Global Health Action

Supplement 1, 2012

CLIMO - Climate and Mortality

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Public health challenges in a global context are to be found in the widening gap between the winners and losers of globalisation. To meet these challenges it is crucial not only to act constructively on what is already known and evaluate the results, but also to establish what we have yet to learn and still need to implement. The Journal therefore specifically welcomes papers that report on results and evidence derived from practical implementations of current knowledge, but also papers suggesting strategies for practical implementations where none already exist. Thus the aim of *Global Health Action* is to contribute to fuelling a more concrete, hands-on approach to global health challenges. The journal particularly invites articles from low- and mid-income countries, while also welcoming South-South and South-North collaborations. All papers are expected to address a global agenda and include a strong implementation or policy component.

Global Health Action welcomes Original Articles, Short Communications, Debate Articles, as well as PhD Reviews in which recently graduated PhD students review their thesis. Study Design Articles, for example on longitudinal infrastructures for population research, may well precede the publication of results. If manuscripts are received that are not up to the standard required for publication in the journal but relate to work that has publication potential, the author(s) will be offered mentorship from a senior academic who will work collaboratively to make the article publishable. In such a case, the mentor would not expect to become a co-author but would be named in the published article as a Contributing Editor.

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In addition to the mentorship and editing provided by Guest Editors Joacim Rocklöv, Osman Sankoh and Rainer Sauerborn, each paper has been subjected to regular peer review.

It is indeed with great honour and humility that I have accepted the invitation to write the Foreword to this supplement of the Global Health Action, exclusively dedicated to a collection of articles generated from the research project of the INDEPTH Network, Climate and Mortality (CLIMO). I hope that future data analyses will also generate insights on migration as an effect of weather and climate change.

In 2009/10, the Social and Human Sciences Sector of UNESCO, through its office in Ghana, and in the context of its regional activities in Africa, provided modest financial support to INDEPTH Network, which initiated a research activity designed to analyse data on temperature, rainfall, and mortality with a view to a scientific understanding of a potential nexus between and among them, and consequently, use the findings to inform policy making in member states in Africa.

The activity brought together researchers from several HDSS centres in Africa, affiliated with INDEPTH Network, along with counterparts from India and Bangladesh, as well as partners in the North, to use existing data-sets to improve our understanding of climate and mortality. This supplement provides a first step in this direction as it analyses the effect that temperature and rainfall have on the subsequent risk of dying.

The United National Framework Convention on Climate change mandated the Intergovernmental Panel on Climate Change (IPCC) to regularly assess the state of the entire evidence available on the scientific basis of climate change, its impacts on life on the planet including human health and the most effective policy responses. However, this assessment report is only as good as the state of research, which—in the health field—is particularly patchy, as far as low-income countries are concerned.

UNESCO's mission is to contribute to the building of peace, the eradication of poverty, sustainable development and intercultural dialogue through education, science, culture, communication, and information. I am particularly proud that the work to which we modestly contributed to was not only one of knowledge generation but also included a strong component of research capacity strengthening. Young African and Asian scientists were trained in state-of-the art statistical tools and guided in the data analysis process as well as in the skills of writing up the results in scientific papers.

It is my hope that the scientific evidence presented in this supplement will assist policy making in the countries represented in the studies, to tackle the challenges of climate change. I would therefore like to congratulate INDEPTH Network and all the researchers involved in the studies, and hope that future opportunities will continue to make it possible to strengthen our collaboration.

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Weather conditions and population level mortality in resource-poor settings – understanding the past before projecting the future

This supplement of *Global Health Action* shows how retrospective, longitudinal, population-based health data from several resource poor settings in Africa and Asia can enhance the understanding of the impact of the variability extremes of weather on mortality. This information is key to our understanding of the local impacts following from climate change, and to the development of adaptation strategies to mitigate such impacts. While the editors realize the strength of the empirical evidence generated, they also emphasize that this is merely a first step in the right direction 'a proof of principle' and that there are obvious needs to continue this work by widening and deepening the research efforts.

Severe and sometimes devastating consequences are considered to be associated with future climate change, with the largest potential impacts occurring in areas with the least means to adapt. Impacts on health range from those related to malnutrition, fresh water scarcity, and changes in the range and transmission of many infectious diseases to those directly related to weather or climate extremes, such as those caused by tropical storms, floods or heat waves (1).

Understanding future hazards and their health impacts is important for adaptation and mitigation policies. The former seeks to build climate change resilience into health systems; the latter brings the information on adverse health impacts into the climate policy debate as a further motivation to reduce net emissions (2).

The current understanding of health impacts from climate and weather is much better in high-income countries, while there is a strong belief that the impacts will be much more severe in low- and middle-income countries (LMICs). Although this belief is likely to be true, it still relies on limited empirical evidence. At present there is a lack of studies on the current health impacts from climate and weather on the population health in LMICs, particularly in rural Africa and Asia (1, 3, 4). This gap has immediate consequences for the understanding of the future local impacts on public health in these regions. One important factor related to the scarce evidence is the limited knowledge of even the simplest demographic and health statistics, such as the number of people living in a defined geographical area, the number of people that are born or deceased each year and the actual cause of death.

The INDEPTH network has collected high-quality standardized data on demographics and mortality for geographically defined populations over many years, particularly in regions of Africa and Asia (5). This effort has resulted in retrospective high-quality registers representative for regions where such information is rarely known (5). In addition to existing usage and implementation of health policies developed in collaboration with the INDEPTH network, this information can also provide a valuable basis for sound policy and decision-making with respect to climate change mitigation and adaptation. The papers in this supplement of *Global Health Action* describe the complex relationships between weather conditions and mortality in resource-poor settings of Africa and Asia. This is a first step in the process of learning from the past to understanding the future impacts of climate change.

In high-income areas, many studies have focused on the relationship between variability in weather, mortality and health, identifying stressors such as extreme heat and humidity (4, 6) and heavy downpours and floodings (7–10) as highly related to population health. Census and well-established retrospective health register data are commonly used. Analyses have been conducted to study, for example, the severe health impacts caused by extreme heat waves (11), susceptibility and vulnerability factors to temperature extremes (12), years of life lost due to heat and cold exposure (13), health impacts from drinking contaminated water associated with floodings and heavy rainfalls (7, 8), and the evaluation of adaptation measures such as warning systems and related action plans. Many of these studies have analysed the temporal relationship within time series of health conditions and weather exposures (14, 15). The rationale behind these studies is to estimate an expected event rate at a specific time of the year for a specific year, and then compare the observed event rate during specific weather conditions to the expected event rate forming a relative risk. In doing so, these studies incorporate trends and other time-varying factors known to be influential on the outcome necessary for predicting the expected event rates at specific time points, as well as variables related to weather conditions

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as explanatory variables. However, in LMICs, such relationships have been very sparsely studied using established and robust methodological considerations.

On these premises the INDEPTH Network, together with a number of south–south and north–south collaborating institutions, initiated a research and capacity-strengthening workshop in Nouna, Burkina Faso, in February 2011. Fifteen out of the 42 INDEPTH network member Health and Demographic Surveillance Systems (HDSSs) were represented by their analysts during a one-week workshop. The workshop was funded by UNESCO, Ghana, and UNESCO was represented at the workshop by Dr. Abdul Lamin. The facilitators of the workshop were from the INDEPTH Network secretariat, Accra, Ghana; Umeå University, Sweden; Heidelberg University, Germany; Columbia University, USA; and the Nouna Health Research Centre, Burkina Faso. The aim of the group was to work towards a special issue in the journal *Global Health Action* focusing on the relationship between weather conditions and mortality in HDSS areas. This activity goes under the name of CLIMO[1] (Climate and Mortality).

Subsequently, a second follow-up workshop, funded by Doris Duke Charitable Foundation, was organised in Accra in May 2012. In between the two workshops, the analysts continued the work on their data with mentorship from the facilitators and commenced paper writing. The objective of the second workshop was to help the analysts develop their writing and scientific presentation skills in order to meet the standards of the upcoming scientific supplement in *Global Health Action*. This time, the facilitator group included the INDEPTH Network secretariat, Accra, Ghana; Umeå University, Sweden; Heidelberg University, Germany; London School of Hygiene and Medicine, UK; Virginia University, USA; and the Nouna Health Research Centre, Burkina Faso.

The facilitators laid out the objectives of the analyses and corresponding papers to be invited for submission to the supplement in *Global Health Action* in order to achieve a level of comparability of the individual papers. The analysts were asked to study the following: the relationship between weather and mortality in their HDSS registers; daily mortality (if possible) over a sufficiently long retrospective period; to incorporate the delayed effects associated with continuous weather exposures; investigate non-linearity; adjusting for confounding time-varying factors; to evaluate the model; and to stratify the analyses and presentations by age and sex. In addition, some researchers incorporated cause-specific mortality analyses, but this was not a uniform requirement.

[1]A second branch of data analysis, currently underway, refers to the link between weather and migration patterns: hence the acronym for the full study CLIMIMO (Climate Migration and Mortality).

The HDSS-associated analysts and researchers who contribute to the supplement have a wide geographical spread ranging from the west of sub-Saharan Africa to Bangladesh: Nouna HDSS (16), Burkina Faso; Navrongo HDSS (17), Ghana; Nairobi HDSS (18), Kenya; Rufiji HDSS (19), Tanzania; Vadu HDSS (20), India; AMK HDSS (21), Bangladesh; and Matlab HDSS (22), Bangladesh. All but one HDSS is situated in a rural area. The urban representation was based on data from the informal settlements of Nairobi. In general, income conditions in the regions are low or medium, with the African rural HDSSs representing the poorest regions.

The past, present and potentially future climatological contexts of the study areas are described in one of the papers (23). This paper makes an important contextual contribution to the supplement by describing the past to present changes in climate in the regions, as well as the projected changes in climate under different scenarios of greenhouse gas emissions. Hondula et al. (23) not only describe the changes in terms of temperature and rainfall trends in the study regions, but also transform and link the past to future climate in terms of the Köppen climate classification scheme. The results show potential substantial shifts in the climate type in a few of the study areas in the future, much larger than the observed past to present changes.

In their study, Egondi and co-workers describe the direct and delayed associations between cold and warm temperatures and the amount of rainfall on daily mortality in the informal settlements of Nairobi, Kenya, over the period 2003–2008 (18). Few studies, if any before, have studied an urban population under such poor living and sanitary conditions. The study reveals significant associations between both hot and cold temperatures and increasing amounts of rainfall, and for example deaths in children in infectious and non-communicable disease.

Azongo and co-workers have studied the relationship between daily mortality and temperature and rainfall including delays up to a few weeks between exposure and events (17) based on registers from the rural parts of the Kassena-Nankana District of northern Ghana, 1995–2010. In general, they have found the study population to be negatively affected by heavy rains, and that children and the elderly population appeared to suffer the most. The strongest associations were found with less than a week's lag.

In the study by Diboulo's group, the authors describe how the population mortality from northern Burkina Faso (bordering to the Saharan desert) is affected by different weather conditions on a daily scale over the period 1999–2009 (16). It appears children are most negatively affected by hot temperature, while the adult and elderly population appeared more susceptible to the effects related to heavy rainfalls. The authors discuss and present a U-shaped relationship between mortality and temperature in the elderly population, just like the ones found in most studies from more developed countries in the elderly population.

In a study from Rufiji, Tanzania, Mrema and co-workers describe how rainfall and temperature on a monthly timescale are related to mortality (19). They describe how much of the annual seasonality in mortality that disappears after adjustment for the direct and lagged indicated effects from the meteorological conditions. They, like many of the other studies, reach the conclusion that children and the elderly population appear most sensitive to the effects associated with different weather conditions.

Ingole's group studied daily population level mortality in relation to weather in the rural area of Vadu, India, 2003–2010 (20). The weather conditions can get extremely hot during certain periods of the year in this region. The authors found that children appear most susceptible to hot temperatures, and most population subgroups to be negatively affected during heavy rainfalls. The indicated effect from rainfall was particularly strong among women.

The longest daily time series studied as part of the supplement is based on data from the Matlab and the Abhoynagar areas in Bangladesh, 1983–2009. Using the Matlab registers, Lindeboom and co-workers describe the associations between mortality, temperature, rainfall and cyclones (22). In this study population it appears that the relationship between mortality and temperature is non-linear and U-shaped, while the relationship with rainfall is rather weak. In addition, cyclones were found to be associated with increased mortality among adult women. The study based on the Abhoynagar registers shows weekly associations between mortality and weather (21). In this population it appears that low temperatures are more strongly associated with increases in mortality. However, heavy rainfall also positively correlated with increased mortality rates.

Overall, the results from the site-specific analyses are in line with many studies from more developed countries. They show that meteorological conditions are related to mortality days and/or weeks later. On the other hand, many of the studies also show that children under 5 years of age appear sensitive to mortality during extreme weather conditions. Some of the studies indicate a surprising absence of mortality impacts related to hot temperature. This may be related to the low prevalence of non-communicable diseases in the early stage of the epidemiological transitions (24). The studies also indicate that populations in sub-tropical areas of the world may suffer from cold-related mortality, which may be due to poor housing conditions and a lack of available fuel for heating. The populations studied appear vulnerable to heavy rainfall events with corresponding upsurges in mortality a few days or weeks after such events. Overall, the different studies point to local differences in impacts and susceptibilities, which is valuable for the development of local adaption strategies to current weather situations. It seems possible that simple measures such as improved hygiene and housing conditions may prove effective in reducing the weather-related burden of deaths in the study regions.

Relating the supplemental findings to the current body of evidence (mainly from developed regions), it is important to consider the state of demographic and epidemiological transitions in the study population. Most certainly, this is particularly important when considering future impacts of weather and climate change on non-communicable diseases, as such diseases are likely to become much more prevalent in the future (24).

Further studies are needed to study these relationships in more detail and to compare the results between the HDSS areas. For example, using cause-specific data and identifying factors related to increased vulnerability and susceptibility to get a better understanding of the causal pathways of these effects, and also on how to enhance the local resilience to the current environmental stressors, are important next steps. A mixed methods approach using qualitative studies of people's perceptions, current knowledge of weather and climate change-related health risks, and describing peoples means to adapt, together with quantitative studies describing and enumerating the health impacts would benefit both local and national policies and decision making by jointly describing a width and depth, and possibilities for adaptation in the communities. Studies should also be designed to better understand the global and local health impacts following from climate change. For example, using projections of disease and deaths based on epidemiological transitions and climate change scenarios can help the development of longer-term adaptation programmes and global policies.

The INDEPTH network provides a possibility to expand the observation period onwards. As where longer time series are and become readily available, it is important to study the health effects related to climate variability and change directly, for example in a detection and attribution to past to present climate change framework.

Further research should develop the use of climate and weather information in increasing public health preparedness (e.g. early warning systems) to, for example, extreme climate and weather events and infectious outbreaks. The INDEPTH network offers an opportunity for development and evaluation of such interventions based on the retrospective registers and prospective data collection.

The joint work of the INDEPTH network members, analysts and facilitators described in this supplement is therefore a first step in building capacity for enhancing the long-term resilience for the population in resource-poor settings of Africa and Asia to climate and climate change. Our collaborative effort using INDEPTH data to study the effects of weather on mortality is an important first step in the challenging and hitherto under-explored road of what the health impacts of climate change in low-income countries are and how populations in theses resource-poor countries can be protected from them.

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Weather and mortality: a 10 year retrospective analysis of the Nouna Health and Demographic Surveillance System, Burkina Faso

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Background: A growing body of evidence points to the emission of greenhouse gases from human activity as a key factor in climate change. This in turn affects human health and wellbeing through consequential changes in weather extremes. At present, little is known about the effects of weather on the health of sub-Saharan African populations, as well as the related anticipated effects of climate change partly due to scarcity of good quality data. We aimed to study the association between weather patterns and daily mortality in the Nouna Health and Demographic Surveillance System (HDSS) area during 1999–2009.

Methods: Meteorological data were obtained from a nearby weather station in the Nouna HDSS area and linked to mortality data on a daily basis. Time series Poisson regression models were established to estimate the association between the lags of weather and daily population-level mortality, adjusting for time trends. The analyses were stratified by age and sex to study differential population susceptibility.

Results: We found profound associations between higher temperature and daily mortality in the Nouna HDSS, Burkina Faso. The short-term direct heat effect was particularly strong on the under-five child mortality rate. We also found independent coherent effects and strong associations between rainfall events and daily mortality, particularly in elderly populations.

Conclusion: Mortality patterns in the Nouna HDSS appear to be closely related to weather conditions. Further investigation on cause-specific mortality, as well as on vulnerability and susceptibility is required. Studies on local adaptation and mitigation measures to avoid health impacts from weather and climate change is also needed to reduce negative effects from weather and climate change on population health in rural areas of the sub-Saharan Africa.

Keywords: *weather*; *mortality*; *Burkina Faso*; *sub-Saharan Africa*; *Nouna HDSS*; *lag*; *time series*; *precipitation*; *temperature*; *climate change*; *vulnerability*; *susceptibility*

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Weather has been found to have a bearing on mortality in most parts of the world, manifested through infectious diseases as well as numerous deaths related to, for example, heat waves (1–4). Existing literature, although mainly focused on urban settings, suggests differential weather-related mortality and morbidity between rural and urban populations. It is believed that urban populations are more affected than rural populations, especially by oppressive heat (5).

Despite indications of adaptation/acclimatization in warm regions, it has been suggested that urban populations in tropical climates may also be vulnerable to high temperatures (2). The population vulnerability to heat-related mortality is often characterized and modified by the underlying prevalence of temperature-sensitive dis-

§The Guest Editors, Joacim Rocklöv and Rainer Sauerborn, have not had any part in the review and decision process for this paper.

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eases, the level of socioeconomic development, and the age structure of population (6).

Some studies have reported short-term associations between rainfall and mortality. Rainfall is known to be associated with, in particular, gastrointestinal/diarrheal diseases, which show increasing rates following floods or elevated amounts of rainfall (7, 8). However, also tropical vector-borne diseases, such as the malaria mosquitoes biting rate and the related human incidence rates, are exacerbated shortly after a rainfall event (3).

At present, and from now on, climate change resulting in extreme weather conditions is expected to have a marked impact on weather-related mortality (9). However, at present the knowledge of the impact and how to avoid harmful effects related to weather and extreme climatic events are sparse, particularly, in rural Africa. This article studies the association between weather and daily mortality in the Nouna Health and Demographic Surveillance System (HDSS) area in Burkina Faso.

Objectives

The objectives of this study are:

(1) To investigate the association between temperature, rainfall, and mortality in the Nouna HDSS.
(2) To study the lag between weather variables and mortality.
(3) To contrast the associations in groups of age and sex.

Methods

Study site

The HDSS site of the Centre de recherche en santé de Nouna (CRSN, Nouna Health Research Centre) is located in the Nouna health district's catchment area in northwest Burkina Faso, 300 km from the capital, Ouagadougou.

The current geographic extent of the HDSS comprises one district hospital and 14 peripheral health facilities.

The Nouna area is a dry orchard savannah with a sub-Saharan climate and a mean annual rainfall of 796 mm (range 483–1,083 mm) over the past five decades. The population size is about 90,000, settled over 1,775 km^2. The population is rural and semi urban (essentially living in Nouna town) and almost exclusively subsistence farmers of the Marka, Bwaba, Samo, Mossi, and Foulani ethnic groups (Fig. 1).

The Nouna HDSS of CRSN has conducted regular population censuses since 1992 (baseline of individuals), maintained a vital-events-registration system, and performed routine verbal autopsy (VA) interviews (10).

The Nouna HDSS is a set of field and computing operations that handle the longitudinal follow-up of well-defined entities or primary subjects (individuals, households, and residential units) plus all related demographic and health outcomes within a clearly circumscribed geographical area.

The HDSS follow the entire population of a defined geographical area and monitors demographic and health

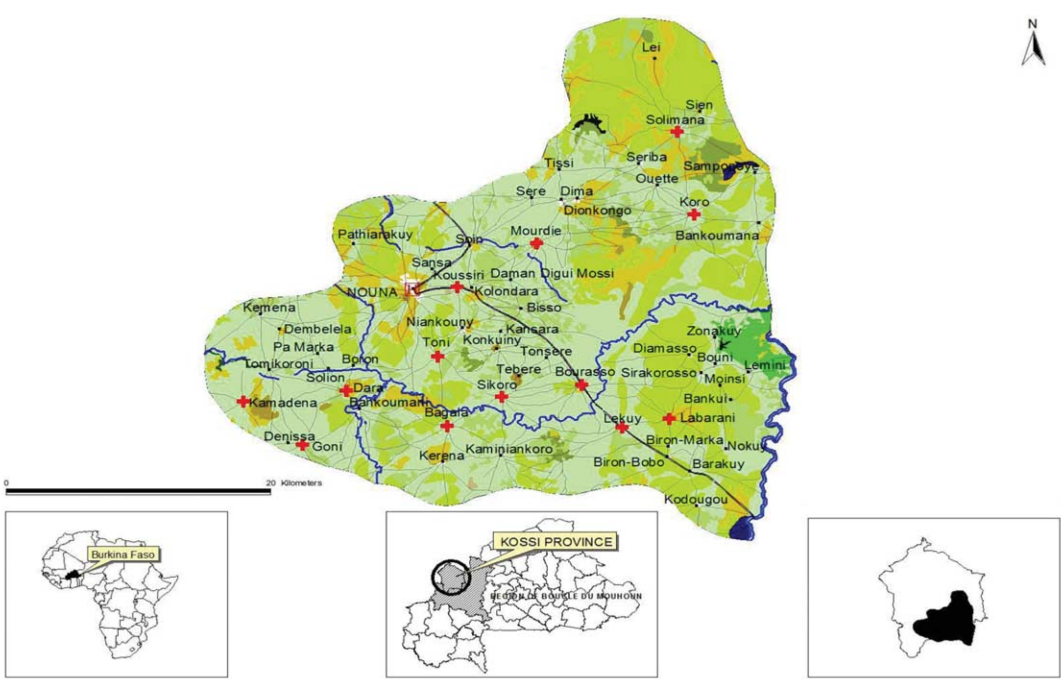

Fig. 1. Map of Nouna Health and Demographic Surveillance System (HDSS's) catchment area.

characteristics over time. Initially, a census is carried out to define and register the target population where registered subjects are consistently and uniquely identified. Regular subsequent rounds of data collection at prescribed intervals (every 4 months) make it possible to register all new individuals, households, residential units and to update key attributes of existing subjects.

The core system monitors population dynamics through routine collection and processing of information on vital events such as births, deaths, and migrations which are the only demographic events that lead to any change in the initial size of the resident population.

In addition, the HDSS collects information on health outcomes (such as causes of death using VA, incidence, and prevalence of particular diseases of public health importance), performs routine surveillance of malaria indicators in randomly selected households, and conducts education and socio-economic surveys.

We observed clustering of deaths with unknown death date on the 1st and the 15th of each month. However, because we aim to study the weather-related mortality on a daily basis, we removed these dates from the analysis by imputing a missing value on these days. This made the total number of deaths at hand to study to decrease by 32% as can be seen in Table 1. Table 1 also shows the aggregated number of deaths over the study period in groups of age.

Weather data

Data were collected from 10 onsite meteorological stations run by the Nouna Health Centre as well as from the nearest monitoring station associated with the World Meteorological Organization (WMO). Collection was done from 1999 to 2009 on a daily basis from the WMO station. The observations from the site-specific stations were compared to the one from the WMO station during the shorter period when the onsite stations were in use (2004–2009). Daily weather was aggregated from hourly measurements to daily mean, max and minimum temperature, as well as daily cumulative rainfall. Missing observations were not imputed. Lagged effects of daily weather were studied using lag strata of average meteorology respectively for lag 0–1, lag 2–6, and lag 7–13 to avoid problems arising from using highly correlated lags of weather variables in the same model.

Daily mean, maximum, and minimum temperature, as well as daily cumulative precipitation is presented in Table 2.

Table 1. Aggregated number of deaths over the study period (1999–2009) by age groups (after removing clustering of deaths on the 1st and 15th of each month)

Months	U5 (0–4)	All cause mortality Teenager (5–19)	Adults (20–59)	Elderly (60+)	Total
January	246	34	114	206	600
February	229	50	134	181	594
March	229	57	137	190	615
April	242	63	125	227	658
May	200	40	121	160	521
June	180	54	116	152	502
July	239	39	89	128	496
August	397	53	127	118	695
September	365	47	110	130	652
October	391	54	118	148	711
November	361	52	105	147	666
December	300	65	134	193	692

Statistical analysis

We used a time series approach to study the association of weather variables with daily mortality series (11). Daily mortality was assumed to follow an over-dispersed Poisson distribution. Time trends were estimated with natural cubic spline function, allowing a degree of freedom (df) of five per year of data using the mgcv package in R, but without penalizing the complexity of the smooth function of time trends. The adjustment for time trends and seasonality allowed us to study how well weather variables predicted deviations in mortality from what is expected at a given time (season, year), that is, the short-term relationship between a weather stressor and succeeding mortality. In this way, the adjustment for time trends also adjusts for slowly varying changes in population size on a seasonal or annual basis.

Penalized smooth functions were used when estimating the exposure–response associations between lags of weather and daily mortality. This allowed the model to iteratively estimate the complexity of this relationship and enhance the fitting of a smoother relationship rather than noisy. These functions were allowed a maximum df of 10 before penalization. Linear exposure–response relationships were also estimated.

Because there was a large proportion of missing recordings of precipitation (see Table 2), we modelled the effects of the different weather stressors separately.

Models were evaluated on the basis of generalized cross validation (GCV) score. The GCV score is a rapidly computed metric that is based on a leave-one-observation-out method of maximizing the fit of the model through minimizing residual error. A smaller GCV corresponds to a better fit of the weather variables to the daily mortality data.

Sensitivity analyses of estimates were performed by changing the df per year of data from 5 to 8 in the spline

Table 2. Summary of weather data over the study period (1999–2009)

Months	Mean temperature (°C)	Minimum temperature (°C)	Maximum temperature (°C)	Mean precipitation (mm)
January	26.1	20.0	30.8	0
February	29.0	22.5	33.9	0
March	32.3	25.9	37.2	14.7
April	33.4	28.1	38.0	50.7
May	32.3	27.7	36.6	50.5
June	29.8	25.6	33.6	135
July	27.3	23.8	30.8	215.5
August	26.23	23.1	29.5	339.7
September	26.83	23.0	30.8	194.6
October	29.1	23.9	34.3	47.9
November	29.0	22.3	34.8	16.5
December	26.9	20.0	32.7	0

function, estimating season and time trends, so as to assess the robustness of the estimates presented to the adjustment for time trends.

The fitted regression model was of the form:

$$\text{mortality}_t \sim \text{Poisson}(\text{mean}_t)$$

$$\begin{aligned}\log(\text{mean}_t) = {} & s(\text{weather lag } 0\text{–}1,\ \text{df} < 10)\\ & + s(\text{weather lag } 2\text{–}6,\ \text{df} < 10)\\ & + s(\text{weather lag } 7\text{–}13,\ \text{df} < 10)\\ & + s(\text{time},\ \text{df} = 5 \text{ per year of data})\end{aligned}$$

and

$$\begin{aligned}\log(\text{mean}_t) = {} & \text{weather lag } 0\text{–}1 + \text{weather lag } 2\text{–}6\\ & + \text{weather lag } 7\text{–}13,\\ & + s(\text{time},\ \text{df} = 5 \text{ per year of data})\end{aligned}$$

where t denotes the time in days, s denotes a smooth cubic spline function, and df denotes the degrees of freedom.

Results

The annual seasonal mortality patterns are described in Table 1. Overall, the monthly number of deaths was 61.68 over the study period. Weather was hottest in April with a minimum and maximum temperature of 28.1°C and 38.0°C, respectively, and coldest in January, with a minimum and maximum temperature of 20.0°C and 30.8°C (Table 2). The rainiest month was August with a mean precipitation of 339.7 mm (Table 2).

For total all-age mortality, we estimated an approximate linear significant increase with increasing temperature in lag 0–1, and a slightly decreasing mortality (but not significantly) in lag 2–6, and lag 7–13 (Fig. 2). The increase in mortality in lag 0–1 corresponds to an approximate 50% increase in mortality over the range of temperature. In this group, rainfall is estimated as not being significantly related to mortality, but 2–6 days

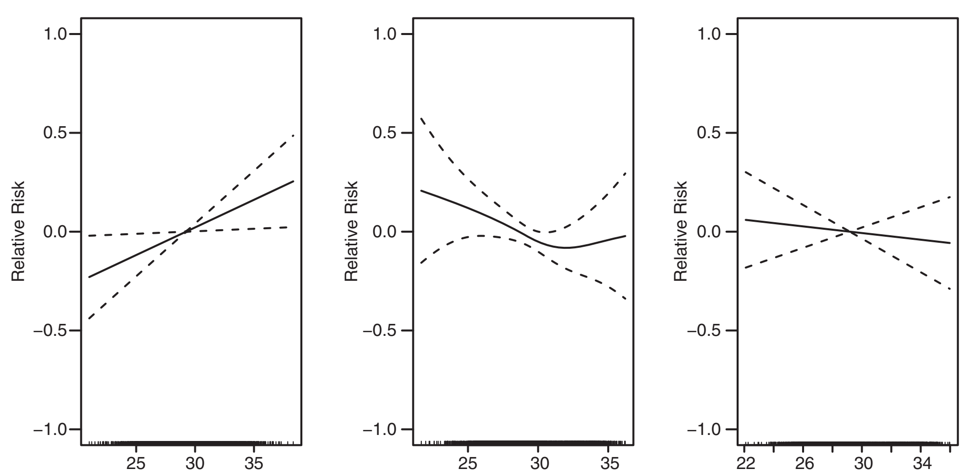

Fig. 2. The association between temperature and all-cause and all age daily mortality in Nouna, Burkina Faso, over the lag 0–1, 2–6, and 7–13 (from left to right). The scale of the vertical axis is the log (relative risk [RR]), 95% confidence limits are shown as dotted lines.

after rainfall mortality indicated an increase (Fig. 3). We note that the reliability of this test is lessened due to the large number of missing days with rainfall records.

The analysis using smooth curves show approximate linear relationships overall. As linear estimates the group of all-ages appear to experience significant elevated risks to temperature increases in lag 0–1 only. This association is particularly apparent in the age group of 0–4 (Table 3). Rainfall shows no significant association with mortality in this group, however.

Tables 3 and 4 also describe the relationship estimated between temperature and rainfall and daily deaths in the age group of 20–59 years. In this age group, increasing temperature indicates no association with mortality over the lags studied, however, rainfall shows increasing mortality but with decreasing levels in the lag 7–13.

The group of 5–19 years of age appears more sensitive to high rainfall. Table 4 describes an increasing mortality with increasing levels of rainfall in the lag period of 7–13 days in this age group.

The elderly population (60+ of age) in Nouna appears sensitive to both extreme high and low temperatures in lag 0–1 (Fig. 4). However, when studied linearly no significant associations are estimated. More intensive rainfall in the lag 2–6 days is significantly associated with mortality showing a substantial increase in mortality following such events (Table 4).

Sensitivity analyses showed no changes in the relationship estimated between temperature and daily deaths (Table 5). However, the estimated relationship between rainfall and daily deaths indicates no further association with mortality in the group of 5–15 years of age and elderly population (Table 6).

Discussion

We found profound associations between higher temperature and daily mortality in the Nouna HDSS, Burkina Faso. The short-term direct heat effects lag 0–1 was particularly strong among the younger population, but also apparent in all ages. We also found coherent strong associations between rainfall events and daily mortality delayed 2–6 days, particularly, in the elderly populations. Also, interestingly, temperature indicated a U-shaped relationship with mortality over lag 0–1 in the elderly population (60+ of age). This resembles the relationship between elderly populations and mortality in developed countries today (1, 12).

Future studies should investigate these associations in cause-specific groups to better understand the underlying chain of events that are potentially involved in causing harmful effects from weather among the population of Nouna HDSS.

The increasing mortality seen in lag 2–6 with increasing rainfall could be related to pathogen contamination of fresh water, and intensified biting rate of mosquito and transmission of malaria (13). The increasing mortality with increasing temperature in lag 0–1 is most likely a heat effect known to exacerbate a wide range of communicable and non-communicable diseases (14). The slight decrease in mortality in lag 2–6 and lag 7–13 may be related to effects from cold exposure known to correlate to cardiovascular and respiratory diseases (15). In general, temperature effects are known to be exacerbated and increase with age through deterioration of the body's thermoregulation system and the ability to sense and act on heat and cold impulses (16).

Future studies should investigate who is vulnerable and susceptible to the effects from weather in more detail in order to target populations and individuals at more

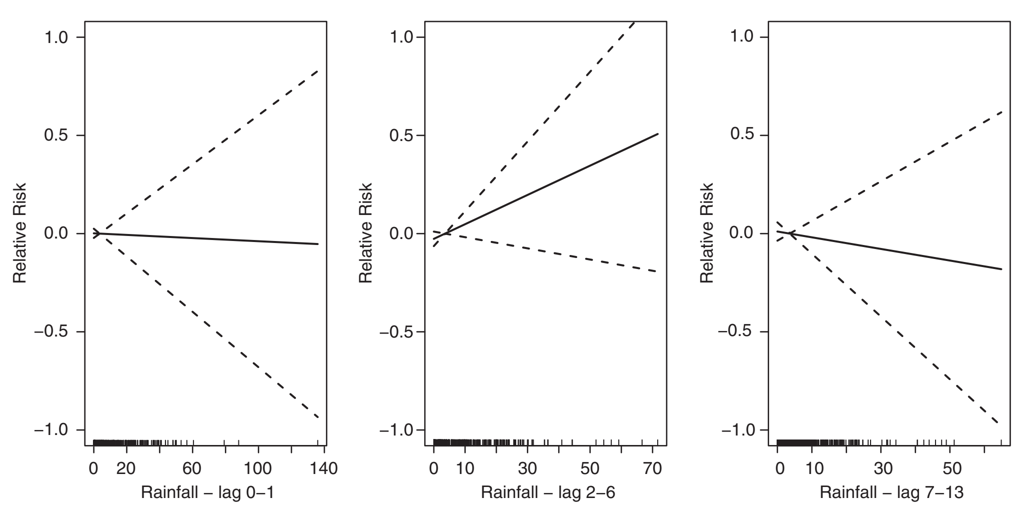

Fig. 3. The association between precipitation and all-cause and all-age daily mortality in Nouna, Burkina Faso, over the lag 0–1, 2–6, and 7–13 (from left to right). The scale of the vertical axis is the log (relative risk [RR]), 95% confidence limits are shown as dotted lines.

Table 3. Relative risk (RR) in % associated with a 1°C increase of temperature per lag strata

	Lag 0–1		Lag 2–6		Lag 7–13	
Age group	RR	CI (95%)	RR	CI (95%)	RR	CI (95%)
0–4	**3.7**	(0.3, 7.3)	−1.6	(−6.0, 3.0)	0.4	(−4.2, 5.2)
5–19	3.2	(−1.9, 8.6)	1.6	(−5.2, 8.9)	−0.4	(−7.1, 6.9)
20–59	2.3	(−1.6, 6.5)	−4.2	(−9.1, 0.9)	0.3	(−4.9, 5.7)
60+	1.1	(−2.4, 4.6)	−2.6	(−7.1, 1.7)	−4	(−8.3, 0.5)
All ages	**2.6**	(0.1, 5.2)	−2.4	(−5.5, 0.9)	−1	(−4.3, 2.3)
Men	2.5	(−0.5, 5.6)	−2.9	(−6.7, 0.1)	1.3	(−2.7, 5.5)
Women	2.8	(−0.5, 6.1)	−1.8	(−5.8, 2.4)	−3.6	(−7.6, 0.6)

Estimates significant at the 95% level are marked as bold.

Table 4. Relative risk (RR) in % associated with a 1 mm increase of rainfall per lag strata

	Lag 0–1		Lag 2–6		Lag 7–13	
Age group	RR	CI (95%)	RR	CI (95%)	RR	CI (95%)
0–4	0.01	(−0.8, 0.8)	0.06	(−1.2, 1.4)	0.2	(−1.4, 1.8)
5–19	0.02	(−1.3, 1.3)	**2.4**	(0.5, 4.5)	0.6	(−2.0, 0.6)
20–59	−0.23	(−1.5, 1.1)	0.3	(−1.7, 2.3)	**−3.3**	(−2.1, −0.7)
60+	−0.05	(−1.08, 0.1)	**1.9**	(0.3, 1.9)	0.01	(−2.1, 2.2)
All ages	−0.04	(−0.7, 0.6)	0.8	(−0.3, 1.8)	−0.3	(−1.6, 1.0)
Men	−0.07	(−0.1, 0.8)	0.8	(−0.6, 2.1)	−0.5	(−2.1, 1.2)
Women	−0.01	(−0.8, 0.8)	0.8	(−0.5, 2.0)	−0.1	(−1.7, 1.5)

Estimates significant at the 95% level are marked as bold.

increased risk and relative risk (RR) when developing adaptive measures to protect against harmful effects from weather and climate changes.

At present, childhood mortality seems to be most affected by high temperature and children suffer the most from extreme heat conditions resulting from climate change. If this continues, it may partly hinder the overall aim of reducing child mortality.

These results indicate that rural populations in sub-Saharan Africa are likely to experience harmful effects from increasing heat levels from climate change as suggested by the IPCC (17).

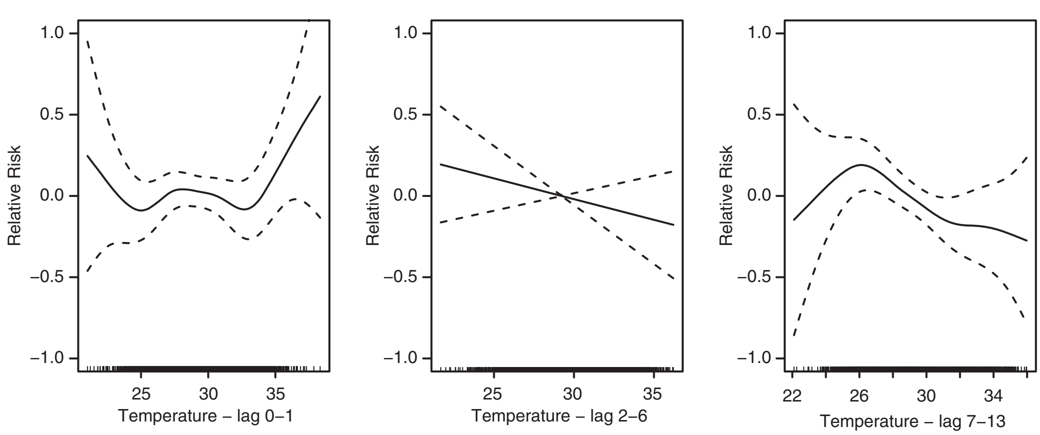

Fig. 4. The association between temperature and elderly (60+ of age) daily mortality in Nouna, Burkina Faso, over the lag 0–1, 2–6, and 7–13 (from left to right). The scale of the vertical axis is the log (relative risk [RR]), 95% confidence limits are shown as dotted lines.

Table 5. Sensitivity analysis for df = 8: Relative risk (RR) in % associated with a 1°C increase of temperature per lag strata

	Lag 0–1		Lag 2–6		Lag 7–13	
Age group	RR	CI (95%)	RR	CI (95%)	RR	CI (95%)
0–4	**4.04**	(4.0, 7.8)	−2.32	(−7.0, 2.6)	−1.3	(−6.6, 4.3)
5–19	1.23	(−4.0, 6.8)	−3.54	(−10.4, 3.9)	−7.2	(−14.7, 0.9)
20–59	2.6	(−1.6, 6.9)	−4.14	(−9.4, 1.4)	2.4	(−3.9, 9.2)
60+	1.8	(−1.8, 5.6)	−0.8	(−5.5, 4.1)	−1.7	(−6.8, 3.7)
All ages	**2.9**	(0.29, 5.6)	−2.3	(−5.7, 1.2)	−1.0	(−4.9, 2.9)
Men	2.89	(−0.3, 6.2)	−2.7	(−6.7, 1.6)	1.3	(−3.4, 16.3)
Women	2.89	(−0.5, 6.4)	−2.0	(−6.3, 2.5)	−3.7	(−8.4, 1.3)

Estimates significant at the 95% level are marked as bold.

Table 6. Sensitivity analysis for df = 8: Relative risk (RR) in % associated with a 1 mm increase of rainfall per lag strata

	Lag 0–1		Lag 2–6		Lag 7–13	
Age group	RR	CI (95%)	RR	CI (95%)	RR	CI (95%)
0–4	0.06	(−0.8, 0.9)	0.2	(−1.4, 1.8)	0.4	(−1.6, 2.3)
5–19	−0.7	(−2.2, 0.8)	0.7	(−2.1, 3.7)	−1.2	(−4.3, 2.0)
20–59	−0.1	(−1.5, 1.2)	0.6	(−1.8, 3.0)	−3.2	(6.1, −0.2)
60+	−0.1	(−1.3, 1.0)	1.8	(−0.2, 3.9)	0.02	(−2.5, 2.7)
All ages	−0.8	(−0.8, 0.6)	0.7	(−0.6, 2.0)	−0.3	(−1.9, 1.2)
Men	2.9	(−0.3, 6.2)	−2.7	(−6.7, 1.6)	1.3	(−3.4, 6.3)
Women	0.05	(−0.8, 0.9)	1.1	(−0.5, 2.6)	0.4	(−1.5, 2.4)

However, there are several limitations in this study. First, we used population-level exposures to temperature and rainfall, which within the HDSS can vary. In particular, rainfall is often more heterogeneous in space. However, due to the lack of spatial and temporal finely resolved data such exposure differences cannot be taken into account. Moreover, there was a large number of missing observations of, primarily, rainfall but also temperature. This will have reduced the statistical reliability of the study, but is unlikely to have caused any systematic errors. Furthermore, the clustering of events on the 1st and 15th of each month also weakened the study, but there is currently no reason to suspect that the events that were removed caused any systematic bias in the estimates.

Conclusion

Our study highlighted that the population in Nouna, Burkina Faso, experience short-term increases in mortality in relation to specific meteorological events. In particular, those under five years of age appear more susceptible to hot temperatures, while the elderly population is more susceptible to increasing levels of rainfall. However, the elderly population appeared to be affected by both low and high temperatures – resembling a u-shaped relationship similar to those estimated on the elderly populations in developed cities. However, future studies are needed to confirm this.

Overall, mortality patterns in the Nouna HDSS appear to be closely related with short-term weather conditions; hence, further investigation on cause-specific mortality, vulnerability, and susceptibility factors to better understand the particular effects of weather and climate change on population health in rural areas of sub-Saharan Africa is required.

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A time series analysis of weather variability and all-cause mortality in the Kasena-Nankana Districts of Northern Ghana, 1995–2010

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Introduction: Climate and weather variability can have significant health consequences of increased morbidity and mortality. However, today the impact of climate and weather variability, and consequentially, of climate change on population health in sub-Saharan Africa is not well understood. In this study, we assessed the association of daily temperature and precipitation with daily mortality by age and sex groups in Northern Ghana.

Methods: We analysed daily mortality and weather data from 1995 to 2010. We adopted a time-series Poisson regression approach to examine the short-term association of daily mean temperature and daily mean precipitation with daily mortality. We included time factors and daily lagged weather predictors. The correlation between lagged weather predictors was also considered.

Results: For all populations, a statistically significant association of mean daily temperature with mortality at lag days 0–1 was observed below and above the 25th (27.48°C) and 75th (30.68°C) percentiles (0.19%; 95% confidence interval CI: 0.05%, 0.21%) and (1.14%; 95% CI: 0.12%, 1.54%), respectively. We also observed a statistically significant association of mean daily temperature above 75th percentile at lag days 2–6 and lag days 7–13 (0.32%; 95% CI: 0.16%, 0.25%) and (0.31% 95% CI: 0.14%, 0.26%), respectively. A 10 mm increase in precipitation was significantly associated with a 1.71% (95% CI: 0.10%, 3.34.9%) increase in mortality for all ages and sex groups at lag days 2–6. Similar results were also observed at lag days 2–6 and 14–27 for males, 2.92% (95% CI: 0.80%, 5.09%) and 2.35% (95% CI: 0.28%, 4.45%).

Conclusion: Short-term weather variability is strongly associated with mortality in Northern Ghana. The associations appear to differ among different age and sex groups. The elderly and young children were found to be more susceptible to short-term temperature-related mortality. The association of precipitation with mortality is more pronounced at the short-term for all age and sex groups and in the medium short-term among males. Reducing exposure to extreme temperature, particularly among the elderly and young children, should reduce the number of daily deaths attributable to weather-related mortality.

Keywords: *mortality*; *temperature*; *precipitation*; *time series analysis*; *distributed lag model*; *season*

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Climate and weather variability can have significant health consequences, resulting in increases in morbidity and mortality (1–3). However, their impact on people living in tropical regions has not been as well described. The prevention of deaths caused by extreme weather conditions, including temperatures and precipitation is an issue of importance concerning public health (4, 5). There is a continuous flow of hospitalizations and deaths attributed to extreme ambient temperatures (3, 6). Elevated short-term weather variations are known to be associated with morbidity and mortality, including heatwaves (3), cold exposure (7), and heavy rains and dust (8). Studies on the relationship between weather variations and mortality are common in high-income countries but limited in low- and middle-income countries.

Projections of future climate scenarios suggest that higher global mean temperatures could result in marked changes in the frequency of temperature extremes and

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could result in substantial increase in temperature-related mortality (9). Quantification of the population mortality burden attributable to adverse changes in weather conditions are essential for planning of adaptive approaches to minimize the impact of climate change on population, particularly in less developed countries in sub-Saharan Africa.

For instance, in Northern Ghana, drastic changes in weather conditions occur every year. The Harmattan season (December–February) is usually characterized by very cold weather conditions in the early morning followed by very hot temperature, sometimes above 40°C, during the day. On the contrary, during the peak of the wet season (July–August), the weather is usually characterized by heavy rainfall and flooding, sometimes destroying houses and displacing families. However, the extent of the association of these weather conditions with population health is currently unknown. Studies in Europe and North America have shown significant association between increases in mortality and elevated temperature, measured by maximum or minimum temperature, heat index, and sometimes, other weather indices (10). The elderly, young children, and the poor and the sick are particularly at risk (3, 11, 12).

Studies in tropical countries have also shown that there is strong seasonal variation in *Plasmodium falciparum* malaria infection incidence with the peak observed in August and September, which corresponds to the peak of the rainy season (13, 14). Therefore, a better understanding of the factors that increase mortality as a result of the association of temperature and precipitation are needed to adequately define high-risk groups among the population. In this study, we assessed the association between temperature and precipitation on all-cause mortality in Northern Ghana.

Methods and materials

The study was conducted in the Kassena-Nankana District[1] (KND) of the Upper East region of Ghana, which covers an area of 1,675 km^2 in size, and is between latitude 10° 30′ and 11°00′ north and longitude 0°50′ and 1°30′ west of the equator. Ecologically, the area is in the guinea savanna belt, characterized by semi-arid conditions with the vegetation consisting of grassland interspersed with short trees. There are two main seasons, the dry and wet seasons, which are influenced by two main air masses – the North-East Trade winds (Harmattan air mass) and the South-Westerlies (Tropical Maritime air mass), respectively. During the dry season (November–April), these winds are usually dry and dusty as they originate from the Sahara Desert. Minimum and maximum temperature during the day can range from 38°C to 42°C and night temperatures can fall below 18°C. During such periods, precipitation is virtually absent due to low relative humidity, which rarely exceeds 20%. During the wet season (May–October), the district experiences the tropical maritime air mass, which comes along with precipitation. Annual precipitation figures are in the range of 850 mm and 950 mm.

Previous studies have described the health profile of the people in the district (15–18). Malaria and diarrhea continue to account for a large proportion of deaths (14, 19, 20), but a recent study has shown a gradual transition from infectious disease to non-communicable disease (15).

Mortality data for the study comes from the longitudinal population surveillance data of the Navrongo Health and Demographic Surveillance System (NHDSS). Starting with an initial census of the population in July 1993, the HDSS has continuously followed the population every 4 months, monitoring vital events, including births, deaths, and in and out migrations. Mortality variables were stratified by sex and four categorized age groups: (0–4), (5–19), (20–59), and (60+). Table 1 summarizes the mean, maximum, and minimum daily mortality in the dataset. Weather data (daily minimum, maximum temperature and daily precipitation data) from January 1995 to December 2010 were obtained from the Navrongo Meteorology Station. Daily mean temperature data were aggregated from daily minimum and maximum temperatures, an index designed to better estimate exposure as it uses multiple observations per day and so should be less prone to measurement error compared with other temperature indices (21).

Statistical analysis

We used a time series Poisson regression approach allowing for over-dispersion (for the mortality versus precipitation model) that included time-varying factors, such as time trend and season. We used a range of short-term lags of daily weather variables to assess the

Table 1. Summary statistics of daily mortality data by age and sex in the Kassena-Nankana Districts (KNDs) of Northern Ghana (1995–2010)

Population groups	Daily mortality count(*n*)	Mean deaths	SD	Min–max	Percent (%)
All	31,144	5.3	2.4	0.1–21.2	100
Age group					
0–4	8,551	1.5	1.3	0.0–11.0	27.5
5–19	2,315	0.4	0.5	0.0–4.6	7.4
20–59	9,417	1.6	1.1	0.0–7.8	30.2
60+	10,861	1.9	1.2	0.0–9.1	34.9
Gender					
Female	14,812	2.5	1.5	0.0–14.0	47.6
Male	16,332	2.8	1.6	0.1–12.2	52.4

[1]In 2008, a new district, Kassena-Nankana West District, was carved out of the initial Kassena-Nankana District. Consequently, the NDSS now covers two districts.

association between daily mean temperature and precipitation on mortality.

The daily mortality data from the NHDSS has some groupings of deaths on the 15th day of the month. This follows an earlier practice by field staff to record the 15th day of the month if the exact date of death could not be established. The date of death grouping was taken care of by replacing the deaths on the 15th day of each month with the monthly average. The remaining deaths for the given month were then distributed equally across the days of the month.

We fitted models to assess the association of mean daily temperature and precipitation on all-cause mortality by age groups and gender. We assumed that mortality patterns in the study area could be driven by a range of mediating factors (disease mechanisms) that are weather related. Adjustment for time trends and seasonality were done using natural cubic spline functions allowing for fixed (3) degrees of freedom (df) per year. The association of precipitation on daily mortality was statistically tested and found to be linear. We tested the sensitivity of the df of the smooth function of time trend by allowing for different df (i.e. 2, 3, 4, 6 and 8). Similarly, the df for the smooth function for the lag days temperature and precipitation variables were tested for sensitivity using df ranging from 2 to 6. We tested the association of 0–1, 2–6, 7–13, and 14–27 lag days of precipitation on mortality and chose to exclude results for 7–13 lag days for precipitation. Similarly, the lag day terms tested for association between temperature and mortality were of 0–1, 2–6, and 7–13. These lag strata are the mean of daily temperature and precipitation of lag day periods. Model fit was assessed using deviance statistic and Akaike Information Criterion (AIC) to arrive at a more parsimonious model. In addition, partial autocorrelation, heteroscedasticity and Q-Q plots were used to assess model assumptions.

We estimated the relative risks (RRs) for the association of daily mean temperature and precipitation with daily mortality using lag strata. The cumulative lag day's association for temperature was calculated for all lag days at the 25th and 75th percentile assuming linearity. The RRs for precipitation were fitted as linear terms, as suggested above. Days within the study period without data on temperature and precipitation were treated as missing values in the analysis. Data preparation and analysis were carried out using Stata version 11.2 (Stata Corp., College Station, TX), whereas regression models were fitted using the statistical software R version 2.12.1 Copyright (C) 2010 (The R Foundation for Statistical Computing).

Results

The total deaths reported within the period (1995–2010) were 31,144. A longitudinal analysis shows that the study area has witnessed a general decline in all-cause mortality over the study period (results not shown). Most of the deaths occurred among the older population, that is, 60+ (34.9%), while the highest maximum daily deaths occurred among children younger than age 5 (11.0). Average daily mortality was relatively raised round the 90th day of the year coinciding with the peak of the temperature period (March–April). However, the peak in mortality seems a little delayed compared with the peak in precipitation as shown in Fig. 1. Minimum and maximum daily temperature and precipitation are also shown in Table 2.

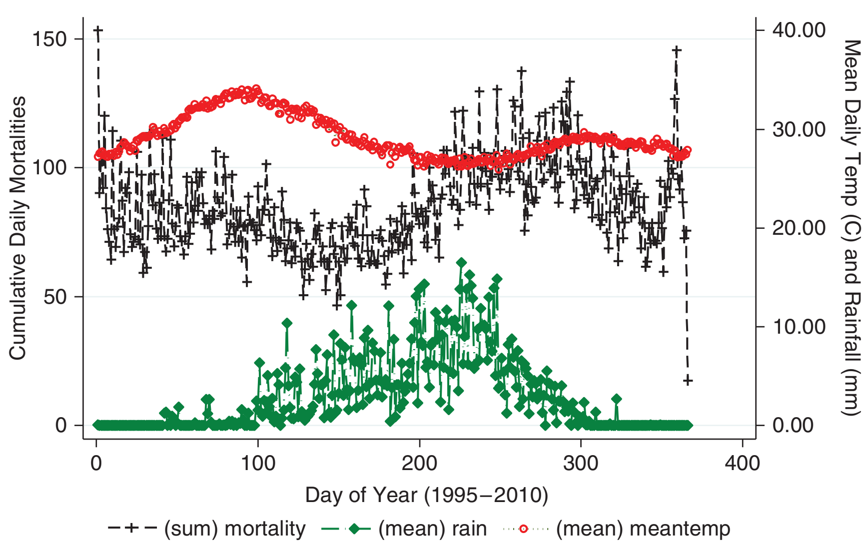

Fig. 1. Seasonal pattern in daily mortality, daily mean temperature and precipitation in the Kassena-Nankana Districts (KNDs) of Northern Ghana (1995–2010).

Table 2. Summary statistics of daily temperature and precipitation in the Kassena-Nankana Districts (KNDs) of Northern Ghana (1995–2010)

Variable	Mean	SD	Min	Max	25th	75th	% missing
Temperature (°C)							
Maximum	35.3	3.8	20.4	44.2	32.5	35.6	4.0
Minimum	23.0	2.8	12.1	33.0	21.3	23.0	4.0
Mean	29.2	2.7	21.4	37.0	27.3	30.8	4.0
Precipitation (mm)	3.0	9.3	0.0	93.0	0.0	0.0	5.5

Association of daily mean temperature (°C) on daily mortality over lagged strata

The relationship between daily mean temperature and mortality is generally 'U' shaped for the short-term lag days of mean daily temperature (Fig. 2). There is a decrease in mortality from lower temperature up to about 30°C and then an increase upwards with increasing temperature. The thresholds for the 25th and 75th percentiles for the lag strata are 27.4°C and 30.6°C, respectively. The relationship tends to be linear for the association between temperature and mortality for lag days 2–6 among the 5–19 years age group and lag days 0–1 and 7–13 for the 20–59 years age group (results not shown).

For all populations, a statistically significant association of mean daily temperature on mortality at lag days 0–1 was observed below and above the 25th and 75th percentiles (*p*-value 0.029 and 0.008), respectively (Table 3). We also observed a statistically significant association of mean daily temperature above 75th (30.6°C) percentile for lag days 2–6 and 7–13 but not at the 25th percentile (27.4°C), as shown in Table 3. However, the cumulative effect of lag days at the 25th and 75th percentiles were 1.0% (95% confidence interval [CI]: −0.8%, 2.8%) and 1.8% (95% CI: 0.7%, 2.9%), respectively (Table 4).

The results also show that a 1°C increase in mean daily temperature above the 75th percentile at lag days 2–6 and 7–13 was significantly associated with an increase in risk of mortality among children younger than age 5 (Fig. 3), 0.7% (95% CI: 0.4%, 0.5%) and 0.5% (95% CI: 0.2%, 0.5%), respectively (Table 3).

Among children aged 5–19 years, temperature at the 75th percentile of lag days 7–13 was significantly associated with mean daily mortality 0.7% (95% CI: 0.2%, 0.7%).

Among the elderly adults, 60+, the only significant (10% level of significance) association of temperature was observed at lag days 0–1 below and above the 25th and 75th percentiles (Fig. 4). Among this age group, the cumulative lagged days' associations were estimated to be 0.8% (95% CI: −2.1%, 3.7%) and 1.8% (95% CI: 0.2%, 3.5%), respectively, for the 25th and 75th percentiles (Table 3). Cumulatively, the lag days were not significantly associated with mortality below the 25th percentile 1.0% (95% CI: −1.5%, 3.5%) but significant at the 75th percentile 1.5% (95% CI: 0.1%, 3.0%) (Table 4).

Mortality among men seems to be higher per 1°C increase in daily mean temperature above the 30.6°C threshold for all the lag days but this was more pronounced in the 0–1 lag days (Table 3). Also, the cumulative association of the lag days strata were estimated to be 2.1% (95% CI: −1.4%, 3.4%) and 2.0% (95% CI: 0.6%, 3.4%), respectively, at the 25th and 75th percentiles (Table 4).

Association of daily precipitation (mm) on daily mortality over lagged strata

Precipitation in the study area has a linear relationship with daily mortality (Fig. 5). The results show that short-term precipitation has an increasing association on mortality among the whole population (Table 5). A 10-mm increase in precipitation was found to be associated with a 1.7% (95% CI: 0.1%, 3.3%), at lag days 2–6 for the whole population (Table 5).

For children younger than age 5, the association of a 10-mm increase in precipitation though was not observed

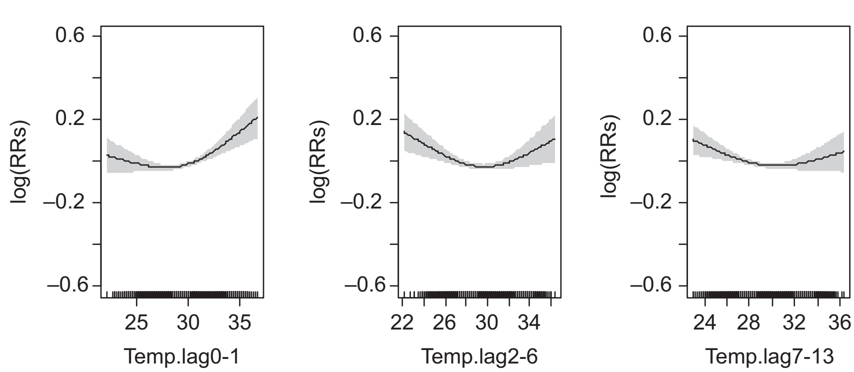

Fig. 2. Relative risks (RRs) of daily mortality among age and sex groups with daily mean temperature over lagged strata. Gray regions are corresponding 95% confidence intervals.

Table 3. Percent increase (95% confidence interval [CI]) for all cause daily mortality associated with 1°C increase in mean daily temperature

Variable	Effect estimates			
	25th percentile		75th percentile	
Temperature (C)	% increase	95% CI	% increase	95% CI
All cause				
Lag 0–1	**0.19**	**(0.05, 0.21)**	**1.14**	**(0.12, 1.54)**
Lag 2–6	0.75	(−0.53, 1.94)	**0.32**	**(0.16, 0.25)**
Lag 7–13	0.06	(−1.21, 1.95)	**0.31**	**(0.14, 0.26)**
Males				
Lag 0–1	**0.22**	**(0.03, 0.28)**	1.11	(−0.23, 2.04)
Lag 2–6	0.82	(−0.86, 2.56)	**0.43**	**(0.21, 0.34)**
Lag 7–13	−0.04	(−1.72, 2.58)	**0.43**	**(0.21, 0.34)**
Female				
Lag 0–1	0.15	(−0.03, 0.28)	1.16	(−0.23, 2.11)
Lag 2–6	0.67	(−1.06, 2.64)	0.20	(−0.03, 0.35)
Lag 7–13	0.18	(−1.55, 2.66)	0.17	(−0.06, 0.35)
Age groups 0–4				
Lag 0–1	0.05	(−0.19, 0.36)	0.61	(−1.20, 2.78)
Lag 2–6	−0.13	(−2.37, 3.48)	**0.67**	**(0.36, 0.47)**
Lag 7–13	1.14	(−1.14, 3.51)	**0.50**	**(0.19, 0.47)**
Age groups 5–19				
Lag 0–1	0.34	(−0.05, 0.58)	2.35	(−0.40, 4.20)
Lag 2–6	3.08	(−0.40, 5.31)	0.38	(−0.05, 0.66)
Lag 7–13	0.63	(−2.77, 5.33)	**0.66**	**(0.22, 0.66)**
Age groups 20–59				
Lag 0–1	0.14	(−0.09, 0.35)	0.52	(−1.11, 2.50)
Lag 2–6	0.33	(−1.71, 3.15)	0.19	(−0.08, 0.40)
Lag 7–13	−0.39	(−2.42, 3.17)	0.14	(−0.13, 0.41)
Age groups 60+				
Lag 0–1	**0.29**	**(0.07, 0.33)**	1.52	(−0.09, 2.45)
Lag 2–6	1.09	(−0.92, 3.08)	0.12	(−0.14, 0.40)
Lag 7–13	−0.63	(−2.62, 3.10)	0.19	(−0.07, 0.40)

Note: Bold figures show statistical significant results.

to be significantly related with daily mortality, a higher risk was observed with increasing lagged days: 0.4% (95% CI: −2.4%, 3.3%), 1.4% (95% CI: −1.3%, 4.1%), and 1.8% (95% CI: −0.8%, 4.5%) for lag days 0–1, 2–6, and 14–27, respectively (Table 5).

Even though the association of 10 mm increase in precipitation at lag days 0–1, 2–6, and 14–27 strata among the age groups were found not to be statistically significant, the association of precipitation with gender presented mixed results. While mortality among females does not seem to be affected by both short-term and medium short-term lag days of precipitation, mortality among males seems to be more relatively affected by long-term lag days (between 2 and 4 weeks) (Table 5).

For instance, daily mortality per a 10-mm increase in precipitation among females were observed to be 0.6% (95% CI: −1.7%, 2.8%), 0.4% (95% CI: −1.8%, 2.6%), and 0.0% (95% CI: −2.1%, 2.1%), respectively, at lags days 0–1, 2–6, and 14–27 (Table 5). Similarly for males, the association with mortality per a 10-mm increase in precipitation were 1.8% (95% CI: −0.4%, 4.0%) at lag days 0–1, 2.9% (95% CI: 0.8%, 5.1%) at lag days 2–6, and 2.3% (95% CI: 0.3%, 4.5%) at lag days 14–27 (Fig. 6 and Table 5).

Discussion

Northern Ghana like other tropical climatic regions is characterized by seasonal variations in climatic conditions. However, there are no known studies or only few studies have examined the association between weather variation and mortality. The results show that both short-term daily mean temperature and long-term

Table 4. Cumulative lag effect as a percent increase (95% confidence interval [CI]) for all cause mortality associated with 1°C increase in mean daily temperature

	Cumulative effect at 25th percentile for all lags		Cumulative effect at 75th percentile for all lags	
Category	% increase	95% CI	% increase	95% CI
All cause	1.00	(−0.82, 2.84)	**1.78**	**(0.73, 2.85)**
Male	0.99	(−1.39, 3.43)	**1.99**	**(0.60, 3.40)**
Female	1.00	(−1.45, 3.52)	**1.54**	**(0.11, 2.99)**
Age groups 0–4	1.06	(−2.15, 4.37)	1.79	(−0.09, 3.71)
Age groups 5–19	4.08	(−0.87, 9.27)	**3.42**	**(0.57, 6.35)**
Age roups 20–59	0.08	(−2.80, 3.05)	0.85	(−0.83, 2.56)
Age groups 60+	0.75	(−2.09, 3.68)	**1.84**	**(0.18, 3.53)**

Note: Bold figures show statistical significant results.

excess precipitation have a significant association on all-cause mortality in the whole population.

The cumulative association of temperature over the lag strata was estimated to be 1.8% higher per 1°C increase in daily mean temperature (above 30.6°C) on all-cause mortality across the whole population. Our study has corroborated well with previous studies showing that the elderly in society are among the most vulnerable groups during periods of increase in temperature (3, 11). For instance, Hales et al. (22) in their study found that a 1.8°F increase in temperature was associated with 1% (95% CI: 04%, 2.1%) in all-cause mortality.

Furthermore, we found that the association of temperature above the 75th percentile between lag weeks 1 and 2 was significant with a relative risk of 0.7% (95% CI: 0.2%, 0.7%) among children and young adolescents in the 5–19 age group. However, in the 20–59 age group, the effect was not significant.

Furthermore, we found that mortality related to long-term association of excess precipitation dramatically increased per a 10-mm increase in precipitation with an associated risk of 2.3% (95% CI: 0.3%, 4.5%) and 2.9% (95% CI: 0.8%, 5.1%) in the short-term and medium short-term lag days, respectively, among the male population.

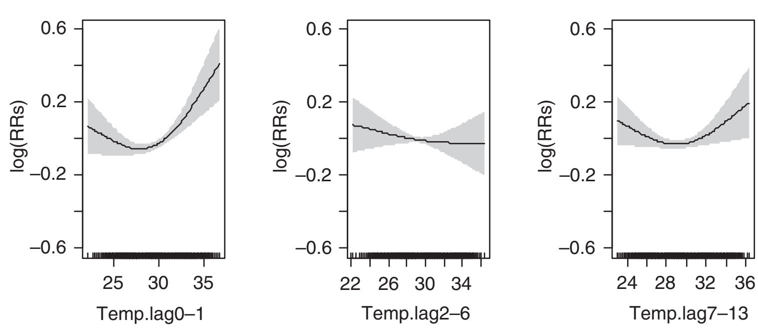

Fig. 3. Relative risks (RRs) of daily mortality among children under 5 years of age with daily mean temperature over lagged strata. Gray regions are corresponding 95% confidence intervals.

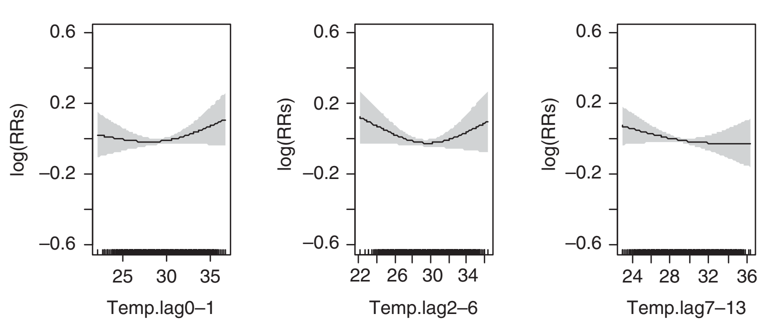

Fig. 4. Relative risks (RRs) of daily mortality among adults 60 years and above with daily mean temperature over lagged strata. Gray regions are corresponding 95% confidence intervals.

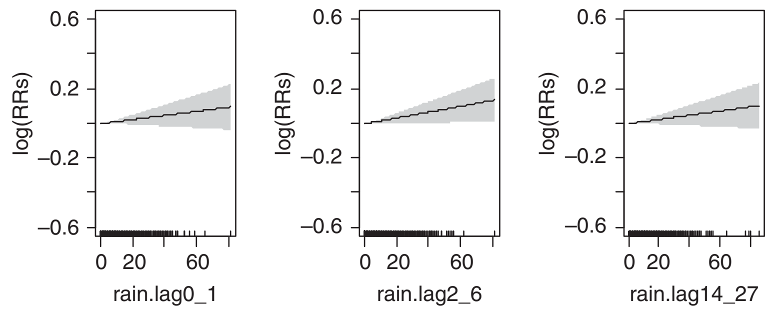

Fig. 5. Relative risks (RRs) of daily mortality among all age and sex groups with daily precipitation over lagged strata. Gray regions are corresponding 95% confidence intervals.

Higher precipitation patterns may increase the burden of mortality as a result of increase in the risk of infectious diseases, such as malaria, diarrhea, and respiratory infections. Coincidentally, incidences of these diseases among the vulnerable populations are heightened during the peak raining season. Malaria is the most widespread disease in the districts during this time of the year, affecting both infants and the elderly (14). In a previous study by Armah et al. (23), it was found that diarrhea and mortality also peak during the wet season and may explain the excess mortality that have been observed in our study. One previous study showed that any precipitation, 4 days prior, was significantly associated with an 11% increase in acute gastrointestinal illness visits to pediatric emergency department (24). In a study on the seasonal pattern of pneumonia-related mortality among children younger than age 5, Ye et al. (25) provided evidence that mortality in this age group in Nairobi's slums peaks during the rainy season. The explanations for this association are varied and as this study did not examine the associations between precipitation and cause-specific mortality, we are presently not in a position to explain the reasons for the association of precipitation with the male gender.

Table 5. Percent increase (95% confidence interval [CI]) for all cause daily mortality associated with 10 mm increased in precipitation

Variable Precipitation (mm)	Linear effect %	 95% CI
All cause		
Lag 0–1	1.19	(−0.46, 2.87)
Lag 2–6	1.71	(0.10, 3.34)
Lag 14–27	1.22	(−0.35, 2.81)
Males		
Lag 0–1	1.79	(−0.39, 4.00)
Lag 2–6	2.92	(0.80, 5.09)
Lag 14–27	2.35	(0.28, 4.45)
Female		
Lag 0–1	0.55	(−1.67, 2.82)
Lag 2–6	0.38	(−1.77, 2.59)
Lag 14–27	−0.02	(−2.13, 2.13)
Age groups 0–4		
Lag 0–1	0.42	(−2.39, 3.32)
Lag 2–6	1.36	(−1.34, 4.13)
Lag 14–27	1.84	(−0.75, 4.51)
Age groups 5–19		
Lag 0–1	−3.04	(−7.63, 1.78)
Lag 2–6	0.42	(−4.07, 5.12)
Lag 14–27	0.33	(−4.15, 5.03)
Age groups 20–59		
Lag 0–1	1.86	(−0.90, 4.70)
Lag 2–6	2.09	(−0.62, 4.88)
Lag 14–27	−0.24	(−2.90, 2.50)
Age groups 60+		
Lag 0–1	2.11	(−0.43, 4.70)
Lag 2–6	1.92	(−0.57, 4.47)
Lag 14–27	1.78	(−0.64, 4.27)

The study area has witnessed a couple of meningitis epidemics in recent years, mostly at a time when temperature is at its peak (March–April). Previous studies conducted in the study area have shown that more deaths attributable to meningitis have been observed in the dry seasons compared to any time of the year (26, 27). This could be explained by the long dry and hot season coupled with the housing architecture (poor ventilation) and sleeping arrangement of the population during these hot weather conditions. In a study by Scovronick et al. (28) in South Africa, the authors found that future mortality burdens would be reduced by over 50% (approximately 5,000 deaths annually) under a development policy that prioritizes the replacement of informal housing compared to one that prioritizes the replacement of traditional dwellings. Our results have highlighted the population groups that are most vulnerable to excess weather conditions, thus allowing for the formulation of better policy interventions to minimizing the adverse effects of climate change on population health in Northern Ghana.

There are some potential limitations to this study. First, some deaths in the HDSS data were recorded on the 15th day of the month when data collectors fail to

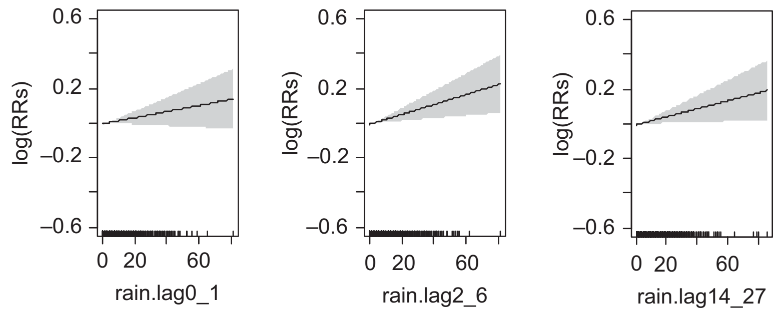

Fig. 6. Relative risks (RRs) of daily mortality among males with daily precipitation over lagged strata. Gray regions are corresponding 95% confidence intervals.

establish the exact date of death. In the analysis, we addressed this problem by replacing the deaths on the 15th day of the month with the monthly average number of deaths and then redistributing the rest of the deaths equally across the days of the month. This methodological approach of handling age grouping has not been reported in the research literature and, therefore, needs further investigation and validation. Second, we also did not adjust for confounding factors, such as air pollution (visibility), on the association between temperature and mortality. Previous studies have been able to establish mediating effect of air pollution on the association between daily mean temperature and mortality (29, 30). Finally, the weather data contained about 4% missing values. However, these data were randomly distributed and adjusted for in the analysis and, therefore, could not affect the validity of our results.

Conclusion

This study has explored the relationship between temperature and precipitation variability with all-cause mortality to inform climate adaptation interventions in Northern Ghana. We provide evidence of increase in mortality associated with short-term increase in daily mean temperature exposure, particularly during the dry season on vulnerable populations, especially the young and elderly. We also observed statistically significant increased mortality associated with excess precipitation at medium short-term among males. The RRs associated with increased short-term daily mean temperature above the upper threshold seems to be stronger than short-term cool association and thus poses a serious public health hazard in the light of the global warming.

These new results provide a good basis for further research to elucidate the health impact and risk factors related to weather and climate change in Northern Ghana. They also support the call to develop interventions to control human activities on climate change and establish stronger public health systems to handle the consequences that future adverse climatic conditions will have on the population's health in Northern Ghana.

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Time-series analysis of weather and mortality patterns in Nairobi's informal settlements

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Background: Many studies have established a link between weather (primarily temperature) and daily mortality in developed countries. However, little is known about this relationship in urban populations in sub-Saharan Africa.

Objectives: The objective of this study was to describe the relationship between daily weather and mortality in Nairobi, Kenya, and to evaluate this relationship with regard to cause of death, age, and sex.

Methods: We utilized mortality data from the Nairobi Urban Health and Demographic Surveillance System and applied time-series models to study the relationship between daily weather and mortality for a population of approximately 60,000 during the period 2003–2008. We used a distributed lag approach to model the delayed effect of weather on mortality, stratified by cause of death, age, and sex.

Results: Increasing temperatures (above 75th percentile) were significantly associated with mortality in children and non-communicable disease (NCD) deaths. We found all-cause mortality of shorter lag of same day and previous day to increase by 3.0% for a 1 degree decrease from the 25th percentile of 18°C (not statistically significant). Mortality among people aged 50+ and children aged below 5 years appeared most susceptible to cold compared to other age groups. Rainfall, in the lag period of 0–29 days, increased all-cause mortality in general, but was found strongest related to mortality among females. Low temperatures were associated with deaths due to acute infections, whereas rainfall was associated with all-cause pneumonia and NCD deaths.

Conclusions: Increases in mortality were associated with both hot and cold weather as well as rainfall in Nairobi, but the relationship differed with regard to age, sex, and cause of death. Our findings indicate that weather-related mortality is a public health concern for the population in the informal settlements of Nairobi, Kenya, especially if current trends in climate change continue.

Keywords: *time-series*; *temperature*; *rainfall*; *mortality*; *climate*; *urban*

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Climate change arising from human activity has been acknowledged as both an environmental and public health concern. The World Meteorological Organization (WMO) estimates that globally averaged temperatures in 2011 were 0.40°C above the 1961–1990 annual average of 14°C. East Africa was the sixth-warmest region at 1.17°C above normal (1). There is growing evidence that an increase in temperature is associated with short-term increase in morbidity and mortality in several cities across the world (2–6). However, a warmer climate could also correspond to decreases in cold-related mortality, although this has recently been questioned (7). To date, the extent to which cold-related mortality is a problem in East Africa has hardly been explored in the literature. The groups most vulnerable to increasing temperatures are older people and those with pre-existing conditions, such as cardiovascular and respiratory illnesses (3, 5). Some studies have also found that children aged below 5 years are vulnerable as well (8). The effect of rising temperatures is amplified in urban areas where ambient temperatures are compounded by the interaction between air pollution and

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temperature, the ‘urban heat island effect’ (3), and urban sprawl (9).

The developing world is rapidly urbanizing and estimates show that urban centers will house about 60% of the global population by 2030, with major growth occurring in developing countries. Because of rapid urbanization in periods of poor economic performance, slum settlements are set to increase and population estimates indicate that 41% of global urban population will reside in slums by year 2030 (10). Poor housing characterized by temporary structures is a common feature of slum settlements with most ill-equipped to deal with any adverse events associated with climate change. In addition, increasing urban poverty consigns slum residents to live on the edge with little or no resources to deal with climate-change-related events, including sudden onset of ill health brought on by extreme high or low temperatures (11, 12).

Most studies on temperature-related mortality have been conducted in temperate regions, but little is known about this relationship in developing countries, especially in sub-Saharan Africa. Most sub-Saharan countries lack reliable health outcome data to enable analysis of the impact of weather factors on health. Health Demographic Surveillance Systems (HDSS) provide an opportunity for analyzing the impact of weather on health by providing longitudinal mortality data that allow for time-series analysis. This study investigates:

(i) the existence of a seasonal pattern in mortality in the Nairobi population,
(ii) the relationship between daily mortality and weather variables (temperature and rainfall), and
(iii) the association between weather and mortality by age, gender, and cause of death.

Overall, this study facilitates a better understanding of weather-related mortality patterns in sub-Saharan Africa and, to the best of our knowledge, the study is the first to explore the weather–mortality linkage for an urban population in Kenya.

Materials and methods

Study area and population

The study area covered two informal settlements of Korogocho and Viwandani in Nairobi, which are covered by the Nairobi Urban Health and Demographic Surveillance System (NUHDSS) run by the African Population and Health Research Center. The population under surveillance as on 31 December 2008 was 60,416 individuals from 24,875 households. The study area was characterized by overcrowding, poor sanitation, and poor access to basic health care services. The population in the NUHDSS was mostly youth drawn to the city by the job opportunities (13). The health of the population under surveillance was characterized by high prevalence of infectious diseases and an increasing burden of non-communicable diseases (NCDs). Among the under-five population, diarrheal diseases, perinatal causes, and pneumonia were the leading causes of mortality, whereas HIV and tuberculosis were the major causes of mortality among the population aged five and above (14).

Nairobi city is situated about 1,700 meters above sea level, giving the city a sub-tropical climate. The average daily minimum and maximum temperatures is 11°C and 26°C, respectively. In Nairobi, there are two rainy seasons in a year with the long rainy season from March to May and the short rainy season from October to December. The period from June to August is typically dry and cold, with daily minimum and maximum temperatures reaching 10°C and 21°C, respectively, whereas September, January, and February are hot and dry with daily maximum temperature of 24°C (15, 16).

Data

Daily mortality data for the study period 2003–2008 was obtained from routinely collected data by the NUHDSS. The analyses were carried out within four age groups: 0–4, 5–19, 20–49, and over 50 years. Age fifty was used as a lower threshold of old age in sub-Saharan Africa based on life expectancy and biomarkers of ageing and the social construction (17, 18). Ascertaining cause of death at NUHDSS was done through the verbal autopsy procedure, which is based on recollections of the deceased person’s close relative/caregiver, with the most detailed and credible information regarding the circumstances leading to the death of the individual. Where a close relative or household member cannot be found either due to family relocation after the death or because the deceased lived alone, a credible neighbor is interviewed. Two physicians reviewed verbal autopsy records and when they both agreed on a probable cause of death, it was assigned. If they did not agree, a third physician convened a consensus meeting with the other two, where the disagreement was discussed and if two out of the three agreed on the cause of death, it was assigned. Otherwise, it was designated as indeterminate. Causes of death were classified according to the *International Classification of Diseases*, 10th Revision (ICD-10) using a modified and shortened code list (19). A detailed description of the process is given elsewhere (20). Cause of death was classified into five broad categories: HIV/AIDS related, including TB, (cancer, hypertension, diabetes, and other NCDs), pneumonia, acute infections (meningitis, measles, malaria, and other acute infections) and other natural deaths (perinatal, preterm, and undetermined). For the causes that were determined, HIV/AIDs and TB were the leading causes of mortality with 25.2% of all mortality. The cause of death profile, classified into five groups, is

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presented in Table 1. Mortality data were broken down to daily series for analysis.

Meteorological data on temperature and rainfall were obtained from the Meteorological Department of Kenya for the period of 2003–2008. The data were obtained from the Moi Airbase weather station, situated between the two study sites and about 3 km away from each site. Weather data included daily minimum and maximum temperatures and daily rainfall. Daily average temperatures were calculated from minimum and maximum temperatures. The weather data were complete, with no missing information for the study period.

Statistical methods

We used time-series data analysis adapting the Poisson regression model to quantify the relationship between temperature, rainfall, and daily mortality. This approach compared the daily observed and expected mortality based on time trends so as to analyze the deviations from the expected mortality related to variation in the exposure variables, in this case temperature and rainfall. Rainfall was adjusted for temperature effect and vice versa. We investigated the daily weather–mortality relationship allowing for variation in mortality over time by adjusting for season and trend.

To adjust for the influence of seasonal and long-term trends, we included both long and short 'time' indicators in the models. The long-term trend was modeled through a natural spline curve with 3 degrees of freedom (df) per year (18 df for 6 years). The annual seasonal variation was also modeled through natural cubic splines with 3 degrees of freedom. Therefore, the combined degrees of freedom for both season and trend added to 6 df per year. Sensitivity analysis was used to assess how the estimates changed for varying degrees of freedom per year (21) to show the sensitivity of results to this choice as described in literature. We examined the relationship between daily deaths and mean temperature to use as baseline analysis. We then assessed the delayed effect through refitting the models using daily mean temperature on the day of death and the previous 13 days using distributed lag models with lag terms 0–1 days, 2–6 days, and 7–13 days. The delayed effect of rainfall over 30 days was assessed considering lag terms of 0–6 days, 7–13 days, 0–13 days, and 14–29 days. Stratified data analysis was conducted with regard to age groups, gender, and cause of death.

Heat and cold temperature thresholds were estimated by visually inspecting the original graph of mean temperature and comparing with different percentiles. The final generalized additive model (GAM) model was given by:

$$Y_t \sim \text{Poisson}(\mu_t)$$

$$\log(\mu_t) = \alpha + \sum_{i=1}^{3} s(x_{it}, df) + s(\text{time}_t, df)$$

where t refers to the day of the observation; (Y_t) denotes the observed daily death counts on day t; $s(.)$ denotes smooth function; df denotes degrees of freedom; x_i denotes the mean temperature at lag 0–1, rainfall at lag 0–13, and rainfall at lag 14–29; and 'time' represents both trend and seasonal associations.

To quantify the associations between weather and mortality in different groups of the population, the aforementioned equation was fitted separately for each stratum category of age, gender, and cause. In addition to evaluating the confidence limits and size of coefficients, the relationship was measured by a factor of 1°C for temperature and 1 inch (25 mm) for rainfall. All data management was conducted in STATA version 11 and statistical analyses were conducted using the *mgcv* package in R2.14.2. Quasi-Poisson family was used instead of Poisson for adjustment of over-dispersion that may partly result because of many zero counts. Quasi-Poisson does not change the estimates for the coefficients, but adjusts the standard errors to account for over-dispersion.

Table 1. Cause of death profiles for the study period 2003–2008

Underlying cause of death	*n*	%
HIV related		
AIDS	281	11.18
HIV+TB	127	5.05
TB	225	8.95
Non-communicable		
Cancers	55	2.19
Diabetes	30	1.19
Hypertension	19	0.76
Other NCDs	209	8.32
Acute infections		
Malaria	90	3.58
Measles	61	2.43
Meningitis	77	3.06
Other acute infection	191	7.6
Pneumonia	223	8.87
Other causes		
Maternal-related death	58	2.31
Malnutrition	50	1.99
Perinatal death	70	2.79
Prematurity/pre-term	29	1.15
Indeterminate	718	28.57

Results

Description

The distribution of mortality by cause, sex, and age for the period of 2003 to 2008 is presented in Table 2. There were 2,512 non-accidental deaths during the study period (excluding deaths due to injuries). The proportion of deaths among children younger than five years was 33.7%, whereas older persons (50+ years) accounted for 13.9% of deaths. People aged between 5 and 19 accounted for about 5% of the deaths and because of this small proportion, it was combined with deaths among people aged between 20 and 49 (whose proportion was 47.2%).

Summary statistics for weather variables over the study period indicate that the average daily mean temperature was 18.8°C (SD = 1.7). The average daily minimum temperature was 13.5°C and the average daily maximum temperature was 23.4°C. During this period, the lowest temperature experienced was 5.2°C and the maximum was 30.7°. The daily average temperature range was 10.3°C with the highest difference of 19.9°C. The highest amount of rainfall was 99.7 mm observed in the year 2007 and on rain-days the average amount of rainfall was 8.2 mm.

Seasonal variability of weather and mortality

Seasonal variation in all-cause mortality and mean temperature for the period 2003–2008 is shown in Fig. 1. Overall, there are seasonal fluctuations in mortality, with the highest rates of death occurring during periods of relative cold, which coincides with high amounts of rainfall. In contrast to the broadly observed association between cold periods and mortality, no seasonal increase in mortality was clearly discernible from this graph during periods of highest temperature.

There was no strong seasonal pattern observed for mortality among the ages 5–49 and 50+ years except

Table 2. Distribution of mortality by age, gender, and cause of death

	n	Percent	Daily average	Daily maximum
Age				
All ages	2,512	100	1.19	13
0–4 years	847	33.7	0.40	4
5–19 years	131	5.2	0.06	2
20–49 years	1,186	47.2	0.56	10
50+ years	348	13.9	0.16	4
Sex				
Female	1,180	47.0	0.56	7
Male	1,332	53.0	0.63	9
Cause of death				
HIV	632	25.2	0.30	5
NCDs	313	12.5	0.15	4
Pneumonia	223	8.9	0.11	3
Acute infections	419	16.7	0.20	4
Other causes	925	36.8	0.44	9

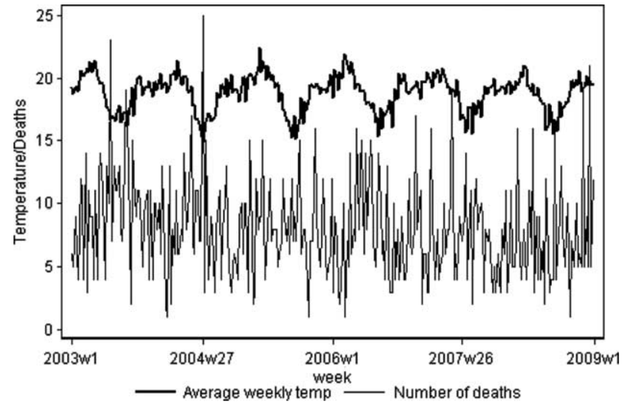

Fig. 1. Time series of all-cause (weekly) mortality and temperature (°C).

for under-five mortality. The two plots for seasonal mortality, all-age and under-five, are shown in Fig. 2. We observed a similar pattern for the two plots, but a strong seasonal pattern is observed for under-five mortality. This result implies that the seasonal pattern observed for all-age mortality was driven mainly by the under-five deaths. High mortality was observed during the month of June to July, the period corresponding to low temperatures. The plots show that mortality risk over the year rises from the lowest mortality risk by about 40% in the 0–4 age group and by about 20% for all ages. These estimates are obtained by exponentiation of the values of log relative risk shown in Fig. 2.

Temperature and rainfall mortality plots

The graphs in Fig. 3 show smoothed plots of log relative risk of mortality against the mean of the current and previous day's temperature. The graphs reveal non-linear temperature–mortality relationships. From the figure, it is evident that a threshold temperature exists somewhere between 18°C and 20°C for all-age mortality. These thresholds from the initial graphical inspection revealed cold and heat threshold corresponding to 25th and 75th percentiles, respectively. The actual daily average temperatures corresponding to 25th and 75th percentiles were 17.9°C and 20°C, respectively. These thresholds were used for all subsequent analysis for quantifying the relationship between temperature and mortality as linear functions. The pattern of temperature and mortality association exhibits J-shape for all-ages mortality and U-shape for under-five mortality. The negative association was observed for the temperature range below the 25th percentile threshold of 17.9°C, whereas a positive association existed for the temperature range above the 75th percentile threshold of 20°C. The slopes for under-five were steeper than for all mortality but both non-linear relationships were statistically significant at lag 0–1. This relationship implies that decrease or increase from the average daily temperature was associated with

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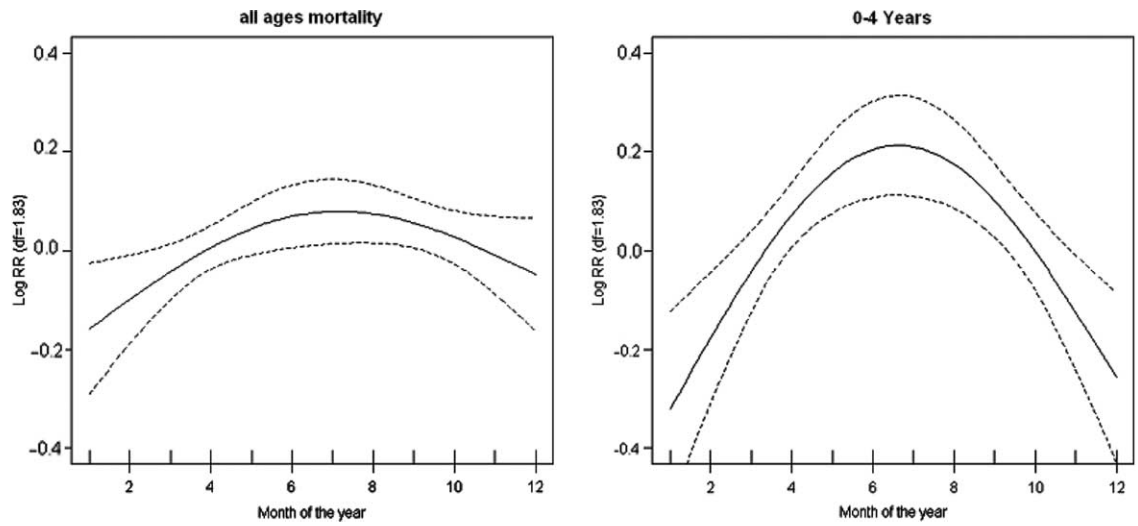

Fig. 2. Annual seasonal variation plots for all-age and under-five mortality. The vertical axes show the log (relative risk) and the horizontal axis show the month starting with January. Confidence intervals (95%) are shown as dotted lines.

increase in mortality. The smooth function of the relationship between rainfall and mortality shows a linear increase, significant at lag of 0–13 days and 14–29 days for all-cause mortality. These associations are also illustrated in Fig. 3.

Quantification of weather–mortality relationships

Table 3 shows the results of a quantified relationship varied by age, gender, and cause of death. The results show no significant relationship for high temperature on all mortality, but significant positive relationship for high temperatures is observed in deaths in the 0–4 age group and among people with NCD. Low temperatures were associated with mortality of varying magnitude by age, gender, and cause of death though none of the relationships was statistically significant. There was an increase of 13% in deaths due to acute infections associated with decrease in temperature but this was not statistically significant. Deaths among males and people aged 50+ were associated with low temperatures though these relationships were not statistically significant. It was also observed that rainfall was significantly associated with female NCDs and pneumonia deaths. Cumulatively, mortality increased by 3% for 1 inch (25 mm) increase in the amount of rainfall and this relationship was statistically significant. There was also an increase of 5% in female mortality for 1 inch (25 mm) increase in rainfall after 2 weeks and this increase was statistically significant. The relationship of rainfall to NCDs and pneumonia accumulated over 1 month was 12% and 24%, respectively, and this was statistically significant.

Sensitivity analysis

Figure 4 illustrates a sensitivity analysis of the percentage increase in mortality for a decrease or an increase in temperature of 1°C at lag 0–1 for both cold and heat effects with respect to the number of degrees of freedom assigned to the smooth function of time per year. The figure shows the change in the temperature-associated coefficient as the degree of freedom is varied. The different axes are used for cold and heat correlations because of the difference in the magnitude of the effect on the percentage change on mortality. When using natural splines, the estimates reach the maximum when degree of freedom is about six per year. This implies that a choice of degrees of freedom lower or higher than this optimal value will lead to over- or under-estimation of the effect of weather variables.

Discussion

The aim of this study was to assess the relationship between daily weather and mortality in two informal settlements in Nairobi, Kenya. The findings show a relationship between both low and high temperature with mortality. The observed linear associations between temperatures below 25th percentile were not statistically significant. Increase in temperature above the 75th percentile showed statistically significant but moderate increases in mortality in children/infants and for NCDs. The lack of significance for the relationship between cold temperature and mortality may be due to low daily death counts resulting in high variability or due to the particular thresholds chosen since some of the non-linear curves were significant. The results also show strong statistically significant positive relationships between rainfall and mortality, with cumulative lagged effect over 30 days in the following groups: all ages, NCDs, and pneumonia.

The temperature-related mortality was observed with a short lag of the same day and the following day. The low

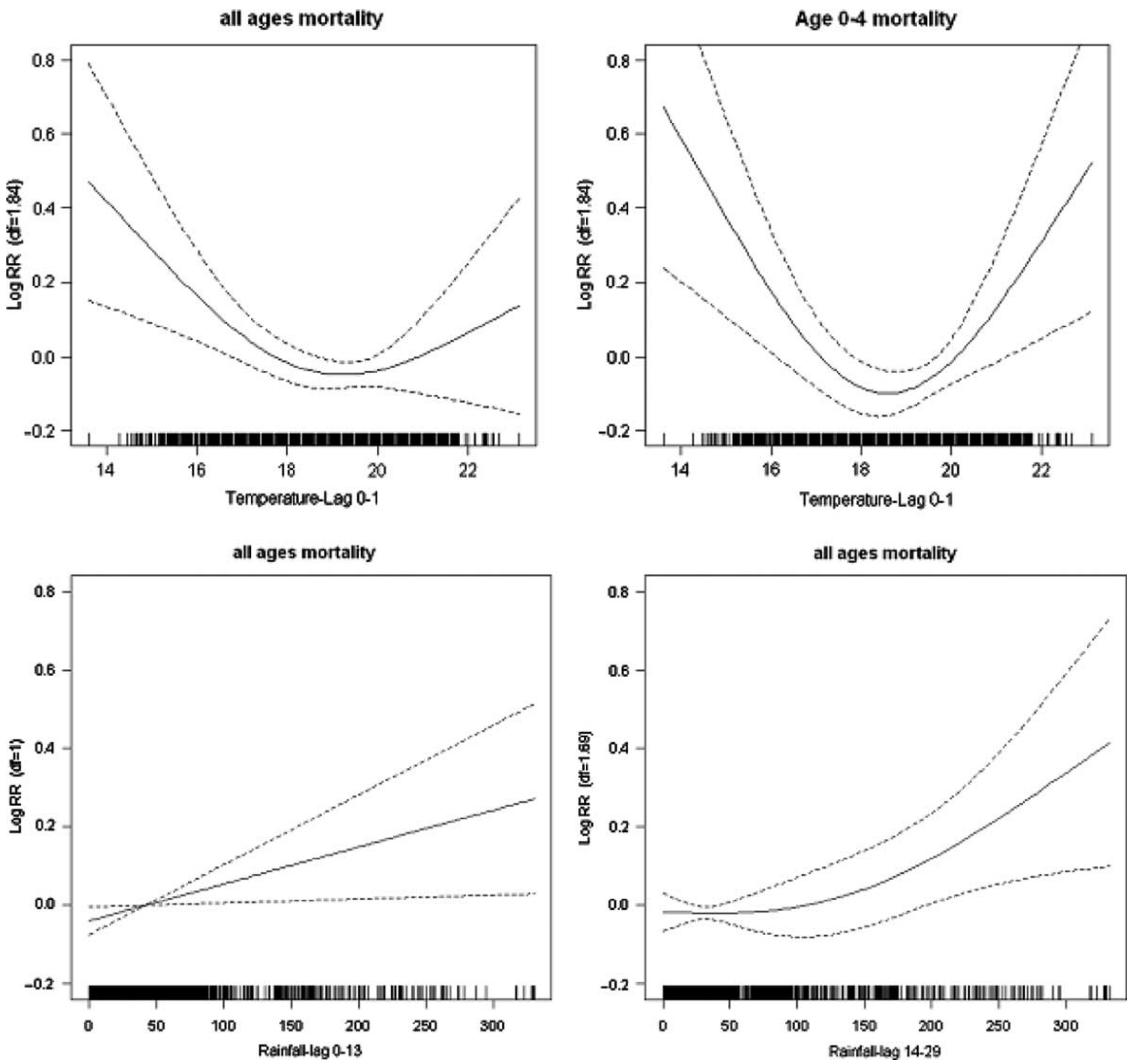

Fig. 3. Smooth functions of temperature for all and under-five mortality, and rainfall for all ages allowing lags of 0–13 days and 14–29 days. The vertical axes show the log (relative risk) and the horizontal axis show the scale of the explanatory variable. Confidence intervals (95%) are shown as dotted lines.

temperature effect could be explained by the high elevation of the city, resulting in a sub-tropical (almost temperate) climate, which is cool almost all year round, with no temperature extremes reported so far. It is plausible therefore that a cold effect can be found in this kind of climate where temperature extremes on the cold scale have been reported, especially at nighttime, and housing lacks insulation or proper heating, with natural heating fuels being limited or relatively expensive. The low temperatures may be associated with use of various fuels to generate warmth increasing exposure to indoor pollution. Commonly used fuel types by the residents in the two study areas are kerosene and charcoal, which are the main sources of indoor air pollutants. This may be a probable explanation for the association of low temperatures with mortality. Our results are in line with previous findings assessing weather-related mortality. Other studies in temperate countries have reported increased mortality associated with cold waves (22, 23). Although the temperatures in Nairobi are not fully comparable to those in the studies above, a parallel can be drawn in the increased mortality observed during cold days. Studies of temperature-related mortality in Bangladesh observed an increase in all-cause deaths at low temperatures and no clear heat effects in both rural and urban areas (24, 25).

Earlier studies focused on the effect of short temperature extremes, such as heat waves (26). Temperature-related mortality typically demonstrates a J or U shaped response, in which mortality rates are highest at low and high temperatures. All-cause mortality is associated with a decrease in temperature from a cold threshold (27–30), and in this study low-temperature-related mortality was higher than high-temperature-related mortality though it was not statistically significant. The effects of low

Table 3. Percentage change associated with 1°C decrease in temperature below 25th percentile, 1°C increase in temperature above 75th percentile and 25.4 mm (1 inch) increase in amount of rainfall. 95% confidence intervals are given in the parentheses

	Temperature		Rainfall		
	25th percentile	75th percentile	Lag 0–13 days	Lag 14–29 days	Cumulative
All deaths	3 (−5, 13)	0 (−1, 1)	2 (−1, 5)	1 (−1, 4)	3 (0, 7)
Age groups					
0–4 years	3 (−9, 16)	1 (0, 2)	2 (−2, 6)	0 (−3, 4)	2 (−3, 8)
5–49 years	2 (−8, 14)	0 (−1, 1)	2 (−1, 6)	1 (−2, 4)	3 (−1, 8)
50+ years	9 (−6, 28)	1 (−1, 2)	3 (−2, 8)	3 (−2, 7)	5 (−1, 13)
Gender					
Female	−3 (−8, 13)	0 (−1, 2)	5 (1, 8)	2 (−1, 6)	7 (2, 12)
Male	10 (−1, 22)	0 (−1, 1)	0 (−3, 3)	0 (−3, 4)	0 (−4, 5)
Cause of death					
HIV	2 (−11, 17)	0 (−2, 1)	1 (−3, 5)	−1 (−5, 3)	0 (−5, 6)
NCDs	−9 (−22, 6)	1 (0, 3)	6 (1, 12)	6 (1, 11)	12 (5, 20)
Pneumonia	6 (−21, 11)	1 (−1, 2)	13 (7, 19)	10 (5, 15)	24 (16, 33)
Acute	13 (−2, 30)	1 (−1, 2)	−2 (−7, 2)	0 (−4, 4)	−2 (−8, 4)
Other	1 (−11, 14)	0 (−1, 2)	2 (−2, 6)	1 (−3, 4)	2 (−3, 8)

temperatures on mortality can last for days, with the greatest association sometimes observed on the same day (31) as observed in this study. Infectious diseases such as pneumonia and influenza are more common in the winter season in temperate countries and contribute to the observed high rates of winter mortality (32–34). In contrast, we found that pneumonia deaths increased with high temperatures and vice versa. There was no information about influenza in this area. Respiratory tract infections are more likely to occur during periods of low temperatures and low humidity (35).

We also observed an association between rainfall and mortality, particularly with pneumonia deaths. Previous work showed an association between rainfall and pediatric visits for acute gastrointestinal illness (36). In addressing climate change, it is better to understand the rainfall-associated illness or mortality. Establishing the impact of rainfall on health in the absence of any outbreaks is important in public health reporting, not to underestimate rainfall-associated mortality or illness. Further studies on impact of rainfall are warranted to better understand this association and potential mechanisms as well as establish different lag effects of rainfall.

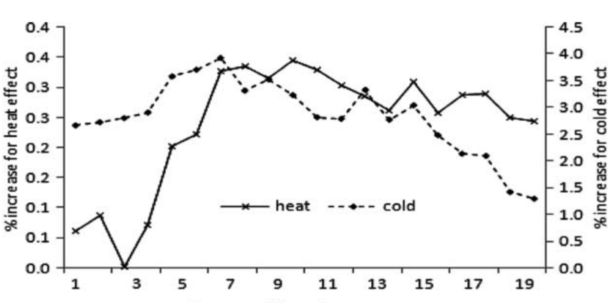

Fig. 4. Sensitivity analyses, with increasing degrees of freedom, of the percentage increase in mortality for an increase in temperature of 1°C at lag 0–1 days for both cold and heat effects. The left vertical axis shows the heat effect and right vertical axis shows cold effect in percentages.

Older populations are considered particularly vulnerable to extreme weather because a person's ability to thermo-regulate can become impaired with age. Underlying chronic diseases, such as diabetes, and medications can modify blood pressure, circulation, perspiration rates, and some mental capacities such as warmth perception, thus complicating people's ability to identify when they are experiencing extreme weather (37). Several reports have shown that excess weather-related mortality is higher in older people (22, 38, 39). Infants are also often identified as a population that is vulnerable to extreme heat conditions; however, information on heat and infant mortality is scarce, with no studies reporting on cause-specific temperature-related mortality in children (8). In an effort to address Millennium Development Goal (MDG) 4, it is important to confirm weather-related mortality among children to understand factors contributing to child mortality. The strong association observed between temperature and mortality among children aged 0–4 years show the need of further cause-specific analysis for this age group.

Gender has been found to be associated with temperature-related mortality. Some studies have shown that women are more sensitive to cold than men, with reports showing that women living in colder climates have a higher risk of cold-related death than their male counterparts (27, 40, 41). We found increased cold-related mortality among men although previous work shows contrasting results. However, this could be explained by the difference in the age, culture, and behavior of the population under study. A similar finding was observed in a study among older people (42) though a contradicting result was also observed in a different study among older people of a similar age group (43). Little modification of the cold effect by sex was observed in England and Wales (44). We further observed a significant relationship between increasing rainfall and mortality in women, but not in men. The reason for this relationship needs to be further assessed.

In spite of an overall trend toward increasing global temperatures, climate models forecast more variable weather. This will result in important weather-related health consequences for humans. Coupling archived climatologic data with health outcome data has aided researchers (45) in projecting mortality rates and in this study the NUHDSS provides this opportunity. Further epidemiologic studies that incorporate archived climatological and environmental data in modeling specific health outcomes in vulnerable populations would aid adaptation to climate-change-related health effects through preparedness strategies implemented at various scales (37). Although the world will get warmer in the future, the low temperature-related mortality is likely to remain an important concern (7).

This study has a number of limitations. The first limitation relates to the validity of the causes of death based on verbal autopsy. However, verbal autopsies are at present the best possible method for obtaining information on cause-specific deaths in many low- and middle-income countries (46) that lack vital registration systems and where most deaths occur outside the formal health care system. Another limitation with mortality data is the large percentage of deaths with unknown or ill-defined causes, making cause-specific mortality analysis difficult. Nevertheless, the data provide a great opportunity for all-cause mortality analysis. A further limitation is the lack of data on daily levels of air pollution, which would enable the control of its health impact while assessing weather-related mortality. Low death counts may be also a limitation, resulting in large variability that renders the observed differences as not significant, although this has no significant effect on the Poisson distribution of the model we used. The adjustment to standard errors is done through quasi-likelihood estimation. Despite these limitations, the study confirms that extremes of temperature affect mortality in the Nairobi Urban HDSS and highlights seasonal variations in mortality. Further investigations of weather-related mortality are warranted.

In conclusion, we found the highest susceptibility to heat among children younger than five years and an indication of cold-related mortality among the older people. Results from stratifying effect estimates by age were consistent with earlier results based on community-level and individual-level data (47–49). Further investigation using individual-level data is needed to improve exposure estimates, especially for longer lag structures. These findings on the impact of weather on mortality have implications for policymakers and health protection for vulnerable urban populations to weather extremes. The identified susceptible subpopulations signify the need for targeted weather-mortality prevention efforts such as proper housing and clothing.

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Conflict of interest and funding

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The influence of weather on mortality in rural Tanzania: a time-series analysis 1999–2010

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Background: Weather and climate changes are associated with a number of immediate and long-term impacts on human health that occur directly or indirectly, through mediating variables. Few studies to date have established the empirical relationship between monthly weather and mortality in sub-Saharan Africa.

Objectives: The objectives of this study were to assess the association between monthly weather (temperature and rainfall) on all-cause mortality by age in Rufiji, Tanzania, and to determine the differential susceptibility by age groups.

Methods: We used mortality data from Rufiji Health and Demographic Surveillance System (RHDSS) for the period 1999 to 2010. Time-series Poisson regression models were used to estimate the association between monthly weather and mortality adjusted for long-term trends. We used a distributed lag model to estimate the delayed association of monthly weather on mortality. We stratified the analyses per age group to assess susceptibility.

Results: In general, rainfall was found to have a stronger association in the age group 0–4 years (RR = 1.001, 95% CI = 0.961–1.041) in both short and long lag times, with an overall increase of 1.4% in mortality risk for a 10 mm rise in rainfall. On the other hand, monthly average temperature had a stronger association with death in all ages while mortality increased with falling monthly temperature. The association per age group was estimated as: age group 0–4 (RR = 0.934, 95% CI = 0.894–0.974), age group 5–59 (RR = 0.956, 95% CI = 0.928–0.985) and age group over 60 (RR = 0.946, 95% CI = 0.912–0.979). The age group 5–59 experienced more delayed lag associations. This suggests that children and older adults are most sensitive to weather related mortality.

Conclusion: These results suggest that an early alert system based on monthly weather information may be useful for disease control management, to reduce and prevent fatal effects related to weather and monthly weather.

Keywords: *time-series*; *monthly weather*; *all-cause mortality*; *monthly temperature and monthly average temperature climate*; *climate change*

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Weather and climate changes are likely to have adverse effects on human health, particularly among the most vulnerable populations (1). Their effects can be both direct, through extreme events and changes in the disease environment, and indirect through their impact on the economic livelihood of the population (1, 2). The World Health Organization (WHO) estimated that the warming and rainfall trends due to anthropogenic climate change of the past 30 years already claim over 150,000 lives annually (3). In most cases the poorer regions are highly vulnerable (4). Of the 14 million deaths that occurred in Southeast Asia annually, 40% are attributable to communicable diseases (5). Increased average temperatures could prolong peak periods for vector-borne diseases (6) and extreme weather events such as cyclones and floods can create ideal conditions for the spread of vector-borne and diarrheal diseases such as cholera (7). Malaria is the most important vector-borne disease related to climate change in the world; it is also a preventable disease. About 40% of the world's population is at risk of contracting malaria, and roughly 75% of cases occur in Africa, with the remainder occurring in Southeast Asia, the western Pacific, and the Americas (8).

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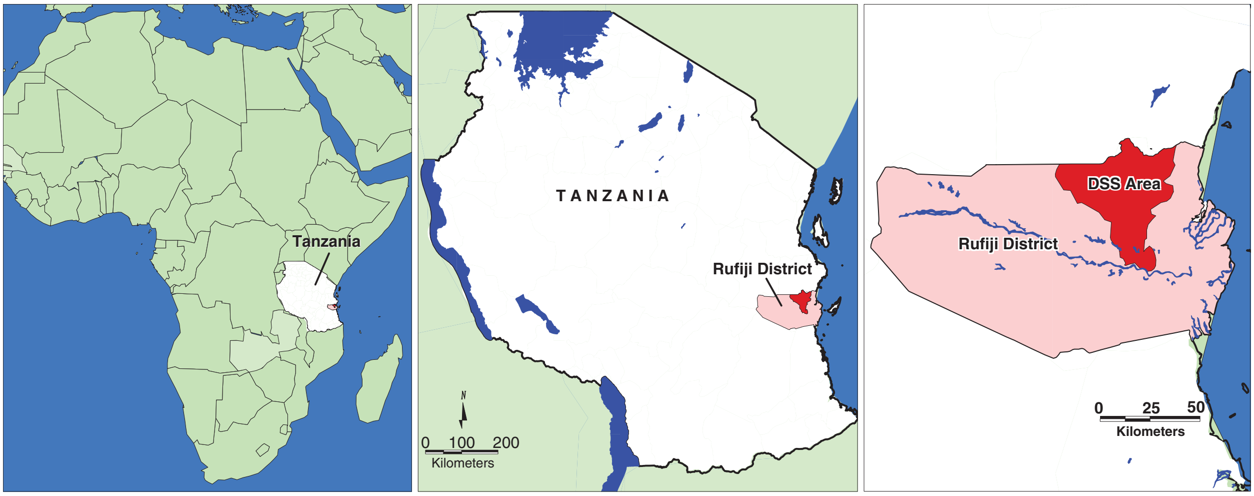

LOCATION OF RUFIJI DSS SITE, TANZANIA: Monitored Population 85,000

Fig. 1. Location of Rufiji HDSS.

In sub-Saharan Africa, malaria remains the most common parasitic disease and is the main cause of morbidity and mortality among children less than 5 years of age, elderly people, and among pregnant women (9). The estimates provided by Murray and Lopez (1996) suggested that malaria caused about 15% of deaths of children under the age of 5 years in sub-Saharan Africa in 1990. However, children are highly affected by weather and climate by virtue of their early stages of development, while a study done in Kenya in 2008, revealed that climate change has emerged as a new driver of malnutrition and increasing the child mortality rate by 5–20 times (10).

Tanzania is the largest country in East Africa, covering an area of 945,200 km^2, 60,000 km^2 of which is inland water (11). Tanzania lies close to the equator on the east coast of Africa between latitude 1°S and 12°S and longitude 30°E and 40°E. By being close to the equator, the climate variations in temperature are not very extreme (11). Changes in temperature and rainfall resulting in changes in soil moisture, increase in sea level, and more extreme weather events, such as floods and droughts, are among the most known impacts of global climate change in the region (12, 13). The major impacts of climate change are expected to include severe floods, frequent and prolonged droughts, rising sea levels, crop failure, loss of livestock, lower water availability and quality, and an increase in vector and water-borne diseases (14, 15). However, heavy rains, flood, drought, and landslides in Tanzania have already resulted into internal displacement,

Table 1. Summary of monthly mortality data, 1999–2010

		All cause, by age			
Months	U5 (0–4)	Children (5–19)	Adults (20–59)	Adults (60+)	Total
January	276	54	177	325	832
February	290	55	216	318	879
March	201	42	172	264	679
April	325	63	224	346	958
May	317	57	225	336	935
June	315	79	236	370	1,000
July	228	43	173	319	763
August	228	65	205	406	904
September	237	73	195	377	882
October	216	73	207	355	851
November	167	45	132	248	592
December	223	64	200	354	841
Total	3,023 (30%)	713 (7%)	2,362 (23%)	4,018 (40%)	10,116

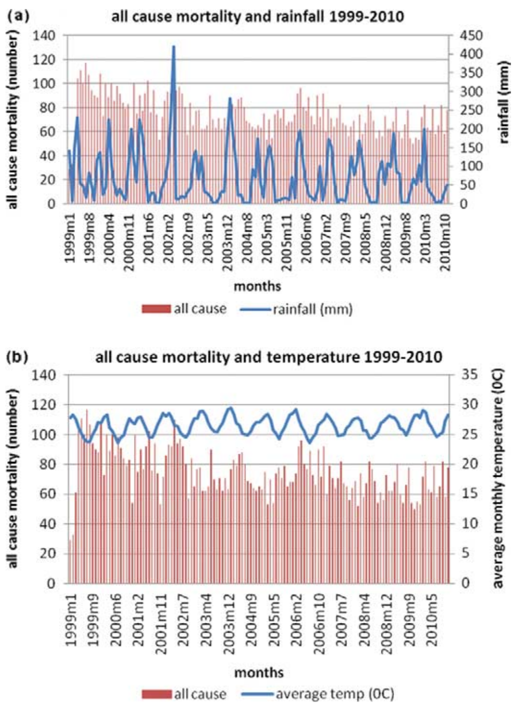

Fig. 2. (a) Time series of all-cause mortality and rainfall; (b) Time series of all-cause mortality and temperature.

food shortages, and increased disease transmissions. Drought itself has significantly contributed to malnutrition due to lack of adequate food, increased infectious disease transmission, and scarcity of clean and safe water (16). Landslides, droughts, and floods are becoming common in Tanzania. In recent years (2009–2011), heavy rains accompanied with strong winds have left thousands of people displaced and without food in Muleba, Kilosa, Same, and Dar es Salaam (17). Weather and climate

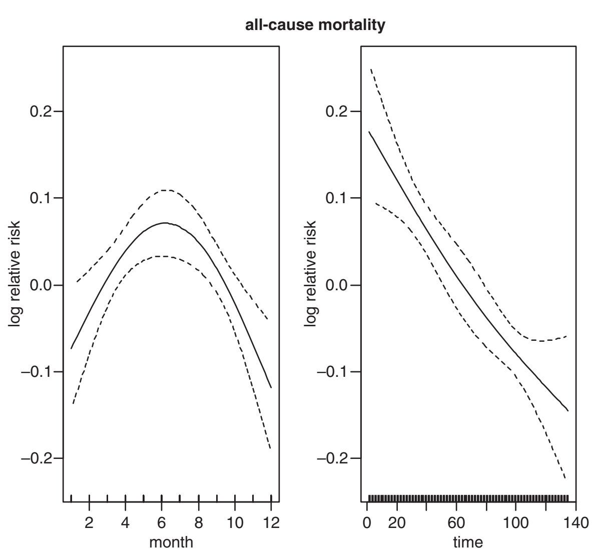

Fig. 3. Seasonality (left) and time trends (right) in all-cause mortality over the study period.

change can affect human health and well-being through a variety of mechanisms (14, 15, 18). The risk of emerging diseases may increase due to changes and survival of pathogens in the environment, changes in migration pathways, carriers and vectors, and changes in the natural ecosystems (18). Infectious agents are in a state of perpetual adaptation to their new host(s) or vectors which can lead to the emergence of 'new' disease(s) or the spread of known diseases in previously unaffected areas. Malaria is by far the most important vector-borne disease causing high morbidity and mortality in Tanzania (19). The endemicity and pattern of malaria transmission is focal and varies from place to place depending on many factors including weather and topography. Modeling malaria endemicity in Tanzania using outpatient cases (2004–2008) in relation to mean temperature and mean rainfall has shown that almost the whole of Tanzania is endemic for malaria, although with some spatial variation between areas. Mean rainfall accounts for 72% of the variation in malaria, while mean maximum temperature accounts for 14.1% and mean minimum temperature 13.1% (19).

The main objective of this paper is to show a detailed analysis of the association between changes of monthly weather (temperature and rainfall) on all-cause mortality by age groups, using the data from Rufiji Health and Demographic Surveillance System (RHDSS) and metrological data of rainfall and temperature for the period of 1999–2010.

Methods

Study area

The RHDSS is located in eastern Tanzania 7.47° to 8.03° south latitude and 38.62° to 39.17° east longitude (Fig. 1). The RHDSS is in the Rufiji district of Tanzania about 178 km south of Dar es Salaam. The district is among the six districts in the Coastal Region of Tanzania. The RHDSS constitutes 31 villages covering an area of 1813 km^2 (20, 21).

Rufiji has a mean altitude of $<$500 meters above sea level. Tropical forests and grassland dominated the vegetation cover of Rufiji. The weather is hot all over the year and with rainy seasons: short rains (October–December) and long rains (February–May). The average annual rainfall in the district is between 800 and 1,000 mm (21). The population size of the Rufiji District is about 203,102 of which more than 85,000 (about 42% of the district population) are covered by the surveillance system (22). The mean household size for the whole district is about five people per house (22). The district is largely rural and the population is clustered in small townships in the district (21).

RHDSS has a total of 18 health facilities. These include one hospital, two health centers, and 15 dispensaries. However, there are a proportion of people who

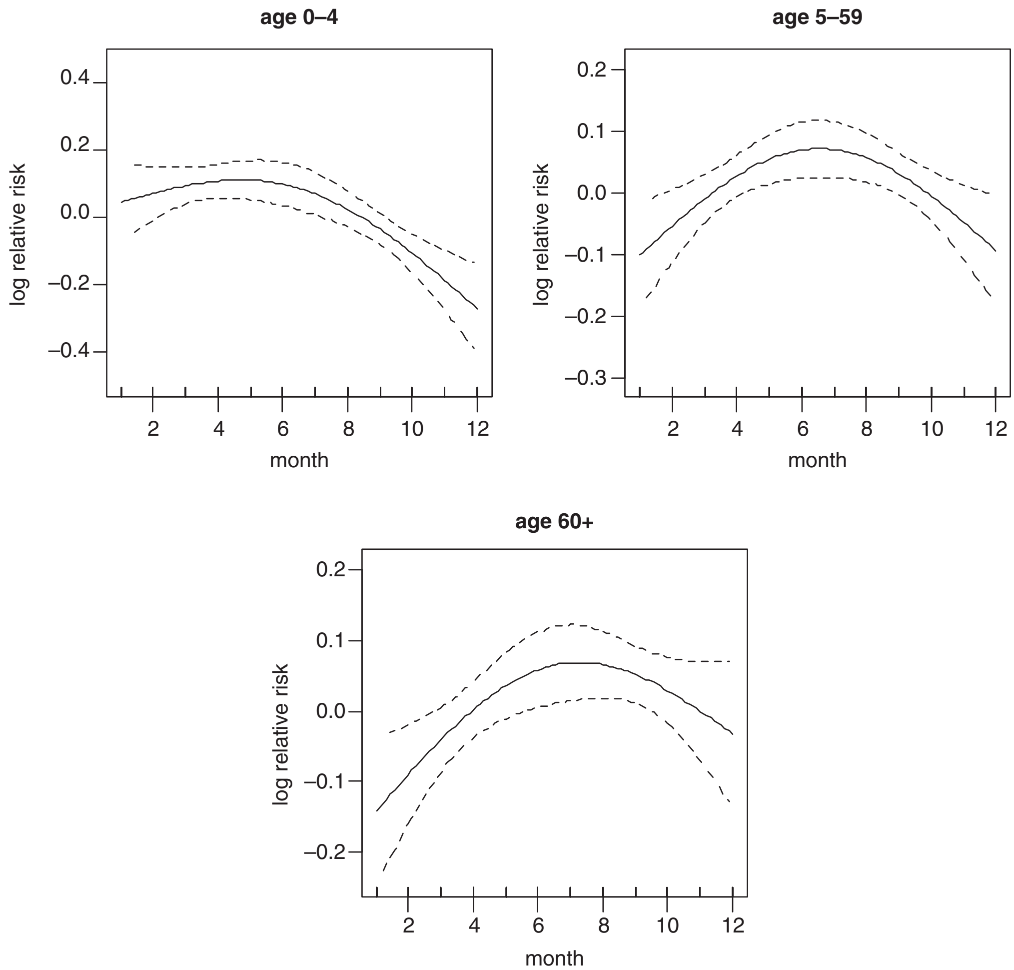

Fig. 4. Seasonality of all-cause mortality by age group.

receive health services from traditional healers and traditional birth attendants. The major causes of mortality include acute febrile illness such as malaria, AIDS, acute lower respiratory infections, tuberculosis, and perinatal causes. Immunization coverage ranges from 66% for measles in children that are 12–23 months of age to 85% for the Bacillus Calmette-Gue'rin (BCG; tuberculosis). About 89% of the population lives within 5 km of a formal health facility. All villages and health facilities in the district have been positioned by a global position system and mapped in a geographic information system database of the district health resources.

Data and study population

This study used longitudinal data collected in the RHDSS over an 11-year period from 1 January 1999 to 31 December 2010. A DSS is a longitudinal, population-based, health and vital events registration system that monitors demographic events such as births, deaths, pregnancies, migrations and socioeconomic status of a geographically well-defined setting of individuals, households, and residential units. In the RHDSS, every household is visited once in every 4 months in order to update previously recorded household information, which also includes registering new demographic events that may have occurred. Between household visits, community-based key informants report births and deaths as they occur, and when it does, a household is revisited in order to record such events.

Since the main focus of this study was to analyze the association of rainfall and temperature on all-cause mortality by age; all deaths that occurred and were recorded during the study period were of interest. Data on monthly rainfall (mm) and temperature (°C) were obtained from the Tanzania Meteorological Authority (TMA) head office in Dar es Salaam. TMA provides meteorological services, weather forecasts, climate services, and warnings including daily forecast information for each region in Tanzania (23).

Statistical analysis

Data management was done by using Intercooled Stata 11 (24) and analysis was performed using the MGCV package in R2.14.2 is a system for statistical computation

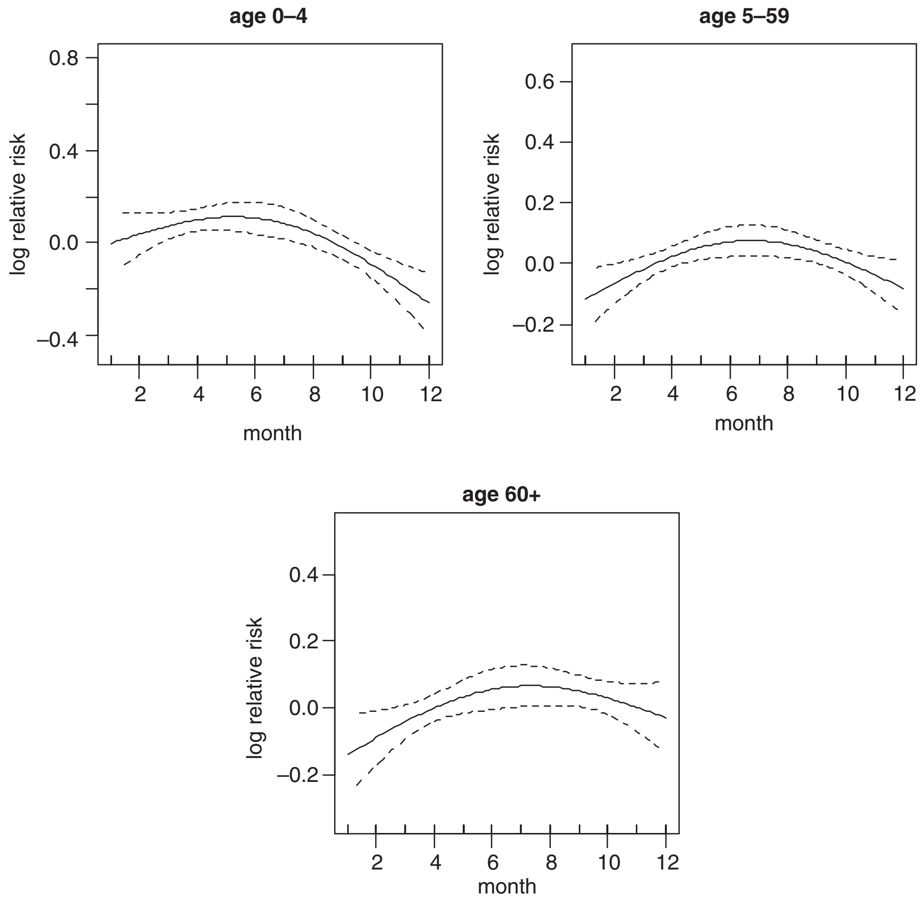

Fig. 5. Seasonality of all-cause mortality by age group adjusted for rainfall.

and graphics. It consists of a language plus a run-time envirnment with graphics, a debugger, access tocertain system functions, and the ability to run programs sorted to script files (25). The MGCV package provides tools for generalized additive models (GAMs) and other generalized ridge regression (26). GAMs have been widely used in many time-series analyses and have been effectively applied in a variety of research areas (27). Data process was performed to generate the variables for time-series analysis as follows: all-causes mortality from the year 1999 to 2010; data on rainfall; and data for temperature were reported in mean, maximum and minimum. Age at death was grouped into three age groups: 0–4, 5–59, and over 60 years. A division was made between male and female. Season, time, and lags (lag 0–4) for both monthly rainfall and average monthly temperature were generated as well. Time-series Poisson regression models, using the MGCV package in this study, account for autocorrelation, seasonality, long-term trends, and lag effects that determine the best-fit model in relation to all-cause mortality attributed by monthly rainfall and monthly average temperature by age. The long-term trend was modeled through a natural cubic spline curve with 3 degrees of freedom per year of data. The degree of freedom for each smooth term in the model are chosen simultaneously as part of model fitting by minimizing the generalized cross-validation score of the whole model (26). The annual seasonal variation was modeled through natural cubic splines with 3 degrees of freedom also. Thus, the combined degree of freedom for both season and trend add up to 6 degrees of freedom per year. Four lags for rainfall and temperature were created in order to assess the delayed association of the previuos rainfall and temperature values on the current level of mortality. The GAM model used in this analysis was given by:

$$Y_t \sim \text{Poisson}(\mu_t)$$

$$\log(\mu_t) = \alpha + \sum_{t=1}^{12} s(x_{it}, df) + s(\text{time}_t, df)$$

Where t refers to the month of the observation; (Y_t) denotes the observed monthly mortality counts on month t; $s(.)$ denotes a smooth cubic spline function, df denotes degrees of freedom, xi denotes the monthly rainfall at lag 0–4 and monthly average temperature at lag 0–4, and 'time' represents both seasonal and trend pattern. We quantified the associations between the weather variables and mortality by strata of age, and the equation above was fitted for each age group.

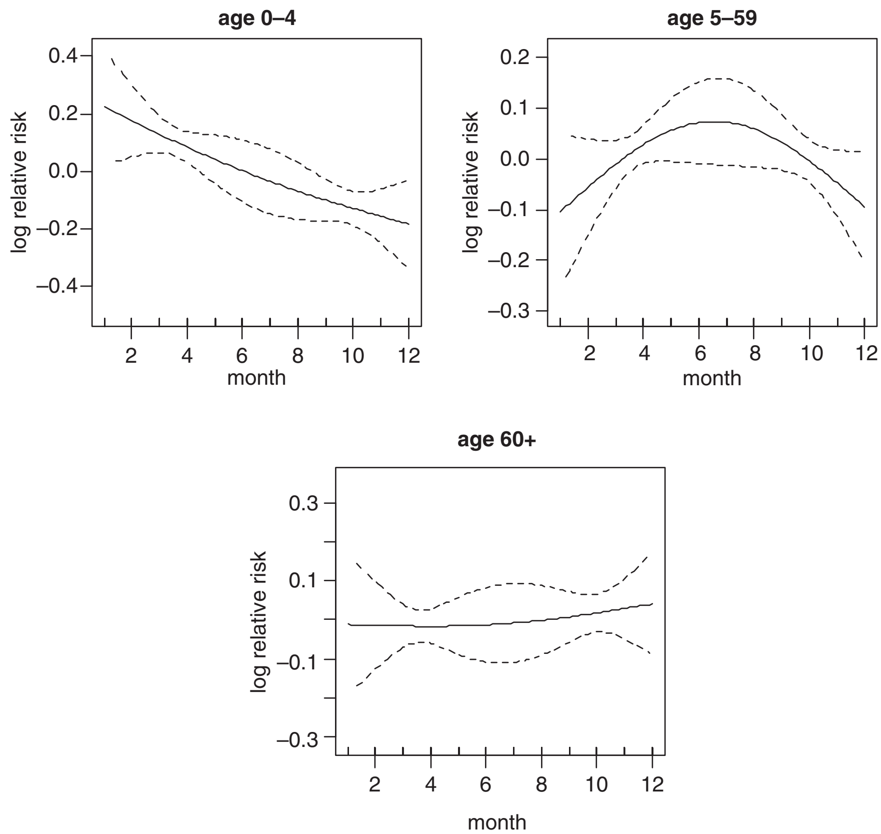

Fig. 6. Seasonality of all-cause mortality by age group adjusted for temperature.

Ethical approval
The ethical clearance for RHDSS was approved by local and national ethical committees.

Results

Description
Table 1 represents the summary of all deaths recorded in the RHDSS aggregated per month from 1999 to 2010. A total of 10,116 deaths over the 11 years of observation (1999–2010) were recorded. The percentages of total deaths by age group were 30% for 0–4 years, 7% for 5–19 years, 23% for 20–59 years, and 40% for over 60 years. Since the proportion of age group 5–19 was very small we merged it with the age group 20–59 for further analysis. According to the RHDSS burden of disease profiles of 1999 to 2010, the large proportion of all-causes of deaths in the region were from communicable diseases. Malaria, HIV/AIDS, TB, and pneumonia are the leading cause of mortality for all age groups followed by a variety of neonatal and under-fives' problems such as low birth weight and birth asphyxia.

Seasonal variability of weather and mortality
Since Rufiji has a tropical environment the monthly average temperature varied between 27.91°C and 34.4°C with a mean of 31.22°C. Monthly rainfall varied between 0 and 420.7 mm during the study period. Fig. 2a and 2b present the seasonal variations in all-cause mortality and rainfall and all-cause mortality and temperature variables, respectively, during the study period. Generally, there are seasonal fluctuations in mortality, with the highest peaks of deaths occurring during the periods of relative cold and high levels of rainfall.

Seasonality of mortality
Fig. 3 shows the strong crude seasonality and long-term trend of all-cause mortality. It shows that most of the deaths are concentrated in the middle of the year and also that there is a downward trend of mortality over time. The crude seasonality of all-cause mortality by specific age groups is shown in Fig. 4. A strong mortality pattern is observed in all age groups, that is, 0–4, 5–59, and over 60. High mortality is observed during March–May for the age group 0–4 and 5–59, the period that coincides with the long rain season. For the over 60 age group, mortality peaks during the months of June–September which corresponds with the dry and cold temperature period. Fig. 5 shows the adjusted seasonality of all-cause mortality for monthly rainfall by age group. It shows that for all age groups (0–4, 5–59, and over 60), the mortality pattern peaks during the period of rain. The estimated

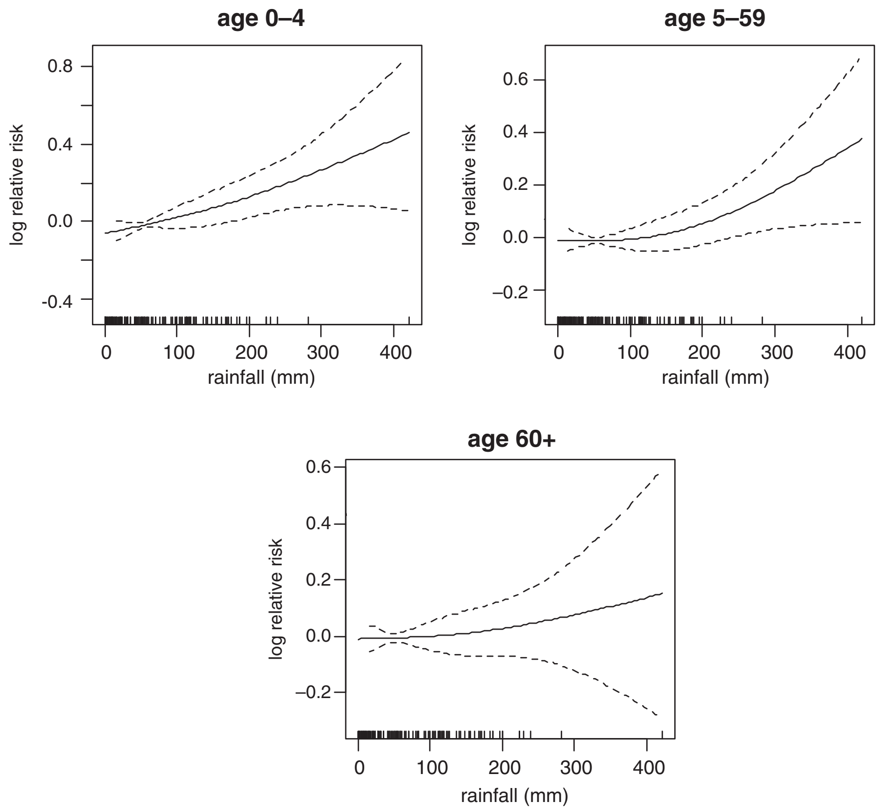

Fig. 7. The influence of rainfall on mortality by age group.

curve of seasonality adjusted for weather shows a similar pattern in children under five, but a less clear seasonal pattern in the older age group indicating that weather variables explain part of the seasonal pattern for these age groups.

The adjusted seasonality of all cause mortality for monthly temperature by age group are presented in Fig. 6. The patterns show that mortality in all age groups peaked up at the mid of the year. This correspond with the time when the temperature is relatively lower compared to other periods of the year in Rufiji.

Temperature and rainfall mortality plots

In Fig. 7, the graphs show smoothed plots of logged relative risk of mortality against monthly rainfall. It shows a positive linear rainfall-mortality relationship in all age groups. Based on the plots, only the slope of age group 0–4 is statistically significant (RR = 1.001, 95% CI = 0.961–1.041) whereby an increase of 10 mm of rainfall will increase mortality in the age group 0–4 by 1.4% (Table 2). Correspondingly, if the monthly rainfall rises to 400 mm, it will correspond with a 72% increase in under-five mortality.

Fig. 8 shows linear plots of logged relative risk of mortality against the monthly average temperature. The graph reveals linear temperature-mortality relationships over lags. In Fig. 8, the threshold temperature exists somewhere between 26°C and 27°C for all age groups. Negative associations were observed for the temperature range below the thresholds. The monthly average temperature was significantly associated with all-cause mortality in all age groups (Table 2). If the monthly average

Table 2. Correlations between all-cause mortality and climate variables in RHDSS

Age group	Monthly climate variables	Coefficient	RR	95% CI	N
0–4	Monthly rainfall	0.0013662	1.001	(0.961, 1.041)	135
5–59	Monthly rainfall	0.0005424	1.001	(0.999, 1.001)	
60	Monthly rainfall	0.0001606	1.000	(0.999, 1.001)	
0–4	Monthly average temp	−0.0683968	0.934	(0.894, 0.974)	135
5–59	Monthly average temp	−0.0446006	0.956	(0.928, 0.985)	
60	Monthly average temp	−0.0560136	0.946	(0.912, 0.979)	

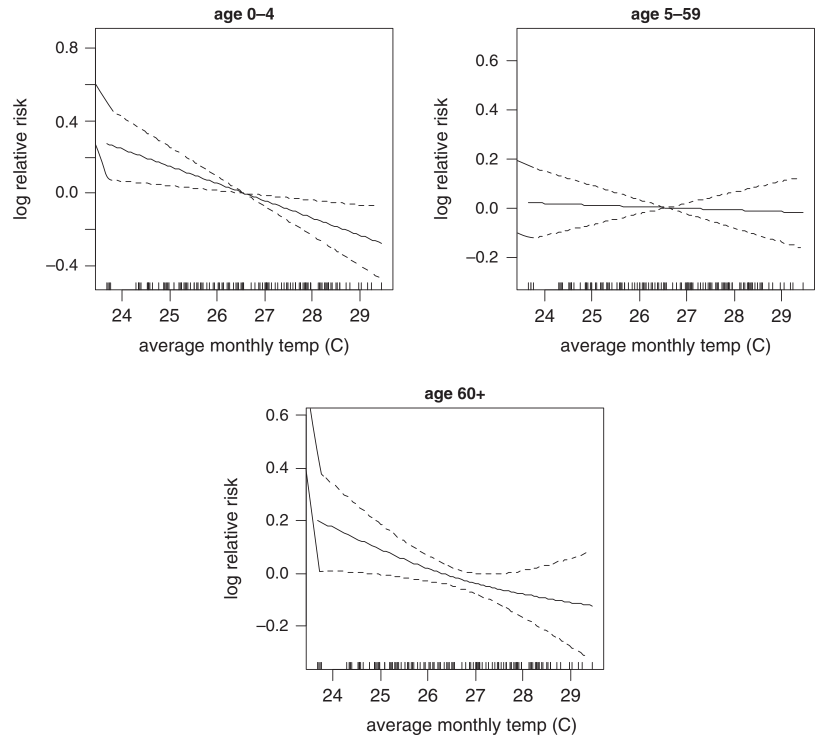

Fig. 8. The influence of temperature on mortality by age group.

temperature will decrease up to 24°C from the threshold, mortality will increase by 80.7%, 65.7% and 74% in age groups 0–4, 5–59, and over 60, respectively. The linear function of monthly rainfall effects on all-cause mortality shows a linear increase significant at lag of 0, 1, 2, and 3 in age group 0–4 (Table 3), while the effects of monthly average temperature on all-cause mortality is significant at lag of 2 in age group 5–59. There are no strong lag effects in the association of climatic variables (monthly rainfall and average temperature) on mortality in the age group 60 years and above (Table 3).

Discussion

The main focus of this study was to investigate the influence of rainfall and temperature on all-cause mortality patterns in Rufiji, Tanzania. The findings show, in particular, an association between rainfall and mortality in children. This finding was similar to that observed by other studies (17). The observed rainfall association can be substantiated by the location of Rufiji where it experiences a tropical climate with a long rainy season from February to May and short a rainy season from October to December. This pattern is consistent with deaths caused by malaria, which also peak in the long and short rains, and is the single largest disease component contributing to the burden of disease in all ages in Rufiji (28). The findings of this study are similar to previous assessments of weather related mortality (29–31). Recent studies conducted in Africa revealed that the outbreak of cholera and malaria support the causal link between monthly weather and health (32). Rainfall anomalies are widely considered to be a major driver of inter-annual variability of malaria incidence in Africa. About 90% of the deaths occurred in sub-Saharan Africa are believed to be due to malaria (12). Studies show that rainfall excess is correlated with changes in malaria incidence in certain eco-epidemiologic settings, apparently as a result of its impact on the population dynamics of the *Anopheles* spp. mosquito vector (29, 33). Weather shocks raise exposure to malaria as shown by the significant rise in the incidences of infant death (34). This is similar to our findings where rainfall is significantly associated with mortality in under-fives. The effect of rainfall on mortality can last for days, with the greatest association sometimes observed in the same month (30), which is similar to results in this study.

The association between ambient temperature and daily mortality has been well documented in the developed countries of the Northern Hemisphere (35). This study shows a relationship between both hot and cold temperature associations on mortality, although cold temperatures had a stronger association with mortality. Generally, Rufiji did not experience any extreme cold events that could directly cause mortality like that in the Northern Hemisphere countries. However, Rufiji's population is accustomed to a tropical climate and, like any other population, is exposed to cold temperatures relative

Table 3. Lag correlations between all-cause mortality and climate variables in Rufiji DSS, 1999–2010

Age Group	Monthly climate variables	Lag (months)	Coefficient	RR	95% CI	N
0–4	Monthly rainfall	0	0.000791	1.001	(1.000, 1.001)	98
	Monthly rainfall	1	0.00107	1.001	(1.000, 1.002)	
	Monthly rainfall	2	0.000893	1.001	(1.000, 1.002)	
	Monthly rainfall	3	0.000863	1.001	(1.000, 1.002)	
	Monthly rainfall	4	−0.0000627	0.999	(0.999, 1.001)	
	Monthly average temperature	0	−0.01711	0.964	(0.866, 1.062)	
	Monthly average temperature	1	−0.01111	0.995	(0.857, 1.124)	
	Monthly average temperature	2	0.071511	1.074	(0.941, 1.208)	
	Monthly average temperature	3	0.064105	1.078	(0.949, 1.207)	
	Monthly average temperature	4	−0.00736	0.969	(0.874, 1.066)	
5–59	Monthly rainfall	0	0.0004944	1.001	(0.999, 1.001)	98
	Monthly rainfall	1	−0.0001282	0.999	(0.999, 1.000)	
	Monthly rainfall	2	0.0003587	1.000	(0.999, 1.001)	
	Monthly rainfall	3	0.0003253	1.000	(0.999, 1.000)	
	Monthly rainfall	4	0.0002049	1.000	(0.999, 1.000)	
	Monthly average temperature	0	−0.009272	0.991	(0.920, 1.062)	
	Monthly average temperature	1	0.06344	1.066	(0.971, 1.161)	
	Monthly average temperature	2	−0.108909	0.897	(0.801, 0.993)	
	Monthly average temperature	3	0.080517	1.084	(0.991, 1.176)	
	Monthly average temperature	4	0.020678	1.021	(0.952, 1.089)	
60	Monthly rainfall	0	−0.0000986	0.999	(0.999, 1.001)	98
	Monthly rainfall	1	−0.000259	0.999	(0.999, 1.001)	
	Monthly rainfall	2	−0.000509	0.999	(0.999, 1.000)	
	Monthly rainfall	3	0.000454	1.000	(0.999, 1.001)	
	Monthly rainfall	4	0.000447	1.001	(0.999, 1.001)	
	Monthly average temperature	0	−0.04728	0.953	(0.857, 1.048)	
	Monthly average temperature	1	−0.00626	0.995	(0.867, 1.122)	
	Monthly average temperature	2	−0.0267	0.974	(0.845, 1.103)	
	Monthly average temperature	3	0.038513	1.039	(0.915, 1.163)	
	Monthly average temperature	4	−0.03235	0.967	(0.875, 1.060)	

to its average climate. This often occurs during the rainy season (which is consistent with the high malaria transmission season). Also it has been suggested that increased mortality is connected with cold weather because of elevated occurrences of influenza and other respiratory infections (36). Other studies show that housing factors and the substantial numbers of elderly living in 'fuel' poverty may influence the risk of excess winter deaths (31, 37), which is similar to results in this study. Inadequate indoor heating and outdoor clothing are likely to be important factors, therefore, in the observed associations with social deprivation. The effect of cold temperatures on mortality can be observed in the same month and can continue to last for months, as also observed in our investigation.

In conclusion, monthly weather showed a strong association on all-cause mortality. Younger age groups and the elderly population are more susceptible to the influence of monthly weather. Results of the present study show similarities with some previous findings, but also contradict other findings. The conflicting findings are mainly attributable to the multiple weather variables included in a range of studies, and to the different underlying disease burdens in studies from developed settings. This study highlights that the influence of monthly weather on all-cause mortality/morbidity is not well understood, and needs to be further studied in order to better comprehend causal mechanisms and to develop preventive actions.

This study has some limitations. For example, the analyses are based on all-cause mortality, but since the causes of death are driven by different mechanisms they also respond differently to monthly weather.

Finally, with a better understanding of health responses to weather conditions then better health services and policies could be formulated, such as stressful weather episode warnings to susceptible populations and the proper allocation of limited resources.

Authors' contributions

SM wrote the manuscript first draft, AS and MS revised the paper and contributed to the discussion. SM, AS, and MS analyzed data, revised the manuscript, and contributed to the discussion. HM participated in designing the study and critically reviewed the manuscript drafts. All authors read and approved the final manuscript.

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Conflict of interest and funding

The authors declare that they have no competing interests.

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The short-term association of temperature and rainfall with mortality in Vadu Health and Demographic Surveillance System: a population level time series analysis

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Background: Research in mainly developed countries has shown that some changes in weather are associated with increased mortality. However, due to the lack of accessible data, few studies have examined such effects of weather on mortality, particularly in rural regions in developing countries.

Objective: In this study, we aimed to investigate the relationship between temperature and rainfall with daily mortality in rural India.

Design: Daily mortality data were obtained from the Health and Demographic Surveillance System (HDSS) in Vadu, India. Daily mean temperature and rainfall data were obtained from a regional meteorological center, India Meteorological Department (IMD), Pune. A Poisson regression model was established over the study period (January 2003–May 2010) to assess the short-term relationship between weather variables and total mortality, adjusting for time trends and stratifying by both age and sex.

Result: Mortality was found to be significantly associated with daily ambient temperatures and rainfall, after controlling for seasonality and long-term time trends. Children aged 5 years or below appear particularly susceptible to the effects of warm and cold temperatures and heavy rainfall. The population aged 20–59 years appeared to face increased mortality on hot days. Most age groups were found to have increased mortality rates 7–13 days after rainfall events. This association was particularly evident in women.

Conclusion: We found the level of mortality in Vadu HDSS in rural India to be highly affected by both high and low temperatures and rainfall events, with time lags of up to 2 weeks. These results suggest that weather-related mortality may be a public health problem in rural India today. Furthermore, as changes in local climate occur, adaptation measures should be considered to mitigate the potentially negative impacts on public health in these rural communities.

Keywords: *temperature*; *rainfall*; *precipitation*; *climate extreme*; *extreme weather*; *HDSS*; *time series*; *climate*; *climate change*; *weather*; *precipitation*; *death*; *mortality*; *India*

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Climate change is often described as the greatest challenge faced by humanity, with a potentially severe adverse impact on the environment and global population (1). While specific, local outcomes of climate change are uncertain, recent assessments forecast alteration in the frequency, intensity, spatial extent, and duration of weather and climate extremes. This includes climate and hydrometeorological events such as heat waves, heavy precipitation events, drought, and tropical cyclones (2). Some changes in weather will most likely lead to increased stress on human health and environmental systems, both directly and indirectly (2). Weather is commonly identified and studied in terms of sunlight, cloudiness, humidity, precipitation, temperature, and wind, and the local weather depends on the local climate regimen (1). The direct effect of weather, such as extreme temperatures, can disrupt the homeostasis of the body, including the regulation of body heat. Within certain limits, thermal

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comfort can be maintained by appropriate thermoregulatory responses so that physical and mental activities can be pursued without any damage to health (3). Changes in climate can also lead to proliferation of increasing numbers of vectors known to transmit infectious diseases, or enhance the replication rate of virus and bacteria affecting the transmission of food and waterborne diseases. The prevalence and range of a particular microbe, disease vector, or animal reservoir is dependent on specific ranges of temperature, precipitation, and humidity (4, 5). The geographical and temporal distributions as well as the incidence of many vector-borne diseases (i.e. malaria and dengue), particularly those spending part of their lifecycle outside the human body, are sensitive to temperature and rainfall. Pathogens that are carried by insects are exposed to ambient weather. Vector-borne diseases typically exhibit seasonal patterns in which the role of temperature and rainfall is well reported (17). In India, diarrheal diseases typically peak during the rainy season. Floods and droughts increase the risk of diarrheal diseases, and the major causes of diarrhea associated with heavy rainfall and contaminated water supplies include cholera, cryptosporidium, *Escherichia coli* infection, giardia, shigella, typhoid, and viruses such as hepatitis A (17). Furthermore, cholera outbreaks in coastal areas of Bangladesh have been linked with sea-surface temperature and abundance of plankton, which are thought to be an environmental reservoir for the cholera pathogen (6, 7).

The effects of low temperatures should be stressed as they can result in additional adverse health consequences, including deaths from cardiovascular stress, respiratory disease, impaired mental abilities, and loss of motivation as found in cases of hypothermia (3).

Many studies have been carried out in developed countries, which reported evidence of increased mortality in association with extreme ambient temperatures (9) However, few studies have examined the temperature–mortality relationship in rural areas of developing countries (10, 11). In India, where the heat wave of 1998 was estimated to have caused 1,658 excess deaths, there are grounds for changes in climate to serve as a significant public health concern (12). Studies have reported that excessive rain events that cause flooding can also play an important role in aggravating the public health problems, that is, the spread of water-related communicable diseases, such as diarrhea (13). In India, it was reported that increasing rates of diarrhea disease, also including cholera, are related to poor sanitation facilities and extreme rainfall events (9). Diarrhea is a major cause of mortality among children under 5 years of age in India and is considered to be a significant public health problem (14). A study in Bangladesh, investigating the effects of floods on health, found that the size of the family and low economic status were associated with higher diarrhea incidents (15). During 2000 and 2001 in Mumbai, outbreaks of leptospirosis were reported in children living in informal settlements after floods and the prevalence of leptospirosis increased eight-fold following the major flood event in July 2005 (18). Studies on hospital-based observation found that the risk of disease was associated with children either playing in the floodwater or wading through it while going to school and, in some cases, where floodwater was inside the house (19).

The aforementioned studies suggest that a significant amount of work has already been done. However, there are very few studies that have assessed and quantified the association between population level mortality and exposure to temperature and rainfall in rural populations of developing countries.

Objectives

The aim of this study was to estimate the short-term immediate and delayed association of temperature and rainfall on daily mortality in different strata of age and sex in Vadu HDSS and to quantify relative risk per lag strata by groups of age and sex.

Materials and methods

Study area and population

Vadu HDSS is a member of the International Network for the Demographic Evaluation of Populations and Their Health (INDEPTH) in developing countries, a global network of centers that conduct longitudinal health and demographic evaluation of populations in low- and middle-income countries. Vadu HDSS covers 22 villages from two administrative blocks in the Pune District of India. Its geographical extent is 18°30′ to 18°47′ N Latitude and 73°58′ to 74°12′ E Longitude, covering a 232 km^2 geographical unit, with an average altitude of 560 m. Winter lasts from November to February and is followed by a summer that lasts up to early June. The monsoon in the Vadu HDSS area starts from early June and continues until the beginning of October. The latter part of October is the post-monsoon season. November to February is winter. After February, the temperature rises rapidly until April or May corresponding to the hottest

Table 1. Mortality frequencies stratified by groups of age and sex in Vadu HDSS, 2003–2010

Age-group	Daily maximum	Daily minimum	Total mortality
0–4 years	2	0	46
5–19 years	2	0	62
20–59 years	4	0	627
>60 years	13	0	927
Men	8	0	954
Women	10	0	708
Total	18	0	1,662

Table 2. Descriptive statistics of daily meteorologic measurement in Vadu HDSS, 2003–2010

Meteorological variables	Mean (°C)	Maximum (°C)	Minimum (°C)	Std. dev.
Daily maximum temperature	32.2	42.4	21.1	3.9
Daily minimum temperature	18.3	28.0	4.7	4.7
Daily mean temperature	25.2	34.9	15.5	3.2
Rainfall (mm)	1.3	95.0	0.0	6.5

months of the year, on average. While days are generally hotter during April with a mean daily maximum of 40–42°C, nights are warmer during May and June with a mean daily minimum of 23–24°C. Toward the end of the monsoon in October, there is a slight increase in the day temperature, but the nights become progressively cooler. December is the coldest month with mean daily minimum temperature of about 12–13°C (India Meteorological Department [IMD] Pune, 2010). Among the total population of approximately 100,000, about 46% are workers employed in the manufacturing sector, service industry, or non-household industry, whereas 20% are cultivators. Of the total population, 23% work at home, and 11% are students or children not in school. The female to male ratio in Vadu HDSS for the total population was 770: 1,000 over the period of January 2003 to May 2010.

HDSS data collection

Since 2003, the HDSS data have been collected biannually from January to June and July to December. Field research assistants (FRA) visit every household in all villages to record demographic events, including births, deaths, in-migrations, out-migrations, and pregnancies within the Vadu HDSS area. Each event is recorded for all families residing within the area using questionnaires administered by the FRAs who are also local residents. Hence, for the current analysis, information on sex and date of death, and reported cause of death was retrieved from the HDSS data over the study period. The deaths reported during the study period were 1,662. We stratified the number of daily deaths in groups by age, 0–4, 5–19, 20–59, 60+, and by males and females over the study period. The total number of deaths in all groups as well as the maximum and minimum per day over the study period are presented in Table 1.

Meteorological data

Daily weather data were obtained from IMD Pune for a period of 8 years (January 2003–May 2010). We obtained recordings of the mean daily temperature and cumulative daily precipitation (Table 2).

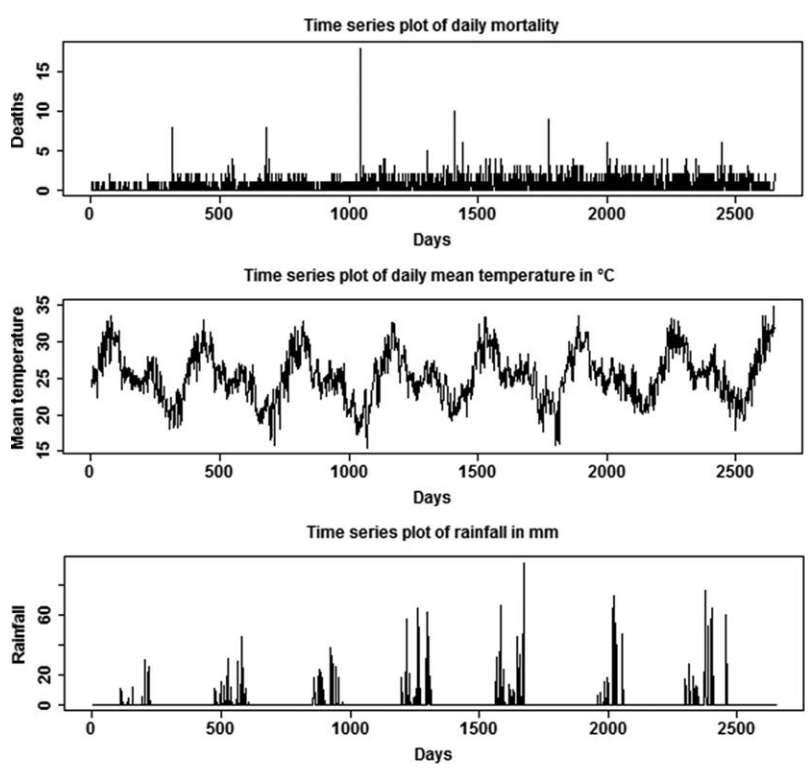

Fig. 1. Time series plot of daily mortality, daily mean temperature (°C), and rainfall (mm) in Vadu HDSS, 2003–2010.

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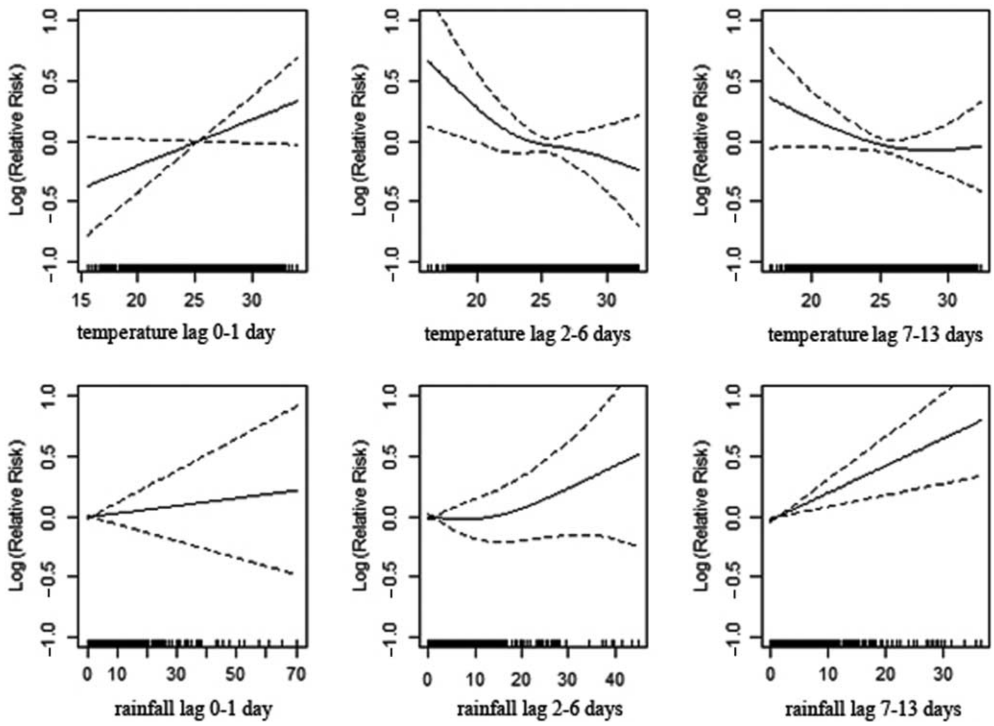

Fig. 2. Association of mortality with daily temperature and rainfall in Vadu HDSS, 2003–2010.

Statistical analysis

We used daily mean temperature and daily cumulative rainfall as explanatory variables of daily mortality. We examined the relationship between daily mortality and the weather variables using time series Poisson regression models allowing for over-dispersion. We used a smooth cubic spline function to adjust for season and time trends allowing six degrees of freedom (df) per year of data over

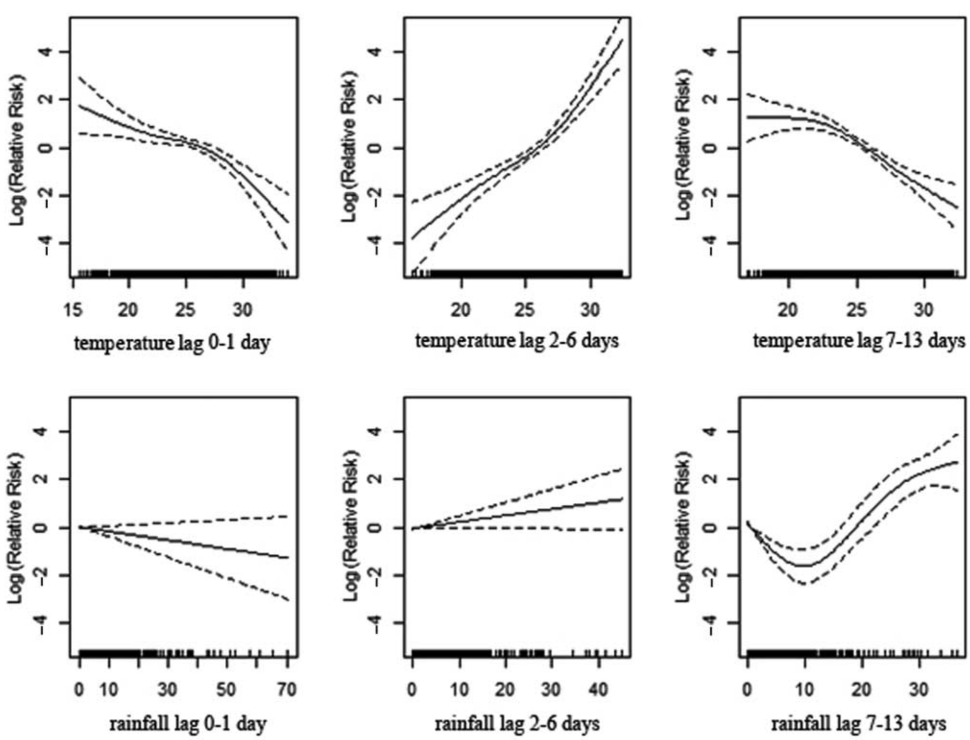

Fig. 3. Association of mortality with daily temperature and rainfall in the age strata of 0–4 years in Vadu HDSS, 2003–2010.

the study period. The short-term weather mortality relationship was estimated using smooth penalized cubic spline functions to avoid too complex fits. Exposure–response functions were also estimated linearly for temperature and rainfall and indicated little deviation from linearity. Potential delayed effects from the weather variables on mortality were assessed via lag strata and averaged the temperature versus rainfall over the periods of lag 0–1, lag 2–6, and lag 7–13 days The purpose was to avoid collinearity introduced by having several highly correlated explanatory variables in the regression model simultaneously.

The models used for this analysis could be expressed as:

$$\text{Deaths}_t \sim \text{Poisson}\ (\text{mean}_t)$$
$$\begin{aligned}\log\ (\text{mean}_t) = \text{intercept} &+ s(\text{temperature lag } 0\text{–}1,\ df = 4)\\ &+ s(\text{temperature lag } 2\text{–}6,\ df = 4)\\ &+ s(\text{temperature lag } 7\text{–}13,\ df = 4)\\ &+ s(\text{rain lag } 0\text{–}1,\ df = 4)\\ &+ s(\text{rain lag } 2\text{–}6,\ df = 4)\\ &+ s(\text{rain lag } 7\text{–}13,\ df = 4)\\ &+ s(\text{time},\ df = 6 \text{ per year of data}).\end{aligned}$$

And,

$$\begin{aligned}\log\ (\text{meant}) = \text{intercept} &+ \text{temperature lag } 0\text{–}1\\ &+ \text{temperature lag } 2\text{–}6\\ &+ \text{temperature lag } 7\text{–}13\\ &+ \text{rain lag } 0\text{–}1\\ &+ \text{rain lag } 2\text{–}6\\ &+ \text{rain lag } 7\text{–}13\\ &+ s(\text{time},\ df = 6 \text{ per year of data}).\end{aligned}$$

Where ‘s’ denotes a cubic spline function with ‘df’ number of degrees of freedom (df), and ‘t’ denotes the time of observation. The autocorrelation function was estimated and assessed to examine potential residual confounding patterns. Relative risks (RR) corresponding to a 1°C increase in temperature and a 1 mm increase in rainfall are presented with 95% confidence limits for the linear estimates.

Results

The time series plots for daily mortality, daily mean temperature, and cumulative rainfall are presented in Fig. 1. Temperature is strongly seasonal with peaks in March, April, and May, and rainfall shows an increasing trend and peaks during the months of June, July, and August. The highest peak indicated by the plot is for August 2008 where rainfall was >90 mm in a single day.

Figure 2 shows the association between temperature and rainfall with daily mortality in total population over all time lagged strata studied. These associations indicate that elevated temperature drives effects in lag 0–1, whereas depressed temperatures drive the trend in lags 2–6. A strong positive correlation is evident between the onset of rainfall and subsequent mortality for the period of 7–13 days.

To better understand the relationship among daily mortality, mean temperature, and cumulative rainfall, we created regression models for mortality, stratifying by age and sex. (Table 3; Fig. 3), shows a significant association between mortality and temperature for the age group of 0–4 years, apparent with lower temperature in lag 0–1 and 7–13 and with high temperature in lag 2–6. High levels of rainfall significantly increase deaths among children with a 1–2 week delay. In the age group 5–19 (Table 3; Fig. 4), the lag 7–13 temperatures show positive associations with mortality during extreme hot

Table 3. Relative risks (% per degree increase) and 95% confidence intervals for temperature and rainfall in different lag periods stratified by age (bold indicates significances at 5% level)

Age 0–4 years	RR (%)	CI (%)
Temperature lag 0–1	**−18.8**	**(−24.9, −12.2)**
Temperature lag 2–6	**66.5**	**(50.0, 84.9)**
Temperature lag 7–13	**−29.3**	**(−36.6, −21.1)**
Rainfall lag 0–1	**−3.6**	**(−5.7, −1.5)**
Rainfall lag 2–6	0.5	(−1.9, 3.0)
Rainfall lag 7–13	−0.1	(−2.8, 2.5)
Age 5–19 years	**RR (%)**	**CI (%)**
Temperature lag 0–1	−2.3	(−10.0, 6.2)
Temperature lag 2–6	7.1	(−9.7, 19.1)
Temperature lag 7–13	**15.7**	**(5.0, 27.5)**
Rainfall lag 0–1	1.1	(−1.0, 3.3)
Rainfall lag 2–6	**−6**	**(−1.8, −1.0)**
Rainfall lag 7–13	**6**	**(3.0, 9.2)**
Age 20–59 years	**RR (%)**	**CI (%)**
Temperature lag 0–1	**9.4**	**(3.6, 15.5)**
Temperature lag 2–6	**−9.5**	**(−15.5, −3.2)**
Temperature lag 7–13	1.8	(−4.1, 8.1)
Rainfall lag 0–1	0.7	(−0.3,1.9)
Rainfall lag 2–6	−1.1	(−3.0, 7.5)
Rainfall lag 7–13	**3**	**(1.3, 4.0)**
Age >60 years	**RR (%)**	**CI (%)**
Temperature lag 0–1	2.9	(−2.1, 8.0)
Temperature lag 2–6	−3.3	(−1.8, 2.8)
Temperature lag 7–13	2	(−3.4, 7.8)
Rainfall lag 0–1	−0.5	(−1.7, 0.7)
Rainfall lag 2–6	0.8	(−0.6, 2.2)
Rainfall lag 7–13	0.4	(−1.2, 2.0)

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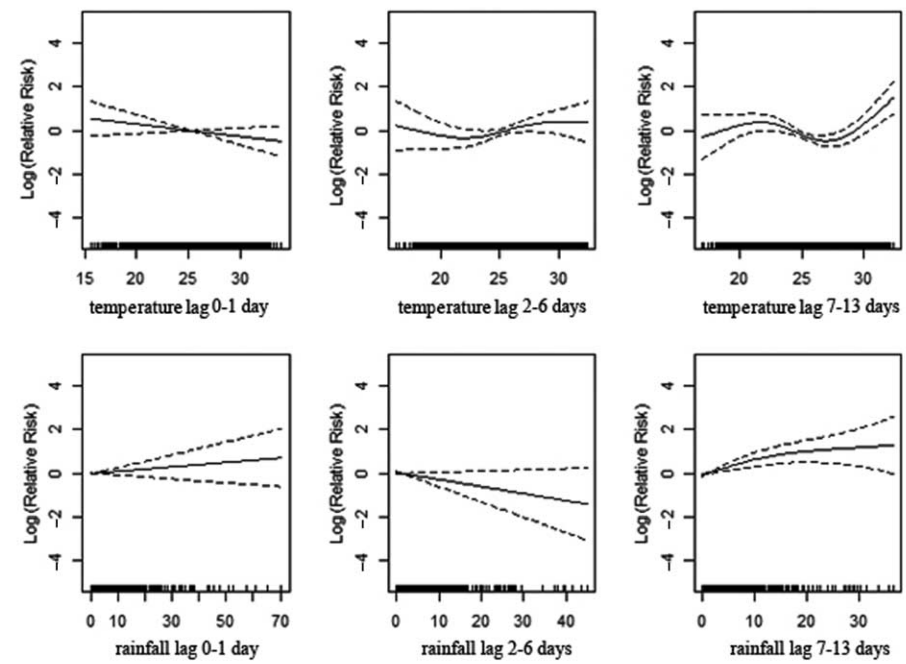

Fig. 4. Association of mortality with daily temperature and rainfall in the age strata of 5–19 years in Vadu HDSS, 2003–2010.

conditions. However, the association is weaker compared to the younger age group. Increasing amounts of rainfall in lag 7–13 were strongly associated with increasing mortality while a reduction in deaths was observed during the first week following rainfall (Table 3; Fig. 4). In the age group 20–59 (Table 3; Fig. 5), a positive association is reported with higher temperatures in lag 0–1, whereas the opposite pattern is present in lag 2–6. Rainfall shows a positive association with mortality in lag 0–1 and, in particular, a strong significant association in 1–2 weeks after rainfall. The elderly appear susceptible to increasing rainfall (lag 2–13). However, there are no strong apparent

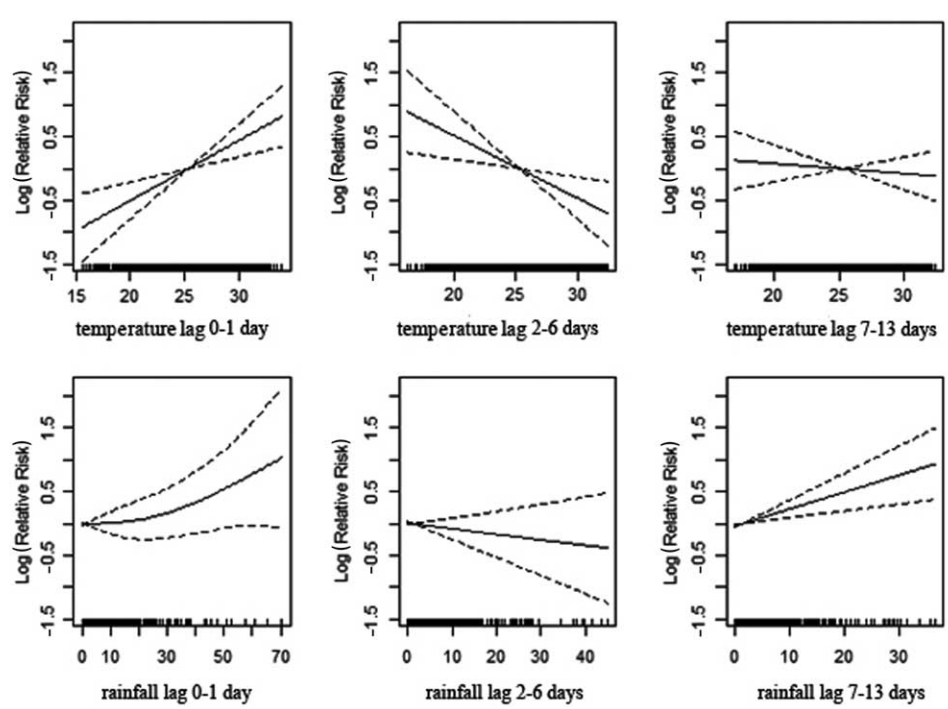

Fig. 5. Association of mortality with daily temperature and rainfall in the age strata of 20–59 years in Vadu HDSS, 2003–2010.

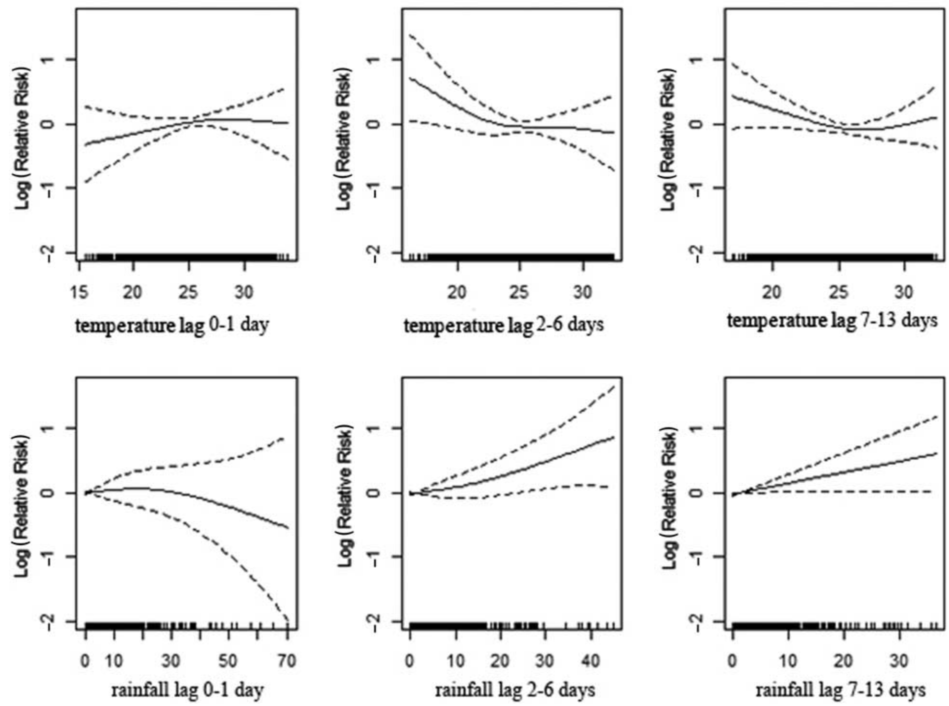

Fig. 6. Association of mortality with daily temperature and rainfall at the age of 60 years in Vadu HDSS, 2003–2010.

patterns associated with temperature in this age group (Table 3; Fig. 6). Figures 7 and 8 and Table 4 show the corresponding associations in the groups of men and women. The graphs and Table 4 indicate that women may be more susceptible to the mortality effects following rainfall events (lag 7–13) compared to men.

Discussion and conclusion

The present study was designed to determine the associations of mortality with temperature and rainfall. The results of this study primarily indicate that strong associations with temperature and rainfall exist for all-cause mortality over all age groups. The effects could be

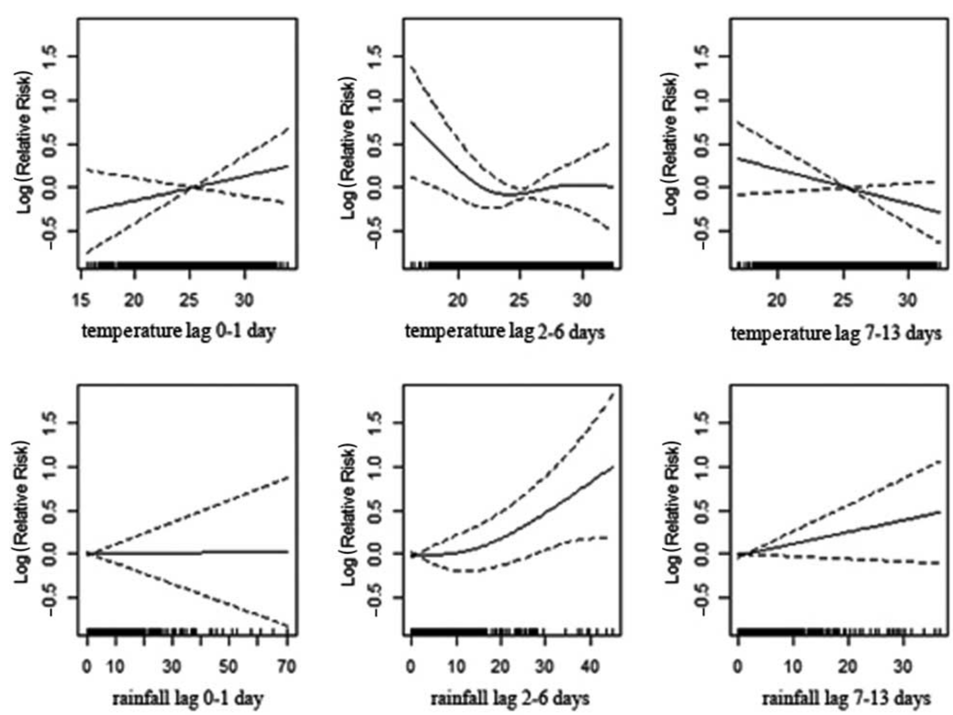

Fig. 7. Association of mortality among men and daily temperature and rainfall in Vadu HDSS, 2003–2010.

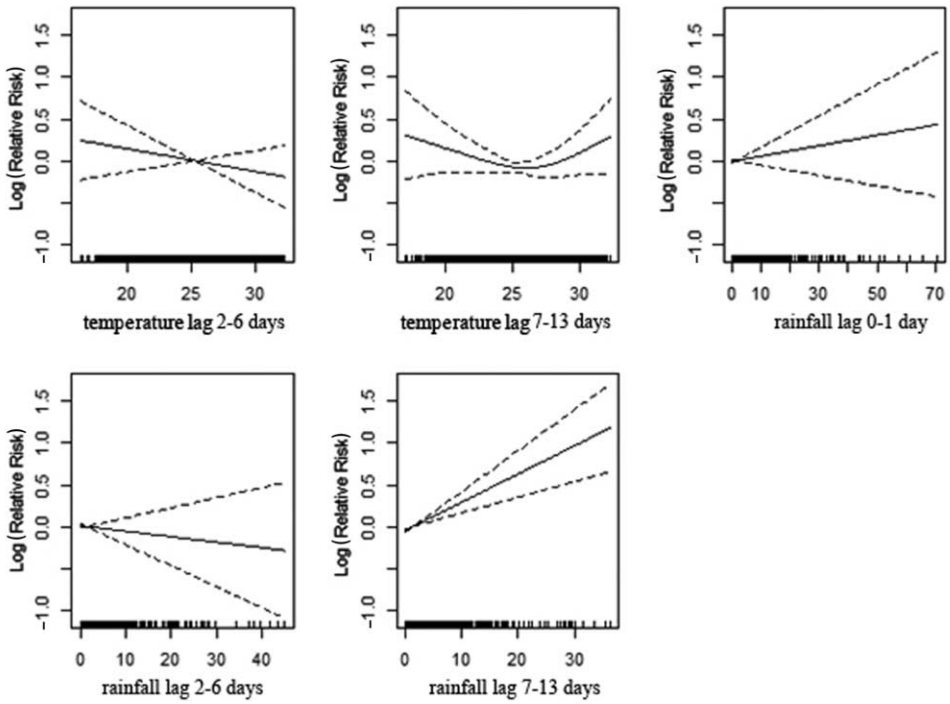

Fig. 8. Association of mortality among women and daily temperature and rainfall in Vadu HDSS, 2003–2010.

seen for both high and low temperatures, and up to 2 weeks following rainfall. In particular, the associations were strongest among children, women, and the elderly. In this respect, it appears that the population of Vadu HDSS in rural India is particularly vulnerable to changing weather conditions. It is important to increase resilience to weather, climate change, and climate extreme events in these regions to achieve the millennium development goals (MDGs) and to mitigate harmful effects (8).

Table 4. Relative risks (% per degree increase) and 95% confidence intervals for temperature and rainfall in different lag periods stratified by sex (bold indicates significances at 5% level)

Men	RR (%)	CI (%)
Temperature lag 0–1	3.1	(−1.7, 8.1)
Temperature lag 2–6	−2.3	(−8.2, 3.8)
Temperature lag 7–13	2	(−3.4, 7.6)
Rainfall lag 0–1	−0.2	(−1.5, 0.9)
Rainfall lag 2–6	0.8	(−0.6, 2.2)
Rainfall lag 7–13	2.2	(−1.4, 1.9)
Women	**RR (%)**	**CI (%)**
Temperature lag 2–6	−6.5	(−12.6, 0.1)
Temperature lag 7–13	1.5	(−4.3, 7.7)
Rainfall lag 0–1	0.3	(−0.9, 1.5)
Rainfall lag 7–13	**2.3**	**(0.7, 3.9)**

It is well known that extreme temperature and rainfall are potent risk factors for certain diseases, including heat stroke, dengue, malaria, and cholera (20). There is further evidence that disease incidences increase during heavy rainfall, as flood water could mix with drinking water, resulting in an increase in mortality (20).

Future studies should elaborate more on the environmental risk factors on a daily basis and their relationship to mortality so as to understand and mitigate potential negative health effects. There is also a need for more studies within this population to describe the roles of socioeconomic and physiologic factors in relation to weather and mortality. To refine the studies, there is also a need to improve environmental monitoring and surveillance systems in developing countries. Research initiatives could focus on long-term data collection on climate-related mortality with the aim of understanding current weather-related associations with mortality and to predict future scenarios. Health outcomes of interest, for which such data should be collected, include total morbidity and mortality and non-communicable diseases, such as cardiovascular, respiratory, circulatory diseases, and asthma, as well as infectious diseases, such as cholera, malaria, tuberculosis, typhoid, hepatitis, and other vector-borne and waterborne diseases. So far in India, health impacts of climate change have not been studied much in detail. However, it is a known fact that the current burden of climate is related to diseases (16). In summary, this study clearly indicates the value of the HDSS for such a purpose and the potential to further refine and identify susceptible groups and hazardous climate-related events to increase resilience of the rural communities to these impacts.

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Conflict of interest and funding

The authors have not received any funding or benefits from industry or elsewhere to conduct this study.

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The association of weather and mortality in Bangladesh from 1983–2009

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Introduction: The association of weather and mortality have not been widely studied in subtropical monsoon regions, particularly in Bangladesh. This study aims to assess the association of weather and mortality (measured with temperature and rainfall), adjusting for time trend and seasonal patterns in Abhoynagar, Bangladesh.

Material and methods: A sample vital registration system (SVRS) was set up in 1982 to facilitate operational research in family planning and maternal and child health. SVRS provided data on death counts and population from 1983–2009. The Bangladesh Meteorological Department provided data on daily temperature and rainfall for the same period. Time series Poisson regression with cubic spline functions was used, allowing for over-dispersion, including lagged weather parameters, and adjusting for time trends and seasonal patterns. Analysis was carried out using R statistical software.

Results: Both weekly mean temperature and rainfall showed strong seasonal patterns. After adjusting for seasonal pattern and time trend, weekly mean temperatures (lag 0) below the 25th percentile and between the 25th and 75th percentiles were associated with increased mortality risk, particularly in females and adults aged 20–59 years by 2.3–2.4% for every 1°C decrease. Temperature above the 75th percentile did not increase the risk. Every 1 mm increase in rainfall up to 14 mm of weekly average rainfall over lag 0–4 weeks was associated with decreased mortality risks. Rainfall above 14 mm was associated with increased mortality risk.

Conclusion: The relationships between temperature, rainfall and mortality reveal the importance of understanding the current factors contributing to adaptation and acclimatization, and how these can be enhanced to reduce negative impacts from weather.

Keywords: *weather*; *temperature*; *rainfall*; *mortality*; *rural*; *Abhoynagar*; *Bangladesh*

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The effect of weather on health is undeniable. Interest in the effect of weather change on health is increasing, especially in the light of global concern for potential climate change. Climate change affects every aspect of the society, from the health of the global economy to the health of our children (Ban Ki-Moon, UN Secretary General, speech 24 May 2009). It echoes the importance of research on mitigation and adaptation to climate change in vulnerable and resource-limited countries. Bangladesh has been found to be one of the most vulnerable countries to the adverse effects of climate change (1). Planning interventions require evidence. Such evidence is far less than what is required for formulating mitigation, adaptation, and poverty alleviation strategies.

Weather data from the Bangladesh Meteorological Department (BMD) on temperature (minimum and maximum), rainfall, and cyclones observed in 1950–2010 exhibited a sign of climate change (2). Daily temperatures showed an increasing trend and the increase was faster for minimum temperature. Frequency of heavy rainfall in a short span of time in pre-monsoon and monsoon has exhibited a considerable increase in recent years. With ongoing climate change, extreme weather events, such as floods, drought, or cyclones, are predicted to increase in frequency and duration (3). During 1960–1990, there were two intense cyclones with wind speeds more than 200 km/hour and 3–10 m high waves in the North Bay of Bengal; however, there were seven cyclones during 1991–2010 (2). Devastating cyclones caused extensive

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damage to life, property, and livestock. Human sufferings in terms of food, water, shelter, health, and overall livelihood were enormous because of the low flat terrain, high population density, poorly built houses, high level of poverty, natural-resource-dependent economy, and low adaptive capacity (4). Other impacts of climate change in this low-lying delta includes inundation of arable land, salinity intrusion, reduced fresh water, and persistence of transboundary pests and diseases (4–6). Furthermore, drinking water from natural sources in coastal areas has become contaminated by varying degrees of salinity due to salt water intrusion from rising sea levels, cyclone and storm surges, and upstream withdrawal of freshwater and affected health indicated by excess hypertension in pregnancy (6).

The association between high and low temperature and mortality has been investigated in several studies. The heterogeneity of the effects of temperature across geographic, climatic, and cultural zones was evident. In a multi-country ecological comparison in Europe, higher excess mortality rates were found in less severe, milder winters, where, all else being equal, there should be less potential for cold strains and cold-related mortality (7, 8). In 16 European cities characterized by different weather conditions, analysis reveals that in both summer and winter the strongest effects were observed in the Mediterranean cities, where winter is less severe or milder (9). These studies reveal that, in developed countries, the lower the temperature range the stronger the temperature–mortality relationship at low temperature. The effect of temperature variation in subtropical monsoon regions is unknown.

Weather in Bangladesh with its subtropical climate varies considerably between regions. On the basis of entire climatic conditions, the country is divided into seven distinct climatic zones (17). The International Centre for Diarrhoeal Disease Research, Bangladesh (icddr,b), has set up longitudinal vital registration systems in Matlab and Abhoynagar in 1966 and 1982, respectively, for conducting operational research in family planning, maternal, and child health. These two rural areas are in two climatic zones, which provide a rare opportunity to examine the weather–mortality relationships in different climatic conditions. Matlab is located in the south-central zone characterized by more frequent and severe hail storms, nor'westers, and tornadoes, and Abhoynagar is located in the south-western zone characterized by higher dew-rate. According to the BMD data, during 1983–2009 temperature and rainfall differ substantially; Abhoynagar showed both lower minimum temperatures (5.0°C vs. 8.6°C) and higher maximum temperatures (43.2°C vs. 37.8°C) than Matlab. Average rainfall in Abhoynagar was 4.8 mm with standard deviation 14.3, lower than 5.8 mm with a standard deviation of 16.4 in Matlab. The highest rainfall in a single day was 255 mm in Abhoynagar, lower than 334 mm in Matlab.

With respect to temperature and rainfall, Abhoynagar is different from Matlab, but no study has so far examined the weather–mortality relationships other than in Matlab. One study showed seasonal patterns of deaths in Matlab and another study reported that daily mortality increased with low temperatures in the preceding weeks and no association between high temperature and daily mortality during the period 1994–2002 (10, 11). These studies were limited to the association between temperature and mortality, excluding rainfall. The present study will examine the temperature– and rainfall–mortality relationships in Abhoynagar where temperature varies more and rainfall less than those in Matlab.

Objectives

The overall objectives of this study are to investigate the effects of temperature and rainfall on all-cause mortality in different age and sex groups in Abhoynagar and to compare the results with those of studies carried out in other climatic zone in Bangladesh (12).

Methods and data

This study used total deaths and total population at risk in Abhoynagar subdistrict and weather data from a nearby weather station of the BMD in Jessore district. Abhoynagar is predominantly rural, located in Khulna division in the southwest of Bangladesh, between Jessore and Khulna cities – about 30 km away from each (13). Khulna division reached the replacement level of fertility around the year 2000. A sample vital registration system (SVRS) was set up in the division by icddr,b in late 1982 to conduct operational research in the areas of family planning, infant, child, adolescent and maternal health, and health equity. SVRS covered 122 villages in 7 out of 17 unions selected randomly since late 1982 and another 32 villages in 2 unions since early 1984. A household listing operation was carried out in selected villages to prepare the sampling frame. The systematic random sampling was used to select every sixth household in sampled villages to prepare a sociodemographic profile of the households for surveillance. Trained field research assistants visited sampled households in 3-monthly rounds to record vital events; births, deaths, migrations, and marriages and marital disruptions. Two field research supervisors supervised their data collection activities on a regular basis. The vital events recorded were edited for consistencies and added to the longitudinal relational database.

BMD is responsible for observation, recording, and archiving of climate data for various stations in the country. BMD continuously uses weather data for monitoring time trends. We retrieved daily maximum and minimum temperature and rainfall from Jessore weather station for 1983–2009. Daily temperature or

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rainfall, if missing, was replaced by the estimate derived from the linear interpolation. Mean temperature was calculated as the average of minimum and maximum temperature of the day.

Statistical analysis

During the period 1983–2009 (or 9,862 days), the Abhoynagar SVRS recorded 4,850 deaths. Weeks rather than days was chosen as unit of analysis to minimize fluctuations due to small number. The relationship between the average weekly temperature (minimum, maximum, and mean) and average weekly rainfall with weekly death count was examined using graphics followed by generalized additive Poisson regression models with cubic spline functions, allowing for overdispersion. The model is expressed with the formula:

$$\text{Mortality}_t - \text{Poisson}(\text{mean}_t)$$
$$\text{mean}_t = b_0 + s(\text{time}_t;\ df = 4 \text{ per year})$$
$$+ s(\text{temperature}_t;\ df = 10) + s(\text{rainfall}_t;\ df = 10)$$

where t denotes time, df denotes degrees of freedom, and s denotes a cubic spline function. Models were fitted to the average weekly death count, to weekly mean temperature of up to 3 weeks (lag 0–3) and rainfall up to 4 weeks prior to the week of death (lag 0–4), to assess the effects of low or high temperature or low or high rainfall over longer periods. Combined time trend and seasonal pattern were included with four unpenalized degrees of freedom for seasonal patterns and trends per year. The exposure response to meteorological factors was penalized, allowing a maximum of 10 degrees of freedom.

Results

During the observation period of 27 years (or 1,409 weeks), the population of the Abhoynagar surveillance site increased from 21,547 during the first week of 1983 to 34,774 during the last week of 2009. During this period, SVRS registered an average of 3.4 deaths per week. Infants accounted for 26% of all deaths and the elderly (aged 60 years and above) for 44%, totaling 70%. During this period, the lowest weekly minimum temperature observed was 14.3°C and the highest weekly maximum temperature was 34.3°C. Average daily rainfall was 4.8 mm with a peak of 255 mm in a single day.

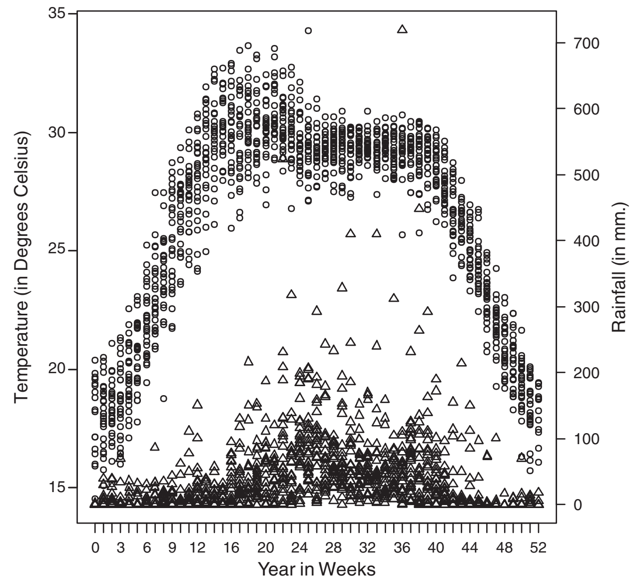

Fig. 1. Annual pattern of weekly temperature (circle) and rainfall (pyramid), 1983–2009.

Weekly temperature showed a seasonal pattern, with the peak in April–May and the lowest at the beginning and the end of the calendar year (Fig. 1). Overall, temperature and rainfall are positively correlated ($r = 0.09$, $p < 0.01$); however, during the rainy season (June–September) rainfall has a moderating effect on temperature ($r = -0.49$, $p < 0.001$).

The temperature–mortality associations are displayed in Fig. 2 for average weekly minimum, maximum, and mean temperature. Maximum temperature showed the strongest graphical association with mortality followed by mean temperature. Generalized linear Poisson regression models show that weekly mean temperature had the

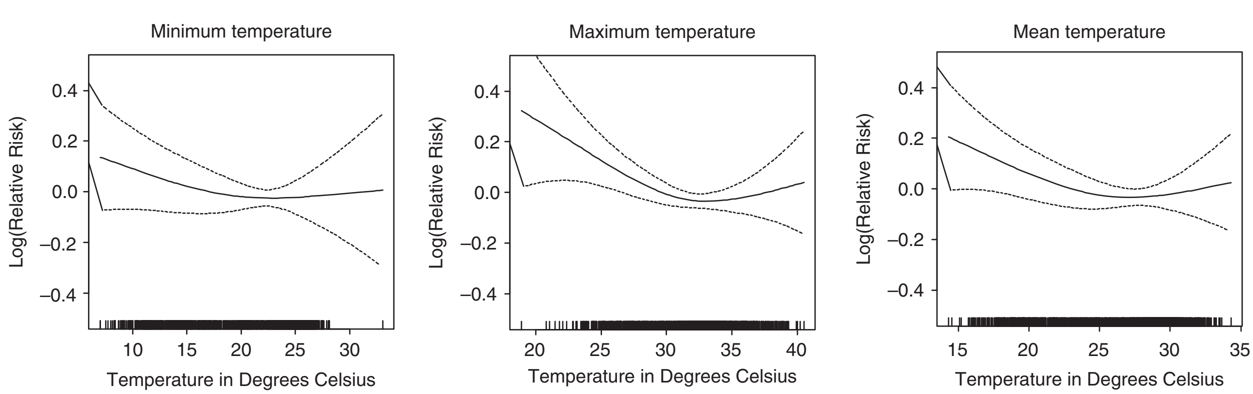

Fig. 2. Association of temperature and mortality, after adjusting for trend and seasonality.

Table 1. Linear approximation of the association of mortality with minimum, maximum and mean temperature, after adjusting for time trend and seasonality

Temperature in °C	<25% (first quartile)			25%–75% (2nd and 3rd quartile)		>75% (last quartile)				
	Tem[1] <	RR^2 (%)	95% CI[3]	RR^2 (%)	95% CI	Tem >	RR^2 (%)	95% CI	% DE[4]	GCV[5]
Maximum	29.6	−1.8	(−4.1, −0.5)	−2.2	(−4.1, −3.0)	34.0	0.1	(−0.2, +0.4)	13.70	1.1838
Minimum	16.1	−2.2*	(−4.1, −0.3)	−2.2***	(−3.2, −1.1)	25.7	0.3	(−0.1, +0.6)	13.30	1.1892
Mean	23.0	−2.3*	(−4.4, −0.1)	−2.4**	(−3.9, −0.9)	29.6	−2.3*	(−2.6, −2.0)	13.60	1.1858

[1]Temperature.
[2]Change in relative risk in percent.
[3]95% confidence interval.
[4]Deviance explained.
[5]Geometric coefficient of variation.
*$P<0.05$, **$P<0.01$, ***$P<0.001$.

strongest association with weekly mortality; below 23.0°C, the relative mortality risk increased by 2.3% with every 1°C decrease in temperature, and between 23.0 and 29.6°C, the relative risk increased by 2.4% with a 1°C decrease (Table 1). Above 29.6°C, higher temperature was also associated with a lower mortality risk (relative risk = −2.3%).

Weekly mean temperature was included in the models to assess the temperature–mortality associations over different time lags. The average temperature over a 2-week period (temperature in the week of occurrence of death and during the preceding week) has the strongest association with weekly mortality (Fig. 3). Lag 0–1 temperature was used to assess the temperature–mortality associations by sex and age groups.

Linear approximations of the associations of lag 0–1 mean temperature with mortality were statistically significant across temperatures; below 25th percentile and between 25th and 75th percentiles (Table 2). Disaggregation of the temperature–mortality association by sex and age reveals sex and age differences in the temperature effect. Low temperature (below 75th percentile) was associated with increased mortality risk of females, but not males. The low-temperature–mortality risk was significantly higher for age groups 5–19 and 20–59 years. This was not the case for infants, children 1–4 years, and elderly (60+years). Temperature above 75th percentile was not associated with mortality risk of any sex and age group. Mortality of females increased by 4.3% with every 1°C decrease in temperature below the 25th percentile and increased by 3.8% with every 1°C decrease in temperature between the 25th and 75th percentile. For the age group 5–19 years, the temperature–mortality association below the 75th percentile was opposite the direction of the temperature–mortality association for the age group 20–59 years. A detailed study would be needed to understand the reverse temperature–mortality relationship.

Weekly mean rainfall was included in the models to assess the rainfall–mortality associations over different time lags (Fig. 4). Mortality as smoothed functions of rainfall, using 3 mm (59th percentile) and 14 mm (91st percentile) as cut-off values for these rainfall models, showed significant associations for the longer time lags. The optimal rainfall model seemed to be the lag 0–4 model (up to 4 weeks preceding the week of death) with, below 3 mm rainfall, a relative mortality risk of −7.0% (95% CI: −11.7%, −2.1%); between 3 and 14 mm rainfall, a relative risk of −1.7% (95% CI: −2.7%, −0.7%); and above 14 mm rainfall a relative mortality risk of 1.2% (95% CI: 0.1%, −2.2%) (Table 3).

Gender disaggregated models showed a reduction in female mortality risks below 14 mm of average rainfall with every 1 mm increase in rainfall and increased mortality risks of both males and females ($p<0.05$) at

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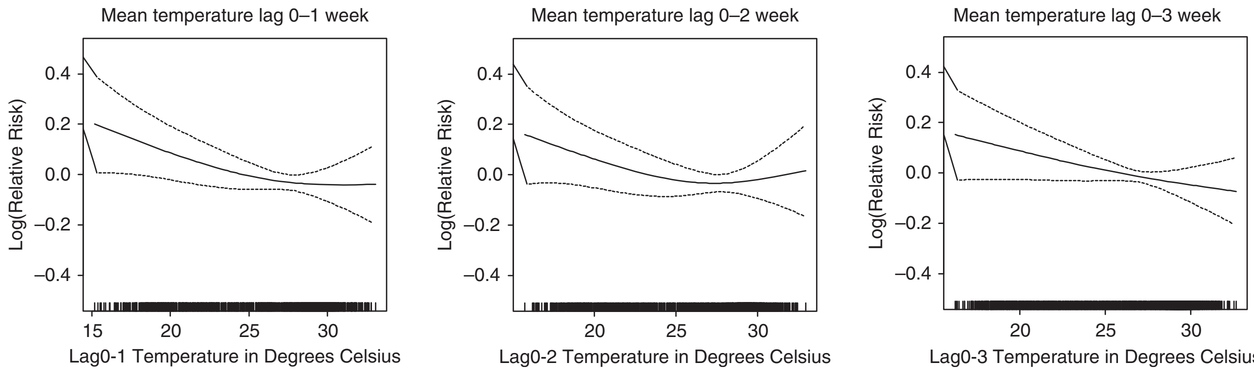

Fig. 3. Association of mortality with mean temperature at different time lags, after adjusting for trend and seasonality.

rainfall levels over 14 mm (Fig. 4 and Table 3). The rainfall–mortality associations also depend on age of the individuals. The association for the age group 5–19 years was opposite the associations for the age groups 20–59 and 60+years. Mortality risks of the adults (aged 20–59 years) and elderly decreased with every 1 mm increase in rainfall below 14 mm rainfall and increased above 14 mm rainfall.

Discussion

This study showed, after adjustment for time trend and seasonality, a moderate but significant increase in all-cause mortality at lower temperature in Abhoynagar compared to a more marked increase in Matlab (11, 12). Compared to Matlab, temperature (minimum and maximum) in Abhoynagar was more extreme. This suggests that variations in temperature influence the temperature–mortality relationship at lower temperatures. This finding is consistent with the findings of several studies. In Europe, countries with the mildest winter climates exhibited the highest excess winter mortality than countries with severe winter climates (7–9). The heterogeneity of the effect reflects the capacity to adapt to extreme temperature. Data on cross-country thermal-efficiency standards in housing indicated that those countries with poorest housing demonstrated the highest excess winter mortality and poorest housing was more common in countries with mildest winter climate (7). The thermal efficiency of the house is perhaps on the causal pathways between low temperature and mortality risk.

The temperature–mortality relationships between these two areas in different climatic zones may be due to difference in weather and adaptation than other health-related factors. Communities naturally adapt – physiologically, culturally, and behaviorally – to living in cold and warmer climates. Common adaptive

Table 2. Associations of lag 0–1 mean temperature and mortality for sex and age groups, after adjusting for trend and seasonality, 1983–2009

	Tem[1] <25% (first quartile)		Tem[1] 25%–75% (2nd and 3rd quartile)		Tem[1] >75% (last quartile)			
Sex and age group	RR[2] (%)	95% CI[3]	RR[2] (%)	95% CI	RR[2] (%)	95% CI	% DE[4]	GCV[5]
Overall	−2.5*	(−3.5, −1.5)	−2.4**	(−3.9, −0.8)	−0.1	(−0.4, +0.2)	13.60	1.1858
Male	−0.5	(−3.6, +2.6)	−1.0	(−3.2, +1.2)	−0.3	(−0.7, +0.2)	6.02	1.1757
Female	−4.3**	(−7.3, −1.3)	−3.8**	(−5.9, −1.5)	0.0	(−0.5, +0.4)	9.27	1.2252
Age group								
Infant	−3.5	(−10.7, +4.2)	−0.9	(−6.2, +4.7)	0.1	(−0.8, +1.1)	10.40	0.6085
1–4	−3.5	(−10.7, +4.2)	−0.9	(−6.2, +.7)	0.1	(−0.8, +1.1)	10.40	0.6085
5–19	9.0*	(0.7, +18.1)	7.6*	(1.6, +13.9)	−0.2	(−1.1, +0.7)	13.60	1.1858
20–59	−6.3**	(−10.6, −1.7)	−4.8**	(−8.0, −1.5)	0.2	(−0.4, +0.9)	3.61	1.1054
60+	−1.0	(−4.3, +2.3)	−2.0	(−4.3, +0.4)	−0.3	(−0.8, +0.2)	4.85	1.2109

[1]Temperature.
[2]Change in relative risk in percent.
[3]95% confidence interval.
[4]Deviance explained.
[5]Geometric coefficient of variation.
*$P<0.05$, **$P<0.01$, ***$P<0.001$.

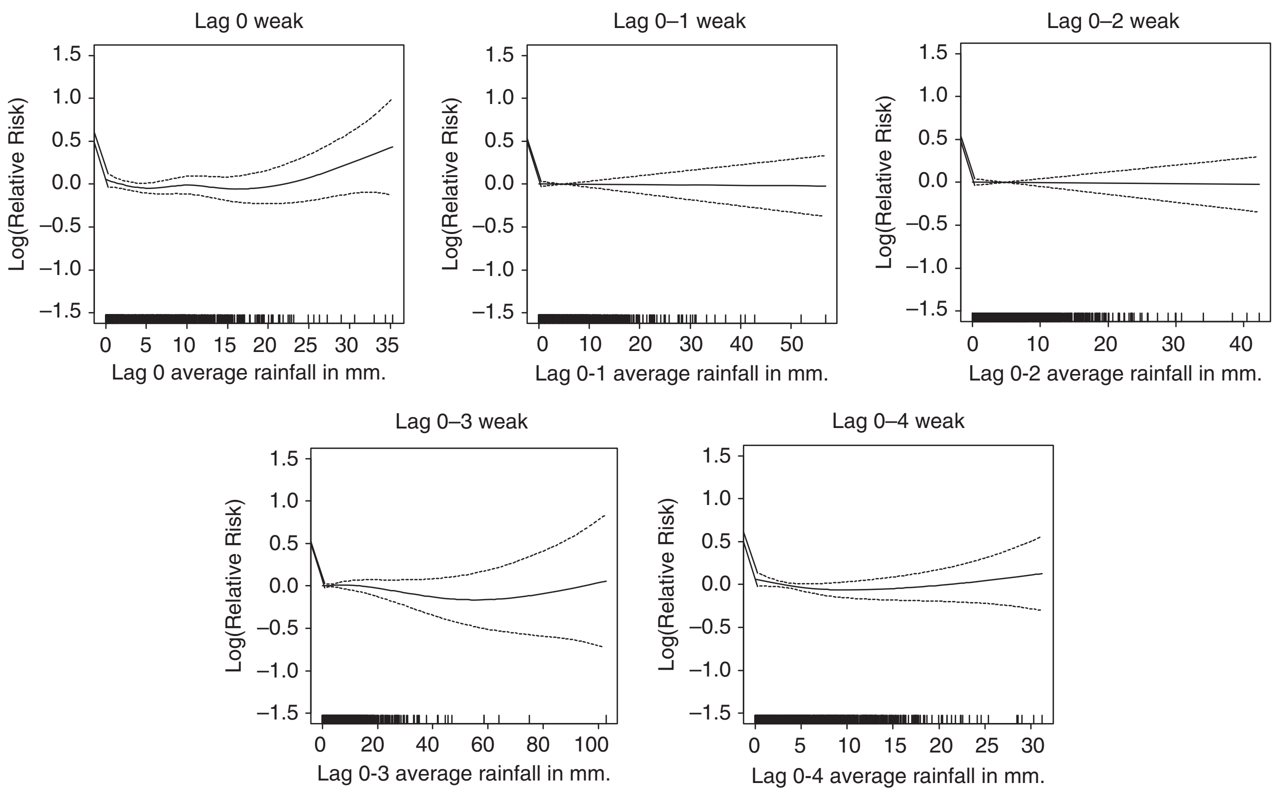

Fig. 4. Association of mortality with rainfall at different time lags, after adjusting for trend and seasonality.

measures that match with large temperature variation at microlevel are thermal efficiency in housing and clothing. Available data on the quality of housing revealed that more houses in Abhoynagar have walls and roofs with cement/concrete than in Matlab. In 2008 in Abhoynagar, 30% of the houses were roofed and 41% were walled with cement/concrete compared to 2% houses roofed and 4% walled with cement/concrete in Matlab in 2005 (13, 14). In winter, the indoor temperature at night in houses roofed and walled with tin or

Table 3. Associations of mortality with lag 0–4 rainfall for sex and age groups, after adjusting for trend and seasonality, 1983–2009

	Rainfall <3 mm		Rainfall 3–14 mm		Rainfall >14 mm			
Sub group	RR[1] (%)	95% CI[2]	RR[1] (%)	95% CI	RR[1] (%)	95% CI	% DE[3]	GCV[4]
Overall	−7.0***	(−11.7, −2.1)	−1.7***	(−2.7, −0.7)	1.2*	(0.1, +2.2)	17.20	1.1275
Male	−1.8	(−8.2, +5.1)	−0.9	(−2.1, +0.2)	1.2•	(−0.2, +2.5)	5.04	1.1925
Female	−14.0***	(−19.6, −7.9)	−2.8***	(−3.9, −1.6)	1.4•	(−0.1, +2.9)	8.19	1.2288
Age group								
Infant	−4.3	(−13.4, +5.7)	−1.4	(−3.1, +0.4)	1.0	(−1.0, +3.0)	16.0	1.2438
1–4	3.8	(−11.8, +22.1)	2.2	(−0.5, +5.0)	3.8*	(0.7, +6.9)	13.0	0.61279
5–19	15.7•	(−0.4, +34.3)	4.0**	(1.3, +6.8)	−2.3	(−5.2, +0.6)	8.65	0.68735
20–59	−10.5*	(−19.6, −0.3)	−2.2*	(−4.0, −0.4)	2.0•	(−0.1, +4.1)	1.75	1.1068
60+	−12.0**	(−18.5, +5.0)	−3.0***	(−4.2, −1.7)	1.7*	(0.2, +3.3)	4.14	1.2463

[1]Change in relative risk in percent.
[2]95% confidence interval.
[3]Deviance explained.
[4]Geometric coefficient of variation.
•*P* <0.1, **P* <0.05, ***P* <0.01, ****P* <0.001.

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straw is the same as the outdoor temperature. Cold temperature accompanied by chill and fog makes people sick as many do not have enough cold-protective measures. However, data on possession of winter clothes at individual and household levels are not available in either area. The finding emphasizes the need to revisit local adaptive measures to explain and combat cold-related mortality in the community.

There was a gender difference in temperature–mortality relationship in Abhoynagar. Why females were more vulnerable at lower temperature needs more in-depth investigation. In rural areas, women are usually home-makers and men are the main income earners (13, 14). This gender-based division of labor might have played a role in increasing vulnerability of females. Women do washing and cleaning for all household members. Such frequent and prolonged washing and cleaning with cold water in cold weather may have contributed to the increased mortality risk in females at lower temperature. Gender difference in treatment seeking cannot be ruled out.

Abhoynagar with less rainfall and less variation (daily average 4.8 mm ranging from 0 to 255 mm) exhibited the rainfall–mortality relationship, which was not the case in Matlab with more rainfall and large variation (daily average 5.8 mm ranging from 0 to 334 mm). In Abhoynagar, every 1 mm increase in rainfall up to 14 mm of weekly average rainfall over lag 0–4 weeks decreased the mortality risk and above 14 mm increased the risk. This finding is consistent with the finding that in Dhaka, every 10 mm increase in rainfall above the threshold of 45 mm of average rainfall over lags 0–8 weeks was associated with increased weekly number of hospital visits due to cholera and non-cholera diarrhea in 1996–2002 (Hasizume 2007, 2008). Many infectious diseases, for example, diarrhea and outbreaks of Giardia and Cryptosporidium, reach their peak during the rainy season (15, 16). Rainfall may have contributed to pathogenic contamination of drinking water, causing water-borne disease, and such contamination may differ between Matlab and Abhoynagar.

These two areas, Matlab and Abhoynagar, are comparable in terms of demography of mortality statistics. For example, under-five mortality rates in Matlab comparison area and Abhoynagar were 46 and 42, respectively, in 2009 (10, 12). The life expectancy at birth in Matlab in 2009 was 68.9 years for males and 71.5 years for females, and in Abhoynagar, it was 70.4 years for males and 71.6 years for females in 2008–2009. However, the fertility rate was a little higher in Matlab area than in Abhoynagar (TFR = 2.5 vs. 2.2). As expected, younger population (age below 15 years) was higher by 5% in Matlab than Abhoynagar. The difference in the weather–mortality relationship between the two areas at 142 km (linear distance) apart may not be influenced very much by the difference in demographic factors.

Such as no effect of rainfall on mortality in Matlab compared to the positive effect of moderate rainfall and the negative effect of high rainfall on mortality in Abhoynagar. Some of the differences may be attributed to the small sample in Abhoynagar. Weekly death counts regressed on weekly average temperature and rainfall may have smoothed out some short-term effects. Another limitation is that the distance from the study area to the nearest weather station is not close by and is 30 km away in Jessore. Despite these various limitations, the spatial differences in the effects of temperature and rainfall on mortality reveal the importance of studying local adaptation and the acclimatization process for a better understanding of the community responses to weather variation and the weather–mortality relationship. Further studies on cause-specific mortality may reveal details about the origin of susceptibilities and differences.

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The association of meteorological factors and mortality in rural Bangladesh, 1983–2009

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Introduction: While the association of weather and mortality has been well documented for moderate climate zones, little is known about sub-tropical zones, particularly Bangladesh. This study aims to assess the short-term relationship of temperature and rainfall on daily mortality after controlling for seasonality and time-trends. The study used data from Matlab, Bangladesh, where a rigorous health and demographic surveillance system (HDSS) has been operational since 1966.

Material and methods: Matlab HDSS data on mortality and population for the period 1983–2009 were used. Weather data for the same period were obtained from a nearby government weather station. Time series Poisson regression with cubic spline functions was applied allowing for lagged effects of weather and extreme weather events on mortality, and controlling for time trends and seasonal patterns. Analysis was carried out using R statistical software.

Results: Both temperature and rainfall showed strong seasonal patterns, explaining a significant part of mortality in all age groups. After adjusting for seasonality and trend, mortality and temperature show a U-shaped pattern; below a temperature of around 29°C, a decrease in temperature resulted in an increase in mortality, whereas above 29°C, increased temperature resulted in increased mortality. The strongest negative mortality temperature association was observed in the elderly (5.4% increase with every 1°C decrease in temperature at temperatures below 23°C), and the opposite trend was observed in the age groups 1–4 and 5–19 years old. At aggregate level, the rainfall–mortality association is statistically weak. However in the age group 5–19, a 0.6% increase in mortality per 1 mm additional rainfall was found, at rainfall levels over 100 mm per day. Multivariate analysis showed high mortality risks for women aged 20–59 years of age during cyclone episodes.

Discussion: Weather and extreme weather were associated with mortality with differential impacts in age and sex sub-groups. Further studies should investigate these findings more closely and develop policy recommendations targeted at improving public health and protecting population groups susceptible to environmental stressors.

Keywords: *climate change*; *mortality*; *Matlab*

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Extreme climate events, such as extreme daily temperatures, extreme daily rainfall amounts, large areas experiencing unusually warm temperatures, or storms, are predicted to increase in frequency and duration with ongoing climate change (1). As per the Bangladesh Bureau of Statistics, the number of major cyclones was 13 during 1897–1947 and rose to 51 during the next 50 years. Bangladesh Meteorological Department (BMD) data on minimum and maximum temperatures observed in 1950–2010 showed an increasing trend and the increase was faster for minimum temperature (2). Frequency of extreme events such as cyclones with wind speed of >200 km/hour and heavy rainfall in pre-monsoon has increased in recent years. The rate of wet days is high in the North-east and has increased in the South-east regions of Bangladesh. Both temperature and rainfall data show signs of climate change. Increase in extreme events and vulnerability to climate change raises the importance of more accurate forecast and warning at local level for mitigation and adaptation of climate effects.

In recent decades, several devastating heat weaves have caused large health consequences in urban areas across the globe (3). The effects of heat waves on morbidity were

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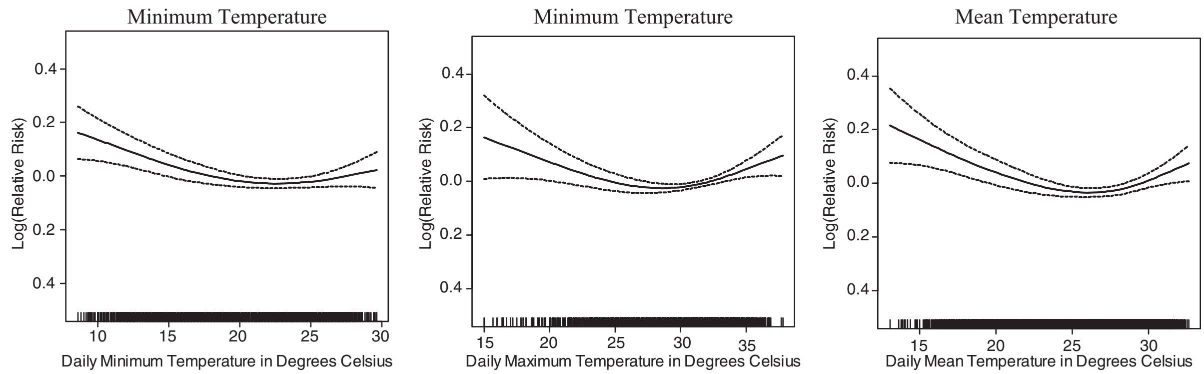

Fig. 1. Association of mortality with minimum, maximum and mean temperature, after adjusting for trend and seasonality.

less obvious than on mortality in developed countries. Heat waves were associated with increased mortality amongst the elderly in developed countries, while cold waves were associated with increased mortality of children and the elderly in developed and developing countries (4, 5).

Studies examining health effects of extreme climate events (hot or cold) were far less in developing countries – the main reason being the lack of reasonable quality health data over a longer period of time. One study examined seasonal patterns of deaths in Matlab, Bangladesh while another study reported that daily mortality increased with low temperatures in the preceding weeks and no association between high temperature and daily mortality during 1994–2002 (5, 6). These studies were limited to examine associations between mortality and temperature, excluding rainfall and extreme weather events.

Objectives

The objectives are to investigate the short-term association between weather and day-to-day causes of mortality in Matlab, a rural area of Bangladesh, where a rigorous demographic surveillance has been operating since 1966. Disaggregating the effect by age and gender is another objective of the study.

Methods and data

This study used high quality longitudinal vital registration data in Matlab and daily weather data from a nearby weather station of the metrological department of the government of Bangladesh. The health and demographic surveillance system (HDSS) maintained by the International Centre for Diarrhoeal Disease Research, Bangladesh (icddr,b) in Matlab, recorded vital events, that is, births, deaths, and migrations since 1966 and marriage and marital disruptions from 1975, visiting households monthly until 2000 and bimonthly thereafter.

Meteorological data (daily minimum and maximum temperature, rainfall, and relative humidity) for 1983–2009 from Chandpur district, located 10 km from Matlab town, were provided by the BMD. Missing values were replaced through linear interpolation.

Counts of deaths and population at risk each day were linked with daily weather data to examine the seasonal patterns of temperature, rainfall and mortality and also to estimate effects of temperature and rainfall on mortality of different age groups and sexes, accounting

Table 1. Linear approximation of the association of mortality with minimum, maximum and mean daily temperature, after adjusting for trend and seasonality

	<25% (first quartile)			25%–75% (2nd and 3rd quartile)		>75% (last quartile)				
Daily temperature	Temperatures below	Change (%)	95% Confidence Interval	Change (%)	95% Confidence Interval	Temperatures above	Change (%)	95% Confidence Interval	Deviance explained	GCV[2]
Maximum	28.2	**−0.7**[1]	(−1.5, −0.0)	**−0.8**	(−1.5, −0.2)	32.9	**0.2**	(0.1, 0.3)	26.9%	1.1285
Minimum	18.0	**−1.1**	(−1.8, −0.3)	**−1.1**	(−1.7, −0.6)	25.9	**0.1**	(0.0, 0.2)	26.8%	1.1291
Mean	23.3	**−1.4**	(−2.2, −0.6)	**−1.4**	(−2.0, −0.7)	29.2	**0.2**	(0.1, 0.3)	26.8%	1.1283

[1]Change less than 0% indicates decrease in mortality risk with increase in temperature, or at lower temperature ranges, decrease in temperature results in increased mortality risk.

[2]GCV Geometric Coefficient of Variation gives an indication of the 'variance – mean ratio; higher values indicate higher level of variation.

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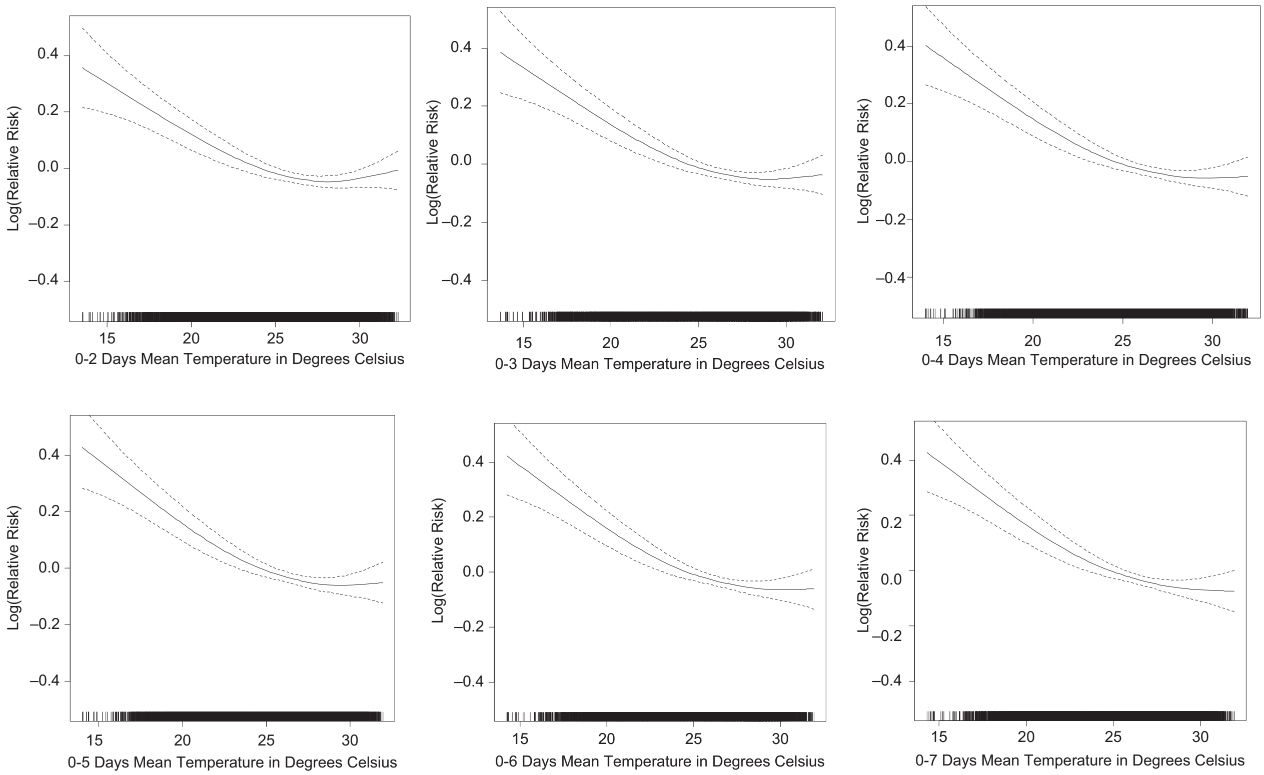

Fig. 2. Association of mortality with mean temperature at different time lags, after adjusting for trend and seasonality.

for long terms trends and seasonal patterns. Information on cyclones in Bangladesh was obtained from Banglapedia and SMRC No. 1. (7, 8).

Statistical analysis

The association between daily temperature (minimum, maximum, and mean), rainfall and mortality was examined using graphs followed by generalized additive Poisson regression models with cubic spline functions, allowing for over dispersion, using the following general formula:

$$\text{Mortality}_t \sim \text{Poisson}(\text{mean}_t)$$
$$\log(\text{mean}_t) = b_0 + s(\text{time}_t, df = 6 \text{ per year}) + s(\text{temperature}_t, df = 10) + s(\text{rainfall}_t, df = 10)$$

Where t denotes time, s denotes a natural cubic spline function and df denotes the degrees of freedom of the natural cubic spline function.

For linear segmented approximation of the weather-mortality relationships separate slopes of the weather variables below the 25th percentile, between the 25th and 75th percentile, and above the 75th percentile were determined. When appropriate alternative cut-off points were used, dummy variables were used to indicate occurrences of extreme events, that is, cyclones. The indicator variables, public holidays, and festivals were incorporated into the model to estimate variation in mortality relating to change in behavior.

Models were fitted to daily temperature and rainfall of the day of death and of mean temperature and rainfall up by 21 days prior to the day of death (lags 0–21) to identify the effects of longer periods with high or low temperatures or high or low rainfall. Combined time trend and seasonal pattern were included in cubic splines with six un-penalized degrees of freedom for seasonal pattern and trend, per year. The exposure-response to meteorological factor was penalized allowing a maximum of 10 degrees of freedom.

Results

During the 9,862 days of observation, equivalent to 27 years, 48,238 deaths were registered, which was on average 4.9 deaths per day, with a peak of 59 deaths registered on February 19, 2005, due to a launch (large commuter boat carrying passengers) accident. Infants (23.3%) and elderly (42.3%), defined as age 60 and above, account for over 65% of all deaths. During the observation period, the population increased from 190,183 on the first day of 1983 to 225,002 on the last day, that is, December 31, 2009. Between January 1, 1983, and December 31, 2009, the lowest minimum temperature observed was 8.6°C, and the highest maximum was 37.8°C, with mean temperatures ranging from 13.1°C to 32.6°C. Average daily rainfall was 5.8 mm with a peak rainfall of 334 mm in a single day. In Matlab, and Bangladesh in general, three seasons can be distinguished. 1) A calendar starts and

Table 2. Linear approximation of the association of mortality with mean temperature at different time lags, after adjusting for trend and seasonality

	<25% (first quartile)			25%–75% (2nd and 3rd quartile)		>75% (last quartile)				
Lag	Temperatures below	Change (%)	95% Confidence Interval	Change (%)	95% Confidence Interval	Temperatures above	Change (%)	95% Confidence Interval	Deviance explained (%)	GCV
0–1	23.4	**−1.8**	(−2.6, −1.0)	**−1.8**	(−2.5, −1.2)	29	**0.20**	(0.1, 0.3)	26.9	1.1268
0–2	23.4	**−2.0**	(−2.8, −1.2)	**−2.0**	(−2.7, −1.3)	29	**0.20**	(0.1, 0.3)	27	1.1259
0–3	23.4	**−1.9**	(−2.8, −1.1)	**−2.0**	(−2.7, −1.3)	29	0.10	(0.0, 0.2)	27	1.1259
0–4	23.4	**−2.2**	(−3.0, −1.3)	**−2.2**	(−2.9, −1.4)	29	0.10	(0.0, 0.2)	27	1.1262
0–5	23.4	**−2.4**	(−3.3, −1.5)	**−2.3**	(−3.1, −1.6)	29	0.10	(0.0, 0.2)	27	1.1261
0–6	23.4	**−2.3**	(−3.2, −1.4)	**−2.3**	(−3.0, −1.5)	29	0.10	(0.0, 0.2)	27	1.1263
0–7	23.4	**−2.1**	(−3.0, −1.1)	**−2.1**	(−2.9, −1.3)	29	0.10	(0.0, 0.2)	27	1.1264
0–8	23.3	**−2.2**	(−3.2, −1.3)	**−2.2**	(−3.0, −1.4)	28.9	0.00	(−0.1, 0.1)	27	1.1268
0–9	23.3	**−2.2**	(−3.2, −1.3)	**−2.2**	(−3.0, −1.4)	28.9	0.00	(−0.1, 0.1)	27	1.1269
0–10	23.3	**−1.9**	(−2.9, −0.9)	**−1.9**	(−2.7, −1.1)	28.9	0.00	(−0.1, 0.1)	27	1.1269
0–14	23.4	**−2.1**	(−3.1, −1.1)	**−2.0**	(−2.9, −1.2)	28.9	0.00	(−0.1, 0.1)	27	1.1279
0–21	23.4	**−1.3**	(−2.3, −0.2)	**−1.3**	(−2.2, −0.4)	28.9	−0.10	(−0.2, 0.0)	26.8	1.1292

Note: Statistically significant (0.05 level) relative risk estimates are marked in bold.

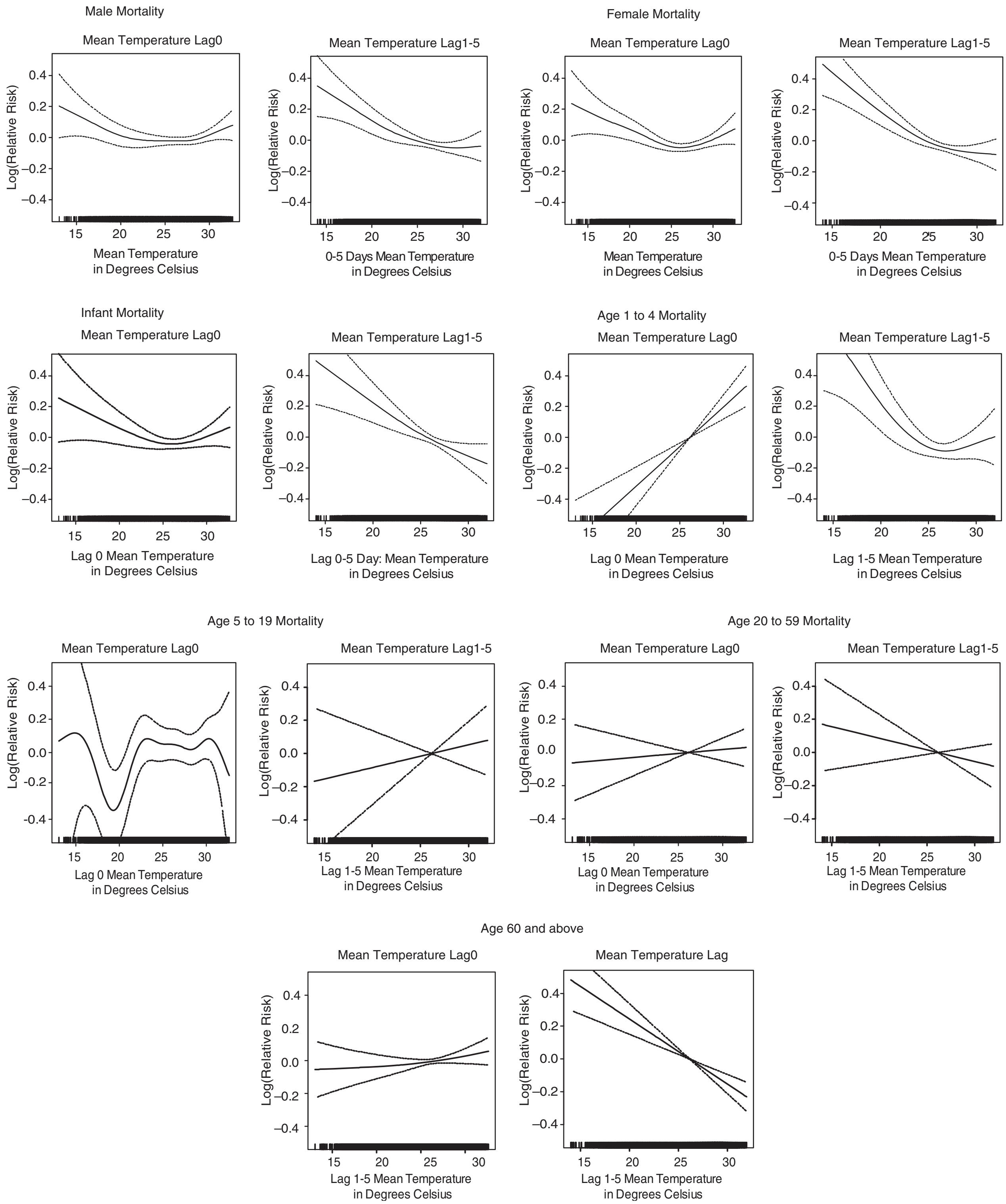

Fig. 3. Association of mortality with lag 0 and lag 1–5 mean temperature for different strata, after adjusting for trend and seasonality.

ends with a winter season (November–February), with a mean temperature ± standard deviation of 21.6°C ± 2.8, and 0.6 mm ± 5.4 daily rainfall. 2) The hot and dry season runs from March to May with a second period in October, with a mean temperature of 27.9°C ± 2.1 and an average daily rainfall 5.2 mm ± 15.1. 3) The middle of a calendar year is characterized by hot and humid weather, temperatures range from 22.9°C to 32.6°C, with a

Table 3. Linear approximation of the association of mortality with combined lag 0 and lag 1–5 mean temperature for different strata, after adjusting for trend and seasonality

	25 percentile		25–75 percentile		75 percentile	
	Change (%)	95% CI	Change (%)	95% CI	Change (%)	95% CI
Sub groups						
Male	**−3.2**	(−5.1, −1.3)	**−2.9**	(−4.6, −1.2)	**0.2**	(0.0, 0.4)
Female	**−2.2**	(−4.3, −0.2)	**−2.3**	(−4.1, −0.5)	0.2	(−0.1, 0.4)
Age groups						
Infants	−2.4	(−5.2, 0.5)	−2.3	(−4.8, 0.3)	0.2	(−0.2, 0.5)
1–4	2.9	(−1.1, 7.0)	2.9	(−0.5, 6.6)	**0.4**	(0.0, 0.9)
5–19	3.6	(−1.8, 9.2)	3.7	(−1.1, 8.7)	−0.2	(−0.8, 0.4)
20–59	−1.6	(−4.8, 1.6)	−1.7	(−4.4, 1.2)	0.0	(−0.4, 0.4)
60+	**−5.4**	(−7.4, −3.5)	**−5.3**	(−7.0, −3.6)	0.2	(−0.1, 0.4)

Note: Statistically significant (0.05 level) relative risk estimates are marked in bold.

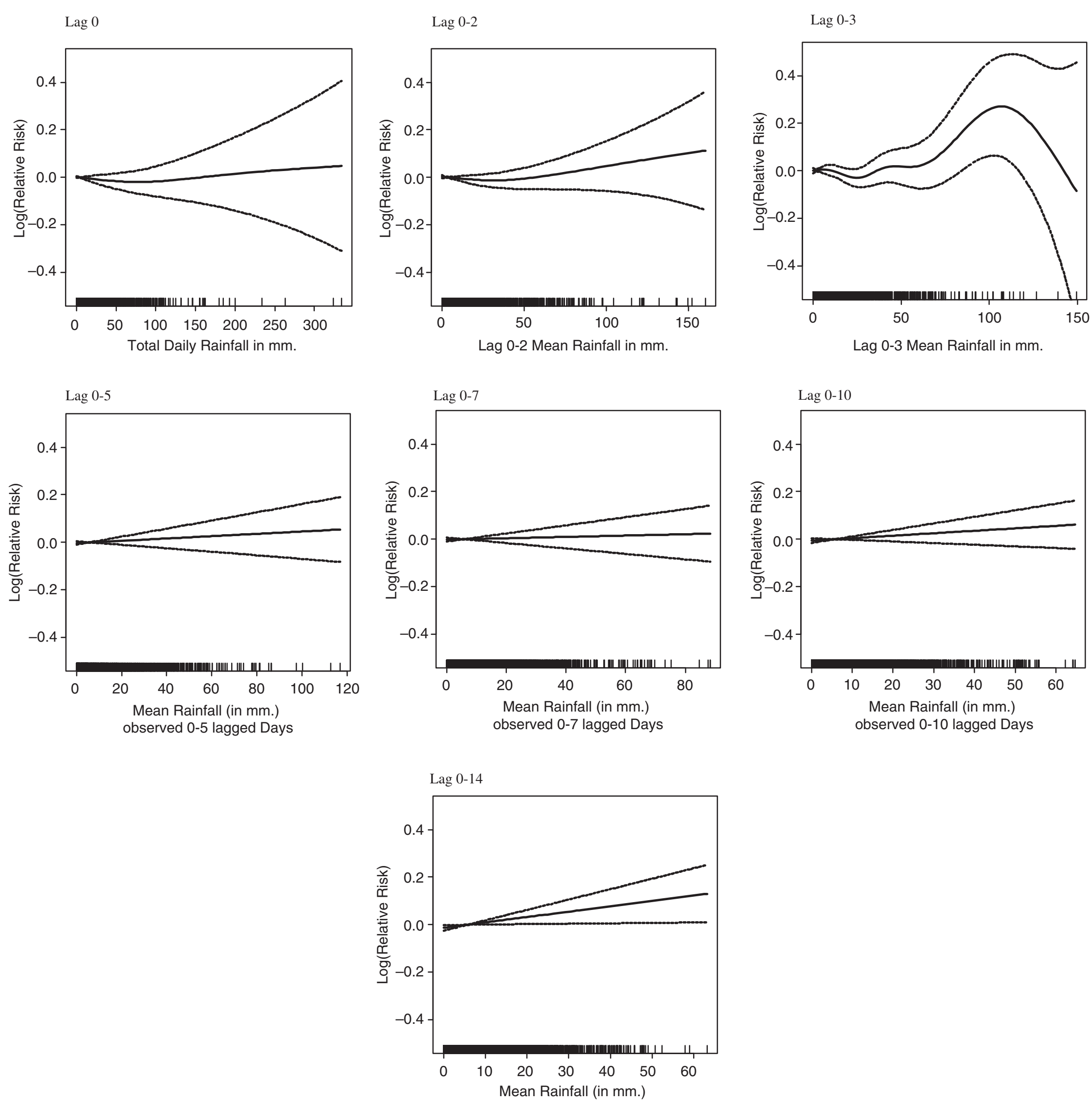

Fig. 4. Association of mortality with rainfall at different time lags, after adjusting for trend and seasonality.

Table 4. Linear approximation of the association of mortality with rainfall at different time lags, after adjusting for trend and seasonality

	Rainfall below 3 mm		Rainfall between 3 and 100 mm		Rainfall above 100 mm	
Lag	Change (%)	95% CI	Change (%)	95% CI	Change (%)	95% CI
0	−1.2	(−4.0, 1.7)	**−0.1**	(−0.2, 0.0)	**0.1**	(0.0, 0.2)
0–2	0.0	(−0.2, 0.1)	0.0	(−0.1, 0.1)	0.1	(−0.1, 0.3)
0–3	0.0	(−0.1, 0.2)	0.0	(−0.1, 0.1)	0.1	(−0.1, 0.3)
0–5	0.1	(−0.1, 0.2)	0.0	(−0.1, 0.1)	0.2	(−0.2, 0.5)
0–7	0.0	(−0.2, 0.2)	0.0	(−0.2, 0.2)	0.2	(−0.2, 0.6)
0–10	0.1	(−0.1, 0.3)	0.0	(−0.1, 0.2)	0.3	(−0.2, 0.8)
0–14	0.0	(0.0, 0.0)	0.0	(0.0, 0.1)	0.0	(0.0, 0.1)

Note: Statistically significant (0.05 level) relative risk estimates are marked in bold.

mean of 28.9°C ± 1.3 and an average daily rainfall of 11.6 mm ± 22.0. Between 1983 and 2009, Bangladesh was hit 14 times by major cyclones where the centre of the last two major cyclones, reported in 2007 and 2009, did not pass through the Matlab research area.

To assess the association between weather, weather extremes and mortality, daily minimum and maximum temperatures and rainfall measures were used. Analysis showed that the mean (average of the daily minimum and maximum) temperatures exhibited stronger associations with mortality across the temperature range than minimum and maximum temperature. Fig. 1 shows the smoothed functions of the relative overall mortality risk in association with daily minimum, maximum and mean temperature, after adjusting for trend and seasonality. In Table 1 the adjusted linear approximations of the above mentioned smoothed functions are given for temperatures below the first quartile (lowest 25%), between the first and last quartiles and for temperatures above the last quartile (above the 75th percentile). The smoothed functions showed only minor differences between the three temperature measures in model fit statistics. However, mean daily temperature showed slightly stronger association in the linear approximation over the first, second to third and fourth quintile, with a linear negative relationship resulting in a 1.4% increase in mortality with every 1°C decrease in mean temperature, at temperatures below 29.2°C, and a positive relationship between mortality and mean temperature, at temperatures over 29.2°C, with a 0.2% increase in mortality with every 1°C increase in mean temperature. For further modeling, and determination of optimal time-lag between temperature and mortality, mean daily temperature was be used.

Associations between mean temperature at different time lags and mortality, after adjusting for trend and seasonality, are presented in Fig. 2. Assessment of the graphs and the relative risks presented in Table 2 shows that the lag 1–5 temperature model better predicts mortality at temperature below the 75th percentile (2.4 and 2.3% increase in mortality per 1°C decrease

Table 5. Linear approximation of the association of mortality with rainfall for different strata, after adjusting for trend and seasonality

	Rainfall below 3 mm		Rainfall between 3 and 100 mm		Rainfall above 100 mm	
	Change (%)	95% CI	Change (%)	95% CI	Change (%)	95% CI
Sub groups						
Male	−1.3	(−5.2, 2.7)	−0.1	(−0.3, 0.0)	**0.2**	(0.0, 0.3)
Female	0.0	(0.0, 0.0)	0.0	(0.0, 0.1)	0.0	(0.0, 0.1)
Age groups						
Infants	−1.3	(−7.1, 4.9)	−0.1	(−0.3, 0.0)	0.2	(−0.1, 0.4)
1–4	1.7	(−5.6, 9.5)	−0.2	(−0.4, 0.0)	0.1	(−0.1, 0.4)
5–19	−5.6	(−15.0, 5.0)	−0.3	(−0.6, 0.0)	**0.6**	(0.2, 0.9)
20–59	−3.3	(−9.4, 3.3)	−0.2	(−0.4, 0.0)	0.2	(−0.1, 0.5)
60+	0.1	(−0.1, 0.2)	0.0	(−0.1, 0.1)	0.2	(−0.2, 0.5)

Note: Statistically significant (0.05 level) relative risk estimates are marked in bold.

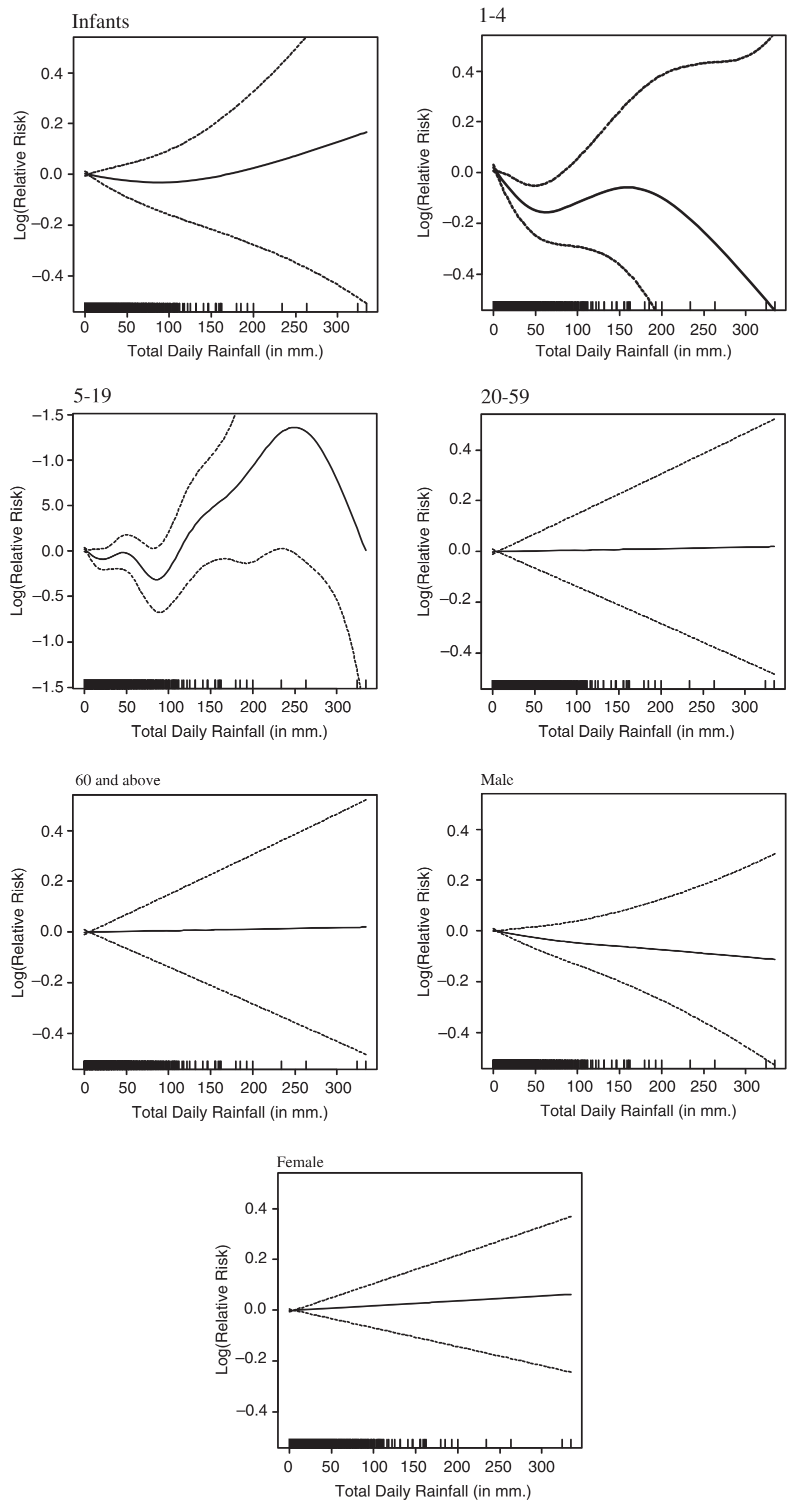

Fig. 5. Association of mortality with rainfall for different strata, after adjusting for trend and seasonality.

in temperature), while shorter time lags show stronger associations of mortality and mean temperature at temperatures above the 75th percentile. Model fit statistics only slightly differ between the different time lags – deviance ranged from 26.8% to 27.0% and the geometric coefficient of variance (GCV) ranged from 1.1259 to 1.1292. To capture the short term temperature effect at higher temperatures and the longer term effect of increased mortality at lower temperatures simultaneously, lag 0 and lag 1–5 mean temperatures were used to assess the association between temperature and mortality in different age groups and for men and

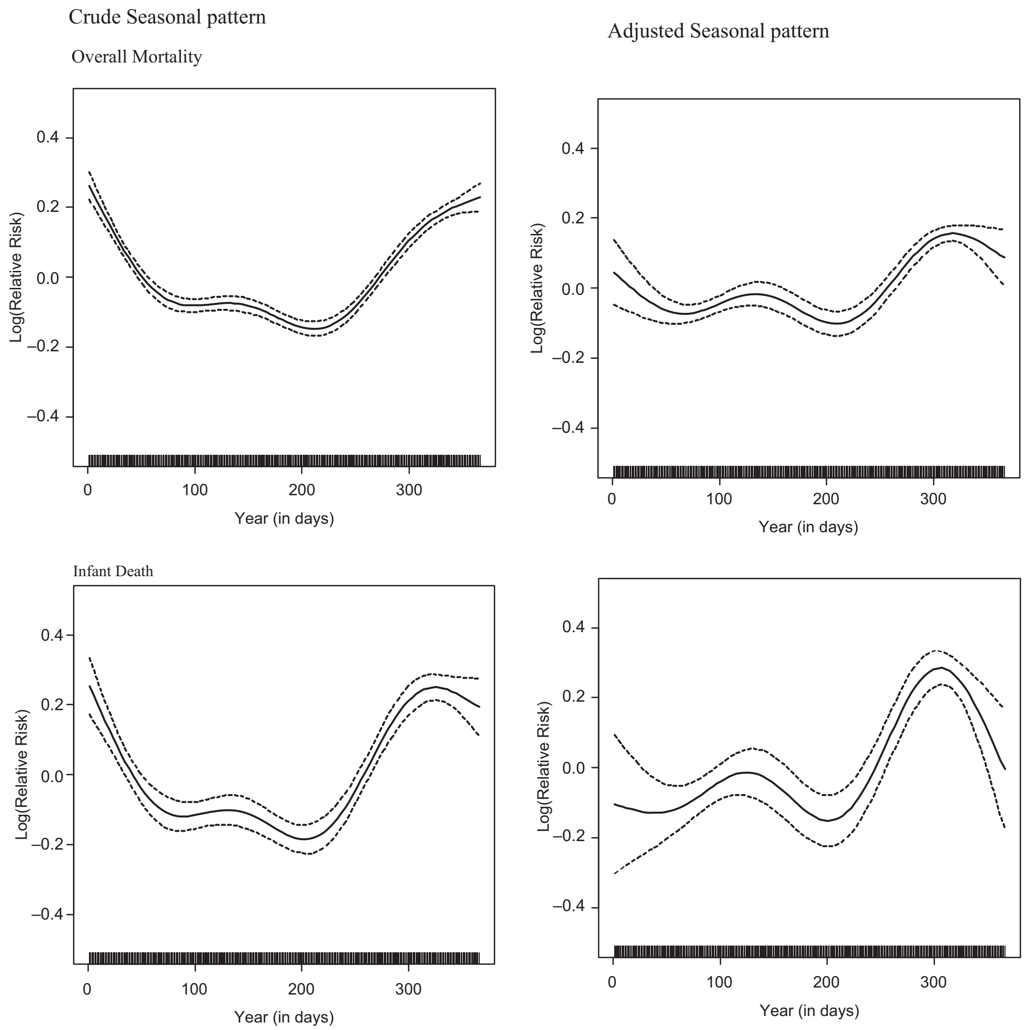

Fig. 6. Seasonality of mortality, adjusting for trend only, and adjusting for weather variables and trend.

women. In general, the stratified models showed a positive association between mortality and daily temperature, whereas the lag 1–5 models demonstrate a negative association between temperature increase and mortality (Fig. 3). Age group 5–19, with a relatively small number of deaths, showed an irregular association of temperature and mortality. The combined segmented linear approximations association of lag 0 and lag 1–5 mean temperatures are shown in Table 3. Elderly, aged 60 years and above, seem to be most effected at lower temperatures, with a 5.4% increase in mortality with every 1°C decrease in temperature, at temperatures below 23°C. Though not statistically significant, the age groups 1–4 years and 5–19 years showed the opposite trend.

The average daily rainfall of 5.8 mm is the result of a skewed rainfall pattern, with an average 251 days per year with rainfall below 1 mm. For the linear approximation of rainfall models, the 75 and 95% cut-off points were chosen, corresponding with 3 mm and 34 mm rainfall for lag 0. Associations between rainfall at different lags and mortality were weak – only lag 0–3 rainfall deviated from the other presented models (see Fig. 4). None of the segmented linear associations were statistically significant at aggregate level. Moving the upper cut-off point for lag 0 rainfall up from 34 to 100 mm (99.6%) resulted in statistically significant slopes between 3 mm and 100 mm, with a 0.1% reduction in mortality per 1 mm additional rainfall, and above 100 mm a 0.1% increase in mortality per 1 mm increase in rainfall (Table 4). When studying age groups (Table 5 and Fig. 5), a pronounced and statistically significant association was found in the age group 5–19 years when daily precipitation was above 100 mm (0.6% mortality increase per 1 mm additional rainfall).

To assess joint association of weather variables with mortality, models were built that included lag 0, lag 1–5 mean temperature, and lag 0 mean rainfall. Occurrence of cyclones was included as an exponent of extreme weather events. When statistically significant, national festivals,

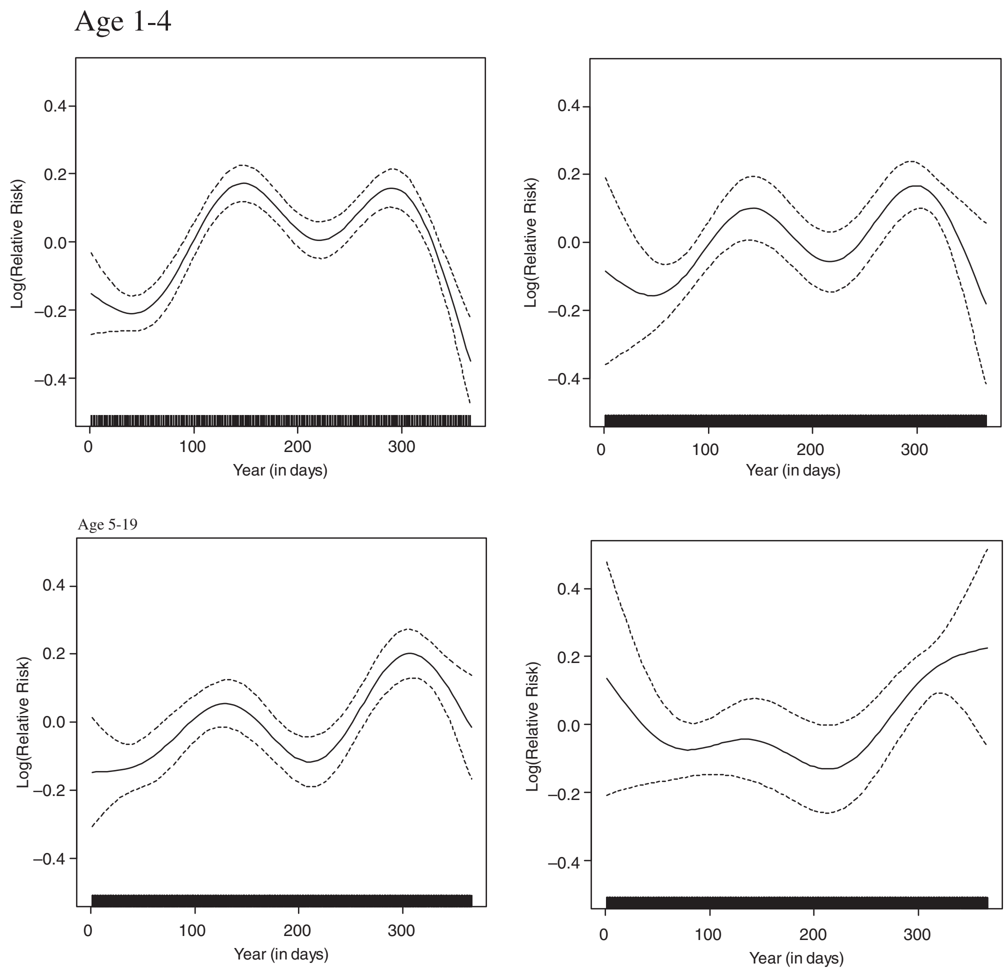

Fig. 6. Continues

the Holy month of Ramadan and related feasts were included in the model as co-variates. To increase comparability, identical models were used in the different age groups and for both sexes. In none of the age groups or sex groups, the national festivals, the Holy month of Ramadan and related feasts showed significant associations with mortality. The occurrence of cyclones was associated with a 34% (0.0%, 77%) increase in mortality in the age group 20–59 and for 24% for women (95% CI 4%, 48%), resulting in an increased mortality risk of 58% for women in the age group 20–59, with 95% confidence limits of 10 and 124%.

Mortality in the Matlab surveillance area shows overall weak associations with rainfall (in all but age groups 15–19), and stronger negative association with temperature. Temperature and rainfall both show peaks around the middle of the year, consequently mortality rates will be higher at the beginning and towards the end of the calendar year. Consistent with temperature associations, overall mortality shows U-shaped seasonal pattern with higher mortality risks during the first two and last 2 months of the year, and the lowest risk in June–August. With the exception of the age groups 1–4 and 5–19 years, the other age groups follow the same seasonal pattern. The age groups 1–4 and 5–19 years both show a bi-modal pattern, the first peak accruing around April-May and the second peak around October–November. The left hand panel of Fig. 6 shows the seasonal pattern of mortality risks before adjusting for weather covariates; the right-hand panel shows the seasonal pattern for log transformed relative mortality risks for the different strata after adjusting for weather co-variates. The graphs in Fig. 6 clearly show that part of the seasonal pattern in overall mortality is removed by the weather covariates, which means that short-term temperature and rainfall shape seasonality, but that there are also other unknown factors that are important determinants of seasonality. The adjusted seasonal patterns for different age groups range from little change in the age group 1–4 years to an almost reversed pattern in the age groups of 0 years and of 5–19 years; the infant mortality risk around the pre-monsoon period becomes more pronounced after adjusting for weather effects; the peak around October–November coincides with higher daily birth

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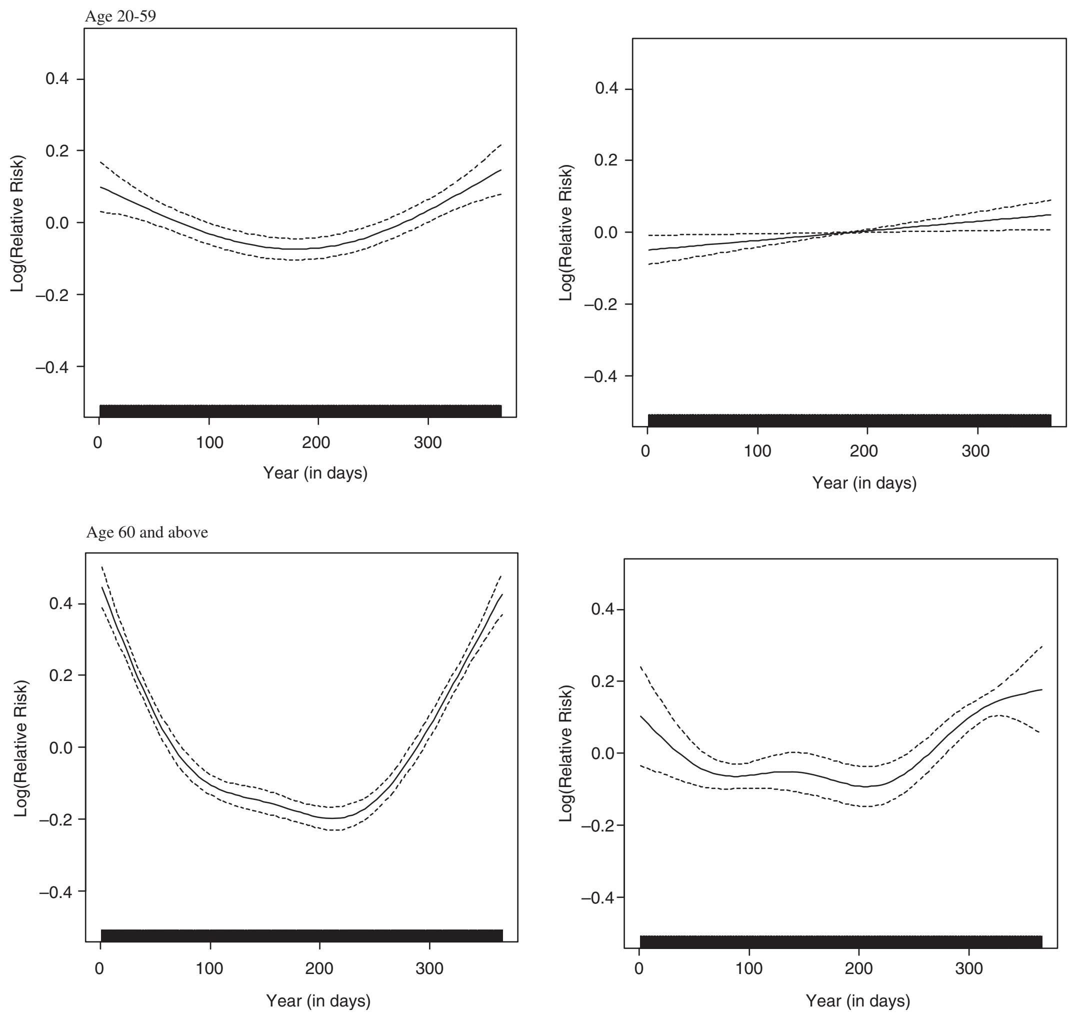

Fig. 6. Continues

rates during these months and associated larger numbers of neonatal deaths.

Discussion

In Bangladesh, both births and deaths have striking seasonal patterns and so does temperature and rainfall (2, 6). This study revealed, after adjusting for trend and seasonal patterns in mortality, a marked increase in overall mortality at lower temperature with age and sex effects in the Matlab area. In particular, deaths of infants and the elderly (aged 60 years and older) were more frequent in periods of lower temperature compared to days with higher average temperature. The result of excess mortality of infants and elderly in the cold period is consistent with the findings of the previous studies that marked higher mortality in perinatal age and elderly (65 years and older) in winter months even as the level of mortality has declined (5, 6).

With the exception of the age groups 1–4 and 5–19, the other age groups followed the same seasonal pattern. The age groups 1–4 and 5–19 years both showed a bi-modal pattern, the first peak accruing around April–May and the second peak around October–November. In many tropical developing nations, the peak of deaths in 1–4 years was in the summer (9). Seasonality became weaker, after adjusting for the weather co-variates; the U-shaped seasonal pattern of infant mortality changes into a bi-modal pattern, with elevated mortality risks around April–May and higher peaks starting in October. For the age group 5–19, the change is in the opposite direction, from a bi-modal crude seasonality pattern to a U-shaped adjusted seasonality of mortality.

Mortality in the age group 20–59 year exhibited a weaker seasonal pattern compared to the other age groups. Though the cyclones Sidr on November 15, 2007, and Aila on May 25, 2009, did not hit the study area hard, women and not men aged 20–59 experienced extremely high mortality risks (58% increase) during the cyclone episodes. We did not find an explanation as to why only this specific group experienced an increased

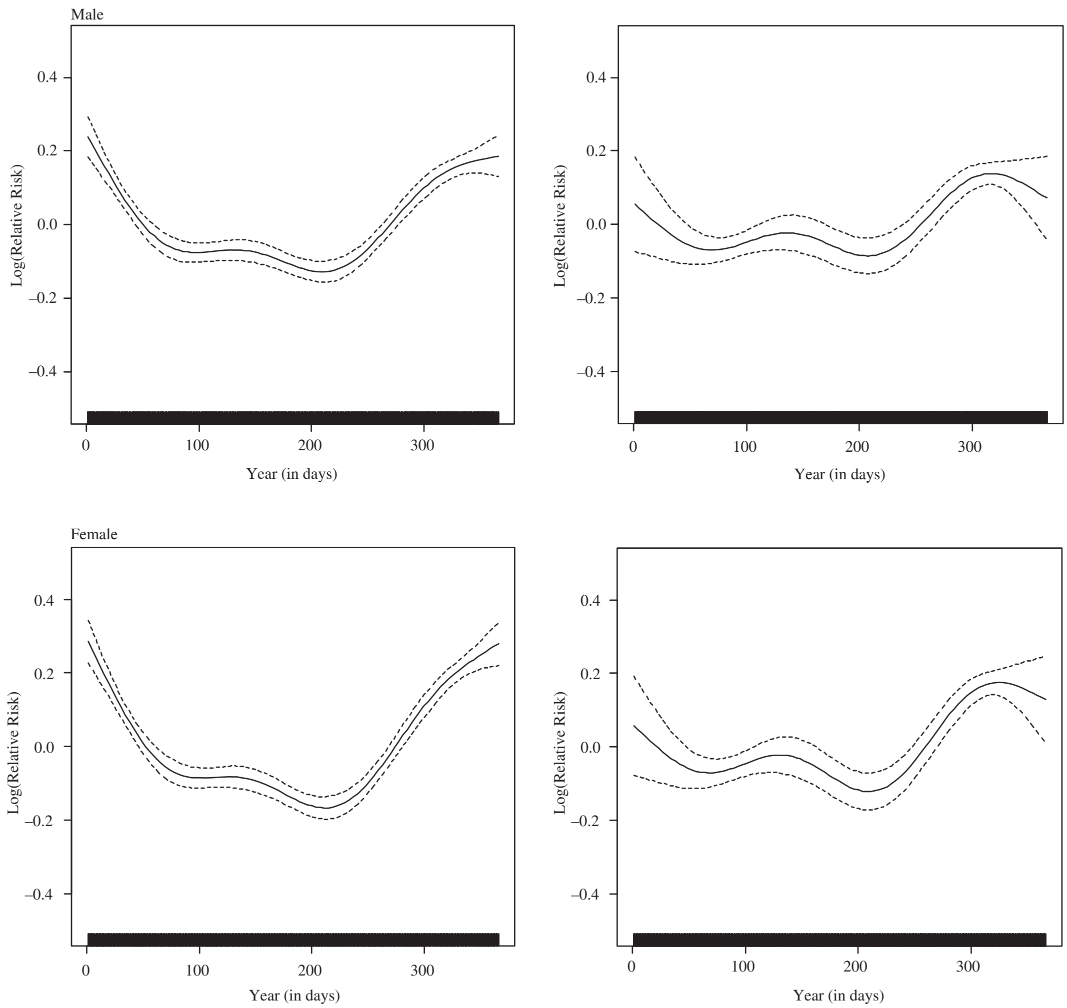

Fig. 6. Continues

mortality risk during cyclones. However we may asssume that women, especially those with younger children are less mobile and therefore more susceptible.

Mortality in the Matlab surveillance area shows overall weak associations with rainfall, and stronger negative association with temperature. High mortality at lower temperature has some implications. In a tropical country with a short winter season and limited resources like Matlab, houses in rural areas are mostly roofed and walled with corrugated iron sheets. Particularly in the winter, the night temperatures inside and outside the house are the same. The cold wave accompanied by chill and fogs makes people ill as many do not have enough warm clothes. The short-term solution is to provide warm clothes to vulnerable groups, shifting them to nearby buildings for the time being and treating any illness. The long-term solution is socioeconomic development to enable houses to be built that can control temperatures.

Effect of rainfall on mortality might be more indirect. Cholera and non-cholera diarrhea peak pre-monsoon (April–May) and post-monsoon (September–October). Flooding, due to heavy rainfall, may be associated with an increase in diarrhea cases during the post-monsoon period (10), whereas high temperatures and long hours of sunshine (absence of rainfall) might explain the pre-monsoon peak (11). The pre and post-monsoon diarrhea peaks correspond with the higher mortality levels in infants and children aged 1–4 years old.

Small but significant heat effects on daily mortality in Matlab were found and it may be partly due to the absence of extreme heat waves or 'heat island' in rural environments. Large numbers of water bodies, trees, greenery fields and lower population density may make the relation weak (12). The possibility of gradual acclimatization/adaptation to hot weather in tropical conditions cannot be ruled out. Communities naturally adapt – physiologically, culturally and behaviorally – to living in warmer climates. Some evidence of adaptation was provided by previous studies. Minimum mortality temperature defined as the temperature of the lowest temperature-associated mortality observed in a city, was

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higher in the southern warmer cities than in the cooler northern cities in the United States (13). Alternatively, lower proportion of elderly population and cardiovascular deaths in this study population than in high-income urban cities may have resulted in weak heat effects on all-cause mortality; elderly and cardiovascular deaths have been generally sensitive to high temperature in previous studies in urban cities.

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Past, present, and future climate at select INDEPTH member Health and Demographic Surveillance Systems in Africa and Asia

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Background: Climate and weather affect human health directly and indirectly. There is a renewed interest in various aspects of environmental health as our understanding of ongoing climate change improves. In particular, today, the health effects in low- and middle-income countries (LMICs) are not well understood. Many computer models predict some of the biggest changes in places where people are equipped with minimal resources to combat the effects of a changing environment, particularly with regard to human health.

Objective: This article documents the observed and projected climate profiles of select sites within the International Network for the Demographic Evaluation of Populations and Their Health (INDEPTH) network of Health and Demographic Surveillance System sites in Africa and Asia to support the integration of climate research with health practice and policy.

Design: The climatology of four meteorological stations representative of a suite of INDEPTH Health and Demographic Surveillance Systems (HDSSs) was assessed using daily data of 10 years. Historical and future trends were analyzed using reanalysis products and global climate model projections.

Results: The climate characteristics of the HDSS sites investigated suggest vulnerability to different environmental stressors, and the changes expected over the next century are far greater in magnitude than those observed at many of the INDEPTH member sites.

Conclusions: The magnitude of potential future climate changes in the LMICs highlights the need for improvements in collaborative climate–health research in these countries. Climate data resources are available to support such research efforts. The INDEPTH studies presented in this supplement are the first attempt to assess and document associations of climatic factors with mortality at the HDSSs.

Keywords: *INDEPTH*; *CLIMO*; *climate change*; *climatology*; *temperature*; *precipitation*; *seasonality*; *vulnerability*; *LMICs*

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Ever since industrialization, the global climate has undergone rapid changes in patterns and distributions, and climate models predict further large-scale changes on the basis of greenhouse emission scenarios. Observations show that the global temperature has increased by 0.84°C over the past century (1) and the rate of rise in temperature is projected to increase over the coming decades (2). This global temperature trend is accompanied by a larger suite of climatic changes that will continue to impact people and the environment over the coming decades. The frequencies of extreme weather events, for example, are projected to increase in many regions of the world (3). Of increasing interest is determining the potential impacts of future climate change on human health and well-being. Weather and climate are key drivers of human mortality, morbidity,

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and migration in many locations across the globe, and as the global climate changes so will the impact on people, whether through direct mechanisms (e.g. heat-related deaths during heat waves) or indirect processes (e.g. long-term droughts restricting food supplies). Current knowledge of the relationship between climate and health varies geographically, and in some regions the linkages are poorly understood. These regions include low- and middle-income regions of Africa and Asia.

Residents of low- and middle-income countries (LMICs) are commonly identified as the most vulnerable to climate change because many of the projected changes are the most severe in regions where the people have limited resources for adaptation and mitigation (4, 5). Under this broad context, a growing literature identifies specific linkages between a wide range of climate factors and health outcomes in the developing world. As health surveillance programs continue to develop, reliable heath outcome data sets are becoming available and, as a result, researchers are able to link various diseases to climatic factors. One mature health surveillance network is the International Network for the Demographic Evaluation of Populations and Their Health (INDEPTH) in LMICs. This global alliance includes over 30 research centers in LMICs that host Health and Demographic Surveillance Systems (HDSSs) and provides continuous and regular monitoring of demographic variables, including birth rate, death rate, and migrations with the goal of 'providing a better, empirical understanding of health and social issues, and to apply this understanding to alleviate the most severe health and social challenges' (http://www.indepth-network.org).

Today, it is recognized that the health impacts related to climate variability and long-term change are severe, and that the health burden in the developing world could be lessened if these effects were more fully understood to promote strategic improvements to public health policy and practice. This calls for the integration of health science with climate and climate change science and associated partnerships amongst scientists from a variety of disciplines. In the developed world, where climate and health data are often more accessible, well-documented, and continuous over both space and time, this type of cross-disciplinary coordination of research efforts has led to public health infrastructural improvements that increase the capability of the population to recognize and mitigate primarily extreme events. Cities in developed countries across the globe have implemented heat health watch warning systems, for example, based on research demonstrating the positive relationship between human mortality and high temperatures during the warm season (6, 7). In LMICs, however, the picture is much different, as the integration of climate and health research has been inhibited by the availability of high-quality data from both the climate and health communities.

Our goal is to document the current climate profiles of select INDEPTH member sites that are participating in the Climate and Mortality (CLIMO) project featured throughout this supplement. The CLIMO collaboration offers researchers at specific INDEPTH member centers access to very high quality health and climate data to model current impacts of weather and climate on human health. In addition to assessing the present-day climatology, we also sought to investigate historical changes and projected future trends in several climate variables. In doing so, this manuscript aims to: (1) deepen the background on local climate to better understand the public health challenges related to climate and climate change and (2) document some of the climate data resources available to those studying health impacts in the LMICs.

Methods

The current climate of the INDEPTH member HDSS sites was evaluated via weather station data from four proximate sites that are representative of the regional climate of the HDSSs in the study (Table 1 and Fig. 1). We downloaded monthly station data from the US National Climatic Data Center's Global Historical Climatology Network, a publicly accessible compilation

Table 1. Location of INDEPTH member sites and proximate meteorological stations

Site	Country	Latitude	Longitude	Elevation (m)
INDEPTH HDSS and CLIMO sites				
West Africa (Boromo meteorological station)				
Kaya	Burkina Faso	13.08	−1.08	329
Nanoro	Burkina Faso	12.35	−1.52	295
Nouna	Burkina Faso	12.62	−3.82	276
Kintampo	Ghana	7.99	−1.72	352
Navrongo	Ghana	10.65	−1.15	198
East Africa (Jomo Kenyatta meteorological station)				
Kisumu	Kenya	−0.14	34.75	1188
Nairobi	Kenya	−1.28	36.82	1677
Magu	Tanzania	−2.62	33.46	1180
Rufiji	Tanzania	−7.75	39.17	70
Rakai	Uganda	−0.5	31.5	1278
India (Poona meteorological station)				
Vadu	India	17.89	73.92	91
Bangladesh (Agartala meteorological station)				
AMK	Bangladesh	23.7	90.42	11
Meteorological stations				
Agartala	India	23.883	91.25	16
Boromo	Burkina Faso	11.73	−2.92	264
Jomo Kenyatta	Kenya	−1.317	36.917	1624
Poona	India	18.533	73.85	559

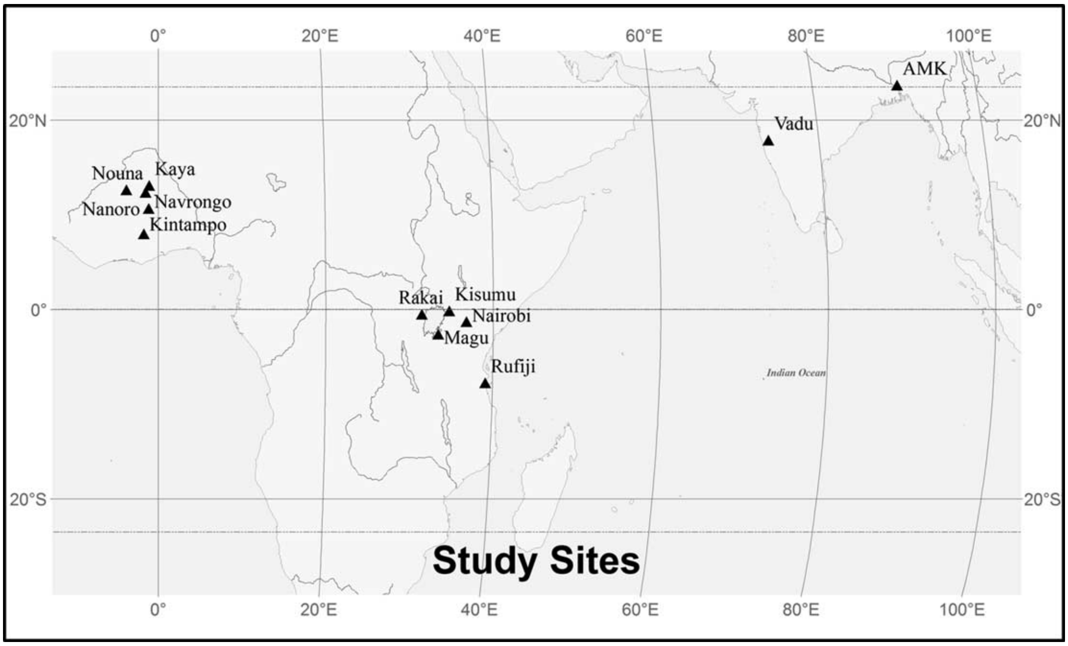

Fig. 1. Locations of the 12 INDEPTH member HDSSs evaluated in this study.

of quality-controlled weather station data from national and international agencies (www.ncdc.noaa.gov). Data from Agartala and Poona date back to 1901, but temperature measurements were reliably available only over the last 40 years of the record. Jomo and Boromo had shorter periods of record with the stations coming online in 1957 and 1945, respectively. Although the data sets are not 100% complete, beginning in the late 1970s there are very few cases where consecutive months are missing and it is rare that the same month is missing for multiple years within a decade. These stations represent the best available data at the monthly scale for evaluating the climate of these locations that we are aware of; the density of stations in these locations is relatively sparse. We examined eight variables: the number of days in each month with precipitation >0.25 cm ('rain days'), the number of days in each month with >2.5 cm of precipitation ('heavy rain days'), the total monthly precipitation, the mean monthly temperature, the mean monthly minimum and maximum temperature, and the monthly extreme minimum and maximum temperature.

Historical temperature trends at the sites were evaluated with reanalysis data from the Climatic Research Unit (CRU) downloaded from the Intergovernmental Panel on Climate Change (IPCC) Data Distribution Centre (http://www.ipcc-data.org). We extracted the decadal average mean annual temperature and precipitation for the $0.5^\circ \times 0.5^\circ$ grid cell that contained the latitude and longitude of each of the HDSS. These values were available from each of the 10 decades between 1901 and 2000. We similarly downloaded the decadal average yearly maximum and minimum temperature for the same time period. Trends were analyzed with linear regression; those trends with p-values ≤ 0.05 were deemed significant.

A 30-year average temperature as well as precipitation projections was obtained from two different climate models and three future growth scenarios, also from the IPCC's Data Distribution Centre. We examined the UKMO HADCM3 and NCAR CCSM3 model output under the A1B, A2, and B1 scenarios. Annual average air temperature and precipitation values were available along with monthly averages by decade for each 30-year interval. We were not able to obtain 30-year maximum or minimum temperatures for this particular combination of models and scenarios. Projections were merged with historical data by scaling the projection for the first decade to the most recent observation from the 1990s. In cases where the historical data exhibited a significant trend, the projection was based on the last historical observation plus or minus a continuation of the linear trend until the time point of the first projection.

We also evaluated the current and future climate using the Köppen Climate Classification. Köppen is the most commonly utilized global classification scheme and the system was updated in 2006 to be more compatible with current reanalysis data sets and projections (8). The system, originally developed in 1900, relates the climate to vegetation and identifies five major climate types: equatorial, arid, warm temperate, snow, and polar. Within each of these broad categories, there are additional classification characteristics based on temperature and precipitation, resulting in a total of 31 different climate regimes that cover the entire globe.

Climate classification systems like Köppen provide a different perspective for evaluating climate shifts by providing a more integrated view of multiple variables simultaneously. A change in classification type is indicative of substantial changes in a suite of climate variables that would impact vegetation types, and more broadly impact the environmental systems of the area with implications for human health and welfare. Applying future climate models to the Köppen classification system indicates some degree of change across all latitudes and climate types, with approximately 3% of the current polar climate shifting to a warmer snow climate by 2100 and 1.7% of the current warm temperate climate in the lower latitudes shifting to an arid climate related to a reduction in precipitation (using the A1F1 and B1 scenarios) (9). We downloaded the global GIS shapefiles of Köppen types for the years 2000–2025 and 2076–2100 using A1F1, A2, B1, and B2 scenarios run with the Tyndall Centre for Climate Change Research model from http://koeppen-geiger.vu-wien.ac.at/shifts.htm. We then extracted the classification type for the grid cell containing the coordinates of each of the INDEPTH member sites.

Results

Current climate

All 12 INDEPTH member sites we investigated fall within the tropics and subtropics; the station farthest from the equator Abhoynagar, Mirsarai, and Kamlapu (AMK in Bangladesh) falls just north of the Tropic of Cancer at 23.7°N. Thus, all of the sites experience high temperatures throughout the year, with very few days near or below freezing across the entire network. Residents of the INDEPTH study areas are regularly exposed to high temperatures, but future changes in the distribution of high temperatures could directly impact human health via additional thermal stress and indirectly through modifying the rate and likelihood of disease transmission throughout the population. Precipitation variability across the sites was found to be greater than temperature variability because of the relative positioning of the sites to major water bodies and predominant air flows.

The western Africa INDEPTH member sites (Kaya, Nouna, Nanoro, Navrongo, and Kintampo) were represented through analysis of the Boromo weather station in Burkina Faso (see Fig. 1). This region experiences a seasonal pattern, where the temperature peaks in both April and October. The highest mean, maximum, and extreme temperatures are observed during these months, with a tendency for spring to be slightly warmer than the fall (Fig. 2).

The summer months at these locations are characterized by high precipitation totals with 3 months of >100 mm each and lower temperatures as cloud cover suppresses incoming solar radiation and evaporation of ground and atmospheric moisture contribute to cooling. This strong seasonality is driven by the intertropical convergence zone (ITCZ), a latitudinal band of low pressure and convective precipitation that circles the globe and migrates northward and southward across the tropics following the seasonal progression of the sun. During the summer, the ITCZ moves northward bringing regular convective activity and precipitation to the West African INDEPTH sites. In the winter months, the northeasterly trades become more persistent as the ITCZ moves southward and dry air is advected from interior northern Africa. Between November and March, these sites experience <1 day of 0.25 cm of precipitation per year (Fig. 2).

The climate at the East African INDEPTH member sites (Rakai, Kisumu, Nairobi, Magu, and Rufiji) was evaluated with meteorological data from Jomo Kenyatta airport in Nairobi. The data from this airport are typical of an equatorial climate with the mean monthly, minimum, and maximum temperatures very consistent throughout the year (Fig. 3). The temperature is lower than would otherwise be expected for equatorial Africa because of the high elevation: Jomo Kenyatta is located at approximately 1,500 m above sea level and the three

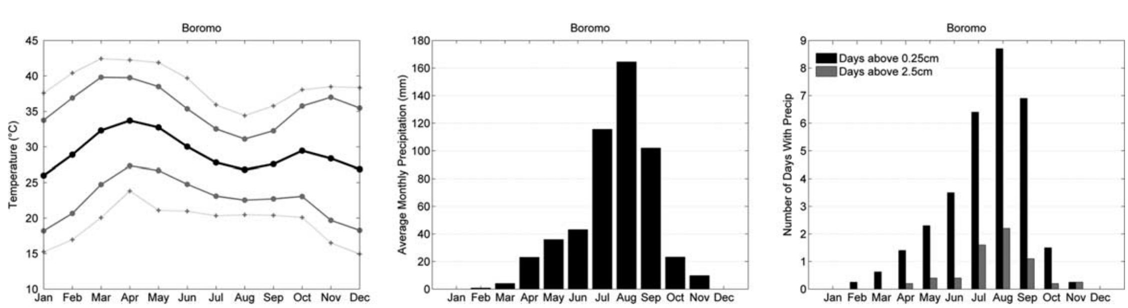

Fig. 2. Climate characteristics of Boromo, Burkina Faso, 2000–2009. (a) shows the temperature seasonality. The solid black line represents the mean monthly temperature. The upper and lower solid gray lines represent the mean monthly maximum and minimum temperature, respectively. The dashed gray lines represent the extreme monthly maximum and minimum temperature. (b) shows the precipitation seasonality with the average monthly precipitation (mm). (c) shows the precipitation seasonality based on the number of days with rainfall greater than 0.25 cm (black bars) and 2.5 cm (gray bars) per month.

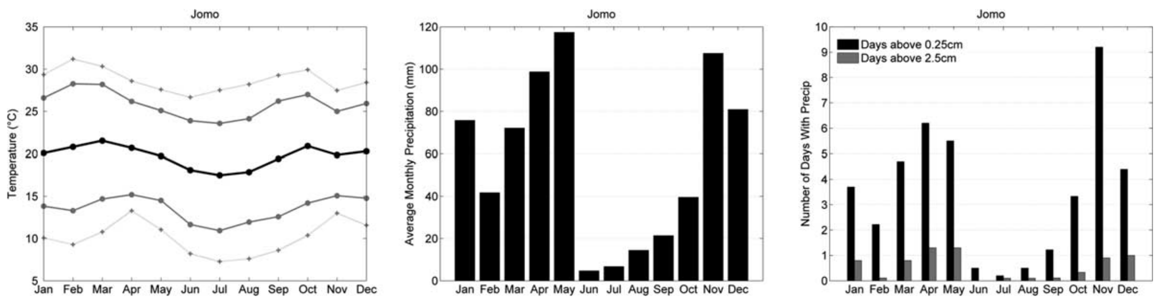

Fig. 3. Climate characteristics of Nairobi, Kenya, 2000–2009 as in Fig. 2.

closest sites are roughly 1,000 m above sea level. The Rufiji site, the farthest south of this cluster, is located less than 100 m above sea level and thus the data from Jomo Kenyatta are less representative of Rufiji's coastal climate.

The precipitation pattern for these stations is contrary to that of the West African sites. Here the majority of the precipitation falls from November through May, with very few precipitation days in the months of June, July, and August. The months with the most precipitation are May and November, but November experiences more days with significant rainfall (>0.25 cm) on average than May. The double precipitation maximum arises from the ITCZ passing through the region twice a year. Average annual precipitation at these sites approaches 700 mm.

The climate of the Vadu site was evaluated with data from the nearby Poona meteorological station and is similar in temperature and precipitation characteristics to the West African sites (Fig. 4). Temperatures are relatively high throughout the year with monthly maximum temperatures >30°C and extremes in the vicinity of 40°C in the spring. Mean monthly temperatures are highest in the spring months.

Like much of the Indian subcontinent, Poona's precipitation pattern is driven by the regional monsoon. As the land surface over the Asian continent warms in the summer months and the ITCZ moves northward, low pressure persists in the region and moist air is advected northward from the Indian Ocean. As a coastal site, Poona has direct access to summer moisture, with 4 months averaging >100 mm each. The most significant and heavy precipitation days fall in the wettest months of June to September. The regional flow completely reverses in the winter months and accordingly there is nearly no rainfall between December and April.

Data from the Agartala meteorological station in northeastern India were used to represent the climate of the AMK site in Bangladesh (Fig. 5). Temperature seasonality at Agartala is more characteristic of the northern hemisphere subtropics, with the highest temperatures in the months of May through September and a decline to minimum temperatures in December and January. During the warm season, temperatures may be quite high, with monthly maxima >30°C and extremes upwards of 35°C. Temperatures are somewhat moderated from other locations in the subtropics because of Agartala's proximity to the coast.

The Agartala/AMK region experiences some of the highest monthly precipitation totals observed anywhere on the planet, with >350 mm falling on average in the months of June and July. As with Poona, the thermal low over the Asian continent and the northward position of the ITCZ drive moist air into the region, but here the site is located much closer to the Himalayan mountains, which enhance uplift and dramatically increase precipitation totals. This south Asian summer monsoon is one of the most significant climatic phenomena with respect to human health and well-being, as the region boasts some of the highest population densities on the planet that are impacted by the extreme precipitation and regular flooding (10).

Historical and future changes

Change in climate at the INDEPTH member sites could have important implications in terms of public health,

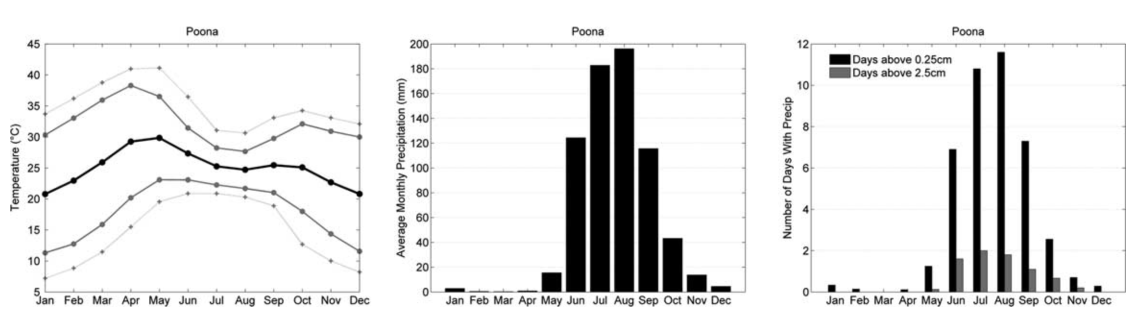

Fig. 4. Climate characteristics of Vadu. India, 2000–2009 as in Fig. 2.

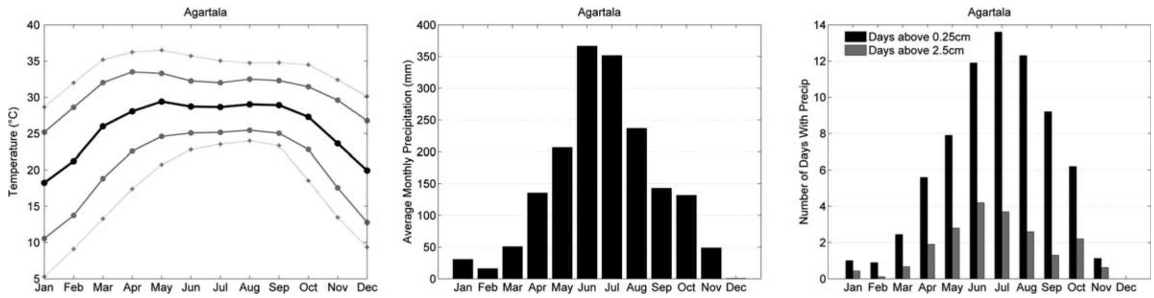

Fig. 5. Climate characteristics of Agartala, India, 2000–2009 as in Fig. 2.

and, as such, we used observational data and projections to examine past and expected future changes. With respect to the historical temperature record, the decadal annual mean temperature time series only identified significant increases at 2 of the 12 study sites, AMK and Vadu. At 8 of the 12 sites, however, the 1990–2000 decadal average temperature was the highest of the time series. The lack of significant trends at some of the sites might be attributed to the coarse time increment, small sample size, and other decadal-scale variability. Using decadal average temperatures, we cannot conclude that significant warming has occurred at most of the INDEPTH HDSS sites over the 20th century. At the majority of sites, the total range in decadal average temperatures was $<1°C$.

Future projections for all sites, however, place year 2100 temperatures above the 1990–2000 decadal average across all six model–scenario combinations evaluated (Fig. 6). Even more striking is that the rate of temperature change is projected to increase dramatically. In many cases, the temperature increase over the next century is expected to be 2–3°C. The most conservative model–scenario combination (CCSM3 A1B) predicts increases of 0.5–1°C. The highest projections were typically associated with the HADCM3 model and the A2 scenario.

We also investigated historical trends in decadal average maximum and minimum annual temperature. As with mean temperature, only 2 of the 12 stations (Vadu and AMK) showed a statistically significant trend using simple linear regression through the 10 data points, and we caution the robustness of such results given the small sample size. As with mean temperature, we found that at the majority of the stations, the highest minimum and maximum temperatures were found in the most recent decade of the time series (Fig. 7).

No significant trends were evident in the decadal-scale time series of annual average precipitation, with the exception of Kintampo where we found a significant decline. There was no tendency for the 1990–2000 decadal average precipitation to fall above or below the rest of the time series across the network of 12 stations (Fig. 8).

Projections for future annual precipitation averages varied considerably across models and scenarios (Fig. 8). At most stations, there was some disagreement on the *sign* of the expected change between model–scenario combinations, with even further discord on the magnitude of the changes. At Nairobi, all three HADCM3 projections indicate an increase in precipitation over the next century, with year 2100 annual averages falling between 20 and 50% above the current average. Changes of this magnitude would have severe consequences for the regional water budget. Only one of the CCSM3 model runs (A2) is consistent with the HADCM3 projections, while the A1B and B1 scenarios show a slight decrease in precipitation through mid-century and then a return to present-day averages by year 2100. At AMK and Nouna, the majority of the projections indicate an increase in precipitation over the next century, while projections for Vadu were nearly evenly split amongst increasing, no change, and decreasing precipitation.

We returned to the GHCN-Monthly station data to determine if there were significant trends in any of the eight variables we evaluated for the current climate profiles of the INDEPTH member sites over recent decades (Fig. 9). At the West African sites, there was limited evidence of changes in the seasonality of precipitation, with significant negative trends for the months of May and June. These are the months immediately preceding the wet season, and, thus, although they do not account for a significant portion of the total annual precipitation, they do represent rain at the end of the dry season that provides some of the first relief. The magnitude of the trends (approximately -2 mm/year) is substantial compared to the approximately 40 mm/month of rainfall received at this station during May and June. Changes in the temperature distribution point toward higher minimum and extreme minimum temperatures during the warm and wet seasons. Mean and maximum temperatures have increased during certain months in the cool season and higher means and maximums are also evident in June.

Historical trends in precipitation at Jomo Kenyatta are limited to April and May, with April showing a decrease in rain days and total monthly precipitation. There is evidence of changes in the temperature distribution

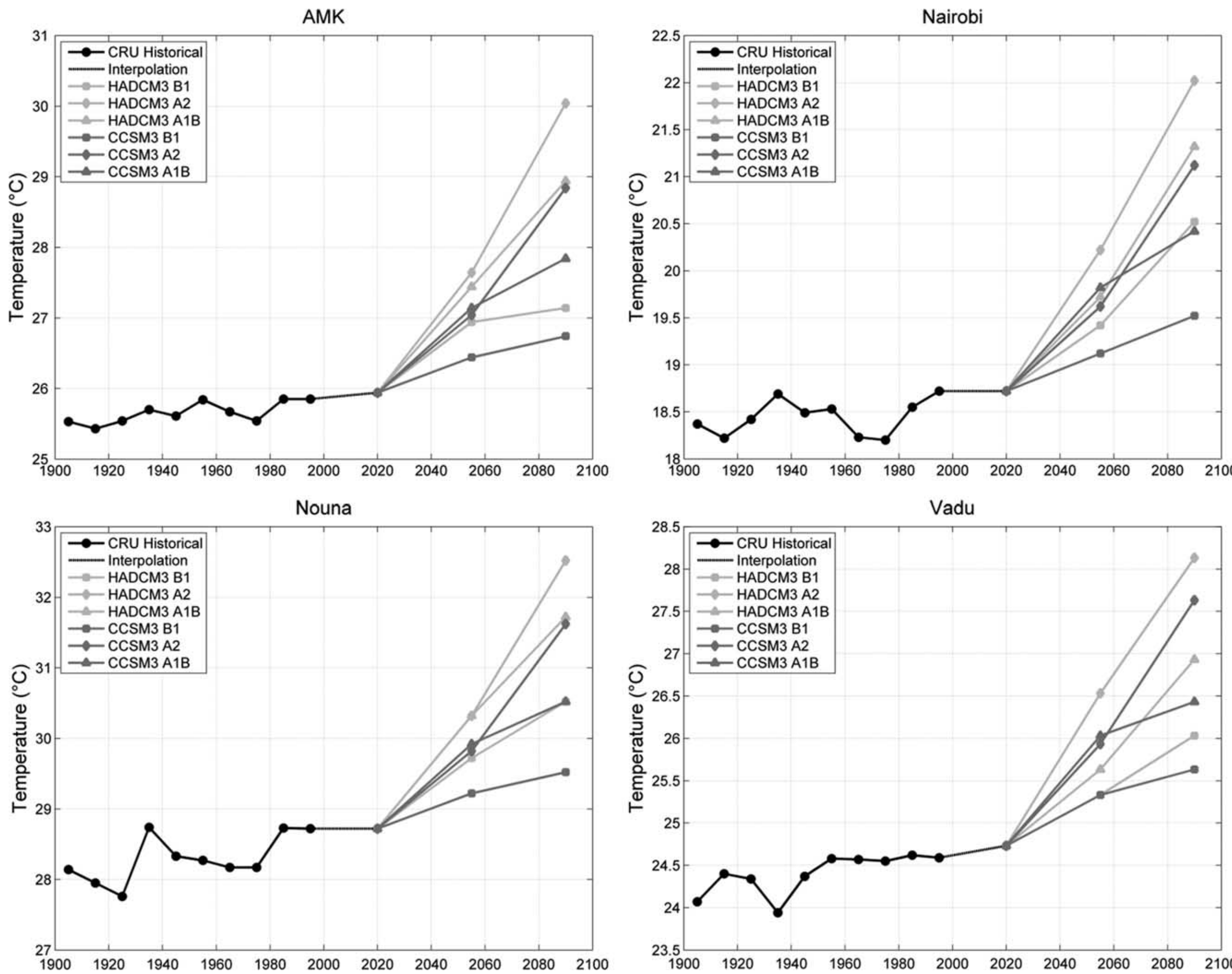

Fig. 6. Historical and projected future temperatures at four INDEPTH member sites. The black dots represent the mean decadal temperature for each decade of the 1900s based on the Climate Research Unit reanalysis record. The dashed line extrapolates the historical data to the start of the modeling period; a slope in the dashed line indicates a statistically significant linear trend from 1900–2000. The gray lines each show mean temperature projections for twenty-year intervals from the HADCM3 and CCSM3 models for three different climate change scenarios. All points are shown at the midpoint of the appropriate time interval.

throughout the year, with either higher extreme or mean minimum temperatures observed in all months except May and June. Mean monthly temperatures have increased throughout most of the year as well. In general, there are no significant trends in mean or extreme maximum temperatures at this site.

We did not find evidence of any changes in precipitation days or total at Poona when the analysis was divided by month. Minimum and mean temperatures were found to be increasing in the late winter and early spring months, with higher maximum temperatures in the mid-winter. There were very few significant trends present for Agartala.

Using the Köppen climate classification, we identified major shifts at 2–3 of the 12 sites investigated using the A1F1, A2, B1, and B2 scenarios in the Tyndall temperature and precipitation projections for the 21st century. Under the 'A' scenarios, two sites are associated with a change in climate classification, Nairobi and Vadu. The shift in Nairobi is from the 'Cfb' type (Warm temperate fully humid [no dry months], warm summers) to 'Aw' (Equatorial with dry winter). The change in type is suggestive of higher temperatures throughout the year and a decrease in wintertime moisture. At Vadu, the change is also to 'Aw' but here the shift is from 'Am', Equatorial monsoon, indiciative of a possible increase in moisture in the winter months. Under the 'B' scenario, Rakai was added as a site with a projected change, moving from Am to Aw. We found that the number of sites with changes was sensitive to the start value used: the 1951–2000 historical average differed from the four model projections for the 2001–2025 time period in

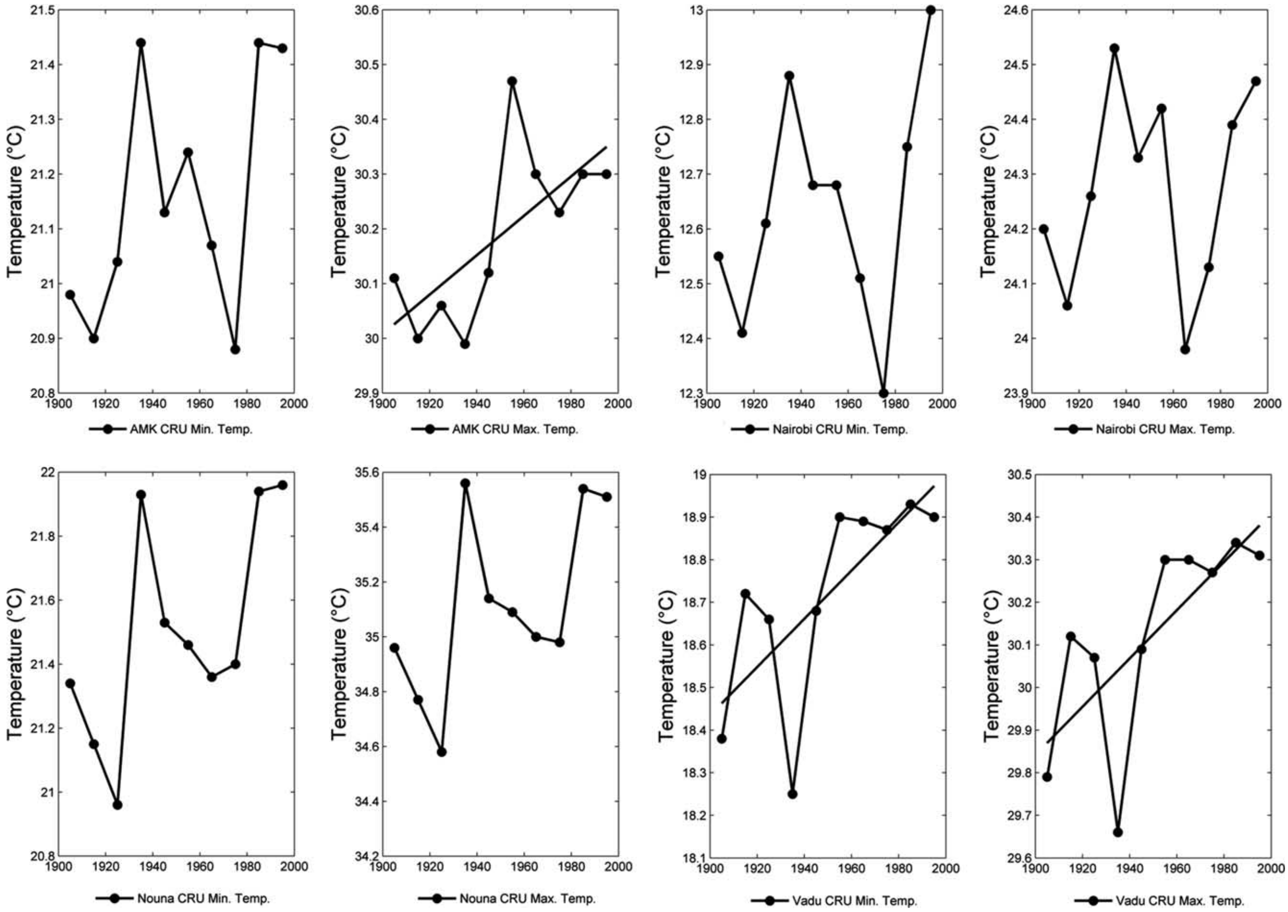

Fig. 7. Historical mean decadal minimum (left) and maximum (right) temperatures at four INDEPTH member sites, 1900–2000, based on CRU reanalysis data. A line is drawn for cases where simple linear regression indicated a statistically significant trend in the historical data. All points are shown at the midpoint of each decade.

a few cases. Furthermore, within the model projections for the first quarter of the 21st century, there were differences between the four scenarios.

A site that does not experience a change in Köppen types may still undergo a change in climate that impacts human health. The classification scheme is discrete, whereas changes are likely to occur over a continuous gradient. Under the A2 scenario, for example, none of the five West African INDEPTH member HDSSs show a change in the climate regime. But, examination of the map indicates that the regional climate is clearly varying – the zone of hot arid steppe climate, for example, migrates southward over the study period and the hot arid desert zone's southern edge encroaches on the study region (Fig. 10). Farther south, away from the INDEPTH sites, the equatorially fully humid climate regime appears in the years 2076–2100, with no regional presence in the past half-century.

Discussion

The climates of the INDEPTH member HDSSs we examined are relatively diverse given their similar latitude. This is consistent with previous work that demonstrated that the African INDEPTH HDSSs represent a wide range of environmental and climatic regimes across the continent (11). All of the sites we examined are representative of warm climates, as expected for tropical and subtropical locations, but the strong seasonality in temperature and precipitation add an additional dimension of vulnerability to weather and climate. Cold weather effects, for example, might occur at Jomo Kenyatta, Poona, or Agartala, where the temperature may fall into the single digits during a few months of the year. The sensitivity of the populations near Agartala and Boromo to high temperatures may differ because Boromo has a consistently warm climate throughout the year (so there are no 'unusual' heat events), whereas the temperature at Agartala is much more seasonally variable.

With respect to precipitation, at the West African sites, >75% of the total annual precipitation falls in the three months of July, August, and September. Locations like these with a highly seasonal climate could be most sensitive to a change in the seasonality of rainfall or

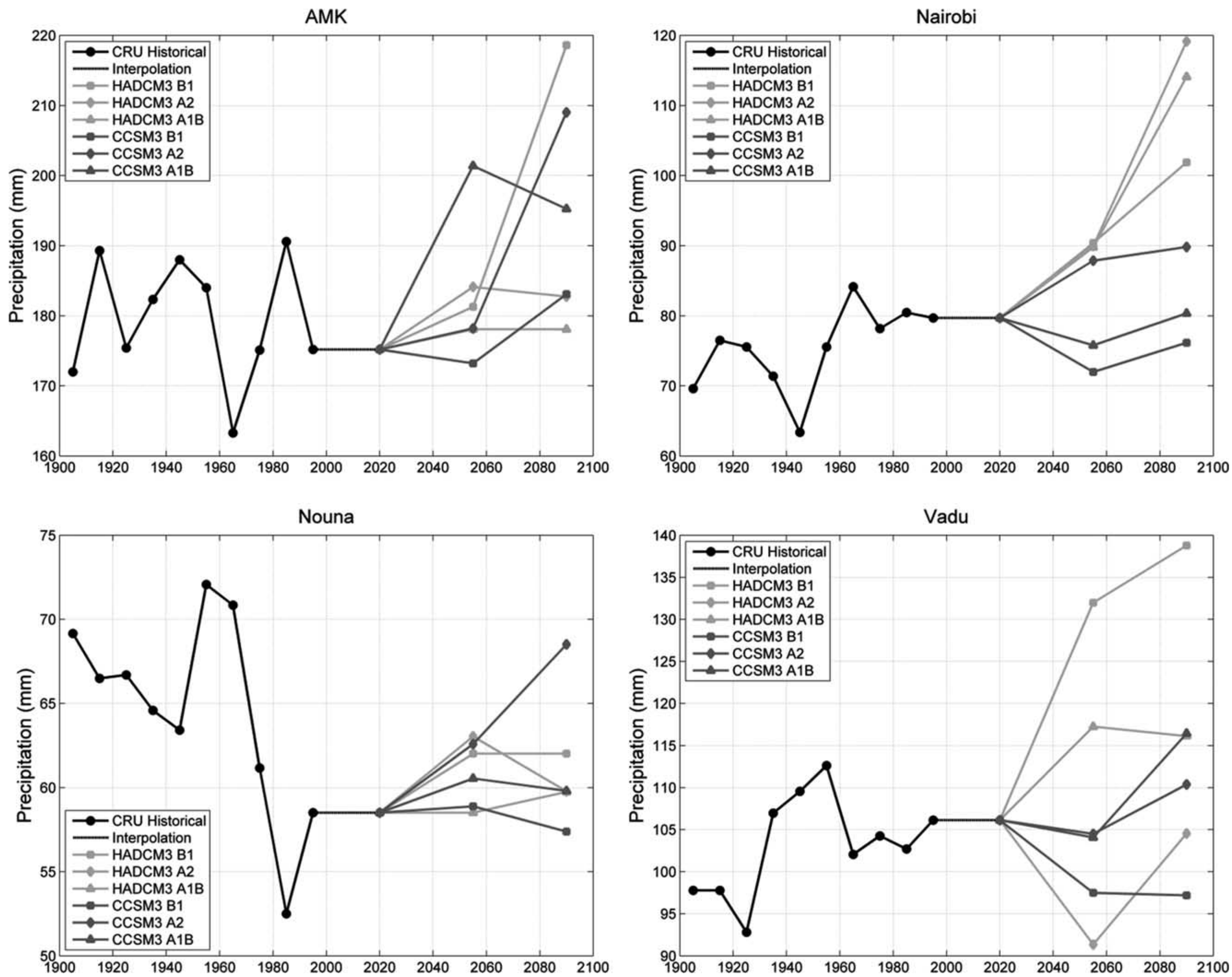

Fig. 8. Historical and projected future precipitation (mm per month) at four INDEPTH member sites, similar to Fig. 6.

a disruption in precipitation patterns during the rainy season. Continued improvement of seasonal projections in precipitation may be especially helpful in preparing these locations for climate change, as changes in the seasonal climate pattern can have devastating effects on agricultural production and human health (12). The health of people at the West African sites might be more impacted by a decrease in precipitation relative to those in eastern India and Bangladesh, where rainfall is more abundant. Like the West African sites, these locations demonstrate considerable seasonality in precipitation. In contrast, however, populations in eastern India and Bangladesh may be more sensitive to increases in precipitation, as flooding events are, as such, regular occurrences.

Changes to Earth's climate over the past and coming century will manifest in many different ways across the globe. Although the general trend is toward a warmer planet, the specific rate of warming can vary considerably, and in some locations there have even been a slight cooling trend (13). Thus, the result we are presenting that all of the HDSSs have not seen statistically significant warming using decadal-scale temperature data should not be entirely surprising. The gridded global temperature trends shown in the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC FAR, 14) show the greatest changes over the northern hemisphere high latitudes, with only slight trends over many of the regions where the HDSSs we examined are located. Further, in some of these regions, the IPCC FAR acknowledges that there are no sufficient data to produce reliable trends. In terms of projections of the future climate, similar spatial heterogeneity exists. The African continent as a whole is expected to warm, in many places at a faster rate than the global mean. The same is true for southern Asia. Considerable uncertainty exists regarding future precipitation in the regions where INDEPTH member sites we examined are located (14).

LMICs are commonly identified as being especially sensitive to climate change, and many of the model projections for the INDEPTH member sites indicate that the rate of temperature change will accelerate considerably over the coming decades. From a health perspective,

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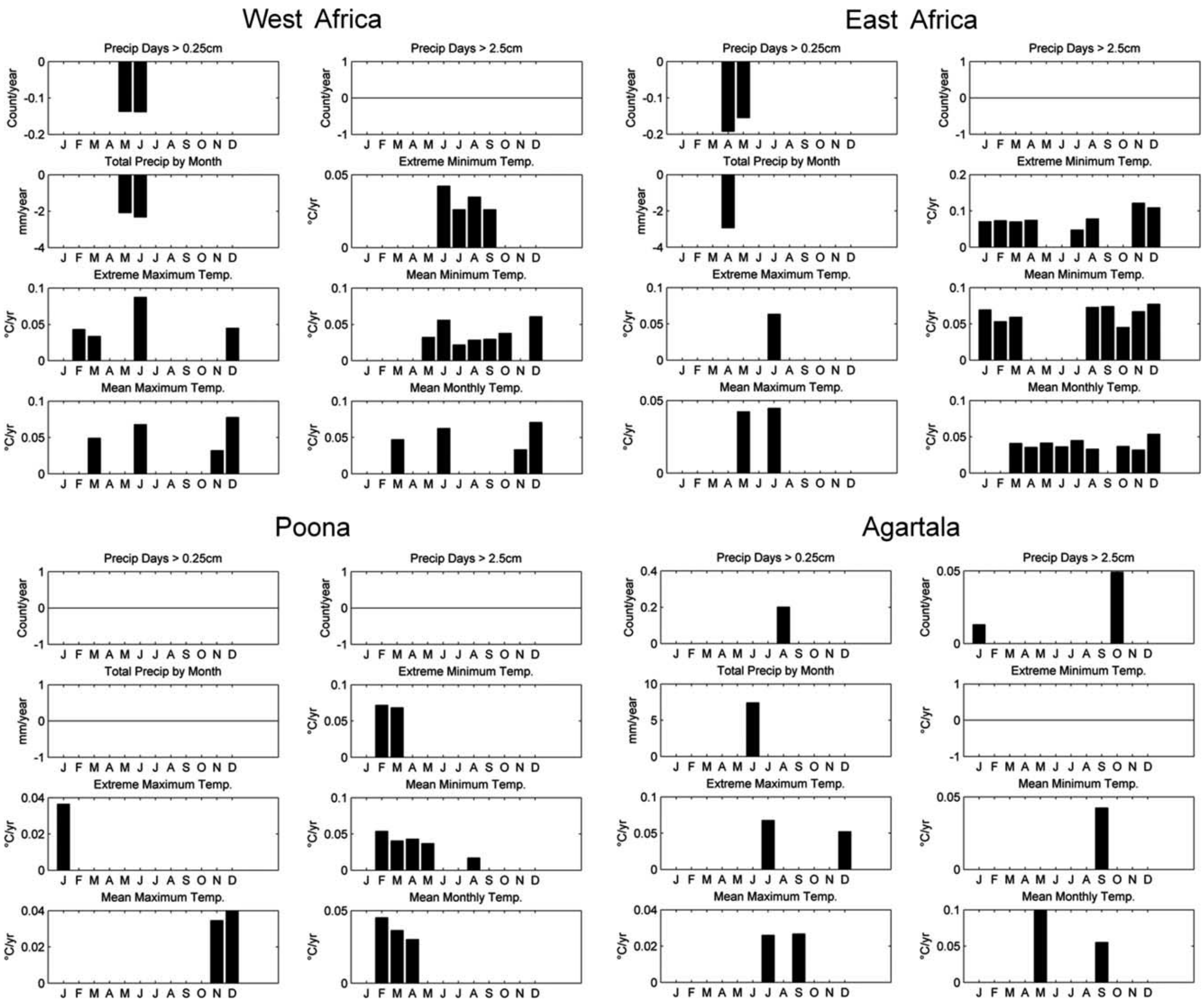

Fig. 9. Trends in historical climate characteristics by month at meteorological stations proximate to INDEPTH member sites. A bar is drawn in all cases where simple linear regression through the yearly time series data (1979–2011) indicated a significant trend: the bar height corresponds to the regression slope B. For each station, the panels show trends per month in (a) the number of days with precipitation >0.25 cm, (b) the number of days with precipitation above 2.5cm, (c) total precipitation, (d) extreme minimum temperature, (e) extreme maximum temperature, (f) mean minimum temperature, (g) mean maximum temperature, and (h) mean monthly temperature.

significant impacts from climate change might occur via a large range of different mechanisms (15). An increase in temperature will directly add thermal stress, for example, and if the change is manifested through increased and more severe extreme heat events, the population may not have time to acclimatize to new extremes. If the change is manifested through a more consistent increase throughout the year, the spread of diseases and food and water resources may be impacted as the change in temperature impacts the hydrologic cycle.

The potential health impacts of climate change are not only dependent on changes in the means and extremes but also on changes to the timing of high and low temperatures and precipitation events. Adding rainfall in the wet season for the Vadu and AMK sites, for example, would have significantly different (and negative) consequences relative to adding moisture during the half of the year when nearly none falls. We sought to use the CRU, HADCM3, and CCSM3 datasets to evaluate changes in seasonality using a similar framework as above but found that the modeled current and future seasonality patterns were too different from observations (and across models/scenarios) for useful analysis. The magnitude of the differences between models and scenarios was far greater than any projected change in seasonality, and in many cases the warmest or wettest months of the year were not correctly depicted by the modeled data. Using regional instead of global climate models to evaluate changes

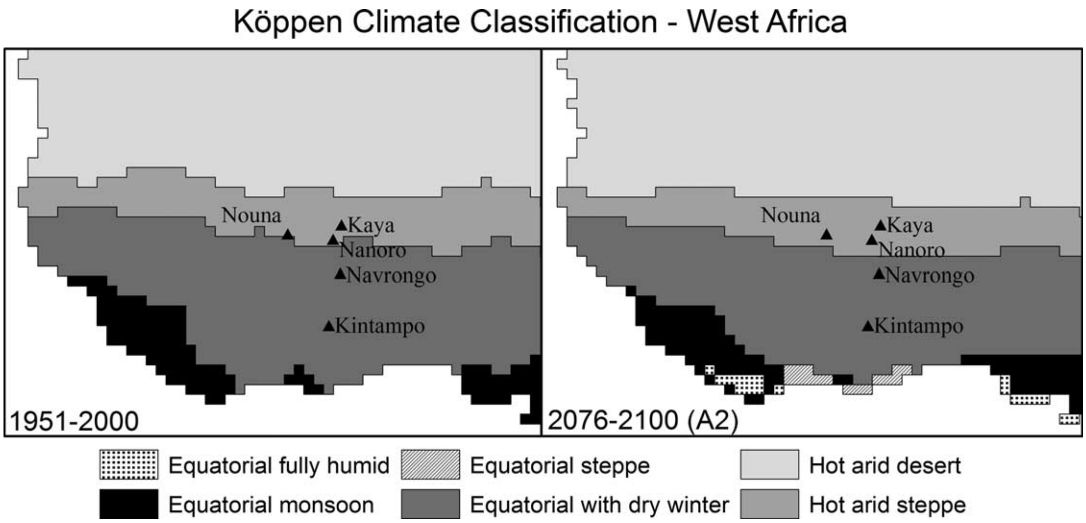

Fig. 10. Estimated Köppen climate classification types in West Africa for (a) the second half of the twentieth century and (b) the final 25 years of the 21st century projected with the Tyndall climate model and the A2 scenario.

in seasonality is recommended for future studies examining such possible changes in these locations. This particular analysis suggests that resources be devoted toward infrastructural adaptations that accommodate precipitation variability in either direction until model certainty improves.

It is our intention that this climatological survey of the CLIMO sites serves as a useful resource for those who focus on climate–health issues throughout the INDEPTH network and other populations in LMICs. Future researchers may find the data sources we used – weather station data obtained from the US National Climatic Data Center's online portal and reanalysis and model projection data from the IPCC data distribution center – beneficial in their own work. Both resources are freely available and present differing strengths and challenges. The weather station data are true measurements obtained from point locations, and in many cases are available at various time scales (hourly, daily, or monthly) even in LMICs. However, at some stations, particularly in the regions we examined, the records often contain long periods of missing values. The reanalysis data from the IPCC data distribution center can be seen as complementary to the station observations. Working with these derived gridded data not only provides continuous spatial and temporal coverage but also adds uncertainty regarding the representativeness of grid cell values for individual locations. The same scaling uncertainty is present in the gridded model projections as well, with an added layer of uncertainty related to making a prediction for the future. Our recommendation is that station data be used wherever possible, but in regions where meteorological observing sites are sparse, other validated products may still be useful in exploring climate change or climate–health linkages.

We acknowledge that while we have provided several analyses to highlight elements of the past, current, and future climates at these locations, each analysis in this manuscript could be improved upon in some way. Most notably, the data we used are readily available but are at coarse spatial and temporal scales, and this limited the application of statistical techniques to identify variability and trends. Downscaling coarsely measured trends to specific locations is an imperfect process with high levels of uncertainty, and, thus, the changes we have presented in this manuscript should not be viewed as tailored predictions for the individual INDEPTH HDSSs, but instead as examples of the types of changes that could occur in these regions. The IPCC FAR explicitly acknowledges considerable uncertainty in downscaled projections for these regions (14). Nonetheless, these projections can and should be examined in synthesis with research examining climate–health linkages, including those presented in this supplement, to gain a sense of perspective regarding potential climate-driven changes in population health. Policymakers and planners can use this information to anticipate the range of future health burdens and develop strategies to minimize the impact of environmental changes on human health. Research groups with expertise in regional climate models could make a useful contribution in preparing and reporting expected changes in the seasonality and precipitation at these locations, including assessments of the uncertainty, based on models with a higher spatial and temporal resolution, and indeed much ongoing effort is devoted to this very challenge (16). The long-term historical trends could also be reanalyzed using daily data (where it is available) which, in turn, could be merged with model projections on a daily scale. Furthermore, while we documented inter-site variability, there is likely also intra-site variability, as the HDSS are regions spanning hundreds of square kilometers. Intra-site variability in microclimates could impact vulnerability and could be assessed via remote sensing resources or improved meteorological monitoring networks. The Rufiji and Kintampo sites are located a considerable distance from the meteorological station they were linked to, and, thus, the results are likely to be least representative of those two HDSSs. Our focus was to provide an easily accessible guide to the climate at these sites. We also strongly encourage a deeper level of study of both the climate, and perhaps more importantly, climate–health linkages in these locations.

Conclusion

Climate data resources are available to study the relationship between weather and health across the 12 HDSS sites participating in the INDEPTH CLIMO initiative. Although very few sites exhibited significant trends in temperature or precipitation using decadal-scale data from the past 100 years, climate models predict large changes in both variables at many locations. Projections for all sites consistently pointed toward a warm climate over the next century, but there was little agreement between climate models and scenarios in how precipitation might change in these locations. Across all sites, projections indicate that the climate may change dramatically in the coming years relative to the past century. Some sites may experience changes of a magnitude large enough to change their climate classification type. Collaborative efforts to link climate and health data sets to understand the sensitivity of low- and middle-income populations to various climate and weather phenomena can help guide adaptation efforts for those who might be most vulnerable as the global climate changes.

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Conflict of interest and funding

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