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Assessment of Social Vulnerability for River-Floods in Germany

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Abstract

The assessment of social vulnerability unveils hidden weaknesses and strengths of the human society towards a certain stressor or hazard. In this study, vulnerability is analysed in its relation to the hazard posed by extreme river-floods. The study starts with an assessment of the varying impacts that river-floods typically produce in Germany. Severe cases of floods of the rivers Danube in 2002, the river Elbe in 2002 and 2006 and at the river Rhine in 1993 and 1995 affected large areas in Germany. The review of the published research reveals that few studies have tackled hidden issues of flood risk like social vulnerability here.

At the county level, this study develops a pilot approach on how to identify and compare social vulnerability along river-channels in Germany. The concept enables later cross-validation with data and studies from other sources and other spatial levels. The theoretical foundation of this vulnerability assessment is the base-line for the methodological development of the vulnerability indicators which capture the exposure, susceptibility and capacities of social groups concerning river-floods.

One important cornerstone of this study is a Social Susceptibility Index (SSI) map based on population characteristics for counties in Germany. This map is based on a composite index of three main indicators for social susceptibility in Germany - *fragility, socio-economic conditions* and *regional conditions*. These indicators have been identified by a factor analysis of selected demographic variables obtained from the Federal Statistical Office. Therefore, these indicators can be updated annually based on a reliable data source.

The influence of the susceptibility patterns on disaster outcome is shown by an independent second data set of a real case event. It comprises a survey of flood-affected households in three federal states. By using logistic regression, it is demonstrated that the theoretically presumed indications of susceptibility are correct and that the indicators are valid. It is shown that indeed certain social groups like the elderly, the financially weak or the urban residents are susceptible groups. Additionally, the Social and Infrastructure Flood Vulnerability Index (SIFVI) map combines both social and infrastructure vulnerability as well as flood exposure scenarios and demonstrates the integration of hazard and vulnerability information. The SIFVI map is thus the first comprehensive map of its kind for Germany that identifies vulnerable counties and delivers validation. As part of the DISFLOOD project, this study is furthermore an example of how theoretically and methodologically a multi-disciplinary research can be carried out.

Abstract (German)

Die Abschätzung von sozialer Verwundbarkeit hat zum Ziel, potentielle Schwächen und Stärken der Gesellschaft gegenüber einem bestimmten Hazard, hier Hochwasser an Flüssen, aufzudecken. Die Studie beginnt mit einem Überblick über typische Auswirkungen von Hochwasser an Flussläufen in Deutschland. Hochwasser schweren Ausmaßes traten zuletzt an der Donau 2002, an der Elbe 2002 und 2006 und am Rhein 1993 und 1995 auf. Die Auswertung wissenschaftlicher Studien zeigt, dass nur wenige Ansätze bislang hierzu existieren, die soziale Verwundbarkeit behandeln.

Die vorliegende Arbeit ist eine Pilotstudie darüber, wie soziale Verwundbarkeit auf Landkreisebene für ganze Flussläufe in Deutschland erkannt und verglichen werden kann. Das Konzept ermöglicht unter anderem eine spätere Kreuzvalidierung mit Quellen und Studien auf anderen räumlichen Ebenen. Das theoretische Konzept der Verwundbarkeitsabschätzung ist der Unterbau für eine Entwicklung von Verwundbarkeits-Indikatoren, welche die Exponiertheit, Anfälligkeit und Kapazitäten sozialer Gruppen gegenüber Hochwasser erfassen.

Ein Hauptbestandteil dieser Studie ist eine Karte der sozialen Anfälligkeit für Landkreise in Deutschland, welche aufgrund von statistisch erfassten Bevölkerungsmerkmalen erstellt wurde. Diese Karte basiert auf drei Hauptindikatoren, welche für soziale Anfälligkeit in Deutschland identifiziert werden – Fragilität, sozio-ökonomische Bedingungen und regionale Bedingungen. Diese Indikatoren stammen aus einer Faktorenanalyse demographischer Daten des Statistischen Bundesamtes und können jährlich aktualisiert werden.

Die Muster, die durch die Faktorenanalyse aufgedeckt werden, konnten mittels logistischer Regression aufgrund einer unabhängigen Datenbasis für einen realen Hochwasserkatastrophenfall bestätigt werden. Dieser unabhängige zweite Datensatz besteht aus einer Befragung betroffener Haushalte in drei Bundesländern. Die Ergebnisse zeigen, dass in der Tat bestimmte soziale Gruppen wie etwa die Älteren, die finanziell Schwächergestellten oder Stadteinwohner anfälliger sind. Ein kombinierter Index für Soziale Verwundbarkeit und die Verwundbarkeit von Infrastruktur gegenüber Hochwasser zeigt die Integrationsfähigkeit von Hazard- und Verwundbarkeitsinformationen auf. Als Teil des multidisziplinären Projekts DISFLOOD wird hiermit die erste validierte Karte sozialer Verwundbarkeit auf Landkreisebene in Deutschland vorgestellt.

Content

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Figures

Tables

Abbreviations

BBC model	= Vulnerability framework of the authors Bogardi, Birkmann and Cardona
CI	= Confidence Interval
DIS	= Disaster Information System
DLR	= Deutsches Zentrum für Luft- und Raumfahrt (German Aerospace Centre)
SIFVI	= Social and Infrastructure Flood Vulnerability Index
DRM	= Disaster Risk Management
DSS	= Decision Support System
EWS	= Early Warning System
GDP	= Gross Domestic Product
GFZ	= Deutsches GeoForschungszentrum Potsdam (=German Research Centre for Geosciences Potsdam)
GIS	= Geographic Information System
hh	= household
KMO	= Kaiser-Meyer-Olkin Measure of Sampling Adequacy
PAR model	= Pressure And Release model
PCA	= Principal Component Analysis
pp	= per person
pphh	= per person per household
SV	= Social Vulnerability
SSI	= Social Susceptibility Index
UNU	= UNITED NATIONS UNIVERSITY
UNU-EHS	= UNITED NATIONS UNIVERSITY – Institute for Environment and Human Security
VA	= Vulnerability Assessment
VI	= Vulnerability Index
VIF	= Variance Inflation Factor

Glossary

Capacities
'Capacities' are characteristics to resist, resile from, cope with, or adapt to stresses. 'Capacities' therefore encompasses all terms of capacities in the vulnerability or disaster context.

Damage
Damage is directly measurable loss.

Disaster
A serious disruption of the functioning of a community or a society causing widespread human, material, economic or environmental losses which exceed the ability of the affected community or society to cope using its own resources (ISDR definition).

Exposure
Exposure is the presence of susceptible elements within a zone affected by a hazard.

Hazard
A hazard is an event or a process that is perceived as a threat.

Indicator
An indicator is a quantified measure for a real phenomenon. It aims to explain a phenomenon by comprising indirect or surrogate information. Several indicators can be aggregated to an index.
Progression chain: phenomenon - data – variable – indicator – index

Level and scale
A scale can be any type of ranking, while a level is a fixed rank. For example, the spatial scale of administrative boundaries contains the household level, the community level, the county level or the national level.

Risk
Risk is the potential of humans to encounter disaster. Risk encompasses the hazard and the vulnerability of the human-environment system.

Susceptibility
Susceptibility contains the passive characteristics of humans that render them generally disadvantaged in the face of disaster. Susceptibility is hazard-independent.

Vulnerability
Vulnerability captures the conditions of an object of observation (e.g. humans, communities, counties, etc.) – that characterise disadvantages in the face of natural hazards (i.e. to a given stressor). Vulnerability is analysed by capturing the components exposure, susceptibility and capacities. Vulnerability is hazard-related.

Social vulnerability is the predisposition of society and individuals towards a stressor or hazard to be harmed. It is the potential to be wounded or to continue to be wounded.

Potential vulnerability describes vulnerability before a disaster strikes
Revealed vulnerability describes vulnerability after a disaster struck

1 Introduction

The consciousness of the Western world has been especially irritated by hurricane Katrina in 2005. It vividly revealed this disaster as man-made, despite its natural origin. The former secretary general of the United Nations, Kofi Annan stated: “Disasters are a problem that we can and must reduce.” (UN/ISDR 2002: vii). A report by UN/ISDR (2002: 392) also stresses the need to “develop indicators for disaster risk reduction measures.” The research mandate for monitoring disaster risk was elaborated by scientists and policy-makers in the Hyogo Framework for Action (UN/ISDR 2005b). The framework does not only formulate the overall value of disaster risk reduction but explicitly mentions national and local risk assessments and maps as well as indicators and vulnerability as major foci (UN/ISDR 2005a: 46). Floods are one area where indicators of social vulnerability are needed to prepare strategies and countermeasures to disaster risk (Bogardi 2004: 361). Research on vulnerability is acknowledged as an important field within recent natural hazards science (Dikau and Weichselgartner 2005, Felgentreff and Glade 2008) and disaster risk management (FIG 2006). This study is part of four PhDs within the DISFLOOD project on the topic of integrated hazard and vulnerability assessment of river-floods in Germany (see Chapter 6).

Could a disaster like Katrina happen in Germany? This seems at first glance to be a question of whether a hurricane like Katrina could happen in Germany. But extreme events in this magnitude are only one half of what makes a disaster. The other half is how this disaster is constructed by the fabric of the German society. This vulnerability of society is the focus of this study. The scope is on worst-case scenarios, when extreme weather events hit people who are unaware, unprepared, lack resources and skills for mitigation of and recovery from the hazard event. The flood in Hamburg in 1962 caused by a storm surge hit many new residents behind the dykes who had no awareness of the hazard (Geipel 1992: 221). They were caught by surprise of rapidly rising water levels after wave overtopping and a dyke breach during night time: 347 people drowned. In recent times several river floods left an imprint on social awareness. Some of them labelled ‘century floods’, they caused major damage, for example, the floods of the river Rhine in 1993 and 1995, the transboundary flood of the river Oder in 1997, floods along the river Danube in 1999 and 2002, and the floods along the river Elbe in 2002 and 2006. At first glance it might be surprising to compare Katrina 2005, Hamburg 1962 and the recent river floods. But it is not the type of hazard that urges for comparison but the underlying social patterns that determine whether an extreme event turns into a disaster or not. What about the demographic profile of the residents, how did social vulnerability make some people suffer differently to other people? Are there patterns of society detectable that would influence the impact of a future extreme flood event? By which categories and indicators can these patterns be detected and measured? Which regions would suffer most when hit by a river flood, not only because of the hazard magnitude but also because of the social characteristics of the people living there? Are these regional patterns observable at a sub-national level like counties? These are the core questions and motivation to conduct this study.

1.1 Objective of this study

Currently, there exists no satisfying assessment of social vulnerability to river floods that is capable of comparing larger regions within Germany. Social vulnerability characterises the predisposition of society to be hurt by hazards like river flooding. It approaches fields that go beyond traditional hazard and risk assessments that mainly focus on economic damage and structural defence measures. Social vulnerability is often a neglected aspect of these types of assessments. An overview on the extent and patterns of social vulnerability to river-floods in Germany is clearly missing.

One of the main research questions of this study is to identify those social characteristics which render people vulnerable to flooding hazards in Germany and, whether these characteristics are identifiable as regional patterns at county level. Based on the vulnerability assessment it is later on possible to allocate resources to counteract potential weaknesses. It is especially challenging to identify which social problems exist and which of these make people vulnerable concerning floods. It is especially interesting to exhibit what kind of parameters describe these problems best, how these parameters can be measured at regional level and how to link them with hazard parameters for an integrated vulnerability assessment.

1.2 Procedure of analysis

The second chapter presents background information on the research area, Germany. Potential impacts of river-floods and common disaster mitigation approaches are shortly outlined. Then literature is reviewed regarding evidence about social vulnerability to flooding in Germany. The understanding of both hazard and social vulnerability setting helps to justify the chosen variables for constructing the vulnerability indices.

The third chapter describes the conceptual frame for the social vulnerability and the Social and Infrastructure Flood Vulnerability Index (see **Figure 1**). Terminology is clarified, and a working definition given. The conceptual framework frames the objectives of vulnerability assessment and illustrates the procedure of analysis. This analytical structure serves the reader to understand the logical concept and the construction of the indices.

In the fourth chapter the vulnerability assessment is carried out. As the main target, a Social Susceptibility Index for German counties is developed (**Figure 1**). This is done by selecting and aggregating demographic statistical data. Single variables are grouped by factor analysis to identify social profiles. These profiles are validated to have an impact by analysis of an independent second data set for a real case flood event. The data source is a household questionnaire survey of flood affected persons. The resulting social profiles at household level are compared with the county profiles, and a validated index is derived. A composite Social Susceptibility Index is the main results of aggregating these single indicators. Additionally the Social Susceptibility Index is demonstrated to be integrable with hazard information. Data input is the hazard map derived from inundation maps of rivers. The result is a Social and Infrastructure Flood Vulnerability Index that combines the Social Susceptibility Index with an exposure analysis carried out for two major streams in Germany. This step shows the potential of the susceptibility index for integration with other relevant flood vulnerability information. The vulnerability maps should be comprehensible and useful for both science and decision-making.

The fifth chapter is a synthesis that discusses the results concerning validity and limitations. Technical implications as well as findings on social vulnerability in Germany to flooding are discussed. The theoretical assumptions are reflected and possible opportunities for further development considered.

In the sixth chapter, the results of this study are analysed, whether they can be transferred to and interlinked with several fields of application. Consequences and interlinkages of this study are discussed in the combination with other hazard scenarios and the dynamic development of society. Finally, recommendations for the application of vulnerability assessments are provided for decision makers.

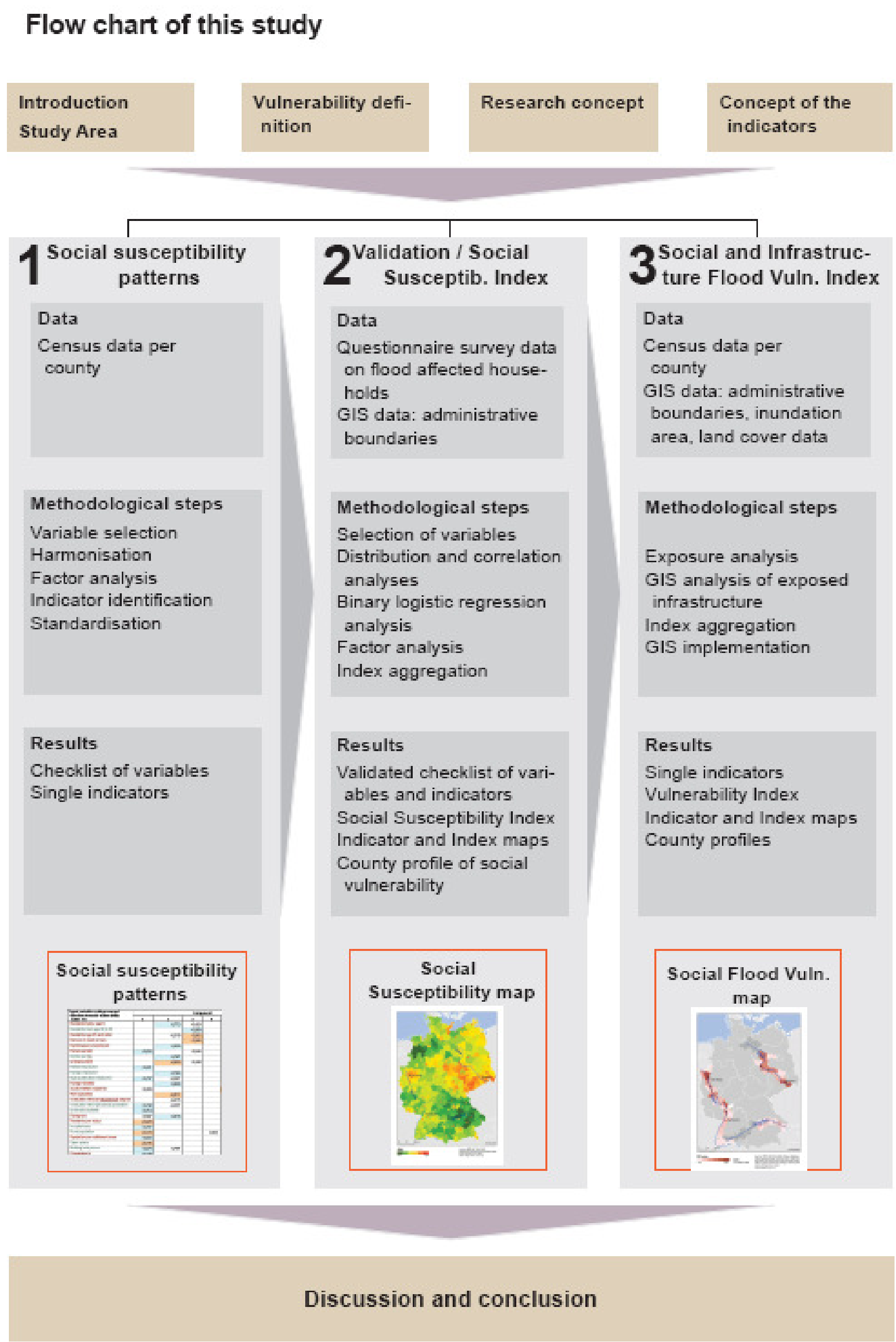


Figure 1. Flow chart of the research procedure and structure of the chapters

2 Hazard and Vulnerability Context

The context for this study lies in the characteristics of the selected hazard and the German society. One part is information about the specific hazard, its characteristics, impacts and mitigation strategies. The other part is an investigation of the fabric of society and how it frames potential weaknesses and peculiarities towards a potential disaster impact. The Pressure and Release (PAR) model (Wisner et al. 2004: 51) is used to elicit such latent deficiencies in society. It provides however, similarly as the access model of the same authors (Wisner et al. 2004: 89) or the livelihood approach (DFID 2000), less guidance about the hazard background. Since both information about the hazard and the social fabric are important for the context of this study, this chapter starts with a review of hazard peculiarities.

2.1 Flood impact in Germany

Three major streams, Elbe, Danube and Rhine, are in the centre of interest of this study (see **Figure 2**). Although the river regimes of these long streams change downstream due to topography, watershed and precipitation characteristics (Marcinek 1997: 470, Smith and Ward 1998), they have certain aspects in common. The floods are characterised by slow increase of the water level and propagation of the flood wave. The lateral diffusion and groundwater level rise is greater in low lying areas of the northern parts of Germany; for example, the North-East German lowland, the North-West German lowland or the West German lowland bay (see **Figure 2**). The Upper Rhine rift is a special case of geologic graben which is also characterised by low topography. The southern parts close to the Alps and Erz mountains are more directly dependent on discharge feed in the spring months by snow melt. Even downstream along the Elbe or Rhine, snow melt in combination with frozen ice caused severe damages. For example, a flood with sheets of ice destroyed 161 houses, caused 21 casualties and left 1800 people without home at the Rhine in 1784 (Bröhl 1996: 45). In recent times floods with ice have been rare and less severe. Still, some experts warn not to underestimate the hazard (Jochen Steiner, head of the fire and ambulance service in Bonn, Steiner 2007). Tributary rivers like the Mosel increase the flood wave enormously, which happened in the 1993 flood along the Rhine.

The hazard is aggravated by secondary effects arising from land use and infrastructure. Soil-sealing is a major problem within densely populated areas in Germany (see **Figure 2**). Imperviousness increases surface run-off (UBA 2006: 28, BBR 2005: 333) and it is one goal of the government to reduce the rate of newly sealed area (BBR 2002: 7). Dykes are a precarious issue in terms of creating faster flow conditions and, regarding the risk of a dyke breach. In this case a disaster can happen to an unprepared population behind the dyke, the so-called “levee effect” (White 1945, Deutsche Rück 1999: 2). Climate change is supposed to alter the flood hazard accordingly to topographical regions in Germany (Spekat et al. 2007, Zebisch et al. 2005, Schmidtke 2004). Especially the seasonal patterns, snow melt and glacier feed are supposed to change. There is still a great amount of uncertainty in the predictions and some studies raise doubts about the occurrence of more extreme events (Mudelsee et al. 2003).

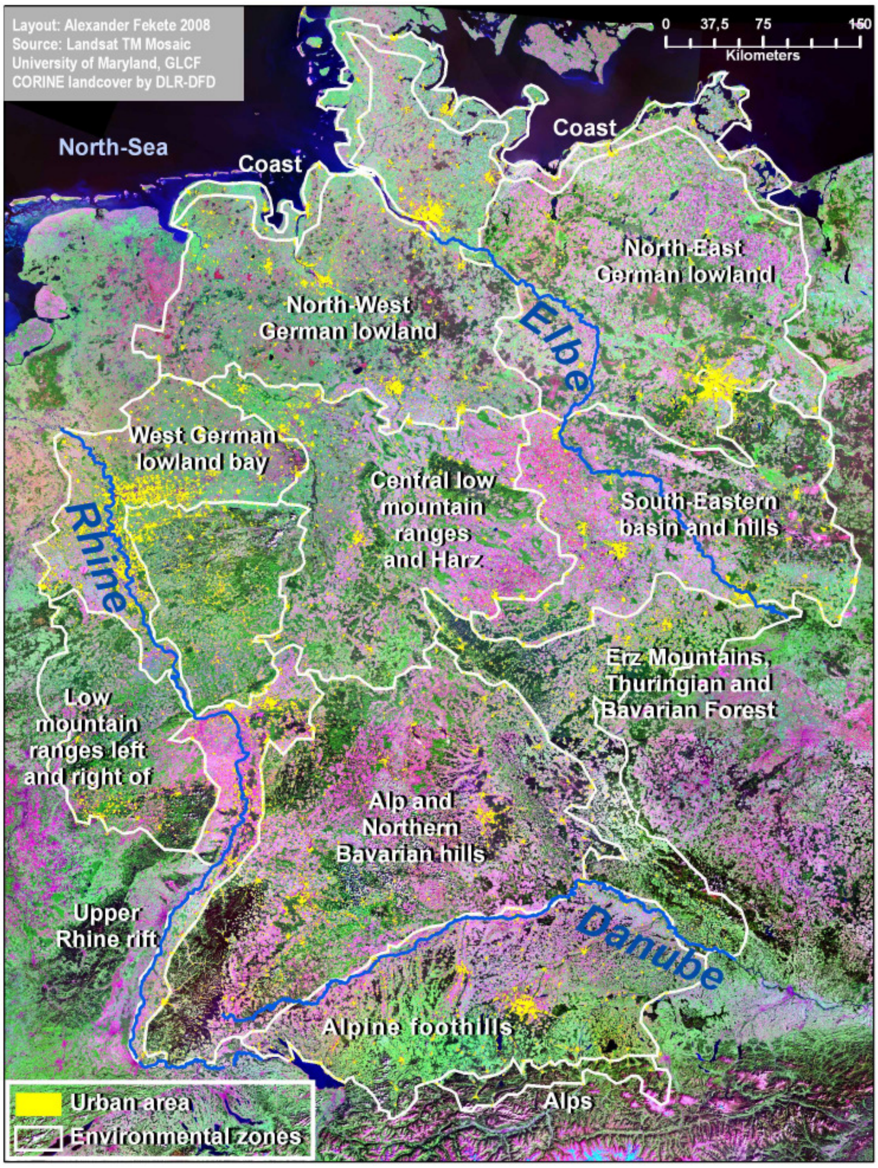


Figure 2. Map of Germany displaying the main environmental zones
Source: environmental zones of Germany, modified after Zebisch et al. 2005: 169, Landsat images by GLCF, University of Maryland 2005, CORINE landcover 2000 by DLR, administrative boundaries by BKG 2007.

River valleys are primarily attractive locations for settlement, economic activities and traffic connections. This is the case since at least 7000 years which is known by erosion deposits and traces of fire-stone trade (Jäger 1994: 33). The distance to rivers or smaller water courses is a major settlement distribution factor since that time (Schier 1990). Today, the population density along rivers in Germany is 8%, which is double the average settlement density in Germany (DKKV 2003: 35). Hence, approximately 2 million people are exposed to floods just along the German part of the river Rhine (IKSR 2001: 8).

In recent years, so-called ‘century floods’ have left an imprint on German society as communicated by mass media (Thorwarth 2001: 426). Especially disturbing to the public is why these ‘century floods’ occurred at the same river twice within a few years and not every 100 years as expected (**Table 1**). The statistical value of a given water discharge of a recurrence interval level of 100 years is difficult to conceive for laymen. Within 10.000 years such a discharge is on average expected to happen 100 times, which gives no direction however, when each event is exactly going to happen (Smith and Ward 1998: 17, Kron 2006). This value is even more difficult since it is subject to change after each new flood event (German Federal Institute of Hydrology (BfG), oral com. 2006, Merz and Emmermann 2006).

Table 1. River floods in Germany: magnitude of recurrence rate and economic damage

River and Year	**Discharge – Q statistical equivalent on years of recurrence**	**Economic damage in Germany** m = million	**People affected**
1954 Danube	No data	50 m US$	0 casualties
1993 Rhine	100	600 m US$	5 casualties
1995 Rhine	100	320 m US$	5 casualties
1997 Oder		360 m US$	0 casualties
1999 Several rivers in Bavaria, Baden-Württemberg	>100 (300)	350 m US$	5 casualties
2002 Elbe	150-200	11.6 billion US$	21 casualties, 110 injured, 337.000 directly affected, 35.000 evacuated in the city of Dresden
2002 Danube	100	100 m US$	0 casualties
2006 Elbe	Discharge at the Elbe was 13 cm higher than in 2002 in the town of Hitzacker and was the highest in Boizenburg and Doemitz since records began 110 years ago	No data	1,000 evacuated along the Czech border

Sources: DKKV 2003: 21,22, Darthmouth Flood Observatory, accessed 24 July 2008, Deutsche Rück 1999, Deutsche Rück 2002, Freistaat Sachsen 2002, NATHAN by MunichRe, accessed 15 May 2008, UBA 2006

Table 2. The disaster risk index of UNEP-GRID for natural hazards in Germany

	Disasters per year [nb/year]	Causalities [killed/year]	Physical exposure [nb/year]	Relative vulnerability [killed/mio. exp.]
Droughts	x	x	x	x
Earthquakes	0.05	0.0	357.730	0.1
Floods	0.38	1.0	3.976.284	0.3
Tropical Cyclones	x	x	x	x

Relative vulnerability: The average number of killed divided by the number of exposed in millions
Source: UNEP-GRID 2003, http://gridca.grid.unep.ch/undp/, accessed 14 May 2008, UNDP

The impacts of river floods in Germany are characterised by economic damage and less by mortality (UNEP-GRID 2003, UNDP 2004: 31,41, and see **Table 1** and **Table 2**). Germany however, ranks second only to Italy in occurrence of severe river flood disasters within Europe from 1950 to 2005 (Barredo 2007: 141). Flooding (both coastal and riverine) has been identified as the “most important potential disaster in Germany”, even compared to technical risks (Lass et al. 1998: 23). The flood disaster along the Elbe 2002 caused the death of 21 people (DKKV 2003: 29). Severe health impacts are not reported except for single cases. The damage recorded so far is greatest in the destruction of houses and infrastructure, economic values, contamination by fuel tanks (Deutsche Rück 1999: 27, UBA 2006: 26) and chemical industry (WBGU 2000: 140, von Tümpling et al. 2006). Damage to personal belongings, work-interruptions, trade-interruptions, costs for evacuation and technical protection measures are upon other additional effects of river floods (Merz 2006: 189). Information about non-structural harm caused by flooding is more difficult to obtain. These include the so-called ‘indirect’ and ‘intangible’ damage aspects (Smith and Ward 1998: 35) like disruption of daily life, stress and trauma and prolonged recovery processes (White 1945, Tapsell et al. 2002).

2.2 Flood mitigation in Germany

"It is very easy for me to calculate the positions of the sun, moon, and any planet, but I cannot calculate the positions of water particles as they move through the earth."
Galileo

Germany has a long tradition of water engineering. Dams and dykes were first technical feats and not perceived as threats. The ‘conquest of nature’ (Blackbourn 2006) by river training produced foremost economic benefits for trade, turning streams in Germany into highly important European waterways. As a side-effect of river training and drainage of wetlands, the swamps were dried out and related diseases reduced (Pohl 2002: 33). Since the 18th century however, the failure of dams and negative side-effects of river training changed public and expert opinion about overly trust in technical protection only (Blackbourn 2006, Plate et al. 2001: 14). This paradigm shift however transforms structural water engineering and traditional flood risk management only slowly (Merz and Emmermann 2006, Kuhlicke and Steinführer 2007). Events like the Rhine floods of 1993 and 1995, and the Elbe flood in 2002 instigated citizens' initiatives and considerations of non-structural flood defence measures (DKKV 2003).

Flood mitigation in Germany is characterised by traditions in administration and governmental system. Spatial planning tradition for instance not only governs the management of space by regulating land use and determining administrative boundaries (Blackbourn 2006). It also reflects the mindset of controlling nature and the hierarchical structure of spatial units. In combination with the historical background of the federal system, this provides a confusing array of multiple levels of responsibility for disaster risk management (von Kirchbach et al. 2002: 215). The responsibility is distributed among the multiple levels for different tasks (Lass et al. 1998: 31), encompassing states, counties, municipalities, villages and the citizen itself.

Volunteerism and responsibility of the citizens are important features of German flood mitigation. This can be traced back to centuries of dyke construction and maintenance in the coastal areas but also along rivers. Dyke reeves (German: Deichgraf; Storm 1888) were elected by the people and even today dyke maintenance and patrols are organised by the citizens themselves. Volunteerism for emergency help and sand bag defences is widespread among life rescue organisations and encroachers in cases of floods (information after interviews with relief organisations at the Elbe flood 2006). This has also negative consequences for the varying degree of professionalism in some organisations (Lass et al. 1998: 31). Responsibility for preparation and information about flood hazards is on the citizens themselves, too (Bundesgesetzblatt 2005). This, on the other hand is not always perceived as such by the people themselves (Steinführer and Kuhlicke 2007: 119). People utter that they don't believe a single person can sufficiently protect itself (Wöst 1992: 63).

Currently there is ample activity in the preparation of flood-related disaster information. Recent incentives of disaster risk management include the development of hazard maps (Baden-Württemberg 2005, MUNLV 2003) as commissioned by the European Union (EC 2007). Other incentives are guidelines for flood preparedness of the population

(UBA 2006), buildings (BBR 2004), spatial planning (BBR 2002), or critical infrastructure (BMI 2006, BBK 2009). Transboundary cooperation for integrated flood risk management (IKSE 2003, IKSR 2001) and the improvement of early warning systems are also fields of action (von Kirchbach et al. 2002). While more and more flood risk maps are available on the internet, they rarely include information more than flooded area over a topographical map. The insurance industry has developed its own system that contains four risk zones including the location of buildings (ZÜRS; Müller 2002). However, it is not accessible for the public or for science. Increasingly, information about the vulnerability of the population is requested (UN/ECE 2003, Plate 2001: 159, Lass et al. 1998).

2.3 Flood vulnerability assessments

"Germany lacks complete and generally accessible data on disasters and disaster management" (Lass et al. 1998: 41). Lack of data, expert analysis and integration to planning are observed among other deficits (Dombrowsky and Brauner 1998: 13). Ten years later, there is still a lack of accessible information or maps including aspects of social vulnerability. Information systems with a Decision Support System (DSS) character typically focus on implementing early warning systems or hazard measurement (cf. overview on 42 flood projects on http://www.eu-medin.org/, accessed 26 May 2008). When demographic information is included it is often limited to one or two variables and regarded as an appendix. The same can be said about most classical flood risk assessments, where risk is mainly regarded as a hazard probability or economic loss probability. The loss function often reduces human harm to measurable monetary units, for example buildings or economic values. The insurance industry measures vulnerability mainly by monetary values. For example, the 'natural hazard risk index for megacities' measures vulnerability by building values, building regulations, flood protection and population density among other criteria (MunichRe 2004: 41). Reduction of social aspects into economic values or mortality is also common for global or national risk or development assessments. The Centre for Research on the Epidemiology of Disasters (CRED) database (www.cred.be/), the Human Development Index (http://hdr.undp.org), or various global or national risk indices (cf. discussion in Birkmann 2007) share this limitation, mostly due to lack of data.

Vulnerability is a previously neglected component in disaster risk management and research. This is not only for lack of data but also because of a lack of research. Even at local level there are only very few studies carried out on non-structural aspects of flooding impact including social vulnerability. Studies on risk perception concerning floods (Plapp 2004) focus on specific aspects of risk behaviour and include demographic and social structures only partially. Such local studies are, however very important to identify empirical information about social vulnerability patterns (e.g. Pfeil 2000). Still, they are naturally very context and locality specific and are very limited in extrapolating the characteristics of the flood affected people to greater regions or even to the whole area of Germany. In recent years an increase in studies can be observed which research social patterns of diverging preparedness and recovery from flooding events. Especially the Elbe flood in 2002 stimulated such research (Steinführer and Kuhlicke 2007, Thieken et al. 2007).

For a comparison of whole regions within Germany, however, still no satisfying social vulnerability maps exist. A recent example of a study captures social risk criteria, however, the information depth is limited to total population and population density (Meyer et al. 2007: 40). Another comparable study has carried out a multi-hazard assessment with a multitude of variables on social vulnerability but only for one federal state (Kropp et al. 2006). Recent approaches for coastal flooding head in a similar direction (Sterr et al. 2007). For the current state of the art it can be observed that social vulnerability detection, measuring by quantification and mapping of regions in Germany is certainly a recent agenda. The focus has shifted from hazard and previously only structural risk assessments to the inclusion of human risk dimensions. In this perspective, the aim of vulnerability assessments is to enrich risk assessments on important aspects of human characteristics of flood vulnerability.

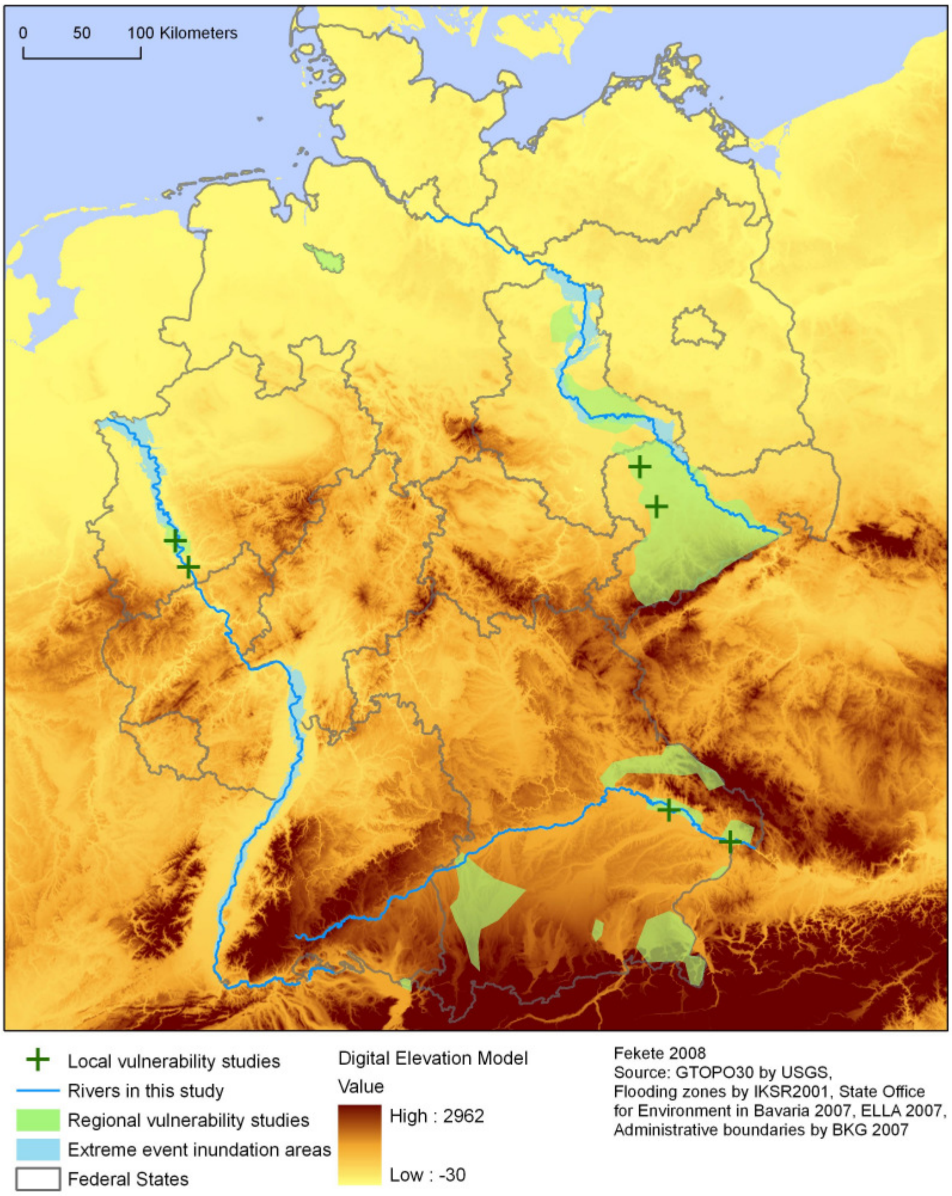


Figure 3. Map of the existing local and regional vulnerability studies (in Table 3).

The map (**Figure 3**) shows the limited regional cover of the local studies on social vulnerability aspects in relation to floods (cf. **Table 3**). Still no sufficient local information is available to allow for a comparability of regions along the Rhine with the Elbe or Danube. This research gap is to be filled with this study at county level.

2.4 Who are the vulnerable to flooding?

"We are not an endangered species ourselves yet, but this is not for lack of trying."
Douglas Noel Adams

When looking at humans they are not determined by a single factor like poverty only. Human profiles are composed of several characteristics and conditions. With a limited set of characteristics, certain 'typical' social groups can be identified. Of course, such a typology necessarily comes too short in explaining the complexity of human facets. It is yet helpful to identify patterns of vulnerable groups. Studies on social milieus or class describe disadvantaged people. For example, the social or political milieu of 'the precarious group' is characterised by low social status, downward social mobility, low to middle level of education, the highest ratio of unemployment, blue-collar working class, predominantly male sex, and is living in Eastern Germany and in rural areas (Neugebauer 2007: 82). Eight percent of the population belong to this milieu, according to this study. This group is much related to social welfare and unemployment, especially long-time unemployment. Social milieus and class are constantly shifting. End of the 1980s, the German poor were elderly women, in the 2000s the poor are the young children and young mothers (Strohmeier and Kersting 2003). Children of single-mothers are especially hit by poverty, as are children of immigrants and recipients of social welfare (UNICEF 2008). The education opportunities of children are linked to family structure and social class, however less in Eastern Germany (Baumert et al. 2003). All here presented typified groups are rendered disadvantaged concerning general social standards. They struggle mostly for economic equality but also for status recognition.

But are those groups 'the vulnerable' to natural disasters, or more precisely to river floods? This is a very difficult question to answer for at least three reasons: First, there are yet too few studies on this issue in Germany to have clear criteria what makes a person vulnerable to natural hazards. Second, those who are most social disadvantaged must not be the same that are exposed or get most severely affected by floods. The affluent, one may argue, have more values to lose and can afford to live more exposed along attractive river-side locations. Third, who is vulnerable is very much dependent on interpretation and definition. If vulnerability is a function of economic loss, then start-up entrepreneurs who bear a high financial risk would be the most vulnerable group, not the poor.

Few studies have established a relationship between flood impact and social groups in Germany (cf. **Table 3** & **Figure 3**). The studies are typically of a very local focus and the findings cannot easily be generalised. In Beuel, a city quarter in Bonn, new and inexperienced residents had been more affected by the floods of the Rhine in 1993 and 1995 than the old population (Pfeil 2000). The new residents were not yet integrated and familiarised with flood protection and emergency behaviour. Conversely, in Eilenburg and surrounding towns at the flood of 2006 of the river Elbe, the elderly and long time residents were especially hit. They believed the flood would not rise above previous flood levels. They were sceptical about preparedness measures and evacuation, whereas young working people were more mobile, flexible and better informed (Kuhlicke, pers. com. 2006, Steinführer and Kuhlicke 2007: 64). The study of Eilenburg seems to support that old age and tenure played a key role (Steinführer and Kuhlicke 2007: 114). The following table reviews typical characteristics of social vulnerability as found in studies in Germany (**Table 3**).

Table 3. Review of vulnerability characteristics of humans to flooding in Germany

Demographic characteristics	**Characteristics of higher vulnerability**	**Characteristics of higher capacities**
Old people	Suffering physical/health consequences Received less support (Steinführer and Kuhlicke 2007: 113, 114) Less capable of performing emergency measures effectively (Thieken et al. 2007: 1031) Forced to seek shelter in emergency accommodations (Birkmann et al. 2008: 134-6)	Holding insurance (Steinführer and Kuhlicke 2007: 113)
Very young people	Need more time to evacuate (Birkmann et al. 2008: 134-8)	Suffering less physical/health consequences Suffering lower general impact on household (Steinführer and Kuhlicke 2007: 113)
Gender		Female gender: Higher risk perception and preparedness for action (Martens and Ramm 2007, for city of Bremen)
Income	Lower income: Lesser degree of insurance (special case of Easter Germany) (Steinführer and Kuhlicke 2007: 113)	Higher Income: Insurance more common (Steinführer and Kuhlicke 2007: 114, Birkmann et al. 2008: 134-7) Capable of performing emergency measures effectively (Thieken et al. 2007: 1031)
Education	Lower education: Received less support (Steinführer and Kuhlicke 2007: 114)	Higher education: Capable of performing emergency measures effectively (Thieken et al. 2007: 1031)
Home owners	Properties are more affected Suffering general high impact on household (Steinführer and Kuhlicke 2007: 113)	Applying precautionary measures (Steinführer and Kuhlicke 2007: 113) (Thieken et al. 2007: 1034, Reusswig and Grothmann 2004: 99 for the city of Cologne)
People without local networks	Experiencing lack of information (Steinführer and Kuhlicke 2007: 113)	
Household size	One person households: A majority considers itself dependent on others in case of an evacuation (Birkmann et al. 2008: 134-6) They spend the least amount of money for flood protection (Kreibich et al. 2005a: 122)	Younger families seem to invest in insurance and retrofitting Household size correlated with taking effective emergency measures (Thieken et al. 2007: 1031, 1034) 3-5 person households are more ready to take action and take more responsibility (Martens and Ramm 2007, for city of Bremen)

Long term residents	Better informed than new residents (Pfeil 2000: 57, for city quarter of Beuel, for certain aspects Wöst 1992: 60 for community Irlbach at the Danube)
Students	Less damage and loss (Plapp 2004: 396, for city of Passau)

The social vulnerability characteristics have to be regarded in the context of international vulnerability studies. Lists and reviews of social vulnerability parameters are provided by several authors (Morrow 1999: 10, Tapsell et al. 2002: 1520, Cutter et al. 2003: 246, Schneiderbauer and Ehrlich 2006: 88, Simpson and Katirai 2006: 14, Masozera et al. 2007: 301) and Annexes 1, 2 and 3 summarise social vulnerability characteristics found in other countries for comparison. This comparison is valid, since characteristics like old age generally correlate with higher degrees of mortality to floods. Eight of nine persons killed within buildings by a flash flood in Southern France in 1999 were of retirement age (IKSR 2002: 14). A study in the UK (Tapsell et al. 2002: 1522) states that age of 75+ has been shown in epidemiological research to display a sharp increase in health problems. Experiments reveal thresholds up to which people of average age and constitution could withstand loss of stability or manoeuvrability due to water height and velocity (RESCDAM 2000: 44). The findings conclude that people with reduced physical strength would have lower thresholds to withstand. This would typically include the elderly, disabled or persons with additional loads like women caring for children.

Regarding income deficiencies, the financially deprived are less likely to be insured and therefore have more difficulties in recovery (Tapsell et al. 2002). But there are also special groups severely affected by floods which are often forgotten in standard vulnerability assessments. One of them are the transient or homeless who typically are not recorded in standard statistics (Wisner 1998, Masozera et al. 2007). Campers are often highly exposed as camp sites are often situated in flood plains. 23 campers died in Savoy 1983 when camping in a flood plain (IKSR 2002: 15). 10 of 24 persons during a flash flood in Southern France in 1999 were killed inside their cars (IKSR 2002: 14). Evacuation assistance needs are identified as a major indicator of social vulnerability (Chakraborty et al. 2005). Certain variables have been analysed for the construction of a social vulnerability for evacuation assistance index. They include the population up to 5 years of age and population over 85 years (Chakraborty et al. 2005: 26). Similar observations on evacuation needs of special needs groups like children, the handicapped or persons in need of special medical care have been made for Germany and neighbouring countries (IKSR 2002: 16).

3 Research Concept

"Problem formulation is more difficult than problem solution"
Murray Gell-Mann

Within the field of vulnerability assessments it is important to state how the terminology is used (Section 3.1) and which concept is applied. The concept is in this case a vulnerability framework established by UNU-EHS (see Section 3.2). Based on this framework, the goal, procedure and the components of measurement are identified for the development of the vulnerability indicators.

3.1 Vulnerability terminology

Researchers dealing with the term vulnerability encounter a variety of definitions. While this is often stated as a major problem that hinders the applicability (Cannon 2006: 41, Füssel 2007: 155), uncertainty in definitions is a common course in science (Feynman 2007). For example, terms like ‘risk’, ‘disaster’, ‘uncertainty’, ‘sustainability’ or even terms like ‘system’, ‘probability’ or ‘flood’ are defined in multiple ways (Rothman et al. 2008, Quarantelli 1998). By etymology, the term ‘vulnerability’ stems from Latin ‘vulnus’, the wound and ‘vulnerabilis’ – being wounded.

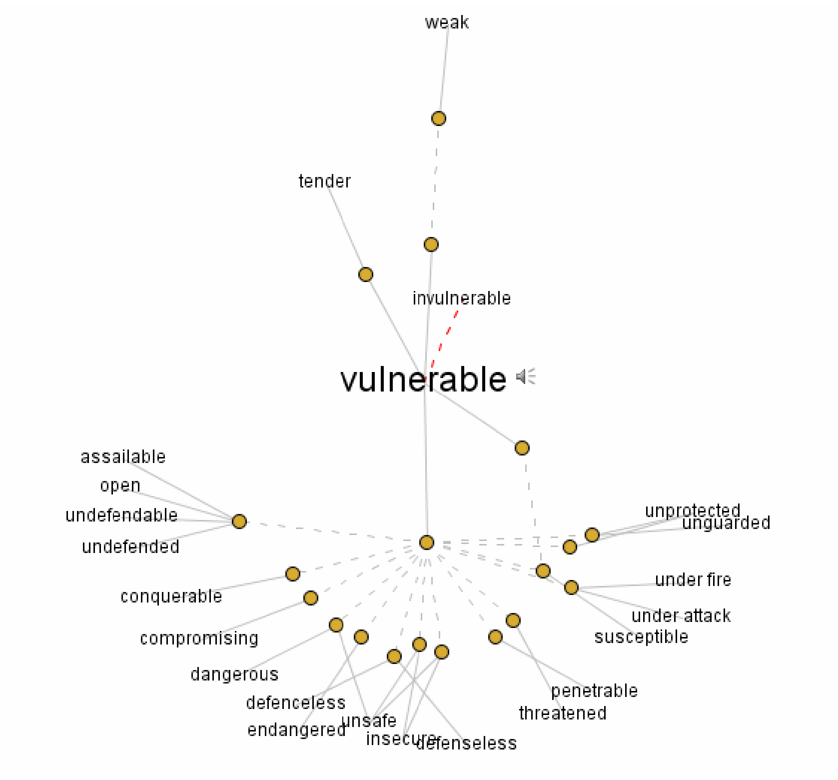


Figure 4. Diagram of the relations of the term vulnerability to similar expressions
Source: www.visualthesaurus.com, accessed 21 May 2008

The confusion around the different interpretations of vulnerability arises from the differing meanings and normative attributions assigned to it. Adding new definitions to the already long list is no aim of this study. However, in the research community it is demanded to provide a working definition to enable an understanding of the research stance. Prior to this, it is necessary to highlight some important points of the discussion in vulnerability terminology.

3.1.1 Important points of discussion in vulnerability terminology

Vulnerability is by etymology a negative expression, but there is a trend to attach a positive side to it. The chart of the term vulnerability illustrates its relation to similar expressions and denotes its closeness to negative attributions in common language (**Figure 4**). The attachment of a positive side of the coin is driven by relief organisations and some disciplinary schools (Anderson and Woodrow 1998: 11, Twigg 2004: 19, Wisner et al. 2004: 112). They stress viewing humans not only as victims but emphasise their capacities as well (Wisner et al. 2004). In this respect it is instructive to know the disciplinary discourse of different schools of vulnerability that have been extensively reviewed (Hewitt 1983, Cutter 1996, Weichselgartner 2001, White et al. 2001, Brooks 2003, Few 2003, Adger 2006, Birkmann 2006). On the backdrop of different disciplines and fields of application – from food security to climate change, the variety of definitions (Cutter 1996, Weichselgartner 2001, Thywissen 2006) can be understood. The range of definitions is given by normative views of disciplines but also by the fundamental difference in science philosophy between reductionist' and holistic views.

Reductionist' versus holistic viewpoints are two ends to a spectrum of vulnerability definitions. The first analyses vulnerability in a single dimension of real existing objects, for example the porosity of a wall. The holistic view synthesises a wide range of facets. Often, heterogeneous facets are in this basket and thus comprise an analytical construct. An example for a holistic approach is the research not only of one human individual, but of a social system. There are many transitions in between the two extreme ends of a spectrum of strictly reductionist and holistic views. This division of definitions is helpful to understand the diverging mindsets and analytical structures behind vulnerability assessments.

Vulnerability is often regarded as connected to a specific context. This context can be the type of external stressor, for example natural hazards or civil conflict. Also important is the spatial and temporal context as it is stressed in place-based approaches (Cutter 1996, Research and Assessment Systems for Sustainability Program 2001: 4, Steinführer and Kuhlicke 2007: 115). The vulnerability to a certain hazard in the spatial and temporal context further demands clarification of who or what is vulnerable. But there are also standpoints of a general vulnerability that is more or less prevailing as a general condition (Wisner et al. 2004, Bohle 2007: 808) or is even hazard-independent (Schneiderbauer 2007: 27). The term 'overall-vulnerability' (Kleinosky et al. 2007) signifies different vulnerabilities that can be individually researched and then aggregated. There is a range of spheres for which vulnerability can be assessed.

There are considerable overlaps of vulnerability with terms like damage potential or loss. The lack of concise separation of these terms hampers common understanding. A new term should not be introduced when it can be substituted by one already existing. One example is the common definition of vulnerability as loss or damage potential. This conveys economic assessments which reduce vulnerability to a single dimension view of monetary damage. For reductionist' vulnerability assessments this provides a very precise definition, but it is less useful for holistic vulnerability assessments. Damage can be thought to be subdivided into direct and indirect, tangible and intangible damage (Smith and Ward 1998: 35). Still, this bears resemblance to measurable units like money or body counts and to economic measurements like damage functions. Normative views of anthropologists and social scientists stress human capabilities that seem hardly congruent with this perspective (Wisner et al. 2004, Bohle 2007). The composition of the vulnerability definition is dependent on who or what is the object of interest. When humans are in the centre of interest, non-structural aspects like social networks and human behaviour have to be included into risk assessments.

3.1.2 Working definitions

Disaster is "a serious disruption of the functioning of a community or a society causing widespread human, material, economic or environmental losses which exceed the ability of the affected community or society to cope using its own resources." (ISDR definition, http://www.unisdr.org/eng/library/lib-terminology-eng%20home.htm, accessed 18. April 2009).

Risk is the state prior to a disaster. Risk is perceived here as encompassing aspects of the hazard and the vulnerability of the human-environmental system towards extreme river floods. Risk = f(vulnerability, hazard). It comprises the probability of frequency and magnitude of the hazard as well as the inherent weaknesses and strengths of humans. This is therefore an integrated and constructed notion of risk, combining technical and social risk conceptions.

The *hazard* is in the case of river-floods a natural event that is perceived as a threat and not as a resource by humans. It can be thought of as a natural process that exceeds a certain threshold of a 'negotiated balance' between human and environmental system. When a certain criticality level is exceeded, the resource, for example, the river, becomes a threat. When this threat transgresses certain spatial and temporal boundaries of human safety spheres, the hazard realises as an impact. The hazard is revealed in the state of exposure, when the natural event actually hits the vulnerable elements.

Vulnerability captures the conditions of a phenomenon of observation – that characterise its disadvantages in the face of natural hazards (i.e. to a given stressor). Vulnerability encompasses exposure, susceptibility and capacities of the unit of research and is related to a specific hazard or stress context.

Vulnerability is integrated with hazard components in the risk formula; risk = f(vulnerability, hazard). Vulnerability changes in time and space and aims at identifying and explaining why the object of research is at risk and how risk can be mitigated. Vulnerability is both state and degree: everyone is vulnerable in the state of exposure to a hazard and is vulnerable to a certain degree. Vulnerability is a constructed analysis concept since the content and research scope is selected after arbitrary decisions of the researcher or target group.

One critical problem in understanding the term vulnerability rests within the phase in time observed – before, during or after a disaster. People are always vulnerable, regardless of the time phase. Still, it might be useful to distinguish between *potential vulnerability* and *revealed vulnerability*. *Potential vulnerability* describes the pre-disaster conditions of the components exposure, susceptibility and capacities. This is the type of vulnerability typically addressed by vulnerability indicators that aim at prediction of potential disasters to come. *Revealed vulnerability* shows itself in a post-disaster situation as an impact measure of unequally distributed loss and hardships amongst social groups, for instance.

Vulnerability can be subdivided into analytical *components*.
Exposure is the measure of susceptible elements within a region threatened by a hazard. The *exposure potential* is the predisposition of a region due to the portfolio of its physical assets.
Susceptibility describes the characteristics that render persons or groups of people generally weak or negatively constituted against stresses and threats.
Capacities are positive characteristics that comprise all phases of the disaster cycle, from preparedness, response or coping during the disaster, and recovery and adaptation after the disaster.

Social vulnerability is the predisposition of society and individuals towards a stressor or hazard to be harmed (cf. definition by Wisner et al. 2004: 11). It is the potential to be wounded or to continue to be wounded. Social vulnerability is bound to human beings; all constituting factors are solely relevant in their function to humans (cf. Wisner et al. 2004). Social vulnerability is understood as a specific focus on the social features of a social-environmental system that create vulnerability, in this case towards river-floods.
Society is regarded as a social system. The social system consists of elements, humans, who interact with other humans and the environment. Within system boundaries, elements and internal processes take place that are qualitatively different to the system environment outside the spatial and cognitive boundaries of this system. A social system can be for example a county. This is therefore a place-based vulnerability view (Cutter 1996). The environment is on the one side nature as transformed by human action. On the other side there is a system environment which is an artificial distinction between the internal and external realm of the social system level of interest, here counties. The human system as object of interest is vulnerable due to its own properties and stressors from nature, but also due to stressors from the human system itself.

In order to put vulnerability in context to the hazard, several models or conceptual frameworks exist, that have been already extensively reviewed (e.g. Birkmann 2006, Villagrán de León 2006). Bogardi (2006, as cited in Villagrán de León, 2006: 51) provides a concept which visualises how the hazard impacts on vulnerability and how the system performs after the impact (**Figure 5**).

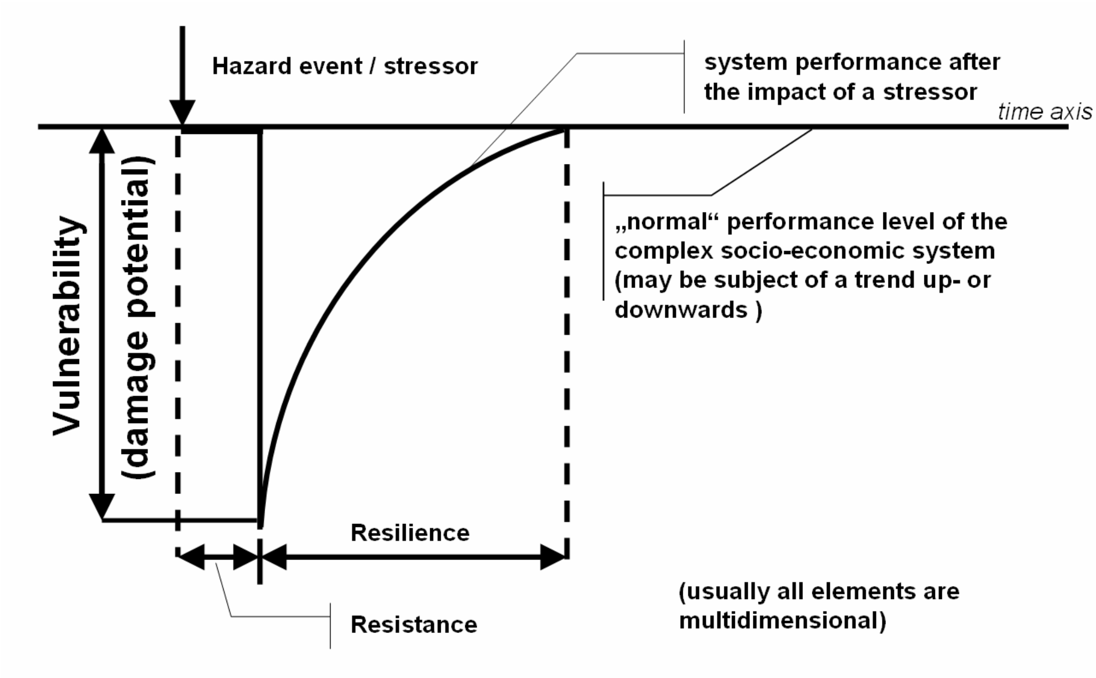


Figure 5. Visualisation of the concept of vulnerability
Source: Bogardi 2006, as cited in Villagrán de León, 2006: 51

This concept (Figure 5) also displays a precise distinction of the resistance and resilience and the system performance after the impact of a stressor on a time line. For this study it is interesting to see the capacities of a system divided into a phase where the system still can resist (resistance) and a phase where the recovery from the impact (resilience) takes place. This concept is one example from a more engineering point of view on how to embed vulnerability into a system perspective and how to link it to the resilience debate. This study targets specifically social vulnerability and for the sake of simplicity and stringency does not embark on the larger debates of coupled human-environmental systems, resilience or adaptation. Still, it is important to highlight that vulnerability assessment is an important precursor of risk, adaptation and resilience studies. Without the knowledge about inherent system weaknesses and strengths, the development of risk management or adaptation strategies will be rather haphazard.

3.2 Conceptual frame of the vulnerability indicators

Since at least the 1960s, social indicators and indices have been used for monitoring social processes (Simpson and Katirai 2006). The attraction of indices lies in the summation of complex information into intuitively conceivable numbers. In the context of this study they would allow for spatial and temporal comparison of vulnerability between different communities. General problems known for indicators and indices include subjectivity, bias, weighting, aggregation, normalisation and selection of indicators and data sources. The purpose of building indicators is to derive general approximations over a number of research units and to be able to draw comparisons on these units. The aim is to organise information in order to derive knowledge about spatial distribution patterns, thus attempting to 'measure' social vulnerability in this case. Indicators are numerical values that represent real world phenomena in a highly reduced form. An indicator can itself be either a single variable or a composite number of various variables. However, it seems generally accepted that there is a progression from information to data to indicators to indices (Birkmann 2006: 59, Simpson and Katirai 2006: 2).

Other terms like attribute, metric, parameter, value or variable are used to explain the components of indicators as pieces of quantified data that contain an order, ranking or more generally, direction. An indicator is thus the contrary of unorganised and non-valuing information. It is oftentimes a statistical measurement value which in its variations signifies a change of magnitude, but is usually not an accurate measurement of a phenomenon easily observed in the real world (Simpson and Katirai 2006).

Various sources provide an introductory overview on characteristics of vulnerability indicators (Birkmann 2006, Villagran 2006). The design of indicators is dependent on their expected use, inherent properties of the phenomenon of research, methodologies and, the availability of data (Villagran 2006: 26). The selection process is key to ensure the quality of indicators (Briguglio 2003, Hahn et al. 2003, Villagran 2006) and receives special attention in this study.

Why measuring vulnerability? Answers to this discussion were provided in the UNU-EHS / MunichRe foundation summer academy on water-related social vulnerability at Schloss Hohenkammer in 2006:

- To define, where the greatest need is (Erich Plate)
- Assess socially distributed vulnerability (Anthony Oliver-Smith)
- Alert the public, improve the intervention tools (Melanie Gall)
- To represent social responsibility (Ursula Oswald Spring)
- Taking the naturalness of natural disasters (Ben Wisner)
- Anticipate undesirable states (Ricardo Guimaraes)
- To look at the social roots of vulnerability (Dirk Reinhard)

The measurement of vulnerability demands for a model, which delivers the structure, context and objectives of the analysis. The BBC framework (see Birkmann 2006: 34, see **Figure 6**) explicitly links vulnerability to the three spheres of sustainability; society, economy and environment. One could argue that institutions or politics also play a role, but they are already existent in these three spheres. This framework, as developed at UNU-EHS, is based on theoretical considerations, how social, economical and environmental dimensions of human security can be integrated with existing hazard and risk concepts. This framework thus displays recent research considerations and the paradigm shift from a hazard-orientated research towards integrative risk reduction perspective (Bogardi and Birkmann 2004).

In the BBC framework, vulnerability is put into a succession chain starting from a natural phenomenon that evolves to a hazard event and hits an exposed, susceptible population that could be equipped with coping capacities. By combination of vulnerability and hazard, risk is created. This risk is dynamic, and there are two entry points for risk mitigation provided by the framework: during the pending risk and after the hazard event has started to affect the people. The BBC framework is therefore especially useful to show the interconnections of hazard, vulnerability, risk and disaster risk management.

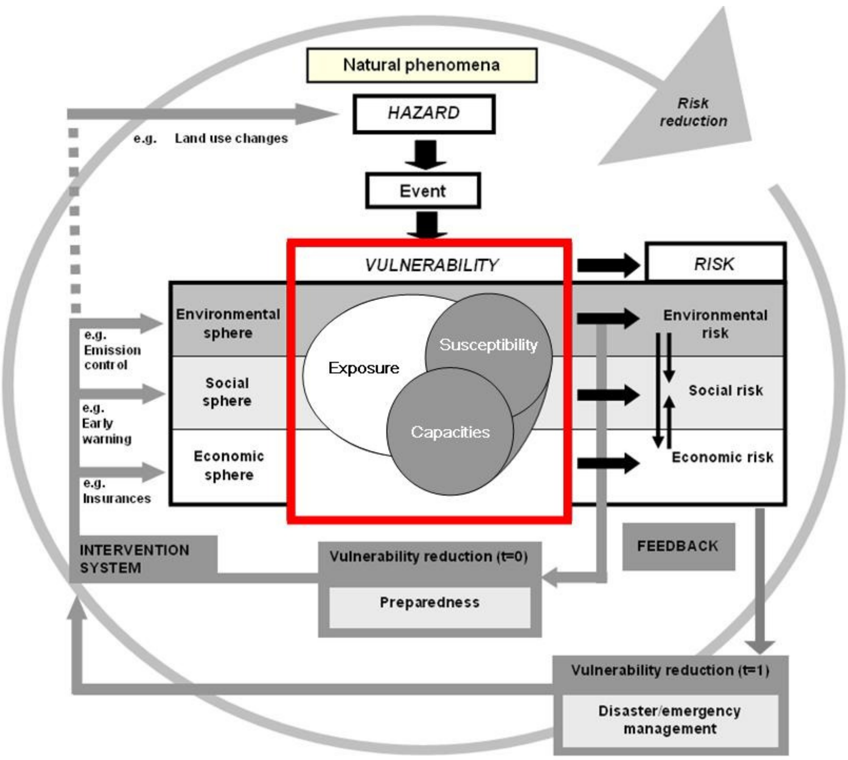


Figure 6. BBC framework with red highlighting of the main focus of this study
Source: modified after Bogardi / Birkmann 2004 and Cardona 1999/2001, as cited in Birkmann 2006, red box highlighting by the author

The BBC framework puts the main analytical components of vulnerability into focus for an assessment. These three components, exposure, susceptibility and coping capacity, provide the main entry and structuring points for the development of vulnerability indicators in this study. The main focus lies in this study on the assessment of the social component of susceptibility and social vulnerability. Indicators are linked to distinct objectives and context (Birkmann 2005: 3). Both objectives and context are provided by the BBC framework.

For the purpose of this study, the assessment of the vulnerability of the social sphere is of main interest. The social sphere is nested within the environmental sphere and is also deeply interlinked with the economical sphere (see the red box highlighting in **Figure 6**). However, the aim of this study is to analyse how a focus on the social aspects other than on economical and environmental aspects contributes to knowledge of the overall vulnerability of the population. As outlined in the previous chapters, economical and environmental aspects are different foci of research. The social vulnerability assessment focuses on aspects of potential weaknesses and also capacities of the human population. The BBC model displays risk as the outcome of a chain of hazard and vulnerability. This implies that vulnerability cannot be understood without taking into account the specifics of the hazard context.

This means that indicators for social vulnerability have to be selected to be relevant to a hazard context. For example, GDP can not be taken as a general measure, only with a commented relation to river-flood related vulnerability. On the other hand, the BBC model shows the distinction of hazard analysis as being a different field from vulnerability analysis. The outcome of both hazard and vulnerability results in specific spheres of risk being created. For the purpose of this study, it is interesting to identify how the social components of susceptibility together with exposure construct a certain vulnerability to the population per county. In this case, the 'social vulnerability' component will be assessed by combining a Social Susceptibility Index, including capacities to reduce this susceptibility, with exposure information. Within this study, the contribution of the social parameters is in the centre of interest, yet, naturally, the term 'social' is fuzzy, since certainly the economy and also the environment as many argue, are socially constructed or, at least heavily influenced by society. This study is focusing only on the social vulnerability aspects, since this study is set in a larger project context where the other project partners will provide in-depth information about environmental vulnerability, economic damage and hazard estimations (project DISFLOOD, see Section 6.1).

The steps in creating the Social Susceptibility Index following the BBC framework are:

- The identification and definition of the goal of this study: the detection of spatial patterns of vulnerability for the whole area of Germany at county-level. Identification of the role of social vulnerability in the construction of risk
- Scoping: Domain of research is the population per county. The target audience is scientists and decision-makers dealing with disaster risk.
- Temporal and spatial spans: annual data at county level to enable a snap-shot of the current vulnerability conditions. This serves as a starting point for monitoring and risk reduction.
- The context setting of hazard and different spheres in which vulnerability takes place. The display of interlinkages between the spheres. The hazard – vulnerability – risk chain
- Identification and selection of the set of indicators regarding exposure, susceptibility and capacities (see in Chapter 4)
- Aggregation and validation of a Social Susceptibility Index (see in Chapter 4)
- Integration of susceptibility with exposure into a vulnerability index (see in Chapter 4)
- Synthesis of how the results reflect on the concept (see in Chapters 4 and 5)

Table 4. Indicator development as based on the BBC framework

Goal	Disaster risk reduction
Target group	Scientists and decision-makers dealing with disaster risk
Focus	Social sphere of vulnerability
Components of analysis	Exposure, susceptibility and capacities
Elements	The population per county
Context	Hazard: river-floods
Research area and scale	German counties
Point in time	Before the next flood event

The indicators are measures of the components (exposure, susceptibility, capacities) of social vulnerability. The index is the aggregated form.

4 Vulnerability Assessment

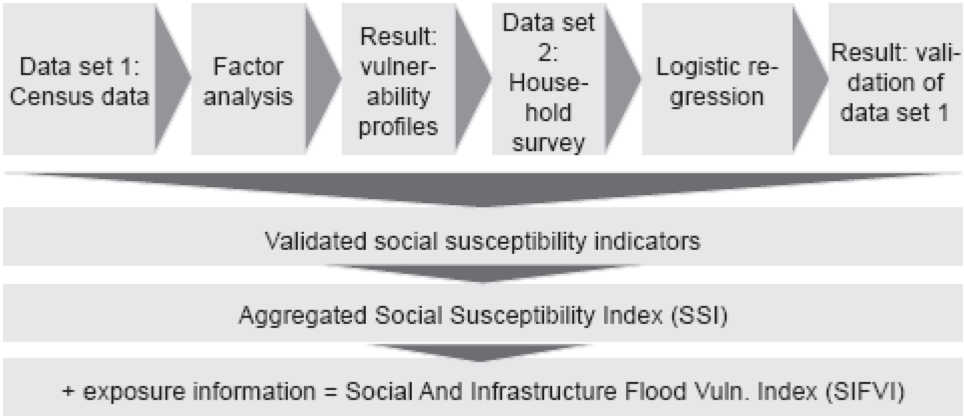


Figure 7. Structure of Chapter 4

Chapter 4 applies the theoretical concept of vulnerability (Chapter 3) on the basis of the findings about the study area of Germany (Chapter 2). The technical aim of the vulnerability assessment is the creation of a Social Susceptibility Index. This index is based on susceptibility profiles of the population per county. These profiles are derived by factor analysis of census data. An independent second data set is used for the validation of these susceptibility profiles. The results are susceptibility indicators that are aggregated to an index. By adding exposure information, a Social and Infrastructure Flood Vulnerability Index is created after the BBC framework in Section 3.2 (**Figure 7**).

4.1 Objective

The objective behind the social vulnerability assessment in the context of river-flooding is to identify and to profile potential social vulnerability in Germany. The input parameters to this index are selected after literature review and theoretical considerations as outlined in the previous chapters. The selection criteria and thresholds are explicitly developed in the river flood context, for example capturing elderly people above a certain age as vulnerable due to increased fragility. The created index can be principally applied to all potential flooding areas in Germany, to some extent even for coastal areas. Developing vulnerability indices at sub-national level is a common approach that is increasingly applied in other countries, like the United States of America (Clark et al. 1998, Cutter et al. 2000, Wu et al. 2002, Chakraborty et al. 2005, Olfert et al. 2006, Rygel et al. 2006, Kleinosky et al. 2007, Yarnal 2007) the United Kingdom (Tapsell et al. 2002), Spain (Weichselgartner 2002), Latin America (Hahn et al. 2003, Cardona 2005), Australia (Dwyer et al. 2004) the Philippines (Acosta-Michlik 2005) or generally for regions worldwide (Nakamura et al. 2001). In Germany there are yet only few attempts that either capture only one federal state (Kropp et al. 2006) or reduce social vulnerability to very few variables (Meyer et al. 2007). There is still no satisfying profile of social vulnerability or sub-national index map for the whole territory of Germany. This gap is to be filled by the Social Susceptibility and Social Vulnerability Indices for River-Flooding.

The application area of this assessment is the whole territory of Germany, with the aim of discerning sub-national regions. Counties were chosen as units for the sub-national level of analysis for several reasons: a) counties are relatively homogeneous in size in comparison to municipalities and postal code areas, b) disaster management as well as many other political processes are organised and supervised at the county level, c) the objective to provide an overview of regional patterns with regard to large-scale flood events can be provided best at county level, d) a sufficient number of variables is available by federal statistical data, e) counties correspond to the designated European administrative unit NUTS3. This enables to transfer the approach to other European countries, f) counties are as administrative units readily understood by decision-makers and g) Government and Reinsurance implement commissions assess damage caused by floods on county-scale (Deutsche Rück 1999: 18). Furthermore, the county level was found as an interface for combining this study's vulnerability assessment with the other project partners of the DISFLOOD project (see Section 6.1). It also enables multi-scale verification with local studies carried out at the partner institutions and at UNU-EHS (Fekete et al. 2009).

4.2 Social susceptibility per county

Susceptibility describes the general weakness of in this case the human population per county towards stresses like natural hazards. Susceptibility is one of the major components of social vulnerability. Although several characteristics of susceptibility are valid for several natural hazards, for the purpose of this study, the specific susceptibility towards river-floods is analysed. The advantage of this approach lies in the applicability for all regions in Germany. At the same time, there are not only weaknesses, but also specific capacities to reduce the susceptibility, which are also captured.

4.2.1 Data

The data used are standard census data of the Federal Statistical Office in Germany. The Federal Statistical Office releases demographic statistics of all counties annually. This enables an annual updating of the index and continuous monitoring for longitudinal studies. The data of variables like age comes in classes of age groups, per gender, unemployment sub-classes, etc. The used data set, released in the middle of 2007, covers 439 counties and contains 33 categories with around 1100 variable classes from the end of 2004 (Destatis 2006a). The Federal Office for Building and Regional Planning (BBR) releases the same data set in a convenient end-user format (BBR 2007). This data set released in mid-2007 contains 800 ‘indicators’ of 23 categories of data from the end of 2004. At finer resolution some data is available for municipalities, however for a significantly reduced number of categories (only 12). For example, data on medical care or education is not available on municipal level (Destatis 2006b). Single categories have data gaps and could therefore not be used. The range of available data and the level of resolution are subject to data protection laws. Therefore, income and ethnicity are available only at county level although the data is collected at a finer resolution. The data and sampling can be regarded as very reliable, since federal institutions conduct the sampling with long experience using a standardised methodology. The number of counties and especially municipalities is changing throughout the years and hence, some manual data checking is unavoidable. Especially in the interplay with GIS data on administrative boundaries, the comparison of the number of counties and the harmonisation of ID numbers need careful manual revision. The administrative boundaries are provided by the Federal Agency for Cartography and Geodesy (BKG 2007) as GIS files. The number of 439 counties encompasses all rural counties and city counties in Germany.

The terminology used for discerning the different steps of creating the indicators and the final index progresses from data – variables and sub-variables – single indicators to a composite index. The artificial term sub-variable stands for sub-classes or sub-categories of variables and is used consequently to avoid confusion.

Before running statistical analyses, the **variable selection** has to follow certain selection criteria and goals of measurement (Nardo et al. 2005, see Section 3.2). **Table 5** summarises the chosen variables and arguments for susceptibility and capacities. Arguments for and against the selected indicators are taken after literature sources as included in **Table 3**, after considerations in **Table 7**, the review of social vulnerability findings in Section 2.4 and Annexes 1 & 3. The objective of the following explorative factor analysis is to find whether the single variables can be grouped to certain social profiles. Main topics of interest that are to be analysed on potential linkages are age, gender, ethnic background, education and income.

Table 5. Analytical categories and assumptions on the explanation of the variables

Main categories of variables	**Assumptions of social vulnerability**
FRAGILITY	
Age	Susceptibility: Physical fragility and dependency of very young and very old people Capacities: More experience and knowledge of elderly people
DEPENDENCY	
Special needs groups	Susceptibility: Handicapped people and persons in need of medical care are highly dependent on the help and assistance of other people
Gender	Susceptibility: Women in general and especially single mothers have lower income resources Capacities: Females have family and take over responsibility
KNOWLEDGE	
Education	Susceptibility: Linked to income groups Capacities: Could show level of knowledge or access to news
Ethnical background (Foreigners)	Susceptibility: Language problems for understanding flood warnings, less included in flood preparedness institutions Capacities: Own networks, neighbourhood help
INCOME RESOURCES	
	Low income Susceptibility: Precarious income situation Capacities: Less financial resources for private protection measures or insurance
Income (/Job qualification)	*High income* Susceptibility: More values to lose, less neighbourhood help Capacities: More financial resources for private protection measures or insurance

Additionally to the social group variables, measurable physical contexts like infrastructure variables are included in the factor analysis (**Table 6**). The purpose is to show relationships of certain social profiles to certain infrastructure or regions. It is further investigated, whether the social groups bear relations to the economic potential or demographic development of a region.

Table 6. Second set of variable groups containing context variables

Measurable context	**Social vulnerability context**
Medical supply	Major capacity to reduce mortality and health problems
Urban – rural context	Capacities like disaster management institutions higher in urban areas More surface sealing in urban areas = hazard aggravation. More social focal points in urban areas (see also Fekete 2009a).
Building or apartment type	Bigger apartments or single family homes are more related to higher income and home-ownership which means more financial resources and awareness towards private preparedness measures like insurance or retrofitting
Potential of the region / county	Economic prosperity of a region as a capacity in terms of financial resources for flood protection measures. Future development of demographic composition like ageing of the population as a susceptibility factor

The selected variables are to show the vulnerability of a county, as a profile of typified demographic profiles, settlement patterns and infrastructure information. It is not a target to capture profiles of single individuals or buildings at this level. Therefore, variables like the number of unemployed people per county point at general characteristics of the county (**Table 7**). While many unemployed individuals might not suffer from financial shortcomings, this is however a most likely assumption for the group of unemployed people per county.

Table 7. Variable matrix with presumed direction of each sub-variable for or against susceptibility

	Sub-variables	**Physical fragility towards mortality or severe health impact**	**Dependency on medical assistance, children to supply for, on welfare and supply**	**Experience, knowledge, awareness, language skills**	**Financial resources for private preparedness measures like insurance or retrofitting**
Resulting predominating direction of susceptibility: increase: -, reduction: +, neutral: o			s = higher susceptibility than average; c = predominant capacities		
Age variables					
-	Residents below age 6	s	(s)	s	s
-	Residents from age 6 to 18	(c)	s	s	(s)
o	Residents from age 18 to 25	c			(s)
+	Residents from age 25 to 30	c			
+	Residents from age 30 to 50	c	(s)		(c)
o	Residents from age 50 to 65			(c)	(s)
-	Residents age 65 and older	s	s	c	(s)
-	Dependency ratio age 0-15		s	s	(s)
-	Dependency ratio age 65+	s	s	c	(s)
Dependency variables					
-	Persons in need of care	s	s		
-	Handicapped unemployed ratio	s	s		s
-	Female sex		s		(s)
+	Male sex		c		
Education and knowledge variables					
-	Graduates without Hauptschule degree			s	s
(-)	Graduates with Hauptschule degree			(s)	(s)
o	Gymnasium pupils				
+	Graduates with high school graduation				c
+	University students			(c)	c
-	Foreigners			s	
Income resources variables					
+	Income per hh				c
-	Unemployment				s
-	Females unemployment		s		s
-	Foreigners unemployment			s	s
-	Young people unemployment		s		s
o	Elderly unemployment			c	s
-	Long term unemployment		(s)		s
+	Female employed		(s)		c
+	Foreign employed			(s)	c
o	Low qualification employed				
+	High qualification employed				c
-	Foreign females		s	(s)	
-	Social welfare recipients				s
-	Female social welfare recipients		s		s
-	Foreign social welfare recipients			s	s
-	Rent subsidies				s
-	Youth social welfare recipients				s

	Sub-variables	Physical fragility towards mortality or severe health impact	Dependency on medical assistance, children to supply for, on welfare and supply	Experience, knowledge, awareness, language skills	Financial resources for private preparedness measures like insurance or retrofitting
Resulting predominating direction of susceptibility: increase: -, reduction: -, neutral: o			s = higher susceptibility than average; c = predominant capacities		
Medical care variables					
+	Doctors		c		c
-	Residents per doctor		s		(s)
+	Hospital beds		c		c
Urban – rural type variables					
-	Built area per undeveloped area				
c	Open space				
-	Population per settlement area				
+	Rural population			(c)	
o	Urban centre closeness				
+	Building land prices				c
-	Commuters in				
Building type / living conditions variables					
c	New apartments				c
+	One and two family homes			(c)	c
-	*Multi family homes (variable was corrupt)*				s
-	Small apartments				s
+	Big apartments				c
-	Persons per room		s		s
-	Persons per apartment		s		
+	Living space pp				c
-	Persons per hh		(c, s)		(s, c)
+	Single hh		c		(s)
-	New residents			s	
Potential of the region / county variables					
-	Municipality debts per resident				s
-	Tourist overnight stays		(c)	s	s
-	Key funds allocation				s
+	Fixed investments				c
+	GDP per labour force				c
+	Regional population potential (=contact potential)			c	c
o	Residents per workplace				c
o	Value added by primary sector				
o	Voter participation (federal parliament elections)			(c)	
-	Elementary schools per resident		s		
-	Day-care centre		s		
-	Rehabilitation centres per Resident		s		
-	Medical care centres	(s)	c		
-	Population projection age 0-20	s			
+	Population projection age 20-60	c			c
-	Population projection age 60+	s			

The overview table on the variables used for the factor analysis (**Table 7**) arranges each variable regarding the categories susceptibility and capacities. The sub-categories fragility, dependency, knowledge and income resources guide the analytical scrutiny of gathering arguments for and against the indication of susceptibility by these variables. These arguments are based on the analysis of evidence on social susceptibility from other studies (Section 2.4), literature review (Annexes 1 & 3) and interpretations of the author. Hence this compiles only a preliminary list of assumptions for an exploratory study. The reasoning follows established argumentations of the federal offices concerning the general demographic indication potential of the variables (detailed documentation in INKAR 2006). However, for the context of this study, these argumentations are only treated regarding the context of deficiencies and advantages of the demographic indications towards river floods. This implies that for example, the variable *new residents* is a negative measure of increased susceptibility although in the usual context of demography this variable indicates a positive measure of increased attractiveness of a region. The negative indication is given due to an assumed average deficiency in local knowledge about river floods and lack of involvement in community preparedness. When the indication is found weak, it is put into brackets. The extreme left column shows the resulting overall positive or negative indication of each variable regarding susceptibility (Resulting predominating direction of susceptibility: increase: -, reduction: +, neutral: o). The variable *tourist overnight stays* is difficult to interpret; on the one hand it shows the positive economic attractiveness of a region, on the other hand this economy is dependent on the tourists. At the same time, this indicator indicates that a high number of tourists is located in a potential disaster area. In case of a disaster the tourists typically have less local knowledge, but at the same time possess a greater flexibility to abandon the place of stay.

The number of sub-variables differs, for example, there are eight sub-variables of age groups but only one for income. The reason is that there are less sub-variables of income available. For social weaknesses relatively many variables were chosen, for example, unemployment, rent subsidy and welfare recipients, although it is quite likely from the beginning that they are highly correlated. However these variables were included on purpose, since the aim was to find as many linkages of these indicators describing social difficulties to the other variables like age or education as possible. In many cases the opposites of the ends of a spectrum are chosen, for reasons of enabling a linkage of positive and negative indications. For example, the variable *doctors per total population* is measuring quite the same pattern as *residents per doctors*. But the indication of a higher numbers of doctors is a positive indicator and related to other groups of socio-economic strengths, while the higher number of residents per doctors is linked to socio-economic weakness groups.

Standardisation: Within the harmonisation step, ratios are built for certain variables like the absolute number of unemployed people per total population. The variables are all interval scaled, no categorical or nominal variables are included. The term standardisation (=normalisation) is used for transforming these harmonised values into equal intervals from zero to one. Population characteristics like unemployment or age sub-variables are harmonised as ratio per total settlement area of the county and not per total area of the county in order to enable the best possible precision from the data. There are contrary procedures whether harmonisation and standardisation steps are conducted before (Bühl and Zöfel 2002: 465, Schneiderbauer 2007: 54) or after the PCA and / or factor analysis (Nardo et al. 2005). In a trial phase, all three versions, raw data, harmonised and additionally standardised data to equal ranges (zero to one) were computed. The resulting factors differed (Annexe 4). Some variables switched from the first to the second factor, while the overall picture did not change substantially.

The data is harmonised first for enabling a certain comparability of the counties which do not have a uniform spatial coverage of settlement area. For example, the total number of unemployed people is set into relation to total population per county. With this step of harmonisation, a rural county is not automatically lower in the unemployment profile compared to a large city county. Since the harmonisation step builds variables with a certain content of argumentation, this step is performed before the factor analysis. The data set INKAR 2006 (BBR 2007) is selected since it already contains most variables of interest of the federal statistics and has already a standardised harmonisation applied. The documentation of INKAR 2006 provides an overview on each variable and its harmonisation (BBR 2007). Only the variables *male gender, voter participation, municipality debts and unemployed handicapped people* are added from the data set of Statistik Regional (Destatis 2006a) and are harmonised accordingly to the data set by dividing per total population per county.

One form of standardisation is already built into the procedure of factor analysis (SPSS 14.0). This is but one argument not to perform an additional standardisation step prior to the factor analysis. The standardisation step which puts the variables to equal ranges is performed after the factor analysis to enable an equal range summation of the variables for the creation of the indicators. The minimum-maximum technique scales all variables to a common base and to an identical range (Cardona 2005: 157). Standardisation (normalisation) can be conducted by building percentages or by using z-scores (Simpson and Katirai 2006: 3). Equal ranges form zero to one are selected as a conservative approach, since no reasons for highlighting extreme values (as in z-scores) were found.

4.2.2 Statistical analysis

The scope of this factor analysis is to extract profiles of social groups regarding certain characteristics like income, gender or age that can be linked to a certain extent to measurable variables like building type, urban or rural context, and medical care. The aim of using factor analysis as a method lies in variable reduction in order to derive a set of variables that summarise social susceptibility characteristics. Additionally, underlying structures of interdependencies between variables can be extracted to build a social susceptibility profile.

Methodology: Factor analysis is a multivariate analysis technique used to identify information packaging considering the interdependencies between all variables (Bernard 2006: 495). The factor analysis is carried out in SPSS version 14.0 with a Principal Component Analysis for data reduction and identification of variable groupings. The methodology of the factor analysis follows standard procedure (e.g. Nardo et al. 2005). First, the principal component analysis aims at finding a linear combination of variables that accounts for as much variation in the original variables as possible. A Varimax rotation with Kaiser Normalisation is applied to the component matrix in order to ease the interpretation (Schneiderbauer 2007: 55) by rotating the axes of the components perpendicular to each other. This step places the respective components as much apart from each other as possible. The extracted communalities are all above 0.5 which indicates that the extracted components represent the variables well. For the interpretation, only eigenvalues greater than one are regarded and absolute loading values below 0.30 suppressed (Nardo et al. 2005: 40, 43, Bühner 2006: 200, 211, Bernard 2006: 677). The eigenvalue is the standardised variance associated with a particular factor. The scree plot serves as another criterion to limit the number of factors. The factors on the steep slope up to the 'scree elbow' in the curve are especially able to explain the most of the data (**Figure 8**).

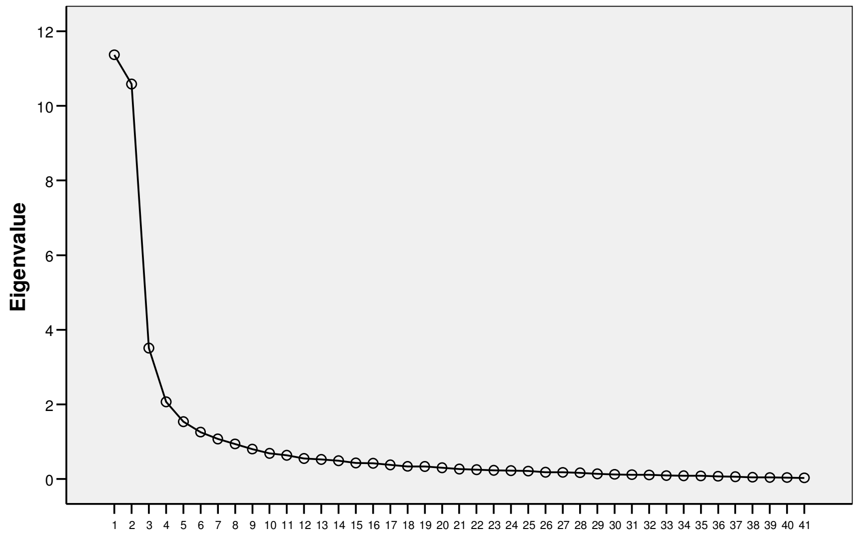


Figure 8. Scree plot of the factor analysis showing the eigenvalues (y-axis) explained by the resulting factors (x-axis)

The factor analysis follows the principle of variance maximisation, wherein those factors are sought-after that explain most of the variance of all items (Bühner 2006: 182). The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) of 0.905 indicates that the variable selection is suitable for factor analysis (Annexe 5). The KMO explains the proportion of variance in the variables that might be caused by underlying factors. KMO-values above 0.60 indicate an acceptable level, and from 0.80 a good level of compatibility of the variables with the test (as cited in Bühner 2006: 207). The value below 0.05 of the Bartlett's test of sphericity rejects that the variables are unrelated and therefore unsuitable for structure detection (Annexe 5).

Pre-processing procedure: First, a full-model approach is carried out containing all variables and a consequent stepwise exclusion, as this is an exploratory approach. Starting with single variables and exploring how stable the pattern is after adding other variables is found problematic in this context. That is since it is not one factor that is mainly the concern, but at least eight categories like age, income, education, ethnic background, gender, urban or rural context, individual house or apartment style and medical care supply. Selecting one category to start with implies a priori judgements and selection biases.

After the factor analysis is carried out, a final set of variables with a stable pattern establishes, and explanation patterns of the correlations are analysed (**Table 9** further below). The factor analysis is repeated, this time stepwise in the other direction, starting with only age variables, adding all fragility variables, then the dependency variables, then experience and knowledge variables, then financial variables and finally exposure variables. Up to the third category, experience and knowledge, the patterns develop slowly, are stable and the KMO increases to over 0.70. The same patterns as in the stepwise exclusion procedure are found which supports the validity of these resulting components.

Certain sub-variables like *unemployed females, female social welfare recipients* etc. are removed after trial runs as they distort the factors. The reason behind is that these sub-variables are mainly correlated to the *female gender* variable. Finding this correlation is not the target, rather finding correlations of female gender to other social groups. For the same reason *unemployed foreigners* and other sub-variables of unemployment are excluded. However, the major variables like *females* or *foreigners* are still included.

From initially 69 variables, 41 are used on the factor analysis, while 28 are excluded due to various reasons. Excluded variables that are stepwise excluded because they are sub-variables of a latent main variable:

- Female unemployment
- Female social welfare recipients
- Female university students
- Foreigners unemployment
- Foreign vocational trainees
- Foreign pupils
- Foreign high school students
- Foreign social welfare recipients
- Foreign university students
- Unemployed young people
- Unemployed elderly
- Long-term unemployment
- Young social welfare recipients

Excluded variables that are redundant or can be explained by similar variables

- Dependency ratio of the 0-15 year old
- Dependency ratio of age 65 and older

Excluded variables that are the contrary to a second variable

- Commuters out
- Moved away

The anti-image correlation matrix (= the individual KMO statistics) reveals that some variables like the age sub-variables are all highly correlated. No variables have to be excluded to the criterion of the measure of sampling adequacy (MSA), since the values on the diagonal of the anti-image matrix are all above 0.6, which is regarded sufficient to show that each variable fits the factor (Backhaus et al. 2006: 310). However, those variables with off-diagonal correlation values of 0.5 and more are consequently excluded.

- Residents from age 6-18
- Residents from age 18-25 (has no directed assumption of susceptibility and can therefore be easily excluded)
- Residents from age 50-65 (has no directed assumption of susceptibility and can therefore be easily excluded)
- Male gender (is the opposite of female gender)
- Multi-family homes (is the opposite of one and two family homes)
- Single households (is contained in persons per household)
- Doctors (is the opposite of residents per doctor)
- Built area per undeveloped area (is highly related to population per settlement area)
- Big apartments (is the opposite of small apartments)
- Population projection age 20-60

After the first exclusion of values higher than 0.5 the anti image matrix still reveals three variables with values higher than 0.5. However, they are not excluded since they contain important information about social susceptibility. Two of the variables belong to age groups; *residents aged 65 and older* and *population projection of age 0-20*. Especially the elderly group but also the projection of the very young are key information on social susceptibility and can not be discarded. The third variable, *commuters*, is correlated to a value-loading of 0.5 with new residents. Both variables indicate different aspects of susceptibility (see **Table 7**) and therefore should not be excluded. Commuters are potentially vulnerable due to interruption of traffic lines while new residents are vulnerable due to lack of local experience, for example.

4.2.3 Results

The cumulative rotation sums of squared loadings of the first three factors together explain 59.0% and seven factors explain 76.6% of the cumulative variance (**Table 8**).

Table 8. Variance explained by the components after the PCA and the rotation

Com-ponent	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	10.700	26.096	26.096
2	9.057	22.091	48.187
3	4.448	10.848	59.035
4	2.228	5.434	64.469
5	1.938	4.727	69.196
6	1.880	4.586	73.782
7	1.147	2.798	76.580
41	…	…	…

Extraction Method: Principal Component Analysis.

The value loadings are compared per component in the rotated component matrix. Positive values comprise one group of variables in the components while the negative loadings represent another group. The two groups differ either in one or more distinct variables that logically belong to ends of a spectrum, for example high income versus high unemployment. Therefore, the two groups within a component represent two sides of the coin of susceptibility. The groups can be interpreted and named according to dominant variables within that group with a high value loading. Still, all variables in each factor are considered in the interpretation.

Table 9. Rotated component matrix of the factor analysis showing the computed value loadings

Input variables with presumed direction towards susceptibility: *- more vulnerable*, + more capacities	**Component**						
	1	**2**	**3**	**4**	**5**	**6**	**7**
- Residents below age 6		0.773	-0.423				
+ Residents from age 30 to 50			-0.850				
- Residents age 65 and older		-0.318	0.882				
- Persons in need of care			0.586			0.377	
- Handicapped unemployed		0.629					
- Female gender	0.632		0.545				
+ Income per hh		0.767			-0.343		
- Unemployment		-0.830	0.330				
+ Female employed	0.821						
+ Foreign employed		0.705					
+ High qualification employed	0.737	-0.307				-0.329	
- Foreign females		0.828					
- Social welfare recipients	0.433				0.655		
- Rent subsidies		-0.811					
- Graduates without basic education		-0.415			0.380		0.540
+ Graduates with high school graduation	0.740	-0.337					
+ University students	0.719						-0.454
- Foreigners	0.597	0.618					
- Residents per doctor	-0.829						
+ Hospital beds	0.707					0.348	
+ Rural population	-0.724			0.303			
- Population per settlement area	0.833					-0.358	
+ Open space	-0.735				-0.383		
+ Building land prices	0.634	0.484					
- Commuters in	0.734						
+ New apartments		0.350	-0.681				
+ One and two family homes	-0.819						
- Small apartments	0.824			0.378			
+ Living space pp	-0.351	0.583				0.444	
- Persons per hh	-0.756		-0.376				
- New residents	0.697	0.340	-0.369				
- Municipality debts per resident					0.567		
- Tourist overnight stays				0.904			
+ GDP per labour force		0.637					0.396
- Key funds allocation		-0.800					
+ Fixed investments	-0.375	-0.613			-0.359		
- Day-care centre		-0.866					
- Rehabilitation centres per Resident				0.840			
- Elementary Schools per Resident	-0.649						
- Medical care centres			0.451			0.618	
- Population projection age 60+		-0.736	0.580				
Interpretation:							
Positive value loadings	Urban	Young, income, foreigners	Old, fragile	Tourism	Welfare, debts	Care centres	Low education
Negative value loadings	Rural	Financial deficiencies	Mid-age, home owners				
Percent variance explained	26.1%	22.1%	10.9%	5.4%	4.7%	4.6%	2.8%
Factor name	**Regional conditions**	**Socio-economic conditions**	**Fragility**				

Abbreviations: hh = household, pp = per person. Varimax rotation, PCA, N = 439

4.2.4 Discussion

The factor analysis of an input of 41 variables uncovers seven latent factors that describe relationships between all variables to 76.6% of the cumulative variance (**Table 9**). From these seven factors (or components), only the first three factors contain more than two loading values that get marked per column (**Table 9**). Marked are those values per variable which load highest within the seven factors matrix. The value loadings are usually displayed as sorted after the highest value loadings in each component. No sorting is applied here in order to avoid the impression of a logical hierarchy which should not be interpreted from this explorative approach. Value loadings below 0.3 are suppressed and not visible, since they do not represent a strong explanation of the variance. The absolute value loadings with a precision of three positions after the comma might be misleading. Factor analysis contains a lot of uncertainty and subjectivity in the selection process. Therefore, one position after the comma is sufficient for the precision of interpretation. This is recommendable, since only minor modifications of the input selection or standardisation process lead to shifting positions within the matrix of the highest loading values per variable. Considering only one position after the comma reveals that for example, the variable *foreigners* is as much in component 1 as it is in component 2, with a value of 0.6. Foreigners are related to the regional conditions as much as to the socio-economic conditions factor. The resulting matrix can therefore never be considered as definite. It is only an exploratory suggestion of groupings and patterns. In several intermediate steps the same patterns of variable groupings could be observed. They were relatively stable and support the interpretation of this rotated matrix.

The **first factor** is named **regional conditions** because the variables can logically be related to either more urban or rural environments. For positive value loadings, *population density per settlement area* is the highest loading value, followed by *small apartments, employed females* and *graduates with high school graduation*. This urban environment is also associated with *hospital beds* as a sign of density of medical care. Following the arguments outlined in **Table 7**, no univocal picture of increased susceptibility can be framed. The variables with positive argumentation for predominant coping capacities of urban environments prevail, but with six positive versus five negative variables this is no clear profile. Especially when considering that the variable *foreigners* can also be associated with component one, adding one more negatively assumed variable.

The profile of the positive value loadings in component one describes urban environments. It is composed of variables that are positively associated with high levels of education, medical care supply and employment opportunities. It is also characterised by variables that would usually describe the attraction of urban space like *new residents* and *commuters*. However, the latter two variables bear negative assumptions concerning the vulnerability of humans towards river-floods. New residents could on average be assumed to possess less experience with local floods, less local knowledge of preparedness against floods and maybe less networks with neighbours. *Commuters* are dependent on daily access to their work place and may be affected by job interruption. *Population density per settlement area* carries not only attractiveness of job opportunities but also social problems of social segregation and social focal points (Section 2.4). And of course, more population density means more exposure of human beings, more needs in terms of evacuation and emergency shelters. *Female gender* is ambiguous, since females are generally more responsible of taking care of children and infirm people. They are therefore bound to rescue other people than just themselves, and are often financially dependent on their partners or the government. On the other hand, females are more risk averse (**Table 3**, Section 2.4) and more responsibility for other people can also mean more awareness and preparedness. It must be reiterated that there is no intention to stereotype people in this context; the scope is solely on finding general profiles for whole regions like counties. *Building land prices* is also on the one hand very positive, since it indicates high financial resources, for example for retrofitting or other measures. On the other hand, river front properties are often expensive, which attracts the affluent but also increases their exposure.

The profile of the negative value loadings in component one also allows no association with negative profiling of susceptibility. Following **Table 7**, indeed the positive arguments prevail for the six variables that are associated with more rural environments. *Rural population* has less population density and settlement area that is exposed, more *open space* indicates less surface sealing and less surface run-off. The high number of *one and two family homes* suggests more home owners who typically are more interested in preserving their property compared to tenants for example. This implies that awareness as well as more financial resources for private preparedness like insurance or mobile defence measures is likely higher for this settlement type than compared to low income groups who reside as tenants in multi-family homes. However, living on the countryside has some disadvantages in the perspective of a vulnerability assessment as well. More *residents per doctor* and longer distances to hospitals increase susceptibility. The number of *persons per household* is critical to interpret; on the one hand more family members are available for helping each other. On the other hand, larger families often have to share the income sources and have more dependent people like children and elderly to evacuate and supply for. *Elementary schools* provide education; but this makes a region also vulnerable, when this central infrastructure is exposed.

The **second factor**, **socio-economic conditions**, explains a little bit less percent variance (22%) than the first factor (26%). Like the first factor, regional conditions, it bundles a high number of variables which partly explains why these two factors share high percentages of total variance. Contrary to the regional conditions factor however, the factor socio-economic conditions paints a clearer picture of positive and negative direction of measurement.

The negative loadings are related to variables with predominant negative assumptions on susceptibility. The variables *unemployment, rent subsidies* and the high number of *key funds allocation* that are distributed to this type of regions all insinuate financial deficiencies. These financial deficiencies of a county could lead to less investment in technical and non-technical preparedness measures towards floods. While unemployment may not render an individual automatically poor, it is a reliable general indicator for the average income situation in a county. Unemployment is highly associated with the long-term unemployed and the female and foreign unemployed. These are special needs groups that are more dependent on other family members and the government. One might argue that the poor have less to lose, but one might as well argue that the low income groups suffer more from minor cuts and losses. Low income groups are also associated with low education and social focal points. Like for all variables, precise local studies are necessary to verify such assumptions. The only variable thought to represent a positive argument, *fixed investments*, could be related to the high number of *key funds allocation* and therefore misleading for the interpretation. The high number of *day care centres* and the *population projection age 60+* of a disproportional increase of elderly people in these regions all indicate that elderly people are associated with regions of less income. Elderly people are not only more fragile in terms of health but are also more dependent on medical care and financial supply.

The positive loadings of factor two represent the opposite; it is dominated by young age people (*residents below age 6*) and high *income*. *Foreigners* are a strong group, too, which is likely an artefact of the three variables of foreigners in this component. The grouping of the positive loadings can be interpreted as dependent people of up to six years of age, who reside in good living conditions like large *living space per person* and high *GDP per labour force*. Dependent are also the *handicapped unemployed* people. This variable is a surrogate for handicapped people in general, since this data is not available from the federal statistics data sets. The association of foreigners with high income variables was found a steady pattern throughout several trial steps in the factor analyses. This indicates that foreigners are not automatically to be stereotyped as poor, at least not from this factor analysis. The highest loading value in this grouping is *foreign females* who are attributed with a potential lack of language skills, and dependency in terms of caring for children concerning flood hazard (**Table 7**). The variable *foreign employed* typically hints at low wage jobs in general (BBR 2007) which makes this group especially interesting for further investigation. Low income jobs can for example indicate susceptibility to even minor cuts in income.

The **third factor, <u>fragility</u>,** denotes age as a discriminator of physically fit against physically more fragile age groups like the elderly. Only four variables carry value loadings high enough to separate them into the third component. This <u>fragility</u> factor explains about 10,9 percent of the variance, which is only the half of the first two factors, but still the double of the residual four factors in the rotated component matrix. The positive value loadings clearly designate *residents age 65 and older* to be related to *persons in need of* (medical) *care* and nursing assistance. Obviously, this group is also associated with areas of a projected relative population increase of the elderly above 60 years of age. There is also a high relation to female gender, which might be explained by the higher number of females who reach old age, especially in Western Germany. The negative value loadings of the fragility factor indicate people of middle age, *residents from age 30 to 50*. They are related to *new apartments* which could indicate their financial resources and typical time phase for being able to afford a home. In previous trial runs of the factor analysis, this group was also related to male gender and sometimes to persons per household. Generally this group stands for the opposite of physical fragility, which is an important discriminator of survival and evacuation needs in case of an extreme river flood.

Factors four to seven load high on only one or two values and are all attributed with negative explanations in terms of the presumptions of higher susceptibility as denoted in **Table 9**. This is at least partly due to an overall overrepresentation of negatively attributed variables in the selection of this factor analysis. It must be emphasised however, that this patterns remains stable in other configurations of the same data sets even when the ratio of positively and negatively labelled variables (**Table 7**) is equal. This was tested in several trial configurations with variables sets between five and over 60 variables. The main purpose of this factor analysis is to elicit potential weaknesses. Therefore it is justifiable to have factors four to seven included in the factor analysis with only negatively attributed variables. These factors pinpoint additional factors that explain much variance and singular characteristics of susceptibility. The inclusion of more variables that compensate the mere negative susceptibility indication is hampered by an increase of partial correlation values above 0.6 in the anti image matrix.

Factor four contains *tourist overnight stays* as related highly with *rehabilitation centres*. Both variables bear a negative susceptibility indication, since regions with this characteristics are dependent on income by tourism. When tourists stay away due to floods or in flood damage recovery phases, these regions are economically affected. Additionally, a high number of tourists might be a difficult task for evacuation in case of an unexpected sudden onset flood. Likewise, rehabilitation centres increase the exposure potential of people dependent on assistance, medical care and evacuation help. Factor five bundles *social welfare recipients* with *municipality debts*. This indicates financial problems of residents and the government of a county. Factor six contains only one variable*, medical care centres*. These centres are mainly nursing homes which carry a high number of infirm and fragile people. Factor seven is equal to the variable graduates without ‘Hauptschule’ degree. ‘Hauptschule’ is a distinct German type of school like a secondary modern school. The absence of this education level indicates low income resources and low job opportunities (BBR 2007). This variable is also highly related to the income deficiencies group in factor two.

The factors allow for profiling the German counties regarding a general susceptibility to stresses and natural hazards, but most precisely to river floods. These profiles are patterns of social demographic groups that can be identified per county. Therefore this is an excellent tool to compare all counties in Germany by regarding arguments for and against increased social susceptibility to floods. While the argument categories are amendable and extendable, this profile is a starting point for tagging areas of special concern regarding flood vulnerability as determined by the social composition of the population.

4.3 Flood impact assessment

For the purpose of testing the social susceptibility profiles on a real flood event, a second data set is selected. The research question is whether a real extreme flood event reveals some of the potential social susceptibility that is expected from the literature review and the susceptibility factors developed. Due to the lack of data on extreme event evidence in Germany, validation is difficult. Therefore the author is very grateful to the partner of the DISFLOOD project, GFZ, who provided a data set developed from a household survey conducted after the extreme floods of 2002 in Germany. While the scope of this survey is mainly on flood damage characteristics of buildings and properties (Kreibich et al. 2005a), it also deals with flood preparedness and recovery (Thieken et al. 2007). Additionally, the survey captures demographic categories which are of special interest for validating the social susceptibility profiles.

4.3.1 Data

The data set of a telephone survey involving 1697 households affected by the floods in 2002 is provided by GFZ and Deutsche Rückversicherung. The survey is entitled „Flooding in 2002: Damage of private households", GFZ Potsdam und Deutsche Rückversicherung AG, 2003. The survey covered three major regions, the River Elbe and the lower Mulde River; the Erzgebirge (Ore Mountains) and the River Mulde in Saxony; and the Bavarian Danube catchment (**Figure 3**, Thieken et al. 2007: 1020). In each region about the same number of interviews was conducted. For the sample design, the authors provide the following detailed description:

"On the basis of information from the affected communities and districts, lists of affected streets in the investigated areas were compiled. A random sample was generated on the condition that each street should be represented in the data set at least once and that each building should be included only once. Thus, only one household was selected in multiple-occupancy houses, so that the sample is representative for buildings. In total, 11 146 households (with telephone number) were selected. Computer-aided telephone interviews were undertaken using the VOXCO software package by the SOKO-Institute, Bielefeld, Germany, between 8 April 2003 and 10 June 2003. In each case, the person in the household who had the best knowledge about the flood event was questioned. Tenants were only asked about their household and the content damage. To complete the interview, the building owner was questioned about the building and damage to it. In total, 1697 interviews were carried out; on average, an interview lasted 30 minutes." (Thieken et al. 2007: 1021)

In order to find evidence whether the presumed social susceptibility concept and -profiles play a role in the outcome of disaster, a testing category has to be identified. The questionnaire data provide some categories that compare the damage to the building and the damage to the household properties of the affected households. This test category is not used because economic damage evidence alone might be misleading concerning the whole range of social susceptibility as outlined in Chapters 2, 3 and Section 4.2. Furthermore, this analysis is the domain of the original authors and has been analysed extensively (Kreibich et al. 2005a, Kreibich et al. 2005b). For the purpose of this study, the question 'Did you have to leave your home due to the flood?' is identified as a much better discriminator of people severely affected by the flood in terms of social vulnerability. This question is not focusing on the economic perspective only, but captures a broader scope of exposure, susceptibility and capacities. The people who had to leave their home were especially exposed to floods, and had to cope with finding an interim shelter and the recovery phase after the flood. For this they needed financial resources but also social networks like friends and relatives.

A certain amount of those people (N = 765) who had to leave their home, had to seek emergency shelter (N=70). This is an especially interesting sub-group, because it can be assumed that these persons lacked alternative social networks or financial resources. Since the questionnaire contains no questions about the exact reasons for each decision of the single individuals in the survey, these are mere assumptions. They can be however compared to findings on social vulnerability in evacuation groups (Cutter et al. 2003, Chakraborty et al. 2005 and Section 2.4). Therefore, 'people forced to leave their home' and 'people who had to seek emergency shelter' are apt test categories for eliciting different social group profiles. It permits comparing those who had to leave and those who could stay in their homes, despite being affected by the flood.

The third test category is taken from the question 'are you satisfied with the status of damage regulation'. The answers were expressed in a positive to negative range from one to six. This range is transformed into binary coding for enabling bivariate comparison. Indirectly, financial needs and satisfaction with administration are to a certain degree identified by this dependent variable. This type of susceptibility measure therefore complements the other two dependent variables, which capture evacuation needs.

4.3.2 Statistical analysis

The binary logistic regression analysis is a statistical model which is used for predicting a binary dependent variable using one or more independent variables. The dependent variable is the test category for flood impact, for example, whether the people had to leave their home or not. The independent variables are demographic variables like age, income, job situation etc. Both interval and categorical variables can be used, yet categorical variables with more than two parameter values have to be transformed into dichotomous sub-variables (Fromm 2005: 5). Logistic regression analysis is used for explaining differences between groups or for predicting membership of groups. No assumptions on (normal-) distributions have to be met, while multi-collinearity should be avoided and monotony of the variables should be observed (Fromm 2005: 6, 12). The following variables are selected for the binary logistic regression analysis after the theoretical categories in the BBC framework; susceptibility, capacity and exposure (**Table 7**). Three binary dependent variables allow testing this adverse outcome; if people had to leave their home or not, if the people had to seek a public emergency shelter and if the people were content with the damage regulation after the flood. The binary logistic regression is computed in SPSS 14.0 and STATA 10.0 SE.

Selection: First, variables are selected, missing values defined, then cross-tables and correlation are checked. The number of cases per variable is high enough to permit logistic regression analysis (Fromm 2005: 6) and the number of missing values tolerable, except for the variable income. *Income* is a sensitive issue in questionnaires and the high number of no responses is not surprising. Therefore this variable has to be interpreted with care. The ordinal variables like *home ownership, school, job* or *income* are arranged in logical order of the respective sub-variables. This logical order is consistent in the sense that it spans from negatively attributed income or education levels to positively attributed levels. *Job types* however have to be treated with caution. While this ordinal variable is also oriented along a logical order, it would be misleading to attribute absolute negative and positive directions to it. Only those job types present in the data set of the factor analysis are selected. In this case, unemployed persons are of special interest. Also, a *high qualification employees* sub-variable is created from doctors, lawyers, commerce, trade, business and magistrates.

Table 10. Variables and sub-variables for input into the logistic regression analysis

Variable label	**Explanation** phh = per household	**Scaling**	**Min / max values**	**Number of cases**	**Missing values**
independent variables					
age	Age in years	interval	16-95 years	1663	34
gender	Female gender	binary	0; 1	1697	none
school	Education type	ordinal	1-7	1648	49
	1: No degree	binary			
	2: Elementary school degree	binary			
	3: Secondary school degree	binary			
	4: Polytechnic degree	binary			
	5: Technical college degree	binary			
	6: High school degree	binary			
	/: University degree	binary			
income	Income class phh	ordinal	1-6	1351	342
	1: Income of up to 500€ per month	binary			
	2: Income from 500 to 1000€	binary			
	3: Income from 1000 to 1500€	binary			
	4: Income from 1500 to 2000€	binary			
	5: Income from 2000 to 3000€	binary			
	6: Income 3000€ and more	binary			
job	Job type	ordinal	1-13	1629	68
	1: Doctor, lawyer	binary			
	2: Commerce, trade, business	binary			
	3: Magistrate	binary			
	4: White collar employee	binary			
	5: Farmer	binary			
	6: Blue collar worker	binary			
	7: Apprenticeship, student	binary			
	8: Family member, assistance	binary			
	9: Retired	binary			
	10: Home maker	binary			
	11: Parental leave	binary			
	12: Advanced training	binary			
unemployed	13: Unemployed	binary	0; 1		
high_qual_employed	recoded: high qualification employed = sub-classes 1,2,3	binary	0; 1		
pop14	Number of persons under 14 years of age phh	interval	0-5 phh	1697	none
pphh	Persons per household	interval	1-11 phh	1674	23
rooms	Number of rooms per household	interval	1-32	1653	44
ownership	Ownership	binary	0; 1	1697	none
	Tenant, renter		0		
	Owner of the home / house Owner of the apartment		1		
urbanity	Urbanity of the region	binary	1; 0	1697	none
dependent variables					
leave_home	Persons who had to leave their home due to the flood	binary	1; 0	1690 (N yes =765)	7
emergency_shelter	Persons who had to leave their home and seek shelter in public emergency shelters	binary	1; 0	1690 (N yes=70)	7
damage regulation	Persons who express satisfaction with the status of damage regulation after the flood	binary	1; 0	1167 (N yes = 974)	530

Sources: all GFZ / Deutsche Rück 2002, except urbanity calculated by the author

In order to avoid multi-collinearities, only those variables are selected for the regression, which are not highly correlated with each other. The variable ‘persons under 14 years of age per household' (*pop14*) is included additionally to the so named *age* variable. The reason for this decision lies in the limited range of the *age* variable in this data set which ranges only from 16 to 95 years. This is due to the survey methodology, wherein only persons older than 15 years were interviewed as representatives of one household. In order not to omit children which are an interesting group, the variable *pop14* is added as it includes persons younger than age 14. *Urbanity* is calculated according to the definition of rural areas for the respective variable of the first data set of the Federal Offices (BBR 2007). Rural areas are regions with up to 150 persons per km² per municipality. These areas are calculated in the GIS using the federal statistical data. They are added to the second data set as a binary variable (*urbanity*) separating urban from rural areas. The dependent variable damage regulation is transformed into a binary variable from the range of answers from one to six (one = very satisfied, two = satisfied; … six = not at all satisfied).

Table 11. Sub-set of independent variables and sub-variables used for all three logistic regressions with the three dependent variables

Independent variables or sub-variables
age
gender
high_school_degree
elementary_school
income_very_high
income_1000
high_qual_employed
unemployed
retired
pop14
pphh
rooms
home ownership
urbanity

Methodology: The logistic regression is computed for the three binary dependent variables individually. Each dependent variable is analysed with the same pre-selected sub-set of independent variables (**Table 11**). From the set of independent variables a sub-set is selected after the scrutiny of three criteria; whether they are contained in the first data set of the factor analysis as well, whether each sub-variable contains enough cases (Fromm 2005: 6) and whether the bivariate distributions already indicate strong differences. The procedure of selection is documented in Annexe 5. The resulting set of independent variables (**Table 11**) is tested against each of the three dependent variables separately (**Table 13, Table 15** & **Table 17** further below) The aim is to validate as many variables of the factor analysis set as possible.

The quality of the statistical model is analysed by the Hosmer and Lemeshow Test which describes the model-goodness of fit of the input data for values with significance values above 0.05 (Backhaus et al. 2006: 457). The same variables are tested within a linear regression model in SPSS to identify multi-collinearities. Tolerance values above zero and Variance Inflation Factors (VIF) lower than 10 suggest no difficulties with multi-collinearity of the model (Nardo et al. 2005). Outliers that could distort the model are identified by z residuals and removed (**Table 12**). The respective confidence intervals for the variables are observed whether they are either both below or above one, which supports that these independent variables deliver a valid explanation (Fromm 2005: 24). Error margins are indicated by the quality tests described above, or by the confidence intervals. Additionally, Jacknife replication tests (Backhaus et al. 2006: 454) and bootstrapping analyses with 1000 repetitions (Moore and MacCabe 2006: 14-27) are applied for testing the model stability.

Table 12. Data description and model tests of the logistic regression for the three dependent variables

Dependent variable	Cases included; (missing values)	Prediction after running the model; (initial prediction)	removed outliers (exceeding 2 standard deviations)	Hosmer and Lemeshow Test	Variance inflation factor
leave_home	960 (737)	57.0% (50.1%)	0	0.7	2.3
emergency_shelter	958 (739)	95.5% (95.5%)	2	0.6	2.3
damage regulation	765 (932)	85.6% (85.6%)	9	0.6	2.3

The main purpose of the logistic regression is to show whether there exists a significant difference in the independent variables. The independent variables contain demographic susceptibility characteristics (e.g. age of persons) and are checked against dependent variables that contain binary yes / no cases. For example, independent variables like *age* are checked within the full logistic regression model against the dependent variable *leave_home* whether age is a factor that characterises human groups as more vulnerable. The logistic regression provides two types of measurement that are of interest here. First, the regression model indicates which independent variables are significant within the full model; only these are selected for calculating the probabilities. Second, the probabilities calculated for the minimum and maximum values per independent variable predict the direction of impact of the dependent variable. This direction can be positive or negative, meaning that flood impact either rises with increasing values like higher income or is inversely related to it. Only those variables are displayed that are significant for the test.

The probabilities are used here only for the identification of the direction of influence of flood impact. The probabilities are not used for weighting or relative ranking of the variables since this only an explorative approach. Further uncertainty analyses and additional confirmative analyses of flood impact cases would be a prerequisite for justifying the use of exact numerical values for weighting and ranking.

4.3.3 Results

Table 13. Significances and confidence intervals of the independent variables to the explanation of the dependent variable *leave_home*

		95.0% C.I.for EXP(B)	
	Sig.	Lower	Upper
age	.750	.988	1.017
gender	.960	.770	1.316
high_school_degree	.205	.887	1.753
elementary_school	.590	.660	1.266
income_very_high	.631	.752	1.599
income_1000	.601	.706	1.824
high_qual_employed	.468	.588	1.276
unemployed	.691	.668	1.837
retired	.250	.834	2.006
pop14	.637	.762	1.181
pphh	.580	.818	1.119
rooms	.024	.877	.991
home ownership	.019	1.066	2.053
urbanity	.000	1.272	2.261
Constant	.599		

Variable(s) entered on step 1: age, gender, high_school_degree, elementary_school, income_very_high, income_1000, high_qual, unemployed, retired, pop14, pphh, rooms, ownership, urban_rural.

Logistic regression no. 1 for *leave_home*: Table 13 reveals that three variables, *rooms, home ownership* and *urbanity* are significant for the regression model at the 0.05 significance value. The range of the confidence intervals of *rooms* is low, while *ownership* and *urbanity* have a range large enough to expect a strong explanation of difference.

Table 14. Calculated probabilities and confidence intervals for *leave_home*

Variable	P min	P max	Change	95% CI change min	95% CI change max
rooms [2;21]	0.5755	0.2624	-0.3131	-0.5506	-0.0756
home ownership	0.4272	0.5245	0.0973	0.0167	0.1779
urbanity	0.4091	0.5399	0.1309	0.0608	0.201

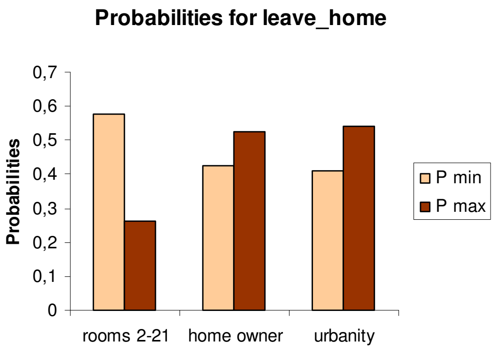


Figure 9. Minimum and maximum probabilities for the dependent variable *leave_home*

From 14 independent variables the number of *rooms*, *home ownership* and degree of *urbanity* are apt to explain the distribution of those who had to leave their home and those who had not (**Table 14** and **Figure 9**). The probability for the dependent variable (*leave_home*, answer 'yes') can increase or decrease for each independent variable. Therefore, the variable *rooms* (number of rooms 2-21) shows an inverse relationship of probability (**Figure 9**). The higher the number of rooms, the lower is the quota of those in the group who had to leave their home. In other words, people living in apartments with fewer rooms had to leave their home more often.

Table 15. Significances and confidence intervals of the independent variables to the explanation of the dependent variable *emergency_shelter*

		95.0% C.I.for EXP(B)	
	Sig.	**Lower**	**Upper**
age	.012	1.010	1.081
gender	.957	.502	1.920
high_school_degree	.480	.272	1.845
elementary_school	.507	.357	1.664
income_very_high	.218	.086	1.748
income_1000	.233	.698	4.386
high_qual_employed	.211	.696	5.149
unemployed	.461	.473	5.210
retired	.620	.484	3.377
pop14	.878	.500	2.248
pphh	.597	.541	1.423
rooms	.961	.841	1.200
home ownership	.003	.175	.707
urbanity	.619	.419	1.678
Constant	.003		

Variable(s) entered on step 1: age, gender, high_school_degree, elementary_school, income_very_high, income_1000, high_qual, unemployed, retired, pop14, pphh, rooms, ownership, urban_rural.

The higher the number of home owners in comparison to tenants the more likely it has been that these households had to leave their home due to the flood. Persons in rural areas (up to 150 people per km²: definition of BBR 2007) are less affected than residents in urban areas.

Logistic regression no. 2 for *emergency_shelter*: **Table 15** reveals that two variables, *age* and *home ownership* are significant for the regression model at the 0.05 significance value.

Table 16. Calculated probabilities and confidence intervals for *emergency_shelter*

Variable	Case	P min	P max	Change	95% CI for change min	95% CI for change max
age	Pr(y=yes|x):	0.0067	0.1785	0.1718	-0.0537	0.3974
home ownership	Pr(y=yes|x):	0.0636	0.0233	-0.0402	-0.0752	-0.0052

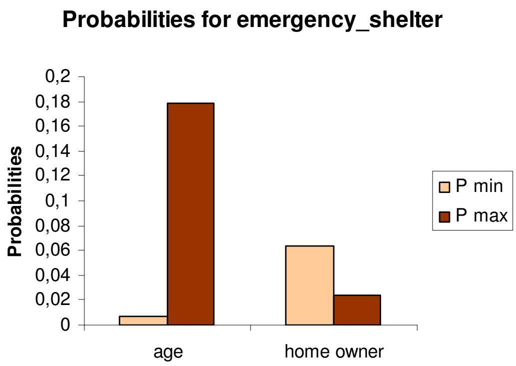


Figure 10. Minimum and maximum probabilities for the dependent variable *emergency_shelter*

From 14 independent variables, *age* (from 16-95) and *home ownership* are apt to explain the distribution of those who had to seek emergency shelter and those who had not (**Table 16** and **Figure 10**). Higher age was a reason to seek emergency shelter. The higher the number of home owners in comparison to tenants the more likely it has been that these households had not to seek emergency shelter due to the flood. This contradicts the prediction direction of ownership in the dependent variable *leave_home*.

Table 17. Significances and confidence intervals of the independent variables to the explanation of the dependent variable *damage regulation*

		95.0% C.I.for EXP(B)	
	Sig.	**Lower**	**Upper**
age	.619	.982	1.030
gender	.623	.726	1.706
high_school_degree	.715	.501	1.606
elementary_school	.019	.325	.905
income_very_high	.459	.431	1.463
income_1000	.605	.421	1.656
high_qual	.413	.665	2.697
unemployed	.020	.221	.881
retired	.183	.316	1.247
pop14	.527	.783	1.614
pphh	.442	.708	1.163
rooms	.229	.862	1.036
home ownership	.683	.516	1.543
urbanity	.645	.710	1.737
Constant	.007		

Variable(s) entered on step 1: age, gender, high_school_degree, elementary_school, income_very_high, income_1000, high_qual, unemployed, retired, pop14, pphh, rooms, ownership, urban_rural.

Logistic regression no. 3 for *damage regulation*: Table 17 exhibits that two variables, *elementary_school* and *unemployed* are significant for the regression model at the 0.05 significance value.

Table 18. Calculated probabilities and confidence intervals for *damage regulation*

Variable	Case	P min	P max	Change	95% CI for change min	95% CI for change max
elementary school	Pr(y=yes|x):	0.8873	0.8102	-0.0771	-0.1453	-0.0089
unemployed	Pr(y=yes|x):	0.8719	0.7502	-0.1217	-0.2457	0.0024

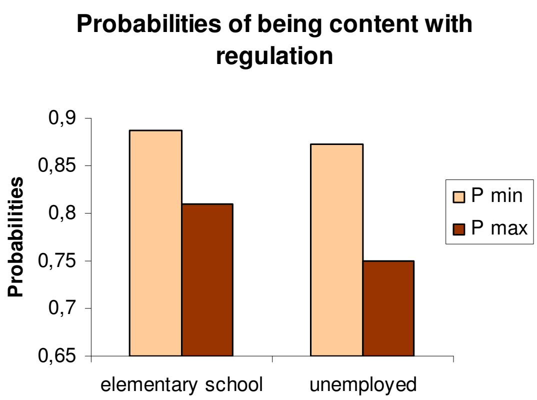


Figure 11. Minimum and maximum probabilities for the dependent variable *damage regulation*

From 14 independent variables, *elementary school* and *unemployment* are apt to explain the distribution of satisfaction with *damage regulation* (**Table 18** and **Figure 11**). Persons with low education background (elementary school or Hauptschule degree) are more dissatisfied with damage regulation. The same observation is made for unemployed people.

4.3.4 Discussion

"Not everything that can be counted counts, and not everything that counts can be counted."
Albert Einstein

Potential: The purpose of the analysis of the questionnaire data is to find evidence of social susceptibility linked to a real flood event impact. For this purpose the independent input variables for the logistic regression analysis are of paramount interest. They are tested against dependent variables that discriminate negative or positive outcomes of the flood impact to affected people. The independent variables and sub-variables are scrutinised by comparing distribution percentages, significance values regarding the usefulness for logistic regression analysis and finally by binary logistic regression of a full variable set model. Some trends can be interpreted from the data and linked to certain assumptions of family type, income groups etc. Since no additional qualitative information is available on the reasons why the people had to leave their home, seek emergency shelter or are satisfied with damage regulations, these interpretations are limited in validity. Due to the lack of qualitative information it seems advisable to focus solely on the outcome of the regression analysis. The following table summarises the outcomes produced by the regression models regarding positive or negative trends towards the dependent variables (**Table 19**). The observations made are confirmed by several trial runs of different compositions of the variables. Additionally, Jacknife replication tests and bootstrapping with 1000 repetitions underscore the stability of the results for the dependent variables *leave_home* and *emergency_shelter*, while *damage regulation* was not stable with the current variable set in the bootstrap test

Table 19. Summarised outcomes of the regression analysis and the according prior analyses

	leave_home		emergency_shelter		damage regulation	
Test scenario	**More affected**	**Less affected**	**More affected**	**Less affected**	**More satisfied**	**Less satisfied**
Binary logistic regression – significances and probabilities at the 0.05 level	home ownership urbanity	rooms	age	home ownership		elementary school degree unemployed

The summarised outcomes (**Table 19**) suggest safe and unambiguous assumptions on five variables regarding increased or reduced susceptibility towards flood impact. The sixth variable, *home ownership,* is ambiguous. Here it is interesting to differentiate between the measurement categories. Home owners are generally more affected by having to leave their home. On the other hand they had to take to a lesser degree the last option of going to public emergency shelters. It seems necessary to differentiate the contexts that the three dependent variables are capturing. While *leave_home* is apt to indicate general exposure, *emergency_shelter* sheds light on special need groups or susceptibility. *Leave_home* therefore differentiates the general population and the spatial context of the region and the dwelling type. Higher age is an indicator when it comes to extreme measures like having to evacuate to public emergency shelters. Satisfaction with *damage regulation* is a measure of the group of people who feel disadvantaged regarding damage regulation. This captures several facets, financial needs, administration problems and perception of the people themselves. Persons with a lower education level and the unemployed seem to have less coping capacities compared to the average of all persons affected by the floods in 2002.

Limitations: The results can serve as a validation basis of the factor analysis and the selection of variables for a social susceptibility index (Fekete 2009b). Of course, at the same time certain conditions and limitations of validation must be emphasised. Although the research area for this questionnaire is relatively large and covers three federal states, it still is difficult to generalise the results for the whole territory of Germany. More case studies are necessary to cover other regions in Germany. The questionnaire contains vital data categories, but was not specifically designed for the purpose of validating a social susceptibility index or the data of this study. Therefore not all variables can be covered for validation.

The choice of the dependent variables is based on the assumption, that the fact that someone has to leave his home or seek emergency shelter is a severe impact. Although this type of measure is used in literature to identify social vulnerability (Chakraborty et al. 2005) it is not sufficiently explored to which extent it reveals social susceptibility or vulnerability in Germany. Therefore, damage regulation satisfaction is additionally chosen to elicit coping problems of an indirect economic, administrative and perception character. The selection of variables, the exclusion of sub-variables and the setting of thresholds is to a similar degree dependent on assumptions and decisions of the author as is the case in the factor analysis. Besides all these necessary disclaimers it is satisfying that the overall picture complies with a great extent to the findings of previous studies in Germany (**Table 3**) and other countries (Annexes 1 and 3) and the grouping of the factor analysis in Subheading 4.2.6. Therefore the directions of impact of **Table 19** are useful to justify the use of the variables that characterise age, settlement and apartment type, education and financial deficiencies for the construction of a social susceptibility index.

4.4 Validation of the social susceptibility factors

The objective behind the validation is to find evidence whether the construction of a social susceptibility index without direct relation to disaster impact or hazard parameters is valid. That means that first, test categories have to be found, which allow probing for revealed social susceptibility. Second, the independent variables that are the input data for social susceptibility indicators have to be checked on validity. Third, the methodology of grouping variables to indicators has to be checked. Only then conclusions can be drawn on the construction of an index composed of the single indicators and the patterns of social susceptibility that are indicated by such an index for spatial regions such as counties.

From 41 variables and sub-variables that are used for input in the first data set (federal statistics) of the factor analysis, nine variables can be directly validated with the results of the logistic regression observations. Nine of 41 variables of the factor analysis are covered by the data set of the questionnaire (**Table 20**).

Table 20. Comparison of the nine variables of the federal statistics with the according variables of the logistic regression

Variables of the logistic regression	Variables of the factor analysis from the first data set
urbanity (urban areas have more than150 persons per km² per municipality)	Population per settlement area
home ownership	One and two family homes
urbanity (rural areas have less than150 persons per km² per municipality)	Rural population
rooms [2;21]	Small apartments
age	Residents from age 30 to 50
age	Residents age 65 and older
unemployed	Unemployment
rooms [2;21]	Living space pp
elementary school	Graduates with only elementary education
Data source: GFZ and Deutsche Rück household survey 2002, urbanity definition after BBR 2007	Data source: Destatis 2006a

The validation procedure comprises two steps (**Table 21**); first the independent variables of the factor analysis (census data) are checked for validity by using the independent variables of the independent second data set and running a logistic regression model. Since the second data set did not capture exactly the same demographic variables, only a few independent variables of the first data set are at the same time available from the second data set (household survey). The logistic regression analysis reveals that six independent variables of the second data set are able to discriminate susceptibility. These six variables capture demographic as well as spatial parameters that are also captured by nine independent variables of the first data set. That means that in the first step, nine variables have been validated as having a significant effect in determining susceptibility.

It would be unsafe to suggest that the full model of 41 variables of the first data set is validated by this process. However, at least nine variables of the first data set can be assumed to describe susceptibility. The remaining 32 independent variables are not significant within the regression model or can not be tested as they are not contained in the second data set. Of course, this does not imply that they cannot be significant within another model or are not meaningful.

Table 21. Procedure of validation

Data	Step 1	Step 2
Data set 1 Data set to be validated: Census data Data set 2 Independent second data set used for the validation: Household survey	Validation of the social susceptibility variables (data set 1) by flood impact analysis (data set 2) = Section 4.3	Validation of the social susceptibility factors (data set 1) by repetition of the factor analysis with the reduced variable set of the census data (data set 1) = Section 4.4

In the second step of the validation (**Table 21**), the factor analysis is repeated with the subset of nine independent variables of the federal statistics. The objective behind this second step of validation is to check whether the factors (or social susceptibility indicators) obtained without any direct disaster-relation are similarly revealed by the reduced set of nine validated variables.

In this second step, the factor analysis is rerun with the nine variables of the federal statistical data that are validated by the results of the logistic regression. The nine variables accord to the six variables of the logistic regression analysis (**Table 19**). The factor analysis test carries a satisfying Kaiser-Meyer-Olkin Measure of Sampling Adequacy of 0.7. The anti image matrix reveals high correlations over 0.6 off-diagonal only for age above 64 years and age 30-50. Three factors with eigenvalues above one show up in the scree plot and these three components explain 78.8% of the cumulative variance (**Table 22**). Each component explains about one third of the total variance in a Varimax rotation with Kaiser Normalisation.

Table 22. Variance of the factor analysis with the validation data set

Component	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	3.130	34.780	34.780
2	1.992	22.129	56.909
3	1.963	21.816	78.725

Table 23. Rotated Component Matrix of the nine variables of the federal statistics that are validated by the logistic regression

	Component		
	1	2	3
Population per settlement area	-.951		
One and two family homes	.856		-.358
Rural population	.831		
Small apartments	-.788		
Residents from age 30 to 50		-.935	
Residents age 65 and older		.913	
Unemployment		.383	.853
Living space pp	.416		-.716
Graduates without Hauptschule degree			.697
Factor name	**Regional conditions**	**Fragility**	**Socio-economic conditions**

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalisation.
a. Rotation converged in 4 iterations

The three factors as grouped in the rotated component matrix (**Table 23**) display the same factors that have been identified with the full variable set of 41 variables of the full federal statistics set (**Table 9**). This excellent result reveals that the groupings are generally valid. Some of the interpretations what these factors explain can be improved with the results of the logistic regression validation by the second data set. For example, urban areas are likely to be more affected. Urban areas and smaller apartments or living space characterise urban areas and are more susceptible as it is tested with the second data set. Rural areas are less populated, yet it can not be concluded that these areas are not prone to harm. Especially the high ratio of one and two family homes indicates a high ratio of home ownership, which was found as an indication of susceptibility in the sense of having to leave their home in the 2002 flood. This should warn of stereotyping rural areas as safer, and supports the ambiguous picture of this factor, regional conditions, as it is also shown by the factor analysis of the 41 variables (**Table 9**).

The second component clearly separates elderly people from mid-aged adults. The group of 30 to 50 year olds is a surrogate for younger adult age groups in this case. The other adult age groups were excluded to avoid partial correlations, but trial runs of the factor analysis had shown that old age is always dichotomous to younger age. There is no conclusion possible about people younger than 16 years however, since this group did not show as significant in the logistic regression. Old age is shown to indicate fragility and need of assistance as shown by the probabilities of the emergency shelter group (**Table 16** and **Figure 10**).

The third factor depicts unemployed and lower education groups as opposite to greater living space. All three variables are validated in their direction of susceptibility measurement by the second data set of the household questionnaire. Therefore this third factor describes financial deficiencies in terms of employment, employment qualification and living standard.

The same observation of factors can be made with a factor analysis of all 15 variables that are indirectly related to the validated variables in the second data set and with a factor analysis of the 14 variables of the second data set themselves (Annexe 6).

4.5 Social Susceptibility Index

Data: The data set used for the Social Susceptibility Index is the federal statistical data (BBR 2007, Destatis 2006a). Only those variables are selected that have a counterpart in the validated second data set. At the same time the condition must be met that only variables or sub-variables are selected that are already in the selection of the 41 variables for the first factor analysis. This implies that sub-variables like *residents of age 18 to 25* can not be included, since they had been excluded in the first factor set due to high partial correlations. Variables like *residents below 6 years of age* are not included since the second data set gives no evidence on a direction within the tested models. Other variables like *population per settlement area* are redundant for the index creation, since they are already contained inversely in *rural population*. For the set of 41 variables this variable had been necessary to identify groupings. For the index, this variable, *population per settlement area*, is dropped. The same redundancy is met with the sub-variable *residents from age 30 to 50*. The variable *residents from age 65 and older* already contains both directions of a high number of elderly people and the contrary. Therefore *residents from age 30 to 50* can be deleted. The variable *home ownership* is related to *one and two family homes*. Since the direction towards susceptibility is ambiguous in the regression models, this variable (*home ownership*) is treated neutral and excluded from the composition of the index.

Table 24. Variables used for the construction of the SSI

	Component		
	1	2	3
Population per settlement area	-.951		
One and two family homes	.856		-.358
Rural population	.831		
Small apartments	-.788		
Residents from age 30 to 50		-.935	
Residents age 65 and older		.913	
Unemployment		.383	.853
Living space pp	.416		-.716
Graduates without Hauptschule degree			.697
Factor name	**regional conditions**	**fragility**	**socio-economic conditions**

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation. Rotation converged in 4 iterations. Red marking indicates higher susceptibility as validated by the regression model, green marking the opposite.

Methodology: The groups derived from the factor analysis are the basis for the selection and aggregation of the Social Susceptibility Index (**Table 24**). Each factor delivers one indicator, the indicators aggregate to the index. In order to enable negative indications of susceptibility but also positive directions of prevailing capacities, each factor must have the potential to indicate both directions equally. The variables are first standardised to equal intervals from zero to one. Missing values are replaced with the average value of the variable so that in the average of all either negative or positive variables they do not invoke a trend. Since there are more negatively attributed variables in the set of the factor analysis (**Table 24**), the respective negative and positive variables are first aggregated separately. In this way, they either represent susceptibility or capacities. The averages per negative or positive variable group are calculated separately. Only then the positive and negative halves of each factor are aggregated. The resulting direction of susceptibility/capacities is different for each county. The three factors are used as the three indicators of social susceptibility.

$$Indicator = \frac{sum(\text{var}\ pos) - sum(\text{var}\ neg)}{N(\text{var})}$$

var pos = variables with positive factor loads
var neg = variables with negative factor loads
Variable ranges (min/max.): 0 to 1
Indicator range (min/max.): -1 to 1

The indicator fragility is the rate of *residents of age 65 and older*. The indicator socio-economic conditions, is aggregated per county as: *living space per person - (unemployment + graduates without Hauptschule degree*) /2. The indicator regional conditions is aggregated per county as: *rural population - small apartments*. All indicators range from minus one to one as the maximum possible range. Zero is the average and indicates no direction of neither increased nor decreased susceptibility. The Social Susceptibility Index is an aggregation of the simple sum of the three indicators. Positive and negative deviations of both negative and positive directed variables must be able to level out. Negative resulting values indicate a relatively higher susceptibility of the county, positive values the opposite. The results can theoretically achieve a maximum range of minus three to three. The result is the susceptibility map of **Figure 12** (further below). It displays the counties in Germany coded in colours by defined intervals (0,2). Green colours indicate prevailing positive capacities; red colours indicate increased potential susceptibility of the counties.

$$SVI = Indicator1 + Indicator2 + Indicator3$$

SSI range (max.): 3 (lowest susceptibility) to -3 (highest susceptibility)

The main result of the susceptibility assessment of Chapter 4 is the SSI (**Figure 12**), composed of three indicators and validated by an independent second data set. The SSI identifies counties in Germany with a potentially strong or weak social susceptibility to floods. Since social susceptibility is regarded independent of the individual river flood hazard, this index contains no hazard information. The three indicators that compose the SSI are groupings derived from the factor analysis. The set of 41 demographic variables of the federal statistics in the first exploratory factor analysis is successfully validated by the second data set of the questionnaire on flood affected households. This set of 41 input variables could be reduced to six variables. These six variables compose the same factors that are derived from the 41 variables. The three resulting factors are used as indicators of social susceptibility, named *fragility*, *socio-economic conditions* and *regional conditions*. The SSI is aggregated from these three indicators with equal weighting.

The single results are:

- A composite Social Susceptibility Index (SSI)
- The SSI choropleth map
- Three indicators of social susceptibility: fragility, socio-economic conditions and regional conditions
- A validated set of demographic predictors (6 variables) of social susceptibility
- An extended set of theoretically founded demographic predictors (41 variables) of social susceptibility

The variable sets serve as checklists for the identification of social susceptibility. This checklist uses standard census data and it is demonstrated that even without direct flood impact evidence, the derived susceptibility factors are valid. This suggests that this methodology can be principally applied in other countries and regions as well. The reduced and validated variable set enhances the feasibility of such an approach since even by a small number of variables, social susceptibility can be detected.

Social Susceptibility Index (SSI)

Data Sources: BBR 2007: INKAR 2006, Statistisches Bundesamt Deutschland (Destatis 2006a): Statistik regional, BKG 2007: county shape files

Description:

The SSI is an index that is aggregated by equal weighting and simple summation from three main indicators of social susceptibility:

- fragility: elderly persons above 64 years per total population
- socio-economic conditions: unemployed persons and graduates with only basic education per total population; apartment living space per person
- regional conditions: degree of urbanity or rural area, measured by population density lower / higher than 150 persons per km² and the number of apartments with 1-2 rooms per total number of apartments

Indicator creation: the 6 input variables are normalised to values from 0 to 1 and by simple summation the three indicators are created. The SSI contains value ranges from 1,8 to -1,8 and is displayed in defined equal intervals in 0,2 steps. The indicators contain value ranges from -1 to 1 and are displayed in defined equal colour intervals in 0,1 steps.

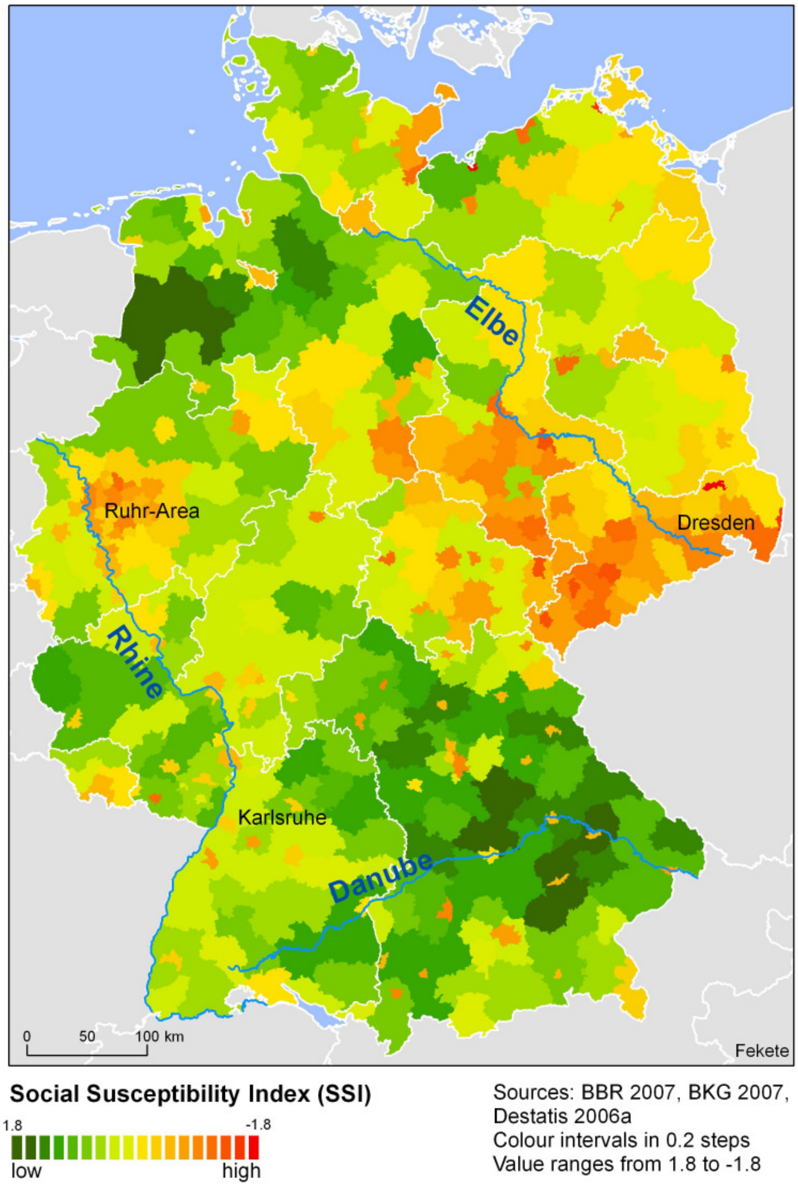
Description:

Low SSI counties are characterised by strengths towards river-floods. These strengths are prevailing capacities for river-flood mitigation, for example, financial capacities for private preparedness measures and recovery from floods by high-income sources. Physical fragility of elderly citizens is typically low. These counties also lack indications for a potential exposure to floods like high population density

Counties with high SSI are characterised by predominating weaknesses towards river-floods. These weaknesses are lack of capacities and high degrees of susceptibility.

Hazard context:

The SSI detects potential strengths and weaknesses of counties, not the actual river-flood exposure or -risk. The SSI contains no hazard information and therefore no actual exposure. However, the SSI is not an index for any kind of natural hazard, since the variables are selected and aggregated only after flood impact evidence. The input variables for the indicators are created after verified unequal flood impact to different social groups and settlement types. Counties have distinct profiles of social susceptibility, composed of demographic characteristics and land use. The strength of the SSI is its independence from direct hazard information. It identifies key aspects of flood impact and –risk not identified by hazard assessments. The computation of actual exposure by hazard information is carried out for the Social and Infrastructure Flood Vulnerability Index (SIFVI).



Social Susceptibility Index (SSI) per county in Germany

Objective: identifies demographic patterns of susceptibility and capacities towards stresses like river-floods

Aggregation: the simple sum of three indicators:

- Fragility
- Socio-economic conditions
- Regional conditions

Indicator fragility: ratio of elderly residents (>64 years)

Indicator socio-economic conditions: living space per person; (un)employment ratio; education type

Indicator regional conditions: population density; housing type

Data: census data of the Federal Statistical Office in Germany

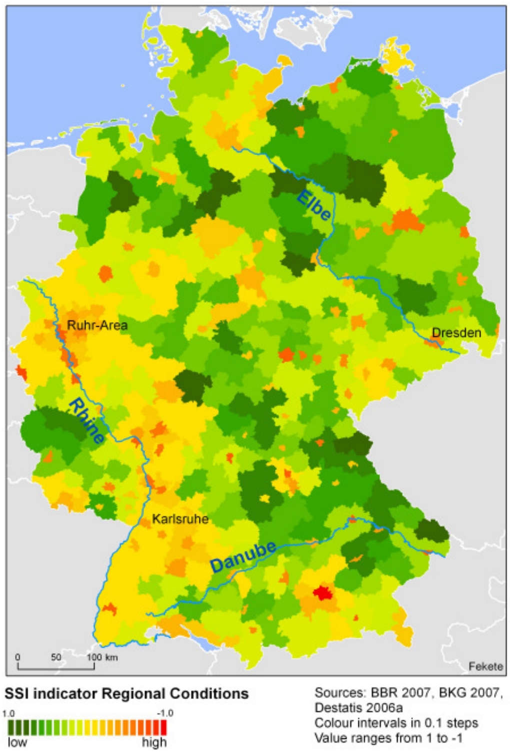
Standardisation: ratios per county; equal intervals from 1,8 to -1,8

Figure 12. Main result of the social susceptibility assessment, the map of the Social Susceptibility Index (SSI) per county

It is interesting to observe the concentration of higher susceptibility in areas like the Ruhr-Area close to the Western border and in the Eastern part of central Germany. It is therefore not only urban areas with high population density that are highlighted as susceptible, but also some rural areas. There is a slight general tendency for urban areas to be more susceptible, though. The scrutiny of the single indicators that compose the index (**Table 25**) reveals that socio-economic conditions or fragility is not concentrated in urban areas only, while indicator three, regional conditions, highlights urban areas. The maps of **Figure 13**, **Figure 14** & **Figure 15** illustrate the contribution of the single factors to the overall index, but at the same time demonstrate their potential to highlight different areas. These areas indicate diverging aspects of susceptibility and are helpful to identify more specific susceptibility information like concentration of elderly people, socio-economic conditions or regional conditions.

Table 25. Overview on the map products of the SSI

Composite Map	Composite Social Susceptibility Index (SSI) map		
Components	SSI indicator regional conditions	SSI indicator fragility	SSI indicator socio-economic conditions
Input variables	population density; housing type	ratio of elderly residents (>64 years)	living space per person; (un)employment ratio; education type



Indicator regional conditions per county in Germany

Objective: describes patterns of social susceptibility related to settlement density and -type

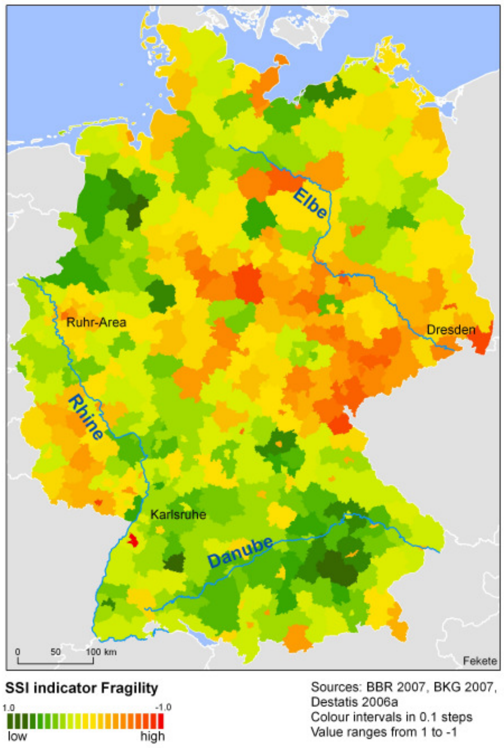
Aggregation: the sum of two variables:

- population density
- housing type

Data: census data of the Federal Statistical Office in Germany

Standardisation: ratios per county; equal intervals from 1 to -1

Figure 13. Map of the SSI indicator *regional conditions* per county.



Indicator <u>fragility</u> per county in Germany

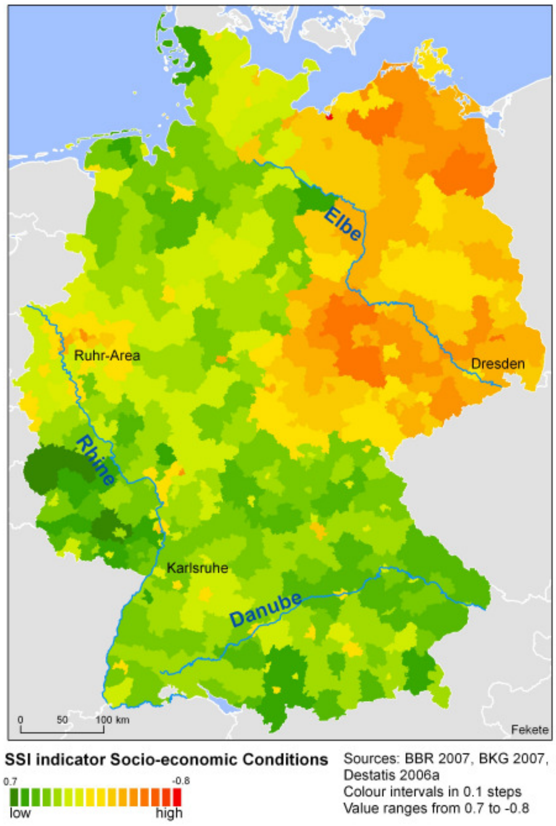
Objective: describes patterns of social susceptibility related to age of the population

Consists of the ratio of elderly residents of 65 years and older

Data: census data of the Federal Statistical Office in Germany

Standardisation: ratios per county; equal intervals from 1 to -1

Figure 14. Map of the SSI indicator *fragility* per county.



Indicator <u>socio-economic conditions</u> per county in Germany

Objective: describes patterns of social susceptibility related to living conditions and financial resources

Aggregation: the sum of three variables:

- living space per person
- (un)employment
- education

Data: census data of the Federal Statistical Office in Germany

Standardisation: ratios per county; equal intervals from 0,7 to -0,8

Figure 15. Map of SSI indicator *socio-economic conditions* per county.

The indicator regional conditions (**Figure 13**) has a tendency to highlight urban counties all over Germany as more susceptible. Urban regions are a heterogeneous landscape of urban problems but also of strengths regarding social susceptibility. For example, urban areas are characterised by a high concentration of people but also by higher education and more doctors per resident.

The fragility indicator shows a heterogeneous pattern of the distribution of elderly people in Germany (**Figure 14**). As in the composite SSI, the indicator fragility also depicts the Eastern part of central Germany by containing a relative higher proportion of elderly people. These are areas where river floods, but also flash floods and other natural hazards like heat waves are likely to kill and adversely affect the health of more people than in other regions in Germany.

The indicator of socio-economic conditions clearly identifies Eastern Germany as more susceptible (**Figure 15**). This is an obvious result since the ratio of unemployment and related social welfare is generally higher in the East ever since the German reunification. Some regions like the Ruhr area and some urban areas in West Germany are characterised by higher susceptibility due to fragility.

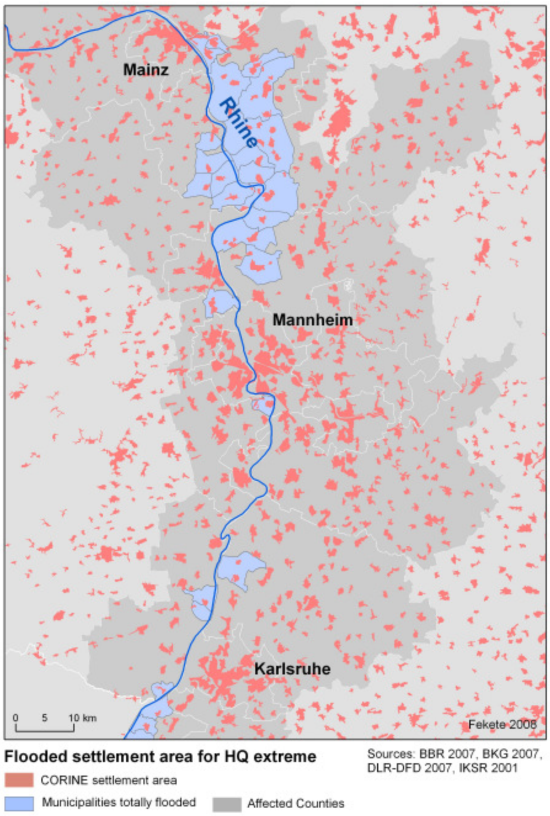
4.6 Social and Infrastructure Flood Vulnerability Index

The objective of constructing a Social and Infrastructure Flood Vulnerability Index is to identify regions which bear not only high social vulnerability but at the same time a high flood hazard potential. Additionally, infrastructure is a key source for supply of vital resources like energy and is therefore added to the social susceptibility index. The reasons for including a measure of critical infrastructure are first, the importance of this infrastructure for society, second, as critical infrastructure is a key topic of current civil protection and disaster assistance efforts in Germany (BMI 2006, BBK 2009) and third, since critical infrastructure is not covered by the other project partners of DISFLOOD. This index combines the susceptibility index with an index of infrastructure and flood hazard information, in this case extreme events scenarios of maximum inundation areas of three major streams in Germany. The three streams Danube, Elbe and Rhine are of interest for the large areas along these rivers which are exposed to floods. Historically, several disastrous floods happened along those three streams (**Table 1**, Section 2.1). Susceptibility, as conceived in this study, stands out by identifying areas independently of direct hazard impact. It is of special interest to demonstrate how this approach can be integrated into traditional flood risk identification. Hazard maps are but one data source that can be integrated into a flood vulnerability index.

4.6.1 Exposure assessment

The flood hazard data consists of hazard maps that are provided for the river Danube by the State Office for Environment in Bavaria (LfU Bavaria 2007) for the river Elbe by the State Office for Environment and Geology in Saxony (LfUG Saxony 2007), for Saxony-Anhalt the State Management Agency for Flood Protection and Water Management (LHW Saxony-Anhalt 2007) with data from the Elbe Atlas (ELLA 2007) and for the river Rhine by the International Commission for the Protection of the Rhine (IKSR 2001). These hazard maps display the inundation areas of statistical extreme event scenarios. The development of these maps is still in process; therefore these maps are not accessible for all areas of the three streams. This data gap also sets limits to the application of this assessment for other great rivers in Germany, not to mention the smaller ones. The extreme event scenarios are not consistent, they comprise statistical return periods of 100 (occasionally to 200) years flooding for the river Danube, and 500 year floods for the rivers Elbe and 200+x to 500 year floods for the Rhine, depending on the section of the river (see the detailed description in IKSR 2001). Despite the heterogeneity of the data, this set is the most comprehensive on maximum flood inundation scenarios to date and are therefore the best solution for analysing large areas along river channels in Germany. However, since extreme flooding scenarios for the river Danube of is still under development, and the 200 years areas are still scarce, it was decided to exclude the river Danube from the final index. As soon as more extreme inundation scenarios are completed, the river Danube and other rivers in Germany can be used for the calculation of the index at once, as the social susceptibility information is already computed.

The exposure of the counties is calculated as the percentage of settlement area inundated at the given extreme event scenario. This provides a measure that allows for ranking of the counties regarding how severe the impact on the population is likely to be. This exposure is analysed in the GIS by overlaying the digital vector polygon data of the inundation areas with the settlement polygon data of the land use classification data set of CORINE 2000. The CORINE Land Cover (CLC) data set is provided by the German Aerospace Centre (DLR-DFD 2007) and delivers settlement areas greater than 25 ha, as captured by satellite remote sensing (Keil et al. 2005).



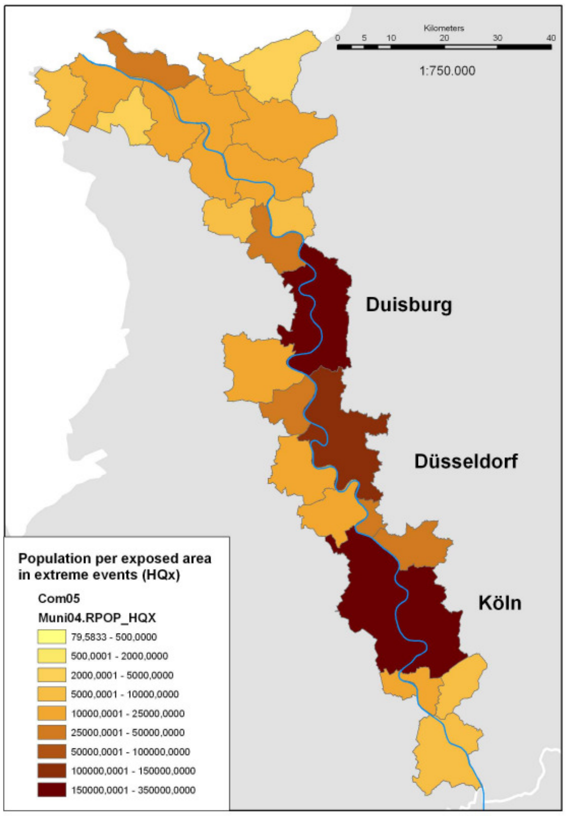


Figure 16. Municipalities with settlement areas totally flooded in a HQ extreme scenario (blue polygons) in the middle section of the Rhine river
Figure 17. The number of exposed residents per municipality

The exposure analysis exhibits that several villages and even whole municipalities are exposed to flooding (**Figure 16**). A total amount of 7.5 million of 16.4 million people living in those 73 counties (including the inundation scenarios HQ100 and HQ200 for the Danube) is exposed to river flooding alone, disregarding flash floods and the inundation areas of other rivers and tributaries. The accuracy of these numbers depends on the resolution and quality of the available data. Since the CORINE land cover captures only settlements above 25ha, these numbers are probably underestimated. For the purpose of comparing the exposure with the susceptibility index, the county level has to be used. The exposure information is therefore aggregated to percentage of settlement area per county (**Figure 17** & **Figure 18**). 57 of 62 counties at the Elbe and Rhine, for which hazard information of extreme event scenarios greater than HQ200 is available, are at least partly prone to flooding (**Figure 18**).

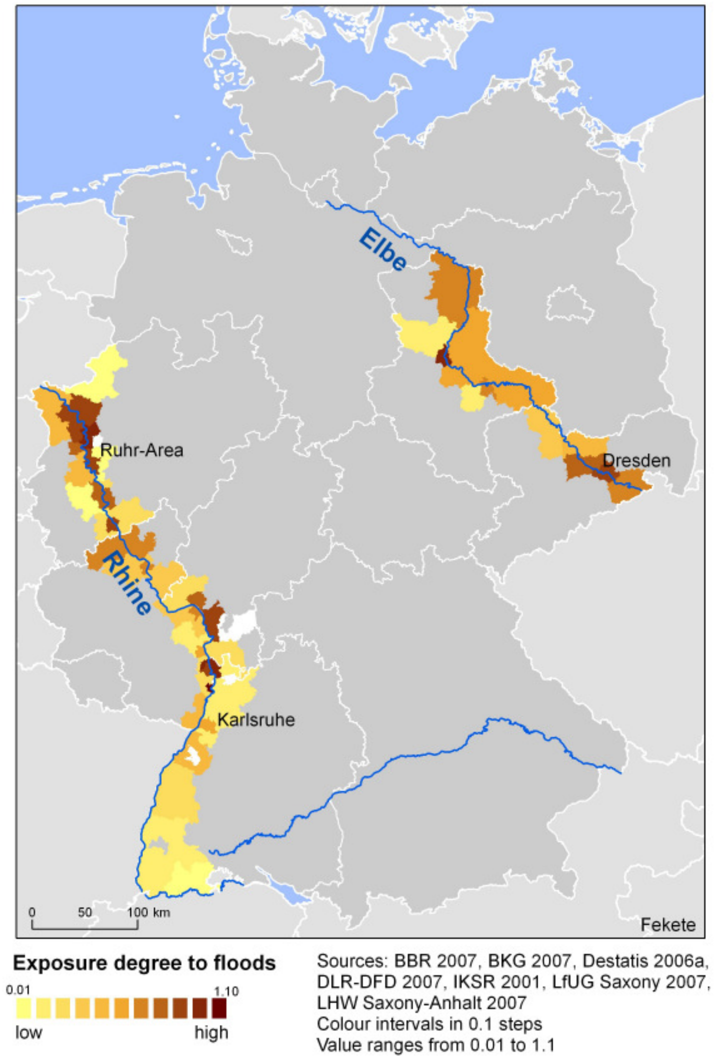


Figure 18. Map of the percentage of the counties exposed to floods (no extreme flood data for the Danube)

The exposure map depicts urbanised areas and lowland areas downstream as especially exposed, for example at the lower Rhine at the border to the Netherlands in the West of Germany (**Figure 17** & **Figure 18**). Since Saxony-Anhalt is characterised by lowland terrain as well, the inundation areas are also wide in lateral spread here. The Dresden area in the South of Eastern Germany is especially exposed because of the tributaries from steeper terrain.

Exposure information

Data sources:

The flood hazard data consists of hazard maps that are provided for the river Elbe by the State Office for Environment and Geology in Saxony (LfUG Saxony 2007), for Saxony-Anhalt the State Management Agency for Flood Protection and Water Management (LHW Saxony-Anhalt 2007) with data from the Elbe Atlas (ELLA 2007) and for the river Rhine by the International Commission for the Protection of the Rhine (IKSR 2001).The settlement areas are provided by the CORINE land cover data 2000, DLR-DFD 2007.

Description:

The Exposure of settlements to river-floods is calculated as the ratio of CORINE settlements per county inundated by the HQ extreme data scenarios. The HQ extreme scenarios are statistical recurrence estimations of a 200 year plus safety margin flood event or up to a 500 year flood event, depending on the data source.

As an additional information layer, the location and ratio of the critical infrastructure per county is calculated in the GIS (**Figure 19**). The data on critical infrastructure is provided by the Federal Agency for Cartography and Geodesy (BKG 2007, Basis-DLM). It contains infrastructure than can be categorised as important supply infrastructure, in this case power plants, electricity facilities, heating and water supply. Some of the infrastructure bears also important supply functions but is at the same time a secondary hazard itself by posing the threat of potential contamination when inundated. In this category are refineries, dumpsites, sewage facilities and waste treatment facilities. Certainly, an in-depth analysis of the real danger and exposure of these infrastructures would be necessary as well as the inclusion of other infrastructure. This data set can therefore serve only as a demonstrator for the extension and advancement of the whole vulnerability index. The point data of the eight infrastructure classes is analysed in the GIS by calculating the number of all critical infrastructure items per county. The infrastructure items are summed up and the result is rescaled to the range of zero to one, where zero indicates low density of critical infrastructure and one signifies the maximum number of critical infrastructure observed in the data. The map shows that only few areas have a higher than average concentration of critical infrastructure (**Figure 19**). This additional infrastructure information will therefore not severely change the pattern show by the susceptibility index in the overall flood vulnerability index.

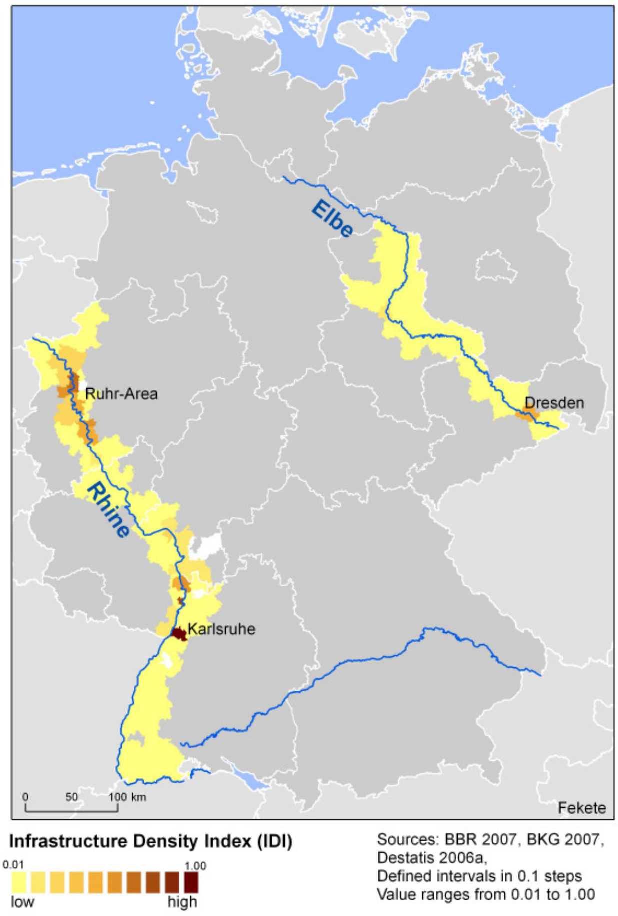


Figure 19. Map of the Infrastructure Density Index (IDI) per county

Infrastructure Density Index (IDI)
Data Sources: BKG 2007: point data of selected infrastructure (BASIS DLM) Description: The IDI is an index that is aggregated by equal weighting and simple summation of two groups of infrastructure: • supply infrastructure: power plants, electricity facilities, heating and water supply. • contamination infrastructure: refineries, dumpsites, sewage facilities and waste treatment facilities. The IDI contains value ranges from 0 to 1 and is displayed by defined intervals

4.6.2 Flood Vulnerability Index calculation and results

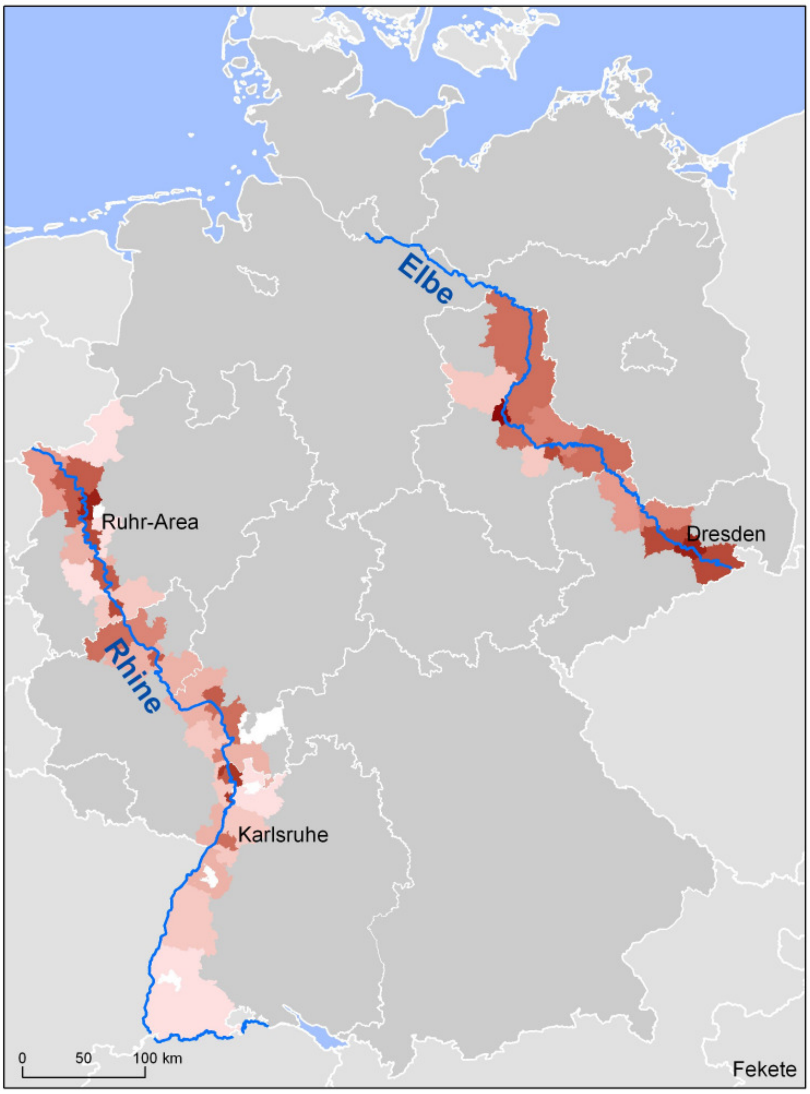
The flood vulnerability index is calculated as the product of the SSI, the IDI and the exposure area. Of course, this index shows only certain aspects of vulnerability, not all. The reason for this is that the vulnerability of the economy and of the ecosystem will be assessed separately by other project partners of DISFLOOD. Therefore, the scope of this study lies mostly on the social aspects of vulnerability. It additionally integrates critical infrastructure for two purposes; first to illustrate that generally this index can be extended to include all vulnerability aspects necessary to capture flood vulnerability. Second, because critical infrastructure is a key element determining the adverse effects of floods on society.

Prior to the calculation, the SSI is transformed to a range, wherein the minimum value is for lowest susceptibility and the highest value is for highest susceptibility. The exposure degree is multiplied by ten to put it into the same value range as the SSI and to facilitate the multiplication. The result is rescaled to the range of zero to one, where zero indicates no vulnerability and one signifies the maximum vulnerability observed in the data. The resulting vulnerability index thus is dependent on the prevalence of the degree of exposure. If there is zero exposure, there is no vulnerability. The higher the exposure area the higher is the vulnerability. The vulnerability degree is also meliorated by the susceptibility profile of each county. Lower susceptibility buffers the vulnerability to a certain degree, high susceptibility exacerbates the vulnerability.

$$SIFVI = (SSI - 3) * (Exposure\_area * 10) * (\mathrm{IDI} * 10)$$

*The value 3 is subtracted from the SSI to harmonise it with the other data

The resulting Social and Infrastructure Flood Vulnerability Index map (**Figure 20**) is composed of the SSI map (**Figure 12**), the IDI map (**Figure 19**) and the exposure area map (**Figure 18**). Urban counties but also the lowland counties of Eastern and Western Germany, as well as the Dresden area are characterised by higher vulnerability to river flooding. Counties in white colour show no exposure as measured by the available data sources. For counties along the Danube, the hazard data is still lacking, so that no exposure and therefore no vulnerability could be computed.



Social and Infrastructure Flood Vulnerability Index (SIFVI)

0 — 1.1

low — high

Sources: BBR 2007, BKG 2007, Destatis 2006a, DLR-DFD 2007, IKSR 2001, LfUG Saxony 2007, LHW Saxony-Anhalt 2007
Colour intervals in 0.1 steps
Value ranges from 0 to 1.1

Social and Infrastructure Flood Vulnerability Index (SIFVI) per county in Germany

Objective: identifies the vulnerability towards river-floods by the social and infrastructure vulnerability considering the hazard exposure per county

Aggregation: multiplication of
- SSI
- IDI (Infrastructure)
- Exposure to floods

SSI: Social Susceptibility Index, measuring fragility, socio-economic conditions and regional conditions

IDI: Index for supply infrastructure, but also for potentially contaminating infrastructure

Actual exposure: settlement area per county inundated by a statistical extreme event scenario (200-500 years flood)

Data: census data of the Federal Statistical Office in Germany, land cover data, hazard maps

Standardisation: ratios per county; equal intervals from 0 to 1,1

Figure 20. Main result of the vulnerability assessment, the map of the Social and Infrastructure Flood Vulnerability Index (SIFVI) per county

Description:
Flood vulnerability is the vulnerability of the population per county facing river floods and is to even parts composed of the hazard and the vulnerability components. Disaster occurs when either the hazard or the social vulnerability is especially high. It is aggravated by additional harm to infrastructure and disaster is highest when all factors play together.

Hazard context:
The flood vulnerability is directly dependent on hazard information. When there is no indication of an actual exposure to river-floods there is no indication of flood vulnerability.

Like the other indices, the Social and Infrastructure Flood Vulnerability Index (SIFVI, **Figure 20**) uses a standardised procedure of data harmonisation, standardisation, equal weighting and ranking. This Social and Infrastructure Flood Vulnerability Index is open for additional vulnerability data like for example environmental vulnerability, but also for additional hazard information such as flood depth, velocity, etc. The methodology of quantified parameters and the simple aggregation technique enable an aggregation of this index with other vulnerability information such as economic damage vulnerability of buildings.

The following individual results have been obtained:

- A composite Social and Infrastructure Flood Vulnerability Index (SIFVI)
- The SIFVI choropleth map
- An exposure map of the settlement area and population threatened by extreme flood scenarios
- The SSI choropleth map per exposed county
- An index of critical infrastructure per exposed county

Social and Infrastructure Flood Vulnerability Index (SIFVI)

Description:

The SIFVI is an index that is aggregated by equal weighting and multiplication of three components:

- SSI: Social Susceptibility Index
- IDI: Infrastructure Density Index
- Exposure information

Aggregation:

$$SIFVI = (SSI - 3) * (Exposure\_area * 10) * (\mathrm{IDI} * 10)$$

The Social Susceptibility Index is subtracted by 3 to transform all values to a positive range in order to enable multiplication. The SIFVI is standardised to value ranges from 0 to 1,1 and is displayed in defined equal intervals in 0,1steps.

The SIFVI delivers an index, as well as information about its components per county. This information is available on the DIFLOOD platform on NaDiNe (http://nadine.helmholtz-eos.de/projects/disflood/disflood_de.html), where the user, both public and experts can access the colour-coded map and documentation. The results per county are also documented in a table listing the counties in Annexe 9. Only those counties carry values of the SIFVI, where exposure information is available by hazard maps. For all counties in Germany however, the values of the SSI and its components are available.

5 Synthesis - Reflection of strengths and limitations of the assessment

A theory is something nobody believes, except the person who made it.
An experiment is something everybody believes, except the person who made it.
Albert Einstein

This synthesis is a quality assessment of this study that compares the findings to the background of the knowledge before the assessment and reflects how these findings confirm or modify the theoretical considerations about social vulnerability in Germany. The key aspects of the vulnerability assessment in this study are discussed concerning the methodology, the results and the implications for the theoretical research perspectives.

Quality assessment suggests for comparing whether the study design assumptions are still relevant after analysing the data (Van den Berghe 1995: 26). The vulnerability concept has proven to be a valuable lens to identify latent patterns of social groups with specific characteristics towards natural hazards like floods. The conceptual assumptions about the construction of indicators are justified in the sense that a vulnerability index could be constructed for the context of river floods. The feasibility of the theoretical as well as the methodological approach could be shown. Data availability over large areas like a whole country and depth of data resolution are probably one major bottleneck for carrying out such an approach in other countries, especially in developing countries.

The objectives of achieving a composite vulnerability index are only to a limited extent realistic. While it is technically feasible, the validation is a major challenge. It is a luxury to have an independent second data source available, as in this study. And still, one big unsolved question remains - which test categories should be applied for 'validating' or 'verifying' social vulnerability. In this study, three test categories were used; *leave_home, emergency_shelter* and *damage regulation* satisfaction. No definite conclusion can be drawn from this set of categories however, whether social vulnerability is adequately described. At this point it must be stressed that the approach in this study is only a modest attempt at finding out how to possibly measure social vulnerability. It resembles a starting point for falsification and the development of better approaches.

An indication for the vibrancy of the topic of vulnerability is the ongoing theoretical discussion in the scientific community. The lack of a unified definition and lack of 'real theory' stems from the complex topic. Overlaps exist with similar approaches like sustainable development. For scientific housekeeping it is useful to question whether each term can be easily replaced by another already existing term. This simple lesson should be an interrogative for multi-disciplinary research groups who attempt integrating terms like risk, damage, vulnerability, susceptibility, probability or uncertainty. In many cases, one term can be replaced by another term with the prefix “potential of…” or “degree of…”. In such cases it should be considered whether terms like vulnerability describe more than a “degree of damage” or “hazard potential”. Vulnerability should describe a phenomenon that is unique, new and more than the sum of its parts. Therefore in this study, the components which make vulnerability a specifically composed phenomenon are in the focus. This helps to identify the contribution of susceptibility, capacities and exposure factors to the overall vulnerability. It stresses the identification of areas not determined by high hazard potential only, but characterises areas that are threatened by its internal predisposition.

The main players of social susceptibility and vulnerability are the people. This fact is stressed by the Social Susceptibility Index in a way novel to traditional risk and disaster management in Germany. The maps developed in this approach are one attempt to introduce this topic and enable access of lay people and experts alike. The factors that render people vulnerable comprise a number of characteristics like lack of physical fitness, social background and dwelling type among others.

5.1 Discussion of the methodology of indicators

Science means three things; it is a special method of finding things out, it is the body of knowledge and it is new technology or applications (Feynman 2007: 5). Vulnerability indicators are in this respect the technical application of the vulnerability concept (Chapter 3). The systematisation of the technical application is guided by the conceptual frame, yet there are many technical specifications that shape the result of the vulnerability analyses. These technical specifications are either beneficial or constraining for the realisation of the conceptual idea:

5.1.1 Selection process

The selection process by which variables or sub-variables are included or excluded is the most difficult part in the technical application of this study. This selection is based on the BBC framework and the analytical categories exposure, susceptibility and capacities. Still, the technical procedure is subject to arbitrary and subjective decisions (Briguglio 2003: 11, Nardo et al. 2005: 13). Additionally, the concept is underpinned by international studies and an evaluation of the German setting (Section 2.4) is provided. Still, the selection of variables is to a certain extent due to the subjective scope and assumptions of the author. Only those sub-variables are selected, for which arguments from literature can be found, even if some of them are only indirectly related to the variable. For example, unemployment is not a variable used in other studies, however, it is an important feature identified for the context of Germany (Section 2.4). Other sub-variables might have been overlooked - not because they do not represent social vulnerability, but because they were not recognised as such. Additionally, economic damage, buildings and values were not the main scope of this type of vulnerability assessment (cf. Chapter 3). And of course, many variables are not included for lack of data coverage. For this reason, a number of aspects outlined in the BBC framework (**Figure 6**) could not be captured. Still, the BBC framework was a precondition for the successful integration of all aspects of vulnerability, including exposure, susceptibility and capacities' parameters.

Exclusion from the factor analysis or logistic regression does not mean these variables can not be integrated into a composite index. While the procedure of exclusion due to trial experience is disputed in the theory of the statistical methodology (Nardo et al. 2005: 40, 43), it might be common practice, yet rarely stated. By stating it here explicitly, the impression should be avoided that the selected variables and the sub-variables are the one and only ideal solution. The selection is a result of the state-of-the-art values, objectives, experience and findings of the scientific community and the author. Also, if more variables on risk perception, flood experience, insurance cover, disabilities and illnesses would have been available, they would certainly have been included and possibly shifted the overall profile of vulnerability.

> "In many instances vulnerability will be defined through the availability of datasets rather than because the data truly represents vulnerability." (King 2001).

It must be emphasised however, that the constraints described here are a normal part of critical scientific evaluation. It is a pity that occasionally in scientific studies the constraints and failures of measurement are not more explicitly described which hinders advancement of the methodology.

Lack of evidence on thresholds for the creation of sub-variables is a problem. For example, only for the extreme ends of the age profiles arguments could be found. Still, most arguments of previous studies (Annexes 2 and 3) are also based on assumptions only and a convincing linkage to causality in dividing demographic age groups is lacking. For age above 64, the relation of increased health problems due to the typical age of retirement have been described, as well as an increase of fragility above 75 years of age (Tapsell et al. 2002). While this seems plausible, evidence for very young age could not be found and almost no literature on adults and other age groups.

The ambiguousness of the variables is both a problem and an opportunity for interpretation. It is disturbing at first that certain variables like *urban area* allow not for a stereotype characterisation of being an either only negative or positive measurement of vulnerability. But especially when putting these variables into context to other variables like income, education age etc. like in the factor analysis or regression analysis, certain relations and patterns appear. It shows on the one hand, that urban areas are not to be simplified as problem areas. This accords with findings of local studies at the river Elbe, that conclude that vulnerability is difficult to capture by a single variable (Steinführer and Kuhlicke 2007: 115). On the other hand, the variable *urbanity* is only valid in the context of the specific variable set of the full regression model – in other words in the context to the other variables like selected age groups, income groups etc. It means that certain variables describe complex phenomena that allow no uniform interpretation, and which are dependent no only on the local context but also on the context of other variables that are being observed.

5.1.2 Aggregation and weighting

> "Composite indicators are useful in their ability to integrate large amounts of information into easily understood formats and are valued as a communication and political tool. However, the construction of composites suffers from many methodological difficulties, with the result that they can be misleading and easily manipulated." (Freudenberg 2003: 3)

One drawback of a composite indicator is the loss of information of single indicator extremes. To a certain extent this can be compensated by weighting and normalisation methods of the variables, for example z-scores (Nardo et al. 2005: 18), Pareto-ranking (Rygel et al. 2006) or else (Nardo et al. 2005: 59, 64, see Annexe 2). Alternatives include multi-variate statistical techniques, decision tree analysis, counting the indicators that exceed a threshold (Downing et al. 2005: 6), or data envelopment analysis (Clark et al. 1998: 71). On the other hand these technical solutions also carry an increase in technical complexity and reduce the comprehensibility for non-experts (Gall 2007). Weighting generally introduces the problem of subjectivity.

Weighting schemes are often either arbitrary or unreliable (cf. Cardona 2005: 65) and "… weighting is subjective in nature" (Simpson and Katirai 2006: 4). The level of subjectivity in weighting can be reduced by mathematical procedures such as standard regression analysis, factor analysis or by the Delphi method of asking experts (Schmidt-Thomé 2006: 156). However, even these techniques reach their limits in large-scale studies (Schmidt-Thomé 2006: 86) and the human factor of choice in selection and implementation process remains. Also, 'objectivity' remains a difficult goal, even when the average of several 'subjective' opinions is collected and revised over and over. Some studies state that weightings are arbitrarily chosen even by methods like regression analysis (Briguglio 2003: 8). It is also warned against using highly sophisticated aggregation and calculation methods in constructing indices like the Human Development Index, since they hinder interpretation (Gall 2007) and sometimes even produce statistical artefacts (Lüchters and Menkhoff 1996).

Advanced weighting techniques are advisable when there is a sound theoretical argumentation why some extreme values or specific variables should be weighted higher. When such an argumentation is missing, simplification and standard techniques seem advisable. Therefore, equal weighting, simple sum aggregation and equal interval normalisation are considered the best solution for the approach in this study.

> “A mathematical combination (or aggregation as it is termed) of a set of indicators is most often called an ‘index’ or a ‘composite indicator’. It is often a compromise between scientific accuracy and the information available at a reasonable cost.” (Cardona 2005: 65).

> “[…] it is hard to imagine that debate on the use of composite indicators will ever be settled […] official statisticians may tend to resent composite indicators, whereby a lot of work in data collection and editing is “wasted” or “hidden” behind a single number of dubious significance. On the other hand, the temptation of stakeholders and practitioners to summarise complex and sometime elusive processes (e.g. sustainability, single market policy, etc.) into a single figure to benchmark country performance for policy consumption seems likewise irresistible.” Andrea Saltelli, JRC, http://composite-indicators.jrc.ec.europa.eu/, accessed 13 June 2008

It is important to denote both benefits and limitations of social vulnerability indicators (Briguglio 2003, Cardona 2005, Nardo et al. 2005). Composite indicators hold many advantages, like summarising complex phenomena, showing directions for development; allow comparison across places or identification of areas for action (**Table 26**).

Table 26. List of pros and cons of composite indicators

Pros	Composite indicators • summarise complex issues • are easier to compare than separate indicators • help attracting public interest • include more information while reducing the amount of data • prepare the visualisation and localisation of vulnerability • enable a regional comparability
Cons	Composite indicators • include the possibility of sending a misleading signal • include simplification and generalisation • include subjective judgment in construction • are subject to misuse and at disposal of politics • increase the quantity of data needed • often do not document the process of aggregation transparently • carry problems of measurement: absence of data, different methods of statistical compilation and errors in measurement • carry problems of the averaging procedure: composite indices and averaging may conceal divergences and some variables may cancel out the effect of another variable • carry problems of the weighting: subjective discretion plays a role in assigning the values • are a trade-off between simple averaging and weighting • carry problems of aggregation, for example vulnerable communities that differ in size; and hiding of disparities by generalising parameters • are imbued by political aspects

Source: modified and supplemented after Saisana and Tarantola 2002 and Briguglio 2003: 11

5.1.3 Comparison to other social development indicators

The monitoring of the demographic composition of Germany by social indicators is not a new phenomenon (Zapf 1979). Neither is the monitoring of social-environment relations in Germany like sustainable development (Birkmann 2004) or of the flood risk in an economic or hazard parameter related sense (Sections 2.2 and 2.3). Social vulnerability assessment as conceived in this study strives at the explicit linkage of social to natural phenomena. The aim is to make these phenomena measurable in the sense of making them comparable by a semi-quantitative approach. This exploratory pilot approach is a potential starting point for longer-term monitoring of both social and environmental changes over time. One must be aware though, that the theoretical frame as well as the political scope of using such indicators are also subject to changes over time.

'Quality of life' indicators aim at estimating the 'degrees of well-being' of the population (Bunge 1975, Zapf 1979). The scope of these indicators is to widen the previously economy driven demographic monitoring on physical (environmental), biosocial (health), psychological, technical, social, political and cultural aspects (Bunge 1975: 75). A number of observations are comparable to recent social-environmental indicator approaches like in the social vulnerability assessment. The goal of an indicator is to derive information by an observable variable over another, usually unobservable symptom (Bunge 1975: 65). So even methodologically, the indicator approach of 'quality of life' indicators is similar to the social vulnerability indicators. The elicitation of latent symptoms like weaknesses or strength of humans against natural hazards is technically achieved by the factor analysis in this study. The resulting factors thus are the indicators of social vulnerability in Germany. Still, indicators remain an indirect measurement tool that can explain no causality, only patterns. This is not only subject to the technical aggregation, or the ambiguous character (Bunge 1975: 67) of each indicator or variable. The quality of an index and its components largely depends on the quality of the theoretical framework. This obvious observation as well as the demand for improvements in this direction are perpetuated over many types of social / environmental indicators (Bunge 1975: 75, King and MacGregor 2000) and are no specific weakness of social vulnerability indicators per se.

Many synergies are seen between the related fields of human well-being, development, human rights and vulnerability (UNEP 2007: 303) assessments. However, the closeness of vulnerability to these fields is also regarded as a problem in the distinction of measurements by common human development, sustainability, well-being and social vulnerability indicators (Gall 2007). This is to a great extent due to the similarity of the indices by using similar construction techniques and input variables. For example, most country-level indicators have to rely on a few number of variables for which data is available like GDP or population density. This similarity blurs the distinction of social vulnerability and development measurements. The separation of various social-environmental indicator approaches is certainly hampered by the similarity of the theoretical concepts.

5.2 Evaluation of vulnerability in Germany

It is quite challenging to assess how social vulnerability is composed in Germany towards river floods and how it ranges between localities and groups. Even more challenging is it to assess this on a resolution as coarse as county-level for the whole territory of Germany. Obviously, such an assessment demands for ground-truthing or validation by local studies. The feasibility of cross-validation by studies at local level has been demonstrated for this vulnerability assessment at county-level (Fekete et al. 2009). Using a vulnerability framework and applying semi-quantitative methods allows for cross-scale comparability of both levels. The findings on social vulnerability by questionnaire survey in Cologne are one source of arguments supporting the selection of the variables for the approach of this study (**Table 3**). Similarly, the vulnerability profiles of households derived by the logistic regression in Section 4.3 serve to validate the vulnerability profiles of counties. Apart from validating the content of the indicators, it can also be shown that the spatial patterns derived by the indices are not randomly distributed, as can be shown by spatial autocorrelation tests (Annexe 8).

5.2.1 Other sources of validation

Of approximately 300 city-quarters in 500 municipalities participating in governmental programmes of mitigating social focal point quarters (BMVBW 2003, http://sozialestadt.de, viewed 24 July 2008), around 29 are in the vicinity of the three major streams Danube, Elbe and Rhine. This is too few to make statistical tests whether social problem zones are especially prone to exposure. However, the distribution of the locations displays a match with areas of high social susceptibility as detected by the SSI (**Figure 21**). It must be emphasised that mainly cities and few rural areas participate in the programmes, and that only those city quarters with social focal points are recorded, which applied for the programme. Therefore the map showing the locations of the programmes does not capture all social focal points in Germany, yet probably most of them within urban areas. The map shows that the SSI in many cases captures urban areas as highly susceptible, where at the same time the density of social problem quarters is high, for example the Ruhr-area, in the Saarland and around Frankfurt am Main. Due the lack of equal representation of rural areas this can not serve for a true validation of the SSI. The programme called “social city” (BMVBW 2003) is yet a useful source for probing the SSI since it captures social problem zones by local information of the respective local administrations. It is quite interesting to observe that similar zones are detected by the SSI on the much coarser scale of counties.

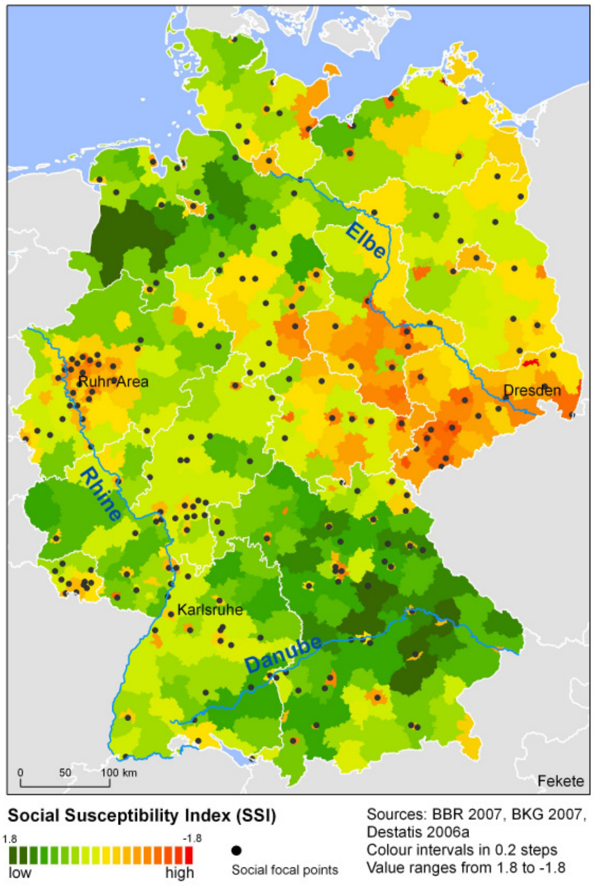


Figure 21. Matching of the social focal programme locations with the SSI in Germany
Source: social focal points by BMVBW 2003: 60

It is furthermore interesting to analyse to which extent the assessment of social susceptibility and vulnerability in this study is comparable to existing social vulnerability indicators of Germany. Currently, only one approach is found to use a comparable spatial resolution and area coverage concerning semi-quantitative social vulnerability measurement in Germany. The European Spatial Planning Observation Network (ESPON) analysed natural and technological hazard and vulnerability patterns related to climate change impacts on European administrative monitoring areas (NUTS3 level, Schmidt-Thomé 2006). In Germany, this is the spatial level of counties. The ESPON integrated vulnerability map consists of four variables; GDP per capita, population density, national GDP (inverse) and proportion of fragmented natural areas to all natural areas.

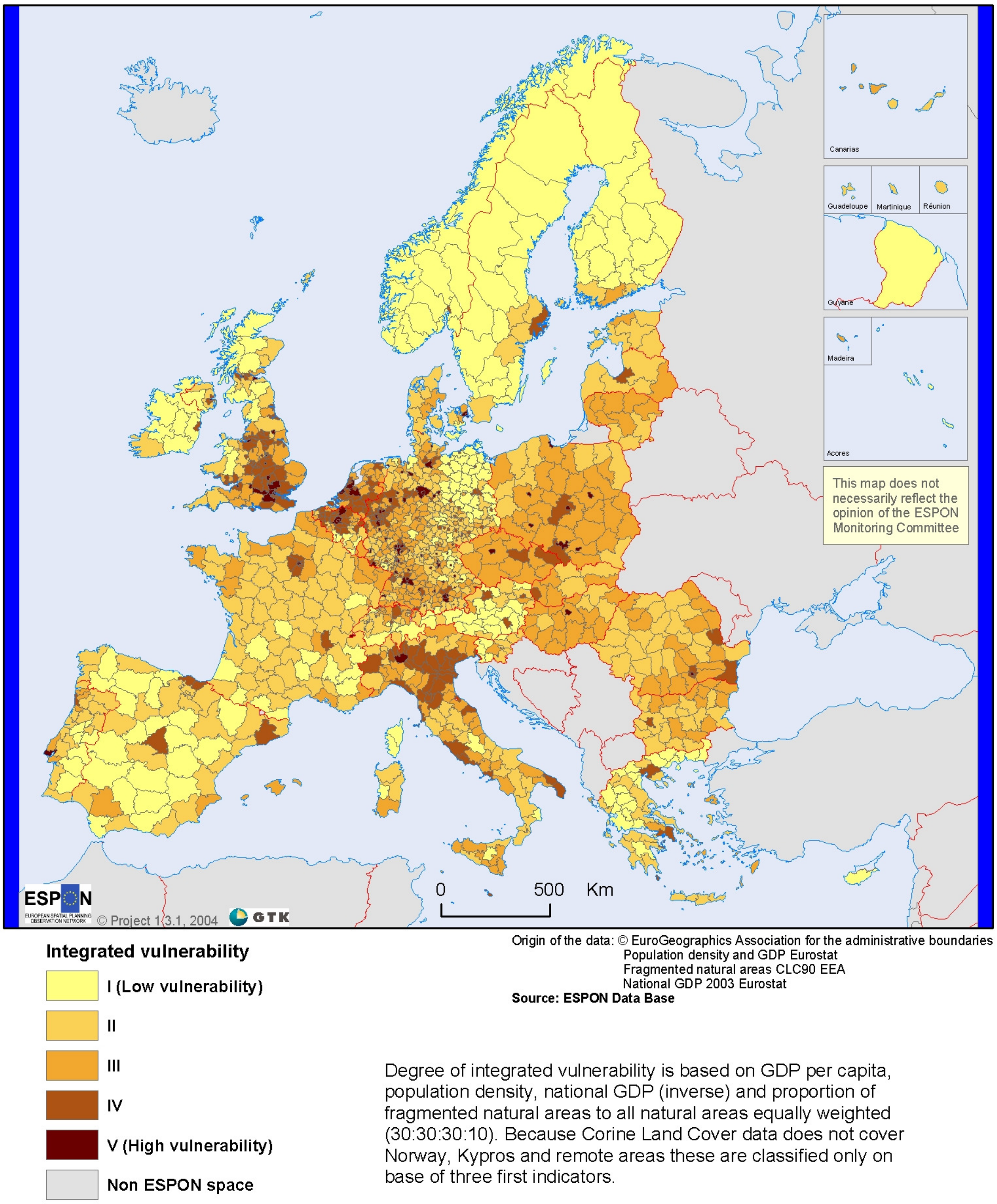


Figure 22. The ESPON integrated vulnerability map
Source: ESPON map from Schmidt-Thomé 2006: 89, with courtesy of the author

The comparison of the ESPON integrated vulnerability map with the SSI (**Figure 12**) and SIFVI (**Figure 20**) maps of this study reveals similar patterns of pockets of vulnerability concentrated in urbanised areas (**Figure 22**). However, the intensity of the highest vulnerable class differs; some of the counties with the highest vulnerability class in the ESPON map are not displayed as highly vulnerable in the SSI and SIFVI maps. Similarly, lower classes of vulnerability show also different regional patterns.

The vulnerability map of the ESPON approach must be compared with the susceptibility map of this study. It is only a difference in terminology; what is depicted by the ESPON map as 'vulnerability' is captured in this study as 'susceptibility'.
It is also very difficult to technically compare the two maps, since the ESPON map is colour-coded by five classes of defined values and the SSI by 18 classes of defined equal intervals. The SSI can also be recoded into 5 classes but since the classification of the break values of the ESPON index is not explicitly described (Schmidt-Thomé 2006: 88), a real comparison is not feasible. After comparing the ESPON map with various 5 class coding of the SSI it seemed more appropriate to keep the higher range of classes of the SSI (Annexe 7). Due to the difficulties of comparison one must be careful about interpretations. The SSI shows a higher resolution of sub-classes of susceptibility. It distinguishes regions not only of negative susceptibility but to the same extent regions with predominant coping capacities. The SSI furthermore is built upon an advanced theoretical background of social vulnerability and contains three indicators built on a depth of nine validated variables in the SSI.

While the SSI of this study can not compete with the coverage of Europe of the ESPON approach, it is successfully demonstrated, that the depth of information can be improved for the spatial resolution of counties in Germany. Even more importantly, the results of the validation in this study help to confirm the validity of social vulnerability indicators concerning natural hazards (Section 4.3). Moreover, the validation step confirmed that social susceptibility (and vulnerability) indicators can be measured by a reduced set of variables. This enables a more theoretically as well as methodologically underpinned application of social vulnerability indices on the basis of reduced data sets. This finding is especially valuable for monitoring by indicators on large-scale areas where data availability is often a problem.

5.2.2 Limitations of expert interviews

For even more extensive verification, expert interviews and field trips were conducted. While some interesting insights were gained, it was difficult to find experts both versed in social issues and flood mitigation. By telephone interviews, randomly picked disaster managers of municipalities and counties were asked on topics like preparedness measures against floods and potentially threatened persons. The interviews revealed a strong emphasis on technical preparedness measures, especially in Bavaria along the Danube river, but also in some cases along the river Elbe and Rhine. The interviewed persons were mostly convinced that the population in the respective area was well informed by the administration about the flood hazard. It was found difficult to direct the experts to questions on persons especially in need of assistance or especially threatened. Most were quite open to talk about weaknesses and rooms for improvement in the local disaster management, but most of these issues had to do with technical measures, which gained not much more insight into social vulnerabilities. Most interviewees identified residents closer to the river as more threatened, and few described special need groups like the immobile people as especially vulnerable, without further suggestive questions beforehand.

In April 2006 a field trip was conducted to the river Elbe which flooded parts of the city of Dresden and nearby cities of Meißen and Pirna to this time. Interviews were carried out with disaster managers of the city of Dresden and the relief organisation 'German life saving community' (DLRG) in Meißen. The interviews revealed that the greatest concern of the relief organisations were information flow and communication difficulties with several levels of administration. This suggests for further research of institutional vulnerability and information networks. Major cities like the city of Dresden were found to be better equipped with technical information systems but also commanded more diverse levels of disaster management as compared to smaller cities like Meißen. Transboundary communication with Czech colleagues was another topic where the city of Dresden has direct access, whereas the volunteers of the relief organisation in Meißen expressed lack of information access.

For the purpose of generating an overview on counties in Germany it was found difficult to make use of singular expert information. Field trips and random sample interviews allow for unmatched detailed information and the generation of crucial new aspects about root causes of vulnerability. However, it was difficult to find evidence about characteristics of potentially affected citizens among flood experts and disaster managers. Most information was found to be locally specific and not generalisable for whole regions. There are clear constraints about the use of singular local evidence for building indices for large areas as in this study. These local facts are valuable and in individual cases might be more important than the more general facets measured by an index. But for repeating occurrences of extreme events and especially for larger regions, other patterns might be responsible for large-scale disasters. In order to validate such large-scale patterns, the requirements are a large sample size and a monitoring over many years, both costly and time consuming (King and MacGregor 2000: 54). The recurrence of several hazard cases is certainly not to be hoped for. It is perpetuated among experts however, that such repetitive events are necessary for the awareness of the population (Vogt 2006) and the investment activity of administrations (Bednarz 2008). Such events are also windows of opportunity for the observation of flood preparedness, awareness and institutional vulnerability. However, social vulnerability as addressed in this study will only be revealed in case of a disaster. Since this is not an issue to allow waiting for, indices like the SSI and SIFVI are crucial to proactively identify potential disaster areas and potential disaster victims before any impact. Even if this index information is preliminary and amendable, it is an important basis for further research activities and counselling of disaster management and decision makers.

5.2.3 Limitations of weightings by experts

After the construction of the indicators, experts on the field of vulnerability and floods were asked to feedback on the approach. They were provided a questionnaire wherein the variables used for the indicator approach are listed. These variables should be commented whether they presumably indicate higher or lower vulnerability to floods. Additional flood parameters and perception of importance of technical and non-technical measures are further points in the questionnaire. Finally, it is asked to weight the social vulnerability indicator in relation to the hazard information to construct a vulnerability index. This survey consists of several steps of feedback with the experts, a methodology known as Delphi method and commonly applied for the weighting of such indices (Schmidt-Thomé 2006). Several pre-tests were run with colleagues and experts working in the field of vulnerability assessment, most of them additionally acquainted with flood hazard.

The survey revealed very interesting results. Most experts assumed similar directions of the indication of vulnerability of each variable. The strength of indication of the variables as well as the weighting of the final index is slightly related to the background of experience of the experts, whether of more natural science or social science background. Even more interesting however are the comments to the questionnaire. Many experts observed that it is a very difficult task to obtain both hazard expertise and social demographic knowledge. Many experts felt more comfortable with only a limited range of the questions and expressed difficulties with the weighting of all aspects. The ambiguity of the variables was commented as a major constraint. Many were uncomfortable to assign directions of vulnerability to certain variables like the unemployed or the group of foreigners per county.

Several experts refused to stereotype certain social groups without any evidence. This example shows the limitations of validation of such an index by the assumptions of experts, when no concrete evidence is available. Three experts refused to fill out the questionnaire, while 12 experts commented on these aspects but completed the questionnaire. These concerns persisted throughout several pre-test rounds with modifications of the questionnaire in consultation with the experts. Therefore the idea of weighting of the variables or index was abandoned. Improving such a questionnaire exceeded the initial scope and temporal resources of this study but is a future field of advancement.

The experience with the Delphi method shows that social vulnerability is still a field few experts are familiar with and too few case studies exist as to make precise assumptions. It is especially difficult to find experts with expertise in both hazard and vulnerability fields and for areas as large as whole river basins or for whole Germany. Before such a survey is thoroughly conducted with a sample of experts large enough, it seems more confident to rely on the quantitative validation by a real case event as carried out in Section 4.3. It is an especially interesting interim result that there seems to be no established body of knowledge about differences of social groups with regard to potential disaster impact. This study is therefore a pilot study in a direction where more research is needed.

5.3 Reflections on theory

Vulnerability research is a concept that has been exposed to several modifications and is becoming more and more an established application. It bears some resemblance to the term sustainability not only for similar goals but also for confusion about what it actually means. Some authors have already lamented that the term is at risk of becoming meaningless when it is not more precisely defined (Cannon 2006). But it can already be described as a matured concept as, upon the plethora of definitions, researchers have agreed not to agree. The consensus is to state the view of vulnerability definition and theoretical frame for orientation before elaborating on the findings. Still, the quest for a unifying theoretical foundation behind it is a major demand on social vulnerability assessments (King and MacGregor 2000: 52).

Vulnerability is one fine example of interdisciplinary science. In context to “natural hazards”, food security, climate change etc. several scholarly disciplines strive for integration of disciplines. This is found necessary in complex and messy real world problems like “natural disasters” that can seldom be reduced to a singular explanation. One sided hazard-oriented technical solutions have been criticised in the International Decade of Natural Disaster Reduction of (IDNDR) as not sufficient to treat humanitarian crises (Wisner et al. 2004: xvii). The same could probably be said about approaches focusing only on social science. However, at the same time it must be stated that interdisciplinary work is a field full of “landmines”. It is difficult to find a common language between natural science, social science and engineering. It is not uncommon to meet researchers who simply gave up talking to “the other side”. Still, vulnerability and resilience are spearheading interdisciplinary human-environment science with intensive push for advancement of theory and collaboration with other scientists and decision-makers on the application of vulnerability assessments for the mushrooming reports on disasters of natural origin.

‘Measuring’ social vulnerability is certainly a bone of contention for qualitatively oriented social scientists like anthropologists. The background of technical driven worldviews and reduction of human culture and social complexity to a ‘black box’ is looming behind the ‘measurement’ or quantification of human weaknesses to disasters of natural origin. But social vulnerability is at the same time an exciting impetus for trying to find tools that enable natural and social scientists to integrate their findings. Modern GIS, maps and semi-quantitative indicators are such tools it is hypothesised in this study. This is however only the technical application, the engineering side of integrative research. These tools are mere containers for integrating ideas. What is even more interesting is advancing what is actually measured. Vulnerability maps are quickly assembled, but a thorough investigation of the content is paramount. The tools only provide an interface, a platform of communicating the theoretical assumptions.

To which extent was the theoretical background helpful to identify social vulnerability in Germany? First of all, social vulnerability opens a direction for investigation aside from traditional flood risk perspectives. While ‘root causes’ and ‘dynamic pressures’ in societies are a common field of sociology and other social sciences, the bridge to natural hazards is still quite under-researched in Germany. The conceptual BBC framework guides the perspective of interconnections and main categories to be looked at. The theoretical sub-categories of vulnerability; susceptibility, capacities and exposure are especially helpful to structure the identification of vulnerability among the social groups depicted by the statistical variables. ‘Susceptibility’ is a research lens that is especially helpful to identify attributes of humans that can be weighed against each other, and thus help building a more precise argumentation why certain groups are more vulnerable or not. The capacities of humans are a difficult theoretical category, since they are often just the opposite of the susceptibility of the people. Still, it is in some areas helpful to explicitly search for positive attributes that might be overlooked by a mere negative research focus. This bifocal point on positive as well as negative attributes helps to uncover unsuspected coherences. For example, the affluent are not in all respects safer, they are even more exposed when residing in homes along expensive water-front properties. Social networks are not only positive attributes, in some cases the infesting of tradition may hinder taking early warning seriously.

"It is not important to forecast the future, but to be prepared for it"
Perikles 500 B.C.

The limitations of precise prediction of social vulnerability are nested within the complexity of the problem itself. Social interactions are already complex in a sense of defying the reduction to a set of axioms. While patterns of social interaction are observable, it is doubtful whether they are any better for precise prediction than ‘cargo-cults’. The indicators in this study are merely indirect measures of a reduced set of observations. Especially in context of the social interactions with the environment one must refrain from aims like predicting exact timing or extent of potential disasters. Flooding risk is non-linear, non deterministic and contains chaotic features thus making it difficult to predict the probability of flood events. Features of flood risk are hydrological and hydraulic parameters. Another feature is the social system, of which some say (Richardson 2005: 622) that “it is nigh to impossible to get such an accurate appreciation of its current state. If we could view its current state directly its future evolution would be quite easy to ascertain (…)”. An elegant way out of this dilemma is formulated by Cardona (2005: 2): “(…) the concept underlying this methodology is one of controlling risk rather than obtaining a precise evaluation of it (physical truth).”

Constructing a social vulnerability index is a trade-off between direct evidence that is often not available and indirect assumptions that are always preliminary. The construction of a social vulnerability index aims not at examining causality or elicitation of truths. Such an index is always an indirect surrogate of a phenomenon. While it is successfully demonstrated that the social vulnerability index identifies social groups that could be tested on the historic flood disaster of 2002, it cannot be assumed that another event would not reveal a different picture. This situation is comparable to the term "centennial flood". The public audience term confuses this statistical measure with causality in the sense that such a flood is expected only every 100 years. There can never be a real prediction of the exact timing of such weather events as it cannot be predicted to 100 percent accuracy which social group will be affected most. Each disaster is different, and continuous improvement of measurement can only help to verify but never to absolutely predict extent, timing and characteristic of a disaster.

Stressing out these limitations of prediction is especially important in a multi-disciplinary arena where the aims of natural scientists collide with the perceptions of social scientists. This is a bottleneck of interdisciplinary work, when one side wants to measure exactly and predict by reduction and precise definitions while the counterparts believe in the impossibility of reduction and the limitations of quantification. Flood vulnerability is a difficult topic here since it combines both fields and represents a problem that is always subject to changing perceptions. Flood vulnerability as presented in this study is a negotiated balance of humans perceiving the environment and threats posed by hazards. This balance is fragile and subject to change as much as the course of scientific and political aims of decision makers are constant subjects of change.

6 Transfer

The development of social vulnerability indicators is not an end in itself (King and MacGregor 2000: 52). The developed indices are constructed in a way to enable methodological and conceptual coupling with other information and scientific fields. Some of these couplings and mutual benefits are already accomplished, and there are many directions for which the application of the SSI and SIFVI are promising.

6.1 The DISFLOOD project

This study is one major package in the project 'Disaster Information System for Large-Scale Flood Events Using Earth Observation' (DISFLOOD, Damm et al. 2006). The project is a platform for multi-disciplinary and multi-institutional research. It is a joint effort of the German Aerospace Centre (DLR), the German Research Centre for Geosciences Potsdam (GFZ) and the UNITED NATIONS UNIVERSITY – Institute for Environment and Human Security (UNU-EHS). The project as financed by the Helmholtz society started in late 2005 and ended in 2008. The internet platform created by the project targets extreme river floods in Germany by assessing hazard and vulnerability parameters. At the same time DSFLOOD is a pilot study to combine different methods like remote sensing, hydraulic hazard models, and economic damage models with social and environmental vulnerability indicators. The outcome is an online information system that is available on the Natural Disaster Network web site NaDiNe (http://nadine.helmholtz-eos.de/nadine_en.html). The prime target groups of NaDiNe are experts working on flood protection, regional planners and scientists. Moreover, the interactive hazard and vulnerability maps are also accessible by the public to a certain degree.

As a major novelty, a social vulnerability map for whole territory of Germany is available and combinable with the hazard information. The construction of the social vulnerability map by a semi-quantitative indicator approach allows for merging with other quantitative information of the project partners. The hazard information is either derived from hazard scenarios (statistical precipitation or inundation estimation) or, as another novelty, by real event mapping by remote sensing data. This map package 1 (MP1, **Figure 23**) is created by the project partners DLR and GFZ for the two principal application cases; for a real event (part 1 of the flow chart in **Figure 23**) and for scenarios (part 2 of **Figure 23**). The real event mapping delivers exact and timely documentation of the hazard extent for large areas in the case of an event. Such information is lacking until today; former flood events are hardly documented in a concise and comparable way. This hazard information is then merged with the vulnerability maps that are already computed. This step enriches the hazard layer on information about the impact on society (MP 3, **Figure 23**) and the environment (MP 4, **Figure 23**. This allows for a rapid overview on the potential impact of the flood and highlights areas of special concern for evacuation, emergency measures and recovery priorities. Additionally, the rapid economic damage estimation developed by the GFZ can be computed for buildings and related values in the affected area (MP 2, **Figure 23**). Such rapid damage assessment locates flooded regions, settlements and respective population density, and the social vulnerability profile per affected county.

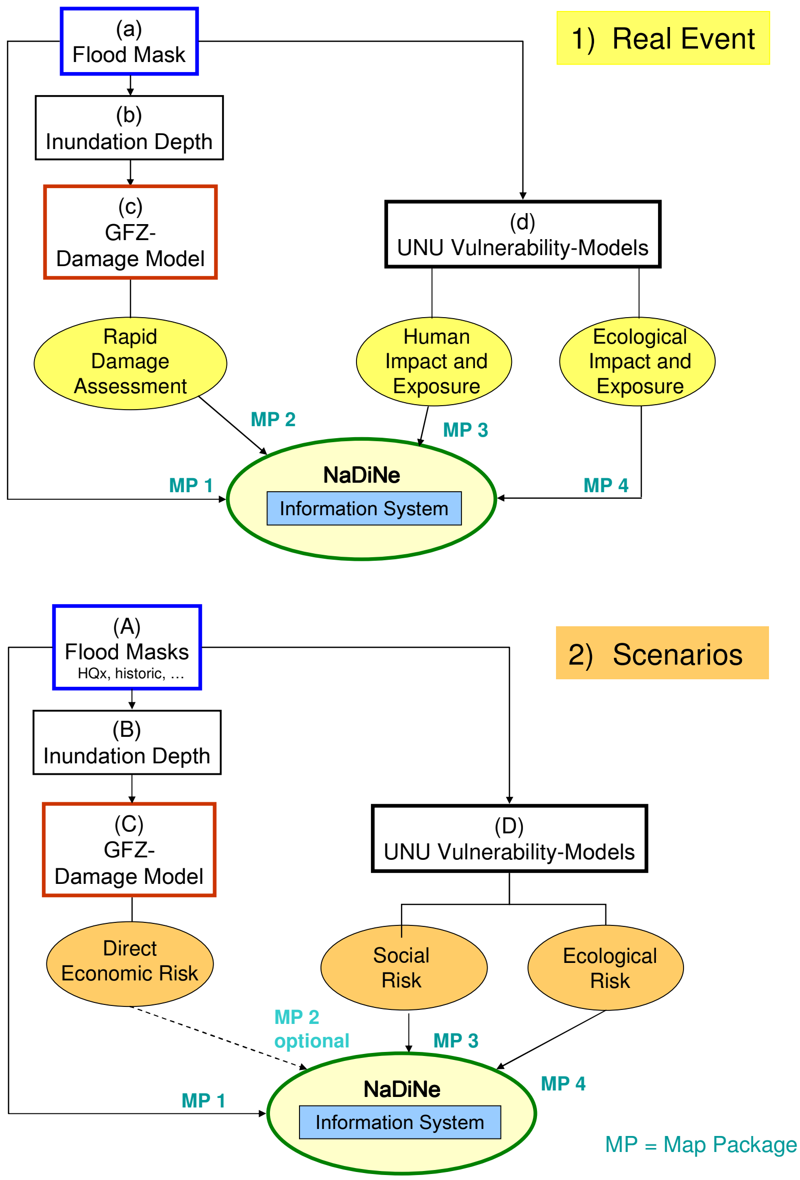


Figure 23. Work flow within the DISFLOOD project for a) a real event and b) scenarios.
Source: created by the DISFLOOD team

Aside from the real event case, the social vulnerability map is an important input for longer term planning by scenarios (part 2 of **Figure 23**). Scenarios of hazard events are for example the historic flood event sets of the GFZ or the hazard inundation maps used in this study (Subheading 4.6.1). The hazard information of the GFZ partner for historic flood event sets will cover the whole territory of Germany. The official extreme event hazard inundation maps are at the present moment available for the river Rhine, the river Elbe within the federal states Saxony and Saxony-Anhalt, and, only to a limited extent for parts of the river Danube (Subheading 4.6.1). Combining these hazard scenarios (MP1, **Figure 23**) with the Social Susceptibility Index (MP3, **Figure 23**), a Social and Infrastructure Flood Vulnerability Index can be computed (Section 4.6). Additionally, this index can be merged with the socio-environmental vulnerability index (MP 4, **Figure 23**) of the project partner at UNU-EHS (Damm 2008). This creates a combined risk index of disaster by flooding for both the human sector as well as for the environmental sector. It allows for a more holistic estimation of potential impacts of hazards on a coupled human-environment system. This risk index is an important planning tool for directing hazard prevention in the context of sustainable development, adaptation to climate change and demographic development of Germany. As an option, the direct economic risk for buildings and related values by the GFZ can be computed for specific regions and then compared with those regions containing high social and socio-environmental vulnerability. This range of different aspects allows for a more precise analysis of the different impacts of a flood. For example, regions with a high economic vulnerability are not automatically congruent with areas of high environmental impact or areas where the most socially vulnerable population resides. DISFLOOD thus provides a concise set of information for decision makers to identify vulnerability mitigation priorities in different sectors; society, environment and economy. The modular composition of the indicators permits the analysis and display of special fields of interest, for example, the location of especially fragile persons. The easily comprehendible maps alleviate the implementation of such complex information for flood experts and politicians alike. DISFLOOD is therefore a true multi-disciplinary platform that translates complex scientific interrelationships into accessible information.

6.2 Future research needs

One field of advancement for this study is seen in obtaining data with finer resolution of settlement areas and the connection to exposure areas. With the available data resolution it can not be captured, for example, whether the hospitals of a county are located far remote of potential inundation areas or whether a social focal point with prevailing low income groups is located within an exposed area. When hazard maps are available though, a rough estimation of affected population and their specific county profile can be accomplished. It would certainly be desirable to obtain data on higher spatial resolution.

Hazard: Hazard scenarios are an important field for applications of social vulnerability indices. Apart from traditional flood hazard parameters like inundation depth, velocity or debris load, it is especially interesting to construct temporal scenarios, for example day and night time, when the distribution of the population is different and the surprise factor of a flood higher. Another example is seasonal differences, where a devastating flood in winter results in cut-off of electricity and heating. Other areas for hazard scenarios are coastal zones or flash floods, but also secondary hazards like cascading effects on drinking water. Climate change is one recent concern that is however just one upon many processes like deforestation and population growth that will raise the number of exposed people until 2050 (UNU 2004). The fourth IPCC report only increased the interest to research the vulnerability of societies, that will be subject to major transformations by extreme events (IPCC 2007: 541). The methodology of semi-quantitative indicators on the background on a common vulnerability research framework is especially apt to allow for cross-scale analyses of climate change hazard impacts, but also of impacts on the population. The SSI and SIFVI as developed in this study can be combined with climate change scenarios, to identify regions in Germany and Europe where increased variability of precipitation patterns coincide with vulnerable population. This approach attracts currently much research interest (EEA 2005, Zebisch et al. 2005) and is a field for scientific and political collaboration opportunities across institutional and disciplinary borders.

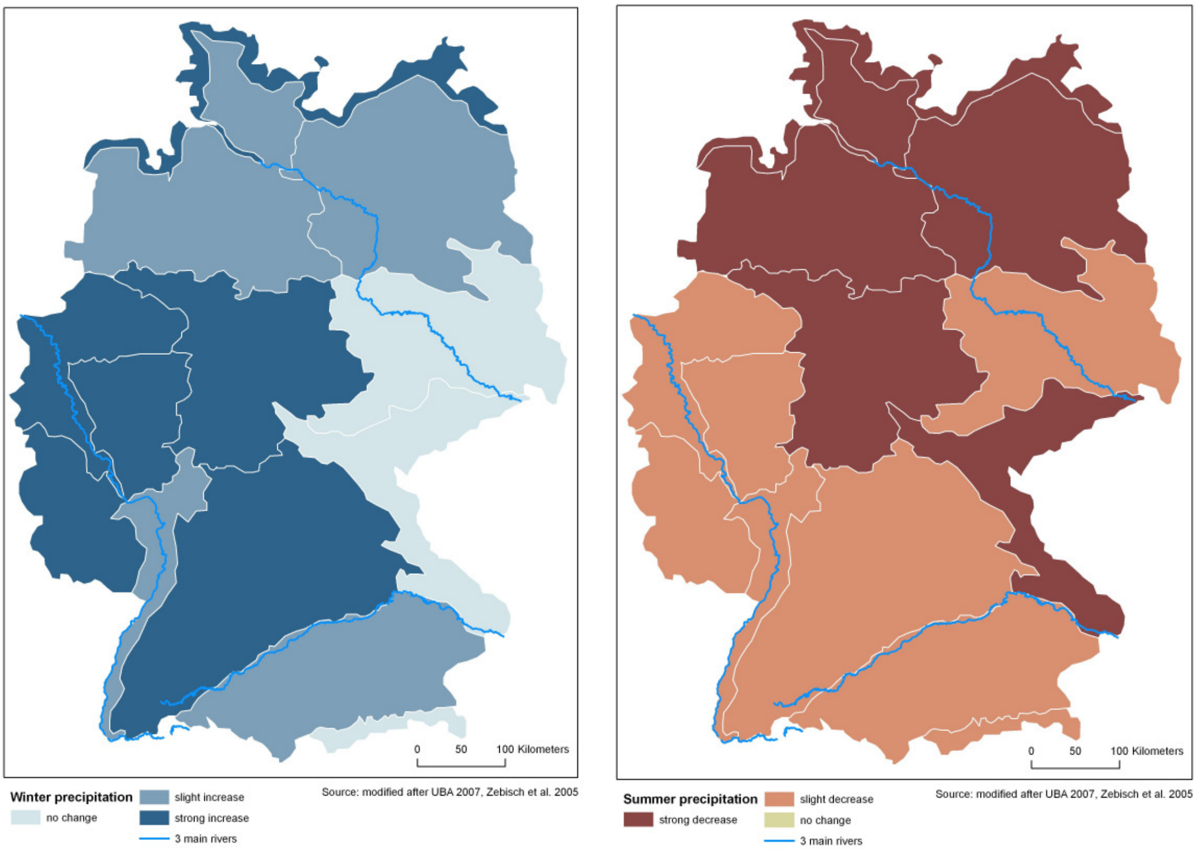


Figure 24. Regional impacts of climate change precipitation scenarios
Source: SRES scenario A2, in Spekat et al. 2007: 70

The recent climate change scenarios (**Figure 24**) suggest that the western parts of Germany and the coast will experience increased winter precipitation. Summer precipitation decreases in some regions and seasonal patterns shift in Germany while at the same time convective precipitation and storm events are expected to increase regionally (cf. Zebisch et al. 2005: 190, Spekat et al. 2007).

Social vulnerability: Demographic change is one key driver transforming the pattern of social vulnerability in Germany. As a main driver of demographic change in Germany (Section 2.4) the ageing of the population is of major concern for aggravating the quota of fragile people in Germany. The distribution of a projected increase of ageing population is not uniquely dispersed over Germany (**Figure 25**). Regions with less economic prosperity especially in the East of Germany are especially prone to this change. The whole population and social system is affected by lesser and lesser working age people to provide for taxes and medical care of the elderly. Since the elderly are those most dependent on assistance for example in the case of evacuation (Section 4.3), these areas with a higher ratio of population increase are priority areas for disaster mitigation planning. The SSI is one tool for monitoring and projecting static as well as dynamic compositions of society in relation to various hazard and demographic change scenarios.

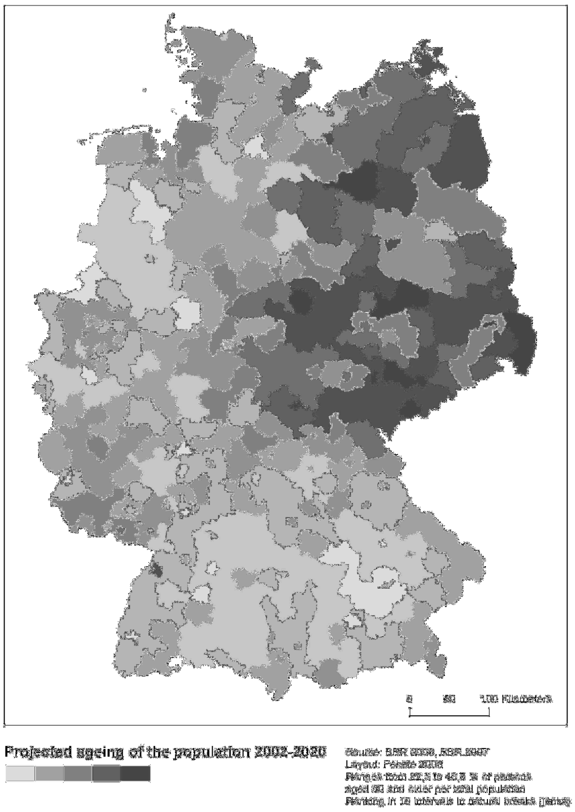


Figure 25. Projection of the ageing of the population in Germany from 2002 to 2020
Source: after BBR 2006 and BBR 2007

This example is just one area for further exploration of the versatility of the social vulnerability indices. Demographic monitoring and natural hazards mitigation will continue to receive attention in the future. Scientists and decision makers will need to explain complex vulnerabilities and developments to the public. The social vulnerability maps presented in this study are one important contribution to this.

6.3 Recommendations for decision-makers

The presented study reveals advancements in scientific methods and results that can be used for overarching political objectives like disaster risk reduction. Such outcomes and tools can be conveyed to decision makers by using the language of project management. Decision-makers as a target group of this study are disaster managers, flood experts and land use planning authorities. A common structure for the implementation of project results and objectives is the logical framework approach. This project management approach is endorsed by the European Commission (EuropeAid 2004) or the Australian Government (AusAID 2005), for example.

Table 27. Logical Framework Matrix of this study

Project Description	Indicators (of how it is achieved and measured)	Means of Verification	Assumptions and Risks
Overall objective: Disaster risk reduction as topic of the Hyogo Framework of Action; Human security policy of the UN	*- Not appropriate for the study itself to provide and collect this information -*		
Purpose: Capacity building of knowledge and awareness about social vulnerability. Inter-disciplinary integration with hazard and risk perspectives	Access to the information, transparency and documentation, publications within the time frame of the project and after.	Publication of thesis in the UNU-EHS series, publications in peer reviewed scientific journals Oral and poster presentations on national and international conferences and meetings Contribution and integration into the International Flood Initiative (IFI) Reports	The connection of the scientific output to the target group and stakeholders must be accomplished Awareness and need for such information must be raised
Results: Disaster Information System, social vulnerability Indices, social vulnerability profiles of counties in Germany, checklist for social vulnerability measurement	Project delivery until the project end in 2008 Work packages delivery and implementation Quality control by scientific review	DISFLOOD Information System of DLR, GFZ and UNU-EHS on the NaDiNe website Doctoral theses	Project coordination and identification of common frame, methods and goals are necessary in a multi-disciplinary project Funding and allocation of resources are important
Activities: Flood impact review Review and assessment of social problems Development of a conceptual framework Vulnerability assessment	Theoretical framework of vulnerability Statistical analyses GIS analyses	Data sources of literature, census data, remote sensing data, GIS data	Data availability and information depth for such large-scale areas is often a problem Access to data is difficult due to various administrative hierarchies in Germany Time and resources constrain more in-depth data collection

The logical framework matrix (**Table 27**, cf. EuropeAid 2004: 73, AusAID 2005: 3) structures research activities, results, purpose and overall objective in a vertical hierarchy. The decisively simple 4x4 matrix provides an overview what these points are in the project, by which indicators they can be measured, verified and which risks and assumptions are behind it. The logical framework matrix identifies activities necessary to achieve the results of the social vulnerability assessment. Project management and external decision-maker appraisal is important to meet the assumptions and avoid the risks in achieving the overall objective. The individual steps can be monitored by the indicators and means of verification.

Achievements and benefits from this study are:

- The successful demonstration that a social vulnerability assessment in Germany can be carried out
- The enhancement of common hazard and vulnerability approaches by developing information about the vulnerable population
- An information tool that allows combination with other data sources
- Maps that are easy to interpret
- An information system that is accessible on a web-based platform

Challenges identified in this study are:

- Data availability and spatial resolution of data can be still improved even for countries like Germany
- Awareness about the availability and versatility of social vulnerability assessments must be raised
- Integrative multi-disciplinary scientific projects require openness and engagement from all project partners and disciplines to accept new ideas

Instructions for the application of the scientific results are:

- The results can be viewed on any web-browser by the public and documentation is provided in standard text formats, as well as in scientific publications
- Certain target groups like flood or vulnerability experts, disaster managers or spatial planners can get access to certain data by request
- Expert knowledge, special software and data access are necessary for reproducing the results and for longer-term monitoring

- Social vulnerability is a topic for the reduction of disaster risk and mitigating natural hazards impact

For the successful implementation of the scientific results in national or regional policies, however, a specific applicability study would be recommendable. There is a need to identify the institutional structures and terminology first, before translating the scientific results into policies and decisions. Otherwise the hazard of misunderstanding exists due to different systems and languages of communication, between science and policy. While the risks and assumptions behind the indices and methodology are stated in this study, they might not be understood by the stakeholders. Though much effort has been invested to create visually easily comprehensible maps, the hazard of misconception cannot be ruled out. Therefore it is necessary to accompany an implementation of social vulnerability aspects into policies or decisions by an expert. Mutual communication between stakeholders, decisions-makers and experts is the key to the successful use of complex disaster risk information.

7 Conclusion

This study demonstrates the merits and feasibility for carrying out a semi-quantitative social vulnerability assessment in Germany. On county-scale, patterns specific for the composition of social vulnerability towards river-floods have been identified, transformed into quantifiable indicators and validated by an independent second data set. Social vulnerability as a concept applied in other countries has been successfully applied and advanced on the validation part. This assessment of social vulnerability captures not only exposure and susceptibility but also indicates capacities of humans to mitigate and adapt to disasters.

There can be no analysis of risk management, resilience and adaptation options without understanding vulnerability first. Vulnerability is a detector of susceptibility and capacities of any system. Social systems in context to a hazard are determined by their physical location, temporal development, their internal and external influences and exchanges. This place-based notion of complex problems can be measured by the exposure of this system to external threats. Place-based exposure however, only manifests as a problem, when certain negative and positive, passive and active abilities and conditions coincide. Encompassing the exposure, susceptibility and capacities of a system at risk provides a broad research lens that helps to capture aspects that might have been neglected by traditional hazard or risk analyses so far.

The Social Susceptibility Index (SSI) as well as the Social and Infrastructure Flood Vulnerability Index (SIFVI) are excellent tools for starting a monitoring process that captures both social dynamics in Germany and links these to environmental processes. The comprehensibility and versatility of these indices and maps provide decision-makers information about complex phenomena that can be used for the development of strategies and policies. The risks and assumptions behind the construction of these indices will be a valuable guideline for experts and scientists working in the field of natural hazards and coupled human-environment systems. The study contributes to the overall objective of disaster risk reduction that is acknowledged on the global level by the Hyogo Framework for Action.

Limitations and challenges must be denoted for avoiding uncritical application and uncommented transfer of the approach of this study. Data availability, spatial and temporal resolution of the data are limitations for capturing certain social aspects like flood experience, preparedness, or risk perception for the large research area. The hazard scenarios are limited to inundation extent and full data coverage was not available for the two of three major streams, the Danube and Elbe, - only for the Rhine. Within the methodology, the challenges lie within an objective selection of the variables and the weighting procedure, even when a comprehensive conceptual framework guides the systematisation. It is within the nature of indicators and quantification that the actual phenomena are only indirectly measured and often generalisations must be made. Therefore, the indicators are valid only for describing average characteristics of the demographic composition of counties, not for capturing the vulnerability of single households. As with every analytical concept, many assumptions are made, and it must be encouraged to regard this study results not as definite but rather as starting point for improvement and further research.

The assessment of social vulnerability is not an end in itself and does not stop at the description of potential demographic weaknesses and strengths. Social vulnerability is one dimension of vulnerability besides the vulnerability of infrastructure, of the environment or else. Social vulnerability is also one part of disaster risk assessments and crucial information for supplementing hazard assessments. The versatility of the developed Social Susceptibility Index is exhibited by integrating it with vulnerable infrastructure and an extreme event hazard scenario. The outcome is a Social and Infrastructure Flood Vulnerability Index which highlights areas of specific vulnerability of flood impact aggravated by social deficiencies. There already exist applications for this index and the methodology by the DISFLOOD project. Within this project, advanced hydrologic modelling and real event rapid hazard mapping by remote sensing are input for the further advancement of the hazard estimation. As another part of the DISFLOOD project, a vulnerability assessment of the social-ecological dimension will be available. By combining the two vulnerability assessments and the two hazard estimation methods, a truly multi-disciplinary, holistic and balanced approach on flood vulnerability is accomplished.

This study contributes to recent research activities around social vulnerability in three respects. First, it increases information about social vulnerability in Germany. Second, the methodology fosters the integration of social vulnerability with more technical and hazard oriented approaches. Third, it aligns with the research direction of interdisciplinary science that is especially enhanced in the field of the human-environment nexus. Vulnerability, resilience, climate change and sustainability are high on the agenda of national policy and research. These are fields where advancement in information depth and awareness are prerequisites for developing strategies for the future in the light of population growth and environmental strain. Knowledge on complex relationships translated into measurable indicators will be a key field for the identification and valuation of future action priorities.

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APPENDIX

ANNEXE 1

Table A1. Social impacts of water-related disasters

Northeast England June 2000 floods. Flooding of1000 properties with the event having a return period of ca. 1:100 years (Tapsell et al. 2002)	- Stress and trauma, intangible effects - Most important losses were irreplaceable personal items and memorabilia - Disruption of daily life - Time off work, loss of income - Health risks - Insecurity feeling regarding “safe home” - Mistrust in authorities’ effectiveness
December 2004 Indian Ocean Tsunami in India and Sri Lanka (Wachtendorf et al. 2006)	- Loss of life - Destruction of property and infrastructure - Impact on livelihoods - A persistent sense of uncertainty - Variation in community-based response and recovery efforts - Inequities in disaster relief distribution - Gender and age vulnerability and capacities - Temporary shelter and housing - Long-term relocation planning
Hurricane Katrina in New Orleans (Masozera et al. 2007)	- Inequality in wealth: wealth dictates the kind of housing, transportation, health care and property insurance - Socio-economic status played a role during the recovery-period: income, savings, employment, access to communication channels and information, insurance - Part-time jobs contribute to insecurity, New Orleans was characterised by high poverty-rates and low-wage jobs before Katrina - Middle and higher income disaster victims were more at ease to negotiate bureaucratic systems - Lower income groups must have access to reconstruction jobs, investment funds, and housing in safe locations - Katrina caused flood damages regardless of income, elevation or social factors. No statistical significant correlation was found between elevation and housing value - The higher the population density the greater the relative amount of poor people in this case - Low-income residents were disadvantaged in the response phase due to lack of transportation; which increased the vulnerability of the poor, elderly and disabled - The rate of homeownership in the city was low; which is also believed to be a surrogate representative of economic stability and neighbourhood stability - The majority of the fatalities were elderly (see also Jonkman 2007)

ANNEXE 2

The following table revises some prominent approaches from literature dealing with normalisation, aggregation and correlation of population variables related to disaster research.

Table A2. Statistical measures applied in previous studies

Literature source	Aims in short; Scale, Unit	Variables; Normalisation; Ranks	Aggregation	Correlation
Cardona 2005	System of Indicators for Disaster Risk Management; National and sub-national. 4 indices on national level, indicators for sub-national	- Population density as people / 5 Km² ; - Unemployment as % of total labour force - Debt servicing, % of GDP; Min-max technique	Weighting by impact factor (index like mortality rate), 'multi attribute technique'	Sensitivity tests, correlation analysis
Clark et al 1998	Coastal communities' vulnerability; one city, group blocks	Percentage of population; 5 ranks	Two methods: - absolute index: averaging - relative measure: data envelopment analysis (DEA)	Factor analysis to simplify a data set of 34 proxies. High correlation detected. Five main factors derived that explain most of the variation in the dataset. The proxies were highly correlated but not the factors.
Cutter et al. 2000	Hazard-of-place model of vulnerability; social indicators and hazard zones: Georgetown county in the U.S., county census blocks	- First determining the ratio of a variable in each census block to the total number of that variable in the county. - Second this value was then divided by the maximum value to create an index that ranges from 0 to 1.00	The index values for each variable were summed to a composite index score. These values were placed into deciles, but visually displayed as five categories on the map. No weighting. Absolute values	No description
IKSR 2001	Hazard zonation maps with damage estimates in context to river flooding in Germany	Population numbers of the communities were divided on the CORINE settlement areas with each community to derive a mean population density per settlement; Three damage ranks	No aggregation, just overlay of hazard zones and damage zones over topographical maps	No description
Kaly et al. 2004	Single index, sub-indices and country profiles for Environmental Vulnerability (EVI); States	Total population, Tourists; Per km² Ranks from 1-7	These indicators are combined by simple averaging and reported simultaneously as a single index, a range of policy-relevant thematic sub-indices and as a profile showing the results for each indicator	Variance analysis, simple correlation coefficient test, regression, Standard deviation, Kolmogorov-Smirnov goodness-of-fit test, frequency distribution
Rygel et al. 2005	Composite index of social vulnerability; census block-group level	Per area in km², and per population; Ranks 1-19	Pareto ranking instead of simple averaging, 57 variables reduced to 3 indicators by Principal Component Analysis: poverty, immigrants, old age / disabilities	Correlation matrix, Varimax orthogonal rotation with Kaiser normalisation, loading of the components
Tapsell et al. 2002	Social Flood Vulnerability Index, England and Wales,	Percentages of total population / objects, standardised z-scores,	4 financial deprivation indicators, multiplied by 0.25; summed with 3	Standard deviation

	statistical enumeration districts	transformations into log natural or square root; 5 ranks	social indicators	
Wu et al. 2002	Coastal communities' vulnerability, composite index; Counties in USA	Ratio of the value of variables in each census block to the maximum value for the variable in the county; Social vulnerability index: 4 quartiles	Simple average, arithmetic mean of the scores of all proxies. No weighting. Overall vulnerability index: hazard scores (1-4) multiplied by social vulnerability index (0 – 1).	Using correlated variables like 'females' and 'single mother households'; Investigating correlation to sea-level rise

ANNEXE 3

Table A3. Common vulnerability characteristics in international studies

Indicators selection derived by literature	Indicators derived by methodological selection	Variables suitable for indication derived by evidence of real events
Cutter et al. 2000; multi-hazard; Georgetown County, USA - age > 65 - age < 18 - non-white - female - total population - housing units, value Wu et al. 2002; coastal hazards; cape may county, USA Same findings, plus - renter-occupied housing units	Rygel et al. 2005; Virginia metropolitan area, USA; PCA, Pareto ranking - poverty - immigrants - old age / disabilities	Yarnal 2007; New Orleans - poverty - old age, ill health - skin colour - language skills - minorities (socio-economic) - female, female headed, children - unemployed - friendless
Nakamura et al. 2001; world - migrants - elderly / disabled - poor - ethnic minorities - female	Clark et al. 1998; coastal hazards; Revere city, USA; factor analysis - poverty - transcience (newcomers) - disabilities - immigrants (foreigners) - young families	IKSR 2002; floods in Europe - old age (pensioners) - persons in cars - people camping - disability, special needs, children
Tapsell et al. 2002; floods in England financial deprivation: - unemployment - overcrowding (persons per room) - non-car ownership - non-home ownership social characteristics: - the long-term sick - single parents - the elderly (75+)	Dwyer et al. 2004; natural hazards in urbanised areas in Western Australia; decision tree analysis - age - income - gender - employment - residence type - insurance - disabilities - etc.	Tapsell et al. 2002; floods in England - pre-existing health problems - children - women - the elderly - disabled

ANNEXE 4

Comparison of harmonisation and standardisation effects in factor analysis

Table A4.1. Raw data

	Rural	Income	*	*	*	*
	Urban	Unemploy	Fragility	*	*	*
	Component					
	1	2	3	4	5	6
Unempl_Ratio		-0.82748				
Unempl_foreigners_ratio	0.739217					
Income_ratio	0.457419	0.682786				
One- and two-apt homes	-0.7055					
Small aptmts	0.506389					
Big aptmts	-0.49286	0.673141				
Sqm_pp		0.583692				
Pop__0-6					0.747635	
Pop_6-18				0.843734		
Pop_15-25		-0.49694		0.492127		
Pop_25-30						0.619678
Pop_30-50			-0.70656			
Pop_50-65				-0.63458		
Pop_65-			0.525253	-0.40876		
Pop_75-			0.727804			
Female_gender_ratio			0.511347			
Imperviousness	0.876553					
Persons_per_settlmt_area						0.647724
Urban_areas	0.850171					
Rural_areas						
New_borns_ratio					0.825558	

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Rotation converged in 7 iterations.

6 factors = 65,087%

* only those columns received a naming which had more than one factor loading

Table A4.2. Harmonised data

HARMONISED

	Income	*				
	Unemploy	Urban	Fragility			
	Component					
	1	2	3	4	5	6
Unempl_Ratio	-0.65882					
Unempl_foreigners_ratio		0.711756				
Income_ratio	0.589845	0.541363				
One- and two-apt homes	0.633229					0.436182
Small aptmts		0.412096				
Big aptmts	0.838739					
Sqm_pp	0.678278		0.424771			
Pop__0-6	0.520292			0.501059		
Pop_6-18				0.709825		
Pop_15-25				0.768021		
Pop_25-30				0.627291		
Pop_30-50				0.754074		
Pop_50-65			0.678497			
Pop_65-			0.798278			
Pop_75-			0.744532			
Female_gender_ratio	0.404408		0.554472			
Imperviousness		0.90751				
Persons_per_settlmt_area					0.669783	
Urban_areas		0.910796				
Rural_areas						0.84494
New_borns_ratio					0.691111	

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Rotation converged in 9 iterations.

6 factors = 68,348%

* only those columns received a naming which had more than one factor loading

Table A4.3. Standardised data

STANDARDISED						
	Apt_size	*				
	Unemploy	Urban		Fragility		
	Component					
	1	2	3	4	5	6
Unempl_Ratio	-0.7133					
Unempl_foreigners_ratio		0.694793				
Income_ratio	0.533272	0.536952				
One- and two-apt homes	0.607693				0.435323	
Small aptmts	-0.40059					
Big aptmts	0.88565					
Sqm_pp	0.551328			0.545943		
Pop__0-6	0.452634		0.462313			0.436986
Pop_6-18	0.426385		0.66906			
Pop_15-25			0.780094			
Pop_25-30			0.648749			
Pop_30-50			0.759684			
Pop_50-65				0.629306		
Pop_65-				0.749699		
Pop_75-				0.730116		
Female_gender_ratio				0.639262		
Imperviousness		0.907616				
Persons_per_settlmt_area						
Urban_areas		0.920598				
Rural_areas					0.816339	
New_borns_ratio						0.783626

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Rotation converged in 9 iterations.

6 factors explain 67,123%

* only those columns received a naming which had more than one factor loading

ANNEXE 5

Pre-analysis of distributions in the input variables for the logistic regression

Table A5.1. KMO and Bartlett's test of the factor analysis

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.905
Bartlett's Test of Sphericity	Approx. Chi-Square	14850.967
	df	820
	Sig.	.000

Dependent variable leave_home: The scrutiny of the distribution of the input variables already displays trends in the data. The following tables illustrate which household groups are more sensitive to the flood impact, as measured by the dependent variable *leave_home*. The selection of suitable sub-variables is decided upon all three dependent variables (tables A5.2, A5.4 and A5.6) and by considering the variable set in the factor analysis. The aim is to validate as many variables of the factor analysis set as possible.

Table A5.2. Distribution (crosstab) of the dependent variable "leave_home" within the ordinal variables

		leave_home			leave_home		
Variable	**Variable description**	**no**	**yes**	**total**	**no % column**	**yes % column**	**% total**
gender	male	436	365	801	47.14	47.71	47.40
	female	489	400	889	52.86	52.29	52.60
Total		925	765	1690	100	100	100
school	no degree	14	10	24	1.57	1.34	1.46
	Hauptschule degree or elementary school	338	275	613	37.81	36.76	37.33
	Realschule degree / secondary school	254	168	422	28.41	22.46	25.70
	polytechnic	58	63	121	6.49	8.42	7.37
	technical college	52	46	98	5.82	6.15	5.97
	high school level	178	186	364	19.91	24.87	22.17
Total		894	748	1642	100	100	100
income	below 500 €	12	11	23	1.67	1.74	1.70
	500 € to 1.000 €	89	87	176	12.38	13.77	13.03
	1.000 € to 1.500 €	156	149	305	21.70	23.58	22.58
	1.500 € to 2.000 €	180	153	333	25.03	24.21	24.65
	2.000 € to 3.000 €	164	145	309	22.81	22.94	22.87
	3.000 € and more	118	87	205	16.41	13.77	15.17
Total		719	632	1351	100	100	100
job	farmer	7	1	8	0.79	0.14	0.49
	university graduate (e.g. doctor, lawyer, ...)	11	12	23	1.24	1.63	1.42
	freelance in commerce, trade, industry	94	77	171	10.60	10.46	10.54
	magistrate, judge, soldier	28	18	46	3.16	2.45	2.83
	white-collar employee	312	265	577	35.17	36.01	35.55
	blue-collar worker	91	56	147	10.26	7.61	9.06
	apprenticeship, student	19	15	34	2.14	2.04	2.09
	assisting family member	4	2	6	0.45	0.27	0.37
	pensioner	230	218	448	25.93	29.62	27.60
	house wife / house husband	46	26	72	5.19	3.53	4.44
	unemployed	45	46	91	5.07	6.25	5.61
Total		887	736	1623	100	100	100
home ownership	no	213	197	410	23.03	25.75	24.26
	yes	712	568	1280	76.97	74.25	75.74
Total		925	765	1690	100	100	100
urbanity	rural	324	185	509	35.03	24.18	30.12
	urban	601	580	1181	64.97	75.82	69.88
Total		925	765	1690	100	100	100
Legend	Variable included in factor analysis data set				Fewer than 25 cases	Fewer than 25 cases	
					Indication of strong difference	Indication of strong difference	

The cross table shows that the distribution of percentages is different among some variables for the dependent variable *leave_home*. Although this table shows only bivariate relationships, it already indicates results for the multivariate analysis where all variables are analysed as a full set. Some sub-variables contain less than 25 cases (marked in darker grey, A5.2) and are not selected for the regression analysis (Fromm 2005: 6). Some variables indicate good differentiation between affected and non-affected groups (marked in lighter grey, A5.2). However, due to the variables available in the factor analysis of the first data set (marked 'variable description' column, table A5.2), some variables with lower indication in the cross table are also selected for the regression. While *secondary school* and *blue-collar worker* indicate good separation of the yes and no cases, these variables are not used for the regression model since this information is not contained in the first data set of the factor analysis. Three sub-variables that indicate high qualification employment are grouped into the variable *high_qual_employed* to provide a variable with a sufficient number of cases of observation. *Female gender, elementary_school*, low income (*income1000* = income from 500 to 1000€), *unemployed* and *urbanity* are also selected though indicating no strong trend for *leave_home*. Reasons for the selection of these variables are given by the correspondence to the factor analysis variables (marked 'variable description' column) and the indications by the other dependent variables (see the respective tables A5.4 and A5.6 in the sections below).

Table A5.3. Bivariate correlations of the dependent variable "leave_home" within the interval variables

		age	pop14	pphh	rooms	leave_home
age	Pearson Correlation	1	-.454(**)	-.442(**)	-.177(**)	.073(**)
	Sig. (2-tailed)		.000	.000	.000	.003
	N	1663	1417	1657	1421	1657
pop14	Pearson Correlation	-.454(**)	1	.633(**)	.148(**)	-.072(**)
	Sig. (2-tailed)	.000		.000	.000	.007
	N	1417	1431	1431	1221	1427
pphh	Pearson Correlation	-.442(**)	.633(**)	1	.318(**)	-.092(**)
	Sig. (2-tailed)	.000	.000		.000	.000
	N	1657	1431	1674	1435	1668
rooms	Pearson Correlation	-.177(**)	.148(**)	.318(**)	1	-.090(**)
	Sig. (2-tailed)	.000	.000	.000		.001
	N	1421	1221	1435	1445	1442
leave_home	Pearson Correlation	.073(**)	-.072(**)	-.092(**)	-.090(**)	1
	Sig. (2-tailed)	.003	.007	.000	.001	
	N	1657	1427	1668	1442	1690

** Correlation is significant at the 0.01 level (2-tailed).

In addition to the ordinal variables, the interval variables are tested for bivariate correlations with the dependent variable *leave_home*. Table A5.3 shows that there is a positive correlation between the dependent variable *leave_home* and increasing age. The correlation of *leave_home* to number of children (*pop14*) and household size (*pphh, rooms*) is negative. Again, this provides only a bivariate comparison of each single variable with the dependent variable and can therefore not serve for interpretation before the full model is run. However, it shows the direction of increased or reduced vulnerability to be expected from the independent variables.

Dependent variable emergency_shelter: The cross table of the independent variables with the dependent variable *emergency_shelter* (table A5.4) indicates trends in the variables *female gender, elementary school, low income, unemployed* and *urbanity* (lighter grey marking) which justify the inclusion of these variables into the regression model set. Variables like additional income classes, *white-collar employees* and *homemaker* would also be of interest, yet are not contained in the first variable set that is to validate.

Table A5.4. Distribution (crosstab) of the dependent variable “emergency_shelter” within the ordinal variables

		emergency_shelter			emergency_shelter		
		no	yes	Total	no %	yes %	Total %
gender	male	333	32	365	47.91	45.71	47.71
	female	362	38	400	52.09	54.29	52.29
Total		695	70	765	100	100	100
school	no degree	9	1	10	1.32	1.47	1.34
	Hauptschule degree or elementary school	243	32	275	35.74	47.06	36.76
	Realschule degree / secondary school	153	15	168	22.50	22.06	22.46
	polytechnic	60	3	63	8.82	4.41	8.42
	technical college	43	3	46	6.32	4.41	6.15
	high school level	172	14	186	25.29	20.59	24.87
Total		680	68	748	100	100	100
income	below 500 €	8	3	11	1.39	5.17	1.74
	500 € to 1.000 €	75	12	87	13.07	20.69	13.77
	1.000 € to 1.500 €	133	16	149	23.17	27.59	23.58
	1.500 € to 2.000 €	138	15	153	24.04	25.86	24.21
	2.000 € to 3.000 €	136	9	145	23.69	15.52	22.94
	3.000 € and more	84	3	87	14.63	5.17	13.77
Total		574	58	632	100	100	100
job	farmer	1	0	1	0.15	0.00	0.14
	university graduate (e.g. doctor, lawyer, ...)	12	0	12	1.79	0.00	1.63
	freelance in commerce, trade, industry	71	6	77	10.61	8.96	10.46
	magistrate, judge, soldier	16	2	18	2.39	2.99	2.45
	white-collar employee	250	15	265	37.37	22.39	36.01
	blue-collar worker	50	6	56	7.47	8.96	7.61
	apprenticeship, student	14	1	15	2.09	1.49	2.04
	assisting family member	1	1	2	0.15	1.49	0.27
	pensioner	188	30	218	28.10	44.78	29.62
	house wife / house husband	25	1	26	3.74	1.49	3.53
	unemployed	41	5	46	6.13	7.46	6.25
Total		669	67	736	100	100	100
home ownership	0	168	29	197	24.17	41.43	25.75
	1	527	41	568	75.83	58.57	74.25
Total		695	70	765	100	100	100
urbanity	rural	162	23	185	23.31	32.86	24.18
	urban	533	47	580	76.69	67.14	75.82
Total		695	70	765	100	100	100

Table A5.5. Bivariate correlations of the dependent variable "emergency_shelter" within the interval variables

		age	pop14	pphh	rooms	emergency_shelter
age	Pearson Correlation	1	-.454(**)	-.442(**)	-.177(**)	.095(**)
	Sig. (2-tailed)		.000	.000	.000	.000
	N	1663	1417	1657	1421	1663
pop14	Pearson Correlation	-.454(**)	1	.633(**)	.148(**)	-.033
	Sig. (2-tailed)	.000		.000	.000	.208
	N	1417	1431	1431	1221	1431
pphh	Pearson Correlation	-.442(**)	.633(**)	1	.318(**)	-.067(**)
	Sig. (2-tailed)	.000	.000		.000	.006
	N	1657	1431	1674	1435	1674
rooms	Pearson Correlation	-.177(**)	.148(**)	.318(**)	1	-.046
	Sig. (2-tailed)	.000	.000	.000		.081
	N	1421	1221	1435	1445	1445
emergency_shelter	Pearson Correlation	.095(**)	-.033	-.067(**)	-.046	1
	Sig. (2-tailed)	.000	.208	.006	.081	
	N	1663	1431	1674	1445	1697

** Correlation is significant at the 0.01 level (2-tailed).

Table A5.5 shows that there is a positive correlation between the dependent variable *emergency_shelter* and increasing age. The correlation of *emergency_shelter* to number of children (*pop14*) and household size (*pphh, rooms*) is negative.

Dependent variable damage regulation: The cross table of the independent variables with the dependent variable *damage regulation* (table A5.6) indicates trends in the variables *female gender, elementary school, high school, low income, high income, pensioner* and *unemployed* (lighter grey marking) which justify the inclusion of these variables into the regression model set. *White-collar employees* would also be of interest, yet are not contained in the variable set to validate.

Table A5.6. Distribution (crosstab) of the dependent variable "damage regulation" within the ordinal variables

			damage regulation			damage regulation		
			satisfied	not satisfied	Total	satisfied in %	not satisfied in %	Total
gender	male		86	464	550	49.43	47.6	47.9
	female		88	510	598	50.57	52.4	52.1
Total			174	974	1148	100	100	100
school	no degree		0	17	17	0	1.76	1.5
	Hauptschule degree or elementary school		75	347	422	44.64	36	37.2
	Realschule degree / secondary school		42	234	276	25	24.2	24.4
	polytechnic		12	88	100	7.143	9.12	8.83
	technical college		13	60	73	7.738	6.22	6.44
	high school level		26	219	245	15.48	22.7	21.6
Total			168	965	1133	100	100	100
income	below 500 €		4	8	12	2.632	0.95	1.21
	500 € to 1.000 €		21	106	127	13.82	12.6	12.8
	1.000 € to 1.500 €		37	187	224	24.34	22.2	22.5
	1.500 € to 2.000 €		32	219	251	21.05	26	25.3
	2.000 € to 3.000 €		39	194	233	25.66	23	23.4
	3.000 € and more		19	128	147	12.5	15.2	14.8
Total			152	842	994	100	100	100
job	farmer		0	4	4	0	0.42	0.36
	university graduate (e.g. doctor, lawyer, ...)		1	14	15	0.606	1.48	1.35
	freelance in commerce, trade, industry		17	106	123	10.3	11.2	11
	magistrate, judge, soldier		3	30	33	1.818	3.16	2.96
	white-collar employee		50	350	400	30.3	36.9	35.9
	blue-collar worker		13	90	103	7.879	9.48	9.25
	apprenticeship, student		4	13	17	2.424	1.37	1.53
	assisting family member		1	2	3	0.606	0.21	0.27
	pensioner		53	246	299	32.12	25.9	26.8
	house wife / house husband		8	39	47	4.848	4.11	4.22
	unemployed		15	55	70	9.091	5.8	6.28
Total			165	949	1114	100	100	100
home ownership		0	39	232	271	22.41	23.8	23.6
		1	135	742	877	77.59	76.2	76.4
Total			174	974	1148	100	100	100
urbanity	rural		51	296	347	29.31	30.4	30.2
	urban		123	678	801	70.69	69.6	69.8
Total			174	974	1148	100	100	100

Table A5.7. Bivariate correlations of the dependent variable "damage regulation" within the interval variables

		age	pop14	pphh	rooms	recomp
age	Pearson Correlation	1	-.454(**)	-.442(**)	-.177(**)	.000
	Sig. (2-tailed)		.000	.000	.000	.999
	N	1663	1417	1657	1421	1139
pop14	Pearson Correlation	-.454(**)	1	.633(**)	.148(**)	.025
	Sig. (2-tailed)	.000		.000	.000	.428
	N	1417	1431	1431	1221	987
pphh	Pearson Correlation	-.442(**)	.633(**)	1	.318(**)	.030
	Sig. (2-tailed)	.000	.000		.000	.317
	N	1657	1431	1674	1435	1140
rooms	Pearson Correlation	-.177(**)	.148(**)	.318(**)	1	-.012
	Sig. (2-tailed)	.000	.000	.000		.703
	N	1421	1221	1435	1445	1025
damage regulation	Pearson Correlation	.000	.025	.030	-.012	1
	Sig. (2-tailed)	.999	.428	.317	.703	
	N	1139	987	1140	1025	1148

** Correlation is significant at the 0.01 level (2-tailed).

Table A5.7 shows that there is no correlation between the dependent variable damage *damage regulation* and *age*. The correlation of damage regulation to number of children (*pop14*) and household size (*pphh, rooms*) is also very weak.

ANNEXE 6

Table A6.1. Factor analysis of 15 variables of the first data set that are indirectly related to the validated variables in the second data set

Rotated Component Matrix[a]

	Component		
	1	2	3
Population per settlement area	.900		
One and two family homes	-.866		
High qualification employed	.836		
Small apartments	.813		
Persons per hh	-.780		-.388
Graduates with high school graduation	.779		
Rural population	-.750		
Unemployment		-.896	
Income per hh		.840	
Residents below age 6		.785	-.347
Graduates without Hauptschulabschluss		-.586	
Living space pp	-.532	.564	.301
Residents age 65 and older		-.408	.859
Residents from age 30 to 50			-.828
Female gender	.566		.656

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 4 iterations.

Table A6.2. Rotated Component Matrix of the variables used in the logistic regression.

	Component				
	1	2	3	4	5
How old are you?	-.744	.350			
Gender				-.672	
high school		-.686			
elementary school		.806			
income very high		-.351		.309	
income 1000		.364			.594
high qualification employee group				.694	
unemployed					.801
pensioner	-.586	.453			
How many persons below 14 years live in your household?	.841				
How many persons live in your household?	.811				
How many rooms does your apartment / home have?			.739		
ownership10			.822		
urbanity				.374	

ANNEXE 7

Comparison of the ESPON integrated vulnerability map with the SSI map

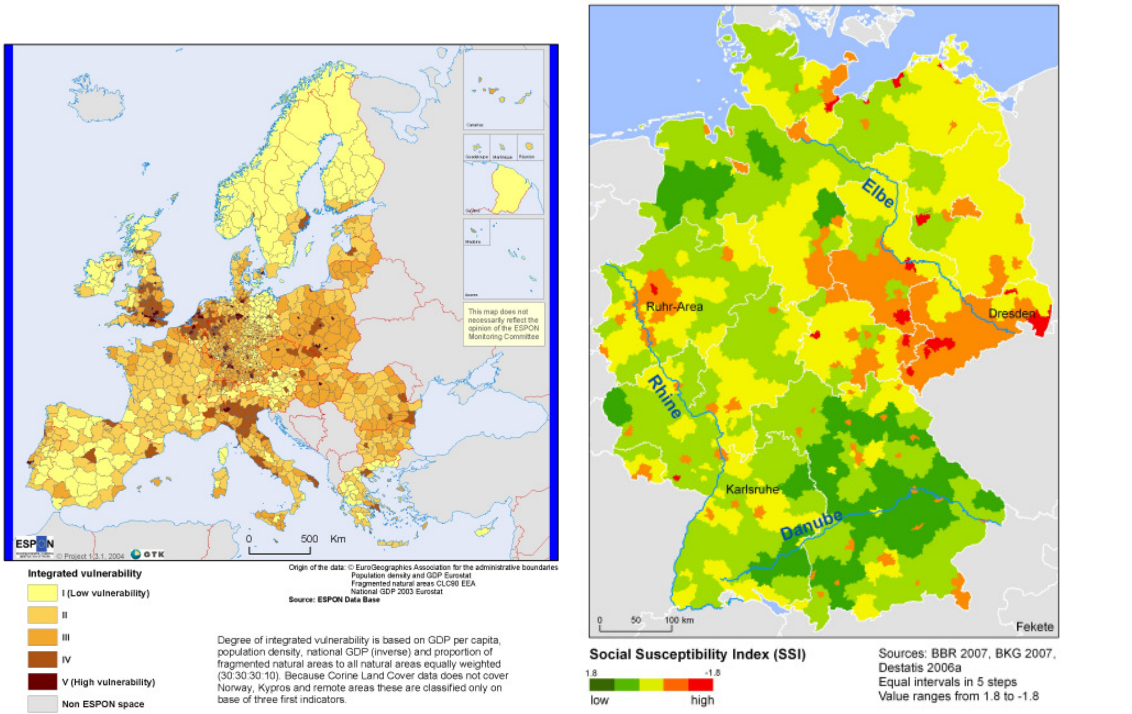

Figure A7.1 The ESPON integrated vulnerability map (adapted from Schmidt-Thomé 2006: 89) in comparison to the SSI map in 5 classes of equal intervals

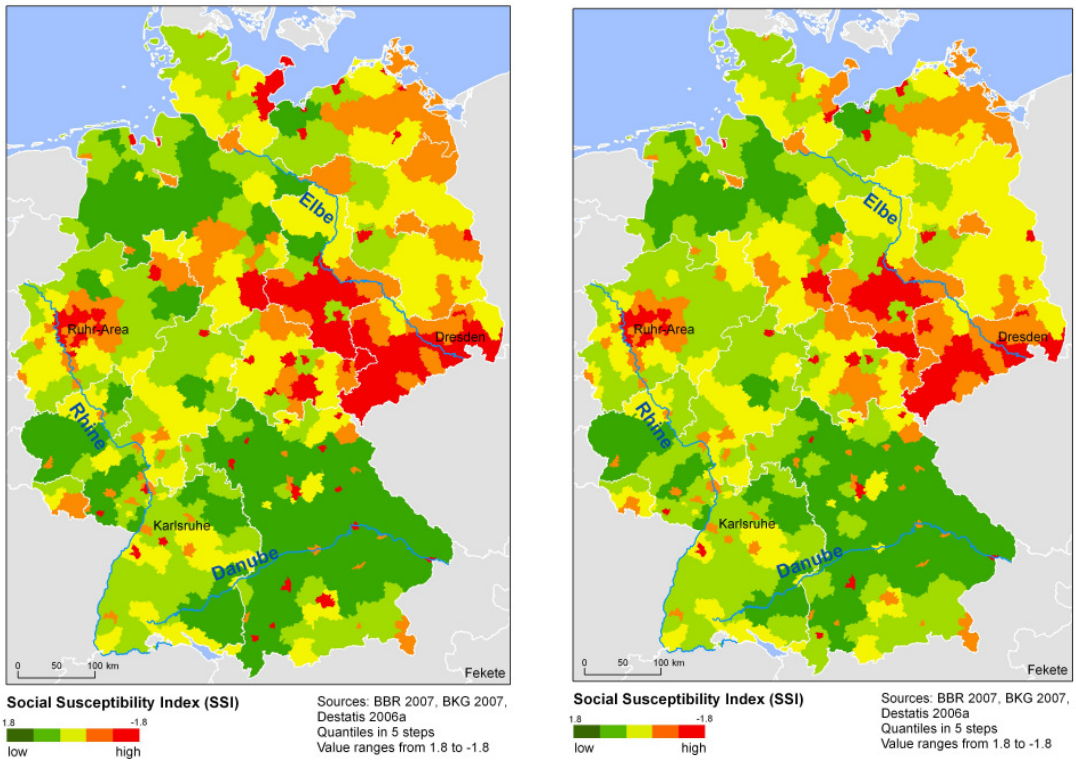

Figure A7.2 SVI1 map in 5 classes of quantiles and in 5 classes of natural breaks (jenks)

ANNEXE 8
Map accuracy assessment

"everything is related to everything else, but near things are more related than distant things"
Waldo Tobler

The potential errors of the statistical analysis are described by the confidence intervals and the quality test values in Sections 4.2 and 4.3. The implementation of the numeric indices in the GIS produces another range of potential errors. The sources of error for both geo-data and statistical data range from errors in the data acquisition, pre-processing, information extraction, data conversion, in the error assessment itself, and the final product (Jensen 2005: 498). While many of these error sources have been described in the text body above, the final choropleth map products still demand for an error assessment. Within the number of traps produced by thematic maps (Meentemeyer 1989), like the modifiable area unit problem (Openshaw 1984), ecological fallacy (Cao and Lam 1997), or implications of multiple scales (Gibson et al. 2000, Fekete et al. 2009), especially spatial autocorrelation tests are emphasised for GIS applications (Cao and Lam 1997: 60, Longley et al. 2005: 87). The widely used spatial autocorrelation test using a global Moran's I function evaluates whether the spatial index patterns are the result of random chance or statistically significant (Longley et al. 2005: 87, 100). The spatial relationship is conceptualised by inverse distance and the Euclidean distance method with a global standardisation of standardised weights.

Table A8. Spatial autocorrelation tests of the SSI and SIFVI

Index map	Moran's I Index	Z Score in standard deviations	Significance value
SSI	0.09	26.3	0.01
SIFVI	0.07	20.1	0.01

As a result, there is less than 1% likelihood that the clustered patterns of the SSI and the SIFVI could be the result of random chance (Table A8). This test underscores that the patterns of the index maps are not random due to spatial autocorrelations. Still, it permits no definite conclusion about the range of errors produced by the thematic analyses of the content. The thematic error range is mainly influenced by the theoretical vulnerability conceptualisation, the technical calculation of the indices, and the data. It is difficult to capture this diverse range within numerical error ranges and is certainly a challenge for future advancement in this field.

ANNEXE 9

The following table contains the values of the three indicators (F1, F2 and F3) of the SSI, the supply and contamination components of the IDI, the calculated exposure and the composite SIFVI index per county

County	Name	F1.Region	F2.Fragility	F3.Socio-Econ	SSI_sum	Supply	Contaminating	IDI	Exposed_area	SIFVI
1001000	Flensburg	-0,2526	0,0351	-0,0619	-0,2794	0	0	0	0	0
1002000	Kiel	-0,3763	0,2632	-0,2385	-0,3517	0	0	0	0	0
1003000	Luebeck	-0,3969	-0,4211	-0,3518	-1,1698	0	0	0	0	0
1004000	Neumuenst	-0,2165	-0,1404	-0,1742	-0,5311	0	0	0	0	0
1051000	Dithmarsc	0,2198	-0,2807	0,2047	0,1438	0	0	0	0	0
1053000	Herzogtum	0,1144	0,0175	0,007	0,1389	0	0	0	0	0
1054000	Nordfries	0,085	-0,1053	0,5026	0,4823	0	0	0	0	0
1055000	Ostholste	-0,2682	-0,5263	0,155	-0,6396	0	0	0	0	0
1056000	Pinneberg	-0,2065	0,0702	0,1	-0,0363	0	0	0	0	0
1057000	Ploen	0,0319	-0,0351	0,0869	0,0837	0	0	0	0	0
1058000	Rendsburg	0,2554	0,1228	0,0582	0,4364	0	0	0	0	0
1059000	Schleswig	0,4673	0,0351	0,1128	0,6151	0	0	0	0	0
1060000	Segeberg	0,0422	0,3684	0,1326	0,5433	0	0	0	0	0
1061000	Steinburg	0,1805	0,0702	0,0032	0,2539	0	0	0	0	0
1062000	Stormarn	-0,0796	0,0175	0,2433	0,1812	0	0	0	0	0
2000000	Hamburg	-0,3866	0,193	-0,2692	-0,4628	0	0	0	0	0
3101000	Braunschw	-0,3763	-0,193	0,1363	-0,4329	0	0	0	0	0
3102000	Salzgitte	-0,1598	-0,386	0,0151	-0,5307	0	0	0	0	0
3103000	Wolfsburg	-0,1959	-0,4737	0,193	-0,4766	0	0	0	0	0
3151000	Gifhorn	0,3274	0,5263	0,3261	1,1798	0	0	0	0	0
3152000	Goettinge	-0,2707	0,2982	0,0104	0,0379	0	0	0	0	0
3153000	Goslar	-0,3255	-0,8596	0,2325	-0,9527	0	0	0	0	0
3154000	Helmstedt	0,2517	-0,3158	0,3197	0,2556	0	0	0	0	0
3155000	Northeim	0,4314	-0,5088	0,2705	0,1931	0	0	0	0	0
3156000	Osterode	-0,1096	-0,8947	0,339	-0,6654	0	0	0	0	0
3157000	Peine	0,1	0,0526	0,3104	0,463	0	0	0	0	0
3158000	Wolfenbue	0,2117	-0,0526	0,2506	0,4097	0	0	0	0	0
3241000	Region Ha	-0,2065	-0,0351	0,0948	-0,1468	0	0	0	0	0
3251000	Diepholz	0,4535	0,0702	0,4254	0,949	0	0	0	0	0
3252000	Hameln-Py	0,0837	-0,5965	0,2068	-0,3059	0	0	0	0	0
3254000	Hildeshei	0,0565	-0,2281	0,2019	0,0303	0	0	0	0	0
3255000	Holzminde	0,263	-0,6842	0,2004	-0,2209	0	0	0	0	0
3256000	Nienburg	0,6133	-0,0526	0,1063	0,667	0	0	0	0	0
3257000	Schaumbur	0,0279	-0,3158	0,1878	-0,1	0	0	0	0	0
3351000	Celle	0,3025	-0,0877	0,1184	0,3332	0	0	0	0	0
3352000	Cuxhaven	0,3375	-0,2456	0,3232	0,4151	0	0	0	0	0
3353000	Harburg	0,0757	0,2105	0,3735	0,6597	0	0	0	0	0
3354000	Luechow-D	0,9021	-0,7368	0,5125	0,6778	0	0	0	0	0
3355000	Lueneburg	0,0853	0,3509	0,1499	0,586	0	0	0	0	0
3356000	Osterholz	0,1481	0,193	0,2935	0,6346	0	0	0	0	0
3357000	Rotenburg	0,5654	0,3333	0,3894	1,2881	0	0	0	0	0
3358000	Soltau-Fa	0,7137	0	0,245	0,9586	0	0	0	0	0
3359000	Stade	0,1932	0,3684	0,2671	0,8288	0	0	0	0	0
3360000	Uelzen	0,3229	-0,5614	0,3674	0,1289	0	0	0	0	0
3361000	Verden	0,2489	0,3158	0,4501	1,0148	0	0	0	0	0
3401000	Delmenhor	-0,1289	0,0877	-0,0191	-0,0602	0	0	0	0	0
3402000	Emden	-0,1907	-0,0175	-0,047	-0,2552	0	0	0	0	0
3403000	Oldenburg	-0,3608	0,3333	0,2133	0,1858	0	0	0	0	0
3404000	Osnabruec	-0,4639	0,0351	0,1605	-0,2684	0	0	0	0	0
3405000	Wilhelmsh	-0,2268	-0,4912	0,0474	-0,6707	0	0	0	0	0
3451000	Ammerland	0,3141	0,193	0,3947	0,9017	0	0	0	0	0
3452000	Aurich	0,1181	0,1579	0,3309	0,6069	0	0	0	0	0
3453000	Cloppenbu	0,797	0,6842	0,2434	1,7246	0	0	0	0	0
3454000	Emsland	0,5188	0,5439	0,3657	1,4283	0	0	0	0	0
3455000	Friesland	0,1277	-0,1228	0,359	0,3639	0	0	0	0	0
3456000	Grafschaf	0,2118	0,2281	0,1954	0,6353	0	0	0	0	0
3457000	Leer	0,1222	0,2456	0,0752	0,443	0	0	0	0	0
3458000	Oldenburg	0,5349	0,4035	0,4035	1,3419	0	0	0	0	0
3459000	Osnabruec	0,1902	0,2807	0,2816	0,7525	0	0	0	0	0
3460000	Vechta	0,2363	0,8246	0,3703	1,4311	0	0	0	0	0
3461000	Wesermars	0,2952	-0,0702	0,3466	0,5716	0	0	0	0	0
3462000	Wittmund	0,407	0,0877	0,5014	0,9961	0	0	0	0	0
4011000	Bremen	-0,3041	-0,1404	-0,1067	-0,5512	0	0	0	0	0
4012000	Bremerhav	-0,2474	-0,2807	-0,1894	-0,7176	0	0	0	0	0
5111000	Duesseldo	-0,732	-0,0175	0,0142	-0,7353	0,8395	0,0736	0,4565	0,8092	0,7783
5112000	Duisburg	-0,2887	-0,2807	-0,3231	-0,8925	0,9999	0,2514	0,6257	0,9977	1
5113000	Essen	-0,4021	-0,4035	-0,1682	-0,9737	0	0	0	0	0
5114000	Krefeld	-0,4021	-0,1053	-0,0235	-0,5308	0,9552	0,1622	0,5587	0,7575	0,6887
5116000	Moencheng	-0,3454	0	-0,1391	-0,4845	0	0	0	0	0
5117000	Muelheim	-0,3196	-0,6316	0,1823	-0,7688	0,5544	0,0233	0,2888	0	0
5119000	Oberhause	-0,2526	-0,1579	-0,3271	-0,7376	0,1314	0	0,0657	0,9812	0,9443
5120000	Remscheid	-0,3196	-0,1228	0,0456	-0,3968	0	0	0	0	0
5122000	Solingen	-0,3918	-0,193	-0,143	-0,7277	0	0	0	0	0
5124000	Wuppertal	-0,5258	-0,1754	-0,18	-0,8812	0	0	0	0	0
5154000	Kleve	0,0044	0,2632	0,166	0,4336	0,115	0,0259	0,0705	0,4803	0,3174
5158000	Mettmann	-0,3247	-0,1053	0,1355	-0,2945	0,1243	0,0235	0,0739	0,0614	0,0521
5162000	Neuss	-0,2629	0,1053	0,1673	0,0096	0,5092	0,0591	0,2841	0,4108	0,3163
5166000	Viersen	-0,1546	0,1579	0,1395	0,1428	0	0	0	0	0
5170000	Wesel	-0,0863	0,0526	-0,0281	-0,0618	0,3689	0,0561	0,2125	0,8926	0,7037
5313000	Aachen	-0,8299	0,386	-0,1015	-0,5454	0	0	0	0	0
5314000	Bonn	-0,7062	0,2456	0,1462	-0,3144	0,215	0,0377	0,1263	0,8414	0,7181
5315000	Koeln	-0,6546	0,2807	-0,0947	-0,4687	0,5246	0,3914	0,458	0,7275	0,6498
5316000	Leverkuse	-0,2938	-0,2807	-0,0718	-0,6463	0,8985	0,1485	0,5235	0,2951	0,2771

5354000	Aachen	-0,0823	0,0702	-0,0469	-0,059	0	0	0	0	0
County	Name	F1.Region	F2.Fragility	F3.Socio-Econ	SSI_sum	Supply	Contaminating	IDI	Exposed_area	SIFVI
5358000	Dueren	-0,0313	0,2456	0,1046	0,3188	0	0	0	0	0
5362000	Erftkreis	-0,1959	0,2632	0,049	0,1163	0,0575	0,1163	0,0869	0,0715	0,0531
5366000	Euskirche	0,2003	0,1754	0,2362	0,6119	0	0	0	0	0
5370000	Heinsberg	-0,0567	0,2982	0,1549	0,3964	0	0	0	0	0
5374000	Oberbergi	-0,1907	0,1404	0,027	-0,0234	0	0	0	0	0
5378000	Rheinisch	-0,2577	-0,0526	0,3013	-0,0091	0	0	0	0	0
5382000	Rhein-Sie	-0,1907	0,3684	0,2205	0,3982	0,0878	0,0166	0,0522	0,2077	0,1391
5512000	Bottrop	-0,1649	-0,1053	-0,2712	-0,5414	0	0	0	0	0
5513000	Gelsenkir	-0,2732	-0,2982	-0,4925	-1,0639	0	0	0	0	0
5515000	Muenster	-0,6856	0,3684	0,2054	-0,1117	0	0	0	0	0
5554000	Borken	-0,0009	0,5614	0,092	0,6525	0,0285	0,006	0,0173	0,0534	0,0323
5558000	Coesfeld	0,0885	0,5263	0,1178	0,7327	0	0	0	0	0
5562000	Recklingh	-0,1598	-0,0877	-0,1466	-0,3941	0	0	0	0	0
5566000	Steinfurt	0,0547	0,3684	0,2332	0,6563	0	0	0	0	0
5570000	Warendorf	0,1201	0,2982	0,1967	0,615	0	0	0	0	0
5711000	Bielefeld	-0,3196	-0,1404	-0,1702	-0,6301	0	0	0	0	0
5754000	Guetersl o	-0,1082	0,3684	0,2213	0,4815	0	0	0	0	0
5758000	Herford	-0,1082	-0,2105	0,1882	-0,1306	0	0	0	0	0
5762000	Hoexter	0,4028	-0,0351	0,3324	0,7001	0	0	0	0	0
5766000	Lippe	-0,0145	-0,193	0,0485	-0,159	0	0	0	0	0
5770000	Minden-Lu	0,1017	-0,1754	0,1537	0,0799	0	0	0	0	0
5774000	Paderborn	-0,0759	0,614	0,1535	0,6916	0	0	0	0	0
5911000	Bochum	-0,3351	-0,193	-0,2236	-0,7516	0	0	0	0	0
5913000	Dortmund	-0,366	-0,1579	-0,2251	-0,749	0	0	0	0	0
5914000	Hagen	-0,3351	-0,3509	-0,0386	-0,7245	0	0	0	0	0
5915000	Hamm	-0,1546	0,1228	-0,1715	-0,2033	0	0	0	0	0
5916000	Herne	-0,2371	-0,2456	-0,353	-0,8357	0	0	0	0	0
5954000	Ennepe-Ru	-0,268	-0,2632	0,0331	-0,4981	0	0	0	0	0
5958000	Hochsauer	0,3904	-0,0877	0,2233	0,526	0	0	0	0	0
5962000	Maerkisch	-0,1995	0,0702	-0,1644	-0,2937	0	0	0	0	0
5966000	Olpe	-0,0008	0,3509	0,1578	0,5079	0	0	0	0	0
5970000	Siegen-Wi	-0,0675	0	0,1876	0,1201	0	0	0	0	0
5974000	Soest	0,0098	0,1404	0,1904	0,3406	0	0	0	0	0
5978000	Unna	-0,1237	0,0702	-0,1789	-0,2324	0	0	0	0	0
6411000	Darmstadt	-0,6598	0,2105	0,1051	-0,3442	0	0	0	0	0
6412000	Frankfurt	-0,6237	0,386	-0,1346	-0,3724	0	0	0	0	0
6413000	Offenbach	-0,4278	0,4035	-0,4509	-0,4752	0	0	0	0	0
6414000	Wiesbaden	-0,4433	0,1053	-0,1238	-0,4619	0,1986	0,0209	0,1097	0,7499	0,6685
6431000	Bergstras	-0,1458	0,1053	0,2858	0,2453	0,2251	0,0133	0,1192	0,2643	0,1875
6432000	Darmstadt	-0,1856	0,4561	0,2293	0,4999	0	0,0032	0,0016	0	0
6433000	Gross-Ger	-0,2835	0,3684	-0,0313	0,0536	0,2904	0,0799	0,1851	0,8053	0,611
6434000	Hochtaunu	-0,2109	0	0,5343	0,3235	0	0	0	0	0
6435000	Main-Kinz	-0,0671	0,2105	0,1148	0,2582	0	0	0	0	0
6436000	Main-Taun	-0,2474	0,1579	0,3073	0,2178	0	0	0	0,0633	0,0453
6437000	Odenwaldk	-0,0176	-0,0175	0,2811	0,2459	0	0	0	0	0
6438000	Offenbach	-0,268	0,2632	0,1127	0,1078	0	0	0	0	0
6439000	Rheingau-	-0,0846	0,2281	0,2462	0,3897	0,0125	0,0026	0,0075	0,2979	0,2002
6440000	Wetterauk	-0,1068	0,2105	0,1347	0,2384	0	0	0	0	0
6531000	Giessen	-0,3519	0,2807	0,1827	0,1115	0	0	0	0	0
6532000	Lahn-Dill	0,0289	0	0,23	0,2589	0	0	0	0	0
6533000	Limburg-W	-0,0332	0,1579	0,2346	0,3593	0	0	0	0	0
6534000	Marburg-B	-0,1178	0,3333	0,1512	0,3667	0	0	0	0	0
6535000	Vogelsber	0,9175	-0,4035	0,3681	0,8821	0	0	0	0	0
6611000	Kassel	-0,3557	-0,1053	-0,3567	-0,8176	0	0	0	0	0
6631000	Fulda	0,3165	0,0702	0,2787	0,6654	0	0	0	0	0
6632000	Hersfeld-	0,4101	-0,4912	0,3338	0,2527	0	0	0	0	0
6633000	Kassel	0,185	-0,1404	0,339	0,3836	0	0	0	0	0
6634000	Schwalm-E	0,3475	-0,1404	0,1614	0,3685	0	0	0	0	0
6635000	Waldeck-F	0,4484	-0,2281	0,2238	0,4441	0	0	0	0	0
6636000	Werra-Mei	0,6698	-0,5789	0,2458	0,3367	0	0	0	0	0
7111000	Koblenz	-0,3402	-0,4035	0,2634	-0,4803	0,0964	0,0203	0,0583	0,6851	0,614
7131000	Ahrweiler	0,0143	-0,2807	0,3766	0,1102	0	0,0041	0,002	0,6753	0,5025
7132000	Altenkirc	0,0852	-0,0702	0,3392	0,3542	0	0	0	0	0
7133000	Bad Krez	0,121	-0,1053	0,2968	0,3125	0	0	0	0,0091	0,0063
7134000	Birkenfel	0,3244	-0,4211	0,4409	0,3442	0	0	0	0	0
7135000	Cochem-Ze	0,6581	-0,4211	0,6659	0,903	0	0	0	0	0
7137000	Mayen-Kob	0,0404	0	0,2168	0,2572	0,0991	0,0104	0,0547	0,3378	0,2386
7138000	Neuwied	-0,0953	-0,0877	0,1658	-0,0172	0,0646	0,0153	0,0399	0,6255	0,486
7140000	Rhein-Hun	0,4205	-0,0526	0,524	0,8919	0	0,0055	0,0028	0,1414	0,0768
7141000	Rhein-Lah	0,2496	-0,2105	0,3876	0,4267	0,0517	0,0082	0,03	0,3424	0,2269
7143000	Westerwal	0,1217	0,1579	0,4392	0,7188	0	0	0	0	0
7211000	Trier	-0,5619	-0,0351	0,1996	-0,3973	0	0	0	0	0
7231000	Bernkaste	0,5471	-0,2105	0,5556	0,8921	0	0	0	0	0
7232000	Bitburg-P	0,5974	-0,1754	0,6772	1,0991	0	0	0	0	0
7233000	Daun	0,6543	-0,3684	0,6858	0,9717	0	0	0	0	0
7235000	Trier-Saa	0,3564	0,1053	0,3878	0,8494	0	0	0	0	0
7311000	Frankenth	-0,2526	-0,3158	0,0858	-0,4826	0,2313	0,5836	0,4075	0,9091	0,8152
7312000	Kaisersla	-0,5464	-0,0526	0,2127	-0,3863	0	0	0	0	0
7313000	Landau	-0,299	0,0702	0,304	0,0752	0	0	0	0	0
7314000	Ludwigsha	-0,3608	0,0175	-0,2508	-0,5941	0,9122	0,0548	0,4835	0,8346	0,7724
7315000	Mainz	-0,7887	0,3333	0,2215	-0,2339	0,5177	0,0218	0,2697	0,6771	0,5638
7316000	Neustadt	-0,268	-0,4737	0,4586	-0,2832	0	0	0	0	0
7317000	Pirmasens	-0,2216	-0,8947	0,0263	-1,0901	0	0	0	0	0
7318000	Speyer	-0,299	0,1053	0,1945	0,0008	0,9508	0,6248	0,7878	1	0,7723
7319000	Worms	-0,3196	0,1053	0,0355	-0,1789	0,1862	0,0391	0,1127	0,5833	0,4775
7320000	Zweibruec	-0,0979	-0,3158	0,2832	-0,1306	0	0	0	0	0
7331000	Alzey-Wor	0,0544	0,4561	0,3443	0,8549	0,0516	0,0072	0,0294	0,1797	0,0993
7332000	Bad Duerk	0,0076	-0,0877	0,5425	0,4623	0	0	0	0	0
7333000	Donnersbe	0,3711	0,2281	0,3833	0,9824	0	0	0	0	0
7334000	Germershe	-0,025	0,5263	0,326	0,8273	0,1966	0,0322	0,1144	0,4539	0,2539
7335000	Kaisersla	0,1418	0,0175	0,6831	0,8425	0	0	0	0	0
7336000	Kusel	0,3959	-0,3333	0,6055	0,6681	0	0	0	0	0
7337000	Suedliche	0,1913	-0,0877	0,474	0,5776	0	0	0	0	0
7338000	Ludwigsha	-0,1082	0,0175	0,5474	0,4567	0,0664	0,0768	0,0716	0,282	0,1847
7339000	Mainz-Bin	-0,1139	0,4386	0,3419	0,6666	0,1169	0,0263	0,0716	0,3997	0,2402

7340000	Suedwestp	0,5173	-0,3158	0,5525	0,754	0	0	0	0	0
County	Name	F1.Region	F2.Fragility	F3.Socio-Econ	SSI_sum	Supply	Contaminating	IDI	Exposed_area	SIFVI
8111000	Stuttgart	-0,4639	0,2105	-0,1229	-0,3763	0	0	0	0	0
8115000	Boeblinge	-0,299	0,4737	0,1746	0,3493	0	0	0	0	0
8116000	Esslingen	-0,2887	0,2632	0,1784	0,1529	0	0	0	0	0
8117000	Goeppinge	-0,0959	0,0877	0,1719	0,1637	0	0	0	0	0
8118000	Ludwigsbu	-0,2577	0,3509	0,1994	0,2925	0	0	0	0	0
8119000	Rems-Murr	-0,1891	0,2281	0,1964	0,2353	0	0	0	0	0
8121000	Heilbronn	-0,2165	0	0,0111	-0,2054	0	0	0	0	0
8125000	Heilbronn	-0,1179	0,4912	0,2298	0,6031	0	0	0	0	0
8126000	Hohenlohe	0,2688	0,3333	0,2718	0,8739	0	0	0	0	0
8127000	Schwaebis	0,3993	0,3509	0,3395	1,0897	0	0	0	0	0
8128000	Main-Taub	0,2799	-0,0175	0,3908	0,6532	0	0	0	0	0
8135000	Heidenhei	0,1448	-0,1053	0,2632	0,3027	0	0	0	0	0
8136000	Ostalbkre	0,0933	0,2456	0,2848	0,6237	0	0	0	0	0
8211000	Baden-Bad	-0,3144	-1	0,5664	-0,748	0	0	0	0	0
8212000	Karlsruhe	-0,4485	0,0526	0,0988	-0,297	0,8753	1	0,9376	0,5809	0,4932
8215000	Karlsruhe	-0,1804	0,2456	0,304	0,3692	0,0653	0,0177	0,0415	0,1906	0,1291
8216000	Rastatt	-0,1348	0,0526	0,2895	0,2074	0,1096	0,0245	0,067	0,4027	0,2896
8221000	Heidelber	-0,6649	0,5965	0,1126	0,0442	0	0	0	0	0
8222000	Mannheim	-0,6082	0,1404	-0,079	-0,5469	0,9775	0,1175	0,5475	0,9429	0,8612
8225000	Neckar-Od	0,4941	0,193	0,3233	1,0104	0	0	0	0	0
8226000	Rhein-Nec	-0,2128	0,2105	0,3317	0,3295	0	0,006	0,003	0,1268	0,0872
8231000	Pforzheim	-0,4175	-0,1754	-0,093	-0,6859	0	0	0	0	0
8235000	Calw	-0,1885	0,2632	0,2301	0,3047	0	0	0	0	0
8236000	Enzkreis	-0,1753	0,3158	0,3613	0,5019	0	0	0	0	0
8237000	Freudenst	-0,0124	0,2281	0,2881	0,5037	0	0	0	0	0
8311000	Freiburg	-0,7629	0,6316	-0,1072	-0,2385	0	0	0	0	0
8315000	Breisgau-	-0,0904	0,2632	0,3019	0,4747	0,0147	0,0108	0,0127	0,1136	0,0739
8316000	Emmending	-0,088	0,3333	0,2534	0,4987	0	0,0094	0,0047	0,1241	0,0799
8317000	Ortenaukr	-0,0599	0,1404	0,3125	0,393	0,0547	0,008	0,0314	0,2082	0,1398
8325000	Rottweil	0,2046	0,0877	0,3267	0,619	0	0	0	0	0
8326000	Schwarzwa	-0,1151	-0,1228	0,2834	0,0456	0	0	0	0	0
8327000	Tuttlinge	0,1761	0,2105	0,2464	0,633	0	0	0	0	0
8335000	Konstanz	-0,3559	0,1228	0,2055	-0,0276	0	0	0	0,0397	0,0309
8336000	Loerrach	-0,1723	0,1754	0,1995	0,2026	0,0376	0,0053	0,0215	0,1042	0,0751
8337000	Waldshut	0,0536	0,1053	0,3992	0,5581	0,0447	0,0056	0,0252	0,0995	0,0626
8415000	Reutlinge	-0,015	0,2281	0,2297	0,4427	0	0	0	0	0
8416000	Tuebingen	-0,4794	0,8421	0,143	0,5058	0	0	0	0	0
8417000	Zollernal	0,1803	0	0,3095	0,4898	0	0	0	0	0
8421000	Ulm	-0,3866	0,2982	-0,0181	-0,1065	0	0	0	0	0
8425000	Alb-Donau	0,3628	0,4386	0,3688	1,1701	0	0	0	0	0
8426000	Biberach	0,2658	0,4561	0,4353	1,1572	0	0	0	0	0
8435000	Bodenseek	-0,2798	0,1754	0,3354	0,231	0	0	0	0	0
8436000	Ravensbur	0,1008	0,4035	0,2182	0,7225	0	0	0	0	0
8437000	Sigmaring	0,4576	0,3684	0,2571	1,0831	0	0	0	0	0
9161000	Ingolstad	-0,3866	0,2456	-0,016	-0,157	0,3036	0	0,1518	0,6612	0,5375
9162000	Muenchen	-1	0,3509	-0,0271	-0,6762	0	0	0	0	0
9163000	Rosenheim	-0,7062	0,1579	0,0307	-0,5176	0	0	0	0	0
9171000	Altoettin	0,0205	0,0526	0,3054	0,3785	0	0	0	0	0
9172000	Berchtesg	-0,2501	-0,386	0,2636	-0,3725	0	0	0	0	0
9173000	Bad Toelz	0,04	0,1754	0,2919	0,5073	0	0	0	0	0
9174000	Dachau	-0,0164	0,614	0,066	0,6637	0	0	0	0	0
9175000	Ebersberg	-0,1296	0,5263	0,3286	0,7253	0	0	0	0	0
9176000	Eichstaet	0,5724	0,5789	0,453	1,6043	0,0083	0	0,0042	0,0082	0,0029
9177000	Erding	0,4026	0,8246	0,2657	1,4928	0	0	0	0	0
9178000	Freising	-0,0649	1	0,2077	1,1428	0	0	0	0	0
9179000	Fuerstenf	-0,2511	0,3509	0,2993	0,3992	0	0	0	0	0
9180000	Garmisch-	0,0547	-0,4035	0,489	0,1402	0	0	0	0	0
9181000	Landsberg	0,3123	0,5965	0,2413	1,1501	0	0	0	0	0
9182000	Miesbach	-0,0499	0,0351	0,4622	0,4474	0	0	0	0	0
9183000	Muehldorf	0,2708	0,2105	0,1953	0,6766	0	0	0	0	0
9184000	Muenchen	-0,3755	0,3684	0,2937	0,2866	0	0	0	0	0
9185000	Neuburg-S	0,3188	0,4386	0,4074	1,1648	0,0547	0,0029	0,0288	0,23	0,1087
9186000	Pfaffenho	0,2829	0,6667	0,2027	1,1523	0,0266	0	0,0133	0,0467	0,0222
9187000	Rosenheim	0,0174	0,3333	0,2717	0,6225	0	0	0	0	0
9188000	Starnberg	-0,3771	0,0526	0,4625	0,1381	0	0	0	0	0
9189000	Traunstei	0,1691	-0,0877	0,5041	0,5855	0	0	0	0	0
9190000	Weilheim-	0,0796	0,2456	0,2232	0,5485	0	0	0	0	0
9261000	Landshut	-0,4175	-0,3509	0,2956	-0,4728	0	0	0	0	0
9262000	Passau	-0,7577	-0,2281	0,2111	-0,7747	0,8732	0,0306	0,4519	0,5504	0,535
9263000	Straubing	-0,4021	-0,2456	0,1621	-0,4855	0	0,0157	0,0079	0,8351	0,7495
9271000	Deggendor	0,276	0,2807	0,3395	0,8963	0,0705	0,0161	0,0433	0,5217	0,2826
9272000	Freyung-G	0,7629	0,193	0,4386	1,3945	0	0	0	0	0
9273000	Kelheim	0,2827	0,4561	0,4115	1,1504	0,0285	0,004	0,0162	0,309	0,1472
9274000	Landshut	0,6372	0,6667	0,4373	1,7412	0	0	0	0	0
9275000	Passau	0,2952	0,193	0,4719	0,9601	0,0397	0,0076	0,0237	0,0882	0,0463
9276000	Regen	0,4238	0,0702	0,4422	0,9362	0	0	0	0	0
9277000	Rottal-In	0,4666	0,0175	0,4393	0,9234	0	0	0	0	0
9278000	Straubing	0,6708	0,4561	0,4728	1,5997	0,0168	0,0044	0,0106	0,1616	0,0583
9279000	Dingolfin	0,59	0,386	0,3646	1,3406	0	0	0	0	0
9361000	Amberg	-0,2474	-0,3684	0,0185	-0,5973	0	0	0	0	0
9362000	Regensbur	-0,7784	0,0526	0,1486	-0,5771	0,5018	0,0132	0,2575	0,9426	0,8682
9363000	Weiden	-0,268	-0,3158	0,1675	-0,4163	0	0	0	0	0
9371000	Amberg-Su	0,5825	0,1754	0,2473	1,0053	0	0	0	0	0
9372000	Cham	0,6328	0,1404	0,4521	1,2253	0	0	0	0	0
9373000	Neumarkt	0,5525	0,4912	0,4265	1,4703	0	0	0	0	0
9374000	Neustadt	0,6518	0,2105	0,388	1,2503	0	0	0	0	0
9375000	Regensbur	0,2538	0,6842	0,3683	1,3064	0,0291	0,0008	0,0149	0,1206	0,0526
9376000	Schwandor	0,5339	0,1228	0,2012	0,8579	0	0	0	0	0
9377000	Tirschenr	0,7482	-0,1228	0,3344	0,9598	0	0	0	0	0
9461000	Bamberg	-0,3505	-0,386	0,2324	-0,5041	0	0	0	0	0
9462000	Bayreuth	-0,6237	0	0,0462	-0,5775	0	0	0	0	0
9463000	Coburg	-0,3557	-0,5789	0,1903	-0,7444	0	0	0	0	0
9464000	Hof	-0,3144	-0,614	-0,0583	-0,9868	0	0	0	0	0
9471000	Bamberg	0,3226	0,614	0,3535	1,2901	0	0	0	0	0
9472000	Bayreuth	0,6743	0,0702	0,4088	1,1533	0	0	0	0	0

9473000	Coburg	0,1394	-0,0877	0,2108	0,2625	0	0	0	0	0
County	Name	F1.Region	F2.Fragility	F3.Socio-Econ	SSI_sum	Supply	Contaminating	IDI	Exposed_area	SIFVI
9474000	Forchheim	0,2891	0,4211	0,4151	1,1252	0	0	0	0	0
9475000	Hof	0,4158	-0,614	0,3157	0,1175	0	0	0	0	0
9476000	Kronach	0,4937	-0,3158	0,338	0,5159	0	0	0	0	0
9477000	Kulmbach	0,3747	-0,2632	0,2007	0,3122	0	0	0	0	0
9478000	Lichtenfe	0,2023	-0,0351	0,3345	0,5017	0	0	0	0	0
9479000	Wunsiedel	0,2105	-0,807	0,2731	-0,3234	0	0	0	0	0
9561000	Ansbach	-0,1546	-0,2807	0,3965	-0,0388	0	0	0	0	0
9562000	Erlangen	-0,732	0,1754	0,1356	-0,4209	0	0	0	0	0
9563000	Fuerth	-0,3041	0,2632	-0,2011	-0,2421	0	0	0	0	0
9564000	Nuernberg	-0,4278	-0,1228	-0,2793	-0,83	0	0	0	0	0
9565000	Schwabach	-0,1701	0,0351	0,206	0,071	0	0	0	0	0
9571000	Ansbach	0,6367	0,2281	0,2201	1,0848	0	0	0	0	0
9572000	Erlangen-	-0,0339	0,5965	0,394	0,9566	0	0	0	0	0
9573000	Fuerth	-0,0661	0,2281	0,294	0,456	0	0	0	0	0
9574000	Nuernberg	0,024	0,0351	0,2161	0,2752	0	0	0	0	0
9575000	Neustadt	0,6535	0,1579	0,463	1,2744	0	0	0	0	0
9576000	Roth	0,4655	0,3509	0,2186	1,0349	0	0	0	0	0
9577000	Weissenbu	0,4778	-0,0175	0,3508	0,811	0	0	0	0	0
9661000	Aschaffen	-0,2835	0	0,0864	-0,1971	0	0	0	0	0
9662000	Schweinfu	-0,2371	-0,6667	0,0422	-0,8616	0	0	0	0	0
9663000	Wuerzburg	-0,7062	0,0702	0,0241	-0,6119	0	0	0	0	0
9671000	Aschaffen	-0,0609	0,2807	0,2097	0,4295	0	0	0	0	0
9672000	Bad Kissi	0,514	-0,2807	0,3935	0,6268	0	0	0	0	0
9673000	Rhoen-Gra	0,6162	0,0877	0,3262	1,0301	0	0	0	0	0
9674000	Hassberge	0,6516	0,2281	0,3154	1,1951	0	0	0	0	0
9675000	Kitzingen	0,2869	0,1579	0,3448	0,7896	0	0	0	0	0
9676000	Miltenber	0,1091	0,2807	0,1713	0,5611	0	0	0	0	0
9677000	Main-Spes	0,2495	0,0526	0,4549	0,757	0	0	0	0	0
9678000	Schweinfu	0,4373	0,1754	0,2637	0,8764	0	0	0	0	0
9679000	Wuerzburg	0,1444	0,386	0,4499	0,9803	0	0	0	0	0
9761000	Augsburg	-0,5052	-0,1404	-0,1705	-0,816	0	0	0	0	0
9762000	Kaufbeure	-0,2938	-0,4035	0,0035	-0,6939	0	0	0	0	0
9763000	Kempten	-0,5309	-0,3509	-0,0936	-0,9754	0	0	0	0	0
9764000	Memmingen	-0,3505	-0,1754	0,0723	-0,4537	0	0	0	0	0
9771000	Aichach-F	0,2844	0,5965	0,3026	1,1835	0	0	0	0	0
9772000	Augsburg	0,0935	0,4561	0,2791	0,8287	0	0	0	0	0
9773000	Dillingen	0,3503	0,4035	0,2057	0,9595	0	0	0	0	0
9774000	Guenzburg	0,2084	0,4035	0,1781	0,7899	0	0	0	0	0
9775000	Neu-Ulm	-0,1563	0,3684	0,1525	0,3646	0	0	0	0	0
9776000	Lindau	-0,2844	-0,1228	0,4468	0,0396	0	0	0	0	0
9777000	Ostallgae	0,3476	0,2281	0,5054	1,0811	0	0	0	0	0
9778000	Unterallg	0,4891	0,1404	0,5619	1,1914	0	0	0	0	0
9779000	Donau-Rie	0,4865	0,2807	0,4511	1,2184	0	0	0	0	0
9780000	Oberallga	0,0248	0,1404	0,5309	0,6961	0	0	0	0	0
10041000	Saarbruec	-0,3557	-0,2632	0,1255	-0,4933	0	0	0	0	0
10042000	Merzig-Wa	-0,005	-0,1404	0,5728	0,4274	0	0	0	0	0
10043000	Neunkirch	-0,1289	-0,3684	0,3217	-0,1756	0	0	0	0	0
10044000	Saarlouis	-0,1082	-0,1754	0,4149	0,1312	0	0	0	0	0
10045000	Saarpfalz	-0,2117	-0,3684	0,4441	-0,136	0	0	0	0	0
10046000	Sankt Wen	0,1656	-0,2105	0,5041	0,4592	0	0	0	0	0
11000000	Berlin	-0,6598	0,4211	-0,2535	-0,4922	0	0	0	0	0
12051000	Brandenbu	-0,3196	-0,5088	-0,2982	-1,1265	0	0	0	0	0
12052000	Cottbus/C	-0,4175	0,0702	-0,1241	-0,4714	0	0	0	0	0
12053000	Frankfurt	-0,6134	0,0877	-0,295	-0,8207	0	0	0	0	0
12054000	Potsdam	-0,4948	0,2281	-0,1573	-0,4241	0	0	0	0	0
12060000	Barnim	0,1668	0,2982	-0,2453	0,2197	0	0	0	0	0
12061000	Dahme-Spr	0,2994	-0,0877	-0,1844	0,0273	0	0	0	0	0
12062000	Elbe-Elst	0,6814	-0,3333	-0,2583	0,0897	0	0	0	0,007	0,0052
12063000	Havelland	0,2305	0,2982	-0,3674	0,1613	0	0	0	0,0037	0,0027
12064000	Maerkisch	0,3034	0,1579	-0,2177	0,2437	0	0	0	0	0
12065000	Oberhavel	0,0634	0,193	-0,1745	0,0819	0	0	0	0	0
12066000	Oberspree	0,4431	-0,4211	-0,4183	-0,3962	0	0	0	0	0
12067000	Oder-Spre	0,2016	-0,0351	-0,3216	-0,1551	0	0	0	0	0
12068000	Ostprigni	0,7732	0,0351	-0,3862	0,4221	0	0	0	0	0
12069000	Potsdam-M	0,3075	0,2807	-0,1028	0,4854	0	0	0	0	0
12070000	Prignitz	0,6368	-0,4912	-0,2578	-0,1122	0	0	0	0	0
12071000	Spree-Nei	0,3088	-0,1053	-0,2527	-0,0491	0	0	0	0	0
12072000	Teltow-Fl	0,2398	0,193	-0,1806	0,2521	0	0	0	0	0
12073000	Uckermark	0,4743	-0,0877	-0,5161	-0,1295	0	0	0	0	0
13001000	Greifswal	-0,4639	0,2807	-0,4765	-0,6598	0	0	0	0	0
13002000	Neubrande	-0,4794	0,2807	-0,4965	-0,6952	0	0	0	0	0
13003000	Rostock	-0,5052	-0,1404	-0,4582	-1,1037	0	0	0	0	0
13004000	Schwerin	-0,433	-0,193	-0,3013	-0,9272	0	0	0	0	0
13005000	Stralsund	-0,4433	-0,5439	-0,4788	-1,4659	0	0	0	0	0
13006000	Wismar	-0,4124	-0,5439	-0,8	-1,7562	0	0	0	0	0
13051000	Bad Dober	0,2133	0,6316	-0,1817	0,6633	0	0	0	0	0
13052000	Demmin	0,4748	-0,1754	-0,4986	-0,1992	0	0	0	0	0
13053000	Guestrow	0,3134	-0,0526	-0,525	-0,2642	0	0	0	0	0
13054000	Ludwigslu	0,5026	0,2632	-0,2209	0,5449	0	0	0	0	0
13055000	Mecklenbu	0,4917	0,0702	-0,4615	0,1004	0	0	0	0	0
13056000	Mueritz	0,4316	0,0526	-0,32	0,1641	0	0	0	0	0
13057000	Nordvorpo	0,5131	0,0175	-0,4283	0,1023	0	0	0	0	0
13058000	Nordwestm	0,6547	0,4737	-0,2393	0,8892	0	0	0	0	0
13059000	Ostvorpom	0,2379	-0,0877	-0,3485	-0,1983	0	0	0	0	0
13060000	Parchim	0,5737	0,1404	-0,2617	0,4523	0	0	0	0	0
13061000	Ruegen	-0,1112	-0,0351	-0,1558	-0,3022	0	0	0	0	0
13062000	Uecker-Ra	0,4759	-0,2105	-0,4962	-0,2308	0	0	0	0	0
14161000	Chemnitz	-0,4021	-0,7544	-0,1957	-1,3522	0	0	0	0	0
14166000	Plauen	-0,4639	-0,5965	-0,1723	-1,2327	0	0	0	0	0
14167000	Zwickau	-0,3711	-0,6491	-0,2066	-1,2268	0	0	0	0	0
14171000	Annaberg	0,0266	-0,4035	-0,2449	-0,6218	0	0	0	0	0
14173000	Chemnitze	-0,1641	-0,7368	-0,2708	-1,1718	0	0	0	0	0
14177000	Freiberg	0,1772	-0,4912	-0,4132	-0,7273	0	0	0	0	0
14178000	Vogtlandk	0,0689	-0,7368	-0,1265	-0,7944	0	0	0	0	0
14181000	Mittlerer	0,3851	-0,4386	-0,4153	-0,4689	0	0	0	0	0

14182000	Mittweida	0,0465	-0,614	-0,306	-0,8735	0	0	0	0	0
County	Name	F1.Region	F2.Fragility	F3.Socio-Econ	SSI_sum	Supply	Contaminating	IDI	Exposed_area	SIFVI
14188000	Stollberg	-0,1522	-0,5789	-0,3199	-1,0511	0	0	0	0	0
14191000	Aue-Schwa	-0,0574	-0,5965	-0,3918	-1,0457	0	0	0	0	0
14193000	Zwickauer	-0,0735	-0,5789	-0,3049	-0,9573	0	0	0	0	0
14262000	Dresden	-0,5258	-0,193	-0,1621	-0,8809	0,8016	0,0259	0,4138	0,8847	0,8841
14263000	Goerlitz	-0,4639	-0,8596	-0,2545	-1,5781	0	0	0	0	0
14264000	Hoyerswer	-0,4227	-0,7544	-0,5758	-1,7528	0	0	0	0	0
14272000	Bautzen	0,1384	-0,386	-0,3549	-0,6025	0	0	0	0	0
14280000	Meissen	0,068	-0,4386	-0,3066	-0,6772	0,1602	0,0084	0,0843	0,723	0,6846
14284000	Niedersch	0,4911	-0,193	-0,3958	-0,0976	0	0	0	0	0
14285000	Riesa-Gro	0,2151	-0,3684	-0,4206	-0,5739	0,0493	0,013	0,0312	0,43	0,3957
14286000	Loebau-Zi	0,055	-0,8246	-0,2917	-1,0612	0	0	0	0	0
14287000	Saechsisc	0,1105	-0,5965	-0,32	-0,806	0,0798	0,006	0,0429	0,6885	0,6748
14290000	Weisserit	0,1781	-0,1579	-0,3916	-0,3714	0	0	0	0	0
14292000	Kamenz	0,2564	-0,1754	-0,344	-0,263	0	0	0	0	0
14365000	Leipzig	-0,4381	-0,2807	-0,1991	-0,9179	0	0	0	0	0
14374000	Delitzsch	0,1425	-0,0877	-0,4525	-0,3977	0	0	0	0	0
14375000	Doebeln	0,0324	-0,6491	-0,4371	-1,0539	0	0	0	0	0
14379000	Leipziger	0,1312	-0,2982	-0,4244	-0,5914	0	0	0	0	0
14383000	Muldental	0,2589	-0,0702	-0,4054	-0,2167	0	0	0	0	0
14389000	Torgau-Os	0,4437	-0,193	-0,342	-0,0913	0,0433	0,0064	0,0249	0,3366	0,2679
15101000	Dessau	-0,3711	-0,7018	-0,22	-1,2929	0,1367	0,0503	0,0935	0,6362	0,7033
15151000	Anhalt-Ze	0,3215	-0,3684	-0,2472	-0,2941	0,0248	0,0017	0,0133	0,5382	0,4565
15153000	Bernburg	0,1212	-0,5088	-0,5377	-0,9253	0	0	0	0	0
15154000	Bitterfel	0,0462	-0,4737	-0,4998	-0,9273	0	0	0	0	0
15159000	Koethen	0,1238	-0,2807	-0,568	-0,7249	0,0421	0,0022	0,0222	0,182	0,1746
15171000	Wittenber	0,4146	-0,3509	-0,3003	-0,2365	0,1007	0,0085	0,0546	0,5954	0,4962
15202000	Halle/Saa	-0,3763	-0,1579	-0,4013	-0,9355	0	0	0	0	0
15256000	Burgenlan	0,219	-0,5965	-0,5198	-0,8973	0	0	0	0	0
15260000	Mansfelde	0,1781	-0,614	-0,555	-0,991	0	0	0	0	0
15261000	Merseburg	0,2849	-0,3509	-0,5377	-0,6036	0	0	0	0	0
15265000	Saalkreis	0,424	0,4386	-0,3783	0,4843	0	0	0	0	0
15266000	Sangerhau	0,4821	-0,4386	-0,4281	-0,3845	0	0	0	0	0
15268000	Weissenfe	0,0504	-0,614	-0,5731	-1,1367	0	0	0	0	0
15303000	Magdeburg	-0,3763	-0,3684	-0,3056	-1,0503	0,3526	0,0265	0,1895	0,9157	0,955
15352000	Aschersle	0,1682	-0,3333	-0,5735	-0,7386	0	0	0	0	0
15355000	Boerdekre	0,7812	-0,0702	-0,3588	0,3522	0	0	0	0	0
15357000	Halbersta	0,2218	-0,3158	-0,3366	-0,4305	0	0	0	0	0
15358000	Jerichowe	0,4111	-0,1228	-0,3548	-0,0665	0,0909	0,0159	0,0534	0,5812	0,4589
15362000	Ohrekreis	0,6044	0,2632	-0,1767	0,6909	0,0068	0,0028	0,0048	0,1517	0,0902
15363000	Stendal	0,2913	-0,0175	-0,3555	-0,0818	0,0292	0,0101	0,0197	0,6591	0,523
15364000	Quedlinbu	0,1984	-0,4912	-0,4819	-0,7747	0	0	0	0	0
15367000	Schoenebe	0,1295	-0,5263	-0,4123	-0,8091	0,044	0	0,022	0,5316	0,5214
15369000	Wernigero	0,1594	-0,4737	-0,2715	-0,5857	0	0	0	0	0
15370000	Altmarkkr	0,5218	-0,0175	-0,2578	0,2464	0	0	0	0	0
16051000	Erfurt	-0,7113	0,1228	-0,3826	-0,9711	0	0	0	0	0
16052000	Gera	-0,5619	-0,4386	-0,2505	-1,2509	0	0	0	0	0
16053000	Jena	-0,5979	0,3158	-0,222	-0,5042	0	0	0	0	0
16054000	Suhl	-0,2423	-0,1404	-0,2505	-0,6332	0	0	0	0	0
16055000	Weimar	-0,6443	0,0702	-0,3002	-0,8744	0	0	0	0	0
16056000	Eisenach	-0,2887	-0,4912	-0,3113	-1,0912	0	0	0	0	0
16061000	Eichsfeld	0,3599	0,3509	-0,1902	0,5206	0	0	0	0	0
16062000	Nordhause	0,2134	-0,2807	-0,368	-0,4353	0	0	0	0	0
16063000	Wartburgk	0,4891	-0,0877	-0,0786	0,3228	0	0	0	0	0
16064000	Unstrut-H	0,2716	-0,0877	-0,2525	-0,0687	0	0	0	0	0
16065000	Kyffhaeus	0,339	-0,2632	-0,3874	-0,3116	0	0	0	0	0
16066000	Schmalkal	0,3585	-0,2281	-0,1221	0,0084	0	0	0	0	0
16067000	Gotha	0,2593	-0,1053	-0,2101	-0,0561	0	0	0	0	0
16068000	Soemmerda	0,4591	0,1754	-0,393	0,2415	0	0	0	0	0
16069000	Hildburgh	0,636	-0,0351	-0,1348	0,4661	0	0	0	0	0
16070000	Ilm-Kreis	0,1522	-0,1404	-0,2325	-0,2206	0	0	0	0	0
16071000	WeimarerL	0,3927	0,2281	-0,2213	0,3994	0	0	0	0	0
16072000	Sonneberg	0,1704	-0,4737	-0,1941	-0,4974	0	0	0	0	0
16073000	Saalfeld-	0,168	-0,5614	-0,2414	-0,6348	0	0	0	0	0
16074000	Saale-Hol	0,2959	0,0526	-0,2239	0,1246	0	0	0	0	0
16075000	Saale-Orl	0,4999	-0,3509	-0,0744	0,0746	0	0	0	0	0
16076000	Greiz	0,1993	-0,4737	-0,1545	-0,4289	0	0	0	0	0
16077000	Altenburg	0,0984	-0,6316	-0,1399	-0,673	0	0	0	0	0