



Project no. GOCE-CT-2003-505539

Project acronym: ENSEMBLES

Project title: ENSEMBLE-based Predictions of Climate Changes and their Impacts

Instrument: Integrated Project

Thematic Priority: Global Change and Ecosystems

D7.5 Health impact interfaces for climate change impact models

Due date of deliverable: Month 24
Actual submission date: May 2007

Start date of project: 1 September 2004

Duration: 60 Months



London School of Hygiene and Tropical Medicine

Revision [draft]

Project co-funded by the European Commission within the Sixth Framework Programme (2002-2006)		
Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the Consortium (including the Commission Services)	

Report authors

R Sari Kovats
Dept of Public Health and Policy
London School of Hygiene and Tropical Medicine, London, UK

Kate Lachowycz
Dept of Public Health and Policy
London School of Hygiene and Tropical Medicine, London, UK

Simon Lloyd
Dept of Public Health and Policy
London School of Hygiene and Tropical Medicine, London, UK

Tord Kjellstrom
Health and Environment International Trust, Nelson, New Zealand

Contact address

R Sari Kovats
Lecturer, Public and Environmental Health Research Unit (PEHRU)
London School of Hygiene and Tropical Medicine
Keppel St, London WC1E 7HT
tel: +44 20 7927 2962
fax: +44 20 7580 4524
sari.kovats@lshtm.ac.uk

Summary

- Methods for estimating the health effects of climate change are at an early stage of development. Inappropriate assumptions have often been included into integrated assessment models with respect to health outcomes and there is a need to improve the relevant health impact models.
- Future disease burdens are sensitive to the underlying assumptions about population growth and ageing and future health status. The WHO has produced projections of cause-specific mortality to the year 2030. Deaths from diarrhoeal disease are projected to decline, but deaths from cardiovascular disease are increasing dramatically due to population growth, population ageing and changes in lifestyle factors.
- Temperature and rainfall both affect the seasonal pattern of diarrhoeal disease. A review of the literature found few good quality studies that quantified the short term effect of weather on diarrhoeal diseases.
- There is some evidence that rainfall is a determinant of diarrhoeal disease at the global level, even once socio-economic factors taken in to account. A global cross-sectional study of diarrhoea incidence in children under five, used regression was used to quantify the associations, controlling for the effects of age, socio-economic conditions and access to improved water and sanitation. The incidence of diarrhoea increases by 4% for each 10mm/month decline in rainfall.
- The sites from which the observed climate or weather-health relationships are derived cover only a small part of the spectrum of global climate variation. Different relationships may apply at higher or lower temperatures. Different relationships also apply in high vs low income populations. Where possible, this has been avoided by using associations from low income populations but there are not well represented in the literature.
- Climate change is estimate to increase the temperature-attributable proportion of diarrhoeal disease, but this is in the context of an overall decline in diarrhoeal disease mortality.
- Climate change will increase heat-related mortality and decrease cold-related mortality. The estimates of changes in attributable cardiovascular mortality are large due to population ageing and the large burden of cardiovascular projected in low and middle income countries.
- Climate change (as projected under the A2 and B2 emissions scenarios) may decrease labour productivity in Africa by 11-14% in 2050s and by 16-20% in 2080s, with similar effects in South-East Asia region.

Acronyms

CGE	Computable general equilibrium models
CI	confidence intervals
CRA	comparative risk assessment
DALY	disability adjusted life year
FUND	Richard's model
GBD	global burden of disease
GDP	gross domestic product
GCP	gross cell product
GTAP	Econometric model, [FEEM]
IAM	integrated assessment model
JMP	WHO/UNICEF Joint Monitoring Programme
RR	relative risk
SMPH	summary measures of population health
SRES	Special Report on the Emission Scenarios (of the IPCC)
WBGT	wet bulb globe temperature
WHO	World Health Organization
YLL	years of life lost

Acknowledgements

Many thanks to

- Tom Holt, UEA, for help with providing climate data and climate advice,
- Alessandra Garbero, Centre for Population Studies, LSHTM, for help and advice on the population projections.
- Colin Mathers, WHO, Geneva, for disease burdens and projections.

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Introduction

The ENSEMBLES project (contract number GOCE-CT-2003-505539) is supported by the European Commission's 6th Framework Programme as a 5 year Integrated Project from 2004-2009 under the Thematic Sub-Priority "Global Change and Ecosystems". The overall coordinator of the project is Dr David Griggs, Director of Climate Research at the Met Office's Hadley Centre for Climate Prediction and Research. This assessment of health impacts is Workpackage 7.3 of RT7 (Research Theme 7) coordinated by Professor Richard Tol at University of Hamburg and ESRI.

Objectives of Workpackage 7.3

- To develop global and regional health impact models to estimate the impacts of climate change, with consideration of changes in adaptive capacity [LSHTM]
- Estimate attributable burden of climate change in terms of mortality for a specified range of climate, population, and GDP scenarios provided in WP7.2 and other partners in ENSEMBLES, and in format required by RT7 coordinator.

Specific objectives

- Review literature on global and regional scenario-based health impacts studies.
- Review published literature on quantitative associations between temperature and health
- Update impact models first developed under global burden of disease (GBD) study, where possible and where appropriate.
- Generate estimates of future health impacts using the climate, population and GDP scenarios.
- Undertake sensitivity and uncertainty analyses.

Following discussion with RT7 and other Ensembles partners, it was agreed that the impact models will be run with the SRES scenarios rather than a developing a new set of emissions scenarios, while acknowledging the limitations of these scenarios. The metric needed for RT7 is mortality (age, gender, region- and hazard-specific). This report describes the methods used to derived these estimates. Methods for the monetization of health impacts are not addressed in this report. The monetization undertaken for the ENSEMBLES project is discussed elsewhere.

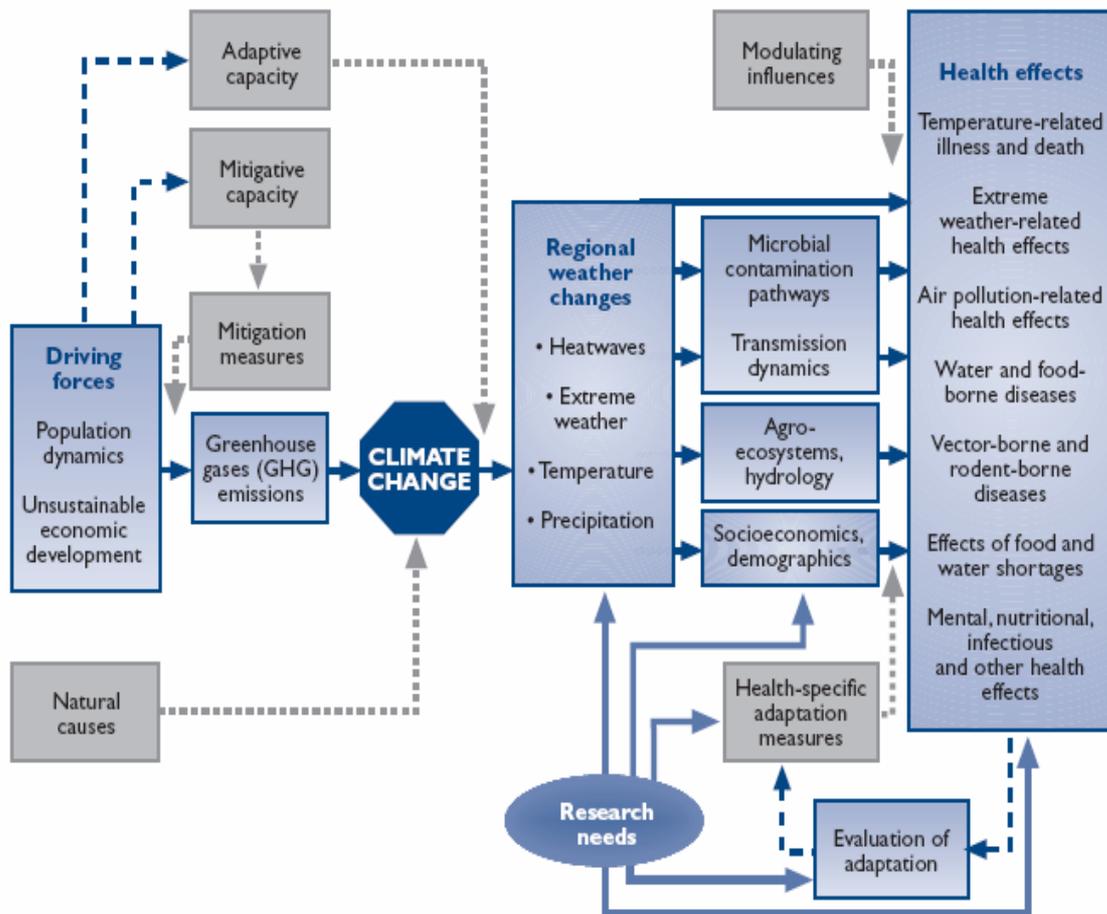
The health effects of climate change

Maintaining and improving human population health is an important justification for taking action on climate change and other environmental problems. We protect environments, water supplies and agricultural production because of the goods and services that they supply to human populations, and implicitly the benefits they confer on wellbeing and health. Health can also be converted to an economic metric and incorporated with econometric integrated assessment models of climate change. Where health effects have been costed, they usually account for a large proportion of the damage costs of climate change.

Climate change can affect human health through a wide range of mechanisms and for a range of diseases or health outcomes (deaths, injuries) (Figure 1). Climate variability, as characterised by weather extreme events, and inter-annual variability, is known to affect certain infectious diseases, such as malaria and cholera. The impacts of long term shifts in climate conditions may lead to shifts in distribution of infectious diseases and areas suitable for food production (2003). The health chapter of the Third Assessment Report of the IPCC concluded that negative impacts on health will outweigh the benefits, and that populations in poorer areas will be the worse affected¹.

Research on the potential health impacts of climate change must rely on observed effects of weather and climate, primarily using epidemiological methods. As climate change requires at least 30 years of data, the opportunities for observing directly the effects on human health are extremely limited, especially in low and middle countries.

Figure 1. Mechanisms by which climate change affects human population health, from ref.²



Good quality empirical studies of the effects of weather or climate on health outcomes can provide the evidence base for developing risk assessment models³. Good quality studies are those that:

- measure and control confounders;
- describe the geographical area from which the health data are derived;
- use appropriate observed meteorological data for population of interest (the use of reanalysis data may give spurious results for studies of local effects);
- have plausible biological explanation for association between weather parameters and disease outcome;
- remove any trend and seasonal patterns when using time-series data prior to assessing relationships;
- report associations both with and without adjustments for spatial or temporal autocorrelation.

A particular problem arises from extrapolating observed weather-health relationships to risk assessment models. Time series methods have been developed to estimate the proportion of disease in a population that is attributable to weather, that is, the short-term variation in meteorological exposures (day-to-day or week-to-week). Strong associations have been found between temperature and daily mortality, and between temperature and cases of types diarrhoea (see reviews in later chapters). However, there is some debate whether it is appropriate to extrapolate long term effects from a short-term acute associations. Alternative study designs involve cross-sectional studies across populations in different climates. Such associations are subject to confounding by socio-economic and other important differences between populations.

Mapping of many vector borne diseases and/or their vectors has been rapidly advanced by improvements in computing as well as in the geo-referencing of disease and exposure data. Vector-borne diseases are not addressed within this report as they are beyond the scope of this Workpackage.

Predictive models of the impact of climate on health have been developed for a very limited range of health outcomes (malaria, dengue, diarrhoeal disease, temperature-related mortality). Health-related or “welfare” outcomes have also been addressed in projections of populations at risk of water stress or at risk of hunger. These studies provide some evidence for fairly monotonic increases in health impacts as climate change increases where those changes are driven by temperature. When rainfall effects are important drivers of disease risk, the results can be very inconsistent. Due to the limited number of models and publications available, there has been some publication bias and a non-systematic approach to reviewing the projected impacts.

Many factors, such as physiological adaptation and individual and community wealth, will influence both the exposure of individuals and populations to climate hazards and their impacts. For some impact models, simple modifying factors (e.g. technological development of crops) are integrated into the models both for present and future impacts (e.g. people at risk of hunger). Other models incorporate the effects of existing modifiers when defining current climate-disease relationships, such as estimates of the global distribution of malaria based on current climate associations. Although such models implicitly capture the current modifying effects of socioeconomic and other influences, they often do not either (i) separately attribute climate and socioeconomic effects, or (ii) attempt to model future changes in these modifiers.

The majority of health models in fact make no estimate of future changes in important modifying influences, either due to economic development, or in relation to specific response to climate change (adaptation). This leads to an over-estimate of future health impacts. The main reason for this is the great uncertainty in socio-economic factors and health burdens in the future.

Integrated Assessment models (IAMs) are narrowly defined here as economic-energy-environment models that are used for the cost-benefit analysis of environmental policy questions such as climate change⁴. Appropriate incorporation of “health” into integrated assessment models will help policymakers understand the dimensions of the possible health impacts of climate change and will inform the design of strategies and policies to address the possible consequences climate change mitigation and adaptation. Methods to cost “non-market” impacts, including health, for global environmental risks such as climate change include contingent valuation and the direct costs of adaptation measures. The methods for costing health impacts is not reviewed here - although clearly the choice of method has a significant effect on the final estimates.

Estimating the global burden of disease due to climate change

In 2002, climate change was one of the environmental exposures analysed in the World Health Organization’s comparative risk assessment of the global burden of disease (GBD)⁵. WHO developed the comparative risk assessment (CRA) to quantify the burden of disease from specific risk factors and to estimate the benefit of realistic interventions that remove or reduce these risk factors. Estimates were derived as relative risks, for each climate scenario compared to the baseline climate. In order to estimate the number of deaths avoided, the relative risks were applied to WHO projections of population and disease-specific incidence.

All environmental risk factors were assessed by the WHO using similar epidemiological criteria. The method has an inherent tendency towards making conservative assumptions, focussing on more easily measurable health risks (i.e. bias towards more immediate risk factors such as smoking or poor water and sanitation), and excluding more diffuse risk factors. In the case of climate change, this leads to completely excluding some impacts that are highly likely (such as drought-related mortality), some impacts that are likely but difficult to quantify (such as diverse health effects on populations displaced from sea level rise), or impacts that are plausible but with low probability (health impacts of acute regional failures in crop production, health impacts of a major flood disaster in Europe).

The modest climate change that occurred between the mid 1970s and the year 2000 was estimated to have caused the loss of approximately 150,000 lives and 5,500,000 DALYs per year⁶. The climate change attributable impacts (as defined under a single unmitigated climate scenario) are projected to approximately double by 2020. The majority of this increased burden of disease will be due to diarrhoeal disease and malnutrition. This is due to the high underlying (baseline) mortality of these diseases at the global level. Estimates were not generated beyond the 2000-2030 time period as this was outside the decision making framework of the World Health Organization.

Climate scenarios

The emissions scenarios: SRES

The IPCC Special Report on Emission Scenarios (SRES)⁷ documents a suite of four global development scenarios, with include trends in population growth and socio-economic development. These scenarios are non-interventionist scenarios and imply no climate policies to reduce emissions.

The scenarios are presented in “storylines” which represent mutually consistent characterisations of future states of the world during the 21st century, including demographic and economic development, energy use and greenhouse gas emissions, together with associated changes in climate and sea level. Each storyline is basically a short "history" of a possible future development, of (a combination of) key scenario characteristics. The storylines identify particular dynamics, visible in the world today, that might have important influences on future greenhouse gas emissions; they deliberately explore what might happen if political, economic, technical and social developments take an alternative direction at the global level. Regional differences and interactions, especially between developing and industrialised countries, are also assessed.

- A2 storyline and scenario family is a very heterogeneous world. The underlying theme is that of strengthening regional cultural identities, with an emphasis on family values and local traditions, high population growth, and less concern for rapid economic development. There is little concern for the environment.
- B2 storyline and scenario family is a world in which the emphasis is on local solutions to economic, social, and environmental sustainability. It is again a heterogeneous world with less rapid, and more diverse technological change but a strong emphasis on community initiative and social innovation to find local, rather than global solutions. However, there is a definite desire to find effective ways of solving environmental problems through policy implementation.

The aim of the scenarios was to provide both a consistent input to both the climate models and impact models. All scenarios are considered equally possible and there is no “best guess”. The limitations of the SRES with respect to population projections are discussed in the next chapter.

Table 1 Summary of SRES scenarios: global mean temperature change °C

Year	IS92a	A1FI	A2	B1	B2
1990	0.00	0.00	0.00	0.00	0.00
2020s	1.10	0.99	0.89	0.84	0.93
2050s	2.06	2.26	1.89	1.45	1.63
2080s	3.00	3.97	3.27	2.06	2.38

Exposure classification: current climate

ENSEMBLES required a global and regional assessment and therefore the populations in different climates needed to be taken into account. Climate-health relationships are determined by climate as well as by socio-economic and other environmental determinants (see above).

The climate data from the HadCM3 climate models were available on a 2.5 x 3.75 ° global grid. In order to take into account the diversity of climates within each world region, we selected climate points from this grid for each climate type within each WHO region. The climate types were based on the recent Köppen climate classification⁸.

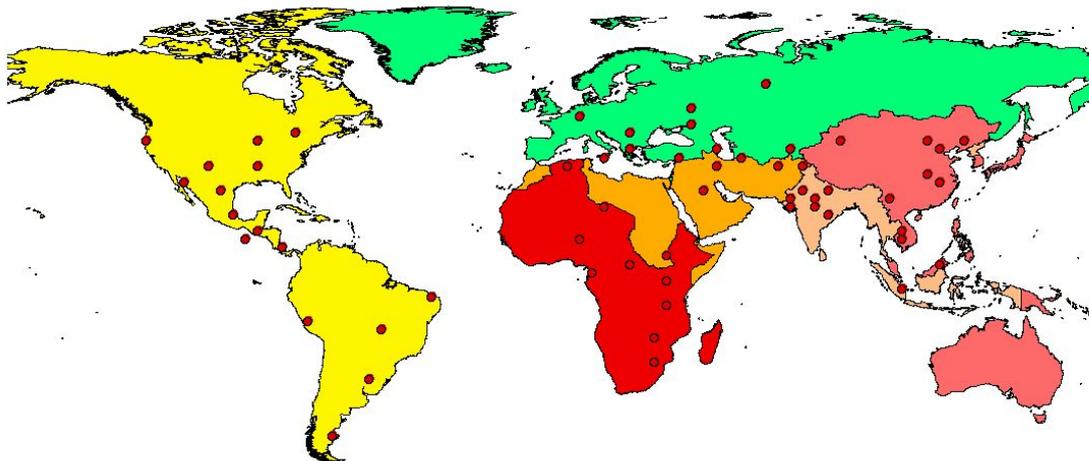
A Geographic Information System (GIS) was used to allocate the global population, defined on a global 2.5x2.5° (CIESIN 2005) for year 2000, to the Köppen climate zones. We then calculated the proportion of the population living in each climate zone per region. A population-weighted centre point was calculated for each climate zone within the region (excluding zones where less than 1% of the region’s population lived). The nearest climate grid point to this location was then chosen as being representative of the climate for this zone within the region. This gave a total of 60 grid cells, which are indicated in Figure 2.

We did not attempt to validate or assess the quality of these climate model data as this was beyond the scope of our expertise and our Workpackage.

Table 2. Proportion of population in each climate zone by WHO world region.

WHO Region	Main climate types*
	(% population in the region)
Africa (AFR)	equatorial, winter dry (48%) hot steppe (13%)
South East Asia (SEAR)	equatorial, winter dry (50%) warm temperate, winter dry, hot summer (27%)
Eastern Mediterranean (EMR)	hot desert (61%) warm temperate, summer dry, hot summer (13%) hot steppe (10%)
Europe (EUR)	warm temperate, fully humid, warm summer (39%) snow, fully humid, warm summer (26%)
Americas (AMR)	warm temperate, fully humid, hot summer (34%) equatorial, winter dry (15%)
Western Pacific (WPR)	warm temperate, fully humid, hot summer (41%) warm temperate, winter dry, hot summer (32%) snow, winter dry, hot summer (11%)

Figure 2. Grid cells selected for climate change exposures – one grid cell is in each climate zone within each world region.



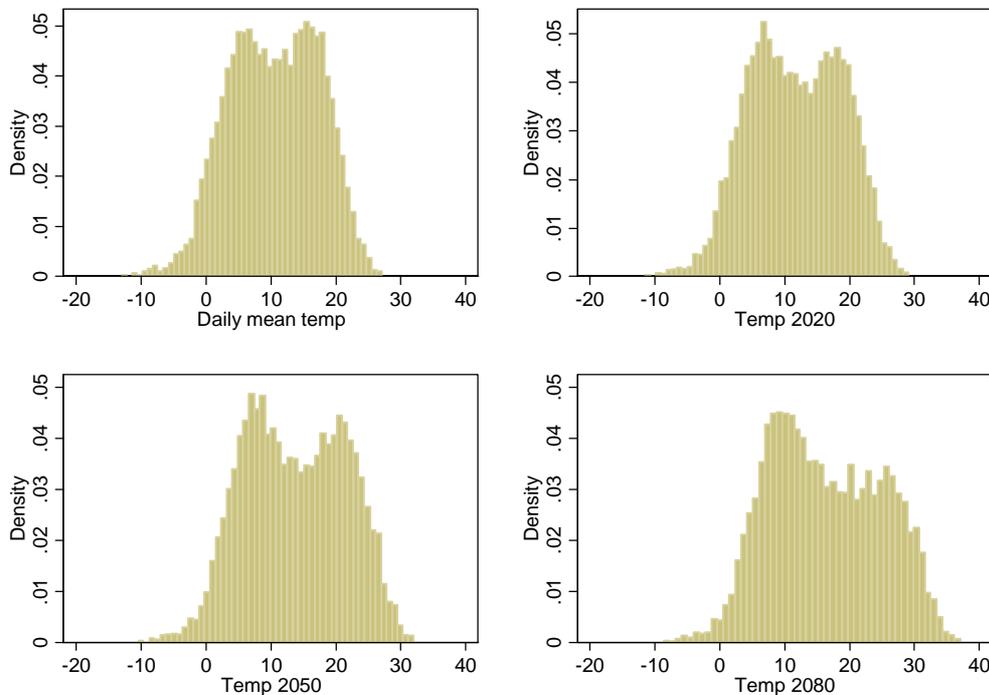
Climate projections: A2 and B2

Daily data were extracted for these climate grid cells for the years 1960 to 2100 for two climate scenarios: A2 and B2 for three time slices. We thank Tom Holt for extracting these data from the HadCM3 model. .

Temperature

We required daily temperature distributions in order to assess the change in the number of hot days. Changes in temperature extremes are more important than changes in mean climate for human health outcomes. Figure 3 illustrates the shift in daily temperature distributions for a climate scenario under the 3 times slices (2020s, 2050s and 2080s).

Figure 3. Changes in daily temperature distribution for a specified mid-latitude grid cell [HadCM3]



Humidity

As with rainfall, the humidity output of climate models is less robust than the temperature data. Models work out surface moisture parameters using a surface flux model, so that there is a balance between the fluxes of energy from different parameters. The fluxes in HadCM3 were revised to give better comparisons with observations but this decreases the confidence in the projections of humidity. It is difficult to assess quality of the grid cell level humidity measure.

We used the daily output for relative humidity to generate a temperature-humidity index (WBGT) (see chapter on productivity). For other outcomes (diarrhoeal disease and cardio-respiratory mortality), only temperature data were used.

Some validation has been undertaken where the HadCM3 output is compared to revised reanalysis data (observational data) [NCEP and ERA-40]. It was found that there is some inconsistency over some tropical grid squares (the humidities from the two reanalysis datasets are negatively correlated (Holt, pers communication)). It is unlikely that HadCM3 gives markedly better humidities than the NCEP dataset. However, without a full study comparing HadCM3 with ERA-40 it is impossible to say more. Over fairly level terrain, HadCM3 humidity is probably reasonable in mid-latitudes.

Population scenarios and health futures

An important component of health impact assessment is the estimates of the baseline mortality. In the context of climate change, this entail robust estimates of current and future baseline (i.e. no climate change) disease rates. There is no information in the SRES on future disease burdens, but there are estimates of population growth (but not population ageing).

At the broad scale, the main determinants of population growth are fertility rates. External factors (epidemics) are unlikely to have a significant impacts on total population size. The HIV/AIDs epidemic, however, is so large as to have affected population patterns and this is now factored into the UN population projections.

There are several important determinants of population growth at global and national level, but not all of them can be incorporated into the projections:

- Fertility (i.e. birth rates) is the most important factor for population growth. Therefore estimates are acutely sensitive to assumptions regarding the average number of births per adult woman. Also contingent on the number of adult women available (population size and structure).
- Migration. Important but very unpredictable, therefore a constant rate is assumed in the projections.
- Mortality. Life expectancy is linked to income and other socio-economic factors. The UNPD projections used data on life expectancy from the WHO. Mortality is more important in high mortality countries than low mortality countries.
- Economic growth is not an important factor, other than its indirect effect via life expectancy.

In general, the determinants of national and regional disease rates are development, health systems, and regulation, rather than per capita income (see reviews elsewhere). The role of regulation and health protection measures (e.g. Clean Air acts) should not be underestimated but after often obscured in the analysis of crude associations between income and health indicators. Further, individual or household income is more important than national income.

SRES Population projections

The population scenarios in the SRES cover a wide range of projections, with estimates of between 7 billion (B1 and A1FI) and 15 billion (A2) global population by 2100⁹. The midrange estimate can be considered to be B2 (close to IS92a) which is 10 billion by 2100. The population projections were developed outside the assumptions of the storylines, i.e. they are not derived from assumptions within the economic models. Figure 4 summarise the global projections under the marker scenarios and the UNPD projections.

Table 3. Population by age group, by WHO region (millions). UNDP midrange projection

Year 2000	Age 0-14	age 15-60	age 60+
Afr	291941	339173	31831
Amr	233709	508816	93223
Emr	190304	268849	27633
Eur	174092	540043	160292
Sear	513363	909848	114218
Wpr	424818	1080630	181734
Year 2030	Age 0-14	age 15-60	age 60+
Afr	453638	704711	71536
Amr	229741	672275	217852
Emr	237769	522767	80706
Eur	141902	511344	236607
Sear	485681	1371743	298242
Wpr	342752	1161792	460818

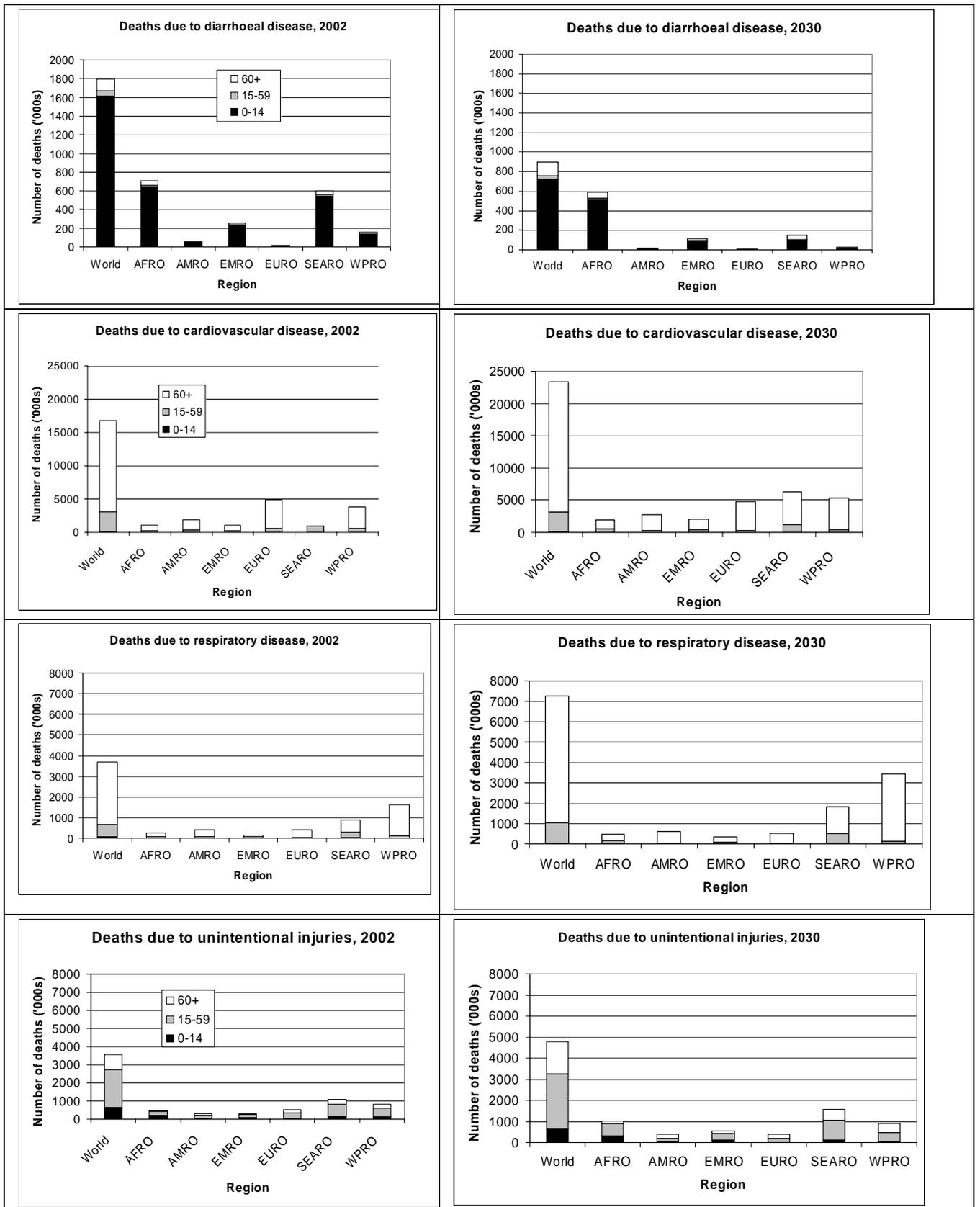
The A2 world has very high population totals and is now thought to be very unlikely. The formal assessment by Lutz and others¹⁰, estimated that A2 projections outside 90th centile for current population trajectory. Risk assessment based on these projections would distort any results. Therefore, we decided not to use the A2 population scenario in our estimate of future disease burdens.

Mortality projections

This health assessment require age, sex and cause-specific deaths (or deaths rates) by region for a range of future time periods (years). Unfortunately, this information could be not obtained form a single source, therefore a range of data sources were used.

WHO has produced mortality projection to 2030 for the Global Burden of Disease project¹¹. These are assumed to be best available projections of mortality and are used in this assessment (for the years for which they are available). We are especially grateful to WHO for providing country-level data. Figure 4 summarise the cause and age-specific burdens for 2002 and 2030 by world region. Note that diarrhoeal disease burdens are declining due to improvements in income and socio-economic factors. There are also important differences in the burden of mortality by age group. Diarrhoeal disease mortality is predominantly in children but has smaller numbers of deaths reflecting that most countries have made improvements in controlling infectious diseases. In contrast, the mortality rates for cardiovascular disease are very high and increasing in 2030 due to changes in lifestyle and also population ageing. Rates of cardiovascular mortality are declining in some countries, such as the UK, but are rapidly increasing in low and middle income countries, particularly India and China. The change in disease profile from infectious to non-communicable diseases as a country increases its economic development is called the epidemiological transition. Unfortunately, some countries will experience the “risk overlap” and experience high burdens of both infectious and chronic diseases due to changes in risk and lifestyle factors^{12,13}. This assessment required both country and age-specific projections for all time periods but these data were not available.

Figure 4. Summary of mortality (total number of deaths) for 2002 and 2030 by cause of death and age group.

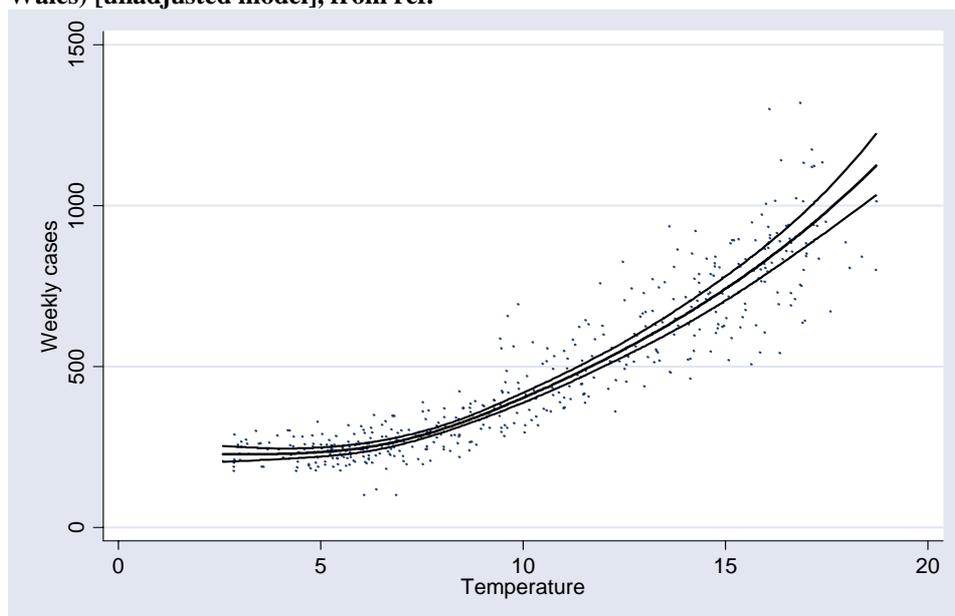


Diarrhoeal disease 1 – Time series studies

Diarrhoeal disease is one of the most important causes of global ill-health in low income countries. It is recognised to be highly sensitive to climate, showing strong seasonal peaks in both winter, summer and in rainy seasons⁵.

Diseases associated with water are varied and cover multiple environmental pathways. Waterborne diseases are usually understood to be those diseases that are spread via water that is contaminated with faecal material and then ingested (so called faecal-oral diseases). Faecal-orally transmitted disease can also be affected by ambient temperatures. Diseases caused by pathogenic organisms (water-based diseases) that spend part of their life cycle in aquatic organisms are often associated with standing water and so are potentially affected by climate. The climate-sensitivity of diarrhoeal disease is consistent with observations of the direct effects of climate variables on the causative agents. Laboratory studies have shown that the proliferation of micro-organisms such as bacteria increases with increasing temperature, up to a threshold value, providing other conditions are met. Epidemiological studies have also shown associations between environmental or outdoor temperature and related outcomes such as reported diarrhoeal episodes or hospital admissions¹⁴. For these reasons, increases in diarrhoeal disease have been identified as a potential health consequence of global climate change¹⁵.

Figure 5. Observed relationship between diarrhoeal disease (salmonellosis) and temperature (England and Wales) [unadjusted model], from ref. ¹⁴



Methods

A review of the published literature was undertaken to identify published quantitative estimates of an association between temperature, rainfall and diarrhoeal disease (mortality or morbidity). Previously, the WHO CRA results were based on two papers that quantified the short term association between temperature and diarrhoeal disease (hospital admission in Lima¹⁶ and in Fiji¹⁷). More recent work in Europe has quantified the effect of temperature on reported cases of salmonella.

Very few studies were found that quantified the effect of rainfall on diarrhoeal disease outcomes. Therefore, we restricted the assessment to the effect of increasing temperatures on the incidence of all-cause diarrhoea, making no prediction of the effect of changing rainfall patterns. Table 4 lists all the studies that met our criteria for including in the model.

Table 4. Published epidemiological studies by population that quantify the effect of temperature on infectious intestinal disease outcomes

Population	Pathogen	Measure	Ref
Pacific Islands	Non-specific	Hosp admissions	17
Lima, Peru	Non-specific	Hosp admissions	16
Lima, Peru	Non-specific	Hosp admissions	18
Adelaide	Non-specific	Hosp admissions	D'souza, [in press]
<i>Queensland</i>	Non-specific, children	Hosp admissions	19
Adelaide	Salmonella	passive surveillance	20
Perth	Salmonella	passive surveillance	20
Brisbane	Salmonella	passive surveillance	20
Melbourne	Salmonella	passive surveillance	20
Sydney	Salmonella	passive surveillance	20
<i>Canada</i>	Salmonella	passive surveillance	21
Poland	Salmonella	passive surveillance	14
Scotland	Salmonella	passive surveillance	14
Denmark	Salmonella	passive surveillance	14
England and Wales	Salmonella	passive surveillance	14
Estonia	Salmonella	passive surveillance	14
Netherlands	Salmonella	passive surveillance	14
Czech Republic	Salmonella	passive surveillance	14
Switzerland	Salmonella	passive surveillance	14
Slovak Republic	Salmonella	passive surveillance	14
Spain	Salmonella	passive surveillance	14
England and Wales	Campylobacter	passive surveillance	22
England and Wales	Campylobacter	passive surveillance	23
England and Wales	Campylobacter	passive surveillance	24
Scotland	Campylobacter	passive surveillance	25

Key findings

In all, 11 published studies were found that met our criteria. The majority of these studies were from mid-latitude populations and there is lack of evidence of the effect of temperature on diarrhoeal disease in tropical and subtropical climates. Temperature was found to increase the risk of diarrhoeal disease (hospital admissions) and reported salmonellosis. The effect of temperature on reported campylobacteriosis is unclear – and this is consistent with what is known about the behaviour of the pathogen in the environment. Campylobacters do not multiply at room temperature.

The majority of the studies were generally of high quality. The exposure (climate) data were recorded at local meteorological stations, and can be considered to have negligible measurement error at the population level. The time-series methods used independently controlled for seasonal variations and long-term trend, giving imparting high confidence in to the observed effect of temperature on the outcome recorded.

The estimates of the change in risk per degree change in temperature (weekly or monthly). Extrapolation of this relationship to the future assumes that there is not change in the temperature-disease relationship. This is unlikely. Further, there is potential bias: if the temperature-responsiveness is indeed greater at low temperatures, extrapolation of an average value will tend to underestimate effects in areas which are on average colder, and overestimate in hotter regions.

A further difficulty in generating a valid temperature-health function is the range of pathogens that cause diarrhoeal disease (Table 5). More importantly, the viral agents (e.g. rotavirus) typically peak in the winter seasons (in temperate countries) and in rain seasons (in tropical countries). While several studies describe climate effects on particular diarrhoea pathogens^{26,27} these cannot be directly used to estimate effects on diarrhoeal disease without information on (1) their relative contribution to overall disease incidence, and (2) equivalent data on climate-sensitivity and relative prevalence for all other diarrhoea pathogens.

Table 5: Percentage of selected enteropathogens in children with diarrhoea in developing countries. Ref. ²⁸

Enteropathogens	Community based studies		Health facility based studies	
	Median	Range	Median	Range
Aeromonas sp	2	<1-13	2.5	<1-42
Campylobacter sp	6	1-24	7	0-32
Cryptosporidium parvum	4	2-7	4	1-12
Entamoeba histolytica	<1	<1-9	1	0-7
Enterotoxigenic Escherichia coli	14	2-41	11	1-54
Giardia lamblia	10.5	<1-24	2	0-28
Rotavirus	6	2-29	20	5-49
Salmonella sp	1	0-6	4	0-38
Shigella sp	4	1-27	5	0-33
Vibrios	<1	0-3	1	0-33

Estimating future diarrhoeal burdens.

The future burden of diarrhoeal disease due to climate change is calculated indirectly by estimating the proportion of infections due to “hot weather” under current and future climates. Table 6 shows country level estimates of the PAF (population attributable fraction) for reported salmonellosis cases in Europe. There is great heterogeneity in the results. For the global assessment, region-specific exposure-response relationships were assumed, following the methods developed in the Global Burden of Disease assessment.

Table 6. Estimated proportion of all cases of salmonella due to high temperatures (current climate)

Country	% increase	threshold	PAF*	PAF 95% ICI	PAF 95% uCI
Czech R	9.46	-2	61.5	56.5	65.9
Denmark	1.08	15	0.2	-0.4	0.9
England	12.43	5	45.3	43.0	47.4
Estonia	18.33	13	10.2	2.2	17.4
Holland	9.25	7	28.9	26.8	30.9
Poland	8.69	6	32.6	19.4	43.6
Scotland	4.69	3	23.6	11.6	33.9
Slovakia	2.48	6	11.1	-13.2	30.2
Spain	4.89	6	34.7	26.1	42.4
Switzerland	8.76	3	44.6	40.4	48.5

* Population attributable fraction.

Diarrhoeal disease 2 – Climate as determinant of current incidence

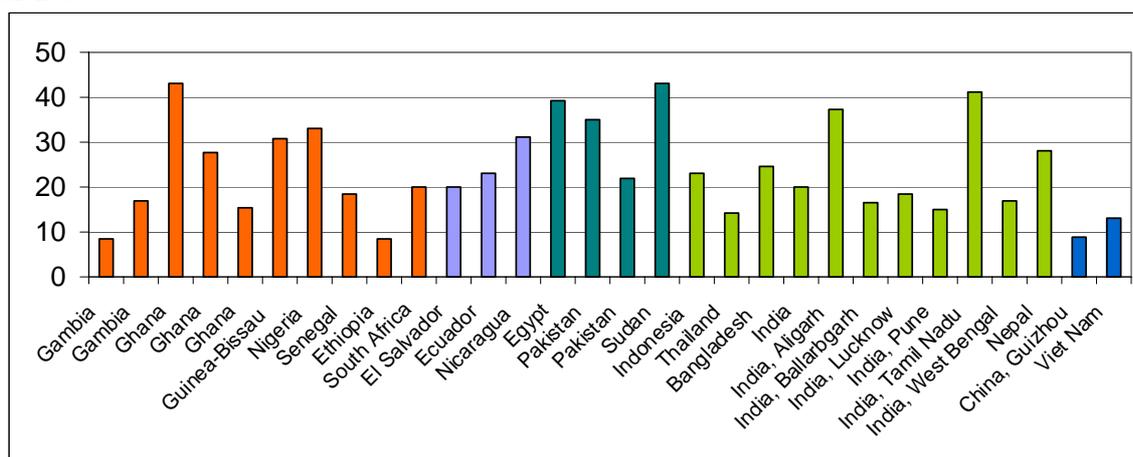
In addition to reviewing the time series studies, a cross sectional study was also undertaken to investigate climate factors as a current determinant of diarrhoeal disease.

Water scarcity, which may be the result of low rainfall, causes a range of health problems in certain populations, including diarrhoea, although there are few studies that directly quantify this relationship. A study in 18 Pacific Islands, considering average weather conditions over a 10 year period, found that all-cause diarrhoea (as measured by hospital admissions) increased with decreasing water availability¹⁷. However, an attempt to quantify this relationship using multiple-regression was uninformative, possibly due to a lack of statistical power. In this study, we describe the influence of climate and weather on diarrhoea incidence using data collated for three global burden of diarrhoeal disease reviews²⁹⁻³¹. Our study concentrates on morbidity rates, which have remained fairly constant over the past decades despite reductions in mortality. We test the hypothesis that climate factors are a determinant of diarrhoeal disease, and consider both long-term climate and average weather conditions (during the survey period), with adjustment for potential confounders such as socio-economic status and access to improved water and sanitation.

Diarrhoeal data

We undertook a global cross-sectional study using age-specific diarrhoeal incidence rates in children under 5 year old as the primary outcome measure. The global burden of diarrhoeal disease was assessed by systematic literature review in papers by Snyder and Merson (1982), Bern et al (1992), and Kosek et al (2003). These reviews have selected primary research publications according to strict inclusion criteria to estimate the true incidence of diarrhoeal morbidity in children. Papers were only included if they were prospective, longitudinal studies, conducted in relatively stable populations over at least 12 months, with morbidity surveillance at a maximum of fortnightly intervals. The reviews focused on children under 5 years old living in low and middle income countries. This population bears the majority of the burden of diarrhoeal disease. Overall, 21% (16-32) of infant mortality is due to diarrhoeal disease, with differences between countries (Figure 6).

Figure 6. The proportion of infant mortality due to diarrhoeal disease, by country, based on data from Kosek et al. 2003.



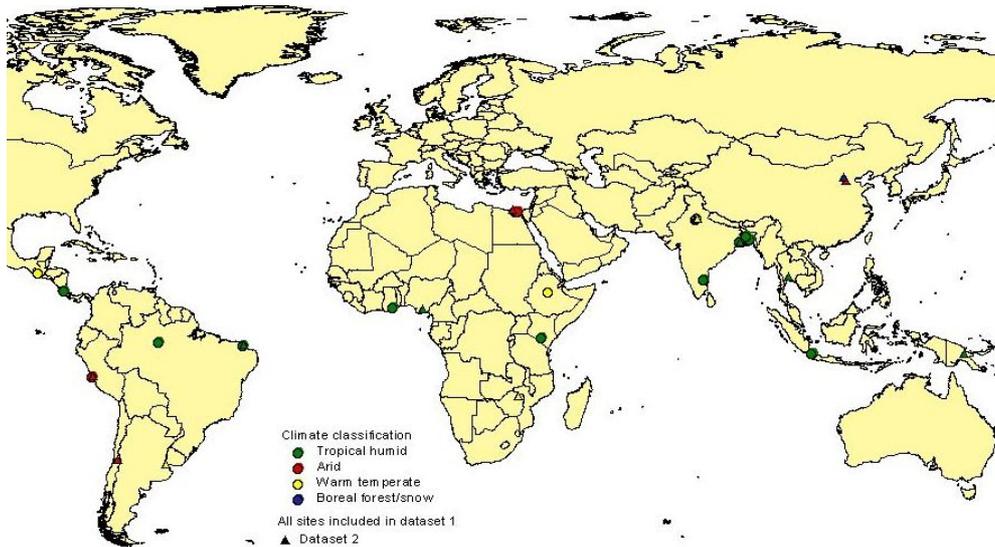
All the morbidity papers included in the above reviews were obtained as our health effect data. We excluded those that took place within an area of more than 100km²; those not specifying the time-period of the study; and those not providing morbidity rates in age-aggregates useful for our analysis. All the remaining studies were included. Study sites were categorised as rural, urban or slum settings, based on the description in the original paper. On-line gazetteers [Falling Rain Genomic Inc] were used to geo-reference the study sites and link the health outcome to environmental and socio-economic variables.

The three reviews included 62 morbidity studies. Of these, two were unavailable, 13 specified no useful rates, and in 10 papers, the location or time period of the study was insufficiently specified. We included the remaining 37 studies. We call the complete “dataset 1”. Because data on sanitation access and local income was not available until 1985 (see below), we separately analysed the 15 studies conducted since 1985, which we called dataset 2. Figure 7 shows the global distribution of these studies, and a summary of the datasets is given in Table 7.

Table 7. Morbidity studies included in the dataset, indicating region and year commenced, showing diarrhoea rates, climate parameter, setting, GDP or GCP, and water and sanitation coverage. Brackets indicate range.

	Global	AFRO	AMRO	EMRO	SEARO	WPRO
Dataset 1						
Studies	37	4	14	3	12	4
Commenced:						
1950s	3	-	2	1	-	-
1960s	6	-	2	-	4	-
1970s	6	-	3	-	3	-
1980s	20	4	7	1	4	4
1990s	2	-	-	1	1	-
Median diarrhoea rate ¹ :						
0-5 months	2.7 (0.7-9.4)	2.7 (1.8-2.7)	3.5 (0.7-9.4)	6.3 (5.3-7.3)	2.2 (0.9-4.9)	2.7
6-11 months	4.0 (0.6-14.1)	4.8 (3.3-5.0)	6.0 (0.8-14.1)	7.4 (5.9-8.8)	3.1 (0.6-7.3)	3.6 (1.8-5.4)
1 year	3.0 (0.3-15.1)	3.7 (2.4-5.0)	3.0 (0.6-15.1)	4.3 (3.0-4.5)	2.8 (0.3-6.0)	3.8 (1.8-5.0)
2 years	2.1 (0.1-12.2)	2.7 (1.6-3.8)	1.7 (1.0-12.2)	2.8 (2.6-3.0)	1.8 (0.1-5.5)	2.3 (1.7-2.8)
3 years	1.2 (0.1-8.7)	1.9 (0.7-3.0)	1.3 (1.0-8.7)	2.6	0.9 (0.1-1.7)	1.6 (1.5-1.6)
4 year	1.0 (0.3-7.2)	1.7 (0.6-2.8)	1.0 (0.3-7.2)	1.7	0.6 (0.4-1.6)	1.5 (1.2-1.7)
Median rainfall (mm/month)	90 (0-331)	66 (58-101)	122 (0-331)	3 (2-6)	141(56-305)	102 (37-204)
Median temperature (°C)	25 (7-28)	26 (21-27)	24 (13-27)	21 (20-21)	26 (24-28)	17 (7-25)
Overall climate:						
Temperate	8	1	4	-	3	-
Arid	8	-	3	3	1	1
Tropical	20	3	7	-	8	2
Boreal forest	1	-	-	-	-	1
Setting:						
rural	18	2	7	3	4	2
urban	12	1	4	-	6	1
slum	6	1	3	-	2	-
mixed	1	-	-	-	-	1
Median GDP/capita (2000 US\$)	564 (185-6546)	322 (189-599)	2132 (391-6545)	949 (548-1335)	241 (185-1263)	476 (326-2328)
Dataset 2²						
Studies	15	2	4	1	5	3
GCP (Millions of 1995 US\$)	5348 (171-27127)	2844 (367-2844)	1052 (367-27127)	3547	9647 (3194-12155)	7969 (171-8662)
Median water coverage (%)	70 (36-97)	52 (36-68)	72 (36-97)	95	71 (70-86)	60 (58-60)
Median sanitation coverage (%)	32 (8-95)	37 (32-42)	62 (11-92)	50	13 (8-95)	10 (8-54)
¹ Rate as episodes/child-year.						
² Diarrhoea rate, rainfall, temperature are not shown for short-term dataset. Median values and distributions were similar to those in the long-term dataset; rainfall 68mm/month (range 2-220), temperature 21°C (range 7-28).						

Figure 7. . Geographic distribution of study sites with Köppen-Geiger climate classification. All sites are included in dataset 1, and those indicated by triangles comprise dataset 2.



Environmental and socio-economic data

Climate data were obtained from the Integrated Database Information System (IDIS), which draws on the 0.5 x 0.5° resolution CRU TS 2.1 dataset³². We used a GIS to link the study sites to grid-cells and extracted the monthly time-series for rainfall and temperature for each month over which the study was conducted. We then averaged the monthly figures to obtain the mean temperature and monthly rainfall during the study period. Sites were also categorised as tropical-humid, arid, warm temperate, or boreal forest and snow, based on the revised Köppen-Geiger climate classification.

In dataset 1, we included data on Gross Domestic Product (GDP)/capita. This was available at the national level from the World Bank Development Indicators database, and the average annual GDP/capita for a study period was calculated. A recently developed measure known as Gross Cell Product (GCP)³³ was used as a proxy for local socio-economic conditions for dataset 2. This is an area-based equivalent of GDP and reflects the geographic intensity of economic activity at a resolution of 1°x1°; approximately 100km². GCP has been calculated for 1990, and we believed that this would provide a reasonable indication of socio-economic conditions for sites in dataset 2, which were conducted between 1985 and 2000.

Water and sanitation coverage data is compiled by the WHO/UNICEF Joint Monitoring Programme (JMP), and is available at the national level, split by rural and urban settings. Since the mid-1980s, the quality of this data has been significantly improved. Despite the lack of local level data, we considered the influence of water and sanitation to be of particular interest and included it in dataset 2. We obtained the national coverage figures applicable to each study site from the JMP website, using the rural or urban estimates as appropriate. No estimates were available for slum settings, however, only two studies in dataset 2 were in “slums”, and these were excluded from the main analysis for reasons outlined ahead.

Statistical methods

We used linear regression to quantify the relationship between the logarithm of diarrhoea rate and the weather variables in both datasets. Variables were added to the models sequentially, beginning with age and socioeconomic conditions

(as GDP/capita or GCP), followed by average rainfall and temperature, and finally, the setting and water and sanitation coverage (for dataset 2 only). Following this, we assessed influence of climate type (as Köppen classification)³⁴ using the same analysis excluding the weather variables. To make the regression coefficients more easily interpretable, we exponentiated them, so that they represent the incremental prevalence rate ratio per unit increase in the explanatory variable. The regression analysis relied on age-specific rates, with multiple rates frequently abstracted for the same study. This left the analysis prone to within-study clustering, and to allow for this we used a mixed model with random study effects.

While all studies included in the dataset were conducted over a period of at least one year, many were not carried out over whole-year periods. As a result, the estimated diarrhoea rates may have been inflated or deflated, depending on the seasonal pattern during the partial year period. We carried out a sensitivity analysis which excluded non-whole year studies to account for this.

Key findings

Overall, we found that the incidence of diarrhoeal disease is higher in areas of low rainfall.

Regression analysis of dataset 1. Using dataset 1, we ran the regression models both including and excluding the outlier identified in the scatter-plots. There was little evidence for association of either GDP or temperature with diarrhoea prevalence. Rainfall, however, was negatively associated with diarrhoea rates, with the final model suggesting that an increase in average rainfall of 10mm/month is associated with a 4% decrease in diarrhoea incidence (95% CI 1-7%, p=0.02). When rainfall was included in this model as a three-level group variable, we found prevalence ratios (relative to 1 at <50 mm/month) of 0.55 (95% CI 0.27-1.13, p=0.1) at 50-149mm/month and 0.39(95% CI 0.18-0.83, p=0.02) at >=150mm/month.

When we excluded the outlier study, the apparent relationship remained the same, however the strength of the evidence increased (p=0.004). We found no strong evidence to suggest an influence due to being in a rural, urban or slum setting, although low power was reflected in wide confidence intervals for these comparisons. The sensitivity analysis, which excluded 17 non-whole year studies (out of 37 studies), found the same point estimate of 4% for the effect of rainfall as in the final model (95% CI 0-7%, p=0.02).

Table 8: Regression coefficients (with 95% CI) for the association between diarrhoea morbidity rates and each variable, using dataset 1.

Variable	Model 1	Model 2	Model 3	Model 4
GDP ¹	1.00 (1.00-1.00)	1.00 (1.00-1.00)	1.00 (1.00-1.00)	1.00 (1.00-1.00)
Rainfall ¹		0.97 (0.94-0.1.00)	0.97 (0.94-1.00)	0.96 (0.93-0.99)
Temperature ¹			1.02 (0.97-1.07)	1.03 (0.97-1.09)
Setting ¹ :				
Rural				1
Urban				0.73 (0.42-1.29)
Slum				1.01 (0.45-2.28)
Mixed				1.63 (0.38-6.93)
¹ All models are adjusted for age group. Coefficients indicate the change in diarrhoea rate (episodes per child-year) for each: 10USD (in 2000 USDs) increase in GDP/capita; 10mm/month increase in average monthly rainfall; and, 1°C increase in average temperature.				

Regression analysis of dataset 2. For dataset 2, initial scatter-plots revealed two studies with very high GCP compared to the others. Both these studies were carried out in slums in Brazil (one being the outlier in dataset 1), but had the highest GCPs in the dataset (\$27 000). As the nearest GCP to this was \$15 000, and the median was just \$5348, we carried out an analysis including and excluding these studies.

The analysis including the outliers provided little evidence of an association between diarrhoea prevalence the weather parameters, GCP, or water and sanitation coverage. The estimate for the effect of rainfall was a 3% reduction for each 10mm/month increase in rainfall (95% CI -3% - 11%, p=0.3).

Table 9 shows the results when the outliers were excluded. Again, our analysis found little evidence for association between diarrhoea morbidity and GCP, temperature, or water and sanitation coverage. As in the data-set 1, there was an apparent negative association between rainfall and diarrhoea morbidity. The final model suggested a 7% fall in diarrhoea rates for each 10mm/month increase in average rainfall; however, the 95% CI ranged from a 15% decrease to a 2% increase (p=0.13). Owing to the small size of this dataset, a sensitivity analysis was not attempted.

Table 9: Regression coefficients (with 95% CI) for the association between diarrhoea morbidity rates and each variable, using dataset 2

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
GCP ¹	0.98 (0.91-1.06)	0.97 (0.90-.06)	0.96 (0.88-1.05)	0.95 (0.88-1.03)	0.95 (0.81-1.13)
Rainfall ¹		0.96 (0.89-1.02)	0.93 (0.85-1.02)	0.93 (0.86-1.01)	0.93 (0.85-1.02)
Temperature ¹			1.04 (0.96-1.11)	1.04 (0.97-1.10)	1.04 (0.96-1.12)
Water				0.91 (0.77-1.08)	0.91 (0.69-1.20)
Sanitation ¹					1.00 (0.77-1.30)

¹All models are adjusted for age group. Coefficients indicate the change in diarrhoea rate (episodes per child-year) for each: 1000millionUSD (in 1995 USDs) increase in GCP; 10mm/month increase in average monthly rainfall; 1°C increase in average temperature; and, 10% increase in water or sanitation coverage.

Climate type and diarrhoea. Arid regions had the highest diarrhoea rates after adjustment . The regression coefficients for Köppen-Geiger classification as predictors of diarrhoea morbidity are shown on [Table x](#). These are controlled for age, GDP and setting, and excluding the outlier study.

Table 10: Regression coefficients for the association between diarrhoea morbidity and climate type, excluding outlier study.

Climate ¹	n	Regression coefficient ² (95% CI)	p
Temperate	8	1	
Arid	8	1.69 (0.87-3.27)	0.12
Tropical	20	0.92 (0.50-1.69)	0.79
Boreal forest/snow	1	0.71 (0.16-3.07)	0.64

¹Köppen-Geiger classification
²Controlled for age group, GDP and setting

Limitations of the study

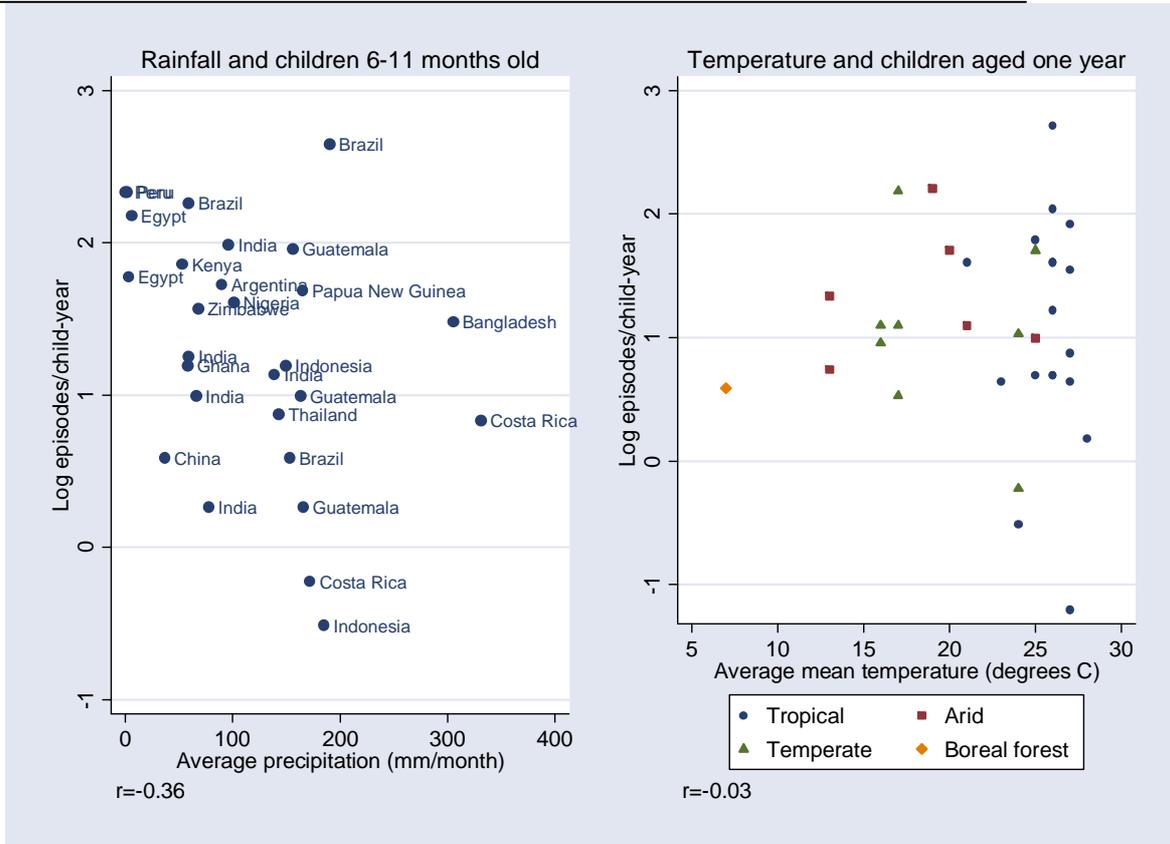
Our analysis suggests that low rainfall is a determinant of childhood diarrhoeal disease in low and middle income countries. Few other studies have examined this association at the global level, but our findings are consistent with the study of Singh et al. (2001) in the Pacific Islands. The plausible mechanism for this association would be the linkage between rainfall and surface water availability. Precipitation is a major determinant of stream flow and ground water recharge, with low levels potentially leading to water scarcity. This may in turn lead people to use less protected water sources, and reduce hygiene behaviour, resulting in increased diarrhoea incidence.

We found no association between average temperature in a location and diarrhoea morbidity. This is not inconsistent with the findings of the time series studies (see previous chapter) as these associations are operating at different spatial and temporal scales. Further, our analysis considered a broad range of sites, possibly with quite different pathogen profiles, and this may explain the lack of linear association between diarrhoea and temperature. However, all diarrhoea rates were from developing regions and bacteria and protozoa tend to dominate in these areas. Uncontrolled biases might have obscured an association. In this study, we used the most valid all-cause diarrhoea morbidity rates that were available. However, ascertaining a case of diarrhoea is not rigorously objective, and the authors of the global burden of diarrhoeal disease reviews each noted that studies employed a number of case definitions, and that, to a degree, rates tended to increase with frequency of ascertainment and decrease with study size³¹. However, as it is unlikely that the resulting variations in estimates were associated with either rainfall or temperature, bias due to this limitation seems unlikely.

We found little evidence for association between the indicators of socio-economic development (GDP and GCP) and diarrhoea rates. As the geographical areas covered by studies included in this analysis were much smaller than countries, variables based on national estimates are of limited value. To partially overcome this, we used a measure with finer geographical resolution (GCP) in dataset 2. GCP and GDP/capita were poorly correlated ($r=0.14$), confirming that they measure different things. However, although GCP measures income in a much smaller area than a country, these areas are still large (around 100km²), within which a variety of socio-economic conditions may be seen. The inclusion of areas of poverty surrounded by wealth may have obscured an association of GCP with diarrhoea rates in our study, although, despite the elimination of two studies that were likely to suffer from such misclassification, an association was still not evident.

The evident limitations of the available measures of economic deprivation and access to sanitation could have biased the association between rainfall and diarrhoea, by residual confounding. Nevertheless, as with misclassification in ascertainment of diarrhoea discussed above, there seems no particular reason suspect that these variables (or other unmeasured risk factors) would be associated with rainfall, so substantial bias does not seem likely.

Figure 8. Scatter-plots of age-specific log diarrhoea morbidity rates and average temperature and monthly rainfall.



A: Average monthly rainfall and log diarrhoea incidence in children aged 6-11 months, showing country.

B: Average temperature and log diarrhoea incidence in children aged 1 year, showing climate classification.

Temperature-related cardio-respiratory mortality

Models that estimate the annual temperature attributable mortality have been generated based on observed short term associations between temperature and mortality. Temperature-mortality relationships are locally specific, and show significant heterogeneity³⁵.

A review was undertaken to identify studies that quantified the relationship between temperature and cardio-respiratory mortality. The criteria used to select studies for deriving the modelled estimates were:

- Study uses daily time series methods to quantify the relationship between daily mean temperature and mortality.
- Study reports a coefficient from log linear regression that estimates the % changes in mortality per degree Centigrade changes in temperature above and below reported threshold temperature.

The best-characterised temperature-mortality relationships are those for total mortality in temperate countries. Fewer studies have also looked at the particular causes of death for which physiological evidence is strongest: cardiovascular disease, respiratory disease.

New daily temperature distributions were estimated for each climate scenario, by shifting the currently observed temperature distributions by the projected change in mean temperatures for each month, and of the variability of daily temperatures as well as changes in the mean. An exposure-response relationship and Tcutoff was applied within each climate zone for cause and age-specific mortality. The number of days above ("hot days") and below ("cold days") this temperature were calculated for baseline climate and the range of climate scenarios.

The proportion of temperature-attributable deaths were calculated using the heat and cold mortality coefficients described in Table 11. Climate change attributable deaths were calculated as the change in proportion of temperature-attributable deaths (i.e. heat-attributable deaths plus cold-attributable deaths) for each climate scenario compared to the baseline climate and each climate zone. The proportional changes in temperature-attributable deaths were therefore calculated by taking the average of the changes in each climate zone represented in the region, weighted by the proportion of the region's population living within that climate zone.

Table 11 Summary of temperature mortality relationships in the literature.[to be updated]

Population/ climate zone	Age	Cause of death	% change per decrease 1° C	Cut point (° C)	Lag	% change per increase 1 ° C	Cut point (° C)	Lag
			COLD			HEAT		
The Netherlands	All	All cause	0.41	16.5	7-15	1.23	16.5	1-2
The Netherlands	All	CVD	0.46	16.5	7-15	1.13	16.5	1-2
The Netherlands	All	Resp	1.43	16.5	7-15	3.11	16.5	1-2
High-latitude		CVD	0.5			1.1		
High-latitude		RESP	1.4			3.1		
Madrid, Spain	All	All	1.7	20	7	0.97	20	0-1
Valencia, Spain	all	All	3.2 (1.8-4.6)	15	7-14	3.6 (1.2-6.0)	24	1-2
Valencia, Spain	>70	All	3.7 (2.1-5.4)	15	7-14	5.0 (2.1-8.0)	24	1-2
Valencia, Spain	all	Cvd	4.3 (2.1-6.4)	15	7-14	2.3 (-1.5-4.5)	24	1-2
Valencia, Spain	all	Cvd	1.5 (-0.3-3.3)	15	3-6	2.9 (-0.4-7.4)	24	3-6
Valencia, Spain	all	Resp	1.7 (-0.4-6.0)	15	7-14	5.7 (-2.9-8.2)	24	1-2
Ljubljana	All	All	0.77 (-0.16- 1.70)	7	0-13	2.25 (1.09-3.42)	17	0-2
Sofia	All	All	2.69 (0.88-4.54)	-2	0-13	1.93 (1.41-2.45)	17	0-2
Santiago	All	All	5.21 (3.55-6.89)	11	0-13	0.92 (0.44-1.31)	16	0-2
Cape Town	All	All	3.32 (2.89- 3.75)	19	0-13	1.02 (-0.32- 2.38)	21	0-2
TEMPERATE		CVD	2.9			2.6		
TEMPERATE		RESP	1.7			5.7		
Monterrey	All	All cause	5.54 (4.52-6.58)	17	0-13	19.85 (14.69-25.25)	31	0-2
Mexico City	All	All cause	8.60 (7.86-9.34)	15	0-13	0.6 (0.21-1.00)	18	0-2
Bangkok	All	All cause	4.13 (1.71-6.61)	28	0-13	7.66 (5.87-9.47)	30	0-2
Salvador	All	All cause	-13.5 (-32.35-10.9)	23	0-13	1.59 (0.86-2.32)	23	0-2
São Paulo	All	All cause	3.92 (3.43-4.40)	19	0-13	2.28 (2.11-3.66)	23	0-2
São Paulo	65+	All cause	5.5	20	0-21	2.5 (2.1-2.8)	20	0-1
WARM HUMID		All cause	5.5			5.7		
Delhi	All	All cause	1.36 (0.56-2.16)	19	0-13	3.03 (2.48-3.58)	28	0-2
HOT DRY		All cause	1.4			3.0		

Notes: % change =(RR-1)*100

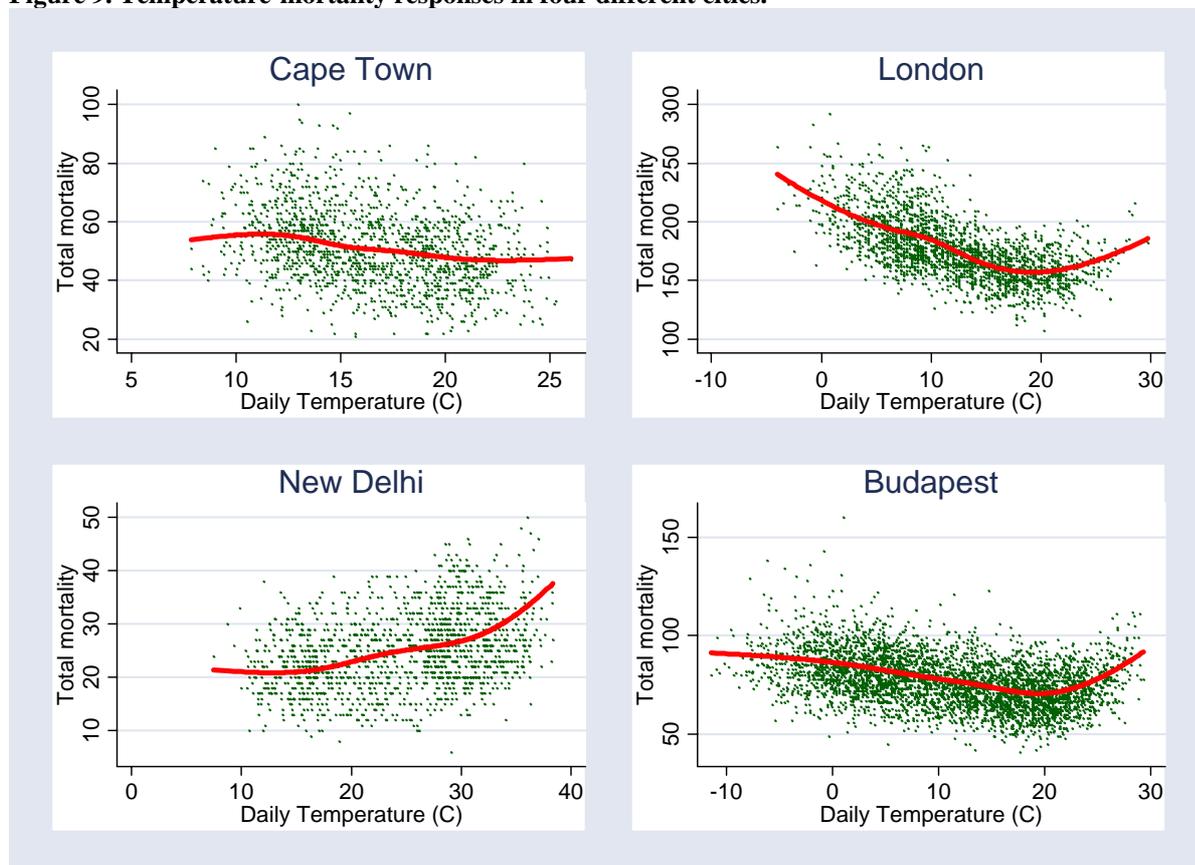
Adaptation and acclimatization

Acclimatisation includes autonomous adaptation in the individual (physiological adaptation, changes in behaviour) and autonomous and planned population-level adaptations (public health interventions and changes in built environment). Acclimatisation would reduce potential increases in heat-related mortality due to climate change. Our estimates incorporate an assumption regarding acclimatisation of the populations to the changing climate that describes this reduced impact. We assume that the threshold temperature (T_{cutoff}) is increased as populations adapt to a new climate regime, reflecting physiological and behavioural acclimatisation which can take place over the timescales of decades. Changes in T_{cutoff} are region and scenario specific, as they reflect the rate of warming experienced. Therefore, they are assumed to be proportional to the projected change in average summer temperature (mean of the 3 hottest months) from the climate scenario. A second assumption, regarding the temperature-mortality relationship, will be tested in a sensitivity analysis. There is now good evidence that populations are becoming less sensitive to both heat and cold over time³⁶⁻³⁸.

In regions with predominantly temperate and cold climates, reductions in cold-related mortality are likely to be greater than increases in heat-related mortality. Therefore, all climate scenarios show a net benefit on mortality in these regions, consistent with previous assessments.

The principal uncertainty in these estimates surround the degree to which populations will adapt to changing temperatures, both in terms of reducing the additional mortality attributable to heat, and the possible benefits of avoiding cold deaths. The mid-range estimate is given by applying the model described above (i.e. making an adjustment for biological adaptation). As the effects appear to be broadly positive, the lowest health impacts are given under the assumption of no adaptation (i.e. that populations remain equally susceptible to variations from their current optimum temperatures). The high estimates are generated under the assumption of complete adaptation (i.e. no change in the balance of positive or negative changes in mortality associated with increasing temperatures).

Figure 9. Temperature-mortality responses in four different cities.



Direct effects on productivity

“Too hot” working environments are not just a question of comfort, but a concern for health protection and the ability to perform work tasks. Many workers are exposed to unacceptably high temperatures and humidity in work situations that cannot be modified, particularly in low and middle income countries, and heat strain and heat stroke are important issues not only for health but also for labour productivity. The direct effect on humans of higher annual temperatures and higher number of very hot days is likely to be the “slowing down” of work and other daily activities³⁹. Whether it occurs through “self-pacing” or occupational health management interventions, the end result is lower economic productivity⁴⁰.

Reduced work capacity in relation to heat is an effect of humidity, radiant heat and ambient temperature. It occurs above 35°C^{41,41}, even in arid climates⁴². It occurs in indoor office environments⁴³ and factories⁴⁴. The economic cost of existing ergonomically suboptimal working environments in the US has been estimated at many billion dollars⁴⁵. An estimate of the impact of climate change on these types of costs has not yet been made and occupational health risk have been largely ignored in climate impact assessments.

A range of ergonomic studies have quantified the effect of temperatures on productivity in both office and industrial settings. An international standard (ISO, 1989) aims at protecting workers from heat stroke by keeping body temperature below 38 degrees C. For unacclimatised persons faced with a very energy demanding work task, the need to reduce heat stress starts at temperatures above 22.5°C; for acclimatized persons, this reduction starts at 26°C (measured as the wet bulb globe temperature, WBGT)^{46,47}. The ISO standard recommends reducing heat stress by shifting the balance between work time and resting time during each hour. We define “work ability” as the percentage of an hour that a worker can be engaged working. The work ability as estimated from these standards is rapidly reduced within a 10-20 degree range above the starting points as mentioned above.

We have developed a method for estimating the extent to which climate change may affect labour productivity due to increased ambient temperatures and or humidity, and to estimate that effect for future climate scenarios. We focus on the impacts on the majority of the world’s population who live in tropical countries.

Methods

We have developed a scenario-based approach to estimating the impact of changes in temperature and humidity on worker productivity at the regional level. The climate-productivity model is based on the application of established physiological associations between productivity and a bioclimatological index. The WBGT is used widely as an indicator of heat stress, and its use is recommended in the International Standard, ISO 7243, used in Occupational Health and Safety guidelines for working in hot environments⁴⁷. The WBGT is measured by a three-temperature element formula –

$$\text{Equation: } \text{WBGT} = 0.7 \times \text{Tnwb} + 0.2 \times \text{Tg} + 0.1 \times \text{Ta}$$

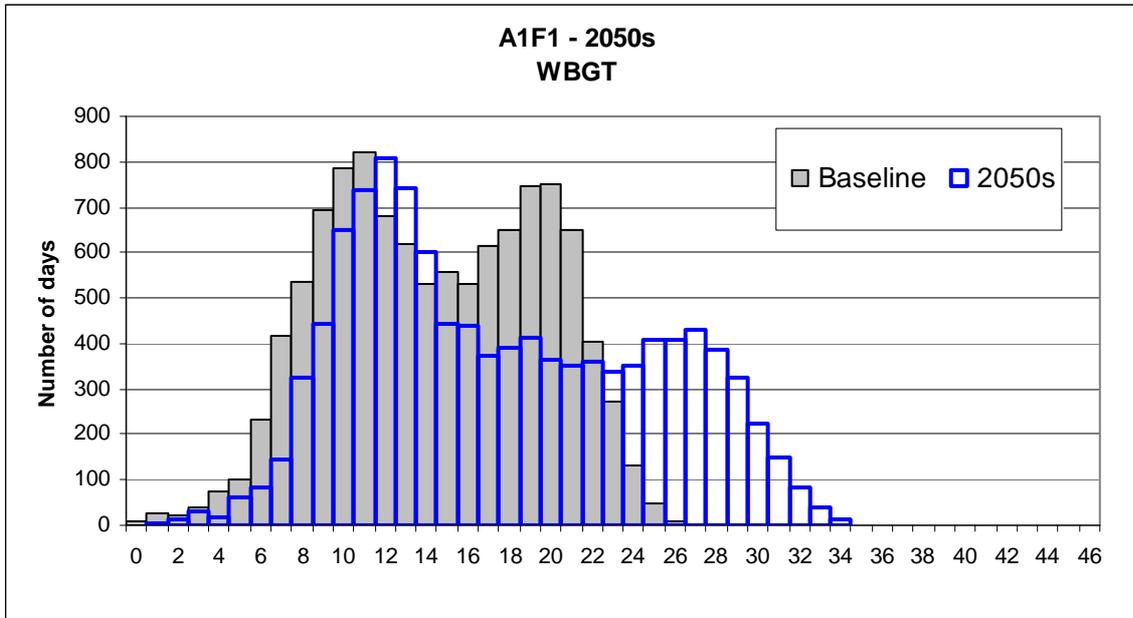
Where Tnwb is the “natural wet bulb temperature” measured with a thermometer where the sensor is covered in a wet wick. Tg is temperature measured by a *black globe thermometer*, and represents the integrated effects of radiation and wind. As the formula shows, WBGT is dominated by Tnwb and Ta. The former can be calculated from air temperature (Ta) and the relative humidity (rh). Wind and radiation, and Tg, will be assumed to remain constant over time in our calculations in the absence of meaningful projections.

We quantified the association between “work ability” and WBGT for four work intensities: office desk work and service industries (200 W); average manufacturing industry work (300 W); construction or agricultural work (400 W) and; very heavy labouring work (500 W). These relationships are derived from physiological calculations of the need for a certain amount of resting time during every working hour in order to avoid body temperature increasing over 38 °C⁴⁷.

Using daily temperature and humidity output from the climate scenarios, daily WBGT was calculated using the equation above for the current climate (years 1961-1990) and three future 30-year time periods centred on the 2020s (2010-2039) , 2050s (2040-2069) and 2080s (2070-2099). The climate change “attributable” affect is the difference between labour productivity (in terms of lost labour days) under the baseline climate and under the climate scenarios.

The daily WBGT time series was summarised to give total number of days at different WBGT values within each future time slice period. Figure 10 illustrates the change in distribution of WBGT under the current climate and future climates for one grid cell. This was summarised at a regional level based on the relative population share of each climate zone and the proportion of the working population in each sector. We then calculated the number of days with reduced work efficiency for each 30 year period and averaged this [decadal] annual estimate.

Figure 10. Distribution of WBGT under current and future climate for a specified grid cell (approximately over France).



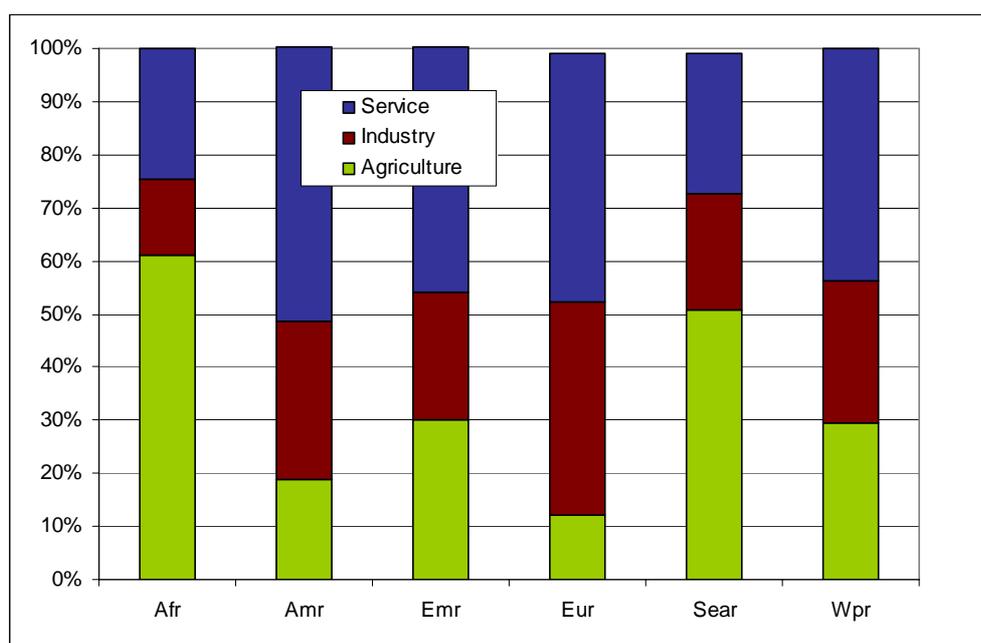
Estimating total labour productivity

The relationship in our model are theoretical and potential and do not reflect actual labour productivity losses as there will be some adaptation measures in place, such as the space cooling of offices and factories. It is not possible to validate the labour productivity loss for the current climate. However, adaptation measures will vary by country, with high income countries having high rates of adaptation. Countries will vary in their willingness or capacity to adapted to the projected climate change. The climate model grid cell output does not represent the observed temperature and humidity exposures for a given location. We therefore only report the change in the labour productivity under climate warming.

We divided the working population of each region into three sectors (service, industry and agriculture) using World Bank data for period 1990-92 (World Bank 2005). More recent data were available but were too incomplete. The final regional estimate is therefore a weighted average based on the distribution of work activities across the three sectors: service, industry and agriculture.

We assumed that changes in labour patterns occur in the future. By 2080s, all regions converge to European 1992 proportions, except Africa, which converges to Western Pacific 1992 proportion. Also estimate using current proportions as a sensitivity analysis.

Figure 11. Summary of working population by sector for 1992, by WHO world region.



Key findings

Table 12 shows the *decreases* in productivity for each region, for the A2 and B2 scenarios, compared to the baseline climate.

		Baseline	2020	2050	2080	Baseline	2020	2050	2080
		A2				B2			
		Baseline	2020	2050	2080	Baseline	2020	2050	2080
AMR	% days lost	8.5%	12.9%	18.1%	25.3%	8.0%	12.1%	15.5%	20.1%
	% decrease		4.3%	9.6%	16.8%		4.1%	7.5%	12.1%
AFR	% days lost	26.6%	33.8%	41.0%	47.4%	26.5%	34.1%	37.7%	42.3%
	% decrease		7.2%	14.4%	20.9%		7.6%	11.2%	15.9%
EMR	% days lost	3.8%	4.7%	6.0%	7.7%	3.9%	5.1%	6.1%	7.1%
	% decrease		0.9%	2.2%	3.9%		1.2%	2.1%	3.1%
EUR	% days lost	0.1%	0.5%	1.3%	3.1%	0.1%	0.7%	1.2%	2.0%
	% decrease		0.4%	1.2%	3.0%		0.6%	1.1%	1.8%
SEAR	% days lost	26.4%	31.4%	37.0%	43.0%	26.4%	31.1%	34.5%	37.1%
	% decrease		5.0%	10.6%	16.6%		4.7%	8.1%	10.7%
WPR	% days lost	9.9%	12.7%	16.7%	22.3%	9.9%	14.7%	17.5%	19.9%
	% decrease		2.9%	6.8%	12.5%		4.8%	7.6%	10.1%

Climate change is associated with shift in the distribution of daily temperatures to include more hot days, and more days with WBGT exceeding the threshold for heat tolerance in individuals. Some regions are more affected than others, with Africa and South East Asia – those that also have the highest baseline loss of worker productivity.. The effects of climate change are least in the European and Eastern Mediterranean Regions. These patterns reflect both the current climate and patterns of future climate change.

The estimates are independent of population growth and population ageing, but are not particularly sensitive to the proportion of workers in manual activities. As the proportion of workers in agriculture declines with economic development, the effect on labour productivity is only moderately reduced.

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