with community residents) approach. Since vulnerability indicators do not require empirical data, it has gained increasing popularity and usability in data scarce regions.

The need for further research to identify vulnerability indicators for hazard impact assessment has been emphasized by the Hyogo Framework for Action 2005-2015 (ISDR, 2005). More recently, several studies have re-emphasized the importance of identifying and understanding vulnerability indicators as a fundamental step in disaster risk reduction (e.g., UN/ISDR, 2015; Zimmermann and Keiler, 2015; Klein et al., 2019). Vulnerability indicators allow the identification of parameters that influence how hazards impact the built environment. These impacts are usually measured in terms of damage or loss. The focus on using vulnerability indicators is particularly encouraged in data scarce regions because of a low demand for empirical data (Papathoma-Köhle et al., 2017). In addition, indicators are more easily communicable to decision makers (Birkmann, 2007) and they have application in several stages of the risk cycle (Papathoma-Köhle et al., 2017). The vulnerability indicator method has been applied for assessing different natural hazards and risks, including studies on earthquakes by Rashed and Weeks (2003), Yüceimen et al. (2004), Schmidtlein et al. (2011), Brink and Davidson (2015), Peng (2015), and Marleen et al. (2017), and on landslides by Silva and Pereira (2014), Guillard-Gonçalves et al. (2016), and Thennavan et al. (2016). Applications for tsunamis include studies by Papathoma-Köhle and Dominey-Howes (2003), Dominey-Howes and Papathoma-Köhle (2007) and Dall'Osso et al. (2009), on debris flows by Kappes et al. (2012), Rheinberger et al. (2013), Thouret et al. (2014), Papathoma-Köhle et al. (2017), and studies on flood hazards by Balica et al. (2009), Akukwe and Ogbodo (2015), and Carlier et al. (2018). However, these studies differ with respect to vulnerability definitions, vulnerability dimensions, the spatial scale of application, the applicability in the risk cycle, and according to the function of the developed index. Detailed reviews on vulnerability assessment methods are given by Papathoma-Köhle et al. (2017) and Fuchs et al. (2019a).

115 Vulnerability assessment methods are mainly used to estimate damage or loss. Kircher et al. (2006) highlighted that damage to buildings is the most important factor for estimating economic and social loss. Consequently, an increased amount of studies have investigated the impacts of hazards and how to predict building damage (Ke et al., 2012). Such predictions of building damage are carried out using flood damage models. Flood damage models (or loss models) show the relationship between the extent of building damage on one hand and hazard and building characteristics (damage influencing factors) on the other hand.

120 Generally, flood damage models are developed using empirical data or synthetic (what-if) approaches (Merz et al., 2004; Naumann et al., 2009; Merz et al., 2010; Maiwald and Schwarz, 2015; Chen et al., 2016). A further classification of flood damage models can be differentiated based on models that predict damage using a single damage influencing parameter (e.g., Penning-Rowsell et al., 2006; Naumann et al., 2009) and models that use multiple damage influencing parameters (e.g., Thieken et al., 2008; Maiwald and Schwarz, 2015). Flood damage models can predict damage patterns or grades (e.g., Maiwald

125 and Schwarz, 2015; Ettinger et al., 2016) or the monetary value of such damage (e.g., Thieken et al., 2008; Merz et al., 2013; Fuchs et al., 2019b). Better suitable for data-scarce regions are damage grades, representing qualitative descriptions of frequently observed damage patterns within a region (for floods: moisture defects, cracks on supporting walls). As they are not dependent on information about monetary loss (e.g., insurance data), damage grades provide a good basis for damage estimation and enhance the comparability of flood impacts between different flood events, regions, and Merz et al., 2013).

130 Since damage grades represent qualitative descriptions of frequently observed damage patterns with a region (moisture defects, cracks on supporting walls), they provide a good basis for damage estimation and enhance comparability of flood impacts between flood events, regions, and between buildings types (Blong, 2003a). Besides ~~In addition~~, since damage grades are comparable for similar building types (Maiwald and Schwarz, 2015), they improve the transferability of flood damage models (Wagenaar et al., 2017). Reviews on flood damage models can be found in Merz et al. (2010), Jongman et al. (2012), Hammond

135 and Chen (2015), Romali et al. (2015) and Gerl et al. (2016).

Another approach increasingly used to assess physical vulnerability is based on vulnerability indicators (Barroca et al., 2006; Barnett et al., 2008; Papathoma-Köhle et al., 2017). Several studies have re-emphasized the importance of identifying and understanding vulnerability indicators as a fundamental step in disaster risk reduction (e.g., UN/ISDR, 2015; Zimmermann and Keiler, 2015; Klein et al., 2019). Vulnerability indicators are based on aggregated variables to communicate the state of a

140 system (e.g., the resistance of a building) and to provide insights in the level to which this system will be impacted by a certain hazard level (Birkmann, 2006). Since the vulnerability indicator approach has a low requirement for empirical damage or loss data, the method has gained increasing popularity in data-scarce regions. In addition, vulnerability indicators supplement the use of stage-damage curves in a way that the overall picture on flood vulnerability becomes clearer. This clarity is achieved by an integration of multiple drivers of vulnerability providing a more holistic perspective of vulnerability-contributing factors.

145 Papathoma-Köhle et al. (2017) recommended a combination of physical vulnerability assessment methods to take advantage of their individual strengths while minimizing their weaknesses. A combination of methods here refers to the integration of approaches (or techniques) from two different physical vulnerability assessment methods into one method (or model). Such a combination of methods that utilize expert-based approaches in place of data-driven methods, might provide a desirable compromise for data-scarce regions. For example, Godfrey et al. (2015), using Romania as a case-study, combined an approach

150 based on vulnerability indicators and an approach based on stage-damage curves to develop an expert-based model for data-scarce regions. However, wider applications of the method have shown to be restricted to regions where stage-damage curves for specific building types already exist. In addition, because of a limited sample size used to test the method, results may be biased (Godfrey et al., 2015).

Only little has been known so far on the flood. Developing flood damage models require empirical data either during model development or for checking model performance. However, due to scarcity of empirical data in many data scarce regions, limitations occur in developing these models. Consequently, data scarcity has been identified to hindered disaster risk reduction efforts in such regions (Niang et al. 2015). More recently, Englhardt et al. (2019) reemphasised data scarcity as the limiting factor in vulnerability assessment in developing countries. Moreover, owing to difference in regional building types, limitations exist in the transfer of damage prediction models from data-rich to data-scarce regions (Tarbotton et al., 2015; Englhardt et al., 2019). For example, studies by Cammerer et al. (2013) and Maiwald and Schwarz (2015) have demonstrated that empirically-deduced damage models only allow a transfer of the damage distribution and vulnerability models in study areas with close agreements to hazard and building characteristics. Thus, there is a strong need for developing further approaches for evaluating the vulnerability of buildings to flood risk in data-scarce regions.

Only little has been known so far on the vulnerability and damage mechanism of buildings exposed in developing countries, such as in Africa. Adelekan et al. (2015) identified ~~population~~populations and assets in African cities to be among the most vulnerable globally. Consequently, with climate change, the number of extreme events and catastrophic impacts in ~~these vulnerable~~ regions ~~is are~~ expected to increase (Mirza, 2003). In Africa particularly, the need to develop a systematic approach in evaluating preconditions of buildings and ~~their impact~~how they are impacted by flood hazards has been stressed by stakeholders and researchers (Komolafe et al., 2015). Although, sandcrete block and clay buildings are the most predominant building types in many African countries (Gasparini, 2013), flood damage models remained underdeveloped for such building types (Komolafe et al., 2015). Commonly, exposure and vulnerability are mainly assessed in a regional context based on very coarse data and aggregated land-use classes resulting in ~~considerable~~very high uncertainties ~~of vulnerability~~, especially in ~~at the~~ rural context (de Moel et al., 2015). ~~Thus, along with~~A recent study by Englhardt et al. (2019) presented a new approach including an object based analysis of buildings and their properties (construction type, building material) based on exposure data from GFDRR (2018) to deduce vulnerability curves. The results provide insights in the influence of different datasets for exposure and hazard models. However, the information of exposure is aggregated in grid cells (15" x 15"), and building types and the related stage damage curves were extracted from available literature, which in combination with the low spatial resolution resulted in high uncertainties. Thus, beside such recent studies addressing flood exposure and vulnerability in data-scarce areas, there is a strong need ~~to refine~~for developing further approaches for vulnerability and risk assessments in ~~such~~these regions.

Papathoma-Köhle et al. (2017) recommended a combination of vulnerability assessment methods to take advantage of their individual strengths while minimizing their weakness. Such combination of methods, particularly expert-based approaches, might provide a desirable compromise for data-scarce regions. For example, Godfrey et al. (2015), using Romania as a case-study, reported a combination of methods to develop an approach for data-scarce regions. However, applicability of the method has shown to be restricted to regions where vulnerability curves for typical building types already exist. In addition, because of a limited sample size used to test the method results may be biased (Godfrey et al., 2015).

Approaches using ~~indicators and~~ damage grades ~~and/or damage indicators~~ are in general more suitable for data-scarce areas, yet, so far there is a gap in systematically linking them. ~~This~~The aim of this paper ~~aims is~~ to develop a conceptual framework for assessing ~~the flood~~ vulnerability of the ~~built~~build environment ~~to floods~~ in data-scarce areas, ~~such as in Africa~~. To do this, we first provide a review ~~of physical~~en vulnerability indicators for flood ~~hazards~~, as well as an overview of flood damage models. ~~Second, we~~We combine the gained knowledge from the review to develop a conceptual framework that links ~~physical~~ vulnerability indicators and flood damage grades by utilizing local expert knowledge. ~~A special focus for the conceptual framework is on transferability and adaptation to specific regional conditions.~~

This paper is structured as follows: Section 2 provides an overview of ~~available information on literature with a critical evaluation of individual elements of~~ vulnerability indicators, ~~including indicator selection, aggregation, and weighting, and unveils challenges and gaps of using this method followed by a review of methodological steps of constructing vulnerability indicators.~~ In Section 3, a brief review of flood damage models is presented ~~with a particular focus on the use of damage grades and associated challenges.~~ While Section 4 addresses the need for linking ~~vulnerability~~ indicators and damage grades, Section 5 introduces the conceptual framework for ~~such the~~ linkage as well as the steps for operationalizing the framework. Discussions and conclusions are presented in the final ~~Section 6~~ section.

## 2 Review of indicators for ~~physical building~~ vulnerability ~~to floods~~ assessment

~~In this section, we present an overview of different studies using indicators to assess the vulnerability of buildings to flood hazards (for details see Table A1 in the appendix).~~

### 2.1 Background

~~A vulnerability index is obtained by selecting, weighting and aggregating vulnerability indicators. The use of vulnerability indicators to assess regional vulnerability is becoming increasingly popular (Papathoma-Köhle et al., 2017). This increase is likely due to the link indicators provide between research, practice and political need (Hinkel, 2011). Hence, indicators serve as a good communication tool to stakeholders or communities exposed to hazards. Another reason for increased popularity applying indicators is a low requirement of empirical data. In addition, vulnerability indicators supplement the use of vulnerability curves and matrices in a way that the overall picture on flood vulnerability becomes clearer. This clarity is achieved by an integration of multiple drivers of vulnerability providing a more holistic perspective of vulnerability contributing factors. Fuchs et al. (2011) noted that holistic evaluation of vulnerability requires the inclusion of all its dimensions (e.g. social, physical, environmental, economic). However, a model that will incorporate all these dimensions will be quite complex. As a result, evaluations of vulnerability are usually carried out for specific dimensions of vulnerability. In this study, we focus on indicators developed for assessing physical vulnerability to floods with a specific attention to buildings.~~

### 2.1 Overview of indicators for flood hazards

~~Prior to developing indicators, the framework has to be set. This framework includes a variety of elements (we refer to these as indicator elements) which helps to clearly outline the extent of applicability of the derived vulnerability index. The framework also helps to transparently communicate the spatial extent within which the index is still valid. Basic elements defining the framework of a vulnerability index include the study aim, the region of application, the vulnerability dimension, the approach, the application in risk cycle, the spatial scale and the index output. For each indicator element, we present an overview from literature (Table 1) for different types of floods and evaluate its specific function. Although further studies exist regarding flood vulnerability indicators, the studies summarized in Table 1 were selected due to their relevance in addressing building vulnerability. Common elements important for framing indicator schemes will be analysed in the following sections.~~

#### 2.1.1 Indicator aims

~~A first step in developing a framework for indicators is to define the aim; this means clearly defining what the indicators (or derived index) are to be used for. Table 1 outlines the different aims of constructing vulnerability indicators for different flood types. Generally, a vulnerability indicator is a parameter (or variable) that can influence and(or) communicate the degree of~~



damage (or loss) of a system (e.g., a building). The indicator approach aims ~~the aim of indicators is~~ to simplify a concept through the use of ~~an index~~~~indices~~ (Heink and Kowarik, 2010; Hinkel, 2011). ~~Before establishing an index, a framework should be developed to address how major components of the indicator fit together (Birkmann, 2006; JRC and OECD, 2008). Moreover, the framework of such an index should allow adaption to possible future system changes such that it can be used to analyze potential disaster risk. Such adaptation may include possible changes in selected indicators or indicator weights. The framework includes a variety of elements (we refer to these as indicator elements), which helps to clearly outline the extent of~~ applicability and validity of the derived index. Basic elements defining the framework of a vulnerability index include the aim, the vulnerability dimension, the spatial scale, and the region of application (see Table A1). ~~Indicators aim to give facts about the present state of a system and support decision-making in risk reduction by aggregating information on an element at risk (Günther, 2006). Using components representing building, human and economic vulnerability, Papathoma et al. (2003) carried out an investigation aimed at assessing the vulnerability of coastal areas to tsunami hazards using an indicator approach, later referred to as the PTVA (Papathoma Vulnerability Assessment Model). However, in a subsequent revision of the PTVA, a modification in the overall aim of the index to assess building vulnerability to tsunami impact resulted in the exclusion of the human and economic dimensions, allowing an in-depth evaluation of parameters that directly influence building damage to tsunami (Dall'Osso et al. 2009). Furthermore, the application of the index was extended to allow the assessment of probable maximum loss. Indicated by this example, we have to consider by developing vulnerability indicators to set first the aim of the~~ vulnerability assessment so that methods and data can be better tailored to the overall aim of the study. This is the reason why indicators that serve to identify hotspot areas either for emergency planning or mitigation purpose draw inference from multiple vulnerability dimensions like social and physical (e.g. Kienberger et al., 2009; Akukwe and Ogbodo, 2015), while others developed for damage evaluation focus on the physical dimension (e.g. Dall'Osso et al., 2009; Godfrey et al., 2015).

A first step in developing a framework for indicators is to define the aim, including the different vulnerability dimensions to be assessed so that the indicators and the finally derived index fit into the overall risk assessment framework. Although some studies focus on one specific dimension of vulnerability (e.g., Dall'Osso et al., 2009) other studies examine multiple dimensions of vulnerability (e.g., 2.1.2—Region of application

Indicators are adaptive to a regional context, hence, a set of indicators selected for a particular region is not necessarily transferable to another region (Papathoma Köhle et al., 2017, 2019). Barroca et al. (2006) emphasized that indicators are context dependent and it will be ineffective to adopt an indicator, or a set of indicators, that are non-existent in a target region. For example, several vulnerability indices use the number of storeys in assessing the impact of floods to buildings (e.g., Kappes et al., 2012; Blanco Vogt and Schanze, 2014; Thouret et al., 2014; Godfrey et al., 2015; Fernandez et al., 2016; Sadeghi Pouya et al., 2017). The underlying theory is well founded based on the prevalence of multi-storey buildings in these regions and from an engineering standpoint since the additional weight of more storeys helps in resisting the impact from flood. Consequently, it is important to highlight the region where the indicator is applicable. In addition, providing information with regards to the characteristics of the built environment (e.g. building typology) as well as hazard types can also serve as a basis with which other regions can assess the functionality of the indicators in other regions.

### 2.1.3—Vulnerability dimension

The interactions between different vulnerability dimensions (physical, social, economic, environmental) generate challenges for assessing vulnerability. Although some studies focus on one specific dimension of vulnerability when assessing indicators (e.g. Dall'Osso et al., 2009; Blanco Vogt and Schanze, 2014; Bagdanavičiute et al., 2015; Godfrey et al., 2015), other studies

focus on multiple dimensions of vulnerability (e.g. Kienberger et al., 2009; Balica, et al., 2012; Krellenberg and Welz, 2017). The interaction between different vulnerability dimensions generates challenges for assessing vulnerability, as well as the use of a high number of indicators in multidimensional studies. Table 1 shows that the majority of vulnerability indicators in the context of flood are multidimensional. Birkmann (2006) noted that the choice of carrying out a multidimensional study might be related to data availability since in some countries, these data are readily available. However, given the complexity of the vulnerability concept, difficulties exist regarding how comprehensive multidimensional studies can be due to challenges arising from having too many indicators (Cutter and Finch, 2008). Birkmann (2006) noted that choosing a multidimensional study design is only worth the effort if data is available in certain quality and quantity, which in turn has to meet the scale requirements of the study (Birkmann, 2007). In addition, care must also be given on how to systematically aggregate different vulnerability dimensions.

#### 2.1.4 Application in the risk cycle

An asset of vulnerability indicators is that they may be used in different stages of the risk management cycle, multiple applications include disaster preparedness, response and mitigation (Papathoma-Köhle et al., 2017). Vulnerability indicators help to identify important parameters influencing the impact of flood on the built environment, hence, emergency planners can identify highly vulnerable areas and prioritize efforts during disaster preparedness and response. For mitigation purpose, decision-makers or community residents can improve the resistance capacity of identified indicators (e.g. building material, construction quality) to reduce hazard impacts. Indicators facilitate the implementation of risk reduction strategies by identifying vulnerability parameters. As shown in Table 1, however, most applications of vulnerability indicators are for preparedness and mitigation purpose. In other studies, indicators are used to estimate building damage potential, hence providing a basis for monetary loss estimation (e.g. Dall'Osso et al., 2009; Blanco-Vogt and Schanze, 2014).

#### 2.1.5 Spatial scale

Spatial scale is identified to be an important issue in evaluating impacts of hazards (Birkmann, 2007; Fuchs et al., 2013; Kundzewicz et al., 2019). Consequently, the spatial scale for applying the vulnerability indicator approach varies depending on the availability of data (Marleen et al., 2017) and the aim of the assessment. Spatial scales for assessing vulnerability can be on micro-, meso- or macro-level. Micro-scale assessment is usually challenging in terms of data collection (Günther, 2006), in particular in developing countries with missing metadata on land-use, exposure, and population. Micro-scale assessments can provide an overview of vulnerability (hotspot assessment) on a larger area, hence, decision-makers can use them in allocating resources for emergency response or risk mitigation. Other indicators operate on a larger scale, for instance, meso- (regional to national) and macro- (international) scale. Moreover, as vulnerability indicators are adaptive to a regional context, a set of indicators selected for a particular region may not necessarily be transferable to another region (Papathoma-Köhle et al., 2017, 2019). or the aim of the assessment. Spatial scales for assessing vulnerability can be on micro-, meso- and macro- scale, however, Table 1 shows that vulnerability indices for assessing physical vulnerability to flood hazards is mostly applied at a local (micro)-scale. Local scale, in this case, refers to either individual building scale (e.g. Papathoma et al., 2003; Kappes et al., 2012; Blanco-Vogt and Schanze, 2014), or to semi-aggregated scales such as entire building blocks (e.g. Müller et al., 2011; Krellenberg and Welz, 2017; Sadeghi Pouya et al., 2017) or neighborhoods (e.g. Fernandez et al., 2016; Percival et al., 2018). Local-scale assessment is usually challenging in terms of data collection (Günther, 2006), in particular in less developed countries with missing metadata on land use, exposure and population. However, other indicators operate on a smaller meso or macro scale, and they are mostly implemented using Geographical Information Systems (GIS).

305 Small-scale assessments can serve to give an overview of vulnerability (hotspot assessment) on a larger area, hence, decision makers are able to use them in allocating resources for emergency response or risk mitigation. Messner and Meyer (2006) stated that while meso-scale assessments deal with regional boundaries, macro-scale assessments focus on national or international boundaries, each approach calling for different interpretation (Eriksen and Kelly, 2007).

## 2.2 Application of physical vulnerability

### 310 1.6—Index output

Index output refers to the aggregated state the indicators. Since indicators is complex and contextual, some studies choose to frame vulnerability not in absolute values, but relatively (e.g. Dall’Osso et al., 2009; Kappes et al., 2012; Sadeghi Pouya et al., 2017). In this way, the vulnerability index serves as a mean to compare between elements of the built environment, expressing which one is more or less vulnerable. However, outside the context of making comparisons, this output might lack  
315 a significant independent meaning (Tarbotton et al., 2015). While some studies formulate a vulnerability index by directly aggregating identified indicators, others develop sub-indices as a preliminary to allow for separate assessment of individual components that contribute to vulnerability. For instance, using a set of multiple indicators, Balica et al. (2009) developed sub-indices for physical, social, environmental and economic vulnerability. In the next step, they aggregated these sub-indices to provide a multidimensional composite index for assessing flood vulnerability. An advantage of the sub-indices is that it  
320 supports policymakers who are only interested in a specific component of vulnerability. Nonetheless, due to the complex interactions of different vulnerability components, Hinkel (2011) recommended that their aggregation should not be purely subjective but supported by data from previous hazard events.

### C2.2—Constructing a vulnerability index

Commonly applied steps. Constructing a vulnerability index involves selecting, weighting and aggregating of indicators. The index carries information on the extent to which an element can be impacted by a hazard, given the combined influence of selected indicators. Figure 1 shows steps and corresponding outputs, and methods commonly applied for constructing a physical vulnerability index are presented in Figure 1 for flood hazards. Different methods used in deriving the index include deductive (based on theories/basic assumptions), inductive (based on empirical data) and normative (based on value judgment) approaches. In physical vulnerability assessment for flood hazards using vulnerability indicators, the deductive approach is the most commonly applied method relying on expert judgment and information provided in the relevant scientific literature without any further empirical data. It is also common to use a combination of inductive and deductive approaches either during the indicator selection or during indicator weighting and aggregation. Table 1 Nevertheless, prior to selecting, weighting and aggregating indicators, a framework should be developed to address how major components of the indicator fit together (Birkmann, 2006; JRC, 2008). The framework should clearly communicate basic data requirements, hazard type applicability, vulnerability dimension, and index generation. In this section, we look at each step of deriving the vulnerability index. Table 2 shows different studies that derived a physical vulnerability index to assess flood hazards and various methods employed. Since our attention is on data-scarce regions, further discussions in this Section will be focused on the deductive and normative approaches since they do not rely on empirical data.

### 2.2.1 Indicator selection

The core element in deriving a vulnerability index is the indicator itself (Krellenberg and Welz, 2017), hence, careful attention has to be given to which variables are chosen as indicators. The selection of indicators is one of the main challenges of vulnerability assessment (Marleen et al., 2017; Papathoma-Köhle et al., 2019) because a suboptimal selection of indicators will consequently lead to an information bias or even information loss (Günther 2006). Before a variable is qualified as an indicator, certain criteria have to be met considered to allow for consistency and methodical soundness. Important criteria for selecting a variable as an indicator include are issues related to measurability, relevance, analytical and statistical soundness, etc. (see Birkmann (2006) and JRC and OECD (2008) Birkmann 2006; JRC, 2008 for a complete list of criteria for indicator selection). Selected indicators should provide good guidance in order to capture how an element will be impacted (e.g., building damage) by a phenomenon (e.g., flood hazard). Capturing physical). Since capturing vulnerability is a complex task, therefore, multiple indicators are usually required for a comprehensive and objective evaluation. However, since the aim of indicators aims to reduce complexity, attention should be given to achieving a balance between the number of indicators selected and the reduction of complexity (Günther, 2006; Barroca et al., 2008). From a practical point of view, it is usually easier to manage a sizable number of indicators which also results in less time needed for data collection and associated cost implications.

The selection of vulnerability indicators can be categorized into two steps phases; a preliminary and a final selection phase (cf. Table 12). In the preliminary step selection phase, an initial selection of a range of identified variables is carried out. This serves to identify all possible parameters variables from e.g. literature or expert knowledge that influence vulnerability within a region. As shown in Fig. 1, the preliminary selection is commonly carried out either using a deductive or normative approach. In the final step phase, the number of variables to be used for weighting or aggregation is reduced. The final selection can be based on data availability, statistical analysis, expert opinion or other evaluation procedures. For example, Kienberger et al. (2009) reported a spatial vulnerability assessment tool using the indicator approach. In their study, expert knowledge was used for the preliminary selection of indicators. Thereafter, based on structured rounds of questionnaire evaluation, a final selection was made based on a Delphi approach. The Delphi approach utilizes several indicator suggestions by different experts and

combines the suggestions after a consensus is reached through several rounds of questionnaire exchange. During the Delphi process, pre-selected indicators that are identified to be less relevant are removed in order to arrive at a set of more effective indicators. The Delphi approach can be applied for selecting both primary indicators and their sub-indicator classes (e.g. building material as an indicator having sub-indicator classes of masonry, wood and reinforced concrete). In another study, Müller et al. (2011) used a combination of literature review, expert opinion, and suggestions by household owners in the study region for preselecting vulnerability indicators. However, the final selection of indicators was based on expert weighting through establishing a cut-off weight to determine important indicators which indicators are to be removed or selected. Another approach recently becoming popular in physical vulnerability assessment is based on Principal Component Analysis (PCA). After pre-selecting indicators, a final selection is achieved based on PCA to reduce the dimensions of a data set to a number of dimensions required to describe the variance of the data set (JRC, 2008). Examples of studies which were based on PCA for final indicator selection include Akukwe and Ogbodo (2015) and Fernandez et al. (2016), see Table 2. In some of these studies, however, the final indicator selection and weighting of indicators overlap.

### 2.2.2 Indicator weighting

After the selection of indicators, ~~the next step is to assign~~ weights are assigned to allocate the extent to which each indicator is relevant with respect to the targeted vulnerability assessment. ~~Birkmann (2006) pointed out that the assignment of weights is what makes an indicator out of a variable.~~ Prior to assigning weights to different indicators, a scoring is assigned for categories components of indicators an indicator, for example, 'building type' type as an indicator can have 'reinforced concrete', 'masonry' ~~concrete, masonry~~ and 'wooden' ~~wooden~~ buildings as sub-categories components: we refer to these sub-categories components as sub-indicators. indicator classes. The scoring of these sub-indicators, which indicator classes is a form ~~offurther based on~~ internal weighting, ~~results since~~ in information on the vulnerability of each case the ~~score for each indicator class is based on~~ individual indicator ~~vulnerabilities observed~~. For example, it is common to assign reinforced concrete ~~buildings~~ building a score that assumes a lower vulnerability to flooding ~~flood~~ impact compared to masonry or wooden buildings if we assume a similar hazard magnitude (~~see thee.g.,~~ building vulnerability classification by Maiwald and Schwarz, 2012). Both the scoring of sub-indicators and the

The weighting of indicators ~~and scoring of indicator classes~~ can be carried out using (i) deductive, (ii) ~~inductive, or~~ normative and (iii) inductive approaches.

- i. The deductive approach is based on research-based knowledge and conclusions of previous studies. The weighting is based on deduction, or inference from frameworks, a set of concepts, or theories on vulnerability (Hinkel, 2011). ~~Commonly applied~~ Different types of deductive weighting includes ~~weights basically include~~ direct expert weights, expert weights in combination with literature analysis ~~and/or~~ the application of an Analytical Hierarchy Process (AHP) from expert knowledge.

Direct expert weights refer to weights assigned to indicators using the knowledge of experts by either questionnaires or interviews. Normally, a scheme of standardized weights (e.g. from 0 to 10) is provided for the weighting in order to maintain a comparable scale of weights by different experts. ~~Firstly, direct expert weights refer to weights assigned to indicators using the knowledge of experts either by questionnaires or interviews. Approaches based on direct expert weights are among the most common types of weighting in physical vulnerability assessment; examples for floods include studies by Kappes et al. (2012), Sadeghi-Pouya et al. (2017) and Carlier et al. (2018), see Table 2. The often observed subjectivity of experts has, however, initiated some critical debates on this method~~ (Karagiorgos et al., 2016;



Thaler et al., 2019). Questions such as “Who qualifies as an expert?”, “How many experts are needed for an objective assessment?” have been raised. As a result, Hinkel (2011) referred to weights directly from expert judgment as a rather weak form of a deductive argument which should only be used for the selection of indicators.

~~Some~~Secondly, ~~some~~ vulnerability studies used weights from literature in combination with expert knowledge to formulate new weights to indicators. However, this is only possible if (i) the vulnerability of the region of interest has been previously studied or (ii) the region of interest is comparable (in building and hazard characteristics) to a previously studied region. For instance, Blanco-Vogt and Schanze (2014) and used weights from previous studies as a basis for subsequent expert weighting to assess the physical vulnerability of building material to floods. In another study, Krellenberg and Welz (2017) have utilized investigated the probability of buildings to be exposed under certain socio-environmental conditions using the indicator approach by combining literature review to complement and expert knowledge opinion for assigning weights to selected variables. Weighted variables from this study included building structure, building surrounding and coping capacity. ~~However, in order to use weights from a literature review as a basis for weighting indicators, there should be comparable regional settings and hazard typologies.~~

~~Another~~Thirdly, ~~a~~ commonly applied weighting method for physical vulnerability assessment is based on the Analytical Hierarchy Process (AHP), a multi-criteria decision tool utilizing a pair-wise comparison system which has clear advantages over the direct weighting techniques (Saaty, 1980). The AHP assigns weights between pairs of indicators instead allows the breakdown of a complex problem into smaller components through a pair wise comparison system. Instead of evaluating each indicator relative to all other indicators, ~~based on an objective weighting consideration, using AHP the weighting is carried out between pairs of indicators.~~ The pair-wise comparison evaluates allows an evaluation of which indicator<sub>i</sub> in every pair<sub>i</sub> is more important than the other one using a scale of 1 (equal importance) to 9 (extreme importance) (Chen et al., 2012). The decision on which indicator is more important can be evaluated from ~~analyzing analysing~~ data or expert knowledge, however, the expression of the extent to which one indicator is more important than another is ~~basically~~ based on expert knowledge. For example, if we assume the same hazard level affecting both in a pairwise comparison for normally built reinforced concrete and a clay building, it is most likely that the clay building will incur higher buildings, we can use damage (see Maiwald and Schwarz, 2012). Therefore, based on such data, experts may to assign a weight a indicating that reinforced concrete building as less vulnerable than the clay building. However, assigning a value that qualifies the extent to which the reinforced concrete building is less vulnerable than clay building (e.g., moderate, high, very high) requires expert knowledge. Such expert knowledge will likely come from information on the quality of regional construction types, material or local protection buildings have lower vulnerability compared to clay buildings, even if the decision to assign a vulnerability level may be quite subjective. To ensure minimal subjectivity in a pairwise comparison, the Consistency Ratio (CR) ~~is can be~~ computed. The CR checks if the subjectivity of pair-wise comparisons are within an allowable limit. ~~If, and once~~ the condition of CR is not fulfilled, a repetition of the process has to be carried out (Golz, 2016). Depending on the total number of indicators, the AHP can be computationally demanding. Studies that applied the AHP include those of Kienberger et al. (2009) and Godfrey et al. (2015), see Table 2. For example, Godfrey et al. (2015) used the AHP for weighting indicators and scoring indicator classes, and showed the consistency ratio in each case. In addition to having an application with both quantitative and qualitative data, another advantage of the AHP is the ability to track errors through the consistency ratio. Depending on the total number of indicators, however, the AHP can be computationally demanding. JRC (2008) pointed out that weights from the AHP should be interpreted more as trade-offs between indicators and not as a direct measure of importance, a conclusion that was also drawn by

Mazzorana and Fuchs (2010). Dodgson et al. (2009) highlighted a lack of internal consistency and lack of theoretical basis in the 1 to 9 scoring system as a limitation of the AHP which is still an ongoing discussion between fellows (DETR, 2009).

ii. ~~Another weighting approach is the inductive approach, using indicator weights from conclusions based on analysing observations. Inductive weights utilize inference from data (Hinkel, 2011). In physical vulnerability assessment, the PCA is the main method employed for extracting inductive weights. The PCA technique uses linear combinations to explain the variance in a data set (JRC, 2008) by reducing the dimensions of the data set to few components that account for most of the variance in the data. The PCA initializes a procedure whereby weights (factor loadings) are assigned to the indicators based on their variance in the original data set. Studies that use the PCA includes Thouret et al. (2014), Akukwe and Ogbodo (2015) and Fernandez et al. (2016), see Table 2. JRC (2008) and Hinkel (2011) argued that PCA results should be interpreted carefully since the underlying theory of the approach does not directly reveal the relationship between the variables and the phenomena. Chow et al. (2019) further emphasized that without a proper standardization of the data sets, resulting factor loadings from PCA would be misleading since the approach does not directly take into account the response variable. Consequently, the use of a direct and measurable proxy for vulnerability, for instance, building damage grade or loss ratio, is important to standardize variables before carrying out the PCA. JRC (2008) pointed out that the PCA is sensitive to the size of variables, number of observations, the presence of outliers and to changes in the original dataset.~~

ii. Another form of weighting which is not very common in physical vulnerability assessment is the normative approach. Using the normative approach, weights can be assigned based on value judgment (Hinkel, 2011). The normative approach is based on the priorities of individuals. A common application of the normative approach is the equal weighting approach. Meaning, based on a value judgment, all parameters influencing vulnerability are taken to be equally important (Frazier et al., 2014). Adopting an equal weights approach is sometimes required in cases where no consensus is reached on a suitable weighting alternative. In studies where multiple dimensions of vulnerability are considered, the equal weights approach will favor dimensions with a higher number of indicators if an unequal number of indicators is used. However, such irregularities can be corrected by a systematic normalization. Furthermore, Chen et al. (2012) noted that the equal weighting approach cannot properly handle indicators that are highly correlated because these are double-counted. Another implication of the approach, particularly at the aggregation step, was noted by Hinkel (2011): Equal weighting means all indicators are ideal replacements of each other, and low values in one indicator can be compensated by high values in another indicator. Other studies applying the equal weights approach include those of Balica et al. (2009), Behanzin et al. (2015), and Ntajal et al. (2016). Another example of the use of value judgment for weighting indicators was demonstrated by Müller et al. (2011) focusing on weighting preferences of homeowners.

iii. A further possibility to weight indicators is based on the inductive approach. This approach uses observed data to generate weights weights can be assigned based on value judgment (Hinkel, 2011). In physical vulnerability assessment, the Principal Component Analysis (PCA) is the main method employed for extracting weights. The PCA technique uses linear combinations to explain the variance in a data set by reducing the dimensions of the data set to few components (indicators) (JRC and OECD, 2008). Hence, the PCA initializes a procedure whereby weights (factor loadings) are assigned to the indicators based on their variance in the original data set. This inductive approach is generally data-driven and difficult to apply in data-scarce regions~~The normative approach is based on priorities of individuals. A common application of the normative approach is the equal weighting approach; based on a value~~

judgment, all variables influencing vulnerability are taken to be equally important (Frazier et al., 2014). However, JRC (2008) argued that equal weighting results in the same level of importance for individual indicators which raises the question which indicators are more important with respect to vulnerability. Adopting an equal weights approach is sometimes required in cases where no consensus is reached on a suitable weighting alternative. Few studies that applied the equal weights approach include those of Balica et al. (2009), Behanzin et al. (2015) and Ntajal et al. (2016), see Table 2. In studies where multiple dimensions of vulnerability are considered, the equal weights approach will favour dimensions with a higher number of indicators if an unequal number of indicators is used. However, such irregularities can be corrected by a systematic normalization. Furthermore, Chen et al. (2012) noted that the equal weighting approach cannot properly handle indicators that are highly correlated because these are double-counted. Another implication of the approach, particularly at the aggregation phase, was noted by Hinkel (2011): Equal weighting means all indicators are ideal replacements of one another, and low values in one indicator can be compensated by high values in another indicator. Another example of the use of value judgment for weighting indicators was demonstrated in Müller et al. (2011), whereby household owners were asked to weight selected indicators. As shown in Table 2, this method is not very popular in physical vulnerability assessment.

### 2.2.3 Indicator aggregation

Indicators aggregation refers to a systematic combination (or joining) of indicator weights to create a single value. This value is usually referred to as an index. The index carries information on the extent to which an element can be impacted by a hazard relative to other elements, given the combined influence of selected indicators.

Physical vulnerability assessment incorporates different types of indicators with non-uniform units, such as building material (no unit) and distance to the hazard source (meters). Therefore, before aggregating indicators, it is necessary to find a systematic and consistent means of representing the (sub-)indicators while retaining their theoretical range. Achieving a rather objective representation of different indicators is carried out by scaling. Asadzadeh et al. (2017) noted that the scaling of indicators is sensitive to the normalization and aggregation method; hence, it is important to adopt a scaling that fits the data and the overall vulnerability framework. In physical vulnerability assessment, it is common to adopt the ordinal scale to represent both qualitative or quantitative (sub-)indicators. On the ordinal scale, indicators are represented using an increasing or decreasing categorical order. The order selected is mostly subjective depending on the indicator framework and data property (JRC and OECD, 2008). A good example of the use of the ordinal scale was demonstrated by Dall'Osso et al. (2009) where five categories were used to transform all (sub-)indicators into an ordinal scale.

Physical vulnerability assessment incorporates different types of indicators with different units of measurement, for example, building material and distance to the hazard source. Therefore, before aggregating different indicators, it is necessary to find a systematic and consistent means of representing the indicators while retaining their conceptual meaning. A first step towards achieving a fair representation of different indicator types for aggregation is to scale the indicators. Qualitative or quantitative indicators are mostly adapted to an ordinal scale whereby data are categorized using an increasing or decreasing order, this order should be based on previous research results. The difference between the categories in the ordinal scale is usually non-uniform, but mostly subjective to fit the indicator framework. A good example of the use of the ordinal scale was demonstrated by Dall'Osso et al. (2009) where five categories were used to scale all selected indicators. Other studies, however, do not provide such details of data transformation techniques used. Asadzadeh et al. (2017) noted that scaling of indicators is sensitive to normalization and aggregation output, hence, it is important to adopt a scaling that fits the data and the overall vulnerability framework

~~Aggregation of indicators refers to a systematic combination of indicators to create an index.~~ Generally, several methods for indicator aggregation exist; however, a commonly applied method for physical vulnerability assessment is the additive method (see Table 12). This method is based on a summation of the product of the weights and scores (or the scaled value) of all selected indicators. The summation can be directly on scores of the indicators (direct additive method) or after multiplying weights and the scores of the indicators (weighted additive method). The result of the indicator aggregation is influenced by the applied aggregation technique as some approaches allow counterbalancing indicators with low values (compensation). In the additive method, a constant level of compensation, for indicators with lower values, is allowed (JRC and OECD, 2008). ~~applying weights to the scores (weighted additive method). The result of the indicator aggregation is influenced by the applied aggregation technique as some approaches allow to counterbalance indicators with low values (compensation). In the additive method, a constant level of compensation for lower values is allowed.~~ For example, the high indicator value of a building with poor construction material can be compensated with a low indicator value because the building is located at a far distance from the river channel. If an equal weighing is applied in combination with a direct additive aggregation method, it will mean all indicators are perfect substitutes (Chen et al., 2012). Other methods ~~offer~~ aggregation include the geometric and multi-criteria method (JRC and OECD, 2008), however, these methods are not usually applied in physical vulnerability assessment.

~~The last step in~~After aggregating indicators ~~is, some studies apply~~ a normalization ~~which ensures~~~~aiming to ensure~~ that the output from indicator aggregation lies within defined intervals. These intervals should ~~directly~~ be suitable to communicate the extent to which an element at risk is vulnerable relative to others. JRC and OECD (2008) pointed out that the choice of a normalization approach should be related to data properties and underlying theoretical frameworks. Although there are several normalization techniques, most studies in physical flood vulnerability assessment apply the minimum-maximum normalization. ~~(detailed descriptions of normalization methods can be found in JRC, 2008).~~ In the minimum-maximum normalization, index outputs are bound within a fixed range, commonly between 0 (not vulnerable) to 1 (highly vulnerable). The minimum-maximum normalization can increase the range of small-interval indicators or reduce the range of large-interval indicators. Hence, all indicators are allowed a proportionate effect on the aggregated index. Detailed descriptions of different normalization methods can be found in JRC and OECD (2008). Other studies, however, do not use any form of index normalization, for example, in Akukwe and Ogbodo (2015), weights from PCA were directly aggregated to create an index without any normalization.

### 2.3 Challenges and gaps in physical vulnerability indicators and indices

Despite current success in the development of physical vulnerability indicators, few challenges persist. We identify these challenges for physical vulnerability indicators focusing on the potential for developing indicator approaches in data-scarce regions and in order to foster adaptability, transferability and harmonizing of indicators across spatial and temporal scales.

Firstly, for the effective operationalization of an index in the vulnerability concept, there is a need for proper management of the underlying data. In many studies, data transformation methods (e.g., of missing data, scaling and normalization) are either not mentioned or only briefly highlighted. Such data operations considerably influence the index output as already demonstrated by several studies (e.g., UNDP, 1992; Tate, 2012; Mosimann et al., 2018; Chow et al., 2019) and, thus, data operations should be carried out using appropriate methods that fit the data type and indicator framework. During the indicator development, the following few points have to be clarified (i) relationship between indicators, (ii) scaling and normalization needed, (iii) necessary range of variables, (iv) data quality and quantity.

Secondly, it is important to understand the sensitivity of the vulnerability index depending on the use of deductive, inductive and normative approaches. So far, no detailed sensitivity analysis has been carried out focusing on physical vulnerability indicators, except for Fernandez et al. (2016) who have taken the first steps by analyzing the sensitivity to different aggregation methods. JRC and OECD (2008), Tate (2012) and Papathoma-Köhle et al. (2019) have stressed the need for such internal validation to assess the robustness of indices and evaluate the influence of each approach on the index stability. Such analysis can convey information on the suitability of different approaches for specific data-sets, hence providing useful guidance for further indicator development.

Furthermore, after developing the vulnerability index, it is important to assess how well the index performs by using hazard impact metrics such as building damage or monetary loss data. However, in physical vulnerability assessment, index performance evaluations have only rarely been carried out (Eriksen and Kelly, 2007; Müller et al., 2011). A performance test will allow robust evaluation of underlying indicator frameworks

2.3.1—Managing input data and pre-processing

Constructing indicators requires a systematic integration of different data sets (qualitative and quantitative, semi-quantitative), and different supporting knowledge (deductive, inductive or normative). For an index to be effectively operationalized in the vulnerability concept, underlying data has to be properly managed. Already UNDP (1992) highlighted that the quality of an index is dependent on the data it is developed from and suggested that careful pre-processing of underlying data should be carried out. For indicators to be policy relevant, care is needed so that developed indices are not unreliable (Chen et al., 2012) or an empty communication tool (Günther, 2006). Data operations, such as filling in of missing data, scaling and normalization, influence the model output considerably and should be carried out using appropriate methods that fit the data type and indicator framework. Normally, in these data operations, several approaches exist and a selection of any approach will have implications on developed indices. For example, Chow et al. (2019) demonstrated the effect of three common methods for imputation of missing data and its implication on transformed data sets. In a study on vulnerability indicators, Tate (2012) asserted that data transformation highly influences index output and should receive the highest critical examination in developing indicators. Mosimann et al. (2018) presented a new way of data transformation for deducing a flood vulnerability model for household content and came to the same conclusion. Few points to examine and clearly communicate during the indicator development phase include questions such as “What relationship exists between indicators?”, “What kind of scaling and normalization will be appropriate and why?”, “How much will scaling and normalization influence the variable range in order to correctly transfer its theoretical meaning?”, and “Which method was used for filling missing data and why?”. In many studies, however, data transformation methods are either not mentioned or only briefly highlighted. Nonetheless, it is important for future research that a proper communication of data transformation methods is carried out to allow for guidance and discussions on harmonizing indicators across scales.

### 2.3.2—Need for improving performance test

Vulnerability indicators are used to analyse disaster risk. Thus, the framework of an index formulation should allow adaption to possible future changes. The accuracy of the constructed index should be checked by applying performance assessment or validation test. A performance test will allow a robust evaluation of underlying indicator framework and basic assumptions (Eddy et al., 2012) and will also identify the suitability of selected indicators with respect to the indicator study aim (Birkmann, 2006). Few studies, however, A performance test will help in developing sound indicators (Asadzadeh et al., 2017) since it will communicate index accuracy and success in achieving a redefined indicator aim. Success in achieving a defined indicator aim will foster transferability to data scarce regions with similar characteristics in hazard and built environment. However, in



physical vulnerability assessment, index performance or validation are rarely carried out. Few studies provide a qualitative description (e.g., level of agreement) as performance analysis ~~using~~ based either on a comparison of ~~the~~ deduced index and observed damage data (e.g., Godfrey et al., 2015; Sadeghi-Pouya et al., 2017) or based on visualizations of ~~visualise~~ the spatial agreement ~~using~~ on GIS ~~maps~~ ~~map~~ by ~~presenting and~~ comparing ~~computed~~ hotspots ~~of the index and the~~ observed damage data (e.g., Fernandez et al., 2016). In general, A lack of performance test might likely be due to (i) the scarcity of empirical data and (ii) the lack of ~~in many regions.~~ A systematic linkage between the vulnerability index and ~~a hazard impact parameter (e.g., building damage or monetary loss.)~~ can be a viable option to support performance check. Due to this linkage, the output of vulnerability index will not only be an index expressing relative vulnerability to other buildings but will be extended to expressing a physical damage state which can be observed and documented.

Furthermore, vulnerability indices have been identified to lack a stand-alone meaning outside a relative comparison of building vulnerability (Tarbotton et al., 2012; Dall’Osso and Dominey-Howes, 2013). This is a major limitation given the quality of information contained in the vulnerability index. Further investigation on additional applicability of the vulnerability index should be carried out. Papathoma-Köhle et al. (2017) recently recommended a combination of methods to fully explore the potential in individual vulnerability assessment methods. Such a combination is particularly encouraged for data-scarce regions.

### **2.3.3 Understanding sensitivity and uncertainty**

## **3 Review of flood damage models**

Several approaches in selecting, weighting, scaling, normalizing and aggregating indicators exist, these consequently introduce different levels of subjectivity into the index output. Hence, it is important that different approaches of index generation are checked against uncertainties and the sensitivity of the index. JRC (2008) and Tate (2012) stressed the need for an internal validation to assess the robustness of indices and check how each approach influence the index stability. Furthermore, such analysis can convey the extent of the index reliability and enhance transparency in indicators to guide future index development. For example, Tate (2012) carried out a sensitivity and uncertainty analysis for each step of indicator generation. One finding from Tate (2012) was that both, inductive and deductive approaches are sensitive to indicator choice, and, as such, statistical properties of an indicator should be thoroughly considered in the selection phase. Another example of a comprehensive sensitivity and uncertainty analysis was carried out by Saisana et al. (2005) using the United Nations Technology Achievement Index (TAI). By contrast, no detailed uncertainty and sensitivity assessment has been carried out yet for physical vulnerability indicators. A study by Fernandez et al. (2016), however, has taken first steps to improve the understanding of the sensitivity of vulnerability index in physical vulnerability assessment. They used a GIS approach to check the sensitivity of index performance to different aggregation methods. Results indicate that while additive methods (direct and weighted additive method) show similar results, an aggregation using cluster analysis exhibited better results in detecting hotspots when compared to recorded damage data. Hence, detailed sensitivity and uncertainty analysis are highly recommended for assessing physical vulnerability.

## **3 Overview of**

Flood damage models ~~(or loss models)~~ are used to show the relationship between the extent of building damage and ~~on one hand and hazard and building characteristics (damage- (or vulnerability-) influencing factors.~~ First, we focus on an analysis of

background information on flood damage models and the application and used methods. Second, we will identify the challenges and current gaps in the context of data-scarce regions.

### 3.1 Background

~~) on the other hand. The applications of these models are varied depending on user need.~~ Flood damage models provide the basis for decision making ~~through multiple applications, such as on~~ cost-benefit analysis of mitigation measures (Thieken et al., 2005; Schröter et al., 2014), economic impact assessment (Jongman et al., 2012), ~~for~~ planning and implementation of implementing individual mitigation measures (Walliman et al., 2011), and flood risk mapping (Meyer et al., 2012). In general developing flood damage models require clear communication of model parameters; e.g., if the model is based on an individual damage parameter (stage-damage curves) or if the model comprised multiple damage-influencing parameters (multivariate methods). Further important information includes data source and sample size, method of analysis to extract the significance of variables, the scale of application, damage-influencing parameters and status of validation or performance test. The different choice of parameters and methods considered within the flood damage models already sets the conditions regarding the model transferability and guide further model development. In Table 2, we highlight these parameters for several studies. ~~and for flood risk mapping (Schröter et al., 2014). In addition, flood damage models provide a basis for estimating compensation costs for individuals and for loss comparison between regions. Additionally, loss estimates are useful for checking the utility of flood protection or mitigation measures between the past and present.~~

~~Prior to developing a damage model, it is important to define important aspects and functions of the model has to be defined. A decision has to be taken if the model is for damage grade evaluation (e.g., Ettinger et al., 2016), absolute or relative monetary loss assessment (e.g., Thieken et al., 2008) or for both (e.g., Maiwald and Schwarz, 2015). The spatial scale (individual or aggregated buildings) and time scale (immediate or long time damage) has to be defined (Blong, 2003b). Some damage models however are applicable for assessing damage at individual and aggregated scales (e.g., Maiwald and Schwarz 2015). Damage models should also be flexible to allow integration of new damage patters over time (Blong, 2003b), such as shown by Maiwald and Schwarz (2015, 2019) when expanding the original five category damage grade scheme to a six category scheme. In the next sections, we further assess specific features of flood damage models to evaluate their suitability or otherwise in a data-scarce region.~~

### 3.1 Damage grade model

~~Developing a flood damage model requires data or knowledge on building damage patterns resulting from hazard impact. Such building damage patterns that are repeatedly observed within a region can be categorized into a damage grade. Building damage occurs in various extents from light to heavy damage or collapse, usually referred to as damage grades. Damage grades vary from non-structural to structural damage. Non-structural damage refers to damage that does not immediately affect the structural integrity of a building. Examples of non-structural damage by floods include moisture defects or light cracks on building finishes. Structural damage mostly occurs on load bearing elements of the building, for example, cracks or collapse of walls, beams, columns (Milanesi et al., 2018). One of the most detailed development of damage grades was contained in the European Macroseismic Scale EMS-98 by Grunthal (1998). The scheme, developed by Grunthal (1998) for earthquakes, was later used as a basis to develop damage models for flood by Schwarz and Maiwald (2007). Grünthal (1993) recommended few guidelines for good practice in developing a damage grades, these include (i) checking a wide range of information sources~~

and consider their value, (ii) focusing more on repetitive damage than on extreme damage pattern, and (iii) additionally considering undamaged buildings.

Table 4 presents the damage grade scheme developed by Schwarz and Maiwald (2007): it shows categories of damage states from water penetration to both structural and non-structural damage. Damage grades express damage patterns as categories on an ordinal scale whereby numbers are assigned to each damage pattern with higher numbers depicting higher degree of damage (see Table 4). Some damage grade models (e.g., Maiwald and Schwarz 2015) are applicable for assessing damage at individual and aggregated scales. As a recommendation for good practice, damage models should be flexible to allow integration of new damage patterns over time (Blong, 2003b). An example of such flexibility is demonstrated in Maiwald and Schwarz (2015, 2019) when expanding the original five category damage grade scheme to a six category scheme.

Although damage prediction models are widely used in several countries, difference in regional building types have limited the transferability of such models (Tarbotton et al., 2015; Enghardt et al., 2019). For example, studies by Maiwald and Schwarz (2015) show that empirically deduced damage grades allow a transfer of the damage distribution and vulnerability models in study areas with close agreements of the observed effects. However, a particular advantage of damage grades is that they are physically observable patterns and can be qualitatively described and used to compare impacts of hazards across spatial and temporal scales. This is particularly useful in many data scarce regions where monetary loss data (e.g., insurance data) are unavailable and the consequence of hazards can only be quantified using observable damage patterns or grades.

### 3.2 Stage damage curves

Stage damage functions are a quantitative method for assessing the vulnerability of buildings, and they are widely used for assessing flood hazard risk where the number of affected buildings is large enough to deduce a reliable curve (Fuchs et al., 2019a). These functions Stage damage curves are continuous curves relating to the magnitude of a hazard process (X-axis) to the damage state of a building (Y-axis), usually expressed as the degree of loss (Fuchs et al., 2019a). Individual buildings are represented as points in the degree of loss. A general requirement of stage damage functions is the confined interval needed, meaning that the function should run through the (0,0) point because zero magnitude causes zero degree of loss (Fuchs et al., 2019b). Moreover, the function should not exceed the limit of degree of loss 1, because a degree of loss higher than 1 is only possible if costs other than direct damage are included in the vulnerability assessment.

Stage damage curves can be developed using empirical data or synthetic approach. The shape of the empirically derived stage damage function depends on the population and spread of data related to buildings within the inundation area under consideration as well as the type of function chosen. Individual buildings are represented as points on a XY axis system and then the function that ensures the best fit may be chosen (Totschnig et al., 2011). Empirically developed stage damage curves are widely used for assessing flood hazard risk where the number of affected buildings is large enough to deduce a reliable curve (Fuchs et al., 2019a). The shape of the empirically derived stage damage function depends on the population and spread of data related to buildings within the inundation area under consideration as well as the type of function chosen. Synthetic stage damage curves are based on expert-knowledge to describe a relationship between flood damage with flood depth for a specific building or land-use type. Synthetic curves Synthetic stage damage curves are developed by utilizing expert-based what-if analysis to develop a relationship between flood damage with flood depth for specific building or land-use types. For example, experts can be asked to estimate the pattern of building damage that will be expected if a specific building type (e.g., masonry building) is inundated with a certain flood depth (e.g., 1 m). Synthetic methods can be developed independently (e.g., Penning-Rowsell et al., 2006; Neubert et al., 2008; Naumann et al., 2009) Penning-Rowsell et al., 2006; Naumann et al.,

2009) or supported by empirical data (e.g., NRE, 2000). For data-scarce regions, utilizing the synthetic (what-if) analysis can serve as an important first step for establishing flood damage models. More details on the synthetic what-if analysis are given by Penning-Rowsell et al. (2005), Neubert et al. (2008) and Naumann et al. (2009).

Despite the wide usage of stage damage curves, several studies have highlighted the high uncertainty in these curves particularly because they only consider flood depth as the only damage influencing parameter (e.g., Merz et al., 2004, 2013; Vogel et al., 2012; Pistrika et al., 2014; Schröter et al., 2014; Wagenaar et al., 2017; Fuchs et al., 2019b). These studies have demonstrated that damage influencing variables are not only related to water depth but also to other flood characteristics (e.g., velocity, duration) and building characteristics (construction type, quality, material). For instance, Merz et al. (2004) demonstrated the poor explanatory power of flood depth in explaining the variance in a damage data set. However, the main advantage of the synthetic stage damage approach is that it can be developed in the absence of empirical data using the what-if analysis. This is particularly useful for data scarce regions especially if it can be used within an approach that considers multiple damage influencing variables.

### 3.3. Multivariate methods/approaches

Multivariate ~~methods~~ Multivariate approaches utilize empirical data to relate multiple ~~develop a relationship between~~ damage influencing variables on one hand and flood and building damage by applying a variety of statistical methods (see Table 2) ~~characteristics on the other hand~~. Such empirical data can be collected from insurance companies (e.g., Chow et al., 2019) ~~Chow et al., 2019~~), through field surveys (e.g., Ettinger et al., 2016), or by telephone interviews (Thieken et al., 2005; Schwarz and Maiwald, 2008; Maiwald and Schwarz, 2015). As ~~Empirical data can also be collected using social media accounts like Twitter as recently~~ demonstrated by Cervone et al. (2016), empirical data can also be collected using social media accounts. Multivariate models may become more common in the near future since they offer a more comprehensive approach compared to the stage-damage curves. Schröter et al. (2014) evaluated the applicability of flood damage models and showed that models that consider a higher number of damage ~~influencing variables~~. Several statistical methods employed in literature for developing multivariate methods include Bayesian network by Vogel et al. (2012), logistic regression by Ettinger et al. (2016), bagging decision trees by Merz et al. (2013) and Wagenaar et al., 2017, and logit linear regression, double generalized linear models and random generalized linear model by Chow et al. (2019). Multivariate models are becoming common since, by including multiple damage influencing variables, they offer a more comprehensive approach compared to the stage damage curves. Schröter et al. (2014) evaluated the usefulness of flood damage models and showed that models that consider higher number of damage influencing variables demonstrated superiority in predictive power both spatially (transfer to other regions) and temporally (different flood events). The multivariate method has ~~Multivariate functions have~~ been shown to better ~~explain better~~ the variability in damage data (Merz et al., 2004) and reduce uncertainty in flood damage prediction (Schröter et al. 2014). Table 3 represents a short overview of multivariate models developed for floods. Although there are many of such models in literature, selected studies are used to show the wide variety of statistical methods employed, damage influencing variables considered, scale of application, data source and performance test. The majority of multivariate models use mainly flood and building characteristics in their models. Some additionally consider building exposure parameters to include the characteristics of the building surrounding. For example, Maiwald and Schwarz (2015) included building location relative to other buildings and to the flood source as part of the damage model. Although it is very important for damage models to capture damage influencing variables so as to improve its accuracy, having too many variables might lead to model complexity. Consequently, Walliman et al. (2011) pointed that damage models must strike a balance between accuracy and complexity

### 745 **3.2 Application of flood damage models**

The applications of both stage-damage curves and multivariate methods vary depending on the user requirements. These user requirements may range from estimating damage grades (e.g., Ettinger et al., 2016), estimating absolute or relative monetary loss (e.g., Thieken et al., 2008) or both (e.g., Maiwald and Schwarz, 2015). In particular, the use of damage grades is especially encouraged for data-scarce regions since it relies only on observable damage patterns within a region and expert knowledge. 750 In addition, damage grades are well understandable by experts and non-experts making them easy communication tools. One of the most prominent damage grades is the European Macroseismic Scale EMS-98 for earthquakes (Grünthal 1998) which was later used as a basis to develop damage grades for flood hazards by Schwarz and Maiwald (2007).

Developing a damage grade requires data (or knowledge) on regional building damage patterns resulting from flood impact. Damage patterns, which are repeatedly observed within a region, can be categorized into damage grades (Schwarz and 755 Maiwald, 2007). Grünthal et al. (1998) and Maiwald and Schwarz (2015) noted that damage grades should not only consider the physical effects of damage but also the number of buildings that show such effects. Hence, in developing damage grades, the focus should be given to both physical damage features and their corresponding proportion. Damage grades express frequently observed damage patterns as categories on an ordinal scale whereby numbers are assigned to each damage pattern with higher numbers depicting a higher degree of damage (see Table 3). Damage grades vary from non-structural to structural 760 damage. Non-structural damage refers to damage that does not immediately affect the structural integrity of a building. Examples of non-structural damage by floods include moisture defects or light cracks on building finishes. Structural damage mostly occurs on load-bearing elements of the building, for example, cracks or collapse of walls, beams, columns (Milanesi et al., 2018).

Generally, there is a wide range of damage patterns available to describe how buildings respond to flood impact. However, 765 including all these patterns will lead to unnecessarily complex flood damage models. Nonetheless, damage grades should be detailed enough to capture predominantly observed patterns of damage within a region. In such a way, damage grades serve as a compromise between comprehensiveness and simplicity (Blong 2003b). Grünthal (1993) recommended guidelines for good practice in developing damage grades, including (i) checking a wide range of information sources and consider their value, (ii) focusing more on repetitive damage than on extreme damage pattern, and (iii) additionally considering undamaged 770 buildings. As an additional recommendation, Blong, (2003b) suggested that damage models should be flexible enough to allow integration of new damage patterns over time. An example of such flexibility is demonstrated in Maiwald and Schwarz (2015, 2019) when expanding an originally five-category damage grade scheme to a six-category scheme. Damage grades are not affected by temporal changes (increase or decrease) in market value or wages, which can affect relative and absolute losses (Blong, 2003a). Due to this robustness to changes, they are easily transferable to regions with comparable building and hazard 775 characteristics. This transferability is particularly important for data-scarce regions, where resources are limited for comprehensive data collection campaigns. Other characteristics of damage grades include simplicity, clarity, reliability, robustness, and spatial suitability (Blong, 2003b).

### **3.3 Challenges and gaps in flood damage models**

Predicting damage grades using commonly-applied stage-damage curves and multivariate methods has some weaknesses. 780 These weaknesses are either manifest in both, data-rich and data-scarce regions, or specific to the latter. For example, despite the wide usage of stage-damage curves, several studies have highlighted inherent uncertainties particularly regarding damage predictions since they consider only flood depth as the damage-influencing parameter (e.g., Merz et al., 2004, 2013; Vogel et



al., 2012; Pistrika et al., 2014; Schröter et al., 2014; Wagenaar et al., 2017; Sturm et al., 2018b, 2018a; Fuchs et al., 2019b). These studies have demonstrated that flood damage is not only influenced by water depth but also by other hazard parameters (e.g., velocity and duration) and building characteristics (e.g., construction type, quality, and material). For instance, Merz et al. (2004) demonstrated the poor explanatory power of flood depth in explaining the variance in a data set. Although applying multivariate methods reduced uncertainties associated with models based on a single damage-influencing parameter, in data-scarce regions a disadvantage of the multivariate method is the lack of empirical data for developing and validating such models.

Several other challenges exist in data-scarce regions, which further limits the development of flood damage models. Merz et al. (2010) noted that selecting a method depends on data availability and knowledge of damage mechanisms. The absence of insurance against damage from natural hazards and effective government compensation schemes, typical for many data-scarce regions, contribute to a lack of data to support physical flood vulnerability assessment. For example, Komolafe et al. (2015) reported that no research institute or agency has a central database to document flood damage in many African countries such as Nigeria. They further pointed out that such scarcity of damage data might be related to the fact that the practice of flood insurance is uncommon and government compensation after flood disasters are flawed. As such, people immediately repair their buildings after a flood event. Additionally, regulatory policies on building standards are less well implemented in many areas. Similar observations were made by Englhardt et al. (2019) in Ethiopia, pointing out a considerable difference in building quality and value, especially in rural areas. Also, in Nigeria, FGN (2013) reported that over 60 percent of households acquire their houses through private resources and initiatives, thus, only a few use the services of formal institutions. This often leads to substantial differences in the quality of buildings, consequently increasing the challenges in developing building-type vulnerability assessment schemes. In addition, such difference in building quality further limits the application of flood damage models that use relative or absolute monetary losses due to a high range in replacement costs and property values.

~~4 A drawback of the multivariate method is the empirical data requirement for deriving and validating such models. Such data require intensive time and human effort to collect (in a data-rich region) or are limited (or unavailable) in data-scarce regions. Nonetheless, a special similarity between the multivariate method and vulnerability indicators is that they both integrate multiple damage-influencing variables. Since the vulnerability indicators can be developed using expert knowledge, we integrate it into the proposed new framework.~~

#### **4—The need for linking indicators and damage grades**

~~A combination of Using a synthetic what-if analysis to link damage grades (representing repeatedly -observed damage patterns) with and the vulnerability indicatorsindicator (capturing important damage-influencing variables within a region) using an expert-based what-if approach offersean produce a convenientvulnerability model that is simplistic and comprehensive method for assessing flood damage. This allows to tailor flood damage models to specific needs of use in data-scarce regions, and simultaneously to take. In general, the linkage of these approaches is a promising pathway taking advantage of the strengths of the two methods while limiting their individual weaknesses.~~

Several weaknesses highlighted in Sections 2.3 and 3.3 have limited the assessment of assessing physical vulnerability. However, specific aspects of these approaches can be utilized for data-scarce regions. Although the vulnerability index hasVulnerability indicators have been identified to lack a stand-alone meaning, its combination with damage grades will extend its applicability for damage prediction. Besides, the use of damage grades will help to evaluate the performance of vulnerability indices. Current flood damage models werepose challenges if transferred between different regions or used to compare the

~~vulnerabilities between regions. In addition, current flood damage models are~~ identified to be either data \_intensive (multivariate methods) or ~~to do~~ not consider other damage-influencing variables (stage-damage curves). However, an integration of damage grades with ~~the vulnerability indicators~~indicator can provide a suitable model ~~to overcome that overcomes~~ these challenges. This integration can be fostered through utilizing the expert-based synthetic what-if analysis, which has been applied for developing synthetic stage-damage curves.

To demonstrate the added value of this linkage, we use a combination of (i) observed flood damage data, (ii) a hypothetical physical vulnerability index for two regions A and B, and (iii) two ~~flood regions A and B, and two~~ damage models developed for predicting damage gradesgrade. The observed damage data (see Fig. 2) was documented from a field survey conducted after the 2017 flood event in Suleja and Tafa, ~~areas in~~ Nigeria. The flood event was caused by prolonged rainfall for about 12 hours ~~between 8 and 9 from 8<sup>th</sup> to 9<sup>th</sup>~~ July 2017. ~~The flood event, which~~ resulted in the loss of lives and ~~damaged~~damage to hundreds of buildings and infrastructure (Adeleye et al., 2019). A field study was conducted in March 2018 in order to document damage to the built environment and to interviewduring which affected homeowners. ~~From the household owners were interviewed and data on damage sustained by affected buildings were~~ documented. ~~Out of the documented damage cases,~~ we use three buildings to illustrate the potential weakness that may occurdraw back in using only the vulnerability index approach and the added value of the suggested linkage with damage grades. The three buildings shown in Figure 2 are constructed from sandcrete block (Fig. 2, buildings i, ii) and clay bricks (Fig. 2, building iii). The buildings have different damage patterns ranging from moisture defects on walls resulting in peeling-off of plaster material and slight cracks (e.g., building i), partial collapse of supporting wall (e.g., building ii) and complete collapse (e.g., building iii). A hypothetical physical vulnerability index is considered for the two regions A and B (see Fig. 2). In the two regions, hypothetical vulnerability indicators were assigned as main damage-influencing parameters, ~~in the regions~~. Indicators for region A included~~include~~ building material, building condition, distance to channel and flood depth. Indicators for region B included~~include~~ building age, building quality, sheltering effect and flood depth. Vulnerability indices for regions A and B both express relative vulnerability from 0 (low vulnerability) to 1 (high vulnerability). Hypothetical vulnerability indices, after aggregating identified indicators, are given in Figure 2. We further consider two damage grades presented~~developed~~ by Maiwald and Schwarz (2015) for Germany and by Ettinger et al. (2016) for Peru. We use identified damage patterns on the buildings from the field study to assign a damage grade to each building. From Fig. 2, we see that although we can use the developed index to identify which building is highly or moderately vulnerable within a region, we cannot compare the indices between different regions because they contain aggregated information from different parameters. However, in the case of damage grades, although they were developed in two different regions, qualitative descriptions of ~~these~~the damage grades can be used to assign damage grade classes for the identified damage patterns in buildings i, ii, iii (Fig. 2). ~~Using such comparability that comes from the consistency of hazard consequence, a model that predicts damage can allow us to compare hazard impacts across spatial and temporal scales.~~

A combination of physical~~between~~ vulnerability indicators and damage grades using the synthetic approach has a number of advantages for data-scarce areas. These include:

- i. ~~Employing the synthetic what-if analysis~~method to link damage grades and damage drivers allow to hazards parameters, ~~we can~~ overcome high data requirementsrequirement of the multivariate~~empirical~~ method. Consequently, the linkage will capture ~~building and hazard characteristics through the vulnerability indicators.~~ This will help overcome limitation of the synthetic stage damage method since multiple damage \_influencing variables. Also, parameters can be integrated

ii. ~~The linkage will allow us to compare consequences of flood hazards in different data scarce regions using the damage grades and at the same time considering regional differences using the vulnerability indicators. This will foster transferability since we can have common observable damage features resulting from flood impact.~~

~~iii.i. Since damage grades are physically observable features, the linkage with vulnerability indicators will allow us to carry out performance checksehek on the effectiveness and robustness of selected vulnerability indicators.index.~~

ii. ~~The linkage will enable to compare consequences of flood hazards across spatial and temporal scales in data-scarce regions. Spatial comparability can be achieved through the identification of similar damage characteristics (Fig. 2) between regions with similar building types and hazard characteristics. Temporal comparability can be achieved by relating the severity of observed damage grades between different flood events since damage grades are not readily affected by market values or wages. In addition, using similar hazard scenarios damage can be estimated and compared between regions while still considering individual damage drivers (Fig. 2).~~

iii. ~~Since damage grades are physically observable features, the linkage will foster the provision of an easy communication tool for stakeholders and community residents on the consequences of hazards.~~

## 5 Conceptual framework

### In this section, we 5.1 Background for operationalizing the new framework

~~We present a new conceptual framework that aims to link physical vulnerability indicators on one hand and damage grades in order on the other hand to make use of their individual strengths for data-scarce regions. We first provide background information on terminologies used within the framework and second present step-by-step details on how to operationalize the framework.~~

### 5.1 Background for operationalizing the new framework

~~Vulnerability. The vulnerability indicators are used to capture damage-influencing variables, which include characteristics of flood hazard, characteristics and the elements of the built environment, and its surroundings. Damages surrounding as shown in Fig. 3. The damage grades represent the physical consequences of hazard impacts on a building that which depends on both hazard and building characteristics. Figure 3 shows the conceptual framework and the proposed approach for linking physical vulnerability indicators and damage grades, the terminology is given below:~~

~~*Vulnerability:* The degree to which an exposed building will experience damage from flood hazards under certain conditions of exposure, susceptibility, and resilience (adapted after Balica et al., 2009).~~

~~*Impact (action) and resistance parameters:* The framework considers two major damage-influencing parameters, action (impact) and resistance parameters. The action and resistance parameters have been identified by The vulnerability indicator considers two major damage-influencing variables; action (impact) and resistance variables Thieken et al. (2005) and Schwarz and Maiwald (2007) as the primary classes of damage drivers. Impact (or action) parameters relate to the flood parameters comprising of hazard frequencies and magnitudes (Thieken et al., 2005). (Thieken et al., 2005; Schwarz and Maiwald, 2007). Action (or impact) parameters relate to the flood parameters comprising of hazard frequencies and magnitudes. Resistance parameters are related to the predisposition of the building to suffer damage, either permanently (e.g., building material) or temporarily (e.g., measures for flood~~

preparedness) (Thieken et al., 2005). In the framework, resistance parameters comprise elements of the building and its surroundings, which are divided into susceptibility, exposure, and local protection parameters. Resistance parameters comprise of elements of the building and its surrounding, which are divided into susceptibility, exposure, and local protection variables. Vulnerability is seen as the degree to which an exposed building will experience damage from flood hazards under certain conditions of susceptibility and resilience (Balica et al., 2009). Exposure refers to the extent to which a building is spatially or temporarily affected by a flood event (Birkmann et al., 2013). Exposure parameters include features of the natural and built environment that either increase or decrease the impact of floods on buildings, such as topography and distance to the flood source. Susceptibility refers to the disposition of a building to be damaged by a flood event (modified after Birkmann et al., 2013). Susceptibility parameters relate specifically to the structural characteristics of the building at risk, neglecting any effects of local protection measures which may provide flood protection. Local protection in this study refers to deliberate or non-deliberate measures that are put in place and can reduce the impact of the floods on a building. These measures can be directly included into the building structure e.g. elevation of entrance door, located in the immediate surrounding of a building. While many local structural protection measures may not be primarily constructed as a protection mechanism against floods, they reduce the impact of floods on a building. In the context of this framework, a fencing wall will be an example of a local protection measure.

Exposure: Refers to the extent to which a building is spatially or temporarily affected by a flood event (adapted after Birkmann et al., 2013). Exposure parameters include features of the natural and built environment that either increase or decrease the impact of floods on buildings, such as topography and distance to the flood source.

Susceptibility: Refers to the disposition of a building to be damaged by a flood event (adapted after Birkmann et al., 2013). Susceptibility parameters relate specifically to the structural characteristics of the building at risk, neglecting any effects of local protection measures that may provide flood protection.

Local protection: Refers to deliberate or non-deliberate measures that are put in place and can reduce the impact of the floods on a building. These measures can be directly included in the building structure e.g. elevation of the entrance door, or measures located in the immediate surrounding of a building. While many local structural protection measures may not be primarily constructed as a protection mechanism against floods, they reduce the impact of floods on a building (Holub and Fuchs, 2008; Attems et al., 2020). In the context of this framework, a fencing wall will be an example of a local protection measure.

5.2 ~~Damage grades represent classes of regularly observed damage patterns (Maiwald and Schwarz 2015). Generally, there are a wide range of damage patterns to describe how buildings respond to flood impact. Including all these patterns however will lead to unnecessarily difficult and complex damage prediction models. Nonetheless, damage grades should be detailed enough to capture predominantly observed patterns of damage within a region. Damage grades serve as a compromise between comprehensiveness and simplicity (Blong 2003b). Some characteristics of a damage grades given by Blong (2003b) include simplicity, clarity, reliability, robustness, and spatial suitability. Damage grade should not only consider physical effects of damage but also the quantity of buildings that show such effects (Grünthal et al., 1998; Maiwald and Schwarz, 2015).~~

## **5.2 Operationalizing the framework**

In order to operationalize the new framework, three ~~basic~~ phases are proposed: (i) developing a vulnerability index, (ii) developing a damage grade classification, and (iii) linking the vulnerability index to the ~~and~~ damage grade classification ~~grades~~.

### 5.2.1 Phase 1: Developing a vulnerability index

935 We develop ~~here~~ a vulnerability index aimed at ~~systematically integrating identifying~~ damage -influencing ~~parameters. These~~  
~~parameters represent vulnerability indicators or damage drivers adapted for a selected region. variables.~~ As a result, we structure  
indicators into impact ~~(action)~~ and resistance parameters as ~~shown seen~~ in Fig. 3 (phase 1). ~~InImplementation of the method~~  
~~will depend on data availability, therefore we propose both a data-driven and an expert-based approach. Both approaches can~~  
~~be supported by literature review. Resistance parameters are categorized into separate components (e.g. exposure,~~  
940 ~~susceptibility, resilience) in order to allowallows~~ an evaluation of how different components contribute to damage. ~~we~~  
~~categorize resistance parameters into separate components, exposure, susceptibility, and local protection.-~~ Application of the  
method is aimed at ~~the~~ micro-scale level, however, it can be applied at meso- or macro -scale if data are available. ~~Generally,~~  
~~the The~~ selection, weighting, and aggregation of indicators are similar to the procedure discussed in ~~Section 2.2. Since our~~  
~~focus is on data-scarce regions, we focus the framework on expert-based approachessection 2.2.~~

945 ~~Indicators are mainly selected using expert surveys. Where possible, experts should include individuals from different~~  
~~disciplines in order to have a wide-ranging assessment. Expert surveys are carried out by conducting standardized interviews~~  
~~using questionnaires. The main focus of the questionnaire is on asking each expert to identify parameters representing damage~~  
~~drivers within a region. A set of indicators can be identified and included in the questionnaire, with the support of a literature~~  
~~review. Experts can then either select from the suggested indicators or propose new ones. All variables suggested by experts~~  
950 ~~at this step serve as pre-selected indicators.~~

~~Indicator (or parameter) weighting is carried out using an expert-based approach. Here, experts are asked to weight how each~~  
~~pre-selected variable influences damage. The weighting is carried out using a scale of influence table based on Saaty (1980),~~  
~~as shown in Table 4. Because the table by Saaty (1980) is originally used for making a pair-wise comparison between two~~  
~~parameters, it was slightly modified so as to be used in weighting pre-selected parameters with respect to how they influence~~  
955 ~~flood damage. The scale (Table 4) will help to bring consistency and comparability in weighting when using the framework.~~  
~~Using Table 4, experts can assign a certain influence (e.g., slight, strong) for each pre-selected indicator. For each parameter,~~  
~~a mean value of the assigned weights from all experts is calculated and checked based on Table 4. The mean value here~~  
~~represents the central value used to communicate how all the experts evaluate a parameter based on its influence on damage~~  
~~within a region. The mean weights for each parameter are used for the final selection of indicators. For example, a mean weight~~  
960 ~~of 2 from Table 4 will infer that on average, experts consider the parameter to have only a slight effect on damage. A decision~~  
~~has to be made on a threshold (e.g., 1, 2 or 3 from Table 4) for parameter inclusion for the final selection. The threshold will~~  
~~depend, however, on the specific need (e.g., level of accuracy) or aim (e.g., identifying major damage-influencing parameters)~~  
~~of the study. Only parameters included in the final selection will be used in the indicator aggregation step. Next, using mean~~  
~~values for each indicator that has passed the final selection, the AHP is implemented to determine indicator weights (see~~  
965 ~~Section 2). For detailed information on the procedure for implementing the AHP, we refer the reader to JRC and OECD (2008)~~  
~~and Saaty (1980).~~

#### **Indicator selection**

~~Selection of indicators is carried out through a data-driven approach or based on expert knowledge. Data driven approaches~~  
~~utilize weights from the PCA to identify important damage influencing parameters. Where such empirical data is not available,~~  
970 ~~as is the case in many developing countries, expert knowledge is utilized through conducting standardized interviews using~~  
~~questionnaires. If there are studies conducted in regions with comparable building and hazard characteristics, identified~~  
~~damage-influencing parameters can be used to provide basis for the pre-selection of indicators. Such pre-selection will guide~~



final selection of indicators in both the data driven and expert approach. Considering regional comparability is highly important as demonstrated in a study by Cammerer et al. (2013); the study showed that damage functions performed considerably well when tested in regions with similar building and flood characteristics. Cammerer et al. (2013) also showed the relatively poor performance of flood damage models from regions with different building and hazard properties.

### **Indicator weighting**

Indicator weighting is carried out using either an expert based or a data driven approach. For the expert weighting, selected group of experts are asked, using questionnaires or through interviews, to weight how each selected indicator influences damage. The weighting is carried out using a scale of influence measure as shown in Table 5 based on Saaty (1980). Although the table by Saaty (1980) is used to make a pair-wise comparison between two parameters, we slightly modified it so as to be used in weighting a parameter with respect to flood damage. The scale (Table 5) will help to bring consistency and comparability in weighting when using the framework. Using the scale, experts can assign a certain influence for each parameter. For each indicator, a mean value of the assigned weights from all experts is calculated. The mean weight for each indicator is used to further determine parameter inclusion in the aggregation step. For the data driven approach, a PCA is employed to weight all selected parameters. PCAs have been employed in previous studies both with (e.g., Thielen et al., 2005; Kreibich et al., 2010) and without empirical flood damage data (e.g., Thouret et al., 2014; Akukwe and Ogbodo, 2015). In both cases, factor loadings from PCA determine the extent of influence a parameter has on damage.

In the two methods outlined, weights extracted from both the PCA (factor loadings) and expert based (mean weights) can be used to determine if a parameter is included for the aggregation or not. For example, a mean weight of 2 from Table 5 will infer that most experts consider the parameter to have only a slight effect on damage. Similar methods for reducing initially selected parameters are used in empirical damage models. For example, initially selected parameters were eliminated during the logistic regression due to low influence on damage by Ettinger et al. (2016). In adopting the procedure, decision has to be made on a threshold for parameter inclusion in the aggregation step. The threshold will depend on specific function (e.g., level of accuracy) or aim (e.g., identifying major damage influencing parameters) of the study.

### **Indicator aggregation**

A normalized weighted additive method is used for aggregating indicators. As shown in Fig. 3 (phase 1), selected parameters for exposure are aggregated to derive a Building Exposure Index (BEI). The BEI is a measure of the extent to which a building is likely to be damaged as a result of (i) the spatial location relative to the flood source and (ii) surrounding buildings. Indicators for Variables of susceptibility and local protection are aggregated to derive a Building Predisposition Index (BPI). The BPI provides a measure of the extent to which a building is likely to be damaged based on the building characteristics and available protection measures. Both BEI and BPI are aggregated to derive a Building Resistance Index (BRI). The BRI measures expected resistance behaviour of a building can offer at a specific degree of impact, given considering its predisposition and exposure. Hence, given the same degree of hazard impact, a building with a high The BRI (high resistance) is expected to experience less damage compared to a building with a low BRI (low resistance). As pointed out earlier, a building-type vulnerability classification can be challenging in data-scarce areas. Therefore, we propose the use of the BRI used to classify buildings into different resistance classes (e.g., low, moderate and high). Such classifications of buildings into vulnerability categories have been shown to facilitate a better understanding of the distribution of a damage data (Schwarz and Maiwald, 2008). Elements within the same vulnerability class are expected to experience similar damage when impacted by the same degree of hazard. hazard level. Furthermore, we utilize an additive model to aggregate flood hazard parameters (e.g. depth,

duration) in order to derive a Building Impact Index (BII). The BII is used to express the combined effect of hazard variables on a building structure. The BII is computed using collected data after a flood event or by utilizing flood scenario modelling to extract hazard parameters (Mark et al., 2019).

The last step in phase 1 is to utilize the additive model to aggregate flood hazard parameters (e.g., depth, duration) in order to derive a Building Impact Index (BII). The BII is used to express the combined effect of hazard parameters on a building structure. The BII is computed using interview data collected after a flood event (Malgwi et al., submitted).

### 5.2.2 Phase 2: Developing the damage grades

We adopt a slightly modified procedure outlined in Naumann et al. (2009) ~~for developing to develop~~ damage grades. Figure 3 (phase 2) shows the systematic steps for developing the damage grades using an expert-based approach. ~~The main~~ Main aim of this step is to identify commonly observed damage patterns within a region and categorize them into classes. As such, basic outputs of this phase are classes of different damage patterns ordered into damage grades.

Sourcing for damage patterns within a region is carried out by analyzing observed damage data or by structured interviews with experts or community residents. Such structured interviews are undertaken using questionnaires in flood-prone communities. Community residents or experts are asked which damage patterns are observed after flood events. They are also asked on how frequent these observed patterns occur after floods. In addition, questions on which damage types are usually repaired (or replaced) after flood events can be asked. From such information, the original damage can be deduced. Other sources of information are literature review, review of damage reports, news and social media (videos and images). Such a wide range of information sources is particularly encouraged by Grünthal (1993) in order to have a comprehensive damage grade classification. Attention should also be given to the proportion of buildings observed to exhibit each damage grade (Grünthal, 1993). The damage grades should not focus on isolated (uncommon) damage patterns, but more attention should be given to frequently observed patterns.

We present an overview of a synthetic method for developing a damage model as described by Naumann et al. (2009). The necessary steps include:

- i. Identification of building types and building representatives: ~~A buildings with representative: An important~~ first step for developing a flood damage model is to assess building types within a region and select building representatives (Walliman et al., 2011; Maiwald and Schwarz, 2015). The assessment of building types can be carried out based on ~~through~~ field surveys, expert surveys or remote sensing. Where a large-scale building assessment is required, a method conceptualized by Blanco-Vogt and Schanze (2014) for semi-automatic extraction and classification of buildings can be applied. The representatives should include building types (material, form of construction and quality) that are predominant within ~~using~~ a region. Additionally, high-resolution remote sensing data can be applied. Naumann et al. (2009) noted ~~other that~~ attributes ~~that are~~ used for classifying buildings, ~~these could~~ include ~~the~~ period of construction and the original use, the characteristic formation of buildings, and spatial ~~patterns~~ pattern and geometry. In the framework, we use the BRI for classifying buildings into different categories since it ideally captures parameters that influence damage. A suitable classification for the BRI is a generic categorization into 'low BRI' class, 'moderate BRI' class and 'high BRI' class (Fig. 3, Phase II). The class represents buildings that will offer a low (low BRI), medium (moderate BRI) and good (high BRI) resistance if we consider the same impact magnitude. Such a generic building classification, which is not building-type based, is especially suitable in areas with a high variability in building quality, and construction details. From each BRI class, a representative building ~~is will be~~ selected.

Suitably, these representatives can be selected from different building types and should communicate the typical characteristics of buildings in the BRI class.

- ii. Identification and grading of regional damage pattern~~categories~~: Flood damage to buildings can be generally categorized into three major parts, ~~according to~~ these include water penetration damage (moisture), chemical damage (pollution and contamination) and structural damage (Schwarz and Maiwald, 2007; Walliman et al., 2011). These three general damage categories can serve as a basis for developing further damage classification in regions where such damage assessment was not previously carried out. For each BRI representative, different patterns of damage are identified. Patterns that are repeatedly observed are indications of a damage grade category (Maiwald and Schwarz, 2015). Where the damage patterns for different representatives are the same, a single damage grade scheme can be adopted. However, where the damage patterns are substantially different, the damage grade is adapted for each BRI representative. This step ensures that predominant building and damage types are considered. ~~These three general damage categories can serve as basis for developing damage classification in regions where such damage assessment was not previously carried out. Structural damage should be further examined to develop sub-categories of damage patterns within a study region. For each BRI representative building, different patterns of structural damage are identified by a group of experts. Patterns which are repeatedly observed are indications of a damage grade category. Decision has to be made on how many damage grades to considered between a minimum damage grade of water penetration and a maximum damage grade of total collapse (see for comparison Table 4). Where studies have been conducted for a region with comparable building types, damage patterns can be used as a guide. Other information sources such as news reports, social media (videos and images) can be utilized in identifying damage patterns. Identified damage categories are assigned to an ordinal scale to show a minimum damage (usually water penetration) to maximum damage (complete collapse or washing away of a building).~~

In the next step, identified damage patterns are assigned to a scale representing the degree of damage severity. A commonly applied scale for damage grades is the ordinal scale (e.g., Table 3). The ordinal scale provides suitable classes for damage grades since the intervals between different categories are not consistent. For example, in Table 3, the difference in severity between damage grades 1 and 2 is not the same as between 2 and 3. Minimum damage (usually water contact with external walls or water penetration) and maximum damage (complete collapse or washing away of a building) have to be decided. Additionally, a decision has to be made on how many damage grades to consider. As earlier pointed out, a balance has to be set between comprehensiveness and simplicity. Where difficulties exist in deciding which damage grade is of higher or lower severity, local technicians or other persons familiar with constructive issues can be asked to estimate repair cost for each damage grade. In this case, a high repair cost will infer a higher damage grade.

### 5.2.3 Phase 3: Expert ‘what-if’ analysis

With a focus on data-scarce regions, we present steps to link damage-influencing variables (from phase 1) and predominant damage patterns (from phase 2). Expert knowledge is utilized to predict damage grade(s) for each representative building type (BRI class) using synthetic flood depths. The synthetic flood depths will represent scenario-based flood depths, which are typical for a region. Intervals for synthetic flood depths are integrated using the BII (Fig. 3).

In the what-if analysis, expert knowledge on regional flood damage mechanisms is crucial. Based on a given flood depth, experts propose a probable damage grade for a specific building type. Estimating a single damage grade for a given water depth can result in uncertainties. Therefore, we propose the use of three probable damage states to capture the range of possible

damage. Figure 3 (phase 3) shows an idealized curve depicting the relationship between damage grades, BII and BRI. The methodical steps for linking damage grades with the BRI and BII were adopted from and modified after Naumann et al. (2009) and Maiwald and Schwarz (2015). Steps for the linkage include:

### *To develop 5.2.3 Phase 3: developing a relationship between vulnerability index and damage grades*

Several methods have been used in relating damage grades to damage influencing variables. Selecting a particular method is likely depending on data availability and knowledge on damage mechanisms (Merz et al., 2010). With a focus on data scarce regions, we outline steps using an expert based approach to link damage grades and damage influencing variables. Blong (2003b) asserted that in absence of empirical data for developing flood damage models, a link between building damage and significant parameters contributing to damage (indicators) can be established. Furthermore, the approach can be enhanced by developing an aggregated value (or index) to qualify damage expressed in terms of damage grades. Here, the basic idea is to use expert knowledge with artificial inundation scenarios to construct a flood damage model as applied in the synthetic method. We use expert knowledge to define probable damage grades for selected intervals of BII. Each BRI class will have a different model. Figure 3 (phase 3) shows an idealized curve depicting the relationship between damage grades, BII and BRI. Methodical steps for developing the link between damage grades with the BRI and BII are modified after a similar approach used in Maiwald and Schwarz (2015). Instead of empirical data however, a synthetic “what if” analysis is adopted for data scarce regions. The following steps are illustrated for linking damage grades with the developed indices.

- i. Classify BRI into five building resistance classes (very low, low, moderate, good, very good)
- ii. Select one building type as representative for each BRI class. Ideally, the representative building should include different building materials or construction types within the BRI class.
- iii-i. Develop suitable intervals for the BII, such as flood depths in steps of 0.5 or 1 meter intervals.
- iv-ii. For each defined interval of BII, local experts are asked to estimate the expected damage for each BRI class. Experts Instead of estimating one single damage grade, however, experts should provide three possible damage grades for each BII interval. The possible damage grades should include (i) most-probable damage grades, grade (ii) lower-probable damage grades, and grade (iii) higher-probable damage grades. As an grade. The three grades are to represent the uncertainty bounds of the actual damage. For example, if a representative building type (e.g., one-story storey sandcrete block building) is selected from the BRI category “low resistance”, experts will estimate for each BII interval (e.g., 1 m water depth) the damage to be expected. Such damage estimates can be:
  - (i) most-probable: slight cracks on supporting walls, (ii) lower-probable damage: only water penetration, and (iii) higher-probable damage: heavy cracks on supporting walls. The need for using three probable damage grades is to capture uncertainty range associated with each BII for given building and surrounding characteristics (BRI class).
- v-iii. For each BRI class, a separate a suitable curve is used to join most-probable, lower-probable link each BII intervals and higher-most probable damage for all BII values, as exemplified in grade. Uncertainty bounds are shown on each curve to communicate possible scatter range. Figure 3 (phase 3) shows an idealized example.

## 6 Conclusion

With increasing magnitudes and frequencies of floods, assessing the physical vulnerability of exposed communities exposed is crucial for reducing risk. The success of risk reduction methods is even more critical for data-scarce areas, which are mostly developing countries with due to their limited capacity to cope with adapt to flood risk. Physical vulnerability events.

Vulnerability assessment incorporates the identification of major damage drivers of damage and the evaluation of possible future damage to loss of exposed buildings. For data-scarce regions, such a vulnerability assessment, which can be adapted to regional building types, Developing a model to estimate future damage under probable scenarios may serve as a first step in overall risk reduction. So far, scarcity of empirical data has limited such efforts in many regions. In this study, we presented reviews and concepts for assessing the physical vulnerability of buildings. Two approaches considered were the vulnerability indicator method, which is used for identifying regional damage drivers, and the damage grades approach, used for classifying commonly observed damage patterns. In the review, we provided background information, applications and specific challenges for implementing these approaches in data-scarce regions. The review provides a state of the art in physical vulnerability assessment, particularly in expert-based methods, and can serve as a useful source of information for future studies. The proposed a conceptual framework focused onfor linking the vulnerability indicator methodapproach to damage grades using an expert-based approach.expert knowledge in order to develop a flood damage model for data-scarce regions. Combining such methods has been identified as a useful way to enhance the utility and robustness of individual physical vulnerability assessment methodsassessments while limiting their weaknesses.drawbacks resulting from the use of only one method. The proposed framework focuses on enhancing regional adaptability of physical vulnerability assessment methods and fostering model transfer between different data-scarce regions. Three phases were requiredadopted to operationalizeddevelop the framework, (i) developing a vulnerability index, (ii) identifying predominant damage grades or patterns, and (iii) carrying out aexpert what-if analysis to link identified damage grades to flood characteristics for each categoryelass of building resistanceandsurrounding characteristics.

In developing the vulnerability index, we considered hazard parameters (BII) and variables relating to the characteristics of a building and its surroundings (BRI). The BRI aggregates information on exposure, susceptibility and local protection of a building, hence connects the resistance of a building relative to other buildings assuming the same hazard magnitude. The proposed classification of the BRI is not based on building types (e.g., Maiwald and Schwarz, 2015) but is rather a classification based on aggregated information on exposure, susceptibility, and local protection such as property-level adaptation measures. We recommend such a generic classification of building types (e.g., low, moderate, high resistance) especially in regions with high variation in building quality. Systematic documentation of regional building damage patterns is required for the framework so that frequently observed damage patterns (e.g., moisture defects, cracks on supporting elements, partial collapse, complete collapse) can be integrated into a damage grade classification. As the framework is not case-study sensitive, damage categories from other studies can provide a useful basis for categorizing damage grades. Furthermore, expert-based what-if analysis is used to assign identified damage grades to each interval of the BII (e.g., 0.5m intervals). As shown in Fig. 3, this is carried out for each class of the BRI (e.g., low, moderate, high resistance). Where empirical data are available, even in limited quantity, they should be used to support the what-if analysis. The use of three damage states (most probable, lower probable and higher probable) for each BII interval is proposed so that the actual damage, for a given impact level and a specific BRI class, can be captured. This range can be reduced as empirical damage data becomes available. In particular, the potential of citizen-based data sources such as information taken from interviews or social media offers a good opportunity for damage data collection. The framework is flexible, allowing vulnerability indicators and damage grades to be updated when new post-flood data becomes available. Consequently, curves generated between BII, BRI and damage grades can be continuously updated over time. In this way, the new framework allows temporal changes in damage drivers to be integrated.

The use of the new framework is recommended especially in data-scarce regions where information on damage drivers and damage patterns are limited. Its applicability for predominant building types, such as the sandcrete block and clay buildings in Africa, has the potential to promote disaster mitigation in such regions. The application of the new framework to evaluate and



compare model performance with a data-driven model is also encouraged. Such an analysis will communicate the success of the framework and also allow for further improvement. Based on the modular structure of the framework, it has the potential to be adapted for different environments, hazard types, and vulnerability types.

~~In developing the vulnerability index, we considered hazard variables (BH) on one hand and the variables relating to the characteristics of a building and its surrounding (BRI) on the other hand. The BRI aggregates information on a building's exposure, susceptibility and local protection and communicates the resistance the building can offer relative to other buildings assuming similar hazard magnitudes. The classification of the BRI here is not building type based (e.g., Maiwald and Schwarz 2015) but based on aggregated information on exposure, susceptibility and local protection such as property level flood risk adaptation measures. Although Maiwald and Schwarz (2015) recommended a building type vulnerability classification, it is, however, not feasible in many regions due to (i) low variability in building types, and (ii) high variability in building quality within the same building type. In some countries of Africa such as Nigeria for example, sanderete block and clay buildings make up over 90 percent of the building types (NBS, 2010) but those buildings show variable susceptibility to flood hazards due to a wide variability in building quality (FGN, 2013). Recently, Enghardt et al. (2019) made similar observations in Ethiopia, pointing out that in many rural areas even a low flood depth can result in high damage due to low building quality. In such areas, where a building type vulnerability classification will be unsuitable, we recommend a generic vulnerability classification (e.g., low, moderate, high resistance) such that buildings are classified into categories based on their expected resistance to flood with respect to identified damage influencing variable. A systematic documentation of building damage grades by local experts is required for the framework allowing the categorization of frequently observed damage patterns (e.g., moisture defects, cracks on supporting elements, partial collapse, complete collapse). As the framework is not case study sensitive, damage categories from other studies can provide useful basis for categorizing probable damage classes.~~

~~Furthermore, a what if analysis is used to assign identified damage grades to each interval of the BH for each class (e.g., low, moderate, high) of the BRI. Since expert knowledge are subjective, the use of three damage states (most probable, lower probable and higher probable) for each BH interval is important for capturing the range within which the damage for a BRI class will lie. A similar approach has been used by Maiwald and Schwarz (2015) for the assessment of building type vulnerability classes. The BH can be adapted to regional requirements such as, for example, in cases where unburnt clay buildings are predominant, a combination of flood depth and duration might be used for BH intervals since long duration floods tends to weaken such building types. The presented framework is flexible so that correlations between BH, BRI and damage grades can be continuously updated with new data within a region or from a region with comparable building and hazard characteristics. In cases few empirical data is available, even in limited quantity, it should be used to support the assignment of damage grades. The framework is flexible and the vulnerability indicators and damage grades can be updated when new post-flood data becomes available. Consequently, temporal changes in damage drivers can be integrated to adapt the model.~~

~~The proposed framework will foster model adaptability to regional conditions and allow transferability between comparable regions. The framework will also extend the application of vulnerability indices towards a value which can be used to predict flood damage. The BRI classification offers information on buildings with low resistance to floods. Such information is important for emergency and mitigation planning. Application of the framework for damage prediction will enable the economic evaluation of disaster scenarios to support planning on disaster risk in data scarce regions. Limitations of the method include the subjectivity of the expert based approach. The potential in utilizing additional data sources such as social media offers a good opportunity for damage data collection to support expert assessment, and may also be used to reduce the subjectivity of initial expert assessments.~~

## Author contributions

MBM designed the study with the support of MK. MBM was responsible for data collection, analysis, and literature review, MK and SF supported with literature review and analysis. All authors were jointly involved in manuscript preparation and editing.

## 1210 Competing interests

Margreth Keiler and Sven Fuchs are members of the Editorial Board of Natural Hazards and Earth System Sciences.

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## References

- Adelekan, I., Johnson, C., Manda, M., Matyas, D., Mberu, B., Parnell, S., Pelling, M., Satterthwaite, D. and Vivekananda, J.: Disaster risk and its reduction: an agenda for urban Africa, *Int. Dev. Plan. Rev.*, 37(1), 33–43, doi: 10.3828/idpr.2015.4, 2015.
- Adeleye, B., Popoola, A., Sanni, L., Zitta, N. and Ayangbile, O.: Poor development control as flood vulnerability factor in Suleja, Nigeria, *T. Reg. Plan.*, (74), 23–35, doi: 10.18820/2415-0495/trp74i1.3, 2019.
- Akukwe, T. I. and Ogbodo, C.: Spatial analysis of vulnerability to flooding in Port Harcourt metropolis, Nigeria, *SAGE Open*, 5(1), doi: 10.1177/2158244015575558, 2015.
- Asadzadeh, A., Kötter, T., Salehi, P. and Birkmann, J.: Operationalizing a concept: The systematic review of composite indicator building for measuring community disaster resilience, *Int. J. Disaster Risk Reduct.*, 25(2), 147–162, doi: 10.1016/j.ijdr.2017.09.015, 2017.
- [Attems, M.-S., Thaler, T., Genovese, E. and Fuchs, S.: Implementation of property level flood risk adaptation \(PLFRA\) measures: choices and decisions, \*WIREs Water\*, 7\(1\). e1404, doi: 10.1002/wat2.1404, 2020.](#)
- Bagdanavičiute, I., Kelpšaitė, L. and Soomere, T.: Multi-criteria evaluation approach to coastal vulnerability index development in micro-tidal low-lying areas, *Ocean Coast. Manag.*, 104, 124–135, doi: 10.1016/j.ocecoaman.2014.12.011, 2015.
- Balica, S. F., Douben, N. and Wright, N. G.: Flood vulnerability indices at varying spatial scales, *Water Sci. Technol.*, 60(10), 2571–2580, doi: 10.2166/wst.2009.183, 2009.
- Balica, S. F., Wright, N. G. and van der Meulen, F.: A flood vulnerability index for coastal cities and its use in assessing climate change impacts, *Nat. Hazards*, 64(1), 73–105, doi: 10.1007/s11069-012-0234-1, 2012.
- Barnett, J., Lambert, S. and Fry, I.: The hazards of indicators: insights from the environmental vulnerability index, *Ann. Assoc. Am. Geogr.*, 98(1), 102–119, doi: 10.1080/00045600701734315, 2008.

- Barroca, B., Mouchel, J.-M., Bonierbale, T. and Hubert, G.: Flood Vulnerability Assessment Tool (FVAT), edited by Thevenot, D. R., *DayWater: an adaptive decision support system for urban stormwater management*, London, IWA Publishing, 119-127, 2008.
- 1240 Behanzin, I. D., Thiel, M., Szarzynski, J. and Boko, M.: GIS-based mapping of flood vulnerability and risk in the Bénin Niger River Valley, *Int. J. Geomatics Geosci.*, 6(3), 1653–1669, 2015.
- Birkmann, J.: *Measuring vulnerability to promote disaster-resilient societies: Conceptual frameworks and definitions*, edited by Birkmann, J., *Measuring vulnerability to natural Hazards*, Tokyo, United Nations University Press, 9–54, 2006.
- Birkmann, J.: Risk and vulnerability indicators at different scales: Applicability, usefulness and policy implications, *Environ. Hazards*, 7(1), 20–31, doi: 10.1016/j.envhaz.2007.04.002, 2007.
- 1245 Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., Kienberger, S., Keiler, M., Alexander, D. and Zeil, P.: Framing vulnerability, risk and societal responses: the MOVE framework, *Nat. Hazards*, 67(2), 193–211, doi: 10.1007/s11069-013-0558-5, 2013.
- Blanco-Vogt, A. and Schanze, J.: Assessment of the physical flood susceptibility of buildings on a large scale - Conceptual and methodological frameworks, *Nat. Hazards Earth Syst. Sci.*, 14(8), 2105–2117, doi: 10.5194/nhess-14-2105-2014, 2014.
- 1250 Blong, R.: A new damage index, *Nat. Hazards*, 30(1), 1–23, doi: 10.1023/A:1025018822429, 2003a.
- Blong, R.: A review of damage intensity scales, *Nat. Hazards*, 29(1), 57–76, doi: 10.1023/A:1022960414329, 2003b.
- Carrier, B., Puissant, A., Dujarric, C. and Arnaud-Fassetta, G.: Upgrading of an index-oriented methodology for consequence analysis of natural hazards: Application to the Upper Guil catchment (southern French Alps), *Nat. Hazards Earth Syst. Sci.*, 18(8), 2221–2239, doi: 10.5194/nhess-18-2221-2018, 2018.
- 1255 Cervone, G., Sava, E., Huang, Q., Schnebele, E., Harrison, J., Cervone, G., Sava, E., Huang, Q., Schnebele, E. and Harrison, J.: Using Twitter for tasking remote-sensing data collection and damage assessment : 2013 Boulder flood case study, *Int. J. Remote Sens.*, 37(1), 100–124, doi: 10.1080/01431161.2015.1117684, 2016.
- Chen, N., Hu, C., Chen, Y., Wang, C. and Gong, J.: Using SensorML to construct a geoprocessing e-Science workflow model under a sensor web environment, *Comput. Geosci.*, 47, 119–129, doi: 10.1016/j.cageo.2011.11.027, 2012.
- 1260 Chow, C., Andrášik, R., Fischer, B. and Keiler, M.: Application of statistical techniques to proportional loss data: Evaluating the predictive accuracy of physical vulnerability to hazardous hydro- meteorological events, *J. Environ. Manage.*, 246, 85–100, doi:10.1016/j.jenvman.2019.05.084, 2019.
- Cutter, S. L. and Finch, C.: Temporal and spatial changes in social vulnerability to natural hazards, *Proc. Natl. Acad. Sci.*, 105(7), 2301–2306, doi:10.1073/pnas.0710375105, 2008.
- 1265 Dall’Osso, F. and Dominey-Howes, D.: *Coastal vulnerability to multiple inundation sources: COVERMAR project. Literature review report*, Sydney, University of New-South Wales and Sydney Coastal Councils Group, 2013.
- Dall’Osso, F., Gonella, M., Gabbianelli, G., Withycombe, G. and Dominey-Howes, D.: A revised (PTVA) model for assessing the vulnerability of buildings to tsunami damage, *Nat. Hazards Earth Syst. Sci.*, 9(5), 1557–1565, doi: 10.5194/nhess-9-1557-2009, 2009.
- 1270

- Dominey-Howes, D. and Papathoma, M.: Validating a tsunami vulnerability assessment model (the PTVA Model) using field data from the 2004 Indian Ocean tsunami, *Nat. Hazards*, 40(1), 113–136, doi: 10.1007/s11069-006-0007-9, 2007.
- Eddy, D. M., Hollingworth, W., Caro, J. J., Tsevat, J., McDonald, K. M. and Wong, J. B.: Model transparency and validation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force-7, *Med. Decis. Mak.*, 32(5), 733–743, doi: 10.1177/0272989X12454579, 2012.
- Englhardt, J., Moel, H. de, Huyck, C. K., Ruiter, M. C. de, Aerts, J. C. J. H. and Ward, P. J.: Enhancement of large-scale flood risk assessments using building-material-based vulnerability curves for an object-based approach in urban and rural areas, *Nat. Hazards Earth Syst. Sci.*, 19(8), 1703–1722, doi: 10.5194/nhess-19-1703-2019, 2019.
- Eriksen, S. H. and Kelly, P. M.: Developing credible vulnerability indicators for climate adaptation policy assessment, *Mitig. Adapt. Strateg. Glob. Chang.*, 12(4), 495–524, doi: 10.1007/s11027-006-3460-6, 2007.
- Ettinger, S., Mounaud, L., Magill, C., Yao-Lafourcade, A. F., Thouret, J. C., Manville, V., Negulescu, C., Zuccaro, G., De Gregorio, D., Nardone, S., Uchuchoque, J. A. L., Arguedas, A., Macedo, L. and Manrique Llerena, N.: Building vulnerability to hydro-geomorphic hazards: Estimating damage probability from qualitative vulnerability assessment using logistic regression, *J. Hydrol.*, 541, 563–581, doi: 10.1016/j.jhydrol.2015.04.017, 2016.
- Fernandez, P., Mourato, S., Moreira, M. and Pereira, L.: A new approach for computing a flood vulnerability index using cluster analysis, *Phys. Chem. Earth*, 94, 47–55, doi: 10.1016/j.pce.2016.04.003, 2016.
- FGN (Federal Government of Nigeria): Nigeria: Post-disaster needs assessment – 2012 floods. [online] Available from: [https://www.gfdr.org/sites/gfdr/files/NIGERIA\\_PDNA\\_PRINT\\_05\\_29\\_2013\\_WEB.pdf](https://www.gfdr.org/sites/gfdr/files/NIGERIA_PDNA_PRINT_05_29_2013_WEB.pdf) (Accessed 1 January 2019), 2013.
- Frazier, T. G., Thompson, C. M. and Dezzani, R. J.: A framework for the development of the SERV model: A Spatially Explicit Resilience-Vulnerability model, *Appl. Geogr.*, 51, 158–172, doi: 10.1016/j.apgeog.2014.04.004, 2014.
- Fuchs, S.: Susceptibility versus resilience to mountain hazards in Austria-paradigms of vulnerability revisited., *Nat. Hazards Earth Syst. Sci.*, 9(2), 337–352, doi: 10.5194/nhess-9-337-2009, 2009.
- Fuchs, S., Keiler, M., Sokratov, S. and Shnyparkov, A.: Spatiotemporal dynamics: the need for an innovative approach in mountain hazard risk management, *Nat. Hazards*, 68(3), 1217–1241, doi: 10.1007/s11069-012-0508-7, 2013.
- Fuchs, S., Keiler, M., Ortlepp, R., Schinke, R. and Papathoma-Köhle, M.: Recent advances in vulnerability assessment for the built environment exposed to torrential hazards: challenges and the way forward, *J. Hydrol.*, 575, 587–595, doi: 10.1016/j.jhydrol.2019.05.067, 2019a.
- Fuchs, S., Heiser, M., Schlögl, M., Zischg, A., Papathoma-Köhle, M. and Keiler, M.: Short communication: A model to predict flood loss in mountain areas, *Environ. Model. Softw.*, 117, 176–180, doi: 10.1016/j.envsoft.2019.03.026, 2019b.
- Gasparini, P.: Analysis and monitoring of environmental risk: CLUVA Final Report, [online], available from: <http://cordis.europa.eu/docs/results/265137/final1-cluva-final-publishable-summary-report.pdf> (Accessed 1 April 2020), 2013.
- Gerl, T., Kreibich, H., Franco, G., Marechal, D. and Schröter, K.: A review of flood loss models as basis for harmonization and benchmarking, *PLoS One*, 11(7), 1–22, doi: 10.1371/journal.pone.0159791, 2016.

- 1305 Godfrey, A., Ciurean, R. L., van Westen, C. J., Kingma, N. C. and Glade, T.: Assessing vulnerability of buildings to hydro-meteorological hazards using an expert based approach – An application in Nehoiu Valley, Romania, *Int. J. Disaster Risk Reduct.*, 13, 229–241, doi: 10.1016/j.ijdr.2015.06.001, 2015.
- Golz, S.: Resilience in the built environment: How to evaluate the impacts of flood resilient building technologies?, *E3S Web Conf.*, 7, 13001, doi: 10.1051/e3sconf/20160713001, 2016.
- 1310 Grünthal, G.: European Macroseismic Scale 1992 (up-dated MSK-scale), edited by Grünthal G, *Cahiers du Centre Européen de Géodynamique et de Seismologie*. Conseil de l'Europe, Conseil de l'Europe, 1992.
- Grünthal, G.: European Macroseismic Scale 1998, edited by Grünthal G, *Cahiers du Centre Européen de Géodynamique et de Seismologie*. Conseil de l'Europe, Conseil de l'Europe, 1998
- Günther, D.: Indicator sets for assessments, [online] available from: [http://www.ivm.vu.nl/en/Images/AT10\\_tcm234-161582.pdf](http://www.ivm.vu.nl/en/Images/AT10_tcm234-161582.pdf) (Accessed 1 January 2019), 2006.
- 1315 Hammond, M. J. and Chen, A. S.: Urban flood impact assessment: A state-of-the-art review, *Urban Water J.*, 12(1), 14–29, doi: 10.1080/1573062X.2013.857421, 2015.
- Heink, U. and Kowarik, I.: What are indicators? On the definition of indicators in ecology and environmental planning, *Ecol. Indic.*, 10(3), 584–593, doi: 10.1016/j.ecolind.2009.09.009, 2010.
- 1320 Hinkel, J.: “Indicators of vulnerability and adaptive capacity”: towards a clarification of the science-policy interface, *Glob. Environ. Chang.*, 21(1), 198–208, doi: 10.1016/j.gloenvcha.2010.08.002, 2011.
- Holub, M. and Fuchs, S.: Benefits of local structural protection to mitigate torrent-related hazards, *WIT Trans. Inf. Commun. Technol.*, 39, 401–411, doi: 10.2495/RISK080391, 2008.
- Jongman, B., Kreibich, H., Apel, H., Barredo, J. I., Bates, P. D., Feyen, L., Gericke, A., Neal, J., Aerts, J. C. J. H. and Ward, P. J.: Comparative flood damage model assessment: Towards a European approach, *Nat. Hazards Earth Syst. Sci.*, 12(12), 3733–3752, doi: 10.5194/nhess-12-3733-2012, 2012.
- 1325 JRC and OECD (Joint Research Centre and Organisation for Economic Co-operation and Development): *Handbook on constructing composite indicators: Methodology and user guide*, Paris, OECD, 2008.
- Kappes, M. S., Papathoma-Köhle, M. and Keiler, M.: Assessing physical vulnerability for multi-hazards using an indicator-based methodology, *Appl. Geogr.*, 32(2), 577–590, doi: 10.1016/j.apgeog.2011.07.002, 2012.
- 1330 [Karagiorgos, K., Thaler, T., Heiser, M., Hübl, J. and Fuchs, S.: Integrated flash flood vulnerability assessment: insights from East Attica, Greece, \*J. Hydrol.\*, 541\(A\), 553–562, doi: 10.1016/j.jhydrol.2016.02.052, 2016.](#)
- Keiler, M., Sailer, R., Jörg, P., Weber, C., Fuchs, S., Zischg, A. and Sauer Moser, S.: Avalanche risk assessment - a multi-temporal approach, results from Galtür, Austria, *Nat. Hazards Earth Syst. Sci.*, 6(4), 637–651, doi: 10.5194/nhess-6-637-2006, 2006.
- 1335 Kienberger, S., Lang, S. and Zeil, P.: Spatial vulnerability units - Expert-based spatial modelling of socio-economic vulnerability in the Salzach catchment, Austria, *Nat. Hazards Earth Syst. Sci.*, 9(3), 767–778, doi: 10.5194/nhess-9-767-2009, 2009.



- Klein, J. A., Tucker, C. M., Nolin, A. W., Hopping, K. A., Reid, R. S., Steger, C., Grêt-Regamey, A., Lavorel, S., Müller, B.,  
1340 Yeh, E. T., Boone, R. B., Bourgeron, P., Butsic, V., Castellanos, E., Chen, X., Dong, S. K., Greenwood, G., Keiler, M.,  
Marchant, R., Seidl, R., Spies, T., Thorn, J., Yager, K. and the Mountain Sentinels Network: Catalyzing transformations to  
sustainability in the world's mountains, *Earth's Futur.*, 7(5), 547–557, doi: 10.1029/2018ef001024, 2019.
- Komolafe, A. A., Adegboyega, S. A. A. and Akinluyi, F. O.: A review of flood risk analysis in Nigeria, *Am. J. Environ. Sci.*,  
11(3), 157–166, doi: 10.3844/ajessp.2015.157.166, 2015.
- 1345 Krellenberg, K. and Welz, J.: Assessing urban vulnerability in the context of flood and heat hazard: Pathways and challenges  
for indicator-based analysis, *Soc. Indic. Res.*, 132(2), 709–731, doi: 10.1007/s11205-016-1324-3, 2017.
- Kundzewicz, Z. W., Su, B., Wang, Y., Wang, G., Wang, G., Huang, J. and Jiang, T.: Flood risk in a range of spatial  
perspectives—from global to local scales, *Nat. Hazards Earth Syst. Sci.*, 19(7), 1319–1328, doi: 10.5194/nhess-19-1319-2019,  
2019.
- 1350 Maiwald, H. and Schwarz, J.: Damage and loss prediction model considering inundation level, flow velocity and vulnerability  
of building types, *WIT Trans. Ecol. Environ.*, 159, 53–65, doi: 10.2495/FRIAR120051, 2012.
- Maiwald, H. and Schwarz, J.: Damage and loss prognosis tools correlating flood action and building's resistance-type  
parameters, *Int. J. Saf. Secur. Eng.*, 5(3), 222–250, doi: 10.2495/SAFE-V5-N3-222-250, 2015.
- Malgwi, M. B., Ramirez, J. A., Zischg, A., Zimmermann, M., Schürmann, S. and Keiler, M.: Flood reconstruction using field  
1355 interview data and hydrodynamic modelling: A method for data scarce regions, *Front. Earth Sci.*, Submitted.
- Marleen, C. de R., Ward, P. J., Daniell, J. E. and Aerts, J. C. J. H.: Review Article: A comparison of flood and earthquake  
vulnerability assessment indicators, *Nat. Hazards Earth Syst. Sci.*, 17(7), 1231–1251, doi: 10.5194/nhess-17-1231-2017, 2017.
- Mazzorana, B., Levaggi, L., Keiler, M. and Fuchs, S.: Towards dynamics in flood risk assessment, *Nat. Hazards Earth Syst.*  
*Sci.*, 12(11), 3571–3587, doi: 10.5194/nhess-12-3571-2012, 2012.
- 1360 Mazzorana, B., Simoni, S., Scherer, C., Gems, B., Fuchs, S. and Keiler, M.: A physical approach on flood risk vulnerability  
of buildings, *Hydrol. Earth Syst. Sci.*, 18(9), 3817–3836, doi: 10.5194/hess-18-3817-2014, 2014.
- Merz, B., Kreibich, H., Thielen, A. and Schmidtke, R.: Estimation uncertainty of direct monetary flood damage to buildings,  
*Nat. Hazards Earth Syst. Sci.*, 4(1), 153–163, doi: 10.5194/nhess-4-153-2004, 2004.
- Merz, B., Kreibich, H., Schwarze, R. and Thielen, A.: Review article “assessment of economic flood damage”, *Nat. Hazards*  
1365 *Earth Syst. Sci.*, 10(8), 1697–1724, doi: 10.5194/nhess-10-1697-2010, 2010.
- Merz, B., Kreibich, H. and Lall, U.: Multi-variate flood damage assessment: A tree-based data-mining approach, *Nat. Hazards*  
*Earth Syst. Sci.*, 13(1), 53–64, doi: 10.5194/nhess-13-53-2013, 2013.
- Meyer, V., Kuhlicke, C., Luther, J., Fuchs, S., Priest, S., Dorner, W., Serrhini, K., Pardoe, J., McCarthy, S. and Seidel, J.:  
Recommendations for the user-specific enhancement of flood maps, *Nat. Hazards Earth Syst. Sci.*, 12(5), 1701–1716, doi:  
1370 10.5194/nhess-12-1701-2012, 2012.
- Milanesi, L., Pilotti, M., Belleri, A., Marini, A. and Fuchs, S.: Vulnerability to flash floods: a simplified structural model for  
masonry buildings, *Water Resour. Res.*, 54(10), 7177–7197, doi: 10.1029/2018WR022577, 2018.

- Mirza, M. M. Q.: Climate change and extreme weather events: can developing countries adapt?, *Clim. policy*, 3(3), 233–248, doi: 10.1016/S1469-3062(03)00052-4, 2003.
- 1375 de Moel, H., Jongman, B., Kreibich, H., Merz, B., Penning-Rowsell, E. and Ward, P. J.: Flood risk assessments at different spatial scales, *Mitig. Adapt. Strateg. Glob. Chang.*, 20(6), 865–890, doi: 10.1007/s1102, 2015.
- Mosimann, M., Frossard, L., Keiler, M., Weingartner, R. and Zischg, A.: A robust and transferable model for the prediction of flood losses on household contents, *Water*, 10(11), 1596, doi: 10.3390/w10111596, 2018.
- Müller, A., Reiter, J. and Weiland, U.: Assessment of urban vulnerability towards floods using an indicator-based approach-a  
1380 case study for Santiago de Chile, *Nat. Hazards Earth Syst. Sci.*, 11(8), 2107–2123, doi: 10.5194/nhess-11-2107-2011, 2011.
- Naumann, T., Nikolowski, J. and Sebastian, G.: Synthetic depth-damage functions – A detailed tool for analysing flood resilience of building types, edited by Pasche, E., Evelpidou, N., Zevenbergen, C., Ashley, R. and Garvin, S., *Road map towards a flood resilient urban environment*, Hamburg: Institut für Wasserbau der TU Hamburg-Harburg, 2009.
- NBS (National Bureau of Statistics): Annual abstract of Nigerian statistics, Abuja, National Bureau of Statistics, [online]  
1385 available from [http://istmat.info/files/uploads/53129/annual\\_abstract\\_of\\_statistics\\_2010.pdf](http://istmat.info/files/uploads/53129/annual_abstract_of_statistics_2010.pdf) (Accessed 1 March 2020), 2010.
- Neubert, M., Naumann, T. and Deilmann, C.: Synthetic water level building damage relationships for GIS-supported flood vulnerability modeling of residential properties, edited by Samuels, P., Huntington, S., Allsop, W. and Harrop, J., *Flood risk management. Research and practice*, London, Taylor & Francis, 1717–1724, doi: 10.1201/9780203883020.ch203, 2008.
- NRE (Department of Natural Resources and Environment): Rapid appraisal method (RAM) for floodplain management,  
1390 Victoria, Department of Natural Resources and Environment, 2000.
- Ntajal, J., Lamptey, B. L. and MianikpoSogbedji, J.: Flood vulnerability mapping in the lower mono river basin in Togo, West Africa, *Int. J. Sci. Eng. Res.*, 7(10), 1553–1562, 2016.
- Papathoma-Köhle, M., Kappes, M., Keiler, M. and Glade, T.: Physical vulnerability assessment for alpine hazards: State of the art and future needs, *Nat. Hazards*, 58(2), 645–680, doi: 10.1007/s11069-010-9632-4, 2011.
- 1395 Papathoma-Köhle, M., Gerns, B., Sturm, M. and Fuchs, S.: Matrices, curves and indicators: A review of approaches to assess physical vulnerability to debris flows, *Earth-Science Rev.*, 171, 272–288, doi: 10.1016/j.earscirev.2017.06.007, 2017.
- Papathoma-Köhle, M., Cristofari, G., Wenk, M. and Fuchs, S.: The importance of indicator weights for vulnerability indices and implications for decision making in disaster management, *Int. J. Disaster Risk Reduct.*, 36, 101103, doi: 10.1016/j.ijdrr.2019.101103, 2019.
- 1400 Papathoma, M., Dominey-Howes, D., Zong, Y. and Smith, D.: Assessing tsunami vulnerability, an example from Herakleio, Crete, *Nat. Hazards Earth Syst. Sci.*, 3(5), 377–389, doi: 10.5194/nhess-3-377-2003, 2003.
- Penning-Rowsell, E., Johnson, C., Tunstall, S., Tapsell, S., Morris, J., Chatterton, J. and Green, C.: *The benefits of flood and coastal risk management: a manual of assessment techniques*, Middlesex, Middlesex University Press, 2005.
- Percival, S., Gaterell, M. and Teeuw, R.: Urban neighbourhood flood vulnerability and risk assessments at different diurnal  
1405 levels, *J. Flood Risk Manag.*, 12(3), 1–14, doi: 10.1111/jfr3.12466, 2018.

- Pistrika, A., Tsakiris, G. and Nalbantis, I.: Flood depth-damage functions for built environment, *Environ. Process.*, 1(4), 553–572, doi: 10.1007/s40710-014-0038-2, 2014.
- Quevauviller, P.: *Hydrometeorological hazards: interfacing science and policy*, Chichester, John Wiley & Sons, 2014.
- Romali, N. S., Sulaiman, M.A.K., Yusop, Z. and Ismail, Z.: Flood damage assessment: A review of flood stage–damage function curve, edited by Abu Bakar, S., Tahir, W., Wahid, M., Mohd Nasir, S. and Hassan, R., *ISFRAM 2014*, pp. 147–159, Singapore, Springer, 2015.
- Saaty, T. L.: *The Analytical Hierarchy Process*, New York, McGraw-Hill, 1980.
- Sadeghi-Pouya, A., Nouri, J., Mansouri, N. and Kia-Lashaki, A.: An indexing approach to assess flood vulnerability in the western coastal cities of Mazandaran, Iran, *Int. J. Disaster Risk Reduct.*, 22, 304–316, doi: 10.1016/j.ijdrr.2017.02.013, 2017.
- 1415 Schröter, K., Kreibich, H., Vogel, K., Riggelsen, C., Scherbaum, F. and Merz, B.: How useful are complex flood damage models?, *Water Resour. Res.*, 50(4), 3378–3395, doi: 10.1002/2013WR014396, 2014.
- Schwarz, J. and Maiwald, H.: Prognose der Bauwerksschädigung unter Hochwassereinwirkung, *Bautechnik*, 84(7), 450–464, doi: 10.1002/bate.200710039, 2007.
- Schwarz, J. and Maiwald, H.: Damage and loss prediction model based on the vulnerability of building types, 4th International Symposium on Flood Defence: Managing Flood Risk, Reliability and Vulnerability, Toronto, Ontario, Canada, May 6-8, 2008, 1420 74-1–74-9, doi:10.13140/2.1.1358.3043, 2008.
- Spekkers, M. H., Kok, M., Clemens, F. H. L. R. and Ten Veldhuis, J. A. E.: Decision-tree analysis of factors influencing rainfall-related building structure and content damage, *Nat. Hazards Earth Syst. Sci.*, 14(9), 2531–2547, doi: 10.5194/nhess-14-2531-2014, 2014.
- 1425 Sturm, M., Gems, B., Keller, F., Mazzorana, B., Fuchs, S., Papathoma-Köhle, M. and Aufleger, M.: Experimental analyses of impact forces on buildings exposed to fluvial hazards, *J. Hydrol.*, 565, 1–13, doi: 10.1016/j.jhydrol.2018.07.070, 2018a.
- Sturm, M., Gems, B., Keller, F., Mazzorana, B., Fuchs, S., Papathoma-Köhle, M. and Aufleger, M.: Understanding impact dynamics on buildings caused by fluvial sediment transport, *Geomorphology*, 321, 45–59, doi: 10.1016/j.geomorph.2018.08.016, 2018b.
- 1430 Tarbotton, C., Dominey-Howes, D., Goff, J. R., Papathoma-Köhle, M., Dall’Osso, F. and Turner, I. L.: GIS-based techniques for assessing the vulnerability of buildings to tsunamis: current approaches and future steps, *Geol. Soc. London, Spec. Publ.*, 361(1), 115–125, doi: 10.1144/SP361.10, 2012.
- Tate, E.: Social vulnerability indices: A comparative assessment using uncertainty and sensitivity analysis, *Nat. Hazards*, 63(2), 325–347, doi: 10.1007/s11069-012-0152-2, 2012.
- 1435 [Thaler, T., Attems, M.-S., Bonnefond, M., Clarke, D., Gatién-Tournat, A., Gralépois, M., Fournier, M., Murphy, C., Rauter, M., Papathoma-Köhle, M., Servain, S. and Fuchs, S.: Drivers and barriers of adaptation initiatives – how societal transformation affects natural hazard management and risk mitigation in Europe. \*Sci. Total Environment\*, 650\(1\), 1073–1082, doi: 10.1016/j.scitotenv.2018.08.306, 2019.](https://doi.org/10.1016/j.scitotenv.2018.08.306)
- Thieken, A. H., Müller, M., Kreibich, H. and Merz, B.: Flood damage and influencing factors: New insights from the August 1440 2002 flood in Germany, *Water Resour. Res.*, 41(12), 1–16, doi: 10.1029/2005WR004177, 2005.

- Thieken, A. H., Olschewski, A., Kreibich, H., Kobsch, S. and Merz, B.: Development and evaluation of FLEMOps - A new Flood Loss Estimation MOdel for the private sector, *WIT Trans. Ecol. Environ.*, 118, 315–324, doi: 10.2495/FRIAR080301, 2008.
- Thouret, J. C., Ettinger, S., Guitton, M., Santoni, O., Magill, C., Martelli, K., Zuccaro, G., Revilla, V., Charca, J. A. and  
 1445 Arguedas, A.: Assessing physical vulnerability in large cities exposed to flash floods and debris flows: the case of Arequipa (Peru), *Nat. Hazards*, 73(3), 1771–1815, doi: 10.1007/s11069-014-1172-x, 2014.
- Totschnig, R. and Fuchs, S.: Mountain torrents: quantifying vulnerability and assessing uncertainties, *Eng. Geol.*, 155, 31–44, doi: 10.1016/j.enggeo.2012.12.019, 2013.
- Totschnig, R., Sedlacek, W. and Fuchs, S.: A quantitative vulnerability function for fluvial sediment transport, *Nat. Hazards*,  
 1450 58(2), 681–703, doi: 10.1007/s11069-010-9623-5, 2011.
- UNDP (United Nations Development Programme): Human Development Report, Geneva, United Nations, 1992.
- UNISDR (United Nations International Strategy for Disaster Reduction): Terminology on disaster risk reduction, United Nations International Strategy for Disaster Reduction Geneva, Geneva, United Nations, 2009.
- UNISDR (United Nations International Strategy for Disaster Reduction): Sendai framework for disaster risk reduction 2015–  
 1455 2030, Geneva, United Nations, 2015.
- Vogel, K., Riggelsen, C., Merz, B., Kreibich, H., and Scherbaum, F.: Flood damage and influencing factors: a Bayesian network perspective, in: *Proceedings of the 6th European workshop on Probabilistic Graphical Models (PGM 2012)*, Granada, Spain, edited by: Cano, A., Gómez-Olmedo, M. G., and Nielsen, T. D., 19–21 September 2012, 314–354, 2012.
- Wagenaar, D., De Jong, J. and Bouwer, L. M.: Multi-variable flood damage modelling with limited data using supervised  
 1460 learning approaches, *Nat. Hazards Earth Syst. Sci.*, 17(9), 1683–1696, doi: 10.5194/nhess-17-1683-2017, 2017.
- Walliman, N., Ogden, R., Baiche, B., Tagg, A. and Escarameia, M.: Development of a tool to estimate individual building vulnerability to floods, *WIT Trans. Ecol. Environ.*, 155, 1005–1016, doi: 10.2495/SC120842, 2011.
- WHO (World Health Organization): WHO Guidelines for indoor air quality: dampness and mould, 2009.
- Yankson, P. W. K., Owusu, A. B., Owusu, G., Boakye-Danquah, J. and Tetteh, J. D.: Assessment of coastal communities’  
 1465 vulnerability to floods using indicator-based approach: a case study of Greater Accra Metropolitan Area, Ghana, *Nat. Hazards*, 89(2), 691, doi: 10.1007/s11069-017-3006-0, 2017.
- Zimmermann, M. and Keiler, M.: International frameworks for disaster risk reduction: Useful guidance for sustainable mountain development?, *Mt. Res. Dev.*, 35(2), 195–202, doi: 10.1659/MRD-JOURNAL-D-15-00006.1, 2015.

Table 1: ~~Overview~~Applications of physical vulnerability indicators including methods used for variable selection, weighting, and aggregation, and ~~providing the~~ parameters needed for assessing physical (building) vulnerability. (AHP = Analytical Hierarchy Process, PCA = Principal Component Analysis).

Author(s)	Variable selection		Variable weighting		Vulnerability aggregation	Parameters considered (pertaining to building vulnerability)
	Preliminary	Final (used in model or equation)	Approach	Consideration for scoring/weighting		
Balica et al. (2009)	Literature	Experts	Equal (no) weights	Conditions that induce flood damage	Direct additive method	Flood depth, duration, velocity and return period, proximity to the river, land use, topography (slope), building codes
Kienberger et al. (2009)	Experts	Experts (Delphi approach)	AHP	Relative importance and contribution to the vulnerability of people	Weighted additive method	Buildings, infrastructure (transportation system), land cover
Müller et al. (2011)	Literature, field survey, experts	Experts	Expert knowledge, household surveys	Relevance of selected variables with respect to flood risk	Weighted additive method	Material for roof, walls, and floor, the position of building in relative to the street level, the proportion of green spaces per building block, flood protection measures
Kappes et al. (2012)	Literature	Experts	Expert appraisals	Ability of the building to withstand the impact of the process	Weighted additive method	Building type, building use, building condition (using age and maintenance), building material, number of floors, row towards the river, trees towards the river
Thouret et al. (2014)	Literature, experts	Experts	Equal weights, experts, PCA	Weakness relative to a given hazard magnitude	Direct additive method	Heterogeneity of city block (using building size and use), building type (height and number of story, construction material, roof type, and building condition), the shape of the city block, building density
Blanco-Vogt and Schanze (2014)	Literature, experts	Literature, experts	Literature, experts	General resistance characteristics after flooding (biological, chemical and material)	Weighted additive method	Building height, size, elongatedness (height/width ratio), building compactness, adjacency, roof, slabs, external fenestration, external wall, floor



Godfrey et al. (2015)	Literature, experts	Experts	AHP	Based on hazard impact	Normalized weighted linear combination	Floor height, number of floors, structural type, building size, wall material, presence of basement, number of openings, quality of construction, building maintenance, protection wall
Behanzin et al. (2015)	Literature	Experts	Equal (no) weights	-	Direct additive method	Building material, roof material, floor material, land cover around the building
Akukwe and Ogbodo (2015)	Literature	PCA	PCA	Significance in explaining the variance in indicator data set	Weighted additive method	Building material, proximity to water, flood depth, flood frequency
Fernandez et al. (2016)	Literature	PCA	No weights and PCA	Significance in explaining the variance in the data set	Direct and weighted additive method	Building density, number of floors, construction period, building material
Ntajal et al. (2016)	Literature, experts	Experts	Equal (no) weights	-	Direct additive method	Distance to the river, flood depth, flood duration, building and roof material, land cover (the area around the building)
Krellenberg and Welz (2017)	Literature, experts	Experts	Equal (no) weights	Probability to be exposed under certain socio-environmental conditions	Direct additive method	Building quality, building structure, protection wall, trees in foreyard, roof form, land cover, housing condition
Sadeghi-Pouya et al. (2017)	Literature, experts	Experts	Experts (scoring)	Variable influence on vulnerability	Direct additive method	Building quality (material), building age, number of floors, land use
Carlier et al. (2018)	Literature	Literature, experts	Experts	Total consequence of a natural hazard on an element at risk	Weighted additive method	Building material, building condition, building age, building function, opening in hazard direction, building in the area affected by flood (recurrence interval), land cover

Table 3: Overview on empirically developed (multivariate)2: Applications of flood damage models, indicating the data source, the approach for evaluating variable significance of variables, the scale of application, the parameters needed for developing the vulnerability function, and, where appropriate, the validation or performance test: (PCA = Principal Component Analysis).






Author	Case study/ region of application	Study aim	Data source for physical vulnerability indicators	Variable significance	Scale of application	Sample size	Parameters considered for developing the vulnerability function (pertaining to physical -building vulnerability)	Validation or performance test
Thieken et al. (2005)	Germany	Investigation of flood damage and influencing factors	Computer-aided phone interviews	PCA and quantile classification	Micro-scale (individual building)	1697	Flood depth, duration and velocity, contamination, precautionary measures, building type, building size, building quality	
Thieken et al. (2008)	Germany	Develop a model for flood loss (direct monetary) estimation for private sector	Computer-aided phone interviews	(Multi)factor analysis	Micro-scale (individual building) and meso-scale (regional)	1697	Flood depth, building type (occupancy), building quality, precaution, contamination	Using a different data set
Vogel et al. (2012)	Germany	Flood damage assessment of residential buildings	Computer-aided phone interviews	Bayesian network	Micro-scale (individual building)	1135	Flood depth, velocity and duration, contamination, return period, precautionary measures, building type (occupancy), building size (floor space), building value, number of flats in a building	Using a subset of training data (bootstrap samples)
Merz et al. (2013)	Germany	Develop tree- based damage prediction models and compare their performance to established models	Computer-aided phone interviews	Regression trees and bagging decision trees	Micro-scale (individual building)	1103	Flood depth, velocity and duration, contamination, return period, precautionary measures, building type (occupancy), building size (floor space), building quality	Using a subset of training data
Spekkers et al. (2014)	The Netherlands	Investigate damage- influencing factors and their relationships with	Insurance data data and data from government agencies	Poisson (decision) trees	Meso-scale (district)		Rainfall (intensity, volume, and duration) related variables, building age, ground floor area, real estate value	Using a subset of training data

		rainfall-related damage						
Ettinger et al. (2016)	Peru	Analysis of building vulnerability	Field Survey and analysis of high spatial resolution images	Logistic regression	Micro-scale (individual buildings)	898	Distance from the channel, distance from bridge, shape of city block, structural building type (material), building footprint	Using a subset of training data
Maiwald and Schwarz (2015)	Germany	Develop engineering vulnerability-oriented for damage and loss prediction	Questionnaire survey, computer-aided phone interviews, evaluation of damage reports, flood simulation	Tangent hyperbolic (damage grade) and an exponential function (relative loss)	Micro-scale (individual building) and meso-scale (regional)		Flood depth and velocity, specific energy (flood depth, velocity, and acceleration due to gravity), building type, presence of basement, building location with respect to flow direction, number of stories	Using a different data set
Wagenaar et al. (2017)	The Netherlands	Prediction of absolute (monetary value for content and structural) flood damage	Experts, flood simulation, cadastre information	Bagging trees	Micro-scale (individual buildings)	4398	Damage data (content and structural), flood depth, duration and velocity, building footprint, return period, building age, building area (footprint, living), basement, detached house	Using a 'withheld' part of the data set

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Table 43: Damage grades developed by Maiwald and Schwarz (2007) showing structural and non-structural damage to buildings. For each damage grade class, a description and a graphical representation are shown. The grey colour in the graphical representation indicates flood depth.

1480

Damage grade class	Damage		Description	Graphical representation
	Structural	Non-structural		
D1	No	Slight	Only penetration and pollution	
D2	No to slight	Moderate	Slight cracks in supporting elements Impressed doors and windows Contamination	
D3	Moderate	Heavy	Major cracks and/or deformations in supporting walls and slabs Settlements	
D4	Heavy	Very heavy	Structural collapse of supporting walls, slabs	
D5	Very heavy	Very heavy	Collapse of the building or of major parts of the building	

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Table 54: Table of influence for indicator weighting, ranging from slight influence of an indicator (1) to extreme influence (9) (modified after Saaty (1980)).

1	2	3	4	5	6	7	8	9
Slight influence	Slight to moderate influence	Moderate influence	Moderate to strong influence	Strong influence	Strong to very strong influence	Very strong influence	Very strong to extreme influence	Extreme influence

Figures

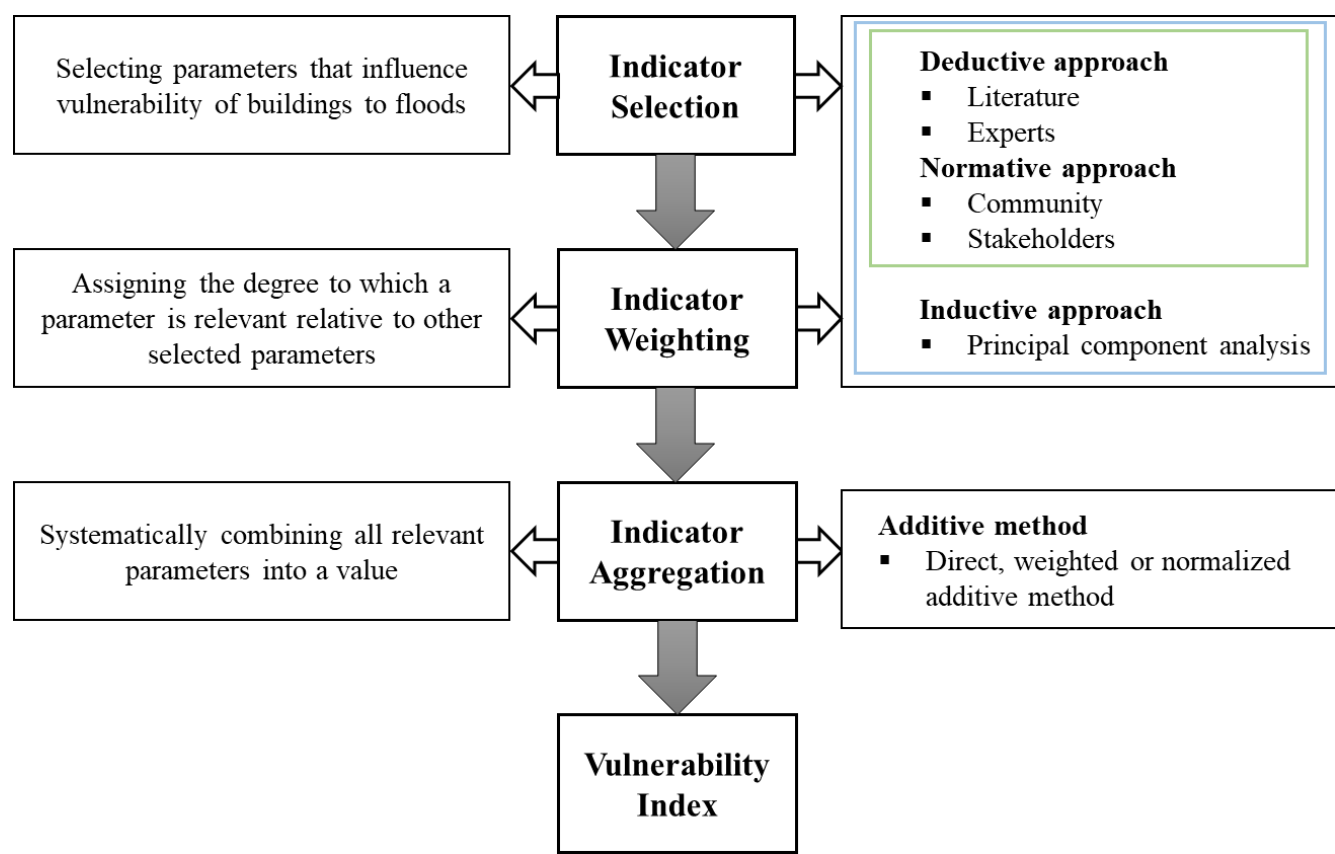





Figure 1: Steps and commonly applied methods for developing a physical flood vulnerability index. Steps include the indicator selection, the indicator weighting, and the indicator aggregation. ~~Methods are indicated~~ Green box (applied for each step-initial indicator selection) and blue box (applied for final indicator selection)



	<b>i</b> 	<b>ii</b> 	<b>iii</b> 
<b>REGION A: Aggregated Index</b>	0.7	0.6	0.9
Vulnerability indicators			
▪ Building material	Sandcrete block	Sandcrete block	Clay
▪ Building condition	Moderate	Good	Poor
▪ Distance to channel	100 m	50 m	< 20 m
▪ Flood depth	1 m	1.2 m	0.60 m
<b>REGION B: Aggregated Index</b>	0.5	0.4	0.7
Vulnerability indicators			
▪ Building age	< 10 years	20 years	> 30 years
▪ Building quality	Good	Moderate	Poor
▪ Sheltering effect	Complete	Partial sheltering	No sheltering
▪ Flood depth	1m	1m	1m
<b>Maiwald and Schwarz (2015)</b> 5-category damage grade Germany	<b>DG 2</b> Slight cracks in supporting element	<b>DG 4</b> Partial collapse of supporting element	<b>DG 5</b> Collapse
<b>Ettinger et al. (2016)</b> 4-category damage grade Peru	<b>Light</b> Signs of impact	<b>Heavy</b> Partial/Total collapse	<b>Heavy</b> Total Collapse

1495 Figure 2: Illustration of the need for linking vulnerability index and damage grades using real damage cases (i, ii, and iii) documented after a 2017 flood in Suleja/Tafa, Nigeria, hypothetical vulnerability indicators and regions (A and B), and damage grades developed from studies by Maiwald and Schwarz (2015) and Ettinger et al. (2016).

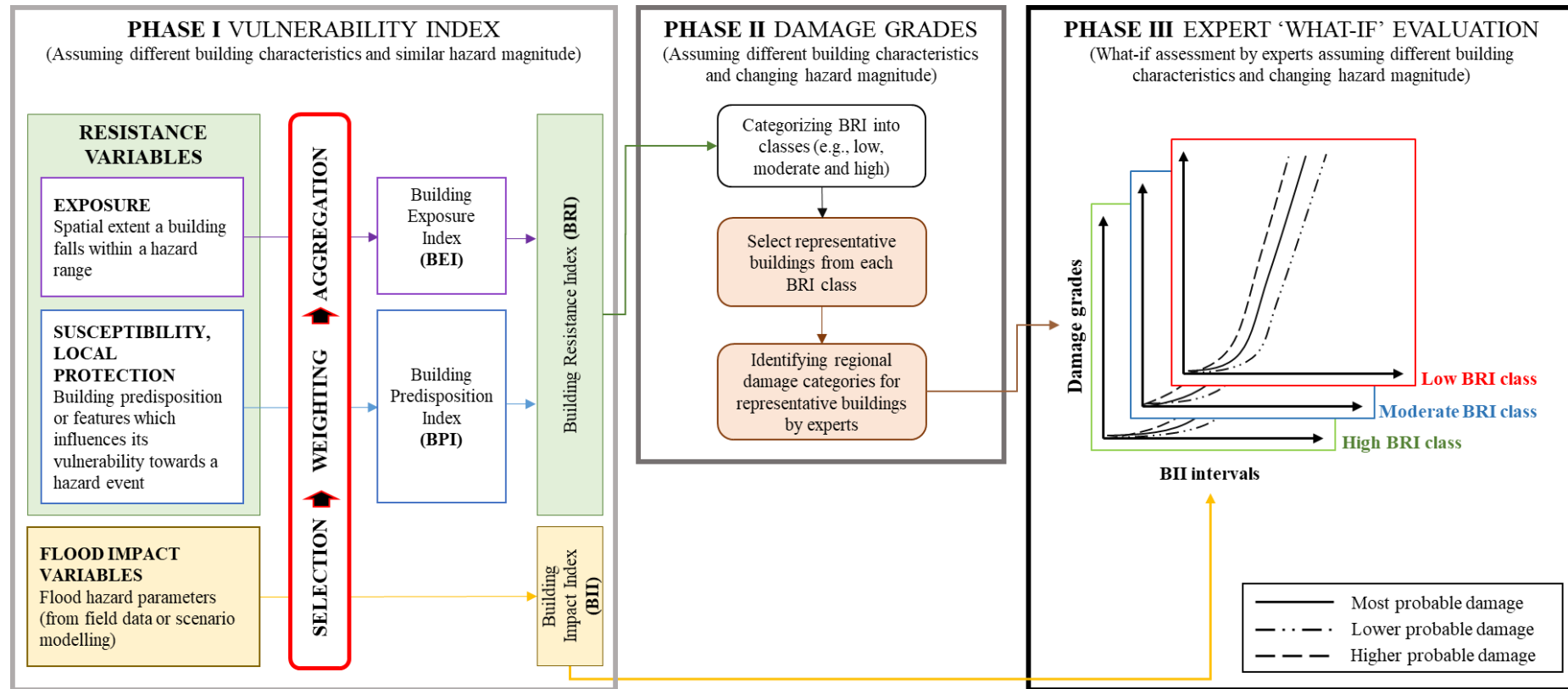


Figure 3: The proposed conceptual framework, linking vulnerability indicators to damage grades so that vulnerability to the built environment can be better assessed in data-scarce regions. The framework consists of three consecutive steps (phases) from the vulnerability index development (assuming different building characteristics but similar hazard magnitudes) to the damage grades (assuming different building characteristics and changing hazard magnitudes) and finally an expert-based “what-if”-evaluation, leading to functions linking damage grades from phase II to Building Impact Indices (BIIs) from phase I for each BRI class.

## Appendix

Table A1: Overview of common elements for framing the vulnerability indicator approach for flood hazards, indicating the hazard type and vulnerability dimensions, the implementation in the risk cycle, the scale, and the index output as well as the data source (PTVA = Papathoma-Koehle Vulnerability Assessment Model).

Author	Hazard type	Region of application	Aim of the assessment	Vulnerability dimension	Implementation in risk cycle	Scale	Index output	Data source
Papathoma et al. (2003)	Tsunami	Gulf of Corinth, Greece	Assessing the vulnerability of coastal areas to tsunami	Physical, economic and social	Preparedness	Micro-scale (individual buildings)	Building and human vulnerability index	Field survey
Dominey-Howes and Papathoma (2007)	Tsunami	Maldives, India	Checking the performance of PTVA	Physical, economic, social and environmental	Preparedness	Micro-scale (individual buildings)	Building and human vulnerability index	Field survey
Balica et al. (2009)	River flood	Timisoara, Romania; Mannheim, Germany; Phnom Penh, Cambodia	Assessing the conditions influencing flood damage at various spatial scales	Physical, economic, social and environmental	Preparedness	Meso-scale (regional)	Flood vulnerability index	-
Kienberger et al. (2009)	River flood	Salzach catchment, Austria	Identification of hotspots	Physical, economic and social	Mitigation and preparedness	Meso-scale (regional)	Vulnerability index	Government agency
Dall'Osso et al. (2009)	Tsunami	Sydney, Australia	Assessing the vulnerability of buildings to tsunami and evaluating the use of the PTVA	Physical	Mitigation and preparedness	Micro-scale (individual buildings)	Relative vulnerability index	Field survey
Müller et al. (2011)	(Urban) flood	Peñalolén and La Reina Municipalities, Santiago de Chile	Empirical investigation of vulnerability towards flood	Physical and social	Mitigation	Micro-scale (entire building blocks)	Vulnerability index (adapted after Haki et al., 2004)	Census data, field survey and satellite data

Kappes et al. (2012)	River flood, flash flood (among others)	Faucon municipality, Barcelonnette basin, France	Assessing the hazard-specific physical vulnerability of buildings towards multi-hazard	Physical, social and environmental	Mitigation and preparedness	Micro-scale (individual building)	Relative vulnerability index	Research agency and aerial-photo-interpretation
Balica et al. (2012)	Coastal flood	Buenos Aires, Argentina; Calcutta, India; Casablanca, Morocco; Dhaka, Bangladesh; Manila, Philippines; Marseille, France; Osaka, Japan; Shanghai, China; Rotterdam, The Netherlands	Developing a coastal city flood vulnerability index	Physical, social, economic and administrative	Preparedness	Meso-scale (regional)	Coastal city flood vulnerability index	Government agencies and data available online
Blanco-Vogt and Schanze (2014)	River flood	Magangué, Columbia	Assessing physical flood susceptibility on a large scale	Physical	Recovery, mitigation, and preparedness	Micro-scale (individual buildings)	Function relating susceptible material volume and water depth	Very high resolution spectral and elevation data and field survey
Thouret et al. (2014)	Flash flood	Arequipa, Peru	Assessing vulnerability	Physical and environmental	Mitigation	Micro-scale (entire building blocks)	Vulnerability index	Field survey
Bagdanavičiute et al. (2015)	Coastal flood	Coast of Lithuania	Assessing coastal vulnerability	Physical	Mitigation	Meso-scale (regional)	Coastal vulnerability index	Field survey
Behanzin et al. (2015)	River flood	Niger River Valley, Bénin	Assess vulnerability and risk	Physical, economic, social and environmental	Mitigation and preparedness	Meso-scale (community)	Vulnerability and risk index	Field survey, other agencies
Godfrey et al. (2015)	River and flash flood, slow-moving landslide, debris flow	Nehoiu City, Buzău County, Romania	Assessing the physical vulnerability of buildings to hydro-meteorological hazards in data-scarce regions	Physical	Mitigation and preparedness	Micro-scale (individual buildings)	Vulnerability index	Field survey and orthophoto interpretation
Akukwe and Ogbodo (2015)	River and coastal flood	Port Harcourt, Nigeria	Showing spatial variations in vulnerability	Physical, economic and social	Mitigation and preparedness	Meso-scale (regional)	Vulnerability Index (adapted after Deressa et al., 2008)	Field survey, survey and map measurements

Fernandez et al. (2016)	River flood	Vila Nova de Gaia, Northern Portugal	Providing an automated framework for classifying vulnerability of neighborhoods	Physical, economic, social and environmental	Preparedness	Micro-scale (neighborhood)	Flood Vulnerability Index and	Government agency
Ntajal et al. (2016)	River flood	Mono River Basin, Togo	Assessing and mapping vulnerable communities	Physical, economic, social and environmental	Mitigation and preparedness	Meso-scale (community)	Index for exposure, susceptibility, capacity, and vulnerability	Field survey, other agencies
Krellenberg and Welz (2017)	Flood (urban)	Metropolitan area of Santiago de Chile	Assessing urban vulnerability	Physical, economic, social and environmental	Mitigation	Micro-scale (building block)	Vulnerability Index	Field survey, government agency, and satellite imagery
Sadeghi-Pouya et al. (2017)	River flood	Mazandaran, Iran	Assessing vulnerability	Physical, economic, social and environmental	Mitigation and preparedness	Micro-scale (building block)	Relative vulnerability index	Field survey and government agency
Carlier et al. (2018)	River flood	Upper Guil catchment, southern French Alps	Assessing the physical and socio-economic consequence of hazards on elements at risk	Physical and social	Mitigation	Micro-scale (individual buildings)	Potential damage index, potential consequence index	Government agency, field survey, and aerial imagery
Yankson et al, (2017)	Coastal flood	Accra, Ghana	Understanding flood risk in coastal communities	Physical and social	Mitigation	Meso-scale (community)	Impact index vulnerability index	Field survey
Percival et al. (2018)	Coastal flood	Portsmouth, United Kingdom	Assessing risk from diurnal floods	Physical, environmental, social, economic	Mitigation	Micro-scale (neighborhood)	Coastal flood vulnerability Index, Coastal flood hazard Index, Coastal flood risk index	Census data
Papathoma-Köhle et al. (2019)	Tsunami	Apulia, Italy	Assessing vulnerability from tsunami hazards to the built environment	Physical vulnerability	Mitigation and preparedness	Micro-scale (neighborhood)	Building vulnerability index	Field survey