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Towards sectoral and standardised vulnerability assessments: the example of heatwave impacts on human health*

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Abstract

The relevance of climate change is especially apparent through the impacts it has on natural and societal systems. A standardised methodology to assess these impacts in order to produce comparable results is still lacking. We propose a semi-quantitative approach to calculate vulnerability to climate change, with the ability to capture complex mechanisms in the human-environmental system. The key mechanisms are delineated and translated into a deterministic graph (impact chain). A fuzzy logic algorithm is then applied to address uncertainty regarding the definition of clear threshold values. We exemplify our approach by analysing the direct impacts of climate change on human health in North Rhine-Westphalia, Germany, where the urban heat island potential, the percentage of elderly population as well as the occurrence of heat waves determine impact intensity. Increases in heatwaves and elderly population will aggravate the impacts. While the influence of climatic changes is apparent on larger spatial scales, societal factors determine the small scale distribution of impacts within our regional case study. In addition to identifying climate change impact hot spots, the structured approach of the impact chain and the methodology of aggregation enable to infer from the results back to the main constituents of vulnerability. Thus, it can provide a basis for decision-makers to set priorities for specific adaptation measures within the complex field of climate change impacts.

keywords: heat waves, human health, climate change, vulnerability, fuzzy logic, impact chain

1 Introduction

The relevance of climate change for humankind is revealed through the impacts it has on natural and societal systems. The severity of these impacts depends on a variety of factors, which are critically dependent on the specific properties of a given system or sector. To address the context specific impacts of climate change, impact and vulnerability assessment methodologies have been developed. The Intergovernmental Panel on Climate Change has provided an encompassing definition of vulnerability, aiming to incorporate the specific properties of the systems under analysis through considering that sectors react differently to climatic stimuli, and have different capacities to withstand adverse effects of accelerated climate change (Adger et al, 2007; IPCC, 2007). Conceptually, vulnerability is a powerful concept, as it aims to consider the whole continuum of possible impacts and allows to delineate comparable situations. However, the concept is weak in terms of its mathematical foundations. A general methodology that allows a standardised assessment and produces comparable results is still lacking (see e.g. Ionescu et al, 2009; Füssel and Klein, 2006). Consequently vast numbers of impact and vulnerability studies exist which employ diverse methodologies and produce inconsistent results.

Comparable small-scale vulnerability assessments, however, are a precondition for identifying regional hot-spots and for prioritizing adaptation to efficiently allocate available funds (Adger et al, 2007; Carter et al, 2007). These assessments have to consider the interdependencies involved while being as simple as possible in order to deliver tangible results to decision-makers and provide transferability to other regions. An understanding of the cause-and-effect chains that govern the processes that lead to a situation of vulnerability is essential. Some singular properties of a system may only lead to negative impacts if they occur in specific socio-economic settings. Thus a focus of the interrelations between climatic and socio-economic variables

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should be a central point in any analysis of impacts and vulnerability. Certain properties of a system may render it more vulnerable. Their spatial concomitance further increases the risk of adverse effects. Thus, the spatially explicit depiction of properties and processes is expedient.

The present article proposes a semi-quantitative synoptic approach which is developed closely to concrete climate related problem complexes, thus relating to the reality decision-makers are facing. A qualitative description of the climatic sensitivities of a given sector delineates the key mechanisms relevant within the analysis context. These are derived from literature as well as from plausible expert knowledge. Subsequently, these mechanisms are translated into a deterministic graph (impact chain), which describes critical elements determining impacts and vulnerability. This systematic conceptualization reduces highly complex systems to the relevant cause-and-effect relationships. To quantify this qualitative representation, indicators are derived. A fuzzy logic algorithm is applied to master the challenges posed by uncertainty and context-specific unclarity. We will exemplify the proposed approach by analysing the direct impacts of climate change on human health for the administrative level of municipalities in the study region of North Rhine-Westphalia (NRW), Germany.

Many similar and overlapping definitions and concepts to describe and assess how systems can adversely be affected by natural hazards have emerged from different schools of research (see e.g. Birkmann, 2006; Adger, 2006; Brooks, 2003; Miller et al, 2010). For our analysis we draw on the vulnerability framework provided by the IPCC, where it is defined as *"the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity."*(IPCC, 2007). We thus see vulnerability as resulting from the specific properties of the system under analysis, which determine its sensitivity to a hazard that it is exposed to. Following the nomenclature introduced by Füssel (2007), we examine the impacts on human health *(attribute of concern)* due to heat stress *(exposure)* in the context of climate change *(temporal reference)*.

Various studies have been carried out that clearly relate increased mortality and morbidity rates to above normal temperature (Laschewski and Jendritzky, 2002; Havenith, 2005; Kovats and Jendritzky, 2006; Hajat et al, 2007; Menne and Ebi, 2006; Baccini et al, 2008). These analyses are often motivated by concrete events such as the Chicago heatwave in 1995 (Klinenberg, 2002; Semenza et al, 1996) or the European heatwave in 2003, with approx. 40.000 excess deaths over Europe and highest mortality rates in older age groups (see e.g. Borrell et al, 2006; Kosatsky, 2005; Vandentorren and Empereur-Bissonnet, 2005; Rebetez et al, 2006). Beside higher age also the duration and intensity of a period with heat stress (Huynen et al, 2001; Kysely, 2004) or the urban structure (Upmanis and Chen, 1999; Eliasson and Upmanis, 2000) contribute to above normal mortality rates. The causal relations between specific attributes and impacts of heat stress are thus well established. Less attention has been given to concepts and methods to depict the spatial occurrence of these attributes. While it has been recognized that an increase in temperature extremes is likely over the course of the century, and that climate change may be a threat to human health in the future (Costello et al, 2009), only few approaches assess possible future risks to human health (Vescovi et al, 2005; Meyer et al, 2009).

Through the underlying impact chain and the translation of these cause-and-effect chains into a fuzzy logic based decision tree, our approach provides several improvements relative to similar approaches presented by Vescovi et al (2005) and Meyer et al (2009). On the one hand the use of fuzzy logic allows the consideration of uncertainty, both stemming from data as well as from the use of scenarios. More importantly, we clearly relate the analysis to the cause-and-effect relationships that define the impact. The approach allows to identify those factors most relevant for the smallest unit of analysis, thus giving indications on how to most effectively cope with vulnerable situations. Previous approaches, such as the integrated neural networks approach by Kropp et al (2006), aggregate sectoral impacts in such a way that underlying processes become unidentifiable from the results. While they depict impact hot-spots, response options become blurred. Our methodology retains the important properties, thus providing indication towards effective adaptation.

We outline the pertinent features of our approach in the following pages and have organised this article as follows. After a short overview of the study region in Section 2 the methods and the input data sets are described in Section 3. The resulting distribution of impacts is presented in Section 4 while Section 5 discusses the results achieved in details, followed by a conclusion in Section 6.

2 Study site

The state of North Rhine-Westphalia (NRW) is situated in the north-west of Germany and comprises 396 municipalities (Figure 1). With a population of 18 millions (2008) and an average population density of over 500 cap/km^2 NRW is the most populous and at the same time most densely populated state in Germany. Regional characteristics are quite diverse in terms of climate and geomorphology. Two main types of landscape can be found in NRW, namely the North German Lowlands with elevations just a few meters above sea level and the northern German Low Mountain Range with elevations of up to 850m. The lowlands comprise the Rhine-Ruhr Area which is one of the largest metropolitan areas in Europe with a population of approx. 10 million and very high population density of 2.100 cap/km^2. Opposed to this, in the mountain regions population density is rather low with 150 cap/km^2. NRW contributes over 20% of the overall German GDP (2008) (DESTATIS, 2009). The above mentioned two main landscape types are also distinguishable in the climatic characteristics of the region: Annual mean temperature amounts to around 10 °C (1961-1990)[1] in the lowlands and about 5 °C in the mountain regions. This spatial variation is also reflected in the occurrence of temperature extremes, both in terms of frequency and intensity. Yearly mean precipitation of up to 1.500 mm has been recorded in higher elevations, while the Rhine valley received a mean sum of 620 mm per year.

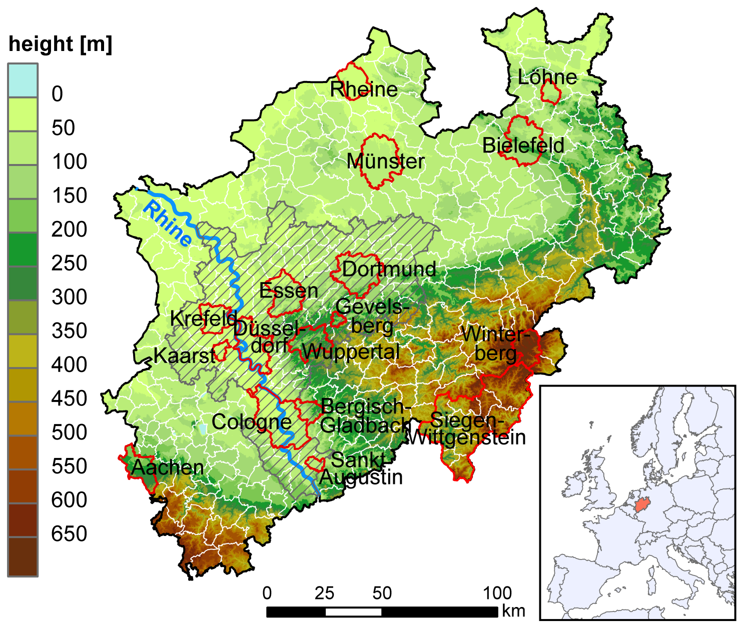

Figure 1: The study region North Rhine-Westphalia and its location within the European Union (Municipalities discussed in Sect. 4 and 5 are marked red, the metropolitan region is delineated in grey)

Demographic change towards an elderly population is apparent in NRW; in the year 2008, 19% of the population were over 65 years old and an increase up to 29% is expected until 2030 (LandesdatenbankNRW, 2010).

3 Methods and data

3.1 The concept of impact chains

The term 'impact chain' describes the systematic depiction of the processes triggered within a given system deriving from a (climate) stimulus. The structured approach allows for a conceptualized visualization of the complex interrelations found in coupled human-environmental systems. The focus lies on the effects a certain

[1] Measured temperature and precipition values for the baseline period as provided in the regional climate model STAR (Werner and Gerstengarbe, 1997; Orlowsky et al, 2008)

climatic stimulus has on the system and how this effect propagates through the system, depending on its inherent characteristics, which in turn influence the severity of the impacts.

A systematic literature review provides information of these properties, including reaction, processes and feedbacks between important elements (see e.g. for similar methods Geist and Lambin, 2004, 2002). This information is translated into a stylized representation by means of a directed graph, clearly describing the impacts deriving from a specific climate stimulus (upper part of Figure 2). Each node of the graph describes a key element of the system, while the edges represent the nature of their interaction. This impact chain comprises only those elements that critically determine the impacts and can be attributed with a measurement. The elements of the impact chain are translated into quantifiable indicators and aggregated with operators to derive an integrated measure of impacts and vulnerability (lower part of Figure 2). Corresponding to the definition of vulnerability given in the introduction, the climate stimulus represents the hazard that the system of analysis is exposed to (exposure). The system properties describe the socio-economic setting that may aggravate or relieve the pressure that the system is exposed to (sensitivity, adaptive capacity). The impact chain thus depicts how impacts related to a climate stimulus propagate through the system, with the vulnerability critically determined by the system properties.

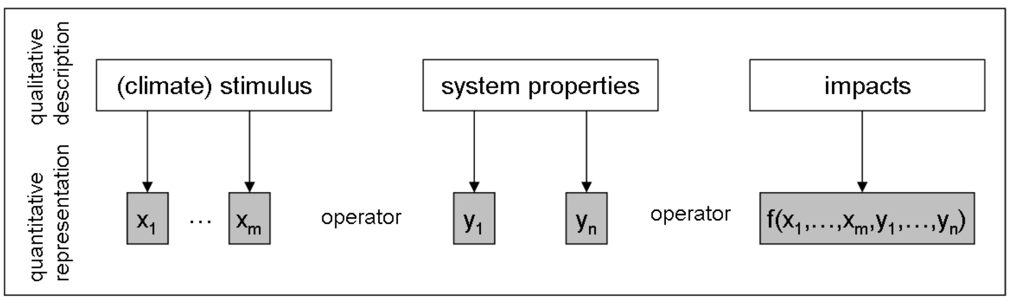

Figure 2: Schematic overview of the impact chain approach: the systematic qualitative description contains influences, causes and effects for a specific system; these are quantitatively represented by indicators (x, y) and aggregated through operators

From the manifold impacts deriving from heat waves we choose the system 'human health' to demonstrate the approach and develop an impact methodology. The direct impact of interest is the increase of morbidity as well as mortality rates under conditions of heat extremes. For this, the following key factors are relevant (presented in the order of the subsequent analysis, see Figure 3):

- Regional and local air temperature and resulting heat stress is not determined by atmospheric processes alone, but urban areas can significantly alter regional climate patterns through the formation of an urban heat island (UHI) (Oke, 1982; Kuttler, 2008). Due to the specific heat absorption, retention and conduction capacities of urban materials urban temperature can be $5 - 11\,°C$ higher than surrounding areas (see e.g. Oke, 1973; Matzarakis, 2001; Stathopoulou and Cartalis, 2007; Kuttler, 2008; Hupfer and Kuttler, 2005). Further, reduced plant cover decreases the evaporative cooling capacities of cities. This temperature gradient is especially pronounced just after nightfall (Matzarakis, 2001). The proportion of sealed surfaces is one important contributing factor favouring the formation of a UHI.

- Additionally, the height of buildings can further increase the UHI as the surface area for heat retention is increased (Hupfer and Kuttler, 2005; Matzarakis and Mayer, 2008) and more radiation is trapped between buildings (Arnfield, 2003; Kuttler, 2008). Population density can be used as proxy variable to indicate the degree of urbanity and corresponding higher residential houses. This has the additional value of only including those areas into the assessment where many people are at risk.

- The UHI plays a critical role in exacerbating heat stress (Koppe et al, 2004; Koppe, 2005; Mavrogianni et al, 2009), since high temperatures are increased at all times of day, while nighttime cooling is reduced (Kovats and Hajat, 2008).

- Extremely high temperatures are clearly associated with significantly increased mortality and morbidity rates (Semenza et al, 1996, 1999; Kosatsky, 2005; Vandentorren and Empereur-Bissonnet, 2005).

The additional heat load may overexert the cardiovascular system in particular for the elderly people (Wainwright et al, 1999; Hodgkinson et al, 2003). Consequently, there is a clear correlation between a mortality increase in population aged 65 or older (population ≥ 65) and periods of extremely high temperatures (Huynen et al, 2001; Laschewski and Jendritzky, 2002; Kovats and Jendritzky, 2006). The proportion of this age group can thus indicate a higher regional sensitivity towards the impacts of heat waves.

- As definitions of heat waves are context and location dependent, we use a regional definition, applicable for temperate climate regions such as NRW. Here, periods of at least three consecutive days with maximum temperatures (Tmax) $\geq 30\,^{\circ}$C correlate with significantly increased mortality and morbidity rates, especially in age groups of 65 years or older (Huynen et al, 2001; Kysely, 2004). Consequently, a heat wave for the purpose of this study is defined as a period of at least three consecutive days with Tmax $\geq 30\,^{\circ}$C. All days constituting a heat wave are further referred to as heat wave days (HWD).

Thus, the sensitivity of a region to be negatively impacted by heat waves can be delineated by two spatially resolved key factors, namely the potential intensity of the UHI (potential UHI), represented by the sealed surface area and the population density, as well as the proportion of population ≥ 65. Where all of these occur in conjunction a significantly augmented regional sensitivity has to be expected. To finally describe regional impacts, the regional number of HWD as a measure of exposure is combined with the previously aggregated measure of sensitivity.

3.2 Data

We selected spatially resolved data, which are easily accessible and useful to indicate the above described processes. The data includes the percentage of sealed surfaces, population density, the proportion of population ≥ 65 and the number of HWD. The analysis is performed for a baseline period (1961-1990) and a scenario period (2031-2060) with a spatial resolution of the 396 municipalities.

Sociogeographic data from the Statistical Agency NRW (Landesbetrieb für Information und Technik Nordrhein-Westfalen, IT.NRW) is available for all determinants of sensitivity. The sealed surface area is represented by the proportion of settlement and traffic area per municipality as proxy, as this can sufficiently represent the surface properties favouring a UHI development (Meinel and Hernig, 2005). We compared this dataset to the Authorative Topographic-Cartographic Information System (ATKIS) landuse classification and found only slight variations. Therefore either dataset was considered equally suitable for the analysis; we chose data provided by IT.NRW to ensure consistency across the used datasets. There are currently no future projections for sealed surface area and past developments show no clear trends that can be extrapolated into the future. Therefore most recent values of 2008 are introduced for both analysis time frames. Data on the percentage of population ≥ 65 per municipality is retrievable for the year 2008 (baseline period) as well as for a projection to 2030 (scenario period).

Two regional climate models, CCLM and STAR, were applied to estimate the number of HWD for the baseline and scenario period considering a forcing according to the emission scenario A1B (Nakicenovic and Swart, 2000). The CCLM model is a full-dynamic and non-hydrostatic unified weather forecast and regional climate model with a grid size of 0.2 degrees (Lautenschlager et al, 2009), nested into the General Circulation Model (GCM) ECHAM 5/MPI-OM (Roeckner et al, 2003). The model STAR is a statistical model based on temperature trends from the same GCM, but considering statistical features from empirical measures from 1951 to 2003 which are re-sampled using cluster analysis to provide scenario data up to 2060 (Werner and Gerstengarbe, 1997; Orlowsky et al, 2008). We extracted the number of days from both models which are part of at least three consecutive days with Tmax $\geq 30\,^{\circ}$C. The data from the STAR model is provided for 244 stations across NRW and was spatially interpolated by inverse distance weighing. To approximate the number of heat waves per municipality we used the yearly mean over the 30-year periods of all values within the respective polygon for each model and assigned to respective number to the polygon for the analysis.

3.3 The fuzzy logic algorithm to calculate heat wave impacts

The structural composition of our analysis approach is motivated by the elements of the identified impact chain (Section 3.1). The translation of these into a quantifiable methodological framework poses several challenges, such as inconsistent units and uncertainties from scenarios and projections. Moreover, boolean-type either-or decision rules are difficult to apply within qualitative contexts, where gradual membership to classes may be needed. Fuzzy reasoning provides a means to approach these challenges (for details see e.g. Zimmermann, 2001; Zadeh, 1965; Kropp et al, 2001). The first step of any fuzzy analysis is the fuzzyfication of the base variables of the system with respect to defined logical clause (lingustic categories). A function to define the degree of membership to linguistic categories, such as *high* or *low* is then defined for each of the base variables. These categories relate to the analysis context, in our case to health related risks for humans.

Upper and lower thresholds for membership (ι_1, ι_2) are defined to calculate continuous degrees of membership through Equation 1.

$$\mu_{zi}(\iota) = \begin{cases} 0, & \iota \leq \iota_1 \\ \frac{\iota-\iota_1}{\iota_1-\iota_2}, & \iota_1 < \iota < \iota_2 \\ 1, & \iota_2 \leq \iota \end{cases} \tag{1}$$

$$\text{with} \quad \iota_1 < \iota_2$$

Fuzzified datasets take values between 0 and 1, with a value of 1 indicating full membership to the linguistic variable. Subsequently, the datasets are combined using fuzzy operators, such as a FUZZY_OR ($\vee$) (MAX) or FUZZY_AND ($\wedge$) (MIN). Unlike the strict application of boolean MIN or MAX operators, fuzzy operators allow for compensation through a γ-value, which can take values between 0 and 1 (Equation 2).

$$\mu(z_1 \wedge z_2 \wedge \ldots \wedge z_n) = \gamma * \min(\mu_{z1}, \mu_{z2}, \ldots, \mu_{zn}) + (1-\gamma) * \frac{1}{N} \sum_{i=1}^{N} \mu_{zi} \tag{2}$$

The introduction of γ results in the consideration of the arithmetic mean of all input values to some extent, thus diluting the strict application of the operator to the extent of γ, with values near to 1 resulting in a rather strict application of the operator and values near 0 introducing significant compensation. To aggregate the variables that determine the impacts within our study we use a decision tree, which is structured according to the insights from the impact chain (Figure 3).

The heating effect of different surfaces can be clearly distinguished on building block scale (Lo et al, 1997; Stathopoulou et al, 2004) and sealed areas of minor extent can alter the local temperature regime significantly (Matzarakis, 2001; Hupfer and Kuttler, 2005). The regional mean of sealed surface area for NRW lies at 22% of the total surface. The German mean is currently at approx. 12.5%. To account for this local heating effect of sealed surfaces of minor extent we chose a lower value of 12.5% and an upper threshold value of 40% to define membership to the linguistic variable $\mu\left(\substack{\text{sealed surface area} \\ \text{high}}\right)$. Population density as a measure of urbanity is in use in many regions with values ranging from up 4 000 cap/km^2 (Japan) to 200 cap/km^2 (Australia). Thus regional differences are substantial and the local characteristics play an important role. We chose a lower threshold of 250 cap/km^2, corresponding to the German average and an upper threshold of 1 000 cap/km^2, corresponding to twice the regional mean in NRW to calculate membership to $\mu\left(\substack{\text{population density} \\ \text{high}}\right)$ as these thresholds can best describe the spatial variations of population density within the study region.

We derive a measure for potential UHI intensity via the logical clause

$$\mu\left(\substack{\text{sealed surface area} \\ \text{high}}\right) \wedge \mu\left(\substack{\text{population density} \\ \text{high}}\right) = \mu\left(\substack{\text{potential UHI} \\ \text{high}}\right)$$

where $\wedge$ is applied as a strict AND operator. The proportion of sealed surface describes a physical property of a municipality to develop a UHI. Additionally, the degree of urbanity indicates a higher building density, which may augment the excess heat and point to where a substantial number of people are at risk. Therefore only if both variables are high, a high level of sensitivity can be assumed.

Different data sets for current and future analysis periods are available for the variable population ≥ 65. Therefore, threshold values were chosen to cover both datasets by setting the lower threshold at the average values for the baseline period and the upper one for the average value of projection period. Above average municipalities will be partly a member of the variable in all cases while at the same time those municipalities are well captured that experience an extreme increase in sensitive population groups. Lower and upper thresholds for the membership function $\mu\left(\substack{\text{population} \geq 65 \\ \text{high}}\right)$ are set to 19% and 29% respectively.

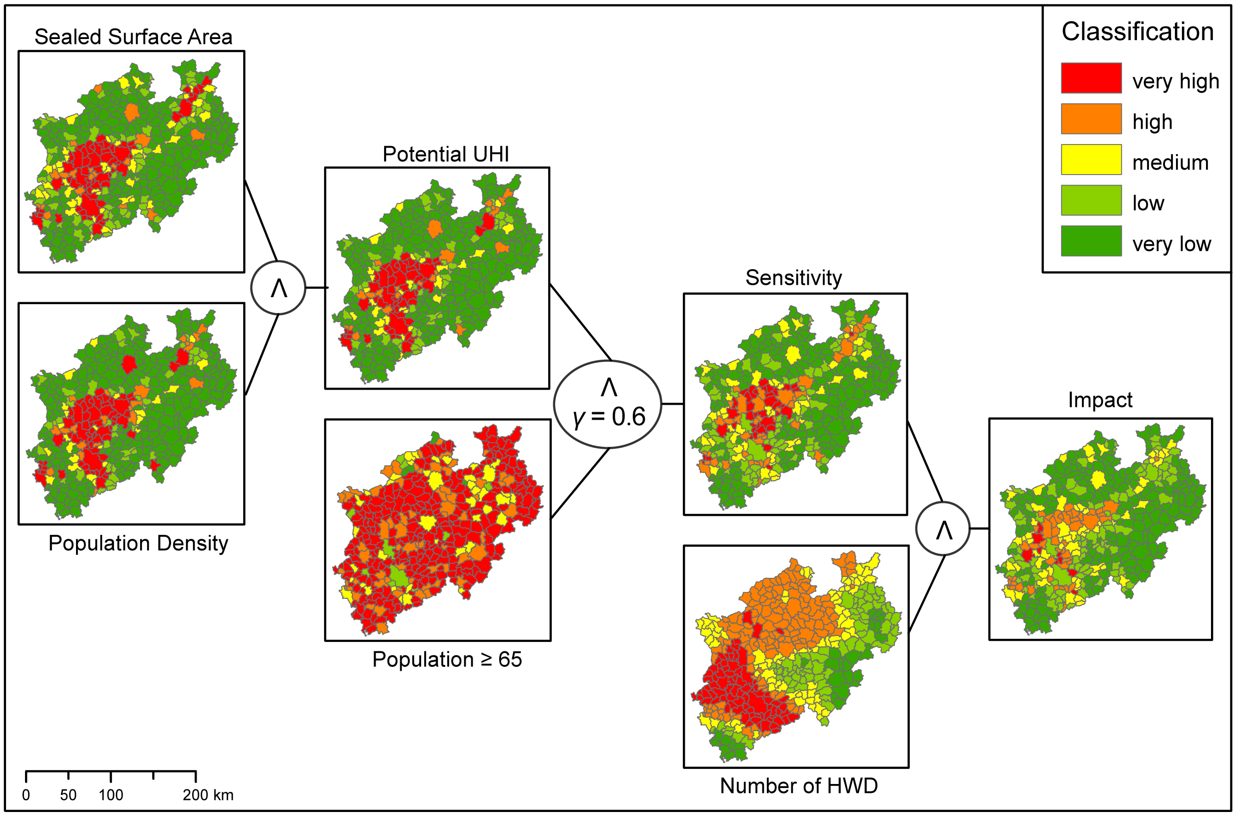

Figure 3: Fuzzy-logic based decision tree to assess the impacts of heat waves on human health; all maps show the fuzzified data; derived maps present the results obtained using climate data from the model STAR

$$\mu\binom{\text{potential UHI}}{\text{high}} \wedge \mu\binom{\text{population} \geq 65}{\text{high}} = \mu\binom{\text{sensitivity}}{\text{high}}$$

is the logical clause to represent the sensitivity of a municipality towards heat waves.

Here, we introduce a compensatory γ-value of 0.6 to account for the fact that population with no individual prior risk factors may be adversely affected by an intense UHI while the elderly are susceptible to heat stress without further intensification. The γ-value of 0.6 gives higher impact to the minimum factor, thus a concomitant occurrence of both factors renders a municipality more vulnerable, as the strongest impacts occur where the population has multiple sensitivities. Yet, negative impacts also occur where singular sensitivities are apparent (Luber and McGeehin, 2008; Basu, 2002), therefore 0.4 of the result value is compensated with the arithmetic mean of both variables.

Threshold values for the fuzzification of heat wave data were chosen analogous to the definition of heat waves applied in this analysis. The lower threshold for membership to $\mu\binom{\text{number of HWD}}{\text{high}}$ of three consecutive heat wave days corresponds to at least one heat wave every year while the upper threshold of nine days per year corresponds to a yearly average of three heat waves or a heat wave of a very long duration. The upper threshold also accommodates the records of the heatwave summer of 2003, when the study region experienced an average of 10 HWD with negative consequences for human health (Hellmeier et al, 2007).

The use of a strict AND operator within the statement

$$\mu\binom{\text{sensitivity}}{\text{high}} \wedge \mu\binom{\text{number of HWD}}{\text{high}} = \mu\binom{\text{impact}}{\text{high}}$$

aggregates all variables to the final measure of impacts.

Figure 4 illustrates the membership functions in this study.

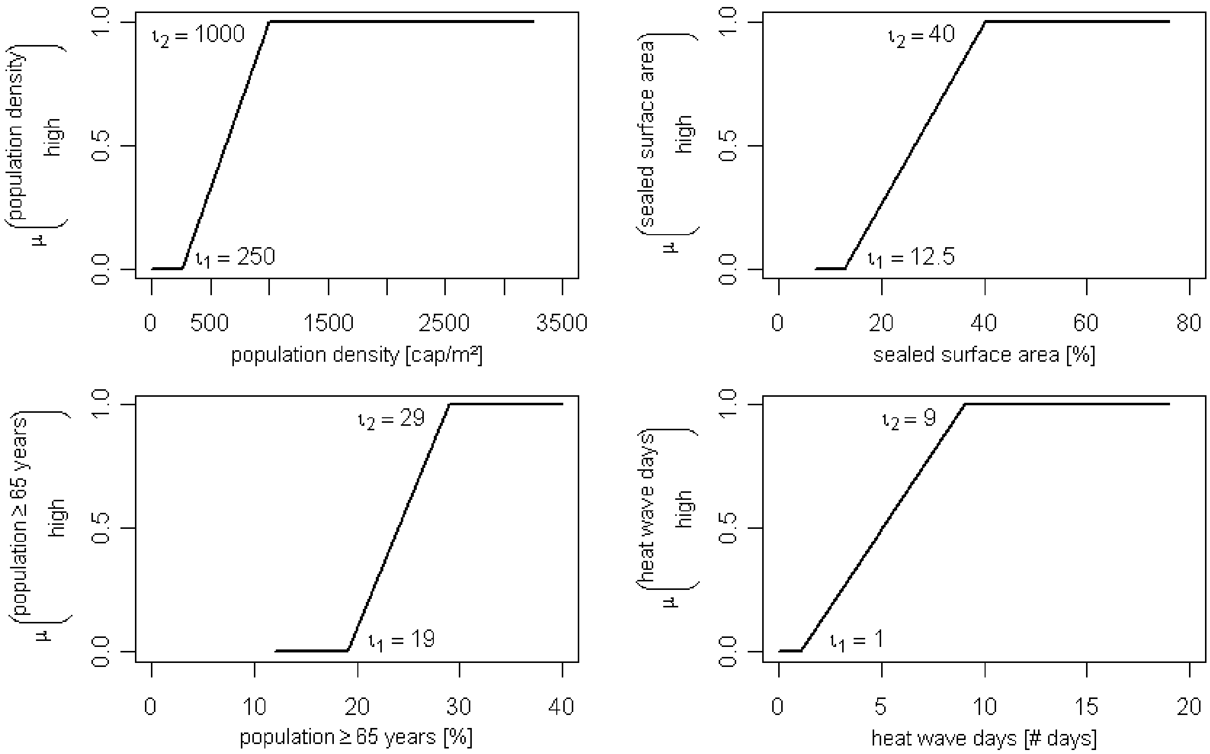

Figure 4: Threshold values ι_1 and ι_2 and corresponding ramps of fuzzy membership functions to fuzzify input variables for the decision tree; graphs cover the range of input values for each variable

4 Results

Under climate conditions as projected by the model STAR, the mean values of impacts for NRW municipalities amount to 0.33, while the mean impacts for CCLM are slightly higher(0.36). While overall impacts are higher with CCLM assumptions, however the increase in impacts in relation to the baseline period is higher for the STAR model with 0.3 (0.25 with CCLM). Table 1 summarizes the results for all municipalities for both models. Under assumptions of the STAR model 13% of all municipalities have high to very high impacts, 71% display low to very low impacts while the remaining 16% have a medium level of impacts. In contrast to that, the results for the CCLM model classify 19% of all municipalities as highly to very highly impacted. A proportion of 69% falls into the classes low and very low with the remaining 12% displaying medium impacts.

Table 1: Number of municipalities corresponding to the five impact classes in the scenario period for the models STAR and CCLM. Impacts are classified from very low to very high, with equal class sizes of 0.2.

Vulnerability class	STAR	CCLM
Very high	9	37
High	47	41
Medium	61	47
Low	94	81
Very low	185	190

For a total of 274 municipalities the intensity of impacts is identical for both climate models; in 90 cases the results for the CCLM model are higher while in 32 cases the STAR model produces higher degrees of vulnerability. Altogether more municipalities are ranked as highly or very highly impacted under CCLM assumptions (78 municipalities). The smaller share of highly or very highly impacted municipalities under

STAR (56 municipalities) correspond to those under CCLM except for one of the municipalities (Hagen), where impacts are projected under the model STAR and not under CCLM.

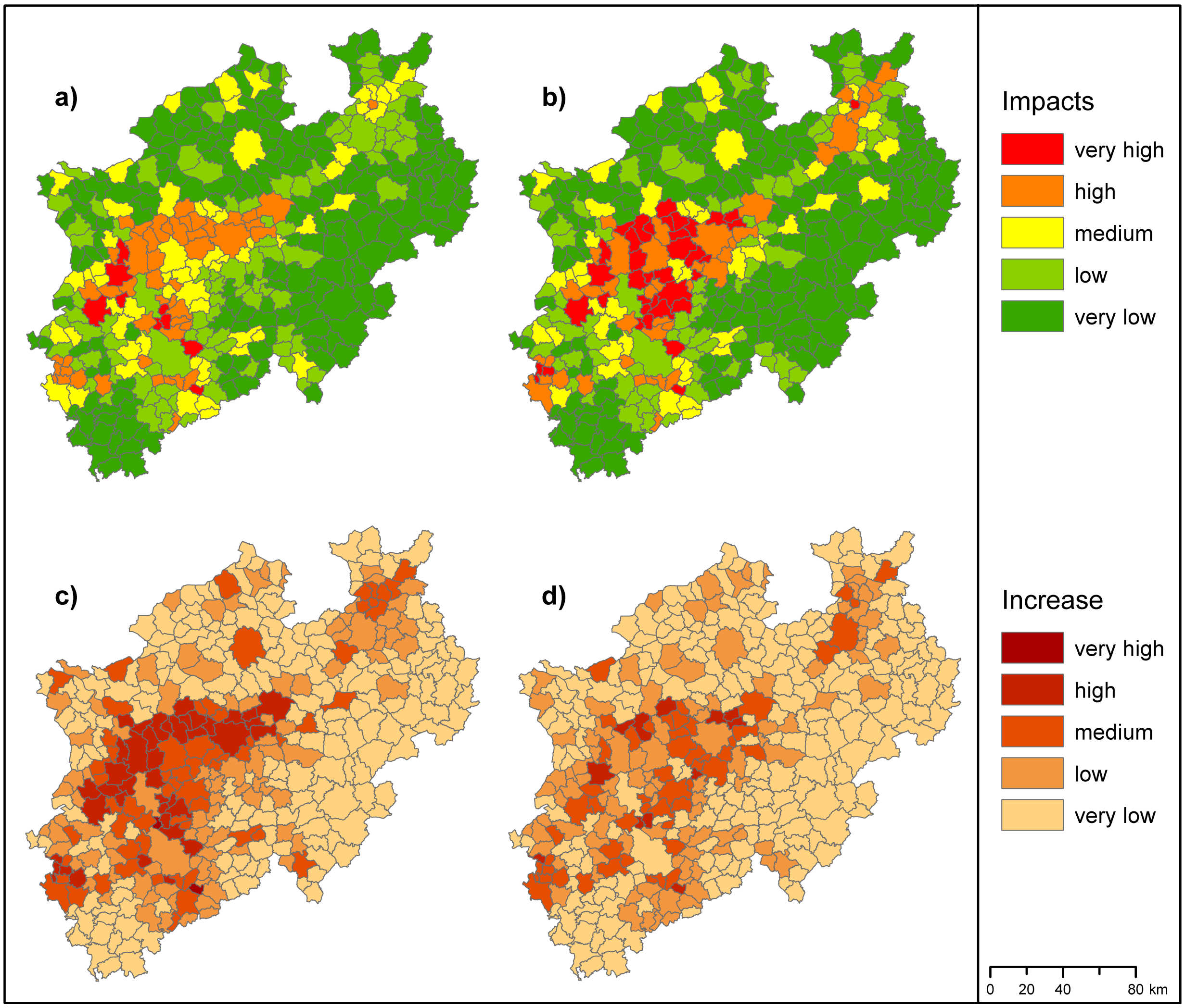

Figure 5: Impacts of heat waves on human health for the scenario period 2031-2060 for a) STAR and b) CCLM climate models and increase of impacts relative to the baseline period 1961-1990 for c) STAR and d) CCLM.

Our results show an overall increase in impacts over time, especially so in the densely populated Ruhr area and in parts of the Rhine valley (Fig 5). The spatial distribution of impacts as well as changes between the analysis periods show a distinct spatial pattern, which is apparent in the results of both climate models. With some exceptions, low-lying and densely populated areas are most vulnerable. A general gradient of impacts is apparent from densely populated areas towards those less densely populated, with the mountainous regions displaying the lowest levels of impacts. The metropolitan region is distinguishable, with higher levels of impacts compared to surrounding areas, however the southern municipalities along the river Rhine are distinctly less affected. The large cities of Cologne and Düsseldorf, for example, though very densely populated, show low impacts.

Clusters of high to very high impacts emerge in the metropolitan Ruhr region, as well as in the North-East around the city of Bielefeld under both climate models. With exception of the city of Münster the northern lowlands exhibit very low levels of impacts. The mountainous areas in the southwest of the state constitute regions of very low impacts across both data sets, while dense settlements along the foothill regions of both

Sauerland and Eifel, such as Aachen and Wuppertal display elevated levels of impacts.

The cause-and-effect relationships translated into a quantitative representation via fuzzy logic are clearly determinable within our results. The maps in the decision tree (Figure 3) exemplify this using scenario data obtained from the STAR model. The resulting impacts can be traced back to the input values along the graph. In the cities of Cologne and Düsseldorf, for example, the low impacts can be clearly ascribed to the very low percentage of population ≥ 65 (0.2). While the potential UHI is very high, there are only very low numbers of especially sensitive age groups within both analysis periods. While all other input variables here are very high, the minor number of elderly as an especially sensitive age group significantly reduces impacts. Due to the γ-value, the results show a slightly augmented sensitivity and consequent impacts of 0.36 (low), thus taking into account the excess heat exposure through the UHI. Though the exposure is very high in this region, the low sensitivity determines the outcome. In the case of Dortmund, where a medium number of elderly population is present, the intense UHI leads to a high local sensitivity, again exemplifying the effect of the applied γ-value: without introducing this compensation, the UHI would not be accounted for and consequent impacts would be lower. In both of these examples the results correspond for both applied climate models. The example of Münster demonstrates that the area of sealed surfaces reduces the potential UHI, even though there is a high population density. With additional lower levels of population ≥ 65 the sensitivity as well as the impacts remain at a medium level with both climate models. In municipalities in the mountainous Sauerland region, for example in Winterberg, a very high proportion of sensitive elderly population coincides with very low values for all other variables, resulting in very low levels of impacts.

In several municipalities significant differences between the applied climate models can be observed in the results, as the models show different spatial characteristics (Fig.6). Gevelsberg, situated within the metropolitan region, shows the highest difference between the models: impacts are very high under the CCLM model with a value of 1 and medium under STAR assumptions with a value of 0.4. This is due to the different projections of HWD, with STAR projecting less HWD than CCLM under the A1B emission scenario. Similarly, for the city of Wuppertal, also situated in the metropolitan region, the number of HWD determine the level of impacts with very high levels for CCLM (0.81) and medium levels for STAR (0.45). The high percentage of sensitive age groups in the region of Rheine in the north of NRW entails medium levels of sensitivity. With input from the STAR model the results show medium impacts as there are significant numbers of HWD projected for the region. Results from the CCLM model, however, project a low number of HWD, consequently, the impacts are low.

4.1 Sensitivity analysis of model parameters and input data

Climate models present possible future developments on the basis of emission scenarios, which present possible future developments with no likelihood of occurrence ascribed (Nakicenovic and Swart, 2000). The results of modeling runs depend on the underlying emission scenarios as well as the applied modeling technique (Gerstengarbe et al, 2004; Lautenschlager et al, 2009). The results of climate models present a range of possibilities. The climate models used in our study are based on the same emission scenario, yet the different modeling techniques lead to significant differences in the levels of HWD. Both regional models are currently considered equally valid.

The mean annual number of HWD simulated[2] with the CCLM model amounts to 3.4 for the baseline period, indicating one stronger heat wave per year on average. For the scenario period the mean number of HWD under CCLM amounts to 8 HWD per year. The observed data for the same period used within the STAR model shows an annual average of 1.2 HWD for the baseline period, amounting to one heat wave every three years and 5.8 HWD per year in the scenario period. Nevertheless, both models project a comparable increase in mean annual HWD of 4.6 (CCLM) and 4.5 (STAR). Thus, while the absolute numbers of HWD occurrence differ between the models the direction and magnitude of the projected changes are similar. These differences between climate models are also apparent in the results of our study. Overall levels of vulnerability are higher under CCLM assumptions, but the increases between baseline and scenario period are similar under both climate models (Figure 5).

Additionally, the spatial distribution of the projected increase differs between models (Figure 6). Within the CCLM model a visible regional differentiation is apparent with higher increases in the western part of

[2]For dynamical models such as CCLM data for the baseline period is modeled, while statistical models such as STAR are based on measured station data.

the state and lower increases in the East. The STAR model on the other hand projects a more homogeneous increase across the state, which corresponds to the orography of the state. Both models agree that the strongest increase may occur in the Rhine valley; under CCLM this regional is increase more pronounced. In mountainous regions very slight increases in HWD are expected under both models, with lower increases under CCLM.

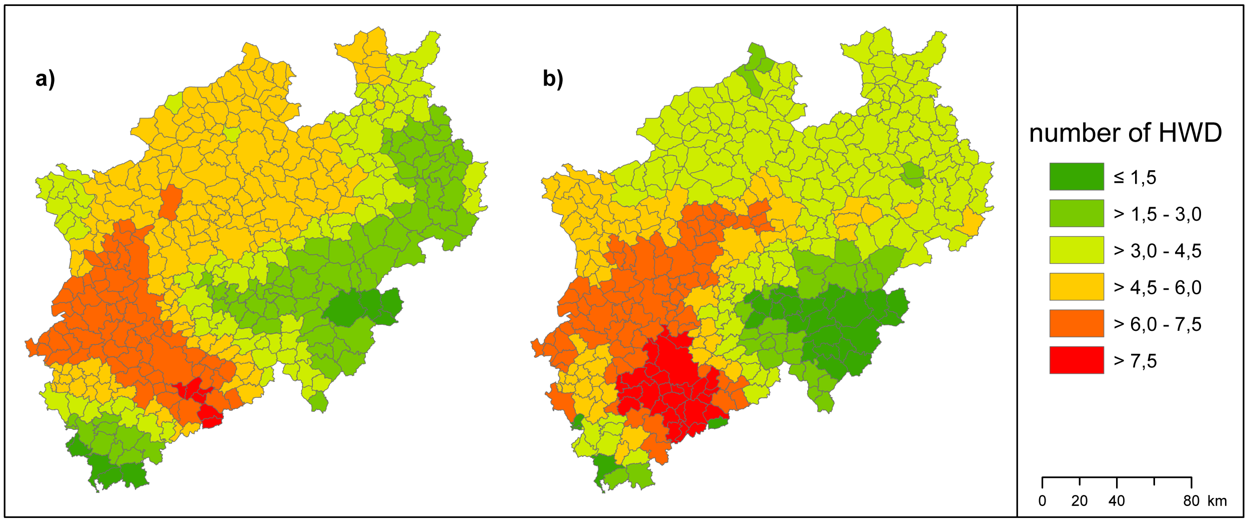

Figure 6: Increases in mean annual number of heatwave days between 1961-1990 and 2031-2060 for a) STAR and b) CCLM model results

The influence of the variables on the overall results is critically determined by the membership functions. Figure 7 presents the normalised frequency distributions of the original data sets (a,c) and the respective membership functions (b,d) for the baseline values (a, b) and the scenario values (c, d).

The fuzzified data for those variables kept constant across both analysis periods show a U-distribution. Variables with projected values show left skewed (baseline) and right skewed (scenario) distributions, which correspond to a U-shape across both data sets. This means that most of the data is clearly ascribed to full (or respectively no) membership, while a smaller part is attributed to partial membership.

A higher proportion of the dynamic variables have full membership to the respective linguistic categories relative to the constant variables. This is founded in the cause-and-effect relationships identified in the impact chain, where a large increase in the dynamic variables augments the pressure on the system. Our fuzzified variables allow for the consideration of these ranges, as the threshold values for membership are motivated by the situation in the study region. Again, the differences between the climate models are visible: the frequency of full membership to $\mu\left(\substack{\text{number of HWD}\\\text{high}}\right)$ for scenario values is significantly higher for CCLM compared to STAR data.

We examined the sensitivity of the model results with respect to the input data values. For each variable at a time, the fuzzified data sets were set to minimum (0), then calculations were conducted as described in Section 3.3. To determine the impact of each variable, we assessed the resulting deviation from the original results. The variation of data sets to minimum clearly influences the analysis outcome, deriving from the application of the FUZZY_AND operator.

Those variables introduced into the decision tree at a later point have a higher impact on the overall outcome. The variables sealed surface area and population density have equal positions within the decision tree, therefore the model sensitivity is equal. A minimum value of population ≥ 65 has a much stronger influence on the result compared to the other variables. The highest deviations are observable resulting from variations in the variable number of HWD. Furthermore, in municipalities that display a high degree of vulnerability, results are most sensitive to changes in the input. The deviations from the original results are higher under CCLM assumptions across all varied input data sets. This is due to higher numbers of HWD projected by this climate model (see Figure 6). The difference between the climate models is higher than the difference between variables under the assumptions of the same model.

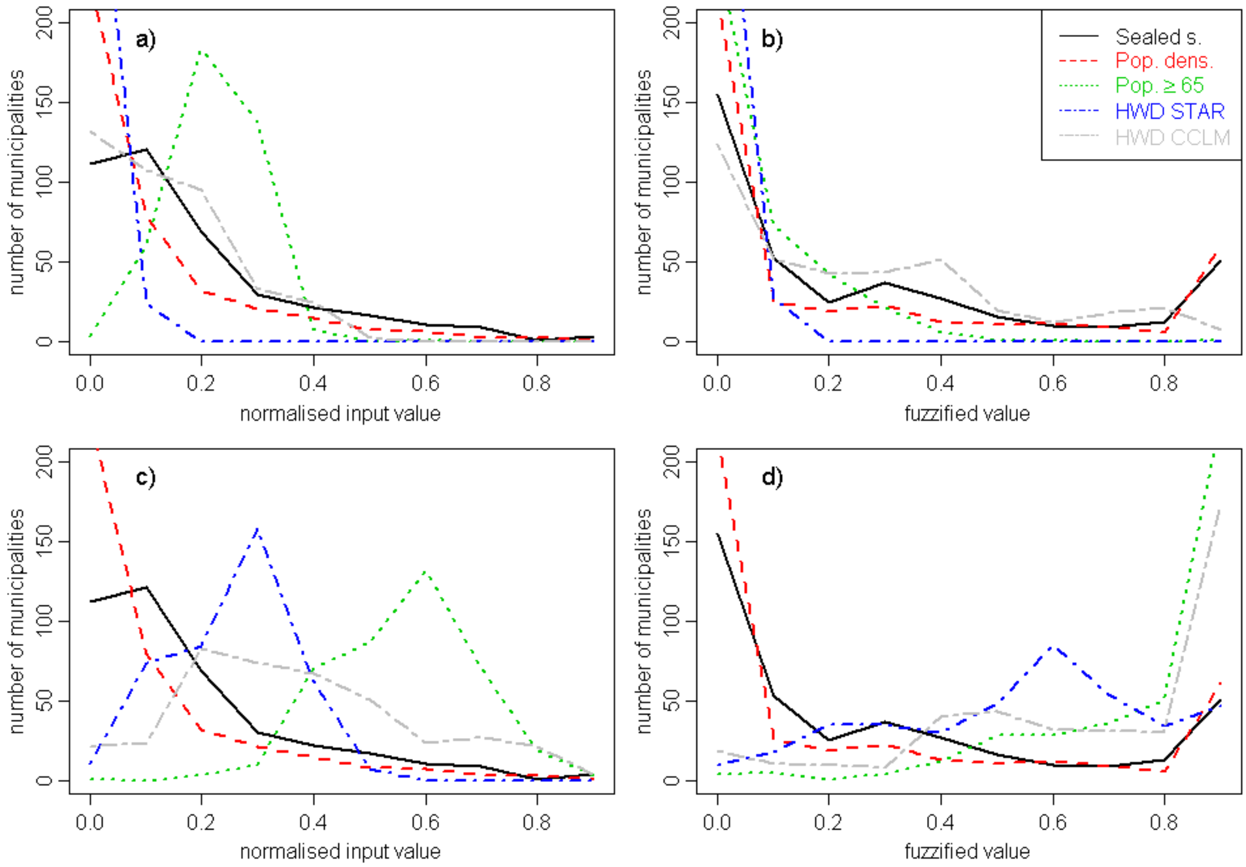

Figure 7: Frequency distributions of the normalised input variables (a,c) and the corresponding fuzzified variables (b,d) for values for the baseline period 1961-1990 (top) and the scenario period 2031-2060 (bottom)

The maps in Figure 8 depict which of the input variables has the strongest influence on the degree of impacts in each municipality for the scenario results.

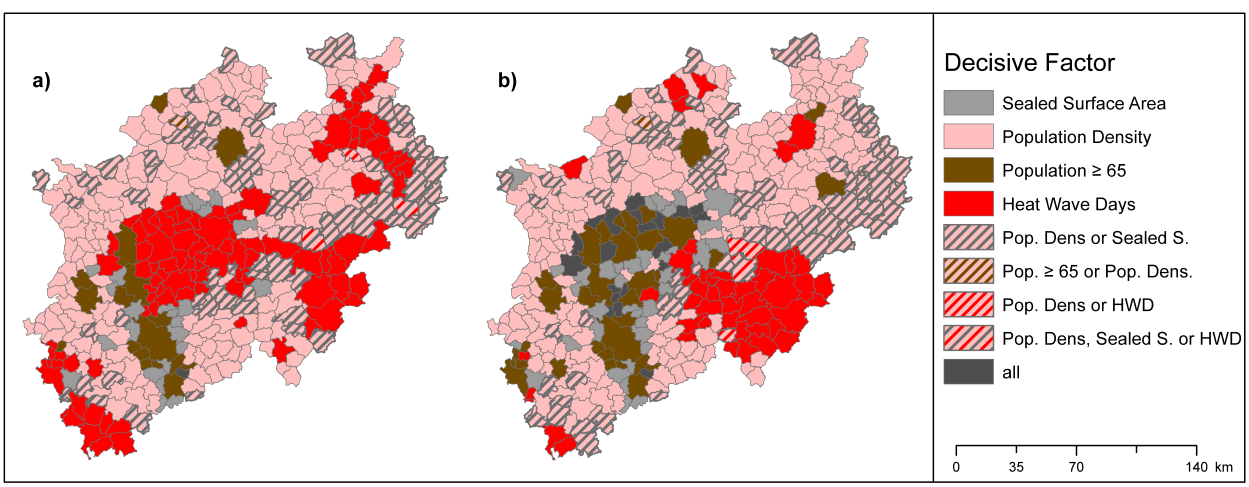

Figure 8: Factors most decisive for the resulting impacts in the scenario period for input data from the climate models a) STAR and b) CCLM

In municipalities with high impacts the decisive factors differ between climate models. Where impacts are low, the decisive factors correspond. Generally the lower population determines the outcome with both models in rural areas. The lower percentage of population ≥ 65 determines the results in many urban areas, while in transition zones between urban and rural areas the sealed surfaces have a high influence on the results. The spatial differentiation of the occurrence of HWD is reflected in both maps. The STAR results project a spatially more homogenous distribution of HWD, however the overall numbers are lower than those of the CCLM model. Accordingly, a higher number of municipalities can be attributed to the decisive factor HWD within the STAR results (Fig. 8a). In the mountainous Sauerland region however, the projected number of HWD in the CCLM model is low (Fig. 8b) as this is the most decisive factor for the region. Again, the importance of the applied climate model becomes apparent.

5 Discussion

The clear cause-and-effect linkages implemented through the impact chain and represented through a fuzzy logic algorithm can depict a spatially explicit measure of impacts, while allowing for the identification of those factors where intervention may be most effective. Some general statements on the reasons for increasing impacts across the state can be drawn from the methodology. Additionally, specific constellations for the single municipalities can be traced through the methodology to derive suggestions for efficient adaptation possibilities.

We showed that the general spatial pattern of impacts is consistent across both climate models, with highest values in large metropolitan agglomerations and lowest values in the mountainous regions. These results are consistent with an analysis of heat related mortality in NRW for the hot summer in the year 2003 (Hertel et al, 2009; Hellmeier et al, 2007). For the medium sized city of Essen, located within the metropolitan region, a moderate increase in mortality was recorded. The rural and mountainous area of Siegen-Wittgenstein, however, exhibited no significant rise in mortality, even though the duration and intensity of excess heat was similar in the two regions. This discrepancy can be explained with a stronger UHI in the urban region of Essen.

The amount of HWD as defined by the applied climate model has a large effect on the mean impacts across the state and a smaller influence on the spatial variation. The main determinant of the spatial variation is the potential UHI. For determining hot-spot regions, the influence of sensitivity factors is higher than the influence of the applied climate models, as shown in the comparison of the climate models. This allows for a finer spatial resolution, which supports the focus of our analysis, namely the well-being of the population. Those municipalities, identified as highly or very highly impacted in the future under the assumptions of the STAR (55 municipalities) and CCLM model (78 municipalities), can be grouped by the input factor determining their impact value (Table 2). The resulting grouping differs for both models, especially regarding the factor heat waves, since these values are generally higher under CCLM, and thus a different decisive factor emerges (see also Fig.8). Nevertheless, for the other factors, the distribution of municipalities concerning these categories is quite similar under both models.

Further reduction of the input variable that mainly determines the result value will be most effective in reducing impacts. It is thus possible to identify measures that may most efficiently use available adaptation funds. We will exemplify this approach by means of selected municipalities (see Figure 1 for locations). A reduction in sealed surface could be advisable for municipalities like Kaarst or Bergisch Gladbach, where the sealed surface area is the decisive factor. It could thus be advisable to increase green spaces to reduce the urban heat island effect. This may hold true also for Löhne, where the population density determines the result and thus a reduction of the UHI may be especially beneficial. In cases like Münster where the number of elderly is the decisive factor, policies that ensure adequate education and awareness as well as access to medical services may be advisable.

Sankt Augustin, as one of the smallest municipalities in NRW shows the highest value for all factors under both models. The size of a municipality can influence the average values of population density and sealed surface area, increasing the resulting impacts in small urban municipalities. The spatial extent of the single municipalities influences our results as all input values are averages across these administrative units. Consequently, the spatial boundaries may not ideally reflect the distribution of land use types and distort the results. However, municipalities as administrative units are usually in the operational focus of decision makers and are thus the most suitable scale for our analysis.

Table 2: Number of municipalities with high and very high future impacts (value > 0.6) under the climate models STAR and CCLM grouped by the factor determining the result impact value (minimum) and indicating how the respective factors differ between models

	all factors	heat wave days	population aged 65 or older	population density	sealed surface area
No. municipalities (STAR)	1	34	9	3	9
Same factor under CCLM	1	1	9	3	9
Different factor under CCLM	0	33	0	0	0
Not highly vulnerable under CCLM	0	0	0	0	0
No. municipalities (CCLM)	20	6	24	11	17
Same factor under STAR	1	1	9	3	9
Different factor under STAR	17	0	10	3	3
Not highly vulnerable under STAR	2	5	5	5	5

While we found the spatial variation to be mainly determined by potential UHI, the number of HWD is of critical importance for levels of impacts in the single municipalities. As we showed in the analysis, the results are highly sensitive to the climate information. Available projections of future climates are subject to considerable uncertainty. They only present possible future developments with no likelihood of occurrence ascribed (Nakicenovic and Swart, 2000). It is therefore important to base results on a range of climate models, when assessing possible future impacts. It would therefore be revealing to introduce further scenarios in addition to the A1B assumptions, especially so since currently this scenario proves to be very optimistic, considering current greenhouse gas emissions (Le Quéré et al, 2009). Projections for the variable population $\geq$ 65 are restricted up to the year 2030 while the climate data allows an analysis until 2060. We therefore assume constant values from 2030 onwards, which is rather conservative. Our assumption of a constant share of sealed surface area in the future is rather strong, yet no projections for this variable exist.

Our approach is helpful to identify climate change impact hot-spots where more detailed examination of local and regional vulnerability should be carried out. Local characteristics that are not captured at the present resolution of analysis may have a strong influence on the local and even individual susceptibility to suffer harm from heat waves. City-scale analysis of local characteristics, as presented by Mavrogianni et al (2010) for example, can provide more detailed accounts in this context. Additionally, the issue of adaptive and coping capacities is difficult to capture at municipality resolution. Here, other methodologies, such as the analysis by Wolf et al (2010) which assesses individual risk factors of sensitive population groups on city scale, can provide information on a lower scale. An analysis of this kind could complement our results for highly vulnerable municipalities to reveal detailed risk characteristics.

Our methodology can provide a basis for decision-makers on which to set priorities within the complex field of climate impacts. The structured approach through the impact chain as well as the aggregation methodology opens the possibility to infer from the outcome back to the main constituents of vulnerability. The reasoning thus works in both directions of the impact chain. It also offers ways of addressing similar problems in different regions in a consistent manner, thus opening ways of comparing and ranking impacts.

6 Conclusions

The presented assessment of spatially differentiated vulnerability of human health to heat waves within a standardized framework allows to identify local and regional hot spots in a comparable manner. The application of theoretically and empirically founded impact chains ensure contextual consistency. The use of fuzzy logic provides a means of dealing with uncertainty and inherently fuzzy thresholds or boundaries. In such a way health vulnerability has not yet been explained. As the study region covers spatially differentiated characteristics from dense urban to rural regions, as well as higher and lower elevation and gradients of heat exposure and could suitably exemplify the value of our approach: namely to present a spatially explicit depiction of differential impact severity in a reduced form model.

One major advantage of the applied method is the simplicity: we restrict the analysis to those input variables that are sufficient to describe vulnerability within the regional settings and necessary for the scale of analysis. To corroborate results it would be interesting to compare data of climate-related morbidity and mortality rates in the region with our results. The method presented is not limited to the analysis of health risks; it can be applied to other problem complexes, if one follows the clear-cut analytical framework as it was presented in this article. Future work will focus on refining the methodology to apply similar approaches to other areas affected by climate change. Although the presented method is not a model in a dynamical sense, the impact chain shows the relevant mechanism described in literature and thus provides an important diagnostic tool in the context of directed and efficient adaptation.

Summing up, the results obtained pave a promising road towards semi-quantitative description of climate change related risks. Decision makers facing a changing climate are often trapped in a no action situation, because comparable analysis are seldomly provided. By the simple approach presented here hot spots of future change are easily identified. Our approach thus clearly supports knowledge based decision making.

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