

Review

A review of climate risk information for adaptation and development planning

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ABSTRACT: Although the use of climate scenarios for impact assessment has grown steadily since the 1990s, uptake of such information for adaptation is lagging by nearly a decade in terms of scientific output. Nonetheless, integration of climate risk information in development planning is now a priority for donor agencies because of the need to prepare for climate change impacts across different sectors and countries. This urgency stems from concerns that progress made against Millennium Development Goals (MDGs) could be threatened by anthropogenic climate change beyond 2015. Up to this time the human signal, though detectable and growing, will be a relatively small component of climate variability and change. This implies the need for a twin-track approach: on the one hand, vulnerability assessments of social and economic strategies for coping with present climate extremes and variability, and, on the other hand, development of climate forecast tools and scenarios to evaluate sector-specific, incremental changes in risk over the next few decades. This review starts by describing the climate outlook for the next couple of decades and the implications for adaptation assessments. We then review ways in which climate risk information is already being used in adaptation assessments and evaluate the strengths and weaknesses of three groups of techniques. Next we identify knowledge gaps and opportunities for improving the production and uptake of climate risk information for the 2020s. We assert that climate change scenarios can meet some, but not all, of the needs of adaptation planning. Even then, the choice of scenario technique must be matched to the intended application, taking into account local constraints of time, resources, human capacity and supporting infrastructure. We also show that much greater attention should be given to improving and critiquing models used for climate impact assessment, as standard practice. Finally, we highlight the over-arching need for the scientific community to provide more information and guidance on adapting to the risks of climate variability and change over nearer time horizons (i.e. the 2020s). Although the focus of the review is on information provision and uptake in developing regions, it is clear that many developed countries are facing the same challenges. Copyright © 2009 Royal Meteorological Society

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1. Introduction

Integration of climate risk information in adaptation planning is now a priority for donor and environmental agencies alike (DFID, 2005; World Bank, 2006; EEA, 2007; UNDP, 2007; WRI, 2007). Success will depend on improving access to high-quality meteorological data to characterize present climate variability; credible climate change scenarios at the spatial and temporal scales needed to support decision-making; technical capacity to undertake impact assessment, options appraisal and adaptation planning; institutional and sectoral structures in place

to deliver climate-proofed development programmes and projects; and the type of adaptation. Use of climate scenarios for impact assessment has grown steadily since the 1990s, yet scientific output on adaptation to climate change is trailing impact assessment by nearly a decade (Figure 1). Possible explanations might be that, to date, there has been much greater policy emphasis on climate mitigation than adaptation, or that a critical mass of impacts knowledge must accrue before scenario-led adaptation thinking can begin, or that there are fewer incentives for professionals to undertake the applied research needed for adaptation.

However, climatologists and policy-makers are now calling for a much more practical approach to the use of climate change scenarios – shifting the debate from high-level advocacy on ‘the need to act’, to regional- and

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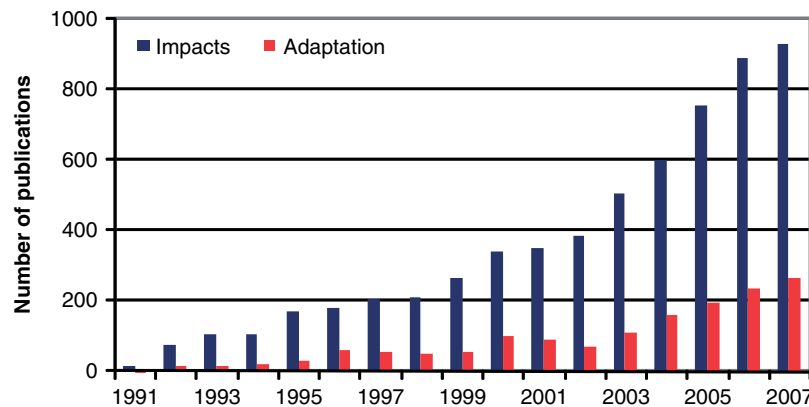


Figure 1. Annual number of climate change science publications with the words 'impact' or 'adaptation' in either the title or abstract. Source of data: Web of Science (accessed 8 December 2007). This figure is available in colour online at www.interscience.wiley.com/ijoc

country-level responses on 'how to' adapt (Schiermeier, 2007). However, the scope for mainstreaming scenario information in adaptation planning depends on the adaptation assessment approach, availability of technical and financial capacity, scale of the risk(s) and the type(s) of adaptation being considered (Adger *et al.*, 2005; Dessai *et al.*, 2005). Top-down (the so-called Intergovernmental Panel on Climate Change (IPCC)) approaches rely heavily on climate change scenarios, culminating in an evaluation of the adjustments needed to adapt to the projected scenarios. Conversely, portfolio-screening and human development approaches focus on reducing vulnerability to known climate variability and hence do not necessarily require climate change scenarios (but may deploy seasonal forecasting to provide early warning as in Dilley, 2000). Risk management frameworks lie somewhere in between because climate change scenarios are analysed, but with respect to critical impact thresholds defined by stakeholders.

The time-scale for adaptation activity is also an important consideration. Fears that climate change could undermine the United Nations Millennium Development Goals (MDGs), or that new investments could underperform (or even lead to maladaptation), mean that users of climate risk information are most interested in the next few decades. This poses huge technical problems because the global climate of coming decades will be dominated by natural variations from year-to-year and decade-to-decade arising from the chaotic nature of ocean-atmosphere (OA) interactions, changes in the output of the sun and the amount of aerosol injected into the stratosphere by explosive volcanic eruptions.

Uncertainty of the climate is magnified still further at continental and country scales, and the human signal, though detectable and growing, is a relatively small component of the change. However, the risk exposure of donor portfolios will be most immediate where human and environmental systems are already marginal (such as semi-arid regions, or coastal zones subject to frequent flooding). In these cases, even modest changes in the mean climate or to extremes could be sufficient to cross a threshold or tipping point. Furthermore, meteorological

changes could be amplified by nonlinear responses in secondary impacts.

This implies the need for a twin-track approach: on the one hand, the development of the scientific and economic capacity to identify critical thresholds, then better understand and adapt to climate variability (Washington *et al.*, 2006), and, on the other hand, the development of climate scenario tools and data sets that capture incremental changes in risk over the scales needed for adaptation planning. Although scenario methods will be the focus of the remainder of this review, it should be recognized that the two are related. Improved understanding of the causes of decadal climate variability should translate into improved predictability of regional climates and explanations for abrupt changes. For example, many studies highlight the role played by sea surface temperatures (SSTs) in forcing rainfall variability across Africa (Gianini *et al.*, 2003), India (Wang *et al.*, 2006) and Latin America (Nobre *et al.*, 2004). Hence, improved monitoring of the changing conditions of oceans should, in turn, lead to more accurate seasonal to decadal forecasts (see below).

This review considers sources of climate risk information for adapting infrastructure investments and economic planning to climate variability and change over the next couple of decades. To date, most technical guidance has tended to focus on climate scenarios for the end of the 21st century, using examples for developed regions (e.g. Carter, 2007; Mearns *et al.*, 2003; Wilby *et al.*, 2004), but this situation is beginning to change (e.g. Lu, 2006). We address the near-term climate information needs for Africa, Asia and Latin America. The following sections will: (1) describe climate forecasts for the next couple of decades; (2) review ways in which climate risk information is already being incorporated in adaptation assessments; (3) explain the factors affecting choice of climate scenario method; (4) describe the strengths and weaknesses of the available approaches (from the perspective of secondary impacts modelling); and (5) identify opportunities for improving production and uptake of climate change risk information for the 2020s (defined hereon as 2011–2040). For convenience, the scenario methods

are grouped by three levels of sophistication (low, modest and high). Although arbitrary, the categories broadly reflect increasing demands on technical, infrastructure and resource capacity.

2. The climate outlook for the next 20 years

Global Climate Models (GCMs) are powerful tools for representing the three-dimensional climate system using equations describing the movement of energy (first law of thermodynamics) and momentum (Newton's second law of motion), along with the conservation of mass (continuity equation) and water vapour (ideal gas law). Each equation is solved at discrete points on the entire surface of the Earth, at a fixed time interval (typically 10–30 min), and for separate layers in the atmosphere defined by a regular grid. For example, the UK Met Office Hadley Centre third generation OA/GCM (HadCM3) has an atmospheric model with a horizontal resolution of $2.5 \times 3.75^\circ$ and 19 vertical levels, and an ocean model with a horizontal resolution of $1.25 \times 1.25^\circ$ and 20 vertical levels.

GCMs compute radiative transfers through the atmosphere (involving water vapour and cloud interactions), the direct and indirect effects of aerosols (on radiation and precipitation), changes in snow cover and sea ice, the storage of heat in soils and oceans, surface fluxes of heat and moisture, and finally, the large-scale transport of heat and water by the atmosphere and ocean. Some GCMs incorporate land-surface schemes including the freezing and melting of soil moisture, and the regulation of evaporation by plant stomata due to variations in temperature, vapour pressure and CO₂ concentration (e.g. Betts *et al.*, 2007). More sophisticated models include carbon cycling and atmospheric chemistry for trace gases (e.g. CH₄, N₂O, CFC₁₁, CFC₁₂ and HCFC₂₂). However, representation of urban surfaces is seldom incorporated.

The computational burden of solving equations at thousands of grid-points means the horizontal resolution of GCMs is coarse, typically 100–400 km. Many components of the climate system have scales much finer than this (e.g. convective clouds, coastal breezes, urban landscapes) so must be parameterized. This involves simplifying the effect of small-scale processes on large-scale responses in all GCMs. The representation of clouds in GCMs is particularly challenging, not least because of their role in the energy balance and feedbacks arising from increased atmospheric moisture with global warming. As well as simplifying key processes through parameterization, GCMs also average conditions over the entire grid-box. For example, precipitation is assumed to occur at a uniform rate everywhere within the cell, leading to an overestimation of rainfall frequencies and underestimation of intensities compared with reality.

Despite variations in process representation, there is now remarkable agreement among different GCMs on the projected global mean temperatures for the next two or three decades (Zwiers, 2002; IPCC, 2007). The agreement stems from the fact that much of the warming in

coming years will reflect the climate's response to past emissions and the thermal inertia of the oceans. The consensus is also largely independent of the assumed emission scenario. Regardless of the GCM or Special Report on Emissions Scenarios (SRES) pathway, the change in global mean temperature is projected to be $\sim 0.2^\circ\text{C}/\text{decade}$, compared with $\sim 0.1^\circ\text{C}/\text{decade}$ if emissions are held at year 2000 levels (Table I). Furthermore, the projected global mean warming to 2030 is twice as large as model-estimated natural variability during the 20th century (Meehl *et al.*, 2007).

Natural climate variability over decades is closely connected to the behaviour of major ocean circulations in the Atlantic and Pacific. For example, the Atlantic Meridional Overturning Circulation (MOC) charts variations in the conveyance of warm surface water from the Caribbean to the North Atlantic that have been linked to a host of global climate shifts including drought in the Sahel, levels of hurricane activity and rainfall anomalies over Brazil (Baines and Folland, 2007). It is now recognized that a trend from a warm to a cool state could, in the short-term, counteract long-term anthropogenic warming. Indeed, a regional cooling has been predicted for Europe and North America over the next decade as a consequence of an expected weakening of the North Atlantic MOC (Keenlyside *et al.*, 2008). Such a cool downturn could pose a significant reputational risk to organizations that communicate or plan only for a warming scenario over the next few decades.

Despite improving understanding of decadal climate controls, there is less certainty about temperature forecasts for individual years over the next 10 years. On this time-scale, temperature forecasts are dominated by higher frequency climate variations and external forcing by natural and anthropogenic factors. Although changes in forcing by external factors such as solar irradiance and volcanic eruptions can have a substantial and lasting impact on the climate system (e.g. Gleckler *et al.*, 2006), their magnitude in the near-term is much harder to predict. However, multi-decadal climate variations are potentially predictable if the initial state of the ocean is known (Pielke, 1998; Keenlyside *et al.*, 2008).

Hence, the long-term 'memory' of ocean heat content is now being exploited in state-of-the-art decadal climate forecasts. According to the UK Met Office, the year 2014 is predicted to be $0.30^\circ \pm 0.21^\circ\text{C}$ warmer than 2004,

Table I. Global mean warming from the IPCC multi-model ensemble mean for three periods relative to 1980–1999 under A2, A1B and B1 SRES emissions scenarios.

Emissions	2011–2030	2046–2065	2080–2099
A2	0.64	1.65	3.13
A1B	0.69	1.75	2.65
B1	0.66	1.29	1.79
Commit	0.37	0.47	0.56

The 'Commit' row refers to the committed warming with emissions stabilized at year 2000. Source: IPCC (2007).

and at least half the years after 2009 are expected to be warmer than 1998, currently the warmest year on record (Smith *et al.*, 2007). However, global averages conceal significant regional variations in temperature anomalies and, despite significant technical advances in decadal forecasting capability, the products will remain of limited value to policy-makers and planners until skilful forecasts of regional climate anomalies become available. Even if perfect forecasts could be issued, it is currently unclear how this information might be assimilated by the development community.

Nonetheless, existing technology *could* help quantify changes in the *risk* of occurrence of certain types of extreme (such as severe heatwaves). For example, it has been estimated that emissions of atmospheric greenhouse gases to date have more than doubled the risk of a European heatwave exceeding that of summer 2003 (Stott *et al.*, 2004). However, formal detection and attribution of human influences in regional precipitation records will not be possible for decades because of the relatively small anthropogenic climate change signal in relation to large natural variability. The human climate signal will be even harder to discern at the water management scale of individual river basins (e.g. Ziegler *et al.*, 2005; Wilby *et al.*, 2008).

Given such uncertainty in regional-scale climate projections as well as small increments expected over the next 15–20 years, the question arises as to whether climate change will have a discernible impact, especially when compared with rapid human development changes (as witnessed, for example, in China and India)? Or put another way, how much climate change has to happen to be of *practical* significance (i.e. beyond what can be addressed by autonomous adaptation)? The answer(s) have a significant bearing on how climate risk information might be used for anticipatory adaptation – a point that is explored further in the next section.

3. Uses of climate risk information for adaptation planning

Several agencies have already undertaken portfolio-screening for climate risks, but less thought has been given to how different development pathways might affect vulnerability to climate change (Klein *et al.*, 2007). Nonetheless, climate information can be used to answer

a wide range of questions related to adaptation (see Table II, after Smit *et al.*, 2000). These activities are not mutually exclusive and often overlap. As will be shown, some methods are better placed than others to meet the specific needs of different adaptation assessments. There are also large disparities between techniques in terms of their respective technical capacity and resource requirements – factors that can narrow the choice still further.

Adaptations involving *new infrastructure* typically require data for a cost-function (such as annual flood damages) in relation to climate event magnitude. The function is adjusted upwards or downwards in line with anticipated changes in risk, or assumed adaptation measures, to assess long-term benefits of a scheme (e.g. Conway *et al.*, 2006). At the screening stage, coarse resolution climate data can help compare adaptation options, or determine whether a given scheme should proceed. At the design step, more detailed information on conditions (such as water-levels at a flood defence site, or reservoir inflows) are needed to assess structure performance throughout the intended life (e.g. Caspary and Katzenberger, 2006).

Natural *resource management* has been the subject of many climate change impact studies to date (see IPCC, 2007 or Warren *et al.*, 2006). Spatial scales of interest span from the crop yields of individual plots (Abraha and Savage, 2006), through the disproportionate contribution of mountain regions (Viviroli *et al.*, 2007) to the global water balance (Alcamo *et al.*, 2007). Time-scales vary from soil loss over a few hours through to the changing mass balance of glaciers over decades (Schneeberger *et al.*, 2003). The adaptation responses vary accordingly and may include integrated natural resource management plans, re-allocation of resources between users, and/or reduction of co-stressors on ecosystems.

Adjustment to natural hazards and measures to reduce exposure to extreme events are often compatible with adaptation to climate change, albeit at finer spatial and temporal scales. For example, climate information might be used to *retrofit* existing buildings to improve human comfort or reduce risks from excessive heat (Hacker *et al.*, (in press)). The scenario tool might also be required to incorporate local feedbacks, for example, between heat dissipation, city design and intensity of the urban heat island (Betts and Best, 2004). A key challenge for modelling extreme events is representing both the

Table II. Examples of adaptation activities that require climate risk information.

Adaptation	Examples of activity using climate information
New infrastructure	Cost–benefit analysis, infrastructure performance and design
Resource management	Assessment of natural resource availability, status and allocation
Retrofit	Scoping assessments to identify risks and reduce exposure to extreme events
Behavioural	Measures that optimize scheduling or performance of existing infrastructure
Institutional	Regulation, monitoring and reporting
Sectoral	Economic planning, sector restructuring, guidance and standards
Communication	Communicating risks to stakeholders, high-level advocacy and planning
Financial	Services to transfer risk, incentives and insurance

frequency and magnitude of phenomena that are, by definition, at the very margins of statistical distributions (Tebaldi *et al.*, 2006).

Other categories of adaptation involve non-structural *behavioural* measures. Here, climate risk information can be used operationally to optimize the performance of existing assets (such as reservoirs and irrigation systems) or to adjust scheduling of activities (such as cropping patterns or water releases for hydropower). In these cases, information on the changing temporal sequencing of weather events is of interest: for example, onset of the spring snowpack melt, limiting soil moistures or first/last frost dates (Payne *et al.*, 2004). This requires that the scenario method produces realistic daily sequences of weather.

Institutional and multi-sector-wide adjustments to climate change must account for changes in physical drivers as well as shifts in policy, regulatory and planning controls. Although country-level assessments based on macro-economic modelling may have relatively modest climate information needs, micro-economic studies require data at finer resolutions (*cf* Mendelsohn *et al.*, 2000). For example, fine resolution scenarios are needed when evaluating changes in competitive advantage between regions and cropping systems under different climate scenarios (e.g. Maksholo and Jooste, 2006). In this case, accurately resolving spatial patterns of climate change (because of variations in altitude, land cover, proximity to major water bodies, etc.) may be of particular importance (see Vuille and Bradley, 2000).

Climate information for *communicating* risks and raising awareness depends on the target stakeholder group(s) and their level of scientific understanding. Core scenarios help build capacity, benchmark impact studies and mainstream adaptation (McKenzie-Hedger *et al.*, 2006), but there is a danger that wider uncertainties are not recognized (for instance, over-reliance on a single climate model). Scenarios used for high-level advocacy or policy change may focus on a very specific aspect of climate change to achieve a shift in (funding) priorities. For example recognition of the need for greater investment in flood defences in the UK has followed a string of damaging flash-flooding episodes (see McKenzie-Hedger, 2005 or the Pitt Review, 2008).

The *financial* sector already relies on risk information (e.g. Rodwell and Doblas-Reyes, 2006; Mills, 2007). Insurance mechanisms that spread costs of adverse climatic conditions between regions require an accurate picture of expected patterns of risk. For example, maps of coincident drought and flooding (as shown by McCabe and Palecki, 2006) could be used to hedge losses of hydropower in one region with gains in another. Future scenario needs may be met by maps of global 'hot spots' (Giorgi, 2006). The World Bank and UN World Food Program favour the development of weather indices that trigger payouts in developing countries following weather disasters or collapses in commodity prices. If these indices are to promote activities that are compatible with projected climate changes then scenarios must

provide meaningful information on metrics such as cumulative rainfall totals or soil moisture deficits.

The above examples show that no single climate information source meets all needs of different adaptation activities. The following section sets out some criteria for comparing scenario methods, and is followed by an overview of the properties, strengths and weaknesses in each case. Again, it is assumed that the intended purpose is scenario-led, adaptation planning, and that the time horizon is the 2020s.

4. Criteria for evaluating scenario methods

Regional climate change projections have been reviewed at length elsewhere (see Christensen *et al.*, 2007). Although the comparison of different scenario methods has become a trade-mark activity for parts of the climate science community (Fowler and Wilby, 2007), there is no agreed set of diagnostics for appraising tools from the development planning point of view. However, there have been recent moves to bring together and better coordinate groups interested in climate adaptation tools, recognizing that there may be advantages from shared approaches to G8, Organisation for Economic Co-operation and Development (OECD) and United Nations Framework Convention on Climate Change (UNFCCC) processes (Tanner, 2007).

In some contexts it may be advantageous if the scenario method has low demands for technical capacity, supporting infrastructure or data for calibration and simulation. Additionally, it may be helpful if scenarios can be prepared in minutes rather than in months, and the necessary tools are freely available. More rapid production of scenarios, for example, can release time for repeat investigations of key uncertainties, such as sensitivity of impacts to choice of climate model.

In addition to logistical considerations there are several properties that constrain the ultimate use of the scenario. The low spatial resolution of GCMs has often been cited as the rationale for downscaling. So for site to river basin scale applications, direct use of GCM outputs may not be appropriate. Applications demanding finer spatial scales often require finer temporal resolution, as in the example of urban drainage design. Conversely, if global assessments of water resources are needed, then monthly or annual GCM scenarios may suffice.

Many assessments require realistic behaviour for several outputs, such as daily temperature, wind speeds, solar radiation and cloud cover, to compute evaporation in ecosystem or crop models. Others may depend on local estimates of climate change, but simultaneously across multiple sites, for example within a single river basin to simulate flood peaks. Still others need information on the time-evolving climate, rather than shifts in climatological mean, say between 1961–1990 and the 2020s. In all cases, the relationship among climate and non-climate influences should be internally consistent such as between socio-economic, population and atmospheric

CO₂ concentration scenarios, when assessing direct and indirect climate change effects on crop or water yields (e.g. Arnell, 2004).

Over the next four decades, global mean temperature rise is largely insensitive to differences among emission scenarios (Stott and Kettleborough, 2002). Over the longer term, climate change projections are couched in uncertainty about future forcing by solar output, volcanic eruptions, rates of ocean heat uptake, and human activity affecting the composition of the atmosphere and feedbacks from the land-surface. Some techniques can accommodate these components alongside model uncertainty but are very demanding computationally. Even so, increased supercomputer power and distributed climate modelling experiments are enabling multi-model ensemble and multi-physics ensemble experiments and hence the development of probabilistic scenarios (e.g. Stainforth *et al.*, 2005).

Whether or not the term 'probabilistic' is fully justified, or indeed if such information is actually helpful except for high-risk adaptation decisions is debatable (Hall, 2007). This is because results from even the most complex experiments are still conditional on a host of factors (such as the suite of climate models or statistical assumptions applied). The value-added to decision-making by probabilistic climate change scenarios is, to date, largely untested except for a few pilot studies (as in New *et al.*, 2007).

Finally, it is evident that regional predictability of climate is not the same everywhere, and gaps in knowledge of climatology are revealed wherever there is a lack of consensus between climate model projections. Although there is now higher confidence in future patterns of warming and sea-level rise, there is much less confidence in projections of the numbers of tropical storms and of precipitation changes over large parts of Africa, South Asia and Latin America (Table III). Indeed, the most poorly understood regional climates tend to be found in the tropics where there is high inter-annual variability, strong forcing by El Niño Southern Oscillation (ENSO) and other teleconnections, major land cover changes (and

dust generation), sparse and/or degrading observation networks. Table III also shows where reliance on a single climate model is especially inadvisable, and where weighting models by skill at reproducing observed climatology could yield more robust ensemble mean forecasts.

With the above points in mind, the next three sections critique the strengths and weakness of different methods of producing climate risk information for the 2020s. These options are organized in order of increasing resource requirements.

5. Methods requiring limited resources

Four methods are considered: sensitivity analysis, change factors, climate analogues and trend extrapolation. This group tends to offer site- or area-specific climate risk information, and is modestly data dependent, but places minimal demands on technical resources. As such the approaches can be valuable for scoping assessments.

5.1. Sensitivity analysis

A climate sensitivity analysis does not depend on any climate change scenarios, but the assessment may be directed by accepted regional temperature and precipitation changes, such as those published in IPCC AR4. The main requirement is a fully calibrated and validated model of the chosen system, whether it is for snow cover in the Himalayas (Singh and Bengtsson, 2003) or for coastal zone inundation in the Philippines (Perez *et al.*, 1999). First, observed climate data are fed into the model to establish the baseline condition of the response variable (e.g. snow cover area, seasonal runoff volume). Next, the same input data are perturbed by a fixed amount to reflect an arbitrary rise in temperature for instance (such as +0.5, 1, 1.5 and 2°C). A model simulation is performed for each change and any response is measured against the baseline. In this way, it is possible to build up a picture of the system sensitivity to changes in climate element. It is also possible to co-vary other system properties such as crop type or atmospheric concentration of CO₂ (as in Abraha and Savage, 2006).

Table III. A summary of climate model consistency in regional precipitation projections for 2090–2099 under SRES A1B emissions.

Region	December–January	June–August
Sahara	Small decrease	Inconsistent
West Africa	Inconsistent	Inconsistent
East Africa	Small increase	Inconsistent
Southern Africa	Inconsistent	Large decrease
Northern Asia	Large increase	Small increase
Central Asia	Inconsistent	Small decrease
Tibetan Plateau	Small increase	Inconsistent
East Asia	Small increase	Small increase
South Asia	Inconsistent	Small increase
Southeast Asia	Small increase	Small increase
Central America	Small decrease	Small decrease
Amazonia	Inconsistent	Inconsistent
Southern South America	Inconsistent	Inconsistent

Regions in which the middle half of all model projections show disagreement on the sign of change are classified as inconsistent. Regions showing model consensus are indicated as small (5–20%) or large (>20%) increases or decreases. Source: IPCC (2007).

The sensitivity method has some distinct advantages. The resulting climate–response relationships can reveal critical thresholds, amplification by combinations of stressors and nonlinear behaviour, or help isolate outcomes from individual stressors. For example, a 10% reduction in rainfall over the Ketar River basin, Ethiopia produces a 30% reduction in simulated annual runoff, whereas conversion of grazing/cultivated land to woodland reduces modelled runoff by ~8% (Legesse *et al.*, 2003). Once calibrated, the model parameters and inputs can also be modified to represent adaptation measures, such as changes in land use to reduce diffuse pollution (Whitehead *et al.*, 2006). The method is also portable in the sense that responses of different sectors or locations can be compared using the same arbitrary changes.

However, without reference to historic trends or climate change scenarios cited elsewhere, it is not possible to comment on the likelihood or timing of simulated responses to given adjustments. As an observed climate series underpins both the baseline and perturbed experiment, the effects of unseen sequences of weather events (such as more protracted wet or dry-spells) cannot be investigated. Furthermore, the uncertainty due to the impact model *per se* is seldom reported (Section 8), but can be substantial relative to climate change impacts expected by the 2020s.

5.2. Change factors

This method is one of the most straightforward and popular procedures for climate risk assessment, provided that the prerequisite climate model outputs are available. Change factors are typically calculated for calendar months by comparing the present and projected climatology in a Regional Climate Model (RCM) (as in Sato *et al.*, 2007) or GCM (as in Tate *et al.*, 2004) for grid-box(es) overlying the target region. Alternatively, change factors can be obtained from ensemble experiments by sampling distributions of present and future climate scenarios produced by a single GCM (as in New *et al.*, 2007) or by several different GCMs (Favis-Mortlock and Guerra, 1999).

Change factors for temperature (ΔT) are calculated by subtracting the model averages representing baseline (1961–1990) from the future (e.g. 2020s, 2050s or 2080s) temperatures (Figure 2). Change factors for precipitation (ΔP) are normally derived from the ratio of the projected-to-baseline averages, but absolute differences can also be applied. The ΔT quantities are then added to observations (or in the case of ΔP multiplied by observations) to yield perturbed climate series at the study location.

A major disadvantage of change factors is that perturbed and baseline series differ only in terms of their respective means, maxima and minima; all other properties of the data are unchanged. The procedure can also yield quite erratic changes in monthly factors when applied to the 2020s due to relatively large statistical uncertainty in the baseline and future climatology

compared with the actual change expressed by different GCMs. As with sensitivity analyses, the method does not change the frequency of rainfalls or temporal sequencing of events. Hence, the method may not be helpful in circumstances where changes in drought duration or onset are critical to the assessment. Change factors will also reflect any gross biases in GCM climatology at the scale of individual model grid cells, such as timing of the monsoon onset. Most critically, the method is only feasible if the underlying RCM and GCM scenarios are freely available and accessible for the 2020s. Unfortunately, many archives hold only products for the 2080s (as in Figure 2), so additional steps are needed to scale back to the 2020s (Section 6.1).

5.3. Climate analogues

Analogue scenarios are constructed from palaeo- or more recent instrumental records that give plausible representations of the future climate of a region. Temporal analogues are taken from the previous climate of the region; spatial analogues are taken from another region that presently has conditions that could become the future climate at the study site. For example, the present rainfall and temperature regime of Mauritania could be a spatial analogue for expected climate changes across Morocco. In doing so, the assumptions are made that the geographic context (e.g. land–sea juxtaposition or continentality) is comparable, and that latitudinal controls (e.g. day length or storm track position) are not important to the impact assessment.

A major advantage of the analogue approach is that the climate scenario and associated impacts may be described in far greater temporal and spatial detail than might otherwise be possible. For example, the summer 2003 heatwave in Europe provided early sight of possible environmental (Fink *et al.*, 2004), societal (Palutikof *et al.*, 2004) and health (Haines *et al.*, 2006) impacts of extreme temperatures that could become the norm by the 2040s (Stott *et al.*, 2004). Similarly, the severe drought of 1991/1992 in southern Africa gave proxy evidence of actual impacts on vegetation condition and ground cover under higher temperatures and evaporation rates as projected by several GCMs (Mkanda, 1999). Like sensitivity analysis, the given impacts can be explicitly linked to a tangible climate anomaly or extreme event which is helpful for visualizing consequences and identifying critical thresholds.

The most significant disadvantage of temporal analogues is that the climate forcing that led to the extremes is unlikely to be repeated over coming decades. Past vegetation–climate feedbacks, for example, may not be applicable in the future due to recent human modifications of land cover (Claussen *et al.*, 2003). There is also little scope for exploring uncertainties in future climate forcing because of the small sample of events. Furthermore, even if the same extreme event recurred, the human impacts would almost certainly differ because of confounding factors such as changes in economy, infrastructure developments or adaptation measures invoked during the interim.

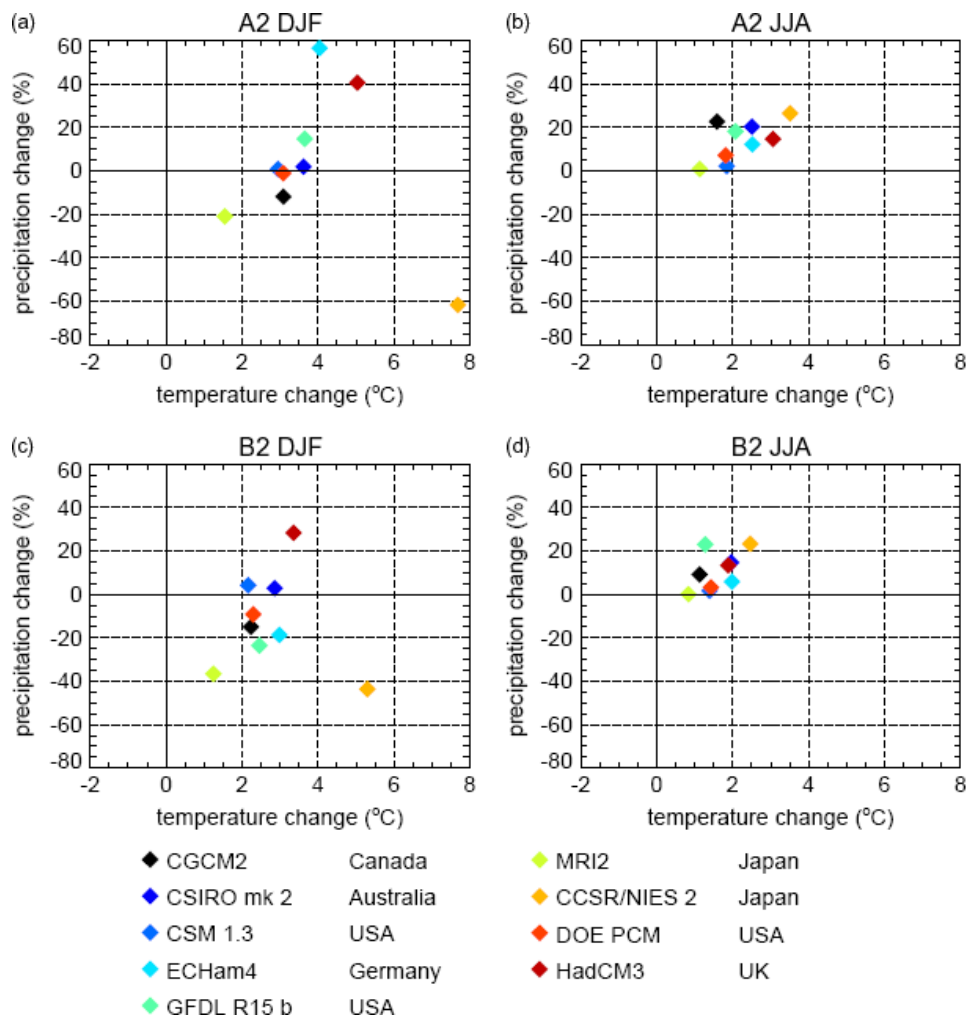


Figure 2. Change factors for seasonal precipitation and temperature over Bangladesh for the 2080s under A2 and B2 emissions projected by nine GCMs. Source: Mitchell *et al.* (2002). This figure is available in colour online at www.interscience.wiley.com/ijoc

The analogue method is also relatively data demanding; in the absence of surveillance systems, necessary human and environmental statistics may be hard to assemble. Even so, catastrophic weather events (such as Hurricane Katrina) can trigger major shifts in policy and attitudes to risk despite being problematic to attribute to climate change.

5.4. Trend extrapolation

Climate trend analysis can be a very appealing option, at least when extrapolating over the next few years. The attendant data and technical requirements are low compared with other scenario methods. But an assumption is made that recent climate behaviour is a sound basis for predicting the future. This may be reasonable for slowly varying components of the earth system such as sea level, or ocean temperatures which are highly correlated between successive years, even decades (Section 7.2). Regional climate trends that are largely driven by these elements may be robust in the near term (e.g. Marengo and Camargo, 2008). The trend need not be linear as testified by the extensive literature on climate cycles (e.g. Becker *et al.*, 2008).

However, trends are highly susceptible to false tendency (Chappell and Agnew, 2004; Legates *et al.*, 2005). This can arise because data are not homogeneous, having been affected by a host of non-climatic influences such as encroachment of urban areas, changes in observer, instrumentation, monitoring network density, station location or exposure (Kalnay and Cai, 2003; Davey and Pielke, 2005). Even if a physically plausible climate trend is found, the amount of explained variance may be low as in the case of regional rates of sea-level rise (Plag, 2006). There is also no guarantee that a trend will persist, as evidenced by the abrupt changes in rainfall and atmospheric circulation of the last century (Baines and Folland, 2007; Narisma *et al.*, 2007).

Apparent trends can also emerge because of the undue influence of a single outlier, particularly if it occurs towards the end of the record. Multi-decadal variability in annual rainfall totals can cause the strength and/or even the sign of an extrapolated trend to change depending on the period and/or length of record chosen (Figure 3). Others have demonstrated that misleading trends can be an artefact of the statistical method used to divide data, such as percentile-based indices for temperature

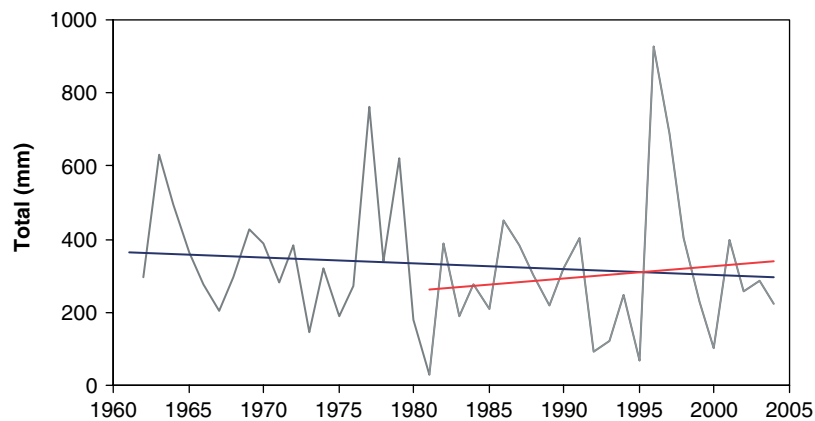


Figure 3. Annual winter rainfall trends at Tanger in Morocco since 1961 (blue line) and 1981 (red line). Extrapolating each trend forward to the year 2015 gives changes of -16% and $+14\%$, respectively, compared with the 1961–1990 mean. If the 1996 outlier is removed, the post-1981 gradient weakens by 55% . This figure is available in colour online at www.interscience.wiley.com/ijoc

and precipitation extremes (Michaels *et al.*, 2004; Zhang *et al.*, 2005).

In short, trend analysis plays an important role in climate change detection and attribution (e.g. Zhang *et al.*, 2007), but is problematic when extrapolating variables such as regional rainfall. Even where the causes of a trend are well understood, the inherent variability of the climate system can cause the trend to break down from one decade to the next.

6. Methods with modest resource needs

Three methods are considered: pattern-scaling, weather generation and empirical downscaling. This group is founded on statistical methods for characterizing present and future climate behaviour at regional scales. In some cases, bespoke software allows broader access to sophisticated models through user-friendly interfaces. All methods depend on climate model output to run future scenarios.

6.1. Pattern-scaling

The pattern-scaling method has similarities with the change factor approach (see above). In both cases, a ‘change field’ or pattern is derived by taking differences between a baseline (1961–1990) and future (typically 2071–2100) climate scenario. Although change factor methods tend to rely on differences for a single climate model grid-box, change fields are derived for multiple grid boxes using either RCM or GCM outputs. These local patterns are then scaled for intervening periods using projections of the global mean temperature (Mitchell *et al.*, 1999). For example, one GCM might suggest a 40% reduction in spring rainfall over a region by the 2080s associated with a 4°C global mean temperature rise. Hence, precipitation decreases at an average rate of 10% per 1°C in global mean temperature change. With scenarios of annual global mean temperature changes for the period 2000–2100 expressed as a ratio of the mean in

the 2080s (centred on 2085), it is possible to scale quantities such as regional rainfall for intervening periods.

Future emissions drive transient temperature changes projected by climate models, so each emission pathway has a different scaler trajectory (Figure 4). For example, under high (A1FI) and low (B1) emissions, the Parallel Climate Model (PCM) yields scalars of 0.248 and 0.477, respectively, for 2025. In the example above, these scalars translate into 10 and 19% reductions in spring rainfall. (The apparent paradox of smaller changes under higher emissions is due to higher concentrations of sulphate aerosols and hence cooling under the A1FI scenario.) Differences between climate models are also negligible if each is scaled by their respective global mean temperature change for the 2080s. However, if different climate models are scaled by a common reference temperature change (such as their ensemble mean), the resulting scalars would differ. This is the method applied by the MAGICC/SCENGEN system to scale baseline data from a range of climate models and emission scenarios (Hulme *et al.*, 2000).

Pattern-scaling is convenient for exploring uncertainty because the technique can ‘infill’ between scenarios run for different periods, emissions or initial conditions. For example, pattern-scaled (PAT) and empirically downscaled [Statistical DownScaling Model (SDSM), University of Cape Town (UCT)], scenarios were constructed for annual rainfall changes at Casablanca, Morocco. Comparing PAT-HadCM3 and SDSM-HadCM3 scenarios reveals the effect of the scaling method because both have the same host GCM (HadCM3) and emissions (Figure 5). PAT eliminates variability because all changes are scaled back from the 2080s using the ratio between local (Morocco) to global mean temperature change. Precipitation changes for Marrakech and Tangier would have the same pattern as Casablanca, but would differ in terms of their magnitude. In contrast, SDSM and UCT yield transient scenarios that have site-specific patterns and magnitudes of precipitation change. When aggregated to annual totals most methods point to long-term reductions in annual rainfall (Table IV). (The 7% increase returned

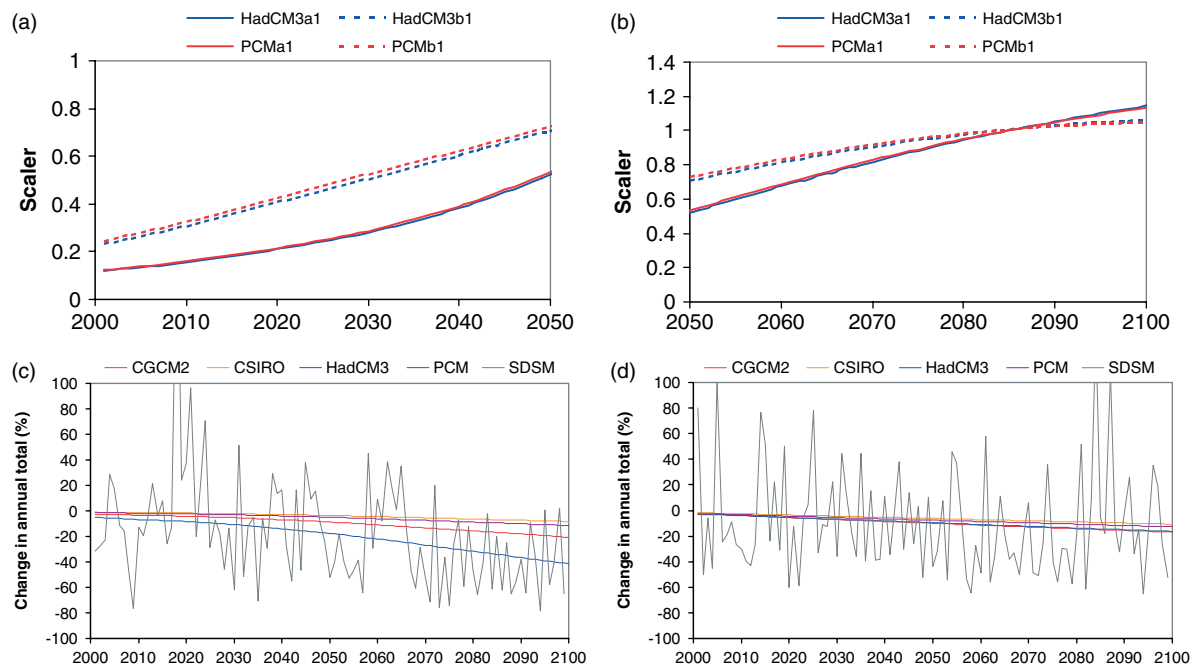


Figure 4. Top row: Annual scalars for 2000–2050 (left panel) and 2050–2100 (right panel) derived from the climate models HadCM3 (blue) and PCM (red) under A1FI (solid) and B1 (dashed) SRES emissions. Bottom row: Annual series of precipitation changes at Casablanca under SRES A2 (left) and B2 (right) emissions. Data Source: http://www.cru.uea.ac.uk/~timm/climate/ateam/TYN_CY_3_0.html (accessed 2 August 2007). This figure is available in colour online at www.interscience.wiley.com/ijoc

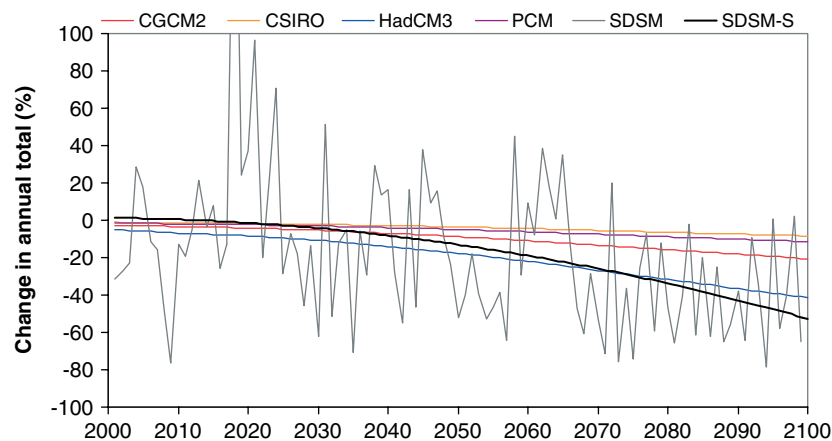


Figure 5. Changes (%) in annual precipitation totals at Casablanca under SRES A2 emissions comparing pattern-scaled (CGCM2, CSIRO, HadCM3, PCM) and empirically downscaled (SDSM) scenarios. SDSM results were downscaled from HadCM3. SDSM-S was smoothed to remove inter-annual variability. This figure is available in colour online at www.interscience.wiley.com/ijoc

by SDSM for the 2020s lies within the bounds of natural variability.) However, the uncertainty due to the choice of host GCM and downscaling method spans -7 to -49% by the 2080s.

As high-resolution RCM simulations are costly and time-consuming to perform, very few transient experiments for 1961–2100 have been undertaken to date. This means that without pattern-scaling, information from RCMs would rarely be available for the 2020s. Furthermore, it is assumed that by the 2080s, the regional climate change pattern emerges more strongly from the 'noise' of natural variability. Hence, there is greater confidence that a climate change signal, rather than variability, is being scaled backward to earlier decades.

Pattern-scaling rests on several major assumptions. First, that the regional climate change *pattern* is constant between decades, and that only the *magnitude* of change varies. This may be invalidated where the pattern is affected by land-surface feedbacks on albedo or by changing spatial patterns of aerosols composed of sulphate, soot and dust (Shine and Forster, 1999). Second, that the regional response depends on a linear relationship with global mean temperature. This may be reasonable for temperature, but less so for seasonal precipitation, or climate extremes (Good *et al.*, 2006). Third, that the patterns of change can be scaled between different emission scenarios (such as A1FI to estimate B1). In this case, errors may be minimized by scaling from a stronger to

Table IV. Changes (%) in annual precipitation totals at Casablanca, Morocco projected by different scenario methods (UCT, SDSM, PAT) and GCM forcing (CSIRO, ECHAM4, HadAM3, HadCM3, PSM) under SRES A2 and B2 emissions for the 2020s, 2050s and 2080s.

Scenarios	2020s		2050s		2080s	
	A2	B2	A2	B2	A2	B2
UCT-CSIRO	–	–	–	–	–44	–
UCT-ECHAM4	–	–	–	–	–49	–
UCT-HadAM3	–	–	–	–	–20	–
SDSM ^a -HadCM3	7	–4	–18	–17	–40	–9
PAT-CGCM2	–5	–6	–10	–11	–17	–15
PAT-CSIRO	–2	–4	–4	–7	–7	–10
PAT-HadCM3	–10	–6	–20	–10	–34	–14
PAT-PSM	–3	–5	–6	–8	–10	–11
Ensemble mean	–3	–5	–12	–11	–28	–12

Key to scenarios methods: UCT, University of Cape Town tool: Hewitson and Crane (2006); SDSM, Statistical DownScaling Model: Wilby *et al.* (2002); PAT, Pattern-scaling from Tyndal CY 3.0 scalars: Mitchell *et al.* (2002).

^a Ensemble member M1.

a weaker forcing scenario (Mitchell, 2003). Finally, the temporal and spatial scales of the resultant scenarios will depend on the resolution of the RCM or GCM supplying the patterns of change. Subtle variations in responses at sub-grid scales due to orography or land-surface may not be captured.

6.2. Weather generation

Weather generators are models that replicate statistical attributes of meteorological station records (such as the mean and variance), but do not reproduce actual sequences of observed events (Wilks and Wilby, 1999). At the heart of most weather generators is a Markov model that emulates transitions between wet- and dry-spells or dry-days. The optimum statistical distribution for representing daily rainfall totals varies from place to place, but the gamma, exponential and fourth root are most popular (Figure 6). Secondary variables such as maximum and minimum temperatures, solar radiation and wind speed are grouped into sets of wet and dry-days. Inter-variable relationships are preserved using multiple regression equations and it makes sense, for example, that dry-days have on average more sunshine than wet-days. The whole process is driven by random number generation to determine whether a day is wet or dry, if wet how wet, how warm, how windy and so on. This enables weather generators to efficiently simulate long synthetic series, useful for estimating extreme events for design purposes (e.g. Smithers *et al.*, 2002).

Adapting weather generators for climate change assessment involves adjusting model parameters in one of two ways. First by relating key parameters such as wet-day probabilities to other, slowly varying indices of atmospheric circulation (e.g. ENSO or North Atlantic Oscillation (NAO)) (Katz, 1996). Inter-annual or decadal changes in the frequency of these patterns (as projected by GCMs) are then translated into revised weather generator parameters, and hence daily weather sequences under

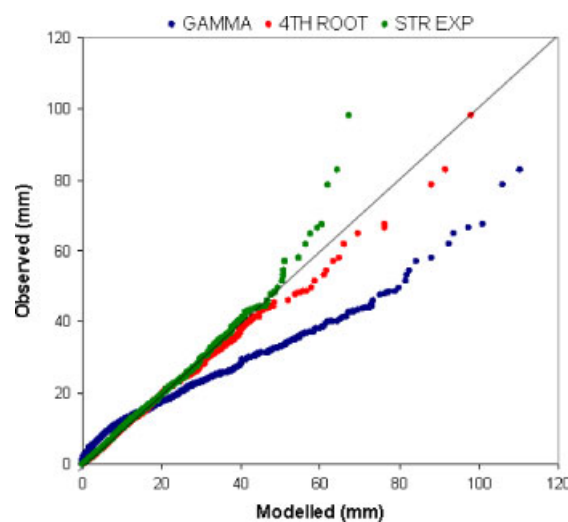


Figure 6. Comparison of observed and modelled distributions of daily rainfall at Addis Ababa, Ethiopia. In this case the fourth root transformation (4TH ROOT) would be used in preference to the gamma or stretched exponential distributions. This figure is available in colour online at www.interscience.wiley.com/ijoc

future forcing. The second approach involves recalibrating the weather generator using daily weather series that have been derived from the change factor method (Section 5.2) (Kilsby *et al.*, 2007). Hence change factors for the 2020s would be applied to each weather variable, the model recalibrated, then run to synthesize infinitely long daily sequences with the same statistical properties as the 2020s series.

Unfortunately, weather generator parameter modification for future climate scenarios can cause unanticipated outcomes (Katz, 1996). For example, changes to parameters governing rainfall occurrence can have unintended effects on secondary variables such as temperature and solar radiation. Moreover, weather generators based on first-order Markov chains (i.e. one-day-to-the-next transitions) typically underestimate the persistence of wet- and dry-spells. More sophisticated procedures are also needed

for multi-site applications, or to disaggregate daily series into sub-daily quantities, or to simulate lower frequency variability, such as inter-annual rainfall totals (Wilks and Wilby, 1999).

Weather generators are relatively data-intensive, requiring at least a decade of daily data, or more for arid sites (Soltani and Hoogenboom, 2005). The parameters are sensitive to missing or erroneous data, as well as to the number of rain days in the calibration set (Taulis and Milke, 2005). However, weather generators are already in widespread use and there is scope for their extension to climate change assessments.

6.3. Empirical downscaling

Empirical downscaling methods overcome one of the most serious limitations of applying raw GCM output to regional impact assessment – the mismatch in scale between climate model projections (~300 km) and the response units under investigation (~individual sites to river basin areas). One of the simplest forms of downscaling involves spatial interpolation of gridded GCM or RCM output to required locations (so-called ‘unintelligent’ downscaling). More sophisticated techniques rely on building quantitative relationships between large-scale atmospheric variables (predictors) and local surface variables (predictands). So, for example, the strength of airflow and humidity has been used to downscale daily precipitation totals at sites across South Africa (Hewitson and Crane, 2006). Different downscaling approaches are often distinguished by their predictor variable(s) suite, or by the form of the statistical term relating predictors to predictands. The merits of different empirical methods have been exhaustively reviewed elsewhere (Wilby and Wigley, 1997; Christensen *et al.*, 2007; Fowler *et al.*, 2007; Goodess *et al.*, 2007). These reviews indicate that there are no universally optimal sets of predictors, or forms of relationship, each must be assessed on a case by case basis.

Provided that predictor variables are available, empirical downscaling can be an efficient tool for exploring uncertainties in climate change scenarios (Prudhomme *et al.*, 2003; Wilby and Harris, 2006), or for producing fully transient daily scenarios up to 2100 (Immerzeel, 2008). This enables appraisal of near-term changes in both the mean and variability of climate. Methods are also being developed to apply probabilistic climate change information within downscaling schemes (Benestad, 2004). Other advantages include the ability to downscale ‘exotic’ predictands (e.g. tidal surges, air quality, extreme event indices) assuming that physically plausible relationships to large-scale weather can be found. Where predictor variables are difficult to obtain, direct scaling relationships can be applied, for example, between daily GCM- and station-scale precipitation (Schmidli *et al.*, 2006).

Uptake of empirical downscaling techniques has been encouraged by publicly available software and documentation (Table V). Nonetheless, access to the predictor variables necessary for calibration and scenario

development continues to be a major constraint to their widespread use. Even if (daily or monthly) GCM outputs are available, further processing may be needed to derive predictors (such as vorticity from pressure data) or to ensure compatibility between different climate model grids. Likewise the reliability of downscaled scenarios depends on the quality of observations used for model calibration, the predictability of the local variable from the large-scale forcing, and the constancy of these relationships under changing climate conditions. Above all, results are highly sensitive to the choice of GCM providing the predictor variables and (to a lesser extent) the choice of downscaling technique (Figure 7).

There have been relatively few empirical downscaling studies for Africa, Asia or Latin America, and even fewer that explicitly deal with climate changes for the 2020s (as in Immerzeel, 2008). In the tropics and for small islands, strong ocean-atmosphere coupling makes consideration of the role of the ocean unavoidable, thus enlarging the set of potential predictors. Also the relationships between these predictors and local variables may vary strongly within the annual cycle. In the case of precipitation, statistical models especially designed for a particular month (such as the start or end of rainy season) may be needed (Jimoh and Webster, 1999).

7. Methods with high resource needs

Two methods are considered: dynamical downscaling and coupled OA/GCMs. Both require a high degree of ongoing technical support and computing resource, but these are the only methods that can produce internally consistent climate behaviour in response to the full range of climate forcings (i.e. radiative and land-surface feedbacks). GCMs are, therefore, the primary tool for representing the global climate system and nearly all other scenario methods rely on their output.

7.1. Dynamical downscaling

RCMs simulate climate features dynamically at resolutions of 10–50 km given time-varying atmospheric conditions at the boundary of a specified domain (Figure 8). Atmospheric fields simulated by a GCM (such as surface pressure, wind, temperature and vapour) are fed into the boundary of the RCM at different vertical and horizontal levels. This information is then processed by the RCM such that the internal model physics and dynamics can generate patterns of climate change that differ from those of the ‘host’ GCM. The nesting of the RCM within the GCM is typically one way, so the behaviour of the RCM cannot influence the GCM scenario. To date, RCMs have been used for a wide variety of applications, including numerical weather prediction, studies of palaeoclimates, the effects of land-surface modification(s) and future climate change in selected regions of the world.

A key advantage of RCMs is their ability to model regional climate responses to changes in land cover or atmospheric chemistry in physically consistent ways. The

Table V. Examples of climate scenario, risk screening and adaptation tools (updated 6 August 2008).

Tool/source	Description
Clim. pact	R functions for downscaling monthly and daily mean climate scenarios (http://cran.r-project.org/src/contrib/Descriptions/clim.pact.html)
CRiSTAL	Community-based Risk Screening – Adaptation and Livelihoods (http://www.iisd.org/pdf/2008/cristal-manual.pdf)
CSAG	Data portal for downscaled African precipitation scenarios for the 2080s (http://data.csag.uct.ac.za/)
ENSEMBLES	Experimental portal for downscaling tools applied to Europe (http://grupos.unican.es/ai/meteo/ensembles/index.html)
FINESSI	Multi-sector/multi-variable climate change scenarios for Finland (http://www.finessi.info/finessi/?page=explore)
LARS-WG	Tool for producing time series of a suite of climate variables at single sites (http://www.rothamsted.bbsrc.ac.uk/mas-models/larswg.php)
LCA	Linking Climate Adaptation – community-based adaptation (http://www.cba-exchange.org/)
MAGICC/SCENGEN	Interactive software for investigations of global/regional climate change (http://www.cgd.ucar.edu/cas/wigley/magicc/)
PRECIS	UK Met Office portable RCM (http://precis.metoffice.com/)
RCLimex	Graphical interface to compute 27 core indices of climate extremes (http://cccma.seos.uvic.ca/ETCCDMI/software.shtml)
SDSM	Downscaling tool for scenario production at single sites (http://www-staff.lboro.ac.uk/~cocwd/SDSM/)
SERVIR	The Climate Mapper and SERVIR Viz (http://www.servir.net/index.php?option=com_content&task=view&id=101&Itemid=57&lang=en)
Tearfund	Mainstreaming disaster risk reduction: a tool for development organizations (http://www.tearfund.org/webdocs/Website/Campaigning/Policy%20and%20research/Mainstreaming%20disaster%20risk%20reduction.pdf)
UKCIP	Online adaptation data base (UK) http://www.ukcip.org.uk/resources/tools/database.asp
UNFCCC	Database on local coping strategies (http://maindb.unfccc.int/public/adaptation/)
World Bank	Indigenous Knowledge Practices Database (http://www4.worldbank.org/afr/ikdb/search.cfm)
WRI	Climate Analysis Indicators Tool (CAIT) (http://cait.wri.org/)
WWF	Climate Witness Community Toolkit (http://www.wwpacific.org/fj/publications/climate_change/cw_toolkit.pdf)

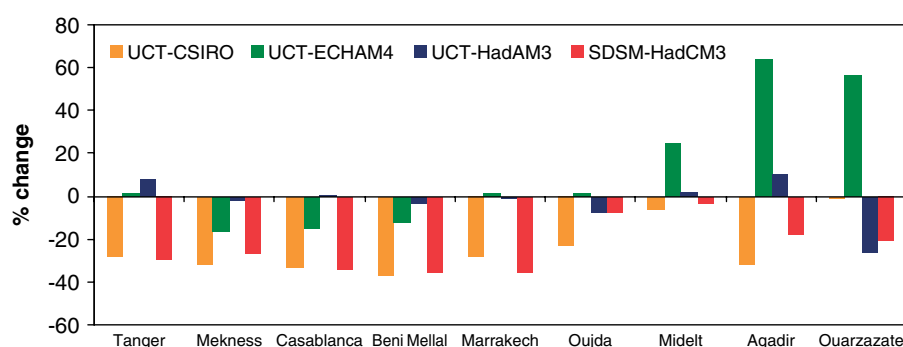


Figure 7. Changes (%) in winter precipitation totals for sites across Morocco, projected by different downscaling methods (UCT, SDSM) and GCM forcing (ECHAM4, CSIRO, HadAM3, HadCM3) under A2 emissions by the 2080s. Source: Wilby and DMN (2007). This figure is available in colour online at www.interscience.wiley.com/ijoc

higher spatial resolution and hence improved representation of surface elevations enable RCMs to resolve important atmospheric processes (such as orographic rainfall or interactions with water bodies) better than the host GCM (e.g. Song *et al.*, 2004; Ekström *et al.*, 2005). However, RCMs are computationally demanding, requiring as much processor time as the GCM to compute equivalent scenarios. Projections for extreme precipitation events may differ between RCMs because of the parametrization schemes used to represent sub-grid processes such as convective rainfall.

Like empirical downscaling, the quality of regional climate simulations depends not only on the validity of the RCM physics but also, more critically, on the realism of GCM boundary information. For example, gross errors in an RCM's precipitation climatology may arise, if the GCM misplaces storm tracks. The results are also sensitive to the size of model domain and grid-spacing. Ideally, the domain should be large enough to allow the free development of mesoscale atmospheric circulations, and the grid-spacing fine enough to capture detailed topographic, coastal or dynamical features such

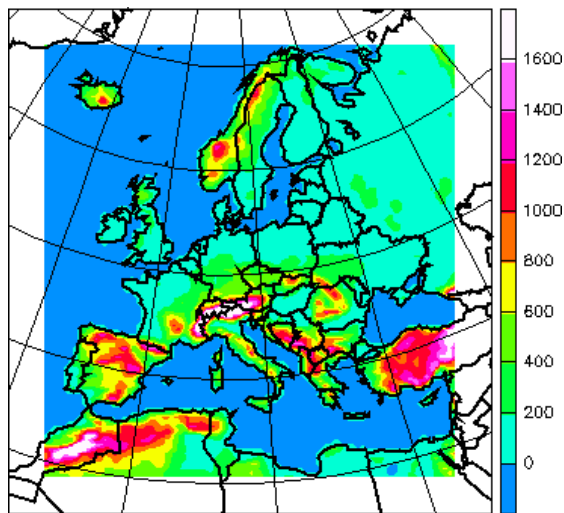


Figure 8. Domain and elevations (m) of the Met Office Hadley Centre's regional climate model HadRM3. Source: <http://prudence.dmi.dk/> (accessed 8 August 2007). This figure is available in colour online at www.interscience.wiley.com/ijoc

as tropical cyclones (Walsh, 2004). In practice, domain size and grid-spacing are constrained by computational resources, as simulation times increase exponentially with increasing vertical and horizontal resolution. The actual location of the domain should capture the most significant circulations that affect climate over the region of interest (e.g. low-level jets, storm tracks, cyclones).

Tools such as RegCM3 and PRECIS are opening the way for more widespread use of RCMs in climate vulnerability and adaptation studies (Islam *et al.*, 2008; Pal *et al.*, 2007). Results from the Earth Simulator (an RCM-resolution GCM) are also being employed in regional assessments (e.g. World Bank, 2007). However, in common with empirical downscaling, there is still a real paucity of published dynamical downscaling studies for developing regions, and especially for the 2020s.

7.2. Coupled climate models

Recent GCM experiments show that global (and some regional) mean temperatures are hindcast with substantially improved skill when provided with information about the upper ocean heat content (Smith *et al.*, 2007; Keenlyside *et al.*, 2008). Much of the increased skill arises from the persistence and predictability of ocean temperatures over decadal time-scales (Sutton and Allen, 1997). This underlines the importance of maintaining ocean-monitoring systems (Dickey and Bidigare, 2005), such as the ARGO floats, to provide initial conditions for decadal forecasting systems, as well as early detection of changes in water properties (King and McDonagh, 2005). Forecast skill is expected to improve with time as more data on ocean conditions become available. Even so, decadal forecasts will continue to be accompanied by strong caveats for unforeseen volcanic activity and/or rapid nonlinear climate change and feedbacks, both of

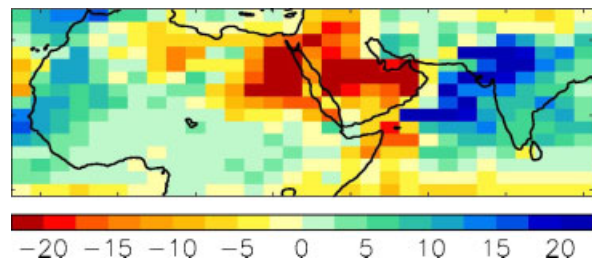


Figure 9. DePreSys minus NoAssim precipitation anomalies for 2007–2017 as a percentage of the 1979–2001 mean. This prototype forecast was based on information on upper ocean heat content up to March 2007. Source: Met Office. This figure is available in colour online at www.interscience.wiley.com/ijoc

which could cause a sudden cool downturn (Lee *et al.*, 2006).

Despite significant technical advances in decadal forecasting capability, the products will remain of limited value to policy-makers and planners until skilful forecasts of regional climate anomalies become available. Work in this area has only just begun. For example, Figure 9 shows a prototype forecast of regional precipitation anomalies out to 2017 based on the UK Met Office's Decadal Climate Prediction System (DePreSys) (Smith *et al.*, 2007). The plot shows the difference between model runs with (DePreSys) and without assimilated (NoAssim) ocean temperature information. Although the ocean temperature forcing yields strong positive anomalies over the Indian subcontinent and negative anomalies over East Africa, much more research is needed to try to understand whether the signals are robust, and if so, the underlying physical mechanisms. This would require multi-model and multi-physics ensemble experiments to quantify the large uncertainty that exists in (precipitation) forecasts at such fine resolutions. Further work is also needed to determine whether the rainfall anomalies have any practical significance when propagated through secondary impact models. Taken at face value, this particular forecast implies greater flood risk over India, and higher soil moisture deficits and/or less river flow in the Nile basin, than would be expected from greenhouse-gas-forced climate change alone. However, the extent to which even a perfect decadal forecast provides information that is useful for adaptation planning is a legitimate research question in its own right.

8. Secondary impacts modelling

Environmental models play an integral part in many climate risk assessments (whether for water resource, crop-yield, ecosystem response, coastal inundation, human health or multi-sectoral). The impact model can even be the most complex element in the case of sensitivity analyses (Section 5.1). However, uncertainty in responses due to the impact model structure and/or parameters is very seldom specified let alone reported; much more attention is typically given to the influence of different climate models or downscaling methods on the outcome.

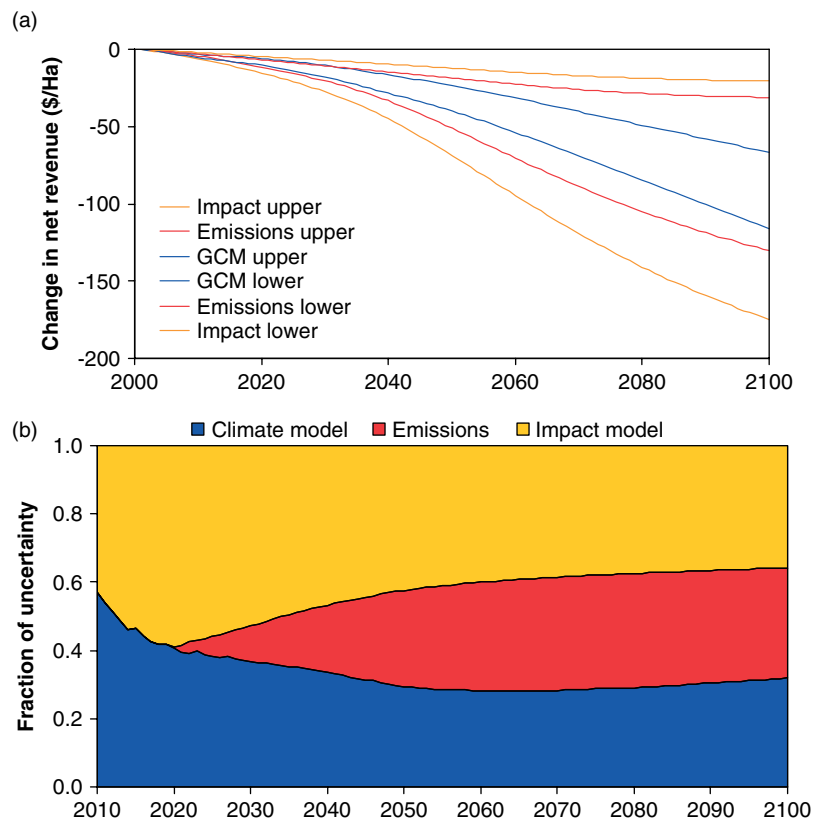


Figure 10. (a) Changing net revenue (\$/Ha) reflecting uncertainty in GCM projections of temperature (blue envelope) combined with emissions (red envelope) and impact model parameter uncertainty (gold envelope). (b) The contribution of climate model, emissions and impact model uncertainty as a time-varying fraction of the total uncertainty in net farm revenues for Sri Lanka under projected increases in annual mean temperature. This figure is available in colour online at www.interscience.wiley.com/ijoc

This oversight is of particular concern whenever scenarios for the 2020s are applied because the emission uncertainty is negligible and the climate change signal can be weak relative to climate variability or non-homogeneity of the model calibration data (Niel *et al.*, 2003). Under these circumstances impact model uncertainties can be prominent, particularly for extreme events (Cameron *et al.*, 2000). From the handful of published studies it is evident that uncertainty in both model *structure* (processes included) and *parameterization* (process representation) should be considered (just as in the case of climate model ensemble experiments): Boorman and Sefton (1997); Fussler (2007); Jiang *et al.* (2007) and Wilby (2005). In extreme cases, inadequate process representation undermines confidence in projections (e.g. Arnell *et al.*, 2003).

To illustrate the extent of impact model uncertainty, a Ricardian model of net farm revenues (Kurukulasuriya and Ajwad, 2006) was run using annual mean temperature projections originating from different climate models and emissions scenarios for the period 2010–2100. This model was chosen because the authors provided a clear description of several model structures and associated parameter uncertainty. As expected, the analysis reveals declining farm revenues with rising annual temperatures (Figure 10(a)). By 2030 estimated uncertainty in the net revenue is ~\$20/Ha, compared with ~\$150/Ha by 2100.

Initially, climate model uncertainty is the dominant component, but this is soon replaced by impact model uncertainty which contributes the largest fraction of total uncertainty around the 2020s (Figure 10(b)). Thereafter, both climate and impact model uncertainty contribute proportionately less uncertainty as emission scenario uncertainty gains prominence. This simple example highlights the potential reductions in uncertainty that could be achieved by improving a linear impact model, at least for the 2020s. The benefits could be even greater for nonlinear response models.

9. Criteria for method selection

This review has critiqued climate scenario methods from the perspective of impacts modelling and adaptation planning over the next 20–30 years (Table VI). Decadal forecasting presents special technical challenges, but there is growing evidence that models are skilful over this time horizon, at least for global mean temperatures (Smith *et al.*, 2007). The traditional distinction between weather forecasting and climate change prediction is thus becoming increasingly blurred at these time-scales.

There are a growing number of techniques that allow inference to be made about medium-term trends in local climate variables of use to decision makers. However, this review has identified very few examples of studies for the

Table VI. Options for constructing regional climate change scenarios, listed in the order of increasing complexity and resource demand.

Method (application)	Advantages	Disadvantages
Sensitivity analysis <i>Resource management, Sectoral</i>	1. Easy to apply; 2. Requires no future climate change information; 3. Shows most important variables/ system thresholds; 4. Allows comparison between studies.	1. Provides no insight into the likelihood of associated impacts unless benchmarked to other scenarios; 2. Impact model uncertainty seldom reported or unknown.
Change factors <i>Most adaptation activities</i>	1. Easy to apply; 2. Can handle probabilistic climate model output	1. Perturbs only baseline mean and variance; 2. Limited availability of scenarios for 2020s.
Climate analogues <i>Communication, Institutional, Sectoral</i>	1. Easy to apply; 2. Requires no future climate change information; 3. Reveals multi-sector impacts/vulnerability to past. climate conditions or extreme events, such as a flood or drought episode.	1. Assumes that the same socio-economic or environmental responses recur under similar climate conditions; 2. Requires data on confounding factors such as population growth, technological advance, conflict.
Trend extrapolation <i>New infrastructure (coastal)</i>	1. Easy to apply; 2. Reflects local conditions; 3. Uses recent patterns of climate variability and change; 4. Instrumented series can be extended through environmental reconstruction; 5. Tools freely available.	1. Typically assumes linear change; 2. Trends (sign and magnitude) are sensitive to the choice/length of record; 3. Assumes underlying climatology of a region is unchanged; 4. Needs high quality observational data for calibration; 5. Confounding factors can cause false trends.
Pattern-scaling <i>Institutional, Sectoral</i>	1. Modest computational demand; 2. Allows analysis of GCM and emissions uncertainty; 3. Shows regional and transient patterns of climate change; 4. Tools freely available.	1. Assumes climate change pattern for 2080s maps to earlier periods; 2. Assumes linear relationship with global mean temperatures; 3. Coarse spatial resolution.
Weather generators <i>Resource management, Retrofitting, Behavioural</i>	1. Modest computational demand; 2. Provides daily or sub-daily meteorological variables; 3. Preserves relationships between weather variables; 4. Already in widespread use for simulating present climate; 5. Tools freely available.	1. Needs high quality observational data for calibration and verification; 2. Assumes a constant relationship between large-scale circulation patterns and local weather; 3. Scenarios are sensitive to choice of predictors and quality of GCM output; 4. Scenarios are typically time-slice rather than transient.
Empirical downscaling <i>New infrastructure, Resource management, Behavioural</i>	1. Modest computational demand; 2. Provides transient daily variables; 3. Reflects local conditions; 4. Can provide scenarios for exotic variables (e.g., urban heat island, air quality); 5. Tools freely available.	1. Requires high quality observational data for calibration and verification; 2. Assumes a constant relationship between large-scale circulation patterns and local weather; 3. Scenarios are sensitive to choice of forcing factors and host GCM; 4. Choice of host GCM constrained by archived outputs.
Dynamical downscaling <i>New infrastructure, Resource management, Behavioural, Communication</i>	1. Maps regional climate scenarios at 20-50km resolution; 2. Reflects underlying land-surface controls and feedbacks; 3. Preserves relationships between weather variables; 4. Ensemble experiments are becoming available for uncertainty analysis.	1. Computational and technical demand high; 2. Scenarios are sensitive to choice of host GCM; 3. Requires high quality observational data for model verification; 4. Scenarios are typically time-slice rather than transient; 5. Limited availability of scenarios for 2020s.
Coupled AO/GCMs <i>Communication, Financial</i>	1. Forecasts of global mean and regional temperature changes for the 2020s; 2. Reflects dominant earth system processes and feedbacks affecting global climate; 3. Ensemble experiments are becoming available for uncertainty analysis.	1. Computational and technical demand high (supercomputing); 2. Scenarios are sensitive to initial conditions (sea surface temperatures) and external factors (such as volcanic eruptions); 3. Scenarios are sensitive to choice of host GCM; 4. Coarse spatial resolution.

Example adaptation activities (from Table II) are shown in *italics*.

2020s, or even 2050s, so many of the scenario methods remain largely untested for these time periods. Table VII provides a summary of desirable attributes which are mapped in Table VIII to produce a ready-reckoner of scenario methods, based largely on applications to the 2080s.

At the very least, Table VIII helps to exclude methods that would be wholly inappropriate for a given activity or level of resources. For example, temperature forecasting with weather generator or empirical downscaling methods

would not be recommended for regions that are likely to experience dramatic changes in land-surface properties (such as snow cover, water body or irrigated areas); this would be better addressed by dynamical downscaling (e.g. Snyder *et al.*, 2004). Conversely, a capability in dynamical downscaling will be hard to sustain without continued investment in infrastructure and training.

In practice, local expertise in one or more of the above methods develops through related activities such as weather hazard prediction or seasonal forecasting.

Table VII. Summary of attributes used to assess the relative merits of different scenario options.

Indicator	Preferred attributes for development and adaptation planning
Capacity	Low personnel, technical and infrastructure requirements
Resources	Low data, time and financial costs
Spatial	High spatial resolution (site or region, not continental or global)
Temporal	High temporal resolution (hourly or daily, not monthly or annual)
Outputs	High realism and joint behaviour of weather variables
Forcing	High ability to represent different external forcing (land cover, aerosols)
Uncertainty	High capability for providing probabilistic information
Pattern	High ability to produce surfaces or maps of climate change
Transient	High ability to produce transient (rather than time-slice) scenarios
Tools	High availability of tools, supporting data and guidance

These indicators cross-reference to the columns in Table VIII.

Likewise, weather generators are already in relatively widespread use for crop-yield and water resource modelling. Under these circumstances, it is advisable to build on existing knowledge and capabilities. However, the

over-riding imperative is that the most appropriate scenario method is matched to the intended application (Section 3). For example, sensitivity analysis or change factors for macro-economic analysis; climate analogues or empirical downscaling for the design of community-based livelihoods programmes; dynamical downscaling for communicating with stakeholders and national policy-making across multiple sectors; pattern-scaling or weather generators for natural resource assessment; and coupled OA/GCMs for international advocacy.

Regardless of the intended application and choice of method, consideration should be given to how the scenarios will enable stakeholders and managers to make more informed, robust decisions on adaptation in the face of deep uncertainty. This means that the suppliers and users of climate risk information need to be closely aligned from outset. It also makes sense to demonstrate the value-added (if any) when more sophisticated scenario methods are applied – underlining the merit of benchmarking against simpler procedures whenever time and resources permit.

10. Future opportunities to improve the science and information

This final section offers suggestions for improving the technical base for the production and uptake of climate risk information for the 2020s. The options are grouped into three themes: (i) basic science, (ii) uncertainty and (iii) decision support.

Table VIII. A qualitative assessment of the extent to which different scenario methods can support climate impact and adaptation assessments for the 2020s.

Scenario methods	Capacity	Resources	Spatial	Temporal	Outputs	Forcing	Uncertainty	Pattern	Transient	Tools
Sensitivity analysis										
Change factors										
Climate analogues										
Trend extrapolation										
Pattern-scaling										
Weather generation										
Empirical downscaling										
Dynamical downscaling										
Coupled OA/GCMs										

The headings refer to the desirable attributes listed in Table VII.

Key to cells: red (disagree), amber (neutral or depends), green (agree).

10.1. Basic science

From outset it was recognized that benefits arise from a combined approach to adaptation involving vulnerability assessment and scenario development. Both strategies require high-quality information to characterize the full range of climate variability together with associated societal and environmental consequences; both are hampered by deteriorating meteorological networks. Indeed, without basic meteorological data to verify model representations of the present climate, there can be little confidence in future projections or interpolated information, no matter how sophisticated the tool. Similarly, secondary impacts modelling presupposes the existence of reliable records of river flow, crop yields, groundwater levels and so on. The need for collective action to improve the status of all such observing systems, especially in Africa, has been stated many times before. It may be timely and sobering to measure progress against the specific recommendations made before the Gleneagles G8 summit in 2005 (Washington *et al.*, 2004).

There are also gaps in understanding of fundamental climate controls for large parts of Africa (including Central-east Africa, the Ethiopian Highlands and Sahel), as well as tropical cyclone behaviour (over Madagascar), stability of Arctic Oscillation/El Niño teleconnections and land-surface feedbacks on regional climate. This is evidenced by divergent outlooks for vulnerable regions such as the Sahel (where Held *et al.*, 2005 assert that the future will be 'drier' and Hoerling *et al.*, 2006 'wetter'). Part of the solution involves supporting intense field campaigns [like the EU African Monsoon Multidisciplinary Analyses (AMMA) project] to collect data on poorly understood climate processes, or primary information for data sparse regions, especially in the Tropics. More could be done to assess the realism of teleconnection patterns within GCMs using *existing* model runs. This might involve evaluations of the stability of known teleconnections over multi-decadal time-scales, or the consequences of poorly understood teleconnections (such as the warming of the Southwest Atlantic).

Improved skill at forecasting decadal temperatures is expected to translate into improved skill at forecasting regional water cycle components (e.g. rainfall, evaporation, soil moisture, groundwater and river flow). These products are potentially of greater interest to planners than global mean temperatures alone. However, natural internal climate variability will be magnified at finer spatial scales, increasing uncertainty in forecasts. An interim step might be to test probabilistic decadal forecasts for strategically significant sub-continental regions such as the River Yangtze (Weng *et al.*, 1999; Blender and Fraedrich, 2006), or the Nile basin, where environmental and human responses to decadal climate variability are already well understood (Eltahir, 1996; Conway, 2005). River flow forecasts may be more skilful if decadal forecasts are downscaled to river basins *before* water balance modelling (Lettenmaier, *pers. comm.*) rather than relying on flows computed within the coarse resolution

GCM itself (as in Manabe *et al.*, 2004) – but this needs to be tested.

10.2. Uncertainty

Decadal forecasting and empirical downscaling are forward running scenario methods that emphasize the importance of initial conditions and GCM predictors, respectively. Pattern-scaling methods typically hindcast scenarios for the 2020s from emergent regional climate change patterns in multi-GCM ensembles or RCM runs for the 2080s (as in Hulme *et al.*, 2002; Xiong *et al.*, 2007). The latter is preferable to bespoke RCM simulations for the 2020s because RCMs are sensitive to initial conditions and the regional climate change signal is expected to be small relative to inter-annual variability. Furthermore, pattern-scaling offers the prospect of extrapolation beyond the limited set of RCM experiments to evaluate uncertainties due to the host GCM forcing or emission scenario. In contrast, decadal forecasting and empirical downscaling can be more resource-intensive but provide information on inter-annual behaviour. Thus, it would be informative to compare the value-added of forward running experiments for the 2020s with pattern-scaling back from the 2080s (as in Figure 5). Conversely, the same experiments could test the validity of assumptions about invariant patterns, and linear scaling of regional climate (including extremes) by global mean temperatures (Section 6.1).

Uncertainties in climate change impacts attributed to the secondary impact model *per se* are seldom recognized let alone quantified alongside those due to the climate model or translation of emissions pathways into greenhouse gas concentrations. To date, climate risk assessments have focussed almost exclusively on climate model uncertainty and have, therefore, overlooked major components of uncertainty. Part of the responsibility lies with the research community taking a much broader perspective on uncertainty and combining traditionally separate elements within unifying assessment frameworks (Wilby and Harris, 2006). The problem can also be addressed closer to source whenever climate information is being generated centrally on behalf of a broader constituency. For example, the latest set of river flow change factors provided to UK water utilities to inform their 25-year plans incorporate both climate and hydrological model uncertainty (UKWIR, 2007). Guidance for climate risk assessment should reflect latest understanding of impact model uncertainty and stress its importance particularly when nonlinear and/or discontinuous responses are likely.

10.3. Decision support systems

There is a growing appreciation that the populations, infrastructure and ecology of cities are at risk from the impacts of climate change. At present, roughly 50% of the world's population live in cities, but this is expected to rise to more than 60% over the next 30 years. Most of the future growth of the urban population is anticipated in the developing world. Vulnerable populations of many

low-income countries are already exposed to shortages of clean drinking water and poor sanitation, and often occupy high-risk areas such as floodplains and coastal zones (Haines *et al.*, 2006). Target 11 of MDG7 ('ensure environmental sustainability') aims to achieve a significant improvement in the lives of at least 100 million slum dwellers by 2020. Although the situation is improving, surprisingly little is known about how built environments will respond to climate change (Hunt *et al.*, 2007; Walsh *et al.*, 2007; Wilby, 2007, 2008) especially in developing regions (Magadza, 2000; du Plessis *et al.*, 2003). Adaptation options include improving preparedness and forecasting of climatic hazards, such as intense heat island or air pollution episodes, to safeguard human comfort and health. Technical guidance is also needed for appropriate building design and climate-sensitive planning, avoidance of high-risk areas through more stringent development control, incorporation of climate change allowances in engineering standards applied to flood defences and water supply systems, and for optimum management of green spaces for urban cooling and flood attenuation.

Downscaling methods provide finer resolution scenarios for impacts modelling, but adaptation policy and planning typically require economic information at national and local tiers of government (Burton, 2007). New conceptual and modelling frameworks will be required to 'upscale' from the plethora of local studies. Macro-models and integrated assessment tools already exist for testing multi-sector impacts of climate and socio-economic change (e.g. Hayhoe *et al.*, 2004; Holman *et al.*, 2005), but what is still lacking are the means to incorporate plausible adaptation mechanisms at such coarse scales. Above all, there is an urgent need to convert awareness of local climate change impacts into tangible adaptation measures that span local-government levels (where planning decisions are made to specific requirements) to national levels (where informed policies must be set in climate sensitive sectors). Available scientific evidence must also be translated into guidance for practitioners in both public and private sectors. In addition, composite indices of the strength of future climate change relative to natural variability, alongside measures of human development and vulnerability, could help target resources for adaptation. Existing indices could be enhanced by inclusion of sea-level rise alongside metrics of temperature and precipitation change (Baettig *et al.*, 2007) and applied to the 2020s and 2050s.

Improved access to climate model products and scenario tools would significantly increase opportunities for generation and uptake of climate risk information at the country-level. There are a few good examples of online tools that exploit climate products, combined with local meteorological data, to deliver climate simulations at time and space scales relevant to stakeholders (Table V). Other public domain tools are less quantitative or share indigenous knowledge and practical experience from disaster risk reduction to help inform adaptation strategies. However, a more strategic approach is needed to better coordinate and maintain existing portals, as well as

to provide guidance in the appropriate choice and use of tools, at the country-level. Online training materials tailored to local adaptation priorities and capacity needs could be delivered through the same portal. A specific need is to continually improve the accessibility and format of AR4 climate change scenarios distributed by the IPCC Data Distribution Centre (DDC) portal.

11. Concluding remarks

This review provides a compendium of tools for constructing climate change risk information for the 2020s timeframe. The emphasis was on the needs of developing regions because of the greater economic significance of climate variability and extremes, greater vulnerability of populations and lesser capacity to adapt. However, it is clear that many developed countries face similar challenges. In either context, it is necessary to evaluate the available scenario methods, their comparative strengths and weakness, infrastructure and capacity requirements. However, entry points for mainstreaming scenario information in adaptation planning depend on the country-level technical and financial capacity, scale of the risk(s), as well as the timing and type(s) of adaptation being considered.

One option is to begin by evaluating the sensitivity of infrastructure and processes to observed climate variability – this does not even require climate model information but can highlight key vulnerabilities. Scenario-led adaptation and development planning requires climate risk information tailored to the specific needs of different audiences, especially critical sectors, and where early or severe impacts are anticipated. Clearly, the two approaches are complimentary: vulnerability assessment to identify measures that address climate variability and climate model uncertainty in the short-term; and climate scenarios to test measures that counteract incremental changes in risk over coming decades. Above all, the scientific community will need to pay much greater attention to the production of climate risk information and guidance on appropriate use over typical planning horizons – this means shifting emphasis from the 2080s to the 2020s and 2050s.

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References

- Abraham MG, Savage MJ. 2006. Potential impacts of climate change on the grain yield of maize for the midlands of KwaZulu-Natal, South Africa. *Agriculture Ecosystems & Environment* **115**: 150–160.

- Adger WN, Arnell NW, Tomkins EL. 2005. Successful adaptation to climate change across scales. *Global Environmental Change* **15**: 77–86.
- Alcamo J, Flörke M, Märker M. 2007. Future long-term changes in global water resources driven by socio-economic and climatic changes. *Hydrological Sciences Journal* **52**: 247–275.
- Arnell NW, Hudson DA, Jones RG. 2003. Climate change scenarios from a regional climate model: Estimating change in runoff in southern Africa. *Journal of Geophysical Research* **108**: 9–17, DOI:10.1029/2002JD002782.
- Arnell NW. 2004. Climate change and global water resources: SRES emissions and socio-economic scenarios. *Global Environmental Change* **14**: 31–52.
- Baettig M, Wild M, Imboden DM. 2007. A climate change index: Where climate change may be most prominent in the 21st century. *Geophysical Research Letters* **34**: L01705.
- Baines PG, Folland CK. 2007. Evidence for a rapid global climate shift across the late 1960s. *Journal of Climate* **20**: 2721–2744.
- Becker S, Hartmann H, Zhang Q, Wu Y, Jiang T. 2008. Cyclicity analysis of precipitation regimes in the Yangtze River basin, China. *International Journal of Climatology* **28**: 579–588.
- Benestad RE. 2004. Tentative probabilistic temperature scenarios for northern Europe. *Tellus* **56A**: 89–101.
- Betts R, Best M. 2004. *Simulating climate change in urban areas: interactions between radiative forcing, landscape effects and heat sources*, BETWIXT Technical Briefing Note 3, Met Office, UK.
- Betts RA, Boucher O, Collins M, Cox PM, Falloon PD, Gedney N, Hemming DL, Huntingford C, Jones CD, Sexton DMH, Webb MJ. 2007. Projected increase in continental runoff due to plant responses to increasing carbon dioxide. *Nature* **448**: 1037–1041.
- Blender R, Fraedrich K. 2006. Long-term memory of the hydrological cycle and river runoffs in China in a high-resolution climate model. *International Journal of Climatology* **26**: 1547–1565.
- Boorman DD, Sefton CEM. 1997. Recognising the uncertainty in the quantification of the effects of climate change on hydrological response. *Climatic Change* **35**: 415–434.
- Burton I. 2007. Modelling adaptation? *Tiempo* **62**: 28.
- Cameron D, Beven K, Naden P. 2000. Flood frequency estimation under climate change (with uncertainty). *Hydrology and Earth System Sciences* **4**: 393–405.
- Carter T. 2007. *General Guidelines on the Use of Scenario Data for Climate Impact and Adaptation Assessment*, IPCC Task Group on Scenarios for Climate Impact Assessment (TGICIA). Web link: http://www.ipcc-data.org/guidelines/TGICIA_guidance_sdciaa_v2_final.pdf.
- Caspary H, Katzenberger B. 2006. Adaptation of design flood calculation standards to climate change in southern Germany using downscaling from ECHAM4. *European Geophysical Union General Assembly*. European Environment Agency: Vienna.
- Chappell A, Agnew CT. 2004. Modelling climate change in West African Sahel rainfall (1931–1990) as an artefact of changing station locations. *International Journal of Climatology* **24**: 547–554.
- Christensen JH, Hewitson B, Busiuc A, Chen A, Gao X, Held I, Jones R, Kolli R.K, Kwon W.-T, Laprise R, Magaña Rueda V, Means L, Menéndez C.G, Räisänen J, Rinke A, Sarr A, Whetton P. 2007. Regional Climate Projections. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Solomon S, Quin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds). Cambridge University Press: Cambridge.
- Claussen M, Brovkin V, Ganopolski A, Kubatzki C, Petoukhov V. 2003. Climate change in northern Africa: The past is not the future. *Climatic Change* **57**: 99–118.
- Conway D. 2005. From headwater tributaries to international river: Observing and adapting to climate variability and change in the Nile basin. *Global Environmental Change-Human and Policy Dimensions* **15**: 99–114.
- Conway D, Dessai S, O'Mahony P. 2006. ORCHID Bangladesh: Development of Climate Scenarios (ToR Ibi) October 2006, 13.
- Davey CA, Pielke RA. 2005. Microclimate exposures of surface-based weather stations: implications for the assessment of long-term temperature trends. *Bulletin of the American Meteorological Society* **86**: 497–504.
- Dessai S, Lu X, Risbey JS. 2005. On the role of climate scenarios for adaptation planning. *Global Environmental Change* **15**: 87–97.
- DFID. 2005. *Climate Proofing Africa: Climate and Africa's Development Challenge*, UK Government Department for International Development: London; 26.
- Dickey TD, Bidigare RR. 2005. Interdisciplinary oceanographic observations: the wave of the future. *Scientia Marina* **69**: 23–42.
- Dilley M. 2000. Reducing vulnerability to climate variability in Southern Africa: the growing role of climate information. *Climatic Change* **45**: 63–73.
- du Plessis C, Irurah DK, Scholes RJ. 2003. The built environment and climate change in South Africa. *Building Research and Information* **31**: 240–256.
- Ekström M, Fowler HJ, Kilsby CG, Jones PD. 2005. New estimates of future changes in extreme rainfall across the UK using regional climate model integrations. 2. Future estimates and use in impact studies. *Journal of Hydrology* **300**: 234–251.
- Eltahir EAB. 1996. El Niño and the natural variability in the flow of the Nile River. *Water Resources Research* **32**: 131–137.
- European Environment Agency (EEA). 2007. Climate change and water adaptation issues. EEA Technical Report No. 2/2007, European Environment Agency: Copenhagen; 110.
- Favis-Mortlock DT, Guerra SGT. 1999. The implications of General Circulation Model estimates of rainfall for future erosion: a case study from Brazil. *Catena* **37**: 329–354.
- Fink AH, Brücher T, Krüger A, Leckebusch GC, Pinto JG, Ulbrich U. 2004. The 2003 European summer heatwaves and drought – synoptic diagnosis and impacts. *Weather* **59**: 209–216.
- Fowler H, Blenkinsop S, Tebaldi C. 2007. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology* **27**: 1547–1578.
- Fowler HJ, Wilby RL. 2007. Beyond the downscaling comparison study. *International Journal of Climatology* **27**: 1543–1545.
- Füssel H-M. 2007. Methodological and empirical flaws in the design and application of simple climate-economy models. *Climatic Change* **81**: 161–185.
- Giannini A, Saravanan R, Chang P. 2003. Oceanic forcing of Sahel rainfall on interannual to interdecadal time scales. *Science* **302**: 1027–1030.
- Giorgi F. 2006. Climate change hot-spots. *Geophysical Research Letters* **33**: L08707.
- Gleckler PJ, Wigley TML, Santer PD, Gregory JM, AchutaRao K, Taylor KE. 2006. Krakatoa's signature persists in the ocean. *Nature* **439**: 675.
- Good P, Barring L, Giannakopoulos C, Holt T, Palutikof J. 2006. Non-linear regional relationships between climate extremes and annual mean temperatures in model projections for 1961–2099 over Europe. *Climate Research* **31**: 19–34.
- Goodess CM, Anagnostopoulou C, Bardossy A, Frei C, Harpham C, Haylock M.R, Hindecha Y, Maheras P, Ribalaygua J, Schmidli J, Schmith T, Tolika K, Tomozeiu R, Wilby R.L. 2007. An intercomparison of statistical downscaling methods for Europe and European regions – assessing their performance with respect to extreme temperature and precipitation events. *Climatic Change in press*.
- Hacker JN, Belcher SE, Goodess CM, Holmes MJ, Roaf S. Building scale scenarios: climate change and their applications to the design of climatically-sensitive buildings. *Planning and Environment B* (in press).
- Haines A, Kovats RS, Campbell-Lendrum D, Corvalan C. 2006. Climate change and human health: impacts, vulnerability, and public health. *Lancet* **367**: 2101–2109.
- Hall J. 2007. Probabilistic climate scenarios may misrepresent uncertainty and lead to bad adaptation decisions. *Hydrological Processes* **21**: 1127–1129.
- Hayhoe K, Cayan D, Field CB, Frumhoff PC, Maurer EP, Miller NL, Moser SC, Schneider SH, Cahill KN, Cleland EE, Dale L, Drapek R, Hanemann RM, Kalkstein LS, Lenihan J, Lunch CK, Neilson RP, Sheridan SC, Verville JH. 2004. Emissions pathways, climate change, and impacts on California. *Proceedings of the National Academy of Sciences of the United States of America* **101**: 12422–12427.
- Held IM, Delworth TL, Lu J, Findell KL, Knutson TR. 2005. Simulation of Sahel drought in the 20th and 21st centuries. *Proceedings of the National Academy of Sciences of the United States of America* **102**: 17891–17896.
- Hewitson BC, Crane RG. 2006. Consensus between GCM climate change projections with empirical downscaling: precipitation downscaling over South Africa. *International Journal of Climatology* **26**: 1315–1337.
- Hoerling M, Hurrell J, Eischeid J, Phillips A. 2006. Detection and attribution of 20th century northern and southern African rainfall change. *Journal of Climate* **19**: 3989–4008.

- Holman IP, Rounsevell MDA, Shackley S, Harrison PA, Nicholls RJ, Berry PM, Audsley E. 2005. A regional, multi-sectoral and integrated assessment of the impacts of climate and socio-economic change in the UK. Part 1. Methodology. *Climatic Change* **71**: 9–41.
- Hulme M, Jenkins PJ, Lu X, Turnpenny JR, Mitchell TD, Jones RG, Lowe J, Murphy JM, Hassell D, Boorman P, McDonald R, Hill S. 2002. *Climate Change Scenarios for the UK: The UKCIP02 Scientific Report*. Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia: Norwich; 120.
- Hulme M, Wigley TML, Barrow EM, Raper SCB, Centella A, Smith S, Chipanshi AC. 2000. *Using a Climate Scenario Generator for Vulnerability and Adaptation Assessments: MAGICC and SCENGEN Version 2.4 Workbook*. Climatic Research Unit: Norwich; 52.
- Hunt JCR, Maslin M, Killeen T, Backlund P, Schellnhuber HJ. 2007. Introduction. Climate change and urban areas: research dialogue in a policy framework. *Philosophical Transactions of the Royal Society A* **365**: 2615–2629.
- Immerzeel W. 2008. Historical trends and future predictions of climate variability in the Brahmaputra basin. *International Journal of Climatology* **28**: 243–254.
- Intergovernmental Panel on Climate Change (IPCC). 2007. Summary for policy makers. *Climate Change 2007: The Physical Science Basis. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press: Cambridge; UK.
- Islam MN, Rafiuddin M, Ahmed AU, Kholli RK. 2008. Calibration of PRECIS in employing future scenarios in Bangladesh. *International Journal of Climatology* **28**: 617–628.
- Jiang T, Chen YD, Xu C, Chen X, Chen X, Singh VP. 2007. Comparison of hydrological impacts of climate change simulated by six hydrological models in the Dongjiang Basin, South China. *Journal of Hydrology* **336**: 316–333.
- Jimoh OD, Webster P. 1999. Stochastic modelling of daily rainfall in Nigeria: intra-annual variation of model parameters. *Journal of Hydrology* **222**: 1–17.
- Kalnay E, Cai M. 2003. Impact of urbanization and land-use change on climate. *Nature* **423**: 528–531.
- Katz RW. 1996. Use of conditional stochastic models to generate climate change scenarios. *Climatic Change* **32**: 237–255.
- Keenlyside NS, Latif M, Jungclauss J, Kornbluh L, Roeckner E. 2008. Advancing decadal-scale climate prediction in the North Atlantic sector. *Nature* **453**: 84–88.
- Kilsby CG, Jones PD, Burton A, Ford AC, Fowler HJ, Harpham C, James P, Smith A, Wilby RL. 2007. A daily weather generator for use in climate change studies. *Environmental Modelling & Software* **22**: 1705.
- King BA, McDonagh EL. 2005. Decadal changes in ocean properties revealed by ARGO floats. *Geophysical Research Letters* **32**: L15601.
- Klein RJT, Eriksen SEH, Naess LO, Hammill A, Tanner TM, Robledo C, O'Brien L. 2007. Portfolio screening to support the mainstreaming of climate change into development assistance. *Climatic Change* **84**: 23–44.
- Kurukulasuriya P, Ajwad MI. 2006. Application of the Ricardian technique to estimate the impact of climate change on smallholder farming in Sri Lanka. *Climatic Change* **81**: 39–59.
- Lee TCK, Zwiars FW, Zhang XB, Tsao M. 2006. Evidence of decadal climate prediction skill resulting from changes in anthropogenic forcing. *Journal of Climate* **19**: 5305–5318.
- Legates DR, Lins HF, McCabe GJ. 2005. Comments on “Evidence for global runoff increase related to climate warming” by Labat, *et al.* *Advances in Water Resources* **28**: 1310–1315.
- Legesse D, Vallet-Coulomb C, Gasse F. 2003. Hydrological response of a catchment to climate and land use changes in tropical Africa: Case study south central Ethiopia. *Journal of Hydrology* **275**: 67–85.
- Lu X. 2006. *Guidance on the Development of Regional Climate Scenarios for Application in Climate Change Vulnerability and Adaptation Assessments* within the Framework of National Communications from Parties not included in Annex 1 to the United Nations Framework Convention on Climate Change. National Communications Support Programme, UNDP-UNEP-GEF, New York, 42.
- Magadza CHD. 2000. Climate change impacts and human settlements in Africa: prospects for adaptation. *Environmental Monitoring and Assessment* **61**: 193–205.
- Manabe S, Milly PCD, Wetherald R. 2004. Simulated long term changes in river discharge and soil moisture due to global warming. *Hydrological Sciences Journal* **49**: 625–642.
- Makosholo ML, Jooste A. 2006. The comparative advantage of selected long-term crops in Lesotho. *Agrekon* **45**: 173–184.
- Marengo JA, Camargo CC. 2008. Surface air temperature trends in Southern Brazil for 1960–2002. *International Journal of Climatology* **28**: 893–904.
- McCabe GJ, Palecki MA. 2006. Multidecadal climate variability of global lands and oceans. *International Journal of Climatology* **26**: 849–865.
- McKenzie-Hedger M. 2005. Learning from experience: Evolving responses to flooding events in the UK. In *Extreme Weather Events and Public Health Responses*, Kirch W, Menne B, Bertolini R (eds). Springer Publishing Company: Heidelberg; 225–234.
- McKenzie-Hedger M, Connell R, Bramwell P. 2006. Bridging the gap: empowering decision-making for adaptation through the UK Climate Impacts Programme. *Climate Policy* **6**: 201–215.
- Mearns LO, Giorgi F, Whetton P, Pabon D, Hulme M, Lal M. 2003. *Guidelines for use of climate scenarios developed from Regional Climate Model experiments*, IPCC Task Group on Scenarios for Climate Impact Assessment (TG CIA). Web link: http://www.ipcc-data.org/guidelines/dgm_no1_v1_10-2003.pdf.
- Meehl GA, Stocker TF, Collins WD, Friedlingstein P, Gaye AT, Gregory JM, Kitoh A, Knutti R, Murphy JM, Noda A, Raper SCB, Watterson IG, Weaver AJ, Zhao Z-C. 2007. Global climate projections. In *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds). Cambridge University Press: Cambridge; UK.
- Mendelsohn R, Morrison W, Schlesinger ME, Andronova NG. 2000. Country-specific market impacts of climate change. *Climatic Change* **45**: 3–4.
- Michaels PJ, Knappenberger PC, Frauenfeld OW, Davis RE. 2004. Trends in precipitation on the wettest days of the year across the contiguous USA. *International Journal of Climatology* **24**: 1873–1882.
- Mills E. 2007. *From Risk to Opportunity: 2007. Insurer Responses to Climate Change*. Ceres; 55. <http://www.ceres.org/Document.Doc?id=225>.
- Mitchell TD. 2003. Pattern scaling: An examination of the accuracy of the technique for describing future climates. *Climatic Change* **60**: 217–242.
- Mitchell TD, Hulme M, New M. 2002. Climate data for political areas. *Area* **34**: 109–112.
- Mitchell JFB, Johns TC, Eagles M, Ingram WJ, Davis RA. 1999. Towards the construction of climate change scenarios. *Climatic Change* **41**: 547–581.
- Mkanda FX. 1999. Drought as an analogue climate change scenario for prediction of potential impacts on Malawi's wildlife habitats. *Climate Research* **12**: 215–222.
- Narisma GT, Foley JA, Licker R, Ramankutty N. 2007. Abrupt changes in rainfall during the twentieth century. *Geophysical Research Letters* **34**: L06710.
- New M, Dessai S, Lopez A, Wilby RL. 2007. Challenges in using probabilistic climate change information for impacts and adaptation decision-making: an example from the water sector. *Philosophical Transactions of the Royal Society* **365**: 2117–2131.
- Niel H, Paturol J-E, Servat E. 2003. Study of parameter stability of a lumped hydrologic model in a context of climate variability. *Journal of Hydrology* **278**: 213–230.
- Nobre P, Marengo I, Cavalcanti IAF, Obregon G, Barros V, Camilloni I, Campos N, Ferreira AG. 2004. *Seasonal-to-decadal predictability and prediction of South American climate*. White Paper prepared for the CLIVAR Workshop on Atlantic Predictability, Reading, 19–23 April 2004, 42.
- Pal JS, Giorgi F, Bi X, Elguindi N, Solomon F, Gao XJ, Rauscher SA, Francisco R, Zakey A, Winter J, Ashfaq M, Syed FS, Bell JL, Diffenbaugh NS, Karmacharya J, Konare A, Martinez D, da Rocha RP, Sloan LC, Steiner AL. 2007. RegCM3 and RegCNET: Regional climate modeling for the developing world. *Bulletin of the American Meteorological Society* **88**: 1395–1409.
- Palutikof JP, Agnew MD, Hoar MR. 2004. Public perceptions of unusually warm weather in the UK: impacts, responses and adaptations. *Climate Research* **26**: 43–59.
- Payne JT, Wood AW, Hamlet AF, Palmer RN, Lettermaier DP. 2004. Mitigating the effects of climate change on the water resources of the Columbia River Basin. *Climatic Change* **62**: 233–256.
- Perez RT, Amadore LA, Feir RB. 1999. Climate change impacts and responses in the Philippines coastal sector. *Climate Research* **12**: 97–107.

- Pielke RA Sr. 1998. Climate prediction as an initial value problem. *Bulletin of the American Meteorological Society* **79**: 2743–2746.
- Pitt Review. 2008. *Learning Lessons from the 2007 Floods: An Independent Review by Sir Michael Pitt*. Cabinet Office: London; 160.
- Plag HP. 2006. Recent relative sea-level trends: an attempt to quantify the forcing factors. *Philosophical Transactions of the Royal Society A* **364**: 821–844.
- Prudhomme C, Jakob D, Svensson C. 2003. Uncertainty and climate change impact on the flood regime of small UK catchments. *Journal of Hydrology* **277**: 1–23.
- Rodwell MJ, Doblas-Reyes FJ. 2006. Medium-range, monthly, and seasonal prediction for Europe and the use of forecast information. *Journal of Climate* **19**: 6025–6046.
- Sato T, Kimura F, Kitoh A. 2007. Projection of global warming onto regional precipitation over Mongolia using a regional climate model. *Journal of Hydrology* **333**: 144–154.
- Schiermeier Q. 2007. Get practical, urge climatologists. *Nature* **448**: 234–235.
- Schmidli J, Frei C, Vidale PL. 2006. Downscaling from GCM precipitation: A benchmark for dynamical and statistical downscaling methods. *International Journal of Climatology* **26**: 679–689.
- Schneeberger C, Blatter H, Abe-Ouchi A, Wild M. 2003. Modelling changes in the mass balance of glaciers of the northern hemisphere for a transient 2 x CO₂ scenario. *Journal of Hydrology* **282**: 145–163.
- Shine KP, Forster PMD. 1999. The effect of human activity on radiative forcing of climate change: a review of recent developments. *Global and Planetary Change* **20**: 205–225.
- Singh P, Bengtsson L. 2003. Effect of a warmer climate on the depletion of snowcovered area in the Satluj basin in the western Himalayan region. *Hydrological Sciences Journal* **48**: 413–425.
- Smit B, Burton I, Klein RJT, Wandel J. 2000. An anatomy of adaptation to climate change and variability. *Climatic Change* **45**: 223–251.
- Smith DM, Cusack S, Colman AW, Folland CK, Harris GR, Murphy JM. 2007. Improved surface temperature prediction for the coming decade from a global climate model. *Science* **317**: 796–799.
- Smithers J, Pegram G, Schulze R. 2002. Design rainfall estimation in South Africa using Bartlett-Lewis rectangular pulse rainfall models. *Journal of Hydrology* **258**: 83–99.
- Snyder P, Foley JA, Hitcham MH, Delire C. 2004. Analyzing the effects of complete tropical forest removal on the regional climate using a detailed three-dimensional energy budget: An application to Africa. *Journal of Geophysical Research* **109**: D21102.
- Soltani A, Hoogenboom G. 2005. Minimum data requirements for parameter estimation of stochastic weather generators. *Climate Research* **25**: 109–119.
- Song Y, Semazzi FHM, Xie L, Ogallo LA. 2004. A coupled regional climate model for Lake Victoria basin of East Africa. *International Journal of Climatology* **24**: 57–75.
- Stainforth DA, Aina T, Christensen C, Collins M, Faull N, Frame DJ, Kettleborough JA, Knight S, Martin A, Murphy JM, Piani C, Sexton D, Smith LA, Spicer RA, Thorpe AJ, Allen MR. 2005. Uncertainty in predictions of the climate response to rising levels of greenhouse gases. *Nature* **433**: 403–406.
- Stott PA, Kettleborough JA. 2002. Origins and estimates of uncertainty in predictions of twenty-first century temperature rise. *Nature* **416**: 723–726.
- Stott PA, Stone DA, Allen MR. 2004. Human contribution to the European heatwave of 2003. *Nature* **432**: 610–614.
- Sutton RT, Allen MR. 1997. Decadal predictability of North Atlantic sea surface temperature and climate. *Nature* **388**: 563–567.
- Tanner T. 2007. Sharing climate adaptation tools: Improving decision-making for development. In *Proceedings of the Geneva Workshop*, Geneva, 11–12 April 2007, 10.
- Tate E, Sutcliffe J, Conway P, Farquharson F. 2004. Water balance of Lake Victoria: update to 2000 and climate change modelling to 2100. *Hydrological Sciences Journal* **49**: 563–574.
- Taulis ME, Milke MW. 2005. Estimation of WGEN weather generation parameters in arid climates. *Ecological Modelling* **184**: 177–191.
- Tebaldi C, Arblaster J, Hayhoe K, Meehl G. 2006. Going to extremes: an intercomparison of model-simulated historical and future changes in extreme events. *Climatic Change* **79**: 185–211.
- UKWIR. 2007. *Effects of Climate Change on River Flows and Groundwater Recharge, a Practical Methodology: Synthesis Report*, UKWIR Report 07/CL/04/10.
- United Nations Development Programme (UNDP). 2007. Human Development Report 2007/2008, Fighting climate change: Human solidarity in a divided world.
- Viviroli D, Dür H, Messerli B, Meybeck M, Weingartner R. 2007. Mountains of the world, water towers for humanity: Typology, mapping, and global significance. *Water Resources Research* **43**: W07477.
- Vuille M, Bradley RS. 2000. Mean annual temperature trends and their vertical structure in the tropical Andes. *Geophysical Research Letters* **27**: 3885–3888.
- Walsh K. 2004. Tropical cyclones and climate change: unresolved issues. *Climate Research* **27**: 77–83.
- Walsh CL, Hall JW, Street RB, Blanksby J, Cassar M, Ekins P, Glendinning S, Goodess CM, Handley J, Noland R, Watson SJ. 2007. *Building Knowledge for a Changing Climate: Collaborative Research to Understand and Adapt to the Impacts of Climate Change on Infrastructure, The Built Environment and Utilities*. Newcastle University; 76.
- Wang X, Li C, Zhou W. 2006. Interdecadal variation of the relationship between Indian rainfall and SSTA modes in the Indian Ocean. *International Journal of Climatology* **26**: 595–606.
- Warren R, Arnell N, Nicholls R, Levy P, Price J. 2006. Understanding the regional impacts of climate change. *Research Report Prepared for the Stern Review on the Economics of Climate Change*. Tyndall Centre for Climate Change Research: University of East Anglia, Norwich Working Paper 90, UEA; 223.
- Washington R, Harrison M, Conway D. 2004. *African climate report: A report commissioned by the UK Government to review African climate science, policy and options for action*, DFID/DEFRA, 45.
- Washington R, Harrison M, Conway D, Black E, Challinor A, Grimes D, Jones R, Morse A, Kay G, Todd M. 2006. African climate change: taking the shorter route. *Bulletin of the American Meteorological Society* **87**: 1355–1366.
- Weng HY, Lau KM, Xue YK. 1999. Multi-scale summer rainfall variability over China and its long-term link to global sea surface temperature. *Journal of the Meteorological Society of Japan* **77**: 845–857.
- Whitehead PG, Wilby RL, Butterfield D, Wade AJ. 2006. Impacts of climate change on nitrogen in a lowland chalk stream: An appraisal of adaptation strategies. *Science of the Total Environment* **365**: 260–273.
- Wilby RL. 2005. Uncertainty in water resource model parameters used for climate change impact assessment. *Hydrological Processes* **19**: 3201–3219.
- Wilby RL. 2007. A review of climate change impacts on the built environment. *Built Environment Journal* **33**: 31–45.
- Wilby RL, Direction de la Météorologie Nationale (DMN), 2007. *Climate change scenarios for Morocco*. Technical Report, World Bank, Washington, 23pp.
- Wilby RL. 2008. Constructing climate change scenarios of urban heat island intensity and air quality. *Environment and Planning B-Planning & Design* **35**: 902–919.
- Wilby RL, Beven KJ, Reynard NS. 2008. Climate change and fluvial flood risk in the UK: More of the same? *Hydrological Processes* **22**: 2511–2523.
- Wilby RL, Charles S, Mearns LO, Whetton P, Zorito E, Timbal B. 2004. *Guidelines for Use of Climate Scenarios Developed from Statistical Downscaling Methods*, IPCC Task Group on Scenarios for Climate Impact Assessment (TGSCIA). Web link: http://www.ipcc-data.org/guidelines/dgm_no2_v1_09_2004.pdf.
- Wilby RL, Dawson CW, Barrow EM. 2002. SDSM – a decision support tool for the assessment of regional climate change impacts. *Environmental and Modelling Software* **17**: 145–157.
- Wilby RL, Harris I. 2006. A framework for assessing uncertainties in climate change impacts: low flow scenarios for the River Thames, UK. *Water Resources Research* **42**: W02419, DOI:10.1029/2005WR004065.
- Wilby RL, Wigley TML. 1997. Downscaling general circulation model output: a review of methods and limitations. *Progress in Physical Geography* **21**: 530–548.
- Wilks DS, Wilby RL. 1999. The weather generation game: A review of stochastic weather models. *Progress in Physical Geography* **23**: 329–357.
- World Bank. 2006. *Managing Climate Risk: Integrating Adaptation into World Bank Group Operations*. Global Environment Facility Program: Washington, DC; 32.
- World Bank. 2007. *Visualizing Future Climate in Latin America: Results from the Application of the Earth Simulator*, Latin America

- and Caribbean Region Sustainable Development Working Paper 30, November, 2007.
- World Resources Institute (WRI). 2007. *Weather the Storm: Options for Framing Adaptation and Development*. Washington, DC: 57.
- Xiong W, Lin E, Ju H, Xu Y. 2007. Climate change and critical thresholds in China's food security. *Climatic Change* **81**: 205–221.
- Zhang X, Hegerl G, Zwiers FW, Kenyon J. 2005. Avoiding inhomogeneity in percentile-based indices of temperature extremes. *Journal of Climate* **18**: 1641–1651.
- Zhang X, Zwiers FW, Hegerl GC, Lambert FG, Gillett NP, Solomon S, Stott PA, Nozawa T. 2007. Detection of human influence on twentieth-century precipitation trends. *Nature* **448**: 461–465.
- Ziegler AD, Maurer EP, Sheffield J, Nijssen B, Wood EF, Lettenmaier D. 2005. Detection time for plausible changes in annual precipitation, evapotranspiration, and streamflow in three Mississippi River sub-basins. *Climatic Change* **72**: 17–36.
- Zwiers FW. 2002. The 20-year forecast. *Nature* **416**: 690–691.