



Representing Climate and Extreme Weather Events in Integrated Assessment Models: A Review of Existing Methods and Options for Development

C.M. GOODESS¹, C. HANSON¹, M. HULME² AND T.J. OSBORN^{1,2}

¹Climatic Research Unit, School of Environmental Sciences, University of East Anglia, Norwich, NR4 7TJ, UK
and ²Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich, NR4 7TJ, UK

ABSTRACT

The lack of information about future changes in extreme weather is a major constraint of Integrated Assessment Models (IAMs) of climate change. The generation of descriptions of future climate in current IAMs is assessed. We also review recent work on scenario development methods for weather extremes, focusing on those issues which are most relevant to the needs of IAMs. Finally, some options for implementing scenarios of weather extremes in IAMs are considered.

Keywords: Integrated Assessment Models, climate change, scenarios, extreme weather events, general circulation models, regional climate models.

1. INTEGRATED ASSESSMENT AND CLIMATE CHANGE

One of the essential characteristics of integrated assessment is the simultaneous consideration of the multiple dimensions of environmental problems such as climate change. A number of formal integrated assessment models (IAMs) for climate change have been developed over the last decade, starting with the models IMAGE 1.0 and ESCAPE in the early 1990s [1, 2]. These models were constructed using modules that are reduced-form versions of more complex models, for example of the climate system, the economy and ecosystems. Most climate modules in IAMs generate zero (i.e., globally-averaged; e.g., PAGE) or one (i.e., zonally-averaged; e.g., IMAGE) dimensional descriptions of future climate, usually at a mean (e.g., 30-year average) seasonal or annual resolution [3–5]. Some IAMs (e.g., IMAGE 2.2 and AIM) then generate spatially explicit, i.e., two-dimensional, descriptions of future climate, usually by accessing stored patterns of climate change derived from more complex General Circulation Model (GCM) experiments [6–8].

These approaches to generating future climate descriptions in IAMs, which are reviewed in Section 2, are computationally efficient and allow multiple experiments to be easily conducted in an integrated framework. The climate output is then input into an ecosystem, agriculture or

health impacts module (e.g., AIM), or used directly to estimate the economic cost of climate damage from a look-up climate damage function (e.g., DICE). In either case, the current lack of any information about changes in daily or extreme weather (the focus of this review) is a major weakness. Agriculture, for example, is likely to be as, or more, sensitive to changes in daily weather sequences and the occurrence of extreme weather events than to changes in mean monthly or seasonal climate [9–11]. Potential changes in extremes and the ensuing changes in risk are also important for sectors such as water resources and insurance [12, 13]. Climate damage functions that express the economic impact of climate change as a function of global- (or regional-) mean climate alone are likely to underestimate the economic damage associated with extreme events such as flooding and storms (e.g., in the UK, the October 1987 windstorm event is estimated to have cost insurers 3.1 billion US dollars, with further economic losses of 2.7 billion US dollars [14]). The lack of information about changes in daily weather and extreme events also limits simulation of adaptive processes in social institutions and environmental systems: an important objective of the emerging third generation of IAMs [15].

Identification and definition of the weather extremes which should be considered in IAMs is not straightforward, although a number of indicators of temperature (e.g., 90th

percentile, frost severity index, heat wave duration index) and precipitation (e.g., 90th percentile/quantile, maximum length of wet/dry spell, magnitude of the 20 year return period event) weather extremes have recently been recommended for use in climate-change studies [12, 16]. Appropriate temporal and spatial scales also need to be identified [17]. It is generally assumed that information at the daily time scale is necessary to investigate extreme events. However, extreme events such as drought (e.g., the 1976 multi-season drought in the UK) can usefully be defined using monthly data and at the regional spatial scale (e.g., greater than 1000 km² for the UK). Intense rainfall events leading to flooding are more appropriately investigated at higher resolutions (e.g., durations of 12–72 hours and spatial scales of about 100 km² are relevant in Scotland).

For many impact sectors it may be necessary to consider other variables, such as wind, hail, fog, lightning and storm surges. Joint probability events may also be important (e.g., wind storms with snow/rain, heavy snow followed by rapid thaw, coastal storm surge with river flood), together with changes in the persistence and sequence of extreme events (e.g., sequences of long dry/hot summers) and seasonal changes in the timing of extremes (e.g., changes in the season of maximum frequency of occurrence). Finally, a distinction needs to be made between meteorological information on extremes (i.e., statistics concerning their frequency and magnitude) and their impacts. What, for example, is the relationship between the 99th percentile precipitation event and the 1 in 100-year flood event? And how might this relationship be affected by factors such as land-use change? It should also be noted that some weather events may be extreme in terms of their impact, although the weather event itself is not extreme (e.g., for air quality and building comfort, ‘non-events’ such as very low wind speed may be important). Thus, even for single-sector climate impacts studies, the incorporation of changes in weather extremes is potentially complex and places additional demands on scenario development methods compared with changes in mean climate. In IAMs, these complexities must be balanced against the need for computational efficiency (see Section 4).

Recent work on scenario development methods for weather extremes is reviewed in Section 3, focusing on temperature and precipitation extremes and the issues which are most relevant to the needs of integrated assessment modelling. Ways in which these methods could be implemented in IAMs in order to overcome one of the shortcomings of the current generation of IAMs, i.e., the failure to represent extreme weather events, are discussed in Section 4, focusing on the UK and European perspectives.

Together with the growing recognition of the need to incorporate information about changes in interannual climate variability and the occurrence of extremes into integrated assessments, there is also growing concern to take into account the full range of uncertainties in scenario

construction and, at the same time, to distinguish between the inherent unpredictability of climate and climate model deficiencies [18–29]. The IPCC Third Assessment Report (TAR) [30, 31] and many of the references cited above, refer to a cascade of climate prediction uncertainty related to:

- the forcing emissions scenarios, i.e., inter-scenario variability;
- the response of different climate models, i.e., inter-model variability;
- different realizations of a given forcing scenario with a given climate model, i.e., internal model variability (which is, in part, a reflection of natural climate variability); and,
- sub-grid scale forcings and processes.

Appropriate techniques for handling the first three sources of uncertainty are widely recognised (see references above, also [32–38]), although they are not yet routinely or comprehensively applied in impacts assessments. Thus,

- uncertainties due to inter-scenario variability can be handled by using more than one forcing scenario;
- uncertainties due to inter-model variability can be handled by using output from more than one climate model; and,
- uncertainties due to internal model variability and thus, in part, natural climate variability, can be handled by using single-model ensembles (i.e., simulations performed with the same climate models and forcing, but starting from different initial conditions).

The application of these techniques in IAMs is reviewed in Section 2.7, while the additional issues that arise in applying them to extremes, together with the less-widely addressed problem of uncertainties arising from sub-grid scale forcings and processes, are discussed briefly in Section 3.5.

The IPCC Second Assessment Report (SAR) [39] concluded that one of the biggest challenges facing integrated assessment was the consideration, assessment and incorporation of low probability/high consequence events into IAMs. This need was re-emphasised by the Third Assessment Report [31] which identifies events such as ‘abrupt’ reorganisation of the thermohaline circulation and the collapse of the West Antarctic ice sheet that could arise due to non-linearities in the climate system. Reviewing knowledge of such events is beyond the scope of this paper, although it is noted that the DICE and ICLIPS IAMs have been used to explore abrupt thermohaline circulation changes [40–44]. Future integrated assessments of these changes will benefit from ongoing research on (i) the conditional probability of the event occurring, and (ii) the response of the climate system to the event.

The focus of this paper is climate and extreme weather events. Thus potential problems relating to the representation of social, economic and technological aspects, and the associated feedbacks, are not discussed.

2. THE TREATMENT OF CLIMATE IN IAMs

2.1. The Development of IAMs

The criterion used to determine whether a model is 'integrated' is subjective. The problem stems from the fact that IAMs are supposedly all encompassing; replicating not only the primary dynamic interactions between society and environment, but also the secondary feedback mechanisms. In trying to embrace all aspects of environmental change, the developers of such models have to make decisions about the focus of their study and how they wish to express the impacts they are attempting to estimate, whether this be through the reporting of physical changes in emissions, shifts in land-use activity or mortality rates, or through cost-benefit analysis of damages resulting from climate change [39]. This in many cases leads to certain components or modules within the IAM – those most closely linked to the exposure unit being studied – being more complex than those other modules that are included in the IAM in order to close the loop.

The origins of integrated assessment modelling lie with the "Club of Rome" models developed in the 1970s. These used a holistic approach to look at issues such as resource depletion, population growth and environmental pollution [45]. The late 1970s saw the development of formally-modelled integrated assessments of energy policy. The role of such models in environmental policy formation was further enhanced in the early 1980s when the RAINS model played a key part in the process that brought about a European-wide agreement to control acid rain [46]. But, while many environmental issues were explored using an integrated approach, climate change impact assessment studies carried out during the 1980s tended to be more focused in nature, looking only at single exposure units.

The earliest integrated global climate change models were conceived in the late 1980s, when the first model to fully encompass energy, climate and impacts was IMAGE 1.0 [1]. At the regional level, the MINK project [47] and the Atmospheric Stabilisation Framework (ASF) were initiated to examine the problem of climate change in an integrated way and looked at climate impacts on sectors such as forestry, agriculture and water resources [39].

The early 1990s witnessed the development of several global and regional integrated climate change models. IMAGE reached version 2 and a European consortium developed the ESCAPE model. As the models became more complex, so the size and nature of the modelling effort changed, from models such as DICE, PAGE and FUND developed by individuals, to models such as IMAGE 2.2 developed by whole research institutes and eventually to models such as ICLIPS developed by research networks spanning continents. The representation of climate in these IAMs has become more sophisticated and diverse over time. Methods used in the current generation of IAMs are reviewed in the next section.

2.2. Representation of Climate in the Currently-used Second Generation of IAMs

Here, thirteen of the more established climate change IAMs (Table 1) which illustrate the different approaches to integrated assessment modelling are reviewed. The IAM literature is extensive and the list of models in Table 1 is not exhaustive. However, it encompasses all the internationally better known IAMs. All listed IAMs are referenced in the IPCC SAR and TAR and some have been used most recently to investigate the impacts associated with the SRES marker scenarios [48]. The focus here is on how they use observed climatologies and climate model projections: summarised in Table 2. It is immediately apparent that the type of climate data and models utilised by each IAM is highly dependent on its particular focus, i.e., economic costs and benefits, biophysical impacts, policy guidance or adaptation.

The aim of the climate model component of any IAM is to produce plausible future climates, linked to prior emissions, in order to assess the impacts of climate change. Two approaches are taken (Fig. 1). The first approach, used in IAMs focusing on economic costs and benefits, is to estimate global temperature between two time periods and the second approach, used in IAMs focusing on biophysical impacts, is to perturb observed baseline regional climatologies using climate model output.

The majority of IAMs adopt the second approach, i.e., future climate is constructed by combining an observed baseline climatology with future regional climate change patterns produced by GCMs, scaled using estimates of changes in global mean temperature generated by Simple Climate Models (SCMs) such as COSMIC [49, 50] or MAGICC [51]. This approach is typified by the IMAGE model [52] in which future greenhouse gas emissions are calculated by the energy-industry module for each economic region as a function of energy consumption and industrial production. These emissions are combined with emissions released from the terrestrial biosphere to the atmosphere which are produced by the terrestrial-environment module (which simulates land use and land-cover dynamics for a $0.5^\circ \times 0.5^\circ$ grid). The combined emissions are globally aggregated and then input into a SCM, in this case an upwelling-diffusion model based on MAGICC. The output from this module is used to scale the regional climate change pattern, which is then added to the 1961–1990 baseline climatology.

CETA, DICE, FUND, ICAM-3, MERGE, MiniCAM and PAGE95 all adopt the first approach, i.e., they use an observed reference point, rather than a baseline climatology, from which to calculate changes in atmospheric greenhouse gas concentrations and global temperature. These models tend to operate at the global level, using SCM output to produce an aggregated average global change in climate. This approach is illustrated by MERGE. Future concentrations of greenhouse gases (CO_2 , CH_4 and N_2O) are simulated

Table 1. Model names, developers and key references for the 13 IAMs reviewed in the paper.

Model	Developers	Key references
Cost-benefit analysis models		
CETA	EPRI and Teisberg Associates, USA	[4, 66, 170]
DICE	Nordhaus, Yale University, USA	[171]
Related models:		
PRICE		
RICE		
FUND	RSJ Tol, University of Hamburg	[5, 68]
ICAM-3	Carnegie Mellon University, USA	[172, 173]
MERGE 4.4	Stanford University, USA	http://www.stanford.edu/group/MERGE/ [53, 67]
MiniCAM	Global Change Group at Pacific Northwest Laboratory, USA.	http://www.grida.no/climate/ipcc/emission/154.htm http://sedac.ciesin.org/mva/MCPAPER/mcpaper.html [174, 175]
PAGE95	Judge Institute of Management Studies, University of Cambridge, UK	[3, 85]
Biophysical-impacts models		
AIM	National Institute for Environmental Studies, Japan and Kyoto University	http://www-cger.nies.go.jp/ipcc/aim/ [6]
CLIMACTS	International Global Change Institute (IGCI), University of Waikato, New Zealand	http://www.waikato.ac.nz/igci/climacts_webpage/ [83]
Related models: OzCLIM, BDCLIM, VANDACLIM		
ESCAPE	Climatic Research Unit, UK and RIVM, The Netherlands	[2, 54]
IMAGE 2.2	RIVM, The Netherlands	http://www.rivm.nl/image/home.html [52, 176]
MIT IGSM	Joint Program on the Science and Policy of Global Change, Massachusetts Institute of Technology, USA	http://web.mit.edu/globalchange/www/if.html [8, 177]
Tolerable windows approach		
ICLIPS	Potsdam Institute for Climate Impact Research (PIK), Germany	http://www.pik-potsdam.de/cp/iclips [43, 75, 79]

and then the change in temperature calculated relative to 2000. The global equilibrium (surface) temperature change (ΔPT) is calculated by aggregating the radiative effects (ΔF) of CO_2 , CH_4 and N_2O :

$$\Delta PT = d^* \Delta F \quad (1)$$

where: d determines the equilibrium climate sensitivity (assumed to be $0.555^\circ\text{C W m}^{-2}$ in MERGE) and $\Delta F = \Delta F_{\text{CO}_2} + \Delta F_{\text{CH}_4} + \Delta F_{\text{N}_2\text{O}}$.

Actual temperature change, ΔAT , is then calculated:

$$\Delta AT_{t+1} - \Delta AT_t = c_1^* (\Delta PT_t - \Delta AT_t) \quad (2)$$

where: $c_1 = 0.05$ (representing a 20 year mean lag to reflect the slower warming of the oceans) and ΔAT_t is the actual temperature change in year t relative to 2000 [53].

One of the greatest challenges for IAMs is that the climatic conditions need to be calculated online. A technique that is commonly used to generate a large range of climate scenarios internally is pattern-scaling. SCENGEN [54] and COSMIC [49, 50] are widely used pattern-scaling tools. Pattern-scaling works by standardising the climate change pattern derived from a GCM by dividing by the global mean warming for a particular climate change experiment, which

then expresses the climate change per $^\circ\text{C}$ global warming [55–60]. The standardised pattern can then be re-scaled using the global temperature change simulated under any other scenario by an SCM such as MAGICC. A typical two-stage approach for temperature is illustrated in Equations 3 and 4 [61].

$$\left(\frac{T_{i2x\text{CO}_2} - T_{i1x\text{CO}_2}}{\Delta T_{2x}} \right) = \Delta T_i^* \quad (3)$$

where:

ΔT_{2x} = Equilibrium GCM climate sensitivity
 $T_{i1x\text{CO}_2}$ = Temperature for $1 \times \text{CO}_2$ experiments at grid point i
 $T_{i2x\text{CO}_2}$ = Temperature for $2 \times \text{CO}_2$ experiments at grid point i
 ΔT_i^* = Standardised temperature change value for grid point i from a GCM experiment

The actual climate change scenario is then constructed by:

$$\Delta T_i^* \times \text{MAGICC} \Delta T_{\text{year}} \quad (4)$$

where:

$\text{MAGICC} \Delta T_{\text{year}}$ = the global-mean temperature change for a given year with respect to 1990.

Table 2. Summary of how the 13 IAMs reviewed in the paper use observed climatologies and climate model projections.

Model	Geographical Focus of IAM	No. of Emissions Regions ^a	Baseline Climatology/ Reference Data	Simple Climate Model (SCM) Description	Description of internally calculated climate change (ΔC) variables ^b	Treatment of uncertainty
Cost-benefit analysis models						
CETA	Global and 2 regions	1 – Global or 2 – OECD plus the Commonwealth of Independent States and Eastern Europe, Rest of World.	Global temperature at pre-industrial levels.	Global 2100 model [179] incorporating a global warming module and adaptation/damage cost function representing damage from warming.	1990–2200 at 10-yr intervals. Global temperature change related to temperature at pre-industrial levels.	Sensitivity analysis of changes to various parameters within the IAM. Use of different climate sensitivities ranging from 1–5 °C
DICE	Global	1 – Global	Temperature only. Historical time series of annual averages 1862–1989 [180]	1965–2105. Box-Advection Model. SCM calibrated against historical temperature series 1862–1989 [180] and runs of 3 GCMs [181–183].	1965–2105 at 10-yr intervals. Global temperature change.	Stochastic treatment of uncertainty utilising Monte Carlo distributions of the IAM parameters. Use of different climate sensitivities.
FUND	Global and 9 regions	9 – OECD-America, OECD-Europe, OECD-Pacific, Central and Eastern Europe and the Former Soviet Union, Middle East, Latin America, South and Southeast Asia, Centrally Planned Asia, Africa.	Observed global annual average temperature time series from 1950 to 1990. (IMAGE database: [184]).	FUND consists of a set of exogenous scenarios and endogenous perturbations, [68]	1950–2200. Global temperature change at 1-yr intervals. Global temperature change. Area weighted average regional temperature increase is used to approximate mean global temperature increase.	Stochastic treatment of uncertainty utilising probability distributions of the IAM parameters.
ICAM-3	Global and 12 regions	12 – US and Canada, Western Europe, China and East Asia, Eastern Europe, India and South Asia, Southeast Asia, North Asia, C and S Africa, North Africa and the Middle East, Latin America, Australia and New Zealand, Japan.	Temperature. Model initialised with a global temperature anomaly drawn from a normal distribution with a mean of 0.4 K and standard deviation 0.3 K. This is based on the IPCC consensus that global temperature change from pre-industrial times to 1995 was in the range of 0.3 to 0.5 K.	Global temperature response to a perturbation in the greenhouse gas radiative forcing. A simple model is used to achieve temperature change consistent with observed energy transport from equator to pole [185]. Local temperature anomalies are adjusted based on the radiative cooling due to regional aerosols.	1975–2100. Temperature at 5-yr intervals. Can be divided into an arbitrary number of latitudinal bands to estimate regional temperature change. The regional model uses 7 latitudinal bands: 90–75°N; 75–50°N; 50–30°N; 30°N–0°; 0°–30°S; 30–55°S; 55–90°S. The middle five bands cover the 12 UN-defined regions.	Stochastic treatment of uncertainty utilising probability distributions of the IAM parameters. Sensitivity analysis of changes to various IAM parameters.

Table 2. (continued).

Model	Geographical Focus of IAM	No. of Emissions Regions ^a	Baseline Climatology/ Reference Data	Simple Climate Model (SCM) Description	Description of internally calculated climate change (ΔC) variables ^b	Treatment of uncertainty
MERGE 4.4	Global and 9 regions	9 – USA, OECDE (Western Europe), Japan, CANZ (Canada, Australia, New Zealand), EEFSU (Eastern Europe and the Former Soviet Union), China, India, MOPEC (Mexico and OPEC), ROW (Rest of World)	Global temperature at 2000.	The SCM is composed of the Global 2200 emissions model which then inputs into the climate submodel. The SCM therefore represents atmospheric lifetimes of the three main greenhouse gases and then yields a global change in radiative forcing and global average temperature change.	2000 to 2200. 2000–2050 at 10-yr intervals and then 25-yr intervals up to 2200. Global temperature change only.	Sensitivity analysis of changes to various IAM parameters.
MiniCAM	Global and 11 regions (14 region version nearing completion)	11 – USA, Canada, Western Europe, Japan, Australia and New Zealand, Eastern Europe and the Former Soviet Union, Centrally Planned Asia, Middle East, Africa, Latin America and Caribbean, South and East Asia.	Reference period can be defined by the user in MAGICC – default is 1990.	1990 to 2095. Upwelling-Diffusion Climate Model (MAGICC). Emissions calculations are made by the ERB model for CO ₂ , CH ₄ and N ₂ O. Input to SCM and then scaled to give regional change in temperature using SCENGE.	1990–2095 at 15-yr intervals. Global temperature change and sea level rise.	Use of different climate sensitivities ranging from 1.5–4.5 °C
PAGE95	Global and 8 regions	8 – European Union, Eastern Europe and the Former Soviet Union, USA, other OECD nations, Africa and the Middle East, China and centrally planned Asia, India and Southeast Asia, Latin America. (These are aggregated to form a global total before entry into the SCM).	Global temperature at pre-industrial (1765) levels.	1990–2200. Reduced form of the STUGE model [186] updated to include sulphates.	The output interval is user specified between 1990 to 2200. The default is a 20-yr interval up to 2100, and every 25-yrs from 2100 to 2200. Annual global and regional temperature changes. Temperature rise computed by relating temperature to the difference in concentration in the base year (1990) and the pre-industrial concentration of greenhouse gases to produce the realised regional temperature increase in each year compared with the pre-industrial temperature in 1765. Area weighted average regional temperature increase is used to approximate mean global temperature increase.	Stochastic treatment of uncertainty utilising probability distributions of the IAM parameters.

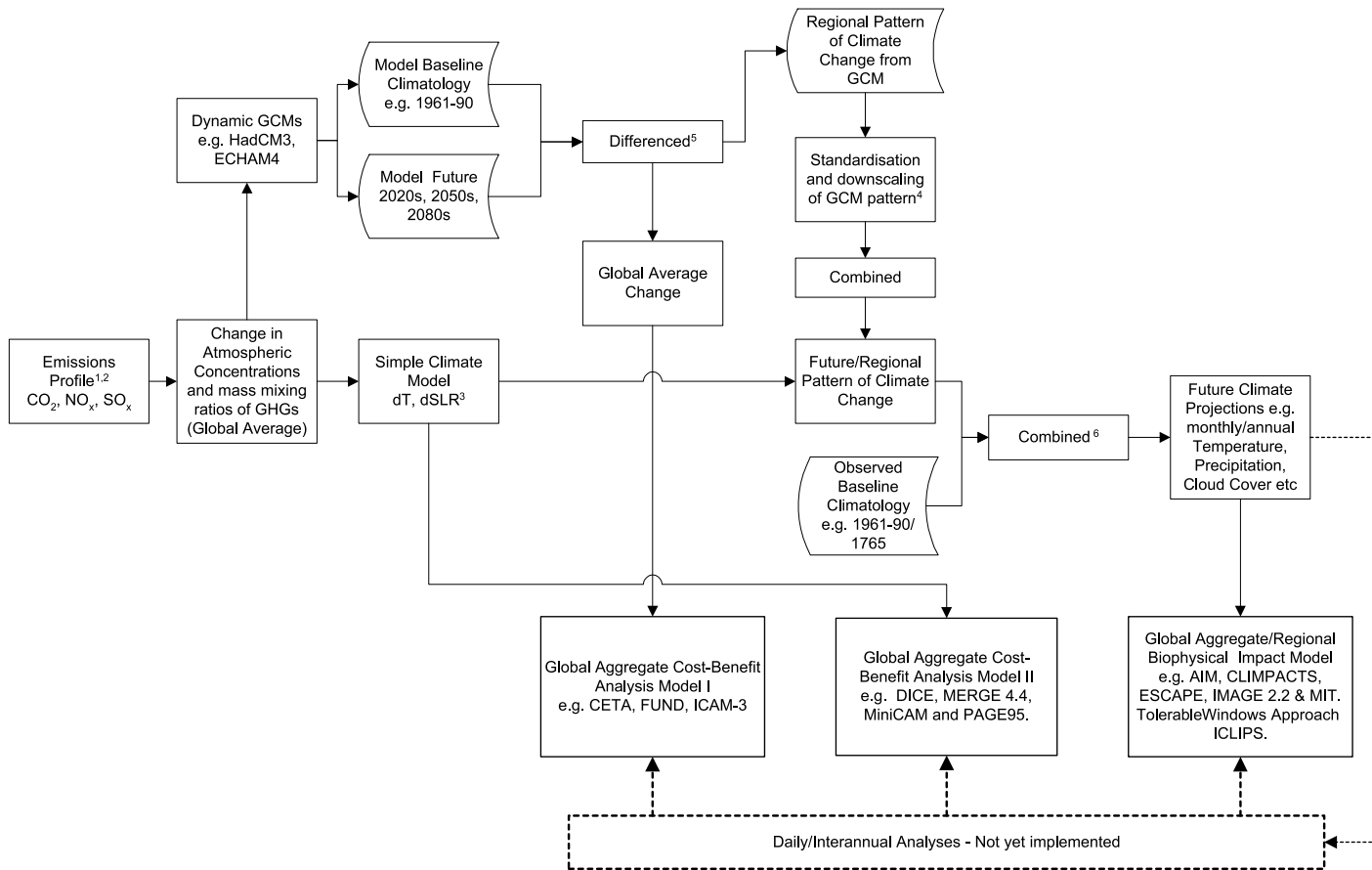
Biophysical-impacts models						
AIM	Global and Asian-Pacific Region	9 – USA, Western Europe, OECD and Canada, Pacific OECD, Eastern Europe and Former Soviet Union, China and Central Planned Asia, South and East Asia, Middle East, Africa, Middle and South America	1920–1980 long-term monthly averages. $0.5^\circ \times 0.5^\circ$ grids. Monthly Tmax, Tmin, solar radiation & precipitation (extrapolated from observed data: [187])	Greenhouse Gas Cycle Model and Climate Change Model (AIM/climate).	1990–2100. Global change in Tmean at 5-yr intervals until 2030 and then at 2050, 2075 and 2100. GCM resolution data interpolated to $0.5^\circ \times 0.5^\circ$ grids. Monthly, regionalized temperature and precipitation changes.	Calculation of ΔC using different $2 \times CO_2$ sensitivities. Use of different AOGCM ΔC patterns including GISS, GFDL, HadCM2, CCC & ECHAM2. Use of different socio-economic scenarios.
CLIMPACTS	New Zealand	1 – Global	30-yr normal (1951–1980). $0.05^\circ \times 0.05^\circ$ grids. Monthly Tmax, Tmin, solar radiation & precipitation (extrapolated from observed data).	Upwelling-Diffusion Climate Model (MAGICC).	1990–2100 at 5-yr intervals. $0.05^\circ \times 0.05^\circ$ grids. Monthly Tmax, Tmin, solar radiation & precipitation. Global mean change Tmean and sea level rise at 5-yr intervals.	Calculation of ΔC using different $2 \times CO_2$ sensitivities. Use of different GCM ΔC patterns – CSIRO4 and GFDLQ. Use of different socio-economic scenarios.
ESCAPE	EU 10+15 and EU nation states	4 – EU, Other OECD, Former Soviet Union & Rest of World (these are aggregated to form a global total before entry into the SCM)	30-yr normal (1951–1980). $0.5^\circ \times 1.0^\circ$ grids. Monthly Tmean Tmax, Tmin & precipitation (extrapolated from observed data).	Upwelling-Diffusion Climate Model (IMAGE 1.0/STAGGER).	1990–2100 at 5-yr intervals. $0.5^\circ \times 1.0^\circ$ grids; Mean Monthly and Seasonal Tmax, Tmin & precipitation. Global mean change Tmean and sea level rise at 5-yr intervals.	Calculation of ΔC using different $2 \times CO_2$ sensitivities. Use of different socio-economic scenarios. Regional patterns of climate change estimated using GFDL, GISS, Oregon State University, Lawrence Livermore Nat. Lab., UKMO & MPI GCMs.
IMAGE 2.2	Global and nation state	17 – Canada, USA, Central America, Northern Africa, Western Africa, Eastern Africa, Middle East, South Asia, OECD Europe, Eastern Europe, Former USSR, East Asia, South East Asia, Japan, South America, Southern Africa, Oceania (these are aggregated to form a global total before entry into the SCM)	30-yr normal (1961–1990). $0.5^\circ \times 0.5^\circ$ grids. Monthly Tmax, Tmin, solar radiation & precipitation (extrapolated from observed data: [73])	Upwelling-Diffusion Climate Model (MAGICC). Global mean change Tmean and sea level rise.	1990–2100 at 5-yr intervals. $0.5^\circ \times 0.5^\circ$ grids. Monthly, regionalized temperature and precipitation changes, and daily temperatures (the latter are used in the terrestrial vegetation and carbon modules).	Calculation of ΔC using different $2 \times CO_2$ sensitivities. Use of different ΔC patterns: ECHAM4, CGCM1, GFDL-LR15-a, HadCM2 and CSIRO-MK2 GCMs. Use of different socio-economic scenarios. Sensitivity analysis of changes to various IAM parameters.

Table 2. (continued).

Model	Geographical Focus of IAM	No. of Emissions Regions ^a	Baseline Climatology/ Reference Data	Simple Climate Model (SCM) Description	Description of internally calculated climate change (ΔC) variables ^b	Treatment of uncertainty
MIT IGSM	Global and 12 regions	12 – USA, Japan, European Community, Other OECD, Central and Eastern Europe, Former Soviet Union, Energy-exporting LCDs, China, India, Dynamic Asian Economies, Brazil, Rest of World	Climate model initialised with greenhouse gas concentrations of year specified by user. Observed climate used in Terrestrial Ecosystem Model (TEM) and Natural Emissions Models (NEM).	The Intermediate Complexity Model (ICM) is a simplified 2D atmosphere 3D ocean model coupled with atmospheric chemistry, run at 20 minute time steps integrated to monthly resolution. Climate variables include temperature, cloudiness, humidity, precipitation, and sea level.	Monthly average zonal climate values over land at 7.826° latitudinal resolution. Used to perturb observed climate to produce future climate in e.g., TEM or NEM. Climate variables include temperature, cloudiness, humidity, precipitation, greenhouse gas and air pollution levels, sea level. Data interpolated to varying resolutions dependent on model being input to e.g., TEM 0.5° × 0.5° or NEM 2.5° × 2.5° and 1° × 1°.	Sensitivity analysis of changes to various IAM parameters.
Tolerable windows approach ICLIPS	Global and 11 regions	11 – Sub-Saharan Africa, Centrally Planned Asia (mainly China), Former Soviet Union, Middle East/ North Africa, North America, South Asia (mainly India), Western Europe, Eastern Europe, Latin America and the Caribbean, Pacific OECD (Australia, New Zealand, Japan), Other Pacific Asia.	30-yr normal (1961–90). 0.5° × 0.5° grids. Monthly Tmax, Tmin, solar radiation & precipitation (extrapolated from observed data: [73]), i.e., same as IMAGE2.2.	Energy-balance model. Modules for non-CO ₂ GHGs based on MAGICC. Climate indicators e.g., global Tmean, precipitation, cloud cover and sea level rise can be combined with static climate change patterns derived from GCMs in order to obtain an approximation of regional change in climate attributes.	1990–2200 at 5-yr intervals. Global Tmean, precipitation, cloud cover and sea level rise.	Use of different socio-economic scenarios e.g., SRES A1, A2, B1, B2. Use of different AOGCM ΔC patterns – ECHAM3GGa1 (ECHAM4/OPYC3 at T42 resolution) and HadCM2GGaX ensemble mean (HadCM2 2.5° × 3.75°).

Note. ^aThis refers to the number of regions explicitly mentioned within emissions scenarios in the SCM. It should be noted that in many cases regional variations can still be calculated exogenously and aggregated to form a global total before input to the SCM. However, this method is less suited to the analysis of different emissions pathways and the evaluation of different environmental policies.

^bUnless otherwise stated, future climate data for any individual meteorological variable is calculated by scaling standardised 1 or 2-dimensional future climate change fields from a predefined GCM with the output from the SCM acting as a scaling coefficient. This change field is then added, in the case of temperature, or applied as a percentage change, in the case of precipitation, to the observed baseline. For more information see [178].



1. From a scenario e.g. IS92a or SRES or arbitrary increase/reduction in one or more GHGs.
2. Can be global or region specific depending on climate model requirements.
3. dT and dSLR are reported with respect to a baseline; normally 1961-90 but can be pre-industrial e.g. 1765 and as a global average.
4. Climate change pattern is taken from the end of a climate model experiment where climate signal to noise ratio is maximised. The pattern is then normalised to give regional changes in desired meteorological variables with every 1degC increase in global temperatures.
5. The difference is achieved by subtracting the model baseline climate from the modelled future climate: $\text{FutureClimate}_m - \text{BaselineClimate}_m = \text{ClimateChange}_m$ (can be global average on grid cell (Regional ClimateChange)).
6. Future climate variables derived by adding scaled climate to baseline climate.

- Represents stored data.
- Represents processed data.

Fig. 1. Approaches to the representation of climate change in IAMs.

Equation (3) shows how a standardised pattern of regional climate change is expressed as a response per °C increase in global temperature. Equation (4) shows how the pattern is then combined with SCM output to generate a future climate at a particular point in time.

Pattern-scaling allows a much wider range of forcing scenarios and climate sensitivities to be considered than is possible from the limited number of GCM simulations which have been performed using a limited range of emissions scenarios. Thus it provides a way of addressing uncertainties due to inter-scenario and inter-model variability. Recent investigations of this technique indicate that it is a legitimate approach, certainly so far as mean climate is concerned [56, 58, 59]. However, disadvantages include the underlying assumptions that the spatial pattern of change remains constant over time and linearly related to global-mean temperature change [62, 63] and that the climate response to all greenhouse gases is identical [57, 61], and the applicability of this method to regional climate model output, to statistical downscaling and to weather extremes has not been investigated (see Section 3.3).

IAMs have traditionally been divided into two generic categories based on their application to policy issues [39] and which are also reflected in their representation of climate. The first category (see Cost-Benefit Analysis models in Table 3) includes models developed to carry out 'policy optimisation' analyses which explore the economic costs and benefits of implementing controls on greenhouse gas emissions and policies such as the carbon tax [64]. The second category (see Biophysical-impacts models in Table 3) includes models developed to carry out 'policy evaluation' exercises, e.g., to look at physical changes in the ecosystem and land-use changes in response to the

introduction of regional or global climate change policies such as the Kyoto Protocol. The representation of climate in these two categories is reviewed in Sections 2.3 and 2.4 respectively. More recently, a third category has been developed in which methods such as the Tolerable Windows Approach (see Section 2.5) and Safe Landing Analysis have been applied. The representation of climate in this category of IAMs is based on the same approach as used in Biophysical-impacts models and is reviewed in Section 2.5. IAMs can also be categorised as to whether or not they can be used to analyse adaptation strategies (see Table 3), as discussed in Section 2.6.

Within these four main categories, IAMs can also be classified according to their spatial characteristics, i.e., global, regional and grid box (Table 3). Care is needed, however, in identifying the effective spatial scale of climate information. The baseline climatologies used in many Biophysical-impacts models, for example, have a spatial resolution of 0.5° by 0.5°, while the GCM-derived perturbations have a much coarser resolution, 2.5° latitude by 3.75° longitude in the case of HadCM2 (Table 2). Simply interpolating the GCM output to the higher resolution of the baseline climatology cannot add any physically-based information about sub-grid scale processes. Thus the effective spatial scale of climate change information is limited by the GCM resolution.

2.3. Cost-Benefit Analysis IAMs for Policy Optimisation

IAMs such as CETA, DICE, FUND, ICAM-3, MERGE and MiniCAM are primarily concerned with quantifying the economic costs and benefits associated with climate change,

Table 3. Categorisation (✓) of the 13 IAMs reviewed in the paper. ? means status is not clear from the published literature.

	Spatial coverage			Used to analyse adaptation strategies		
	Global	Regional	Grid box	Global	Regional	Grid box
Cost-benefit analysis						
CETA	✓			?		
DICE	✓					
FUND	✓	✓		✓	✓	
ICAM-3	✓	✓			✓	
MERGE 4.4	✓	✓				
MiniCAM	✓	✓				
PAGE95	✓	✓		✓		
Biophysical-impacts						
AIM	✓	✓	✓	✓	✓	?
CLIMPACTS		✓	✓			
ESCAPE		✓	✓		✓	✓
IMAGE 2.2	✓	✓	✓	✓	✓	?
MIT	✓	✓	✓			
Tolerable windows approach						
ICLIPS	✓	✓	✓	✓	✓	✓

i.e., with the cost of environmental degradation versus the cost of adaptation and mitigation strategies, in order to evaluate possible policy options (see the cost-benefit analysis models in Fig. 1 and Tables 1 and 2). These IAMs generally consist of economic, climate and damage modules [65]. They deal with measures of time-dependent global climate change and provide a global assessment of damage, usually as a function of the change in global-mean temperature. Thus observed baseline or two-dimensional gridded climate data sets are not explicitly referenced or manipulated in such IAMs (but may be implicitly included in construction of the damage functions). The global climate change estimates are derived from predefined emissions scenarios (such as the IPCC's IS92 and SRES scenarios, or those of the Energy Modelling Forum [5]) or from scenarios created by the IAM. Some of these models, such as FUND, use the global temperature change defined by GCMs, while others, such as DICE, MERGE and MiniCAM, use output from SCMs such as global temperature and sea level change.

One of the key features and strengths of such models is their ability to incorporate some stakeholder perceptions of climate change, i.e., those based on monetary proxies such as 'willingness-to-pay' for mitigation strategies. Perceptions which cannot be treated in monetary terms cannot, however, be incorporated. The form of damage functions used in IAMs is well documented in the literature [3–5, 64, 66, 67]. MERGE [67], for example, categorises damage as 'market' (easily quantified economically, e.g., damages to agriculture, forestry and property) and 'non-market' (e.g., damages to biodiversity, human well being and environmental quality). Market damages are assumed to be a quadratic function of temperature change, while non-market damages are modelled using an S-shaped function of regional income and are based on the willingness-to-pay of each of the nine world regions in order to avoid a specified change in temperature.

The other strength of these models is their low computational demand. This means that they can be run on a PC in a matter of hours, and are thus able to provide many estimates of the global and regional burden of climate change, allowing the rapid appraisal of various policy options such as the Kyoto Protocol [5]. However, their use of zero-dimensional (i.e., global) climate data highlights two major weaknesses. First, there is the assumption that the regional weightings based on the pattern of climate change, applied when assimilating the global mean changes into region-specific damage functions, will remain constant through time. For example, Tol [68] assumes that for the OECD-America and OECD-Pacific regions, the monetised loss of species (estimated at US\$0.3 billion and US\$0.2 billion per year for a temperature increase of 0.04 °C per annum, respectively) will remain constant with time. Second, the lack of any dynamic climate simulation model means that feedback mechanisms in the climate system cannot be incorporated.

2.4. Biophysical-Impact Based IAMs for Policy Evaluation

Biophysical-impact based IAMs (see Fig. 1 and Tables 1 and 2) simulate quantitative and regionally explicit biophysical impacts rather than focusing on policy optimisation and economic damages [65]. They tend to have a regional focus, but some can be aggregated to the global level e.g., AIM, CLIMPACTS, ESCAPE, IMAGE and MIT IGSM [8]. Of this group of models, IMAGE 2.2 is probably the most sophisticated. Even those without the ability to aggregate to the global level, such as CLIMPACTS, retain a global element, normally concerning (i) the conversion of regional greenhouse gas emissions to global climate change, and (ii) economic development and population growth. The majority of these models determine future climates relative to 30-year baseline climatologies (typically 1961–1990). However, the global part of such IAMs tends to be relatively simple. As Table 2 indicates, this sort of model (like some of the globally-aggregated economic models) uses an upwelling-diffusion model, such as MAGICC [51], to calculate global changes in temperature. These are combined with pattern-scaling (e.g., SCENGEN [57]) to produce regional time-dependent climate change scenarios.

The MIT IGSM model also uses a reference baseline climate from which to create future climates but, unlike other Biophysical-impact based models, obtains spatially-resolved scenarios from an Intermediate Complexity Model (ICM) rather than from the combination of SCM and GCM described above. The ICM consists of a coupled atmospheric chemistry/2D-climate model and a 3D-ocean model. It has 24 latitude grid points (7.826° resolution) and nine vertical levels, whilst the ocean model is a simplified version of the GISS Ocean Circulation Model. The coupled model is run at 20-minute intervals but output is aggregated to monthly averages. Comparisons with GCM output indicate that the ICM is capable of replicating present-day climate, together with the climate change patterns produced by GCMs using different emissions scenarios. Emissions are output from the Emissions Prediction and Policy Analysis (EPPA) model and input into the ICM. Output from the latter model is interpolated and used to adjust the observed climatology employed, for example, in the Terrestrial-Ecosystem Model at a 0.5° × 0.5° resolution, which estimates the terrestrial carbon flux, and the Natural Emissions Models at a 1° × 1° resolution.

A potential advantage of the Biophysical-impact based IAMs is that they are able to produce estimates of the regional impacts of climate change at a relatively high spatial resolution. Thus they are able to provide information about regional variations in potential impacts and highlight sub-national scale vulnerabilities, while also assimilating the influence of global climate change forcing from outside the immediate region(s) of interest. However, the reliability of such high-resolution information should be carefully

assessed by users, and the effective scale of the climate change information identified (see Section 2.2).

Biophysical-impacts based IAMs also have a number of shortcomings, which partly stem from their relatively poorly defined economic modules. For example, stakeholder perceptions cannot be included. In addition, it is not generally possible to incorporate large-scale feedbacks due to a mismatch in spatial coverage. For example, while it is possible to simulate a decrease in biological diversity at the regional level (for example, New Zealand in the case of CLIMPACTS), the *global* increase in carbon release through enhanced soil respiration is not calculated and does not, therefore, enhance global anthropogenic climate change (a feedback quantified by Cox *et al.* [69] and White *et al.* [70]). Thus, although these models incorporate global climate change, the regional impacts, such as additional carbon emissions, are not transferred back to the global scale.

Biophysical-impact based IAMs are, however, able to incorporate some feedback mechanisms. The IMAGE model [71], for example, incorporates not only population growth and energy/emission modules but also dynamic ecosystem and climate modules, which allow the incorporation of some complex feedback mechanisms, such as carbon cycle-ecosystem die-back due to climate change, which leads to increased levels of CO₂ in the atmosphere, which in turn leads to an accelerated rate of climate change [72]. IMAGE provides an insight into changes in land cover over time due to climatic, demographic and economic factors and links these explicitly with CO₂ and other greenhouse gas fluxes [39].

The IMAGE model has a global coverage, dividing the world into 19 political entities (see Table 2), 17 of which have their own emissions information which can be specified in the climate module. The other two regions are Antarctica and Greenland, neither of which contribute significantly in terms of emissions. The climate module itself is an upwelling-diffusion model, based on MAGICC [51], which provides global changes in mean temperature and precipitation. This is combined with a pattern-scaling routine, which takes into account the role of sulphate aerosols in the atmosphere, to generate two-dimensional, time-dependent climate change futures. The standardised patterns used for scaling come from several coupled atmosphere-ocean GCMs. The default pattern, for example, is constructed using HadCM2 output. MAGICC is driven by standard emissions scenarios such as those published in the IPCC SRES, however, carbon emissions at the regional level can be modified within IMAGE by the user if required.

While socio-economic input data (such as emissions, gross domestic product and population growth) and impact analyses are reported for 17 world regions in IMAGE, the climate data (observed and future projections) used in the agricultural and dynamic vegetation modules are handled at the gridbox level. The size of the gridbox is determined by the resolution of the observed baseline climatology: currently 0.5° × 0.5° [73].

An IAM with the complexity of IMAGE has a number of advantages. The first is its diverse applications. It can be used to assess the potential economic costs and benefits of mitigation and adaptation policies [74] and can also be used to quantify the potential impacts of climate change on various exposure units, such as the risk to human health from the spread of disease, the loss of natural habitats, and changes in yields of the world's major crops. However, it still relies on the use of an SCM and pattern-scaling techniques to produce climate scenarios. Furthermore, whilst it is able to calculate climate and the resulting impacts at the individual gridbox level, the spatial scale is still relatively coarse (i.e., 0.5° × 0.5° for the baseline climatology and, typically, 2.5° by 3.75° for the climate change information). Gridboxes are categorised by the dominant characteristics of the box which means that broad generalisations regarding factors such as land cover and soil type are made and no account is taken of variability within a box. In addition, while mean daily meteorological data are used in the terrestrial vegetation and carbon modules of IMAGE, there is no way of assessing the impacts resulting from changes in variability (on interannual and decadal timescales, for example). Future monthly mean daily temperatures are derived from an observed monthly mean daily temperature series to which the monthly mean temperature increase is simply added every five years. Thus changes in the frequency of extreme weather events can only occur due to changes in mean climate and not due to changes in variability.

2.5. Policy Guidance IAMs

ICLIPS represents this third group of models and incorporates elements of both policy-optimisation and policy-evaluation frameworks whilst also enabling stakeholder perception, in the form of willingness-to-pay, to be included in the analysis [75–77]. It starts with the explicit specification of “guardrails,” i.e., climate impacts, mitigation costs and burden sharing schemes that are perceived as intolerable by stakeholders. Its aims are to identify critical thresholds of climate change by exploring an extended range of changes in climate and CO₂ concentrations and to determine emission paths that are compatible with the predefined guardrails. It produces regionalised impacts projections specified in biophysical units (such as the percentage of protected areas (e.g., nature reserves) that are in danger of becoming unviable). Climate impact response functions are developed which incorporate elements from both policy evaluation and optimisation models, such as the regional specificity of policy evaluation models and the damage functions used in policy optimisation models [78, 79]. Extensions of the ICLIPS model have been used to explore the conditions under which a major change in the thermohaline circulation could occur [44].

At the core of ICLIPS is the Tolerable Windows Approach (TWA). This works by allowing policymakers

and other social actors to specify their willingness to accept and pay for a certain amount of climate change in their region. These decisions are made with the assistance of climate impact response functions [80]. Tolerable climate windows are then produced which incorporate the acceptable level of climate change previously identified, for example, temperature change, precipitation change and sea level rise. Climate constraints are then input to a greenhouse gas emissions-climate model to produce sets of emissions paths that keep the climate within the tolerable climate window.

2.6. IAMs and Adaptation

As well as being used to assess impacts and mitigation strategies, IAMs can also be used to analyse adaptation strategies. Out of the thirteen IAMs reviewed here, seven (AIM, ESCAPE, FUND, ICAM-3, ICLIPS, IMAGE and PAGE95) incorporate some element of adaptation (Table 3). Of these, three deal with adaptation exogenously (ESCAPE, ICLIPS and FUND). In all seven models, adaptation is only very crudely incorporated: impacts are only identified when increases in temperature exceed a time-variant tolerance level.

In the case of PAGE95, for example, the tolerance level can be raised by the implementation of, or investment in, adaptive policies, meaning that the magnitude and rate of climate change required to impact on an exposure unit are increased. Such policies include the building of sea walls and the development of drought resistant crops. AIM uses global and regional climatic impacts generated by the AIM/impact module to assess the effectiveness of adaptation strategies in terms of their modification of the direct impacts. AIM can, for example, assess the costs and benefits associated with the implementation of policy measures such as short-term mitigation strategies and long-term adaptation policies (for example, increased use of renewable energy and energy-saving technologies and reforestation) [81]. ESCAPE feeds adaptive strategies into the ‘climate and sea level change to impacts’ module. The strategies include, for example, the adaptation of wheat crops to temperature change through genetic modification by raising the threshold temperature for damage.

The adaptive measures mentioned above are all implemented at the governmental or institutional level. IAMs do not currently take into account local adaptive strategies, nor do they simulate the role of extreme weather events in stimulating adaptive behaviour.

2.7. IAMs and Uncertainties

The processes represented in all IAM modules are subject to uncertainties due to errors or unknown quantities, for example, errors in data collection, gaps in knowledge and the inability to model complex processes sufficiently accurately [65]. The treatment of uncertainty varies from

IAM to IAM, based on the structure and form of the individual model – there is no standard method. However, the main methods for dealing with uncertainty include:

- (1) using a set of future emissions scenarios which are selected to span a subjectively-determined range of representative futures and also by using different climate sensitivities (thus addressing inter-scenario and inter-model variability in climate scenarios, see Section 1);
- (2) sensitivity analysis to examine the sensitivity of outputs to changes in key parameters or models or policies (selected subjectively); and,
- (3) specifying probability distributions for many inputs and running the models many times, sampling over the input values in some efficient way. This enables the investigator to determine both how uncertain an input value is, and how sensitive an output value is to that uncertainty.

Biophysical-impact models such as AIM, CLIMACTS, ESCAPE and IMAGE, together with the ICLIPS model, take some account of uncertainty by using different climate sensitivities, different GCM climate change patterns and different socio-economic scenarios. AIM uses several GCMs including GISS, GFDL, HadCM2 and CCC [82]. CLIMACTS uses only two, drawn from a set of six GCMs found to accurately replicate observed climate over the Australian-New Zealand region. The two selected models are CISIRO4 and GFDLQ, both of which have been shown to have superior performance over the region of interest [83]. ESCAPE also uses output from a range of GCMs and examines climate change impacts for different climate sensitivities. However, uncertainties are not passed on to other modules. IMAGE 2.2 evaluates uncertainty due to climate sensitivity by simulating global temperature changes for 2.5 °C (median IPCC sensitivity value), 1.5 °C (low sensitivity) and 4.5 °C (high sensitivity). Uncertainty in regional climate change patterns is evaluated by using several different GCMs (i.e., ECHAM4, CGCM1, GFDL-LR15-a, HadCM2 and CSIRO-MK2). ICLIPS takes account of different climate sensitivities and uses a number of different emissions scenarios and GCMs [78, 79].

The MIT IGSM carries out a series of runs, varying key parameters and assumptions by finite amounts from their initial values. On the climate side, variations can be made in the EPPA and the coupled 2D chemistry/climate models. The climate model has recently been used to derive a joint probability distribution function of three uncertain properties of the climate system: (i) climate sensitivity; (ii) rate of heat uptake by the ocean; and, (iii) strength of anthropogenic aerosol forcing [84]. For climate sensitivity, for example, the 5 to 95% confidence intervals are estimated to be 1.4 to 7.7° K [84].

PAGE95 and FUND use probability distributions to explore uncertainty. PAGE95 [3, 85], for example, uses a triangular probability distribution to represent uncertainty in each input parameter. Between 50 and 108 “uncertain”

parameters are used, depending on the regions and impact sectors being investigated. For a full assessment, PAGE95 carries out 250 calculations for variables representing global warming over time, damages, adaptive costs and preventative costs. Latin hypercube sampling [86–88] is used to select a different set of values for the “uncertain” input parameters in each of the 250 calculations in order to build up an approximate probability distribution. Tol [5, 68] quantifies the uncertainties in FUND based on expert knowledge, i.e., from qualitative interpretation of the appropriate literature and discussions with relevant experts. He has identified appropriate distribution types for different sensitivities, for example, climate sensitivity is based on a gamma distribution, as is sea level sensitivity, whilst hurricane and storm sensitivity are based on a normal distribution and the atmospheric lifetime of methane is based on a triangular distribution. In the case of FUND, the best guesses are equal to the modal values of the distribution (the most likely value). The advantages of this method include a better estimate of mean outputs, a probability distribution of outputs can be produced and the relative importance of inputs identified.

The FUND model is unusual in that it not only calculates annual change in global mean temperature, but also incorporates some climate extremes such as sea level rise, hurricane activity, winter precipitation and winter storm activity [5, 64, 68]. However, the frequency and intensity of these events are determined solely as a linear function of global mean temperature (details of how this is done are not given in the published literature).

None of the current IAMs take into account the influence of natural climate variability, including interannual and decadal variability. Only two of the IAMs listed in Table 2 (DICE and FUND) use time-series data for their baseline climatology although, in both cases, only annual averages are used. All the other IAMs use annual, seasonal or monthly long-term averages (typically 30-year normals). Wider use of time-series data would allow some representation of natural climate variability. The use of ensembles from the GCM experiments used to derive climate change patterns would also be of benefit, because intra-ensemble variability is a direct reflection of natural climate variability (Section 1).

Thus the inability of IAMs to incorporate extreme weather events remains a major weakness, although opportunities for representing scenarios of extremes are beginning to emerge, as discussed in the next section.

3. EVALUATION OF SCENARIO DEVELOPMENT METHODS FOR WEATHER EXTREMES AND THEIR POTENTIAL FOR USE IN IAMs

3.1. Recent Work on Scenario Development Methods for Extremes

Relatively few studies have focused specifically on the construction of scenarios of extremes rather than mean

climate, in part, because of the problems associated with the reliability and availability of high spatial and temporal resolution climate model output [89, 90]. Initial studies, particularly of precipitation, have tended to focus more on changes in interannual variability [23, 91–93] or changes in distributions rather than specific extreme events. Gregory and Mitchell [94], for example, examined changes in the parameters characterising daily temperature and precipitation simulated by the Hadley Centre UKHI GCM, while Hennessy *et al.* [95] investigated changes in precipitation frequency distributions and in the relative contributions of convective and non-convective precipitation mechanisms in the UKHI and CSIRO9 GCMs. Wetherald and Manabe [96] focused on changes in soil moisture (particularly as an indicator of summer dryness) simulated in four GFDL GCM experiments.

With the greater availability of daily output from GCMs, this output has begun to be used directly to construct scenarios of specific extremes. A number of these studies are summarised in Table 4, focusing on temperature and precipitation extremes. Some of them use time slices which are relatively short for the analysis of extremes (10 or 20 years) and some are based on equilibrium rather than the newer generation of transient, coupled atmosphere–ocean GCMs.

Most recently, a few studies have used output from regional climate models (RCMs) to construct scenarios of extremes [97–102]. Durman *et al.* [100], for example, focus on the occurrence of intense precipitation events over Europe and the UK defined using two different thresholds (15 mm per day and the upper 1% percentile calculated from the model control run). A comparison is made of future scenarios (for 2080–2100) constructed from Hadley Centre HadCM2 GCM and RCM output in order to determine the added value of using high-resolution model output [100]. Jones and Reid [101] also use the HadCM2 RCM to construct future scenarios of extreme precipitation for the UK, in this case focusing on the occurrence of the top 10% quantile events (calculated using the method of Osborn *et al.* [103]) and 5, 10, 20 and 50 year return period events. This RCM was also used by Booij [102] to construct scenarios of return period precipitation events for the Meuse catchment in western Europe and to compare these with HIRHAM4 RCM and three GCM-based scenarios. The most recent generation of the Hadley Centre RCM, HadRM3, was used to construct the UKCIP02 scenarios for the UK [60] which provide some information about changes in extreme events (e.g., “intense” precipitation days and “extremely” warm days).

RCMs allow the dynamical downscaling of GCM output to the higher spatial resolutions which are more appropriate for the construction of scenarios of extremes. Statistical downscaling provides a less computer-intensive method of downscaling [104–106], but has not been widely used to investigate changes in extremes. Wagner [107] used a probability model based on thresholds to show that changes in temperature extremes are more sensitive to changes in

Table 4. Summary of recent studies which use GCM output directly to construct scenarios of temperature and precipitation extremes.

Study	Extremes	Region	GCM
Booij [102]	Precipitation: 10, 20, 50, 100 year return periods	Meuse, western Europe	CGCM1, HadCM3, CSIRO9 20/30 year time slices
Dai <i>et al.</i> [188]	Frequency and persistence of 'hot' days (> 80th percentile) Storm activity	Global, USA	NCAR CSM Coupled model 2 scenarios 20 year time slices
Delworth <i>et al.</i> [189]	Steadman heat index (based on monthly temperature and atmospheric moisture)	Global	GFDL Coupled model 20 simulations 30 year time slices
Huth <i>et al.</i> [190]	Heat waves/dry spells	Czech Republic	ECHAM3 Equilibrium model 30 year time slices
Kharin and Zwiers [89]	Temperature, precipitation, wind: 20 year return periods, thresholds, cooling & heating degree days	Global, Canada	CGCM1 Coupled model 20 ensembles 21 year time slices
Kothavala [191]	Precipitation: return periods, percentiles and Palmer Drought Severity Index (PDSI)	Midwest USA	CCM1-OZ Equilibrium model 10 year time slices
Kothavala [192]	PDSI (based on monthly temperature and precipitation)	Eastern Australia	CCM0 Coupled model 30 year time slices
Kyselý [110]	Temperature (max/min): 20 and 50 year return periods	Central Europe	ECHAM/CCCM 30/20 year time slices
McGuffie <i>et al.</i> [193]	Temperature and precipitation: Return periods and range of descriptive regional statistics	Global, 5 IPCC regions	20 equilibrium GCMs 10 year time slices
Palmer and Räisänen [157]	Precipitation: 'Very wet' winters/summers	Europe, Asian monsoon region	19 coupled GCMs used in TAR 30 year time slices
Yonetani and Gordon [194]	Temperature, precipitation: max/min $1 \times \text{CO}_2$ seasonal/annual values	Global	CSIRO Coupled model $1 \times \text{CO}_2/2 \times \text{CO}_2$ 100/30 year time slices
Zwiers and Kharin [113]	Temperature, precipitation and wind: 20 year return periods and thresholds	Global, Canada	CCC GCM2 Equilibrium model 20 year time slices

variability than mean climate (using output from the ECHAM GCM and daily temperature data for Berlin). A similar conclusion was reached using a first order autoregressive Markov Chain model [108]. Although statistical downscaling has rarely been used specifically to construct scenarios of extremes (exceptions are Brandsma and Buishand [109] with respect to precipitation and Kyselý [110] with respect to temperature), a number of studies do include analyses of relevant indicators, particularly as part of the validation of the methodology (Table 5).

The IPCC TAR gives greater consideration to extreme events than previous assessments and cites many of the references identified above. The most concise summary of observed and projected changes in extreme events is provided by Table 1 from the Working Group 1 Summary for Policymakers. It provides an assessment of confidence in

the observed and projected changes based on observational and modelling studies, as well as the physical plausibility of future projections across all commonly-used emissions scenarios, based on expert judgement. Higher maximum temperatures and more hot days over nearly all land areas, together with higher minimum temperatures, fewer cold days and frost days over nearly all land areas, for example, are considered 'very likely' (i.e., 90–99% chance) during the 21st century. More intense precipitation events are also projected to be 'very likely' over many areas, while increased summer continental drying and the associated risk of drought are considered 'likely' (i.e., 66–90% chance) over most mid-latitude continental interiors.

While reflecting the advances that have made in the study of observed and projected changes in extremes since the SAR, the TAR stresses the continuing problems and

Table 5. Statistical downscaling studies which include analysis of extreme event indicators.

Indicators studied	Study
Studies which include analysis of precipitation-related extreme indicators, e.g., length of (longest) wet/dry spells, return period events, ranked extremes	Bardossy and Plate [135, 195] Bates <i>et al.</i> [196] Beckman and Buishand [152] Bogardi <i>et al.</i> [138] Brandsma and Buishand [109] Charles <i>et al.</i> [159] Conway and Jones [129] Corte-Real <i>et al.</i> [143] Goodess [126] Hay <i>et al.</i> [133, 136] Hughes <i>et al.</i> [197] Semenov <i>et al.</i> [198] Weichert and Burger [199] Wilby [149] Wilby <i>et al.</i> [141, 150] Wilks [200] Wilson <i>et al.</i> [134, 137]
Studies which include analysis of storm-related indicators, e.g., storm length, inter-storm arrival time	Hughes <i>et al.</i> [139] Hughes and Guttorp [140] Schnur and Lettenmaier [130]
Studies which include analysis of temperature-related extreme indicators, e.g., annual maxima/minima, heat waves and cold spells, frosts, threshold exceedence	Hayhoe [201] Huth <i>et al.</i> [144] Kysely [110] Palutikof <i>et al.</i> [131] Schubert [148] Schubert and Henderson-Sellers [145] Trigo and Palutikof [202] Winkler <i>et al.</i> [146]

uncertainties associated with extreme weather events and recommends further research effort to address these issues.

3.2. Suitability of Scenario Development Methods

The IPCC TAR identifies five criteria, adapted from Smith and Hulme [111], for assessing the suitability of each type of climate scenario for use in impact assessment:

1. Consistency at regional level with global projections. Scenario changes in regional climate may lie outside the range of global mean changes but should be consistent with theory and model-based results.
2. Physical plausibility and realism. Changes in climate should be physically plausible, such that changes in different climatic variables are mutually consistent and credible.
3. Appropriateness of information for impact assessments. Scenarios should present climate changes at an appropriate temporal and spatial scale, for a sufficient

number of variables, and over an adequate time horizon to allow for impact assessments.

4. Representativeness of the potential range of future regional climate change.
5. Accessibility. The information required for developing climate scenarios should be readily available and easily accessible for use in impact assessments.

These criteria are all applicable to scenarios of extremes and their use in IAMs, with the appropriateness of information, and the associated issues of scale, being of particular concern (see Sections 1 and 4). Extremes place additional demands on climate models and scenario development methods: higher-order statistics (such as standard deviations and skewness), together with the tails of distributions, not just mean values, must be well reproduced. Different extreme events/variables exhibit different characteristics that must be reliably captured by climate-change scenarios, and hence place different demands upon climate models and scenario development methods. For example, the demands arising from the need to reproduce daily precipitation totals which are typically described by a mixed statistical distribution are different to the case of variables with a quasi-Gaussian distribution such as daily temperature. In both cases, extreme events are highly dependent on spatial scale, while multi-month drought occurrence is less so, but instead introduces a need to reproduce the correct persistence levels. Certain sectors also require that realistic inter-site relationships are maintained (e.g., hydrological modelling), while others (e.g., certain crop models [112]) require realistic inter-variable relationships.

While the need to generate scenarios that successfully reproduce present-day climate variability and extremes and that also give reliable and plausible estimates of climate change is paramount, a number of other issues must also be addressed, particularly with respect to integrated assessment. Ideally, scenarios should have estimates of their associated uncertainty (see Sections 1 and 3.5) and should be able to be scaled to reflect a range of possible greenhouse gas emissions pathways. In the following section, the advantages and disadvantages of various methods for the construction of scenarios of extremes are summarised in the light of these additional criteria.

3.3. Direct Use of Climate Model Output

An overriding problem – and hence the need for more sophisticated scenario development methods – is that output from GCMs cannot, in general, be used to directly quantify future variability and extremes, particularly at the station or local level, because of bias in simulated means and variability of present-day climate and weather [90, 113]. This bias may originate from systematic model errors [94, 95], from spatial scale incompatibilities (area-mean grid-box output has different statistical properties to station

data [114, 115]) and due to the exclusion of sub-grid-scale processes.

In the development of scenarios of mean climate change, the bias in simulated means is the main difficulty and can be “overcome” by assuming that the climate change is independent of these mean biases and, therefore, applying climate change fields to appropriate observed baseline climatologies (as is currently done in IAMs, see Section 2.2). A similar approach can be used for the development of scenarios that focus on climate variability and extremes [116, 117], i.e., by assuming that changes in higher-order statistical parameters (such as variance, skewness and persistence) are reliable, despite differences between observed and simulated present-day values of these parameters. Additionally, it may be possible to use appropriate statistical manipulation to reproduce the present-day climate characteristics. Alternatively, extremes and their changes can be defined in a relative rather than absolute sense (i.e., percentile or quantile values rather than absolute thresholds) in order to reduce model biases. The advantages and disadvantages of these various approaches are summarised in Table 6. Single examples of the implementation of each

approach are given, though it should be noted that the range of choices that could be made when implementing each approach is potentially very broad.

For GCMs to become more reliable in their simulation of variability and extremes as well as means, requires not only an improvement in the models, but also a solution to the two major spatial resolution problems of scale incompatibilities and sub-grid-scale processes. If direct model output is to be used, then these problems can only be overcome by an increase in the spatial resolution of climate models together with improvement in their reliability. Higher-resolution global (such as timeslice [118]) or regional (nested within a global model [119, 120]) models have begun to address this problem. Time-slice simulations have recently been used to explore changes in intense rainfall and wet/dry day spells [121], but output from RCMs is more widely available than output from timeslice simulations and thus provides a more viable approach. It should not, however, be assumed that the higher resolution of RCMs automatically provides more meaningful or reliable spatial detail [60, 100, 122, 123].

RCM output has been less widely used than GCM output for constructing scenarios of extremes (because the latter is

Table 6. Summary of the advantages and disadvantages of the direct use of General Circulation Model output to construct scenarios of extremes. ✓ = advantage, ✗ = disadvantage, ? = advantage/disadvantage of the method is uncertain.

Advantages/disadvantages of the general approach

- ✓ Provides physically-consistent multi-variate information
 - ✗ Spatial-scale problems arise, i.e., grid box rather than point values
 - ✗ Even area-averaged extremes (i.e., grid-box values) may not be reliably simulated
1. *Diagnosed changes in statistical parameters (mean, plus higher-order parameters, such as variance, scale and shape, etc.) applied to observed baseline time series. For example of implementation see [203]*
 - ✓ Simple method
 - ✓ Suitable for scaling
 - ✗ Non-realistic scenarios, e.g., negative precipitation, may occur when the changes are applied to the baseline climatology
 - ✗ Assumes biases will be unchanged in the future
 2. *As 1, but changes are applied to weather generator parameters, previously tuned to reproduce observed climate. For example of implementation see [204]*
 - ✓ Long and/or multiple time series can be generated for analysis of extremes/uncertainties
 - ✓ Suitable for scaling
 - ✗ Weather generators tend to underestimate variability and persistence, e.g., length of wet/dry spells
 - ✗ May be difficult to adjust weather generator parameters in a consistent way
 3. *Direct model time series used, after appropriate statistical manipulation to reproduce present-day climate characteristics. For example of implementation see [205]*
 - ✓ May overcome some model biases
 - ✗ May be more difficult to manipulate extremes than mean values
 - ✗ Assumes model biases will be unchanged in the future
 - ? Either ‘un-intelligent’ or ‘informed’ manipulation may be applied, the latter using validation/statistical downscaling approaches to adjust model output for specific physically-identified biases
 - ? Less suitable for scaling
 4. *Model output used to assess specific extremes (via percentile or extreme value distribution approaches), which are defined in a relative rather than absolute sense. For example of implementation see [100]*
 - ✓ May avoid some systematic model deficiencies and facilitates model inter-comparisons
 - ✓ May overcome some spatial-scale incompatibilities
 - ✗ Assumes model biases will be unchanged in the future (because percentiles or thresholds are defined from the model control period)
 - ? Less suitable for scaling
 - ? Stakeholders may find it harder to relate to ‘relative’ extremes
-

Table 7. Summary of the advantages and disadvantages of the direct use of regional climate model output to construct scenarios of extremes. ✓ = advantage, ✗ = disadvantage, ? = advantage/disadvantage of the method is uncertain.

Advantages/disadvantages of the general approach. For example of implementation see [97–102]

✓	Provides physically-consistent multi-variate information
✓	Higher spatial resolution than GCMs should reduce some biases (e.g., more intense extremes)
✗	Relatively short (e.g., 30 year) runs make it difficult to assess multi-decadal natural variability
✗	Runs may not be available for time periods of interest (e.g., 2020s)
✗	Relatively few simulations/ensembles available
✗	Affected by biases in the underlying GCM
?	Added value of higher spatial resolution needs to be demonstrated
?	Scaling may be less robust than from GCMs and for mean climate, in part, because of shorter model simulations

more widely available), however, the advantages and disadvantages of this general approach are outlined in Table 7. RCM output can be used in the same way as GCM output, thus the potential advantages/disadvantages of methods 1 to 4 listed in Table 6 are also applicable to RCM output.

GCMs/RCMs must be run off-line rather than on-line in IAMs because they are so computationally complex and demanding. Their output is currently utilised in IAMs to provide information about changes in mean climate, but this requires pattern-scaling, the advantages and disadvantages of which are discussed in Section 2.2 with respect to mean climate. Additional concerns arise with respect to the scaling of extremes.

The most detailed assessment of pattern-scaling to date is that of Mitchell [59]. His study, like that of Mitchell *et al.* [56], focused on changes in mean climate rather than extremes. However, a number of its conclusions may be relevant to scaling extremes. The sources of error identified by the study, for example, include non-linear grid-box responses to radiative forcing, which undermine the underlying assumption of linearity. The preferred method is to take the pattern from a regression based on the full model period rather than from a short (e.g., 20 year) period at the end of the simulation because, if the response is non-linear, the magnitudes of any instantaneous errors will be minimised (though they may change sign during the course of the simulation).

The Mitchell study [59] also suggests that it is possible to scale interannual variability (i.e., standard deviations), although the errors (i.e., due to deviations from linearity) are larger than for mean values. If, furthermore, it is assumed that the variable in question has a Gaussian distribution, changes in the entire probability distribution may be estimated by individually scaling the mean and standard deviation. It may also be possible to scale non-Gaussian variables by estimating secondary parameters: for example, it may be possible to estimate precipitation by scaling the

mean and standard deviation and estimating from them the shape and scale parameters of the gamma distribution.

The Mitchell study [59] is, however, largely based on a single model (HadCM2), which raises a question as to whether the findings are model dependent. Clearly, the legitimacy of using scaling techniques for extremes, which may change non-linearly [10, 108] needs specific investigation. Is it possible, for example, to capture the non-linearities by using quadratic rather than linear regression or by using a variable other than global temperature as the scalar? Another important question for extremes is whether it is possible to scale daily time series? And, if temperature and precipitation are scaled separately, is the spatial coherence of these variables maintained? Thus there are a number of issues that must be addressed before GCM or RCM output can be used to provide information about extreme weather events in IAMs.

3.4. Statistical Downscaling

A range of statistical downscaling methods has been developed in recent years (see the following reviews: [104–106, 124–126]), though these have not been designed specifically for downscaling weather extremes. Relationships between larger-scale climate variables (such as atmospheric circulation) and local surface climate variables (such as daily temperature and precipitation), derived empirically using observed data, can be applied to the generation of climate scenarios, under the two assumptions that the larger-scale climate variables are more reliably simulated by climate models, and that the relationships remain valid under a changed climate. Theoretically, the latter assumption (of stationarity) should be valid if all the necessary predictor variables (such as atmospheric circulation, temperature and humidity [125, 127]) are used and the statistical model is appropriately structured to enable it to represent interactions and non-linearities. In practice, however, this may be limited by the availability of sufficiently long data series to determine the important predictors on all necessary time scales (a problem that is exacerbated if the variables that generate inter-daily to inter-annual variability are different to those that cause climate change). Nevertheless, given adequate data, statistical downscaling has sufficient advantages to warrant consideration as a scenario-generation method in IAMs. The common advantages and disadvantages of this approach are summarised in Table 8.

From the range of statistical downscaling methods that are available, three of the most commonly-used methods are considered most appropriate for extremes and the needs of integrated assessment modelling:

- resampling of observed data conditioned by large-scale climate variables [106, 109, 118, 128–132];
- weather generator (with the option of conditioning parameters upon large-scale climate variables) [126, 133–144]; and,
- regression-based methods [144–153].

Table 8. Summary of the advantages and disadvantages of statistical downscaling for the construction of scenarios of extremes. ✓ = advantage, ✗ = disadvantage, ? = advantage/disadvantage of the method is uncertain.

✓	Provides station/point values of extremes
✓	Less computer intensive than dynamical downscaling
✓	Can be applied to GCM and/or RCM output
✗	Assumes that predictor/predictand relationships will be unchanged in the future (the stationarity issue)
✗	Requires long/reliable observed data series
✗	Affected by biases in the underlying GCM
?	May be possible to ‘correct’ predictors for systematic model biases
?	Scenarios may indicate changes which differ substantially in magnitude, and even in direction, from those based directly on model output
?	Ideally, downscaling methods should reflect the underlying physical mechanisms and processes, but statistical downscaling is unlikely, for example, to treat convective rainfall events in a physically realistic way
?	Suitability for scaling needs to be investigated
?	Sensitive to specific methodology, choice of predictor variables, etc.

The specific advantages and disadvantages of these three methods are summarised in Table 9.

3.5. Scenarios of Weather Extremes and Associated Uncertainties

Comparative studies of the first three sources of uncertainty listed in Section 1 indicate that, for changes in mean climate, inter-model variability tends to be greater than inter-scenario or internal model variability, particularly over the earlier part of the 21st century [23, 24, 154, 155]. The uncertainties are, however, likely to depend on the variable being addressed. In an intercomparison of four RCMs, for example, Christensen *et al.* [156] concluded that inter-scenario uncertainties dominate in the case of mean temperature in Nordic regions.

Uncertainties in extreme event scenarios have rarely been studied. A recent exception is Palmer and Räisänen [157] who used an ensemble of 19 GCMs to construct probabilistic scenarios of ‘very wet,’ defined as greater than the mean plus two standard deviations, European winters and Asian monsoon region summers. In a study of 20-year return period precipitation values in the Meuse region using output from a number of GCMs and RCMs, Booij [102] concludes that the uncertainties due to model errors and inter-model differences amount to 50% of the present-day return values (i.e., they are significantly larger than the projected change of ~18%). Further research is needed to determine which sources of uncertainty dominate for extremes.

The fourth source of uncertainty identified in Section 1, sub-grid scale forcings and processes, has not yet been adequately addressed in the literature, but may be particularly important for extreme weather events with high

Table 9. Summary of the advantages and disadvantages of three specific statistical downscaling methods for the construction of scenarios of extremes. ✓ = advantage, ✗ = disadvantage, ? = advantage/disadvantage of the method is uncertain.

1. <i>Resampling of observed data conditioned by large-scale climate variables</i>	
✓	Provides self-consistent multi-site, multi-variate scenarios
✓	Multiple time series can be generated
✓	Relatively simple method
✗	Magnitude (but not frequency) of the largest extreme is limited by the observations
✗	Difficult to extend to multiple predictors if sample size is limited
?	Requires climate classification
2. <i>Weather generator (with the option of conditioning the parameters upon large-scale climate variables)</i>	
✓	Long/multiple time series can be generated
✓	Provides self-consistent, multi-variate scenarios
✗	Variability and persistence tend to be underestimated (the overdispersion problem)
✗	May be difficult to perturb the parameters in a consistent way for future climates
?	Methods are being developed for the production of self-consistent multi-site scenarios, but tend to be complex and subject to technical/statistical problems
?	May require climate classification for conditioning the parameters
3. <i>Regression-based techniques</i>	
✓	Climate classification is not required
✓	A wide range of potential predictors can be used
✗	Danger of over extrapolation in the future
✗	Danger of overfitting
✗	Difficult to identify best suite of predictors for present-day and future climates
✗	Tend to perform less well for precipitation than temperature
?	Stochastic elements can be introduced, e.g., to increase variability

temporal and spatial resolutions. RCMs provide information at the sub-GCM grid scale, so ensemble RCM output provides one way of exploring this issue [154]. However, the current resolution of RCMs, 50 km × 50 km for HadRM3, is still relatively coarse for some extreme event processes, such as convective precipitation. Statistical downscaling methods provide station or point values and thus may provide another way of exploring this issue, but introduce additional uncertainties due to the methods themselves. Similarly, statistical manipulation methods which attempt to correct for model biases (Table 6) are also likely to introduce new uncertainties.

Another aspect of uncertainty which needs to be addressed concerns the relationship between the future climate-change uncertainties discussed above and multi-decadal climate variability [20], i.e., the issue of signal-to-noise ratios (which is particularly important for determining the significance of projected climate changes and for detection and attribution studies). Changes in extreme events may be greater than changes in mean climate [10, 108], but

because the natural variability of extremes is also greater than that of mean climate, the signal-to-noise ratio may be lower for extremes than for mean climate, making it more difficult to identify significant changes in extremes.

The associated uncertainties are dependent on the variable and spatial/temporal scale considered, generally increasing with increased resolution. The focus of this review is temperature and precipitation extremes. The uncertainties are likely to be greater for other variables such as wind, hail, fog, lightning, and storm surges. In the case of the UKCIP02 scenarios, for example, the uncertainties were considered so large, that the authors could not even assign a low level of confidence to the wind scenarios [60].

4. OPTIONS FOR IMPROVING SCENARIOS OF EXTREMES IN IAMs

From Sections 1 and 2, it is clear that there is a need for modification of the representation of climate information in IAMs in order to include extreme weather events. A range of potential methods for the construction of scenarios of extreme events is reviewed in Section 3, focusing on the advantages/disadvantages of the various methods and the issues which are most relevant to the needs of integrated assessment modelling. However, only limited inter-comparisons of dynamical versus statistical approaches [99, 158–161] or of different statistical approaches [104–106, 124, 125] to downscaling have been carried out. Inter-comparisons focusing on extreme events are even rarer [110, 144]. These issues are being addressed by ongoing research programmes (funded by the European Commission, for example (<http://www.cru.uea.ac.uk/projects/mps/>)), but there are currently no systematic or comprehensive inter-comparisons or recommendations on ‘best’ methods. Thus, detailed validation and evaluation studies are required on a case-by-case basis before any of the methods reviewed in Section 3 can be used with confidence in integrated assessments.

Additional evaluation criteria need to be considered when using any of these scenario construction methods in IAMs as it is important that the key characteristics and advantages of IAMs, i.e., their computational efficiency and comprehensive nature, are not lost. In order to maintain computational efficiency and to limit the amount of data handled within IAMs, it is likely that much of the scenario analysis involving extreme weather events will be carried out offline. This will be particularly true for those extremes which must be considered at high spatial and temporal resolutions (see Section 1). These resolutions mean that large amounts of scenario data tend to be produced for extremes, compounded by the need to address the full range of uncertainty, using Monte Carlo and probabilistic approaches, for example. Thus considerable care is needed in identifying the key extreme events which should be incorporated in IAMs. Ideally, a limited range of indicators of extremes can be

identified which are not highly correlated and which provide information on all relevant aspects, for example, changes in different seasons, changes in the magnitude of individual events and changes in persistence, of the key extremes. The appropriate extremes will, however, depend on the sectors being assessed and on the focus of the IAM. For planned adaptation, for example, projections of changes in the occurrence of experienced events, such as, for the UK, the 1953 storm surge event and the October 2000 floods, may be important.

The primary output from both dynamical and statistical downscaling methods focusing on extremes tends to be in the form of streams of daily data, which can conventionally be used in the following ways:

- (i) relative changes can be added to baseline daily climatologies to create scenarios;
- (ii) probability distribution functions can be constructed to reflect the uncertainties;
- (iii) time series (either the downscaled series or adjusted baseline climatologies) can be provided.

Approach (i) could be used directly in IAMs, although appropriate and reliable global/regional gridded daily climatologies would be required. Approach (iii) could in theory be used directly in Biophysical-impact based IAMs (Section 2.4) and has the advantage of encompassing interannual variability. Some impacts modules would, however, need modification in order to handle daily data and there is a danger that this would make them too computationally demanding. These potential problems provide further justification for carrying out more of the scenario analysis offline, particularly if dynamical downscaling is the preferred option.

If extreme event scenario analysis is carried out offline, a mechanism is needed to tie this in with the IAM, in the same way that pattern-scaling of mean climate is tied to mean global temperature change in the current generation of IAMs (Section 2.2). For extremes, however, it may be appropriate to use some other large-scale variable (e.g., pressure patterns) as the scalar and/or to use a non-linear relationship (Section 3.3).

The structure of cost-benefit analysis IAMs incorporating damage functions (Section 2.3) is more immediately suitable for the incorporation of offline analysis of extremes than that of Biophysical impacts-based models. In the case of flooding events, for example, the cost-benefit analysis models require a conditional damage function (CDF) for estimation of the economic damage associated with a particular flood event given its probability of exceedence. Such a CDF could be constructed by: first, generating daily regional precipitation scenarios using dynamical or statistical downscaling; inputting these scenarios to a hydrological model in order to simulate flood peaks; fitting a distribution to the flood peaks to show the relationship between magnitude and probability of exceedence; and finally, translating this

distribution in to the CDF for economic damages/probability of exceedence (Arnell, *personal correspondence*).

Ideally, this CDF should reflect the full cascade of uncertainty. Palmer and Räisänen [157], for example, have recently demonstrated that use of a single deterministic scenario underestimates the risk of making the wrong hypothetical investment decision with respect to flooding, compared with the use of inter-model ensemble scenarios (based on output from 19 GCMs). This study focuses on Europe and the Asian monsoon region: it is concluded that larger model ensembles would be needed in order to assess risks at the country, for example, UK or Bangladesh, scale. Palmer and Räisänen also conclude that GCMs may provide adequate information for large catchments such as the Ganges and Brahmaputra (a conclusion supported by Milly *et al.* [162] for catchments including the St Lawrence, Mississippi, Danube and Ob), but downscaling to resolutions of tens of kilometres is required for smaller catchments.

In order to construct some CDFs (and for some impacts modules), it may be necessary to consider joint probabilities of extremes (although it is noted that no general statistical solutions for such problems are available [163]). It is estimated, for example, that 50% of the capital value of UK assets potentially at risk from sea, tidal and fluvial flooding lie within the River Thames region [164]. Flooding in estuaries in eastern Britain could occur due to the simultaneous occurrence of high sea level and high river flow [165]. Thus a CDF for overtopping of the Thames barrier would need to consider changes in storm surges (which can be estimated using a storm surge model combined with GCM/RCM output [166] or by statistical downscaling [167, 168]), together with consistent (i.e., based on the same large-scale predictor variables) changes in river flooding (derived from downscaled precipitation changes input to a hydrological model). The joint probability of exceedence would then need to be calculated in order to construct the CDF.

Although the conventional approach for scenarios of extreme weather is to generate streams of daily data using dynamical or statistical downscaling and then calculate the frequency of occurrence and magnitude of extreme events, a more direct, but untested, approach to statistical downscaling could be used to construct CDFs for use in cost-benefit analysis IAMs. This would entail identification of statistical relationships between the extremes themselves and the predictor variables. It has the potential advantage that these relationships might be stronger and more robust than those between the underlying daily temperature/precipitation series and the same predictors. It would certainly have the advantage of producing smaller volumes of data and would be particularly suitable for the construction of probabilistic scenarios.

One of the major issues associated with the representation of extreme weather events in IAMs is the potential spatial scale mismatch between the scenario construction methods described in Section 3 and IAMs (Tables 2 and 3). There are

two questions: first, is it physically meaningful to consider extremes at the IAM scale, and second, if it is, can the scenario construction methods provide information at the necessary scale? With respect to the first question, globally-averaged extremes are not considered meaningful. Thus in IAMs that only operate at the global scale, i.e., the CETA and DICE cost-benefit analysis models (Table 3), it would not be appropriate to construct global damage functions using global indices of extremes. Global damage functions could, however, be constructed off-line using regional indices of extremes, as described earlier. Although the other cost-benefit analysis models listed in Table 3 are shown as having a regional spatial coverage, most of them (FUND, MERGE4.4 and MiniCAM) only calculate global temperature changes and would need modification in order to operate with damage functions incorporating regional climate information.

All the Biophysical-impacts models listed in Table 3 use grid-box information. Thus using higher-resolution RCM output rather than GCM output (i.e., dynamical downscaling) to derive the regional patterns of change would entail an increase in the volume of data handled, but would not require major modifications. The major constraints would be the availability of RCM output for all required regions and reliable gridded baseline climatologies (also required for validation). Tools such as the PRECIS (Providing REgional Climates for Impact Studies) regional modelling system being developed by the Hadley Centre [169] make this potentially feasible. Although most statistical downscaling methods focus on the station scale (because their ability to provide point-specific information is one of their major advantages), they could be applied at the grid-box scale of the baseline climatologies used in IAMs. This would, however, again require the availability of reliable gridded climatologies for all regions.

Rigorous testing of the methods identified here is needed in order to implement optimal methods for the incorporation of information about extreme weather events in IAMs. However, from the methods reviewed here, it is concluded that the less-computationally demanding statistical approaches to scenario construction, such as weather generators and patterns of change derived from RCMs, are likely to be more suitable for use in Biophysical impacts-based IAMs, while both dynamical and a number of different statistical approaches are potentially suitable for use in cost-benefit analysis IAMs and are likely to be easier to implement because more analysis can be carried out offline in these economic-based models.

ACKNOWLEDGEMENTS

This work was funded as part of the Tyndall Centre for Climate Change Research projects on *Estimating the Future Probabilities of Extreme Weather Events* (IT1.16: CM

Goodess, M Hulme and TJ Osborn) and *A Blueprint for Integrated Assessment of Climate Change* (IT1.3: C Hanson). The two anonymous reviewers are thanked for their comments on the manuscript.

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