WIREs CLIMATE CHANGE

Article type: Advanced Review

Article title: Assessment of vulnerability to climate change using indicators: a meta-analysis of the literature

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Published in WIRES Climate Change in November 2014

WIREs Clim Change 2014. doi: 10.1002/wcc.314

ABSTRACT

Climate change vulnerability assessment (CCVA) can inform adaptation policy and help in incorporating climate futures in planning. The literature on CCVA stem from a number of research paradigms (e.g., risk assessment, natural disaster management, urban planning), therefore making it difficult to extract major directions and methodologies from this body of work. A large number of assessments are based, partly or totally, on indicators which bring up specific methodological problems and constraints. In this paper, first, we discuss the most important methodological challenges facing indicator-based vulnerability assessment (IBVA) based on a set of key conceptual

papers in the field. Second, we conduct a meta-analysis of a representative sample of peer-reviewed IBVA studies, in order to identify how current research on IBVA is engaging with these challenges. We attempt to elicit major thematic and methodological trends in this corpus with specific focus on issues related to geographical and temporal scales, aggregation and nonlinearity.

We find that health of ecosystems and biodiversity (28%), freshwater quantity and quality (14%) and public health (10%) have attracted the highest number of studies. Less than a third of the papers in our sample give some consideration to uncertainty and non-linearity. Assessments typically use aggregation methods that are based on the Multiple Attribute Utility Theory (MAUT) despite the fact that IBVA rarely satisfies the theoretical requirements of this approach. A small percentage of studies critically scrutinize prevalent assessment methodologies or attempt to develop new ones, despite the raised questions in key theoretical papers about its methodological aspects.

1.0 INTRODUCTION

In order to integrate climate change into strategic decision making and planning the dynamic interactions between humans and the ecological systems on which they depend need to be understood and knowledge about the processes generating vulnerability to climate change needs to be built [1]. In the literature, this exercise is usually termed Climate Change Vulnerability Assessment (CCVA). CCVA can help policymakers in identifying vulnerable "hot spots" and better allocating adaptation resources, better understanding structural weaknesses which make a given system vulnerable, monitoring the effects of adaptation measures or better communicating risk and justifying policy to the public [2-4].

CCVA can be viewed as an analytical exercise whose goal is to assess the vulnerability of a valued attribute (e.g., health, safety, economic prosperity) of a social-ecological system (SES) (e.g., locality, community, economic sector, infrastructure and its users) to one or more climate-change-related hazards (e.g., heat waves, flood events, rise in sea levels). Here we understand SES as a set of interactions between a 'bio-geo-physical' unit and its associated social actors and institutions [5, 6] or as a coherent system of biophysical and social factors that interact regularly in a resilient, sustained manner [7]. Given the wide variety of SESs (e.g., agricultural, marine, urban, sylvan) subject to a number of possible climatic stresses, the CCVA literature is highly diverse in terms of content.

In addition, different approaches to assessment, quantitative and qualitative, have emerged. For example, so-called top-down approaches typically use output of Global Circulation Models (GCMs) to examine how projected changes in climate variables might propagate through biophysical systems at regional to local scales (e.g., [8-10]). On the other hand, temporal and spatial analogues typically study a *reference* region or a *reference* time to determine how a *target* region or a *target* time might be (or has been) affected by climate change [8]. Yet another approach, indicator-based vulnerability assessment (IBVA), has been widely used because it allows the incorporation of biophysical and socioeconomic components of vulnerability, and is relatively simple to conduct and easy to communicate to the public and policymakers. All in all, this diversity in content and approaches has generated a CCVA literature that is large, multidisciplinary and stems from a number of different paradigms (e.g., risk assessment, natural disaster management, urban planning, food security, etc.). As a result, eliciting major directions, findings and methodologies from this body of work is an important but not trivial task.

This task is further complicated by the fact that no single, widely accepted definition of vulnerability exists in the literature, although a number of authors have attempted to pinpoint the concept. One commonly used definition has been presented by the International Panel on Climate Change (IPCC) in its Third Assessment Report:

> "[Vulnerability is] the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity" [11].

The three dimensions of vulnerability articulated in this definition, namely exposure, sensitivity and adaptive capacity, can be seen as the outcome of the interaction of two traditions of vulnerability research in physical and social sciences—a synthesis that provides a better account of the contextual and social dynamics of climate hazards and the multiple linkages that govern their impacts [4, 12, 13]. Although these three dimensions have gained wide acceptance, the operationalization of the concept of vulnerability through these dimensions has remained problematic. Criticism has been levelled at the lack of precision and inconsistent definitions in relation to the concepts of exposure, sensitivity and adaptive capacity, the relationship between them, as well as their relationship to vulnerability [14,15]. This might partly explain the change of the definition of vulnerability in the latest IPCC report (5th Assessment Report-AR5 draft) with less explicit emphasis placed on the three dimensions:

> "[Vulnerability is] the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts including sensitivity or susceptibility to harm and lack of capacity to cope and adapt[15]."

Conceptual models of vulnerability found in the literature broadly fall in one of three categories. The first category represents a “biophysical” approach within a risk-hazard framework, which conceptualizes vulnerability of a system as a dose-response relationship between an exogenous hazard and its effect on that system [16, 17]. The second category is inscribed within a social constructivist framework which regards social vulnerability as a pre-existing condition of a household or a community generated by unequal access to resources[14, 18-20]. The third group of studies conceptualizes vulnerability as the differential abilities of communities to cope with external stress[14, 21]. This approach recognises that it is not the mere availability of adaptation options, but the capacity of communities and institutions to actually implement them that determines their vulnerability to climate change [14]. For more discussion of conceptual frameworks of vulnerability, readers are referred to Watts and Bohle [22], Bohle [23], Adger [24], Kasperson, Kasperson [25], Turner, Kasperson [21], Luers [26] Füssel [4], Ionescu, Klein [27], Wolf, Hinkel [28] and Geldermann, Spengler [29].

A number of attempts have been made to classify knowledge on vulnerability to climate change. The assessment reports of the IPCC [30], identify major developments, approaches and methods in climate change vulnerability research. Hofmann, Hinkel [31] offer a classification of knowledge on climate change impacts, adaptation and vulnerability in Europe through a conceptual meta-analysis, identifying key assessment approaches in use and key sectors in which they have been applied. However, the study is limited to publications that are a) relevant to Europe and b) cited by the Working Group II contribution to Fourth Assessment report [30]. Ford, Keskitalo [8] examine how case studies and analogue methodologies have been used in climate change vulnerability research. However, no meta-analysis of the literature on vulnerability appear to have paid sufficient attention to other, equally important aspects of assessment such as spatial scale, temporal framework of analysis, aggregation and uncertainty.

Of particular interest is a widely used approach, namely indicator-based vulnerability assessment (IBVA). IBVA is attractive to policymakers because it is usually based on readily available indicators and its rationale is relatively easy to communicate to stakeholders and the wider public. Yet, IBVA has come under significant criticism, by a number of key theoretical papers over the last 10 years, on account of its methodological shortcomings[32-34]. In addition, advances in our understanding of aggregation of indicators, uncertainty as well as spatial and temporal scales of analysis, have been achieved in development studies, climate science and urban planning [14, 35-38]. However, given the large size of the vulnerability literature, the extent to which these theoretical and methodological advances have made their way into IBVA is uncertain. Our goal in this paper is therefore threefold: a) to describe the broad characteristics of the IBVA literature in terms of its themes and focus; b) to elicit the more significant methodological challenges of IBVA, based on the key papers mentioned above and our own analyses and c) to assess the extent to which the IBVA literature has engaged with these challenges.

To this end, we conduct a meta-analysis of the literature based on a set of representative peer-reviewed publications selected through a structured approach. The paper is divided into three parts. First, we present and discuss the most important methodological challenges of IBVA. Second, we describe the methodology followed in our meta-analysis of the literature. Third, we present and discuss our findings."

2.0 VULNERABILITY INDICATORS

2.1 Fundamental concepts

We call Climate Change Vulnerability Assessment (CCVA) any attempt at assessing vulnerability to climate change, be it quantitative or qualitative. Approaches can be based on indicators, simulation models or a mix of both [28, 39]. Vulnerability indicators are applied because vulnerability is a theoretical concept and thus cannot be measured in the way an observable phenomenon such as the mass of an object, energy or temperature are measured [40],15. Consequently, there is a lack of consensus on vulnerability metrics [33, 41].

It is important to note that, unlike more conventional indicators such as the human development index (HDI), vulnerability indicators refer to a possible future state of the world, and not its current actual state [32]. Following Hinkel [32], we thus distinguish between:

- Indicators of harm, which are those that evaluate the (current or future) state of an SES based on normative judgements of what constitutes a good or bad state. Examples of such indicators are the number of people affected by a flood event or the decline in the population of a given species due to ocean acidification.
- Indicators of vulnerability, which are those that indicate the possibility of being harmed [27]. Saying that someone is vulnerable to malaria does not mean she actually has malaria, but only that she can potentially be infected. This potential may be evaluated either for current time or in the future (See Section 3.6).

We refer to vulnerability assessments that involve vulnerability indicators as Indicator-Based Vulnerability Assessment (IBVA). Some IBVAs may involve both vulnerability and harm indicators.

In this case, vulnerability indicators are typically applied to data describing the current state of the social subsystem and harm indicators commonly use data on the future state of the SES that are simulated using mechanistic climate and impact models. The project ATEAM (Advanced Terrestrial Ecosystem Analysis and Modelling), for example, combines harm indicators evaluated on the output of ecosystem and hydrology models with vulnerability indicators [42]. Box-1 provides some fundamental definitions.

2.2 Steps involved in developing vulnerability indices

Three steps may be distinguished in the development of IBVA [32]. The first step consists in defining the problem at hand by answering the following three questions:

1. Which *socio-ecological system* (SES) is the object of study, e.g., locality, community, industrial sector, ecosystem?
2. Vulnerabilities of which *valued attributes* of this SES are to be assessed, e.g., health, prosperity, biological productivity, biodiversity?
3. Vulnerabilities to which *climate-related stress(es)* are to be assessed?

The second step consists of the selection of indicators. This selection is conditioned by the choice of valued attributes and SES of concern and aims to represent all of the important processes generating vulnerability [32]. A combination of biophysical and social processes generates vulnerability. Both of these processes are critical and knowledge about them is generated through evidence-based research. However, in social sciences, quantification is usually more difficult, and perhaps less vital. Mechanistic models, when available or possible to build, are usually preferred because they are able to represent processes more accurately than indicators. Indicators are essentially “weak” models: we know that the indicator bears a relationship to vulnerability; we know the direction of the relationship (increasing or decreasing vulnerability with increasing indicator); however, we are not always able to characterise this relationship with accuracy. Nor do we usually have access to deductive arguments that can guide us in combining these indicators to build a proxy measure of vulnerability. It is precisely because of this epistemic uncertainty and the importance of incorporating all three dimensions of vulnerability, including those of a predominantly social and institutional nature, that aggregation, discussed next, is critical, since it can only be partly guided by mechanistic knowledge of the system under study.

BOX 1: Some basic definition

Harm indicator	Indicators that evaluate a state of a SES based on normative judgements of what constitutes a good or bad state. Examples of such harm indicators are the number of people affected by a flood event or the decline in the population of a given species due to ocean acidification.
Vulnerability Indicator	Indicators of possible future harm.
Deductive approach	"Using deductive arguments in the development of vulnerability indicators means using available scientific knowledge in form of frameworks, theories or models about the vulnerable system of interest in the selection and aggregation of indicating variables" [32]
Inductive approach	"Using inductive arguments in the development of vulnerability indicators means using data for building statistical models that explain observed harm through some indicating variables." [32]
Normative approach	Using normative arguments in the development of indicators means using (individual or collective) value judgments in the selection and aggregation of indicating variables. [32]
Role expert	Role experts provide technical knowledge about the processes that generate vulnerability
Stakeholder expert	Stakeholder experts are generally the repository of deductive and inductive knowledge about vulnerability
Socio Ecological System (SES)	We understand SES as a set of interactions between a 'bio-geo-physical' unit and its associated social actors and institutions [5, 43] or as a coherent system of biophysical and social factors that interact regularly in a resilient, sustained manner [7].

A possible third step consists in aggregating the indicators into an overall “measure” of vulnerability. At its simplest, aggregation is a form of mapping which aims to identify those SESs for which a confluence of indicators points to higher vulnerability. At its more complex, it can generate vulnerability indices or vulnerability rankings.

As mentioned above, aggregation must be understood as an alternative to mechanistic modelling in the case when the latter is not possible. Mechanistic modelling is possible when the exact relationships between system variables (indicators) are known via simple closed-form equations or more complex relationships implemented in a simulation model. Modelling is often used in the assessment of vulnerability of natural ecosystems. This is because it is usually possible to simulate the exogenous climatic impacts and the ecosystem's sensitivity to those impacts. The vulnerabilities of anthropogenic systems, on the other hand, are more difficult to model in a mechanistic sense, not least because of the complexity of processes determining sensitivity and adaptive capacity, and the necessarily qualitative nature of at least some of the research generating knowledge about it. For example, adaptive capacity is a critical system property which describes the ability to cope or mobilize scarce resources to anticipate or respond to climate-related stresses and is determined by a wide range of socio-economic, cultural, institutional and political factors [44]. Aggregation, therefore, becomes the only available option if some ranking of vulnerabilities is to be generated, based on the assembled indicators.

3. CLASSIFICATION SCHEME OF IBVA STUDIES AND AVAILABLE METHODOLOGICAL CHOICES

IBVA is a multi-disciplinary exercise and methodological choices of IBVA vary based on factors such as context, objective and data availability. In the following section, we develop a classification scheme for IBVA studies. We discuss methodological choices and challenges associated with IBVA, based on a set of key conceptual papers[32, 45].

3.1 Classification schemes

What has been the thematic and methodological focus of the IBVA literature? Towards this end, we considered the following classification criteria:

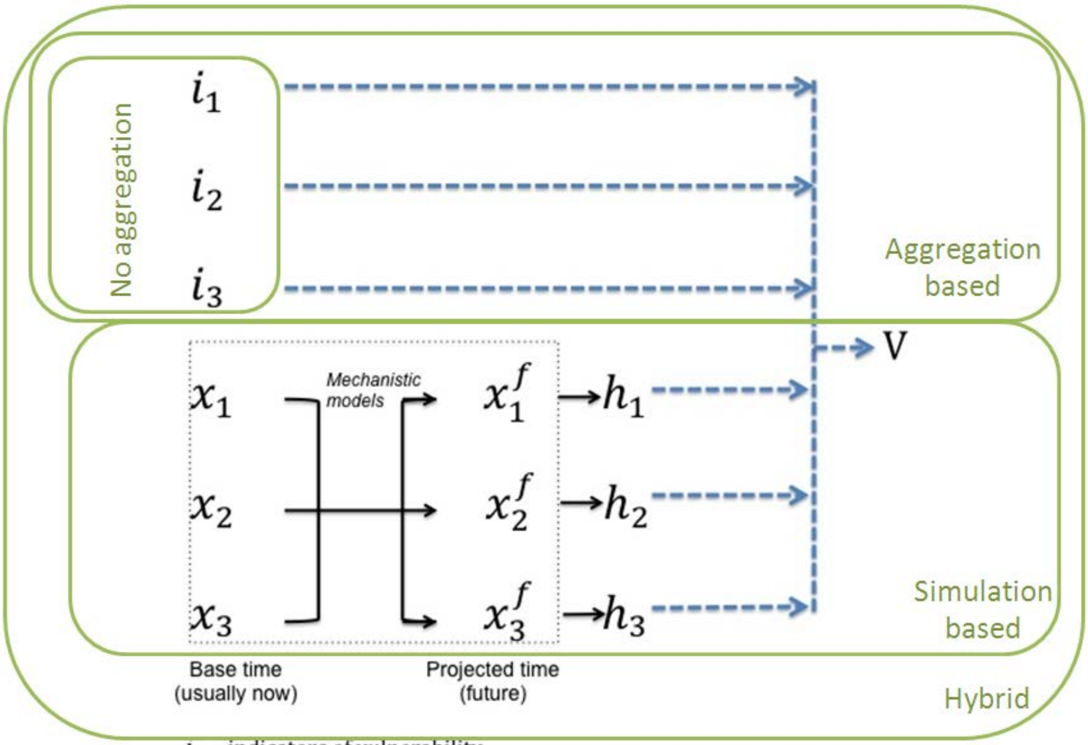
1. broad content (theoretical, methodological, applied or a combination of these);
2. knowledge domain (biophysical dimension of risk, socio-economic and institutional dimension of vulnerability, or a combination of these);
3. Socio-Ecological System (SES) under consideration (e.g., crop production systems, coastal communities, emergency response systems, species under threat);
4. valued attribute(s) of the SES to be protected/maximised (e.g., economic productivity, well-being, health);
5. types of vulnerability assessment (further elaborated below);

6. physical hazard(s) under consideration (e.g., sea level rise, heat waves, floods);
7. geographical scale (e.g., local, municipal, regional, national; further elaborated below);
8. temporal frame of reference (e.g., its consistency or lack thereof, present versus future vulnerability, 2050, 2100; further elaborated below);
9. aggregation methods employed (e.g., multi-attribute utility theory, GIS overlaying; further elaborated below);
10. weight estimation methods (e.g., equal weights, stakeholders interviews, mathematical methods; further elaborated below);
11. explicit consideration of uncertainty or lack thereof (further elaborated below);
12. explicit consideration of non-linear and threshold processes or lack thereof (further elaborated below).

3.2. Types of vulnerability assessment

We distinguish between four types of vulnerability assessments as schematized in Figure 1.

1. *Simulation based assessments* simulate the future using models and apply harm indicators to model outputs. (e.g., vulnerability of an organism living in the sea to an increase in ocean acidification). Models are applied to the current state of the SES (x1, x2, …) and emission or climate scenarios to project future states (x1f, x2f, …), which in turn are evaluated using harm indicators. In this case, indicators are an *output* of the assessment, rather than an input to it, and no aggregation of indicators are conducted.
2. *Aggregation based assessments* gather data on present value of indicators (i1, i2, …) and then aggregate these into an overall measure of future vulnerability (e.g., social vulnerability due to a combined impact of climate change and globalization).
3. *Hybrid approaches* combine simulation-based and aggregation based approaches: Some system variables are projected into the future and evaluated using harm indicators, which in turn are aggregated with some present value of socio-economic indicators (that indicate future vulnerability) (e.g., vulnerability of a coastal community to sea level rise).
4. *No simulation and/or no aggregation* approaches gather data on present values of vulnerability indicators and discuss these qualitatively without aggregating them into an index (e.g., qualitative analysis of vulnerability using spider diagram).
5. *Theoretical and methodological studies* are those that focus on theoretical or methodological developments of IBVA and do not conduct any assessment; therefore none of the above four categories apply to them.



i indicators of vulnerability
x state variables
h harm indicators
V vulnerability

Figure 1: Vulnerability assessment approaches as commonly practiced.

3.3 Aggregation (and normalization) methods employed

We distinguish between the following aggregation methods

1. No aggregation, no normalization: The individual indicators are not made comparable
2. Normalization without aggregation (for the purpose of "Visual aggregation": all indicators are converted to the same scale, but no further aggregation is made. Examples are presentation of multi-dimensional indicators using spider diagrams or radar charts [46].
3. Geometric mean (i.e. y = x1^a1 * x2^a2 * …)
4. Arithmetic mean (y=a1*x1 + a2*x2 + ..)
5. Non-linear function of indicators

Each of these approaches faces theoretical and practical difficulties which have been recognized by a number of authors [4, 33, 35, 38, 47]. For example, geometric mean and arithmetic mean should be seen as a part of a larger theoretical edifice, multiple attribute utility theory (MAUT), which has a strict theoretical requirement, such as additive independence of indicators and complete knowledge of the system, that are virtually impossible to achieve in the context of IBVA. Additive independence of indicators are important, because otherwise the utility function (i.e., the arithmetic means) might be double counting a single causality effect (if indicators are dependent), implicitly destabilising the weight allocation and making it arbitrary, not taking into account the interaction between the indicators, etc. and overall making the utility function rather meaningless except in some rough, qualitative way. Furthermore, aggregation based on arithmetic means allows complete compensation between different indicators when in fact this may not be realistic (e.g., beyond a certain level of sea rise, no degree of adaptive capacity can help small island states cope with inundation). Another problem of both arithmetic and geometric mean approaches is that they assume a monotonic relationship between indicator and vulnerability and thus disregard potential nonlinearities and thresholds in this relationship [48-51]. Non-linearity has been recognised in the conceptual literature on vulnerability, most prominently with Luers [52] defining vulnerability as a degree of departure from a threshold.

As the exact relationship between an indicator and vulnerability is not usually known, IBVA uses a form of aggregation most commonly performed by combining multiple indicators into single indices of vulnerability for a given stressor under a given dimension, and then combining multiple indices in order to build an overall, relative estimate of vulnerability (e.g., [53, 54]). These "combinations" are usually simple arithmetic or geometric means, based on Multiple Attribute Utility Theory (MAUT) widely used in economics, engineering, decision science, development studies and, to a lesser extent, social sciences [55-58].

3.4 Weight estimation methods employed

Almost all aggregation methods involve weights that reflect the relative importance of the indicators and these weights need to be established through a weight estimation method. Here, we follow Hinkel [32] and further distinguish between the following five different approaches (See also Table 6):

a. Descriptive approaches that estimate weights based on the variability of the data for a given indicator (e.g., principle component analysis).

b. Inductive approach using data of observed harm (Multi-Way Data Analysis). It consists in building a statistical model that explains observed harm through indicators.

c. Deductive approaches which use established theory or knowledge to identify, how indicators that represent a process combine to form vulnerability. For example, if the literature has found that the number of doctors in a community is more significant in explaining an adverse impact than the age structure, then the former indicator should receive a higher weight in the aggregation.

d. Deductive approach using expert judgment: a variant of the deductive approach is to have experts choose weights.

e. Normative approach that elicits preferences from stakeholders together with methods from decision analysis such as AHP, MAUT, etc.

Again, each of these approaches comes with limitations. Descriptive approaches are generally problematic as the values of the data of the indicators do not reveal anything about causal processes, i.e. how these indicators combine to reflect vulnerability[32]. Only when data on observed harm is available, as well as data on indicators, can an inductive approach be used to build a statistical model that explains the former through the latter. Both the inductive and deductive approaches are sound from a theoretical point of view, but difficulties arise in practice. For inductive approaches, poor availability of data on observed harm (as climate change is a long term process) as well as the complexity of the systems considered, limit feasibility of multi-way data analysis. For deductive approaches, limited availability of theories and models representing the complex SES considered are serious constraints.

3.5 Spatial Scale

Processes generating vulnerability can be fundamentally different at different scales. As an example, on the one hand, access to resources, diversity of income sources as well as social status of individuals play a vital role in determining vulnerability at a household level. On the other hand, vulnerability at a larger scale (e.g., regional or national) is determined more strongly by market structures, such as prevalence of informal and formal social security and insurance, infrastructure and income [19, 32]. A number of scholars have argued that, because at local—compared to regional, national and international scales—it is easier to define systems, identify socioeconomic and biophysical processes that determine vulnerability and build inductive arguments to characterise them, IBVAs should be conducted at smaller rather than larger scales [19].

3.6 Temporal Scale

Implicit in the concept of vulnerability is, as mentioned above, the idea of *potential* harm [32]. However, the question remains as to whether the framework is referring to potential harm from today's standpoint or some point in the future. In other words, it is important to be clear as to whether the object of the assessment is today's vulnerability (determined in part by past adaptation) or one which might unfold in the future depending on prior adaptation. The answer to this question should in turn dictate the point in time at which indicators are measured and provide a degree of temporal consistency to the analysis. Dessai and Hulme [59] pointed out that the temporal framework adopted in studies usually reflect epistemic choices and disciplinary boundaries; specifically, while research into climate impacts, emanating from physical sciences tends to project into the future, social scientists are often more interested in understanding processes generating vulnerability *today*.

3.7 Uncertainty

The most vexing form of uncertainty is epistemic, emanating from imperfect knowledge of processes in making predictions of climate futures [59-61]. The uncertainties in social processes are considerable, creating significant problems in projecting specific indicators into the future[62]. However, additional sources of uncertainty are attached specifically to IBVA. First, some processes generating vulnerability may not be known or quantifiable. Second, as discussed above, while individual indicators hold a relationship to a process generating vulnerability, a quantitative description of this relationship is often lacking. These two sources of uncertainty are also epistemic. Third, random and non-random fluctuations of indicators, especially if they are averaged over spatial or temporal scales and/or projected into the future, can generate a high level of imprecision. Fourth, indicators and the weights attached to them are sometimes evaluated by interviewing stakeholders or experts and the process inevitably carries a level of subjectivity, as well as possible variances between the opinions of different informants. Table 1 shows different sources of uncertainty and some of the possible ways of addressing them.

4. META-ANALYSIS MATERIALS AND METHODS

4.1 Papers Selection

We aimed for a sample of between 100 and 150 publications, i.e. one that is sufficiently large yet reasonably manageable. We achieved this through trial and error in order to generate a reasonable selection process that yields a number of publications within this range. The selection process we settled on was as follows.

We targeted two prominent and multidisciplinary science databases, Scopus and Web of Science. We started with a keyword search that aimed to capture as much of the relevant literature as possible. Hence, we used the terms [“climate change” OR “global warm”] and intersected them with [“vulnerability” OR “resilience”], to be found in keyword, title or abstract of publication. The word “resilience” was used because it is associated with (and can be seen as the flip side of vulnerability).

In fact, Janssen et al. [63] found that the two terms resilience, on the one hand, and vulnerability/adaptation, on the other hand, correspond to two different epistemologies, the former arising from ecology and mathematics, while the latter is associated with geography and natural hazards. Although the two knowledge domains fundamentally address similar research questions and do refer to each other, they remain separate in terms of their output and research communities that produce them.

Table 1: Sources of uncertainty

Sources of uncertainty	**Methods of addressing uncertainty**
General epistemic uncertainty of climate change	Use of multiple expressions, multiple models
Selection of indicators	Robustness of selected indicators across literature and experts
Aggregation of indicators	Sensitivity analysis (e.g., sensitivity to changes in weights variability, sensitivity to change in aggregation methods)
Measurement of indicators	Sensitivity analysis (e.g., sensitivity to fluctuations in indicator values)

The resulting sample, called search set 1, yielded over 3000 papers in each database, there was, of course, a significant overlap between the two databases but we chose to deal with this further down the selection process. Then, we performed the following operations on search set 1 progressively reducing it in size and making it more sharply relevant to our topic, namely research around IBVA:

a. We selected only publications containing the word “indicator” (search set 2).
b. We limited our interest to journal articles because they are usually more rigorously peer-reviewed and therefore of higher quality than other types of publications (search set 3).
c. In Scopus, we selected all papers from journals which had yielded at least 2 papers on our query in search set 3. Among the 114 journals brought up by search set 3, 20 yielded at least 2 papers hence reducing the number of papers to 67 (search set 4).
d. From the remaining 94 papers in Scopus (search set 3 minus search set 4), we re-included all papers that have been cited at-least 9 times (search set 5). This has resulted in a total of 89

papers from Scopus when all papers from search set 4 and search set 5 were included in the sample.

e. We conducted the same procedure in WS (except that journals with 3 rather than 2 papers were included), with a total number of 109 papers from WS in the sample.

f. Finally, we conducted a manual search of the papers dropped from search set 3 (159) of both databases and, considering the relevance to our objectives, we re-included 14 more papers (search set 8).

g. When search set 4, 5 and 8 from both databases were combined, a total of 212 papers were obtained (search set 9).

h. Removing an overlap of 56 papers between the 2 databases, as well as 24 papers that turned out to have only weak links to climate change, we were left with a final study sample of 134 papers.

Clearly, choosing cut-off points of 9 citations and 2 or 3 articles per journal (points c, d and e) is arbitrary. These numbers were reached by trial and error with the aim of achieving sample of manageable size.

A comparison of search sets 1 and 2 indicates that the number of IBVA journal papers is about 6%-7% of the total number of papers on vulnerability to climate change over that period of time. Our final study sample contains at least 37% of all indicator-based papers identified in the two databases. This is the final number of selected papers, as a percentage of papers in search set 2, assuming that search set 2 has the same number of overlap and weak-link papers as search set 9. The actual percentage is likely higher since search set 2 will most probably have a larger number of duplicates and weak-link papers than search set 9. Hence, our final study sample is expected to be highly representative of the peer-reviewed IBVA corpus.

5 RESULTS

5.1 Yearly Distribution

Figure 2 shows the yearly distribution of the papers in our study sample and in the larger search set 1. In both cases, the number of yearly publications rose almost tenfold in ten years. Around 77% of the total number of papers in each set was published between 2006 and 2011. This suggests an exponential growth of climate change vulnerability research. In addition, the similarity in the patterns observed in the 2 data sets supports our hypothesis that our study sample (134 papers) is a reasonably representative sample of the targeted literature, albeit skewed towards the peer-reviewed journal publications.

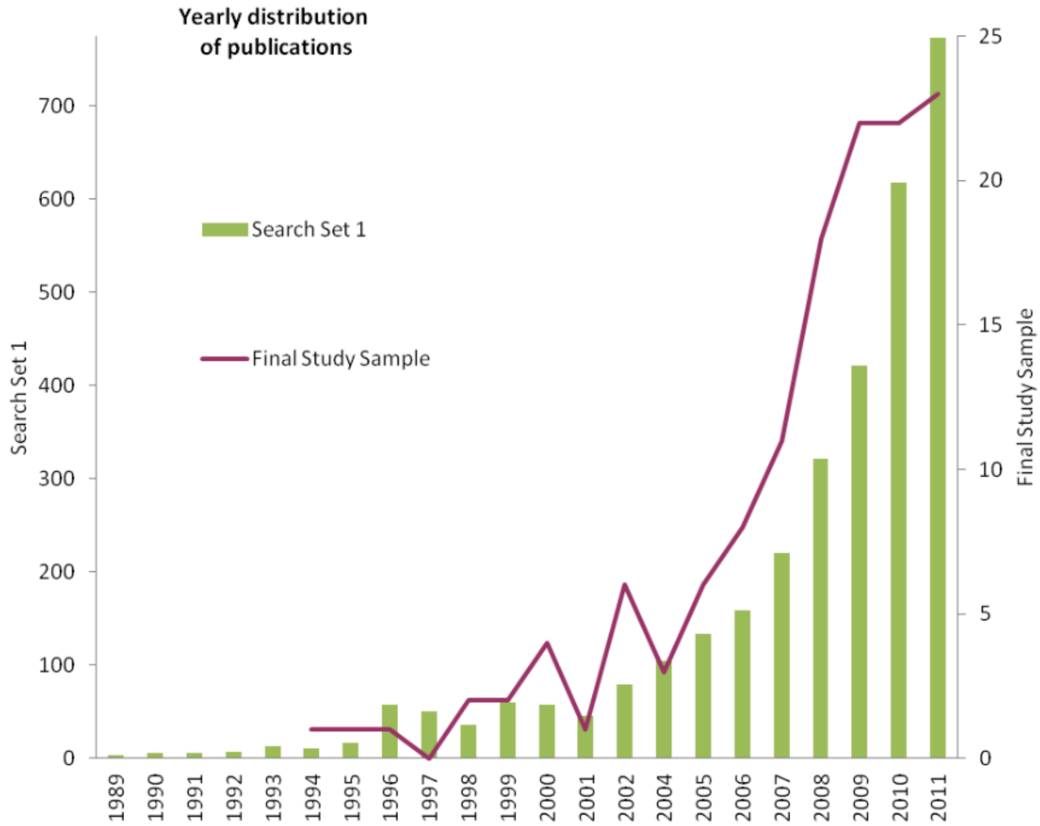


Figure 2: Yearly distribution of publications

5.2 Thematic Focus

65% of papers in our study sample consist of vulnerability assessment studies applied to a specific setting (see Table 2). 16% of papers are dedicated to theoretical issues around vulnerability assessment (definitions, conceptual frameworks, measurability and so on), with another 9% engaging with theoretical aspects of vulnerability assessment and reporting an assessment study. Most methodological papers (9% of the total) also contain an applied component, while another 1% are dedicated exclusively to methodological issues.

5.3 Types of Vulnerability Assessment

Table 3 shows that 55% of papers in our study sample were hybrid in nature, whereby bio-physical variables are projected into the future and then aggregated with current socio-economic indicators to measure the vulnerability of an SES (e.g.,[28, 64]). 19% of the study sample used simulation-based approaches in which the biophysical risk to a valued attribute of an SES under future climatic stress is assessed. Only 4% of papers followed an aggregation-based approach with bio-physical and/or socioeconomic indicators aggregated to measure vulnerability without any simulation models used. 4% of studies conduct no aggregation or simulation in the assessment. Finally, as shown in both Tables (Table 2 and Table 3), 17% of papers are theoretical or methodological in scope and do not conduct any assessment.

5.4 Socio-Ecological Systems

For the purpose of this meta-analysis, we define two broad categories of SES: "Natural Systems" and "Human Systems". The latter refers to any study that focuses, in part or in total, on some aspect of the well-being of an individual or groups of people related to the ecological, social and institutional systems on which it depends. "Natural systems", on the other hand, refer to studies that focus on ecosystem irrespective of the significance of these systems for human well-being.

Table 2: thematic focus of the papers

Thematic Focus	**Human systems**				**Natural systems**		**Total Count**	**% of total**
	Both biophysical and socio-economic knowledge domain (A)		**Only biophysical knowledge domain (B)**		**Only biophysical knowledge domain (C)**			
	Count	**% of A**	**Count**	**% of B**	**Count**	**% of C**		
Theoretical	19	24%	0	0	1	3%	**20**	**15%**
Theoretical and Applied*	11	14%	0	0	2	5%	**13**	**10%**
Applied*	40	51%	15	79%	32	86%	**87**	**65%**
Methodological	0	0%	0	0	2	5%	**2**	**1%**
Methodological and Applied*	8	10%	4	21%	0	0%	**12**	**9%**
Total	**78**	**100%**	**19**	**100%**	**37**	**100%**	**134**	**100%**

(*Applied means that the paper conducts an indicator-based assessment of a specific SES)

28% and 72% of publications study "natural systems" and "human systems", respectively (Figure 3). 22% of the studies focusing on "natural systems", analyse "marine ecosystems" (e.g., barrier reefs) and 78% "terrestrial and atmospheric ecosystems" (e.g., vulnerability of national park, forests, specific flora or fauna species, etc.).

19% of "human systems" studies in our sample focus on hydrology (e.g., how climate change might impact rainfall and water budgets in a given region), 15% on agricultural systems (e.g., vulnerability of crop production of a specific community), 16% on urban ecosystems (e.g., vulnerability of a specific urban setting or community) and 8% on coastal settlements (e.g., vulnerability of a coastal community or its infrastructure). On the other hand, around 29% of studies do not focus on a single SES but multiple ones. For example, Brenkert and Malone [56] assessed overall vulnerability for India and Indian states by selecting and aggregating vulnerability indicators from multiple sectors (e.g., agriculture, water resources, health systems). Moss [65] used an indicator-based approach to assess national vulnerability of a number of countries by extracting a set of key indicators for key sectors (e.g., water sector, environment), without explicitly identifying the valued attribute in each of these sectors.

Table 3: Types of vulnerability assessment

	Vulnerability Assessment types	Count	%
Application studies	Simulation	26	19%
	Aggregation	5	4%
	Hybrid	74	55%
	No simulation and/or no aggregation	6	4%
Non-application studies	Theoretical and methodological studies	23	17%

Table 2 also shows the thematic focus of "human systems" papers. 78 out of 97 papers combine socio-economic and biophysical indicators, consistently with the IPCC vulnerability framework they use. This would suggest that the methodological problems associated with this combination, which we discussed earlier, are highly relevant to this particular segment of the literature.

5.5 Valued Attribute of Concern

When assessing vulnerability to climate-change-related hazards, one or more attributes of the socio-ecological systems in question usually come under scrutiny. This "valued attribute" is either implicitly assumed or explicitly articulated in the studies. Table 4 shows the distribution of valued attributes of concern in our study sample. Ecosystem health and biodiversity together account for about 28% of all studies, while soil quality and agricultural productivity make up another 7.5%. A relatively large number of studies (12%) are concerned with the quality and quantity of freshwater resources. Public health has also attracted a high level of interest (around 10% of studies). For example, Van Lieshout, Kovats [66] have developed a global model of malaria transmission to estimate the potential impact of climate change on seasonal transmission and populations at risk of the disease.

On the other hand, a significant proportion of papers (22%) consider a large geographical scale (regional or national) and thus combine a collection of indicators that reflects a mix of valued attributes, usually without specifying what they are. One such example is the study by Brenkert and Malone [56], referred to earlier. Another example is provided by Vincent [67] who discusses critical issues of uncertainty in determining adaptive capacity at different scales, from a household to a nation, and uses indicators from a mixed bag of sectors with different valued attributes (e.g., economic wellbeing, institutional stability, global interconnectivity, access to water resources).

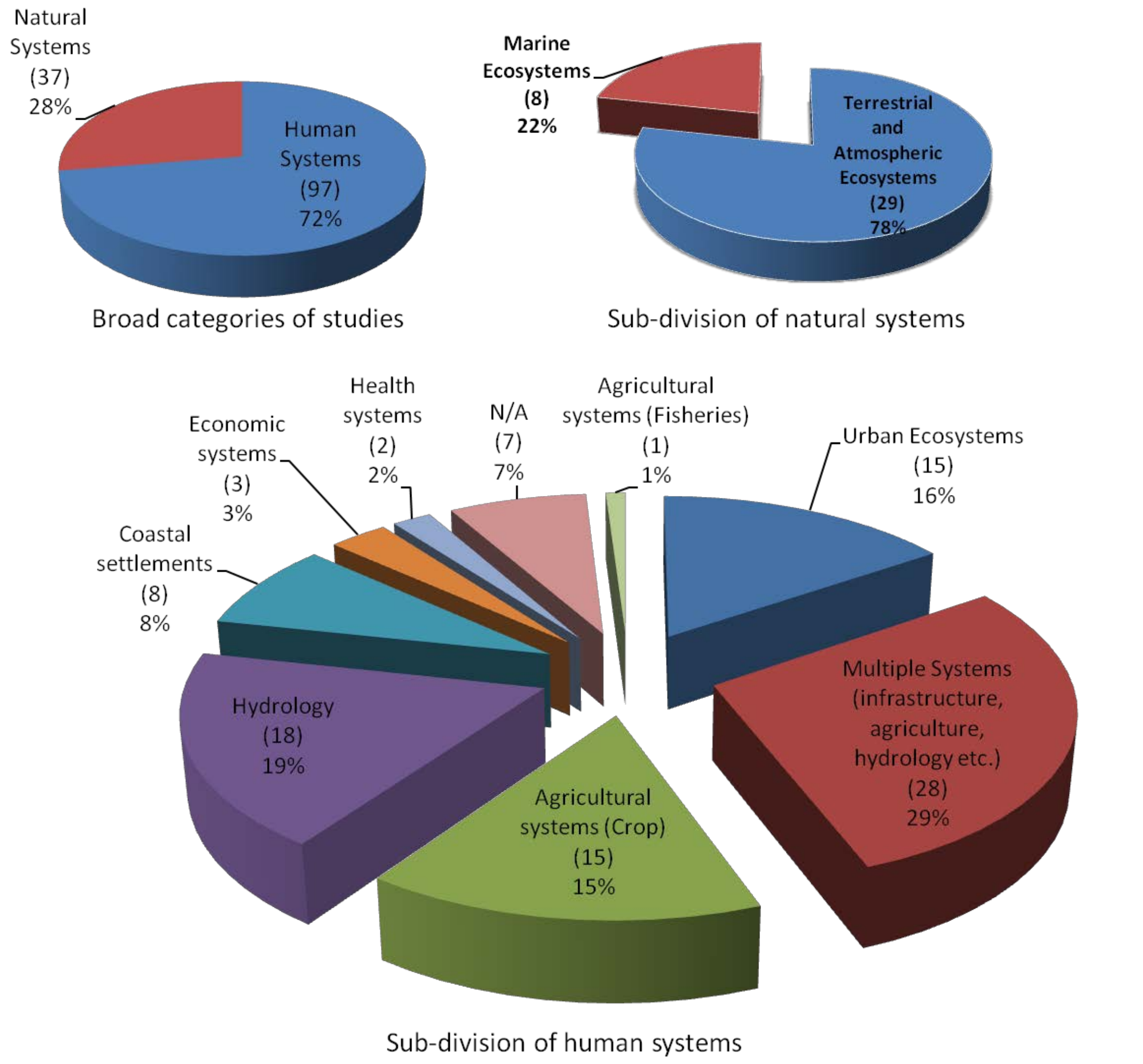


Figure 3: Distribution of papers according to the socio-ecological system under consideration (number of papers shown in brackets).

Finally, the relatively small number of papers dealing with the integrity of infrastructure systems is notable, although this may be due to the fact that these systems lend themselves to mechanistic simulations that do not require the use of indicators.

5.6 Physical Hazard under Consideration

30% of papers in our study sample are concerned with single hazards, with the remaining 70% (93 papers) addressing multiple ones. This is unsurprising since the compound effect of multiple hazards can be significant and difficult to predict from consideration of single hazards separately. Figure 4 shows the distribution of hazards considered in single-hazard studies. Increased frequency of droughts and temperature extremes together account for more than 50% of the studies, with the figure increasing to around 75%, if sea level rise and ocean acidification and warming are included. This distribution seems to match the most important biophysical climate stressors identified by the IPCC working group 1 (e.g., [11, 30]).

5.7 Geographical Scale

Geographical scale plays an important role in determining relevant processes generating vulnerability. Here, studies termed "global" generally assess the impact of a specific hazard on the whole world, at least nominally. Studies grouped under "national" compare vulnerabilities of different nations. "Regional" scale refers to studies conducted at a sub-national level that is typically larger than a city. "Urban/suburban" refers to studies conducted at city scale or smaller geographical unit. Finally, studies that consider the vulnerability of a specific community, usually defined by a given locality (e.g., a specific suburb, a group of neighbouring villages) down to a household level are termed "local". Figure 5 shows that 65% of studies are conducted at regional or higher levels. Only 17% of vulnerability studies have been conducted at a local level which is, arguably, the scale at which processes generating vulnerability are most well defined and the scientific validity of the assessment is likely to be at its highest [19, 32].

5.8 Temporal Frame of Reference

Vulnerability is expected to change over time. It is therefore important that vulnerability studies are conducted within a well-defined time frame. A simple but fundamental temporal element consists of specifying whether present vulnerability or vulnerability at some given time in the future is being sought in the study. This is, unfortunately, the exception rather than the norm in the literature: 91 out of 134 studies in our sample are non-specific on this issue. It is unsurprising, therefore, that apart from papers presenting "temporal analogues", little appears to be said in the IBVA literature about the way vulnerability might have changed in the past or might evolve in the future.

Table 4: Distribution of valued attributes of concern

Distribution of valued attribute of concern	**Count**	**%**
Health of ecosystems	**35**	**26.2%**
Marine ecosystems	5	3.7%
Fauna species	12	9.0%
Flora species	4	3.0%
Vegetation cover and forests	8	6.0%
Other ecosystems	6	4.5%
Biodiversity	**2**	**1.5%**
Soil quality	**2**	**1.5%**
Agricultural productivity	**8**	**6.0%**
Water resources quality and quantity	**16**	**11.9%**
Physical integrity of shorelines	**4**	**3.0%**
Integrity of infrastructure	**2**	**1.5%**
Well-being of farmers	**6**	**4.5%**
Well-being of coastal population	**4**	**3.0%**
Household livelihood	**2**	**1.5%**
Public health	**14**	**10.4%**
Economic returns of tourism	**2**	**1.5%**
National economy	**2**	**1.5%**
Large scale mixed social and economic attributes (e.g., socio economic well-being)	**29**	**21.6%**
Not applicable	**6**	**4.5%**

5.9 Aggregation Methods Employed

Figure 6a shows that arithmetic mean and geometric mean account for 33% of aggregation methods employed in our study sample. However, when we exclude studies that do not aggregate indicators as well as those that focus exclusively on natural ecosystems, we find that, in this smaller sample, arithmetic mean and geometric mean are employed in 82% of publications (Figure 6b). This is due to the fact, discussed earlier, that mechanistic simulation models accounting for socio-economic and institutional factors are much more difficult to build, with researchers resorting instead to the simplicity of arithmetic mean or geometric mean aggregation. Only 18% of studies in the smaller sample use methods such as multi-criteria decision analysis or fuzzy logic which can be considered as more sophisticated in compared to other aggregation methods (i.e., arithmetic mean and geometric mean) that require all indicators to be converted to a one single comparable scale (i.e., through normalization). These fuzzy methods are usually better suited for the mix of quantitative and qualitative data that characterizes indicator-based vulnerability models [68].

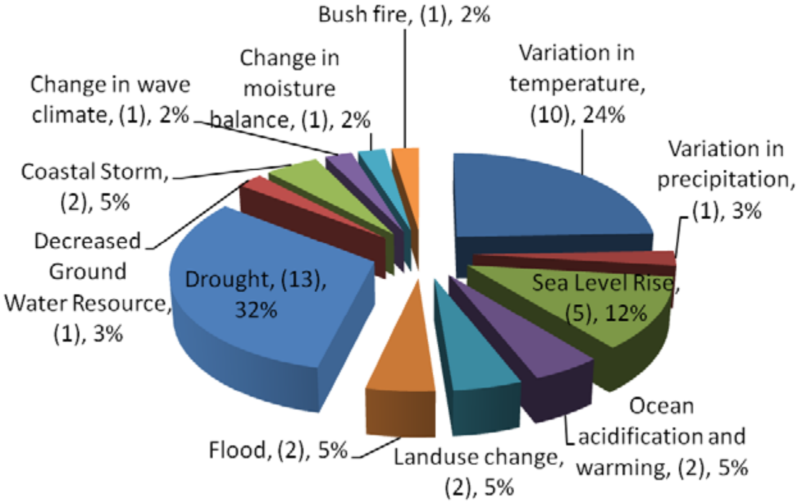


Figure 4: Distribution of papers according to climate-related stress considered in single-stress studies (number of papers shown in brackets)

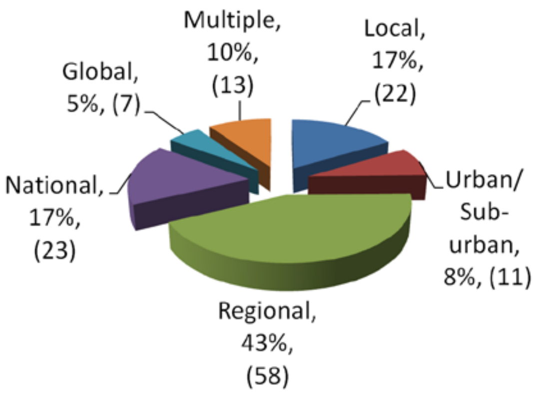


Figure 5: Distribution of papers according to the geographical scale of studies (number of papers shown in brackets).

5.10 Weight Estimation Method Employed

61% (82) papers of our study sample did not use indicator weights while conducting IBVA (Table 5). This includes papers that are either purely theoretical or qualitative in nature or simulation-based approaches that do not aggregate. Among the remaining 52 papers that specify their weight estimation method, equal weights turned out to be the most common method with 42% of papers using them, usually with little justification provided. 37% of the 41 papers employed expert judgment as a method of generating weights (Table 5). This is consistent with the fact that modelling a complex system involves multiple stakeholders and expert judgment from stakeholders is an important source of knowledge.

A few studies used Principal Component Analysis (PCA) as a method to estimate weights. PCA is data intensive and derive weights based on the intrinsic variability of the indicators rather than the relationship between indicator and vulnerability [32, 68]. A very small number of studies in the sample used more sophisticated mathematical methods shown in Table 5.

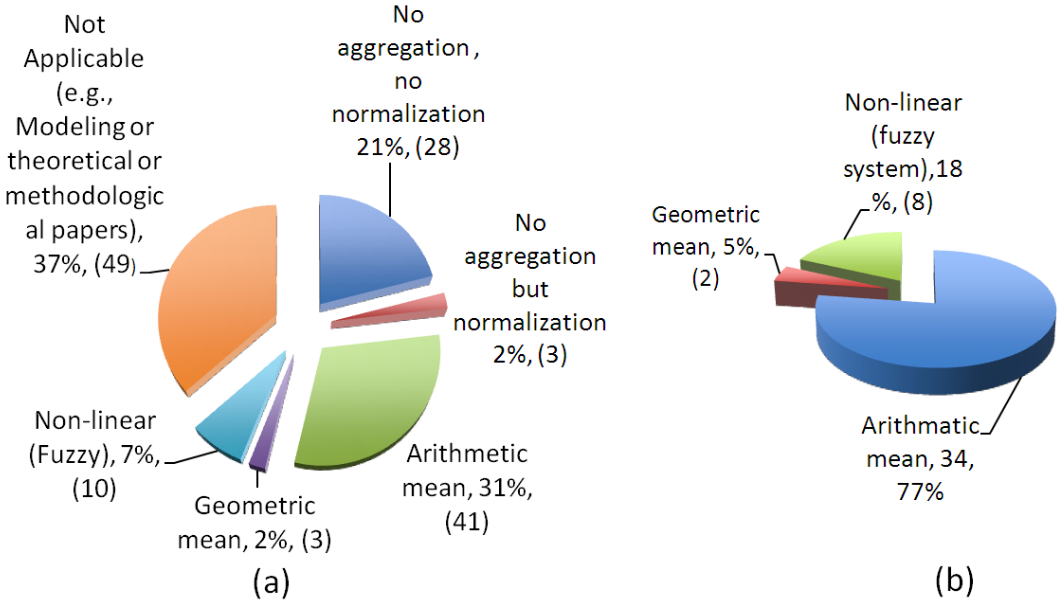


Figure 6: Distribution of papers by aggregation methods used: a) for the whole study sample (134 papers) and b) 44 studies that consider both biophysical and socio-economic domains, excluding 37% of studies with not applicable (number of papers shown in brackets).

5.11 Explicit Consideration of Uncertainty, Nonlinearities and Thresholds

Only 23% of papers in our study sample explicitly engage with one or more of the different sources of uncertainty we discussed earlier (Table 1). For example, in assessing susceptibility to drought, Eierdanz, Alcamo [69] use fuzzy-set theory to incorporate uncertainty stemming from vague definitions and lack of knowledge about vulnerability. Eakin and Bojórquez-Tapia [70] take into account the uncertainty inherent in weights allocated to household vulnerability indicators, through multi-criteria analysis and fuzzy logic.

Table 6 shows the proportion of papers assessing vulnerability of human systems that have explicitly considered one or more forms of nonlinearity. Only around 10-12% of papers have done so. Since the biophysical dimension of risk usually lends itself more easily to mechanistic modelling than its socio-economic and institutional dimensions, one might have expected a higher proportion of papers focusing on the former to have attempted to incorporate nonlinearity in the models. However, this is not borne out by our sample. The small number of studies that have considered non-linearity mainly use the "vulnerability surface approach" proposed by Luers [26] which defines vulnerability as a degree of departure from a threshold. Studies such as those conducted by Seidl [71] and Lexer [72] use MCDA methods (e.g., PROMETHEE) to characterize non-linearity.

6. DISCUSSION

Mounting interest in vulnerability to climate change has generated a large and diverse literature over the last few decades. The IBVA body of work that we have examined in this paper is only one part of the larger vulnerability literature: around 6%-7%, based on our own publication count. The former, therefore, does not necessarily reflect trends and methods prevalent in the latter. Nevertheless, IBVA has been widely used because it is relatively easy to apply and its outcomes (e.g., indices, rankings or "hot spots"), and the rationale behind them, can be readily communicated to policy makers and to the public. More importantly, IBVA allows knowledge from different scientific ends of vulnerability research (climatic, geo- and bio-physical, social and institutional) to be combined, which is necessary and more difficult to achieve by other methods.

However, as we have shown earlier, these advantages can come at the cost of decreased analytical validity. In fact, two sets of limitations, discussed next, can be discerned in IBVA through an examination of the literature. The first one is inherent to the IBVA and needs to be recognised rather than changed or improved upon, while the second can be avoided through methodological developments and research.

The IBVA's reliance on indicators clearly sets epistemological limits on its scope and relative ability to answer pertinent research questions for a number of reasons. First, IBVA is premised on our ability to identify and characterise processes generating vulnerability. In other words, it is made possible by quantitative and qualitative research in climatic, physical and social science research that is very much a work in progress. The extent of our understanding of these processes will always constitute a constraint on the validity and usefulness of IBVA. Second, the uncertainties we discussed earlier, especially those related to the relationship between vulnerability and indicators are likely to remain

Table 5: Distribution of papers by weight estimation methods employed for the whole study sample

Approach	Weight estimation Method	Description	Count	% of study sample
Equal weights		All attributes of the analysis is assumed equally important	22	16%
Inductive	Multi-Way Data Analysis and other statistical analysis	Multi-way analysis examines the association of one dependent variable with a set of independent, determining or classifying variables.	6	4%
Descriptive	Principal Component Analysis	Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.	5	4%
Deductive	Expert Judgment,	A group of experts decide about the importance of different attributes of the analysis	15	11%
Normative	Analytic Hierarchy Process (AHP)	The analytic hierarchy process (AHP) is a structured technique for organizing and analyzing complex decisions. Rather than prescribing a "correct" decision, the AHP helps decision makers find one that best suits their goal and their understanding of the problem	4	3%
No aggregation	Not Applicable	This includes studies that followed a simulation based approach, purely theoretical in nature and do not aggregate indicators	82	61%

because of heuristic and epistemological limits on our ability to understand and quantify vulnerability. Third, the economy of indicators genesis and maintenance will always constrain IBVA models, especially their ability to simulate the dynamic nature of vulnerability. All of these constraints need to be recognised by practitioners so as not to have unrealistic expectations about what IBVA can and cannot do.

Table 6: Distribution of studies according to their explicit consideration of non-linearities for different knowledge domains

	Knowledge domain	**Count**	**Non-Linearity Considered?**	**Count**	**% of Group HSA**	**% of Group HSB**	**% of Group NSB**
Human Systems	Biophysical and socio economic (Group HSA)	84	YES	8	10%	-	-
			NO	65	77%	-	-
			Not Relevant	11	13%	-	-
	Only Biophysical (Group HSB)	18	YES	2	-	11%	-
			NO	16	-	89%	-
			Not Relevant	0	-	0%	-
Natural Systems	Only Biophysical (Group NSB)	32	YES	5	-	-	16%
			NO	26	-	-	81%
			Not Relevant	1	-	-	3%

The second set of limitations, on the other hand, consists of a number of methodological practices or lacks, identified in this meta-analysis, which can be avoided or overcome. For example, many multi-sectoral papers remain vague about the valued attribute of concern that the vulnerability analysis is meant to capture, or about the temporal framework within which the analysis is set. Despite the fact that more sophisticated aggregation techniques have been built and refined in development studies, and social and decision-making sciences, additive summation remains dominant in the literature. Simple linear relationships are often assumed between indicator and vulnerability, even when evidence from climate studies point to thresholds and non-linear effects. Significant progress in the characterisation of uncertainty in climate change and impact predictions, as well as adaptation policy-making, has been made over the last decade, but nevertheless remains under-utilized in IBVA. These limitations can and should be overcome.

What does the future hold for IBVA? Given the inevitable rise of interest in climate change adaptation in the coming years and decades, the pressure on policymakers to justify allocation of resources, at local, regional, national and international levels, on the basis of equity and vulnerability, will only increase. For example, article 4.4 of the UNFCCC states that "developed country Parties …shall… assist the developing country Parties that are particularly vulnerable to the adverse effects of climate change in meeting the costs of adaptation to those adverse effects". Assessment of vulnerability at national and sub-national levels will inevitably play an important role in deciding the modalities of such assistance. IBVA can play an important role at each spatial scales, from the local to the global, provided the methodological challenges identified here are tackled by the IBVA community.

It is possible to envisage three plausible "futures" for IBVA:

a) business as usual in which IBVA is used in assessments, as it is now, without a strong methodological foundation and with sometimes scientifically doubtful outcomes;

b) a gradual decline in interest in IBVA; or

c) a concerted research effort over the next few years to clarify the uses to which IBVA can be put and to build methodological protocols and guidelines about how it should be applied.

Clearly, we believe that the last outcome is the most desirable but this requires a conscious effort on the part of the vulnerability assessment community. Two developments are key in this respect. First, while the IBVA can be a powerful synthesis tool, it is clearly a "downstream" method in vulnerability research, i.e. it will only be useful once we have identified and understood a set of key indicators for key sectors. IBVA cannot *build* such an understanding; it can only build *on it*. Converting qualitative and quantitative research into key indicators that reflect key processes generating vulnerability is an obvious necessity in this respect. Second, scientifically sound aggregation approaches that recognize and incorporate various sources of uncertainty are essential for producing assessments that are valid and consistent. It is important here to note that the use of indicator-based vulnerability assessment is not confined to climate change studies and that, as mentioned earlier, extensive experience in aggregation and index building based on indicators is available in other disciplines.

6. CONCLUSION

In summary, our meta-analysis of the literature on IBVA, revealed the following:

a. Public health and water resources are the two sectors that have attracted the highest number of IBVA studies. Multi-sectoral papers tend to be national in scale and unspecific about the valued attribute of concern. Most assessments in our sample consider multiple climate-related stresses. In those papers considering a single stress, droughts, temperature extremes and sea-level rise, acidification and warming have been the most prevalent hazards.

b. Only 10% of the IBVA studies are concerned with the conceptual and methodological foundations of this approach. This is despite the fact that serious questions have been raised in the literature about the methodological aspects of this form of vulnerability assessment.

c. A number of theoretical papers have argued that indicator-based vulnerability assessment is likely to be most valid at smaller rather than larger geographical scales. However, only 17% of studies appear to be conducted at local scales. In addition, most studies remain unspecific about their temporal frame of reference, ie whether vulnerability is being assessed in the present or at some specific point in the future.

d. Among the studies that aggregate indicators and consider both biophysical and socio-economic processes generating vulnerability, 82% use methods which are based on arithmetic means or geometric means, approaches whose theoretical requirements are difficult to satisfy in the context of IBVA. Among the studies that are explicit about their weight estimation method, 42% simplify the analysis by using equal weights, usually without providing a suitable rationale. Only a third of papers in our sample considered issues associated with uncertainty, while an even smaller proportion included some form of non-linearity and threshold effects.

The IBVA can be a powerful analytical tool in combining data and knowledge from the quantitative and qualitative ends of research on vulnerability to climate change. This is because it allows, in theory, the combination of indicators that are of very different origin and nature. Its role as a policy communication tool has also been recognised in the literature. However, for this potential to be realised without compromising scientific robustness and coherence, more attention needs to be given to fundamental methodological questions surrounding the approach, far more, in our opinion, than what can be found so far in the literature.

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