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CLIMATE INFORMATION FOR ADAPTATION

From years to decades

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> The blessed gods
> Purge all infection from our air while you
> Do climate here!
>
> The Winter's Tale *by William Shakespeare*

9.1 Introduction

Climate change was likened to the fifth horseman of the apocalypse by Margaret Chan in November 2007 in the first speech on the subject by a World Health Organization (WHO) Director. The following May, health protection from climate change was identified as the priority issue of concern at the 2008 World Health Assembly through a resolution ratified by its 193 member states.[1] The threat that a changing climate poses to global health was starkly elaborated by the 2009 Lancet Commission on 'Managing the Health Effects of Climate Change'.[2] While direct effects of climate change on the health of vulnerable populations, e.g., from heat waves, were a major concern the indirect impact of climate change on water, food security and extreme climate events was considered to pose a greater health threat.

Managing the effects of climate change on human health will require inputs from all sectors of government and civil society, as well as collaboration between many academic, governmental, private sector and community organizations. Effective management must be informed by the best available science and, in part, this requires the use of long-term projections of the climate over the coming century. Long-term projections are particularly important for the development of policies to *mitigate* climate change through reductions in carbon emissions. These reductions have measurable health co-benefits. Long-term projections can help quantify the extent to which these co-benefits can compensate for the mitigation cost of achieving the targets of the Paris climate agreement.[3]

Weather and climate vary on multiple timescales (§§ 3.2 and §§ 5.3), and climate information (historical, current or future) must target the specific time and space scales of the decisions being made. Observed climate is the result of the interaction of natural climate variability and the anthropogenic climate-change signal associated with increasing greenhouse gas emissions (§ 5.4.2). Today's climate is dominated by natural variability, but the climate-change signal is already emerging and is expected to strengthen as concentrations of greenhouse gases in the atmosphere increase. However, gradual, long-term trends in climate are not the means by which people will experience most aspects of climate change. Instead, impacts will be felt primarily through changes in the weather (including extreme events like heat and cold waves and extreme rainfall), the seasons and potentially through alterations to longer-term components of climate variability, such as the El Niño – Southern Oscillation (see Box 5.1). The predictability of all these different timescales varies by location and period under consideration (see Chapters 7 and 8).

In writing this book, we have prioritized shorter timescales of weather and climate variability because these have most direct relevance to the types of operational and planning decisions made in the health sector. However, in this chapter, we focus on longer-term health decisions that require climate knowledge and information at timescales beyond a year to multiple decades (up to 50 years). This time span incorporates both natural decadal variability and the influences of anthropogenic climate change. It is an extremely challenging timeframe at which to work because of the very limited operational predictive skill at multi-annual timescales, and limited confidence about how rainfall may change on longer timescales. Despite these challenges, the timescales under consideration, especially the next five to 20 years, are particularly important when considering how to *adapt* to climate change. Here we discuss what we do and do not know about the climate in the coming years. We then focus on the practical use of climate information in understanding observed climate impacts on health as well as the prediction of multi-annual to multi-decadal risks. The multi-annual timescale is often referred to as 'decadal', even though the forecasts are for periods less than a decade.

9.2 How increasing concentrations of CO_2 can impact health

Instead of presenting a comprehensive overview of the causes and consequences of anthropogenic climate change (see Box 9.1 for a brief history of the science), we illustrate some of the ways by which health is affected by focusing on one of the main greenhouse gases of concern, namely CO_2. The steady increase of CO_2 in our atmosphere, associated with burning fossil fuels, deforestation and agricultural practices, is routinely observed.[4] Its impact on the environmental determinants of health manifests through a number of pathways (Figure 9.1). We now explore how CO_2 in the atmosphere and oceans ultimately impact the three health concerns we have focused on throughout this book, namely the health impacts of disasters, infectious diseases and nutrition.

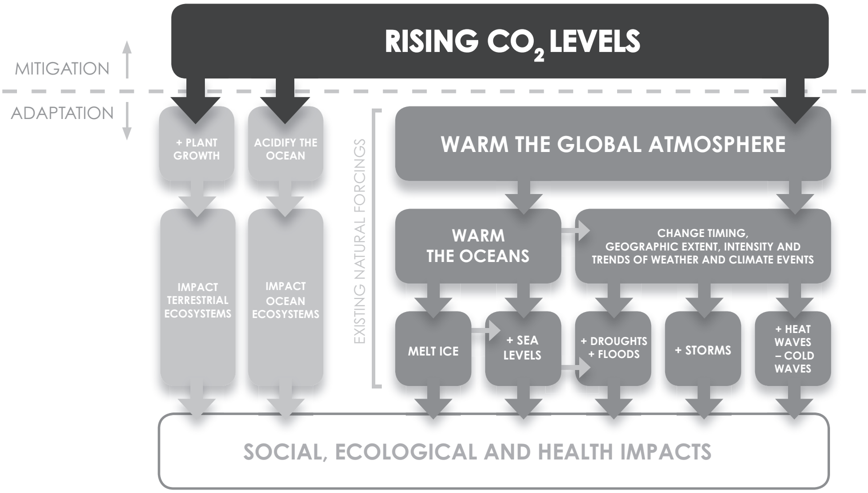

FIGURE 9.1 Impact pathways of rising CO_2 on social, ecological and health outcomes. Pathways include plant fertilization, ocean acidification and a warming atmosphere. The latter has a direct and indirect (via oceanic warming) impact on our climate. Both atmospheric and ocean warming impact on sea levels through thermal expansion of the seas, destabilization of coastal land ice, and melting of land ice and snow.

BOX 9.1 A BRIEF HISTORY OF THE SCIENCE OF GLOBAL WARMING

The origins of the science of global warming

The physical basis for what we now call climate change was established in the 19th century. As early as 1861, the physicist John Tyndall[5] provided empirical evidence of the critical role of greenhouse gases (including CO_2) in maintaining Earth's temperature.[6] His findings demonstrated the importance of CO_2 and water vapour in trapping heat in Earth's climate system (see Chapter 4). He established the physical basis for the first prediction of the magnitude of expected global warming as a result of increasing CO_2 levels, made by Svante Arrhenius in 1896.[7]

Thus, climate-change science is based on the physical laws of properties of gases in the air – laws which have been known for well over 100 years. Evidence of these expected changes are increasingly being observed through extensive analyses not only of climate, but also of environmental and impact data from around the world.[8]

Mauna Loa carbon dioxide monitoring

In 1958, Charles Keeling began collecting data on CO_2 in the air at the Mauna Loa Observatory, in Hawaii, and on Antarctica.[9] The Antarctica site was discontinued because of lack of funding, but the site at Mauna Loa has been operating continuously to this day. The data from Mauna Loa constitute the oldest continuous record of atmospheric CO_2. This record is known as the Keeling Curve, and indicates an increase in CO_2 concentrations from 315 ppmv in 1958 to 407 ppmv in 2017. Keeling's data provided the first significant evidence that concentrations of CO_2 in the air were increasing. Subsequent measurements of CO_2 trapped in air bubbles in ice cores indicate that CO_2 concentrations prior to the industrial era were around 275–285 ppmv. The increase in CO_2 since the pre-industrial era is therefore about 45%.

Intergovernmental Panel on Climate Change (IPCC)

In 1988, the Intergovernmental Panel on Climate Change (IPCC) was formed 'to provide policymakers with regular assessments of the scientific basis of climate change, its impacts and future risks, and options for adaptation and mitigation'.[i] The primary outputs of the IPCC are Assessment Reports, in which available literature and published analyses documenting the state of climate change and its impacts are reviewed. These Assessment Reports are updated approximately every five to seven years. Additional special reports and supporting documents provide further information. Since its First Assessment Report in 1990, the IPCC has involved thousands of scientists around the world in pushing forward the frontiers of climate science, estimating the economic costs and benefits of mitigation and, in the Fourth Assessment and subsequent reports, identifying needs and opportunities for adaptation.

9.2.1 Hydro-meteorological disasters

During 26–28 August 2017, Hurricane Harvey poured over a trillion gallons of water over Texas, causing unprecedented floods. The rainfall directly impacted millions of people whose lives and livelihoods were put at risk. The capacity of the weather services to predict the development and movement of the storm (see § 7.5.3), thus forewarning the population and emergency response teams, came about because of massive investments in computational capacity for weather modelling in Europe and the USA. The disastrous 2017 hurricane season for the Caribbean and USA raises a critical question: are tropical cyclones becoming more extreme and is this a consequence of climate change?

It remains unclear whether observed changes in tropical cyclone activity have exceeded natural variability to date, in part because of strong decadal variability in activity, at least in the North Atlantic.[10] Tropical cyclones are driven by energy from the warmth of the sea-surface (see § 4.2.8). Evidence from modelling and theory indicates that tropical cyclones will become stronger, larger and more destructive in the future as the oceans warm in response to increasing atmospheric temperatures.[11] However, other factors are involved in hurricane and typhoon occurrence, and there is substantial variation among projections of how the frequency of such storms may change in the future. Modelling studies suggest that the global average frequency of tropical cyclones may decrease, but the most intense cyclones could become more frequent.[12] For example, although higher concentrations of CO_2 are expected to increase peak hurricane intensity during future La Niña years in the Atlantic, changes of wind patterns in the same ocean could suppress hurricane activity during El Niño events.[13]

9.2.2 Infectious diseases

Trends in average climate (particularly temperature) as well as changes in extreme weather events and seasonality resulting from increasing greenhouse gas concentrations have already been detected. However, because of the paucity of both historical climate and health data over decadal and longer timescales (i.e., > 30 years), evidence showing how observed climate-change trends have influenced disease transmission at a local level is rare. The scarcity of historical health data from developing countries has meant that a few datasets are used repeatedly in a large number of studies. These include malaria data from Kericho, Kenya[14–18] and cholera data from the International Center for Diarrhoeal Disease Research (ICDDR), Bangladesh.[19–21] A detailed database has been developed for Zimbabwe, in which daily meteorological information is matched with 60 years of data on disease vectors (see Case Study 9.1).

CASE STUDY 9.1 TSETSE – CHANGES IN CLIMATE IN THE ZAMBEZI VALLEY: IMPACT ON TSETSE FLIES

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Rekomitjie Research Station (16°8'S, 29°25'E, altitude 503 m), in the Zambezi Valley of Zimbabwe, was founded in 1959 for studies of the ecology and behaviour of tsetse flies, which are the vectors of the trypanosomes that cause the diseases of sleeping sickness in humans and nagana in livestock. The location was chosen because the two species of tsetse present, namely *Glossina pallidipes* and *G. morsitans morsitans*, could be caught in numbers large enough to facilitate investigations.[22] Moreover, since the station is in the Mana Pools National Park, which was designated a United Nations Educational, Scientific and Cultural Organization (UNESCO) World Heritage Site in 1984, the area has been largely free of anthropogenic changes to woodland cover and tsetse hosts, leading to the expectation that large catches of tsetse would be maintained indefinitely. However, in the 1990s the annual average catches began to show a net downward trend,[23] and in the last five years the abundances of *G, pallidipes* and *G. m. morsitans* have been the lowest on record, at only 1% and 5%, respectively, of the levels recorded in the 1960s (Vale, pers. comm.). Climate change is suspected of being the main cause of this population decline.

Daily meteorological records taken at the station show no material change in rainfall in the last 57 years, but annual average minimum and maximum temperatures have increased by 1.81 °C and 1.08 °C, respectively (Figure 9.2).[24] Most of the rise in minimum temperature has occurred in the dry months of May to November. Changes in maximum temperature have taken place during the hot dry season of September to November (Figure 9.2), when the maximum temperature is at least 32 °C on most days and can occasionally exceed 40 °C. The greatest increase in temperatures was in November, at the end of the hot dry season, when daily minima and maxima rose by 2.62 °C and 2.44 °C, respectively. The increase in temperatures during the hottest months was not due simply to an increase in the temperature of unusually hot days, with maxima up to 44 °C, but due also to a greater frequency of such days. An appreciation of the details of these temperature variations is essential for understanding the impact of climate change on the dynamics of tsetse populations. The hot dry season is commonly a period in which tsetse abundance declines by around 60–80%, with reductions of > 90% if the season is especially hot,[23,25] due largely to the direct physiological effects of high temperature, which raise the death rate of the flies much more than they enhance the birth rate.[26] The problem is especially severe with the immature flies, i.e., pupae and very young adults. Moreover, high temperatures are associated with increased rates of parasitism and predation of pupae.[26] The upshot is that breeding becomes progressively less successful as daily maximum temperatures rise above 35 °C. As a result, at the end of the hot dry season there is a marked paucity of young flies in the adult population.[26] The reduction in tsetse abundance during the hot dry season is potentially significant since tsetse can breed only slowly,[26] even in the favourable weather of cooler months, so limiting the ability of population numbers to recover after a knock-back.

The salient point is that the greatest increases in temperature have occurred at the end of the hot dry season – the very time when tsetse populations are most vulnerable to a greater intensity and duration of heat stress.

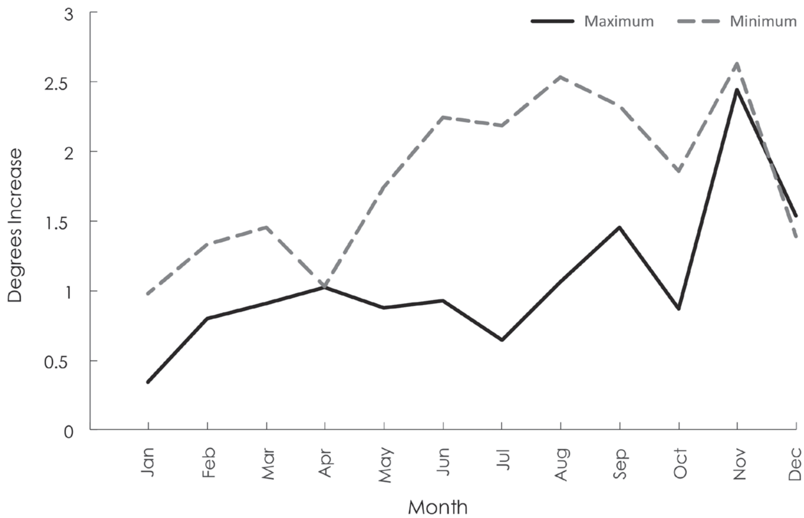

FIGURE 9.2 Increase in the average minimum and maximum temperatures of each calendar month, from 1960 to 2016, at Rekomitjie Research Station in Zimbabwe. Data from linear regression where the dependent variable was either the mean maximum or mean minimum, in the pertinent month of each year, and the independent variable was the year since 1960. The increases in the minima are significant ($P < 0.05$) for all months except April. For the maxima the increases are significant only for August, September and November.

Observational studies that use less than 30 years of data risk confusing long-term climate-change trends with natural decadal variations over ten to 30 year timescales (Box 9.2). The challenge that decadal climate variability poses to forecasting future long-term climate risks are elaborated in § 9.4.2. An example of the practical impact of decadal variability on decision-making is outlined in Case Study 9.2.

9.2.3 Nutrition

CO_2 is an important trace gas of the atmosphere and part of the natural carbon-cycle. It is the sole source of carbon for photosynthesis, by which it is converted to carbohydrates by plants, which are then use as food or fibre by all manner of creatures, including ourselves. Under normal conditions most plants are carbon-hungry and will readily convert additional atmospheric CO_2 to plant growth. The gas is often added to greenhouses to increase yields; a process called the 'fertilization

BOX 9.2 FILTERING THE CLIMATE SIGNAL BY TIMESCALES

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It may be useful, for planning or adaptation purposes, to understand the way in which the different components of observed climate variability combine to produce the resulting 'signal' that we experience. For example, if, in a particular region, rainfall variations tend to be dominated by year-to-year (*interannual*) variations while decadal-scale variability is relatively weak, attention can be focused on prediction of, and adaptation to, interannual swings. On the other hand, the presence of strong decadal variations may prompt research into attribution of its causes in an attempt to shed light on potential future variations, as well as adaptation measures that might be undertaken with those longer time-horizons in mind.

In order to facilitate our understanding of how observed variations may be thus decomposed by timescale, a Maproom was created in 2010,[27] accessible via the Data Library of the International Research Institute for Climate and Society (IRI). The decomposition process technically consists of a linear regression (a projection) of the original rainfall or temperature time series onto an anthropogenic climate-change signal, followed by successive filtering operations.[27,28] The resultant series comprises three components: a) a climate-change signal; b) decadal, or low-frequency variation; and c) interannual fluctuations. The first of these may be thought of as a 'drift' term, describing long-term variations linked to the anthropogenic climate-change signal. When this first component is subtracted from the original time series, the result is a new series that contains the rest of the timescales. This secondary series is then filtered using a particular window (size of the filter), yielding the 'decadal' component. Subtracting this component in turn yields the high-frequency, or interannual, component of the original series.

This approach was used during the 2014–2016 Zika epidemic to contextualize the role of climate. Contrary to what was being assumed at the time, a combination of signals involving El Niño, climate change and other climate drivers were responsible for setting suitable conditions for the transmission of Zika, with implications for disease response measures.[29]

effect'. One might argue, as some do, that there are positive food-security benefits from human-induced increases in atmospheric CO_2. While enhanced crop yields for C3 plants, such as rice, wheat, barley and soya bean, are a potentially positive outcome of increased atmospheric CO_2, the actual impact is highly dependent on changes in temperature and rainfall that will occur alongside CO_2 increases.

CASE STUDY 9.2 THE EAST AFRICAN PARADOX

Bradfield Lyon, University of Maine, USA, Madeleine C. Thomson, IRI, Columbia University, New York, USA

Over roughly the past two decades East Africa has experienced an increasing frequency of drought, particularly during the 'long rains' season, which typically runs from March to May. This increasing frequency of drought is linked to an overall downward trend in East African rainfall that has been underway since the 1980s. Some climate scientists have argued that this drying trend is associated with an upward trend in sea-surface temperature, especially in the tropical Indian Ocean.[30] In simplest terms, the argument is that higher ocean temperatures lead to increased rainfall over the ocean that ultimately robs East Africa of its moisture and rain. Meanwhile, climate-change projections suggest that the climate of East Africa will become wetter, not drier, by the end of the current century.[31]

This situation presents an apparent contradiction, with observations over recent decades indicating more frequent drought conditions while long-term climate projections suggest that the region will in fact become wetter. This 'East Africa Paradox' highlights two important factors for assessing climate-change impacts: considering climate variability on multiple timescales, and understanding the strengths and limitations of climate-change projections. Rather than a gradual decline in rainfall since the 1980s, the long rains of East Africa have instead undergone an abrupt decline that occurred around 1998–1999.[32] At the same time, similarly abrupt changes in sea-surface temperatures, mainly in the tropical Pacific Ocean, were observed (Figure 9.3). Such a decadal shift does not preclude a longer-term wetting trend as indicated by the IPCC,[31] but highlights the importance of distinguishing between the two timescales, as adaptation plans developed for a wetter future could leave the region more vulnerable to drought in the shorter term.

The inability of coupled models to capture key physical drivers of East African climate, particularly conditions in the tropical Pacific and Indian oceans, undermines confidence in the future climate projections of the region. Anthropogenic climate change could thus potentially contribute to drying rather than wetting. When these issues were presented to the executive board of Roll Back Malaria in a workshop in Tanzania in 2014, the group of experts recommended that attention be paid by the malaria community to the risks associated with a return of higher rains in the region in the medium term. In addition to the possible public health impacts, such a change could impact perceptions of the success of malaria programs and pose a risk to donor confidence.

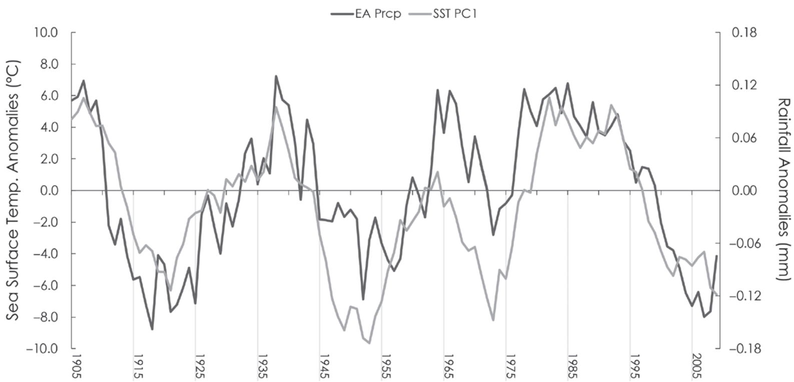

FIGURE 9.3 Sea-surface temperature anomalies and March–May (MAM) rainfall anomalies in Eastern Africa. Time series of the leading sea-surface temperature mode (anomalies in °C, see left scale) and the de-trended East African rainfall anomaly (mm/month, right scale) for MAM. A nine-year moving average has been applied to both series (1905–2008). Adapted from Lyon (2014) and extended in time

Besides, crops are not the only plants to be affected: there is a fertilization effect of CO_2 on poison ivy photosynthesis, and a shift toward a more allergenic form of urushiol.[33] The fertilization effect may also have negative consequences for human nutrition as it has been associated with a 5–10% reduction in micronutrients such as iron and zinc and lower protein content of food staples.[34]

The warming from the enhanced greenhouse effect has a direct impact on the climate system and is the primary cause of sea-level rise (Figure 9.1). Global sea levels have been increasing at the rate of about 15 mm per decade (primarily measured using tide stations and satellite laser altimeters). Because CO_2 remains in the atmosphere for a long time, this rise is expected to continue in the coming centuries even if global emissions are seriously curtailed. For now, the predominant cause of sea-level rise is due to the thermal expansion of the water in the oceans and the melting of ice sheets and glaciers on land. More than 10% of the world's population live in low-elevation coastal zones prone to floods from sea-level rise.[35] Many of these regions are already experiencing the impacts of climate change and are trying to prepare for worse to come. In particular, the impact of sea-level rise on Small Island Developing States (SIDS), which risk being inundated, has long been recognized.[36] Coastal flooding results in increased salinity of drinking water, decreased habitable and agricultural land area, disrupted fisheries and diminished food security.

Sea-level rise is not the only negative impact of increasing CO_2 on the sea: when CO_2 dissolves in seawater it makes the oceans more acidic. This decline in oceanic pH has a damaging effect on marine ecosystems and the food chains that rely on them. Ocean warming and acidification have the potential to impact the quality and quantity of seafood with follow-on effects for future food security and ecosystem stability.[37]

9.3 How climate-change projections are made

The starting point for generating climate-change projections is to set plausible socioeconomic story-lines for the coming century based on economic and population forecasts.[38] These trajectories are then translated into emissions scenarios with associated concentrations of greenhouse gases and aerosols. Finally, the effects on the global climate are modelled using general circulation models (GCMs; similar to those used for seasonal forecasting [§ 8.2.2]), which produce projections of future climate using the greenhouse gas and aerosol concentrations specified by these scenarios.[39] Probabilistic projections are generated for each scenario by running simulations using multiple models with different initial conditions (see Box 7.6).

The models used to predict weather and climate from days to decades ahead are similar, but the complexity of physical processes and the components of the Earth system that must be included in the models increases with lead-time. For example, seasonal forecast models must have some representation of the ocean as it is the sea-surface temperatures that are most important for predictions on this timescale, whereas some numerical weather prediction models do not consider changing surface conditions (see Table 5.1 and § 5.4). The models used for climate-change projections must include full ocean models, since the circulation of the deep ocean is a crucial component of longer-term climate change. Just as for the models used in both weather and seasonal forecasting, the models used for climate-change projections involve simplifications (*parameterizations* – § 7.4.4). Because of the need for these parameterizations, features such as clouds, radiation processes, carbon chemistry and small-scale weather features, such as thunderstorms, local rainfall and flooding are not explicitly simulated, and so global climate models should not be used to directly infer information about local climate.[40]

9.3.1 Downscaling

Information is often required at smaller spatial and temporal scales than can be provided by global models, to assist with local, national or regional decision-making. Output from GCMs can be 'downscaled' dynamically (using a limited area regional climate model, RCM) or statistically (using statistical relationships determined from historical observations). Dynamical high resolution RCMs (such as the PRECIS model developed by the UK Met Office, or the WRF model developed by the National Center for Atmospheric Research) take the large-scale climate fields provided by the global models as boundary conditions and use the same fundamental laws of physics to simulate the climate on a grid of (approximately) 1–50 km^2. Regional models are commonly used to develop projections of the future climate at the national level. In statistical downscaling, which is less resource intensive, quantitative relationships are developed between local climate variables (e.g., near-surface air temperature and rainfall) and large-scale predictors (such as pressure fields). These statistical functions are then applied to the output of GCMs to simulate the future climate at a higher resolution. The post-processing steps of weather and seasonal forecasting are equivalent to statistical downscaling (§§ 7.4.5 and 8.2.2). The two approaches have different advantages and disadvantages (see Table 9.1).

TABLE 9.1 The main advantages and disadvantages of downscaling using statistical methods or regional climate models (RCMs)

Statistical downscaling	*Dynamical downscaling (RCMs)*
Main advantages: • Requires fewer computational resources • A wide variety of methods can be used • Bias correction is an integral part of the process	**Main advantages:** • Within the RCM domain, individual variables and inter-variable dependencies are physically consistent in time and space • The same fundamental physical laws are used in both an RCM and a GCM • RCMs do not assume stationarity in the climate system except for sub-grid parameterizations • No specific calibration data are required (though evaluation with observations is essential)
Main disadvantages: • Requires a long meteorological record • Any quality problems in the calibration data will be transferred to the downscaled data ('rubbish in, rubbish out') • The climate is changing, but this approach assumes that statistical relationships between large-scale predictors and local climate remain stationary • The higher the requirements regarding spatial, temporal and inter-variable consistency, the more complex and computationally demanding the statistical procedures become	**Main disadvantages:** • RCMs require substantial computational resources • RCMs have their own biases and errors, which compound the problems inherited from the parent GCM • Near the boundary of the RCM domain, spurious effects can occur

9.3.2 Multi-annual to multi-decadal prediction

It is often surprising to learn that climate experts are more confident in their predictions of the 30-year average climate towards the end of the century than the evolution of the climate over the next ten years. However, a similarly counter-intuitive increase in confidence with longer lead-times was noted when comparing seasonal forecasts with long-term weather forecasts (§ 8.2). Recall from Chapter 7 that the weather is unpredictable beyond about seven to ten days because of errors in the initial conditions. Nevertheless, the climate (defined here as the statistics of weather over a period of time; Box 4.1) can be predicted with some skill at a range of lead-times (see § 8.2). For longer-term climate prediction, it is the current state of the land surface and oceans, rather than more volatile atmospheric conditions, that provide a basis for prediction.

Multi-annual to multi-decadal prediction (two to thirty years ahead), is at the forefront of climate research because of the value of this timeframe for adaptation planning and the inherent forecasting challenges involved.[41] On this timescale, both natural interannual-to-decadal variability and long-term trends are important. Near-term climate change is a transition timeframe: these lead-times combine the difficulties of seasonal and long-term climate-change projections, as both initial conditions (primarily in the oceans and land surface) and externally forced trends play a role (see Table 9.2).

The Coupled Model Intercomparison Project (CMIP)[42] is a key activity in research on multi-annual to multi-decadal predictions. The Project started in 1995 as a means to compare climate models. It has emerged as a powerful resource to advance model development and scientific understanding of the Earth system through systematic comparisons of climate model outputs from multiple climate modelling centres. To meet its current objectives CMIP has developed well-defined protocols for climate model simulations. The most recent set of protocols, CMIP5, sets out to promote a standard set of model simulations in order to:

- evaluate how well the models reproduce the recent past.
- make available model projections of future climate change on two timescales, *near-term* (out to about 2035) and *long-term* (out to 2100 and beyond), and.
- improve understanding of differences in model projections.

The long-term CMIP5 (Coupled Model Intercomparison Project Phase 5) projections have been a key input to the WHO's Climate and Health Country Profile reports (Box 9.3).

There are important differences between the CMIP5 long-term projections developed for the IPCC, and the near-term predictions used in the experimental development of multi-annual forecasts (currently limited to two to nine-year lead-times; see Table 9.2). The near-term predictions require initialized runs (see §§ 7.4.3 and 8.2.2 on initialization) that start from current observations of the climate and predict how the system will evolve from there. The long-term projections

BOX 9.3 CLIMATE AND HEALTH COUNTRY PROFILES

The WHO has published a series of Climate and Health Country Profile reports[ii] which provide country-specific estimates of current and future climate hazards and the expected burden of climate change on human health. Country-specific, national level, time series plots of specific projections are provided up to the year 2100 for climate hazards using CMIP5 projections. A high-emissions 'business as usual' Representative Concentration Pathway 8.5 (RCP8.5) scenario is compared to projections under a 'two-degree' scenario with rapidly decreasing emissions following Representative Concentration Pathway 2.6 (RCP2.6). The profiles include several plots of future climate conditions: mean annual surface temperature, warm spell days, days with extreme rainfall and consecutive dry days. For some countries, cold spell days and warm nights are also presented. In addition, the profiles track current national policy responses and identify opportunities for health co-benefits from climate mitigation actions. While these figures do give some representation of uncertainty it is impossible to estimate how accurate these forecasts may be.

TABLE 9.2 Projections of near-term climate change (multi-annual to multi-decadal) with CMIP5

	Multi- decadal projections	*Multi-annual predictions*
Model simulations used	Uninitialized CMIP5 model projections for the IPCC	Interannual-to-decadal forecasts from the Decadal Climate Prediction Project initialized with current observations
Processes simulated	Anthropogenically-forced trend; natural decadal variability is simulated but its timing does not align with the real world	Anthropogenically-forced trend; natural decadal variability
Model run time-line	Centennial lead-times	2- to 9-year lead-times
Modelling approach	Multi-model ensemble (from CMIP5) for a variety of anthropogenic emissions scenarios	Multi-model ensemble (subset of CMIP5 models) initialized using current observations
What the models can tell you	Long-term trends and the statistics of climate over three or more decades, but cannot be used in forecasting individual decades	Trend and decadal variability; where skilful, they could be used in forecasting

are unitialized. These runs simulate natural variability, but; without initialization, these cycles are not in phase with the real world, so they cannot be used to forecast climate impacts at specific dates. Instead, they can be used to infer statistics about the climate over several decades (30 years or more). In both cases, a multi-model ensemble average (§ 7.6) is often calculated in an attempt to iron out model errors. However, in the case of the uninitialized projections, this average smoothes out the natural decadal variability simulated by each model, and therefore only captures the climate-change trend. The natural variability around this trend is an additional source of uncertainty in these projections and must be factored in if they are to be used effectively in decision-making.

An approach to incorporating climate change into long-term malaria planning that considers these uncertainties is illustrated here:

> *Climate-proofing the malaria eradication strategy should begin with an assessment of the vulnerabilities of existing plans to climate variability and change. Identifying and reducing these vulnerabilities will ensure that plans are robust to uncertainty by avoiding the more common approach of tailoring decisions to specific (and highly uncertain) projections of future climate change. Analyses of climate variability and change in specific areas and on relevant timescales can then be conducted* [Box 9.1]. *Confidence in future climate projections can only be assessed through thorough model evaluation, focused on understanding the timescales and locations for which models perform well and, conversely, where they fail. To place trust in future projections, it further needs to be demonstrated that when models do succeed, they do so for the right reasons, by capturing the appropriate physical processes and large-scale drivers of local impacts. Such assessments require bespoke analyses targeting specific regions and applications, and cannot be shortcut through a one-size-fits-all approach.*[43]

The example of the East Africa Paradox (Case Study 9.2) illustrates the pitfalls of an off-the-shelf method.

9.4 How accurate are multi-annual to multi-decadal forecasts?

9.4.1 Climate model errors

Climate models have been evaluated extensively; they can reproduce many of the most important aspects of the climate. The global warming trend observed over the last century, including an acceleration in warming since the mid-1900s, is well captured by most models. Many of the key spatial temperature patterns (Figure 5.1) and some important weather features like extratropical cyclones (§ 4.2.8) are also represented. However, systematic problems in temperature persist in some regions, and rainfall remains a significant modelling challenge and a major research priority, as models still fail to capture some key features of large-scale rainfall patterns.[44]

As we have seen throughout this book, the temporal variability of climate is crucial for anticipating and managing climate-sensitive health risks. The climate models can reproduce important features of sub-seasonal to year-to-year variability, particularly for temperature on large spatial scales. However, other features are poorly reproduced: for example, decadal variability in the Atlantic Ocean, which is important for climate prediction over the next 20–30 years.[44]

At the regional to sub-national scales of most interest to policy-makers, model performance is problematic. For example, the CMIP5 models reverse the observed relative intensities of Eastern Africa's two rainy seasons.[45] RCMs (see Section 9.3.1) are often used to add detail to coarse resolution GCM projections with the assumption that at least some of these global model biases are a result of regional-scale errors. However, these models inherit large-scale biases of the global model providing the boundary conditions, as well as adding their own assumptions and approximations with each step of processing. The Coordinated Regional Downscaling Experiment (CORDEX) has produced a wealth of downscaled climate-change projections that have been valuable for research purposes. However, it remains unclear how such experiments can be used in health applications because assessing confidence in regional model projections is even more challenging than for global models. High-resolution maps produced from these RCMs can give a misleading impression of high confidence in local climate-change impacts. These models and such products should not be used directly in decision-making without a thorough assessment of their strengths and weaknesses.

9.4.2 How accurate are the predictions?

In earlier chapters we discussed the importance of forecast skill (§§ 7.5 and 8.4) in understanding the utility of weather and climate information in decision-making. Skill can only be estimated given adequate samples of observations and historical or retrospective forecasts. For decadal and longer lead-times these data requirements are extensive, as the longer the lead-time of a prediction, the longer it takes to build up a sufficient sample to estimate the skill and reliability of the forecasts.

Currently, multi-annual (sometimes called 'decadal') prediction skill has only been assessed for lead-times of up to nine years.[46] Temperature forecasts at these lead-times have some skill when the forecasts are averaged over large regions, but not at the local levels desired for planning. Where the long-term temperature trends can be predicted with some skill, there is difficulty in predicting the natural variability around the trend.[41,47,48] In general, the temperature forecasts are best in regions where the externally forced trend is strong and there is minimal decadal variability about that trend.[46]

Skill for rainfall is marginal over most areas. Rainfall is more variable in both space and time than temperature (§ 5.2.5), and is less well simulated by climate models.[44] Although observed temperature trends are pronounced in most parts of the world, long-term trends in rainfall are, so far, undetectable above the background of year-to-year and decadal variability in most areas. In areas such as the Sahel, where there is significant decadal variability in rainfall, some of this variability may be predictable. At local scales, of most interest for societal impact, year-to-year fluctuations in rainfall can be substantial and rainfall projections are unlikely to be accurate.

Uncertainty in rainfall projections throughout the 21st century is dominated by this natural year-to-year and decadal variability and by climate model errors. For temperature, the importance of natural variability diminishes after a few decades, but model uncertainty causes substantial spread among longer-term projections. Divergence in anthropogenic emissions scenarios only becomes really important after several decades.[49,50]

The challenges of capturing decadal variability have significant implications for the development of long-term climate information services for the health sector. Planning cycles predominate at shorter timescales (see Chapter 3, Table 3.1), but even when longer-term information is desired it will likely be within the five to 20- or 30-year range when predicting the climate system is most difficult.

9.5 Conclusions

Changes in the patterns of weather and climate have already been observed and will become more pronounced as greenhouse gas concentrations in the atmosphere increase. Adaptation planning is therefore required to ensure that health systems are able to manage the impacts of the changing climate on public health.

Climate prediction on decadal and multi-decadal timescales has many challenges, particularly on the local and regional scales of most interest to policy and decision-makers. The cascading uncertainties of using outputs from such climate models to drive disease transmission models are significant impediments to developing robust predictions of specific diseases. However, the problems outlined in this chapter do not preclude any and all robust statements about the future impacts of climate change. Before using climate model outputs to assess future health impacts, it is essential to evaluate whether they are able to simulate the aspects of the climate system that are relevant to the particular health challenge being addressed. Where predictions are supported by physical understanding, and in cases where the observational record already shows evidence of local changes that corroborate predictions, we can place more confidence in those outcomes. As the impacts of climate change on the numerous pathways that influence disease transmission become detectable, a multidisciplinary approach to identifying vulnerabilities to climate change can be advanced.

Notes

i IPCC Fact Sheet: What is the IPCC? Available online at: www.ipcc.ch/news_and_events/docs/factsheets/FS_what_ipcc.pdf.

ii www.who.int/globalchange/resources/countries/en/.

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