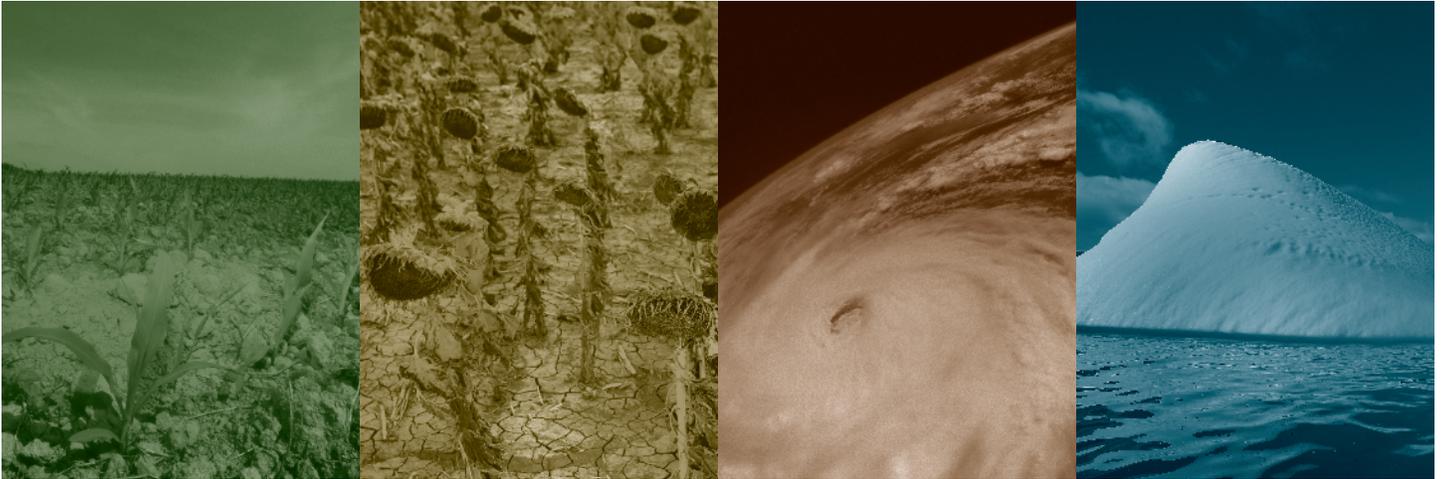# Projecting Climate-Related Disease Burden:

A Guide for Health Departments

Climate and Health Technical Report Series

Climate and Health Program,
Centers for Disease Control and Prevention

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*The findings and conclusions in this report are those of the authors and
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Projecting Climate-Related Disease Burden

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Executive Summary

Climate change is expected to adversely affect public health through multiple pathways.[1] Assessing the projected health burden is an important step for public health agencies to prepare for these impacts. This can be done qualitatively or quantitatively, but quantitative projections may provide more useful information about likely impacts.

Many health departments are not particularly familiar with scenario-based, quantitative disease projections.[2] To facilitate this process, the Climate and Health Program (CHP) at the Centers for Disease Control and Prevention (CDC) developed the Building Resilience Against Climate Effects (BRACE) framework.[3] As part of BRACE, health agencies are encouraged to produce estimates of the future burden of disease for climate-related health outcomes. These estimates can then be used to rank the health outcomes, prioritize preventive actions, and design health adaptation plans.

This guide presents a starting point for health departments interested in developing climate change health impact projections and lays out a general map of the process of establishing exposure-response relationships and developing scenario-based projections. The specifics of the process used to project future disease burden will vary greatly depending on local climate impacts, underlying vulnerabilities, the disease of interest, and other factors. While there is no "gold standard" for projecting the health impacts of climate change, our goal is to provide a digestible but thorough overview that will orient those interested in projecting climate change disease burden to facilitate public health preparedness for the challenges ahead.

The iterative use of models in an adaptive management approach is an important part of this process. Agencies can revisit steps to update their assessment of future health projections as the scientific evidence-base grows about climate impacts mediated through complex human-environment systems affecting public health, and relevant datasets become available to model pathways.

To illustrate the process, two examples—one on heat-related disease and one on waterborne disease—are used to demonstrate the steps in the process, highlight specific issues that might be encountered, and outline potential solutions.

Projecting Climate-Related Disease Burden

Introduction

Weather and climate have a wide range of impacts on human health. Climate change, which is expected to shift weather patterns and modify weather extremes, will likely influence public health via multiple pathways, with adverse impacts predominating.[1] Some health impacts are already apparent.[4]

Public health agencies can take a host of steps to minimize and prepare for associated risks.[5] One important step is assessment of key public health vulnerabilities.[6] Another important and related step entails projecting the disease burden that climate change may cause.[3] Such climate change disease burden projections can be considered a form of comparative risk assessment as advanced by the World Health Organization.[7] One significant difference between climate change disease burden projections and other Health Impact Assessment (HIA) efforts is that the exposures being projected are weather variables generated by global climate models. These variables are then linked with functions that describe observed relationships between environmental exposures and disease outcomes to quantify human health impacts.[8]

Climate change disease burden projections are similar to other scenario-based modeling efforts used in public health. Examples include projections of the cholera outbreak trajectory in Haiti,[9] the Ebola epidemic in West Africa,[10] and long-term projections of public health resource needs.[11] While methodological specifics vary, all are *decision support tools* that can help clarify how disease dynamics may shift in the future, highlight the consequences of particular management choices, and determine what resources are needed to achieve disease prevention and control goals.

Climate change disease burden projections also have potential for iterative use in an adaptive management process that will allow practitioners to continuously update their models with new information as the climate shifts and stakeholder needs evolve.[12-14]

Because climate change disease burden projections are so central to public health preparedness for climate change, the Climate and Health Program (CHP) at the Centers for Disease Control and Prevention (CDC) has strongly encouraged its state and local public health department partners to use them in their adaptation planning efforts. In particular, the CHP has made climate change disease burden projections a central component of its Building Resilience Against Climate Effects (BRACE) framework,[3] depicted in Figure 1. This report provides specific guidance related to BRACE Step 2, the projection of climate change health impacts.

Reader's Note

This report is designed to be read both as a standalone document and online. As such, it has multiple internal links to definitions in the glossary, figures, and other parts of the report; it also has external links to outside resources. Important concepts are emphasized with *italics*.

The BRACE framework is diagrammed below in Figure 1. The first step of BRACE outlines how agencies can incorporate projections of climate impacts (e.g., changes in temperature and precipitation) in their jurisdictions, identify relevant environmental hazards and associated health effects, and conduct a vulnerability assessment to identify places and communities at risk from those health outcomes. The second step builds on the first in terms of estimating the future burden of the identified health risks.
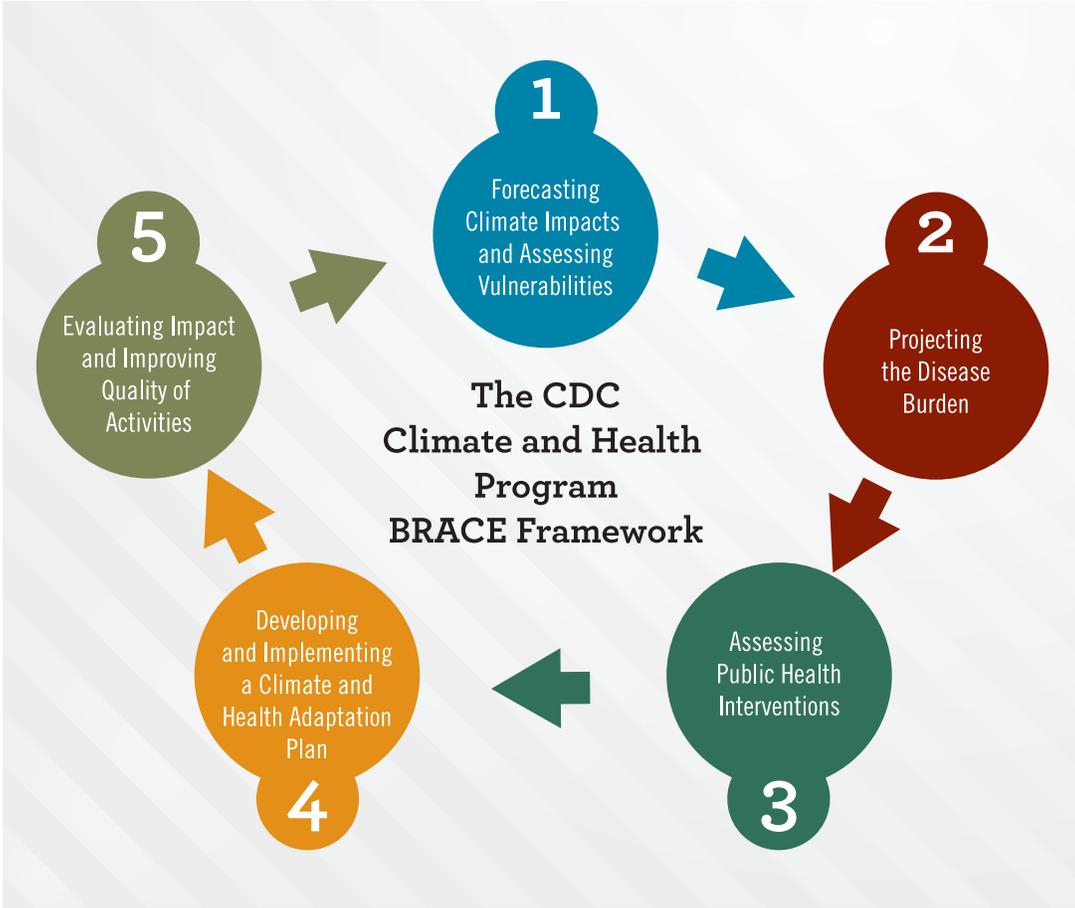
Figure 1. Steps in the BRACE (Building Resilience Against Climate Effects) framework.

This guidance document elaborates on the second step of BRACE by providing details of the different tasks involved and practical examples highlighting applications relevant to that process.

The second step of BRACE includes this sequence of activities:

1. *Develop a causal pathway* linking exposures/environmental hazards to health outcome(s). While not all steps in the pathway will be explicitly modeled, it is important to have an in-depth understanding of etiologic processes and important influences.

2. *Use ensemble projections from global climate models* to identify how the exposure/environmental hazard may change in intensity and duration in the future.

3. *Establish the baseline disease burden* of the health outcome in the population of concern.

4. *Assess the exposure-outcome association* that denotes how an increase in the exposure affects the health outcome. Since the exposure-outcome associations may vary across different places, using locally available data to derive quantitative estimates may be beneficial. However, lack of local data and inadequate scientific information may lead to reliance on qualitative assessment or use of estimates available in the literature.

5. *Project the health burden in a changed climate* using a mathematical model to combine these different estimates. Conjectures regarding how future adaptation efforts can reduce the adverse health impacts may be included in deriving these estimates.

6. *Evaluate the uncertainty* inherent in the derivation of these different estimates.

This report is divided into three parts: the first section goes through each of the components of BRACE Step 2, providing a general conceptual overview with some technical information. The second section is a short discussion of the iterative use of modeling efforts in ongoing adaptation planning. The third section provides two examples of how BRACE Step 2 can be performed to project specific health impacts.

Conceptual Overview

There are several steps involved in generating climate change disease burden projections. The process can be qualitative or quantitative, but typically more useful information and insight are gained from quantitative projections. A general diagram of the steps involved is in Figure 2; we will return to versions of this diagram throughout the report to help orient readers.
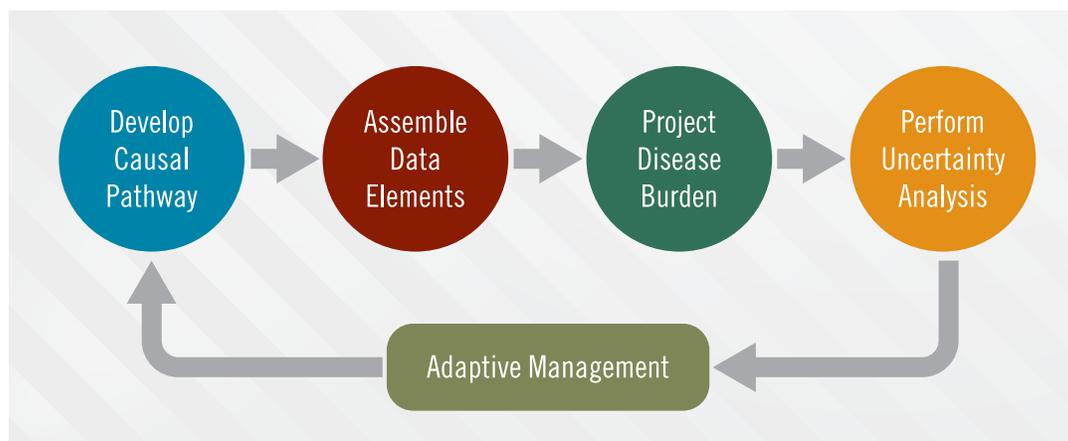
Figure 2. The generic steps involved in generating climate change disease burden projections.

Develop Causal Pathway

As described further in the Causal Pathway section, *causal pathways linking a climate-sensitive exposure to health outcome(s) of interest are central to climate change disease burden projections*. Causal pathways (also known as exposure pathways or causal process diagrams) are schematic representations of how an exposure affects health outcomes. They can be elaborated with varying degrees of complexity by adding potential modifiers and can be static or dynamic,[15] and are particularly useful for identifying and assembling the data elements that will be needed to pursue the modeling effort.

Assemble Data Elements

Once a causal pathway has been developed, the next step is to assemble the necessary data, including projections of climatic shifts using global climate models (GCMs). GCMs project future climate states using scenarios, sets of assumptions about the trajectories of major climate drivers (also known as forcings) including greenhouse gas emissions; this is explained further in the Climate Data section. *The cardinal environmental impacts projected by GCMs are warming, more variable weather, and rising sea levels.* In many cases, these are the exposures of interest for disease burden projections, though sometimes relevant exposures are the combined result of shifts in temperature and precipitation (e.g., drought), or more complex secondary ecological shifts.

Another important data element is baseline health data, as projections of health outcomes require a baseline from which to start. Such baseline data are the subject of the

Baseline Disease Burden section and are typically in the form of a disease prevalence or incidence (e.g., annual rates of emergency department visits for heat stroke). In addition to the baseline rate, it is important to know details related to the baseline population demographics, as these can affect exposure and disease susceptibility and significantly affect projected disease estimates.

Baseline health data serve as the starting point for projecting health impacts using modeled exposures from GCMs and retrospectively derived associations between observed exposures and outcomes (termed exposure-outcome response functions or concentration-response functions and sometimes denoted as α). Discussed further in the Exposure-Outcome Response Function section, these functions can be empirically derived from observational studies or obtained from the literature. Regardless of how the function is derived, the section on Source Populations highlights the importance of paying close attention to the source population characteristics so that equitable comparisons can be made.

Project Disease Burden

Once all data elements are assembled, they are combined using a modeling approach that captures the relationships outlined in the causal pathway to project the health burden in the future. Some of the most common approaches used in public health are described in detail in the Project Disease Burden section.

Perform Uncertainty Analysis

There are many sources of uncertainty in climate change health impact projections which, like other modeling efforts, are inherently uncertain due to both model uncertainty (i.e. uncertainty resulting from simplification of complicated real-world processes) and parameter uncertainty (i.e. uncertainty resulting from incomplete knowledge regarding the specifics of model parameters and their interactions in future). There are established methods for identifying and quantifying uncertainty in climate change disease burden projection efforts that will be discussed further in the Evaluating Uncertainty section.

One significant source of uncertainty specific to climate change health impact projections is whether and how to model climate change adaptation, which has the potential to reduce climate change impacts, including those on public health. Failure to account for adaptation in disease burden projections can introduce a systematic bias that will likely result in overestimation of effect. Various ways to account for adaptation in disease burden projections are discussed in the section on Adaptation.

Adaptive Management

Adaptive management entails the use of models to help make management decisions about complex systems. An adaptive management approach is iterative and couples model development and outputs with stakeholder engagement. Adaptive management is becoming increasingly common in public health; its potential application to climate change adaptation is discussed in the section on Adaptive Management.

Causal Pathways

Figure 3. The elements of a causal pathway and their relationship.

Causal pathways outline and diagram the steps between an exposure and its health outcome.[15] Environmental drivers are seen in causal pathways for a wide range of health outcomes, from physical activity and obesity[16] to cancer.[17] In the case of climate-sensitive health outcomes, causal pathways link an environmental hazard or other environmental exposure to a change in the incidence of specific adverse health outcomes, and many causal pathways for climate sensitive outcomes have already been developed.[18-23]

The links in a causal pathway may be hypothesized – for example, a link between a climate hazard such as sea level rise and a health-relevant exposure such as drinking water salinization that has not been widely documented in the US as yet – but must be consistent with current understanding of the exposure and disease pathogenesis.[24] Consistent with current understanding of the social determinants of health,[25] a range of socio-economic, ecological, infrastructural, and other types of factors should be included if there is reason to believe that these factors may modify the association between the exposure and health outcome.

Practitioners should develop causal pathways tailored to their jurisdiction for each climate-related hazard they wish to study. These pathways should be developed with attention to scope and scale, both of which should be matched to the health department's jurisdiction. The complexity of these pathways is likely to increase with the inclusion of intermediate factors that modify the hypothesized association, and this has implications for modeling the association. The pathways will serve several purposes:

1. Characterization of the health outcome's climate sensitivity.

2. Identification of important underlying drivers and potential effect modifiers.

3. Development of an inventory of variables to include in the exposure-outcome model.

4. Identification of data needs for the modeling effort.

5. Characterization of knowledge gaps and significant areas of uncertainty.

In scaling the exercise, practitioners may want to be attentive to the points at which interventions—behavioral, medical, and otherwise—might be applied.[24] For example, in regards to climate change and heat-related illness, local conditions such as population exposure (e.g., proportion of the population with air conditioning, proportion of the population working outdoors, etc.) and population vulnerability (e.g., proportion of

elderly in exposed population, proportion of school-age athletes practicing outdoors during summer months, etc.), as well as local modifying factors (e.g., magnitude and extent of the urban heat island, distribution of green space, and other concomitant non-climate stressors) are all important to consider.

Practitioners should also attend to how climate change is likely to impact the exposure(s) in their causal pathways. This is particularly important when climate change is expected to have multiple relevant environmental impacts. For instance, changes in temperature and precipitation can lead to drought, which is hypothesized to impact the incidence of coccidioidomycosis, a fungal respiratory infection.[26] A causal pathway for this disease might thus include temperature and rainfall as drivers distinct from drought to capture independent associations. Similar concerns emerge in relation to many different climate-sensitive infectious diseases,[27] other ecologically-driven health impacts,[28] and impacts mediated by changes in ecosystem services.[29] In addition to interactions between specific drivers and health impacts, this set of concerns may also relate to the nature of the associations, i.e., whether there is a threshold effect above or below which health impacts are observed or the relationship between exposures and outcomes may change.

Some causal pathways may be more comprehensive than the health outcome that is eventually modeled. For instance, many relationships between climate change and mental health impacts have been postulated and a causal pathway has been developed.[23] This pathway outlines direct mental health impacts such as post-traumatic stress disorder after weather-related disasters and displacement, but also indirect pathways such as degradation of community well-being and associated mental health impacts. Modelers may include a wide range of impacts in their causal pathway but not model each due to lack of validated measures for particular exposures or outcomes or lack of available data, perhaps due to lack of prior exposure (e.g., disaster and displacement) in their jurisdiction. Similarly, not all the steps in a causal pathway may be explicitly modeled, but they should be included to facilitate in uncertainty analysis and consideration of adaptation options.

In many cases, the pathways leading from environmental conditions to human exposure to actual morbidity and mortality are remarkably complex.[1] Consequently, the easiest pathways to model are the ones that are most direct, i.e., the ones with the *shortest and least complex causal pathways*, and the *most consistent pathways*, i.e., those that depend on physiological mechanisms that have been shown to be consistent across populations, at least in settings relevant to the modeling effort. This is not to divert attention away from complex pathways or to discourage modeling of pathways that may be relatively specific to a given location, however, but to highlight that some modeling efforts will be able to build on prior work while others will break new ground. Table 1 presents a range of causal pathways developed for various climate-related health outcomes, illustrating the variety of complexity for characterizing causal pathways.

Questions to consider…

1. Have there been epidemiologic studies in your geographic location relevant to this causal pathway?

2. Is there more than one route of exposure?

3. If there are multiple modifiers in the causal pathway, how will you decide which to include in your disease burden projection?

Table 1. Examples of causal pathways linking climate-related exposure and health outcome.
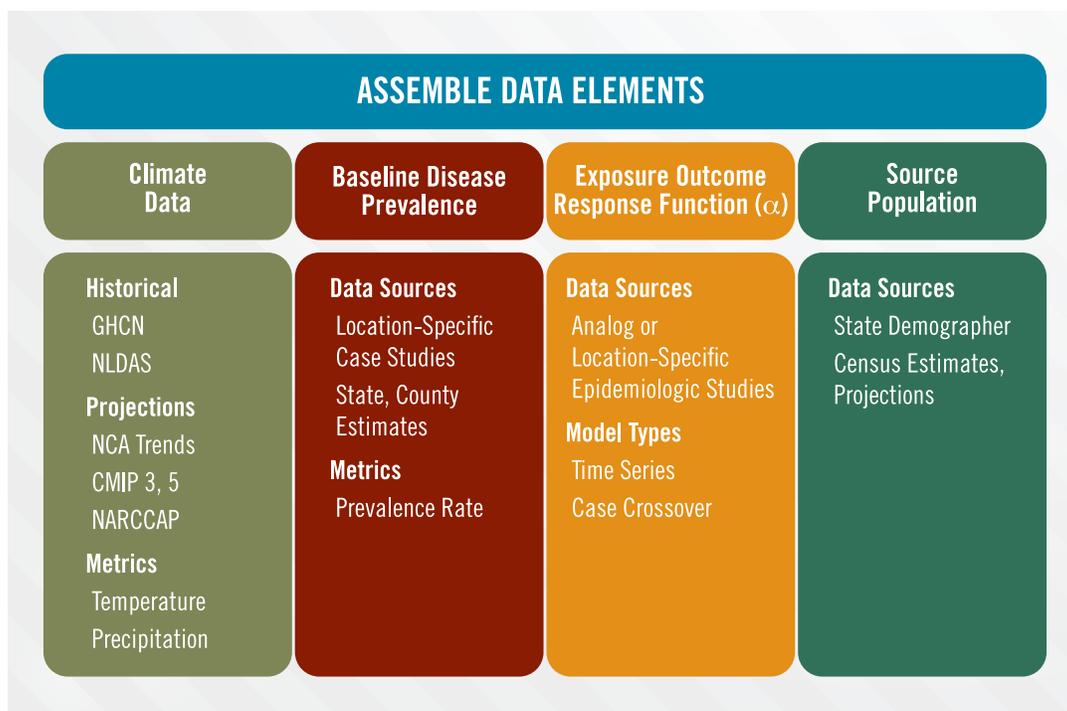
AUTHOR(S)	YEAR	EXPOSURE	HEALTH OUTCOME	NOTES	CITATION
McMichael, AJ, et al [30]	2013	Extreme heat, Temperature variability, Social disruption	Human Health (general)	Contains direct and indirect pathways between environmental systems and human health	McMichael, A.J., *Globalization, Climate Change, and Human Health.* New England Journal of Medicine, 2013. 368(14): p. 1335-1343.
Gronlund, CJ [31]	2014	Extreme heat	Heat-related adverse health outcome	Proximal racial and social determinants of heat vulnerability	Gronlund, C., Racial and Socioeconomic Disparities in Heat-Related Health Effects and Their Mechanisms: a Review. Current Epidemiology Reports, 2014. 1(3): p. 165-173.
Reid CE, et al [32]	2012	Extreme heat	Mortality	Illustrates how ozone could modify and/or confound heat-related mortality	Reid, C.E., et al, *The role of ambient ozone in epidemiologic studies of heat-related mortality.* Environmental Health Perspectives, 2012. 120(12): p. 1627-1630.
Moors, et al [33]	2013	Bacterial pathogens	Diarrhea incidence	Demonstrates the complexities of transmission cycle of waterborne pathogens, including magnitude and direction of impacts	Moors, E., et al, *Climate change and waterborne diarrhoea in northern India: Impacts and adaptation strategies.* Science of The Total Environment, 2013. 468–469, Supplement(0): p. S139-S151.
McMichael, et al [34]	2011	Temperature, precipitation	Infectious disease	Exhibits the impacts of both temperature and precipitation on the transmission of infectious diseases	McMichael, A.J. and E. Lindgren, *Climate change: present and future risks to health, and necessary responses.* Journal of Internal Medicine, 2011. 270(5): p. 401-413.

AUTHOR(S)	YEAR	EXPOSURE	HEALTH OUTCOME	NOTES	CITATION
Batterman, et al [35]	2009	Waterborne pathogens	Water-related infectious diseases	Contains an interdisciplinary and systems approach that considers distal, medium-term and proximal components of water-related infectious disease cycle	Batterman, S., et al, *Sustainable control of water-related infectious diseases: a review and proposal for interdisciplinary health-based systems research.* Environ Health Perspect, 2009. 117(7): p. 1023-32.
Kjellstrom, et al [36]	2009	Heat, Air pollution, Food scarcity, Extreme weather, Sea level rise	Non-communicable and chronic diseases	Demonstrates how personal exposures to changes in climate will be experienced at a local scale	Kjellstrom, T., et al, *Public health impact of global heating due to climate change: potential effects on chronic non-communicable diseases.* International Journal of Public Health, 2010. 55(2): p. 97-103.
Berry, et al [37]	2010	Natural disasters	Mental health	Presents range of psychological responses to acute, sub-acute and chronic events that can be associated with climate change	Berry, H., K. Bowen, and T. Kjellstrom, *Climate change and mental health: a causal pathways framework.* International Journal of Public Health, 2010. 55(2): p. 123-132.

Assemble Data Elements

Acquiring, organizing, and managing the data elements require explicit understanding of the steps involved for the modeling effort. The causal pathway diagram(s) can be used to develop an inventory of the data needed to model future disease burden. Specifically, climate projections, baseline disease burden, an estimate of the exposure-outcome response, and a characterization of the population of concern will need to be collected. Interdisciplinary collaborations may be necessary for acquiring and using data. An example matrix of needed data elements and some possible sources is presented in Figure 4.

ASSEMBLE DATA ELEMENTS

Climate Data	Baseline Disease Prevalence	Exposure Outcome Response Function (α)	Source Population
Historical GHCN NLDAS **Projections** NCA Trends CMIP 3, 5 NARCCAP **Metrics** Temperature Precipitation	**Data Sources** Location-Specific Case Studies State, County Estimates **Metrics** Prevalence Rate	**Data Sources** Analog or Location-Specific Epidemiologic Studies **Model Types** Time Series Case Crossover	**Data Sources** State Demographer Census Estimates, Projections

Figure 4. The relevant data components and potential sources for modeling future disease burden.

Data Element: Climate Data

Retrospective climate data, particularly metrics pertinent to human health (e.g., daily temperature, precipitation, dew point), can be retrieved in a variety of measurement forms from the National Oceanic and Atmospheric Administration's (NOAA's) Global Historical Climatology Network (GHCN) or the National Land Data Assimilation System (NLDAS). For instance, the CDC's Environmental Public Health Tracking program has archived NLDAS weather data transformed to county centroids. Climate data from the past is linked with retrospective health data in epidemiological analyses to assess how climate-sensitive morbidity and mortality is affected by changes in environmental exposures.

A necessary step in projecting future burden of climate-sensitive disease is projecting the future climate. This is done using global climate models (GCMs). Several GCMs

can be used in tandem to produce groups of projections (termed "ensembles") that can help reduce uncertainty by providing a range of projected outcomes.

Two examples of ensembles are the phase 3 and phase 5 outputs from the Climate Model Intercomparison Project. Phase 3 (CMIP3) was an unprecedented collection of GCM outputs[38] used to support the third U.S. National Climate Assessment (NCA) report. Phase 5 (CMIP5) is an updated ensemble that was used for the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report. CMIP5 created a standard set of climate change experiments and included over forty GCMs projecting future climate conditions for different time periods and levels of greenhouse gas emissions. These ensembles can provide projections of near term (through 2035) and long term (2100 and beyond) climate. Typically, near term projections are more compatible with the timeframe of public health adaptation.

GCMs are the primary tool used to project climate change. The term "projection" is distinct from "prediction." A "prediction" is an estimate of the probability of future events based on current knowledge and assuming that current conditions will remain essentially constant. A "projection" is an estimate of the probability of future events if certain conditions evolve.[39] The distinction is important, as climate projections depend on characterizations of future societal choices likely to generate certain levels of greenhouse gas emissions.

Uncertainty in GCM projections

The three important categories of uncertainty in GCM projections are: (1) that deriving from different approaches to modeling, (2) that deriving from natural climate variability, and (3) that deriving from different emissions scenarios.

The uncertainty associated with different approaches to modeling can, to some degree, be addressed through use of projections from multiple GCMs: Using projections from a random sample of ten or more GCMs may provide a representative sample of scientific uncertainty.[40] Multi-model ensembles do not capture the full range of scientific uncertainty because differences in model outputs may cancel out in the average ensemble output.

The uncertainty associated with natural climate variability can best be managed by increasing the number of model runs included. Due to natural variability, even projections from the same model can be notably different.[41] Each modeling group produces 1–9 GCM runs for each scenario and period. Natural variability can be reduced by using the average of each GCM's runs or propagated by including each run in the sample used to project health impacts.

Societal uncertainty is represented by the emissions scenarios. For the middle of the 21st century, the four RCPs provide largely similar U.S. climate projections. Thus, some studies use an ensemble of GCM from only one RCP for this period. However, there is a large divergence in climate projections from the four RCPs by the end of the century. As a result, climate change health impact projections should use GCM outputs based on two or more RCPs for projections for projections beyond 2050.

Certain scenarios of future conditions agreed upon by expert consensus are used to run the models. These scenarios make assumptions about future conditions such as population, anticipated greenhouse gas emissions, and adaptation efforts. Two main groups of scenarios have been used in recent years. CMIP3 used scenarios from the IPCC Special Report on Emissions Scenarios. CMIP5 and the IPCC Fifth Assessment Report used Representative Concentration Pathways (RCPs) to represent four greenhouse gas emissions trajectories and levels.[42] An RCP can be interpreted as the increase in the amount of energy in the earth system from greenhouse gas emissions. RCP 8.5 is the pathway associated with the highest emissions. In contrast, the pathway associated with the lowest emissions (RCP 2.6) implies immediate and significant emissions reductions. Complimentary Shared Socioeconomic Pathways provide more details on how society may develop to produce different RCPs.[43] At the time the RCPs were developed, none was considered more likely than another; rather, the scenarios provide boundaries within which impacts can be explored.

Of the various outputs from GCMs, several are relevant for public health considerations. Projections of future temperature, precipitation, and sea level rise are outputs commonly used to inform future disease burden attributable to climate change. These outputs are often available in a variety of measurements (e.g., average monthly temperature, days above a certain temperature percentile, nighttime low temperatures, number of annual heat waves, etc.), each of which may be of varying degrees of usefulness depending on the disease of interest. Other available outputs, such as future wind patterns, levels of ocean acidity, and soil moisture, may or may not be useful for health practitioners depending on causal pathway of the disease being projected.

Projecting some localized health outcomes may require precise climate projections provided by downscaled (estimated with finer geographic resolution) climate models. Typically, GCMs produce gridded outputs that operate on the scale of hundreds of miles. Such estimates may not be appropriate for informing interventions aimed at modifying risk at a relatively fine scale. For example, substantial variation of heat exposure at a neighborhood scale has been observed,[44,45] and interventions such as changes in land use and land cover may significantly affect exposure at a fine (e.g. neighborhood) scale.[46-48] Statistical techniques or weather modeling techniques can downscale temperature and precipitation simulations to a finer scale for such applications. The North American Regional Climate Change Assessment Program (NARCCAP) is an international program that provides multi-model regional climate model simulations at a scale (e.g., 50 km²) relevant to public health programs.[49] Health departments can use regional climate models or statistically downscaled projections to obtain future climate data.

In some instances, climate trends may be most appropriate for evaluating changing disease burden in response to a changing climate. NOAA developed eight regional and a national climate trends reports for the third NCA. The reports consider climate-related outcomes, like extreme precipitation, for a future timeframe and provide probabilities that such conditions will be below normal, normal, or above normal. These reports are specific to regional climate, which may not be useful to a city or municipality, but can be useful for state or regional health authorities.

Data Element: Baseline Disease Burden

In order to determine the future impact of climate change, baseline estimates of disease burden must first be established. There are three primary elements to this activity:

1. Determine the scale of the effort as noted in the Causal Pathway section.

2. Choose an indicator of disease burden.

3. Determine baseline disease burden estimates.

Determine the Scale of the Effort

There are two areas in which the scale of the effort needs to be specified: geographic (spatial) and temporal.

The geographic scale has two components: the geographic extent of the area being modeled, and the level of detail at which exposures will be projected. The area being modeled is likely to be determined primarily by the health department's jurisdiction, by ecological considerations related to the disease being modeled, and by scoping exercises undertaken earlier in the BRACE process. In many instances, the exposure (e.g., heat) is local, but in some (e.g., ciguatera fish poisoning),[50] the exposure may have significant remote drivers (fish containing ciguatoxin may be harvested from remote fisheries and shipped long distances, and the relevant weather and climate factors are geographically remote from the actual human exposure). Certain exposures, such as air pollution related to wildfires, may have both local and regional determinants.[51] The level of detail required for exposure modeling will depend on the nature of the exposure and how well it can be captured at the standard scale of GCM outputs. In some instances, e.g., modeling of neighborhood heat exposure,[44-46,48] this scale will not be adequate and additional downscaling will be needed.

Temporal scale is largely determined by the health department's planning time horizon. The time horizon may be influenced by the nature of possible interventions being considered, e.g. changes in land cover patterns to reduce heat exposure, some of which will require decades to mature.[47] The nature of the disease process is also a consideration; health impacts from increased mobilization of carcinogens, for instance, may require a longer time horizon given the nature of carcinogenesis.

Choose an Indicator of Disease Burden

Various data sources and indicators can be used to measure, track, and describe current and future disease burden. Once a health impact has been chosen, the appropriate indicator should be chosen. Health indicators are measures of population health status in relation to environmental factors, in this case climate change. Health departments can adapt existing indicators or develop their own indicators.[52] The State Environmental Health Indicators Collaborative (SEHIC) of the Council of State and Territorial Epidemiologists (CSTE) has developed guidance on developing climate change indicators[53] and also maintains a list of 24 potential climate and health

indicators including information on relevance, data sources, and limitations.[54] Other useful sources for selecting indicators include the Environmental Protection Agency's Climate Change Indicators in the United States, which includes information on potential indicators for Lyme disease and heat, as well as recent research on deriving indicators[55] and choosing which indicators may be particularly useful for specific applications.[56]

Determine Baseline Disease Burden Estimates

Both estimates of baseline prevalence and underlying incidence will be needed. For some health outcomes, such data is regularly collected and is available publicly or to appropriate authorities. Surveillance systems, such as CDC's Environmental Public Health Tracking Program[57,58] are good data sources. State and local health department surveillance systems, such as NC Detect,[59] also contain useful data, although it is not always easily accessible. Some federally-administered datasets, e.g., the National Emergency Department Sample of the Healthcare Cost and Utilization Project,[60] may also be useful in establishing baseline prevalence and annual incidence estimates.

Baseline prevalence can be described in terms of varying health outcomes and geographic and temporal ranges (e.g., heat-related emergency room visits per summer in a certain county; state-wide existing diagnosed asthma cases). The specific measure of prevalence can be chosen based on available data, health priorities, and ability to model the measure.

Example: Baseline asthma prevalence

Asthma is one example of a climate sensitive disease that has readily available prevalence data. CDC's National Environmental Public Health Tracking Network contains multiple indicators for asthma prevalence rates among adults and children as well as number of emergency department visits and hospitalizations at the county level. All of these data are publicly available and downloadable. Climate change has the potential to impact asthma rates through multiple pathways, including increased production of pollen (related to increasing temperature and carbon dioxide levels and lengthening of the growing season) and increased photochemical smog (related to increasing temperatures). Using this prevalence data, health practitioners have a well-established baseline from which to determine an exposure-response relationship and project a future disease burden. Further information on the use of asthma indicators is available from the Council of State and Territorial Epidemiologists.

Data Element: Exposure-Outcome Response Function

An exposure-outcome function describes how the likelihood of an adverse health effect (outcome) is related to an environmental hazard (exposure). In different disciplinary settings, these may also be referred to as 'dose-response' or 'concentration-response' functions. In the context of climate change, the exposures of interest could directly be weather-related, like ambient temperature, precipitation, extreme weather events; or, weather-mediated factors, like pollen levels or factors affecting the environmental presence of water-borne or vector-borne pathogens. A specific exposure could affect multiple health outcomes (e.g., heat can cause exacerbations of a range of diseases leading to morbidity and mortality), and specific health outcomes can have several environmental drivers (e.g., water-borne disease outbreaks may be associated with both temperature and precipitation). As described in the causal pathways section, the complexity in modeling the exposure-outcome relationship increases with the inclusion of intermediate factors affecting the exposure and the outcome.

A standard practice in deriving exposure-outcome functions in environmental epidemiology has been to link health and exposure data by common spatial (county, city or some administrative boundary) and temporal (day, month) variables. This methodology is most well developed in the field of air pollution epidemiology, and in examining the health impacts from ambient temperature. Since health data are commonly available for each day at the city or county scale, exposure data available from weather stations (for temperature) and/or monitoring stations (for air pollutants) located within the city/county jurisdictions are merged by day. In the absence of individual-level exposure information, an implicit assumption in this approach is that all individuals living within the particular jurisdiction were equally exposed.

Once such retrospective datasets are assembled, time-series statistical models are utilized to derive an estimate of the change in the health outcome attributable to change in exposure of interest after controlling for other variables in the causal pathway that could affect that relationship.[61] These models produce odds ratio or relative risk estimates for the health outcomes from changes in exposure. While these two estimates have different interpretations, they are mathematically similar in situations when the health outcome of interest has low prevalence.[62]

Depending on the characterization of exposure as either binary (indicating presence or absence) or continuous, changes in health outcomes could be point estimates or correspond to a range of exposure values, respectively. For the latter, the estimated exposure-outcome relationship over the range of exposure values could be linear or non-linear, with non-linear functions indicating differential health impacts at different levels of exposure.[63] Besides the time-series approach, the case-crossover methodology has been used to control for time-invariant factors (either for individuals or place) that could affect the exposure-outcome relationship.[64]

Data availability to derive exposure-outcome functions is an important issue. For certain specific combinations of health outcome and exposure (e.g., impact of extreme heat on mortality), location-specific exposure-outcome associations can be estimated given available data.[65] For some specific exposure-outcome function, such an empirical approach may be infeasible due to lack of data or scientific knowledge.

In such situations, the alternative may be to borrow an effect estimate derived in a different setting from the literature. While following this approach, there should be careful deliberation on whether the estimate obtained from the literature is appropriate for the specific population and climate where it is being applied. In other situations, there may only be a qualitative assessment about the directionality of change in health outcome from change in exposure. Approaches to obtaining a qualitative estimate could include expert consultation via the Delphi method[66] or other, less systematic approaches.

Regardless of whether the exposure-outcome association is newly derived or taken from the literature it is treated the same way mathematically. The box on the damage function approach illustrates how the exposure outcome association, α, is used to link estimates of relative risk with data on the exposed population and the exposure to generate estimates (expressed as counts) of disease impact.

There are important considerations when deriving, interpreting, and applying exposure-outcome associations. Some of these issues are discussed in the next section on the source population.

Data Element: Source Population

Estimates of the association between an exposure and outcome are specific to the context from which the exposure and outcome data were gathered. While it is possible that associations derived in one context may be applied to another, this introduces potentially significant uncertainty given the important role that population-level characteristics play in many climate and health outcome relationships. Thus, regardless of whether exposure-outcome associations are newly derived and specific to the context in which they will be applied or if they are taken from the literature, it is critical to capture demographic and other information related to the setting from which the estimate was derived and assess for potential biases.

Comparisons between current and projected populations can be important, particularly in areas where large changes in population demographics (e.g., aging or migration) are expected in coming decades. These factors are important to consider in regards to both their role in the association between the exposure and outcome under consideration and in regards to baseline health status. For instance, associations between temperature and exacerbations of respiratory disease such as chronic obstructive pulmonary disease (COPD), which commonly develops after years of tobacco smoke exposure, may depend significantly on the population age distribution in a given region, and crude estimates derived in a high-prevalence region and unadjusted for age may not be appropriate for a region with a young population with lower levels of tobacco exposure.

While data specific to the context in which the health impact is being projected may be desirable analytically, developing new exposure-outcome associations can introduce other challenges. One relates to sample size: there may not be adequate data

FOR YOUR CONSIDERATION…

1. What data sources will be used (e.g., state, county, city)?

2. Which data elements have common geographic and temporal resolutions?

3. How will the data elements be merged?

4. What are the limitations of the data?

to generate sufficiently precise estimates for the projected exposure range in some settings. Another issue relates to data combination. Bridging differentially scaled data can be challenging, but is not impossible. In the case of using fine spatial scale estimates, geographic or political boundaries common to public health interventions (e.g., census tracts) may not align with the gridded climate model output. One option is to conduct a spatial analysis that assigns each geographic unit (e.g., census tract) a climate model output estimate that contains the majority of the geographic unit (e.g., population centroid).
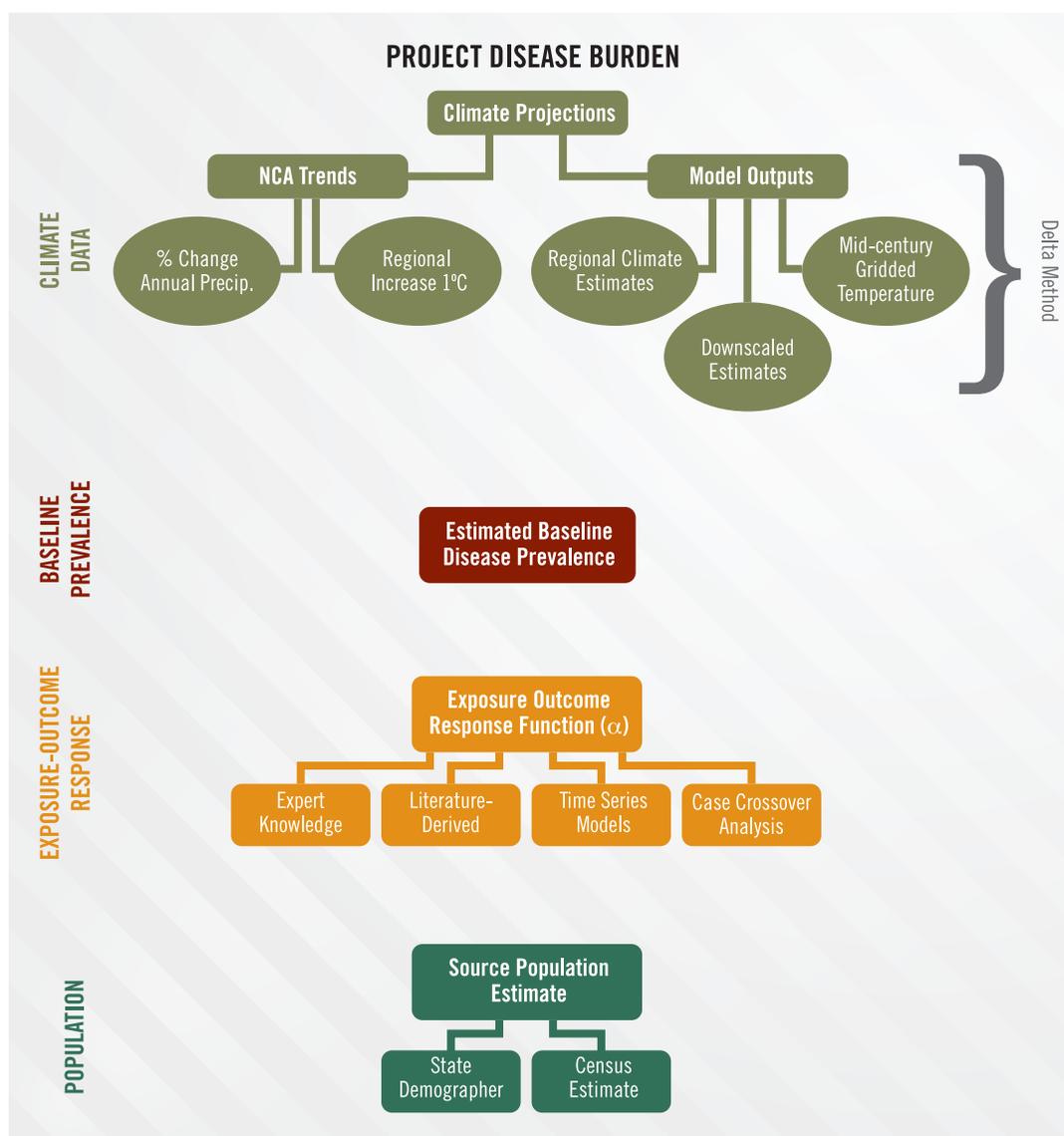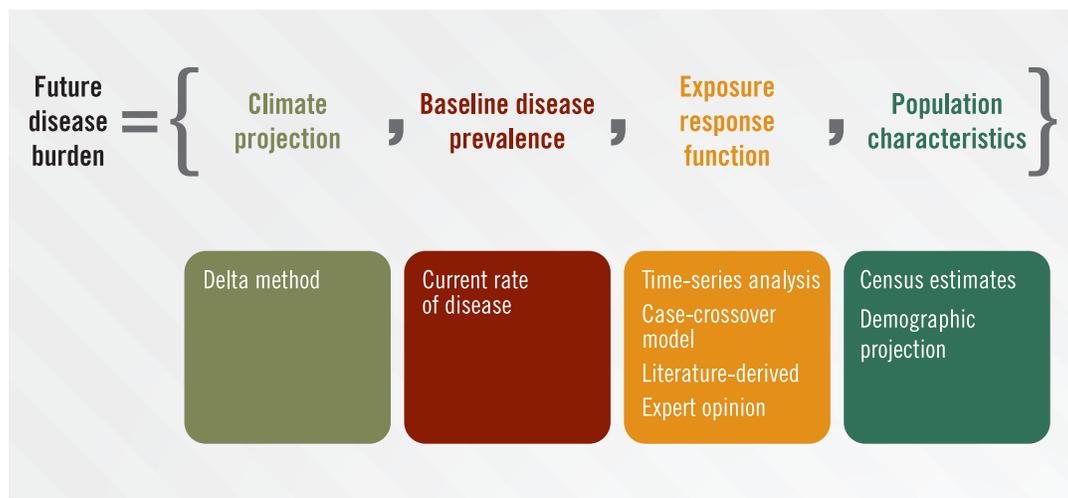
Project Disease Burden

Figure 5. Steps, data sources and suggested approaches for projecting disease burden.

A climate change disease burden projection is a modeled, scenario-based estimate of the range of adverse health impacts associated with specified climatic change scenarios. These projections may focus on determinants of adverse health impacts (the distribution of exposures that serve as risk factors in the causal pathway) or extend the analysis to the health outcomes themselves.[67] Either way, they aim to quantify components of the causal pathway linking environmental hazards and human health impacts on a population basis. Model outputs may be health impacts (such as deaths, disability-adjusted life years or DALYs, all-cause or cause-specific visits to the emergency department, laboratory-confirmed cases of a specific disease diagnosis, etc.) or a risk factor that is a determinant of future health impacts (such as temperature distribution or habitat suitability for vectors),[67] though this document focuses primarily on projections of disease impacts.

Climate-related health effects are sometimes classified as direct (such as heat-related illness) or indirect (such as vector-borne disease), related to how quickly health outcomes are manifest in the exposed and the ecological complexity of the causal pathway. In reality a continuum exists and most health impacts are mediated by a variety of factors. Anticipating and modeling the impact of climate change on these complex factors can be difficult. For example, with vector-borne diseases such as dengue fever and West Nile infection, changes in temperature and precipitation could impact mosquito reproduction and feeding rate, distribution of mosquitoes both geographically and seasonally, viral replication within the mosquito, availability of standing water for breeding, and human exposure rates.[68,69] In addition, the way that humans respond to climate change (such as shifts in land-use, water storage, or use of air conditioning) and events such as long-term droughts, flooding, or power outages will likely also affect future rates of vector-borne disease. The effect of all of these factors on disease prevalence will vary based on specifics of the local population and geography (e.g., demographics, urban/rural divide, local ecosystem dynamics). Since modeling these complex interactions can be a daunting task, simplified models are often employed. While uncertainty is introduced, the models contain components based on educated assumptions and incorporate the best available data. Models can also be used qualitatively for a general assessment of how climate change may affect the risk for certain health outcomes.[70]

The World Health Organization (WHO) has used disease burden projections to estimate the global burden of some diseases attributable to climate change.[71] The health impacts modeled were heat, coastal flooding, diarrheal disease, malaria, dengue, and undernutrition. While many of these outcomes are more applicable to developing countries and resource-poor environments, several (especially heat, flooding, and vector-borne disease) are relevant to the U.S. Cause-specific mortality in 2030 and 2050 with climate change and in the absence of climate change was projected, allowing for calculation of climate change-attributable impacts. The WHO methodology, referred to as "Climate Change Risk Assessment," can be adapted for use by state and local health departments in the U.S. More information on this approach is available in the WHO report.[71]

The exposures of interest in climate change disease burden projections are taken from GCM projections. There are a host of issues related to model outputs that are relevant for generating estimates of these exposures, from which GCMs or ensemble

GCM outputs are used, whether outputs are scaled down from their original relatively coarse resolution to a finer resolution more applicable for health impacts modeling, and what downscaling approaches are used (see Data Element: Climate Data). The issues attending these questions are complex and have been reviewed extensively in the literature. A thorough discussion is beyond the scope of this report, but Carbone has conducted a recent review.[72]

Another issue is the question of how exposures are quantified for disease burden modeling once these other concerns have been addressed. For instance, public health practitioners may be interested in an exposure that is not a direct GCM output, such as a heat wave, which has variable definitions in the literature.[73] In such cases, GCM outputs may need to be analyzed and manipulated to generate estimates of exposures relevant to the disease being projected, e.g., a contiguous series of days with maximum temperatures over some historical threshold.[74]

Most climate change disease burden projections have used what is referred to as "the delta method." The delta method changes parameters in climate models to produce estimates of an exposure of interest both in the current and future scenario (e.g., current temperature compared to projected future temperature). The change, or delta, can be applied to exposure-outcome models to estimate future health burden. An overview of studies using the delta method was conducted by Gosling et al.[75] The "damage function approach," often used to estimate morbidity from air pollution from shifting energy sources,[76,77] is an example of a method that can be applied to projecting health impacts from climate change.[78] Essentially, this combines the different elements described above – projected change in exposure, baseline disease prevalence, the exposure-outcome functions and baseline population – in a mathematical function to derive an estimate of the disease burden. This approach has been widely used in assessing the adverse health outcome that could be avoided from improved air quality.[79,80]

Equation for the damage function approach for projecting health impacts

$$\Delta y = y_0 (e^{\alpha \Delta x} - 1) Pop$$

Where:

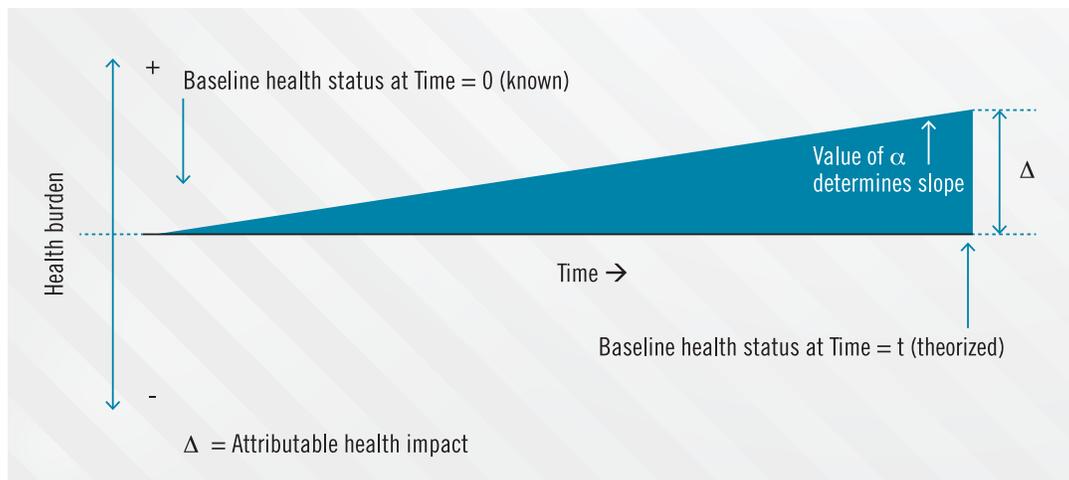Δy is the change in the health effect

y_0 is the baseline incidence rate

α is a coefficient derived from the relative risk (RR) associated with a change in exposure

Δx is the estimated change in exposure

Pop is the exposed population

National Research Council [81]

Figure 6. Changing health status over time, measured by disease prevalence.

A useful tool for projecting health impacts is the Environmental Benefits Mapping and Analysis Program (BenMAP). BenMAP is a software tool developed by the Environmental Protection Agency (EPA) that can be used to estimate health impacts of changes in air quality and is publicly available. While BenMAP has broader uses, it can be applied to health effects of climate change by inputting temperature projections from climate models to estimate future health impacts from decreased air quality. Voorhees et al [82] provide a methodology for estimating future excess heat-related deaths with climate change by adapting BenMAP to incorporate temperature modeling and heat mortality health impact functions.

Other considerations are important, as well, such as how well exposures can be characterized, both in the retrospective analyses and in the GCM projections. For instance, levels of airborne pollutants (e.g. particulate matter) can be measured at monitoring stations and these measurements can serve as proxies for population-level exposure to the same species at a larger spatial scale with some degree of confidence.[83] Alternatively, in some settings, interpolated measurements can be used if direct observations are not available for the region or time frame needed. Similarly, temperature measured at one location is frequently used as a proxy for temperature exposure across a larger area.[84]

In all cases, the assumption of scalability can facilitate health impact projection, though it is important to recognize that this simplification can come at a cost. Assumptions regarding extrapolation of exposure may mask significant variability in actual exposures at the individual level, obscuring dynamics that may be significant for public health action (see, for example, Jerrett et al. (2005) for a discussion related to particulate air pollution,[85] and Harlan et al. (2013) for a discussion related to heat).[86] Periodic consultation with climate scientists may be helpful in clarifying some of the issues related to the GCM projections.

Adaptation

Adaptation is taking action to prepare for the effects of climate change. Public health adaptation efforts, some of which are already underway,[87] are intended to reduce negative human health impacts.[88] These can occur at multiple levels, from local (e.g., city heat wave adaptation plans) to international (e.g., international drought adaptation strategies). In contrast to mitigation, which seeks to limit future anthropogenic greenhouse gas emissions, adaptation seeks to reduce future vulnerability and minimize damages. Some potential mitigation activities, like global reduction in greenhouse gas emissions, are accounted for in some of the climate scenarios used to run GCMs, but adaptation activities typically are not. Thus, anticipated future adaptation can be included in health models so that projected health burdens are not overestimated.

There are many different adaptations to climatic exposures, including passive adaptation (also known as "autonomous" adaptations) such as physiologic adaptation to heat exposure and active adaptations such as expansion in prevalence of mechanical air conditioning.[88,89] The type(s) of adaptation efforts that might be included in health impact projections will depend on the temporal scale of the projection effort.[89] Models can incorporate passive adaptation – for example, natural physiological acclimatization to warmer weather.[90] They can also incorporate a range of potential active adaptations, many of which have been catalogued in the literature. For example, a wide range of adaptations related to climate-sensitive infectious diseases may reduce the impact of climate change on future disease burden, but different strategies are relevant at different time scales (e.g., short term development of an early warning system to ensure that current vulnerabilities to climate variability are effectively addressed, as compared to long term coastal management practices to prevent untreated sewage discharge due to combined sewer overflow during extreme rain events).[91] Including potential adaptations can facilitate the use of projection models in adaptive management efforts.[92]

Educated assumptions will need to be made as to what adaptation efforts are likely at the time scale being modeled. There is, as of yet, no consensus in the climate and health community regarding whether and how adaptations should be included in climate change health impact projections, and a wide range of strategies have been employed. In some cases, modelers choose not to include adaptation in order to avoid uncertainty and ease interpretation of impacts by contextualizing the impacts in the present state. However, if adaptations are not considered, the projected disease burdens are likely to be systematically overestimated, and this should be explicitly stated in reporting of results.

Perform Uncertainty Analysis and Assess Sensitivity

Fundamentally, uncertainty relates to "imperfect knowledge," the inability to fully know all of the factors affecting a particular process.[93] There are many sources of uncertainty in climate change disease burden projections, mandating a strategy for identifying major sources, attempting to characterize their impacts on the analysis, and presenting sensitivity analyses with other findings.

Here we focus primarily on uncertainty in the process of modeling the relationship between exposures and health outcomes and less on uncertainties in climate modeling. Please see the box on page 13 for some additional discussion of that issue.

Identifying Major Sources of Uncertainty

There are two major types of uncertainty: *intrinsic*, which is inherent to the system being studied, and *extrinsic*, which is related to the ways in which problems are conceptualized and data are collected and analyzed.[94] Most effort goes into identifying and treating extrinsic uncertainties in climate change health impact projection as these uncertainties can be more easily quantified and assessed. However, both types of uncertainty are present throughout the modeling process and deserve modelers' attention. Table 2 below outlines some examples of uncertainties specific to climate change disease burden projections.

A wide range of options are available for treating uncertainty at each stage of the modeling process, discussed below with a focus on treatment of extrinsic uncertainty.

UNCERTAINTY TYPE	CONCEPTUALIZATION	ANALYSIS—CLIMATE	ANALYSIS—HEALTH	REPORTING
Intrinsic	Conceptual pathways are often linear and focus on averages rather than extremes, ignoring inherent sources of uncertainty such as sparseness of rare events and nonlinearity in complex systems.	Nonlinearity in a host of underlying processes leading to a general outcome, e.g. sea-level rise, ramifies and leads to wide confidence intervals around estimates.	Complexity of human behavior leads to nonlinearities that are difficult to capture in exposure-outcome equations.	Risks are often reported with incomplete attention to risk tolerance in different communities and incomplete catalogue of available risk management options.
Extrinsic	Limitations related to computing power, costs, and time constrain the range of inputs used, e.g., an ensemble average will be used instead of a random selection of outputs from ensemble members.	Incomplete historical and current weather data resulting from incomplete monitoring system coverage increases uncertainty, particularly at local and regional scales, in ways that may be difficult to fully estimate and predict.	Rarity and particularity of extreme events complicates estimation of parametric uncertainties, i.e. whether exposure-outcome associations are linear and the range of line slopes that should be used in uncertainty analyses.	Uncertainty reporting often focuses on analytical uncertainties and minimizes conceptual and reporting uncertainties, potentially foreclosing important risk management considerations.

Table 2. Some examples of intrinsic and extrinsic sources of uncertainty at different stages in the process of projecting climate change health impacts.

Uncertainty in Causal Pathways

Addressing uncertainty starts in the process of framing and articulating causal pathways.[95] It is important to identify where structural uncertainties may be located (e.g., whether nonlinearities, delays, or threshold dynamics may be major concerns) and where parametric uncertainties are present (e.g., where little is known about the nature of specific relationships between variables in the pathway). Structural uncertainties are particularly common for vector-borne and zoonotic diseases,[96] but can be seen with many different disease processes, while parametric uncertainties are common throughout environmental health.

Uncertainties in causal pathways and framing assumptions have not been a significant part of uncertainty analyses in recently published environmental disease burden assessments.[95] However, examples of how uncertainty associated with framing assumptions might be treated have recently been introduced into the literature.[97,98]

Uncertainty in Analysis

A host of strategies are available for identifying and treating uncertainty in analytic processes.[99] To deal with structural uncertainties it is important to use appropriate modeling approaches. Structural uncertainties identified in the causal pathway may have analytical implications. In instances where dynamics between different actors in a disease process may be unclear, agent-based modeling may have a role,[100] general additive models are appropriate for nonlinear dynamics,[101] and complex dynamics can be handled by dynamic numerical models.[102] In contrast, a more linear health burden assessment framework of the type elaborated on here may be appropriate for systems in which such dynamics provide a fair approximation of exposure-outcome associations. The association between ground-level ozone concentrations and pediatric emergency department visits for asthma is one example.[103,104]

To deal with structural uncertainties it is important to embrace as much diversity as possible in model inputs and evaluating the impacts of this wide input range on the model's estimates. This process of systematically evaluating the effect of variations in model parameters is sometimes referred to as uncertainty analysis and sometimes as sensitivity testing.

Three major categories of uncertainty that are particularly important to acknowledge and incorporate and some strategies for their treatment are listed in Table 3.

MAJOR CATEGORY OF UNCERTAINTY	SOME TREATMENT STRATEGIES
Lack of knowledge regarding future emissions	Include exposures derived from a range of emissions scenarios
Lack of knowledge related to exposure-outcome associations or α	Evaluate values of α within a certain range, e.g., within the bounds of the 95% confidence interval for the original estimate(s)
Lack of knowledge related to future conditions, including adaptation and demographic trends	Evaluate different central assumptions related to future conditions and adaptation, e.g. socioeconomic development, migration, prevalence of mechanical air conditioning

**Table 3.** Major categories of analytic uncertainty and some possible treatment strategies.

Uncertainty related to α, the second category listed in Table 3, bears further explanation. As illustrated in Figure 7, a higher α will, all other things equal, result in larger disease burden estimates (a higher α results in a larger ⅛ as illustrated by Δ_2).

In 2011, Kolstad and colleagues examined uncertainty in projections of the impact of climate change on diarrhea.[105] Their estimates were sensitive to the specific climate model and emissions scenario used and to the value of α, as illustrated in Figure 8 below. Their primary conclusion was that there remains significant uncertainty in projected health impacts due to low confidence in existing α estimates.

Several examples of uncertainty analysis in climate change disease burden projections may be useful. For instance, several studies have evaluated the impact of different emissions scenarios on projections of particular health impacts. Using a variance-decomposition method, Wu and colleagues (2014) examined the effect of various emissions scenarios, definitions of heat waves, and values of α relating heat waves and health impacts. They found that projections of heat-related mortality were particularly sensitive to changes in α, which accounted for 32.2% of the variance in their estimates, while different emissions scenarios accounted for 23.7% and varying heat wave definitions (used to define exposure) accounted for 22.2% (other sources accounted for the remainder).[106]
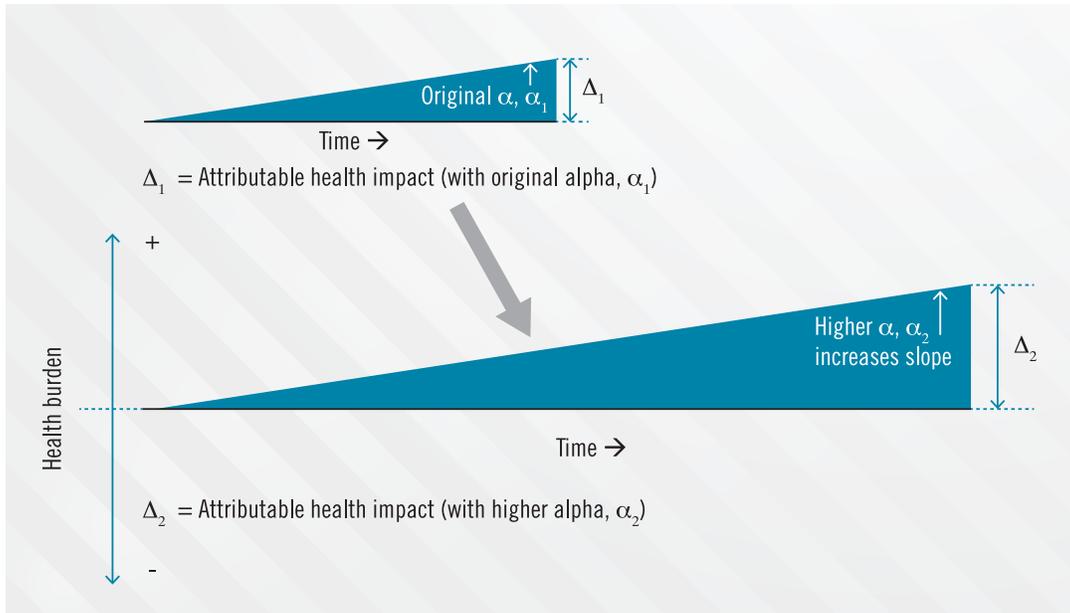
Figure 7. Effect of α on projected health impact. α determines slope; the higher α_2 correlates with a higher slope and thus a larger Δ_2 disease burden.
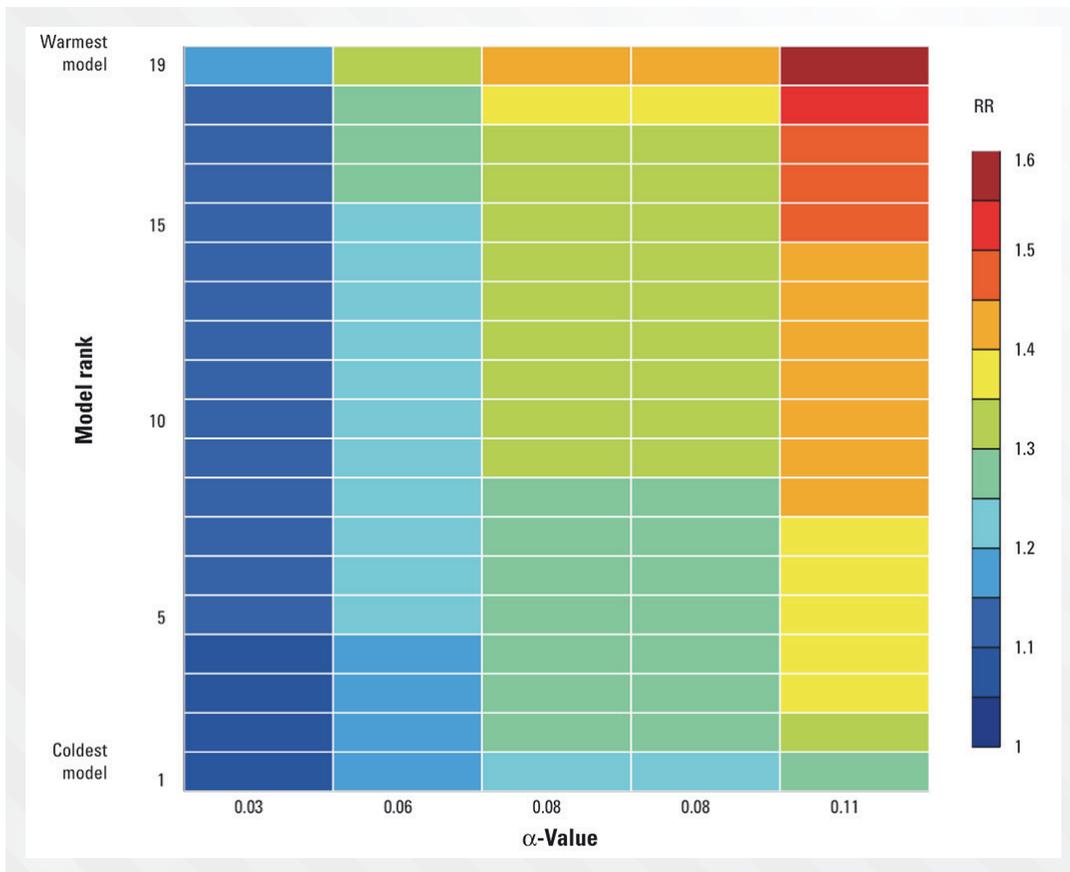
Figure 8. Schematic illustrating the effect of model choice and α on the magnitude of diarrheal disease estimates. In this case, estimates are expressed as relative risk of diarrheal disease in the setting of climate change relative to the risk without. From Kolstad and Johansson,[105] used with permission.

Uncertainty related to future conditions, the third category in Table 3, has been assessed less commonly in climate change disease burden projections to date. Several different studies have attempted to account for adaptation in their modeling, but most have not evaluated sensitivity to different future conditions apart from emissions scenarios. Hodges and colleagues, however, recently published an estimate of projected disease burden attributable to water, sanitation, and hygiene (WSH) conditions in China and included several different developmental pathways associated with varying levels of WSH-related infrastructure.[107] They also accounted for demographic shifts including population growth and rural-to-urban migration, which has impacts on the WSH infrastructure to which people are exposed. They evaluated the sensitivity of their estimates to emissions pathway as well as to α and socioeconomic development trajectory and found that estimates were strongly sensitive to both emissions scenario and development trajectory and marginally so to variations in α.

Reporting

Uncertainty in reporting relates to the inherent difficulties of conveying complicated findings to a wide range of audiences and in supporting policy decisions with science. Reporting uncertainty and determining how much uncertainty analysis to pursue are important considerations for health departments, which operate at the interface between management and public policymaking.

Given their role and limited resources to pursue extensive sensitivity analyses, it is important for health departments to attempt to engage policymakers regarding uncertainty and what types of sensitivity testing might be most useful for decision makers. Health departments will need to determine what uncertainties they feel are appropriate to assess, both as a result of the state of knowledge regarding the disease process(es) being modeled and as a result of policy maker needs.

At a minimum, health departments should include an uncertainty or sensitivity analysis section in their reports highlighting the major uncertainties in their analysis. The section should discuss major sources of uncertainty, their treatment, and the results of sensitivity testing on results.

Health departments may decide to expand this discussion to include a broader discussion of uncertainties along the lines of international assessments like those done by the IPCC.[108] There is now a comprehensive effort to clarify uncertainties and standardize estimates of confidence in assessment findings in IPCC and other high-level assessments.[109] As yet there is no specific guidance for clarifying uncertainties in reporting of health department projections of climate change health impacts, but guidance used in the National Climate Assessment for generating traceable accounts of findings and characterizing likelihood[110] are applicable, as are examples from the National Climate Assessment regarding decision support.

Iterative Use of Disease Burden Projections: Adaptive Management

Many of the climate-sensitive health impacts that public health officials are interested in projecting occur within complex, adaptive socio-ecosystems. These are systems in which humans are the dominant actors and not all of the system's behavioral dynamics are understood. Such systems tend to respond to management interventions in unexpected ways, sometimes leading to unintended consequences.

Because such systems are incompletely understood, models that simulate their behavior can be useful in making management decisions. Adaptive management is an iterative approach to managing complex adaptive systems and designing, testing, and evaluating interventions that incorporates models explicitly into the management process.[111] The approach prioritizes learning and regular modification of the models based on new information and seems better suited to management of complex systems than linear management models.[112]

In 2004 the National Research Council outlined six major elements of settings in which adaptive management may be a useful approach:[113]

1. There are explicit management objectives that are regularly revisited and revised;

2. There is a model of the system(s) being managed;

3. There is a range of management choices to consider;

4. There are provisions for monitoring and evaluating outcomes;

5. There are mechanisms for incorporating learning into future decisions; and

6. There is a collaborative structure for stakeholder participation and learning.

Because the health impacts of climate change are, in many cases, unfolding in the context of complex adaptive systems, several practitioners have suggested that adaptive management may be a useful tool for public health.[12,13,114] The BRACE framework (discussed in the Executive Summary and diagrammed in Figure 1) is built around adaptive management principles.[3]

As yet there are few examples of how adaptive management and modeling have been used iteratively to facilitate public health adaptation to climate change. There are, however, abundant examples of how health impact assessments in other fields have guided public health decision making[115,116] and facilitated interdisciplinary collaboration to better manage systems affecting health.[117] Using climate change disease burden projections in climate change adaptation activities is conceptually very similar, with the distinction that models will be continuously updated as new information about climate change, climate-sensitive disease, and the behavior of complex adaptive systems comes to light.

Limitations

This guide provides practical advice related to climate change health impact projections to health departments. While every effort has been made to make the guide useful, there are some limitations to the guidance in this report and its application.

The first limitation relates to the state of the science of climate change and health, which is in its infancy. There is no "gold standard" approach for projecting climate-related disease burden, as there is limited research and a lack of published literature analyzing the wide range of methodological and parametric issues. This report presents a narrowly-defined approach based on the limited existing research, with a focus on quantitative estimates. It presents an approach that has been applied to several different types of climate-sensitive health outcomes and been evaluated in the peer-reviewed literature. More recent extensions or elaborations of this approach or isolated examples of other approaches that have not been extensively vetted are not included here.

Another limitation is that the guide does not include an extensively-worked example using climate and health data. The next section does include applied discussions of how the report's guidance can be applied to heat-related illness and waterborne disease. Recognizing the value of a stepwise illustration using real data, however, we will be working to develop additional technical guidance to supplement this report at a later date.

Lastly, a note of caution: deriving quantitative estimates of future risk provides a specific number useful for a variety of planning and intervention purposes, but practitioners need to be mindful that despite the fact that the methods presented here can be used to develop quantitative estimates of future disease burden, there is inherent uncertainty in each step of the process. While this uncertainty can be assessed as outlined in the "evaluating uncertainty" section above, health departments should always bear in mind that the estimates are just that.

Practical Examples

The following examples brings together the various elements outlined above to highlight two important health issues related to climate change in the U.S. – heat-related illness and waterborne disease. These examples demonstrate the complexity, range of methodologies used and different datasets needed in order to estimate the potential burden of different diseases from climate change.

Example 1: Heat-Related Illness

Causal Pathway

EXPOSURE → Temperature increase above normal

MODIFIERS → Air conditioner use / Vegetation cover / Social support systems

RESPONSE → Morbidity & mortality
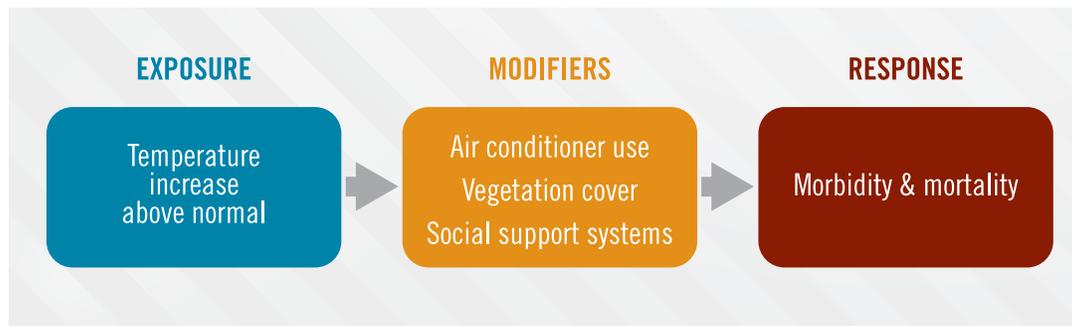
Figure 9. Simplified causal pathway diagram for heat-related illness.

The adverse health impacts during extreme summer temperatures have been experienced across the globe. Populations across different age groups have found it hard to cope with anomalously high local temperatures. A range of mortality and morbidity outcomes have been associated with these high temperatures. All else being equal, certain factors attenuate this adverse effect either by reducing the intensity of heat exposure (via air conditioner use or increasing vegetative cover), or by caring for the people of concern such as the elderly and those with pre-existing medical conditions, or populations who are mobility challenged through establishing social support systems (e.g., cooling shelters).

Assemble Data Elements

Climate Data

While climate model ensembles can project estimates of different metrics of temperature, it needs to be similar to the temperature metric used in derivation of the exposure-outcome function in order to project the disease burden associated with extreme heat. The most commonly used temperature metric used in projecting future burden of temperature has been a variant of observed temperature (maximum temperature or heat index) or the Spatial Synoptic classification.[118] Potential sources of future temperature data include the CDC's Environmental Public Health Tracking Network that hosts county-level measures of future temperature data produced by the CMIP3 models as part of the Third National Climate Assessment. Temperature data is available for the A2 and B1 scenarios defined by the IPCC. In order to derive the

exposure-outcome functions, comparable temperature metrics can be obtained from NOAA weather stations, or modeled data (North American Land Data Assimilation Systems, NLDAS) at the county scale that is also available on the [Environmental Public Health Tracking Network](#).

Baseline Disease Burden

A variety of health data have been used to assess the health risk from extreme heat, ranging from mortality to hospital admission, emergency room visits and emergency medical service calls.[119-121] Most often, daily health data is obtained for a specific city, Metropolitan Statistical Area (MSA) or county. The baseline prevalence of mortality data could be estimated using National Vital Statistics System, while prevalence of morbidity outcomes could be estimated using health records obtained from surveillance systems either at the state or local level.

Exposure-Outcome Response Function

The general approach to derive the health risk from extreme heat for specific locations is outlined.

- Retrospective health outcome data (e.g. daily mortality, cause-specific ED visit or hospitalization data) for specific counties or cities is merged with daily estimates of ambient temperature.

- In a time-series modeling framework, the Poisson generalized additive model (GAM) is used to derive exposure-outcome functions for the smallest spatial unit of analysis (county/city). In the second step, a Bayesian hierarchical modeling technique is used to combine the location-specific estimates to produce regional estimates.[122]

- A variant of this approach has been the case crossover methodology. For each health episode, temperature profiles at the time of each reported "case" is compared to another time when no ill health was reported to determine if the "case" could be attributed to differences in temperature.[123,124]

- Recent development of the distributed lag nonlinear modeling framework offers a flexible modeling approach to characterize the potential non-linear relationship between heat and health over a period of time.[125] The output from these models shows the different levels of health risk at different temperature values.

- These estimated exposure-response functions may vary (i) for specific demographic groups (e.g., age groups, sex); (ii) the kind of health outcome that is being modeled (mortality or morbidity for specific illness); and (iii) the suite of variables that are included in the model (e.g., air pollution, use of air-conditioning that can potentially affect the outcome).

Source Population

The exposure-outcome function will depend on a range of demographic (age distribution, socially isolated), health (access to healthcare, underlying comorbidities)

and socio-economic (income level) factors of the study population. Estimates of exposure-outcome functions for heat will be unreliable in situations where the number of health outcomes being analyzed is too few, particularly in areas with relatively small population. An alternative in these situations would be to obtain an exposure-response function for extreme heat from the literature that has been estimated for an analog region with similar weather patterns and demographic distribution.[126]

Project Disease Burden

The three basic elements required to project the health burden related to future increase in extreme heat are – (i) the baseline risk of the health outcome in the population (M), (ii) the estimated exposure response function describing how the health risk would change over a range of exposures (R), and (iii) projections from climate models as to how the exposure would change in the future (ΔT). Examples of such projections are available both for mortality[126,127] and morbidity outcomes.[128] An example of combining these elements is outlined as:[128]

Excess health outcomes from projected heat = M * R * ΔT

Perform Uncertainty Analysis

Because health data is commonly available only at the county scale, all individuals in a county are assumed to be equally exposed to the temperature measured at the weather station located within the county or somewhere nearby. This often masks the high variability in the spatial distribution of temperature and health risk from extreme heat reported in metropolitan areas. For example, a study in Phoenix showed a large reduction in surface temperature for vegetated surfaces compared to bare surfaces, and that more affluent communities lived in areas with more vegetation.[129] Thus in situations where a combination of higher ambient heat among low socio-economic status (SES) communities could actually lead to high localized health risk in certain areas, aggregating data up to the county and estimating the exposure response function at the county scale could be imprecise. However, the availability of data often limits the choices available for analyses at the fine spatial scales appropriate to capture such spatial variability in health risk.

Example 2: Waterborne Disease (Cryptosporidium)

Climate change is expected to affect waterborne disease in several ways, including impacts on water quantity via precipitation shifts and changes in the timing of snowmelt, impacts on water quality via shifts in precipitation intensity and temperature, and impacts on waterborne pathogen ecology via shifting water temperature.[1,130,131] According to the third National Climate Assessment, drought-like conditions due to high temperatures and severe precipitation events are projected to affect many parts of the US.[132] These changes could increase the potential for waterborne outbreaks.[133-135] Among many potential diseases linked to changes in water quality, this example outlines a framework to quantitatively assess the link between climate change and Cryptosporidiosis.

Causal Pathway
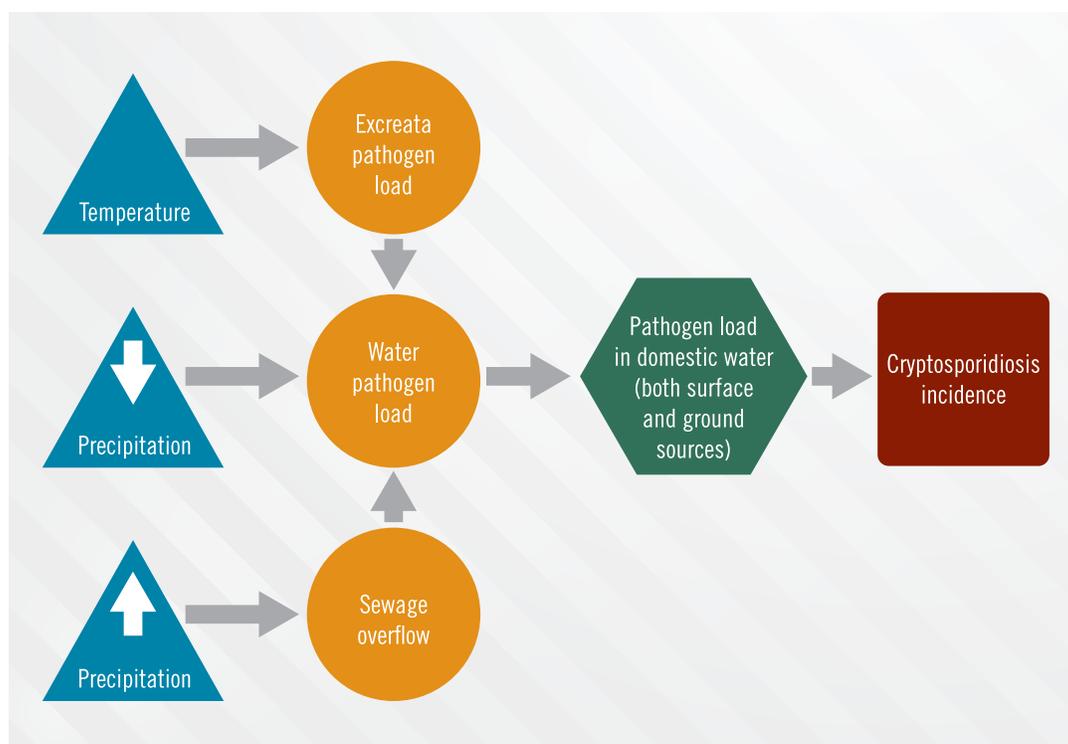
Figure 10. Example causal pathway diagram for Cryptosporidiosis.

Cryptosporidiosis (commonly known as "crypto") is a diarrheal disease caused by parasites, *Cryptosporidium*, that can live in human or animal hosts and are transmitted through infected stools. One of the most common causes of human waterborne disease,[136] crypto caused the largest waterborne disease outbreak in US history.[137] In healthy people it causes nausea, vomiting, cramps, and diarrhea that lasts 1-2 weeks; the infection can be fatal among the immunocompromised. Increased rainfall is associated with crypto outbreaks, particularly in moist tropical locations, whereas temperature is a stronger driver of crypto incidence in temperate regions.[138] Prolonged dry periods often lead to high concentration of the pathogen in surface and groundwater sources[139] and subsequent periods of intense rainfall can increase pathogen loads in drinking and recreational water sources, increasing human

exposure.[140] Proximity to intensive livestock management systems have also been associated with increased disease incidence among humans.[141]

Assemble Data Elements

Depending on the approach taken, several different data elements might be required to model this proposed relationship.

Climate Data

Since *Cryptosporidium* transmission is influenced by temperature and precipitation, the climate models will provide projections for both variables. Compared to temperature, precipitation projections contain much more uncertainty. Specifically, convective summer season precipitation is particularly difficult to model. The preceding extreme heat example discussed using GCM from the Environmental Public Health Tracking Network. For illustration, we briefly discuss accessing statistically downscaled climate projections. The process of statistical downscaling standardizes projections from each model and provides more localized information. The U.S. Geological Survey Geo Data Portal provides access to existing collections of climate projections. Users can select a study area by uploading a geographic file (shapefile) of political boundaries or interactively drawing a study area. For example, the CMIP5 Bias Corrected Constructed Analogs V2 provides both historical daily and future temperature and precipitation projections.

Baseline Disease Burden

In the U.S., clinically diagnosed human *Cryptsporidium* cases must be reported to a local health department (Nationally Notifiable Disease). In turn, the CDC compiles state level information into case counts that are published in the Morbidity and Mortality Weekly Report. Project Tycho provides public access to weekly notifiable disease counts from 2006 to 2014.[142]

Exposure-Outcome Response Function

There are three sources of exposure-outcomes association. The function(s) can be locally derived, pulled from the literature, or mathematically modeled.

1. Deriving local functions requires historic weather and health outcome surveillance information. Individual level risk factors (e.g. immune status) would be beneficial but are not required. The historical daily observations are aggregated (averaged or summed) across the state and over each week. The weekly weather and human weekly reported *Cryptosporidium* counts are aligned for statistical analysis.

   A time-series analysis can be used to associate weather against weekly *Cryptosporidium* counts.[143] Sensitivity testing determines the best fitting temporal lag between weather and human cases. The temporal lag may reflect the pathogen's transportation time, incubation period, or the time between the patient reporting symptoms and seeking healthcare.[144]

A similar suite of time series statistical models used in the extreme heat example can also be applied to waterborne disease modeling. The weekly *Cryptosporidium* counts are commonly modeled with a Poisson or Negative Binomial distribution. Water quality measures may also be used as a proxy of waterborne disease risk.[145] However, there are inconsistent relationships between turbidity and health outcomes.

In addition to case reports, case crossover study designs have been applied to waterborne disease. This methodology is well suited for relatively rare and acute events. In England and Canada, extreme rainfall events increased the odds of a reported waterborne disease outbreak.[146,147] However, in England, multi-week dry periods also increased the chances of an outbreak.[147]

2. If functions are to be derived from the literature, the analyst will need to conduct a comprehensive literature review as discussed above. As of this writing, one meta-analysis of the association between weather variables and crypto infections has been performed.[138] These analysts used locally-derived z-scores of monthly temperature and precipitation as the exposure variables and monthly counts of crypto infection incidence among healthy individuals as the outcome and stratified their analysis based on climate region and distance from the equator. There is thus some ability in this case to choose a response function that is representative of the climate region for which the projection is being done.

3. A third alternative is to use a tool linking exposure with health outcomes. Such tools are not available for all climate-sensitive health outcomes, but for waterborne and foodborne disease, the Quantitative Microbial Risk Assessment tool, developed by the European Centers for Disease Control (ECDC) and one of several QMRA apps, provides a decision support framework to assess disease risk from climate change. The tool uses the following sequence of steps to take users through the assessment:

    ■ Identification of the potential risk and exposure pathway

    ■ Assess the potential individual exposure to the pathogen

    ■ Obtain a dose-response function liking pathogen exposure to health outcome, either from literature or from data analysis depending on availability

    ■ Combine the estimated exposure from the exposure assessment with the dose-response to characterize the risk of infection.

A series of modules with underlying mathematical equations representing pathogen processes are combined with user provided parameter values to produce a comparative risk assessment of infection risk under different climate scenarios.

A user of the QMRA tool can input temperature and precipitation values to characterize current and future climate conditions. There are three different transmission types of *Cryptosporidium* that can be modeled using the tool—drinking water, bathing water and oyster consumption. The pathways driving individual

exposure to the pathogen can be described using a combination of different modules—combined sewer overflow, surface run-off of water, drinking water treatment, volume of ingested water, and temperature dependent inactivation/die-off of pathogen. Each of these modules is based on a series of mathematical equations describing the process that affects the transmission of the pathogen. Users with local knowledge can alter the preset parameter values in these modules for customization. The dose response function for *Cryptosporidium* is preset based on a review of the literature. Once these inputs are provided, the model outputs a relative risk estimate that indicates if the risk of infection is higher or lower after the projected climate change compared to the current conditions.

Source Population

Important at-risk groups include children, the elderly, pregnant women, people with co-morbidities, and the immunocompromised.[148] Similarly, communities that access private wells or minimally treated ground water may face increased risk during extreme weather events.[149,150] Combined sewer overflow events increased pediatric gastrointestinal illness rates in Milwaukee, WI.[151]

Project Disease Burden

The outputs from the QMRA tool provide an estimate of the relative risk of the waterborne disease under the specified climate scenario compared to a current baseline. If dose-response functions can be derived for specific health endpoints and weather variables, then the damage function approach outlined before could be adapted to estimate the changes in the health outcome being examined.

Perform Uncertainty Analysis

Baseline disease burden estimates including prevalence and incidence estimates will be required. Such an analysis will determine the relationships between the exposure variables with all-other-factors held constant, including lag structures, which may be important when considering increased precipitation after periods of drought.

Projecting Climate-Related Disease Burden
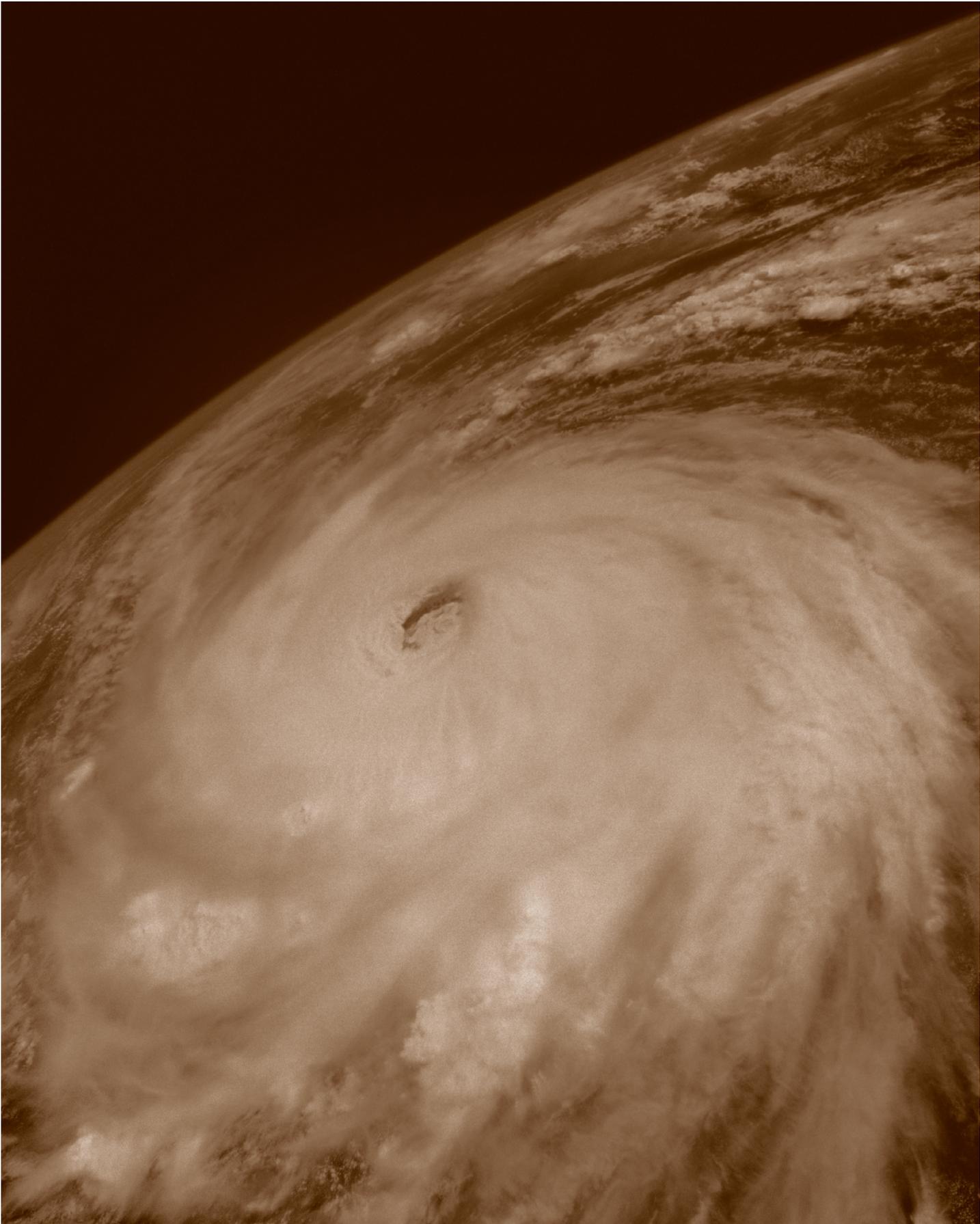
Glossary

α **(alpha):** A symbol often used in the damage function approach to denote the parameter estimate linking exposure with the relative risk of a given health outcome in a linear exposure-response function. α represents the slope of the line linking the risk of a given health outcome at a given exposure (nonlinear exposure-response functions are represented using different equations). Mathematically, α is the natural logarithm of the regression coefficient in a regression model. See the box on the damage approach function for more information on the mathematical expressions and relationships.

Adaptive Management: An iterative or cyclic process meant to facilitate management of complex adaptive systems through the use of models, stakeholder engagement, and continuous integration of new information about the system and its response to management activities.

BRACE—Building Resilience Against Climate Effects: An iterative framework developed by the CDC Climate and Health Program for public health organizations enhancing climate readiness. The framework outlines steps in the process of identifying and estimating possible climate change health impacts in a given location and determining which public health interventions might reduce adverse impacts.

Climate Change Adaptation: The process of making adjustments to reduce climate change impacts or take advantage of anticipated changes. It can be active, i.e., planned explicitly in anticipation of pending change, or passive, i.e., in response to perceived changes and without explicit planning.

Climate Change Disease Burden Projections: Scenario-based estimates of future health impacts associated with changing environmental exposures associated with climate change. Climate change disease burden projections are a variant of disease burden assessment that focus on the potential effects of a changing climate. They are derived using scenario-based projections of climate change impacts (derived from global climate models and used as part of the exposure) and linked, via exposure-outcome functions, to health impacts known to be sensitive to environmental conditions.

Disease Burden Assessment: The National Research Council defines disease burden assessment as "a systematic process that uses an array of data sources and analytic methods, and considers input from stakeholders to determine the potential effects of a proposed policy, plan, program, or project on the health of a population and the distribution of those effects within the population. HIA provides recommendations on monitoring and managing those effects."[152]

Global Climate Models (GCMs): GCMs are complex computer models of the Earth's atmosphere and underlying surfaces, including ocean, land, and ice. They are used to describe, analyze, and project the behavior of the climate system. There are several GCMs housed in different research centers globally, and each GCM is slightly different in its treatment of important atmospheric and other dynamics. Using scenarios of greenhouse gas emissions and other forcings, GCMs simulate future climate states. The data from these simulations are used as exposures in climate change disease burden projections.

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