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Quantification of heat-stress related mortality hazard, vulnerability and risk in Berlin, Germany

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Abstract

Many studies have addressed the challenge of heat stress for human health in recent years. However, appropriate concepts and methods for quantifying heat-stress hazards, vulnerabilities and risks are yet under development. The objective of this study is to test the applicability of a risk concept and associated event-based risk-analysis method for quantifying heat-stress related mortality. The study reveals that about 5 % of all deaths between 2001 and 2010 in Berlin can statistically be related to elevated air temperatures. Most of the affected people are 65 years or older, while the mortality of people below 65 years shows only weak statistical correlation to air temperature. Mean daily air temperature was best suitable for risk analysis. The results demonstrate that the novel approach for quantitative risk analysis delivers statistically highly significant results on the city scale when analysing heat stress on an event basis. Performing the risk analysis on a spatially distributed data basis for city districts would allow to account for spatial variations of urban climates and demographic properties. Using indoor climate data is expected to provide new insight into heat-stress related mortality risks, particularly for highly vulnerable persons like elderly persons or patients residing in hospitals.

Zusammenfassung

In den letzten Jahren haben zahlreiche Studien die Herausforderungen von Hitzestress für die menschliche Gesundheit adressiert. Jedoch sind bis heute geeignete Konzepte und Methoden zur Quantifizierung der Hitzestressgefährdung, der Vulnerabilität sowie der daraus resultierenden Risiken noch in der Entwicklung. Gegenstand dieser Studie ist ein Test der Anwendbarkeit eines Risikokonzepts und einer damit verbundenen ereignisbasierten Risikoanalysemethode zur Quantifizierung der mit Hitzestress einhergehenden Mortalität. Die Studie weist nach, dass ca. 5 % aller Todesfälle in Berlin in den Jahren von 2001 bis 2010 statistisch mit erhöhten Lufttemperaturen korreliert sind. Die betroffenen Personen sind meist 65 Jahre oder älter, während der Zusammenhang zwischen erhöhten Lufttemperaturen und Mortalität bei jüngere Personen statistisch nur schwach ausgeprägt ist. Die besten Ergebnisse wurden dabei auf der Basis von Tagesmittelwerten der Lufttemperatur erzielt. Die Ergebnisse verdeutlichen, dass die neue Methode für eine quantitative Risikoanalyse statistisch hochsignifikante Ergebnisse liefert, wenn Hitzestress ereignisbasiert untersucht wird. Auf der Basis räumlich verteilter Daten würde die Risikoanalyse auch räumliche Variationen des Stadtklimas und demographischer Eigenschaften berücksichtigen können. Es ist darüber hinaus zu erwarten, dass Daten zu klimatischen Bedingungen in Innenräumen vertiefte Einblicke in das mit Hitzestress einhergehende Mortalitätsrisiko erlauben würden, was insbesondere für hochvulnerable Personen, die älter oder stationär in Krankenhäusern untergebracht sind, von großer Bedeutung ist.

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1. Introduction

A large number of studies have addressed the challenge of heat stress for human health in recent years (e.g. *Jendritzky and Koppe 2008; Bassil et al. 2009; Anderson and Bell 2011; Gabriel and Endlicher 2011; Yardley et al. 2011; Montero et al. 2012*). Recent reviews on this field of research are given by *Kovats and Hajat (2008)* and by *Gosling et al. (2009)*, among others. However, appropriate concepts and methods for quantifying heat-stress related hazards, vulnerabilities and risks are yet under development and discussion. The respective approaches frequently remain vague (e.g. *Kovats and Hajat 2008; Costa and Kropp 2013*). Differences in epidemiological studies on heat-stress related mortality are particularly due to the strong dependency of the number of excess deaths related to elevated air temperatures on the methods to define days or episodes (events) of heat stress, on the use of different types of mortality data, or on the methods to estimate base mortality rates (e.g. *Kovats and Hajat 2008; Gosling et al. 2009; Anderson and Bell 2011*).

The objective of this study is to test the applicability of a novel approach for quantifying heat-stress related hazards, vulnerabilities and mortality risks in Berlin. The approach for quantitative risk analysis comprises a risk concept and an associated event-based risk-analysis method, introduced by the Research Unit 1736 "Urban Climate and Heat Stress in mid-latitude cities in view of climate change (UCaHS)" funded by the Deutsche Forschungsgemeinschaft (DFG) since 2012.

One of the main goals of the UCaHS Research Unit is a quantitative analysis of heat-stress related risks in cities under present and future climate conditions. Quantification of heat-stress related hazards, vulnerabilities and risks is a prerequisite for quantifying effectiveness and efficiency of actions to risk reduction. As long as the potential benefits of actions for reducing such risks are only known on a qualitative level, it is difficult to convince stakeholders to design and implement climate-responsive actions with respect to present and future climates (e.g. *Gill et al. 2007; Li et al. 2013a*).

In this initial step, we introduce an event-based risk analysis method using daily air temperature data from an official weather station as a statistical indicator of heat-stress conditions in Berlin. The epidemiological study addresses mortality risks related to heat

stress on the city scale, which qualitatively and quantitatively differs from analyses of individual risks. The large spatial variation of out- and indoor climate conditions within a city, which is not represented by currently available weather data, combined with probably even larger variations of human predispositions (age, health status, etc.), individual activities and responses to heat waves, make it difficult if not impossible to apply approaches for risk analysis that are based on biophysical and physiological cause-effect chains. Instead, the analysis presented here focuses on the integrated probabilistic response of city-wide mortality to hazardous weather situations in Berlin. The probabilistic nature of the risk analysis and the city-scale approach allows to use data from a single weather station inside the city to determine timing and intensity of meso-scale weather situations inducing heat stress as shown in many epidemiological studies.

1.1 Urban climate and heat stress

The steadily increasing urban population leads to an increasing number of people being threatened by heat stress in the built-up environment of cities. Heat island effects in the cities cause significant negative environmental and economic impacts, e.g. on thermal comfort and, more seriously, on the health of the cities' inhabitants, but also on cooling energy demand (e.g. *Gartland 2008*). The impact of higher air temperatures in cities is further aggravated by severe heat-stress events caused by heat waves, which are projected to increase in frequency and intensity in the 21st century (e.g. *Meehl and Tebaldi 2004*).

The heterogeneity of natural risks within a city is not only caused by variable hazard conditions but also by differences in the vulnerability of inhabitants. Health burdens apply most often to physiologically susceptible and economically underprivileged persons in unfavourable environmental conditions (e.g. *Harlan et al. 2006*).

Although Berlin is the city with the largest number of inhabitants in Germany, only few studies have systematically investigated heat-stress related risks. Studies on Berlin could show that heat stress is related to an increase in mortality rates in the region of Berlin-Brandenburg, which differ between the two states (Berlin as an urban region versus Brandenburg with a larger percentage of rural areas), but also between different

age groups and between male and female persons (Gabriel 2009; Gabriel and Endlicher 2011). However, none of these studies has explicitly quantified heat-stress related hazards, vulnerabilities and mortality risks.

1.2 General approaches to risk analysis

Risk assessment is a fundamental part of risk management to safeguard elements at risk. It describes human interactions with hazardous events and allows for development and implementation of adaptation and prevention measures. Analysis of cause-effect relationships helps to design responsive actions for impact mitigation more precisely (e.g. Renn 1998). Risk assessments are well established in the field of disaster risk reduction, and have been adopted within the climate change adaptation community (IPCC 2012; Suroso et al. 2013). Both communities share a common notion of key theoretical aspects and components (Solecki et al. 2011). Heat-stress related risk assessments examine adverse effects of elevated air temperatures on public health, particularly on mortality and morbidity (Kovats and Hajat 2008; Aubrecht and Özceylan 2013).

“... In its simplest form, probabilistic risk analysis defines risk as the product of the probability that some event (or sequence) will occur and the adverse consequences of that event ...” (IPCC 2012: 43, Box: 1-2). Thus, the hazard can be defined by the probability of events to which elements at risk could be eventually exposed. Elements at risk may be populations, communities, the natural or built environment, economic activities and services that are under threat of hazardous impacts (e.g. earthquakes, heat waves) in a certain area (Alexander 2000). Adverse effects will only occur if the elements at risk are actually exposed to a hazardous event. Those elements exposed to a hazardous event will show an adverse effect, but the magnitude of the adverse effect depends on their “... propensity or predisposition to be adversely affected ...” (IPCC 2012 :237).

Unfortunately, different scientific communities use different terms for the linkage between hazard and effect: susceptibility, sensitivity and vulnerability are found in the scientific literature, which is not reviewed here (see IPCC (2012) for a comprehensive review). Also, some authors distinguish between exposure and vulnerability (e.g. IPCC 2012), while others consider exposure being a part of vulnerability (e.g. Turner II et al. 2003). A further topic of

scientific discussion is the question whether the capacity of the elements at risks to adapt to a hazardous event should be part of the vulnerability or not. In this study, we use a risk concept that is based on pragmatic definitions of these terms with respect to quantification. We do, however, neither claim that we are the first ones to use this specific risk concept nor that other risk concepts would be less appropriate.

2. Methodology

First, we introduce a risk concept, which is applicable to systems threatened by and vulnerable to natural hazards. Then, the study design for quantifying the risk of excess mortality in Berlin related to heat stress is presented, followed by a description of the data sets used in the risk analysis. Finally, the risk-analysis method is presented.

2.1 The risk concept

The risk $r_{e,p,s}$ that a system (indicated by the subscript s) experiences an adverse effect (indicated by the subscript e) caused by a hazardous process (indicated by the subscript p) is given by the magnitude $M_{e,p,s}$ per unit of time of the adverse effect integrated over a sufficiently long time period Δt :

$$(1) \quad r_{e,p,s} = \frac{1}{\Delta t} M_{e,p,s} = \overline{\dot{M}_{e,p,s}} = h_{p,s} \cdot v_{e,p,s}.$$

The term $\overline{\dot{M}_{e,p,s}}$ denotes the mean magnitude rate of the adverse effect, i.e. the mean effect rate averaged over the time period Δt :

$$(2) \quad \frac{1}{\Delta t} M_{e,p,s} = \frac{1}{\Delta t} \int_{t_0}^{t_0+\Delta t} dt \cdot \dot{M}_{e,p,s}(t) = \overline{\dot{M}_{e,p,s}}.$$

Throughout this paper, rates (time derivatives) are indicated by overdots while temporal averages (mean values) are marked by overbars.

Hazard $h_{p,s}$ and vulnerability $v_{e,p,s}$ mathematically represent the two interacting subsystems determining the risk, i.e. the ecosystem and its constituting compartments (atmosphere, hydrosphere, cryosphere, pedosphere, lithosphere and biosphere) on the one hand and the anthroposystem (demography, economy, culture, politics) on the other hand. The fact that many processes in ecosystems are nowadays influenced by man-made structures and human activities (e.g. urban climates, global climate

change) demonstrates that natural risks are not just simple causal chains in which nature causes negative impacts on humans. Moreover, natural risks stem from complex interactions between the two subsystems, and thus human actions for risk reduction may address both hazard and vulnerability.

Commonly, a system is spatially defined by inhabitants or objects (elements) in a country, city or an urban quarter, but in general, the definition of a system could also be based on other criteria (e.g. groups of individuals sharing common properties independent of the location of the individuals). In this study, the system is defined by the population of Berlin living within the respective administrative border, separated in three different age groups.

Quantitative analyses of natural risks require precise definitions of the process causing the hazard, as well as of the adverse effect causing the loss. The adverse effect (here increased mortality causing excess deaths due to heat stress) may be possible to define, but one of the main problems is the quantification of the effect rates, since different processes (e.g. further hazards like air pollution) may cause the same adverse effect.

The hazard can be quantified by the magnitude $M_{p,s}$ per unit time of the hazardous process integrated over the time period Δt :

$$(3) \quad h_{p,s} = \frac{1}{\Delta t} \cdot M_{p,s} = \overline{M_{p,s}} = \frac{1}{\Delta t} \int_{t_0}^{t_0+\Delta t} dt \cdot I_{p,s}(t) = \overline{I_{p,s}}.$$

The magnitude rate $\dot{M}_{p,s}$ is thus the intensity mean $I_{p,s}$ of the hazardous process.

The integral used for averaging the time-varying intensity can be approximated by

$$(4) \quad \frac{1}{\Delta t} \int_{t_0}^{t_0+\Delta t} dt \cdot I_{p,s}(t) \cong \frac{1}{N} \sum_{i=1}^N I_{p,s}(t_i),$$

since data on intensity (and analogously effect rate and further risk-related variables) are usually discrete time series of N regular intervals (e.g. days, months) starting at time t_0 covering the entire time period Δt .

Eq. 3 implies that the quantification of the hazard directly depends on the definition of the intensity (or magnitude) of the hazardous process. One of the major practical problems is to have access to accurate data of sufficient temporal resolution. In many cases, daily data would be required to accurately compute the hazard, but only monthly data are available (e.g. long-term climate data).

Here, the vulnerability is the product of the exposure $e_{p,s}$ of the elements at risk within the system to the hazardous process and the sensitivity $s_{e,p,s}$ of the elements at risk actually exposed to the hazard to show a mean effect rate per mean intensity of the hazardous process:

$$(5) \quad v_{e,p,s} = e_{p,s} \cdot s_{e,p,s}.$$

The exposure is determined by the mean number of elements at risk $N_{p,s}$ within the system that are actually exposed to the hazardous process:

$$(6) \quad e_{p,s} = \overline{N_{p,s}} = p_{p,s} \cdot \overline{N_s}.$$

Here, N_s indicates the total number of elements at risk within the system, while $p_{p,s}$ is the degree (or fraction or probability) of exposure.

In this approach, exposure is regarded to be part of the vulnerability since it is a human decision where to place the elements at risk within the system, even when hazardous areas are well known (e.g. flood-prone areas in a city that are nevertheless built-up).

Finally, the sensitivity is given by the mean effect rate of the adverse effect (the risk) that an individual element at risk within the system actually exposed to the hazardous process exhibits for a given mean intensity (the hazard):

$$(7) \quad s_{e,p,s} = \frac{1}{e_{p,s}} \cdot \frac{r_{e,p,s}}{h_{p,s}} = \frac{1}{N_{p,s}} \cdot \frac{\overline{M_{e,p,s}}}{\overline{I_{p,s}}}.$$

One of the main criteria behind the selection of a suitable definition of the intensity (and thus of the hazard) is to make the sensitivity a constant over the full range of intensities, which is always the case when there is a linear relation between intensity and effect rate. As long as there is a strictly monotone functional dependency between them, a new intensity can be defined as a function of the old intensity that makes the relation linear.

The risk concept illustrates that the definition of the vulnerability is depending on the definition of the hazard and vice versa. This is directly seen in Eq. 1 and 7, but is indirectly also present in the exposure term in Eq. 6.

Hazard and vulnerability in Eq. 1 are considered as integral properties for the entire time period Δt . This implies that there are stationary relations between hazard, vulnerability and risk. If observational evi-

dence would indicate that stationary relations are not given, the time period could eventually be split in several shorter periods in which stationarity could be found. Alternatively, the terms in Eq. 1 to 7 could become explicit functions of time t , and the time period would then become a moving time window of length $\Delta\tilde{t}$ starting at $\tilde{t}_0=t-\Delta\tilde{t}$. In this case, stationary relations would only be required for shorter time periods of length $\Delta\tilde{t}$, but the risk analysis could nevertheless be performed for the entire time period Δt .

In a retrospective risk analysis based on observations of effect rates, the risk is a statistical measure, while the risk is a probabilistic assessment of the damage potential of the hazardous process in a prospective study. However, the magnitude-frequency relation of the hazardous process or the structural conditions linking the hazardous process to the adverse effect may change over time, even when stationary relations have been found in a statistical risk analysis. Therefore, it is generally not possible to take the result of a statistical risk analysis directly as prediction of future conditions. However, it is possible to make risk projections based on the assumption that stationarity of the statistical relations is also given in the future. Alternatively, the risk concept enables to statistically determine all relevant variables from observational data, which can then be used as input in a predictive

model in which those variables assumed to change over time can be updated accordingly, e.g. by separate models simulating phenomena like climate change, population dynamics or urban development.

2.2 Study design and data sets

The administrative area of Berlin (892 km²), the capital and largest city of Germany (Fig. 1), is used in this study to spatially define the system (indicated by the subscript B) for which the risk concept and analysis method is tested.

The time period analysed in this study (hereafter called analysis period) covers ten years starting on January 1, 2001. Ten years are regarded to be appropriate for testing the feasibility and applicability of the risk concept, although longer time periods would allow more detailed and robust analyses. Additional data for the year 2011 not included in the analysis were used for validation of the results.

The study comprises three different age groups, where the subscript ag indicates the age group (ag is either *all*, 0-64, or 65+). Data on population and death rates were provided by the Statistical Office

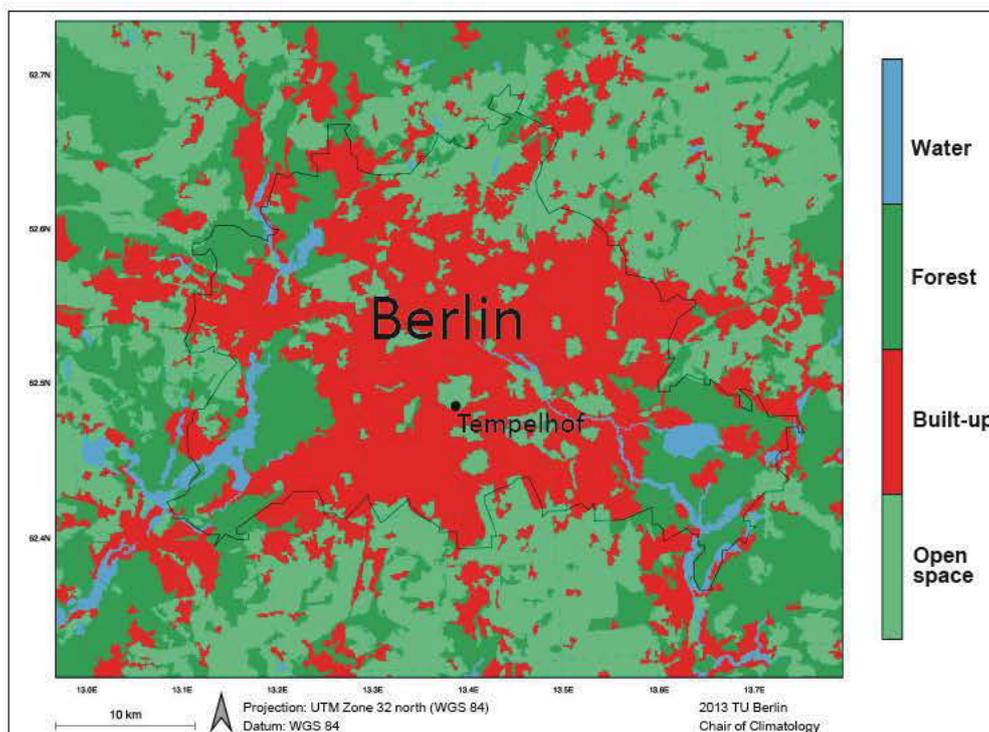


Fig. 1 The study region of Berlin, Germany. The administrative border is shown as black line. The black dot in the centre indicates the position of the Tempelhof weather station. Data source: CORINE

for Berlin-Brandenburg as described below. We separately analysed the entire population N_{all} of Berlin ($\overline{N_{all}} \approx 3.35 \cdot 10^6$ cap), people younger than 65 years N_{0-64} ($\overline{N_{0-64}} \approx 2.77 \cdot 10^6$ cap), and those who are 65 years or older N_{65+} ($\overline{N_{65+}} \approx 0.58 \cdot 10^6$ cap). The number of people in the three age groups are the total number of elements at risk, which are potentially exposed to hazardous high air temperatures during summer, indicated by the subscript hs . The increase in the death rate $\dot{N}_{d,ag}$ related to high air temperatures

defines the effect rate $\dot{M}_{d,hs,ag}$ of the adverse effect indicated by the subscript d , and thus the risk. Hereby, we assume that heat stress is one of the major processes leading to excess deaths during episodes of high air temperature, but we cannot exclude that other hazardous processes related to high air temperatures (e.g. increased concentrations of photo-oxidants) or other seasonal effects (e.g. traffic) may also cause additional excess deaths. Studies of temperature-related excess mortality in Toronto and New York showed that

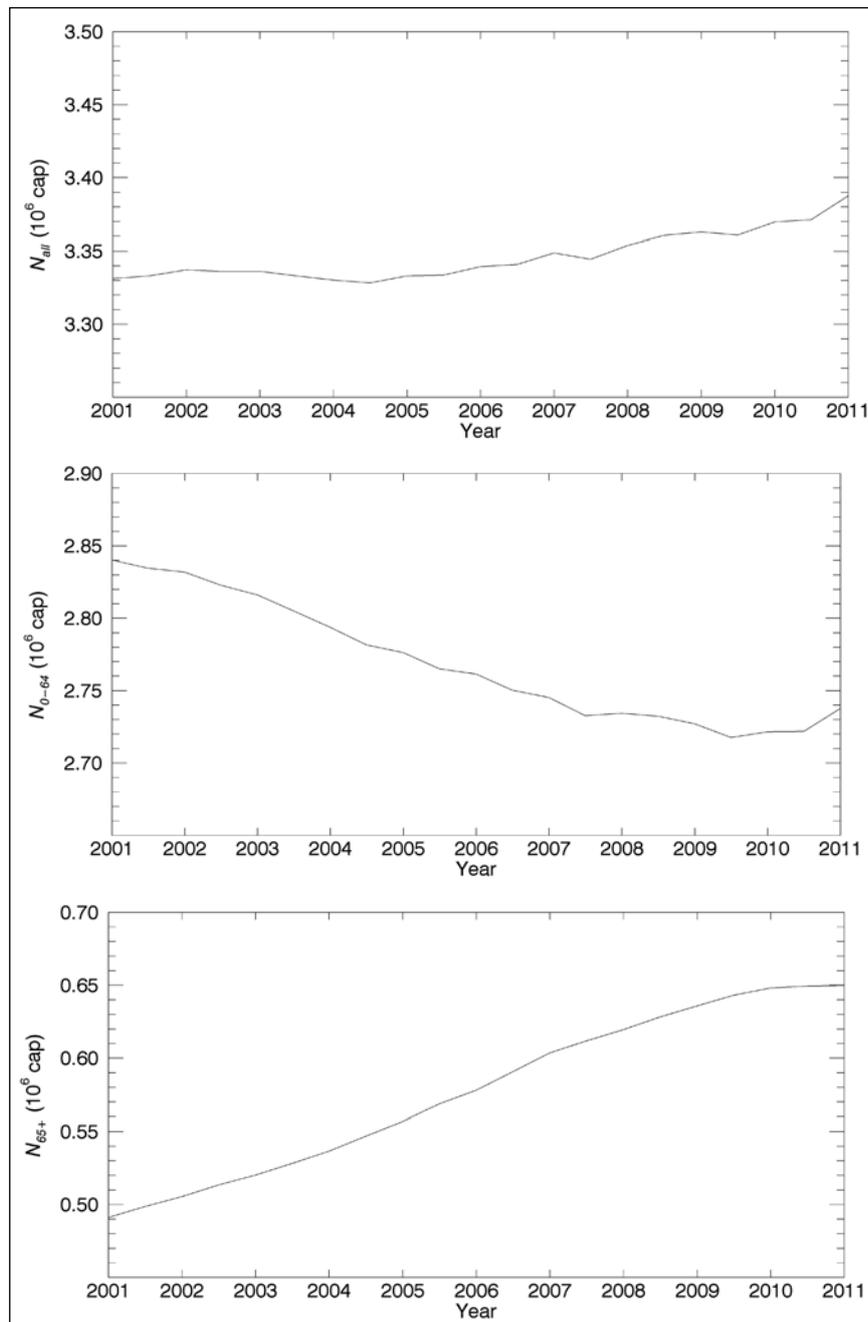


Fig. 2 Daily number of people living in Berlin from 2001 to 2010. Upper: entire population, centre: 0-64 years, lower: 65 years and older. Data source: Statistical Office for Berlin-Brandenburg

other confounding factors exist but are of minor importance (Rainham and Smoyer-Tomic 2003; Li et al. 2013b). For simplicity reasons, we use the notion of heat stress for temperature-related deaths throughout this study. It should be noted that heat stress is generally not the primary cause for deaths but a confounding factor to diseases or medical problems (e.g. Kovats and Hajat 2008).

Half-yearly time series of people N_{ag} in each of the three age groups living in Berlin (valid for December

31 and June 30 of each year) were provided by the Statistical Office for Berlin-Brandenburg for the years 2001 to 2011 (Amt für Statistik 2013). Daily values of N_{ag} were then linearly interpolated from the half-yearly values prior to the risk analysis (Fig. 2).

Daily time series of total death rates $\dot{N}_{d,ag}$ of people in each of the three age groups living in Berlin were provided by the Statistical Office for Berlin-Brandenburg for the years 2001 to 2011 (Fig. 3). No distinction between

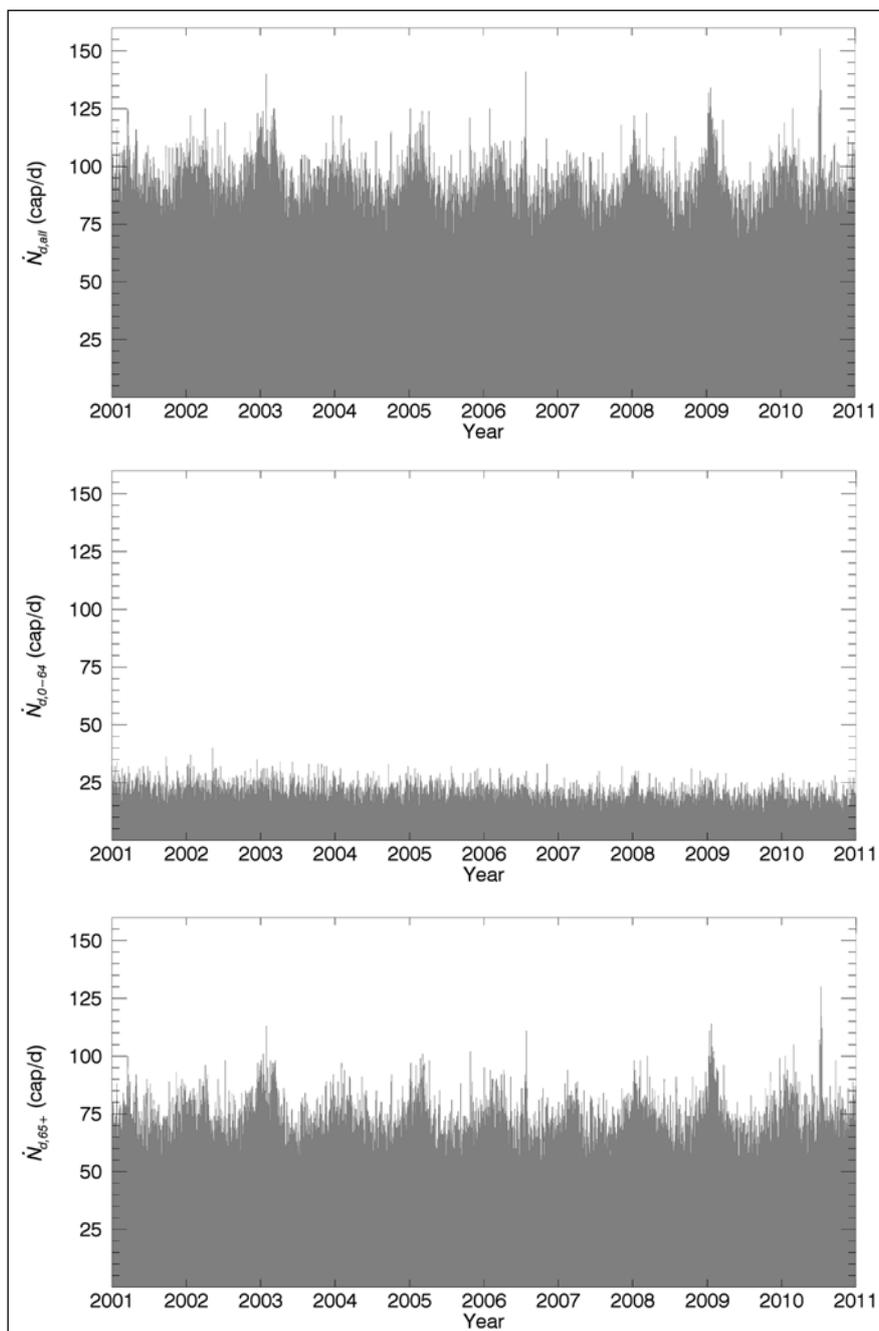


Fig. 3 Daily total death rates of people living in Berlin from 2001 to 2010. Upper: entire population, centre: 0-64 years, lower: 65 years and older. Data source: Statistical Office for Berlin-Brandenburg

different causes of deaths according to the International Classification of Diseases (ICD) was made in this study. In contrast to other studies, we did not distinguish between accidental and non-accidental deaths. The main reason for analysing total death rates in this initial study is the fact that heat-related deaths are not classified separately but contribute to a variety of death causes ranging from heat exhaustion or circulation failure (e.g. Kovats and Hajat 2008) to accidents (e.g. due to heat-related concentration problems). Hereby, we also avoid the problem of misclassifications of ICD codes in the mortality data that is a frequent challenge in other studies.

Daily time series of mean, minimum and maximum air temperatures (T_{mean} , T_{min} and T_{max}) covering the years 2001 to 2011 (Fig. 4) were used to compute the heat-stress magnitude $M_{hs,B}$ in Berlin defining the heat-stress hazard $h_{hs,B}$. Air temperatures were measured at a weather station that is located in the area of the former airport Berlin Tempelhof nearby the city centre (see Fig. 1), operated by the German Weather Service (DWD). Air temperatures at Tempelhof show only very minor influence by the city. In fact, T_{min} at Tempelhof usually shows rather low values in Berlin. None of the air temperatures revealed a statistically significant long-term trend over the study period.

2.3 Risk analysis

A daily time series of total mortality rate $p_{d,ag}$ was computed for each of the three age groups by

$$(8) p_{d,ag} = \frac{N_{d,ag}}{N_{ag}} = p_{d,hs,ag} + p_{d,0,ag}$$

In Eq. 8 the total mortality rate is the sum of the mortality rate related to heat stress (excess mortality rate $p_{d,hs,ag}$) and the mortality rate due to other reasons (base mortality rate $p_{d,0,ag}$). While in many studies excess mortality rates were separated from base mortality rates prior to the risk analysis (e.g. Li et al. 2013b), we directly compute excess and base mortality rates by the event-based risk-analysis method as described below. A comprehensive overview on different methods for computation of base mortality rates is given by Gosling et al. (2009).

The reason for analysing mortality rates instead of death rates is to remove that part of the variance in the effect rates that is caused by the variance in the exposure due to variable population size. As a first-order approximation, other factors influencing heat-stress vulnerability are assumed to be stationary. Thus, a suitable definition of the heat-stress magnitude should allow using it as predictor for explaining a statistically significant part of the variance in total mortality rate.

Total mortality rates were analysed on a daily basis, as well as for different methods of temporal aggregation, i.e. for months and heat-stress events. Figure 5 presents a flow chart of the event-based risk analysis method, which is described below.

In this study, a heat-stress event (indicated by evt_i) is defined as a contiguous sequence of days during

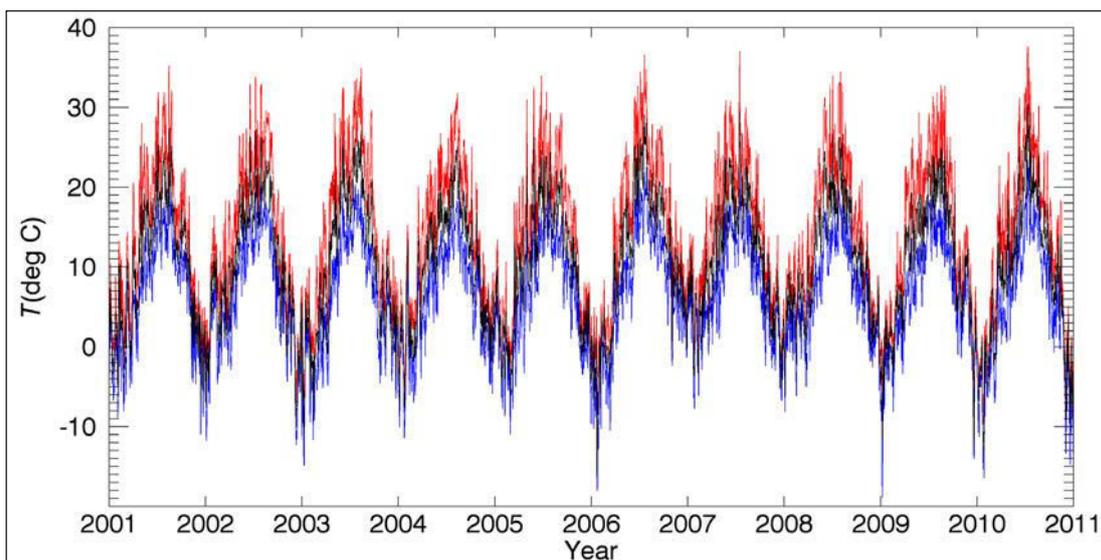


Fig. 4 Daily mean (black), minimum (blue) and maximum (red) air temperatures from 2001 to 2010 measured at the weather station Tempelhof in Berlin. Data source: German Weather Service (DWD)

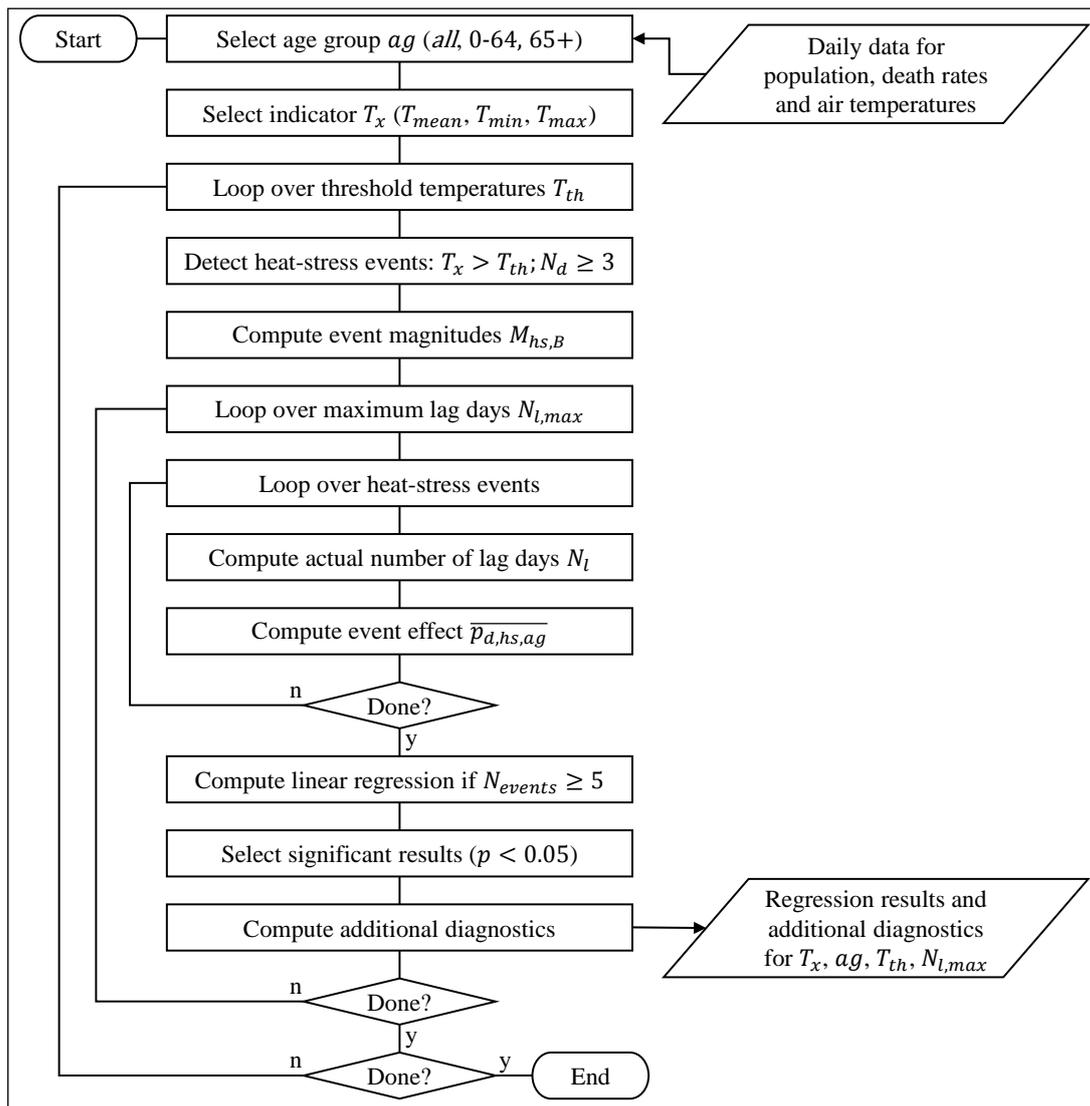


Fig. 5 Flow chart of the event-based risk analysis method

which T_x (either T_{mean} , T_{min} or T_{max}) exceeds a certain threshold temperature T_{th} . Block or moving averages of different but fixed lengths have been used in other studies to capture heat waves (see e.g. Gosling et al. 2009, Anderson and Bell 2011). Here, the length of heat-stress events is variable.

In a first step, the heat sum, i.e. the sum of degree days (dd) of the respective air temperature T_x in Berlin above the threshold temperature, is accumulated over the days of a heat-stress event:

$$(9) \quad dd_B(evt_i) = \sum_{k=d_{1,i}}^{d_{1,i}+D_i-1} (T_x(k) - T_{th}).$$

Each event has a duration of D_i days, starting on day $d_{1,i}$. Since only days belonging to heat-stress events are considered, the summands in Eq. 9 are always pos-

itive. The heat-stress magnitude $M_{hs,B}(evt_i)$ for each event is then computed:

$$(10) \quad M_{hs,B}(evt_i) = \log_{10} \left(\frac{dd_B(evt_i)}{\min(dd_B)} \right),$$

where the heat sum of each event is normalised by the minimum heat sum of a single event in the whole time series. Thus, $M_{hs,B}$ is a dimensionless variable. In a second step, events shorter than three days are discarded, because their magnitudes are generally too weak to cause a temperature signal in the total mortality rates that is larger than the statistical noise in the base mortality rates. The mean intensity of an event is its magnitude divided by the duration of the event. Finally, the heat-stress hazard is computed as the mean heat-stress intensity of the whole time period (regard: days without heat stress do have a zero heat-stress intensity).

The mean total mortality rate of each event $\overline{p_{d,ag}}(evt_i)$ was not only computed for the days of the events but also including a variable number of lag days L_i immediately following each event:

$$(11) \overline{p_{d,ag}}(evt_i) = \frac{1}{D_i+L_i} \sum_{k=d_{1,i}}^{d_{1,i}+D_i+L_i-1} p_{d,ag}(k).$$

Lag days that would be part of a successive heat-stress event were excluded to avoid double counting of deaths, so the term 'maximum number of lag days' L_{max} is used for the whole time series while the actual number of lag days L_i of individual events depends on the timing of the event sequence. We further disallowed lag times longer than two-times the event duration.

The risk analysis, designed as an exploratory methodology, comprises a large number of linear regressions in which heat-stress magnitudes of the events are used as predictor and mean total mortality rates of the events as predictand. The reason for this is given by the fact that the base mortality rate is assumed to be constant over time such that the variance in the effect rate (mean heat-stress related death rate) is identical to the variance in the mean total mortality rate.

Linear regressions were performed for each of the three air-temperature variables using different threshold temperatures for event detection and computation of heat-stress magnitudes. Threshold temperatures were varied in 1 K steps for each of the air-temperature variables starting from values far below expected heat-stress levels. This approach avoids to arbitrarily define heat-stress days by fixed values or percentiles. Instead, the analysis itself provides the threshold temperature that is appropriate to describe heat-stress conditions in Berlin.

For a given combination of air-temperature variable and threshold temperature mean total mortality rates are computed for different numbers of maximum lag days (between 0 and 14 days in one-day steps). Again, the risk analysis is not based on a priori assumptions on the temperature-mortality response function.

Each regression provides a Pearson correlation coefficient r used to compute the explained variance r^2 . Each regression provides a mean value c for the regression coefficient and a standard error σ_c for the regression coefficient. The standard error of the regression is estimated by the root mean square deviation between predicted and observed values of the predictand. Statistical significance was tested by the error probability p ($p < 0.05$) by a two-sided t-test.

Each regression provides a base mortality rate, which is the mean mortality rate for zero heat-stress conditions (intercept). The advantage of this method is given by the fact that the base mortality rate is inferred only from data during heat-stress events, such that other influences (e.g. due to seasonal variations of death rates not related to air temperature) are automatically suppressed. The base mortality rate is used to compute daily excess mortality rates by applying Eq. 8. Then, excess deaths for each heat-stress event $N_{d,hs,ag}(evt_i)$ are computed:

$$(12) \dot{N}_{d,hs,ag}(evt_i) = \sum_{k=d_{1,i}}^{d_{1,i}+D_i+L_i-1} N_{ag}(k) \cdot p_{d,hs,ag}(k).$$

The standard error of the excess death rate is estimated from both the standard error of the regression and the standard error of the base mortality rate. This is a conservative approach to quantify the uncertainty of the risk. The total numbers of heat-stress events, event days and excess deaths are computed for the whole study period and are specified as mean annual values. Finally, the heat-stress hazard of Berlin and the vulnerability of Berlin's population in the different age groups to die from effects related to heat stress are computed.

Please note that no separate quantification of exposure and sensitivity to heat stress was carried out in this initial study, because this would have required to quantify either the number of people in each age group actually exposed to heat stress or the degree of exposure. This is, however, not yet possible due to insufficient data. Also, we did only quantify the vulnerability for the three age groups, but we did not study all aspects of vulnerability, which would go beyond the scope of this study, since vulnerability is a highly complex phenomenon not only related to age.

3. Results

First, daily and monthly total mortality rates and their associations with air temperatures are shown to allow for a comparison with other studies. Then, the results of the event-based risk analysis method are presented.

3.1 Daily analysis

Figure 6 displays the resulting daily total mortality rates of people living in Berlin. A mean value of 32160 deaths per year is registered for the entire population, corre-

responding to a mean total mortality rate of 961 deaths per 100,000 capita and year (i.e. $26.3 \cdot 10^{-6}/d$). The value is much lower for people younger than 65 years (6813 deaths per year, corresponding to 246 deaths per 100,000 capita and year, i.e. $6.7 \cdot 10^{-6}/d$), while being much higher for people 65 years or older (25348 deaths per year, corresponding to 4425 deaths per

100,000 capita and year, i.e. $121.2 \cdot 10^{-6}/d$). The numbers show that almost 80 % of the deaths are in the age group that contributes less than 20 % to the total population.

Statistically highly significant trends ($p < 0.001$) were found for total death and mortality rates of people in all age groups, except for the death rates of the 65+ age

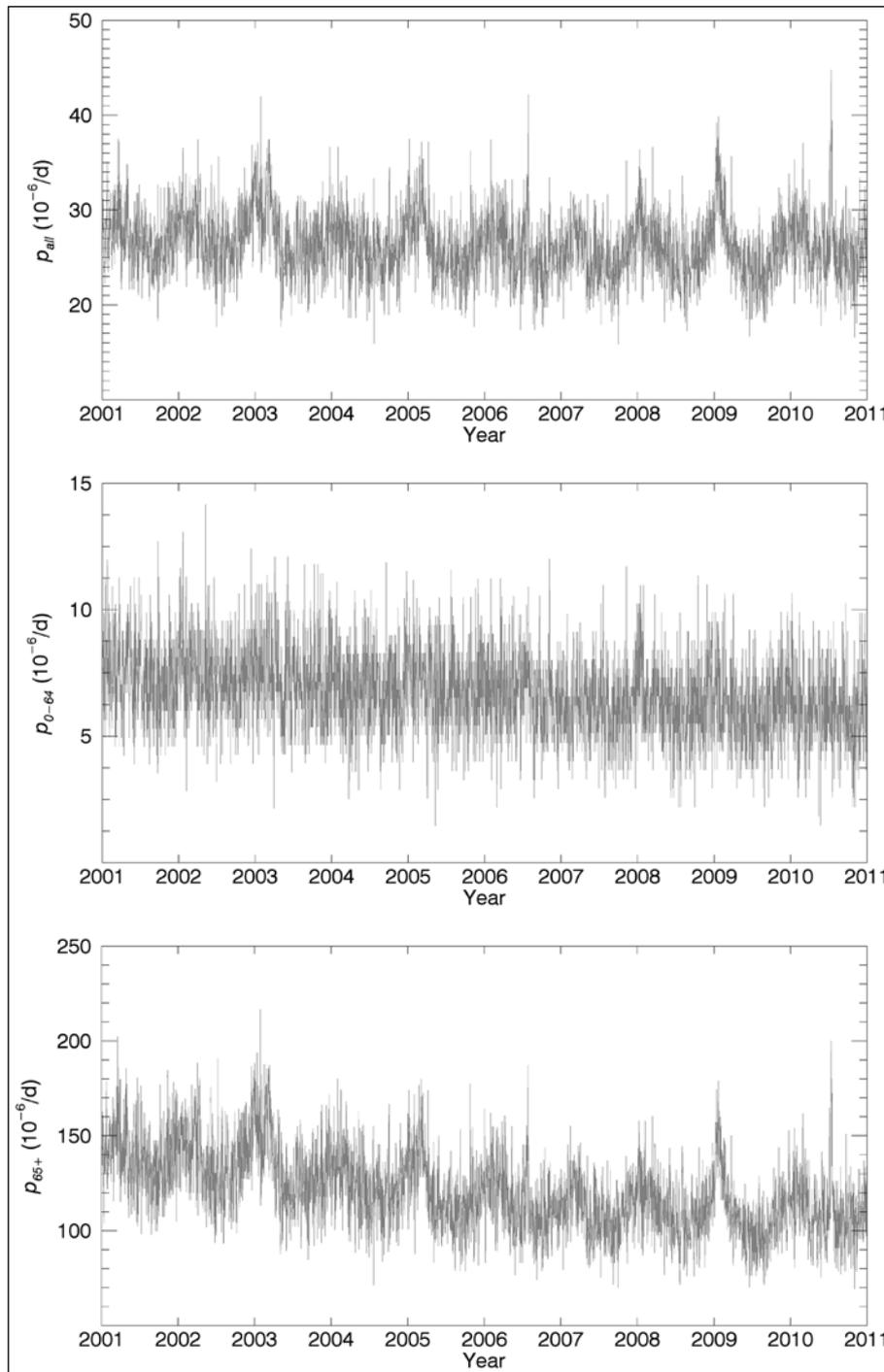


Fig. 6 Daily total mortality rates of people living in Berlin from 2001 to 2010. Upper: entire population, centre: 0-64 years, lower: 65 years and older

group. Death rates decreased by $(6.0 \pm 0.8) \%$ (*all*), and by $(30.5 \pm 1.4) \%$ (0-64) over the analysed decade, while a slight, statistically insignificant increase of $(0.5 \pm 0.8) \%$ was found for the 65+ age group. Total mortality rates decreased by $(7.4 \pm 0.8) \%$ (*all*), $(25.6 \pm 1.4) \%$ (0-64), and $(31.3 \pm 0.9) \%$ (65+). Despite the strongly decreased mortality rates of the 65+ age group, their death rates slightly increased due to the even stronger increase in the number of elderly people living in Berlin (see Fig. 2).

Figure 6 shows seasonal variations in the total daily mortality rates, which are least pronounced in the 0-64 age group. However, the variations are not strictly periodic and vary considerably from year to year.

Figure 7 displays daily mortality rates against daily air temperatures. The large scatter in the diagrams

reveals that there are no simple temperature dependencies in the daily total mortality rates, particular for the 0-64 age group.

There is a general tendency visible in Figure 7 that daily total mortality rates of the entire population and the 65+ age group increase when daily air temperatures decrease below certain thresholds. Minimal total mortality rates are found for T_{mean} of about 16 to 20°C, for T_{min} of about 12 to 16°C, and for T_{max} of about 20 to 24°C. Above these thresholds, total mortality rates show a trend to increase with increasing daily air temperatures. The increasing trend for air temperatures above the thresholds seems to be stronger than that for air temperatures below the thresholds. This is consistent with results from other studies, and is often described as the J-shaped relation (e.g. Basu and Samet 2002).

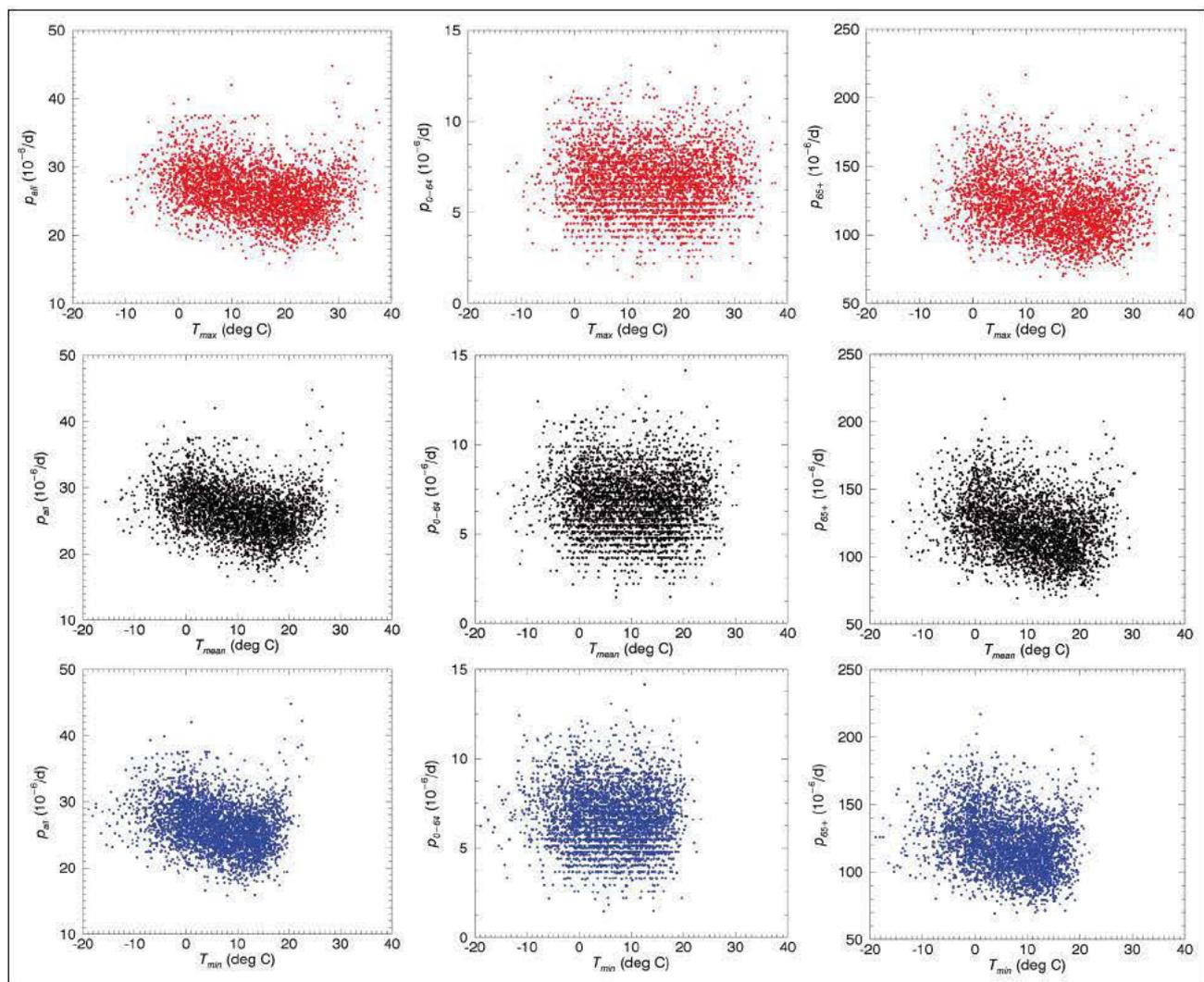


Fig. 7 Daily total mortality rates of people living in Berlin (left column: entire population, centre column: 0-64 years, right column: 65 years and older) versus daily maximum (upper row; red), mean (centre row; black) and minimum air temperature (lower row; blue) measured at the weather station Tempelhof in Berlin from 2001 to 2010

The majority of days is below the threshold. Interestingly and unexpectedly, the signal is better visible in the total daily mortality rates of the entire population than in the data of the 65+ age group.

3.2 Monthly analysis

Figure 8 displays monthly statistics for total mortality rates of people in the three different age groups living in Berlin, while Figure 9 shows the same for the three different air-temperature variables.

The 0-64 age group does not display a clear seasonal signal in total mortality rates except a slight tendency towards higher values during December and January. Remarkable is the rather stable absolute minimum of about $2 \cdot 10^{-6}/d$. In contrast, the 65+ age group and the entire population show a clear seasonality. Higher values are observed during the cold months, while values are lower during the warmer months except for

July. During this month, which is the warmest one in Berlin, the absolute minimum and the minimum of the monthly means show low values, but the mean and maximum values are higher than those observed during the other months of the warm season.

As in the daily analysis, there are two counteracting seasonal trends related to air temperature. In principle, warmer weather would be beneficial for the health state, but when air temperatures rise above certain thresholds, total mortality rates start to increase. Figure 10 illustrates this phenomenon by directly relating monthly means of total mortality rates with monthly means of air temperatures.

Again, the temperature dependency of total mortality rates is less pronounced in the 0-64 age group, but better visible in the monthly data than in the daily data. The temperature thresholds found by the daily analysis are confirmed by the monthly analysis. Again, the signal is best visible in the entire popula-

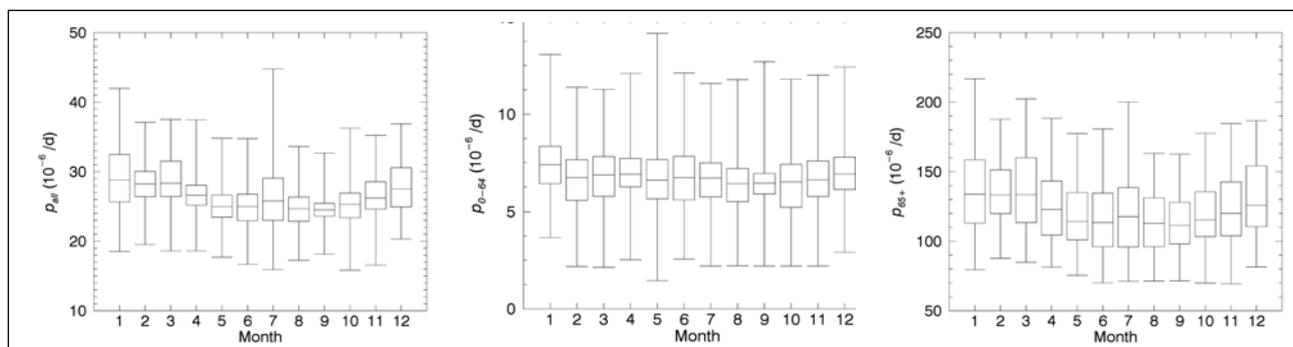


Fig. 8 Seasonal cycle of total mortality rates of people living in Berlin from 2001 to 2010. Left: entire population, centre: 0-64 years, right: 65 years and older. Whiskers indicate absolute extreme daily values while boxes show minimum, maximum and mean values of monthly mean total mortality rates

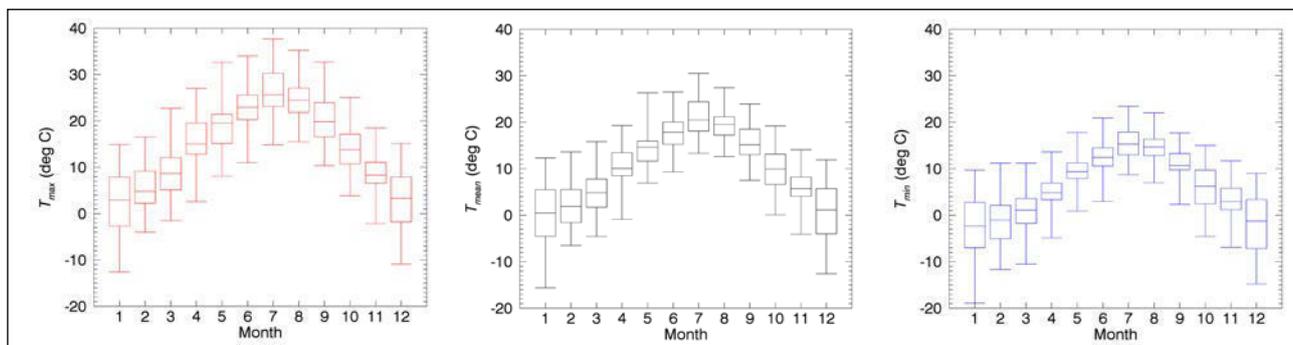


Fig. 9 Seasonal cycle of maximum (left; red), mean (centre; black) and minimum (right; blue) air temperature in Berlin from 2001 to 2010. Whiskers indicate absolute extreme daily values while boxes show minimum, maximum and mean values of monthly mean air temperatures

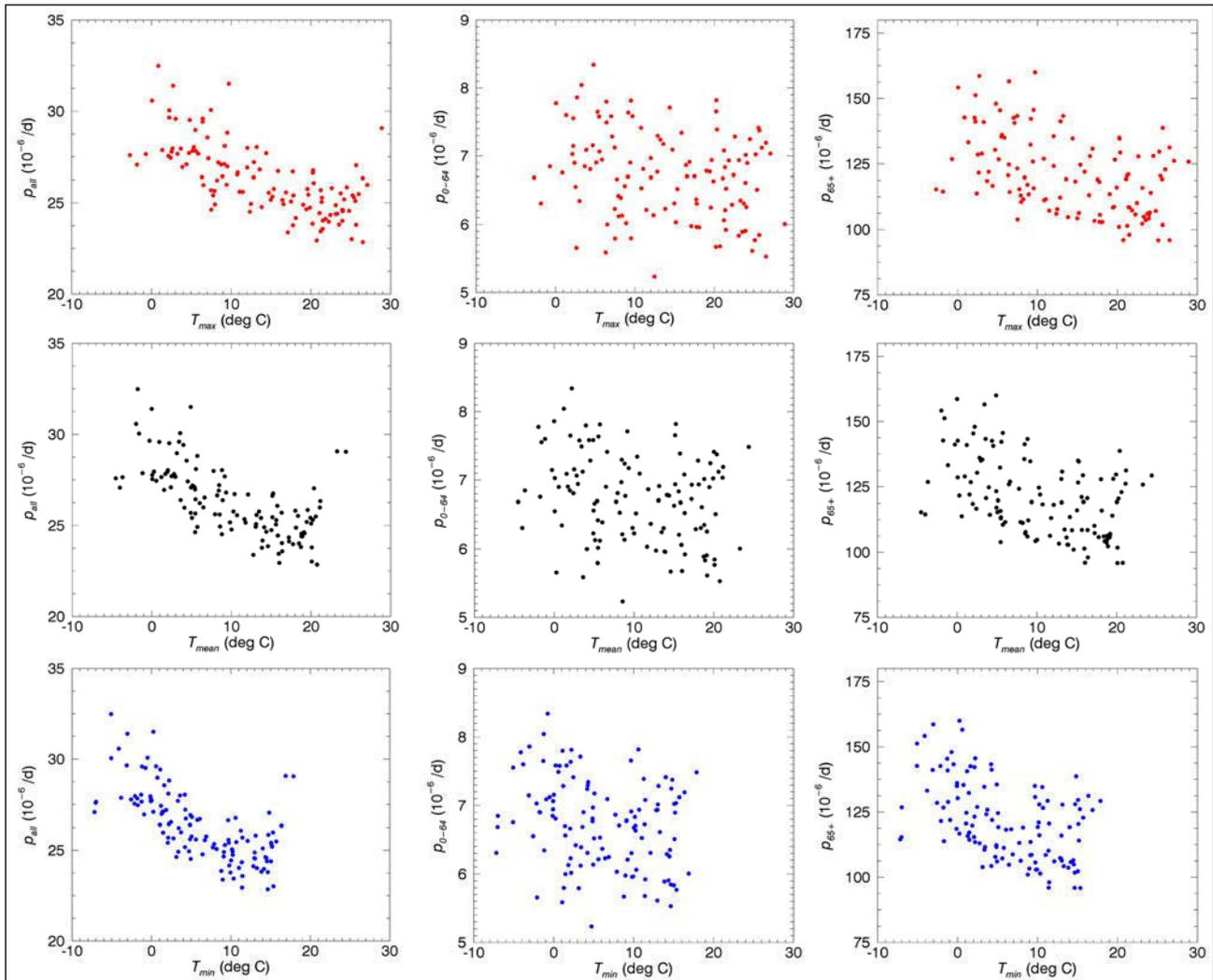


Fig. 10 Monthly total mortality rates of people living in Berlin (left column: entire population, centre column: 0-64 years, right column: 65 years and older) versus monthly maximum (upper row; red), mean (centre row; black) and minimum air temperature (lower row; blue) measured at the weather station Tempelhof in Berlin from 2001 to 2010

tion. The general relations between air temperature and mortality rates are similar between the different air-temperature variables. In all cases, increased total mortality rates related to cold weather are more prominent than those during hot weather.

3.3 Event-based analysis

Tables 1 to 3 display the regression results for each of the three different air-temperature variables and for each threshold temperature, while Tables 4 and 5 present the results for the two other age groups for T_{mean} . Only statistically highly significant results ($p < 0.01$) are displayed in Tables 1 to 3 and 5, while Table 4 presents statistically significant results ($p < 0.05$) since no highly significant regressions could be obtained.

The results for the maximum number of lag days are those that show a maximum in the explained variance for the respective threshold temperature, hereafter called optimum regressions.

Significant correlations between event magnitudes and effect rates start at air temperatures close to those visually inferred from the diagrams for the daily and monthly data (Fig. 7 and 10). The higher the threshold temperature the less heat-stress events are detected, and thus the number of excess deaths is reduced.

On average, highest values for the explained variance are obtained for T_{mean} and for the entire population. However, more than 70 % of the variance in effect rates is explained by the variance in the heat-stress

Tab. 1 Statistically highly significant results ($p < 0.01$; bold: $p < 0.001$) from the event-based regression analysis for the entire population of Berlin using T_{mean} for event detection and computation of heat-stress magnitudes from 2001 to 2010. Explained variance: r^2 ; relative error of the regression coefficient: σ_c/c

Threshold (°C)	HS events (1/a)	HS days (d/a)	Lag days (d)	r^2 (%)	σ_c/c (%)	Excess deaths (cap/a)
18	6.8	58	2	26.1	20.7	1190 ± 388
19	6.7	45	3	28.3	19.8	1106 ± 362
20	5.5	33	5	40.7	16.6	1293 ± 358
21	4.0	23	5	50.4	16.1	1384 ± 288
22	3.6	18	4	49.0	17.5	846 ± 205
23	2.0	9	7	33.7	33.0	298 ± 130
24	1.2	5	6	69.0	21.2	226 ± 58

magnitudes based on T_{min} for the highest threshold temperature of 18°C. The same magnitudes can best explain the variance in total mortality rates for the 65+ age group (51.8%; not shown). Since high threshold temperatures decrease the number of events, the high values for the explained variance are partly due to the lower degree of freedom in the regression, which results in higher errors and lower statistical significance levels.

No statistically significant results could be obtained for the 0-64 age group when using T_{min} and T_{max} . This age group shows the smallest number of excess deaths (Tab. 4). Thus, the results obtained for the entire population mainly reflects the situation of the elderly people. Although the mortality rates are different, the death rates are comparable.

Figure 11 displays the relations between magnitudes of heat-stress events and mean total mortality rates

for the three regressions that are considered to be most appropriate for risk quantification (see Tabs. 1, 4 and 5) as will be discussed below. In addition to the information already provided, the base mortality rates are visible as intercepts in the three regression diagrams. The three age groups show strongly different responses to increased heat-stress magnitudes: A heat stress magnitude of 3 would increase the total mortality rate of elderly people by almost a factor of three, while the effect would be small and only weakly correlated to the heat-stress magnitude for the younger part of Berlin's population.

Figure 12 presents an analysis of the dependency of the regression results on the number of maximum lag days. Figure 12 reveals that explained variance increases with an increasing number of maximum lag days until reaching an optimum. Then, a slight decrease is observable. The same holds true for excess mortality relative to base mortality. Error estimates show a similar but

Tab. 2 Statistically highly significant results ($p < 0.01$; bold: $p < 0.001$) from the event-based regression analysis for the entire population of Berlin using T_{min} for event detection and computation of heat-stress magnitudes from 2001 to 2010. Explained variance: r^2 ; relative error of the regression coefficient: σ_c/c

Threshold (°C)	HS events (1/a)	HS days (d/a)	Lag days (d)	r^2 (%)	σ_c/c (%)	Excess deaths (cap/a)
13	7.2	59	4	17.7	25.7	1015 ± 482
14	6.1	42	3	17.1	28.6	964 ± 439
15	4.5	27	5	29.6	23.5	1161 ± 369
16	3.5	18	2	34.2	24.1	669 ± 210
17	2.2	10	2	39.3	27.8	442 ± 147
18	1.1	5	4	71.2	21.2	336 ± 72

Tab. 3 Statistically highly significant results ($p < 0.01$; bold: $p < 0.001$) from the event-based regression analysis for the entire population of Berlin using T_{max} for event detection and computation of heat-stress magnitudes from 2001 to 2010. Explained variance: r^2 ; relative error of the regression coefficient: σ_c/c

Threshold (°C)	HS events (1/a)	HS days (d/a)	Lag days (d)	r^2 (%)	σ_c/c (%)	Excess deaths (cap/a)
23	8.4	57	6	11.6	30.4	983 ± 521
24	6.6	43	6	27.6	20.2	1353 ± 416
25	5.5	34	4	31.5	20.3	1304 ± 380
26	4.9	27	4	35.8	19.5	1191 ± 328
27	4.0	21	5	47.4	17.1	1248 ± 276
28	3.1	15	5	58.6	15.6	809 ± 177
29	2.1	9	7	49.1	23.3	653 ± 176
30	1.4	5	6	46.6	30.9	386 ± 133

Tab. 4 Statistically significant results ($p < 0.05$) from the event-based regression analysis for the 0-64 age group of Berlin using T_{mean} for event detection and computation of heat-stress magnitudes from 2001 to 2010. Explained variance: r^2 ; relative error of the regression coefficient: σ_c/c

Threshold (°C)	HS events (1/a)	HS days (d/a)	Lag days (d)	r^2 (%)	σ_c/c (%)	Excess deaths (cap/a)
18	6.8	58	1	5.9	49.2	231 ± 170
20	5.5	33	6	10.4	40.3	248 ± 160

Tab. 5 Statistically highly significant results ($p < 0.01$; bold: $p < 0.001$) from the event-based regression analysis for the 65+ age group of Berlin using T_{mean} for event detection and computation of heat-stress magnitudes from 2001 to 2010. Explained variance: r^2 ; relative error of the regression coefficient: σ_c/c

Threshold (°C)	HS events (1/a)	HS days (d/a)	Lag days (d)	r^2 (%)	σ_c/c (%)	Excess deaths (cap/a)
18	6.8	58	4	11.0	34.9	1142 ± 652
19	6.7	45	3	14.2	30.4	985 ± 516
20	5.5	33	5	31.2	20.4	1320 ± 451
21	4.0	23	5	37.6	20.9	1428 ± 388
22	3.6	18	6	18.7	35.8	677 ± 349

reversed behaviour. Lowest relative errors are found for the optimum regression. Mean excess death rates continue to increase beyond the optimum, but, similar to the errors, the changes are rather small, so the regression results are robust, i.e. only slightly depending on the number of maximum lag days.

As shown by Figure 12 for the optimum regression, the uncertainty in the excess death rates of the en-

tire population (20.8 %) is mainly due to the standard error in the base mortality rates (9.8 %), while the standard error of the regression (5.5 %) is of second importance, despite the higher standard error of the regression coefficient (16.1 %). The situation is similar for the 65+ age group, where the errors are generally slightly higher (see Tab. 5), but differs for the 0-64 age group, which shows a rather high uncertainty in excess death rates (Tab. 4).

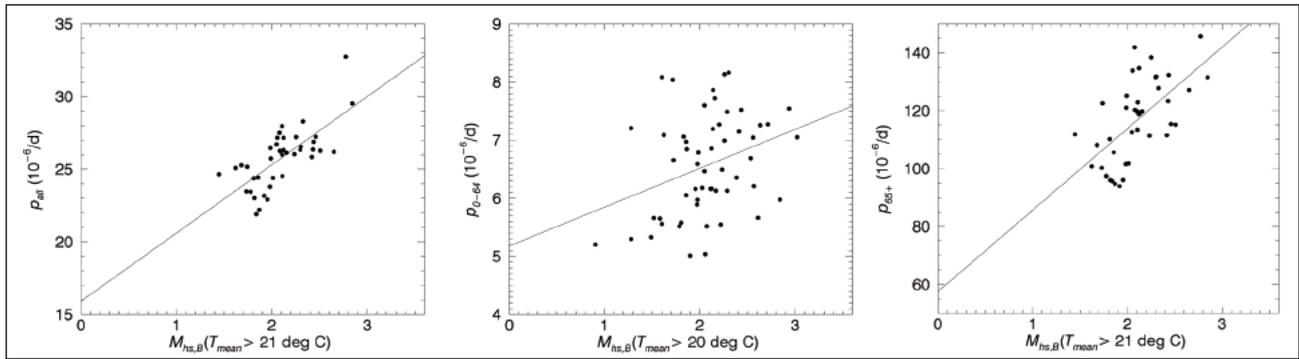


Fig. 11 Mean total mortality rates during heat-stress events of people living in Berlin versus heat-stress magnitudes for selected regressions from 2001 to 2010. Left: entire population (maximum lag days: 5 d), centre: 0-64 years (maximum lag days: 6 d), right: 65 years and older (maximum lag days: 5 d)

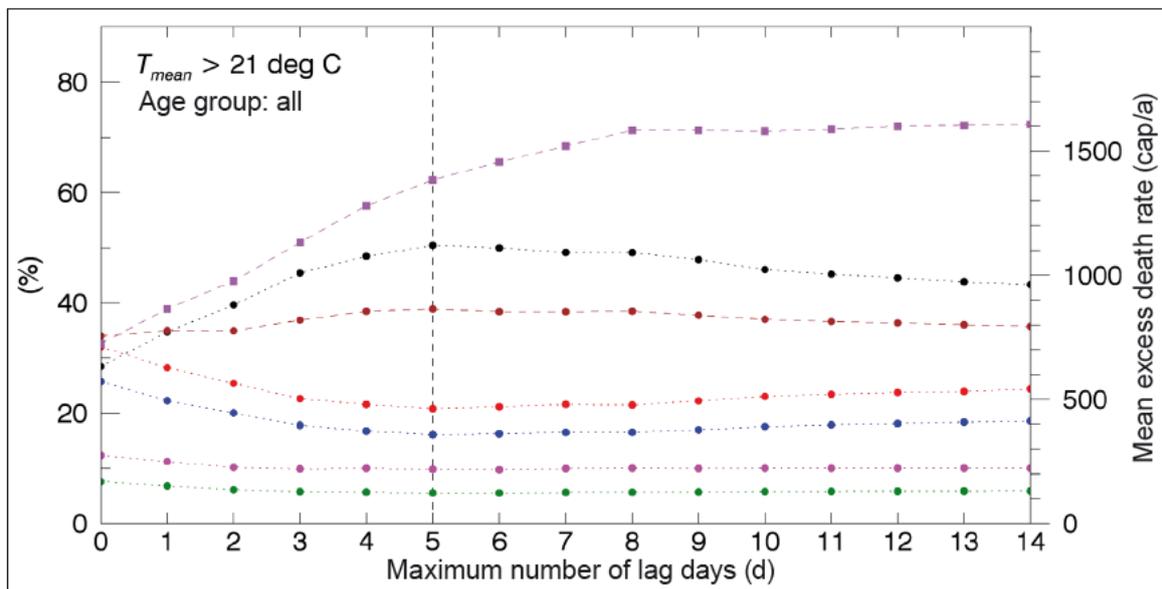


Fig. 12 Dependency of the regression results on the number of maximum lag days for the regressions using $T_{mean} > 21^{\circ}\text{C}$ as threshold temperature for the entire population of Berlin. Left y-axis: black dots: explained variance; brown dots: excess mortality relative to base mortality; red dots: relative error of excess death rates; blue dots: relative standard error of regression coefficients; magenta dots: relative standard error of base mortality rates; green dots: relative error of regressions. Right y-axis: orchid squares: mean excess death rates. The vertical dashed line indicates the regression showing a maximum in the explained variance.

Data for the year 2011 were taken for validation of the regression results (see Tab. 6). Since observational data are only available for total mortality rates but not for excess death rates, the validation only allows to assess the accuracy of the regression. This is, however, not regarded as a serious problem since the relative errors of the statistically significant regression results are strongly correlated as Figure 12 reveals.

In summary, the validation study showed that predicted total deaths during heat-stress events are close to the observations considering the error bounds of the respective regressions.

4. Discussion

The results presented above demonstrate that there is no simple answer to the question how large the risk is for people living in Berlin to die from heat stress. There are a variety of statistically significant regression results that may be used to quantify heat-stress related hazards, vulnerabilities and risks. There are several options for deciding on the best result, assuming that a best result actually exists. One of the options would be looking for the regression that shows the highest explained variance. Another option would be to search for the regression that comes with small-

Tab. 6 Results from the validation study for the year 2011 using the optimum regressions for T_{mean} for the respective age groups (see Tables 1, 4 and 5)

Age group	Threshold (°C)	HS events (1/a)	HS days (d/a)	Lag days (d/a)	Predicted total deaths (cap/a)	Observed total deaths (cap/a)
All	21	3	12	15	2220 ± 122	2243
0-64	20	5	18	30	848 ± 105	760
65+	21	3	12	15	1875 ± 178	1794

est errors. A third option would be to use the regression that has the smallest error probability. One could also search for those regressions that are most consistent among the different age groups. Regressions could be regarded to be most reasonable when confirming findings of other studies. We argue that the whole spectrum of regression results carries information on heat-stress related mortality in Berlin, which can be further exploited.

Why are there different statistically significant results? First, hazard, which is defined here as a city-wide property in this study, may vary spatially. In this case, it would be beneficial to make the risk analysis spatially distributed, e.g. for the different districts in Berlin for which data on population size and age structure exist. Unfortunately, we do not yet have detailed climate data for each of the districts. In addition, there is a statistical limit for the level of spatial detail on which mortality risks could be studied. There is statistical noise in the death rates even when using Berlin-wide data. This particularly affects signal-to-noise ratios in mortality rates of the 0-64 age group. We argue that the spatial limit for analysing heat-stress related mortality risks in Berlin is on the district level. Today, Berlin has twelve districts. Spandau, the smallest one, has only about 230,000 inhabitants such that the mean daily death rate of its entire population is about 6 cap/d. The noise in the base rate will probably make it difficult to obtain statistically significant regression results, at least for the 0-64 age group.

Using the Tempelhof weather data for quantifying the heat-stress hazard for entire Berlin gives a mixed signal of heat-stress intensity. This is a general problem in many epidemiological studies on heat stress. In parts, this limitation may be compensated by the degree of exposure, which tells how many people were, on average, actually exposed to heat stress. The degree of exposure is, however, most probably not a constant but depending on the magnitudes of the heat-stress events.

The well-known urban heat island (UHI) phenomenon causes higher air temperatures, particularly in denser parts of the city but also depending on land cover and other structural details, resulting in higher heat-stress intensities as compared to those computed for Tempelhof weather station. This is regarded as the major reason for the finding that statistically significant results can be obtained even for comparably low threshold temperatures applied to T_{min} and T_{mean} measured at Tempelhof weather station. For instance, statistically highly significant regression results are obtained for T_{min} for threshold temperatures as low as 13°C. However, measurements of air temperatures at different automatic weather stations distributed over Berlin reveal that night-time values during summer days ($T_{max} > 25^\circ\text{C}$) are, on average, about 4 to 5 K (partly more than 11 K) higher in urban quarters belonging to the local climate zone (LCZ) "Compact midrise" according to Stewart and Oke (2012) than in areas that belong to the LCZ "Low plants" (Fenner et al. 2014). Therefore, those parts of the city showing strong UHI effects are expected to show minimum air temperatures above 20°C when T_{min} at Tempelhof weather station is 15 °C or even lower. In contrast, UHI intensity is very low, sometimes even slightly negative, in Berlin during daytime in summer. Thus, regressions for threshold temperatures using T_{max} are regarded not to be strongly influenced by UHI effects.

The large spatial extent of the city area of Berlin and the complex spatial patterns of the UHI cause a spatio-temporal variability of the urban climate that prevents developing a simple scheme relating air temperature to exposure. Even if we could delineate those city quarters actually exposed to heat stress using local outdoor air temperatures we would still face the problem that people are largely if not totally influenced by indoor climates, particularly by nighttime indoor heat-stress due to high air temperatures in sleeping rooms, which are usually not equipped with air conditioning. During longer episodes of heat-stress events

indoor temperatures stay high during the night even when outdoor air temperatures are much lower. Thus, we interpret the finding that regressions based on T_{min} generally deliver less good results and lower numbers of excess deaths than those for the other two air-temperature variables is due to the problem of indicating nighttime indoor heat stress by minimum outdoor air temperatures at one of the coolest sites in Berlin.

In general, the results shown in *Tables 1 to 5* are achieved for threshold temperatures that are compatible with those reported by other studies on heat stress (e.g. *Gabriel 2009; Li et al. 2013b*), particularly when taking UHI effects into account. Direct comparisons with other studies are, however, generally difficult since the methods of determining the threshold (e.g. by fixed values, percentiles or analysis of temperature-mortality relationships), the temporal nature of the air-temperature variable (specific time of the day, daily aggregates, averages over multiple days, etc.), as well as the mortality data (e.g. all-cause versus disease-specific mortality) strongly vary between the studies (see e.g. *Gosling et al. 2009*). Despite these problems, the regressions provide not only statistically highly significant but also coherent and consistent results for different threshold temperatures, air-temperature variables, maximum number of lag days and different age groups. This indicates that the risk analysis reveals systematic effects.

We interpret the different regression results as follows: First, at lowest threshold temperatures, the smaller amount of excess deaths is due to the lower degree of exposure, since only parts of the city are showing hazardous levels of heat stress. Then, heat stress reaches a level where most of the city area is exposed to outdoor heat stress. Depending on the details of the city quarters (urban vegetation, building arrangements and types, etc.) the fraction of people exposed to indoor heat stress, and thus the degree of exposure, still varies but increases with increasing event magnitudes. As a consequence, the number of excess deaths increases, too. However, when threshold temperatures rise the number of heat-stress events is reduced, and thus the total number of excess deaths tends to decrease despite the still increasing degree of exposure. Thus, regressions providing statistically highly significant results for mid-range threshold temperatures causing maximum numbers of excess deaths are regarded to deliver good estimates of the heat-stress related mortality risk. In this respect, the regressions for $T_{mean} > 21$ °C for the entire population and the 65+ age group, as well as

the regression for $T_{mean} > 20$ °C for the 0-64 age group are identified to provide best results. This is further confirmed by the consistency of the results of the other regressions showing similar number of excess deaths for $T_{min} > 15$ °C (*Tab. 2*) and $T_{max} > 24$ °C (*Tab. 3*).

The sum of deaths in the 0-64 and 65+ age groups is the number of deaths for the entire population. Since we can attribute 248 ± 160 deaths per year in the 0-64 age group ($T_{mean} > 20$ °C) and 1428 ± 388 deaths per year in the 65+ age group ($T_{mean} > 21$ °C) we would expect 1676 ± 420 deaths per year for the entire population, which is statistically compatible with the regression result of 1384 ± 288 deaths per year ($T_{mean} > 21$ °C). A reasonable estimate for the entire population of Berlin is about 1600 excess deaths per year, which is slightly lower than the sum of the centre values for the two age groups but still within the error bounds of the regression for the entire population.

Table 7 presents the annual summaries for the $T_{mean} > 21$ °C regression for the entire population (maximum lag days: 5 d; see *Tab. 1*). In total, the year 2006 has caused the highest number of excess deaths per year, followed by 2010, while 2003 was only the fourth deadliest year in Berlin. The same sequence is obtained when using the results of the 65+ age group. However, 2003 was the year that caused the highest number of excess deaths in the 0-64 age group, followed by 2006. The least unhealthy year with respect to heat stress was 2004, followed by 2008. The lowest number of annual excess deaths is smaller by a factor of three than the highest number, so the temporal variability is considerably large. Nevertheless, even in the 'best' year (2004) about 700 excess deaths are found, which illustrates that not only exceptional, infrequent heat waves are hazardous but also ordinary hot weather conditions occurring every year for several times during summer.

Most of the events occurred during the summer months (June to August). The earliest detected event started on May 26, 2005, while the latest one ended on September 10, 2005. The statistically deadliest event started on July 17, 2006. It lasted 16 days, and after additional five lag days 956 ± 148 people had died in relation to heat stress (excess mortality rate at 85.6 % of the base mortality rate). Three events in August 2002, August 2003 and July 2010 caused almost 700 excess deaths, of which the last one showed the highest excess mortality of all heat-stress events (105.9 %). In comparison, an excess mortality of 141 % was found for Paris during the August 2003 heat wave (*Vanden-*

Tab. 7 Annual results from the event-based regression analysis for the entire population of Berlin using $T_{mean} > 21^{\circ}\text{C}$ (maximum lag days: 5 d; see Tab. 1) for event detection and computation of heat-stress magnitudes from 2001 to 2010

Year	HS events (1/a)	HS days (d/a)	Lag days (d/a)	$M_{hs,B}$	Excess mortality (%)	Excess deaths (cap/a)
2001	4	21	20	8.6	66.3	1442 ± 289
2002	4	27	20	8.7	66.1	1647 ± 331
2003	3	30	14	7.2	66.1	1542 ± 310
2004	2	13	8	4.2	62.5	695 ± 147
2005	5	20	25	9.2	59.2	1413 ± 317
2006	6	39	17	13.3	71.2	2118 ± 396
2007	3	18	15	6.2	61.9	1086 ± 233
2008	3	18	12	6.4	61.4	985 ± 213
2009	5	22	24	9.3	44.2	1088 ± 327
2010	5	27	19	10.9	74.2	1832 ± 328

torren et al. 2004), which indicates that the values for Berlin are not exceptionally high. Nevertheless, a mean value of 1600 excess deaths per year for Berlin is rather high when compared with other studies (see e.g. Gosling et al. 2009 for an overview of people killed during heat events from 2000 to 2007). Our analysis indicates that base mortality rates may be overestimated in many studies since they are partly ‘contaminated’ by excess deaths that have not been detected by the analysis method. Considering that our method for detecting heat-stress events excludes any event shorter than three days from the analysis, our number of excess deaths may possibly be slightly too low, which makes the problem even worse. Therefore, we argue that future studies should focus on better methods for the determination of base mortality rates.

Based on the results of the $T_{mean} > 21^{\circ}\text{C}$ regressions the heat-stress hazard in Berlin is 8.4 per year. Assuming 1600 excess deaths per year for the entire population, the vulnerability of the entire population of Berlin is about 191 excess deaths per unit heat-stress magnitude. The vulnerabilities of the two age groups are about 33 excess deaths per unit heat-stress magnitude (0-64) and 158 excess deaths per unit heat-stress magnitude (65+), respectively, as computed from the ratio of the centre values of the excess death rates (248/1428; see Tabs. 4 and 5). This implies that the vulnerability of the elderly people living in Berlin to heat stress is almost six times (5.75) higher than the vulnerability of the younger ones. We argue that this is mainly due to the differences in the sensitivi-

ties rather than due to differences in the degree of exposure. Taking the difference in the total number of people of the two age groups into account, the sensitivity of the 65+ age group would be about 27.6 times higher than that of the 0-64 age group, while mean total mortality rates of the 65+ age group is only 18.0 times higher. This implies that heat stress is particularly hazardous to elderly people, in accordance with other studies (e.g. Kovats and Hajat 2008, Gabriel and Endlicher 2011). This finding also underlines that the regressions are not purely coincidental but indicative for the causal chains behind the influence of increased air temperatures on the mortality of populations.

Other definitions of heat-stress intensities and magnitudes, e.g. such based on human-biometeorological indexes, could eventually deliver better results. However, since the analyses of heat-stress related mortality as presented here are the result of a city-scale study but not of a human-scale study, one cannot expect that human-biometeorological approaches validated by research about the response of individuals to ambient atmospheric conditions better describe the highly mixed response of a population comprised of many different individuals with specific and strongly variable degrees of exposure and sensitivities.

We argue that explicitly taking into account indoor climate conditions or human-biometeorological indexes computed from them instead of outdoor variables could improve the results. Buildings that are not cooled by air conditioning during summer are able to

maintain high indoor air temperatures both during day- and nighttime over prolonged episodes, thus increasing either the hazard or the degree of exposure. This has been shown by various studies (e.g. O'Neill et al. 2005). Many of the elderly people, particularly those suffering from heat-sensitive chronic diseases, are less mobile than younger people and thus remain inside of buildings (e.g. hospitals) most of the day. For these people, definitions of the hazard based on indoor conditions would probably provide better predictors for heat-stress related mortality. This should be studied in detail in the future.

5. Conclusions

A high number of excess deaths per year can statistically be attributed to increased summer air temperatures in Berlin during the years from 2001 to 2010 (Tabs. 1 to 5). We conclude that about 1600 excess deaths per year is a reasonable and conservative estimate for the heat-stress related mortality risk in Berlin. This number is equivalent to about 5 % of all deaths. The high social relevance of heat stress for Berlin becomes prominent when comparing the excess deaths related to heat stress with the number of deaths due to traffic accidents in Berlin, which accounts for 64 deaths per year (averaged from 2001 to 2010; data source: <http://www.berlin.de/polizei/verkehr/statistik.html>; accessed on 11/11/2013). Thus, the mortality risks differ by a factor of about 25!

In general, the results achieved in this study demonstrate that the approach to quantify heat-stress related hazards, vulnerabilities and risks as presented here delivers reasonable, statistically highly significant results when analysing heat-stress related mortality on an event basis. The example of heat stress also illustrates that the risk concept is easy to implement and well suited for the risk assessment of entire systems like city populations. There is, nevertheless, yet a huge potential for further scientific improvement. In particular, spatially distributed data on urban climate are expected to provide new insights when combined with observational risk data for individual city districts for which separate statistical data on population size, age structure and death rates are available. Such data would not only allow better descriptions of representative outdoor weather conditions including UHI effects but also to comprehensively study spatial patterns of vulnerability. We also expect that applying our approach to

indoor climate conditions could improve our understanding of heat-stress related mortality, particularly for elderly people or patients residing in hospitals.

If current demographic trends as observed during the first decade of the 21st century continued over the next decades, the overall vulnerability of Berlin's population to die from heat stress would further increase, even if climate conditions were stationary, i.e. the heat-stress hazard was the same as today. Combined with the perspective of continuing climate change, which is expected to increase the heat-stress hazard in Berlin, new challenges arise to decision-makers, urban planners and architects to explicitly consider heat-stress risks in urban development projects. The study presented here provides sufficient scientific justification for increasing the efforts in reducing heat-stress risks in cities.

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