# Development, mapping and validation of resilience and vulnerability indicators across spatial scales for climate related hazards

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# DECLARATION

I hereby declare that this doctoral dissertation is composed independently, and all the sources of information and material have properly acknowledged.

Daniel Feldmeyer

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# NOTATION

| Abbreviation | Elaboration |
|---|---|
| **ANZ** | Australia/New Zealand |
| **ARP** | Arabian Peninsula |
| **BMBF** | German Federal Ministry of Education and Research |
| **CAF** | Central Africa |
| **CAR** | Caribbean |
| **CEA** | Central E. Africa |
| **CEU** | Central Europe |
| **CRI** | City Resilience Index |
| **DNN** | Deep neural networks |
| **EAS** | E. Asia |
| **EB** | E. Siberia |
| **EERI** | Empirical Evidence Resilience Index |
| **EMBRACE** | Building Resilience Amongst Communities in Europe |
| **EM-DAT** | Emergency and Event Data Base |
| **EmRI** | Empirical Risk Index |
| **GIC** | Greenland/Iceland |
| **GIS** | Geographic Information System |
| **INFORM** | Index for Risk Management |
| **IOC** | Indian Ocean |
| **IOER** | Leibniz Institute of Ecological Urban and Regional Development |
| **IPCC** | Intergovernmental Panel on Climate Change |
| **LR** | Linear Regression |
| **MAE** | Mean Absolute Error |
| **MED** | Mediterranean |
| **MIS** | MONARES Indicator Set |
| **MONARES** | Monitoring of Adaption Measures and Climate Resilience in Cities |
| **MSE** | Mean Squared Error |
| **NCA** | N. Central America |
| **NEA** | N. E. Africa |
| **NES** | N.E. South America |
| **NEU** | N. Europe |
| **NNA** | N. North America |

| | |
|---|---|
| **NPO** | N. Pacific Ocean |
| **NSA** | N. South America |
| **NWS** | N.W. South America |
| **OECD** | Organisation for Economic Co-operation and Development |
| **ORI** | Open Resilience Index |
| **OSM** | OpenStreetMap |
| **PFI** | Feature Performance Index |
| **RAR** | Russian Arctic |
| **RF** | Random Forest |
| **RP** | Random Prediction |
| **SAF** | S.E. Africa |
| **SAH** | Sahara |
| **SAM** | South American Monsoon |
| **SAS** | S. Asia |
| **SCA** | S. Central America |
| **SDG** | Sustainable Development Goal |
| **SEA** | S.E. Asia |
| **SES** | S.E. South America |
| **SPO** | S. Equatorial Pacific Ocean |
| **SSA** | S. South America |
| **SWA** | S.W. Africa |
| **SWS** | S. W. South America |
| **TIB** | Tibetan Plateau |
| **UN** | United Nations |
| **UNFCC** | United Nations Framework Convention on Climate Change |
| **WAF** | W. Africa |
| **WCA** | W. Central Asia |
| **WRI** | WorldRiskIndex |
| **WSB** | W. Siberia/E. Europe |
| **BMEL** | Federal Ministry of Food and Agriculture |
| **BA** | Federal Employment Agency |
| **BKK** | Company Health Insurance |
| **RCRI** | Regional Climate Resilience Index |

# SUMMARY

Climate resilience on all spatial scales is an imperative to tackle climate change. Facing climate change, a reactive and backward-faced disaster and risk management does not meet the upcoming threats. Natural hazards are projected to increase in frequency and magnitude and thus require anticipation and early warning on a local and global scale. The problem for the local societies is not only the increase but also the exposure to new and unknown hazards. Therefore, risk reduction and an increase in resilience are key and core objectives of the Sendai Framework, the Paris Agreement, Sustainable Development Goals, the New Urban Agenda and also, on the national scale, a priority of the German research initiative “Zukunftsstadt”.

Unfortunately, the very nature of climate resilience has - despite an exponential increase of literature addressing the problem over the last decade - not yet been unveiled. In this sense, climate resilience is not a state of a fluent socio-ecological system but a goal that can never be achieved. Moreover, Germany´s climate is different to South Africa´s and even Stuttgart´s to Hamburg´s. Moreover, the vulnerability to the impacts of climate change and the resilience vary from Germany to South Africa, even from Stuttgart to Hamburg.

The overarching goal of this thesis is to develop, test and improve methods to assess risk, resilience at different scales to help strengthening climate resilience. To accomplish this goal, climate resilience needs to be monitored and evaluated. The operationalization of resilience and risk is a broad research field. The assessment requires multiple spatial scales, complex data and challenging validation in order to measure the phenomenon. I therefore approached the goal from the spatial, validation as well as data perspective leading to five main contributions:

**Urban climate resilience indicators.** Firstly, I defined climate resilience and collected a master list of all indicators used in literature to measure and monitor resilience. These indicators were neither specific for Germany nor all on the same spatial scale. In order to condense a set of indicators for Germany, I developed a participatory iterative methodology including scientists and practitioners. From the master list, indicators were filtered by the urban resilience framework and via survey, scientists and practitioners asked to evaluate the set. The results were then presented on a workshop, followed by working groups refining and

overturning the survey results. Lastly, expert interviews closed gaps defined by the experts within the indicator set.

Resilience indicators implemented in literature are often ambiguous in regard of the effect on resilience they are measuring. This requires the adaptation and validation to the specific context and objective. In balancing the competing goals of applicability and comprehensiveness, twenty-four indicators measuring five dimensions and twenty action fields compromised best. In favour of applicability, the approach is based on secondary data despite the acknowledgment of limitations in measuring climate resilience. Especially softer and qualitative factors of resilience - although no less important - are not yet adequately captured by secondary data. Still, in light of monitoring, municipalities lack resources in the sense of labour and knowledge to collect qualitative data on a regular basis.

**Development of a sub-national resilience index and empirical validation.** Based on the previous contribution on urban scale, the first question was to determine the next higher spatial scale and administrative resolution to assess climate resilience. The decision was to choose Baden-Württemberg as the spatial scale with its counties as the resolution due to their responsibilities in the federal system concerning climate resilience topics. Starting from the operationalization of urban resilience, a set of indicators for counties was developed. Additionally, indices in general and resilience indices in particular are, by nature, controversial and validation to foster legitimacy and transparency is essential but rarely conducted. The intense discussion about indicators and their link to climate resilience underlined this point. Therefore, a new methodology with a two-stage supervised machine learning validation approach including empirical data was developed.

The statistical approach of the Wroclaw taxonomic method for index aggregation superseded all other aggregation methods. Consequently, it was selected for the final index and further analysis. None of the five spheres (environment, infrastructure, economy, governance and social) was excluded by the validation. Hence, all of them contributed to county climate resilience. The metropolitan counties had a statistically significant higher level of overall resilience compared to rural counties, despite lower environmental resilience. Life expectancy as one outcome for validation of resilience was able to capture many aspects of climate resilience as defined. The index did not explain insurance damages well, which was partly expected due to the spatial scale and is in line with literature. Nevertheless, further research is needed to better understand this aspect.

**Crowdsourced geodata.** Especially in the context of climate resilience - the previous two studies confirmed that data availability is the major limitation. Firstly, official data are linked to administrative boundaries, and secondly not covering qualitative factors. OpenStreetMap is a global database across administrative boundaries and hidden within qualitative attributes of municipalities. In this context the dissertation examined where and if so - how - such crowdsourced data could be used and applied for resilience assessments. Therefore, the study develops a methodology to deduce such attributes for municipalities in Baden-Württemberg by means of machine learning. Number of residents, migration, proportion of elderly people and unemployment were predicted based on OpenStreetMap data.

In increasing order by means of the mean absolute error, most reliably predicted was the number of residents, followed by migration, elderly people and unemployment. Statistically, Neural Nets performed best. Still, the interpretation of Neural Nets provides difficulties as well and so does finding the best model. OpenStreetMap provides a unique data source to better understand complex interdisciplinary and multifaceted phenomena like vulnerability, sustainability or resilience. Further analysis is needed to test the transferability of models amongst regions and countries in order to deduce spatially fully scalable indicators from local to global meaningful socio-economic indicators.

**Global hotspots of vulnerability.** Negative climate consequences rise not only due to the increase in frequency and magnitude of events, but are rather the result of the combination with the vulnerability of the exposed socio-economic system. Despite the general agreement of the importance of vulnerability, complexity and interdisciplinarity of the topic resulted in manifold definitions and approaches, consequently questioning the robustness and legitimacy of each approach. Moreover, socio-economic vulnerability is not available on the spatial scale of physically-derived climate regions. In order to provide a more robust and administrative cross-border information basis for risk reduction and resilience building, this research compares existing composite indices on the level of the IPCC climate regions. Therefore an approach is developed to aggregate socio-economic vulnerability on climate regions and assess the robustness of the approach.

The results show that, despite differences between the approaches, the agreement of the approaches is high regarding the most vulnerable areas. The persistence of vulnerability in those regions requires transboundary pooling of resources and international assistance. High resolution hazard detection will not contribute to solving deep-rooted human vulnerability.

Instead, building capacities on local, national and transnational level is needed in order to provide enabling conditions and build a sustainable, resilient future.

**Nation´s resilience investigated by disaster data and crowdsourced geodata.** The accepted approach in constructing an index is by starting off with a framework operationalizing the phenomenon. Nevertheless, this means introducing some degree of subjectivity and narrowing down the number of indicators under consideration. To overcome this within this research firstly, a resilience index based on empirical disaster data and theoretical risk is developed. Secondly, with OpenStreetMap, a global database is selected covering qualitative and social as well as environmental and economic attributes. In order to investigate resilience in a first step, this entire database is used to predict the empirical resilience index and hence important attributes deduced therefrom. The most relevant attributes for resilience are: identity and mobility, sustainable infrastructure, social fabric, material supply and social infrastructure. The main conclusion is that resilience is scale- and place-specific. Moreover, social factors cannot be overestimated and to quantify them for being considered within global adaptation strategies, they need to be provided on a global level. Only official data sources do not cover resilience and therefore mining of OpenStreetMap complemented existing official data usefully. Still, the complexity of data mining overwhelms local authorities. Resilience is not yet understood.

# KURZFASSUNG

Klimaresilienz auf allen räumlichen Skalen ist imperativ, um die vor uns liegenden Herausforderungen zu bewältigen. Angesichts des Klimawandels ist ein reaktives und rückwärtsgewandtes Katastrophen- und Risikomanagement den anstehenden Herausforderungen nicht gewachsen. Naturgefahren werden voraussichtlich in Häufigkeit und Ausmaß zunehmen und die Antizipation derselben ist somit auf lokaler und globaler Ebene erforderlich. Das Problem ist also nicht nur die Zunahme, sondern auch die Exposition gegenüber neuen und unbekannten Gefahren für die lokalen Gesellschaften. Obwohl im Allgemeinen Modelle die Folgen des Klimawandels bereits recht gut vorhersagen, sind die sehr lokalen Auswirkungen auf den Umfang der Anpassungsmaßnahmen mit hoher Unsicherheit behaftet. Daher ist die Erhöhung der Widerstandsfähigkeit Teil der Ziele der nachhaltigen Entwicklung, der Neuen Städtischen Agenda und auch auf nationaler Ebene Priorität der deutschen Forschungsinitiative "Zukunftsstadt".

Leider ist das Wesen der Klimaresilienz trotz einer exponentiellen Zunahme der Literatur, die sich in den letzten zehn Jahren mit dem Problem befasst hat, noch nicht enthüllt worden und wird es auch nicht werden. In diesem Sinne ist Klimaresilienz kein Zustand eines fließenden sozio-ökologischen Systems, sondern ein nie erreichtes Ziel. Darüber hinaus unterscheidet sich die Klimaresilienz Deutschlands von der Südafrikas, ja sogar die Stuttgarts von der Klimaresilienz Hamburgs. Die Leitfragen für Resilienz sind: Resilienz für wen, was, wann, wo und warum?

Das übergreifende Ziel dieser These ist die Stärkung der Klimaresilienz. Um dieses Ziel zu erreichen, muss die Klimaresilienz gemessen und bewertet werden. Die Operationalisierung dazu erfordert mehrere räumliche Skalen und Daten zur Messung des Phänomens. Daher erforsche ich das Ziel sowohl aus der räumlichen als auch aus der Datenperspektive, was zu fünf Hauptbeiträgen führt:

**Städtische Klima-Resilienz-Indikatoren** - Zunächst definierte ich die Klimaresilienz und sammelte eine Masterliste aller Indikatoren, die in der Literatur zur Messung der Resilienz für Monitoring verwendet werden. Diese Indikatoren waren weder spezifisch für Deutschland noch alle auf der gleichen räumlichen Skala. Um eine Reihe von Indikatoren für Deutschland zu verdichten, entwickelte ich eine partizipative iterative Methodik unter Einbeziehung von

Wissenschaftlern und Praktikern. Aus der Masterliste wurden die Indikatoren durch das Rahmenwerk zur städtischen Resilienz gefiltert und über eine Umfrage Wissenschaftler und Praktiker gebeten, die Indikatoren zu bewerten. Die Ergebnisse wurden dann auf einem Workshop Arbeitsgruppen vorgestellt, die diese verfeinerten. Schließlich füllten Experteninterviews die von den Experten definierten Lücken innerhalb des Indikatorensatzes aus.

Während des Workshops wurde oft das Verhältnis von literaturbasierten Indikatoren zur Klimaresilienz diskutiert und in Frage gestellt. Bei der Abwägung der konkurrierenden Ziele der Anwendbarkeit und des Umfangs wurden die 24 Indikatoren, die die fünf Dimensionen und zwanzig Handlungsfelder am besten messen, berücksichtigt. Zu Gunsten der Anwendbarkeit bestand ein starker Konsens darin, sich auf Sekundärdaten zu stützen, obwohl man sich der Grenzen bei der Messung der Klimaresilienz bewusst war. Insbesondere weichere und qualitative Faktoren, obzwar nicht weniger wichtig, werden durch Sekundärdaten noch nicht angemessen erfasst. Dennoch fehlt es den Kommunen im Hinblick auf das Monitoring an Ressourcen im Sinne von Arbeitskraft und Wissen, um regelmäßig qualitative Daten zu erheben.

**Regionaler Klimaresilienzindex und empirische Validierung** - basierend auf dem vorherigen Beitrag zur städtischen Skala war die erste Frage die Bestimmung der nächsten räumlichen Skala. Die übergeordnete räumliche Skala war Baden-Württemberg und die räumlich auflösenden Landkreise aufgrund ihrer Zuständigkeiten im föderalen System in Bezug auf Themen der Klimaresilienz. Ausgehend von der Operationalisierung der urbanen Resilienz wurde ein Indikatorensatz für die Kreise entwickelt. Zusätzlich sind Indizes im Allgemeinen und Resilienzindizes im Besonderen naturgemäß umstritten und eine Validierung zur Förderung von Legitimität und Transparenz ist unerlässlich. Die intensive Diskussion über Indikatoren und ihre Verbindung zur Klimaresilienz unterstrich diesen Punkt. Daher wurde eine Methodik mit einer zweistufigen Validierung mit empirischen Daten und einschließlich statistischer Validierung entwickelt.

Der statistische Ansatz der Wrozlaw-Methode zur Indexaggregation konnte besser als die anderen Methoden die unterschiedlichen Daten homogenisieren und aggregieren. Folglich wurde diese Methode für den endgültigen Index und die weitere Analyse ausgewählt. Keiner der fünf Bereiche Umwelt, Infrastruktur, Wirtschaft, Governance und Soziales wurde von der Validierung ausgeschlossen. Daher tragen sie alle zur Klimaresistenz bei. Die großstädtischen Bezirke hatten eine statistisch signifikant höhere Gesamtresilienz im Vergleich zu ländlichen

Bezirken, trotz geringerer Umweltresilienz. Die Lebenserwartung, als ein Ergebnis der Validierung der Resilienz, konnte viele Aspekte der definierten Klimaresilienz erfassen. Weniger gut wurden Versicherungsschäden durch den Index erklärt, was zum Teil aufgrund der räumlichen Skala erwartet wurde und mit der Literatur übereinstimmt. Dennoch sind weitere Forschungsarbeiten erforderlich, um dies besser zu verstehen.

**Ableitung von sozialökonomischen Indikatoren aus OpenStreetMap**. Insbesondere im Kontext der Klimaresistenz - zeigten die beiden vorangegangenen Studien die Abhängigkeit von Daten auf. Einmal sind amtliche Daten mit administrativen Grenzen verknüpft und zweitens decken sie keine qualitativen Faktoren ab. OpenStreetMap ist eine globale Datenbank über Verwaltungsgrenzen hinweg und beinhaltet versteckt qualitative Attribute von Gemeinden. Die Studie entwickelt daher eine Methodik, um solche Attribute für Kommunen in Baden-Württemberg mit Hilfe des maschinellen Lernens abzuleiten. Anzahl der Einwohner, Migration, Anteil älterer Menschen und Arbeitslosigkeit wurden auf Grundlage von OpenStreetMap-Daten vorhergesagt.

In absteigender Reihenfolge anhand des mittleren absoluten Fehlers bewertet war die Zahl der Einwohner am besten vorhergesagt, gefolgt von Migration, Anteil älterer Menschen und Arbeitslosigkeit. Statistisch gesehen schnitten die neuronalen Netze besser ab wie die nächste Methode. Dennoch bereitet die Interpretation der neuronalen Netze Schwierigkeiten, ebenso wie die Suche nach dem besten Modell. OpenStreetMap bietet eine einzigartige Datenquelle, um komplexe, interdisziplinäre und vielschichtige Phänomene wie Verwundbarkeit, Nachhaltigkeit oder Resilienz besser zu verstehen. Weitere Analysen sind erforderlich, um die Übertragbarkeit von Modellen zwischen Regionen und Ländern zu testen, um räumlich voll skalierbare, von lokal bis global aussagekräftige sozioökonomische Indikatoren abzuleiten.

**Globale Hotspots der Verwundbarkeit und Klimaregionen** - zwei wichtige Forschungsfragen, die zuvor diskutiert wurden, sind: a) die Beschränkung der Daten auf die Ebene der Verwaltungsgrenzen und ihre Inkongruenz mit dem Problemraum; b) die unbekannte Unsicherheit und Robustheit zusammengesetzter Indikatoren bei der Erfassung von vielschichtigen Phänomenen.

Negative Klimafolgen sind nicht nur auf die Häufigkeit und das Ausmaß eines Ereignisses zurückzuführen, sondern vielmehr das Ergebnis der Kombination mit der Verwundbarkeit des exponierten sozioökonomischen Systems. Trotz des allgemeinen Einvernehmens über die Bedeutung der Verwundbarkeit führen die Komplexität und Interdisziplinarität des Themas zu vielfältigen Definitionen und Ansätzen, die die Robustheit und Legitimität jedes einzelnen Ansatzes in Frage stellten. Um eine robustere und administrative Grenzen überschreitende Informationsbasis für die Risikominderung und den Aufbau von Widerstandsfähigkeit zu schaffen, vergleicht diese Forschung bestehende zusammengesetzte Indizes auf der Skalenebene der IPCC-Klimaregionen. Die Ergebnisse zeigen, dass trotz der Unterschiede zwischen den Ansätzen die Übereinstimmung der Ansätze in Bezug auf die am stärksten gefährdeten Gebiete hoch ist. Das Fortbestehen der Verwundbarkeit in diesen Regionen erfordert die grenzüberschreitende Bündelung von Ressourcen und internationale Unterstützung. Eine hochauflösende Gefahrenerkennung wird nicht zur Lösung der tief verwurzelten menschlichen Verwundbarkeit beitragen. Stattdessen ist der Aufbau von Kapazitäten auf lokaler, nationaler und transnationaler Ebene erforderlich, um günstige Bedingungen zu schaffen und eine nachhaltig widerstandsfähige Zukunft aufzubauen.

**Nationale Klimaresilienz anhand von Katastrophendaten und OpenStreetMap** - der akzeptierte Ansatz für die Erstellung eines Index besteht darin, mit einem Rahmen zu beginnen, der das Phänomen operationalisiert. Dies bedeutet jedoch, dass ein gewisser Grad an Subjektivität eingeführt und die Anzahl der untersuchten Indikatoren eingegrenzt werden muss. Um dies im Rahmen dieser Forschung zu überwinden, wird zunächst ein auf empirischen Katastrophendaten und theoretischer Vulnerabilität basierender Resilienzindex entwickelt. Zweitens wird mit OpenStreetMap eine globale Datenbank ausgewählt, die sowohl qualitative und soziale als auch ökologische und ökonomische Attribute abdeckt. Um die Resilienz zu untersuchen, wird in einem ersten Schritt diese gesamte Datenbank verwendet, um den empirischen Resilienzindex vorherzusagen und daraus wichtige Attribute abzuleiten. Die für die Resilienz relevantesten Attribute sind: Identität und Mobilität, nachhaltige Infrastruktur, soziales Gefüge, Materialversorgung, soziale Infrastruktur. Die wichtigste Schlussfolgerung ist, dass Resilienz maßstabs- und ortsspezifisch ist. Darüber hinaus können soziale Faktoren nicht überschätzt werden und um sie für die Berücksichtigung in globalen Anpassungsstrategien quantifizieren zu können, müssen sie auf globaler Ebene bereitgestellt werden. Nur offizielle Datenquellen decken die Resilienz nicht ab und Data Mining stellt daher eine wertvolle Ergänzung dar.

# FIRST CHAPTER

# INTRODUCTION

## 1.1 MOTIVATION

*Climate change and its negative consequences plunged from the future into our lives!*

Or - in other words - climate change has become a reality for many people around the globe who are already facing and fighting it. However, the consequences and impacts of climate change significantly depend on the living conditions of human society.

Concerning natural hazards (also associated with climatic changes), an increase in frequency and magnitude is projected, which can threaten the human and environmental systems (IPCC 2012). In addition, megatrends of an increasing world population and its urbanization stressing the human dimension and asking the question how to provide and secure the quality of life in some regions of the world and increase it in others. Climate change not only poses a threat but also provides opportunities. However, these opportunities and challenges will not be equally distributed across the globe. Hence, the inherent challenge will be how to trade and balance those challenges as well as opportunities. Moreover, industrialized, developed countries that have caused climate change are more likely to benefit, whereas least developed countries are more likely to suffer harm.

The analysis and management of natural hazards has a long scientific tradition. Across the European Alps, despite 90 years of hazard mitigation, implementation and spending of public money to reduce risk, losses increased documenting a missing part of the strategy (Fuchs et al. 2017). Sustainability, vulnerability and resilience are three concepts often applied in natural hazard and climate change literature and therefore defined in the following, for the clarity of this work.

Sustainability was first defined in the Brundtland report: "Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs." (Brundtland et al. 1987). United Nation's Sustainable

Development Goals (SDGs) have further provided a pathway to bring sustainability in human and environmental systems. For example, goal 1 explicitly targets to “build the resilience of the poor and those in vulnerable situations, and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters” (UN 2015).

To understand risk and its development the “social construction of risk” (Garschagen and Romero-Lankao 2015) is fundamental where vulnerability emerged as a prominent concept (Birkmann 2013). Vulnerability is defined by the IPCC as “the propensity or predisposition to be adversely affected” (IPCC 2012). A system can be adversely affected when it is susceptible to a hazardous event and lacks the necessary capacities to cope or adapt to such an event (IPCC 2018). Coping capacity is “the ability of people, institutions, organizations, and systems, using available skills, values, beliefs, resources, and opportunities, to address, manage, and overcome adverse conditions in the short to medium term” (IPCC 2018). Adaptive capacity is defined by the IPCC as “the ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences” (IPCC 2018).

In the realm of natural hazards, resilience became increasingly important and documented by an exponential increase in literature. Nevertheless, the term itself dates back a long time. Alexander (2013) sees the first use of the term in mechanics in 1858. Here, the Scottish engineer William J.M. Rankine (1820-72) used it to summarize the abilities (strength, ductility) of steel beams. In the 1950s the term was used in psychology. Werner et al. (1971) used it to describe children who were better able to recover from similar traumata. Two years later Holling (1973) used the term for ecological systems and defined it as the “measure of persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationship between population or state variables”. Just before the turn of the millennium in the context of an increasing discussion on climate change, the term resilience also made its way to describe spatial entities like cities or regions in light of adaptation (Mileti 1999).

To understand how the term is used and applied in academia, Meerow analysed 57 definitions of resilience. Regarding the fundamental understanding of the term of “bouncing back” vs. “bouncing forward” or both, the majority of definitions define or understand resilience as “bouncing back” (Meerow et al. 2016). Nevertheless, in urban planning, the window of opportunity widely opened by a disaster, leads to a more dynamic understanding. This understanding is also supported by Figueiredo et al. (2018), who stresses the change in understanding resilience towards an evolutionary and transformational interpretation.

In this context, adaptation "refers to adjustments in ecological, social, or economic systems in response to actual or expected climatic stimuli and their impacts. It refers to changes in processes, practices, and structures to moderate potential damages or to benefit from opportunities associated with climate change" (UNFCCC) and is part of resilience (Folke et al. 2010). Considering the spatial specificity, urban climate resilience is defined by Feldmeyer et al. (2019b) as"the climate resilience of a city depends on the ability of its sub-systems to anticipate the consequences of extreme weather and climate change, to resist the negative consequences of these events and to recover essential functions after disturbance quickly, as well as to learn from these events and to adapt to the consequences of climate change in the short and medium-term, and transform in the long term. The more pronounced these abilities are, the more resilient a city is to the consequences of climate change."

The overarching goal of this thesis is to improve ways to capture and operationalize multi-faceted concepts through new methods and data mining for assessing vulnerability, urban resilience, sub-national and national resilience.

## 1.2 State of the Art

Vulnerability and resilience are two concepts, which gained increased attention over the last two decades. Although distinct concepts, the same thematic goal of reducing negative impacts due to natural hazards and climate-induced stresses, led to intermingled and varying definitions, even conflicting ones.

**Measuring vulnerability**

Vulnerability is defined by the IPCC (2012) as "the propensity or predisposition to be adversely affected". The operationalization of this general definition requires scale- and hazard-specific elements. Different approaches exist globally to measure vulnerability on the country scale (ND-GAIN 2019; INFORM 2019; Germanwatch 2019; Birkmann and Welle 2016). Within the WorldRiskIndex (Welle and Birkmann 2015; Birkmann and Welle 2016) vulnerability consists of three pillars: susceptibility, the likelihood of suffering harm;

coping capacity, capacities to reduce negative consequences; adaptive capacity, capacities for long-term strategies for societal change (Welle and Birkmann 2015)(Fig. 1). Within the ND-GAIN (2019), exposure is part of vulnerability besides sensitivity and adaptive capacity. The INFORM (2019), in contrast, does not include the lack of coping capacity within vulnerability but rather separates it as its own concept. The vulnerability part is split by the INFORM-approach into a socio-economic and vulnerable groups' dimension.

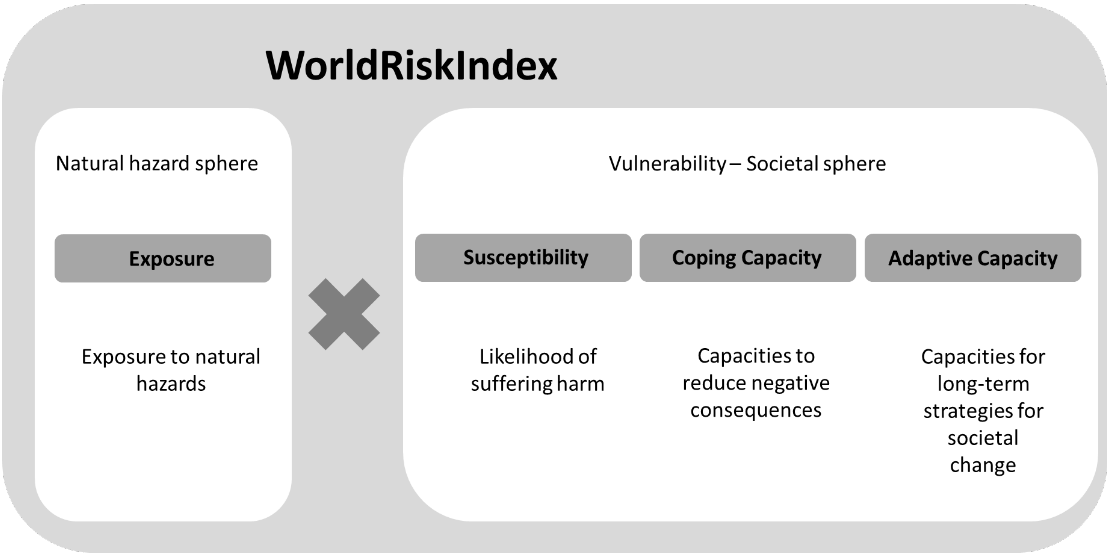



FIGURE 1. WORLDRISKINDEX MAIN CALCULATION SCHEME (WELLE AND BIRKMANN 2015)

Other approaches include multiple stressors (O'Brien et al. 2004) or include specific aspects, for example, heat waves (Depietri et al. 2013; Welle et al. 2014). Similar approaches exist for flash floods (Karagiorgos et al. 2016), tsunamis (Birkmann et al. 2010; Jelínek et al. 2012) or with thematic special focus on cultural heritage (Vojinovic et al. 2016; Ravankhah et al. 2017a; Ravankhah et al. 2017b; Ravankhah et al. 2019). Another thematic focus is to concentrate on rural-urban linkages as important connections for the rural community, hence fundamentally shaping vulnerability of rural communities (Jamshed et al. 2020a; Jamshed et al. 2020b; Jamshed et al. 2020c).

Cities are of special interest on a national level. The adapted BBC framework for the city of Cádiz measures the vulnerability to tsunamis based on exposure susceptibility and coping capacity (Bogardi, Birkmann, Cardona Framework developed in 2004, for more details see Birkmann 2013b: 54). The assessment developed by Karagiorgos (2016) combines a physical and social component to vulnerability. The assessment of heat waves within the city of Cologne (Germany), based on the MOVE framework, deconstructs vulnerability into exposure, susceptibility and lack of resilience (Depietri et al. 2013, Birkmann et al. 2013). Two major challenges remain: First, as shown earlier that numerous approaches exist but no agreed-upon assessment of vulnerability exists while the robustness of the vulnerability assessment and its congruence with other assessments is missing. Second, on a global scale, physical climate regions define the exposure element, but socio-economic data are only available on administrative scales. Therefore, vulnerability assessments are only conducted on a national scale or sub-national scale.

**Measuring resilience**

Resilience is not resilience is the common denominator. Therefore, frameworks have been developed for different objectives (Table 1). Some studies explicitly name climate change as an objective where others do not. Another difference is, whether resilience is rather seen as a general concept against "any" hazard or closely linked to a specific hazard. The aspect of monitoring adds another quality to requirements. Whereas, in a single assessment, the completeness is crucial, for monitoring also the effort necessary becomes crucial. The fact of climate change makes it indispensable to pay tribute to an evolving, changing, fluent status.

TABLE 1. RESILIENCE FRAMEWORKS

| **Framework** | **Author** | **Climate** | **Hazard** | **M&E** |
|---|---|---|---|---|
| Building resilience amongst communities in Europe | Birkmann et al. (2012) | no | multiple hazards | no |
| Urban climate resilience | ARUP and The Rockefeller Foundation (2015) | yes | multiple hazards | no |
| Design, monitoring and evaluation of resilience interventions: conceptual and empirical considerations | Béné et al. (2015) | no | multiple hazards | yes |
| Assessing and monitoring climate resilience | Welle et al. (2014) | yes | multiple hazards | yes |
| Baseline resilience indicators for communities | Cutter et al. (2010) | yes | multiple hazards | yes |
| Smart mature resilience | ICLEI Europe (2017) | yes | multiple hazards | yes |
| Monitor nachhaltige Kommune | Riedel et al. (2016) | yes | multiple hazards | yes |
| Asian cities climate change resilience | Rockefeller (2014) | yes | multiple hazards | yes |
| The PEOPLES resilience framework | Renschler et al. (2010) | no | multiple hazards | no |

| | | | | |
|---|---|---|---|---|
| San Francisco planning and urban research association (SPUR) | Poland (2008) | no | earthquake | no |
| The Oregon resilience plan | Oregon Seismic Safety Policy Advisory Commission (2013) | no | earthquake | no |
| Disaster resilience scorecard for cities | UNISDR (2017) | yes | multiple hazards, not only CC | no |
| Community resilience system | Plodinec et al. (2014) | yes | multiple hazards, not only CC | yes |
| Community advancing resilience toolkit | Pfefferbaum et al. (2015) | no | multiple hazards, not only CC | no |
| Coastal community resilience indicators and rating systems | NOAA (2015) | yes | multiple hazards | no |
| The concept for community resilience indicators | Mitigation Framework Leadership Group (2016) | yes | multiple hazards | no |
| A measurement of community disaster resilience in Korea | Yoon et al. (2016) | no | multiple hazards | no |
| A localized disaster-resilience index to assess coastal communities based on an analytic hierarchy process (AHP) | Orencio and Fujii (2013) | no | multiple hazards | no |
| Community based resilience analysis | UNDP (2013) | yes | multiple hazards | yes |
| A framework for urban climate resilience | Tyler and Moench (2012) | yes | multiple hazards | yes |

Each of the above frameworks defines resilience in a slightly different way. However, most of them apply a hierarchical structure, defining main dimensions or themes which, again, are split into sub-themes. The naming of the categories and levels is different from framework to framework. Additional to the categories, in most frameworks, also abilities are introduced (Fig. 7). Despite many approaches, a lack of empirical validation of climate resilience indicators and indices exist (Bakkensen et al. 2017; Burton 2015). This also partly explains the multitude of approaches and limits the explanatory power of existing approaches due to the fact that the effect is not included and assessed. Composite indicators used to measure multifaceted phenomena are criticized in this regard as to be subjective in the selection of indicators, the often unclear impact of the aggregation method, the increased amount of data needed and being non-robust (Salteli 2007).

The framework of ARUP and the Rockefeller Foundation (2015) defines four categories on the first hierarchical level: “Economy & society”, “Infrastructure & ecosystems”, “Leadership & strategy”, “Health & wellbeing” (Fig. 2). Each dimension is split into three sub-dimensions, each of which consists of several indicators to measure and quantify the sub-dimension. The abilities are added to the concept in such a way that, for each sub-theme, the contribution to the ability is defined. As initially stressed, resilience is specific to place, objectives and scale. In the context of Germany, a research initiative funded by the Ministry of Education and Research (BMBF) funds multiple projects under the roof of resilience.

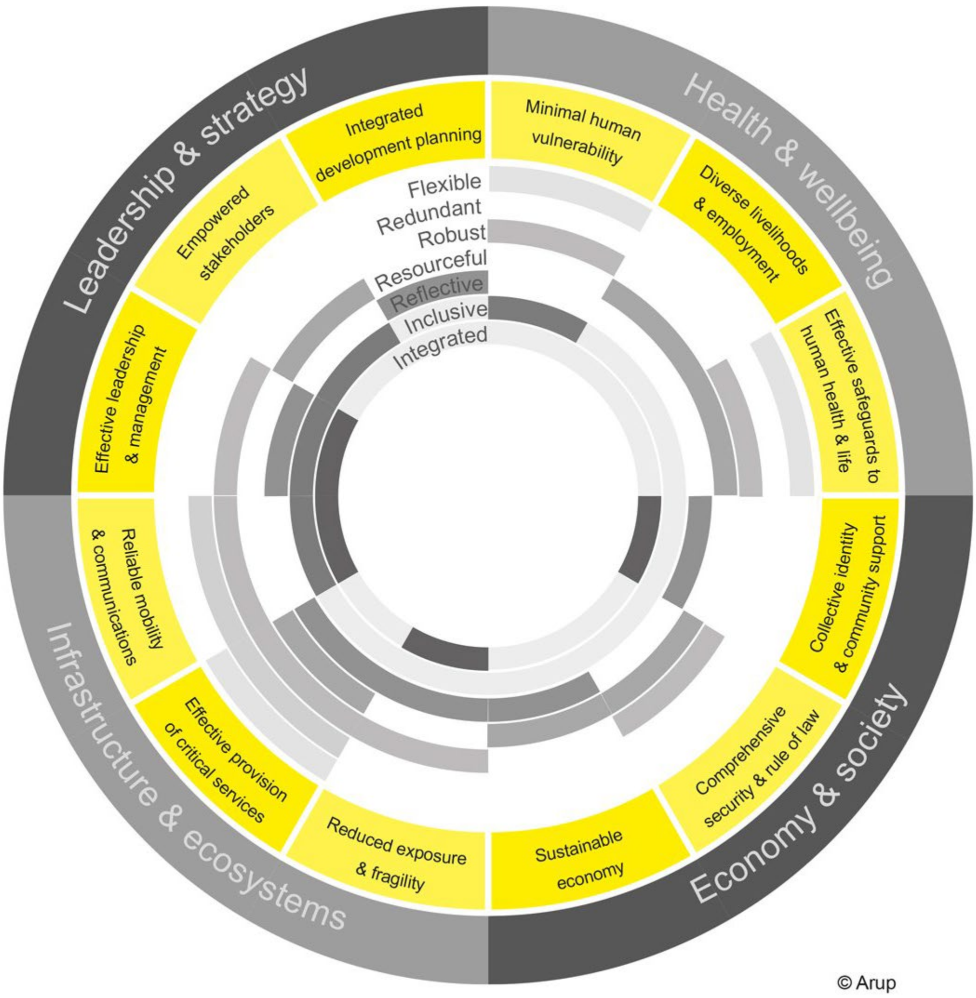



**FIGURE 2. URBAN RESILIENCE FRAMEWORK (ARUP AND THE ROCKEFELLER FOUNDATION 2015)**

The cross-cutting project within the funding initiative Monitoring and Evaluating Urban Climate Resilience (MONARES) focuses on building the roof. Urban climate resilience is - within this context - built by five dimensions (Governance, Economy, Society, Environment, Infrastructure) and six abilities (transform, anticipate, resist, adapt, learn, recover) (Fig 3). Each main dimension is further divided into action fields (Table 2). A total of 24 action fields define and refine important aspects of urban climate resilience. In this way, the framework identifies areas to be measured and monitored. The challenge is how to include and approach the context-specificity and the changing nature of risk (Figueiredo et al. 2018) in this framework. No German urban and regional set of climate resilience indicators exists, which is important as international indicators cannot simply be transferred to the context of Germany due to the aforementioned reason.

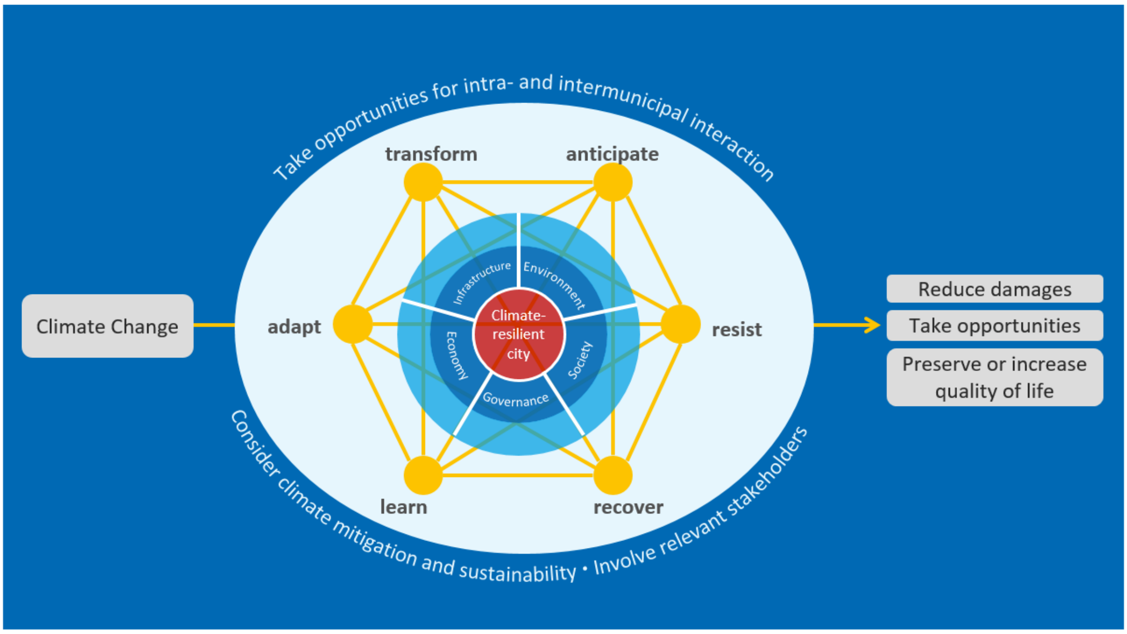



FIGURE 3. CLIMATE RESILIENCE FRAMEWORK FOR GERMANY (KIND ET AL. 2019)

TABLE 2. DIMENSIONS AND ACTION FIELDS OF THE RESILIENCE FRAMEWORK (FELDMEYER ET AL 2019)

| **Dimension** | **Action Field** |
|---|---|
| Environment | Soil and green spaces |
| | Water bodies |
| | Biodiversity |
| | Air |
| Infrastructure | Settlement structure |
| | Energy |
| | Telecommunication |
| | Traffic |
| | Drinking and wastewater |
| Economy | Innovation |

| | |
|---|---|
| | Business |
| | Economic structure |
| Society | Research |
| | Knowledge and risk competence |
| | Health care |
| | Socio-demographic structure |
| | Civil society |
| | Civil protection |
| Governance | Participation |
| | Municipal budget |
| | Strategy, plans and environment |
| | Administration |

In a study about specific indicators in literature, Cutter (2016) analysed the frequency of how often specific indicators are used by different studies to deduce indicators agreed on in scientific literature. The scientific core of resilience measurements comprises 19 specific indicators (Table 3).

**TABLE 3. RESILIENCE MEASUREMENT CORE (CUTTER 2016)**

| **Attribute/assets** | **Capacities** | **Most often used proxy variable** |
|---|---|---|
| Economic | | Income (median household) |
| Social | | Educational attainment/equality; health care access (number of doctors) |
| | Social capital | Civic organizations (number); religious organizations/adherents (number) |
| Institutional | | Mitigation plans (% population covered), mitigation activities (number), or mitigation spending (per capita) |
| | Community assets and functions | Community services (number), community helping |
| Information/communication | Information/communication | Prior experience with recovery, learning from the past; hazard severity |
| Infrastructure | | Buildings of various types (emergency management; government, power, bridges, commercial) |
| | Connectivity | Feeling of belonging to the community; proximity to urban areas |
| | Emergency management | Shelters, evacuation routes |
| Environmental | | Impervious surfaces |

Although those indicators are most often applied in measuring resilience, the set does not represent a commonly agreed set of indicators on how to measure resilience. An important aspect of climate resilience is the social dimension (e.g. community helping, feeling of belonging), which is rarely sufficiently addressed due to a lack of data of such soft elements (Cutter 2008b; Sorg et al. 2018; Feldmeyer et al. 2019b; Schaefer et al. 2020).

**Linkages between resilience and vulnerability**

For the relation between the concept of resilience and vulnerability, no stand-alone definition exists. The study of Yoon et al. (2016) analysed the relation of vulnerability, resilience and adaptation in the literature (Fig. 4). This analysis revealed a highly ambivalent and inconsistent use of the different concepts with regard to one another. Resilience is here seen as part of the adaptive capacity or vice a versa. Similar, vulnerability and resilience, where resilience is used as a part to explain vulnerability or as a separate concept but with some overlay, the relations of the concepts are not defined universally. Considering all three concepts, adaptive capacity is seen in literature as the exact intersection of resilience and vulnerability, but also in other hierarchical sequences. Cutter et al. (2014) in a data-driven analysis of resilience and vulnerability, determined a mainly negative correlation, as expected, for the two concepts, but with some common areas. Sherrieb et al. (2010), in their analysis of resilience and vulnerability, state a 25% overlay, which consists mainly of social and economic attributes. Other attributes like infrastructure, institutional, environmental and community capital of this resilience assessment were inconsistent with vulnerability.

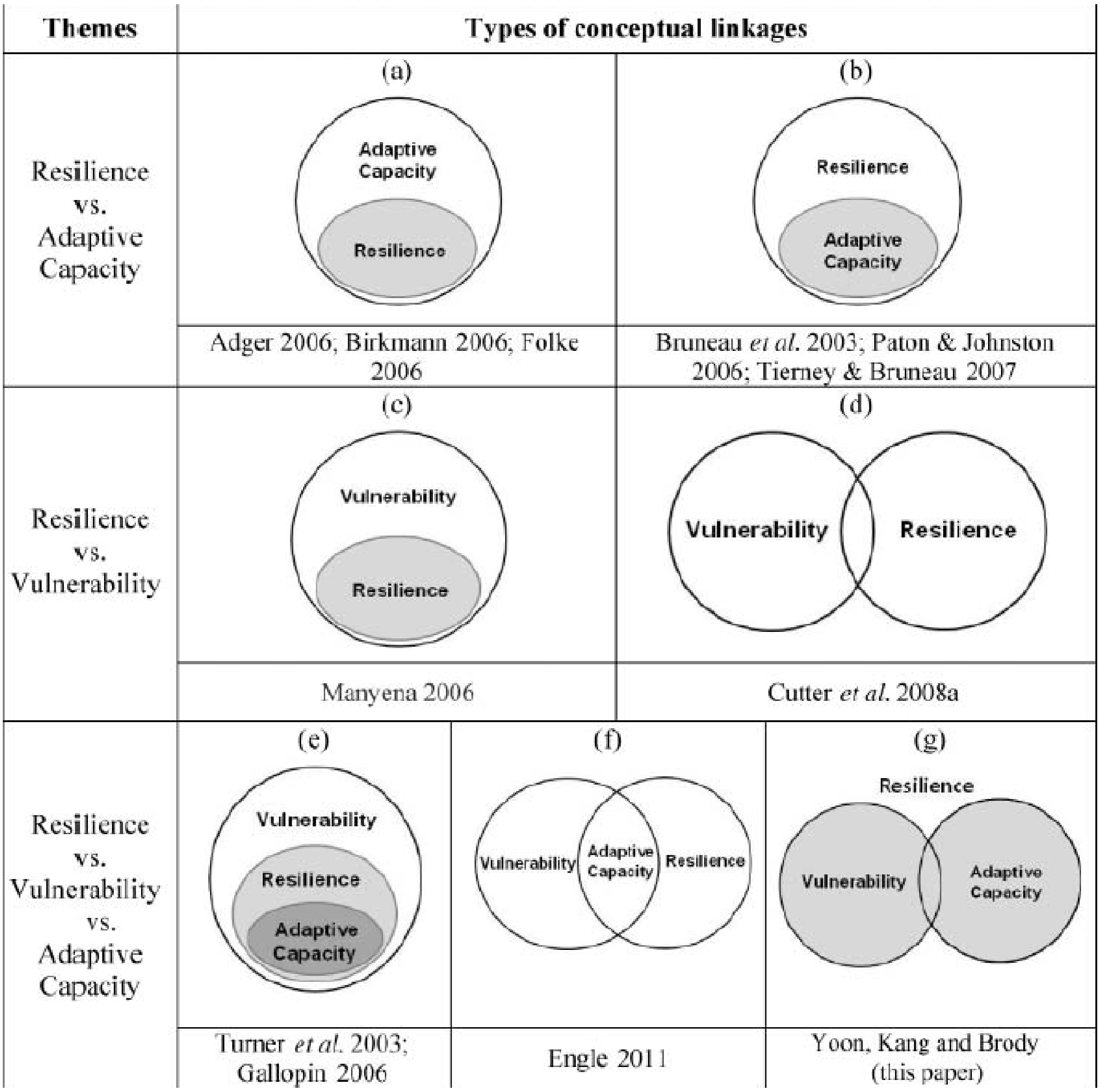



**FIGURE 4. CONCEPTUAL LINKAGES OF VULNERABILITY, RESILIENCE AND ADAPTATION (YOON ET AL. 2016)**

Four interwoven key challenges arise from the current state of the art in assessing vulnerability and climate resilience:

1. Soft factors (e.g. learning from the past, feeling of belonging) are essential in assessing resilience but commonly only measured by surveys. Therefore, new data sources are needed to measure and even monitor them area-wide.
2. Quantification of vulnerability and climate resilience.
3. The assessment scale of vulnerability and climate resilience does not match the adaptation scale and/or problem scale.

4. The innumerable approaches for both phenomena also reveal a lack of validation and raise the question of robustness and transparency, essential in justifying political actions, and provide indisputable arguments.

## 1.3 Research Goal and Linkages

The overarching goal of this thesis is to improve ways to capture and operationalize multi-faceted concepts through new methods and data mining for assessing vulnerability, urban resilience, sub-national and national resilience. The operationalization of resilience and risk is a broad research field. Within my five contributions, I approached this goal from various angles, bound together by four overarching linkages and common elements or challenges:

1. Operationalization and the use and applicability of different data – census versus social-network data
2. Quantitative assessment of multi-faceted complex phenomena in the context of climate change
3. The relevance of spatial scales – and the challenges linked to the "problem space, assessment space and solution space"
4. Validation of indicators and indices to increase robustness and transparency and analysis of spatial differences

Climate resilience and vulnerability are multi-faceted complex phenomena. Thus, compared to a purely single or one-sector approach, the concepts include different dimensions that can also lead to the emergence of tensions or questions about the weighting and synergies and mismatches between different areas and goals within resilience or vulnerability. Despite many approaches and progress achieved in quantifying vulnerability and resilience, many questions and challenges remain unsolved. Hence, this is the first cross-cutting dimension and all five contributions are augmenting and expanding existing knowledge (Fig. 5).

The second cross-cutting dimension is the operationalization of vulnerability and resilience. Both concepts include multiple sectors, government agencies and additional soft factors like personal networks, which combined challenge the quantification and operationalization. Traditional data sources do not cover all aspects of both phenomena. Nevertheless, depending on the goal of the assessment and the need to monitor over time, the requirement of the assessment is also to be cost and time-efficient. For example, in the context of local urban governments, extensive surveys and complex modelling are not feasible. The trade-off between completeness and practicability needs to be balanced. All five contributions present solutions and new results to the challenge of operationalization.

The third cross-cutting dimension is the validation of quantitative multi-faceted phenomena. Vulnerability and resilience are not easily validated as, per definition, no single indicator exists to validate as many indicators are necessary to capture all aspects. Still, validation is fundamental to increase robustness and transparency to provide administrative bodies with the justification for action and/or justify the selection of a specific adaptation measure. All five contributions include thorough validation through a variety of methods and new approaches.

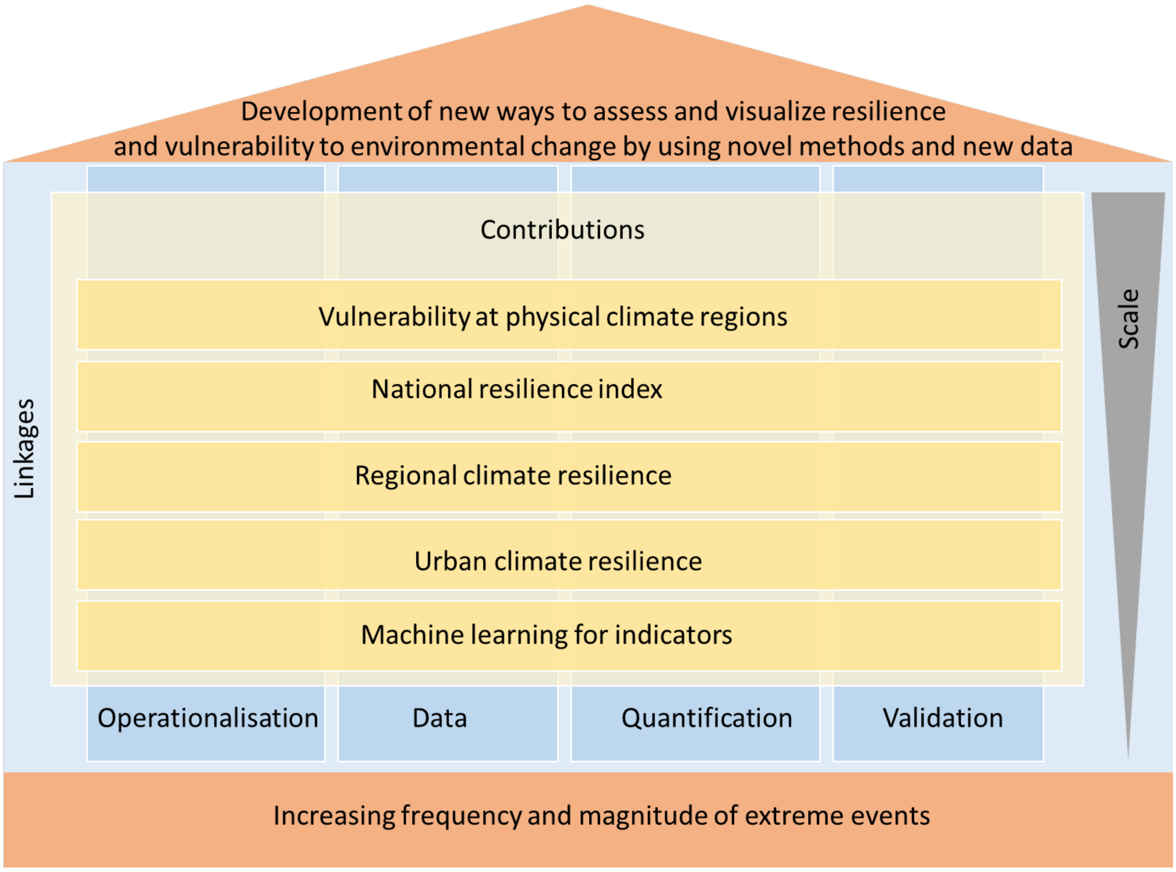



FIGURE 5. RESEARCH FRAMEWORK OF DISSERTATION

The fourth cross-cutting dimension is the relevance of the spatial scale for the assessment – assessing the incongruence of problem, assessment and solution or adaptation scale. First of all, the assessment of vulnerability and resilience is sensitive to the spatial scale of the assessment. Second, the spatial scale of the problem most certainly will not coincide as administrative boundaries "insufficiently" reflect physical dimensions. Last, the solution space for adaptation measures has to be considered for the assessment scale, as specific administrative duties are bound to the hierarchical structure of the ministries.

## 1.4 Research Questions and Approaches

To achieve the overall goal of my disserataion five contributions tackle different angles. Based on the literature overview (section 1.2) I deduce in this section challenges, goals and research question to achieve the overall goal of my dissertation (section 1.3). The subsequent section corresponds to the five contributions (named in section 1.5).

**Urban climate resilience indicators**

The operationalization of urban resilience is, by nature, an interdisciplinary approach. The urban fabric is a complex and multi-layered system. The MONARES project (monitoring of adaptation measure and climate resilience in cities) is funded by the German Ministry of Education and Research (BMBF). The main objectives of the project are: first, bringing together academia and researchers to create a common understanding of resilience. Second, modelling the adaptation process into a guided and transparent governing process. Third, linking and combining resilience to adaptation measures.

In general, the availability of information is not only important for decision makers but also for the society to better able to make informed decisions. Monitoring indicators provide impartial feedback on the status of the resilience-building process and provide credibility, accountability and transparency and especially in times of uncertainty and an unknown future.

*Challenges*

The quantification poses several challenges: first, the conceptual challenge of urban climate resilience. Second, the context specificity of indicators requires acknowledgement. Third, the very fluent fabric of risk and vulnerability in a changing society impacts the interpretation and evaluation of indicators themselves.

*Goal*

The operationalization of urban resilience by quantitative indicators provides the means to not only make informed decisions but to also guide and steer the transformation process. Moreover, linking resilience indicators to adaptation measures provides the concept to evaluate the success and/or effectiveness of those measures in the context of climate change. Hence, the goal is a set of quantitative urban climate resilience indicators reflecting the time, space and place specificity of Germany.

*Questions*

To address these challenges an iterative and participatory research design was developed (Fig. 6). In seven phases including workshops and surveys with practitioners and researchers first, a concept of climate resilience was developed and, continuing the process, a set of indicators to monitor urban climate resilience was established by answering the following research questions:

1. What are indicators in literature to operationalize climate resilience, and how can they be transferred to the context of German municipalities?
2. What are the key criteria and challenges of quantifying climate resilience to effectively monitor and steer municipalities' adaptation processes?
3. What are attributes for urban indicators applicable for both local administration and scientific community?
4. How to ensure robustness and transparency of climate resilience indicators through validation at the science-policy interface?

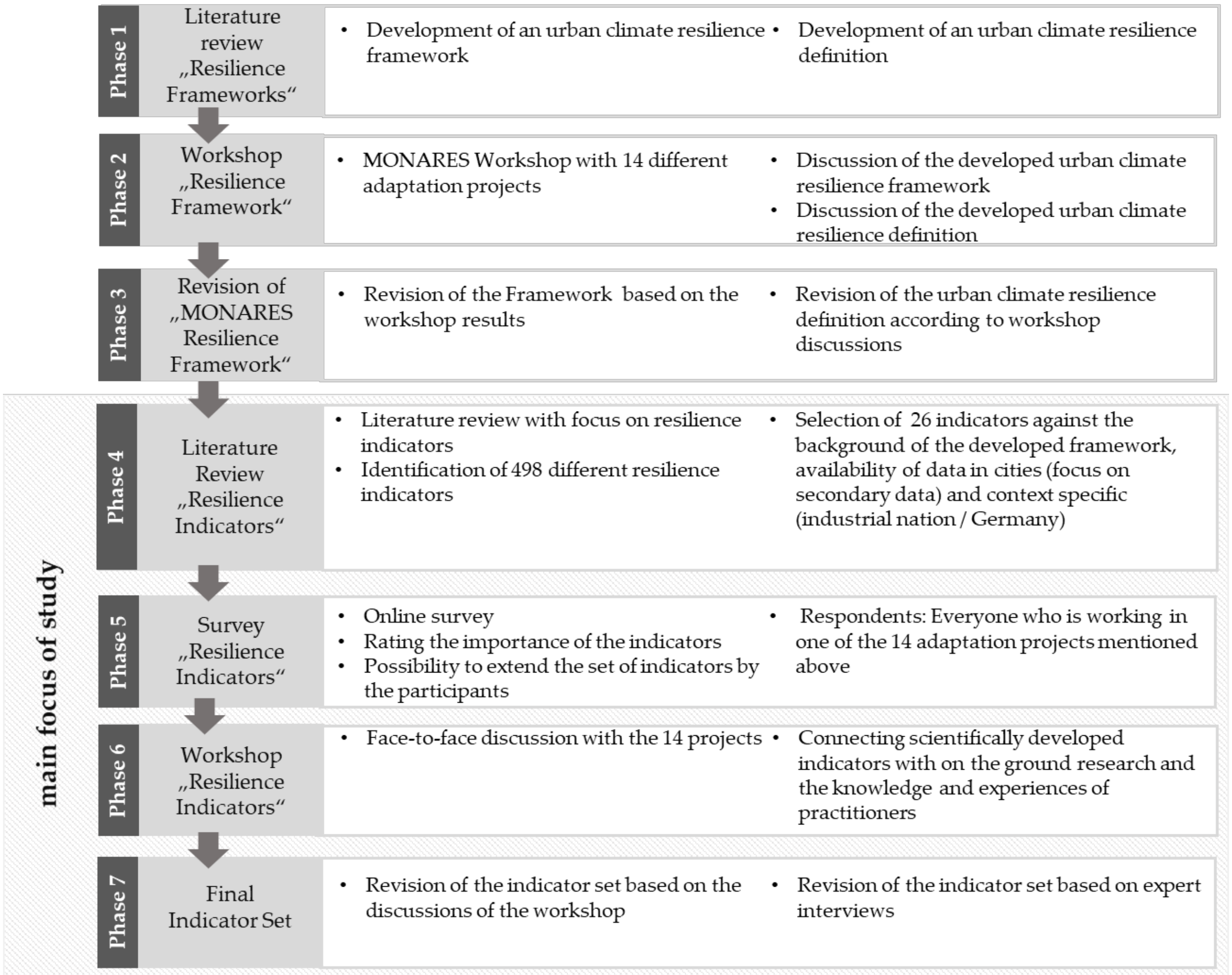



**FIGURE 6. RESEARCH PROCESS FOR URBAN RESILIENCE**

## Resilience data

In measuring climate resilience, data availability is one of the fundamental challenges. Governmental data provided are often limited by administrative boundaries. Moreover, the distribution is not centralized and linked to the ministry or agency respectively to the topic. Interdisciplinary topics like vulnerability or climate resilience therefore rely on multitudinous different data sources. Considering only Germany with its federal structure, the collection of data across all federal states requires sustained efforts. Even for data collection and calculation methods, no unified methodology is applied and therefore, even once all the data have been collected, they are neither comparable nor comprehensive. Some data are only available on the municipal level like local development plans and land use plans. The federal state of Baden-Württemberg alone comprises 1101 municipalities, moreover vulnerability and resilience assessments are often based on surveys or scorecards. But such manual data gathering requires a lot of resources and also knowledge. This might still be possible for a one-time snapshot but poses a barrier for monitoring purposes.

Volunteered Geographic Information (VGI) overcomes several of the previously mentioned shortcomings. It is not limited to administrative boundaries and exists with high spatial and temporal resolution. Specifically, OpenStreetMap (OSM) comprises a massive amount of data with global coverage. The challenge for using OSM is to unlock the information hidden within the semi-structured database and semi-standardized naming of objects. Nevertheless, socio-economic statistics and indicators are concealed and can be excavated by data mining (Jokar Arsanjani 2015; Glasze and Perkins 2015). Within these studies, official statistical indicators are predicted on a municipal level with machine and deep learning algorithms for the federal state of Baden-Württemberg.

*Challenge*

Resilience and vulnerability assessments often rely solely on available governmental data, which not only are thematically limited but also limited in temporal frequency and spatial resolution. Cutter and Finch underscore the fundamental dependency on data availability and quality to measure vulnerability against natural hazards (Cutter and Finch 2008). This also counts for climate resilience (Sauter et al. 2019; Schaefer et al. 2020; Feldmeyer et al. 2019a)

*Goal*

This research aims to develop a machine learning approach to deduce socio-economic indicators from OpenStreetMap (OSM) for municipalities (Fig. 7).

*Questions*

The underlying hypothesis is that there are proxies for socio-economic attributes within the geodata of the OSM database. To test this hypothesis, the research answered the following questions:

1. Can crowdsourced data be operationalized to expand the database for multi-faceted phenomena?
2. What are the challenges and chances of quantification by using machine learning algorithms?
3. How to validate the predictive performance and deduce elements explaining the predictions of black-box machine learning algorithms?
4. What are key elements for the municipalities of Baden-Württemberg predicting number of residents, unemployment, migration and proportion of elderly?

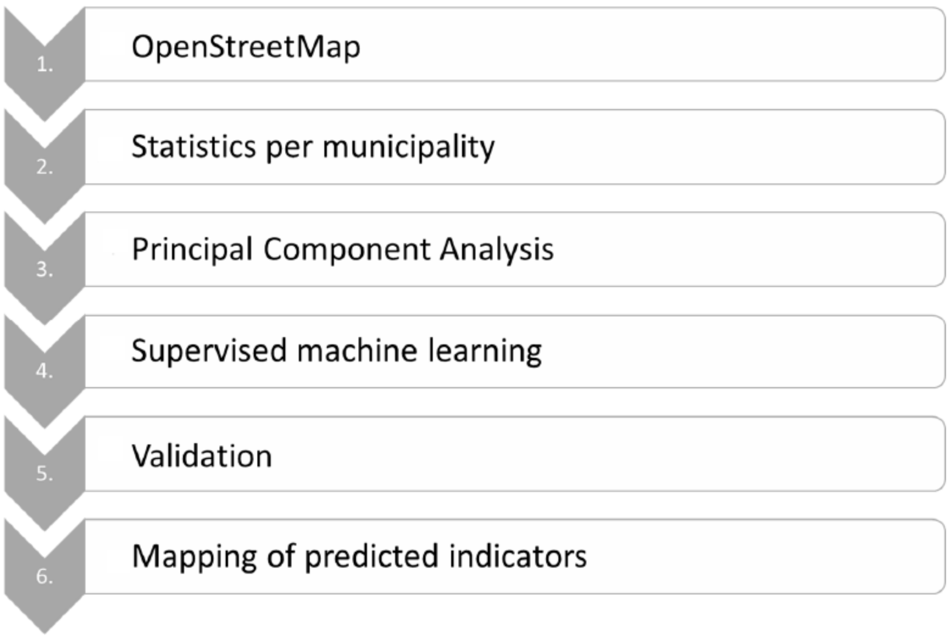



**FIGURE 7. WORFLOW TO DERIVE SOCIO-ECONOMIC INDICATORS BASED ON OSM**

**Regional climate resilience index**

Resilience is inextricably linked to the objective, the spatial and temporal scale as well as the place (Meerow and Newell 2019). Consequently, the indicators previously developed for urban climate resilience are not applicable on a regional scale, despite the same geographical context of Germany. Nevertheless, the objective of climate resilience and its fundamental conceptualization is coherent as well as climate change-induced stresses.

*Challenge*

To measure, monitor and evaluate multi-faceted phenomena, composite indicators are en vogue with an exponential increase of publications during the last decade (Greco et al. 2019). Becker et al. (2017) identify two reasons for this popularity. First, they provide a simplification and enable therefore evaluation and comparison of otherwise too complex issues like vulnerability, climate resilience or human development. Second, they can thereby foster transformation processes of agencies and governments. Despite their huge popularity and possibilities, composite indicators are also harshly criticised. On the one hand, they oversimplify matters and therefore misinform, while on the other hand, the selection of indicators and aggregation methods for index development can be highly subjective and immensely influences the result. To overcome these critics two different approaches are often taken. One is the reason-based thematic-driven approach, justifying indicators and aggregation based on thematic arguments. The other approach taken is data-driven exploring the underlying structure of the data in order to build the index.

*Goal*

Four main objectives are achieved by this approach: first, developing an indicator set for regional climate resilience; second, upscaling of urban climate resilience; third, addressing the criticisms of composite indicators by testing four different aggregation methods and implementing a twofold validation as well as robustness and sensitivity analysis; fourth, filling the gap of empirical validation of resilience measuring approaches (Bakkensen et al. 2017; Burton 2015);

*Questions*

To unfold its potential, the regional climate resilience index needs to withstand the above-mentioned critics. Therefore, the approach developed here is to combine the thematic as well as the data-driven approach (Table 4), answering the following research questions:

1. How to operationalize and upscale a climate resilience framework and indicators from urban to regional scale in the context of Baden-Württemberg, Germany?
2. What are key elements of the quantification of regional climate resilience and explanation of regional differences?
3. What are relevant aspects of regional climate resilience to link the assessment scale to administrative duties and the adaptation or solution space?
4. What are possible indicators for measuring climate resilience that can be utilised for empirical validation and bias reduction of indicator selection and aggregation method?

**TABLE 4. METHODOLOGY - CONCEPT**

| STEP | SUBSTEP | CALCULATIONS |
|---|---|---|
| 1. Spatial scale & initial indicators | 1. Defining the spatial scale | |
| | 2. Upscaling of urban resilience to regional resilience | |
| | 3. Development of the initial indicator set | |
| | 4. Transformation of the initial indicators (normalization) | a. Min-max-tranformation |
| 2. Validation of indicators | 1. Empirical Validation | a. Machine learning (random forest) |
| 3. Aggregation of the index | 1. Aggregation of the Index | a. Equal weights<br>b. Mixed equal hierchical weights<br>c. Wroclaw Taxonomic<br>d. Mazziotta-Pareto-Index |
| 4. Calculation of robustness & sensitivity | 1. Reliablity | a. Cronbach's alpha<br>b. Guttman's Lamda |
| | 2. Global sensitivity analysis | a. Bayesian approach |
| 5. Validation of aggregation method | 1. Empirical Validation | a. Non linear & non parametic correlation |
| 6. Application of the index to the spatial scale | 1. Application of the final index to the Federal State of Baden-Württemberg (Germany)<br>2. Analysis of the climate resilience of the counties of Baden-Württemberg | |

**Vulnerability hotspots and climate regions**

Besides the lack of data for resilience and vulnerability assessments, discussed in the previous section, the incongruence of spatial scale, problem scale and data scale or resolution is important to consider. Major efforts have been put into a better understanding of vulnerability on a global scale following the IPCC Special Report SREX (IPCC 2012) and the Fifth Assessment Report (AR5). In order to assess the systems´ vulnerability to natural hazards and climate change, multiple sets of indicators have been developed, following different schools of thought (INFORM 2019; Feldmeyer et al. 2017; Birkmann and Welle 2016; ND-GAIN 2019).

*Challenge*

Despite the agreement about the importance of assessing and subsequently reducing vulnerability, global and regional patterns are often neglected due to difficulties in quantifying them. Nevertheless, the spatial scale of climate change defined by physical climate regions (Fig. 8) lack matching vulnerability assessments to assess risk.

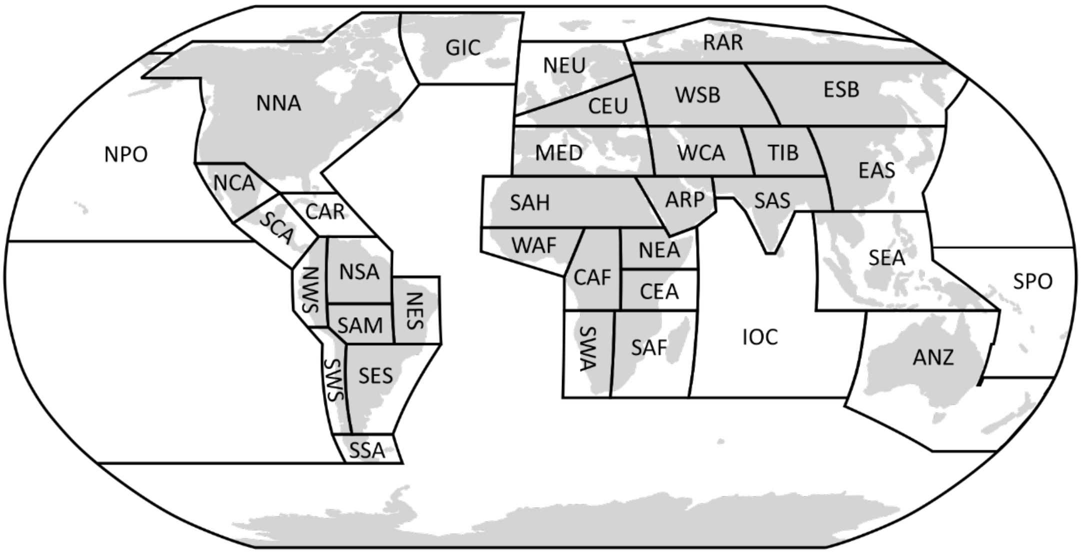
*Goal*

The overarching goal is to increase the robustness and transparency of the assessment of human vulnerability and providing the respective spatial scale for physical climate regions to assess risk by all parts of the risk equation and therefore provide the means and justification for effective adaptation measures and vulnerability reduction.

*Questions*

The purpose of this contribution is to examine and compare some of the key global vulnerability assessments, addressing the following questions:

1. What dimensions do current global assessments of vulnerability to and risk from climate change and natural hazards include?
2. Can these results be usefully up-scaled from the national level to the level of climate regions?
3. What kind of spatial patterns emerge when assessing human vulnerability at the level of climate regions?
4. To what extent do these assessments agree on the classification of regions in terms of their vulnerability level (i.e. low versus high vulnerability and variance)?




| | | | | | |
|---|---|---|---|---|---|
| **ANZ** | Australia/New Zealand | **NES** | N.E. South America | **SEA** | S.E. Asia |
| **ARP** | Arabian Peninsula | **NEU** | N. Europe | **SAF** | S.E. Africa |
| **CAF** | Central-Africa | **NNA** | N. North America | **SES** | S.E. South America |
| **CAR** | Caribbean | **NCA** | N. Central America | **SPO** | S. Equatorial Pacific Ocean |
| **CEA** | Central E. Africa | **NPO** | N. Pacific Ocean | **SSA** | S. South America |
| **CEU** | Central Europe | **NSA** | N. South America | **SWA** | S.W. Africa |
| **EAS** | E. Asia | **NWS** | N.W. South America | **SWS** | S.W. South America |
| **ESB** | E. Siberia | **RAR** | Russian Arctic | **TIB** | Tibetan Plateau |
| **GIC** | Greenland/Iceland | **SAH** | Sahara | **WAF** | W. Africa |
| **IOC** | Indian Ocean | **SAM** | South American Monsoon | **WCA** | W. Central Asia |
| **MED** | Mediterranean | **SAS** | S. Asia | **WSB** | W. Siberia/E. Europe |
| **NEA** | N.E. Africa | **SCA** | S. Central America | | |

FIGURE 8. ADAPTED IPCC CLIMATE REGIONS FOR THE ANALYSIS OF SOCIOECONOMIC VULNERABILITY

## National climate resilience

Resilience indicators based on literature are often criticized by practitioners for their lack of practical connection (Feldmeyer et al. 2019). Despite many approaches in measuring resilience, the vast majority is based on indicators derived from literature. Fewer approaches exist developing or validating indicators based on empirical evidence. Therefore, there is a clear lack of empirically-derived resilience assessments and of validation of existing ones. (Bakkensen et al. 2017; Burton 2015).

The Emergency Event Database comprises of national scale 22,000 disasters, ongoing. To determine resilience, additional information about the risk is necessary. The WorldRiskIndex calculates countries´ risks based on exposure and vulnerability. OpenStreetMap, when analysed by means of data mining, not only provides information about streets and houses, but also socio-economic and qualitative attributes, which is crucial for understanding climate resilience.

*Challenge*

Two key challenges continue to prevail: (a) including the social component of climate resilience and (b) validation with empirical data of indices and indicators to measure climate resilience.

*Goal*

Our goal is to develop an index for the nations' climate resilience, validated with empirical event data and including the social component of climate resilience.

*Questions*

We have developed a two-step solution to overcome these challenges (Fig. 9), the first step involves an empirical resilience index (EERI) based on the Emergency Event Database (EM-DAT) (EM-DAT) and the WorldRiskIndex (WRI) (Welle et al. 2015). Its basis in disaster damage data provides empirical validation. The second step, which involves utilising statistics from OpenStreetMap (OSM), will be used to predict the EERI and infer explanatory elements. OSM includes not only evidence of the physical world, but also information about the socio-economic status (Glasze et al., 2015; Jokar Arsanjani et al., 2015), so that the social component is included. The following research questions have to be answered during the two-step research process:

1. How can countries´ climate resilience be operationalized for measurement based on empirical event data and vulnerability?
2. How to quantify and develop climate resilience indicators, including soft factors based on a global crowdsourced database?
3. What are key elements predicting a nation´s climate resilience?
4. How can empirical event data validate and develop indicators to create a transparent and robust climate resilience index?

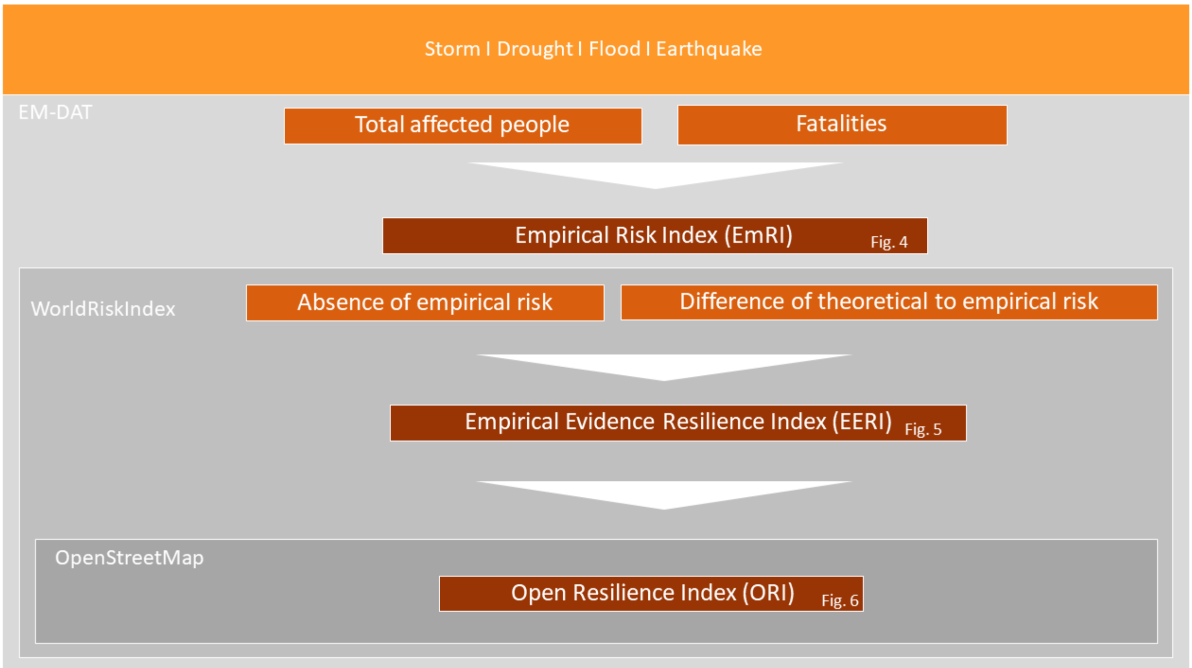



**FIGURE 9. WORKFLOW FOR EMPIRICAL RESILIENCE AND RESILIENCE INDEX**

## 1.5 Contributions and Structure of Work

Figure 10 gives an overview of the contributions, research interests, core methods as well as research outputs:

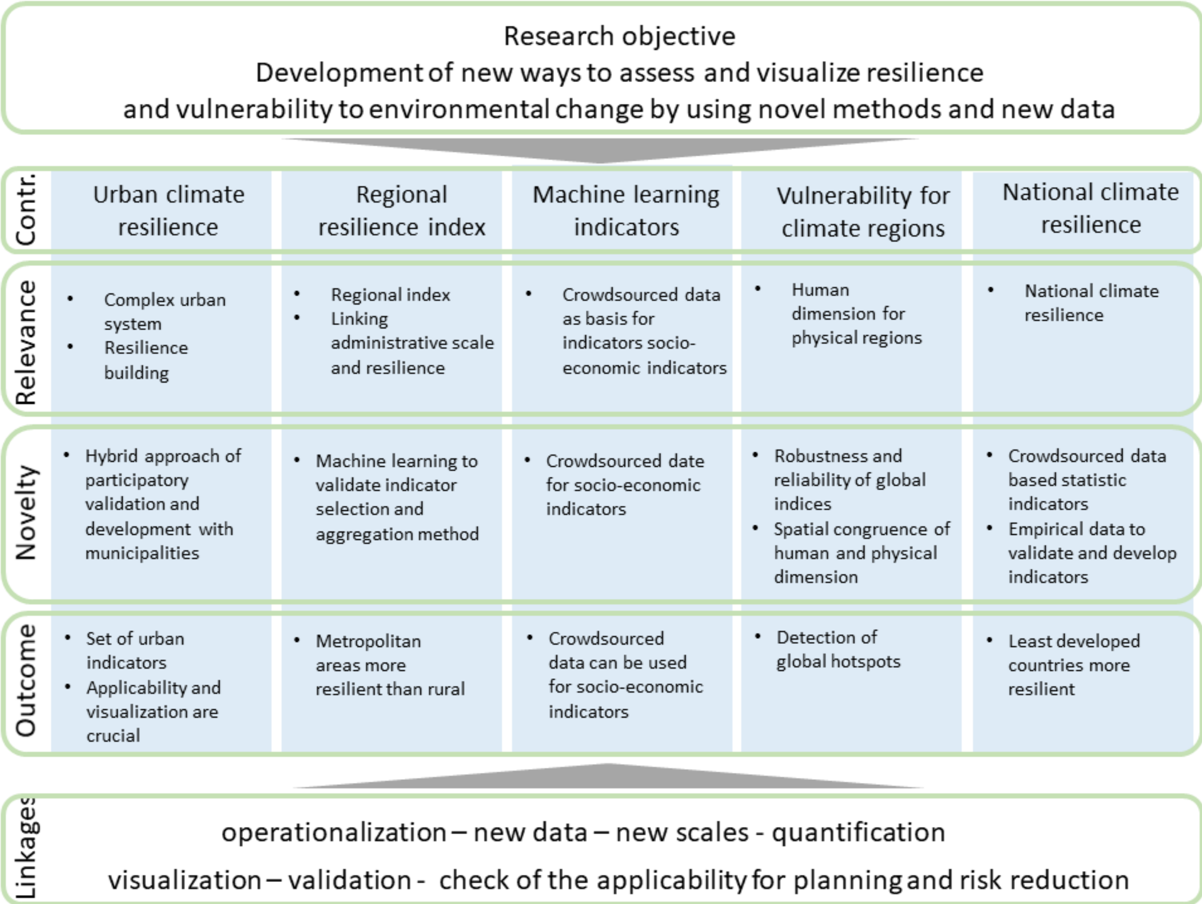



**Figure 10. Research process and contributions of the dissertation**

The thesis is composed of seven chapters which can be divided into three main parts:

**Introduction** – providing the background, motivation, state of the art and structure of the work.

**Contributions** - chapters 2 to 6 are the main part and contain my contributions to the goal of the development of new ways to assess and visualize resilience and vulnerability to environmental change by using novel methods and new data:

1. **Chapter 2: Feldmeyer, D.**; Wilden, D.; Kind, C.; Kaiser, T.; Goldschmidt, R.; Diller, C.; Birkmann, J. (2019b): ***Indicators for Monitoring Urban Climate Change Resilience and Adaptation***. In *Sustainability* 11 (10), p. 2931. DOI: 10.3390/su11102931.

2. **Chapter 3: Feldmeyer, D.,** Meisch, C., Sauter, H., & Birkmann, J. (2020). ***Using OpenStreetMap Data and Machine Learning to Generate Socio-Economic Indicators***. *ISPRS International Journal of Geo-Information*, *9*(9), 498. DOI: https://doi.org/10.3390/ijgi9090498
3. **Chapter 4: Feldmeyer, D.,** Wilden, D., Jamshed, A., & Birkmann, J. (2020). ***Regional climate resilience index: A novel multimethod comparative approach for indicator development, empirical validation and implementation***. *Ecological Indicators*, *119*, 106861.DOI: https://doi.org/10.1016/j.ecolind.2020.106861
4. **Chapter 5: Feldmeyer, D**., Birkmann, J., McMillan, J., Stringer, L., Leal Filho, W., Djalante, R., Pinho, P., Liwenga, E. (2020) ***Global vulnerability hotspots: differences and agreement between international indicator-based assessments.*** *Climatic Change. (Status: submitted)*
5. Chapter 6: Feldmeyer, D., Nowak, W., Jamshed, A., Birkmann, J. (2021) ***An empirically developed vulnerability and resilience index based on damage data and OpenStreetMap***. *Science of Total Environment* 774(3). DOI: 10.1016/j.scitotenv.2021.145734

**Conclusion** – the final chapter summarizes the main conclusions across all five publications and concludes with an outlook.

## CONFERENCES

I presented and discussed my findings at several international conferences:

1. Kind, C., Kaiser, T., Feldmeyer, D., Wilden, D. (2019) "Framing and monitoring urban climate resilience in German municipalities – insights from an ongoing research project" 4th European Climate Change Adaptation conference 28 - 31 May, Lisbon, Portugal
2. Feldmeyer, D., Sauter, H., & Birkmann, J. (2019) "An open risk index with learning indicators from OSM-tags, developed by machine learning and trained with the world risk index" FOSS4G 2019 26 – 30 August, Bucharest, Rumania DOI: 10.5194/isprs-archives-XLII-4-W14-37-2019
3. Sauter, H., Feldmeyer, D., & Birkmann, J. (2019) "Exploratory study of urban resilience in the region of Stuttgart based on OpenStreetMap and literature

resilience indicators” FOSS4G 2019 26 – 30 August, Bucharest, Rumania DOI: 10.5194/isprs-archives-XLII-4-W14-213-2019

4. Wilden, D., Feldmeyer, D., Birkmann, J., Diller, C. (2018) “A conceptual integrative approach to monitoring, evaluation and validation of Climate Change Adaptation measures for urban resilience” 8th International Conference on Building Resilience Lisbon, Portugal
5. Sauter, H., Feldmeyer, D., Birkmann, J. (2018) “Enhancing the spatial and temporal resolution of the WorldRiskIndex with new data sources” FOSS4G 2018 27 – 31 August, Dar es Salaam, Tanzania
6. Feldmeyer, D. (2018) “Development of human vulnerability: learning from past trends for future directions” 5th International climate Change Adaptation Conference 18 – 21 June, Cape Town, South Africa

## FURTHER PUBLICATIONS

Beyond the scope of the thesis, I published and contributed to several additional peer-reviewed scientific publications in the broader context of extreme events, vulnerability and risk management:

**Feldmeyer, D.**; Birkmann, J.; Welle, T. (2017): Development of Human Vulnerability 2012–2017. In *Journal of Extreme Events* 04 (04), p. 1850005. DOI: 10.1142/S2345737618500057.

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# SECOND CHAPTER

## INDICATORS FOR MONITORING URBAN CLIMATE CHANGE RESILIENCE AND ADAPTATION

*sustainability*

MDPI

*Article*

# Indicators for Monitoring Urban Climate Change Resilience and Adaptation

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**Abstract:** In the face of accelerating climate change, urbanization and the need to adapt to these changes, the concept of resilience as an interdisciplinary and positive approach has gained increasing attention over the last decade. However, measuring resilience and monitoring adaptation efforts have received only limited attention from science and practice so far. Thus, this paper aims to provide an indicator set to measure urban climate resilience and monitor adaptation activities. In order to develop this indicator set, a four-step mixed method approach was implemented: (1) based on a literature review, relevant resilience indicators were selected, (2) researchers, consultants and city representatives were then invited to evaluate those indicators in an online survey before the remaining indicator candidates were validated in a workshop (3) and finally reviewed by sector experts (4). This thorough process resulted in 24 indicators distributed over 24 action fields based on secondary data. The participatory approach allowed the research team to take into account the complexity and interdisciplinarity nature of the topic, as well as place- and context-specific parameters. However, it also showed that in order to conduct a holistic assessment of urban climate resilience, a purely quantitative, indicator-based approach is not sufficient, and additional qualitative information is needed.

**Keywords:** resilience; indicator; monitoring; climate change; climate adaptation

## 1. Introduction

Our society is facing multitudinous different challenges—in this paper we are focusing on two main challenges: climate change and urbanization. In 2015, 3.9 billion people were living in cities. By 2050, the population in cities is projected to reach up to 6.7 billion people [1]. Urban agglomerations will continue to grow and are increasingly threatened by the high uncertainty of climate change impacts [2]. In response to these impacts, cities are already implementing climate change adaptation measures in order to prepare for uncertain future changes. Adaptation to climate change and climate variability is not a new phenomenon [3]. However, steadily rising temperatures, increasing magnitude and frequencies of climate-induced extreme events, such as droughts, floods, storms or intense rainfall, as well as the growth of the global human population pose new adaptation challenges to humankind [3]. In our research, we use the term adaptation as defined by the United Nations Climate Change [4]: "Adaptation refers to adjustments in ecological, social, or economic systems in response to actual or expected climatic stimuli and their effects or impacts. It refers to changes in processes, practices, and structures to moderate potential damages or to benefit from opportunities associated with climate change". Furthermore, the ability of adaptation is understood as part of resilience, as described by Folke et al. [5]. The concept of resilience can be attributed to Holling [6] and originates from ecology. He described resilience as the "measure of persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationship between population or state variables" [6]. The original concept of resilience gained increased importance in other disciplines, whereby the definitions of resilience were steadily differentiated, broadened and deepened. There are three main understandings of the character of resilience: "bounce back" which refers to the fast return to an equilibrium state of a system after a shock event, "bounce forward" which focuses on a system which should have capacities to be adapted to uncertainty and "both" which addresses the co-occurrence of the capacities for "bounce back" and "bounce forward" [7]. Meerow et al. [2] analysed 57 academic definitions of urban resilience, with particular regard to these fundamental understandings of urban resilience. The analysis showed that 35 definitions focus on "bouncing back", 15 on "bouncing forward" and only seven see both capacities as elementary for resilience. Figueiredo et al. [8] pointed out that the definitions shifted from an equilibrium-centred understanding of resilience towards an evolutionary/transformational understanding of resilience. Four main approaches to resilience can be identified: disaster risk reduction [9], socio-ecological [10], sustainable livelihoods [11] and the community-oriented approach [12]. Resilience can also be discussed on different scales (county, region, urban area, city, community and household) [8]. Even though it is important to take action on all scales, in this work we are focusing on cities—particularly in Germany—and are using the socio-ecological approach. Besides the definitions and understandings of resilience in academia, it is very important to also consider how practitioners interpret resilience. Practitioners and policy makers are a central part of the resilience-transformation process. Therefore, it is remarkable that the term resilience is interpreted in a much wider range of ways by practitioners than by academia [13].

Adaptation measures are implemented in different sectors of the city system. Since cities are complex and multifaceted systems, which in turn contain other systems, measuring the success of resilience-increasing activities poses a particular challenge. However, measurement is of great importance in order to be able to govern and steer the adaptation and transformation process. Every city has its specific context and needs, and its exposure to risk and vulnerability is dynamic and changes over time [8].

However, it is important to develop measurable indicators for different reasons. Indicators enable monitoring of the resilience-building process, as they provide regular and impartial feedback. They build an evidence base and make resilience more tangible for decision and policy makers as well as society at large. Furthermore, indicators can help to govern and steer the transformation process because they help to structure the new field of urban climate resilience. Clear indicators are not only important for the general measurement of resilience, but also for the analysis of whether adaptation measures were effective and whether the expected results were achieved [14]. Indicators also contribute to the credibility, transparency and accountability of the measures implemented. This in turn is very important for local policy makers to support further adaptation measures.

However, the development of indicators in this context poses particular challenges. In addition to the conceptual challenges of urban climate resilience, context specificity represents another challenge for the development of resilience indicators. Consequently, it is very important to consider how to include context specificity in the indicator set. Another fundamental consideration is in regard to the context-specific, dynamic and ever-changing nature of risk and vulnerability [8].

MONARES (monitoring of adaptation measures and climate resilience in cities), a project funded by the German Federal Ministry of Education and Research (BMBF), was initiated in order to address the main challenges of (1) developing a consistent understanding of resilience for both practitioners and academia, (2) shaping the adaptation and transformation process into a transparent process of governing and steering and (3) the use of resilience and adaptation measurements. The aim of MONARES is to create application-oriented methodologies for monitoring and evaluating local adaptation measures. As we are focusing on the special needs for cities in Germany, we are working together with 14 other projects of the funding initiative "Climate resilience through action in cities and regions" of the BMBF, who are focusing on climate change adaptation measures and urban resilience, as well as doing on-the-ground research in municipalities across Germany. These projects and cities differ considerably concerning scale (street, district, city, suburbs and region), inhabitants and type of adaptation measure (e.g., planning, physical infrastructure, capacity building or greening). Important commonalities of the projects are their interdisciplinary approach, the aim to enhance urban climate resilience and that they conduct on-the-ground research. However, the projects test many different pathways to improve resilience, and MONARES is focusing on how to measure the success and impact of these different projects and activities with a common set of indicators. In order to ensure applicability, we began to involve the projects at an early stage of our research. The first key step (Figure 1 Phase 1) before developing the indicators was to develop a framework [15] to describe urban resilience. Based on 19 frameworks described in the literature [16–34], our first draft was developed, which then was modified together with the projects. This process was indispensable as it resulted in a definition of urban resilience that is suitable for all projects so that there was agreement on common basic principles.

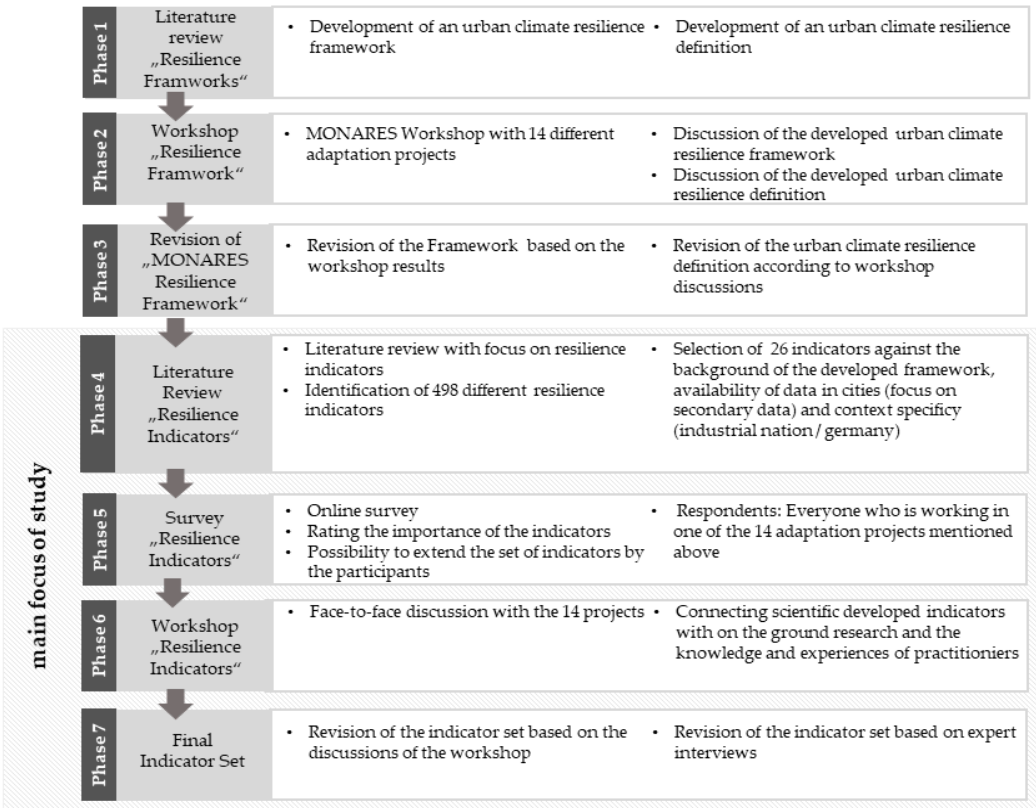


**Figure 1.** MONARES—research process.

Based on steps 1 to 3 as shown in Figure 1, the final definition of urban resilience in MONARES is as follows:

The climate resilience of a city depends on the ability of its sub-systems to anticipate the consequences of extreme weather and climate change, to resist the negative consequences of these events and to recover essential functions after disturbance quickly, as well as to learn from these events and to adapt to the consequences of climate change in the short and medium term, and transform in the long term. The more pronounced these abilities are, the more resilient a city is to the consequences of climate change. All abilities are important.

Based on this preliminary work, a four-step mixed-method approach (Figure 1 Phases 4–7) was designed to develop the indicators for urban climate resilience on which this paper focuses.

## 2. Materials and Methods

The exponential growth of literature concerning urban resilience contains a multitude of approaches, indicators and methods stressing the resistance of an urban system. The development of the method of this paper was guided by the questions: resilience for whom, for what and where [35]. A reflexive approach of input and feedback loops was developed in order to adapt and validate international indicators. A main challenge was to adapt the indicators to the specific context of German communities in the face of climate change.

### *2.1. Literature Review: "Resilience Indicators"*

The selected frameworks (see Figure 1 Phase 1) were identified through an extensive literature review using the key search terms "resilience", "urban resilience", "climate resilience", "adaptive capacity + urban/city", "resistibility + urban" and "learning capacity + urban/city" (in German and English). Based on these frameworks and their operationalisation of resilience, an extensive list of indicators was deduced. These indicators were matched with the MONARES framework, developed in steps 1–3, which consists of dimensions and action fields (see Table 1).

**Table 1.** Dimensions and action field of the resilience framework.

| Dimension | Action Field |
|---|---|
| Environment | Soil and green spaces |
| | Water bodies |
| | Biodiversity |
| | Air |
| Infrastructure | Settlement structure |
| | Energy |
| | Telecommunication |
| | Traffic |
| | Drinking and wastewater |
| Economy | Innovation |
| | Business |
| | Economic structure |
| Society | Research |
| | Knowledge and risk competence |
| | Healthcare |
| | Socio-demographic structure |
| | Civil society |
| | Civil protection |
| Governance | Participation |
| | Municipal budget |
| | Strategy, plans and environment |
| | Administration |

As we have the aim to develop a user-friendly, applicable and transparent indicator set, we firstly reduced the indicators to two indicators per action-field. The two most important selection criteria were (1) context specificity of industrial nations, especially Germany, and (2) data availability. Context specificity is important because many of the indicators in the literature are suitable for the context of the Global South but not for the Global North, and even indicators that might be suitable for the Global North might not be suitable in the German context. The second criteria—data availability—is therefore important because municipalities have, on the one hand, good access to a lot of data but have, on the other hand, resource problems regarding time, finances and human resources. Action fields without literature-based indicators required the development of new ideas within the project. Given the available data, some action fields were difficult to measure without significantly neglecting the complexity of the action field.

### 2.2. Survey to Assimilate the Indicators for Context Specificity

Based on the literature review (see Figure 1 Phase 4) and the described selection process, an online-survey was developed (see Figure 1 Phase 5). The survey was used because, given that the indicators should be transparent and user-friendly, not only the scientific background is important, but a clear understanding of the indicators in the broad community is important also. The survey was sent to all persons who are working in one of the 14 projects mentioned above. 39 people answered the survey.

The main aim of the survey was to measure how participants assess the different indicators. They were requested to rate the importance of every indicator regarding urban climate resilience on a scale from one (low importance) to five (high importance). Each action field was represented by at least one indicator (Table 1). Besides the rating of indicators, the survey consisted of four chapters: First, some general background; Second, the context of urban climate resilience; Thirdly, the indicators; Fourthly, the possibility of extending the set of indicators by indicators without existing data sources, and some final remarks.

### 2.3. Workshop Following the Survey

As mentioned previously, the explanatory power of an indicator set of urban climate resilience is hugely dependent on the context, and therefore we discussed the results of the survey again with the 14 projects (see. Figure 1 Phase 6). Moreover, this feedback loop increases the transparency of the process and the robustness of the results. The workshop started with presenting the survey results and then the participants were split into two groups in order to create two independent feedback loops and cross-validation of the indicator set. For each group, a poster was prepared, listing all indicators included in the survey. The indicators that were ranked lower in the survey were written on the poster in light grey (compared to black), for an improved visualization of the survey results. Hence, both groups had the visual results to discuss and were asked to compare each pair in detail and find explanations for the survey results. In addition, the overall set remained visible, which allowed participants to keep the important question of the overall themes in mind. Therefore, indicators could be moved across the set or could become more important if they were deemed a missing piece in the mosaic. The guiding questions for this phase of the workshop were: (1) Are there enough indicators? (2) How many indicators are needed and sufficient? (3) Are the selected indicators the right ones or should they be changed? And (4) are there important gaps in the set that are yet to be filled?

### 2.4. Finalizing the Indicators Set

In Step 7 (see Figure 1) we analyzed the results of the workshop. Furthermore, expert interviews with practitioners were conducted with the aim to develop indicators in action fields where neither the literature review nor survey and workshop produced results. On this basis, we finalized the urban resilience indicator set.

## 3. Results

In our review of the academic literature, 19 indicator-based resilience frameworks were analyzed. Based on the indicators of these frameworks a list of 498 indicators (including duplicates) was generated. The indicator list was used as an important starting point for developing the MONARES Indicator Set (MIS). After screening the indicators through the lens of the MONARES-framework, some action fields remained empty and were filled by proposed indicators of the MONARES project-team. One to four indicators were selected per action field in order to cover all topics and include sufficient redundancy. Table 2 shows the selected and proposed indicators.

**Table 2.** Delineated indicators and action fields.

| Dimension | Action Field | Indicator | Code | Literature |
|---|---|---|---|---|
| Environment | Soil and green spaces | Degree of soil sealing | A_a_1 | [31] |
| | | Land consumption | A_a_2 | [21] |
| | | Recreational area | A_a_3 | [21] |
| | Water bodies | Share of water bodies | A_b_1 | [36] |
| | | State of water bodies | A_b_2 | [23] |
| | Biodiversity | Share of nature conservation and protection areas | A_c_1 | [23] |
| | | Wetlands and retention areas | A_c_2 | [36] |
| | Air | Cold air parcels | A_d_1 | [23] |
| Infrastructure | Settlement structure | Density of buildings | B_a_1 | [37] |
| | | Accessibility of green spaces | B_a_2 | [38] |
| | Energy | Share renewable energy | B_b_1 | [18] |
| | | Diversity renewable energy | B_b_2 | [18] |
| | Telecommunication | Broadband access | B_c_1 | [37] |
| | Traffic | Concept for sustainable traffic | B_d_1 | [21] |
| | Drinking and wastewater | Number of springs | B_e_1 | [8] |
| Economy | Innovation | Innovation index | C_a_1 | [37] |
| | Business | Ratio of insolvencies to start-ups | C_b_1 | [22] |
| | Economic structure | Share of employees in largest sector | C_c_1 | [39] |
| | | Employees in research intensive companies | C_c_2 | [40] |
| Society | Research | Number of research projects | D_a_1 | [18] |
| | Knowledge and risk competence | Citizen information about heat, heavy rain and flooding | D_b_1 | [37] |
| | | Experience with extreme events in last five years | D_b_2 | [37] |
| | Health care | Accessibility of hospitals | D_c_1 | [41] |
| | | Doctors per 10,000 citizens | D_c_2 | [40] |
| | Socio-demographic structure | Share of citizens ABV6/U65 | D_d_1 | [42] |
| | | Share of employees | D_d_2 | [30] |
| | Civil society | Voter turnout | D_e_1 | [42] |
| | | Number of associations | D_e_2 | [42] |
| | Civil protection | Fire brigade | D_f_1 | [37] |
| | | Citizens in honorary positions | D_f_2 | [31] |
| Governance | Participation | Number of participation processes | E_a_1 | [37] |
| | | Contact point for participation | E_a_2 | [37] |
| | Municipal budget | Depth per citizen | E_b_1 | [21] |
| | | Tax income | E_b_2 | [21] |
| | Strategy, plans and environment | Risk and vulnerability analysis | E_c_1 | [26] |
| | | Strategies against heavy rain and heat in plans | E_c_2 | [26] |
| | | Landscape plan legally binding | E_c_3 | [37] |
| | | Climate change adaptation part of urban development plan | E_c_4 | [30] |
| | Administration | Inter-office working group regarding risk, climate change and resilience | E_d_1 | [37] |
| | | Climate manager | E_d_2 | [37] |

### 3.1. Survey about Resilience Indicators

The survey was structured based on the results of Phase 4. The survey (Figure 1 Phase 5) was filled out by 39 respondents within the funding initiative "Climate resilience through action in cities and regions" of the BMBF. The overall mean perceived importance of the indicators was 3.63 within the complete range from one to five. Considering the complexity of the urban system and the interdisciplinary character of the indicator set, this rating was regarded as high. The median of four was also high. The standard deviation of 1.17 together with the entire evaluation range reflected the diversity of interpretations. Nevertheless, despite this diversity, these core numbers show that the indicators were overall judged as important. Splitting the indicators into the five main dimensions (Figure 2), the median shows that only the indicators within the dimension of economy were rated less important, they are rated in the middle of the range, which might indicate a slight indecisiveness. Several reasons could explain this, such as that the indicators selected were not covering the dimension in a satisfactory manner or that the dimension is perceived as unrelated to urban climate resilience. Those questions were discussed in the workshop (Figure 1 Phase 6) in detail.


**Figure 2.** Median importance of indicators grouped into five dimensions.

All top five ranked indicators had a median rating of 5. The mean values ranged from 4.4 to 4.6. Only two respectively three respondents did not rate the indicators, showing the general agreement regarding the importance. Nevertheless, regarding the minimum values, all had a large range from 2 to 5.

The set of five indicators in Table 3 shows that the three dimensions *environment*, *governance* and *society* were seen as particular important. The indicator rated as the most important was the environment indicator *cold air parcels*. Second and fourth ranked were *governance* indicators, namely *inter-offices working groups regarding risk, climate change and resilience* and *strategies against heavy rain and heat in plans*. Third and fifth ranked were two indicators from the dimension *society*. The respondents saw the importance of *experience with extreme events in the last five years* and *citizen information about heat, heavy rain and flooding* as particularly crucial for building urban resilience.

**Table 3.** The five indicators rated as most important in the survey.

| Dimension | Action field | Indicator | Min. | 1st Quartile | Median | Mean | 3rd Quartile | Max | N/A |
|---|---|---|---|---|---|---|---|---|---|
| **Environment** | Air | Cold air parcels | 2 | 4 | 5 | 4.6 | 5 | 5 | 3 |
| **Governance** | Administration | Inter-offices working group regarding risk, climate change and resilience | 2 | 4 | 5 | 4.5 | 5 | 5 | 2 |
| **Society** | Knowledge and competence | Experience with extreme events in last five years | 3 | 4 | 5 | 4.5 | 5 | 5 | 3 |
| **Governance** | Strategy, planned and environment | Strategies against heavy rain and heat in plans | 2 | 4 | 5 | 4.5 | 5 | 5 | 3 |
| **Society** | Knowledge and competence | Citizen information about heat, heavy rain and flooding | 2 | 4 | 5 | 4.4 | 5 | 5 | 2 |

Table 4 displays the five lowest ranked indicators in context of their relevance related to urban climate resilience. The overall lowest rated indicators were both from the *society* dimension, namely *voter turnout* and *number of associations*. The respondents did not think that they were relevant for measuring and monitoring urban resilience. The third lowest indicator was the *infrastructure* indicator *broadband access*. Fourth and fifth were two *economic* indicators measuring *ratio insolvencies to start-ups* and *share employees in largest sector*.

**Table 4.** Five lowest rated indicators.

| Dimension | Action field | Indicator | Min. | 1st Quartile | Median | Mean | 3rd Quartile | Max | N/A |
|---|---|---|---|---|---|---|---|---|---|
| **Society** | Civil society | Voter turnout | 1 | 2 | 3 | 2.4 | 3 | 4 | 1 |
| **Society** | Civil society | Number of associations | 1 | 2 | 3 | 2.6 | 3 | 4 | 2 |
| **Infrastructur** | Telecommunicatior | Broadband access | 1 | 2 | 3 | 2.8 | 4 | 5 | 3 |
| **Economy** | Business | Ration insolvencies to start-ups | 1 | 2 | 3 | 2.8 | 3.5 | 5 | 4 |
| **Economy** | Economic structure | Share Employees in largest sector | 1 | 2 | 3 | 2.8 | 3 | 4 | 6 |

Figure 3 displays boxplots of all indicators. The main tendency has already been shown in a more condensed form previously in Figure 2. *Share of nature conservation and protection areas (A_c_1)* was the lowest ranking in the dimension *environment*. The second indicator of the action field *biodiversity*, however, received high approval, which emphasised the perceived importance of *biodiversity* considerations for climate resilience in the urban context. *Settlement structure* (B_a_1&2) was seen as vital for structural climate change adaptation, similar to the first action fields of *soil and green spaces* (A_a_1-3).

*Energy* (B_b_1&2) indicators, in contrast, not only ranged from a rating of one to five, but the quartiles of the boxplot also show a comparably high range around the middle of the scale.

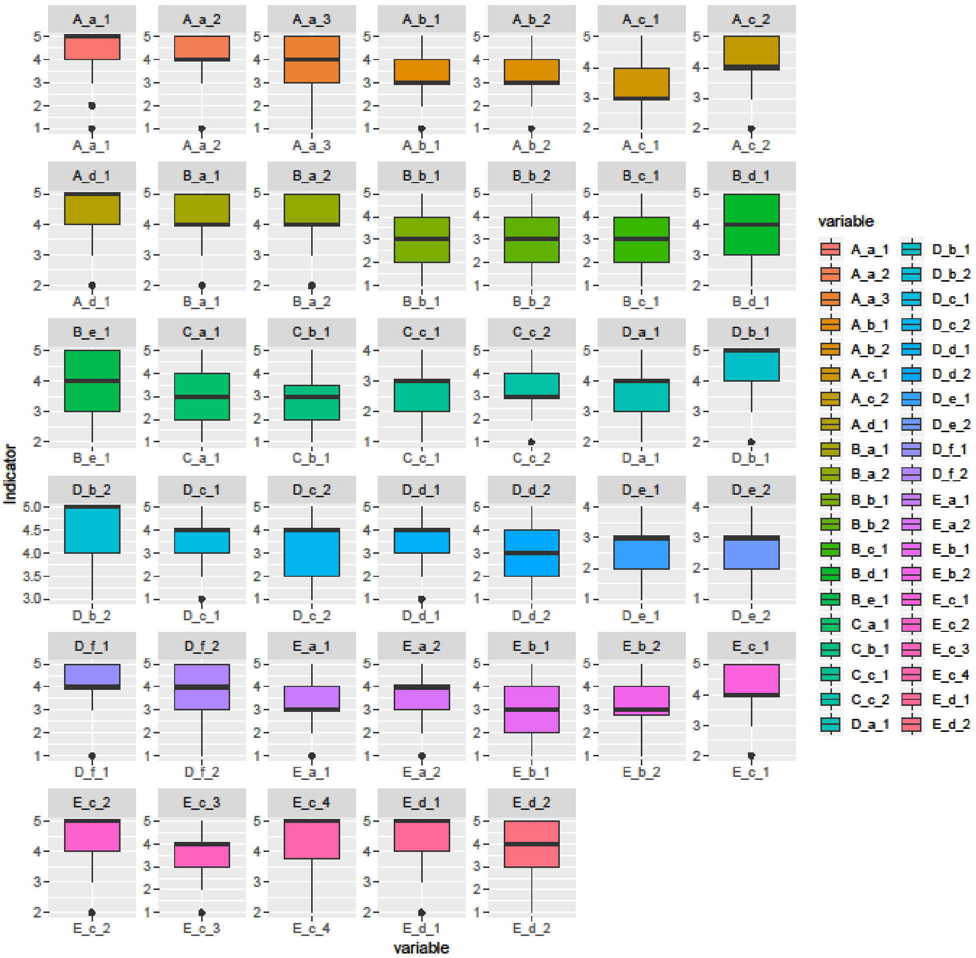


**Figure 3.** Box-plots of all indicators included in the survey (see Table 2 for indicator codes).

### 3.2. General Workshop Results Regarding the MIS

The discussion of the indicators during two discussion groups yielded important feedback on the overarching attributes and requirements of the MIS. They were mentioned several times from different persons and related to different indicators. Firstly, one important aspect was the size of the municipality and hence the scaling of the indicator. No universal scaling was found appropriate, since the different units and scales required indicator-specific scaling. Nevertheless, the scaling was seen as an important factor in order to reach the goal of acquiring indicators for municipalities and therefore an interpretable result on this level of administrative organization.

The overall discussion about applicability and feasibility was touched on in many ways from different angles, most prominently regarding data availability, numbers of indicators and total effort needed. The balancing of the loss of information related to simpler indicators or vice versa with more complex indicators with higher explanatory power but with an infeasibility to be handled by the target group was seen as a key challenge. Therefore, the participants agreed that the indicators should be based solely on existing data, thereby reducing the overall effort and simplifying the calculations and data management.

The idea of detailed factsheets describing the data source and calculation of the indicator and helping with the interpretation of the result was raised by participants and received wide support. Factsheets also help to communicate the meaning of an indicator to uninitiated persons, which was also mentioned as a crucial aspect.

The total number of indicators to be feasible was seen at around 25. Certain gaps were identified during the workshop due to the fact that specific expertise related to certain action fields was missing in the room, specifically regarding the action fields *energy, wastewater* and *civil protection*. Here, single expert interviews were carried out after the workshop to fill in the gaps.

### 3.3. Indicator Specific Workshop Results

Table 5 summarizes the process of indicator development during the three phases of the survey, the workshop and ending in the final set of indicators. The indicators highlighted in grey are those of the initial indicator set that were seen as important by survey respondents and therefore stayed on the list. The indicators highlighted in orange were updated or modified as a result of the survey and/or workshop. The yellow indicators were moved from one action field to another. The indicator *degree of soil sealing* was inverted to *degree of unsealed ground*, as sealing is not per se negative, even may even be desirable or unavoidable in urban areas. The *cold air parcels* was seen as an important factor of resilience but should be updated, adding cold air streams to the indicators. *Biodiversity* was discussed in contradictory ways, as it was not clear to the participants how it is related to climate hazards. Hence, the workshop resulted in representing urban biodiversity with the indicator *wetland and retention areas* in order to include flood protection arguments into the indicator of biodiversity.

Infrastructure was seen undoubtedly as a key area for achieving urban climate resilience, but also related to secondary data and its inherent complexity most difficult to quantify currently. *Accessibility of green spaces* was rather seen as an indicator of social justice and less as a settlement structural indicator and hence the second indicator *building density*, slightly lower ranked in the survey, was included instead. The *share of renewable energy* indicator focused strongly on climate protection and less on resilience factors, such as robustness and redundancy. These factors were seen to be better covered by the *diversity of renewable energy sources*. However, it was also argued that even conventional energy should be included in the indicator. This observation was followed by the consideration that no climate resilience can be achieved without climate protection in the long term. Therefore conventional energy sources cannot be regarded as a positive contribution to climate resilience in the long term. The action field of *telecommunication* was deleted in accordance with the participants' perception of this as being less important than the other action fields, lacking data and having low to no influence of the municipality. Instead, the action field *wastewater treatment* was included, as there was agreement on its importance additionally to the supply side. No specific indicator was defined in the workshop due to missing competence in this regard. *Transportation* was discussed as an important action field for municipalities, but participants agreed that its complexity cannot be covered by one indicator. Therefore, the action field remained as an action field of the framework, reminding of the importance of the topic and urging municipalities to consider and discuss it qualitatively.

The discussion around the *economic* dimension reflected the lower ranking of its indicators in the survey. The dimensions *environment* and *infrastructure* were seen to be more naturally linked to resilience than the *economic* dimension. Nevertheless, discussing the importance of a resilient economy for an urban system generated acceptance for the dimension and its components. This example illustrates one very important lesson of the workshop: the need for explanation and building a common understanding. *Innovation* was seen to be covered best by the *number of employees in research intensive companies* not by the *innovation index*. The *tax income from companies* was considered an important resource for the financial ability of the municipality to adapt. This indicator was part of the action field *municipal budget* in the survey and has since been moved to *business*. Similar to *energy*, a *diverse economy* was considered more robust, flexible and redundant when facing uncertainty of climate impacts. It was also discussed whether there might be sectors with crucial or higher relevance than others, but the group agreed that no single sector could be selected.

There was a general agreement on the importance and contribution of *society* to urban climate resilience, but less agreement on how to measure it quantitatively. Literature shows that the experience with extreme events contributes positively to citizens' resilience. In addition, *citizen information about heat, heavy rain and flooding* (Table 3) was amongst the top five rated indicators. However, regarding the spatial scale of municipalities, it was argued that information is not only provided by the local authority and therefore the indicator was not further considered. *Civil society* started an intense discussion on how to measure it and if the proposed indicators were adequate. In contrast to the survey, where the indicator *voter turnout* ranked higher, the workshop participants disliked this indicator, arguing that *voter turnout* nowadays cannot be seen as a proxy indicator for solidarity and community in Germany. The indicator *associations* was also critically reflected upon as being unable to capture *civil society* entirely. Still, the participants were in favour of the imperfect indicator *associations* instead of deleting the action field. In the survey, the dimension *governance* and its indicators were ranked high, and this result was confirmed in the workshop. Only one change was decided: replacing the *contact point for participation processes* with the *number of conducted participation processes*. Both were ranked very close in the survey with a mean of 3.3 and 3.4, respectively.

**Table 5.** Indicator set after the survey, workshop and final set.

| Dimension | Action Field | Survey Result | Workshop | MIS |
|---|---|---|---|---|
| Environment | Soil and green spaces | Degree of unsealed ground | Degree of unsealed ground | Degree of unsealed ground |
| | Water bodies | State of water bodies | State of water bodies | State of water bodies |
| | Biodiversity | Wetlands and retention areas | Wetlands and retention areas | Nature conservation and protection areas |
| | Air | Cold air parcels | Cold air parcels and flows | Ventilation status |
| Infrastructure | Settlement structure | Accessibility of green spaces | Building density | Building density |
| | Energy | Share renewable energy | Diversity of renewable energy | Diversity of renewable energy |
| | | | Per capita energy consumption | Per capita energy consumption |
| | Water supply and wastewater treatment | Number of springs | Number of springs | Number of springs |
| | | | (Including wastewater indicator) | Adapted sewer system |
| Economy | Innovation | Innovation index | Employees in research intensive companies | Employees in research intensive companies |
| | Business | Ration insolvencies to start-ups | Commercial tax per capita | Commercial tax per capita |
| | Economic structure | Employees in research intensive companies | Diversity of business | Diversity of business |
| Society | Research | Number of research projects | Number of research projects | Number of research projects |
| | Knowledge and risk competence | History with extreme events | History with extreme events | History with extreme events |
| | Health care | Accessibility of hospitals | Accessibility of hospitals | Number of doctors |
| | Sociodemographic structure | Share of citizens ABV6/U65 | Share of citizens ABV6/U65 | Share of citizens ABV6/U65 |
| | Civil society | Voter turnout | Associations per 10000 capita | Associations per 10000 capita |
| | Civil protection | Fire brigade | Fire brigade | Fire brigade volunteers |
| Governance | Participation | Contact point for participation | Number of participation processes | Number of participation processes |
| | Municipal budget | Depth per citizen | Depth per citizen | Depth per citizen |
| | Strategy, plans and environment | Risk and vulnerability analsysis | Risk and vulnerability analsysis | Risk and vulnerability analsysis |
| | | Strategies against heavy rain and heat in plans | Strategies against heavy rain and heat in plans | Strategies against heavy rain and heat in plans |
| | Administration | Inter-offices working group regarding risk, climate change and resilience | Inter-offices working group regarding risk, climate change and resilience | Inter-offices working group regarding risk, climate change and resilience |
| | | updated | switched action field | no change |

### *3.4. Urban Climate Resilience Indicator Set*

Since even the diverse group of participants of the workshop did not cover all topics of the indicator set, experts were interviewed. Furthermore, the results of the survey and the results of the workshop were summarized and merged.

The final set of indicators is shown in Table 5 in the column MIS. Compared with the workshop set, the action field of *biodiversity* was seen crucial in its own right and better approximated by the indicator *nature conservation and protection areas*. Moreover, wetlands and retention areas were already covered by the *state of the water bodies* in line with the European Water Framework Directive regarding good ecological and chemical status. Hence, in order to create a balanced set of indicators, it was seen that the latter indicator added thematically more information and another aspect to the overall set. Secondly, the *air* action field was further developed, as *cold air parcels and flows* was difficult to interpret. The simple number or share of cold air parcels and streams were not clearly related to resulting air status. The *ventilation status* including the effects of air streams and cold air production parcels was therefore selected. For the *wastewater* action field introduced by the workshop, an expert interview recommended the indicator *share of adopted sewer system*. Another interview was conducted with the lower civil protection agency. The interviewee stressed the importance of volunteers across organizations, but as no data were gathered assessing the total numbers of volunteers, the most important one of the fire brigade was considered. Moreover, the municipality may have to consider this important topic even more in the future, as the principle of volunteers may be endangered due to demographic development. Finally, yet importantly, the *accessibility of hospitals* was interchanged with the *density of doctors*.

## 4. Discussion

The results from the work on indicators for monitoring urban climate resilience presented above yields a number of important insights and implications—with respect to previous studies but also for future research and for practitioners in this field.

Existing indicator sets are a good starting point, but adapting and extending them for the context at hand is crucial. There are numerous indicator sets for urban resilience; these provided a good basis from which the MONARES indicator set could be developed. However, many of the indicators analysed in the literature review were aimed at the context of developing countries. To adapt indicators identified in the review for the German context, four steps were important: (A) Disregarding indicators that do not allow sufficient distinction between cities, e.g., literacy rate is favoured as an indicator in many sources, but in Germany the literacy rate is rather high and differences between cities are marginal. (B) Disregarding indicators for which the data availability was rather limited in Germany. (C) Adding new indicators for action fields that are deemed important in the context of MONARES but which were not touched upon in the literature. (D) Focusing on municipalities as the key player for climate change adaptation. These level of municipalities require the set to be manageable in terms of data availability as well as size and complexity of the calculations.

Step A did not pose any major difficulties. Further, step B based on research concerning data availability did not cause problems. However, step C and D need to be examined in more detail.

First, the workshop clearly stated here the conflicting goals when discussing single action fields. It was felt that one indicator does not reflect the entirety of the topic, but at the same time all action fields were considered important and the total number of indicators should not exceed around 20, in order to stay manageable, which is far less than the proposed 52 indicators by the City Resilience Index (CRI) [22] and comparable to the core of 14 by the project Building Resilience Amongst Communities in Europe (embrace) [37] or Cutter's [43] core of 22. Since researchers, as well as practitioners, participated in our workshop, we had the impression that researchers tended to prefer larger, encompassing indicator sets. Compared with the scientists, practitioners were more in favour of concise and compact sets. The discussions in the workshop showed that persons with a research background had numerous ideas for new indicators for all dimensions, and advocated for their inclusion. During the workshop and its aftermath, practitioners working in municipalities displayed a different tendency—their perspective tended to focus more on how to handle the indicators in practice. Hence, what some researchers considered a concise indicator set was perceived by practitioners as overwhelming and too extensive. In order to find an adequate balance between a broad coverage and good usability in practice, it is important to involve both researchers and practitioners in the development of an indicator set. This finding is consistent with the literature and is one strength of the current study. Meerow and Stults [13], for example, stress the need for including practitioners in the process. Consequently, the trade-off between practicability and completeness had to be balanced, leading to the fact that some indicators that were considered important were still sorted out in order to cover all action fields and still achieve a manageable amount of indicators.

Second, it was mentioned that the indicators just by title were not clear in terms of their effect on and relation to urban climate resilience, and were consequently rated around the middle. This fact was considered while developing the survey, but an in-depth explanation of indicators was removed from the survey in favour of including more indicators covering all action fields and in consideration of the time needed to fill out the survey. However, this lack of explanations meant that the disciplinary background of respondents affected the ratings.

Third, indicators from the dimension *environment* were met with relatively high consensus while indicators from the dimension *economy* were faced with more diverging opinions. The indicator selection was dependent on the conceptualization of urban resilience and the urban context. The results contribute to the gap between the understanding of urban resilience by scholars and practitioners [13]. This became apparent both in the survey and the workshop and shows that more research is warranted on what characterizes a climate resilience urban economy. Supporting evidence for this can be taken from the fact that much more has been published on climate resilience and environmental issues than on climate resilience and economic issues. Moreover, this discussion displayed the importance of a negotiation-focused approach for defining place-specific attributes of urban resilience and its measures [44].

Fourth, secondary data was seen as crucial for monitoring purposes in order to reduce resource expenditure by the administration. In other words, "The best indicator is inoperable if there is no feasible way to obtain the required data." [37]. Moreover, there was a strong request from the local administrations for more provision of data from the higher administrations. They argued that data handling, data collection and finances for these activities are lacking. They stressed the need for data provision to be handled at the higher level of administration to avoid scaling and data comparability issues. Hence, data availability for indicators on a municipal level is a strong limiting factor, especially when it comes to indicators concerning infrastructure and social aspects [45]. Parts of the infrastructure related to energy, transport and communication are owned or organized by entities on a higher administrative level, such as the national government or by private entities. This tends to lead to limited data availability when it comes to data with a sufficient resolution on a municipal level. Here it would be favourable if entities in charge of the respective infrastructure made access to data easier and provided data with a resolution that is suitable for analyses on a municipal level. Moreover, the discussion centred around technical measures and physical impacts and less about social drivers and demographic changes. The latter are seen as core aspects of the community's ability to resist unforeseen threats. Nevertheless, the intense discussion around the proxies suggested by literature displayed vividly the intricacy of social dynamics. New data and methods from the higher administration or crowd-sourced databases are needed to better understand and monitor the indicators [43].

Fifth, it is important to mention that a conflict of goals among indicators can arise and can lead to a competition for the scarce resources. These reciprocal processes cannot be completely avoided. For example: impervious surfaces are seen negative regarding heavy rain, fresh air and heat island effects, but they are necessary for a redundant infrastructure and other urban functions. Another example is provided by Meerow and Newell [35] who analysed the negative correlation of park access and stormwater management goals, concluding that resilience measures create winners and losers. This also requires transparency of the data and the method of the indicator definition to understand the root causes of the conflicting goals and find adequate solutions. Here the Rockefeller [22] approach seems like a black box because it is difficult to deduce what adaptation measures are used as a data basis, and indicator calculations are unclear. During the workshop, several practitioners mentioned consequently the necessity of transparency and the need for precise communication and non-scientific language.

Sixth, following the previous point, many indicator approaches are used to build a composite index for resilience [19,22,45–47], vulnerability [18,48–52] or risk [53–55]. Specifically, at the scale of urban resilience, indexing across the multitude of action fields was discussed critically. The different scales, topics and units appeared to not be logically linkable. Moreover, a combined index value was seen to not tell much about the level of resilience. It was seen as more important to see the contribution of each action field to the overall resilience. Also, considering the next step of adaptation measures, it is more relevant to have a resilience profile displaying specific topics to be addressed in the municipal context.

Working at the science-policy interface was challenging for all sides. The mixed method approach proved invaluable in finding a common language, tolerance and understanding. This created an environment that allowed for constructive criticism, which is indispensable for finding a compromise.

## 5. Conclusions

In this study, we developed an indicator set to measure and monitor urban climate resilience for municipalities, thereby assessing the requirements of indicators and implementing a method for adapting global approaches to the local context.

The mixed method approach proved to be essential for the process of indicator development. It provided an adequate frame and time to develop a mutual understanding across disciplines, researchers and practitioners, which is needed in order to select indicators or accept indicators from different fields of expertise. Transparency in the process and the inclusion of feedback builds acceptance and trust. The concept of resilience provided the required assembly hall and saw climate change as the imperative. Even the often-criticized ambiguity of the resilience concept was helpful as it created room for discussion. The number of 24 indicators based on secondary data balanced as well as possible the diverging interests. Amongst the indicators, conflict of goals is unavoidable. Making the conflicts visible is a helpful basis for making informed decisions, which is a strength of this indicator set. In general, the softer and more qualitative aspects of resilience are challenging. They were seen as crucial but very hard to assess by quantitative proxies based on secondary data. Still, representative surveys to cover them in more detail on a regular basis were rejected by municipalities as too expensive and labour-intensive.

Developing an indicator set tends to be easier than assessing the significance or validity of an indicator over time and it requires an extended period of observations to be able to make statements about the significance of a certain indicator. Nevertheless, in order to advance this field of research, it is necessary to pursue this path and start inquiries into the significance or validity of the numerous indicators that are permeating the ongoing discussions. In further research, the indicators need to be tested in reality, and there needs to be more research that addresses the validation of the indicators.

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# THIRD CHAPTER

USING OPENSTREETMAP DATA AND MACHINE LEARNING TO GENERATE SOCIO-ECONOMIC INDICATORS

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# Using OpenStreetMap Data and Machine Learning to Generate Socio-Economic Indicators

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**Abstract:** Socio-economic indicators are key to understanding societal challenges. They disassemble complex phenomena to gain insights and deepen understanding. Specific subsets of indicators have been developed to describe sustainability, human development, vulnerability, risk, resilience and climate change adaptation. Nonetheless, insufficient quality and availability of data often limit their explanatory power. Spatial and temporal resolution are often not at a scale appropriate for monitoring. Socio-economic indicators are mostly provided by governmental institutions and are therefore limited to administrative boundaries. Furthermore, different methodological computation approaches for the same indicator impair comparability between countries and regions. OpenStreetMap (OSM) provides an unparalleled standardized global database with a high spatiotemporal resolution. Surprisingly, the potential of OSM seems largely unexplored in this context. In this study, we used machine learning to predict four exemplary socio-economic indicators for municipalities based on OSM. By comparing the predictive power of neural networks to statistical regression models, we evaluated the unhinged resources of OSM for indicator development. OSM provides prospects for monitoring across administrative boundaries, interdisciplinary topics, and semi-quantitative factors like social cohesion. Further research is still required to, for example, determine the impact of regional and international differences in user contributions on the outputs. Nonetheless, this database can provide meaningful insight into otherwise unknown spatial differences in social, environmental or economic inequalities.

**Keywords:** indicators; machine learning; OpenStreetMap; vulnerability; resilience; climate change adaptation

## 1. Introduction

In current policy and research on adaptation to climate change, resilience and vulnerability are key concepts for understanding the human dimension of strategies and measures to adapt to global change.

Vulnerability is a society's inability to act and hence influence the impacts of global change on its people's wellbeing. Increasing the resilience of societies, reducing disaster risk, and hence reducing the impacts of climate change, requires consideration of the social aspects of sustainable development and tackling causes, not symptoms. Socio-economic indicators are important measures to assess spatial or societal dimensions. Factors such as people's economic or employment status are considered to influence their adaptation and coping capacity [1–4].

Although official socio-economic data from governmental and non-governmental institutions are reliable, comprehensive, and often the best choice to describe societal phenomena, they are only available at specific temporal and spatial resolutions and lack standardization between administrative levels, even within countries. Huge efforts to address this include, for example, the INSPIRE directive of the European Commission with a vision of unprecedented sharing of geospatial data. However, this initiative has not been able to reach its full potential yet, due to many barriers to its implementation [5]. Until now, elaborate surveys have often been necessary to generate knowledge about societal relationships with the natural, cultural, and economic environment.

The growing amount of data, open data policies, and crowd-sourced data has led to an increased availability and accessibility of socio-economic indicators. Nevertheless, the measurement of complex multifaceted phenomena (e.g., resilience, vulnerability, sustainability, adaptation) is still often limited due to unavailability of data [2,4,6,7]. Hence, the need for methods that allow deriving indicators from data sources, that are permanently available and offer spatially scalable information, has become very clear.

In recent years, artificial intelligence, and especially machine learning methods, have been developed and tested in many scientific disciplines in order to predict social characteristics and structures by analyzing implicit patterns in data of the observed systems. Random forest (RF) is one machine learning algorithm widely applied for geodata: e.g., for land cover classification from openly available geodata sets [8], mapping vegetation morphology types [9], habitat prediction of fisher (Pekania pennanti) [10], a multi-data approach to enhance crop classification [11], or downscaling census data [12]. Another machine learning algorithm applied across disciplines is neural networks (NN). Examples are seismic vulnerability assessment [13], modeling of the surface of the sea floor [14], flood hazard assessment [15], and analyzing land pattern evolution [16]. Within machine learning, neural networks belong to the deep learning category.

This research aimed to develop a machine learning approach to deduce socio-economic indicators from OpenStreetMap (OSM) for municipalities. The underlying hypothesis was that there are proxies for socio-economic attributes within the geodata of the OSM database. For example, can park benches be a predictor for an elderly population? Can the size of industrial areas or density of public transportation or infrastructure provide an indication of unemployment rates? Is nature or industry more predictive for migration? With four indicators (residents, unemployment, migration, and elderly) selected based on official statistical data, we tested the suitability of OSM as a data source and compare the predictive performance of three approaches: (1) random prediction as a baseline with linear regression; (2) one machine learning algorithm; and (3) one deep learning algorithm. We assessed the predictive power of each approach by comparing them to the testing regions where we know the actual situation.

This research paper is based on earlier investigations by the authors [17,18] and represents a refined approach to the analysis of the OSM database with artificial intelligence (AI). Section 2 introduces the study area and develops the methodology adopted, including the target indicators and the machine learning algorithms exploited. Section 3 presents the prediction results of the models, including a comparative performance evaluation. Section 4 discusses the findings in regard to each indicator and cross-cutting challenges amongst them, leading to opportunities for future research. Section 5 concludes by summarizing the research question and main results.

## 2. Method

The workflow follows the narrative of the research (Figure 1). Firstly, the OSM dataset was downloaded. Secondly, in a spatial query everything within the area of a municipality was counted. Thirdly, in a data processing step, a principal component analysis (PCA) was conducted to reduce the number of dimensions, resulting in uncorrelated principal components as indicator candidates. Fourthly, the indicator candidates were subsequently used to predict the four socio-economic indicators (unemployment, residents, migration, elderly). Fifthly, the model results were validated and, lastly, they were mapped.

In the following section, the case study and the selected socio-economic indicators are firstly described. Secondly, OSM is described as the data source with its key characteristics and implications for calculating spatial attributes for each municipality. Thirdly, the machine learning algorithms and their implementation, functions, and settings are discussed.

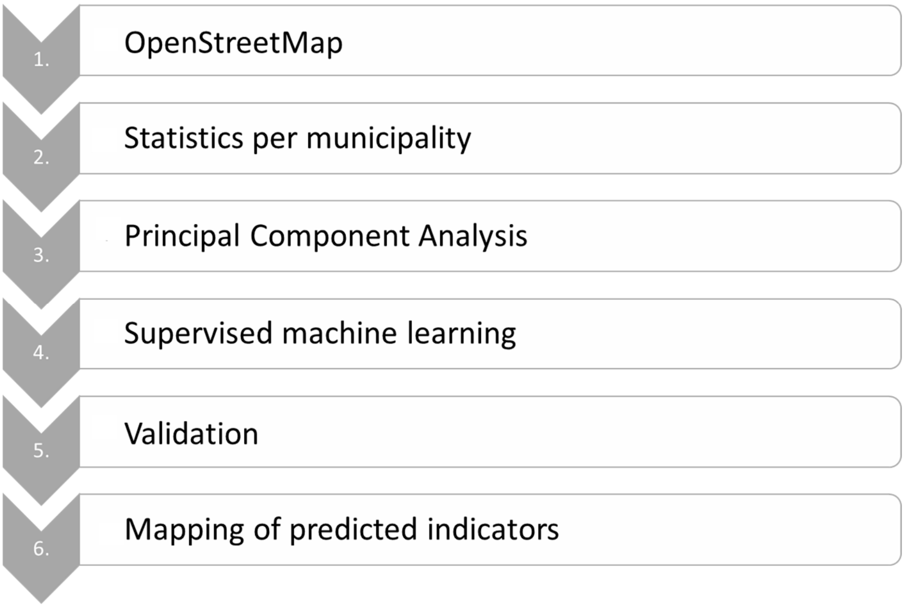


**Figure 1.** Overall workflow of the analysis conducted.

### 2.1. Test Region

As a compromise between computational resources, data handling, and model complexity, the regional scale was chosen. Baden-Württemberg is the south-western federal state of Germany bordering France in the west and Switzerland in the south (Figure 2). The administrative territory with a size of 35,751.46 km$^2$ is subdivided into four administrative districts (Regierungsbezirke) which contain 35 counties (Landkreise) and nine independent cities (Stadtkreise). In total, there are 1101 municipalities populated with around 11 million inhabitants. The density of the population is 310 inhabitants per km$^2$, higher than that of Germany overall which is 232 inhabitants per km$^2$ [19]. Economically, Baden-Württemberg is one of the strongest regions in Europe and is ranked third in Germany in terms of purchasing power after Hamburg and Bavaria [20]. Family-owned businesses are typical for the region. The overall unemployment rate is 3.1% and lower in rural areas [21]. In 2018, the average age was 43.5 years, an increase of 9 years from 1970. Although there has been considerable emigration of young people, the number has not changed much in recent years [22]. Currently, 294,000 people are 85 years or older. This is six times higher than in 1970. The current forecast expects the number to increase up to 805,000 people by 2060 [23].

### 2.2. Selected Socio-Economic Indicators

The selected socio-economic indicators for the purpose of this study were: (a) residents; (b) unemployment; (c) elderly; and (d) migration. Residents refers to the number of inhabitants per municipality. Unemployment refers to the percentage of unemployed people as part of the total number of employable people. The proportion of elderly people gives the percentage of people older than 65 years as part of the total population. Migration is calculated by subtracting emigration from immigration. A positive balance means that more people moved in to the municipality than out of it. These four metrics explain societal and economic conditions and are a common basis for many socio-economic indicators and of relevance for assessing and evaluating complex phenomena such as resilience, vulnerability, and sustainability [6,24–26].

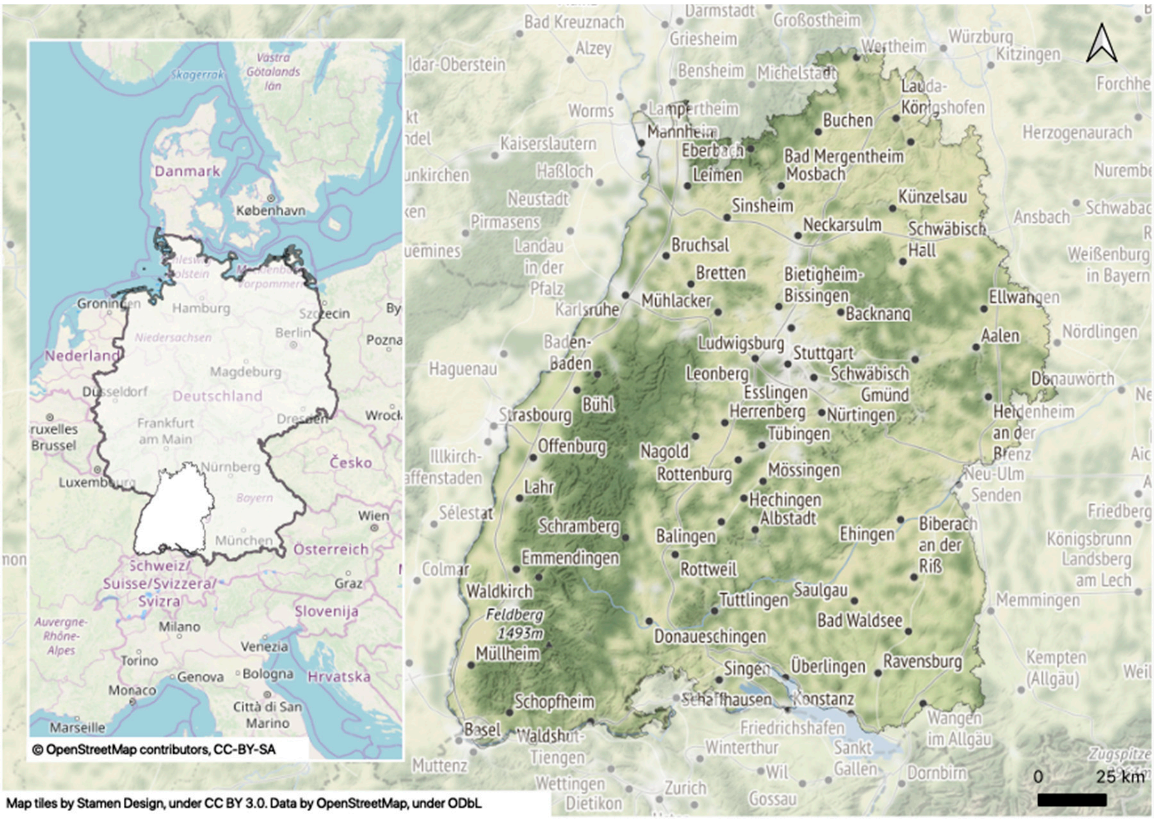


**Figure 2.** Map of study area.

## 2.3. OpenStreetMap—Developing Spatial Features for Municipalities

OSM is a free and collaborative project founded in 2004 [27]. The goal of the project is to create an open access map of the world. All elements of a topographic map, such as houses, streets, railways, and forests are mapped by volunteers around the globe [28]. Crowdsourced data are made public under the Open Database License. Current statistics show more than six million registered users, 5.75 billion nodes, and 3.5 million map changes per day [29].

Every element is described within the database by at least one tag in plain text. The tag consists of a key and a value. The key can describe the represented objects with the functional characteristics or other attributes such as names or owner. The keys are unique and categorical (e.g., land use) and describe the classes or domains that each object belongs to. Values can be used to further specify individual characteristics and explanations (e.g., tag: key = landuse; value = farmland).

For the purpose of this study, we first downloaded the full OSM dataset for the federal state of Baden-Württemberg from the Geofabrik website (https://download.geofabrik.de; October 2019). The downloaded .pbf file was then imported into a PostgreSQL database with PostGIS extension using osm2pgsql (https://github.com/openstreetmap/osm2pgsql). During the import, an initial data reduction took place through the used default import “style”, which excludes certain keys and additional information without explanatory relevance from the dataset. The resulting PostGIS geometry and attribute tables (point, line and polygon) contained 60 of the most relevant keys as columns and respective values as rows. In a further pre-processing step, the OSM data were intersected with the administrative boundaries of the municipalities within the federal state. Consequently, the sums of the geometries (area and length) and point counts for each occurrence of a unique key-value-pair were computed with SQL-queries for every municipality, resulting in a table with 1101 rows, each row representing one sample, meaning one municipality (Table 1).

**Table 1.** Data table of spatial attributes per municipality.

| Name | Key_Value [Count/Municipality] | Key_Value [km/Municipality] | Key_Value [$km^2$/Municipality] |
|---|---|---|---|
| **Municipality 1** | Value | Value | Value |
| **Municipality 2** | Value | Value | Value |

The previous steps resulted in three distinct layers (points, lines, polygons), with the keys and values and the respective sums of their observed spatial occurrence (count, sqm, km). Each line or sample counted for one spatial feature, and therefore, there was an unrestricted number of lines per tag per municipality. All the following steps were conducted using R with R Studio [30,31] (additional packages: "tidyr"; "dplyr" [32,33]). The three tables were imported into R Studio from the PostGIS database (function: dbReadTable(); package: "RPostgres" [34]). In a preliminary data cleaning step, six keys (addr, name, xmas, contact, TMS, openGeoDB) were removed, as they did not contain relevant information for the task ahead. Moreover, only tags appearing in 100 or more municipalities were considered. The key and value columns were then joined to one tag column. Afterwards, the tags were aggregated by sum per municipality and written into one column per tag (function: dcast(); package: "reshape2" [35]). The same steps were taken for the three tables (points, lines, polygons), and the resulting tables were joined by the municipality code to one table. In the next step, these raw data were pre-processed for the machine learning part.

The population of the municipality as well as the area were imported (function: read_excel(); package: "readxl" [36]). The data set was split rather cautiously via random number generation into 50% test municipalities and 50% training municipalities to test the predictive power and increase generalization. To adjust for the different sizes of municipalities, the predictors were set into relation per 1000 capita. The training data were standardized and PCA conducted (function: preProcess(); package: "caret" [37]). The pre-process parameters from the training data were also taken for the test data so as to not blend in future information into the training process via standardization of the entire data set. The PCA was used to reduce dimensions and to have a set of uncorrelated indicator candidates to predict the four socio-economic indicators (see Appendix A).

### *2.4. Machine Learning to Predict Socio-Economic Indicators*

The following section describes the predictive algorithms and their R functions that were applied to this analysis, including model parameters. Firstly, the baseline was established by random prediction and a linear model. Secondly, random forest and deep neural networks (DNN) were applied as a machine learning and deep learning approach. Thirdly, these models were compared to the ground truth and evaluated for predictive power.

For the random prediction (RP), random values within the range of the test data were generated. The mean absolute error (MAE) on the test data was calculated and compared as a baseline. The MAE was selected to test for model performance, which is reported in Table 2. The mean squared error (MSE) was neglected due to the potential overestimation of model performance as all outcome values were min–max normalized for comparison among them. Hence, calculating the square of values between zero and one would have resulted in significantly smaller absolute values and obscured the performance.

Linear regression (LR) was conducted as a basic statistic prediction method to better understand the performance of the machine learning algorithms (function: lm(); package: R base library).

**Table 2.** Mean absolute error of the models for the indicators. RP, random prediction; DNN, deep neural networks; LR, linear regression; RF, random forest.

| Dataset | RP | LR | RF | DNN |
|---|---|---|---|---|
| **Residents** | 0.489 | 0.049 | 0.038 | 0.021 |
| **Unemployment** | 0.280 | 0.119 | 0.099 | 0.095 |
| **Elderly** | 0.311 | 0.090 | 0.074 | 0.071 |
| **Migration** | 0.405 | 0.041 | 0.035 | 0.025 |

Random forest (RF) is a machine learning algorithm based on the statistic of decision trees. In a randomized learning process, multiple uncorrelated decision trees are calculated. In the standard setting, 500 trees are built by subsets of the predictors to avoid the dominance of one very strong predictor (function: randomForest(); package: randomForest [38]). The importance of assessment of the predictors is set to true for detecting relevant predictors. The relevance of the predictors is determined by their contribution in reducing the test error over all trees.

Artificial neural networks are machine learning algorithms that function in a similar way to the human brain. A number of hidden layers and nodes, structure, organize, and detect patterns within data. Multiple sequential models are trained with a maximum of four hidden layers and 256 nodes for each of the four indicators (function: sequential(); package: "keras" [39]). Finally, the best four DNN, one for each indicator, with the lowest MAEs are selected.

Within the keras package, no method is yet included to assess the predictor importance and analyze the black box of the neural network. Similar to the random forest recording of the contribution to the reduction of the error, the permutation feature importance (PFI) was implemented. Here, the approach by Fioruzi (2018) was adopted, which is based on [40,41]. Although methodologically not defined, the method was implemented on the test data. For each predictor, the values are randomly permutated and the error of the neural network calculated. Afterwards, the absolute PFI was calculated by subtracting the original model error from the permutation error, resulting in a value about the contribution of the predictor on the reduction of the MAE.

The method described above was performed for all four outcomes, split into the same test and training sets. The final mapping of the indicators was done implementing a quantile classification with eight classes.

## 3. Results

The following section starts with the overall comparison of the performance of all applied machine learning algorithms on the four indicators. Subsequently, the spatial distribution and predictive elements of OSM for each indicator are presented.

### *3.1. Comparison of Machine Learning Algorithms and Model Performance*

The first column represents the resulting MAE for randomly predicting values to establish the baseline for comparison (Table 2). The second, third, and fourth columns are the LR, RF, and DNN errors. In general, linear regression was better than random prediction, RF was better than LR, and DNN was better than RF. For the DNN model, the number of residents per municipality was best predicted with the lowest error, followed by migration, elderly, and unemployment.

### *3.2. Spatial Features of Number of Residents*

The number of residents of each municipality was in decreasing order of the MAE modeled by random, linear, RF, and best DNN.

The DNN model clearly outperformed the RF model but resulted in the challenge of understanding the model. Performing the feature performance index (PFI), the four most important predictors of residents were (Table 3): *Train system*, *Infrastructure*, *Shopping and culture*, and *Rurality*.

**Table 3.** Most important predictors of residents.

| PFI Rank | Predictor |
|---|---|
| 1 | *Train system* |
| 2 | *Infrastructure* |
| 3 | *Shopping and culture* |
| 4 | *Rurality* |

The highest error was for the state capital of Stuttgart (Figure 3). In fact, Stuttgart was not part of the training data and had a normalized value of over two due to its unmatched size within the training set. The DNN model failed to extrapolate the extraordinary size of the capital from the training data. This is the difficulty of the min–max normalization, which can result in test data values not seen within the training data. Additionally, the city of Karlsruhe emerged as having one of the worst predictions, which again shows the difficulties that the model has in making predictions for relatively large cities compared to the majority of smaller municipalities. Mudau and Talheim, with 5009 and 4830 inhabitants respectively, achieved the lowest errors. The mean number of residents over all 1101 municipalities in Baden-Württemberg is 10,054. Hence, the model performs well around the median and less well in predicting outliers. The areas without value (NA) do not have the legal administrative status of a municipality and are therefore not included in the statistics.

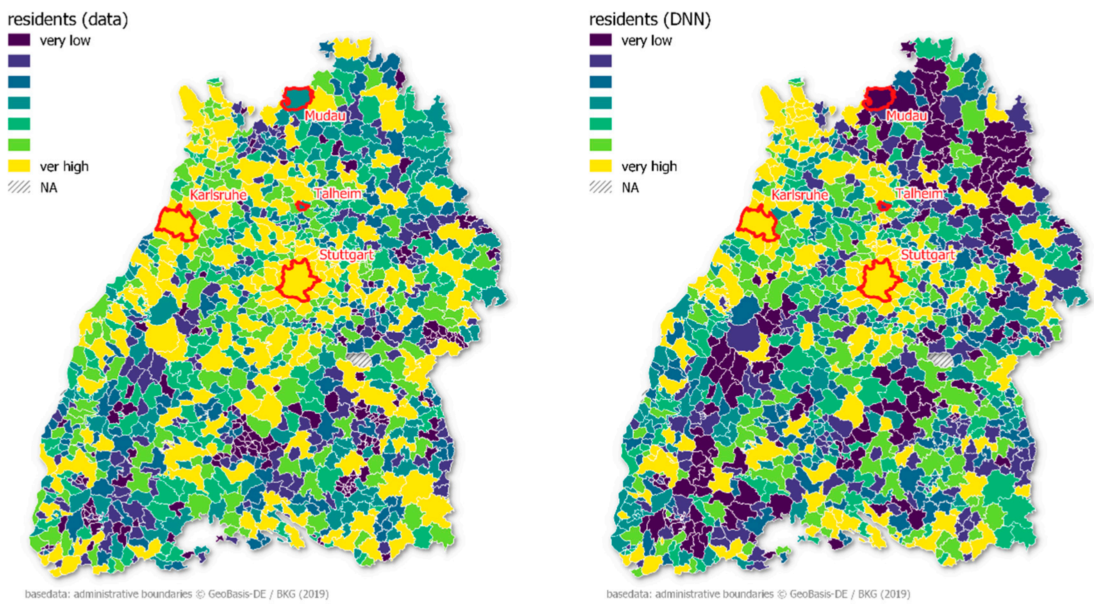


**Figure 3.** Map showing the normalized resident values (**left**) and predicted values (**right**) of the municipalities in Baden-Württemberg.

### 3.3. Predictors of Unemployment

The level of unemployment as a share of the total population per municipality was the most difficult to predict compared to the other socio-economic indicators. Additionally, there was not much difference between DNN and RF. There is close to full employment throughout the entire federal state, with many hidden champions in the countryside. This explains the lower unemployment of rural regions compared to metropolitan areas (Figure 4).

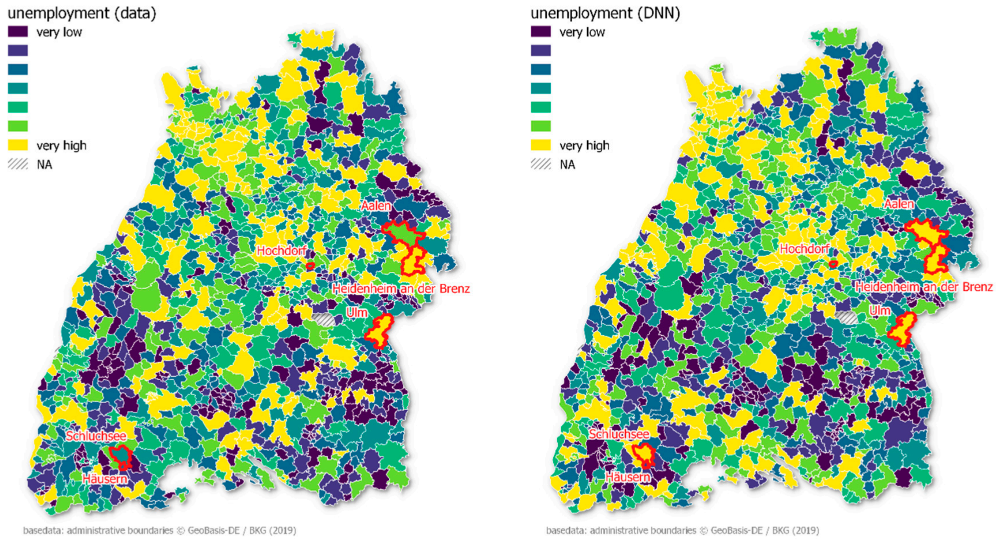


**Figure 4.** Map showing the normalized unemployment values (**left**) and predicted values (**right**) of the municipalities in Baden-Württemberg.

The PCA of *Tourism* scored the highest PFI, followed by *Natural sights*, *Historic rural*, *Train system*, and *Social care* (Table 4). Hence, PCAs describing the typology of the municipality dominated. Schluchsee, located in the Black Forest, showed the highest error among all municipalities.

**Table 4.** Most important predictors of unemployment.

| PFI Rank | Predictor |
|---|---|
| 1 | *Tourism* |
| 2 | *Natural sights* |
| 3 | *Historic rural* |
| 4 | *Train system* |
| 5 | *Social care* |

The prediction overestimated the unemployment in the municipality. The second highest MAE was reported for Heidenheim an der Brenz, where the real unemployment was underestimated. Interestingly, in the spatial proximity of Heidenheim, Ulm had the lowest error, followed by Hochdorf, Häusern, and Aalen.

### 3.4. Predictive Features for the Proportion of Elderly People

The proportion of elderly people in the municipality was modeled slightly better than unemployment. Again, there was only a marginal difference between RF and DNN, though both were superior to the linear model (Table 2). Across Baden-Württemberg, there is no clear pattern between rural and metropolitan areas (Figure 5). In the western Black Forest region, the share of older people is comparatively high, whereas in the north of Stuttgart and in the south-eastern region, the share of the younger population is higher.

Spatial features related to an older population with the highest PFI score are in the *Nature recreation* category, followed by *Infrastructure*, including roads and other elements of infrastructure (Table 5). The third-highest scoring dimension is another facet of the first with *Nature*, followed by *Suburban* and *Nursing home*.

In Untermarchtal, the share of elderly people was underestimated based on OSM, having the highest MAE. Furthermore, Steinheim am Albuch had the second worst prediction scores, as the proportion of elderly people was overestimated. At the other end of the scale are Wittighausen and Kappelrodeck, where the error is close to zero.

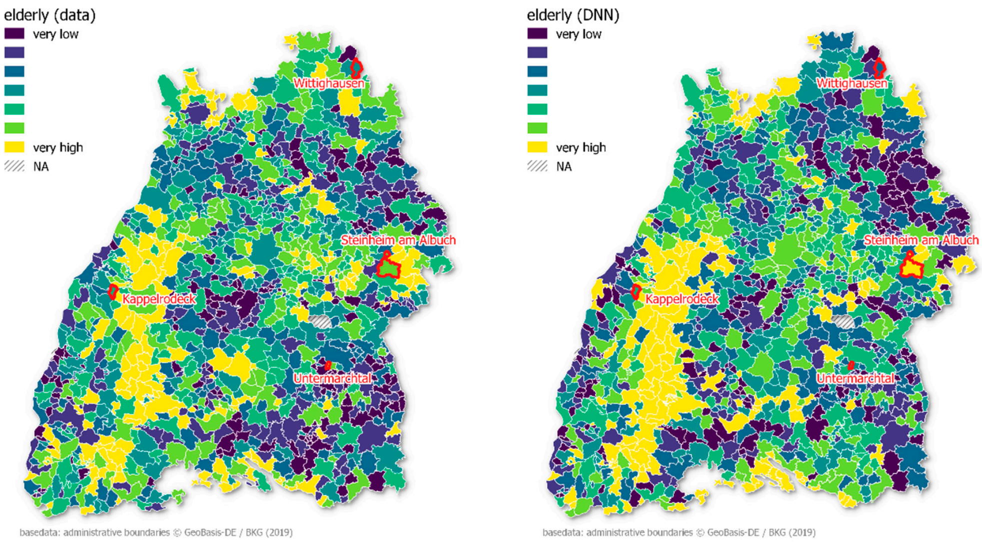


**Figure 5.** Map showing the normalized proportion of elderly people (**left**) and predicted values (**right**) of the municipalities in Baden-Württemberg.

**Table 5.** Most important predictors of the elderly.

| PFI Rank | Predictor |
|---|---|
| 1 | *Nature recreation* |
| 2 | *Infrastructure* |
| 3 | *Nature* |
| 4 | *Suburban* |
| 5 | *Nursing home* |

### *3.5. Spatial Attributes of Migration Balance*

The balance between emigration and immigration and overall spatial attractiveness of a municipality was the third best model. The river Rhine below Freiburg is a highly attractive region after the metropolitan regions of Stuttgart and Karlsruhe (Figure 6).

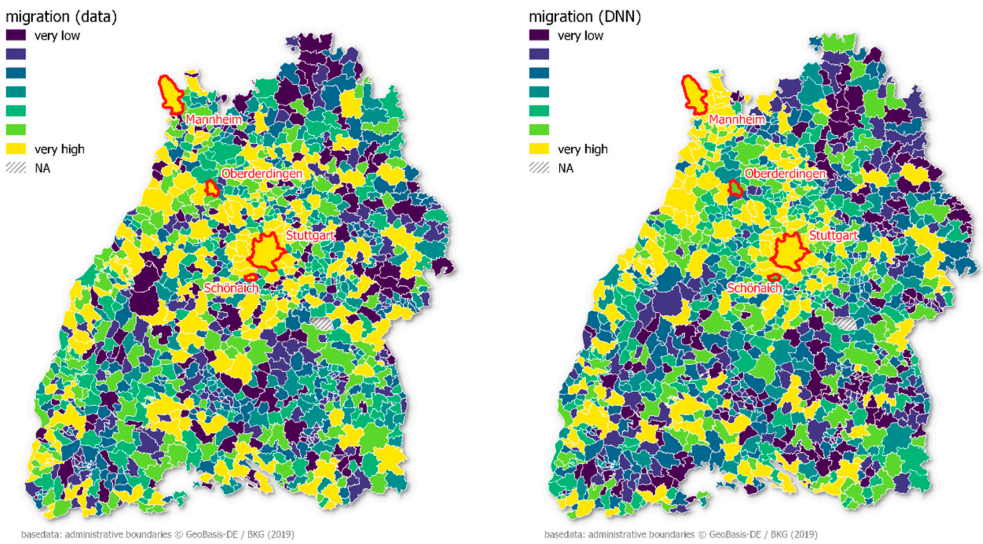


**Figure 6.** Map showing the normalized migration balance (**left**) and predicted values (**right**) of the municipalities in Baden-Württemberg.

The *Train system* is again important for the model, as already observed in the model for the residents. As in the previous model of the elderly population, the dimensions of *Nature recreation* and *Infrastructure* are of permutational importance (Table 6). These are followed by the *Metropolitan* and *Industrial* area. Similar to the number of residents, the model fails to explain outliers in this category, namely, the cities of Stuttgart and Mannheim. By contrast, the model performs excellently for Schönaich and Oberderdingen.

**Table 6.** The most important predictors of migration.

| PFI Rank | Predictor |
|---|---|
| 1 | *Train system* |
| 2 | *Nature recreation* |
| 3 | *Infrastructure* |
| 4 | *Metropolitan* |
| 5 | *Industrial* |

## 4. Discussion

Developing dynamic socio-economic indicators for measuring development or vulnerability and describing complex phenomena remains a challenge despite the overall growth of data availability. In this study, socio-economic indicators for residents, unemployment, elderly, and migration are spatially predicted from OSM data with machine learning algorithms.

### *4.1. Residents*

The DNN model, which performed best for all options, predicted the number of residents with the feature elements from the categories *Train systems*, *Infrastructure*, *Shopping*, and *Cultural rurality*. Stuttgart, the largest urban agglomeration in the dataset, was misrepresented, showing the struggle of the model to differentiate outliers from extreme values. This shows the problem of reproducing extreme values with machine learning algorithms and the need for complete datasets. As these models produce more reliable estimates the more complete the data are, they show weaknesses for the extreme values in narrow datasets when detection of outliers and differentiation from extreme values is unreliable due to similarity in numbers.

### *4.2. Unemployment*

Looking deeper into the modeling of the unemployment rates, we saw that the model largely explained unemployment with *Tourism*, *Natural sights*, and *Historic rurality*. This shows the direct link of natural and cultural heritage to tourism and employment rates in the Black Forest region. If not protected, cultural and natural assets can be shown to have large negative impacts on employment rates.

Unemployment is, however, overestimated for the metropolitan regions. This can be explained by several facts. Firstly, the model explains employment with *Natural* and *Cultural heritage*, which does not reproduce urban agglomerations where the labor market is close to full employment. Furthermore, a specific characteristic of the federal state is a highly decentralized economy with hidden champions on the countryside providing excellent jobs in rural areas but also struggling to get highly qualified employees. The study on the region of Stuttgart revealed similar trends [18]. To further investigate and not only predict unemployment, the normalization of the data needs exploration, which is in line with preceding studies to adjust for OSM spatial diversity in contribution [17,18]. Furthermore, training the model with a larger dataset incorporating more large cities, thus stabilizing the extreme value distribution, might resolve this issue for the machine learning algorithms.

Furthermore, the model showed errors in predicting unemployment for Schluchsee and Heidenheim an der Brenz. The municipality of Schluchsee profits from its large number of recreational options around the lake. A variety of recreational options, such as hiking, diving, sailing, and swimming, and in winter, skiing, makes it a popular tourist destination. Therefore, the better performance of the municipality compared to the region partially explains the higher MAE. In Heidenheim, unemployment increased by 12.6% within the last year, far more than in the rest of the region [42].

Nonetheless, a major strength of the methodology presented is revealed by displaying this spatial assessment of connections. By focusing on the distillation of very complex interrelations, regional decision-makers can see the complex relations between the protection of cultural and natural heritage and employment in the tourism industry displayed on the map. This method has the potential to be developed in further research to extract unknown connections, combining target-oriented regional management with success control.

### *4.3. Elderly*

For elderly people, the DNN model focuses strongly on nature-related variables and care facilities. Looking deeper into the third indicator of elderly people, the model performance of the municipality Untermarchtal stands out. Due to the unique setting of Untermarchtal, with its active monastery, including a special care home and only 893 inhabitants, the model underestimates the high proportion of elderly people. Similar to the findings of [22], rural sites can be dominated by a single economic player, and this situation is not well represented by the models. It could also be helpful to screen the municipalities with very low MAEs, such as Schönaich, Oberderdingen, Wittighausen, and Kappelrodeck, which are well represented due to the median values.

Interestingly, the third explanatory variable was mobility. Relating elderly to public transport, the strength of the method provided here can be seen. In the OSM dataset, information on infrastructure, nature, and cultural heritage, but also mobility and connectivity, can be assessed in depth, gaining knowledge about new relations and connections with machine learning algorithms. This study results in spatial information about the dependence of elderly people on reliable public transport. As such, in combination with ongoing demographic change, a decision-maker would now have the possibility to assess future demand for mobility capacity needs and target the development of specific public transport for the elderly according to the distilled spatial distribution.

### *4.4. Migration*

In addition to the cross-cutting dimension, each indicator is specified by explicit dimensions. Migration can be described by *Infrastructure*, *Economic*, *Provision of services*, and *Natural* characteristics.

In line with residents and unemployment, the DNN model also struggled to predict extreme values for migration balance. The problem was aggravated in cases where extreme values were part of the test data. Predicting the migration balance, the two largest cities of Baden-Württemberg, Stuttgart and Karlsruhe, were not well reproduced.

### *4.5. Model Comparison*

When deepening the analysis of the different model performances, we saw that DNN performs most reliably. The two machine learning algorithm MAEs were much closer to one another. Still, DNN was better than or equal to RF in all four cases. This is in line with current research, as deep neural networks have outperformed many models in previous studies [43–49]. Despite the slightly worse performance of RF, it is worth mentioning that the DNN required substantial model configuration, without which it performed much worse than both other methods. Moreover, RF is easier to communicate and understand. The feature importance of the RF was implemented within the approach. Here, DNN is often seen as a black box, making it difficult to understand driving factors [49]. In addition, the RF proved to be more robust and much easier to execute. Without extensive training, we could observe a deterioration in the DNN model performance, as a sensitivity to the training and test data selection became apparent. RF produced robust and less sensitive results compared to random sampling. The computational needs for RF were also much lower than for DNN. Hence, in cases where maximal model performance is needed, DNN is the model of choice, whereas for data mining and understanding, RF often seems to perform quite well.

In increasing order, starting with the lowest MAE of the DNN, the indicator population was best predicted, followed by migration, elderly, and unemployment. Although DNN had superior predictive power, the model performed badly on the outliers and in the extreme values. This could especially be seen when reproducing the number of residents on a regional scale, as estimations for residents in the larger cities were worse. This was mainly the case for Stuttgart and for Karlsruhe. This might, however, be resolved by deepening the research with larger datasets incorporating more large cities, so that the extreme value distribution is stabilized and produces more reliable estimates.

### 4.6. Challenges

An important part of socio-economic indicators is their explanatory power of unusual phenomena or in extreme situations. Machine learning, and especially DNN, is often seen as a black box, which limits its acceptance and applicability [50]. Nonetheless, the PFI is a very condensed way of interpreting the global feature importance. As the approach is linked to the error of the model, it is only possible to perform with access to the outcome and not for the assessment of a standalone model [51]. By leaving out different explanatory variables, the assessment of their contribution to the overall outcome distills the interconnections of social indicators and spatial attributes, which is key in understanding regional development issues and helps in making target-oriented decisions.

Furthermore, one major challenge that kept coming up in all the indicators was the representation of extreme values. As such, it could be shown in this study that the representation of extreme value distribution is, as is in any modeling effort, one major flaw in the methodology. This being an interwoven problem of the availability of wide-ranging datasets for model training, the complex process of differentiating between outliers and extreme values, and the simultaneous training of models to represent normal distributions and extreme value distributions.

An important common constraint of OSM data is the spatially unbalanced contribution and, hence, the variations in spatial coverage and density of information, especially on a global level. Germany, and especially the selected study region, is among the regions with a comparatively high number of contributors and a high coverage of information, represented, for example, by a completeness index of above 50% in 2016 for Germany [52]. Nevertheless, the completeness within the country still shows a disparity between rural areas and urban regions regarding data coverage and quality [53,54], which could limit the explanatory power of the model results in this study. Therefore, it would be interesting to see if certain thresholds could be established for regions with lower coverage or if the absence of OSM data themselves can be used in this context as a predictor. Another shortcoming is that the handling of the method is not user-friendly. Machine learning techniques remain difficult to handle and require a statistical and analytical skillset. Furthermore, the management of the OSM data structure within the model is not very intuitive which, all in all, makes the approach difficult to be used by decision makers. Nevertheless, we have succeeded in showing that OSM data sets contain a great deal of knowledge about socio-economic realities, and that these can be extracted with machine learning. It is not insignificant that these indicators can be represented spatially in map form, which increases their contribution to decision-making.

### 4.7. Future Research

After having tested the method in the small-scale region of Stuttgart, we further developed the approach. As a compromise between computational resources, data handling, and model complexity, the regional scale was chosen. In further research, the potential at a global scale and transferability of models between regions should be assessed, given the potentially high impact on the results due to different levels of completeness of OSM data and/or the use of different (local) tagging guidelines. In line with a larger dataset, emphasis should be put on better consideration of extreme values. Often decision makers are mainly interested in special cases, i.e., extreme values. Further efforts are needed to be able to provide stable answers to these complex questions at the outer ends of the dataset.

## 5. Conclusions

Living in a globally interwoven world, rarely is any problem restricted to one singular specific point in space and time. As such, the big challenges of global change and, subsequently, resilience, vulnerability, and sustainability that we are facing are not stationary.

In this light, first understanding and later monitoring multifaceted phenomena demands a global temporal interdisciplinary source of data. OSM is a valuable source of data, and machine learning provides the means of deducing interdisciplinary indicators. OSM documents the physical manifestation of human activities, and these data can be used to perform socio-economic analyses by means of machine learning. Neural networks have succeeded in terms of model performance compared to Random Forest. Here we have shown the attractiveness of this untapped potential for knowledge generation by combining machine and deep learning algorithms with OSM for developing socio-economic indicators. The evaluation provided encouraging insights into the manifestation of socio-economic attributes in OSM data. The approach we developed exposes several advantages, but also several issues that need more consideration.

To fully exploit the opportunities of OSM in terms of spatial coverage, personal computers reach their limitations in data wrangling. Further exploration is required into global predictors and the transferability of models across regions or countries. Additional temporal analyses might further improve the performance of models and their predictive power and help to deduce the most relevant predictors.

**Author Contributions:** Conceptualization: Daniel Feldmeyer.; data curation: Holger Sauter. and Daniel Feldmeyer; methodology: Daniel Feldmeyer; writing—original draft: Holger Sauter; Daniel Feldmeyer and Claude Meisch; writing—review and editing: Daniel Feldmeyer, Claude Meisch, Holger Sauter and Joern Birkmann. All authors have read and agreed to the published version of the manuscript.

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**Data & Workflow:** https://github.com/danielfeldmeyer/OSM-indicator (will be provided upon completion of PhD).

## Appendix A. Predictor Related Tags

| Predictor | Tags (Highest Loadings) |
|---|---|
| *Nature recreation* | landuse_forest; route_bycicle; operator_Baden-Würtemberg |
| *Infrastructure* | Highway_traffic_signals; route_train; highway_crossing_railway_rail |
| *Train System* | Route_tracks; railway_rail; operator_DB Netz; route_railway |
| *Natural sights* | Tourism_viewpoint; width_1; boundary_natural; natural_mountain_range; food_yes |
| *Tourism* | Shop_books; tourism_museum; historic_castle; tourism_hotel |
| *Metropolitan* | Route_bus; oneway_yes; highway_milestone |
| *Suburban* | Building_garage; route_power; landuse_recreation_ground; waterway_drain; power_line |
| *Nature* | Natural_mountain_range; place_region; boundary_natural; route_ski; amenity_waste_basket |
| *Historic rural* | Highway_living_street; historic_archeological; man_made_bridge; operator_DHL |
| *Industrial* | Landuse_idustrial; sport_multi; surface_gravel; leisure_track |
| *Rurality* | power_cable; place_hamlet; bicycle_use_sidepath; building_public |
| *Social care* | Building_kindergarten; amenity_nursing_home; leisure_track; |
| *Nursing home* | amenity_nursing_home, width_10; denomination_new_apostolic |
| *Shopping & culture* | Shop_deli; amenity_arts_center; shop_beverages |

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# FOURTH CHAPTER

## REGIONAL CLIMATE RESILIENCE INDEX: A NOVEL MULTIMETHOD COMPARATIVE APPROACH FOR INDICATOR DEVELOPMENT, EMPIRICAL VALIDATION AND IMPLEMENTATION

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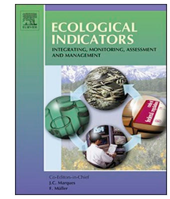

Original Articles

# Regional climate resilience index: A novel multimethod comparative approach for indicator development, empirical validation and implementation

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ABSTRACT

High uncertainty in the occurrence of extreme events and disasters have made resilience-building an imperative part of society. Resilience assessment is an important tool in this context. Resilience is multidimensional as well as place-, scale- and time-specific, which requires a comprehensive approach for measuring and analysing. In this regard, composite indicators are preferred, and extensive literature is available on resilience indices on all spatial and temporal scales as well as hazard-specific or multi-hazard related indicators. However, transparent, robust, validated and transferable metrics are still missing from the scientific discourse. Hence, the research follows a novel composite index development approach: First, to develop and operationalise climate resilience on the county level in the state of Baden-Württemberg, Germany; second, to develop multiple composite indices in order to assess the impact of the construction methodology to increase transparency and decrease uncertainty; third, validating the index by statistical as well as empirical data and machine learning models - which is a novel endeavour so far. The results underscored that the two-step inclusive validation of data-driven statistical analysis in combination with empirical data proved to be essential in developing the index during the selection and aggregation of indicators. The results also highlighted a lower climate resilience of rural regions compared to metropolitan regions despite their better environmental status. Overall, machine learning proved to be essential in understanding and linking indicators and indices to policy, resilience and empirical data. The research contributes to a better understanding of climate resilience as well as to the methodological construction of composite indicators.

## 1. Introduction

Uncertainty in the occurrence of climate change-related extreme events and disasters is growing. The need to deal with this uncertainty has made resilience-building an imperative part of society. Therefore, the application and development of resilience assessment is an essential tool to better understand, identify and deal with these multi-dimensional and complex challenges.

Typically, composite indicators are used for the assessment of many multidimensional phenomena and intend to capture all facets. Over the last decade, literature references on composite indicators grew exponentially (Greco et al. 2019). However, composite indicators are highly criticized, with three major objections cited against them: a) they can send misleading and non-robust messages, b) they are not objective as judgement is included in selecting indicators, c) the amount of data needed is increased, which leads to difficulties in applying the indicators (Saltelli 2007). The construction of indices is often implemented either by solely data-driven approaches criticized for neglecting the phenomena or purely reasoning-driven approaches refusing statistics. Despite this criticism, two main reasons are responsible for their apparent popularity and common use for complex issues: Firstly, they can provide a simple picture, enable comparison and evaluation of complex multidimensional phenomena; secondly, they can function as drivers for behavioural change of governments or agencies (Becker et al. 2016). Therefore, composite indicators became increasingly popular in the complex realm of natural hazards.

Composite indicators have been developed on different scales (e.g., global, country, urban, household, individual) for risk (Welle and Birkmann, 2015; Birkmann and Welle, 2016; Marin-Ferrer et al., 2017), vulnerability (Welle et al., 2014; Depietri et al., 2013; Sorg et al., 2018;

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**Table 1**
Methodology - Concept.

| STEP | SUBSTEP | CALCULATIONS |
|---|---|---|
| 1. Spatial scale & initial indicators | 1. Definition of the spatial scale | |
| | 2. Upscaling from urban resilience to regional resilience | |
| | 3. Development of the initial indicator set | |
| | 4. Transformation of the initial indicators (normalization) | a. min–max-transformation |
| 2. Validation of indicators | 1. Empirical validation | a. Machine learning (random forest) |
| 3. Aggregation of the index | 1. Aggregation of the index | equal weights (eqw) |
| | | mixed equal hierarchical weights (hw) |
| | | Wroclaw Taxonomic |
| | | Mazziotta-Pareto-Index (mpi) |
| 4. Calculation of robustness & sensitivity | 1. Reliablity | a. Cronbachs alpha |
| | | b. Guttman's Lamda |
| | 2. Global sensitivity analysis | a. Bayesian approach |
| 5. Validation of aggregation method | 1. Empirical validation | a. Non linear & non parametric correlation |
| 6. Application of the index to the spatial scale | 1. Application of the final index to the Federal State of Baden-Wurttemberg (Germany) | |
| | 2. Analysis of the regional climate resilience of the counties of Baden-Wurttemberg | |

Karagiorgos et al., 2016; Balica et al., 2009; Jamshed et al., 2019; Cutter et al., 2003) and resilience (Cutter et al., 2010a, 2014; ARUP and Rockefeller Foundation, 2014; Suárez et al., 2016; Keating et al., 2014). However, the criticism mentioned above is addressed less in the scientific discourse.

Present extreme events and disasters are increasing uncertainty, and major efforts are put into researching trends, scenarios and models. In light of this uncertainty, resilience is a positive as well as an interdisciplinary concept which is first defined in ecology by Holling (1973). According to Holling (1973), resilience is a "measure of persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationship between population or state variables". Many frameworks have been developed following Holling's work to evaluate resilience, but there is neither an agreed set of variables nor a comprehensive definition. Moreover, frameworks are established for specific threats and only some are considering climate change (ARUP and Rockefeller Foundation, 2014; Welle et al., 2014; Riedel et al., 2016; United Nations Office for Disaster Risk Reduction (UNISDR), 2017; Morrow, 2008; NOAA, 2015; Tyler and Moench, 2012; United Nations Development Program (UNDP), 2013) whereas in others it is not explicitly targeted (Birkmann et al., 2012; Béné et al., 2015; Renschler et al., 2010; Poland, 2008; Oregon Seismic Safety Policy Advisory Commission, 2013; Yoon et al., 2016). Some approaches are developed to focus on the resilience against specific hazards such as earthquakes (Poland, 2008; Oregon Seismic Safety Policy Advisory Commission, 2013), while others see resilience more generally and consider it is addressing multiple hazards (Cutter et al. 2008).

Besides the specificity of resilience to a particular hazard, resilience depends on the objective, the spatial scale, the temporal scale and the place (Meerow and Newell 2019). Stating the importance of scale and place in measuring resilience, assessment tools need to pass through a scaling process. For connecting resilience monitoring and adaptation measures, it is crucial to consider the scale and country-specific administrative duties. Authorities can only implement measures in the field of their legal competences, which is defined by the legal structure of the state. Therefore, indicators have to measure these areas of competence in regard to resilience that authorities can deduce, implement and evaluate adaptation measures. With the aim to transfer an already existing indicator set on a lower (e.g. urbane) scale to a higher (e.g. regional) scale, an upscaling process - including the mandatory duties of the scale-responsible authorities as well as testing reliability and validation - is needed. Upscaling has the advantage that the overall country-specific themes and challenges of climate change are already considered.

This study uses the case of the federal state of Baden-Württemberg, Germany. Regional climate resilience is not yet defined in Germany, however, urban climate resilience was defined within the German research project MONARES (www.monares.de). Hence we are using the following definition of urban climate resilience as a starting point for the upscaling process: "the climate resilience of a city depends on the ability of its sub-systems to anticipate the consequences of extreme weather and climate change, to resist the negative consequences of these events and to recover essential functions after disturbance quickly, as well as to learn from these events and to adapt to the consequences of climate change in the short and medium-term, and transform in the long term. The more pronounced these abilities are, the more resilient a city is to the consequences of climate change" (Feldmeyer et al. 2019).

The main aims of the research are 1. upscaling of urban climate resilience; 2. addressing the criticisms of composite indicators by testing four different aggregation methods and implementing a twofold validation as well as robustness and sensitivity analysis; 3. filling the gap of empirical validation of resilience measuring approaches (Bakkensen et al., 2017; Burton, 2015); 4. developing an indicator set for regional climate resilience.

## 2. Methodology

The methodological concept is divided into five major parts (see Table 1). The first step includes the definition of the spatial scale (Step 1.1), the upscaling of urban climate resilience to adequately resemble regional resilience (Step 1.2), selection of the initial indicator set (1.3) and the normalisation of all chosen indicators (1.4). Secondly, the indicators of Step 1 are validated using the machine learning package "RandomForest" (Step 2). Based on the outcome, the indicator set is updated accordingly. In Step 3, an index is constructed by applying different aggregation methods (Step 3.1. a.-d.) in order to understand the method's influence on the results. Subsequently, the reliability (Step 4.1) of both the indicators and index is tested, and a sensitivity analysis (Step 3.2) is executed. In Step 5, a validation for the aggregation methods, based on non-linear and non-parametric correlation, is applied. Eventually, the final index is applied to the federal state and a spatial analysis is conducted (Step 6).

### 2.1. Spatial scale and initial indicator set

The spatial scale is important because of the context- and space specificity of climate resilience. Due to the decentralized structure of the Federal Republic of Germany, each administrative level has specific responsibilities resulting in the freedom to adapt to the local characteristics. Therefore, climate resilience cannot be assigned to a single scale only. All levels of administration have responsibilities for

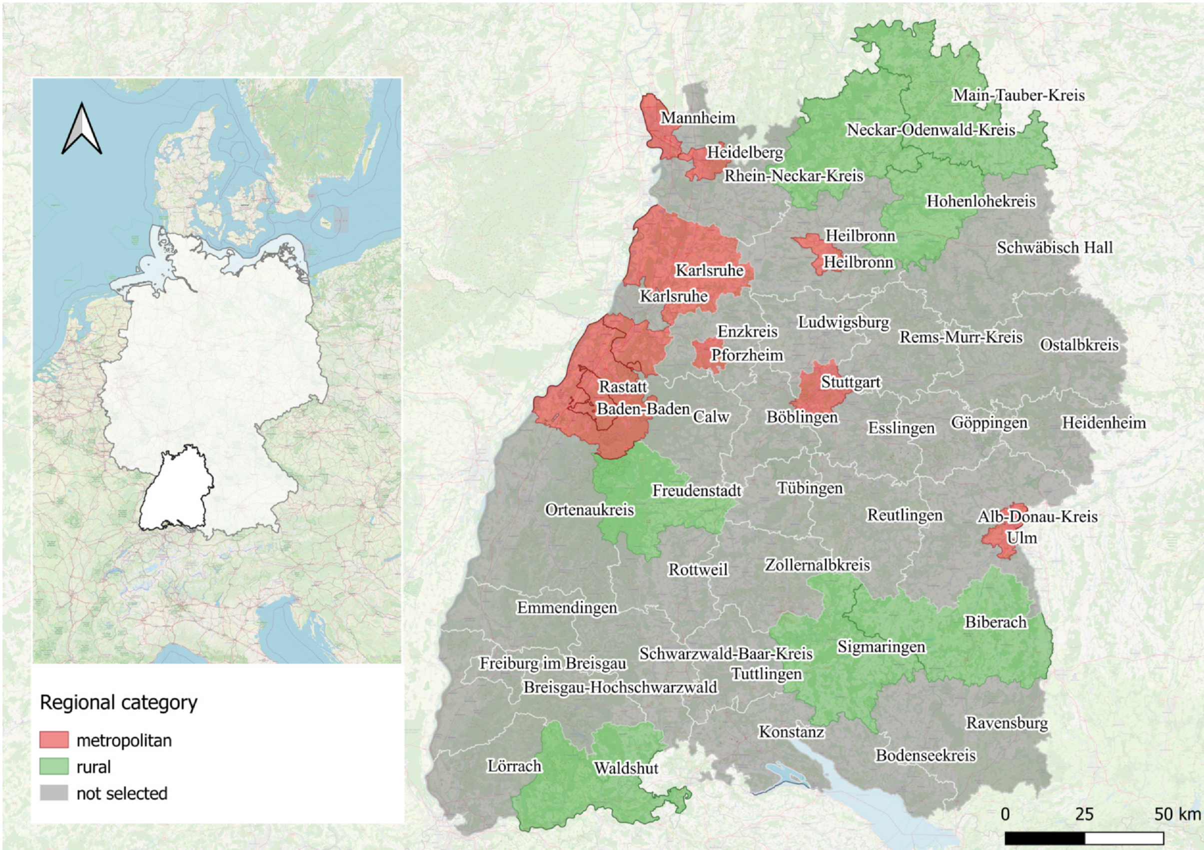


**Fig. 1.** Map of counties of Baden-Württemberg and selected sub-set for rural-metropolitan comparison.

influencing spatial climate resilience. Additional interdependences between scales, up- and downwards, influence the selection of indicators since the effect can be local but the cause regional.

In Step 1.1. the spatial scale is defined. This case study is focused on the regional scale and uses the Federal State of Baden-Württemberg as an example. Baden-Württemberg is divided into four districts, twelve regions and 44 counties (Fig. 1). 69% of the land area of the Federal State of Baden-Württemberg is covered by rural areas (landwirtschaft-bw, 2019). Each region has a regional planning authority. In total, there are 1,101 municipalities, some of which established municipal associations to execute their administrative affairs jointly.

Step 1.2. focuses on the upscaling process from urban to regional resilience. The starting point for the regional climate resilience index were the urban climate resilience indicators developed by Feldmeyer et al. (2019). The process included the upscaling from urban to a regional level. The applied framework is using a hierarchical system: *general spheres*, *theme* and *indicator*. Due to the thematic congruence of the framework the *general spheres* (Table 2) of resilience - environment, infrastructure, economy, society and governance - were completely adapted to the new regional resilience framework.

The second framework level of *themes* was thoroughly modified in consideration of the planning duties of the county level. Each county has mandatory duties as well as some voluntary duties and duties imposed by the federal government and/or state. The following duties are mandatory (Landeszentrale für politische Bildung (LpB), 0000):

- Waste management
- Health system
- Social and youth welfare services
- Public transport
- Environment and nature conservation
- Forest administration
- Road administration
- Agriculture
- Surveying and mapping
- Commercial inspectorate
- Pension office
- Veterinary

In order to develop meaningful indicators on the county level, these mandatory duties have to be considered, so that the authorities can deduce adaptation measures in their area of legal competence. Later on, the indicators should provide the means to monitor and evaluate implemented measures.

During the process of developing the indicator set (Step 1.3), 17 themes were selected for the regional scale. On this basis, a set of 23 indicators was deduced considering the spatial scale at county level (Table 2). The final themes and indicators are shown in Table 2. It also shows the linkage of the themes to a county's planning duties. Further, the public availability of indicator data was a selection criteria, because the developed index should be low-threshold for the application.

Compared to the urban resilience indicator set of Feldmeyer et al. 2019 some indicators were introduced and removed. In the environmental sphere, the theme of *Agriculture and forest* was additionally introduced. The sphere of infrastructure is subdivided into *Street, Health care (epidemiological & individual citizen), Local supply* and *Public transportation.* Those themes replaced the urban themes (Feldmeyer et al. 2019) of *Settlement structure, Energy* and *Drinking and wastewater*. For the economic sphere, a locally-focused view on *Business* was exchanged with the more general descriptive theme of *Unemployment.* The people-centred theme of *Knowledge and risk competence* was disregarded as well as the municipality focused theme of *Research projects* within the municipality. Similarly, on the governance level *Participation* was dropped.

In Step 1.4. the transformation of the initial indicator set is

**Table 2**
Regional climate resilience indicators based on literature analysis and administrative responsibilities of counties.

| Sphere | Theme | Indicator | | Duty | Justification |
|---|---|---|---|---|---|
| Environment | Soil and green spaces | en_pe | Degree of ground sealing[1] | Environment and nature conservation | (Yoon et al. 2016) |
| | Water bodies | en_wa | Proportion of structurally shaped settlement and traffic area in the official flood area[1] | Environment and nature conservation | following (Geis and Kutzmark 1995) |
| | Biodiversity | en_bi | Share of nature conservation and protection areas[1] | Environment and nature conservation | (US Indian Ocean Tsunami Warning System Program 2007) |
| | Air | en_ap | Air emission index[4] | Environment and nature conservation | (Riedel et al., 2016; Mitigation Framework Leadership Group, 2016) |
| | Agriculture and forest | en_ag | Degree of organic farming[4] | Agriculture administration | (Welle et al., 2014; Renschler et al., 2010) |
| | | en_fo | Proportion of undissected forests[1] | Forest administration | (Cutter et al., 2008; Mitigation Framework Leadership Group, 2016) |
| Infrastructure | Streets | in_sp | Accessibility of large centres[3] | Road administration | (Becker et al. 2015) |
| | Health care | in_ho | Hospital beds[2] | Health system | (Cutter et al. 2010a) |
| | | in_dp | Nearby doctors[3] | Health system | (Cutter et al. 2010a) |
| | Local supply | in_lp | Accessibility of supply with daily goods[3] | Road administration | (Renschler et al. 2010) |
| | Public transport | in_pu | Proximity of public transport[2] | Public transport | (ARUP and Rockefeller Foundation 2014) |
| Economy | Innovation | ec_re | Employees in research intensive companies[2] | Business development | (ARUP and Rockefeller Foundation 2014) |
| | Employment | ec_em | Employment[5] | Business development | (Oregon Seismic Safety Policy Advisory Commission 2013) |
| | Economy | ec_gr | Gross Domestic Product[4] | Business development | (Becker et al. 2015) |
| Society | Health | so_he | Sick days[6] | Health system | (Becker et al. 2015) |
| | Sociodemographic | so_ag | Share of citizens ABV6/U65[4] | Social and youth welfare | (Cutter et al. 2010b) |
| | Civil society | so_vo | Voter turnout[4] | Democracy | (Poland 2008) |
| | Social security | so_sp | People in need communities[4] | Social and youth welfare | |
| | Civil protection | so_pp | Nearby police stations[3] | Civil protection | (Becker et al. 2015) |
| | | so_ap | Proximity of hospitals[3] | Civil protection | (ARUP and Rockefeller Foundation 2014) |
| Governance | Budget | go_dp | Municipal debt[4] | not directly | (Abel Schumann 2016) |
| | | go_in | Municipal income[4] | not directly | (Abel Schumann 2016) |
| | Administration | go_su | Support of climate protection agreement[4] | Climate protection | following (Mitigation Framework Leadership Group 2016) |

Data sources: [1](IOER 2019) [2](BBSR 2019)[3] (BMEL 2019) [4] (statistik-bw, 2019) [5] (BA 2019) [6] (BKK 2019).

performed, as the indicators are measured in different measurement scales. For using them in calculations such as aggregations, they need to be transformed.

For the transformation of data, the normalization method was chosen. Several normalization methods exist from which the min–max normalization is selected as depicted in equation (Joint Research Centre-European Commission (JRC), 2008). This normalization results in values from zero to one and shifts the distribution. Important to note is that the distribution of the data itself is not changed.

Equation 1: min–max transformation

$$z = \frac{X_{ij} - X_{(\min)}}{X_{(\max)} - X_{(\min)}}$$

### 2.2. Validation of initial indicators

The amount of literature concerning resilience has exponentially grown over the last decade. Resilience indices are developed for different hazards, scales and definitions of resilience. The vast majority is based on thorough theoretical deduction, but only a few attempts for empirical validation or verification exist (Burton, 2015; Bakkensen et al., 2017). Therefore, although the indicators are theoretically sound, they are not tested if they measure climate resilience in reality.

Indices are used to measure complex phenomena where no single indicator captures all aspects of the indicandum (phenomenon of interest). Hence, starting with the objective of the index stating the indicandum is appropriate (Bastianoni et al. 2012). In order to validate indicators and indices empirically the choice of an outcome to validate against is essential, although the selected outcome can only be a helpful tool to assess for a better understanding. In case of dealing with a multidimensional indicandum, such as resilience, no single outcome exists and different outcomes need to be considered. For example, Bakkensen et al. (2017) selected property damages, fatalities and frequency of disaster declaration as outcomes for the validation of disaster resilience and vulnerability indices. They further stated that resilience and vulnerability are limited to those three outcomes. Burton (2015) used images to measure the recovery process after Hurricane Katrina to validate resilience indicators of communities empirically. This example states, indicators of the same indicandum – in this case disaster resilience – can be validated against different outcomes, which contributes to a broader understanding of the indicandum.

Applied to the context of indicandum climate resilience, life expectancy seems to be able to cover a wide range of the aims of the indicandum. Life expectancy is the number of years a newborn can hope to live, based on the latest mortality table calculations of the federal state of Baden-Württemberg. In order to live a long and healthy life, essential factors are healthcare, health, wealth, education and development (Otoiu et al. 2014). Since climate change projections predict an increasing frequency and magnitude of climate-induced hazards, extreme event related outcomes should be considered. Consequently, insurance data about damages due to floods and storm, reported over a period of 15 years (GDV 2018), are selected as the second and third outcome. The damage data of the insurance companies in Baden-Württemberg have excellent spatial coverage of 95% of all buildings due to the historically compulsory insurance until 1993 (GDV 2018).

In order to validate the indicators, the preliminary analysis shows that non-linearity and violation of the normal distribution (histogram, Kolmogorv-Smirnov-Test) assumption have to be considered. Therefore, a random forest model implemented in the RandomForest Package as a non-linear method is selected (Step 2.1) (Liaw and Wiener, 2002). Three models are calculated, one with each of the three defined outcomes as a prediction. The evaluation criterion was the contribution to reducing the test error. Indicators not decreasing the test error in at least one of the three models (storm, flood, life expectancy) were consequently removed from the index (Table 3).

**Table 3**
Empirical validation of county resilience indicators.

| Code | Indicator | Storm | Flood | Life expectancy |
|---|---|---|---|---|
| en_pe | Degree of ground sealing | No | Yes | Yes |
| en_wa | Proportion of structurally shaped settlement and traffic area in the official flood area | No | No | No |
| en_bi | Share of nature conservation and protection areas | Yes | Yes | No |
| en_ap | Air emission index | No | Yes | Yes |
| en_ag | Degree of organic farming | Yes | Yes | Yes |
| en_fo | Proportion of undissected forests | No | No | No |
| in_sp | Accessibility of large centres | Yes | Yes | Yes |
| in_ho | Hospital beds | No | Yes | No |
| in_dp | Nearby doctors | Yes | Yes | Yes |
| in_lp | Accessibility of supply with daily goods | Yes | Yes | Yes |
| in_pu | Proximity of public transport | Yes | No | No |
| ec_re | Employees in research-intensive companies | No | No | No |
| ec_em | Employment | No | No | Yes |
| ec_gr | Gross Domestic Product | Yes | No | No |
| so_he | Sick days | Yes | No | Yes |
| so_ag | Share of citizens ABV6/U65 | Yes | Yes | No |
| so_vo | Voter turnout | Yes | No | Yes |
| so_sp | People in need communities | Yes | No | Yes |
| so_pp | Nearby police stations | No | No | Yes |
| so_ap | Proximity of hospitals | No | Yes | No |
| go_dp | Municipal debts | No | No | No |
| go_in | Municipal income | No | No | No |
| go_su | Support of climate protection agreement | No | No | Yes |

### 2.3. Aggregation of the index

The aggregation of indicators to a composite index requires two main steps, which both crucially influence the final index (Becker et al. 2017). The aggregation method can be done by different mathematical means. All mathematical calculations are done with R (Team 2019) within R Studio (Team, RStudio, 2016).

To build a composite index, it is important to define indicator weights. There are two main methodological approaches which can be used to build a composite index:

1. The first approach can be described as topic-driven, where weights are developed by experts, surveys or according to thematic groups and are then chosen *equally or hierarchically*. Equal or hierarchical weights are easier to communicate to stakeholders which are especially important in the science-policy interface. Moreover, transferability and transparency are increased, and the weights appear logically justified (Birkmann and Welle, 2016; Cutter et al., 2010b; Rød et al., 2012).
2. The second approach proposes purely data-driven, statistical weights for the indicators. However, as Becker et al. (2017) argue, different variances as well as possible correlations distort the selected weights and result in an undesired impact. Although, even correlated indicators can measure different phenomena and do not necessarily duplicate, hence overstating the same phenomena which cannot be discerned adequately by purely data-driven approaches.

Against this background and acknowledging the logic and correctness of both sides, the present paper implements both approaches and validates them using empirical data to justify the aggregation method. Within these two approaches, four methods were identified and used (Table 1). The implementation of the methods allows to assess the impact of the aggregation method on the index. This contributes to the transparency, robustness and sensitivity assessment of the index. The first method (Step 3.1.a.) explores and understands the data as well as its characteristics when constructing the index with equal weights (eqw).

1. The second method (Step 3.1.b.) implements the mixed equal hierarchical expert weights approach (hw). Within climate resilience, two hierarchical levels are developed. On the first level, five main dimensions are equally weighted. The number of themes within each dimension varies but is covered by a single indicator. Consequently, each theme is represented by a single indicator. Hence, equal weights are assigned within each dimension to each theme resulting in different weights for indicators on an index level. For example, environment has the weight one fifth due to five dimensions. Within the theme environment, air also has one fifth due to five themes within the environment.
2. The third method (Step 3.1.c) is the Wroclaw Taxonomic Method (wroclaw). This method is widely applied for the development of social, as well as economic, indicators (Schifini, 1982; Quirino, 1990; Muro et al., 2011; Cwiakala-Malys, 2009). The method selects one indicator as the benchmark, which comes closest to an ideal unit. For the other indicators thereafter, the Euclidian distances to this benchmark indicator are calculated and ordered in respect of the proportion of the distance to the optimal situation (Vidoli and Fusco, 2018).
3. The fourth method (Step 3.1.d) is the Mazziotta-Pareto-Index method (mpi). This method measures two aspects: the mean level and the unbalance of each indicator. The method is based on a linear aggregation but a penalty in case of unbalance corrects for this unbalance (Muro et al. 2011).

### 2.4. Calculation of robustness and sensitivity

In Step 4.1. the intra-methodological influence is assessed, which contributes to the overall need of a composite index to be transparent, robust and traceable (Welle and Birkmann 2015). Cronbach's Alpha (Step 4.1.a) and Guttman's Lambda (Step 4.1.b) are commonly used tests to describe reliability. These tests assess the homogeneity of items for constructing an index. Considering regional climate resilience, reliability explains the internal consistency of the indicators to the indicandum. According to the JRC (2008), Cronbach́s Alpha within the range 0.6 to 0.8 is desirable. Guttmańs Lambda calculates six lambdas in succession, where Lambda 3 is equal to Cronbach́s Alpha. Guttmańs Lambda presents lower bounds of reliability.

In Step 4.2.a. a global sensitivity analysis (GSA) is applied to all four indices calculated in Step 3.1.a – 3.1.d. The sensitivity analysis adds and quantifies the uncertainty of the composite index, to the knowledge of the internal consistency of the items (Saltelli 2002). For conducting the GSA the free open source tgp package (Gramacy 2007) is applied. In a GSA, all input items are changed at the same time. In contrast, the local sensitivity analysis changes one item at a time. The sensitivity function of the tgp package is an implementation of a Bayesian approach. Normally distributed Gaussian noise is added to the function of each item. The Bayesian approach significantly reduces the computational effort and still produces reliable results (Oakley and O'Hagan 2004).

### 2.5. Validation of indices

In Step 5.1.a. an empirical validation of the aggregation methods is conducted. As already stated in Chapter 2.2, validation is crucial at all stages of the index creation. Therefore, a double validation is performed in this paper. Firstly for the individual indicators (Step 2.1.a) and secondly for the aggregation method (Step 5.1). Hence, a nonlinear and nonparametric correlation was performed for each index in order to assess the impact of the different aggregation method.

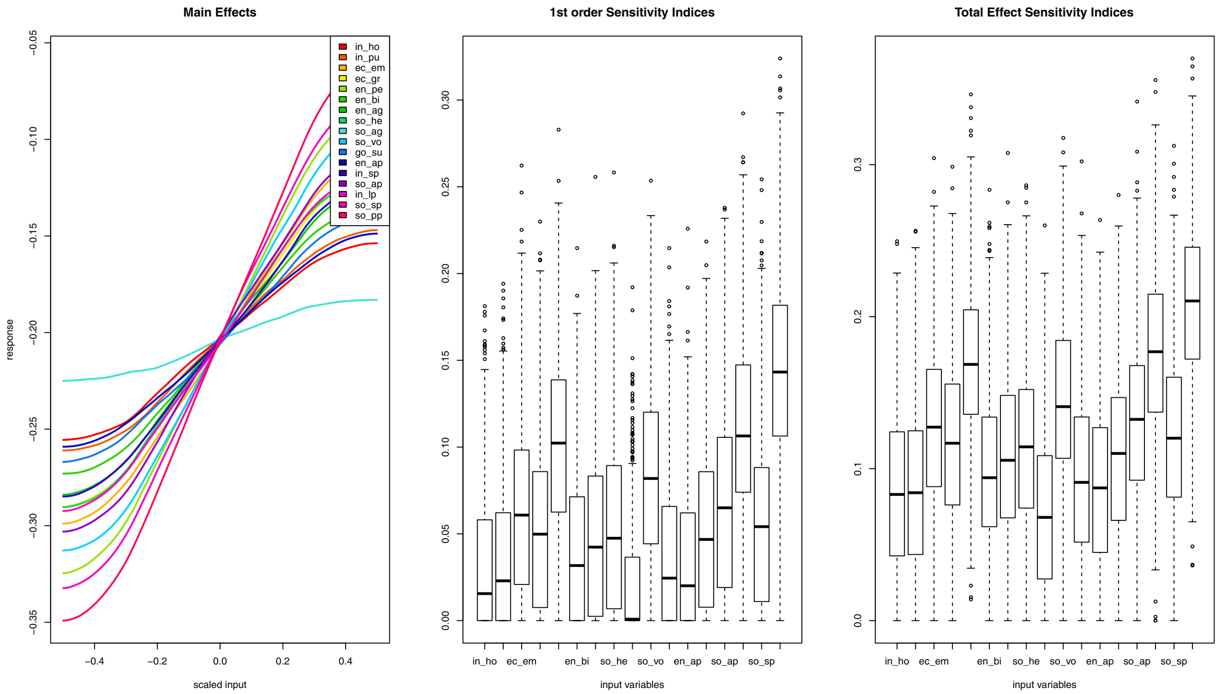


**Fig. 2.** Display of the global sensitivity analysis of the resilience index based on the Wroclaw approach.

### 2.6. Application of the final index to the spatial scale

Finally, the validated indicators and the most adequate aggregation method are selected, and the index is implemented for the federal state of Baden-Württemberg. With the resulting climate resilience index for the state, including a county resolution, the index is initially analysed with regards to indicators which may explain high or low resilience. Furthermore, rural and metropolitan counties are compared (see Fig. 1). For both comparisons, boxplots are plotted. The mean value comparison was conducted with the non-parametric Wilcoxon-Test.

## 3. Results

The results follow the stated objectives and each section builds on the previous but also includes stand-alone results. First, the selection of indicators and reducing them based on statistical tests. Second, the building of the composite index within the sensitivity analysis and second stage validation. Third, the analysis results of regional climate resilience based on the index developed in the previous two sections.

### 3.1. Regional climate resilience indicators (Step 1 – 2)

The proposed indicators are based on literature, administrative responsibilities and the framework for climate resilience (Table 2). They are tested regarding their suitability for a composite index and by their contribution in explaining one of the three outcomes (storm, flood, life expectancy).

Preliminary analysis steps are indicating a violation of the assumption of normality as well as linearity. Therefore, correlation analysis is based on a pairwise nonparametric and nonlinear analysis. High correlation ($R > 0.70$) reveals the three pairwise combinations of the indicators: *Accessibility of supply with daily goods, Nearby doctors* and *Nearby police stations.* All three are covering important aspects of climate resilience but stating a similar problem of the supply of services in rural areas compared to metropolitan areas, thus summarizing the question of accessibility. Based on this analysis, the indicator *Nearby doctors* was removed as not only the accessibility but also the “per capita” number is important while the medical capacity in emergencies is additionally covered by *Hospital beds.* The other two indicators were kept although they are highly correlated because they cover different aspects in different spheres of the framework.

*Degree of ground sealing* was highly negatively correlated with *Accessibility of large centres, Nearby doctors, Accessibility of supply with daily goods, Proximity of hospitals* and *Nearby police stations.* The negative correlations here are somehow expected and revealing conflicting goals within climate resilience. Hence it́s not incoherence of the framework but rather strength in incorporate both perspectives. The necessity of both aspects requires the inclusion of both sides.

In order to the supervised machine learning approach is considering all resilience indicators as input and storm, flood or life expectancy as output (Table 3). Within Table 3, *Yes* states that the indicator contributes to reducing the test error, and *No* declares indicators are irrelevant in the model. The five most important indicators regarding the output life expectancy were *Voter turnout, Degree of organic farming, Nearby police stations, Sick days* and *Accessibility of supply with daily goods.*

For the damage related to the storm, the five most important indicators were *Degree of organic farming, Share of citizens ABV6/65, Gross Domestic Product, Employment, Sick days,* and *Voter turnout.* The five most important indicators regarding the prediction of flood damage were: *Share of citizens ABV6/U65, Accessibility of large centres, Accessibility of supply with daily goods, Hospital beds, and Air emission index.* In all three models, five indicators did not contribute to reducing the test errors on the test data: *Proportion of structurally shaped settlement and traffic area in the official flood area, Proportion of undissected forest, Municipal debts, Municipal income and Employees in research-intensive companies* (Table 3). These five indicators were consequently removed from the further construction of the index.

### 3.2. Regional climate resilience index (Step 3–5)

After determining the reliability of the validated and reduced set of indicators (Step 2), the four aggregation methods are calculated (Step 3). Subsequently, based on the sensitivity analysis in conjunction with the correlation analysis against the outcomes (Step 4), one final index is selected (Step 5).

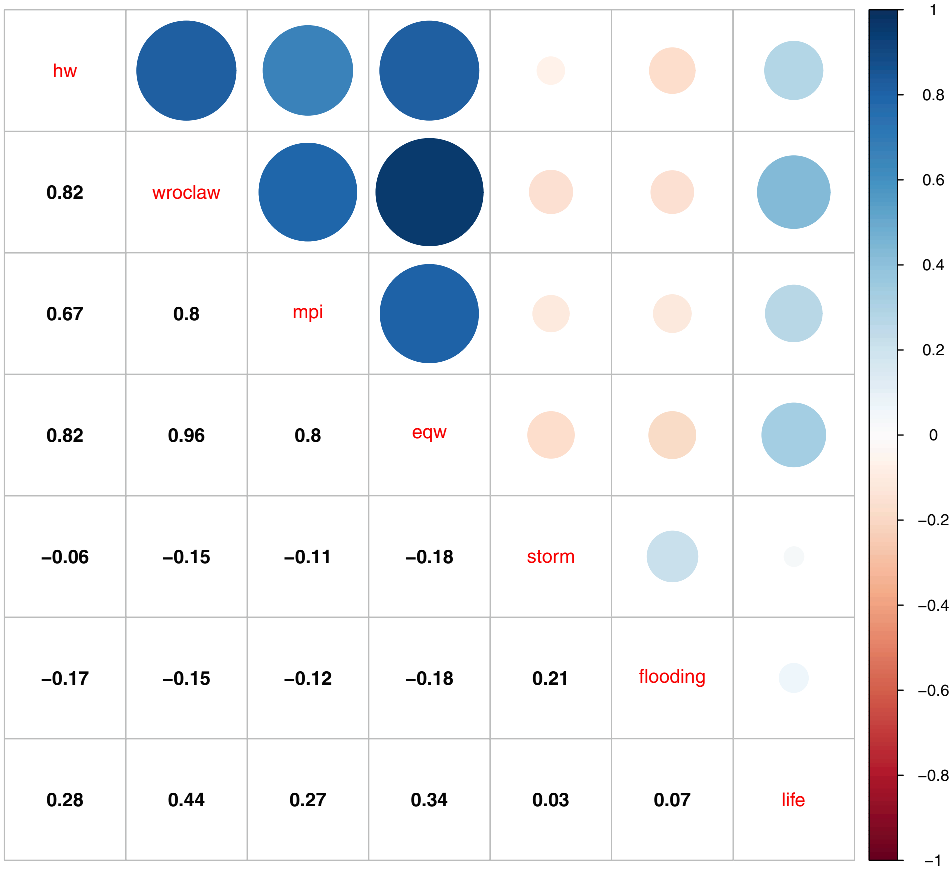


**Fig. 3.** Correlation plot of the four aggregation methods and three outcomes.

The reliability (Step 4.1.a + 4.1.b.) of the indicator set is with a Cronbach's Alpha of 0.84, the lower boundary of the 95% confidence interval of 0.78 and the upper boundary of 0.91, well within recommended values (Revelle and Revelle 2015). Cronbachś Alpha is the most frequently used measure. Still, it tends to underrate the reliability and overrate the first factor saturation. The Guttmańs Lambda for the indicator set is 0.95. Summarizing the set has strong reliability and is suitable for constructing an index.

For all four indices, the global sensitivity analysis was conducted (Step 4.2.a). The result of the Wroclaw aggregation method is shown in Fig. 2. Based on the comparison, the Wroclaw method is best suited to aggregate the set of indicators. Within the other methods (hw, mpi, eqw), the first order, as well as total effect, was unequally distributed amongst the indicators.

Fig. 3 displays the correlation matrix for the indices with the outcome validators. Overall, resilience indices are positively correlated. All indices are also, as expected, positively correlated with life expectancy and negatively correlated with the damages associated with floods and storms. The highest correlation for life expectancy showed the Wroclaw-Index with 0.44, which also correlated negatively with the storm and flood damages. The negative correlation to damages is only slightly better covered by the Equal-Weight-Index. Therefore, consistent with the sensitivity analysis, the Wroclaw-Index performs best. Consequently, the resilience indicators aggregated with Wroclaw Taxonomic are validated as the best Regional-Climate-Resilience-Index (RCRI), which is used for further calculations.

### 3.3. Regional climate resilience implemented on county level (Step 6)

The newly created and validated RCRI is applied to the case study region of Baden-Württemberg. For explaining the spatial attributes in detail, the dataset is split into the most and least resilient counties (Fig. 4) as well as into rural and metropolitan areas (Fig. 5). Furthermore, the county climate resilience is presented in a spatial map (see Fig. 5).

In Fig. 4, the ten most resilient counties were grouped into one group and the ten least resilient counties into a second group. As anticipated, the life expectancy of the top group is significantly higher and the damages caused by storm and flood lower, although not statistically significant. The lower group has higher values in the environmental sphere (e.g., *Degree of ground sealing (en_pe)* or *Share of nature conservation and protection (en_bi)*. Statistically significant indicators in favour of the top group are *GDP (ec_gr), Degree of ground sealing (en_pe), Voter turnout (so_vo), Support of climate protection agreement (go_su), Air emission index (en_ap), Accessibility of large centres (in_sp), Proximity of hospitals (so_ap), Nearby doctors (in_dp), Accessibility of supply with daily goods (in_lp)* and *Nearby police stations (so_pp)*. Eight indicators are not significantly different.

Fig. 5 demonstrates the comparison of the seven metropolitan counties with seven rural counties. These counties are classified as city and rural by the Statistical Office of Baden-Württemberg (statistik-bw, 2019). The results of the aggregated Wroclaw Index suggest that the metropolitan counties are (statistically) significantly more resilient than the rural counties, which is consistent with lower damages although not statistically significant. Life expectancy, in contrast, is slightly higher by means of the mean but also has a greater variance. The rural counties have higher resilience concerning *Employment (ec_em), Degree of ground sealing (en_pe), Share of organic farming (en_ag),* and *people in need communities (so_sp)*. Reciprocal metropolitan areas have a higher *GDP (ec_gr), Accessibility of supply with daily goods (in_lp), Proximity of hospitals (so_ap), Nearby doctors (in_dp)* and *Nearby police stations (so_pp)*.

The map (Fig. 6) shows that the metropolitan regions (Stuttgart, Freiburg im Breisgau, Baden-Baden, Mannheim) tend to have a higher resilience compared to the more rural areas. The obvious exception

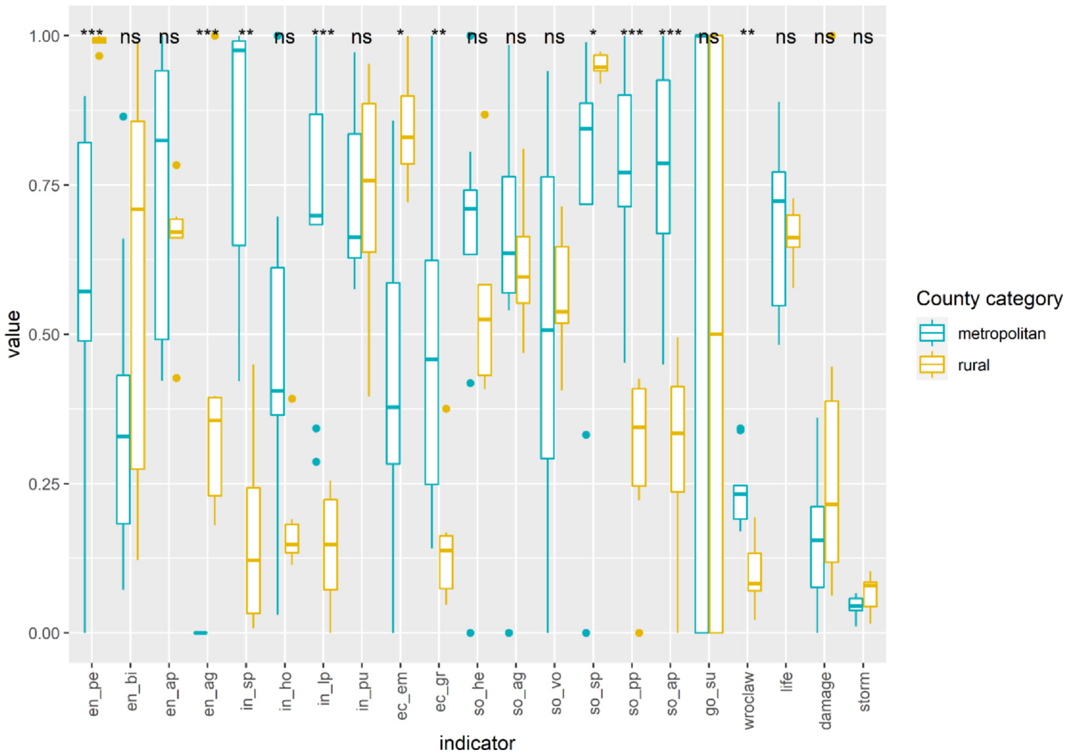


**Fig. 4.** Boxplots and statistical test of mean between high and low resilient counties (ns: p > 0.05; *: p < = 0.05; **: p < = 0.01; *** : p < = 0.001 ****: p < = 0.0001).

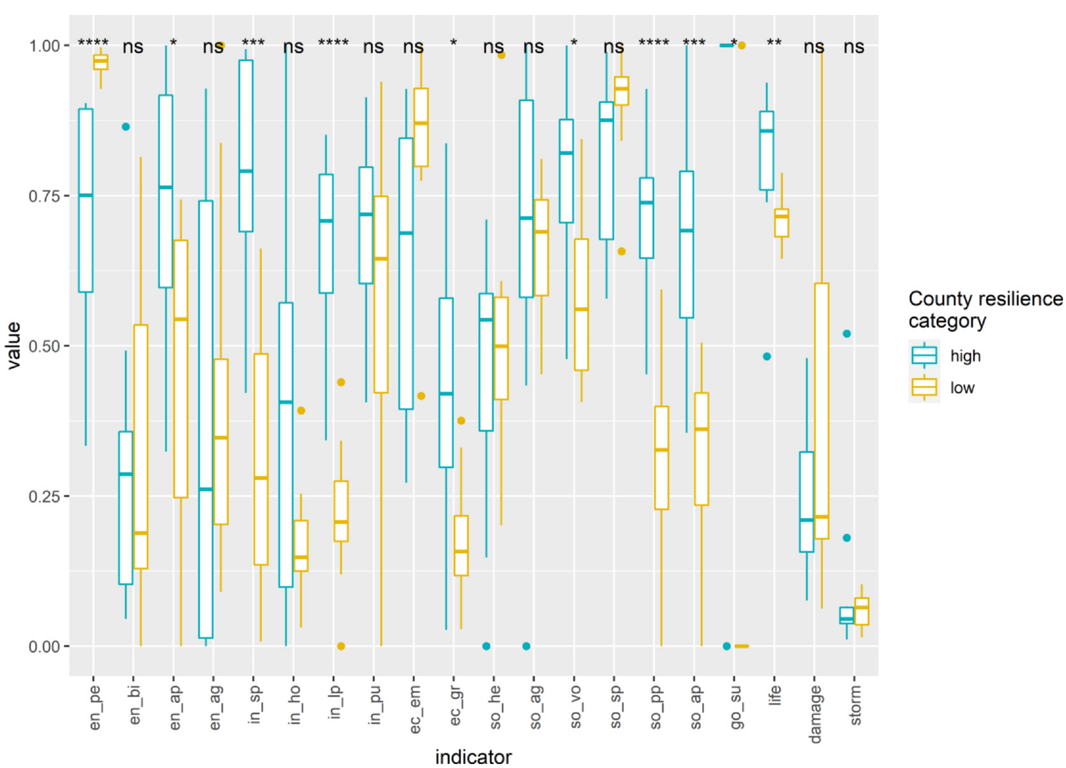


**Fig. 5.** Boxplots and statistical test of mean between rural and metropolitan counties (ns: p > 0.05; *: p < = 0.05; **: p < = 0.01; *** : p < = 0.001 ****: p < = 0.0001).

within this pattern is Pforzheim, which is a metropolitan area but with only low resilience. A deep structural transformation effects the city of Pforzheim due to the decline of the jewellery industry. The rural county of Rottweil, on the other hand, is located in the black forest and is highly resilient despite its rurality.

## 4. Discussion

The accomplished methodological approach and the results are giving interesting insights regarding the importance of indicator selection, indicator validation, aggregation, validation of index

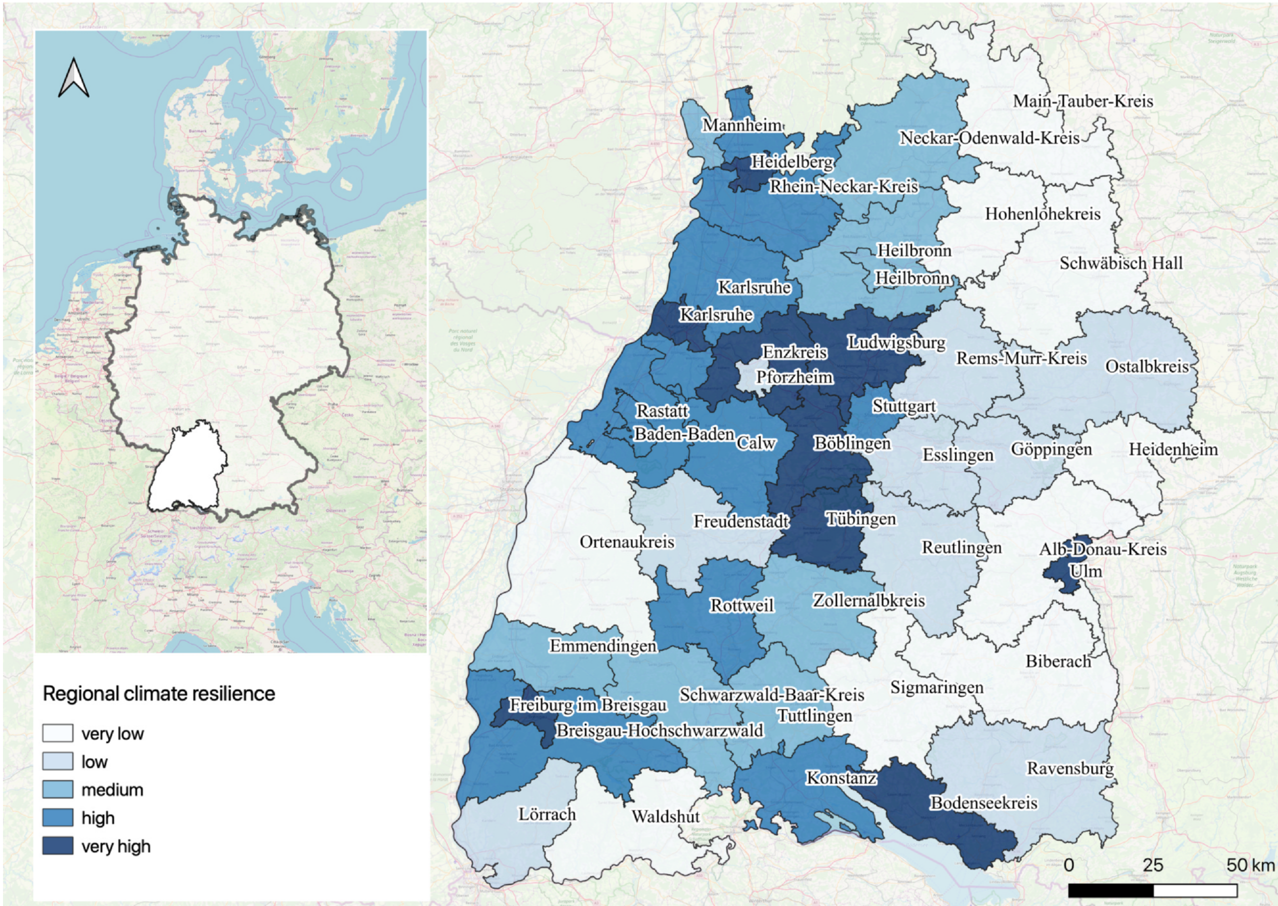


**Fig. 6.** Map of the regional climate resilience index in Baden-Württemberg (resilience classes are based on quantiles).

aggregation methods and the spatial scale which will be examined in the following chapter. Also, the limits of this approach, for example, lack of data or completeness of the indicator set, need to be discussed.

### 4.1. General

The selection of the indicators proved to be equally important as the selection of the aggregation method. Moreover, the only theory-based approach established on the climate resilience framework and indicators based on literature did not perform as predicted by the theory which is in line with the results of Bakkensen et al. (2017). The application of the global sensitivity analysis (Step 4.2.a) proved to be very useful. Comparing the four aggregation methods (Step 3), the Wroclaw-Index (Step 3.1.c.) achieved the best results. The Wroclaw-Index is able to balance the impact and direction of all indicators equally. Subsequently, the correlation (Step 5.1.a.) with the outcomes was also in favour of the Wroclaw-Index approach. The moderate values of the correlation coefficient are due to the fact that the index is designed for a stressor-independent assessment of resilience and not specifically for life expectancy, nor flood damage or storm damage. In comparison, the empirical model and resilience index designed by Burton (2015) achieved low to moderately low model explanatory power. Designed independently of the stressor, the new regional climate resilience index still performed as expected and displayed the stressor-independent resilience of regions. Moreover, the part of climate resilience which was not exposed by the index might be explained by contextual factors such as social networks, feeling of belonging, trust in authorities, knowledge, risk perception - which are quantitatively based on secondary data hard to measure but are also part of climate resilience.

### 4.2. Indicators

Five indicators were removed during the first stage of empirical validation on the indicator level (Step 2.1.a). In the case of water and forest, the included indicators were only second choice. For forest and water, the status of the water bodies and respectively the status of the forest were to be included as indicators. This data based on measures of the status exist but are only published via a WMS service. Hence, it was not possible to aggregate them on the county level to a meaningful indicator. The respective authorities did not want to share the data upon request. As a result, the included indicators were substituted based on available data, but this approach did not allow to capture the themes of water bodies or forests, respectively. The empirical validation revealed that a lack of accessible data in this regard. Thus, such validations suggest a clear need for open data in order to monitor and evaluate interdisciplinary phenomena and climate resilience. Regarding municipal income and debt, two lines of argumentation appear. Firstly, financial ability does not result in any dedicated action by the corresponding communities at the moment. It can be seen as a necessary, but not imperative condition and other factors overrule it. Secondly, the municipal budget is not on the same administrative level as the other indicators. Although the county resilience is based on the municipalities, the county budget would have been a better and more appropriate spatial and administrative scale. The fifth indicator removed, *Employees in research-intensive companies* might have been related to the selected outcomes. The contribution regarding climate resilience is an important aspect for a future resilient economy and the ability to adapt and evolve, which might not have been covered sufficiently within the outcomes.

### 4.3. Assessment of climate resilience

The assessment of resilience is not seen as a substitute for detailed hazard, vulnerability and risk assessment. On the municipal or site level, a detailed multi-hazard assessment (including sudden and slow-onset) and vulnerability assessment on a high spatial resolution may need to be conducted within a multi-criteria assessment framework (Ravankhah et al. 2019). The resilience assessment could be seen within a Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis as the strength, vulnerability as the weakness analysis and the hazard assessment looking into the threats. Understanding all parts of the SWOT analysis is indispensable for effective strategic planning.

In explaining the three empirical outcomes (storm, flood, life expectancy), four out of five spheres proved to be relevant: Environment (*Degree of organic farming, Air emission index),* Infrastructure (*Accessibility of large centres, Accessibility of supply with daily goods)*, Economic (*GDP, Employment),* Social (*Share of citizens ABV6/U65, Sick days, Voter turnout, Nearby police stations)*. Governance (*Support of climate protection agreement)* is not amongst the top five determinants but statistically significant regarding climate resilience (Fig. 5). Thus, all five spheres are essential and underline the socio-economic a socio-ecological character of climate resilience.

By taking a closer look at the five most important indicators regarding the outcome of life expectancy, the most important variable is *voter turnout.* Non-voting attitude is strongly dependent on the social class, and statistically, non-voters have lower incomes and lower education (Güllner, 2013) which are important aspects of resilience in line with literature. *Degree of organic farming* is also a predictor of life expectancy. This might be due to a general higher awareness of organic food, resulting in healthier nutrition. Organic farming also results in a healthier environment, e.g. because of reduced input of pesticides and therefore with a positive impact on health. *Sick days* are an obvious determinant of life expectancy. *Nearby police stations* and *Accessibility of daily goods* can be summarized as the provision of security and other services.

### 4.4. Climate resilience and empirical validation

The empirical validation with damages from storm and flooding events reveals two difficulties regarding the applied definition of climate resilience. Firstly, compared to other resilience approaches, e.g. flooding resilience (Qasim et al., 2016; Shah et al., 2018), the used definition is not specific to one particular threat. Consequently, this approach stresses the importance of increasing the general climate resilience due to the high uncertainty of further extreme events and climate change. This underlying concept results in a lower extreme event specificity of the index, which is reflected in a lower correlation to storm and flood. Hence, it reflects the trade-off between extreme event-specific resilience vs general climate resilience and inclusiveness. Secondly, because of the pronounced context-specific of climate resilience, interpreting the machine learning results of nonlinear problems, where monodirectional effects exist, is challenging. Though, this finding highlights the complexity and multidimensionality of social systems and the phenomenon of climate resilience and offers insights to multifaceted effect directions.

Opportunities for future research are indicators to measure disaster resilience in Baden-Württemberg but also outcome indicators for empirical validation. For example, the voluntary fire brigade is one of the pillars of civil protection, but a number of manpower available at the state level does not exist, although increasing pressure and deployments regarding natural hazards are reported. The number of indicators within this study was relatively limited and the selection based on theory but still to some degree subjective. Further empirical analysis into more indicators can contribute to the understanding of climate resilience. In addition, the combination of machine learning and, e.g. twitter data, phone records or open street map for developing indicators to measure soft attributes of resilience (such as the feeling of belonging or social networks) opens huge opportunities regarding the measurement of resilience. Lastly, heat stress and wildfires - both projected to increase in frequency and magnitude - could not be considered within this study.

### 4.5. Climate resilience and spatial scale

The comparison of rural vs metropolitan areas pointed out a significantly higher resilience of metropolitan areas within Baden-Württemberg (Fig. 5). The rural areas have higher environmental resilience and higher employment, which were overbalanced by the other spheres. The high employment level of rural areas is one particular feature of Baden-Württemberg with hidden champions in those areas and in general a very low unemployment rate. The indicator *sick days (so_he)* needs to be examined because a higher rate of sick days might not be entirely negative. It could also be a sign of health awareness as the balance of working culture and self-awareness can be different between urban and rural regions. The provision of goods, services and connectivity of rural areas - as general themes of the rural development debate - is also reflected within the regional climate resilience. Urban areas are offering benefits in their infrastructure.

In light of this analysis, the recommendation for action regarding the improvement of the infrastructure in rural areas gets more critical. In addition, it becomes apparent that urban areas in Baden-Württemberg need to enhance their environmental resilience and parts of social resilience to boost their overall resilience. Nevertheless, both rural and urban areas need to address all aspects of resilience in balance.

## 5. Conclusion

Only a small number of approaches for empirical validation of resilience indicators are existing, and machine learning approaches are very less used. The study demonstrates the necessity of carefully evaluating every single step in constructing a composite index. Moreover, a thorough theoretical framework for climate resilience in conjunction with literature-based indicators does not necessarily capture the phenomenon. Empirical validation is indispensable but challenging due to the future outcome of climate resilience and lack of empirical data. Especially at the stage of indicator selection and at the stage of choosing the aggregation method, machine learning can be effectively used to reduce bias and improve the index. It was found that different outcomes are essential, where life expectancy was found to be a good approximation in combination with damages from natural hazards. Fostering climate resilience is essential to tackle foreseen and unforeseen challenges which require measurements and the development of composite indicators due to the complex phenomena.

The empirical validation essentially contributes to the performance of the index by giving evidence in selecting the indicators and method. The theory-based expected outcome does not have to coincide with the empirical reality. Global sensitivity analysis further helps in understanding the model and adds to the empirical validation. Life expectancy was found to be a good outcome due to its inclusion of many aspects of resilience, in combination with natural hazards. All five spheres - environment, infrastructure, economy, governance and society - are empirically important for climate resilience. The environmentally better situation of the rural areas does not compensate for the lack of the other spheres and results in an overall lower climate resilience compared to metropolitan areas.

## CRediT authorship contribution statement

**Daniel Feldmeyer:** Conceptualization, Methodology, Data curation, Writing - original draft, Writing - review & editing. **Daniela Wilden:** Methodology, Writing - original draft, Writing - review &

editing. **Ali Jamshed:** Writing - original draft, Writing - review & editing. **Joern Birkmann:** Writing - review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

This research work is a part of the Ph.D. process of the main (corresponding) author, at the Institute of Spatial and Regional Planning (IREUS), University of Stuttgart, Germany, under the supervision of the last author.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2020.106861.

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# FIFTH CHAPTER

GLOBAL VULNERABILITY HOTSPOTS: DIFFERENCES AND AGREEMENT BETWEEN INTERNATIONAL INDICATOR-BASED ASSESSMENTS

# Global vulnerability hotspots: differences and agreement between international indicator-based assessments

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## ABSTRACT

Climate change impacts and their consequences are determined not only by the intensity and frequency of different climatic hazards but also by the vulnerability of the system, society or community exposed. While general agreement exists about the importance of assessing vulnerability to understand climate risks, there is still a tendency to neglect global and regional vulnerability patterns because they are hard to quantify, despite their value in informing adaptation, disaster risk and development policies. Several approaches to quantifying global vulnerability exist. These differ in terms of the indicators they use and how they classify countries or regions into vulnerability classes. The paper presents the structure of selected approaches and explores two indices in depth. The aim of this paper is to assess the level of agreement between selected international indicator-based assessments of vulnerability, at the level of climate regions. Results suggest that the two major global vulnerability assessments analysed largely agree on the location of the most and least vulnerable regions when these assessments are aggregated to a regional scale using the IPCC's climate regions. The paper then discusses the robustness of the information derived and its usefulness for adaptation, disaster risk and development policies. Measuring progress towards reducing vulnerability to climate change and hazards is key for various agencies and actors in order to be able to develop informed policies and strategies for managing climate risks and to promote enabling conditions for achieving the SDGs and building resilience.


**Keywords**: vulnerability, hotspots, indicators, climate change, global mapping

## 1 INTRODUCTION

Since the IPCC Special Report SREX (IPCC 2012) and the Fifth Assessment Report (AR5) (IPCC 2014a) of the Intergovernmental Panel on Climate Change (IPCC) there have been increasing efforts to quantify climate risk at a global scale. Such assessments include examinations of human vulnerability to both climate change and natural hazards (INFORM 2019; ND-GAIN 2019; Feldmeyer et al. 2017). These global assessments all make an important contribution to quantifying human vulnerability and thus to understanding climate risk.

Climate risk is not just determined by the likelihood of climate-related hazards (e.g. extreme heat, flooding, drought) but also by where these occur and how vulnerable the exposed systems are to these hazards (Birkmann 2013; IPCC 2014b, p. 3, IPCC 2019, p. 88). Vulnerability is defined by the IPCC as “the propensity or predisposition to be adversely affected” (IPCC 2018a, p. 560). A system is vulnerable when it is both susceptible to being harmed by (or is sensitive to) a hazardous event and lacks the ability to cope and adapt to this event (IPCC 2018a, p. 560). Adaptive and coping capacity are two important components of vulnerability—adaptive capacity being “the ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences” (IPCC 2018a, p. 542) and coping capacity being “the ability of people, institutions, organizations, and systems, using available skills, values, beliefs, resources, and opportunities, to address, manage, and overcome adverse conditions in the short to medium term” (IPCC 2018a, p. 546).

While vulnerability is accepted as an important factor in determining climate risk, its quantification is lagging behind that of global exposure to climate hazards, preventing an effective and targeted adaptation process to reduce risk. Recent research developments and new methods, such as the Shared Socio-Economic Pathways (SSPs) (O’Neill et al. 2017), have improved the consideration of societal development in climate adaptation research. These tools are important for informing adaptation policies. However, there is a need for them to better capture the multi-dimensional factors that shape human vulnerability—such as issues of poverty, human wellbeing, inequality, access to basic services, governance and safety nets for people at risk—in order to be able to address these issues more effectively. This information and analysis is missing at the transnational scale and needs consideration in order to capture all parts of the risk equation and effectively reduce negative consequences. Global vulnerability assessments have the potential to capture such factors and thus support better exploration of social scenarios and improve the SSPs. Existing global assessments of climate risk and vulnerability (INFORM 2019; Hallegatte et al. 2016; Birkmann and Welle 2016; Feldmeyer et al. 2017; Cardona and Carreño 2013; Birkmann et al. 2011) each use different approaches anchored in different schools of thought. Global climate risk assessments that include measurement of vulnerability to climate change and natural hazards consider a variety of different factors that operationalize human vulnerability (INFORM 2019; Feldmeyer et al. 2017; Birkmann and Welle 2016; ND-GAIN 2019). Likewise, different global vulnerability assessments use different indicator sets to assess and evaluate levels of national vulnerability. Some global assessments encompass indicators that measure wealth and/or poverty, education and access to basic services; others capture in addition issues of governance (state fragility, corruption) and conflict. Despite the use of different indicators, these studies agree that vulnerability to climate change and natural hazards is multi-dimensional and requires the use of indicators that represent these diverse themes and dimensions.

Climate hazard information must be complemented with vulnerability information in order to provide a sound information base for decision making. This has been underscored within IPCC reports since 2012 (IPCC 2012), including the last IPCC assessment report (IPCC 2014a) and the newer IPCC special report (SROCC / IPCC 2019), which have repeatedly highlighted the need to not only to focus on climate hazards, but also to consider exposure and vulnerability (see the so called propeller figure, e.g. IPCC 2012). Newer IPCC Assessment Reports use geographical reference regions to analyse global climate change and related hazards (IPCC 2013). An urgent question is whether such regions—referred to as "climate regions"—intended for the analysis of physical phenomena of climate change can also be used to assess human vulnerability. If this is possible it would provide a way to visualise human vulnerability issues in a way that is compatible with hazard data and disregards national boundaries.

Against this background, the paper addresses the following research questions:

a) Can the results of quantitative vulnerability analyses be usefully aggregated from the national level up to the level of physical climate regions to complement climate hazard assessments?
b) To what extent do these assessments agree on the classification of regions in terms of their level of vulnerability (i.e. low versus high vulnerability and variance)?

c) What kind of spatial patterns emerge when assessing human vulnerability at the level of climate regions?

We answer these questions by comparing the approaches of two prominent global risk assessments: the INFORM Index (Marin-Ferrer et al. 2017) and the WorldRiskIndex (Birkmann et al. 2011; Birkmann and Welle 2016). We chose to compare these two indices in more detail because both indicator systems aim explicitly to capture human vulnerability, while other indices, such as the Global Climate Risk Index (Germanwatch 2019), primarily focus on past harm and losses rather than vulnerability to assess climate risks (e.g. Number of deaths, Sum of losses in US$ in purchasing power parity). Furthermore, these two indices assess vulnerability more comprehensively with larger sets of indicators capturing context conditions as well as issues of access to resources, information and education, which are particularly relevant when aiming to reduce community and individual vulnerability. Additional justification for focusing on these two indices is: a) their international orientation, b) the fact that they are widely acknowledged as valid, c) their inclusive nature, which take into account trends in both industrialised and developing nations, d) the fact that they offer concrete support for adaptation efforts, and c) based on reliable data sources e.g. World Bank, Food and Agriculture Organization of the United Nations (FAO), World Health Organization (WHO).

These two assessments (WorldRiskIndex and INFORM Index) were undertaken by different institutions and groups and each contributes in different ways to a more comprehensive representation of human vulnerability compared to conventional economic risk assessments. In many senses these two approaches are similar in their understanding of vulnerability as conditions that make people more susceptible and likely to face adverse consequences in the context of climate change and extreme events independent of the hazard intensity or past fatalities and harm. Each of these global assessments also have their limitations. Indicator-based quantitative assessments of vulnerability can only capture specific characteristics and not all aspects that determine human vulnerability to climate change hazards. Furthermore, the use of mean values for factors such as poverty has been criticised (Pelling and Garschagen 2019). Nevertheless, the global vulnerability patterns uncovered by these assessments provide new insights into which regions should be prioritised for adaptation and vulnerability reduction, and indicate where issues of governance and state failure are major factors of concern.

In this paper, we analyse the 2019 results of the vulnerability components of the INFORM Index (INFORM 2019) and WorldRiskIndex (Feldmeyer et al. 2017). This detailed comparison of the INFORM and WorldRiskIndex is done by first aggregating the results of the two indices from country-level vulnerability rankings to regional rankings, adapting the climate regions used by climate modellers contributing to the IPCC Sixth Assessment Report (AR6) (IPCC 2020). Climate regions are spatial boundaries delineated for the purpose of better representing climatic data and model result a sub-continental scale. These regions are designed through the lens of physical climate science and disregard sovereign borders. This means they lack the socio-economic dimension at the same spatial scale which often leads to a hazard focused perspective and the negation of the socio-economic dimension at this scale. The IPCC also calls for more integrated perspectives linking climate hazard, exposure and vulnerability information in order to assess risk (IPCC 2014). Therefore, it is important to examine the ability to aggregate socio-economic and demographic information for assessing vulnerability at the level of climate regions. Aggregation and comparison of the two global vulnerability assessments reveals that although there are differences in how the assessments rank the vulnerability of countries in certain regions, they do largely agree on the regions of high human vulnerability to climate change risks, despite their use of different indicators.

In this paper, we first describe the state of the art of global climate risk and vulnerability assessments. Thereafter, we compare two global assessments – namely the WorldRiskIndex and the INFORM Index. We then examine the results of the two indices at the level of climate regions in detail. Finally, we discuss the benefits and limitations of such assessments and our proposed methodology used to represent human vulnerability at the level of physical climate regions.

# 2 State of the Art of Risk and Vulnerability Assessment

## 2.1 Four Global Approaches

A variety of different assessment approaches exist, based on different schools of thought and therefore based on different indicators, each with a different focus, leading to different results. To capture the variety in assessing risk and human vulnerability the following section provides on overview of key differences and similarities of four approaches, with global orientation, acknowledged as valid and including a link to adaptation.

The INFORM Index was developed by international experts of the EU's Joint Research Center. It uses a composite indicator system that identifies and ranks countries at risk to climate change and natural hazards, focusing on national capacities to respond to crises and vulnerability to disaster risk. INFORM aims to support a proactive crisis and disaster management by means of assessing key dimensions of risk: hazard, exposure, vulnerability and lack of coping capacity. The index is based on 54 core indicators, applied to at least the five previous years of data to assess the risk that specific hazards and crises pose to each country (Marin-Ferrer et al. 2017).

The WorldRiskIndex is a mathematical model and a visualization and communication tool that combines the physical and spatial exposure to natural hazards with societal vulnerability, presenting risk values and charts. The methodology was developed by Birkmann and Welle in close cooperation with colleagues from the United Nations University and practitioners of the Alliance Development Works (see Birkmann et al. 2011). The index is based on the analysis of 28 indicators, assessing global risk patterns of over 170 countries. The WorldRiskIndex encompasses human vulnerability as a core component, capturing it in terms of three components: susceptibility, coping capacities and adaptive capacities. The analysis of vulnerability identifies regions and countries that have severe difficulties in dealing with natural hazards and climate change and those countries that are in a better position to cope with and adapt to these impacts. The indicators measure both specific living conditions (for example, access to basic infrastructure and services), and coping capacities determined by larger framework conditions (such as the governance context, which influences people's ability to deal with extreme events directly or indirectly, such as insurance coverage or corruption) (Birkmann et al. 2011; Welle and Birkmann 2015; Birkmann and Welle 2016). Individual indicator values are transformed and aggregated and thereafter mapped within a Geographic Information System (GIS) to visualize the relative level of vulnerability of different regions and countries.

The Global Climate Risk Index is calculated annually and examines the extent to which countries and regions have been affected by the impacts of weather-related loss events (e.g. storms, floods, heat waves) considering data from the past decade (i.e. the 2019 report used data from 1998 to 2017). The Climate Risk Index aims to serve as a kind of information and warning system, showing existing vulnerability that may further increase in regions where extreme events will become more frequent or more severe due to climate change. The index especially focuses on the effects of past impacts of weather-related events on countries and regions. The Global Climate Risk Index 2019 shows that high income countries experienced the impacts of climate change more strongly in this year than in previous decades. In this regard, the losses and damages considered within the index also hint towards the necessity to act both in developing and developed countries.

The Notre Dame Global Adaptation Index (ND-GAIN) has been published annually by the University of Notre Dame since 1998. This index ranks countries' vulnerability to climate change and readiness to adapt. The goal of the index is to inform decision makers in the public and private sector to allow them to prioritize investments and increase resilience. Readiness is measured within social, economic and governance dimensions. The vulnerability matrix is organized into six life supporting sectors (health, food, ecosystems, habitat, water, infrastructure) and three dimensions (adaptive capacity, sensitivity and exposure).

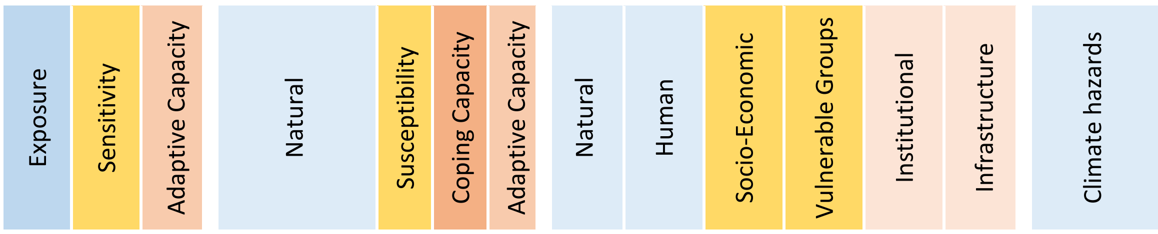
## 2.2 Comparison of the Assessment Approaches

All four assessments described above have a resolution at the individual country scale. While each uses a different set of indicators, most contain parameters that cover aspects of economic poverty, inequality, access to basic infrastructure services (water, sanitation), life expectancy, adult literacy rate and the level of social protection (e.g. insurance). The assessments differ, for example, in terms of their consideration of aspects of governance, such as corruption and conflict, as well as in terms of their consideration of losses experienced in the past (see Feldmeyer et al., 2017).

The Global Climate Risk Index differs most significantly from the other three (Table 1), as it documents what happened in a specific period. It does not include a probabilistic analysis of frequencies and return periods of the events. ND-GAIN is also different from the other indices in that it defines exposure as a component of vulnerability. The WorldRiskIndex and INFORM have separate exposure and vulnerability components, with INFORM also having a component called "lack of coping capacity".

**Table 1** Comparison of the main dimensions and framing of risk and vulnerability in the ND-GAIN, WorldRiskIndex and INFORM approach (ND-GAIN 2019; INFORM 2019; Germanwatch 2019; Birkmann and Welle 2016)

| ND-GAIN | WorldRiskIndex | | INFORM | | | Climate Index |
|---|---|---|---|---|---|---|
| Vulnerability | Exposure | Vulnerability | Hazard & Exposure | Vulnerability | Lack of Coping Capacity | Risk |




In terms of the hazard and exposure components of risk, the four approaches include different aspects (Table 2). The WorldRiskIndex focuses on exposed population to natural hazards; namely earthquakes, cyclones, floods, drought and sea level rise. INFORM considers exposure in a similar way, in that it considers people exposed to natural hazards, but also considers human conflict. The Global Climate Risk Index specifically addresses hazards intensified by climate change, thus excludes earthquakes but includes temperature extremes and mass movements. ND-GAIN uses a significantly different approach in that it defines exposure as "the extent to which human society and its supporting sectors are stressed by the future changing climate conditions" (Chen et al. 2015, p. 3) and thus considers the effects of climatic change on a range of sectors using different exposure indicators for each sector – for example, for the water sector one exposure indicator is "projected change of annual groundwater recharge" (Chen et al. 2015, p. 16).

**Table 2** Hazards considered by the ND-GAIN, WorldRiskIndex, INFORM and Global Climate Risk Index (ND-GAIN 2019; INFORM 2019; Germanwatch 2019; Birkmann and Welle 2016)

| **ND-GAIN** | **WorldRiskIndex** | **INFORM** | **Global Climate Risk Index** |
|---|---|---|---|
| The extent to which the following sectors are stressed by the future changing climate conditions: | The potential average annual number of individuals who are exposed to: | The expected number of people located within the hazard zone for each type of the following hazards: | Deaths and economic losses (absolute and proportional) due to the following hazards: |
| • Food<br>• Water<br>• Health<br>• Ecosystem services<br>• Human habitat<br>• Infrastructure<br>• Governance readiness<br>• Social readiness | • Earthquake<br>• Cyclones<br>• Floods<br>• Droughts<br>• Sea level rise | *Natural*<br>• Earthquake<br>• Cyclones<br>• Flood<br>• Droughts<br>• Tsunami<br>*Human*<br>• Projected conflict risk<br>• Current conflict intensity | • Storm<br>• Floods<br>• Temperature extremes<br>• Mass movements |

# 3 A Comparison of the INFORM Index and WorldRiskIndex

## 3.1 Comparison of the Indicators used by each Index

In this section we compare the indicators used by the WorldRiskIndex and INFORM Index to measure vulnerability and identify similarities and differences between the two indices. We selected these two indices to compare, of the four described above, because they most comprehensively and explicitly assess vulnerability. They also clearly differentiate exposure and vulnerability. The WorldRiskIndex considers vulnerability a function of susceptibility, lack of coping and lack of adaptation, while INFORM considers vulnerability as a function of socio-economic vulnerability and vulnerable groups and calculates lack of coping capacity separately (see Table 1).

A closer examination of these vulnerability components of the WorldRiskIndex and INFORM, found that these have eight indicators in common (Table 3): namely, the Gini Coefficient, adult literacy rate, access to improved sanitation facilities, access to improved water source, physician density, health expenditure per capita, corruption perception index and prevalence of undernourishment. Moreover, two similar indicanda are measured by different indicators: poverty and gender inequality. The WorldRiskIndex has 12 additional indicators with emphasis on the environment. INFORM has 21 additional indicators focusing more on connectivity and diseases.

**Table 3** comparison of the indicators used to assess different dimensions of human or societal vulnerability of the INFORM and WorldRiskIndex (INFORM 2019; Birkmann and Welle 2016)

| Common indicator categories assigned by authors | **INFORM**<br>Indicators of Vulnerability & Lack of Coping Capacity | **WorldRiskIndex**<br>Indicators of Vulnerability |
|---|---|---|
| Income equality | Gini Coefficient | Gini-Index |
| Poverty | Multidimensional Poverty Index | Extreme poverty (pop living on less than 1.25 USD) |
| Development | Human Development Index | Gross Domestic Product per capita |
| | Public Aid per capita | |
| | Net ODA Received (% of GNI) | |
| Gender equality | Gender Inequality Index | Gender parity in education |
| | | Share of female representatives in the National Parliament |
| Corruption | Corruption perception Index | Corruption perception index |
| Governance | Government effectiveness | Failed State Index |
| Literacy | Adult literacy rate | Adult literacy rate |

| | | |
|---|---|---|
| Education | | Combined gross school enrolment |
| Health | Physicians density | Number of physicians per 10,0000 pop |
| | Health expenditure per capita | Public health expenditure |
| | | Private health expenditure |
| | Child Mortality | Life expectancy at birth |
| | Prevalence of HIV-AIDS above 15-years | Number of Hospital beds per 10,000 pop |
| | Tuberculosis prevalence | |
| | Malaria mortality rate | |
| | Measles immunisation coverage | |
| Nourishment & Food Security | Prevalence undernourishment | Share of undernourished population |
| | Children underweight | |
| | Average dietary supply adequacy | |
| | Domestic Food Price Level Index | |
| | Domestic Food Price Volatility Index | |
| Sanitation | Access to improved sanitation facilities (% of pop with access) | Share of population without access to improved sanitation |
| Drinking water | Access to improved water source (% of pop with access) | Share of population without access to clean water |
| Disaster preparedness | Hyogo Framework for Action | Insurance |
| | Relative number of affected population by natural disasters in the last three years | |
| Environment | | Protection of biodiversity and habitats |
| | | Forest management |
| | | Agricultural management |
| | | Water resources |
| Infrastructure | Road density (km of road per 100 km$^2$ of land area) | |
| | Mobile cellular subscription (per 100 people) | |
| | Internet Users (per 100 people) | |
| | Access to electricity (% of population) | |
| Other vulnerable groups | Number of refugees, returned refugees, internally displaced persons (absolute and relative) | Dependency ration (proportion of under 15- and above 65-year olds in relation to working pop) |

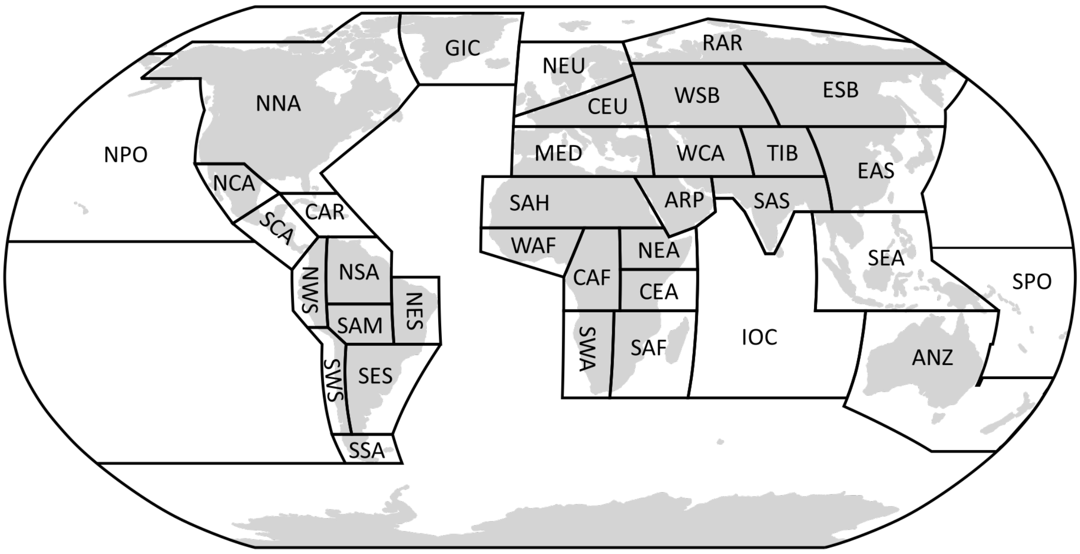
Same indicators Similar indicators Different indicators

## 3.2 Comparing Vulnerability Assessments at the Level of Climate Regions: INFORM and WorldRiskIndex

### *3.2.1 Methodology*

In this section we aggregate the country-level vulnerability rankings of the WorldRiskIndex and INFORM Index to the level of climate region. We then average the two indices to deliver an average vulnerability ranking for each region, achieving an overall ranking of regions in terms of their relative vulnerability. Finally, we calculate the level of agreement between the two indices at this aggregated scale. These steps will be explained in more detail in the following paragraphs.

On a global scale, socio-economic statistics are accessible for individual countries. Climate impacts, in contrast, cross borders and are better approximated by climate regions. Climate regions are geographic areas defined for use in the context of the IPCC Assessment Reports for the purpose of assessing the climate projections produced by climate modellers. We use climate regions in order to better link vulnerability information with information on climate change and its impacts, adapting those used in the Sixth Assessment Report (AR6) for our own purposes of aggregating vulnerability rankings. Figure 1 displays the climate regions used for the analysis of socio-economic vulnerability. With the spatial join tool of ArcGIS 10.5.1 and the intersect option selected, countries were allocated to climate regions. Some changes had to be made to the climate regions because vulnerability rankings are based on socio-economic data, which is mostly collected at a country-level. This means that, for example, although North America contains several different climate regions, it only contains two countries, so we therefore had to combine the seven climate regions into one North American region. Similarly, for the Indian Ocean, New Zealand and Australia, East Europe and Western Siberia and South and Equatorial several smaller climate regions were merged to the higher order of climate regions. Arctic-Ocean, East-Antarctica, West-Antarctica and South-Ocean climate regions were not included.




| | | | | | |
|---|---|---|---|---|---|
| **ANZ** | Australia/New Zealand | **NES** | N.E. South America | **SEA** | S.E. Asia |
| **ARP** | Arabian Peninsula | **NEU** | N. Europe | **SAF** | S.E. Africa |
| **CAF** | Central-Africa | **NNA** | N. North America | **SES** | S.E. South America |
| **CAR** | Caribbean | **NCA** | N. Central America | **SPO** | S. Equatorial Pacific Ocean |
| **CEA** | Central E. Africa | **NPO** | N. Pacific Ocean | **SSA** | S. South America |
| **CEU** | Central Europe | **NSA** | N. South America | **SWA** | S.W. Africa |
| **EAS** | E. Asia | **NWS** | N.W. South America | **SWS** | S.W. South America |
| **ESB** | E. Siberia | **RAR** | Russian Arctic | **TIB** | Tibetan Plateau |
| **GIC** | Greenland/Iceland | **SAH** | Sahara | **WAF** | W. Africa |
| **IOC** | Indian Ocean | **SAM** | South American Monsoon | **WCA** | W. Central Asia |
| **MED** | Mediterranean | **SAS** | S. Asia | **WSB** | W. Siberia/E. Europe |
| **NEA** | N.E. Africa | **SCA** | S. Central America | | |

**Fig. 1** Adapted IPCC climate regions for the analysis of socio-economic vulnerability

The WorldRiskIndex calculates vulnerability as a composite index of the dimensions susceptibility, lack of coping and lack of adaptation. INFORM calculates vulnerability as socio-economic vulnerability and vulnerable groups, and calculates lack of coping capacity separately (see Table 1). We first combine the vulnerability and lack of coping capacity indices of INFORM to make a composite vulnerability index that is comparable to the vulnerability component of the WorldRiskIndex. Subsequently, we calculate the mean vulnerability score for each climate region based on both indices. We then use these vulnerability scores to rank the climate regions (1 low to 35 high) for each index. We use this ranking method because one index (WorldRiskIndex, see Fig. 2) had in general higher vulnerability scores but for the classification of countries or regions the relative ranking is more important and what we aim to analyse.

We then compare the ranking of the climate regions according to vulnerability scores given by the WorldRiskIndex and the INFORM Index as follows (see Fig 3). Firstly, we plot the 35 climate regions on a scatter plot according to how they were ranked according to their vulnerability—on the x-axis showing the rankings derived from the INFORM index and on the y-axis those from the WorldRiskIndex. We then classify the 35 climate regions into four classes (i.e. ranks 1-10, 11-20, 21-30, 31-35 to make 4 classes of vulnerability from lowest to highest). We then overlay these two classifications of the climate regions to create 16 classes using a cartography method described by Strode et. al. (2019) called a "bivariate choropleth map". Each of the 16 classes is assigned a colour, as shown behind the scatter plot, and each climate region is mapped according to the colour of the class in which they are ranked (Fig. 3). The darker more saturated colours show regions of higher vulnerability. This map and corresponding scatter plot diagram show the spatial pattern of vulnerability globally, and also shows the agreement between the two indices on this pattern. This approach therefore includes the assessment of uncertainties in line with the IPCC AR5: "Confidence in the validity of a finding, based on the type, amount, quality, and consistency of evidence (e.g., mechanistic understanding, theory, data, models, expert judgment) and the degree of agreement" (Mastrandrea et al. 2010, p.2). We conduct the spatial analysis in ArcGIS 10.5.1, the data modelling with R in Rstudio.

### *3.2.2 Results*

#### *3.2.2.1 Aggregation of, and agreement between, vulnerability indices*

Figure 2 shows the results of the aggregation of the country-level vulnerability scores of the INFORM and WorldRiskIndex to climate regions. The box plot shows the average vulnerability score for each climate region for each index, as well as the spread and variability of the country-level scores within each region. It can be seen that within each climate region there is often a large variance, especially in the larger climate regions. Overall, the WorldRiskIndex ranks regions to be more vulnerable than the INFORM Index does, with North-East Africa as the single exception. The test for statistical difference of the mean values (Wilcoxon test) with alpha 0.01, shows for 35 climate regions there is no significant difference (ns) while statistically significant differences were revealed for seven regions (W. Africa, S.E. Asia, Mediterranean, Caribbean, S.E. South-America, Central Europe, North Europe) (see Fig. 2). Both assessments agree on the ranking of climate regions for most of the regions examined.

For example, there is high agreement on the three most vulnerable climate regions. In contrast, the mean values of two of the three lowest regions are significantly different between the WorldRiskIndex and INFORM. The disagreement for West-Africa is rooted in a very high lack of coping within the WorldRiskIndex, with 85 points, and a lower score for vulnerable groups in INFORM, with 42 points. For Central Europe the mean vulnerability of the WorldRiskIndex is 34 points whereas in INFORM it is only 18 points. The interquartile range supports the aggregation on climate region scale, showing a clear trend and ranking of them. Moreover, in terms of vulnerability assessment, single outliers cannot counterbalance the overall regional trend. A single country that is much more vulnerable than the rest of the region might benefit and a single country much better is in danger of being affected negatively. Hence the regional classification gives important insights into the regional vulnerability level, despite single outliers.

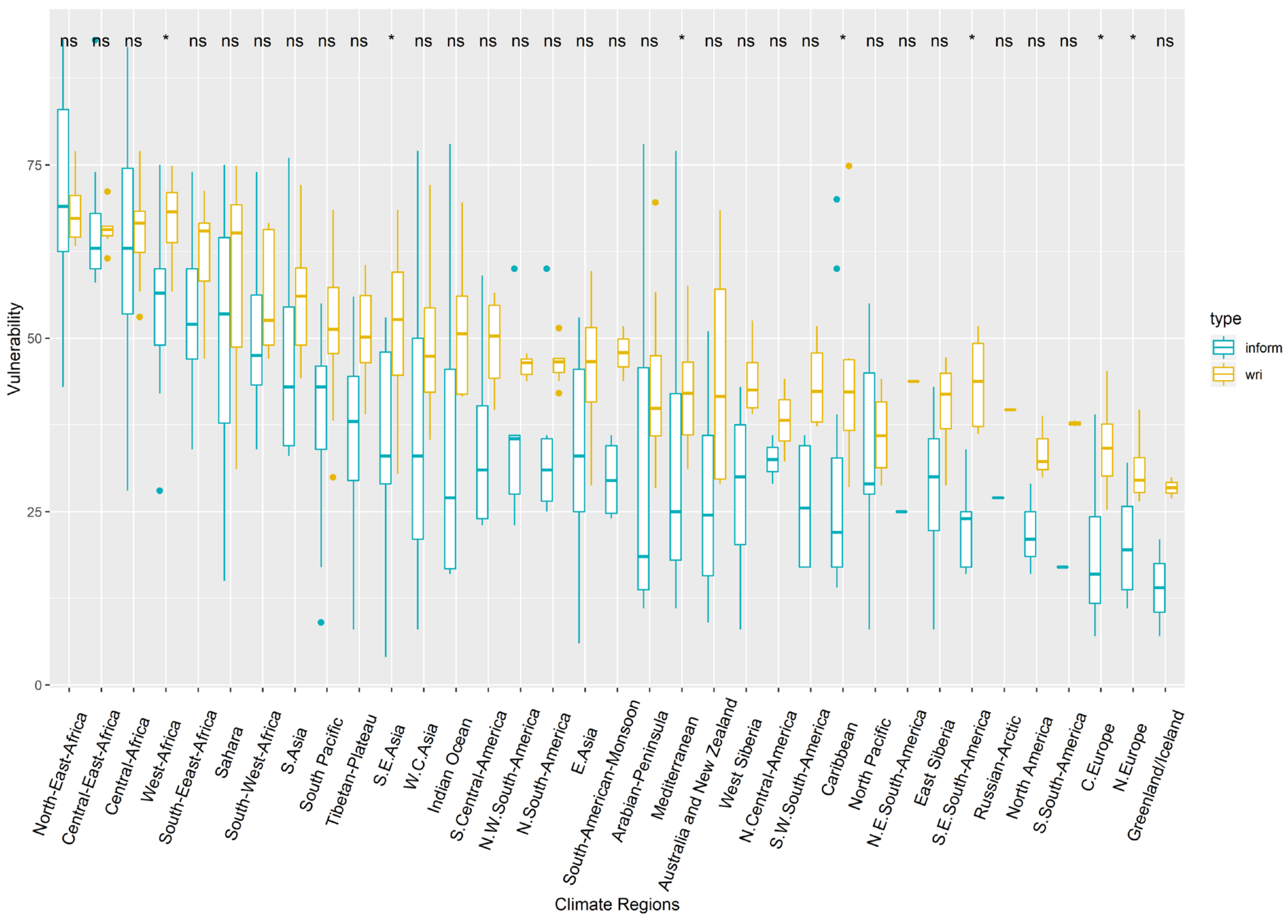



**Fig. 2** Variance of vulnerability within climate regions (Box-plots: ns: p > 0.01; *: p <= 0.01)

Figure 3 shows that the two indices agree on the most and least vulnerable regions. While there is some disagreement, especially for regions in the middle of the rankings, there are no regions where the indices completely disagree (i.e. there are no cases in which one index ranks a region at the lowest end and the other at the highest end of the list of regions ranked by vulnerability). If the indices completely agreed on the order of regions from lowest to highest vulnerability, the dots of the scatter plot would be in a straight diagonal line from the bottom left to the top right corner of the graph – there is some deviation from this perfect agreement but there are no dots in the top left or bottom right corner of the scatter plot diagram, meaning there are no major disagreements.

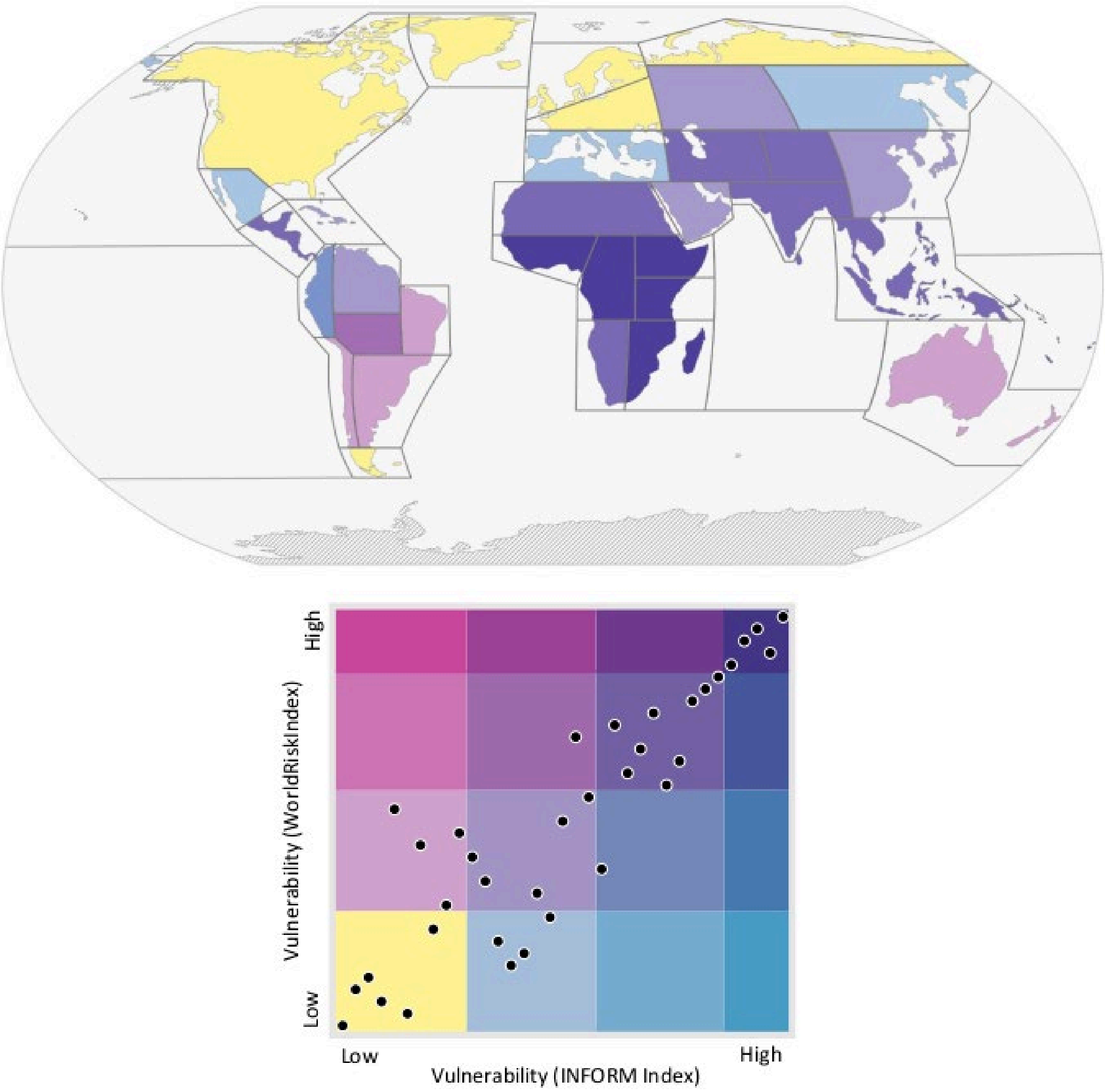



**Fig. 3** Bivariate choropleth map and scatter plot diagram legend showing the agreement between two global vulnerability indices (WorldRiskIndex and INFORM Index) when ranking of climate regions according to their vulnerability. Darker colours show regions of higher vulnerability. The diagram legend shows how the 35 climate regions are ranked by each index. Source: Own map based on the rankings of the INFORM Index (INFORM, 2019) and the WorldRiskIndex (Feldmeyer et al., 2017)

The following paragraphs will take a closer look at some specific climate regions and how their ranking can be explained by the mean vulnerability scores of the two indices and their sub-components. The climate region Australia & New Zealand (ANZ) is judged to be more vulnerable than North America (Fig. 3) by both the WorldRiskIndex, which rates ANZ according to the mean vulnerability score 10 points more vulnerable than North America, and INFORM, which calculates ANZ to be 5 points more vulnerable than North America. ANZ is considered more vulnerable in every aspect of both the WorldRiskIndex (susceptibility, lack of coping, lack of adaptation) and INFORM (socio-economic vulnerability, vulnerable groups) indices. The most significant difference between the two regions being their susceptibility as rated by the WorldRiskIndex, which rates ANZ as 13 points more susceptible than North America. INFORM considers ANZ to be more socio-economically vulnerable but less vulnerable in regard to vulnerable groups. ANZ is also considered more vulnerable than South East South America (SES), although the WorldRiskIndex considers them to have the same level of vulnerability. In addition, the INFORM considers ANZ more vulnerable due to the indicators of vulnerable groups (16 points higher in ANZ than in SES).

Comparing South Central America (SCA) and the Sahara (SAH) climate regions, the latter is more vulnerable. INFORM rates SAH as 16 points more vulnerable than SCA and the WorldRiskIndex rates it 11 points more vulnerable. The high rating in the case of INFORM is due to more people belonging to vulnerable groups (18 points higher in SAH than in SCA) and in the case of the WorldRiskIndex is due to a higher susceptibility rating (14 points higher in SAH than in SCA).

For most of the climate regions, the relative vulnerability rankings of each index did not differ by more than 3 ranks out of 20 and for no climate region was the difference between the indices more than 6 ranks. This suggests a high level of agreement between the vulnerability assessments of the INFORM Index and WorldRiskIndex.

#### *3.2.2.2 Global spatial patterns of vulnerability*

High agreement was found for regions of very high vulnerability. In particular, West, East and Central Africa and South Asia and in part the Pacific Islands were determined to be highly vulnerable by both indices. Agreement between INFORM and the WorldRiskIndex exists despite the use of different indicators, leading us to conclude that there is high confidence as to the locations of major vulnerability hotspots on a global scale.

The two global assessments examined in detail used 56 indicators overall to assess different dimensions of vulnerability. There are several differences in the indicator sets used, especially in the measurement of environmental and governance factors. However, comparison of the two assessments reveal that there is high agreement regarding global hotspots of vulnerability (regions classified as highly vulnerable) at the level of climate regions. It was found that the impact of differences in the indicators used seems to be less significant for countries classified as highly vulnerable. The combined ranking thus shows high agreement on those regions ranked as highly vulnerable, while there is less agreement on those ranked as having medium or low vulnerability for example the climate regions Southeast South America (SES) and South American Monsoon (SAM). In this regard, the hotspots of vulnerability are robust considering that even differences in the sets of indicators do not change them significantly.

Various regions in Africa (e.g. particularly West-Africa, Central-Africa, North-East-Africa, South-East Africa and Sahara) followed by South Asia, appear as climate regions highly vulnerable to climate change due to their socio-economic, demographic, environmental and governance conditions. For example, the proportion of people living with less than 1.9USD a day is 60 times higher in the climate region South-East-Africa compared to the climate region Central-Europe. Next to different levels of poverty, it is also inequality which is higher in most vulnerable regions. In South-East-Africa inequality measured with the Gini coefficient is 1.8 times higher than for Central-Europe. Poverty and inequality are acknowledged as factors that increase human vulnerability to climate change.

In addition, Southeast and Central Asia and the Pacific Island Regions are characterized by high levels of human vulnerability. Central America, parts of South America and East Asia follow as vulnerable regions thereafter, showing still a relatively high level of human vulnerability (see Figure 3). In these regions, climate change adaptation and risk reduction require not only information about future climatic stressors, but also strategies that address the deeper underlying issues that cause human vulnerability and that make people more susceptible to the actual and potential impacts of climate change (Thomas et al. 2018). In these regions, strategies for climate resilience and climate resilient development pathways must address development issues not only at the local or national scale but also particularly at the regional scale, in order to ensure that enabling framework conditions for climate change adaptation of communities are enhanced and strengthened.

In contrast to the regions mentioned above, the regions around the Mediterranean, Australia & New Zealand, and Southern South America show a lower human vulnerability level. North and Central Europe and North America rank among those regions that show a low level of human vulnerability in comparison to other regions (see Figure 3). The level of agreement in the classification of low and medium vulnerable regions, however, is lower compared to the ranking of climate regions in terms of high vulnerability.

### *3.2.3 Discussion*

The comparative assessment of two global index systems for vulnerability points to various similar climate regions classified as highly vulnerable and therefore there is high agreement regarding global hotspots of human vulnerability. However, there is medium agreement in terms of the ranking of climate regions into medium and low vulnerability levels. The analysis revealed that even if larger indicator systems use in part different indicators for assessing human vulnerability, certain regions appear to be consistently ranked as most vulnerable. Therefore, there appear to be structural differences between the climate regions. Consequently, regions with a high level of vulnerability have a strong predisposition to be negatively affected by climate change due to a variety of context conditions that make them more susceptible to the impact and adverse consequences of sudden-onset and slow-onset climate hazards. Furthermore, communities in these regions face the challenge that national institutions and capacities are severely constrained to support risk reduction and adaptation, such as in Sub-Saharan Africa. Various regions classified as highly vulnerable also face governance challenges and problems in terms of chronic poverty.

The identification of spatial hotspots of human vulnerability at the global level is an important prerequisite for the formulation and development of preventive adaptation and risk reduction measures at regional level. In this regard, the two indicator-systems examined in detail fulfil their function to serve as a communication and visualization tool and inform policies or drive behavioural changes (e.g. Becker et al., 2017, Feldmeyer et al. 2021). The global hotspots identified are a first layer of information that show where, independent of a specific hazard, attention and action is needed to improve enabling conditions for adaptation.

The relative assessment of human vulnerability, however, also has some limitations. For example, countries in Latin America are also vulnerable to climate change, however, they often appear to be have a medium level of vulnerability, but do not appear to be hotspots in the global analysis, since various climate regions in Africa and also South Asia are more constrained and characterized by higher levels of human vulnerability. Consequently, the global maps presented show and define human vulnerability in relative terms – highly vulnerable regions are more vulnerable compared to other regions at the global scale. This information is primarily useful for a first global screening, while more detailed information and assessments are needed if specific countries or sectors are going to be addressed. Within large countries and large climate regions, specific pockets of highly vulnerable areas are barely visible. This is because many indicators focus on averages or distributional patterns at the national scale (e.g. GINI index). For example, the newest report on extreme poverty and inequality in the United States and the UK (Alston 2018) shows that extreme poverty is increasing in some high income countries despite a relatively low average poverty level at the national scale. However, the context in which these groups might experience climate-related hazards is different from that of highly vulnerable climate regions, such as those in Africa, which are characterised by overall high levels of poverty, limited access to functioning infrastructure and governance challenges. In addition, the vulnerability information might need to be complemented with information about present and future exposure patterns to climatic hazards, such as sea-level rise, flooding or droughts. In this context, also the medium vulnerability of some Pacific Islands is problematic, since it is likely that with severe increases in exposure the overall risk will also increase.

This paper finds that there is lower agreement between the global vulnerability assessments examined in terms of regions classified as having medium vulnerability. For these regions, the indicators that are different between the two assessments seem to be playing a stronger role. For example, the differences of the WorldRiskIndex and the INFROM Index in terms of the consideration of environmental aspects within the WorldRiskIndex versus the integration of specific infrastructure indicators and issues of displacement in the INFORM Index. These differences might be less relevant in countries and regions classified as highly vulnerable, since in these regions various indicators point towards significant challenges and contextual deficits that make societies more susceptible to the impact of climate change. The cumulative effect of multiple challenges dominate the results for highly vulnerable region. Regarding the spatial pattern of human vulnerability specific indicators are less influential. Overall clear differences between the climate regions emerge. This provides important contextual understanding of vulnerability for climate change adaptation at the level of physically defined climate regions. These indicators and assessments show structural development challenges that increase human vulnerability to climate change and simultaneously also constrain adaptation options independent of the specific hazards. These challenges are not equally distributed between climate regions, rather the assessment clearly reveals regional, spatial patterns that require spatially specific adaptation policies.

The paper also shows that the ranking of regions differs between the WorldRiskIndex and the INFORM Index and the variance of country values can be significant within regions. However, we demonstrated that the variance and disagreement between the assessments is overall lower in climate regions with particularly high or low vulnerability rankings. The study by Hagenlocher & Garschagen (2018) comparing five disaster risk indices, including WorldRiskIndex and INFORM, at the country level, concludes that for disaster risk there is high agreement on low risk and high risk countries. In addition, Garschagen et al. (2021) conclude that spatial hotspots for socio-economic vulnerability at national scale are  more robust and contain a higher agreement between the indicator systems examined than for exposure. .

Overall, each of the global assessments underscore that climatic hazards of the same magnitude, intensity and frequency would cause significantly more harm, damage and suffering within regions classified as highly vulnerable (INFORM 2019, WorldRiskIndex 2019, Germanwatch 2019, Feldmeyer et al., 2017, Hallegatte et al., 2017). While it is crucial to reduce the exposure of people and assets to climatic hazards and to mitigate global warming, our results underscore that it is also essential to address challenges linked to high levels of inequality and poverty and a lack of access to safety nets for most inhabitants in these regions, if climate risks are to be reduced. This need emerges from the assessment of the overall vulnerability of climate regions and specific indicators, as shown above for poverty and the Gini-coefficient. That means risk reduction and adaptation has to address, next to climate hazards, also deeper structural development challenges, captured within the indicator system by, for example, income equality, poverty, literacy, corruption, health, nourishment and food security (Table 3). These findings are confirmed by studies that examine past impacts of climate-related hazards and disasters within different world regions (Formetta and Feyen 2019). However, even moderate changes in the global mean temperature—as identified in the recent IPCC 1.5 report (IPCC 2018b) and the newer published peer-reviewed literature (see Hoegh-Guldberg et al. 2019)—are likely to result in substantial increases in risk due to irreversible environmental degradation combined with high levels of vulnerability for regions such as West Africa and the Sahel or the Pacific.

## 4 CONCLUSION

This paper contributes to the literature by showing how international indicator-based assessments of vulnerability are comparable and to what extent different assessments point towards the same or towards different geographic areas in terms of high, medium and low vulnerability. Our analysis reveals that vulnerability can also be visualized at the level of physical climate regions used by the IPCC and thereby can complement hazard information at this scale. Moreover, the comparison of two comprehensive vulnerability index systems (INFORM and WorldRiskIndex) showed that there is high agreement on most vulnerable and least vulnerable regions, even if different indicators are used. Thus, the two comprehensive global approaches for assessing human vulnerability come to the same conclusion in terms of regional hotspots of human vulnerability.

The findings of the paper and the aggregated results of vulnerability at climate region scale contribute to a more comprehensive information base for adaptation and risk reduction. Various approaches within the international discourse, for example the Reasons of Concern of past IPCC reports (IPCC 2007, 2012, 2014a) and also the discussion of Shared-Socio-Economic Pathways often avoids being spatially specific. While this approach is strategically useful for the communication of results to heads of state, a systematic and informed enhancement of climate risk management and climate resilient development requires also information on where regional or spatial priorities should be. In this regard, the paper shows not only climate regions that should be targeted as a priority, but also reveals spatial patterns of human vulnerability that span over different climate regions. That means, independent of a specific climate hazards, international and transnational adaptation approaches are needed that can build capacities at the local, national and regional levels to enhance adaptation and risk reduction. While different approaches exist to measure vulnerability at the global scale, two very comprehensive approaches differ in terms of single country values or specific indicators, but their relative ranking of vulnerability higher or lower compared to another country or region points in the same direction. Consequently, our paper provides evidence about the fact that high agreement and robustness exist in terms of the spatial patterns of high and low vulnerability at the level of climate regions. These global patterns can inform future adaptation and risk reduction policies in the sense that they indicate the importance of the coordination of such policies beyond national borders, particularly in climate regions classified as most vulnerable. These regions need a climate resilient development approach that addresses the broader development deficits.

Finally, the analysis also reveals limitations of the global assessments. The ranking of each region is influenced by a variety of factors and indicators. Consequently, the ranking of a region alone does not explain the specific development challenges and vulnerability profiles of the countries within it. Nevertheless, the global assessment does show that some global hotspots of human vulnerability have a spatial concentration, for example, in central and Sub-Saharan Africa. Our results underscore the necessity for stronger international cooperation and indicate that some of the structural vulnerabilities might require significant changes also in how we approach adaptation to climate change, shifting the focus from specific climate hazards towards the consideration of drivers of human vulnerability within these regions. This is an important message to agencies dealing with adaptation to climate change, human development programs and disaster risk reduction, since efforts to coordinate approaches to these issues are needed in regions where the lack of community resilience and the individual vulnerability of people is closely interwoven with structural vulnerability at the national and, importantly, the regional scale. Particularly in countries with persistent levels of poverty and severe governance challenges, international assistance and regional cooperation will be needed in order to provide conditions that enable different institutions and social groups to build resilience.

**Declarations**

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## ANNEXE I – CLIMATE REGIONS

**Table 5** Climate regions of the sixth assessment report and their adaptation for the present study

| Region | Code | Aggregated |
|---|---|---|
| Greenland/Iceland | GIC | |
| N.E.Canada | NEC | North America |
| C.North-America | CNA | |
| E.North-America | ENA | |
| N.W.North-America | NWN | |
| W.North-America | WNA | |
| N.Central-America | NCA | |
| S.Central-America | SCA | |
| Caribbean | CAR | |
| N.W.South-America | NWS | |
| South-American-Monsoon | SAM | |
| S.South-America | SSA | |
| S.W.South-America | SWS | |
| S.E.South-America | SES | |
| N.South-America | NSA | |
| N.E.South-America | NES | |
| N.Europe | NEU | |
| C.Europe | CEU | |
| Mediterranean | MED | |
| West-Africa | WAF | |
| Sahara | SAH | |
| North-East-Africa | NEAF | |
| Central-East-Africa | CEAF | |
| South-West-Africa | SWAF | |
| South-Eeast-Africa | SEAF | |
| Central-Africa | CAF | |
| Russian-Arctic | RAR | |
| Russian-Far-East | RFE | |
| E.Siberia | ESB | |
| E.Europe | EEU | East Europe West Siberia |
| W.Siberia | WSB | |
| W.C.Asia | WCA | |
| Tibetan-Plateau | TIB | |
| E.Asia | EAS | |
| Arabian-Peninsula | ARP | |
| S.Asia | SAS | |
| S.E.Asia | SEA | |
| N.Australia | NAU | Australia/New Zealand |
| C.Australia | CAU | |
| S.Australia | SAU | |
| New-Zealand | NZ | |
| E.Antarctica | EAN | Not included |
| W.Antarctica | WAN | Not included |
| Arctic-Ocean | ARO | Not included |
| S.Pacific-Ocean | SPO | South Equatorial Pacific |
| Equatorial.Pacific-Ocean | SPO | |
| N.Pacific-Ocean | NPO | |

| | | |
|---|---|---|
| S.Atlantic-Ocean | SAO | |
| Equatorial.Atlantic-Ocean | EAO | |
| N.Atlantic-Ocean | NAO | |
| Equatorial.Indic-Ocean | EIO | Indian Ocean |
| S.Indic-Ocean | SIO | |
| Arabian-Sea | ARS | |
| Bengal-Gulf | BOB | |
| South-Ocean | SOO | Not included |

# ANNEXE II – INFORM AND WRI VULNERABILITY

| Climate Regions | World Risk Index | | | | INFORM Risk Index | | |
|---|---|---|---|---|---|---|---|
| | Vulnerability | | | | Vulnerability | | |
| | Vulnerability | Susceptibility | Lack of Coping | Lack of Adaptation | Vulnerability | Socio-economic | Vulnerable groups |
| Arabian-Peninsula | 44,1 | 19,8 | 69,1 | 43,4 | 31,7 | 27,0 | 34,8 |
| Australia and New Zealand | 44,2 | 29,2 | 62,6 | 41,0 | 27,3 | 25,0 | 29,3 |
| C.Europe | 34,2 | 17,2 | 52,5 | 32,9 | 18,7 | 11,5 | 24,4 |
| Caribbean | 43,3 | 25,2 | 64,3 | 40,5 | 28,8 | 30,0 | 26,0 |
| Central-Africa | 64,3 | 49,2 | 86,8 | 56,9 | 62,7 | 61,2 | 63,8 |
| Central-East-Africa | 65,2 | 58,1 | 84,2 | 53,4 | 66,7 | 68,0 | 64,2 |
| E.Asia | 46,2 | 26,8 | 68,3 | 43,4 | 33,5 | 32,7 | 33,5 |
| East Siberia | 40,5 | 24,3 | 58,1 | 39,2 | 27,8 | 25,5 | 29,3 |
| Greenland/Iceland | 28,3 | 14,8 | 43,5 | 26,6 | 14,0 | 4,5 | 22,5 |
| Indian Ocean | 51,8 | 30,0 | 74,8 | 50,5 | 35,5 | 36,5 | 34,0 |
| Mediterranean | 42,1 | 20,7 | 65,6 | 40,0 | 32,8 | 25,1 | 38,3 |
| N.Central-America | 38,0 | 20,0 | 60,4 | 33,8 | 32,5 | 21,0 | 42,0 |
| N.E.South-America | 43,9 | 24,5 | 67,8 | 39,5 | 25,0 | 32,0 | 17,0 |
| N.Europe | 30,6 | 16,8 | 45,4 | 29,7 | 20,1 | 7,5 | 30,2 |
| N.South-America | 46,4 | 25,7 | 72,8 | 40,7 | 34,3 | 33,4 | 33,0 |
| N.W.South-America | 46,1 | 26,6 | 72,3 | 39,6 | 35,8 | 32,3 | 37,8 |
| North-East-Africa | 67,5 | 53,5 | 87,5 | 61,5 | 71,5 | 69,7 | 72,3 |
| North America | 33,5 | 16,5 | 49,9 | 34,2 | 22,0 | 12,7 | 29,0 |
| North Pacific | 36,1 | 19,7 | 54,5 | 34,3 | 33,9 | 33,6 | 32,1 |
| Russian-Arctic | 39,6 | 21,4 | 59,0 | 38,5 | 27,0 | 20,0 | 33,0 |
| S.Asia | 55,9 | 33,8 | 81,0 | 53,0 | 46,3 | 42,8 | 48,4 |
| S.Central-America | 49,2 | 29,5 | 74,4 | 43,8 | 35,1 | 38,3 | 31,3 |
| S.E.Asia | 52,1 | 31,9 | 76,2 | 48,1 | 35,0 | 36,4 | 32,7 |
| S.E.South-America | 44,7 | 27,0 | 67,2 | 40,0 | 23,2 | 31,6 | 13,2 |
| S.South-America | 38,0 | 20,8 | 58,7 | 34,6 | 17,0 | 21,5 | 12,5 |
| S.W.South-America | 44,2 | 27,3 | 67,7 | 37,7 | 26,0 | 31,5 | 19,8 |
| Sahara | 60,3 | 43,6 | 80,9 | 56,5 | 50,9 | 51,2 | 49,2 |
| South-American-Monsoon | 49,1 | 30,4 | 75,0 | 41,9 | 29,8 | 38,0 | 19,8 |
| South-Eeast-Africa | 61,8 | 52,6 | 79,9 | 52,8 | 53,2 | 59,2 | 45,7 |
| South-West-Africa | 55,8 | 45,1 | 74,8 | 47,5 | 50,7 | 53,0 | 47,5 |
| South Pacific | 51,0 | 32,5 | 73,9 | 46,5 | 38,7 | 48,3 | 25,7 |
| Tibetan-Plateau | 51,8 | 31,9 | 74,5 | 49,1 | 35,8 | 37,6 | 33,5 |
| W.C.Asia | 49,5 | 26,8 | 74,4 | 47,3 | 37,6 | 32,0 | 41,2 |
| West-Africa | 66,4 | 51,9 | 85,1 | 62,1 | 54,2 | 63,3 | 42,3 |
| West Siberia | 44,6 | 24,7 | 65,9 | 43,3 | 28,0 | 25,3 | 29,2 |

# SIXTH CHAPTER

## CLIMATE RESILIENCE IN NATIONS: EMPIRICALLY-DERIVED ELEMENTS AND AN OPEN RESILIENCE INDEX

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# An open resilience index: Crowdsourced indicators empirically developed from natural hazard and climatic event data

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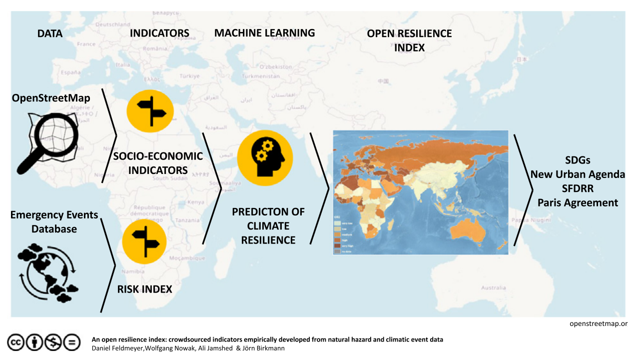
## HIGHLIGHTS

- Empirical risk index investigating the number of affected people and fatalities
- Socio-economic indicators are derived from OpenStreetMap.
- Machine learning is used to predict resilience with socio-economic indicators.
- Soft factors like social cohesion are crucial in shaping nations resilience.

## GRAPHICAL ABSTRACT

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## ABSTRACT

The climate resilience of nations is imperative for a sustainable future. The way that nations respond to climate change needs to adapt from a reactive and backward-focused disaster management approach, to become more proactive and to anticipate what is yet to come. Two key challenges restrict climate resilience. First, the social aspects are relevant to resilience, yet many such aspects are not adequately reflected by available statistics. Second, validating indicators of climate resilience is demanding in terms of data availability and methodology. To overcome these challenges, we develop an Empirical Evidence Resilience Index (EERI) based on the Emergency Event Data Base (EM-DAT) to measure resilience. However, just the measurement of resilience does not provide the explanation necessary to determine planning strategies. Therefore, to understand resilience better, we also use statistics from OpenStreetMap (OSM) to predict the EERI and deduce explanatory elements. This step is achieved with a random forest method. We call the resulting prediction of resilience (EERI) from OSM data the Open Resilience Index (ORI). The used explanatory elements from OSM not only cover the physical characteristics of infrastructures, but also include country-level socio-economic information. The results show the relevance of social cohesion (identity & mobility; religion); human development (leisure & recreation, social fabric); economy (economic status; material supply); sustainable infrastructure (available infrastructure; spatial development); and nature conservation for resilience.

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## 1. Introduction

The increasing frequency and magnitude of droughts, storms and floods, along with growing temperatures and populations, is confronting nations around the world (Biagini et al., 2014; IPCC, 2018). "Climate change" has transformed from an abstract theoretical concept into a

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reality that is now apparent when monitoring databases of natural disasters. Despite major efforts and investments in hazard mitigation strategies, overall exposure to natural hazards has increased over the last 90 years (Fuchs et al., 2017).

Different international agreements and agendas compete in seeking to address challenges posed by natural hazards and climate change impacts. In terms of Sustainable Development Goals (SDGs), target 1.5 of goal 1 calls "…build the resilience of the poor and those in vulnerable situations, and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters", goal 11 calls to "make cities and human settlements inclusive, safe, resilient and sustainable", while goal 13 calls for urgent climate action (United Nations, 2018). Several paragraphs of UNHABITAT's New Urban Agenda have also focused on building the resilience of human settlements to disasters and climatic changes (UNHABITAT, 2016). Goal, Targets and Priorities of UNDRR's Sendai Framework for Disaster Risk Reduction also acknowledged strengthening resilience to reduce disaster risk (UNDRR, 2015). UNFCCC's Paris Agreement also binds nations to build the resilience of human and natural systems (UNFCCC, 2015).

Considering these international discourses, research efforts have contributed well in providing valuable information for further implementation of these agreements and agendas (e.g. Keesstra et al., 2016, 2018; Zhang et al., 2019; Jamshed et al., 2020a, 2020b; Jamshed et al., 2021). Before going into the description of key gaps and problems, three key concepts (adaptation, vulnerability and resilience) that are widely and interchangeably used in literature are discussed to provide a clearer context for our discussion.

Adaptation here is defined as "adjustments in ecological, social, or economic systems in response to actual or expected climatic stimuli and their impacts. It refers to changes in processes, practices, and structures to moderate potential damages or to benefit from opportunities associated with climate change" (UNFCCC, 2021).

Vulnerability deconstructs risk and reveals societal drivers, elements and components, crucial to understand and prevent risk (Adger, 2006; Fuchs, 2009; Wolf and McGregor, 2013; Garschagen and Romero-Lankao, 2015; Rana and Routray, 2018). Since vulnerability is hazard-specific and related to the spatial scale of analysis, numerous approaches have been developed (e.g. Cutter et al., 2003; Sorg et al., 2018; Karagiorgos et al., 2016; Jamshed et al., 2017; Jamshed et al., 2020a, 2020b). Indicators can be utilized to evaluate vulnerability and risk and to provide the means for risk-informed decisions (Mach et al., 2016; de Almeida et al., 2016; Birkmann et al., 2020).

Resilience is described by Holling (1973) as a "measure of persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationship between population or state variables". It is a concept that has evolved and grown in popular use over recent years. Stressing the fact that the bigger end of climate change is yet to come, nations' disaster policies need to be adjusted from reactive to proactive, and strategies need to be developed to increase resilience for what is yet to come (Cutter et al., 2013). The concept of resilience gained huge popularity over the last decade, with an exponential increase in academic publications. In recent years, the understanding of resilience evolved more into the direction of a transformational and evolutionary understanding in contrast to an equilibrium-focused understanding (Figueiredo et al., 2020). Different operationalization approaches have been proposed to measure resilience to climate change (ARUP and Rockefeller Foundation, 2014; Welle et al., 2014; Riedel et al., 2016; UNISDR, 2017; Morrow, 2008; NOAA, 2015; Tyler and Moench, 2012; UNDP, 2013; Schaefer et al., 2020), earthquake (Poland, 2008; OSSPAC, 2013), multiple hazards (Cutter et al., 2008) or unspecific stressors (Birkmann et al., 2012; Béné et al., 2015; Renschler et al., 2010; Poland, 2008; OSSPAC, 2013; Yoon et al., 2016).

Indices are used to measure, monitor and evaluate vulnerability (Welle et al., 2014; Depietri et al., 2013; Sorg et al., 2018; Karagiorgos et al., 2016; Balica et al., 2009; Jamshed et al., 2019; Cutter et al., 2003), risk (Welle and Birkmann, 2015; Birkmann and Welle, 2016; Marin-Ferrer et al., 2017) or resilience (Cutter et al., 2010; ARUP and Rockefeller Foundation, 2014; Suárez et al., 2016; Keating et al., 2014; Cutter et al., 2014). Similar to resilience, the literature about indices in various disciplines has increased exponentially (Greco et al., 2019). The reason for their popularity is that they can easily summarize complex problems and communicate them in a simple way. Indices justify decisions or inform policies and drive behavioural changes (Becker et al., 2017). However, indices have been criticized for their subjectivity in the selection of individual aspects as well as in their aggregation to get a composite score. Hence, indices can generate false or over-simplified results (Saltelli, 2007; Brito, 2018).

Despite the many approaches that exist, there is a real lack of empirical validation of indices (Bakkensen et al., 2017; Burton, 2015). The phenomena of vulnerability, resilience and adaptation often lack data on the social dimension and on specific temporal or spatial scales (Cutter and Finch, 2008; Sorg et al., 2018; Feldmeyer et al., 2019b; Schaefer et al., 2020). Different approaches to fill this gap have been developed in other research fields using satellite imagery, phone records, news, Twitter, social media and Volunteered Geographic Information (VGI) (Deville et al., 2014; Blondel et al., 2015; Stevens et al., 2015; Capineri et al., 2016; Rosales Sánchez et al., 2017; Thakuriah et al., 2017; Di Bella et al., 2018). On the methodological side, machine learning has been successfully applied in this context to improve natural hazard prediction, like landslide susceptibility (Achour and Pourghasemi, 2020).

Thus, for building meaningful indicators for climate resilience, two key challenges continue to prevail: (a) including the social component of climate resilience and (b) validation with empirical data of indices and indicators. We develop a two-step solution to overcome these challenges. The first step results in an Empirical Evidence Resilience Index (EERI). The EERI uses empirical disaster data related to climate change to measure empirical resilience, which is a way to provide an empirical basis for validation. The second step utilises selected statistics from OpenStreetMap (OSM) that we use to predict the EERI and infer explanatory elements. We call the obtained (end empirically validated) prediction model for the EERI from OSM data the Open Resilience Index (ORI). As the used OSM data includes not only evidence of the physical world, but also information about the socio-economic status (Glasze and Perkins, 2015; Jokar Arsanjani et al., 2015), the social component is included.

## 2. Materials and methods

The narrative of our workflow towards the ORI (Fig. 1) is guided by the two challenges indicated above: (a) including the social component and (b) empirical validation.

To tackle challenge (a), we search for and use explanatory elements from OSM to predict the EERI from OSM data. To solve the challenge (b), we build the EERI from empirical damage data on storms, droughts, floods and earthquakes. These disaster data are taken from the Emergency Event Database (EM-DAT) (EM-DAT, 2021). This requires, as a pre-step, the Empirical Risk Index (EmRI) that is yet to be defined. The final EERI is a combination of the EmRI and WorldRiskIndex (WRI) (Welle and Birkmann, 2015). The combination of challenge (a) & (b) is our final product, the ORI. It is validated through the EERI, and it includes social components of climate resilience by means of OSM. In this section, we start in Section 2.1 by explaining the data used and the spatial focus. In Section 2.2, we describe the construction of the EERI from EmRI and WRI (step one). In Section 2.3, we describe the statistical analysis to infer explanatory elements from OSM to obtain the ORI (step two).

### 2.1. Data and study area

Three openly accessible data sets are used here; Open Street Map (OSM), the World Risk Index (WRI) and the Emergency Event Database (EM-DAT):

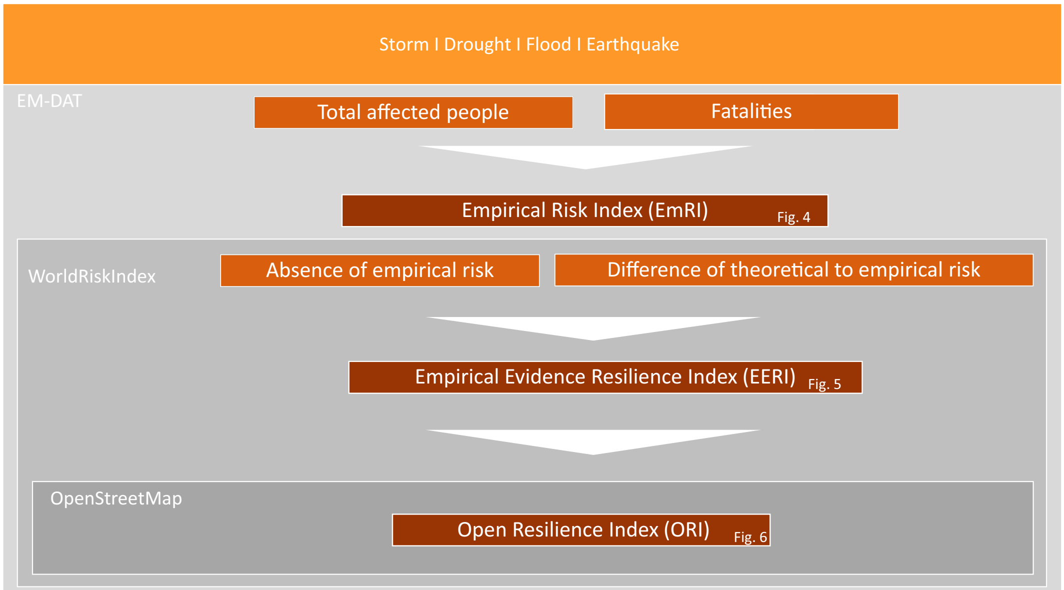



**Fig. 1.** Research workflow and products.

1. OpenStreetMap (OSM) was founded in 2004 and provides not only physical but also socio-economic characteristics for each country (www.openstreetmap.org).
2. The WorldRiskIndex (WRI) was first published in 2011 and calculates countries risk to natural hazards by exposure and vulnerability (Welle and Birkmann, 2015).
3. The Emergency Event Database (EM-DAT) was founded in 1988 and comprises records of 22.000 disasters, still ongoing and growing (www.emdat.de).

The study focused on a global level without the countries of North- and Latin-America. The included countries cover all levels of socio-economic status as well as a variety of characteristics regarding crowdsourced data. More details on the data are provided in the following.

OSM was created to be a free, open and editable world map (OpenStreetMap contributors, 2020). It is a collaborative project, where the crowdsourced data is made public under the Open Database License. The OSM dataset used for this analysis is part of the dataset used in an earlier study by Feldmeyer et al. (2019a). For this, Feldmeyer et al. (2019a) downloaded the entire world planetary file of OSM and imported it into a PostGIS database (PostGIS, 2020; PostgreSQL, 2020). Each map object is described by a tag, consisting of a key and a value (e.g. key: building; value: residential). Then, the authors reduced the data-set by removing generic OSM tags, names and addresses. Subsequently, they conducted a spatial query counting the appearance of each tag per country. Hence, each country is described by the count of each of the 1340 tags remaining after the reduction. This is the final OSM dataset we used within our current analysis.

The WRI calculates the risk of nations by multiplying an exposure index with vulnerability (Fig. 2) (Birkmann and Welle, 2016; Welle and Birkmann, 2015). The exposure index calculates the average number of inhabitants affected by earthquake, storms, floods, droughts and sea-level rise. The probability and magnitude of the event(s) are included. Vulnerability is described as the product of three factors: (1) "Susceptibility" is understood here as the severity of impact due to the hazard and is explained by public infrastructure, housing conditions, nutrition, poverty and dependencies as well as the economic capacity and income. (2) "Coping capacity" covers the short-term aftermath of

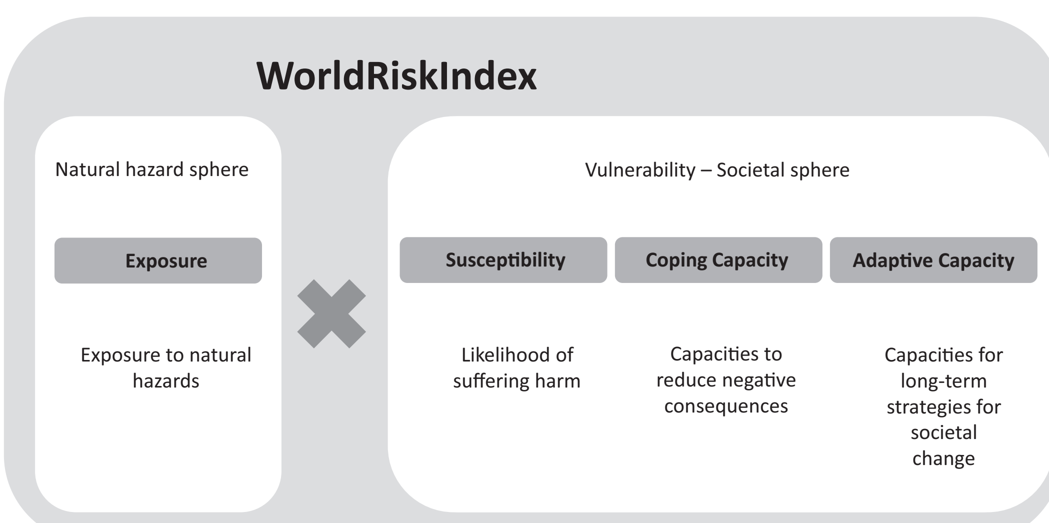



**Fig. 2.** World Risk Index main calculation scheme (Welle and Birkmann, 2015).

the event. Here, elements of disaster preparedness and early warning, medical services, social networks and material coverage and more generally government and authorities are key elements. (3) The "adaptive capacity" is the ability of the society to adapt its habits and activities to avoid future collision with hazards, for which education, gender equity, environment, adaptive strategies and investments are sub-elements. The values of the WRI are between zero and one for each country, where a value of one signifies a large risk.

The EM-DAT provides numbers of fatalities and people affected per country. It applies a hierarchical classification by disaster group, subgroup, main-type, sub-type and sub-sub-type (see Table 1). The groups distinguish between natural and technological disasters. Table 1 presents the classification of natural disasters (EM-DAT, 2021).

As mentioned above, the WRI considers earthquake, storm, flood, drought and sea-level rise. Therefore, data of all these five disaster main-types were taken from the EM-DAT database. The disaster type "flood" includes coastal floods. The database request was natural disasters from 2000 until 2019 per country. Afterwards, in a second query, the aforementioned main types of disasters were selected. The EM-DAT records give people died in the event(s) (fatalities = F) and people affected per country (affected = A) (Fig. 3).

### 2.2. The empirical risk index (EmRI) and the empirical evidence resilience index (EERI)

To tackle the challenge of empirical validation, we develop in this study the Empirical Evidence Resilience Index (EERI) from disaster fatalities and affected people. This is the first step mentioned in Section 1.

**Table 1**
The EM-DAT disaster classification.

| Disaster group | Disaster subgroup | Definition | Disaster main type |
|---|---|---|---|
| Natural | Geophysical | A hazard originating from solid earth. This term is used interchangeably with the term geological hazard. | Earthquake<br>Mass movement (dry)<br>Volcanic activity |
| | Meteorological | A hazard caused by short-lived, micro- to meso-scale extreme weather and atmospheric conditions that last from minutes to days. | Extreme temperature<br>Fog<br>Storm |
| | Hydrological | A hazard caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater. | Flood<br>Landslide<br>Wave action |
| | Climatological | A hazard caused by long-lived, meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability. | Drought<br>Glacial lake outburst<br>Wildfire |
| | Biological | A hazard caused by the exposure to living organisms and their toxic substances (e.g. venom, mold) or vector-borne diseases that they may carry. Examples are venomous wildlife and insects, poisonous plants, and mosquitoes carrying disease-causing agents such as parasites, bacteria, or viruses (e.g. malaria). | Epidemic<br>Insect infestation<br>Animal accident |
| | Extraterrestrial | A hazard caused by asteroids, meteoroids, and comets as they pass near-earth, enter the Earth's atmosphere, and/or strike the Earth, and by changes in interplanetary conditions that effect the Earth's magnetosphere, ionosphere, and thermosphere. | Impact<br>Space weather |

In the first part of this step, we calculate a-so called EmRI. We designed this new risk index to incorporate the human and economic dimension of risk based on two decades of data. It uses Fatalities (F) and Affected People (A) from the EM-DAT database. To obtain F and A per country, we downloaded the EM-DAT data as a .csv file and then imported them into the "R studio" environment (R Core Team, 2019; RStudio Team, 2019). We calculated the fatalities and number of affected people per country for the selected hazards (package: dplyr, Wickham et al., 2019).

Then we min-max normalize the obtained Fatalities (F) and Affected People (A) per country (Eq. (1)). Without a justification for other weights, we build the EmRI by equal weights (Eq. (2)). The values range from zero to one for all countries, where a value of one signifies a large risk. The involved equations are:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

$X'$ = transformed value.$x$ = value of the indicator.$x_{\min}$ = minimum value of the indicator.$x_{\max}$ = maximum value of the indicator.

$$EmRI = {}^{1}/_{2} * (Fatalities' + Affected') \tag{2}$$

$Fatalities'$ = Total deaths: Sum of death and missing.$Affected'$ = Total affected: Sum of injured, homeless, and affected.

In the next step, we compute the EERI (Eq. (3)). It is the average of two aspects: (1) the difference between the theoretical risk given by the WRI and the empirical EmRI and (2) the overall absence of risk. The absence of risk is the antipode to EmRI. Obviously, the second part includes elements of vulnerability. Nevertheless, literature justifies this or even requires to some extent to include vulnerability from a data perspective into resilience because both concepts have an overlap (Cutter et al., 2014; Sherrieb et al., 2010). The resulting EERI is:

$$EERI = {}^{1}\!/_{2} * (WRI - EmRI) + {}^{1}\!/_{2} * (1 - EmRI) \tag{3}$$

$WRI$ = WorldRiskIndex.$EmRI$ = Empirical Risk Index.

The resulting EERI is again between zero and one for each country, where a value of one signifies the largest resilience. Due to the terms in Eq. (3), the EERI has a negative correlation with EmRI.

### 2.3. Explanatory elements of resilience: the open resilience index ORI

The EERI alone has no explanatory power of resilience. Therefore, in the subsequent section, explanatory elements are derived by means of machine learning, trying to predict EERI from infrastructural and social components in the OSM. The resulting explained prediction of resilience, validated through the EERI, is the Open Resilience Index ORI.

To obtain the ORI, we normalized the OSM data again using Eq. (1), and then reduced their dimension to the most relevant components by a Principal Component Analysis (PCA; function: preProcess(); package: caret; Kuhn et al., 2019). The normalization is known to not affect PCA results. The PCA analysis resulted in 80 principal components out of the 1340 tags per country. In the following we use these 80 dimensions of OSM as candidate indicators to predicting the EERI and construct the ORI.

First preliminary results indicated a non-linear relationship between OSM indicators and EERI. Thus, for finding statistical determinants of resilience, we used Random Forest as a non-linear method (function: randomForest(); package: RandomForest; Liaw and Wiener, 2018). The Random Forest algorithm is an advancement of the classic decision tree and can be used for regression with built-in variable selection. Compared to decision trees, random forests build many (here: 1000) trees and summarizes the results. The many random trees are achieved by bootstrapping from the data available for training, and by drawing a random sub-set of predictors from the candidate predictors for each tree. Together, this provides statistical robustness and avoids dominance of one single very strong predictor. The relevance of each single

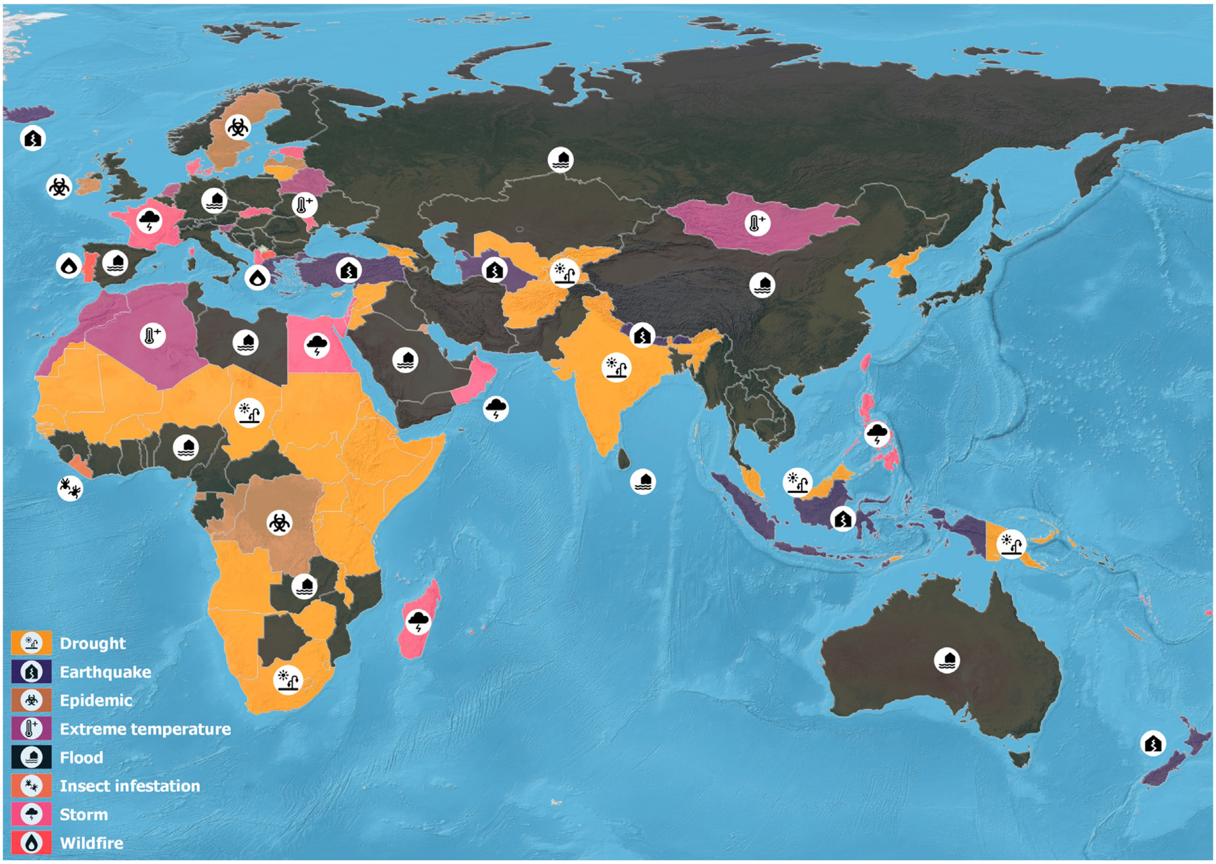



**Fig. 3.** Type of disaster which affected the highest number of people in each country in the last 20 years (data: EM-DAT).

indicator/predictor is determined by their contribution to reduce the test error over all trees of the forest and bootstrap samples, reported by the "%IncMSE" (per cent increase in mean squared error).

The result of random forest is the ORI that predicts (with minimum squared error) the EERI while using the most powerful explanatory variables among the offered 80 PCA components. The individual contribution to ORR reported by random forest quantifies the relevance of the respective component and helps explain and lay open the elements that make up empirically measureable resilience.

## 3. Results

This section is split into three sub-divisions. In Section 3.1, we present the resulting risk according to EmRI, based on EM-DAT data over the last twenty years, and compare it across the study region. Section 3.2 discusses the resulting resilience based on our EERI, and again compares it across the study region. Section 3.3 presents the statistical analysis to help understand resilience and its components, along with the final ORI map.

### *3.1. Empirical risk (EmRI) from EM-DAT*

The empirical risk of being killed or affected according to our EmRI (Section 2.2, Eq. (2)) from earthquake, storm, flood and drought over the last two decades is shown in Fig. 4. The classification into a 5-step color scale is added to avoid the impression of pseudo-accuracy. Details on the class borders for the map are provided in the Appendix.

The ten countries with the lowest risk in increasing order from the bottom are: Latvia, United Arab Emirates, Cyprus, Finland, Estonia, Kuwait, Qatar, Netherlands, Iceland and Denmark.

Six of the top ten (lowest risk) countries are in Europe and four in Asia. All of the top ten countries are, according to the World Bank classification, high-income countries. Looking at political stability (Indicator Id: PV.EST), the countries are ranked from medium to high.

The countries with the highest risk in decreasing order from the top are: Somalia, Micronesia, Myanmar, Swaziland, Mauritania, Philippines, China, Thailand and Lesotho. In the World Bank income classification, these countries are ranked upper middle income to low income. The political stability is low or very low, except for Micronesia which is ranked in the top quantile, very high stability. From a continental perspective; five are in Asia, four in Africa and one in Oceania. Asia appears on both ends of the ranking, where Europe is mostly very low to low risk, and Africa and Oceania are mostly in the medium to high-risk categories.

### *3.2. Resilience according to the empirical evidence resilience index (EERI)*

The EERI based on EmRI and WRI from the last twenty years (Eq. (3)) is displayed in Fig. 5.

The lowest EERI resilience scores are achieved in decreasing order by Zimbabwe, the Philippines, Namibia, Lesotho, Thailand, China, Mauritania, Swaziland, Myanmar and Sri Lanka. These countries are equally split between the continents of Asia and Africa. They are ranked in the middle to low-income groups and the political stability is low or very low with the exception of Sri Lanka (medium) and Namibia, which is ranked high.

The highest EERI resilience scores, in decreasing order, are achieved by: Mauritius, Cameroon, Sierra Leone Timor-Leste, Côte d'Ivoire, Netherland, Togo, Liberia, and Guinea Bissau. The income level is from high to low and also the political stability ranges from high to low.

### *3.3. Open resilience index (ORI)*

The most important determinants for predicting resilience applying the random forest method (Section 2.3) were the principal components:

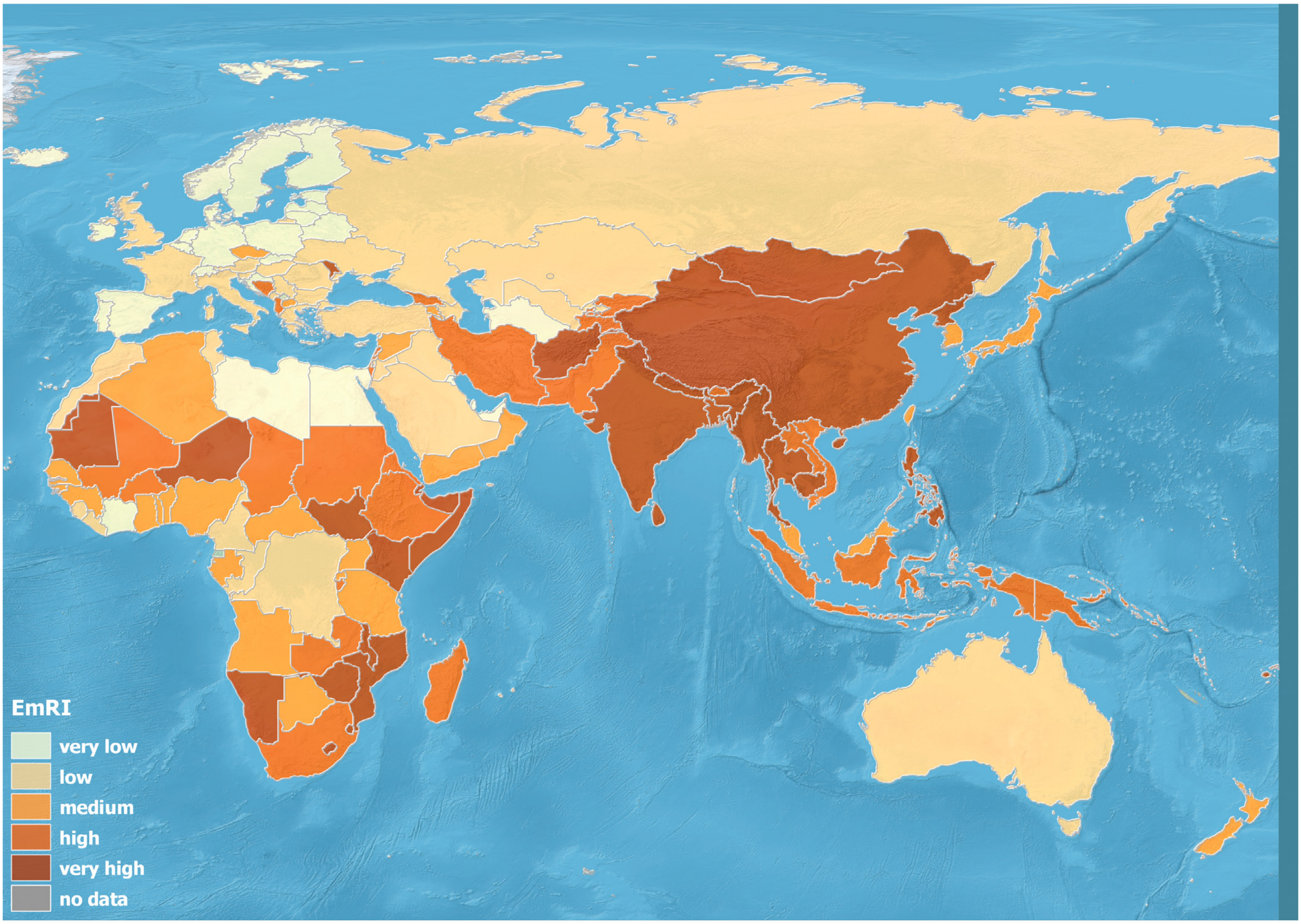



**Fig. 4.** Empirical risk index EmRI (data: EM-DAT).

identity & mobility, sustainable infrastructure, social fabric, material supply, social infrastructure, economic status, religion, spatial development, leisure & recreation, nature conservation (Table 2) (see Annex II).

The lowest resilience points, as predicted by the ORI, scored: Sri Lanka, Mauritania, Lesotho, Swaziland and Malawi (Fig. 6). These countries are ranked in the low and lower middle income classes and low to medium political stability. The highest resilience score is achieved by the Netherlands, a country with a long history of high exposure and also very low vulnerability followed by Turkmenistan, Romania, Jordan and Hungary.

Nevertheless, an indicator is rather a semi-quantitative ranking than a quantitative number. Therefore, the most important aspect is that the rank correlation for the classification within the ordinal color scale is high, i.e. that the ordering of countries is maintained. The resulting Spearman's rank correlation value is 0.73, which we find a satisfying performance of the explained ORI (Fig. 7).

## 4. Discussion

In previous sections, we constructed an empirical risk index (EmRI) from two decades of disaster data (EM-DAT), and then blended it with the existing World Risk Index (WRI) into an Empirical Resilience Index (EERI); finally, we constructed an Open Resilience Index (ORI) that was trained on the EERI. The ORI uses, among others, social components from Open Street Map to explain the resilience values indicated by EERI. In the following, we digest the above results against income, political stability and softer social components; we also discuss the interrelation between our results.

### *4.1. EmRI versus economical aspects*

Based on our EmRI results in Section 3.1, the countries with the highest risk of natural hazards over the last two decades are located in Africa and Asia. High risk coincides with lower political stability and with lower income as also indicated by Byers et al. (2018). These findings underline the importance of socio-economic vulnerability as a determining factor for risk to natural hazards. In both regions, global hotspots of vulnerability are located, with high persistence and cumulative interwoven socio-economic vulnerabilities (Birkmann et al., 2020).

When comparing the risk of countries, in rich developed countries, the economic losses due to natural hazards are often dominant over the number of people affected. This is the effect of corresponding investments into protection and mitigation measures. In less developed countries, the economic losses are lower due to lower exposed values, but the number of people negatively affected is much higher. This finding is also supported by Formetta and Feyen (2019).

### *4.2. EERI versus income, political stability and social components*

Resilience based on the vulnerability component of the WRI and on the historic consequences of natural hazards in EmRI paints a differentiated picture/world map. While the lowest resilience scores are attained by countries in Africa and Asia, the overall map is much more differentiated. Generally, low resilience goes hand-in-hand with low income and low political stability (Cutter and Derakhshan, 2020; Lassa et al.,

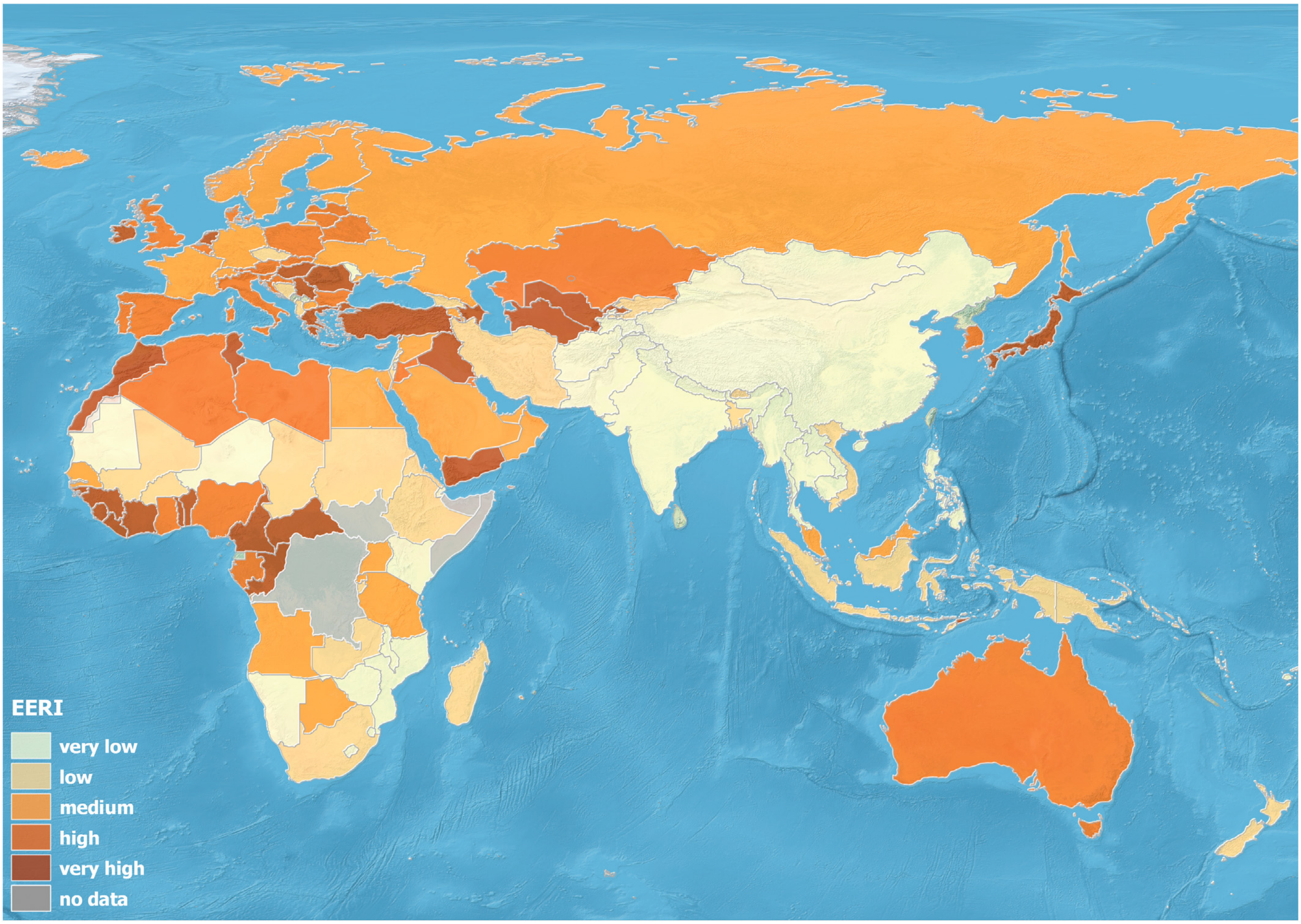



**Fig. 5.** EERI based on own methodology (data: EM-DAT, WRI).

2019). In contrast, high resilience shows income from low to high and political stability from high to low (see Annex III).

This indicates that high income and political stability is sufficient, but not necessary for high resilience: Low resilience has a strong linkage to low income and low political stability, but high resilience seems to be additionally influenced by other factors besides the economic situation. This is in line with literature that attests the importance of softer factors, such as social networks, feelings of belonging, learning, experience (Cutter, 2016, Feldmeyer et al., 2019b, Jamshed et al., 2020a, 2020b).

The making (and name) of the EERI was selected to capture empirical evidence for resilience. Thus, it captures implicitly the effects all the above soft factors (social networks, feelings of belonging etc.) that are typically not available in countries' statistics for building a theoretical index. Nevertheless, the results differentiate between income and political stability and resilience. Hence, we conclude that our EERI index empirically captures all the desired factors, i.e. income, stability and soft factors.

**Table 2**
Ten most important principal components in predicting EERI with random forest.

| PCA | Name | %IncMSE |
|---|---|---|
| PC1 | Identity and mobility | 8,45 |
| PC57 | Sustainable Infrastructure | 5,98 |
| PC5 | Social fabric | 4,33 |
| PC7 | Material supply | 3,38 |
| PC20 | Social infrastructure | 3,22 |
| PC13 | Economic status | 3,16 |
| PC16 | Religion | 3,11 |
| PC55 | Spatial development | 2,57 |
| PC40 | Leisure & Recreation | 2,48 |
| PC45 | Nature conservation | 2,42 |

### *4.3. Open resilience index ORI*

The Open Resilience Index (ORI) is based on the principal components (PCA) per country of the OSM-dataset as explanatory variables. It is derived by predicting the developed EERI with the Random Forest machine learning algorithm, which includes a mechanism for variable selection among the principal components. When manually organizing the ten most predictive indicators from Table 2 into themes, five themes prevail: Social cohesion (identity & mobility; religion); Human development (leisure & recreation, social fabric); Economy (economic status; material supply); Sustainable infrastructure (available infrastructure; spatial development); and Nature conservation.

To counter any issues with the completeness or quality of the OSM as a crowdsourced data-set, we validated the functional purpose of the data for predicting EERI. The scatterplot shows a clear positive correlation between EERI and ORI and a low MAE (0.017). Fig. 7 plots the EERI on the x-axis against the predicted ORI on the y-axis. In general, the frequency distribution is skewed to the upper end around a resilience level of 0.5. Those countries with the highest absolute difference (>0.15) are labelled. For the lower values (Sri Lanka, Mauritania, Swaziland, Thailand), resilience is slightly overestimated. In contrast, on the upper end, ORI tends to underestimate the level of resilience (Nigeria, Cote d'Ivoire, Cape Verde, Mauritius, Cameroon, Togo). The reported Mean Absolute Error (MAE) is low i-e., 0.017.

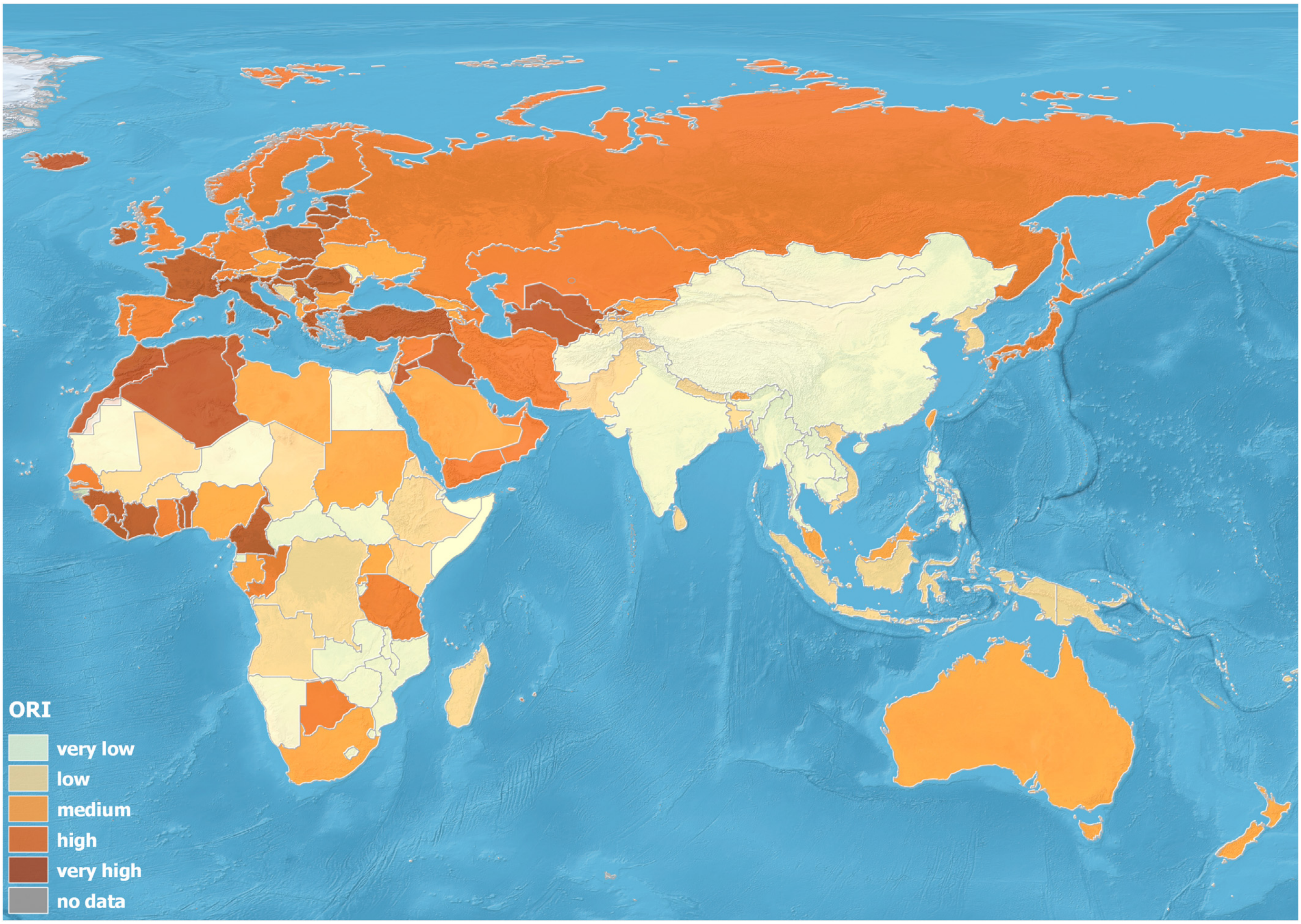



**Fig. 6.** Statistical prediction of resilience based OSM by random forest (data: OSM).

Moreover, resilience assessment is often limited due to the lack of existing indicators assessing soft factors, in line with previous studies (Sauter et al., 2019; Feldmeyer et al., 2019a). OSM in conjunction with machine learning is not only able to predict resilience but also have additional benefits of providing new insights into resilience.

### 4.4. Explanatory elements of resilience in ORI

The literature based disaster resilience indicator core by Cutter comprises six assets and five capacities (Cutter, 2016). In several areas, Cutter's core is consistent with our ten empirically derived elements in Table 2). Congruent elements are economy (economic status), social capital (social fabric, social infrastructure, religion), infrastructure (available infrastructure, material supply), environment (nature conservation). The remaining attributes in Cutter's core, i.e., institutional, information and emergency management, have no equivalent within our ten empirically most important predictors from the OSM dataset. Instead, our OSM-based predictors include spatial development and leisure & recreation, which are not included in Cutter's core.

Our two additional elements (spatial development; leisure & recreation) underline the potential of OSM data to include information typically not covered by governmental data (leisure & recreation) and not available on a global scale available (spatial development) into resilience analysis.

In contrast to that, information and communication is not directly part of the OSM database, but this does not mean that it is not included. The major question here is to what extent difficult social aspects like social capital or feelings of belonging and networks among the population do manifest, directly or indirectly, within OSM. This part is often not quantitatively measured due to high costs of surveys and workshops, and hence less monitored (Birkmann, 2013). Nevertheless, these social aspects contribute substantially to resilience. Here, the results indicate that OSM provides evidence for including such elements in line with previous studies (Feldmeyer et al., 2020).

Challenges: interpretability, dynamic changes and computation.

Both predictive and explanatory elements are needed to develop a comprehensive index for measuring climate resilience. Machine learning is often criticized in this context to be a black-box with low transparency and low explanatory power (Ribeiro, 2016). However, the variable selection of the random forest approach indeed has a high interpretability and allows for meaningful discussion. Only the specific functional-mathematical shape between the inferred explanatory elements and the ORI value are a black box, simply because a non-linear function of 10 or more variables is hard to visualize and/or imagine. Of course, the trained random forest could be used to update the ORI map in the future, but in a changing world one should probably re-evaluate the EERI and then repeat the random forest application to update the ORI.

Updating the ORI when longer historical data are available will require a discussion between the length of statistical records and the dynamics in a changing world. Twenty years of disaster may not be comprehensive in terms of a rigorous probabilistic hazard assessment. Nevertheless, these data clearly illustrate the current

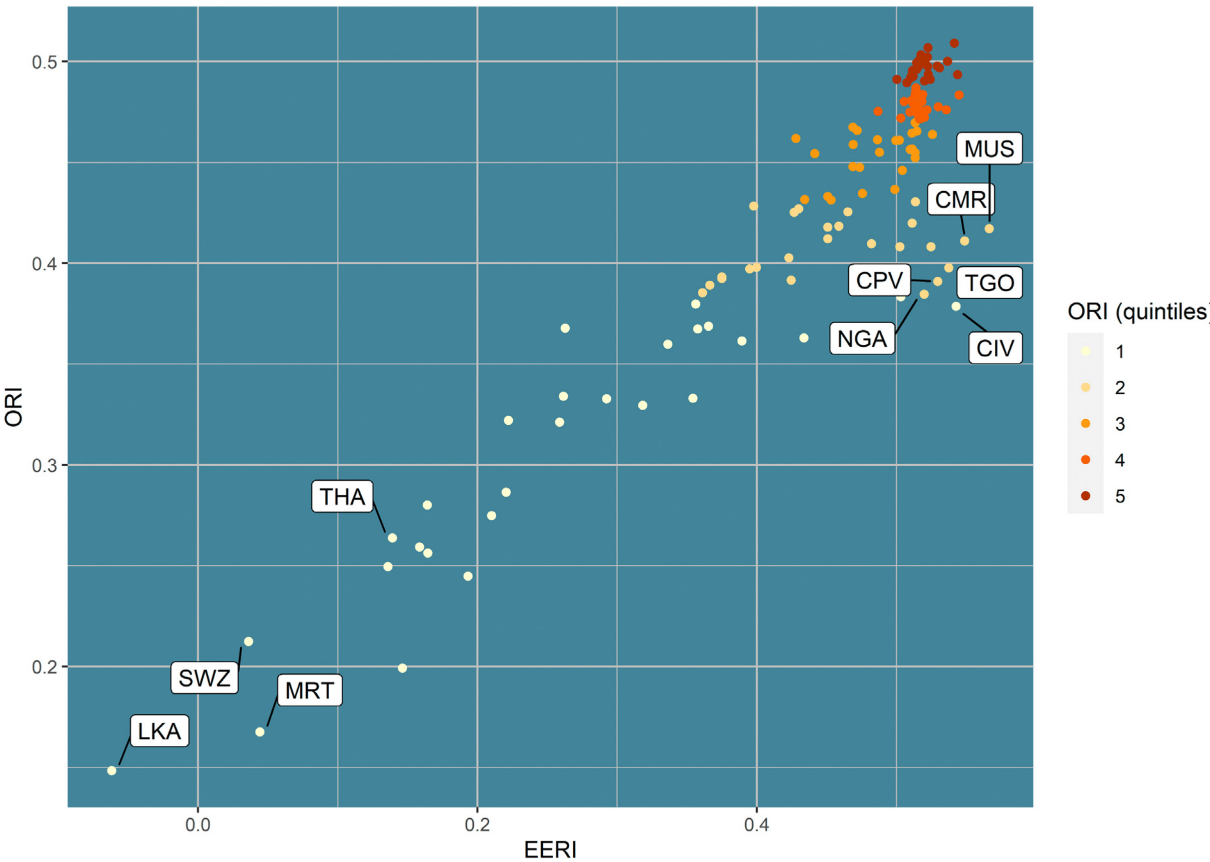



**Fig. 7.** Statistical prediction of resilience based OSM by random forest (data: OSM).

situation and helps in understanding the current spatial distribution. And even within these twenty years, there are already huge developments in the key characteristics of fast-developing countries, in climate, in implementing hazard mitigation and climate change adaptation measures. In this regard, the crowdbased OSM database is important to capture the fast changes occurring. Balancing different timeframes and impacts pose a challenge without one single final solution.

Despite the rapid development of personal computers, computational power is still a limitation to run data-intensive machine learning algorithms (Huntingford et al., 2019). First, the global OSM-dataset currently has about 1.3 TeraByte, which is clearly beyond the capacity of a current common PC. Second, querying this kind of data additionally requires extensive RAM or sophisticated deconstruction of the problem into smaller bites, digestible by the hardware. The tools applied in our current study were rather manual, including command-line tools and R programming. Considering these limitations related to computational power and capabilities of the computer system available to authors, the Americas had to be left out so that machine learning based on OSM could be processed without overloading the computer system. Thus, both hardware and software are issues to overcome.

### *4.5. Future research*

We identified the following three future research directions based on our discussions and findings:

- Social aspects (like social networks and feelings of belonging) are often neglected in resilience assessments due to difficulties in measuring them. Hence, more research is needed to integrate the social dimension into monitoring programmes.
- The scalability of indicators to be aligned with scales of the natural problem space needs further exploration, for example to construct resilience indices on the scale of river basins, climate regions, wildlife parks etc.
- The different levels of hazards as well as cascading effects of natural hazards were beyond the scope of the current research. To deeper understand the nature of resilience, both aspects pose specific challenges and therefore are fields of future research.
- A complete analysis of all the countries (including countries in Americas) can be done using similar methodology on computers with higher computational power and capabilities.
- While using the wider data set of OSM proved a successful strategy for learning about resilience, more data sources may be included, such as Twitter, phone records, satellite imagery; they might provide additional inputs on aspects not yet captured or improve the prediction capability. Any new results then need to be translated and integrated into policy frameworks and adaptation strategies in order to bring about change.

## 5. Conclusion

Monitoring and evaluation of climate resilience across scales in time and space is key to developing proactive management strategies in which to sustainably face climate change. Current challenges in measuring resilience are the empirical validation of resilience indices and the inclusion of soft social factors. In this study, we provided an Open Resilience Index (ORI) that is based on empirical disaster data from the world-wide emergency database EM-DAT, yet lays open explanatory elements provided by OpenStreetMap, and these include social factors. The results provide an evidence-based approach for disaster resilience and deeper knowledge at a national scale. This understanding contributes to the urgent need to change from a reactive to a proactive approach in managing natural hazards.

Empirical validation of resilience remains challenging, due to the fact that the outcome of resilience is the absence of damage, which is difficult to measure. This is in contrast to risk, where the negative consequences of an event are documented and measurable. The empirical evidence resilience index (EERI) developed as an intermediate step on the way to ORI indicates these absences of negative consequences which cannot be explained by exposure, hazard and vulnerability. An additional difficulty is that hard-to-measure soft factors are influential for resilience. In this light, machine learning with crowdsourced data provided new insights into resilience. The results show the relevance of social cohesion (identity & mobility; religion); human development (leisure & recreation, social fabric); economy (economic status; material supply); sustainable infrastructure (available infrastructure; spatial development); and nature conservation.

Our results also show that high income and political stability is sufficient, but not necessary for high resilience, and this again underlines the importance of softer factors. Correspondingly, in future research, it would be interesting to tap even more sources of openly available data, such as Twitter or satellite data; however, more computing power would then be needed. Resilience is dynamic in a changing world, so that resilience indicators have to be updated frequently. A further task is the adaptation of resilience indices to other special or temporal scales that are relevant for regional or continental management structures. Finally, this research can provide useful information for further implementation of SDGs, SFDRR, Paris Agreement and New Urban Agenda by highlighting the hotspots where resources can be invested to build climate and disaster resilience.

## CRediT authorship contribution statement

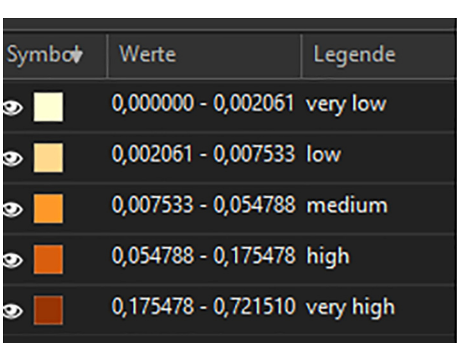
**Daniel Feldmeyer:** Conceptualization, Methodology, Data curation, Software, Writing - original draft. **Wolfgang Nowak:** Conceptualization, Methodology, Writing – original draft. **Ali Jamshed:** Conceptualization, Methodology, Writing – original draft. **Jörn Birkmann:** Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

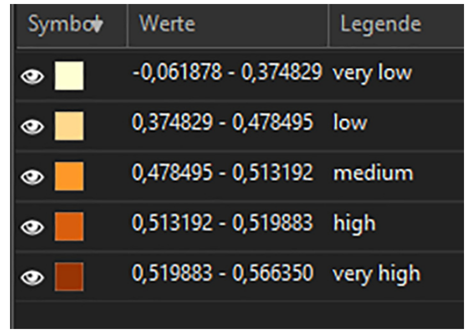
## Annex I. Classification of maps

EmRI – quantile classification and subsequent classes.



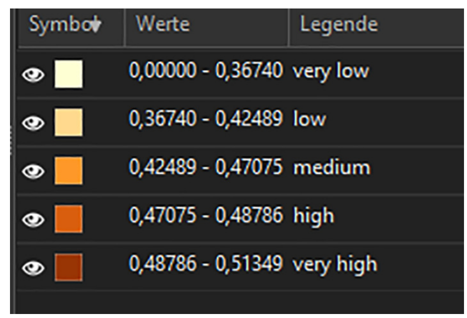
| Symbol | Werte | Legende |
|---|---|---|
| | 0,000000 - 0,002061 | very low |
| | 0,002061 - 0,007533 | low |
| | 0,007533 - 0,054788 | medium |
| | 0,054788 - 0,175478 | high |
| | 0,175478 - 0,721510 | very high |

EERI - quantile classification and subsequent classes.



| Symbol | Werte | Legende |
|---|---|---|
| | -0,061878 - 0,374829 | very low |
| | 0,374829 - 0,478495 | low |
| | 0,478495 - 0,513192 | medium |
| | 0,513192 - 0,519883 | high |
| | 0,519883 - 0,566350 | very high |

ORI - quantile classification and subsequent classes.



| Symbol | Werte | Legende |
|---|---|---|
| | 0,00000 - 0,36740 | very low |
| | 0,36740 - 0,42489 | low |
| | 0,42489 - 0,47075 | medium |
| | 0,47075 - 0,48786 | high |
| | 0,48786 - 0,51349 | very high |

## Annex II. Principal components

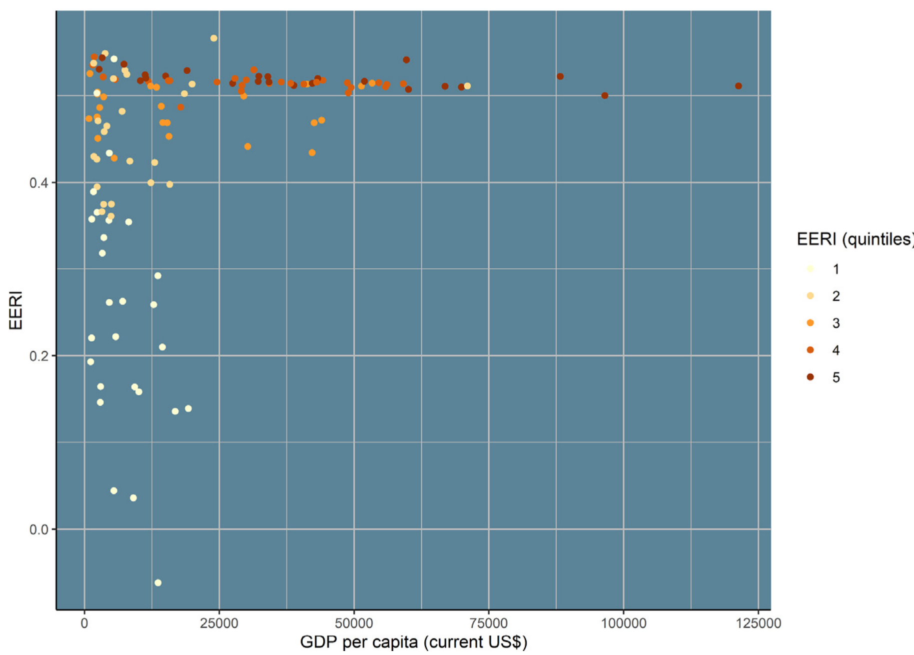
| PCA | Name | Tag (highest loading) |
|---|---|---|
| PC1 | Identity and mobility | amenity_bicycle_parking<br>shop_florist<br>bicycle_no<br>historic_memorial |
| PC57 | Sustainable Infrastructure | bicycle_parking_rack<br>capacity_2<br>amenity_charging_station<br>power_compensator |
| PC5 | Social fabric | railway_signal<br>healthcare_doctor<br>healthcare_psychotherapist<br>building_entrance<br>craft_tiler |
| PC7 | Material supply | shop_fabric<br>direction_S<br>shop_lamps<br>shop_tiles<br>cuisine_italian.pizza |
| PC20 | Social infrastructure | cuisine_fish_and_chips<br>traffic_signals_crossing<br>shop_charity<br>crossing_yes<br>sport_fitness |
| PC13 | Economic status | amenity_yes<br>office_association<br>toilets.wheelchair_yes |
| PC16 | Religion | landuse_cemetery<br>amenity_public_building<br>leaf_type_leafless<br>religion_jewish<br>highway_ford |

(continued)

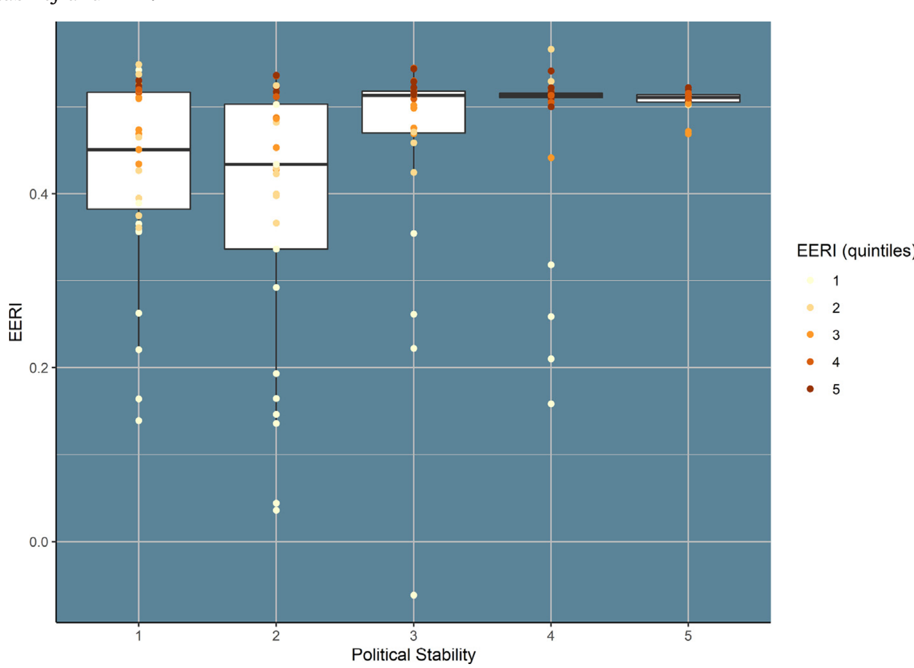
| PCA | Name | Tag (highest loading) |
|---|---|---|
| PC55 | Spatial development | cuisine_breakfast<br>capacity_32<br>railway_construction<br>emergency_assembly_point<br>capacity_36 |
| PC40 | Leisure & Recreation | amenity_spa<br>amenity_food_court<br>shop_lighting |
| PC45 | Nature conservation | amenity_ranger_station<br>historic_tomb<br>power_connection |

## Annex III. EERI, GDP and political stability

Scatterplot of EERI against GDP.




Boxplot of political stability and EERI.



## Annex IV. List of countries included

| ISO3 | Name | Main hazard | ISO3 | Name | Main hazard | ISO3 | Name | Main hazard |
|---|---|---|---|---|---|---|---|---|
| AFG | Afghanistan | Drought | HRV | Croatia | Flood | PHL | Philippines | Storm |
| AGO | Angola | Drought | HUN | Hungary | Flood | PLW | Palau | Epidemic |
| ALB | Albania | Storm | IDN | Indonesia | Earthquake | PNG | Papua New Guinea | Drought |
| ARE | United Arab Emirates | Flood | IND | India | Drought | POL | Poland | Flood |
| ARM | Armenia | Drought | IRL | Ireland | Epidemic | PRK | Korea | Drought |
| ASM | American Samoa | Storm | IRN | Iran | Flood | PRT | Portugal | Wildfire |
| AUS | Australia | Flood | IRQ | Iraq | Flood | PSE | Palestine, State of | Storm |
| AUT | Austria | Flood | ISL | Iceland | Earthquake | PYF | French Polynesia | Flood |
| AZE | Azerbaijan | Flood | ISR | Israel | Storm | QAT | Qatar | Flood |
| BDI | Burundi | Drought | ITA | Italy | Flood | REU | Reunion | Epidemic |
| BEL | Belgium | Flood | JOR | Jordan | Drought | ROU | Romania | Flood |
| BEN | Benin | Flood | JPN | Japan | Flood | RUS | Russian Federation | Flood |
| BFA | Burkina Faso | Drought | KAZ | Kazakhstan | Flood | RWA | Rwanda | Drought |
| BGD | Bangladesh | Flood | KEN | Kenya | Drought | SAU | Saudi Arabia | Flood |
| BGR | Bulgaria | Flood | KGZ | Kyrgyzstan | Drought | SCG | Serbia Montenegro | Flood |
| BIH | Bosnia and Herzegovina | Flood | KHM | Cambodia | Flood | SDN | Sudan | Drought |
| BLR | Belarus | Extreme temperature | KIR | Kiribati | Storm | SEN | Senegal | Drought |
| BTN | Bhutan | Earthquake | KOR | Korea | Flood | SGP | Singapore | Epidemic |
| BWA | Botswana | Flood | KWT | Kuwait | Epidemic | SHN | Saint Helena | Storm |
| CAF | Central African Republic | Flood | LAO | Lao People's Democratic Republic (the) | Flood | SLB | Solomon Islands | Flood |
| CHE | Switzerland | Flood | LBN | Lebanon | Storm | SLE | Sierra Leone | Flood |
| CHN | China | Flood | LBR | Liberia | Insect infestation | SOM | Somalia | Drought |
| CIV | Ivory Coast | Flood | LBY | Libya | Flood | SPI | Canary Is | Flood |
| CMR | Cameroon | Flood | LKA | Sri Lanka | Flood | SRB | Serbia | Flood |
| COD | Congo | Epidemic | LSO | Lesotho | Drought | SSD | South Sudan | Drought |
| COG | Congo | Epidemic | LTU | Lithuania | Drought | STP | Sao Tome and Principe | Epidemic |
| COK | Cook Islands | Storm | LUX | Luxembourg | Storm | SVK | Slovakia | Storm |
| COM | Comoros | Storm | LVA | Latvia | Epidemic | SVN | Slovenia | Extreme temperature |
| CPV | Cabo Verde | Drought | MAC | Macao | Epidemic | SWE | Sweden | Epidemic |
| CYP | Cyprus | Drought | MAR | Morocco | Extreme temperature | SWZ | Swaziland | Drought |
| CZE | Czech Republic | Flood | MDA | Moldova | Storm | SYC | Seychelles | Storm |
| DEU | Germany | Flood | MDG | Madagascar | Storm | SYR | Syrian Arab Republic | Drought |
| DJI | Djibouti | Drought | MDV | Maldives | Earthquake | TCD | Chad | Drought |
| DNK | Denmark | Storm | MHL | Marshall Islands | Drought | TGO | Togo | Flood |
| DZA | Algeria | Extreme temperature | MKD | Macedonia | Wildfire | THA | Thailand | Flood |
| EGY | Egypt | Storm | MLI | Mali | Drought | TJK | Tajikistan | Drought |
| ERI | Eritrea | Drought | MMR | Myanmar | Flood | TKL | Tokelau | Storm |
| ESP | Spain | Flood | MNE | Montenegro | Flood | TKM | Turkmenistan | Earthquake |
| EST | Estonia | Storm | MNG | Mongolia | Extreme temperature | TLS | Timor-Leste | Drought |
| ETH | Ethiopia | Drought | MNP | Northern Mariana Islands (the) | Storm | TON | Tonga | Storm |
| FIN | Finland | Flood | MOZ | Mozambique | Flood | TUN | Tunisia | Flood |
| FJI | Fiji | Storm | MRT | Mauritania | Drought | TUR | Turkey | Earthquake |
| FRA | France | Storm | MUS | Mauritius | Storm | TUV | Tuvalu | Storm |
| FSM | Micronesia | Drought | MWI | Malawi | Drought | TWN | Taiwan | Storm |
| GAB | Gabon | Flood | MYS | Malaysia | Drought | TZA | Tanzania | Drought |
| GBR | United Kingdom | Flood | NAM | Namibia | Drought | UGA | Uganda | Drought |
| GEO | Georgia | Drought | NCL | New Caledonia | Epidemic | UKR | Ukraine | Flood |
| GHA | Ghana | Flood | NER | Niger | Drought | UZB | Uzbekistan | Drought |
| GIN | Guinea | Flood | NGA | Nigeria | Flood | VNM | Viet Nam | Flood |
| GMB | Gambia | Drought | NIU | Niue | Storm | VUT | Vanuatu | Storm |
| GNB | Guinea-Bissau | Drought | NLD | Netherlands | Extreme temperature | WLF | Wallis and Futuna | Storm |
| GNQ | Equatorial Guinea | Epidemic | NOR | Norway | Flood | WSM | Samoa | Storm |
| GRC | Greece | Earthquake | NPL | Nepal | Earthquake | YEM | Yemen | Flood |
| GUM | Guam | Storm | NZL | New Zealand | Earthquake | ZAF | South Africa | Drought |
| HKG | Hong Kong | Storm | OMN | Oman | Storm | ZMB | Zambia | Flood |
| | | | PAK | Pakistan | Flood | ZWE | Zimbabwe | Drought |

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# SEVENTH CHAPTER

## CONCLUSION

Four intermingled and cross-cutting challenges were identified in chapter one, binding all five contributions together: First, operationalization and the use and applicability of different data – census versus social-network data. Second, quantitative assessment of multi-faceted complex phenomena in the context of climate change. Third, the relevance of spatial scales – and the challenges linked to the "problem space, assessment space and solution space". Fourth, validation of indicators and indices to increase robustness, transparency and analysis of spatial differences. The five different contributions add different aspects on different scales to the four challenges recalled here.

The subsequent sections (sections 7.1 to 7.4) discuss these four challenges one by one, cutting through and combining the five contributions, and concluding with a paragraph on climate resilience. Followed by a brief summary, they lead to limitations (section 7.5) and needs or opportunities for future research (section 7.6). Closing the circle, some final remarks are stated. These sections include statements a) which are previously stated as part of the five articles but are important to be restated here and b) statements evolved during the synthesis of the entire work.

### 7.1 OPERATIONALIZATION AND THE USE AND APPLICABILITY OF DIFFERENT DATA – CENSUS VERSUS SOCIAL-NETWORK DATA [CONTRIB. 1 TO 5]

The topic of data in general is crucial in assessing and monitoring climate resilience across scales and poses several implications as a result and synthesis of my research conducted:

**Data availability** is the most important criterion [Contrib. 1]. The interdisciplinary and scale-crossing nature of climate resilience, in combination with the importance of soft and qualitative attributes, poses a great challenge in terms of data needs. Existing data are not yet able to cover all fields of climate resilience sufficiently [Contrib. 1, 2, 3, 5]. Instead, traditional administrative data sources need to be complemented with new data sources. But also administrative data need to be available across departments and across administrative hierarchical levels [Contrib. 2 & 3]. The missing integration of data management, besides neglecting to share data, aggravates the assessment of climate resilience. Last but not least, new data need to be collected by governments in order to successfully monitor climate resilience and to create a data base for informed decision-making on all spatial scales from local, regional, national to global.

There is need for a spatially inclusive and comprehensive indicator base, covering **social and qualitative factors** [Contrib. 1 to 5]. To be more specific than the previous paragraph, in the context of climate resilience, many projects also focus on increasing knowledge, participation, learning, trust, awareness, solidarity, community, building networks or other qualitative aspects of climate resilience. Even on project level, monitoring and evaluation of these factors is sparsely done due to methodological difficulties in the assessment of such factors. Moreover, such measures would need continuous monitoring even after the finalisation of the project. To set the project into a larger context and to be able to evaluate the success or failure, these aspects need to be monitored and/or integrated, e.g. into the census. Essentially, climate resilience cannot be monitored without these soft factors.

Only **secondary data** were seen to be feasible for monitoring purposes [Contrib. 1, 2, 4]. Already on the local level, expensive surveys or workshops were not considered feasible for monitoring purposes [Contrib. 1]. This is even more important on national or even global scale [Contrib. 3, 4]. The reasoning for using secondary data is twofold. First, surveys to gather statistically representative data are expensive and require trained administrative personnel. Even medium-sized municipalities do not have the capacities financially and personnel-wise to conduct extensive surveys every four years [Contrib. 1]. The implications to base the assessment on secondary data need consideration. Important aspects of climate resilience are soft factors (e.g. feeling of belonging, networks, knowledge) which are not yet monitored in municipalities. Hence, selected indicators are only proxies and do not measure the phenomenon directly. How efficiently such proxies, like voter turnout, still capture this phenomenon, is seen differently and is also specific to the place or even city block. Having said that, two crucial requirements arise from my research. First, existing data need to be available and shared. Second, new data need to be collected.

The new option of **machine learning** provides the means to generate indicators which are not covered by traditional data sources across administrative boundaries [Contrib. 3, 5]. In light of the previous discussed shortcomings of existing data, new ways and approaches need to be explored. OpenStreetMap in combination with machine learning proved to be one possible valuable addition [Contrib. 3, 5]. Most importantly, the scepticism against crowdsourced data needs to be overcome in order to fully access its possibilities. Methods for data quality and new methods for validation - as developed within this dissertation - contribute in achieving this goal [Contrib. 3, 5].

Missing **temporal data sets** and emerging effects of climate change aggravate detection of trends and spatio-temporal effects [Contrib. 3, 5]. The shrinking of the presence in combination with the acceleration of climate change adds another challenge to data. Especially on global level, it takes years until the data are provided. First, the data are outdated when available. Second, temporal effects are not sufficiently included to detect shifting baselines. Twitter, news, OSM or satellite imagery need to be further exploited to cover highly fluent and dynamic aspects of resilience.

Data do not provide the means to measure **vulnerability and resilience in a dynamic** way. Climate resilience and socio-economic vulnerability are highly dynamic concepts in space and time and even change within days or hours. These dynamic, spatio-temporal effects are not yet measurable by existing data and all approaches assess resilience and vulnerability only in a static way whereas hazards are monitored fluently adding to the gap in scales also a temporal gap.

## 7.2 Quantitative assessment of multi-faceted complex phenomena in the context of climate change

The synthesis of all five contributions regarding quantitative assessment of multi-faceted complex phenomena leads to following core conclusions:

The **vertical dilemma** is that municipalities have the data but not the capacities, while higher levels have the capacities but not the data. Hence, local administrations require provision of data for complex topics from higher administrative levels [Contrib. 1]. This statement links straight to the previous paragraph and continues the line of thought. Higher administrative levels have the respective personnel at their disposal – trained in the fields of statistics, data and geodata. Lower administrative levels lack such personnel. But local data are still only available on the very local level. The federal structure of Germany further complicates the situation as the same data are often not the same data and are not comparable amongst federal states [Contrib. 2 & 3]. In order to overcome this dilemma, new databases have to provide essential indicators for climate resilience area-wide, which could be achieved by including important aspects to already existing regularly conducted surveys like the census.

The **number of indicators and robustness** is important in the science-policy interface in order to communicate results [Contrib. 1, 2, 4]. Considering the complexity of climate resilience and the number of dimensions and actions fields, this requires careful balancing of indicators [Contrib. 1, 2]. Practitioners and researchers tended to include more indicators when just considering a single topic. No single action field was sufficiently covered by one indicator, so for the best covering the most important aspects needed to be selected. It should be noted that removed indicators often were also considered important but just slightly less contributing in regard to the definition of urban climate resilience. Overall, researchers strived to include more indicators and practitioners urged for fewer but robust, transparent and clearer indicators [Contrib. 1]. The effect measured and its cause direction on climate resilience was an important aspect. New methods to assess the robustness of indices, e.g. as developed in contribution 4, are necessary if indices shall be used to justify political actions [Contrib. 4].

It is better **to not have an indicator** if the data source of choice does not exist, than having an indicator not measuring its indicandum [Contrib. 1, 2, 5]. The empirical validation of regional resilience indicators removed two indicators: Proportion of structurally-shaped settlement and traffic area in the official flood area and proportion of undissected forest were removed. The initial idea was to include the status of the water bodies and the status of the forest. Unfortunately, both data sets actually exist, but are neither freely accessible nor provided by the authorities upon request [Contrib. 2]. The substituted indicators could not cover the field. If they had not been excluded by the empirical validation, wrong information would have been communicated. Therefore, no information is better than wrong information, which leads to the conclusion of carefully-considered substitutions.

**Conflicting goals** between indicators and negative correlations have to be expected when measuring climate resilience [Contrib. 1, 2, 5]. From a theoretical index-composition perspective, negative correlations are sometimes questioned. For climate resilience this cannot be applied, hence, on all spatial scales negative correlations exist, despite the fact that both indicators contribute positively to resilience. One obvious example is the provision of infrastructure vs. environmental indicators. The concept of resilience includes conflict of goals, where trade-offs need to be carefully balanced. This is not a weakness of the concept to be unidimensional but strength, because it fosters the transparent discussion and evidence-based decision-making of conflict topics.

There is high **agreement** regarding areas with high vulnerability [Contrib. 4]. Areas of high vulnerability are characterised by multiple and persistent challenges. Therefore, different approaches coincide and the selection of indicators is less relevant due to the fact that multiple indicators point in the same direction. The agreement is lower for regions with low vulnerability, where single challenges shape the overall vulnerability strongly.

**Political stability** is a prerequisite for low vulnerability but not for low resilience [Contrib. 4 & 5]. Political stability and vulnerability correlates strongly on a global scale. Political stability is persistently low for hotspots - regions of vulnerability which have been further decreasing over the last two decades. These contextual challenges make societies more susceptible to impacts of climate change. But also negative impacts of climate change, e.g. increasing food prices and war for water further destabilize political systems, thus accelerating the downward spiral. In contrast, high resilience shows income from low to high and political stability from high to low [Contrib. 5]. Generally, low resilience goes hand in hand with low income and low political stability. In contrast, high resilience shows income from low to high and political stability from high to low. So in case of an absent state, people organise themselves and create structures to overcome hardships thus building resilience. Hence it is not surprising that resilience is also shown by low-income countries or even especially by them as social aspects are key for a resilient society.

## 7.3 The relevance of spatial scales – and the challenges linked to the "problem space, assessment space and solution space" [Contrib. 1 to 5]

The assessment of climate resilience and vulnerability is specific to the spatial scale. The assessment across different scales within this dissertation leads to several core conclusions:

Single **indicators or composite index** - a spatial perspective. Aggregation of indicators to an index was seen critically on urban scale [Contrib. 1]. Practitioners on urban scale were not in favour of an aggregated resilience index. One reason might be that it was not intended to compare and rank municipalities due to the danger of a bad rating. Also, it was argued that the included topics are too different to be combined to a meaningful composite index. The main objective was a profile of the municipalities to identify key topics for adaptation measures. In contrast, higher scales not only consider a singular spatial entity, so the objective is to rank and rate in order to identify first key areas and subsequently key topics. Therefore, a composite index is helpful to aggregate the information to one score in order to rank spatial entities.

Resilience indicators are mostly developed for the **Global South** [Contrib. 1, 2]. Resilience as a concept is often applied to the development context. Hence, a vast majority of the indicators are developed in the context of the Global South. The specificity of resilience is often not sufficiently incorporated. Transferring indicators from one place to another requires validation. Even indicators developed in the Global North might not be suitable in the context of Germany.

**Practitioners and scholars** understand urban resilience differently [Contrib. 1]. Despite the fact, that the definition of urban climate resilience was developed in a participatory approach with researchers and practitioners, it still caused the most discussions when selecting indicators. Depending on the understanding, indicators were seen included or excluded. In general, resilience was more often linked to disaster resilience than to climate resilience and interpreted more short-term hazard-oriented. One reason is that in the administrative structure it is often linked or included to the civil engineering department. Therefore, also technical solutions and measures are favoured. Climate resilience cannot be localized at one department. Hence, the integral understanding of the concept is in conflict with the administrative divisions. In contrast to literature, climate resilience is understood by practitioners more as an environmental and ecological concept [Contrib. 1]. In general, environmental indicators received higher acceptance rates and less discussion on urban scale. Much less intrinsically-linked are economic indicators. Interestingly, during the workshop when discussing reasons for economic indicators, general consent was achieved. On regional scale economic indicators were also approved by the empirical validation process. But two environmental indicators were removed. The reason was not the topic of the indicator but that the primary data source was not available and the secondary choice was insufficient. Also on national level the empirical evidence index included the economic component.

**Dimensions of resilience** are consistent across scales but not indicators. The three dimensions environment, governance and society are of particular importance for urban resilience [Contrib. 1]. Overall, the three dimensions environment, governance and society were seen as most important. Most important indicators were listed in decreasing order: cold air parcels, inter-office working groups regarding risk, experience with extreme events in the last 5 years, climate change and resilience, strategies against heavy rain and heat in plans, citizens´

information about heat, heavy rain and flooding. Infrastructure was also decided on with high agreement. Least agreement was found in the area of economy. Still, having a diverse and robust economy was regarded as important to face climate change, but it was least intrinsically- linked to climate resilience but rather regarded as a part of sustainability. All five spheres are important and underline the socio-economic and socio-ecological character of climate resilience [Contrib. 1, 2, 5]. The most important determinants of the empirical validation for regional climate resilience were: environment (degree of organic farming, air emission index), infrastructure (accessibility of large centres, accessibility of supply with daily goods), economic (GDP, employment), social (share of citizens ABV6/U65, sick days, voter turnout, nearby police stations). Governance (support of climate protection agreement) is not amongst the top five determinants but statistically significant regarding climate resilience. The most important determinants for predicting resilience applying the random forest method were the principal components: identity & mobility, sustainable infrastructure, social fabric, material supply, social infrastructure, economic status, religion, spatial development, leisure & recreation, nature conservation [Contrib. 5]. The disaster resilience indicator core by Cutter comprises six assets and five capacities (Cutter, 2016). In several areas, Cutter´s core is consistent with the ten elements derived within my empirically-derived elements. Congruent elements are economic (economic status), social capital (social fabric, social infrastructure, religion), infrastructure (sustainable infrastructure, material supply), environmental (nature conservation). The attributes institutional and information, as well as the capacity emergency management, have no equivalent within the ten most important predictors from the OSM dataset. Not within the resilience core but amongst the OSM predictors, spatial development and leisure & recreation can be found. Those two elements also underline the potential of OSM data, due to the fact that information not covered by governmental data (leisure & recreation) or not available on a global scale (spatial development) are documented.

**Urban, regional and national indicators** are overlapping but also have distinct elements [Contrib. 1, 2, 5]. The main dimensions of the framework remain the same throughout the scales: environment, economic, society, government, and infrastructure. For the environment, agriculture and forest was added, moving from urban to regional scale. Settlement structure, drinking water, wastewater and energy as urban action fields were removed and streets, health care, local supply and public transportation introduced. Public transportation is also of concern on urban scale, but data limitation limits quantitative indicators. The very specific field of business on urban scale was replaced by unemployment for the economic dimension.

For the social dimension the people-centred indicators of knowledge and risk competence and the municipality-specific indicator number of research projects were disregarded. In contrast to the urban and regional assessment, the national assessment is not based on traditional data sources but OSM indicators, which does not allow a straight comparison. Public transport is replaced by the more general topic of sustainable infrastructure. The economic dimension is very generally assessed by the economic status. Similar, for the environment no single topic e.g. water, soil etc. remain but instead more generally nature conservation. For the government dimension, a planning aspect is covered by spatial development. OSM does not include politics, plans and strategies; it only monitors their effects or implementation. Interestingly, the most important dimension even on national scale is society with four indicators out of ten: identity & mobility, social fabric, religion, leisure & recreation.

The **problem space** needs to be coherent with the assessment and **solution space** [Contrib. 1 to 5]. A consideration often untouched is the incongruence of data, problem and solution space. All three spaces and spatial scales need to be linked. The increase of the global mean temperature is of no interest to a specific city, nor can a single city change it on its own. River basin-wide approaches are one example where data, problem and solution space is brought together. Less obvious are often socio-ecological spaces spanning across administrative borders with a long historic background. The assessment of vulnerability on climate region level shows the necessity for international and transnational adaptation measures to build capacities, create enabling conditions and merge assessment, problem and solution space.

## 7.4 Validation of indicator and indices to increase robustness and transparency and analysis of spatial differences [Contrib. 1 to 5]

Indicators and indices only provide justification for action if they are robust and well accepted. Within my dissertation I developed new methods to implement validation for multi-faceted phenomena. Key elements and reasons of empirical and statistical validation are as follows:

**Bias is unavoidably** introduced at all steps of index construction [Contrib. 1 to 5]. Most importantly the interdisciplinarity of climate resilience results in the fact, that nobody has studied all areas and each and every one has a different background. Besides this personal bias, scale and data bias always exist. The biggest bias - but often neglected - is the selection or non-selection of indicators. The results showed that also the selection of the aggregation methodology introduced another bias. Equal weights or expert weights failed to understand the data and their hidden structure resulting in unequal contribution of the themes to the index. Data-driven approaches neglect logic facts and resulted in the removal of important aspects. The hybrid-approach, including and acknowledging both sides, proved to be crucial in order to reduce bias.

**Unclear cause-effect relation** of many resilience indicators due to the ambiguity of the concept and conflicting goals cause misunderstandings [Contrib. 1 to 5]. The direction of many indicators often cited in literature is unclear. Or it is clear for one goal but might be negative for another goal of resilience. This ambiguity reduces robustness, transparency and trust thus making it hard for policy makers to deduce measures and decisions. The knowledge about the negative impact is key in order to make informed decisions. Validation increases transparency, points out such conflicting goals and subsequently supports decision-making. But not only decision-making enables evaluation and monitoring of adaptation measures. The measure in itself might be a success, but the negative impacts on other fields might outbalance the total effects in a negative way. Therefore, workshops and participatory approaches for validation including practitioners are essential [Contrib. 1]. Last but not least a common language and understanding are essential. The inclusion of different departments of the administrative bodies and scientific disciplines is crucial to cover all aspects of climate resilience. This requires a lot of time and most important an open environment fostering discussion and conflicts. The discourse provided important insights and increased the validity of the data but also its acceptance.

The **uncertainty about the uncertainty is the only certainty** in climate change and also for composite indicators. The biggest source of uncertainty, which is mostly not even considered, is the selection of indicators [1, 2, 5]. The total number of indicators for resilience or vulnerability is unknown and assessing the ones which have not been measured is rather difficult. Different approaches claiming to assess vulnerability include varying sets of indicators. One possibility to reduce the uncertainty regarding the selection of indicators is to compare different approaches and assess the level of agreement. The comparison of two vulnerability indices shows that there is high agreement on global hotspots. Vulnerability is shaped by multiple intertwined and linked topics. Hence, the selection of indicators is less relevant because all are negative. There is less agreement regarding regions with medium or low vulnerability where single topics dominate vulnerability. Uncertainty regarding the impact of the aggregation method [Contrib. 2, 4, 5]. Another important source of uncertainty is the impact of the method on the result. The combination of different methodologies, often neglected due to the expenses, can give insights into the influence of a method. This increases robustness and transparency whilst reducing uncertainty. The combination of purely data-driven approaches in combination with thematic reasoning was essential in understanding the method and its data in order to compute a meaningful index. Uncertainty regarding the impacts of climate change [Contrib. 2, 5]. The fact that climate change is already part of the presence reduces uncertainty about the impacts we are already able to measure. Also with respect to certain climate change consequences the models predict, with increasing quality and certainty, what will happen. But far less certainty exists about socio-ecological responses and chains of effects. Climate resilience and vulnerability are socio-economic constructs. Where climate models are able to predict future changes in high resolution with high certainty, predictions of vulnerability and climate resilience remain absent. At best, scenarios describe possible development pathways, but models are not able to predict future socio-economic vulnerability. Examples of this inability are the failures to predict the global recession 2007-08 or the COVID-19 pandemic. Still, negative consequences are mainly due to socio-ecological factors, which remain vastly underestimated and the strong focus on physical models obscures the real area of concern. Most importantly the high certainty of such models pretending to know what will happen, but in fact we have no idea hence the uncertainty is exponentially higher than these models suggest. We might get an idea what will happen regarding physical parameters but we do not know what this means for the socio-ecological systems.

Better and new data and indicators as **outcomes for empirical validation** are necessary [Contrib. 2 to 5]. Some aspects of climate resilience are not yet measured and consequently lack empirical validation. New methods and data sources such as phone records, twitter, OSM etc. need to be analysed as to how they can provide the means to monitor such elements. Empirical validation of climate resilience solely based on traditional data sources will not be successful. Still, a small number of approaches for empirical validation of resilience exist [Contrib. 2, 5]. The majority of resilience assessment tools are literature-based. Only few approaches exist validating resilience with empirical data. As previously mentioned one reason is the lack of data, but also the hesitation to use new data sources. Life expectancy was one indicator found to capture many aspects of resilience - often available with high spatial resolution and quality. Still, this only includes indirectly economic losses due to natural hazards. Unfortunately, the best data are owned by insurance companies not willing to share it. On global scale the EM-DAT provides a unique source of data which can be used.

## 7.5 LIMITATIONS IDENTIFIED WITHIN THE RESEARCH PROCESS

Every research undertaken is facing certain challenges and is limited to some extent by constraints which are difficult to overcome. Limitations within this research were:

1. Measuring and understanding of vulnerability and climate resilience as complex multi-faceted concepts is still limited by **missing social spatio-temporal data**.
2. Developing an indicator set tends to be easier than assessing the significance or validity of an indicator over time and it requires an **extended observation period** to be able to make statements about the significance of a certain indicator.
3. The **number of indicators** for regional climate resilience was relatively limited and the selection based on theory but still, to some degree, subjective. Further empirical analysis into more indicators can contribute to the understanding of climate resilience.
4. For regional vulnerability, there are **limitations in terms of the relevance** of some of the indicators used for different country groups or types. For example, the INFORM captures the road density and number of internet users, which may lead to countries with a stronger rural context being rated differently compared to countries that are more urbanized. However, it is important to note that the INFORM and WorldRiskIndex represent approaches that cover human vulnerability more comprehensively and, therefore, these specific issues are not key for the overall results of the assessment.
5. **Computational power** is still a limiting factor despite its rapid development of personal computers. The global OSM-dataset has currently a size of ~1.3 TB which is clearly more than the RAM available in common PCs. Second, querying those kinds of data additionally requires extensive RAM or sophisticated deconstruction of the problem into smaller bites, digestible by the hardware. The tools applied included command line tools and R-programming. Both, the hardware and software are issues to overcome.
6. An important part of socio-economic indicators is their explanatory power of unusual phenomena or in extreme situations. **Machine learning** and especially DNN is often seen as a black box, which limits its acceptance and applicability. Nonetheless, the Feature Perforance Index is a very condensed

way of interpreting the global feature importance. As the approach is linked to the error of the model, it is only possible to perform with access to the outcome and not for the assessment of a stand-alone model. By leaving out different explanatory variables, the assessment of their contribution to the overall outcome distils the interconnections of social indicators and spatial attributes, which is key in understanding regional development issues and helps in making target-oriented decisions.

7. **Limited spatio-temporal event data** including detailed losses across scales and hazards. For Germany no event database exists documenting direct and indirect losses spatially explicit for different hazards. At best some physical events are spatially documented but only to a limited extent. On national and global level the EM-DAT database is a unique approach closing this gap and also showing the importance. Twenty years of disaster records are not comprehensive in terms of probabilistic hazard assessment, but this goes above and beyond the scope of this study. Nevertheless, the data clearly illustrates the current situation and helps in understanding the current spatial distribution. Moreover, twenty years makes a huge difference with respect to the development of fast-developing countries and also in implementing hazard mitigation and climate change adaptation measures. In this regard, the crowd-based OSM database is important to capture the fast changes occurring. Balancing different timeframes and impacts poses a challenge without a single final solution.

## 7.6 Future research

Opportunities for future research revealed through the dissertation:

1. Generate an **event database** for all major hazards, an automated approach using news, satellite imagery, twitter and weather records needs to be developed, including direct and indirect economic as well as human losses.
2. **Dynamic vulnerability** and climate resilience assessments have to be developed. Similar to flood forecasting without hydrological models, based on machine learning algorithms, vulnerability and resilience can be predicted.

3. High resolution models predict the impact of climate change with high certainty. Far less certainty and models exist regarding the **socio-economic** side of **future** vulnerability and climate resilience. Therefore, future research is needed to predict socio-economic vulnerability in congruence with physical models.
4. **Social aspects** (like social networks and the feeling of belonging) are often neglected in resilience assessments due to difficulties in measuring them. Hence, more research is needed to integrate the social dimension into monitoring programmes.
5. The **scalability of indicators** to be aligned with scales of the natural problem space needs further exploration, e.g. the construction of resilience indices on the scale of river basins, climate regions, wildlife parks etc.
6. While using the **wider data set of OSM** proved a successful strategy for learning about resilience, more data sources may be included, such as twitter, phone records, satellite imagery; they might provide additional inputs on aspects not yet captured, or improve the prediction capability. Any new results then need to be translated and integrated into policy frameworks and adaptation strategies in order to bring about change.
7. Vulnerability and climate resilience frameworks have to be **linked to adaptation** measures. This is important for two reasons. First, it helps practitioners to deduce adaptation measures from the assessment of climate resilience or vulnerability. Knowing what is not right is the first step but without knowing how to improve or solve it, this knowledge is meaningless. Therefore, scale- specific adaptation measures have to be linked to the assessment. Second, when linked, the success or failure of adaptation measures can be evaluated with the monitored indicators.

# Curriculum Vitae

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- **Feldmeyer, D**.; Wilden, D.; Kind, C.; Kaiser, T.; Goldschmidt, R.; Diller, C.; Birkmann, J. 2019. "Indicators for Monitoring Urban Climate Change Resilience and Adaptation" *Sustainability* 11, no. 10: 2931. DOI: https://doi.org/10.3390/ijgi9090498
- **Feldmeyer, D**., Meisch, C., Sauter, H., & Birkmann, J. (2020). Using OpenStreetMap Data and Machine Learning to Generate Socio-Economic Indicators. ISPRS International Journal of Geo-Information, 9(9), 498. DOI: https://doi.org/10.3390/ijgi9090498
- **Feldmeyer, D**.; Wilden, D.; Jamshed, A.; Birkmann, J. (2020) "Regional climate resilience index: A novel multimethod comparative approach for indicator development, empirical validation and implementation" Ecological Indicators, 119: 106861. DOI: https://doi.org/10.1016/j.ecolind.2020.106861

**Projects:**

- Monitoring of Adaptation Measures and Urban Climate Resilience (MONARES)
- Inclusive urban risk and land management regarding spatially ubiquitous extreme events in rapidly growing medium-sized cities - Linking formal and informal strategies in Vietnam and

the Philippines (Irima-extreme)

- Preparing for extreme and rare events in coastal regions (PEARL)

- Robustness, resilience and adaptivity of spatial and infrastructures (esp. critical infrastructures) - against extreme events

- Review and further development of the instruments for coordinating settlement and transport development against the backdrop of necessary $CO_2$ reduction and demographic development for the Stuttgart Region (NAMOREG)

**Teaching:**

- Quantitative environmental planning
    - Lecture “Geospatial Analysis and Evaluation Methods”
    - Exercise "GIS and model-based analysis and evaluation methods"

- Applied GIS - GIS in Environmental and Regional Planning

- Methods of analysis and forecasting in spatial and environmental planning