Modelling the Economic and Social Consequences of Drought under Future Projections of Climate Change

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Declaration

This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text or acknowledgements. This dissertation does not exceed the regulation length, including footnotes, references and appendices.

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Abstract

Drought events and their consequences pose a considerable problem for governments, businesses and individuals. Superimposed on this risk is the danger of future anthropogenic climate change. Climate models are increasingly being used to understand how climate change may affect future drought regimes. However, methodologies to quantify the type and scale of social and economic effects that could occur under these future scenarios are virtually non-existent. Consequently, this study developed a methodology for projecting and quantifying future drought risk in terms of economic damages and numbers of lives lost and affected.

In this study, historic drought events were identified in regional precipitation data using the Standardised Precipitation Index, and their magnitude quantified. Drought magnitude was linked to reported historic data on economic damages and the numbers of lives affected and lost, to create country specific economic and social drought damage functions for Australia, Brazil, China, Ethiopia, India, Spain/Portugal and the USA. Future projections of drought magnitude for 2003-2050 were modelled using the integrated assessment model CIAS (Community Integrated Assessment System), for a range of climate and emission scenarios, and applied to the drought damage functions to estimate future economic and social drought effects. Additionally, a preliminary investigation of indirect economic drought damages was conducted using the Adaptive Regional Input-Output model (ARIO).

The analysis identified large variability in the scale and trend of economic and social effects from future drought. Economic benefits projected to occur in some countries were outweighed by negative effects elsewhere, with annual losses to global GDP from drought increasing in the first half of the 21st century. The analysis suggested that severe and extreme SPI-6 and SPI-12 drought events could cause additional losses to global GDP of 0.01% to 0.25% annually. Whilst this effect on global GDP may appear small, this is considered a conservative estimate namely as the analysis is representative of six countries only; the estimates do not incorporate the possibility of successive drought events, or compounding effects on vulnerability from interactions with other extreme events such as floods. Additionally, the global economic estimates exclude indirect economic effects, and social and environmental losses; the possibility of increasing vulnerability due to changing socio-economic conditions; and the possibility of irreversible or systemic collapse of economies as, under future climate change, drought magnitude may exceed current experience and surpass thresholds of social and economic resilience. Yet importantly, even

just considering direct economic effects of individual drought events on a handful of countries still resulted in a noticeable effect on global GDP.

Stringent mitigation had little effect on the increasing economic and social effects of drought in the first half of the 21st century, so in the short-term adaptation in drought ‘hot spots’ is crucial. However, stringent mitigation will be required to reduce increasingly severe drought events that are projected for the second half of the 21st century. A case study of Spain suggested that indirect economic losses increased non-linearly as a function of direct losses, amplifying total economic damages of drought. Importantly the non-linearity seen between direct and indirect economic costs suggests that the benefits of stringent mitigation policies, in terms of avoided indirect losses, may be more substantial than for direct losses in the second half of the 21st century.

The main impact of the research is its contribution to the assessment of economic and social damages from drought events through the creation and application of drought damage functions. The drought damage functions could be incorporated into wider economic assessments of climate change or integrated assessment models that currently exclude extreme weather events. The inclusion of drought related economic and social damages could help to guide appropriate levels of climate change mitigation, help to gauge the vulnerability of communities to future drought events, guide drought risk management, and inform drought adaptation strategies. The application of I-O analysis to estimate indirect economic losses from drought is a relatively new and developing area of research. The research highlights how I-O analysis could be used to provide estimates of economic drought damages under future climate change, which are more comprehensive, and useful for assessing benefits of future mitigation and adaptation strategies. Consequently, there are many gains to be seen from the continued development and application of this research methodology for drought.

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Acronyms

AI	Average Intensity (drought)
ARIO	Adaptive Regional Input-Output Model
BoM	Bureau of Meteorology
CBA	Cost-Benefit Analysis
CEA	Cost-Effectiveness Analysis
CGE	Computable General Equilibrium
CIAS	Community Integrated Assessment System
ClimGen	Climate Generator
CRU	Climatic Research Unit
CSIRO	Commonwealth Scientific and Industrial Research Organisation (Australia)
EAM	Event Accounting Matrix
EAR	Economic Amplification Ratio
EM-DAT	Emergency Disaster Database
ENSO	El Niño-Southern Oscillation
E3MG	Energy-Environment-Economy Global Model
FEMA	Federal Emergency Management Agency (USA)
GCM	General Circulation Model
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic Information System
IAM	Integrated Assessment Model
I-O	Input-Output
IPCC	Intergovernmental Panel on Climate Change
MAGICC	Model for the Assessment of Greenhouse-gas Induced Climate Change
MCA	Multi-Criteria Analysis
MDM	Monthly Drought Magnitude
NAO	North Atlantic Oscillation
NDMC	National Drought Mitigation Centre
NEDyM	Non-Equilibrium Dynamic Model
PDF	Probability Density Function
PDSI	Palmer Drought Severity Index
PI	Peak Intensity (drought)
PP	Precautionary Principle
PRECIS	Providing Regional Climates for Impacts Studies
PRTP	Pure Rate of Time Preference
RCM	Regional Climate Model
SCM	Simple Climate Model
SPI	Standardised Precipitation Index
SRES	Special Report on Emission Scenarios
TAR	IPCC Third Assessment Report
TDM	Total Drought Magnitude
UNFCCC	United Nations Framework Convention on Climate Change
VA	Value Added
WUE	Water Use Efficiency

1. Introduction: Setting the context

Climate change is widely viewed as one of the most serious threats to humanity. It is an extremely difficult issue to manage due to the complex nature of the climate system, the global scale of the problem, and uncertainties over how the climate system will respond in the future to changing greenhouse gas (GHG) emissions. The 2007 review by the Intergovernmental Panel on Climate Change (IPCC) concluded that global atmospheric warming of the climate system is 'unequivocal' and warming over the past 50 years is attributable to human activities. The global temperature has risen by 0.74°C in the last 100 years (from 1906 to 2005) and global temperature is projected to increase by 2.4 to 6.4°C by 2100 (relative to 1980-1999) (IPCC, 2007b).

Changes in long-term mean climate are important, however the consequences of shifts in the intensity and frequency of extreme weather events are likely to result in significantly larger impacts on society, the economy, and the environment (Beniston, 2007). As such, changing characteristics of extreme weather events are expected be one of the most serious consequences of climate change (IPCC, 2007b). Of all extreme weather types, droughts have one of the largest impacts on society. Drought affected over 1.5 billion people during 1980-2008, an average of ~53 million people each year (EM-DAT, 2010). Economic damages from drought events can also be catastrophic, with a single drought event capable of causing tens of billions of dollars of damage. For example, the 2002 drought in the USA was estimated to have caused damages of over 20 billion US$ (Wilhite, 2005). In the EU it is estimated that drought and water scarcity has affected at least 11% of the population to date with economic losses over the past 30 years estimated at ~139 billion US$ (European Commission, 2007).

Evidence already suggests that climate change has begun to affect the intensity and frequency of drought events in some parts of the world, and the IPCC concluded that drought affected areas are *likely*[1] to increase in extent in the future (IPCC, 2007b). Changes in drought patterns and characteristics will affect the type and scale of future economic and social impacts. It is the identification and estimation of potential economic and social effects of drought, under future scenarios of climate change, which forms the basis for this research. The chapter continues with a general introduction to the subject area highlighting current gaps in knowledge, and the important research questions that arise.

[1] The term 'likely' is used by the IPCC to denote a probability greater than 66%.

1.1 Drought

Drought is a weather-related phenomenon that reflects the natural variability of the climate system. Drought is possible in virtually all regions of the world, regardless of precipitation or temperature regimes (Wilhite, 2005). Droughts are slow onset, spatially extensive, events that can affect regions for weeks, months or years. Due to these characteristics droughts are often considered the most complex of all natural hazards to understand and analyse (Wilhite et al., 2007). There is no single, universal definition of drought as definitions can vary depending on the subjective views of the user and the particular regions, impacts and sectors being assessed (Wilhite, 2005). The IPCC define drought as '*a prolonged absence or marked deficiency of precipitation*', a '*deficiency that results in water shortage for some activity or for some group*', or '*a period of abnormally dry weather sufficiently prolonged for the lack of precipitation to cause a serious hydrological imbalance*' (IPCC, 2007b, p.261). Drought events can also be defined based on the duration of the precipitation deficit and the particular impacts that evolve over time. Meteorological drought relates to a deficit in precipitation from average conditions. Hydrological drought implies a departure in surface and sub-surface water supplies from average conditions. Agricultural drought is related to the availability of soil moisture to support crop growth. Socio-economic droughts can be caused by human effects on the supply and demand of water resources in combination with other types of drought (Wilhite and Buchannan-Smith, 2005).

1.1.1 Drought impacts

Drought has the potential to cause severe direct and indirect impacts to society, the economy and the environment. For example, drought can directly cause loss of life, destroy crops and reduce water supply and quality. Direct impacts on food and water supply can indirectly affect quality of life, lead to malnutrition, starvation, disease, and risk of conflict, all triggering humanitarian and human development concerns. Figure 1.1 illustrates direct and indirect social, economic, and environmental impacts of drought.

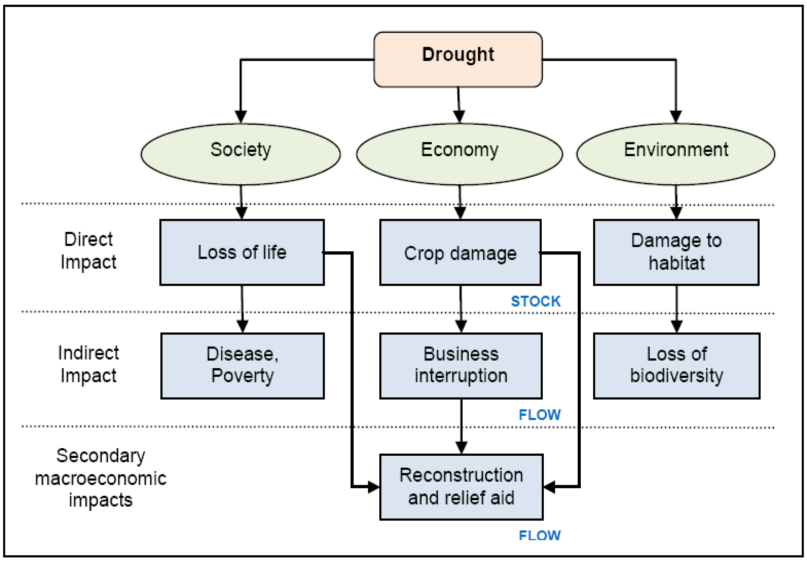


Figure 1.1: An example of direct and indirect social, economic, and environmental drought impacts. Source: Figure adapted from Hochrainer et al., (2007).

Drought is an economically important hazard for many countries. Agriculture, livestock, forestry, energy, industry, and water sectors are all particularly at risk from drought (NDMC, 2006c). Direct economic impacts can indirectly affect business production affecting the flow of goods and services through extensive and complex sectoral linkages. Secondary macroeconomic impacts comprise both the indirect losses and the impacts of government reallocation of resources for reconstruction and relief efforts (Hochrainer et al., 2007, Mechler, 2003).

However, the lack of observable, physical drought damage to assets and capital commonly results in the underestimation of direct and indirect economic damages from drought with most estimates carried out in a haphazard and incomplete manner (Below et al., 2007, Hayes et al., 2004). Agriculture is an exception as Ding et al., (2010) notes that it is highly sensitive to weather variability and so drought impacts can be immediate and physically observable. Data and statistics for the agricultural sector are easier to gain than for other sectors, and monetary estimates of drought losses are often collected for regions that seek disaster aid (with most relief programs available for agriculture only). Consequently, economic impacts of drought are not usually considered as severe as from other extreme weather types like floods or hurricanes. Yet drought is commonly associated with large indirect economic losses due to the dependence of many industrial sectors on water for production, and the importance of water for providing services and recreation. These indirect damages can propagate rapidly through the economic system affecting regions far from the original event (Wilhite et al., 2007), and continuing to be felt long after the drought has ended.

Drought events also have one of the largest impacts on society of all extreme weather types. However, as with economic damages, attributing loss of life and lives affected specifically to drought is complex because of the indirect effects on society via e.g. food and water shortages, poor health, and disease (Sheffield and Wood, 2011). Human activities are linked to hydrological, agricultural and socio-economic droughts highlighting the important interactions that exist between society, environment and water. Therefore, any changes to hydrological systems, such as those caused by drought, pose a significant risk to society. Risk can be defined as the probability of harmful consequences, or expected losses resulting from interactions between natural hazards and vulnerable conditions (UNISDR, 2004). Thus, the scale and severity of drought impacts will be dependent on the underlying vulnerability of the population and particular region exposed to the event, as well as the underlying climate and weather patterns that determine the frequency and severity of the event.

1.1.2 Socio-economic changes and vulnerability

Vulnerability can be defined as '*the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes*' (IPCC, 2007c, p.883). Society is affected by drought when its ability to cope is exceeded due to pre-existing vulnerabilities, or due to an event being of such high magnitude that it overwhelms an otherwise functioning society. Whilst it is expected that climate change will influence the frequency and intensity of future droughts (discussed in section 1.2.3), external changes independent of the climate can also affect the vulnerability of society. For example, increasing and expanding populations in vulnerable areas will increase the number of people at risk, whilst changing infrastructure and developing economies will increase the capital assets at risk. Evidence has already been seen to suggest that drought events of lesser magnitude are resulting in greater impacts as more people and sectors find themselves at risk today than in the past (Wilhite, 2005, Wilhite et al., 2007). In many parts of the world societal vulnerability to drought appears to be increasing, sometimes at a significant rate, for example in the USA (Hayes et al., 2004).

When assessing the vulnerability of a region to an extreme weather event impacts are often considered in terms of economic damages. Consequently, increases in wealth, infrastructure and insured goods will mean that damage losses become higher regardless of the magnitude of the event. Yet whilst economic damages may increase in value over time, the actual percentage loss to a countries total economy may decrease with development making a country less vulnerable overall. Conversely, a developing country may appear economically less vulnerable as economic losses will appear much smaller. However, least developed, simple economies are often perceived as the most vulnerable as economic losses may represent a large percent of a countries total economy (Benson and Clay, 2004). In intermediate-stage economies, increasing inter-sectoral linkages tend to increase the indirect damages that occur. Conversely, governments of countries with intermediate-stage economies may meet a larger share of relief and reconstruction costs rather than receiving external aid, and better-developed financial systems can diffuse some of the impacts. Developed country economies are often less dependent on vulnerable sectors such as agriculture; have higher investment in risk reduction; have improved environmental management and adaptation schemes; lower levels of poverty; and economic assets are likely to be insured both at private and individual household levels. These factors help to reduce vulnerability to extreme weather events (Benson and Clay, 2004). However, this is not to say that wealthier, developed nations are immune to impacts of large-scale weather events. Indeed, it is sometimes their very capability to be able to shield vulnerable regions and cities from ‘ordinary’ weather extremes which can result in countries being unprepared when things do go seriously wrong (Tol et al., 2000).

Mirza (2003) reports that in the 1990s on a per capita GDP basis the developing world absorbed damages 20 times higher than the developed world due to natural disasters. Developing countries are considered especially vulnerable as they do not have the same financial, institutional, or infrastructure settings to adapt or protect themselves from these risks. Moreover, the societal impacts of drought on developing countries can be catastrophic and so impacts may be more severe than macroeconomic data alone would imply. Drought statistics from the International Emergency Disaster Database (EM-DAT) highlight these trends as developing countries feature predominantly in the top ten countries affected by drought events when assessing lives lost or lives affected, whilst developed countries make up the majority of the top ten countries affected when assessing economic impacts (EM-DAT, 2010) (Table 1.1a-b). It is therefore very important to assess consequences of drought in more than just economic terms in order to get a true representation of the vulnerability of a region and the impacts it may suffer.

(a)

Country	Date	Damage (000 US$)
China P Rep	1994	13,755,200
Australia	1981	6,000,000
Spain	1990	4,500,000
Iran Islam Rep	1999	3,300,000
United States	2002	3,300,000
Spain	1999	3,200,000
Canada	1977	3,000,000
China P Rep	2006	2,910,000
Zimbabwe	1982	2,500,000
Brazil	1978	2,300,000

(b)

Country	Date	People Killed
China P Rep	1928	3,000,000
Bangladesh	1943	1,900,000
India	1942	1,500,000
India	1965	1,500,000
India	1900	1,250,000
Soviet Union	1921	1,200,000
China P Rep	1920	500,000
Ethiopia	1983	300,000
Sudan	1983	150,000
Ethiopia	1973	100,000

Table 1.1: Top ten drought disasters during 1900 to 2010 defined by (a) economic damage (000 US$ in year of event), and (b) number of people killed at a country level. Source: EM-DAT, 2010

As illustrated above changes in socio-economic conditions can affect the vulnerability of a region to drought. At the same time, consequences of climate change are also likely to exacerbate economic, social and environmental impacts. The IPCC reports that for most sectors current climate change falls largely within the coping capacity of society, however, extreme weather events are one exception (IPCC, 2007c). Vulnerabilities to extreme weather events are very likely to change as events become more widespread, frequent, and intense with future climate change.

1.2 Climate change and drought

Climate change can affect precipitation patterns and drought due to mechanisms of the atmosphere and climate system. Precipitation is principally driven by mechanisms that cause air to rise, and the moisture content of the atmosphere determined by the temperature and availability of moisture. At higher temperatures, the moisture content of the atmosphere will increase as the Clausius-Clapeyron physical law states that the water holding capacity of the atmosphere increases by about 7% with every 1°C temperature rise. Changes in temperature, radiation, atmospheric humidity, and wind speed will also affect the amount of evaporation which can exaggerate effects of decreased precipitation on surface water and run-off (IPCC, 2007c). Evaporation over land also depends largely on the moisture supply and is thought to be closely related to variations in precipitation and run-off at a global scale

(IPCC, 2007b). The resultant impact of climate change is to affect and alter the hydrological cycle. Climate change can affect both mean precipitation and the variability of precipitation so that an increase in heavy rainfall events is projected, even when there is an overall reduction in precipitation (Trenberth et al., 2003). A warmer climate will therefore increase the risk of both drought, when it is not raining, and flood when it is, at different times and places. Some impacts of climate change on the hydrological cycle have already been observed (Huntington, 2006, IPCC, 2007b, Kundzewicz et al., 2008). Furthermore, in summer temperatures can be closely tied to moisture availability, with heatwaves common during drought conditions as solar heating goes into increasing temperatures rather than evaporating moisture. Thus, reduced moisture availability can enhance heatwaves which themselves can perpetuate the drought further and amplify and potentially prolong the response (Trenberth and Guillemot, 1996).

Research has also identified a link between increasing CO_2 concentrations and physiological forcing on plants. Generally, the increased concentration of atmospheric CO_2 means that plant stomata do not open as wide as they are able to take up CO_2 more efficiently. This results in increased Water-Use Efficiency (WUE) and reduced transpiration (Cruz et al., 2010). Recent studies have suggested that such effects can influence hydrological conditions and surface air temperature (Alo and Wang, 2008). For example, increased WUE in plants can result in increased soil moisture, increased continental run-off, and potentially flooding events. Betts *et al* (2007) simulate a doubling of CO_2 from pre-industrial levels and find that this results in decreased evapo-transpiration and a 6% increase in global mean run-off. On the other hand, as increased WUE of plants leads to reduced transpiration this process may also lower evaporative cooling resulting in increases in regional air temperature. Cruz et al., (2010) suggest that the unusually high maximum surface air temperature during the 2002 drought in the Murray-Darling Basin in Australia was in part linked to the increased WUE of plants in the area. If changes in plant physiology are attributed to CO_2 levels then impacts of climate change on the hydrological cycle may actually be higher than current predictions suggest, although the IPCC (2007c) note that this attribution is still highly uncertain.

Feedback processes between drought events and terrestrial carbon cycling have also been recognized in China. Xiao *et al.,* (2009) find that severe drought events in the past have caused the countrywide terrestrial ecosystem to switch from a carbon sink to a carbon source. Xiao *et al.,* report that drought significantly affects ecosystem carbon exchange processes for a variety of reasons including the direct effect of drought on plant stomata and leaf expansion, which limits transpiration and water uptake and reduces photosynthesis. In addition, repeated episodes of drought can cause a reduction in leaf area in temperate forests reducing gross primary productivity. Consequently, the magnitude of the terrestrial carbon sink could be overestimated if extreme climate events are not considered in future projections. This is especially important for areas projected to suffer increased drying over the 21st century as this feedback could affect future GHG concentrations, and exacerbate future drought regimes.

Large scale circulation patterns, such as the El Niño Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) also effect the frequency, intensity and duration of hydrological weather extremes (IPCC, 2002). ENSO is argued to be the single most important determinant of variability in global precipitation fields, with approximately 30-60% of annual precipitation variance explainable by the ENSO mode (Dai and Wigley, 2000). Droughts are more common during El Niño phases whilst excessively wet conditions are more common during La Niña phases (Lyon and Barnston, 2005). Major peaks in the spatial extent of drought and excessively wet periods are generally associated with extreme phases of ENSO (Lyon, 2004). Likewise, the NAO has an important influence on extreme precipitation in Europe characterised by increased winter precipitation during its positive phase and dryer winter weather in its negative phase, which can contribute to drought. Climate change can affect large-scale atmospheric circulation patterns directly, which could have major implications for the future occurrence of drought and its related impacts. Some observed changes have already been seen in large scale circulation patterns due to climate change (IPCC, 2007b, STARDEX, 2005).

1.2.1 Changes in observed drought events

It is extremely difficult if not impossible to directly link and attribute any particular drought event to anthropogenic climate change, as there is always a finite chance that the event in question might have occurred anyway due to natural climate variability. However, simple statistical reasoning allows us to express how a relatively small change in the mean and/or variance of the observed probability density function (PDF) of precipitation will affect the frequency of drought events. With a global mean warming of 0.74°C over the 20th century (IPCC, 2007b) it is very possible that a change in drought regime will occur in some areas. Importantly, the average global temperature rise of 0.74°C masks local and seasonal variations across the globe with much more warming seen in the northern hemisphere than the southern hemisphere due to the greater extent of land mass, suggesting that there will be spatial variability in drought trends.

One of the biggest obstacles in trying to analyse past and current trends of extreme weather events is the lack of high quality, reliable, and long-term instrumental data (Easterling et al., 2000b, IPCC, 2002). In the case of drought, difficulties in accurately measuring precipitation, especially over the oceans, remain. Long-term data is required when analysing changing trends in drought as a single large historic event can continue to bias future trends. Yet, as climate change has only been affecting the temperature record since the 1970s this results in a relatively short time-period over which to statistically identify any trends in drought events, which by their very definition will be rare (Easterling et al., 2000a). Nonetheless, the observational basis of the analysis of extreme weather events has increased substantially over the 21st century enabling the 2007 IPCC reports to draw a more conclusive link between climate change and drought. Observed precipitation data has highlighted some long-term changes in the intensity and frequency of drought over wide areas, especially in the tropics and sub-tropics, since the 1970s (IPCC, 2007b). A drying trend over many parts of the northern hemisphere, such as Canada, Alaska, southern Eurasia, and northern Africa has also been detected since the 1950s (*ibid.*). A study by Zhang et al., (2007), focusing on the detection of human influence on precipitation, concluded from both observations and climate model simulations that climate change has had a detectable influence on global precipitation during the 20th century. The study finds decreasing precipitation in the northern hemisphere subtropics and tropics, and increasing precipitation in the northern hemisphere mid-latitudes and southern hemisphere sub-tropics and deep tropics. The effect of climate change on soil moisture has also been analysed with the extent of very dry land more than doubling, from 12% to 30%, since the 1970s (IPCC, 2007b). Many country specific studies also indicate changes in national and regional drought patterns over the 20th and early 21st centuries (*inter alia,* studies for the USA (Easterling et al., 2000b), Australia (Lynch et al., 2008), Czech Republic (Dubrovsky et al., 2009), and China (Zou et al., 2005)).

Event specific research, such as that focusing on the European heatwave of 2003, has also enhanced the growing conviction that anthropogenic climate change is already influencing extreme weather events. For example, Europe suffered a severe heatwave in 2003 which was estimated to have caused over 30,000 excess deaths; affected energy supply and demand, hydrological resources and the agricultural sector; and caused damages in excess of €13bn (UNEP, 2004). The summer of 2003 was the warmest ever recorded in Europe, exceeding the 1961-1990 mean by approximately 3°C (Schär et al., 2004). Stott *et al*., (2004) estimated how much human activities may have increased the risk of such an event taking place. Results showed that past human activity has more than doubled the risk of the 2003 heatwave occurring. Likewise, Schär et al., (2004) investigated the scale of the 2003 heatwave in Switzerland and found that statistically the event was extremely unlikely even when observed increases in temperature were taken into account, attributing the event to changes in both the variability and the mean temperature.

In addition to climatological data, disaster statistics used to govern humanitarian action following disasters and for disaster preparedness strategies are available. Figure 1.2 presents global drought statistics from EM-DAT, the only publicly available global drought database. EM-DAT records the occurrence and impacts of large-scale disasters that meet at least one of the following criteria: 10 or more people reported killed; 100 or more people reported affected; a declaration of a state of emergency; or a call for international assistance.

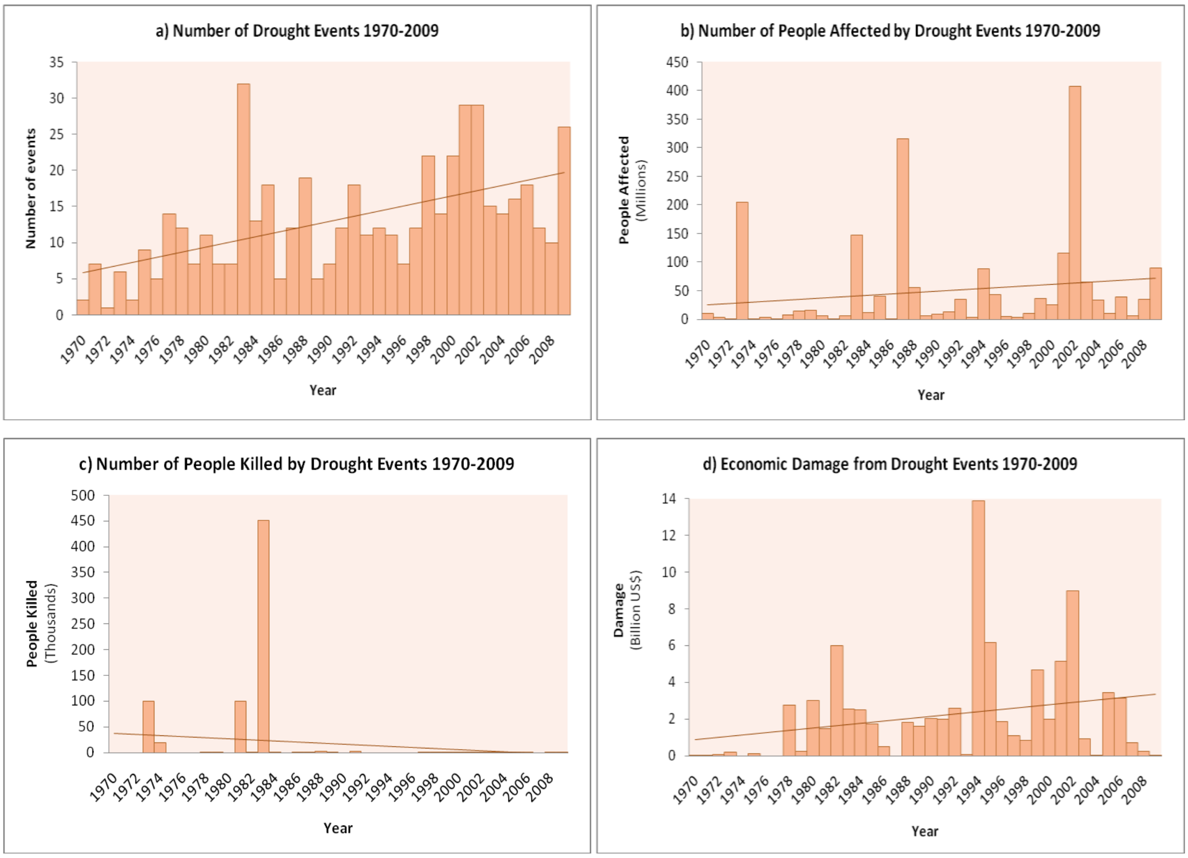


Figure 1.2: Global drought trends from 1970-2009 for: a) number of drought events; b) number of people affected by drought events; c) number of people killed by drought events; and d) economic damages from drought events (billion US$ in the year of the event). Source: EM-DAT (2010).

Figure 1.2a highlights a steadily increasing trend in the number of reported drought events from 1970-2009, although there is considerable annual variability. Likewise, the average number of people affected (that is injured, affected or made homeless) by drought events has increased threefold from the 1970s (figure 1.2b). Conversely, figure 1.2c shows the annual number of drought related deaths has been declining since the 1970s, although this trend is largely biased by intermittent ‘major’ disasters such as the Sahel Drought in the early to mid-1980s (EM-DAT, 2010). Additionally table 1.1b above indicates that mortality rates from drought events appear to have been decreasing since 1900. This trend may suggest that society’s adaptive capacity to drought events has been increasing and society is becoming less vulnerable. Vulnerability of society to droughts may be reduced due to greater wealth, increasing technological options such as early warning systems and drought resistant crops, and quick government, international and aid agency responses in the immediate aftermath of events. Indeed, one of the major tools for preparing for and tackling drought is the use of monitoring and forecasting tools (Sheffield and Wood, 2011). Governments and private organisation increasingly have the capacity to develop real time pictures of drought over large regions, to help predict the likelihood of drought events occurring, the severity of events, and potential cessation of existing conditions. Additionally, global drought monitoring systems are being developed, as well as merging regional and national monitoring systems, to better reflect the large spatial scale of droughts across various national boundaries (*ibid.*). For example, the economic and social effects of drought events linked to the 1997-1998 El Niño were considered to have been mitigated in part as the El Niño event itself, and likely drought effects, were predicted before they occurred, using SST measuring buoys in the equatorial pacific and computer models. The dissemination of such forecasts for use in decision making, and to enhance preparedness, was beneficial and the ability to protect lives and reduce economic losses acknowledged (Buizer et al., 2000). Conversely, drought effects can also be aggravated by government interactions, such as urbanisation changing land use and population numbers in given regions, which may be counter-intuitive to drought mitigation measures. Indeed, there is evidence that certain measures which have been implemented to alleviate drought in the past, such as groundwater pumping and reservoir building, can also exaggerate drought and its effects further (Sheffield and Wood, 2011).

Economic damages appear to have been steadily increasing over the past four decades (figure 1.2d). However, whilst EM-DAT aims to report the economic impacts there is limited information available on damage costs of drought events in the database, especially in the earlier data where cost estimates were either limited or not available at all. Although data recording techniques have improved since the mid 1960s, data limitations can be a real constraint when analysing changing drought trends. In particular, when assessing historic economic impact data a caveat is required as total damage costs can be particularly hard to ascertain; data on non-market impacts are still very much limited; large indirect costs may be excluded; lagged costs may be excluded; or there may be incorrect reporting or analysis of data that is available (Changnon, 2003a).

Figure 1.2 would imply that external factors are already affecting drought frequency, the number of people affected by drought, and the scale of economic damages. Therefore, an important question to address is how far these trends reflect changing socio-economic conditions, and how far, if at all, they reflect climate change? As the criteria for a drought event to be added to the EM-DAT database is based on the scale of reported impacts rather than meteorological data this may bias the trends. The trends may reflect increasing and expanding populations in vulnerable areas, increasing the number of people at risk, and developing economies increasing the infrastructure and capital assets at risk. EM-DAT have also acknowledged that at least some of the increase in trends in natural disasters may be attributed to the improved reporting and monitoring of events by media and special agencies over the past decades.

However, the IPCC state that disaster losses, mostly weather-related, have grown much more rapidly than population or economic growth, suggesting there have been changes in the intensity and frequency of extreme weather events (2007b). In an assessment of damages from extreme weather events, the reinsurance firm Munich-Re found similar results when adjusting for factors of inflation, population growth and growth in global wealth. The study found that economic losses from extreme weather events in the 1990s still showed an increase compared to the 1960s, which they attributed to changes in the frequency of extreme weather events (reported in Vellinga and van Verseveld, 2000). Swiss-Re also concluded that economic losses from natural disasters have increased, even when taking inflation, insurance, price effects and higher standards of living into account (*ibid.*). Similarly, Höppe and Pielke (2006, p.2), who summarise the findings of an international workshop on climate change and damage loss from extreme weather events, state that:

- *Analyses of long-term records of disaster losses indicate that societal change and economic development are the principal factors responsible for the documented increasing losses to date.*
- *There is evidence that changing patterns of extreme events are drivers for recent increases in global losses.*
- *Because of issues related to data quality, the stochastic nature of extreme event impacts, length of time series, and various societal factors present in the disaster loss record, it is still not possible to determine the portion of the increase in damages that might be attributed to climate change due to GHG emissions.*

Consequently, disaster statistics and evidence of changing drought trends ascertained from observed precipitation data would suggest that recent changes in the characteristics and effects of drought events are a consequence of not only socio-economic changes but also changes in the intensity and severity of drought events due to anthropogenic climate change. Whilst socio-economic changes may be the principal factor for current trends in drought impacts, climate change may start to play a more dominant role in the future. This is an ominous course as the IPCC project much greater changes in global temperature over the 21st century, which could further exacerbate drought frequency and intensity in some regions. Therefore, understanding how drought regimes will change under future projections of climate change, and the economic and social implications of this, is a key issue to consider.

1.2.2 Future drought trends

There are numerous types of mathematical climate models which aim to simulate the behaviour of the climate system. Climate models range from very simple zero order models (providing a single global average) to more complex three-dimensional General Circulation Models (GCMs). There is increasing confidence that climate models provide credible estimates, based on the foundations of the models in accepted physical laws and principles, and their ability to reproduce current and past climate change. Based on a suite of 21 GCMs the IPCC concluded that drought affected areas are *likely* to increase in extent in the future. Widespread decreases in precipitation were projected for mid-latitude summer precipitation, except for eastern Asia, and the risk of summer drought is *likely* to increase in central Europe, the Mediterranean, and southern Australia (IPCC, 2007b). By the 2090s the extent of land surface in extreme drought at any one time is projected to increase ten-fold from present, with a global drying trend seen on average (Kundzewicz et al., 2008). As such, future drought severity may be further compounded by positive feedbacks such as increases in the frequency of heatwaves (Sheffield and Wood, 2011). Figure 1.3 illustrates the mean global changes in precipitation and soil moisture, for the period 2080-2099 relative to 1980-1999 (IPCC, 2007b, p.769).

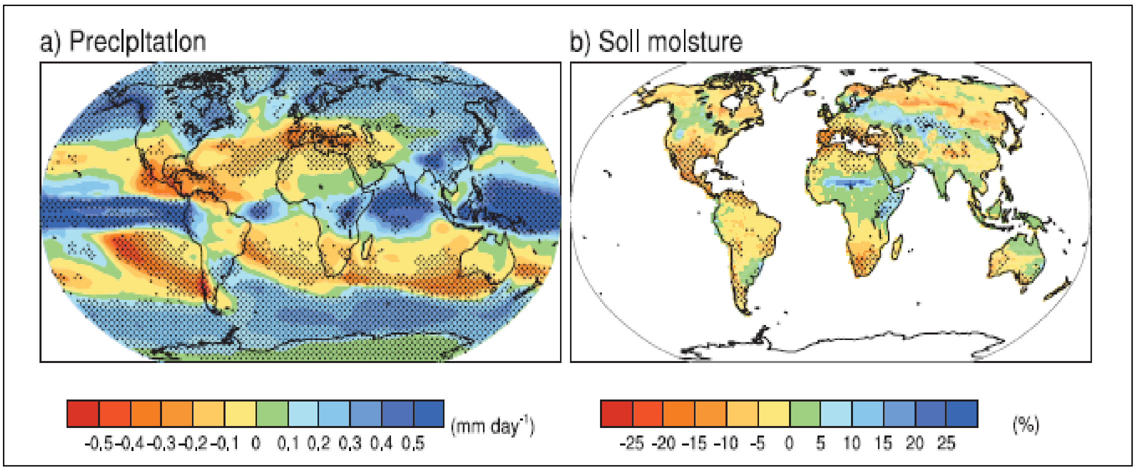


Figure 1.3: Multi-model mean changes in (a) precipitation (mm day^{-1}) and (b) soil moisture content (%). To indicate consistency in the sign of change regions are stippled where at least 80% of models agree on the sign of the mean change. Changes are annual means for the SRES A1B scenario[2] for the period 2080 to 2099 relative to 1980-1999. Soil moisture changes are shown at land points with valid data from at least 10 models. Source: (IPCC, 2007b, p.769).

The findings of the IPCC have been corroborated by recent studies of future drought regimes. At a global scale Sheffield and Wood (2008) projected future drought changes in the 21st century using a suite of eight GCMs, which were included in the 2007 IPCC report, using high, medium and low emission scenarios. Drought was defined as an extended period of anomalously low soil moisture, for a consecutive series of months, and which fell below a pre-defined threshold. Results showed a decrease in soil moisture at a global scale under all scenarios with regional hotspots identified as the Mediterranean, West Africa, central Asia, and Central America (especially for drought events lasting more than a year), as well as mid-latitude North American regions. The study reported less significant changes over high latitudes and eastern mid-latitude Asia. Drought frequency was projected to increase relative to the current climate although significant changes were not seen to occur for several decades. One exception was the Mediterranean region where significant changes were detected by the mid 21st century. In addition, the study highlighted that changes in the frequency of warm season and long-term drought events were likely to be greater than changes in cold season and short-term drought events.

[2] See section 4.1 for further details on the SRES emission scenarios.

Similarly, a global study by Burke et al., (2006), which projected changes in drought conditions in the 21st century, reported drying over Amazonia, the USA, northern Africa, southern Europe and western Eurasia. A wetting trend was projected for central Africa, eastern Asia, and high northern latitudes. Hirabayashi et al., (2008) used a high resolution GCM, which incorporates a land surface model to estimate runoff, to project daily river discharge as an indicator of drought frequency. An increase in drought events globally was projected by 2100 (using the IPCC A1B medium emission scenario) with a significant increase in the number of drought days over North and South America, central and southern Africa, the Middle East, southern Asia from Indochina to southern China, and central and west Australia. Northern high latitudes, eastern Australia and eastern Eurasia showed a decrease or no significant change in drought conditions. Furthermore, several regions were projected to suffer from an increase in both flood and drought frequency reflected changing seasonality.

Numerous regional modelling studies also exist which corroborate the global findings of the IPCC and other studies indicated above. For instance, Europe has been the focus of many modelling studies, which project northern Europe will become wetter with more intense precipitation events whilst southern Europe is projected to suffer more frequent and longer duration droughts in the 21st century. The Mediterranean region is expected to face considerable risk from future drought events (e.g. Beniston et al., 2007, Blenkinsop and Fowler, 2007, Frei et al., 2006, Lehner et al., 2006, Warren et al., In review).

1.2.3 Future drought impacts

The chapter has already highlighted that socio-economic impacts of drought events have been increasing. There is also growing consensus that the economic damages from extreme weather events under future climate change will be profound. Allianz stated that climate change stands to increase losses from all extreme weather events by 31% within a decade *'in an average year'* with losses in a bad year topping 400 billion US$ (Mills, 2007). To put this into perspective 400 billion US$ is double the overall losses reported from 2005, which included damages from Hurricane Katrina in the USA. Climate change impacts on the availability of water is also likely to affect billions of people living in water-stressed areas during the 21st century (Arnell, 2004, Kundzewicz et al., 2008). Consequently, understanding the potential impacts that may occur under future climate change is extremely important for designing appropriate mitigation and adaptation policies. Since the 1990s there has been an increased focus on modelling and understanding changing patterns of extreme weather events (Meehl et al., 2000). However, whilst progress has been made regarding the modelling of future weather extremes, as a whole, the quantification of impacts from extreme weather events, especially on non-market sectors, is still in its infancy and consistent methodologies on economic cost assessments of extreme weather events are still developing (Changnon, 2003b, Hallegatte et al., 2007b, Mendelsohn and Williams, 2004, Pielke, 2007). In addition, studies that do exist have tended to focus on short-term events such as flood and hurricane events, which impose immediate, direct impacts on society and infrastructure. In contrast, droughts are much more complex making identifying, measuring, and quantifying events and subsequent impacts extremely difficult. Thus, very few studies have endeavoured to identify the complexity of drought impacts at the local, regional and national scale (Wilhite and Buchannan-Smith, 2005), and to date, almost no studies have attempted to provide quantitative estimates of the economic and social effects of drought events under future climate change.

It is somewhat disconcerting that a major omission in studies which focus on the costs of climate change are the impacts and damages associated with extreme weather events (Buchner et al., 2006, Tol, 2002a, Tol, 2009). Indeed the analysis of extreme weather events in general is relatively scarce within economic literature (Baade et al., 2007). The exclusion of extreme weather events leads one to question the comprehensiveness and utility of assessments of total climate change costs, and subsequent climate change policies based on them. Ignoring extreme weather events means that such estimates exclude impacts that could appreciably increase cost estimates, and arguably cause the greatest socio-economic and environmental damages. Equally, the exclusion of extreme weather events from economic cost assessments means that the potential benefits of early, stringent mitigation in the form of avoided damages will not be recognised. This void in current climate change research was recently acknowledged by the IPCC who announced in 2009 that they would be increasing their focus on extreme weather events, with more research on modelling and quantifying impacts and the economics of extreme weather events.

1.3 Research questions

The serious societal and economic consequences of drought provide ample motivation for further research into the scale and severity of drought effects that may occur under future climate change. Whilst many studies focus on changing drought regimes at a regional, national and global level, research dealing explicitly with the quantification of associated economic and social drought effects has received scant attention. Therefore, the overarching aim of this research is to **model and quantify the effects of drought on the economy and**

society under future projections of climate change*.* In summary, a number of interesting research questions arise:

1. Is it possible to establish a link between historic drought events and economic damages and societal effects?
2. What are the implications of climate change for future drought patterns, and the subsequent scale and type of direct and indirect economic damages?
3. What are the implications of changing drought patterns for society?
4. What are the implications of climate change mitigation for future drought patterns, and drought related economic and social effects?
5. How would the incorporation of direct and indirect economic damages from drought events affect global estimates of the costs of climate change, and subsequent policy recommendations?

In order to address the above aim **chapter 2** begins with a review of the issues that have limited the inclusion of extreme weather events in climate change impact analysis to date. Various methodological approaches used to quantify drought risk to societies and economies are reviewed, and the main issues and limitations discussed. Methodologies are discussed in light of their potential application to the quantification of drought effects under future projections of climate change. Areas requiring further research are identified, specific research objectives are provided in light of these findings, and the structure of the remaining chapters outlined.

2. Literature Review: Modelling Economic and Social Consequences of Drought

The preceding chapter highlighted how drought frequency and economic and social drought effects have been increasing over the 20th and early 21st century, linked to both changing socio-economic conditions and anthropogenic climate change. Whilst it is not possible to ascertain the proportion of drought damages caused by current climate change, it seems likely that socio-economic effects will increase if drought regimes intensify under future climate change. Climate modelling studies focusing on drought trends at a global, national, and regional level have been developing since the 1990s, yet whilst much is known about the potential risks drought poses, estimates of potential socio-economic damages are much more difficult to model and quantify.

The chapter begins by exploring why, in general, extreme weather events are so difficult to incorporate and model within climate and economic modelling frameworks, and difficulties that exist for estimating future effects of extreme weather under projections of climate change (sections 2.1-2.3). Section 2.4 reviews methodological approaches used for impact analysis of extreme weather events, and potential applications to this study. Section 2.5 reviews modelling techniques and studies that focus on the indirect economic damages of extreme weather events and the potential application to drought. Section 2.6 provides a discussion of the chapter, summarises key findings and issues regarding developing a methodology to model future economic and societal effects of drought, and outlines the research objectives.

2.1 Data requirements

A major barrier for estimating the economic and social effects of drought, as with other extreme weather events, is that of reliable, consistent impact data (Easterling et al., 2000a, IPCC, 2002). In order to provide convincing projections of losses under changing climatic and socio-economic conditions Changnon (2003b) notes that it is essential to have a good understanding of the impacts from historical extreme weather events. Similarly, Hallegatte et al., (2007a) comments that a prerequisite for the economic assessment of climate change impacts is the availability of relevant physical indicators. As well as having a useful application for climate change analysis, the quantification of losses from extreme weather is useful for gauging the vulnerability of communities; guiding risk management strategies; identifying appropriate levels of mitigation; determining disaster assistance levels; improving recovery and reconstruction decisions; and for informing insurers of their potential liability (Okuyama, 2007, Rose, 2004). As such, it would appear an important area of quantitative research, yet there is no consistent methodology for recording or calculating economic losses from extreme weather events (Committee on Assessing the Costs of Natural Disasters and National Research Council, 1999). Damage estimates for a particular event can vary widely depending on the reporting body; the range and type of costs included; and the time in which estimates are reported (cost estimates made in the immediate aftermath of an event are prone to change, usually increasing, over time). In addition, the reporting and accuracy of loss estimates tend to improve with the scale of the event (Muir-Wood et al., 2006).

Importantly, quantitative data on the impacts of past extreme weather events can be used to drive projections of future impacts. This has resulted in an extensive empirical assessment of historical weather events to provide more definitive impact estimates. Insurance and re-insurance companies, who are particularly vulnerable to certain weather types, have primarily driven this exercise for economic and insured losses, e.g. Munich-Re and Swiss-Re both maintain natural catastrophe databases. Good quality data is also essential as issues related to poor data quality result in up to 45% of the gap seen between modelled and actual incurred losses from natural catastrophes, as assessed by insurance and re-insurance industries (Grossi and TeHennepe, 2008). Research centres such as the Centre for Research on the Epidemiology of Disasters (CRED), which maintains EM-DAT, also collect data on extreme weather events, including details on direct and indirect economic losses and non-market effects.

2.2 Extreme weather events and economic modelling

Economic modelling of climate change has been fundamental in identifying and aggregating the scale of future damages, and guiding appropriate mitigation and adaptation strategies. Economic modelling is an extremely useful tool to employ as it allows climate change policies to be based around a theoretical framework and assessed by quantitative methods, something highly desirable to policy makers. As such, climate change costs assessments form a vital component in addressing the climate change problem. However, there are several limitations associated with the economic modelling of climate change and its impacts.

The perceived threat that climate change poses to modern society has been mounting with increased scientific learning. Recent reports (e.g. IPCC, 2007b, Stern, 2007) have emphasised that urgent action is required to address the problem and prevent dangerous or irreversible anthropogenic climate change. Yet, many traditional economists, who use the same mainstream climate science to underpin their analyses, have repeatedly estimated low damage costs from climate change. Tol (2009) reviews the existing 14 peer-reviewed studies which estimate global economic costs of climate change. The economic estimates range from benefits of 2.5% to losses of 4.8% of global GDP. The majority of the studies show that climate change will cost only a few percent of global GDP, with most studies suggesting that economic benefits will be seen in the short term with temperature changes up to 2.5°C. Historically, such findings have led to the conclusion that it is more cost effective to take less action now and more action in the future when damages increase and the science of climate change is more certain (Marechal, 2007). This economic outlook can largely be explained by the traditional and conservative methodological approach used for estimating climate change costs. Since the 1990s, the most common approach for investigating costs of climate change and designing economically efficient policies has been through Cost-Benefit Analysis (CBA). In theory CBA should compare the costs (of implementing mitigation and adaptation) and benefits (from avoided damages and ancillary benefits) of climate change to emphasise the most beneficial (economically efficient) policy response (Desslar and Parson, 2006). Whilst the theory behind CBA seems logical, in reality it is often an assessment of costs only as these are far easier to quantify than avoided damages and ancillary benefits. The resultant impact is that benefits will rarely outweigh costs resulting in a bias towards the status quo and calls for change going unheeded (Frank, 2000). As well as issues with the underlying methodological framework of CBA, the assumptions that underlie traditional economic theory also bias the results. Sections 2.2.1 and 2.2.2 review these issues, and the effects they have on the assessment of extreme weather events, in turn.

2.2.1 Cost-benefit analysis

To create a socially optimal policy response requires quantitative estimates of the full costs and benefits of climate change mitigation, adaptation, and impacts, including the potential for irreversible impacts, across a range of scenarios, times, and regions. However, there are uncertainties over all of these costs and benefits. Whereas the economic costs of mitigation tend to be easier to quantify as they can be represented by market prices, estimates of adaptation costs are much more difficult to determine and are only just becoming available (Parry et al., 2009). Similarly, costs and benefits of climate change impacts are extremely difficult to identify and value. Ackerman and Heinzerling (2004) differentiate between the terms ‘price’ and ‘value’ in CBA, highlighting that non-market costs and benefits may not have a price but can still have substantial value. Nelson (2006, p90-91) emphasises that an activity may be profitable if '*it creates something of greater value than the inputs used to make it*'. Thus profitability, and consequently the benefit gained, will depend on how you measure value. The fact that the value cannot always be expressed in monetary terms does not mean that it should be deemed worthless.

A solution to valuing non-market costs and benefits is to assign monetary values based on, for example, peoples Willingness to Pay (WTP) or Willingness to Accept (WTA)[3]. However, the use of alternative economic methods for valuing non-market impacts is still controversial. They tend to give more weight to higher income persons and still entail difficult ethical decisions, especially when considering the value of human lives. More commonly, non-market costs and benefits are ignored completely in economic assessments. As a result, the potential benefits available from implementing climate change policies will be limited from the outset. Many see this explicit need to monetise all costs and benefits from climate change as the fundamental flaw of CBA. Specifically, the difficulties in comparing economic and non-economic damages from extreme weather events is illustrated by Ackerman (2007) who considers the impacts of Hurricane Katrina in the US. The economic losses from Hurricane Katrina were estimated at $125bn, the most costly disaster ever to strike the US (Graumann et al., 2006). Although such costs are serious, in comparison the costs of the displacement of over 250,000 people, the death of over 1,800 people, and the further impoverishment of hundreds of thousands of people are priceless. CBA does not consider the moral obligations to protect people from such impacts of extreme weather events, or climate change in general. It is therefore an inadequate and often grossly incomplete tool.

The importance of including costs and benefits that cannot be monetised has led to new decision-making tools, or the applied application of older decision-making tools, being increasingly championed to help assess the costs and benefits of climate change more comprehensively. Multi-Criteria Analysis (MCA) evaluates projects based on several criteria. It can be applied to situations in which socio-economic, ecological and ethical perspectives need to be considered together, and does not restrict the analysis to monetary units only. The framework can consider other issues such as morbidity and mortality, equity, environmental damage, avoiding catastrophic risks, and uncertainty. Furthermore MCA does not require results to be amalgamated into a single value as results of specific impacts

[3] Willingness to pay (WTP) is the costs that you would be willing to pay to preserve e.g. a clean environment, whilst willingness to accept (WTA) is the price you would be willing to accept in compensation for a dirty environment.

presented independently can still provide a valuable insight into the overall costs (Smith and Hitz, 2003). These characteristics make MCA particularly useful for investigating damage costs from extreme weather events, which can have an array of market and non-market impacts across many sectors. However, MCA does not provide a perfect solution as due to the disaggregated nature of the analysis it is extremely difficult to compare between different studies (Ackerman and Heinzerling, 2004). Moreover, rankings and weightings assigned to non-market impacts will still reflect value judgements, which may be biased or differ considerably depending on the objectives of the user.

The Precautionary Principle (PP) is an anticipatory, rational decision tool designed to help in the assessment and management of risks. More specifically, the PP can address complex and unquantifiable risks with scientific uncertainties[4] (COMEST, 2005). Current risk from climate change, extreme weather events, and catastrophic events has been a strong motivator for those advocating its use (Kriebel et al., 2001). The PP can be applied to cases with considerable uncertainties over the causality, magnitude, probability and nature of harm, an area where CBA has limited, if any, application. Thus, the PP can help facilitate a move towards a more risk-based approach to climate change. Similarly the decision theory Pascal’s Wager allows the user to make decisions under uncertainty via a simple decision matrix by taking the option where one has most to gain and least to lose, i.e. assessing the risk of consequence. Again, this method employs the precautionary principle in that it identifies the worst-case scenario and invests to avoid this path.

Cost-Effectiveness Analysis (CEA) differs from CBA in that climate change stabilisation targets are not set based on the cost analysis but rather the cost analysis is conducted based on a predefined target. For instance following the PP, emission stabilisation targets that avoid the worst consequences of climate change with a high degree of certainty can be set. Once a target has been set CEA can be implemented to find the most cost-effective way to reach the target. CEA avoids some of the shortfalls of CBA in that it only deals with costs. As these tend to be market values that can be more readily quantified the problem of valuing non-market effects is avoided. In addition, as the initial target is set based on a precautionary approach uncertainty is directly addressed (Ackerman, 2007, 2008). Finally, as it is expected that most costs will be felt in the short-term CEA reduces the need for a discount rate, which as discussed below can also bias CBA.

[4] Knight (1921) defines risk as the property of outcomes with quantifiable probabilities, e.g. the roll of a dice, whereas uncertainty has unknown probabilities.

Recognised as a ‘thorny’ issue back in the early 1990s (Nordhaus, 1991) the use of discount rates in CBA has received renewed attention since the publication of the Stern Review in 2007. Due to the natural inertia of the atmosphere and oceans it is imperative to cover long-term time frames when addressing climate change. To enable the comparison of future costs and benefits to present costs and benefits a discount rate is used to calculate the present value. The present value is calculated on the basis that a given cost or benefit today is worth more than the same cost or benefit in the future. This is based on the premise that people will be better off in the future and so an extra unit of wealth in the future will be worth less to them (growth rate). Secondly, the present value is calculated on the basis that people are impatient and prefer to have things now rather than in the future (time preference). The discount rate, r, is generally derived in climate change studies following equation 2.1 where δ = Pure Rate of Time Preference (PRTP), η = elasticity of marginal utility of consumption (the relationship between utility and consumption), and g = growth rate of per capita consumption.

$$r = \delta + \eta g \qquad \text{Eq.2.1}$$

The present value (PV) is calculated following equation 2.2 where COST = the expected expense, and n = the number of years until the cost is incurred.

$$PV = \frac{COST}{(1 + r)^{n}} \qquad \text{Eq.2.2}$$

However, there are many complications which arise when applying discount rates to the issue of climate change due to the long time horizons of studies; issues of uncertainty over future economic growth; and inter-generational and intra-generational equity concerns (IPCC, 2007a). For example, the PRTP (δ) is the discount rate which would apply if all present and future generations had equal opportunities and resources (Ackerman, 2007). The value of the PRTP has caused much debate with some arguing it should be set to zero as this gives equal weighting to the welfare of all generations. Stern (2007) used a very low PRTP (0.1%) resulting in a low discount rate[5] and higher estimates of future climate costs. This resulted in the conclusion that the benefits of strong, early climate change action far outweighed the costs of inaction. Many traditional economists have argued that Stern’s conclusions are almost entirely due to the use of this very low discount rate, however, Stern

[5] Stern used a discount rate of 1.4% compared to the UK Treasury’s Green Book guideline of 3.5%

(2007) argues that as future generations are expected to suffer more serious consequences of climate change it is important to consider all generations as equal.

Intra-generational issues must also be considered as climate change is likely to affect individuals and societies living at very different welfare levels, both today and in the future (IPCC, 2007a), who will face varying costs and benefits. The second parameter used to calculate the discount rate, the elasticity parameter η, defines how much utility a person will gain from a certain amount of consumption. Assuming all people are of equal wealth the parameter can be taken as a measure of the commodities value to a person. However, this ignores differences in wealth as a poor person will place more value on an extra unit of money than a rich person. As such, the results of any CBA will be highly dependent on the discount rate used. Wright and Erickson (2003) highlight that in policy optimisation studies a small change in the discount rate can have a large impact on the optimal policy recommended. A lower discount rate will put more value on the future and make any future costs or benefits look more important today. As Ackerman (2008, p.7) comments '*if the future matters, the discount rate must be very low*'. The choice of discount rate therefore has strong ethical consequences when applied to climate change, reflecting the implicit or explicit ethical stance of the author (Broome, 2008, European Communities, 2008). Yet, this issue is often inadequately addressed or ignored when undertaking CBA.

A further issue with traditional CBA is that it does not address the uncertainties and risks that surround climate change and its impacts. This is an important issue when considering high-risk consequences of climate change such as extreme weather or catastrophic events[6]. Studies which have attempted to incorporated the risk of catastrophic events, such as Nordhaus and Boyer (2000) and Stern (2007), have reported substantially increased damage costs leading to the conclusion that more stringent climate change mitigation is necessary in the short-term (Azar and Lindgren, 2003). Equally, studies which do not address the uncertainties surrounding future climate change and its impacts, such as the possibility of tipping points (e.g. see Lenton et al., (2008)) tend to estimate lower damages compared to those that do (Dietz et al., 2007, Hallegatte et al., 2007a). Whilst some would view the incorporation of low-probability high-risk events in economic modelling of climate change as 'alarmist', this issue emphasises the ability of CBA to provide significantly

[6] The term 'catastrophic' event is used to represent large-scale system collapses such as the collapse of the Thermohaline Circulation or Greenland Ice sheet, or large-scale abrupt temperature changes associated with runaway global warming.

different policy recommendations depending on the underlying assumptions and factors included.

Consequently, the challenges associated with CBA are large when applied to the specific issue of climate change and extreme weather events. Such flaws have resulted in ineffective climate policy due to incomplete and biased analysis of costs and benefits, the exclusion of risk, uncertainty, and ethical considerations. Azar and Lindgren (2003) highlight that a growing number of studies now challenge CBA results due to such fundamental flaws. This leads one to question the accuracy of past studies that have suggested that economic damages from climate change will be very low, requiring un-ambitious mitigation strategies.

2.2.2 Traditional economic theory

The underlying economic theory used to drive CBA also has repercussions for the assessment of economic damages from extreme weather events. A major flaw of traditional neoclassical economic theory, the main approach used in the economics of climate change, is that it is based upon the notion that the economy has an ‘equilibrium point’ to which it naturally progresses (Beinhocker, 2007). This concept was adopted from equilibrium theory used in physics with the main benefit that it facilitated the workings of the economy to be described through mathematical equations and models. However, turning economics into a ‘hard’ science has undermined the original purpose of the discipline, which is the study of ‘real’ human systems. To believe that economies can be fully represented by rigid mathematical theories is misguided and underestimates the complexity of human behaviour. In order to represent human systems mathematically, traditional economics has to make assumptions as to how the system and actors within it works. For example, it is assumed that people are perfectly rational in their economic choices, which are based on complete information and unlimited foresight, something we know to be untrue in the real world. In addition, it is assumed that markets work at full efficiency and full employment, again something contradicted by real world data.

Traditional economic theory assumes that the economy jumps between equilibrium points with little consideration given to the dynamics in between, although the real economy is susceptible to irregularities and shocks. This is demonstrated by Hallegatte et al., (2007b) who compares a traditional growth model (Solow), assuming equilibrium, to a non-equilibrium model (NEDyM) which can experience exogenous shocks and irregularities during transient phases. The study highlights the impact of including shocks, such as those caused by extreme weather events, in economic analyses of climate change. Figure 2.1

highlights that the effect of a sudden 10% decrease in economic productivity is larger in NEDyM in both the short and medium term. This is due to amplifications of the initial shock through the economic system (i.e. indirect economic losses). As discussed in section 1.2.1 indirect economic costs from extreme weather events can be sizeable, particularly for drought events. The inability of traditional economic models to capture longer-term effects of sudden shocks on the economic system will result in an underestimation of damage costs from extreme weather events.

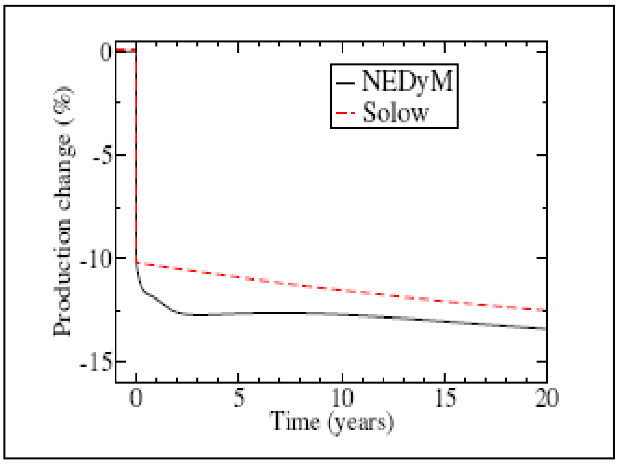


Figure 2.1: The response of a traditional economic growth model (Solow) and a non-equilibrium economic model (NEDyM) to a 10% decrease in economic productivity. Source: Hallegatte et al. (2007b, p.333)

In addition, Frank (2000) and Barker (2008) note that the underlying theory of equilibrium economics is based on a rigid and misinformed interpretation of utilitarian ethics[7]. In particular, critics of CBA disagree with the fundamental utilitarian assumption that it is possible to trade off the utility gains of some against the utility losses of others, as not all losses are equivalent, interchangeable or irreversible. This is especially important when addressing drought events as societies in developing countries are considered especially vulnerable to socio-economic effects, and they do not have the financial means to adapt or protect themselves against these risks (Benson and Clay, 2004). Yet, it is these countries, which have contributed least to the problem of anthropogenic climate change.

As such, assessments of climate change costs and benefits will be heavily dependent on the assumptions incorporated into the economic models used. However, traditional economic

[7] i.e. the morally correct course of action results in the greatest good for the greatest number without regard to the distribution of benefits and burdens.

theory which has predominantly driven CBA and climate policy is often used without caveat or discussion (Marechal, 2007). The inability of traditional economics to represent the workings of real economic systems means that climate change analyses and policy recommendations will be incomplete, inaccurate, and misleading. For instance, assuming the economy is at maximum efficiency and employment means that any climate policy will result in costs due to loss of potential output (Barker, 2008). Likewise, no-regret options which can offer substantial incentives are incompatible with traditional economics as it is assumed that if such options were possible they would have already occurred under equilibrium (Marechal, 2007). The growing criticism of traditional economics has led to the development of an alternative theory, termed ‘complexity economics’ (Arthur, 1999). Complexity economics is based on the premise that the economy evolves and is a complex adaptive system, which is dynamic, open, non-linear and far from equilibrium (Beinhocker, 2007). Thus, the economics of climate change should be more concerned with risk rather than cost, with a move towards more multi-disciplinary risk-based analyses of climate change (Barker, 2008).

2.3 Extreme weather events, impacts, and IAMs

A move towards a more risk-based, multidisciplinary analysis of climate change has been fundamental in the development and use of Integrated Assessment Models (IAMs). Models that focus on just one part of the problem, such as climate or economic models, omit crucial drivers and interactions between systems that are important for the analysis of climate change, impacts, and extreme weather events. IAMs draw on multiple models usually of energy or economic systems, atmospheric chemistry and climate systems, and environmental systems. Consequently, IAMs can consider the complex and multiple dimensions of the climate system, impacts, adaptation, mitigation, and socio-economic factors, simultaneously in a consistent quantitative framework (Carter et al., 2007, Goodess et al., 2003a). IAMs are considered one of the best tools available for assessing climate change impacts, the global costs of climate change, and risks (Stern, 2007). The first IAMs for climate change were developed back in the late 1980s, including IMAGE 1.0 (Global scale) (Rotmans, 1990) and ESCAPE (European scale) (Hulme et al., 1995), with a surge of activity since the early 1990s. The increasing number of IAMs available reflects the shift in political importance of climate change; improvements in computing capabilities; availability of more and better datasets to drive models; and an increase in interest and funding in interdisciplinary research (Parson and Fisher-Vanden, 1997).

Current IAMs all have different model structures, components and outputs depending on the specific research aims and objectives. IAMs can be broadly categorised based on their function and approach to assessing climate change impacts. Goodess et al., (2003a) and Füssel (2010) class *policy evaluation* IAMs as those which assess the effects of various policies on physical systems. This group consists of biophysical IAMs that use climate data as an input to specific geographical impact modules, such as ecosystem or agricultural models. Alternatively, *policy optimisation* models can be defined by their aim to determine the optimal outcome of mitigation measures. This group generally consists of CBA models that use climate output to estimate the costs of climate change through global or regional aggregated, monetary damage functions. In general, cost-benefit IAMs tend to focus on climate change at a global scale using simple climate models, whereas biophysical models commonly use regional scenarios of climate change to assess physical impacts (Goodess et al., 2003a).

Historically, less focus has been placed on adaptation in IAMs (Füssel, 2010). Adaptation is extremely hard to identify and quantify, as it tends to occur at more local and regional scales, and as such has commonly been modelled in IAMs in an erratic fashion (Tol et al., 2000). However, as adaptation is recognised as an important factor for coping with climate change impacts in the shorter term there has been recent development of IAMs that can also incorporate and assess adaptation strategies (Dickinson, 2007, Füssel, 2010). Such model diversity can be an advantage as no single model or hypothesis can comprehensively assess all possible scenarios posed by climate change; explain dynamic behaviour across all scales in socioeconomic and ecological systems; or represent all the interactions and impacts within a single entity (IPCC, 2007c, Tol and Fankhauser, 1998).

The robustness and uncertainty of results from IAMs will relate to the particular models utilized. Climate models used in IAMs can range from simple zero order models to GCMs that are more complex. Whilst GCMs represent the most sophisticated approach to modelling the climate system, the spatial scale of the model output, usually at a resolution of hundreds of kilometres, is inconsistent with the scale of output required for regional studies of weather extremes and climate change impacts. For example, it is found that precipitation is not well simulated in present GCMs, although in certain areas there is greater consistency in the direction of precipitation trends, such as for the Mediterranean basin (Kundzewicz et al., 2008). As such, some IAMs generate more spatially explicit climate projections by incorporating downscaling techniques, whereby climate data at finer spatial scales is derived from the coarser GCM output. This provides a useful bridge between the mismatch in GCM output and the finer resolution data required for hydrological modelling and climate change impact assessment (Fowler and Wilby, 2007). Although, it is important to note that downscaling does not increase confidence in the original climate projections (Wilby and Dessai, 2010). Two categories of downscaling techniques exist, dynamical downscaling and statistical downscaling. Dynamical downscaling involves embedding a high resolution Regional Climate Model (RCM) within the coarser scale GCM to provide regional climate change patterns. Statistical downscaling works by first identifying statistical relationships linking large-scale climate variables to observed local/regional variables. Future projections of local/regional scale climate change are derived by applying the relationships to equivalent variables obtained from GCM projections (Christensen et al., 2007). Statistical downscaling is based on the assumptions that the statistical relationship developed based on present day climate will be applicable to a future warmer climate (stationarity), and that the GCM is better at representing large-scale circulation patterns than the local weather patterns (STARDEX, 2005). There has been extensive growth in the application of statistical downscaling, which is less data intensive and computationally demanding than dynamical downscaling, in past decades. As such a variety of different statistical downscaling methodologies exist (Wilby et al., 2004 provides a good review). However, both statistical and dynamical approaches are thought to be equally appropriate for representing smaller scale climate changes and as such, no best method is offered (Christensen et al., 2007, Goodess et al., 2003a, STARDEX, 2005, Wilby and Fowler, 2011).

This is not to say that different downscaling techniques will produce similar results. Wilby and Fowler (2011) note that the use of different methods for future climate change scenarios have produced divergent outcomes, suggesting that inter-method differences can increase uncertainty in outputs at least as large as seen when using different emission scenarios. Furthermore, the GCM used and in some cases the RCM employed can have large impacts on the climate results generated. This is particularly the case for precipitation scenarios, which are highly sensitive to the climate model used. For example, Beniston et al., (2007) found that for Europe the projected magnitude of change in heavy precipitation events was sensitive to the choice of RCM used, particularly in summer. The detailed patterns of change in heavy precipitation events projected were also sensitive, and less robust, to the choice of GCM. Using different GCMs was also found to have a more influential effect on drought results than changing the emissions scenario (*ibid.*). The underlying assumptions and model components of different IAMs are therefore very important in identifying the robustness of results, and the uncertainties. Indeed, as model complexity increases and linkages are made between different model components uncertainties increase as they cascade from scenarios of socio-economic and demographic change, through global and regional climate change projections, to impacts on natural and human systems (Wilby and Dessai, 2010, Wilby and

Fowler, 2011). Inter-model comparison projects have focused on uncertainties linked to GCMs and downscaling approaches, however much less focus has been placed on uncertainties linked to the quality, resolution and parameterisations of impact modules (Vasiliades et al., 2009, Wilby, 2010).

Numerous reviews of IAMs have been published, from general reviews, to those focusing on the representation of impacts, representation of economic models, and the consideration of adaptation (e.g. Dickinson, 2007, Füssel, 2010, Goodess et al., 2003a, Tol and Fankhauser, 1998). In this study, it was important to understand how IAMs have represented extreme weather events. Thirteen IAMs, which are prominent in the modelling field, which have led to peer-reviewed literature, and which have well documented model structures were reviewed (appendix A, table A1). Despite the advancement of climate modelling techniques, only two of the IAMs reviewed modelled some form of extreme weather. The review also emphasised that very few models consider non-market effects, with none addressing indirect or secondary macroeconomic effects of climate change. Similar gaps in the coverage of IAMs were also noted by Stern (2007) as demonstrated in figure 2.2. The lack of information on extreme weather events in IAMs also restricts the understanding of adaptive capacity to such events (Goodess et al., 2003a). Such research is very important for understanding not only the potential effects of extremes but also the vulnerability of society to extreme weather events, something generally excluded from IAMs (Tol and Fankhauser, 1998).

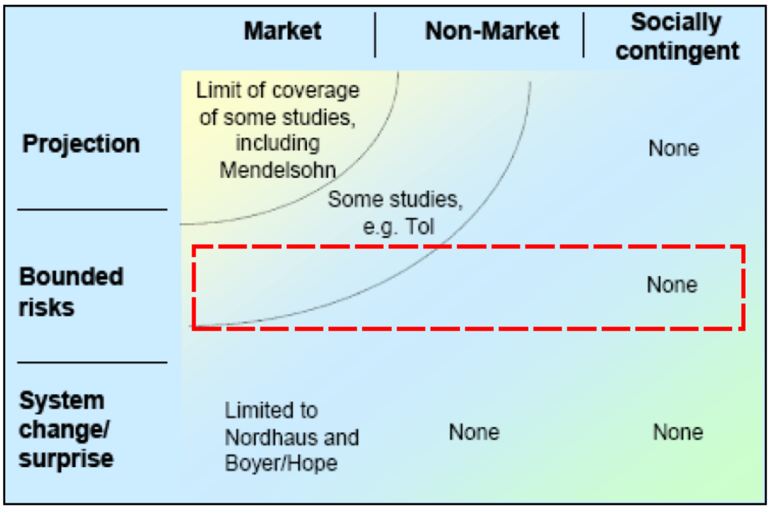


Figure 2.2: Coverage of existing IAMs (the red box highlights the limited coverage of bounded risks)[8]*. Source: Stern (2007, p.150)*

[8] Bounded risks include extreme weather events. Socially contingent refers to second round socio-economic responses to the impacts of climate change such as, conflict, migration and reduced capital investment.

2.3.1 Estimating climate change impacts in IAMs

The exclusion of extreme weather events and their effects from IAMs is largely attributable to the focus of most studies on global mean climate change, and the spatial and temporal resolution of climate model output (Goodess et al., 2003a). Furthermore, it can be difficult to relate GCM output, even when downscaled, to small scale problems for which the climate models were not designed (Kundzewicz and Stakhiv, 2010). For example, policy optimisation models commonly estimate impacts using climate-damage functions to drive CBA. A climate damage function is a reduced form relationship linking market and/or non-market impacts (e.g. GDP) to climate indicators (e.g. mean global temperature change). Climate damage functions are calibrated based on data from a limited number of impact studies, estimates derived from the literature, or expert opinion (e.g. Nordhaus, 1991, Nordhaus and Boyer, 2000, Tol, 2002a, Tol and Fankhauser, 1998). Whilst the focus of most climate-damage functions is on monetary estimates, other physical units such as crop yields or ecosystem loss are also utilised. Less commonly used are lives lost or lives affected, and Tol et al. (2000) notes that these estimates are still poor and are essentially back-of-the-envelope calculations. Moreover, even when non-market effects are included they tend to be represented in monetary terms, as illustrated by Tol (2002a, 2002b) who calculated the cost of lives lost due to climate change.

A simple aggregate damage function is represented in equation 2.3 where D = damage; T = change in temperature from the reference level; t = time; α = scale parameter; and β = shape parameter.

$$D_t = \alpha T_t^{\beta} \qquad \text{Eq. 2.3}$$

Various problems arise in applying climate damage functions to extreme weather events. Firstly, in creating damage-functions some form of impact data is required. In order to make convincing projections of losses under climate change it is essential to have a good understanding of past impacts. However, as discussed in section 2.1 the availability of relevant physical indicators specific to extreme weather events can often be limited. In addition, measures of damages from impact studies can be in different physical and monetary units. This means the aggregation of impacts across all sectors and regions to provide a total damage cost can be very difficult if not impossible. This can have implications for extreme weather events where a wide variety of damages, both monetary and physical, can occur. As noted in section 2.2.1 CBA often excludes non-market effects that are particularly difficult to model and value.

Secondly, the climate indicator used is typically global mean temperature change. The focus on mean global temperature change automatically hinders the incorporation of extreme weather events, which require assessment at appropriate temporal and spatial scales. Essentially, it is the short-term fluctuations and changes in extreme weather events that are expected to cause a major threat to society rather than long-term changes in mean climate (IPCC, 2007a). Ideally, daily climate variables would be required for the investigation of extreme weather events, however, Goodess et al., (2003a) note that for drought events monthly time-series data at a regional scale would be appropriate. In addition, as most IAMs focus on equilibrium climate rather than transient climate, regional and inter-annual variability in the type, severity and frequency of impacts are ignored (Fisher et al., 2007).

The use of mean temperature change also has implications for the shape of the damage function, which will determine the damages before and after the benchmark climate change. Many damage functions are created by estimating damages for global mean temperature change from the literature, often for 2.5°C or less assumed to be the equilibrium climate change associated with a doubling of CO_2 (Stern, 2007), resulting in a single point on a graph. As such, the shape of the damage function before and after the benchmark climate change is speculative and generally reflects the expert opinion of the author. This uncertainty is problematic as results based on the damage function will depend significantly on the shape and scale parameters used (Dumas and Ha-Duong, 2005). Some authors assume a smooth damage function, e.g. those used by Nordhaus and Boyer (2000), however certain climate change dynamics and impacts may be more complex and follow a different path. Coastal impacts are expected to grow continuously over time in proportion to sea level rise. Agricultural impacts are considered to be more complex with some models suggesting positive benefits in the short term and losses in the long term giving a ‘humped’ damage function (Smith et al., 2001, Tol et al., 2000). Dumas and Ha-Duong (2005) have modelled S-Shaped damage functions which allow the possibility of a critical threshold effect to be modelled. This is important as future changes in temperature and subsequent increases in the magnitude and frequency of extreme weather events may cause natural thresholds to be exceeded, and the magnitude of impacts may increase disproportionally. Thus, such events and their consequences may be outside the range of historical events on which damage functions are based. Figure 2.3 demonstrates various shaped climate-damage functions for aggregate global impacts.

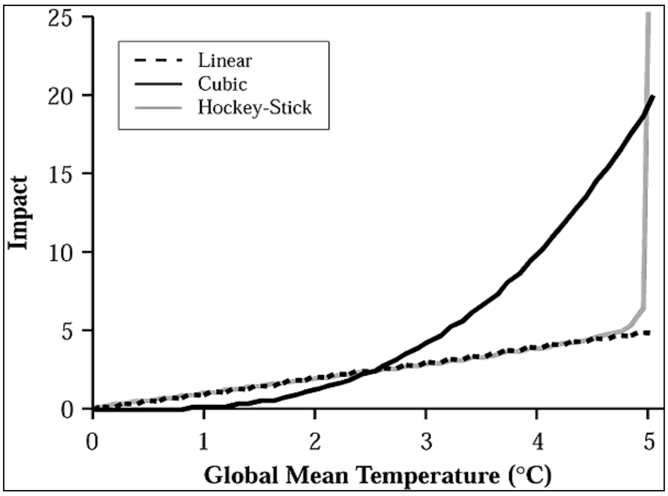


Figure 2.3: Three hypothetical climate-damage functions illustrating the aggregate impact of climate change as a function of global mean temperature. Source: Smith et al., (2001, p.944).

Estimates of damages from climate change, and subsequent policy recommendations, therefore vary depending on the type and shape of damage function used in the study. The issues and gaps in the coverage of climate change impacts means that climate damage functions have predominantly provided illustrative estimates only. As a consequence damage functions are generally considered as ‘placeholders’ which need to be replaced by more accurate functions as knowledge and estimates of impacts improve (Smith et al., 2001). Yet, many IAMs still rely upon the damage functions estimated by Nordhaus and Boyer (2000) and Tol (2002b) (as indicated by table A1, appendix A). As such, there has been limited progress concerning aggregate climate-damage functions utilised in IAMs over the past decade (Füssel, 2010), and limited extension of damage functions to the coverage of extreme weather events and their impacts. For that reason, the following section reviews alternative modelling approaches, which aim to quantify future socio-economic consequences of extreme weather events. As discussed in the introduction this field of research is relatively new and methodologies are still developing and evolving.

2.4 Alternative approaches to modelling effects of extreme weather events

2.4.1 Climate analogues

Section 2.1 highlighted that the availability of historic data on extreme weather events and their impacts is essential for projecting future losses (Changnon, 2003b, Hallegatte et al., 2007a). One practical application is to use historic data on weather extremes as an analogue for conditions and losses that may occur in the future. Recently, climate analogues have focused on temporal changes in extreme weather events (Carter et al., 2007). For example, it is possible to use a historical event, such as the 2003 European heatwave, as an analogue to identify potential effects which may occur in the future as the probability of the event occurring changes due to anthropogenic climate change. For instance, Stott et al., (2004) projects that the likelihood of an event of similar magnitude to the 2003 European heatwave will increase 100-fold over the next four decades. Schär et al., (2004) suggests that for Switzerland about every second summer could be as warm or warmer (and as dry or dryer) than 2003 heatwave by 2100.

Wreford et al., (2007) estimated the net present value of future economic damages from heatwaves on agriculture and health sectors based on the increasing probability of historic events occurring in 2050. The study used the 1995 UK heatwave and the 2003 European heatwave as analogues for consequences of climate change on agriculture and health respectively. The probability of similar magnitude events occurring in the future was based on published estimates from the literature. In addition, the study accounted for the ability of society to adapt to heatwaves over time, reducing the scale of impacts, as there is some research to suggest that learning can play a role in reducing impacts from subsequent extreme weather events. For example, the Sahel drought is thought to have triggered autonomous adaptation making farmers more resilient to future droughts (Adger and Brooks, 2003). Illustrative learning rates used in the study were based on estimates taken from the literature. As would be expected, damage costs from heatwaves increased over time as the probability of events occurring increased. Preliminary estimates of the net present value of damage costs by 2050, for agriculture in the UK and health in Europe, were €2.63 billion and €1,442 billion respectively. Adaptation was projected to reduce damage costs by 15% for agriculture and by 57% for health, illustrating how incorporation of adaptation could reduce economic estimates of impacts from extreme weather events.

The study highlights important benefits of adaptation for reducing future impacts from extreme weather events, in the form of avoided damages, something commonly excluded from climate change cost assessment. The method also provides an alternative to the aggregated global damage estimates of climate change as it is region, sector and event specific. However, the study provided an illustrative example only as results were based on single numeric estimates from the literature on event return periods and learning rates, and adaptation was assumed to happen at no extra cost. Additionally, a disadvantage of using temporal analogues to assess future weather extremes is that the specific climate forcing which led to the extreme weather event is unlikely to be repeated over coming decades, and even if the same event occurred the effects are likely to differ due to socio-economic changes in the intermediate period (Wilby et al., 2009).

Climate variables reflecting historic extreme weather events can also be used for spatial analogues. Spatial analogues match the present day climate regime of one region to another region that is projected to have a similar climate under future climate change, and assuming that the geographic areas are comparable (*ibid.*). This approach has been used by Hallegatte et al., (2007a) for the economic assessment of climate change impacts for 17 urban cities in Europe, although this was not applied specifically to extreme weather events.

2.4.2 Climate damage functions

As introduced in section 2.3, climate damage functions provide a method for projecting future impacts of climate change based on historical data or estimates from published literature. Whilst IAMs have not typically incorporated damage functions applicable to extreme weather events, it is possible to create climate damage functions offline. This provides an alternative to modifying IAMs and restricting their computational efficiency due to the large data requirements needed for analysis of extreme weather events (Goodess et al., 2003a). The complexity of climate damage functions created offline can vary depending on the type of weather event, the scope of the study, and the data availability. An example of a single, aggregated, global damage function is that used by Stern (2007, p.131-132). The damage function was based on the simple extrapolation of an estimate of present day damage costs from extreme weather events (0.2% of GDP) by 2% per year. This resulted in damages from weather extremes of 0.5-1.0% of world GDP by 2050 (above changes in wealth and inflation). However, the methodology used by Stern has received criticism as the increasing trend in annual losses of 2% per year was taken from a single conference paper by Muir-Wood (2006) which itself was biased by recent hurricane events in the US (discussed in Pielke, 2007).

Whilst Stern focused on aggregate global impacts of extreme weather Webster et al., (2008) focused on the humanitarian costs of flood, drought and hurricane events under future climate change. The study focused on four world regions: Central America, East Africa, South Asia and Southeast Asia. The study estimated the historical humanitarian costs of flood, drought and hurricane events based on the amount of international assistance and relief aid provided in the aftermath of disasters from 1992 to 2008. The number of flood, drought and hurricane events that resulted in humanitarian relief during 1992-2008 was also estimated. In order to estimate future economic costs the study defined high, medium and low estimates of the percentage change in event frequency. These scenarios were hypothetical, although they were refined based on expert opinions from climate scientists. It was assumed that the future costs of humanitarian responses to flood, drought and hurricane events would increase linearly with the change in event frequency. Results were presented as aggregate annual changes in humanitarian spending. Under the high scenario the study indicated an increase in costs of 16% from 1992-2008 to 2030, equating to an additional 28 million US$ (in 2006 values) per year.

Secondly, In order to assess the effect of changing intensity as well as frequency, the study incorporated hypothetical estimates from published literature of the percentage change in the intensity of flood and hurricane events. Drought events were excluded, as there was insufficient evidence in the literature to estimate changes in the future intensity of drought events. Results indicated an increase in annual humanitarian spending of 67% by 2030 compared to 1992-2008. Comparatively, the study also extrapolated trends in the frequency of disasters reported in EM-DAT from 1975-2008. The study calculated a best-fit trend line for both a linear and exponential fit and extrapolated this to 2030. This resulted in an annual increase in humanitarian spending of 800% by 2030. The variation in future cost estimates reported by the study highlights the high degree of uncertainty linked to the methodology employed, the features of particular weather events incorporated, and the way in which links are drawn between trends in extreme weather events and impact data. Furthermore, the study focused on relatively large geographical areas; estimates of changing event frequency and intensity were not based on projections from climate models; changing vulnerability of society was not incorporated; and the study focused on humanitarian spending only whilst the total costs of extreme weather events are likely to be significantly higher (Webster et al., 2008). In order to address such issues, the study calls for more data, more research, and a focus on impacts at a country or sub-region scale. However, all the methods employed in the study resulted in increasing costs suggesting that future consequences of floods, hurricanes and droughts are likely to become more severe, at least in certain areas of the world.

A more integrated use of a climate-damage function is illustrated by Genovese et al., (2007) who used a probability based, quantitative approach to assess the risk of flood on specific sectors in Europe. Risk is commonly depicted in natural hazard literature by the ‘risk-triangle’ (Crichton, 1999) with risk the product of the hazard, vulnerability, and exposure. An increase (decrease) in one of the sides of the triangle would increase (decrease) the risk. Genovese et al., (2007) assess and combine the exposure, vulnerability and hazard faced from flood events using this risk-triangle approach. The flood hazard is modelled based on a digital terrain model to provide a classification of flood depth; a hydrological model, calibrated to historical rainfall data and integrated with GIS; and a climate model to calculate flood return periods. The study calculates exposure using a land cover map of European artificial and natural landscapes, so that the physical assets exposed to floods can be assessed. Vulnerability is assessed based on a database of flood depth-damage functions. The depth-damage functions were created based on a thorough literature review of flood events and impacts, and expert opinion. The depth-damage functions represent the potential direct monetary losses that would occur for a given flood depth, for each land use type and country. The risk of a flood occurring is computed and using the flood depth-damage functions direct monetary damages are estimated, providing digital maps of flood related monetary risk for Europe. The authors note that the creative methodology is not without some limitations. For example, the spatial resolution is still too coarse to assess flood impacts at finer regional scales, and there was limited data availability for some EU countries. Concerning the flood damage functions only water depth was considered, although many flood parameters are important in establishing the size and scale of damages. In addition, the damages focused on direct economic losses to human conurbations only, ignoring social, environmental, and indirect effects. However, the study was event and country specific, employing a depth-damage function database calibrated to actual climate data, for each land use type. Furthermore, the future projections of flood events were modelled using a climate model rather than simply relying on estimates from the literature. This approach moves beyond the use of single estimates of extreme weather event impacts, and the creation of single, aggregated, global damage functions. It also highlights the potential to combine projections of extreme weather events with damage functions calibrated to actual impact data.

The studies reviewed above all focus on economic damages only. Studies aiming to quantify social or environmental effects of extreme weather events are extremely uncommon. For example Hirabayashi and Kanae (2009) note that the study by Kleinen and Petschel-Held (2007) focusing on populations at risk from extensive, long-lasting floods caused by heavy precipitation events was the only study of its kind reviewed within the 2007 IPCC report, and it did not validate results against actual flood records. This has in part been addressed by Hirabayashi and Kanae (2009) who estimate the global population at risk from flood under future climate change. The study uses a gridded, global, daily river discharge model to establish changes in 50 and 100 year return period flood events over the 21st century. The affected population was computed annually based on the total population in the flood affected grid cells. The output was compared to data on actual flood affected populations during 1990-2006 based on data from EM-DAT. The modelled results were in line with the historic data giving plausibility to the methodology. The results of the analysis highlighted that 20 to 300 million people per year are currently affected by floods, projected to increase to 350 to 550 million people by 2050 (for a temperature increase of 3°C). By 2100, 800 million to 1.2 billion people may be affected (for a temperature increase of ~4°C). The study accounted for increasing population over the 21st century, although it also found that if the population was static the number of people affected by floods was still set to increase due to climate change. Likewise, Ciscar et al., (2011) recently published projections of the number of people at risk from river flooding in Europe in the 2080s under climate change. A hydrological model was used to estimate river runoff under the IPCC A2 and B2 SRES scenarios, for two GCMs, to derive changes in flood magnitude at different return periods. The population exposed to changing flood magnitude was estimated using country specific information on land-use and population density assuming no change in population or flood protection standards. The study estimated that river flooding would affect 250,000 – 400,000 additional people per year in Europe by the 2080s, compared to 1961-1990.

Numerous issues related to the methodological approach for creating damage functions, and the data on which they are based, have been raised. These issues have led to the argument that climate damage functions are inadequate tools for the assessment of extreme weather events as they are often over-simplified, and estimates are rarely calibrated against empirical evidence of damage costs from historic events (Dietz et al., 2007, Stern, 2007). However, there is great potential for damage functions created offline to address these issues. As highlighted by Genovese et al., (2007) damage functions could provide a very accessible and useful tool for estimating the economic implications of extreme weather events when based on historical impact and climate data, and used in combination with future projections of extreme weather events. In addition, non-market effects could be assessed in a similar way if sufficient event data was available. Subsequently, climate damage functions could be fed back into economic and integrated assessment models. Whilst a suitable mechanism would need to be developed to allow extreme weather impacts assessed offline to be incorporated back into IAMs, Goodess et al. (2003a) considers economic damage functions the most suitable for such a practice.

2.4.3 Catastrophe modelling

A further approach to consider for modelling future effects of extreme weather events is catastrophe modelling, a method commonly used for insurance and disaster risk analysis purposes. The calculation of insurance prices in relation to extreme weather events has typically been backward looking, using stochastic models, based on historical events, rather than dynamical models of the physical system like those used in climate modelling. However, as anthropogenic climate change increases the risks from extreme weather events a forward-looking, probabilistic approach has been viewed as the most appropriate way of managing risks (Grossi and TeHennepe, 2008). Catastrophe models generally work by generating probabilistic direct monetary losses. They do this by simulating a stochastic event set, e.g. for floods, based on realistic parameters and historic data to establish the probability of such events occurring. A hazard module assesses the level of physical hazard for a given region. A vulnerability component calculates the level of expected damages to assets at risk, for a given area (in a similar approach to that of the risk-triangle). The main output of a probabilistic catastrophe model is an exceedance probability curve, which illustrates the annual probability that a certain loss is exceeded for a certain event and return period. The loss results can be used by insurers to provide insight into the potential severity of catastrophe losses; to understand the volatility of analysed risks; and to make informed decisions regarding individual risk assessment, policy pricing, and management of property portfolios (*ibid.*).

Catastrophe models were originally developed to help manage risks in countries with established insurance industries. More recently, they have also been used to help create new risk transfer mechanisms in the developing world. However, as insurance companies focus mainly on risks to infrastructure and assets, extreme weather types that can cause large direct impacts, e.g. floods, windstorms and hurricanes, tend to be the focus. Drought events, which have less direct impact on infrastructure, buildings, and assets, are not commonly modelled. For example drought insurance is only available in 5 out of 18 EU countries, and in these countries it is not compulsory or commonly utilised (CEA, 2007). In addition, due to the commercial sensitivity of the catastrophe models and data collected on insured losses from extreme weather events, the models and data sets are rarely publicly available for use in academic studies.

2.5 Modelling indirect economic costs of extreme weather

Drought events, as with other extreme weather events, can result in severe direct and indirect damages. As noted in section 1.1.1 direct economic costs can be defined as the physical impacts on infrastructure and public sector assets, usually seen immediately. These direct impacts can subsequently affect the flow of goods and services through extensive and complex linkages in the economic system, usually seen in the short to medium-term, i.e. indirect costss. For example, intermediate or final demand may decrease if consumption and investment is reduced following a natural disaster (backward propagation). Demand for certain goods and services can also increase in the event aftermath. For example, the devastating effect of Hurricane Andrew in the US in 1992 was followed by a surge in economic activity in South Florida driven by reinvestment of private and public insurance payments (Baade et al., 2007). Equally, the production capacity of affected industries can be reduced by extreme weather events, affecting the supply of goods (forward propagation). Additionally, disruptions to 'lifelines' such as transport networks, utility services, and communication services can affect production capacities. This can cause significant impacts in the disaster aftermath as lifeline systems are highly exposed, and as most economic transactions rely on such lifelines (Cole, 2003, Rose and Liao, 2005). Large scale disruption to the production capacity of key sectors and/or disruption to lifelines can result in production 'bottlenecks' which can cause considerable constraints on the ability of the economy to function and recover, raising indirect economic losses (Bočkarjova, 2007, van der Veen et al., 2003). It is important to note that in this case indirect losses are defined as any losses other than those caused directly by the extreme weather event, based on Brookshire et al., (1997). However, different definitions and concepts of direct and indirect economic losses exist within the economic literature. For example van den Veen (2003) distinguishes between three approaches: welfare economics; accounting frameworks linked to systems of national accounts; and macroeconomics in which definitions of costs vary.

Rose (2004) suggests that indirect damages from natural disasters may be superior to direct damages for two reasons. Firstly, indirect losses can affect businesses and consumers not directly affected by the event itself. Businesses that did not suffer directly will still have to curtail production if lifeline utilities are disrupted or if intermediate inputs are restricted due to the reduced production capacity of other businesses. Consequently, effects of an event can spill over to the wider national economy. If an event is of sufficient scale it may also have the potential to spill over to the wider international economy with effects seen further afield. For example, the 1998 flood in Australia caused estimated losses of 5.4bn US$ nationally, but the overall global impact was estimated at 6.65bn US$ (Calzadilla et al., 2004). Secondly, indirect damages are able to capture the time-dimension of the event as they reflect losses occurring after the initial shock. The scale of indirect losses and the length of economic disruption will depend on the pre-existing state of the economy, and the ability of individuals, businesses, and markets to adapt in the event aftermath (e.g. through substitution of goods, the use of inventories to meet demands, use of idle capital, or by serving alternative markets (Cochrane, 2003)).

In addition, the scale of impacts and the ability and time society will take to recover are highly dependent on the severity of the event itself. A robust economic system can usually cope with and absorb a small shock. Larger events can overwhelm a system, and a major shock can cause such serious distortion to the economy that a return to normalcy may not be possible (Bočkarjova, 2007). If certain thresholds are passed then the system may not be able to cope with the amount of damages leading to more severe long-term consequences as seen in New Orleans after Hurricane Katrina (*ibid.*). These arguments are supported by recent economic modelling studies, which have highlighted non-linearity between direct and indirect economic losses. The Economic Amplification Ratio (EAR) of an event, defined as the ratio of the total production losses to direct losses from a disaster (Hallegatte et al., 2007b), may be significant and indirect losses may even surpass direct losses for large scale events (Hallegatte, 2008, Yamano et al., 2007). Therefore, the inclusion of indirect economic damages is crucial for evaluating the total economic consequences of extreme weather events. However, published literature and data on the indirect effects of extreme weather events is extremely limited. Moreover, most existing IAMs omit not only extreme weather events but also factors such as cross-sectoral impacts, and implications for labour supply and businesses productivity (Stern, 2007).

As indirect losses are much more difficult to identify and quantify Rose (2004) remarks that the validity of indirect losses has been met by scepticism by some engineers, policy-makers, and economists. The ambiguity over the scale of indirect economic effects is not entirely surprising as this is a comparatively new area of research and published studies are limited. Rose (2004, p.31) concludes that '*improved methods to refine and validate relevant models and the estimates from their application are crucial to the acceptance of this important type of impact*'. More importantly improved understanding and validation of indirect damages from past weather extremes is crucial to help improve the estimation of future losses in the context of climate change analysis. As Brookshire et al., (1997, p.685) notes '*loss estimation is most useful when it has predictive capability or when it provides policy insights*'. This will be particularly important when analysing drought as they are already associated with large indirect costs (Wilhite et al., 2007).

A variety of economic modelling approaches exist which have been used for the analysis of indirect economic costs, including Input-Output (I-O) models, and Computable General Equilibrium (CGE) models. The most widely used method is that of I-O analysis with significant progress made in recent years in relation to natural disaster studies (Okuyama, 2007). I-O analysis is an analytical framework, developed by Wassily Leontief in the late 1930s, to analyse the interdependencies of industries within an economy (Miller and Blair, 2009). The analysis is based on the premise that each industry produces goods and consumes goods from other industries in order to produce such goods. Therefore commodities can have two destinations in I-O tables, firstly the intermediate demand of industries and secondly for final demand (e.g. household consumption, government purchases, exports). Some of the advantages of I-O models for economic loss estimation include the simplicity of the approach, the clear distinction between direct and indirect costs, and the ability to integrate I-O models with other models (Okuyama and Chang, 2004, Rose, 2004, Rose and Liao, 2005). However, the conventional economic theory underlying traditional I-O modelling is not immediately applicable to extreme weather events (Okuyama and Chang, 2004). I-O models are based on traditional economic theory stressing interaction and equilibrium within the economy, whilst in the aftermath of a natural disaster the economy is likely to be in disequilibrium (as discussed in section 2.2.2) and potentially outside the realm of experience. Due to its linear nature I-O analysis is also viewed as being overly rigid and not able to address behavioural changes or market-based mechanisms which may occur in the disaster aftermath, such as substitution of goods or the use of inventories. This rigidity restricts I-O models from capturing resilience or adaptation within an economy. Consequently estimates of indirect economic costs are often viewed as overly pessimistic (Rose and Liao, 2005). In comparison, estimates from CGE models are considered overly optimistic e.g. for agriculture the unit price of goods increase due to shortages during a drought event, which can result in wind-fall gains to farmers who pass these costs on to the consumers. Table 2.1 provides a summary of the main advantages and disadvantages of the traditional I-O modelling approach.

Advantages	**Disadvantages**
• The simplicity of the modelling framework • There is explicit coverage of different sectors which allows analysis of impacts at a sector by sector level • The approach is based on an excellent organisational framework for data collection and display. This provides a transparent and comprehensive view of the structure of the economy • The modelling approach provides a clear distinction between direct and indirect costs • The modelling approach can be used to highlight the strategic importance of various industries and sectors • The framework is well suited to distributional impact analysis • Impacts and changes to the flows of goods and services are represented in monetary units useful for policy analysis • The evaluation of indirect impacts can be insightful for evaluating recovery and response strategies following disasters • The framework is well-suited to short-term recovery periods • There is the ability to integrate I-O models with other models e.g. engineering models • The ability exists to modify the traditional I-O modelling framework to address certain shortcomings, and to apply the models to disaster analysis in a more coherent manner • Ecosystem goods and services can be integrated into I-O models to assess the benefits that natural resources make to economic development (e.g. through a supply orientated approach).	• The approach is seen as being overly rigid due to linearity and as such is characterised as providing overly pessimistic results • The method traditionally stresses interaction and equilibrium whilst natural disasters result in disequilibrium of the system • I-O models still assume that each industry has one, homogenous production function and that each industry produces one product which does not reflect the real economy very well • Technologies are ‘fixed’ and independent of changes in demand • Definitions and concepts of direct and indirect effects can vary and there are potential issues of ‘double-counting’ • Results will be dependent on the availability and accuracy of underlying primary data • The I-O framework ignores behavioural aspects such as substitution or import possibilities • It is not so well suited to long-term analysis as I-O coefficients will not remain static but evolve over time regardless of external shocks (e.g. due to technological or demographic changes) • The approach is not so good for addressing market-based mechanisms, e.g. price dynamics and indirect costs in terms of responses to price changes • It is hard to account for Ricardian rents, as prices are difficult to model • The traditional demand-driven I-O model is not so applicable to the incorporation of ecosystem goods and services as it implies that final consumption, rather than primary supply from nature is the main driver of an economic system

Table 2.1: Advantages and disadvantages of Input-Output Modelling. Sources: (Grêt-Regamey and Kytzia, 2007, Miller and Blair, 2009, Okuyama and Chang, 2004, Rose, 2004, Rose and Liao, 2005)

However, modifications to the I-O framework with specific application to extreme weather events have addressed some of the shortcomings, including relaxing certain traditional modelling assumptions to capture supply and demand imbalances. For example, following the immediate shock the economic structure of the affected region will be directly affected causing a departure from the pre-event equilibrium. In order to address the subsequent indirect effects and options for recovery and reconstruction one needs to understand the scale of the departure from equilibrium in order to know ‘where to start from’ (Bockarjova et al., 2004). A relatively new development to represent the post-disaster phase of disequilibrium is to use an Event Accounting Matrix (EAM) as introduced by Cole et al. (1993). An EAM is essentially one or more tables with entries corresponding to those in the original I-O table, which is initially modified to represent the post-shock conditions so it can then trace the development of the economic system and reconstruction periods at selected intervals. The method attempts to address the failure of an economic system as a whole by mapping the direct effects of the disaster onto the economic system. This allows the magnitude, time-scale of market failures, and options for recovery to be integrated within the I-O framework (Cole, 2003). Such an approach has been used by van der Veen et al., (2003), Steenge and Bočkarjova (2007) and Hallegatte (2008) to address indirect impacts of flood and hurricane events. Further extensions to the traditional I-O methodology, with specific application to extreme weather events, include:

- increased flexibility in the treatment of adaptation by allowing imports, substitution of goods, the ability to over-produce, and the use of existing inventories
- consideration of system bottlenecks
- incorporation of macroeconomic variables such as price effects as used in CGE models
- coverage of different timeframes depending on the type of weather event
- use of multi-regional I-O tables to assess how regional effects can affect the wider economy at a national or international level
- integrative approaches to incorporate the spatial distribution of industries affected by extreme weather events, e.g. through use of GIS
- incorporation of recovery, reconstruction, and mitigation paths

An added challenge in modelling the indirect economic costs of extreme weather events is the need to interpret physical damage data as economic data. As no economic model can deal with physical data directly, they must be interpreted in a way that allows economic models to treat them as inputs (Okuyama and Chang, 2004). This is an important stage of the modelling process as the economic outputs and results will only be as good as the data on which they are based. Two differing approaches, applied to extreme weather events, have been identified in the literature for estimating direct economic losses. Firstly, studies can utilise GIS to map the extent of a historical or hypothetical event and the location of businesses, households, or infrastructure affected. This approach has been used by Van der Veen et al. (2003), Steenge and Bockjavora (2007), and Bockjavora (2007) for flood events. The studies use GIS to map the spatial extent of a historical flood event, and the type, size, and value of infrastructure and businesses in the affected area identified and linked to economic I-O tables. The direct damage is calculated as the replacement cost of the affected infrastructure, buildings and urban property, aggregated by sector. Alternatively, direct losses can be calculated as the percent of productive capacity lost at the sector level assuming total loss to affected businesses in the flood zone (i.e. partial damage is not modelled).

Secondly, studies can use published data on the direct economic damages of historical events, and where available the costs to various sectors. Hallegatte (2008, 2011) uses the I-O model ARIO (Adaptive Regional Input-Output Model) to capture the effects of Hurricane Katrina on households and industries through changing demand and supply relations. The economic input data is based on reports of damage to capital stock of various sectors as reported by the US government in the event aftermath. Where data was only available at a more aggregated level it was disaggregated between sectors based on their relative size. It is assumed that damage to production capital will be equal to damage to production capacity reducing the subsequent production of affected sectors. Similarly, the ARIO model is utilised by Ranger et al., (2011) to assess the indirect effects of large scale flood events in Mumbai. The study is based on reported economic damages from the 2005 Mumbai flood event, for various economic sectors.

Both of these approaches have advantages and disadvantages. The use of GIS linked to I-O tables provides comprehensive information on the specific properties and assets affected and the value of such losses. However, it is difficult to estimate the actual scale of direct damages. As such, it is assumed that businesses or infrastructure in the flood area are totally destroyed. For example, studies using GIS to assess consequences of floods tend to focus on the spatial extent of the flood. Direct and indirect damages will be dependent on other factors such as the depth and velocity of the floodwater. In reality, businesses may be only partially affected and still have some capacity to produce goods and adapt to the new conditions in the event aftermath. Furthermore, results from hypothetical studies are not often calibrated against historical event or impact data to validate the accuracy of the results for making future projections. In comparison, using reported event impact data allows one to model specific, historic, weather events calibrated to actual event data. This also makes it possible to verify results by comparing them to actual economic outcomes. It is also possible, depending on the detail of impact data reported, to make assumptions about the degree of direct economic losses to particular sectors. However, without the use of GIS it is difficult to know how to distribute damages spatially across regions. In general, the assumption is made that all industries within a given sector will be equally affected by the event. Importantly, results will be highly dependent on the availability, accuracy and detail of the reported damage data, which as discussed in section 2.1, can bring with it its own set of caveats.

The application of I-O analysis specifically to extreme weather events is a much newer focus of research, but one that may provide valuable information for climate change cost analysis studies. Indeed, Rose (2004, p.22) highlights the potential role of loss estimation studies to project future losses under climate change scenarios. However, loss estimation from extreme weather events has traditionally focused on direct economic effects only (Webster et al., 2008), and I-O models appear underutilised as a possible methodology for dealing with economic shocks such as those caused by extreme weather events (Bockarjova et al., 2009). Consequently, studies focusing explicitly on the quantitative estimation of indirect economic drought losses are scarce. A review by Ding et al., (2010) highlighted just a handful of state level studies for the USA which used quantitative estimation methods, focusing predominantly on agriculture. This is despite the fact that severe or extreme drought affects some part of the USA each year, and average annual losses are higher than seen for floods or hurricanes (NDMC, 2006a).

As mentioned above, studies focusing specifically on drought tend to estimate direct and indirect economic costs using impact data for the agricultural sector. For example, at a regional level Diersen and Taylor (2003) estimated the direct and indirect costs of the 2002 drought in South Dakota, USA, on farming and agriculture. Direct economic costs to crop and livestock were estimated based on various agricultural statistics, e.g. changes in production yields of crops, area of pasture affected during drought, changes in numbers of culled cattle, costs of additional feed required, and reduced grain and hay inventories. The study estimated the indirect economic costs using an I-O modelling framework. The drought shock was represented as a decrease in economic activity to affected agricultural industries equal to the estimated direct drought damages. Total economic losses were estimated at 1.4bn US$, comprising of 642 million direct damages and 757 million indirect damages. The EAR of the drought was 2.18, i.e. the total economic losses were more than double the direct economic losses. Economic recovery occurred in 2003 following the termination of the drought, however, where crop yields remained below average there were still constraints to supply for the following years inventories of feedstock. The authors noted that increases in crop and cattle prices were observed, which offset some of the previous year's production losses and accounted for economic recovery. However, there is likely to be disparity between the producers directly affected and those receiving the benefits of rebounding market conditions.

At a national scale Wheaton et al., (2008, 2005) assessed the costs of the 2001 and 2002 droughts in Canada. Parts of Canada faced some of its worst drought conditions for at least 100 years during 2001 and 2002 resulting in widespread and devastating impacts. The study focused primarily on agriculture and estimated annual direct drought costs as $1.3bn Canadian dollars in 2001, and $2.2bn Canadian dollars in 2002. Indirect economic costs at a regional and national level were estimated using an Inter-provincial Input-Output Model for Canada. Indirect losses to Canada's GDP were estimated at $2.1bn in 2001 with a loss of 17,637 jobs across the country. The 2002 drought was more intense with indirect economic costs in the region of $3.6bn, and a loss of 23,777 jobs. The severity of the droughts is highlighted by the EARs estimated for 2001 and 2002 of 2.62 and 2.64 respectively. Moreover, the authors note that some consequences of the successive drought events, such as losses to livestock and land degradation, may take years to decades to recover fully back to pre-event conditions.

2.6 Summary and research objectives

Extreme weather events are one of the main channels through which socio-economic impacts of climate change are expected to be felt. However, extreme weather events and their effects are generally excluded from modelling approaches used for climate change cost and risk assessments. The exclusion of extreme weather events, and the risks they pose, can reduce the validity of cost assessments and subsequent policy recommendations. Economic modelling approaches tend to be based on traditional economic theory assuming equilibrium. As such, they are not suited to assessing damage costs from extreme weather events, which can cause sudden shocks to the economy resulting in irregularities and disequilibrium. Furthermore, economic modelling techniques and policy optimisation studies have evolved around the rigid framework of CBA, which has limited application to extreme weather, and climate change analysis as a whole. Similarly, there has only been limited consideration of extreme weather events, and their effects, within IAMs. Problems in incorporating extreme weather events reflects the focus of most modelling studies on mean global or regional temperature change; difficulties in projecting future changes in weather events at appropriate spatial and temporal scales; and difficulties in linking this information, in a consistent and robust manner, to impact data. The lack of a globally consistent and rigorous methodological approach for reporting and recording data on extreme weather events also remains a major obstacle for impact analysis.

Quantitative assessment of impacts from weather extremes can be carried out offline from economic models and IAMs, ranging from simple linkages between event and climate data to more complex probabilistic risk based approaches. A particularly promising development has been the creation of damage functions specifically applied to extreme weather types. Climate damage functions have been criticised in the past as they have been based on limited data; predominantly focus on mean temperature change; use hypothetical shape and scale parameters, often based on exert opinion only; and are rarely calibrated to historical event or impact data. However, studies by Webster et al., (2008) and Genovese et al., (2007) highlight that damage functions created offline can avoid some of these issues. For example, climate damage functions created offline can be calibrated to past weather events and impact data; be developed for a specific weather type; be region or country specific; and linked to specific event characteristics such as intensity or flood depth, without comprising the computational efficiency of IAMs. Climate damage functions can also be used in combination with future projections of extreme weather events from climate models, rather than relying on point estimates from the literature. Furthermore, there is potential for climate damage functions to feed back into economic and integrated assessment models, or be used to drive assessments of indirect losses through I-O models. Whilst damage functions have been created for some extreme weather types, e.g. flood and hurricane events, to the best of the authors' knowledge they have not been applied to drought in any comprehensive manner.

Studies specifically aimed at estimating future economic and social effects from drought events, under future projections of climate change, are almost non-existent. Thus, new ways of approaching and modelling future effects of drought are required. The literature review has also highlighted that current impact studies and methodologies focus predominantly on direct economic costs although indirect economic costs may be substantial, particularly for drought. Therefore, it is essential to calculate both the direct and indirect economic costs of drought to avoid inaccurately low assessments of damages and enable a better understanding of the full economic effects. One potential technique is I-O analysis, which can be used to model and quantify the indirect economic effects caused as the drought shock propagates through the wider economy. The application of I-O analysis to extreme weather events and climate change is a relatively new and developing area of research, and studies focusing specifically on drought events and their effects are very limited.

Similarly, non-market effects, such as changing mortality and morbidity rates, are generally excluded from impact assessments of extreme weather events. Assessing and valuing non-market effects, which can be intangible, is not only very challenging but also a highly contentious issue. Furthermore, when studies do incorporate social effects they tend to be represented in monetary terms within aggregate economic damage functions. Yet, alternative methodological approaches, such as the PP and MCA, suggest that non-market effects can be quantified in metrics more representative of the type of impact, and presented in parallel with market effects. It is argued that specific impacts presented independently can still provide a valuable insight into the overall costs (Smith and Hitz, 2003). Research aimed at quantifying indirect societal effects of drought will be even more challenging. The scale of impacts may be high, especially in developing countries where extreme drought events may lead to mass migration, social and economic instability, conflict, malnutrition or famine.

In summary, some important issues, and current gaps in research, have been highlighted in chapters one and two. These need to be considered when developing a methodology specific to drought. In particular:

- The focus on single event analysis means that current methodologies lack generality and cannot be applied at the macro-scale. Conversely, aggregate global studies can be too generalised and fail to capture spatial variations in weather and impacts. Therefore, a general overall approach is needed that it is not case specific but that can be applied to drought events universally at an international, national and sub-regional level. Studies focused at the country or sub-regional level may provide greater levels of certainty than larger scale studies.
- Additionally, this would be beneficial as drought events of similar scales may result in largely different consequences depending on the country and region affected. Thus, a methodology is needed which accounts for different social and economic conditions (i.e. the method should be applicable across both developed and developing countries).
- Droughts are complex weather extremes, and their specific characteristics will need to be accounted for and considered within the methodology. For example, the onset time, duration, and intensity of events, and the possibility of successive events.

Consideration needs to be given to inter-annual variability, spatial variability, and the possibility of drought events passing historical climate and impact thresholds.

- The methodology should aim to address both market and non-market effects, to provide a comprehensive estimate of drought effects. An approach that does not rely on monetising and aggregating all effects could be employed. Furthermore, the study should account for both direct and indirect economic costs.
- Results should be empirically grounded and calibrated to historical event impact data and climate data.
- Changing socio-economic conditions, which can affect overall societal and economic vulnerability, need to be considered. Consequently, the study would benefit from modelling drought effects as part of a dynamic system, rather than using the typical 'static' approach.
- Where possible the impact of adaptation on future effects from drought needs to be considered. Planned and autonomous adaptation currently receives limited coverage but has the potential to reduce future drought effects.
- Finally, it is important for the research outputs to be policy relevant. The study should provide outputs which are useful and understandable to policy makers; can be incorporated into wider climate change cost assessment studies; and help to guide climate change policy decisions.

The aim of the research is to **model and quantify the effects of drought on the economy and society under future projections of climate change**. As drought is possible in virtually all regions of the world, with the potential to cause severe economic and social effects, a comprehensive, interdisciplinary, and integrated approach is needed to derive a link between factors causing drought, drought characteristics, drought effects, and consequences for society and economies. In order to address the research aim, and in light of the above findings, four objectives are outlined.

Firstly, trends between historic drought events and reported impact data are investigated. A methodology is developed for identifying and quantifying drought events and their characteristics, for given timeframes and regions. Relationships between quantified drought parameters and reported impact data are investigated and used to create drought damage functions, which can be used to estimate future economic and societal consequences of drought. **Chapter 3** provides a justification of the modelling tools and data, and the methodology is described. Results are presented along with a discussion of the main findings and chapter summary.

Secondly, the effect of climate change on future drought regimes needs to be modelled and quantified. The literature review highlighted that IAMs are one of the best tools available for assessing climate change impacts. Therefore, the study utilises the IAM CIAS (Community Integrated Assessment Model) (Warren et al., 2008), which incorporates a range of climate and emission scenarios and a downscaling module, ClimGen, to provide monthly climate data at a grid scale of 0.5° x 0.5°. Based on data from CIAS future drought events and their characteristics are modelled and quantified for the first half of the 21st century, for a range of climate and emission scenarios. Results are compared to drought characteristics modelled for the baseline period 1955-2002. **Chapter 4** provides a justification of the modelling tools and data, and the methodology is described. Results are presented along with a discussion of the main findings and chapter summary.

Thirdly, the drought damage functions need to be applied to the projections of future drought events to provide quantitative estimates of the economic and social effects. Future estimates of drought effects are compared to past estimates to assess the effects of climate change, for a range of climate and emission scenarios. **Chapter 5** presents the methodology, results, discussion, and chapter summary.

Fourthly, a preliminary investigation of indirect economic costs of drought is conducted. The literature review highlighted the potential of I-O analysis for such assessments, although it is a relatively new and developing research area. The study utilises the pre-existing ARIO Model, which is modified to cover specific characteristics of drought. Estimates of direct economic drought costs, presented in chapter five, are fed into the I-O model as a shock to simulate indirect effects on the economy and illustrate the importance for total drought costs. **Chapter 6** provides a justification of the modelling tools and data, and the methodology is described. Illustrative results are presented along with a discussion of the main findings and chapter summary.

3. Creating Drought Damage Functions

In order to assess the economic and social effects of drought the research investigates relationships between characteristics of historical drought events and event impact data. Trends identified are used to create drought damage functions, which can be used to estimate economic and social consequences of future drought events. In carrying out this research objective, a first step was to develop a suitable method for identifying historic drought events in climate data. Section 3.1 discusses options for quantifying drought events using various drought indices, the methodology employed in this study, and data sources. The methodology for quantifying drought events and their characteristics are presented in section 3.2 and the resultant drought damage functions are presented in section 3.3. Section 3.4 provides a discussion of the results, and benefits and limitations of the methodology. Lastly, section 3.5 provides a summary of the chapter and implications for the remaining research objectives.

3.1 Literature and modelling tools

3.1.1 Drought and precipitation indices

As discussed in section 1.1 drought can be defined in different ways and over different timescales, leading to a lack of a single, universal definition. Consequently, a large number of drought indices have been developed over the 20th century for drought analysis in the domains of meteorology, hydrology, and agricultural analysis. Drought indices assimilate climate and hydrological parameters into a single indicator that can be used for analysing trends and relaying information to stakeholders, policy makers and the public in a clear format. Drought and precipitation indices can range from very simple measurements of precipitation to more complex and data intensive algorithms. Thus, it is important to understand fully the different characteristics of drought indices to help select the most appropriate one, and to be fully aware of the assumptions and limitations that underlie their use.

Assessments of meteorological drought using drought indices have received less attention when compared to studies of hydrological extremes focusing on river discharge and low flow regimes (Vasiliades et al., 2009). Yet, such methods require considerably less input data than used by e.g. hydrological or agro-hydrological models, and can reduce the additional uncertainties linked to the quality, resolution and parameterisations of impact modules. Meteorological drought indicators, which consider parameters such as precipitation, temperature, and evaporation include, *inter alia*, Rainfall Deciles (Gibbs and Maher., 1967), Drought Area Index (DAI; Bhalme and Mooley, 1980), Rainfall Anomaly Index (RAI; van Rooy, 1965), Weighted Anomaly Standardised Precipitation (WASP; Lyon, 2004), Palmer Drought Severity Index (PDSI; Palmer, 1965), and the Standardised Precipitation Index (SPI; McKee et al., 1993). Reviews of drought indices and comparison studies have been regularly produced (e.g. Byun and Wilhite, 1999, Hayes, 2006, Heim, 2002, Keyantash and Dracup, 2002). Perhaps the most famous and commonly used index is the PDSI developed in 1965 by William Palmer. The PDSI is still widely used as an independent index, as well as a comparable index when testing newer indices. The PDSI is a standardised index that takes into account precipitation, temperature, evapo-transpiration, and soil moisture conditions to analyse the intensity, onset, cessation and duration of drought. Although the PDSI marked a turning point in the development of drought indices, it has since suffered much criticism over its application as a drought index. Alley (1984) provides a thorough critique of the methodology, assumptions and limitations of the PDSI. In summary, the main issues are:

- Computations of the PDSI are complex and require data for many variables.
- Some very basic assumptions were made in order to develop the PDSI. For example, soil moisture storage is accounted for by dividing soil into two layers and making assumptions about the water storage capacity and moisture removal from the two layers.
- The values of the PDSI used to classify the intensity of drought were arbitrarily selected based on limited data from the USA and have little scientific meaning.
- There are several limitations resulting from the use of a water-balance model in calculating the PDSI. For example, there is no universally accepted way to model potential evapo-transpiration; no lag time is included for potential runoff; forms of precipitation other than rainfall are excluded; and there is a simplistic representation of hydrological phenomena.
- The PDSI fares unfavourably in applications other than that for which it was developed (i.e. agriculture in the mid-west US).

Due to such issues and limitations the SPI was developed by McKee et al. (1993) as an alternative tool to help drought monitoring and analysis. Like the PDSI the SPI is a dimensionless meteorological drought index which can be applied universally to compare droughts from different regions (Heim, 2002). As drought is essentially an accumulated moisture deficit problem then an abnormally wet month in the middle of a long-term drought should not have a major impact on the SPI. Likewise a series of months with near-normal precipitation following a serious drought may not necessarily mean that the drought is over (Hayes, 2006). As precipitation deficit will have different impacts depending on the time over which it occurs, and as accumulated precipitation can be simultaneously in excess and deficit on different timescales (Redmond, 2002), the SPI can be determined for different time periods. This allows the dynamics of different types of droughts (agricultural, hydrological, and meteorological) to be assessed. However, the use of different time periods will directly affect the value of the SPI attained, the drought duration, and the drought frequency. This adds further complexity to the task of analysing drought events as drought can be '*put in some historical perspective at each of several timescales*' (McKee et al., 1995, p.235). Table 3.1 summarises the information provided by the US National Drought Mitigation Centre (NDMC) on interpreting SPI data based on different time periods.

1-month SPI	Similar to the percent of normal precipitation for a month, the 1-month SPI is problematic to use where rainfall is normally very high/low for a given month even if the departure from the mean is relatively small. It is important to be aware of a regions climatology when using SPI-1, and although still useful caution must be observed when analysing maps.
3-month SPI	3-Month SPI reflects short and medium term moisture conditions and provides a seasonal estimation of precipitation. It can be useful for agriculture as an indicator of available soil moisture. It is important to compare the 3-month SPI with longer timescales to prevent the misinterpretation that any drought event has ended. Again it may be misleading in regions with normally very high/low rainfall seasons.
6-month SPI	6-month SPI reflects medium-term trends in precipitation and is very effective at showing the precipitation over distinct seasons. It can also be linked to stream flow and reservoir levels.
9-month SPI	9-month SPI reflects precipitation patterns over the medium-term, which is useful as droughts usually take a season or more to develop. At this time scale, SPI values of -1.5 or less are usually linked to significant impacts to agriculture and other sectors.
12-month SPI	The 12-month SPI reflects long-term precipitation patterns. As SPI values at longer time periods tend towards zero the 12 month SPI is useful for highlighting specific trends such as the wettest/driest year on record. The 12-month SPI can be tied to stream flows, reservoir levels, and even ground water levels.

Table 3.1: Interpretation of SPI time periods as used by the NDMC. Source: Summarised from NDMC, 2006

Other advantages of the SPI is that it is probabilistic and so can be used in risk-analysis and decision making; it is not adversely affected by topography which can affect precipitation levels; and as it is not dependent on soil moisture conditions the SPI can be used effectively in both summer and winter (Lloyd-Hughes and Saunders, 2002). The SPI is also simpler to calculate than the PDSI as it only requires precipitation data. Precipitation is the primary factor in the formation and persistence of drought and simple indexes such as the SPI have been shown to perform better than other indexes, including complex indexes like the PDSI (Guttman, 1998, 1999, Keyantash and Dracup, 2002, Lloyd-Hughes and Saunders, 2002, Redmond, 2002). Consequently, the use of precipitation data alone is considered sufficient when assessing meteorological drought. This approach also has benefits as precipitation data can be collected for more sites than other variables such as soil moisture; precipitation is the key variable in drought definitions as all droughts stem from a precipitation deficit; and precipitation data is available for longer time periods than other meteorological data (Byun and Wilhite, 1999). The potential advantages of modelling drought using the SPI is reflected in its subsequent uptake in over 60 countries, as well as by the NDMC, the National Data Climatic Centre (NCDC), and across many states in the US (Wu et al., 2005). However, the SPI is not without its own limitations. Importantly:

- It is assumed that a suitable probability distribution can be found to model the raw precipitation data for standardisation, which may not always be the case (Lloyd-Hughes and Saunders, 2002).
- As with all indices, the accuracy will be dependent on the quantity and quality of precipitation data used. It is recommended that long periods of observational data be used, depending on the time periods being assessed. Guttman (1999) used at least 60 years of data in his analysis and McKee et al., (1993) recommended a continuous period of data of at least 30 years. In addition the value of the SPI will differ if different lengths of precipitation records are used (Wu et al., 2005). However, these issues can easily be resolved by keeping the length of data as long as possible, and keeping this data length uniform across the study.
- The SPI can be problematic when applied over short time periods (e.g. SPI-1 and SPI-3) for areas with normally low or high seasonal precipitation totals, as a small variance in precipitation over one month would cause a misleadingly high or low SPI value (Hayes et al., 1999).
- As other factors such as evapo-transpiration and temperature are excluded, the severity of drought characteristics calculated using the SPI (and other similar indices) may be underestimated.
- As the SPI is standardised the probability of drought occurring in a given category of severity, (see table 3.2 below for a definition of drought categories), can be given and the rarity of the event can be estimated. However, this means that the probability of drought events falling in each category will be the same for all locations analysed regardless of climate regime. Thus the SPI (like the PDSI) cannot be directly used to compare between regions or timescales as the frequency of drought spells will be

about the same for all areas looked at regardless of the climate regime. However, if past precipitation data is used to generate future precipitation time-series data, and the mean monthly precipitation values are assumed unchanged in the future from the historical values, then any changes seen in the future precipitation distribution and subsequently in drought events can be linked to effects of climate change. This technique has been used by several studies assessing climate change effects on drought (e.g. Vasiliades et al., 2009) and is used in this study for future projections of drought (discussed in chapter 4 section 4.1).

In summary current literature on drought indexes suggests that the SPI may not only be favourable to the PDSI but also to other indexes of a similar nature. Moreover, the application of the SPI to this study is highly desirable as it provides a method for analysing not only the occurrence and intensity of drought events but also for defining drought start and end months, duration, and magnitude. Moreover, as the SPI determines deviations from mean precipitation it could provide an equally effective measure of wetness (Hayes et al., 1999). This hypothesis has been tested for historical flood events in Argentina by Seiler et al. (2002) and for peak stream flow and flood events in Portugal by Guerreiro et al. (2008). Both studies concluded that the SPI satisfactorily explained the development and circumstances leading up to major peak flow and flood events, highlighting the potential for the SPI to be used as a tool for representing historical flood events and future flood risk.

3.1.2 Calculating the SPI

In order to calculate the SPI the first process is to prepare the precipitation data for the required number of months (*m*). A time period (*i*) is selected based on the user objectives, e.g. 3, 6 or 12 months, to create a lagged moving average where each new precipitation value is determined based on the previous *i* months. This new lagged data set is used in computing the SPI. The SPI can be computed in different ways depending on the type of distribution used to model the index. It is relatively straightforward to calculate the SPI based on a normal distribution (Lloyd-Hughes and Saunders, 2002), represented in equation 3.1:

$$SPI = \frac{x_m - \hat{x}_m}{\sigma_m}$$

Eq. 3.1

Where:

x = precipitation value (observed or simulated)

σ = standard deviation

m = month

$\hat{x}$ = monthly precipitation mean (observed)

However, precipitation is not normally distributed for timescales of twelve months or less (McKee et al., 1995). Lloyd-Hughes and Saunders (2002) found that for Europe the fit of the normal distribution improved as the timescale of the data was extended. However, it has poor performance over shorter periods and the fit was worse for arid regions where precipitation distributions are more skewed. In comparison, the gamma distribution was shown to fit the data better and improved as the timeframe of the data was extended. Guttman (1999) also found that a gamma distribution was favourable to the normal distribution. The following computations are used to calculate the SPI based on the gamma distribution (taken from Edwards and McKee (1997)), as used in this study.

The gamma distribution is defined by its PDF:

$$g(x) = \frac{1}{\beta^{\alpha}\,\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \qquad \text{Eq. 3.2}$$

Where:

α = shape parameter

β = scale parameter

x = precipitation amount (observed or simulated)

$\Gamma(\alpha)$ = gamma function defined in equation 3.3

$$\Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1}\, e^{-y} dy \qquad \text{Eq. 3.3}$$

The data needs to be fitted to the gamma function in order to determine the relationship of probability to precipitation. In order to fit the data the shape parameter (α) and scale parameter (β) are estimated for each value in the lagged data set using equations 3.4 to 3.6.

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \qquad \text{Eq. 3.4}$$

$$\hat{\beta} = \frac{\hat{x}}{\hat{\alpha}} \qquad \text{Eq. 3.5}$$

$$A = \ln(\hat{x}) - \frac{\sum \ln(x)}{n} \qquad \text{Eq. 3.6}$$

Where:

n = number of precipitation observations

$\hat{x}$ = monthly precipitation mean (observed)

Integrating the probability density function with respect to x and inserting the estimates of α and β yields an expression for the cumulative probability $G(x)$ of an observed amount of precipitation occurring for month m and time scale i. Where $t = x/\beta$, the equation becomes the incomplete gamma function:

$$G(x) = \frac{1}{\Gamma(\hat{\alpha})} \int_0^x t^{\hat{\alpha}-1} e^{-t} dt \qquad \text{Eq. 3.7}$$

However, as the precipitation data may naturally contain zeros and as the gamma function is undefined for $x=0$ the cumulative probability is calculated following equation 3.8:

$$H(x) = q + (1-q)G(x) \qquad \text{Eq. 3.8}$$

Where:

q = the probability of a zero

The final stage is to transform the cumulative probability $H(x)$ to a standard normal distribution to provide the SPI value, as illustrated in figure 3.1. To compute this for large data sets an approximation conversion process is utilised (from Abramowitz and Stegun, 1965) to quickly convert the cumulative probability to the SPI value (equations 3.9 to 3.12).

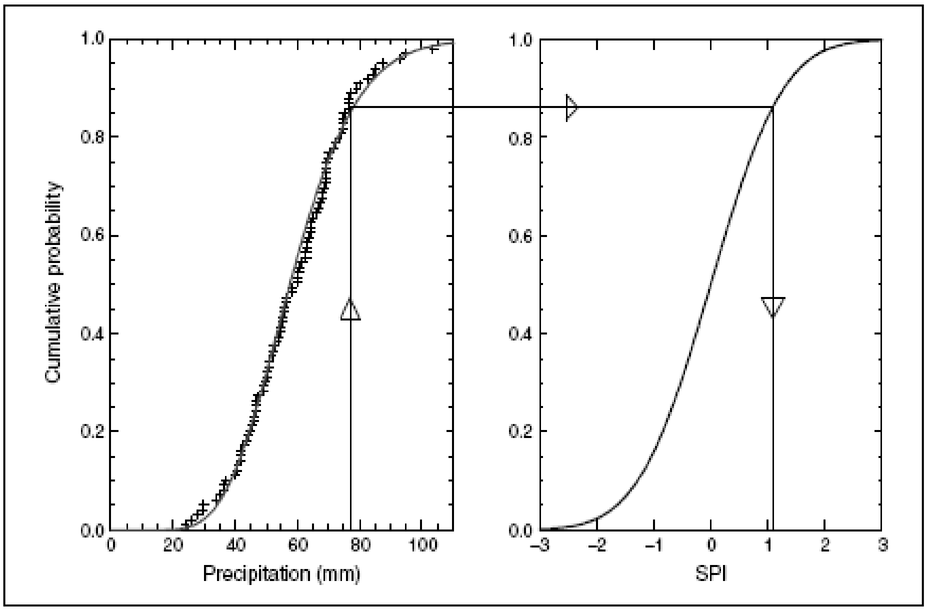


Figure 3.1: Conversion from a gamma distributed cumulative probability to a standard normal distributed cumulative probability. Source: Edwards and McKee (1997)

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \qquad \text{for } 0 < H(x) \leq 0.5 \qquad \text{Eq. 3.9}$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \qquad \text{for } 0.5 < H(x) \leq 1.0 \qquad \text{Eq. 3.10}$$

Where:

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \qquad \text{for } 0 < H(x) \leq 0.5 \qquad \text{Eq. 3.11}$$

$$t = \sqrt{\ln\left(\frac{1}{1.0 - (H(x))^2}\right)} \qquad \text{for } 0.5 < H(x) \leq 1.0 \qquad \text{Eq. 3.12}$$

And:

$c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$

$d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$

The resulting output is the SPI value for a given precipitation data point and time period. A drought can be categorised based on its SPI value, with each category occurring a known percentage of the time (table 3.2). The SPI can be used to establish a definition of drought, drought start and end dates, and drought duration. For example, McKee et al., (1993) define a drought event as a period in which the SPI is continuously negative and reaches a value of -1.0 or less.

SPI Value	Category	Probability (%)
2.00 >	Extremely moist	2.3%
1.50 – 1.99	Severely moist	4.4%
1.00 – 1.49	Moderately moist	9.2%
-0.99 – 0.99	Near Normal	68.2%
-1.00 – -1.49	Moderately dry	9.2%
-1.50 – -1.99	Severely dry	4.4%
-2.00 <	Extremely dry	2.3%

Table 3.2: SPI Categories. Source: McKee et al., (1993)

3.1.3 Precipitation data

The SPI was computed based on precipitation data from the Climatic Research Unit (CRU) TS 2.1 dataset (Mitchell and Jones, 2005). The dataset provides monthly gridded precipitation data for 1901 to 2002, interpolated from observed data to a resolution of 0.5° x 0.5° for the entire terrestrial land surface (excluding Antarctica). A base period of 1940 to 2002 was used to calculate the gamma parameters for the study. The start year was set at 1940 in order to keep the length of the precipitation data record as long as possible to produce robust SPI results, bearing in mind that drought impact data before this time was very limited and less robust. The SPI was calculated based on the gamma distribution (equations 3.4 to 3.12 above) via a program written in C#. The output of the C# code was validated by running a dataset for Denver, Colorado, provided on the Colorado Climate Centre website (McKee, 2008) and checking that results obtained were consistent with those published on the website. In addition, following the approach of Lloyd-Hughes and Saunders (2002), results for the USA, computed using the C# Code, were compared to results computed from station data published by Edwards and McKee (1997). Although a slightly different data length was used, and this study used gridded precipitation data rather than station data, the maps showed excellent agreement (see Appendix B for a comparison of maps). The results also corroborate the finding from Lloyd-Hughes and Saunders (2002, p.1578) that for the USA SPI values computed from gridded data correlated almost exactly to those computed from station data. Thus, it can be argued that for countries which have good observational records of precipitation gridded data is representative of station data. However, it is also important to note that for countries with limited rain gauge stations the reliability of gridded data will be reduced.

3.1.4 Drought event data

In order to link characteristics of historical drought events to their economic and social effects, a global drought database was used. Data is used from EM-DAT for the period 1940-2002 (EM-DAT, 2010). This is the only publicly available drought database that documents global drought events (Below et al., 2007). In the absence of multiple drought databases, information from EM-DAT has been taken as valid and hence results presented here will be highly dependent on the quantity and quality of the data. However, EM-DAT has a clear procedure in place for adding events to the database and once added the new event undergoes a validation process. In addition, the drought database was recently updated to reduce inconsistency in records and problems that arose due to the slow onset, spatially extensive, prolonged and complex characteristics of droughts. The review had a large effect on the database with a reduction in recorded drought events of 57%, an increase in reported deaths of 20% and an increase in economic losses of 35% (*ibid*.). However, drought events are still very difficult to catalogue accurately and there are some important issues to bear in mind when using EM-DAT:

- The database records the drought start date as the date when losses were first reported. Consequently, there may be a lag between the drought start date calculated using the SPI and the start date recorded in EM-DAT.
- Where no details on the end month or year are specified by reports, and no other details can be found, the end date is set to the same year as the start date. Therefore start and end dates are indicative only.
- Only 25% of drought entries (from 1900 to 2004) include data on economic losses, although data does increase in quantity over time (Below et al., 2007). Economic loss data was defined as all losses directly or indirectly related to the disaster. However, as no information is available on the share of direct and indirect losses it is assumed in this study that damages reflect direct losses only.
- States are not required to report to EM-DAT, which is a private non-governmental organisation. Therefore, it is compiled from data reported in the media or by aid agencies. Smaller scale disasters and localised disasters which do not receive international assistance may fail to appear (Webster et al., 2008).
- Due to the validation method, if the drought event is not reported by the international community in at least two suitable sources it is excluded.
- Reporting of economic losses tends to improve over time. Furthermore, past economic losses reported are more likely to solely represent direct losses, whereas

more recent estimates are likely to be more comprehensive and reflect direct and indirect damages (Muir-Wood et al., 2006).

Nevertheless, the event database still provides a useful guide as to which countries, regions and years the SPI drought analysis should focus on. This type of investigative approach has been used by Wu et al., (2005) for Nebraska, USA, and globally by Below et al., (2007) as a means of identifying periods of climate data over which to analyse historical drought events. Additionally, the database has also been used as a means of validating simulated flood events and their effects (Hirabayashi and Kanae, 2009). By focusing on historical drought events reported in EM-DAT the precipitation data can be linked directly to the impact data, and potential relationships identified.

3.2 Quantifying historical drought events

The task of accurately and systematically quantifying historical drought events is not a simple one as each drought event is unique (Wilhite, 2005). Drought analysis is made even more complex as the process of defining drought is very much a subjective affair based on the overall aims and objectives of the researcher. In order to meet the research objective and identify trends between historical drought events and their reported impacts it is necessary to devise a methodology for quantifying drought events which can: be justified in the field of drought analysis; can accurately reflect historical drought events; is suitable for creating drought-damage functions; can be applied to future projections of drought events; and provide a generalised framework that can be applied to other countries and studies. This section summarises the novel methodological approach devised to quantify historical drought events with an application to creating country specific drought damage functions. The focus of the study is on eight countries: Australia, Brazil, China, Ethiopia, India, Portugal, Spain, and the USA. These countries were selected as they have all suffered numerous drought events from 1940-2002, they cover different geographical, climatological, and hydrological regimes, and that have different economic structures. In addition these countries are already known to suffer water stress and are vulnerable to future climate change (Bates et al., 2008).

In devising the methodology it was important to specify which SPI time periods would be used as drought characteristics (duration, intensity and magnitude) can be highly variable over different time periods. Furthermore, the use of multiple time periods are valuable in capturing droughts which may only show up in the short or long-term and which would otherwise be excluded. Following the recommendations of Byun and Wilhite (1999, p.2755) two SPI time periods were used to model and characterise drought. The literature review has highlighted that most economic damages from droughts are related to agriculture (although other sectors vulnerable to drought include recreation and tourism, energy production, forestry and transportation). As such, a shorter, seasonal time period would be useful such as SPI-6, which can be used to represent agricultural drought. Secondly, non-market effects such as the number of lives affected and numbers of lives lost are expected to occur in the longer term due to the cumulative and persistent effects of drought on water supply. Therefore, SPI-12 is used to represent hydrological drought (see table 3.1 for interpretation of the different SPI time-periods and related effects).

Monthly SPI-6 and SPI-12 values were computed for 1940-2002 for each country of interest. For each drought event reported in EM-DAT the SPI data were analysed only for the states or administrative regions that were listed as being affected. This allowed the reported economic and social effects to be linked to the specific drought conditions that prevailed over the affected region. As drought will rarely, if ever, affect an entire country (Wilhite, 2005) it was hoped this approach would focus results on the drought hit areas only and avoid averaging out the SPI data across the whole country, or over large regions, which did not suffer impacts. Bar charts of the average SPI time-series data were created for each drought event analysed to ascertain if the reported drought event could be detected in the precipitation data using SPI-6 and SPI-12. Figure 3.2 provides an example of the time-series graphs for the 1995 to 1996 drought, which affected multiple states in the USA.

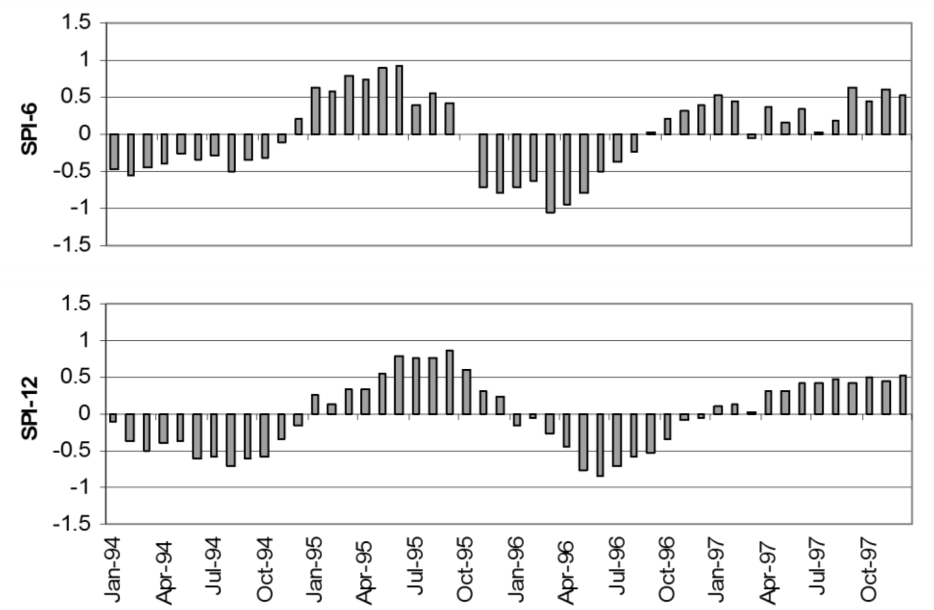


Figure 3.2: Average SPI time-series data for SPI-6 and SPI-12 for the 1995 to1996 drought that affected various states in the USA. Source: Own calculations

Drought was defined as a period where negative SPI values could be identified, which coincided with the drought details reported in EM-DAT. The drought start date was defined as the first month in which the SPI became negative and the drought end date was defined as the first month in which the SPI became positive again. In addition, regional SPI maps were created using DIVA-GIS[9], a free computer program for mapping and analysing spatial data, including gridded data (Hijmans et al., 2005). The maps were used in order to identify visually each drought event, its location, and to check the accuracy of start and end dates ascertained from the average regional time-series data. Once the drought start and end dates were determined the SPI values for the drought-affected cells (i.e. cells that had a SPI value of 0.0 or less) were analysed. As the values of the SPI will differ depending on the time period used drought characteristics were analysed for both SPI-6 and SPI-12 time periods.

McKee et al., (1993, p.2) define drought magnitude as the absolute sum of the SPI values across the duration of the recorded drought. However, this definition of drought magnitude has only been applied to monthly station data, which does not have a spatial aspect. In order to apply the parameter to this study and consider the spatial extent of each drought, the definition of drought magnitude has been modified. Equation 3.13 is used to calculate the Monthly Drought Magnitude (MDM) of the affected region for each drought month. The Total Drought Magnitude (TDM) is then calculated using equation 3.14, which sums the MDM over the duration of the recorded drought.

$$MDM_k = -\left(\sum_{j=1}^{n} SPI_j\right) \qquad \text{Eq. 3.13}$$

$$TDM = \left(\sum_{k=1}^{m} MDM_k\right) \qquad \text{Eq. 3.14}$$

Where:

k = drought month

n = total number of grid cells affected in month *k*

j = grid cells affected in month *k*

m = total number of months affected by drought

[9]Available for free download at: http://www.diva-gis.org/

The drought intensity of each grid cell can be inferred directly from the SPI value. Peak intensity is defined by McKee et al., (1993) as the minimum SPI value reached during the drought event. Again, this definition has been applied to monthly station data that does not have a spatial aspect. In order to apply this parameter to this study the definition of peak intensity has been modified. Equation 3.15 has been used to calculate the monthly Average Intensity (AI) of drought events by averaging the SPI data across all grid cells affected per month. The Peak Intensity (PI) is then defined as the minimum monthly AI recorded during the drought event.

$$AI_k = \left(\sum_{j=1}^{n} SPI_j \right) / n$$

Eq. 3.15

The drought parameters calculated using the above methodology and equations 3.13-3.15 were recorded in country tables for both SPI-6 and SPI-12 time-periods. Results tables are presented in appendix C tables C2, C4, C6, C8, C10, C12 and C14. Blank rows signify that a drought event was not detectable using SPI-6 and/or SPI-12, and therefore the drought event could not be quantified. Drought events were modelled and quantified even when impact data on economic damages, lives lost, or lives affected were not available in EM-DAT. These drought events cannot be included when establishing links between drought parameters and reported impact data, however it does allow a more thorough test of the methodology as additional drought parameter data is available for analysis.

Drought impact tables were also compiled for each country assessed reporting individual drought data from EM-DAT on the drought location, drought year/s, the number of lives lost, the number of lives affected and economic damages, presented in appendix C tables C1, C3, C5, C7, C9, C11 and C13. In addition, for each drought event analysed an internet search was conducted with any additional information on drought characteristics, effects, or specific sectors affected recorded. Data sources were based on those used by EM-DAT (2007) as well as from published journal articles and government reports. Missing values in the table signify that no data was available from EM-DAT on the economic and/or social effects of droughts. Economic damages were reported by EM-DAT in current US$ for the year in which the drought occurred. For multiple year droughts the start year of the event provided by EM-DAT was assumed to be the year in which US$ were reported. In order to account for changing wealth and to enable the comparison of drought events over time the reported damages were inflation adjusted to 2002 US dollars based on GDP data from The

World Bank (2010)[10]. Similarly, the number of lives affected and the number of lives lost due to drought events are normalised to account for changing populations over time. The method proposed by Pielke and Landsea (1998) is used, whereby population is adjusted by multiplying by the ratio of current population to the population in the year of the event. Time-series data for each country's population was taken from The World Bank (2010).

This type of loss normalisation is widely used in the analysis of natural disasters. Various methods exist for loss normalisation, yet, there is no standardised method used consistently across studies (Höppe and Pielke, 2006). Adjusting for inflation based on a countries changing GDP is a relatively simple way to account for changing economic conditions. However, it does not account for changes in socio-economic conditions. Population trends, wealth, and the quantity and value of assets at risk can also account for changes in economic losses. Crompton and McAneney (2008) and Muir-Wood et al., (2006) have argued that a defensible normalisation procedure must also account for changes in population and wealth, not just inflation. For example, Pielke et al. (2008) adjust for wealth, inflation, and population when assessing hurricane losses in the USA. Wealth is incorporated by using the ratio of past fixed assets and consumer durable goods to the current ratio, adjusted for population and inflation. Other studies adjust for the change in the number and/or value of residential properties exposed to risk (Crompton and McAneney, 2008); or changes in regional capital stock (Schmidt et al., 2009, 2010). As this methodology was devised to be applicable across a range of different regions and countries, for the period 1940-2002, it was decided to use inflation only to normalise losses, as detailed consistent economic time-series data needed to normalise losses based on wealth was not readily available for all the countries studied.

3.3 Results

Using regional, gridded, SPI data enabled 61 (76%) of the drought events reported in EM-DAT to be identified and quantified using the above methodology[11]. This is a considerable improvement when compared to results of a feasibility study conducted by the author using average country precipitation data, where only 26 (32.5%) of the drought events were visible. This suggests that the EM-DAT drought data is able to guide an analysis of historical drought events at a regional scale. Table 3.3 compares the results of this study to those of the previously conducted feasibility study. Results for Ethiopia, Portugal, and Spain are

[10] All economic data are presented in US$ (2002) for consistency unless specified otherwise.

[11] Note that not all historical drought events showed up at both SPI-6 and SPI-12 time periods.

similar using both precipitation datasets, suggesting that drought events are more likely to affect large swathes of these countries.

Country	Number of drought events reported in EM-DAT 1940-2002	Total number of droughts reported in EM-DAT visible in country data	Total number of droughts reported in EM-DAT visible in regional data
Australia	9	2 (22%)	8 (89%)
Brazil	13	3(23%)	10 (77%)
China P Rep	22	0 (0%)	14 (64%)
Ethiopia	8	5 (63.5%)	5 (63.5%)
India	12	5 (42%)	10 (83%)
Portugal	2	1 (50%)	1 (50%)
Spain	4	4(100%)	4(100%)
United States	10	6 (60%)	9 (90%)
TOTAL	80	26 (32.5%)	61 (76%)

Table 3.3: The number of historical drought events reported in EM-DAT detectable in regional precipitation data and national precipitation data

Of the 61 drought events quantified by this study 56% had data on economic damages, 52% had data on the numbers of lives affected, and 26% had data on the numbers of lives lost. Of the 19 drought events in the EM-DAT database that could not be quantified using the above methodology, seven were affected by the use of the pre-defined SPI time periods. For example, where a drought was extremely short and severe and only showed up using a smaller SPI time period (e.g. SPI-3), or where multiple year droughts were identified using SPI-6 and SPI-12 suggesting a longer SPI time-period would be required to quantify the drought as a single event. The remaining 12 droughts could not be quantified as:

- the droughts did not show up clearly in the precipitation data, especially where no data was available in EM-DAT or in the wider literature regarding the specific regions affected (5 events)
- the droughts showed up in preceding or following years to those reported by EM-DAT and additional literature could not be found to validate the drought dates (2 events)
- modelled drought events had not terminated by the end of the precipitation data in December 2002 and so could not be fully quantified (5 events)

In addition, drought events were visible in the SPI time-series data which were not reported in EM-DAT. The limitations in using the EM-DAT database, discussed in section 3.1.4, provide possible explanations for why not all historical drought events are included in the EM-DAT database. For example, a severe drought was identified in 1956-57 in north-west China, but was not reported in EM-DAT. A recent study by Xiao et al., (2009) also identifies severe drought in north-west China in 1956-58. An explanation for its exclusion may be the limited reporting of drought impacts in China to the wider international community prior to the 1980s (Schmidt et al., 2009). Hirabayashi *et al.,* (2008) used the EM-DAT database to validate historic flood events simulated with a GCM and found similar issues. Flood events obtained statistically from the daily discharge dataset were not always included in EM-DAT, especially for regions with low populations or for regions where damage due to disasters is not well reported. However, the authors noted that most severe flood events in the daily discharge data were captured by the database.

In order to create country specific drought damage functions relationships between the drought parameters calculated and the event impact data were assessed using scatter plots of economic damages versus drought parameters (duration, intensity, and magnitude). For all countries, the most robust trends were seen when TDM[12] was plotted against the economic data. Drought magnitude is also a particularly useful drought parameter to use as it combines the intensity, duration and spatial extent of drought into one single indicator, encompassing multiple features of each drought event. Magnitude is therefore used as the main drought variable in creating the country specific drought damage functions. Results for the economic drought damage functions are presented in figure 3.3 for both SPI-6 and SPI-12 time-periods. Best-fit trend lines represent the most statistically significant fit to the data, determined by the coefficient of determination (R^2). Due to the limited number of drought events reported for Spain and Portugal it was decided to amalgamate the data as it was deemed that the climate characteristics of the countries were sufficiently similar. This also allows the high-risk area of the Mediterranean basin to be included in the analysis. It was not possible to create a drought damage function for Ethiopia as no economic loss data was available in EM-DAT. The corresponding results tables for all countries analysed are provided in Appendix C, tables C1-C14.

[12] From this point onwards, TDM is referred to simply as drought *magnitude* for succinctness.

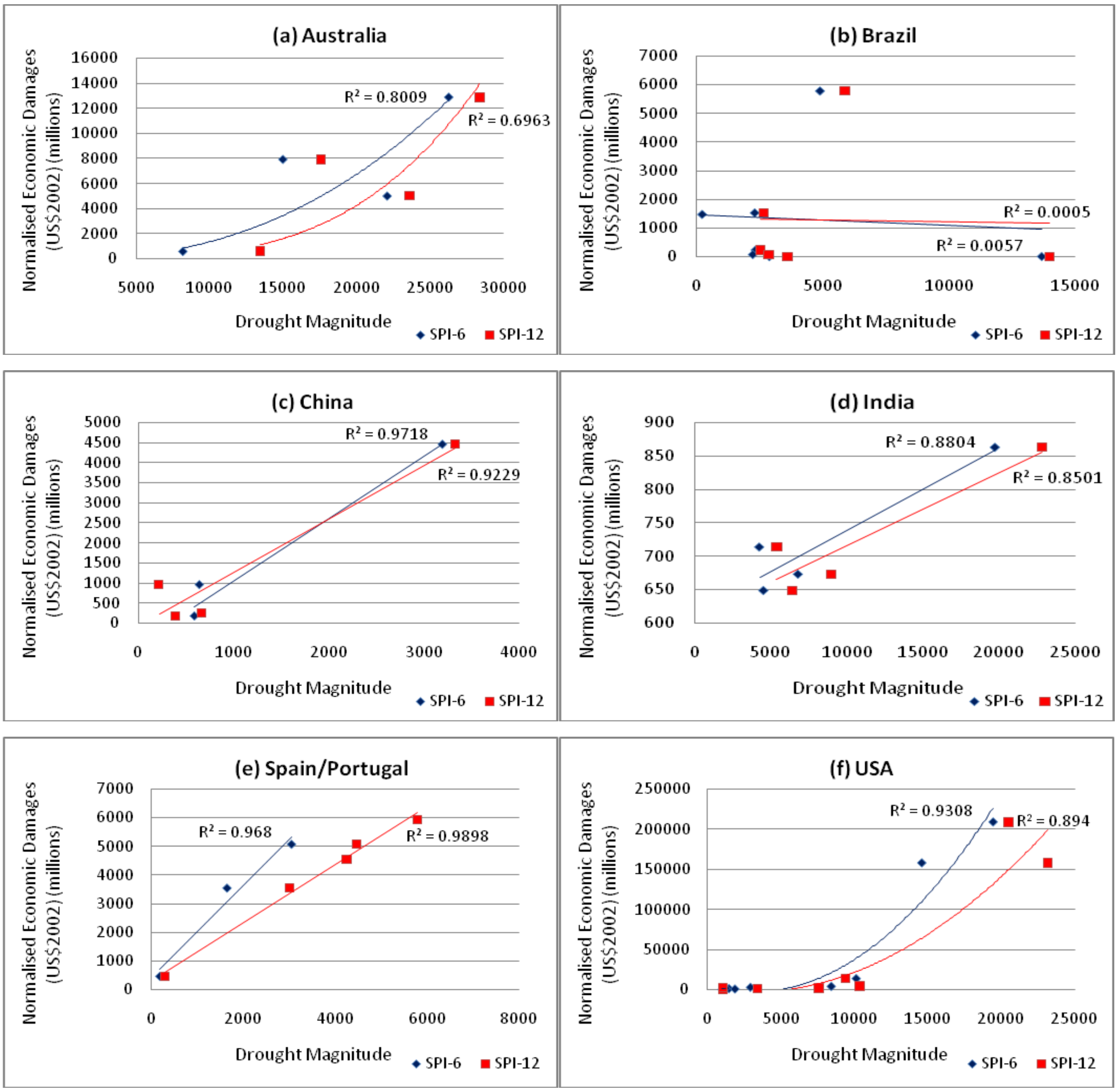


Figure 3.3a-f: Country specific drought damage functions: The relationship between drought magnitude and direct economic damage (US$ 2002)

For Australia (figure 3.3a) the trend line suggests that economic damages increase as drought magnitude increases. The fit of the cubic trend line to the data, as determined by the R^2 values, suggests that the magnitude can account for 70-80% of the variance seen in the economic damages using SPI-12 and SPI-6 respectively. It is also important to highlight that Australia has suffered from more recent severe drought events. For example, below average rainfall and drought conditions have been reported since 2002 in the Murray-Darling Basin (Australian BoM, 2009). Whilst EM-DAT does include entries for drought events in 2002 and 2006, the observed precipitation data is only available until 2002 and so these drought events and their consequences are not included in this analysis.

The trend seen for Brazil is extremely weak (figure 3.3b), and would suggest that economic damages in fact decline as drought magnitude increases. Again, this trend is heavily influenced by a single drought event. The drought of 1983 resulted in the highest drought magnitude (in line with reports that 1983 was the most severe drought year in Brazil), however it had very low damage costs. The reported costs of drought events in Brazil are strongly related to the location where they occur. For example, droughts in south and central Brazil affected coffee crops, a main export for Brazil, which resulted in high economic costs. Droughts in the arid northeast had lower damages as this is a poorer region dominated by subsistence farming. Plotting data points by specific regions highlighted much clearer trends for the northeast (SPI-6 R^2 = 0.9819 and SPI-12 R^2 = 0.9717). This suggests that for Brazil regional damage functions may be more appropriate however sufficient data to do this in a robust manner was not available.

For China (figure 3.3c) data was only used post-1980 as there is concern over the reliability of data before this time (Höppe and Pielke, 2006). As noted by Schmidt et al (2009) data on event losses in China have increased significantly since the country opened up to the outside world in the 1980s. This caveat resulted in the exclusion of the drought event in 1965 that caused damages of $565 million. The inclusion of the 1965 drought affects the trend heavily as it has the largest drought magnitude but relatively small economic damages compared to later events. This may reflect the fact that prior to China opening up to the international community in the early 1980s the country may have underestimated damages to reduce international intervention (*ibid.*). Alternatively, the drought may have affected a region with relatively little economic activity, or it may represent an inaccurate estimation of the economic data.

For China, India, Spain/Portugal and the USA (figures 3.3c-f) the fit of the trend lines to the data is extremely good, suggesting that drought magnitude can largely account for the variance seen in the economic damages. One reason may be that damages are considered primarily agricultural and so economic costs are expected to correlate closely to drought magnitude. The above results are extremely promising in the context of developing drought damage functions, with the exception of Brazil. However, it is also important to note that especially in the cases of China, India and Spain/Portugal the number of data points on which the trends are fitted are extremely limited. Issues of sampling uncertainty, and the subsequent limitations of the damage functions, are discussed in more detail in section 3.4 below.

In the same technique as above relationships between drought parameters and the numbers of lives affected and lives lost were assessed using scatter plots, to ascertain whether social drought damage functions could be created. Again, drought magnitude was shown to provide the most robust trends. Figure 3.4a-d presents results for Brazil, China, Ethiopia and India for the number of lives affected using SPI-6 and SPI-12. It was not possible to create graphs for Australia, Spain/Portugal, or the USA, as there was insufficient impact data.

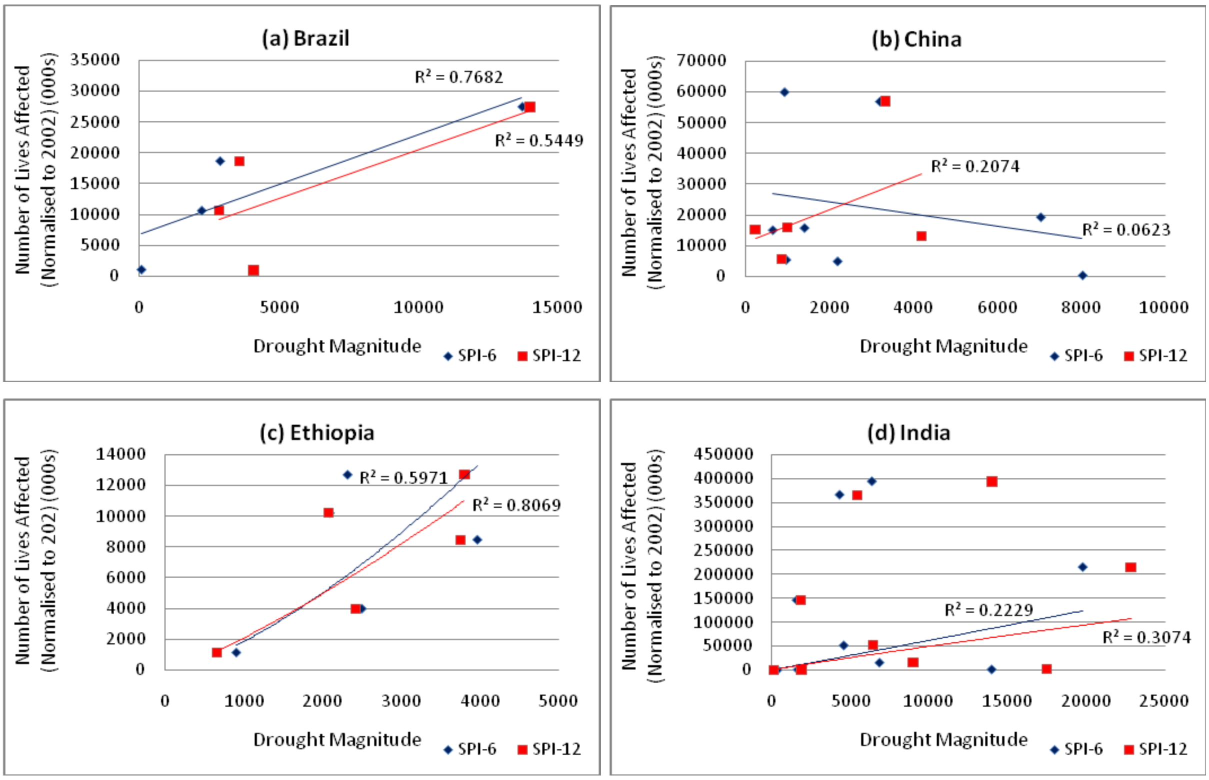


Figure 3.4a-d: Country specific drought-damage functions: The relationship between drought magnitude and the number of lives affected

For Brazil and Ethiopia the graphs show an increase in the number of lives affected as drought magnitude increases, with relatively good R^2 values reported. This would suggest that drought magnitude plays an important part in determining the numbers of lives affected. However, the numbers of drought events on which to base a trend were limited. In contrast, much more data was available for China and India, although the scatter plots show much more variability and limited significance. In the case of Brazil, it is interesting to note that the severe northeast drought in 1983 did not cause large economic costs (previously discussed) but did affect a very large number of lives.

Figure 3.5 presents graphs for drought magnitude versus the numbers of lives lost in Ethiopia, India, and the USA at SPI-6 and SPI-12. It was not possible to create drought-damage functions for Australia, Brazil, China or Spain/Portugal due to limited impact data.

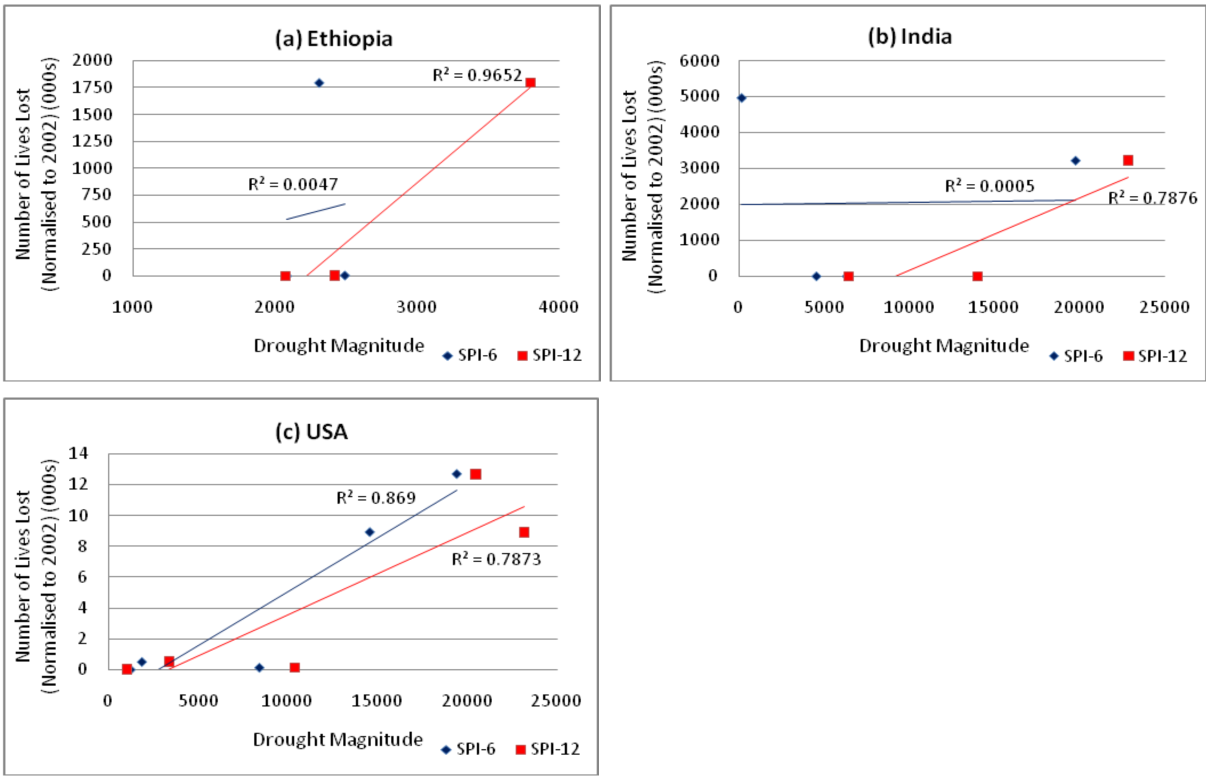


Figure 3.5a-c: Country specific drought-damage functions: The relationship between drought magnitude and the number of lives lost

Results for Ethiopia, India and the USA all highlight an increase in the numbers of lives lost as drought magnitude increases. However, for Ethiopia and India there are limited data points on which to base this trend. In both cases, large differences are seen in the results plotted using SPI-6 and SPI-12 data with a more robust trend seen using SPI-12. For the USA the fit of the trend lines to the data is very good and suggests that the drought magnitude can account for 79-87% of the variance seen in the numbers of lives lost for SPI-12 and SPI-6 respectively. However, it is important to emphasise that data on historical drought related deaths, especially in the USA, is likely to reflect compounding effects such as deaths due to heat stress during heatwaves, effects of heat and dust storms on air quality and implications for ill health, and wildfires. Indeed, the literature review highlights that these are the primary drivers for most deaths in the USA (see Appendix table C.13). As such, the statistics used for lives lost in the USA may more accurately reflect drought and heat related death rates, including direct and indirect drought effects, and the consequences of various social and environmental conditions.

3.4 Discussion

The EM-DAT database was used to determine the particular regions and dates on which to focus when analysing the SPI data. This method has been successful for identifying 76% of the drought events reported in EM-DAT for Australia, Brazil, China, Ethiopia, India, Portugal, Spain, and the USA. As would be expected, table 3.3 indicates that the use of regional, gridded precipitation data for the analysis of historical drought events is more appropriate than using country precipitation data. The consistency between drought events reported in EM-DAT and the SPI time series data validates the accuracy of the methodology for modelling and defining historical drought events. Based on the historical impact data and drought parameters calculated by this study drought damage functions were created for the countries of interest. To the best of the author's knowledge these are the only country specific drought damage functions available.

The economic drought damage functions created are very promising and, with the exception of Brazil, show very good correlation between the magnitude of historic drought events and economic damages. The results also suggest that the methodology employed to identify, and quantify historic drought events has been successful. The social drought damage functions showed less consistency across the various countries. The correlation between drought magnitude and the number of lives affected was respectable for Brazil and Ethiopia. Results for China and India, which were based on a greater number of data points, showed little correlation. When assessing the number of lives lost there was large variability in the results seen for Ethiopia and India depending on the SPI time period used. These findings suggest that other external factors have a large influence on the numbers of lives affected and lost during drought. For example, the underlying social conditions such as levels of poverty and malnutrition, and water scarcity issues. The trend for the USA was more robust with the R^2 suggesting that drought magnitude could account for 80-86% of the variance seen in lives lost. However, it is important to note that a major limitation of the drought damage functions presented is the small number of data points on which the trends are based. Therefore, there is the possibility that the trends in the data identified are due to sampling uncertainty. Similarly, the shape of the damage functions, which are based on the trend line which fits the data with the highest R^2 value, will reflect this uncertainty.

However, the drought damage functions were not expected to show perfect correlation between the economic and social impact data and the drought magnitude. As well as drought events varying between different regions and being dependent on the particular characteristics of that region, economic and social effects may also differ over time due to changes in the economic structure, and due to societal interactions. For instance due to increased water use, or interferences in the hydrological system such as building dams or reservoirs. Indeed, a drought event of similar magnitude which occurs at the same place but at different times may have different effects due to changes in societal characteristics and infrastructure (Wilhite, 2005, Wilhite et al., 2007). This may in part explain why there is less consistency in the trends for lives affected in China and India, and lives lost in Ethiopia and India as circumstances may have changed over the period of this study. Additionally, the study does not consider external social influences on the propagation of drought such as increased water extraction and consumption, changes in land-use, engineering works or changing water management strategies. Conversely, socio-economic interventions can also reduce the effects of drought. As discussed in section 1.2 trends in drought related economic losses, lives lost and lives affected may have been influenced directly over time by better seasonal forecasting and warning systems, changing agricultural practices, and government interactions such as financial assistance to ease drought effects. For example, the drought in Northern Brazil linked to the 1997-1998 El Niño event had significantly smaller economic damages than that of two similar sized magnitude events reported in 1988 and 1994, and less lives were affected than reported for a similar sized magnitude event in 1970. Whilst this could be due to the specific location, economic activities, and social conditions of the region affected, this may also be linked to the successful forecasting of the El Niño event and its likely effects, and dissemination of this information to enhance preparedness (Buizer et al., 2000). These issues may also explain why more drought events appear in the precipitation record than in EM-DAT database, as the effects of less severe drought events may have been adequately mitigated in the past, and so not met the EM-DAT criteria.

The availability of data was a major obstacle in creating the drought damage functions. Damage functions were created based on historical drought events for which there was reported EM-DAT data only. Only 56% of the drought events quantified by this study had data on economic damages. Similarly, only 52% of the droughts assessed had data on the numbers of lives affected, and only 26% of the droughts assessed had data on the numbers of lives lost. Some drought events were also visible in the precipitation record but not in the EM-DAT database due to limitations discussed in section 3.1.4 and as mentioned above. Whilst the results suggest that the most severe drought events do show up, a finding consistent with Hirabayashi et al., (2008), it is important to reiterate the possible effects that the inclusion of such missing events would have on the drought damage functions, and any subsequent estimates made using them. Potentially, the addition of one or two extra events could alter the shape and scale of the country specific damage functions, and any subsequent estimates of socio-economic effects.

In interpreting the above economic and social drought damage functions it is also important to reiterate that results will depend directly on the quality and quantity of the underlying event data. EM-DAT provides the only publicly available, global drought database and data are therefore taken as valid. All entries added to the EM-DAT database follow a pre-defined entry procedure and are subject to subsequent validation. However, Höppe and Pielke (2006) note that the quantity and quality of disaster loss data is of particular concern for China before the 1980s and prior to the 1970s for Australia, Europe, India, the USA and Central America. Data also improves in quality over time as prior to 1980 many smaller events may not have been included and only large scale events recorded, giving an unbalanced view of the effects of drought. Furthermore there is now more data available on direct and indirect losses which may result in recent damage estimates being higher than those reported in the past (Muir-Wood et al., 2006). As such, the data from EM-DAT, which underlies the damage functions, may be biased by changing reporting practices over time.

However, as drought events occur less frequently than other weather extremes such as flood events, it was decided to focus on the period of data in EM-DAT from 1940-2002 so as not to restrict the amount of drought data further. However, only one drought event included in this analysis occurred prior to 1960, and of the drought events used in the economic drought damage functions only two events occurred before the 1970s. As such, it is hoped that the above issues will be minimal in this analysis. Additionally, due to concerns over the accuracy of impact data reported for China data was only used from the 1980s onwards in this case. Unfortunately, there was no economic impact data available for Ethiopia and consequently no part of Africa is represented by an economic drought damage function (although social damage functions were created). One solution may be to amalgamate economic data across multiple countries in Africa, which have similar climate characteristics and economies. However, even this may be difficult as for numerous countries in Africa no economic data is available.

Other important caveats also exist when interpreting the above drought damage functions. Firstly, the drought parameters calculated using the SPI represent meteorological drought caused by precipitation deficits from the monthly mean. The results are therefore heavily dependent on the quality of the gridded precipitation data, which has been interpolated from observed station data. Section 3.1.3 highlighted that for the USA SPI values computed using gridded data correlated almost exactly to those computed using station data. However, the approach will be less effective for regions where observational stations are limited. Secondly, the drought damage functions assume that social and economic losses will be dependent on drought magnitude only. However, the economic and social effects of drought will be dependent upon a range of specific factors, which can vary regionally and nationally. For example, a regions economic activity, the total value of output produced by a region, the geographical features of the region affected, and any external underlying stresses or vulnerabilities (e.g. water supply issues, food shortages, or high incidence of disease). Evidence of this was seen for Brazil as the drought damage functions highlighted regional differences in drought effects on society and the economy between the northeast and south of the country. This suggests real potential for more detailed or weighted drought damage functions to be created in the future for various country regions, which could capture better such vulnerabilities that are overlooked by the country-level damage functions. The use of regional economic and social time series data when carrying out the loss normalisation process may also improve the accuracy of results. Thirdly, the use of only two SPI time-periods may have consequences for the accuracy and robustness of the damage functions. In this study, SPI-6 and SPI-12 time-periods were used but SPI-12 may be too short to interpret accurately multi-year drought events which were reported, and which may instead show up as multiple shorter duration events. Thus, the analysis of long-term droughts may result in smaller drought magnitudes than if a longer SPI time-period had been used. This uncertainty could be reduced by using a wider range of time-periods e.g. extending the analysis to incorporate SPI-18 or SPI-24. As reported in section 3.3 seven drought events in this analysis could not be incorporated due to the use of the pre-defined SPI time periods.

The above limitations will ultimately affect the robustness of any estimates of social and economic losses made through the application of the drought damage functions to future drought events. Nevertheless, the R^2 values reported for economic damages were still extremely promising and do highlight the proportion of damages which could be explained by drought magnitude only. The fit appears more robust for developed countries compared to developing countries, possibly due to the improved stability of the economies and society, and better reporting of drought events. Based on the number of drought events in EM-DAT with related impact data, and which could be identified and quantified, the damage functions show great potential both for this study, and for future development. Furthermore, the coverage of social effects does help to highlight some very interesting regional trends. For example, in Brazil severe drought events in the northeast affect a large number of people but only cause moderate economic damages. On the other hand, less severe drought events in the south affect much fewer people yet cause large economic damages. This information highlights the different vulnerabilities of regions to drought and the particular consequences they may face, and could help inform decisions on the priority of adaptive measures. It also supports the argument for using both economic and social metrics within this study, as economic metrics alone may not always be representative of the full effects of a drought event.

A second advantage of the methodology employed is that the shape of the damage function can be derived directly from the drought magnitude and the reported impact data, rather than reflecting the expert opinion of the author (as discussed in section 2.3.1). This is important as Hallegatte et al., (2007b) notes that economic losses from large-scale extreme weather events do not tend to increase regularly with the intensity of an event. For example, many scientists believe that in the case of hurricanes the relationship between intensity and economic damages is at least cubed (Webster et al., 2008). Similarly, a nonlinear relationship has been reported between temperature and corn, soybeans, and cotton yields in the USA with damages increasing dramatically once a certain threshold has been reached (Schlenker and Roberts, 2009). Interestingly, the trends drawn between crop yields and increasing temperatures show a similar pattern to the economic drought damage function created for the USA by this study. This not only supports the finding but also the above argument that the economic damages are primarily related to agriculture, and hence, good correlation is seen between the magnitude of drought events and the economic damages reported. Consequently, the country specific damage functions not only give some indication as to the vulnerability of particular countries to drought, but could also be used to also highlight potential drought thresholds that should be avoided.

As well as the potential for highlighting drought thresholds above which risks may rise substantially, the above analysis could also form a basis for more conceptually based damage functions. Such damage functions could expand on some of the current limitations noted above in terms of the exclusion of many important socio-economic variables. For example, one could postulate a general drought damage function, based on the above, but also by strategically ranking the effects of various components on drought related losses based on an extended literature review and expert opinion. For example, a regions main economic activity (e.g. the importance of agriculture or water related sectors); the value of related economic output; specific geographical features; the level of vulnerability to drought; socio-economic conditions; the level and type of infrastructure; the level of drought intervention e.g. physical interventions, drought management or forecasting activities; the likelihood of successive or cumulative drought events occurring; the likelihood of compounding weather extremes occurring; and the possibility of surpassing theoretical thresholds. The date and time-scale of historical drought events could also be considered and compared to economic growth in the affected regions to derive and incorporate information on drought effects on a regions economic growth, and how this may change over time. One could also assign a weight or ranking to each of the above components based on the uncertainty and sensitivity of drought related effects to each of the components.

3.5 Summary

This chapter presents a methodological approach for quantifying historical drought events reported in a drought database in order to create economic and social drought damage functions. The approach is novel in both its methods and application. Alternative approaches for analysing drought events using the SPI have tended to be on a much smaller, case-specific basis. To the authors knowledge no other study has systematically assessed and quantified drought events in this manner at a regional and national level, and across multiple countries, and subsequently linked the drought parameters to drought impact data. The damage functions for economic analysis are well represented using drought magnitude as the main parameter. The application of the methodology to non-market effects, an area commonly ignored in assessments of extreme weather events has also been demonstrated. In addition, the methodology addresses many of the common limitations of climate damage functions as discussed in sections 2.3.1 and 2.4.2. Namely:

- The method avoids issues of unknown shape and scale parameters as the shape and scale of the damage functions are a function of the data and are not assumed by the author.
- The damage functions are calibrated to historical climate data, historical event data and historical impact data.
- The damage functions can be applied to market and non-market effects.
- The damage functions are not overly simple in that they are not based on single estimates from literature or on author opinion.
- The damage functions are country and region specific but can also be aggregated to give total costs (although aggregation between market and non-market effects is not possible as non-market effects are not monetised here).
- As the damage-functions are based on actual historical event and climate data it is possible to highlight areas where drought magnitude is/is not severe but the economic and social effects appear disproportionally low/high, and consequently make assumptions regarding the particular vulnerabilities of regions.

These advances are very promising and the damage functions provide a tool in which to estimate economic and social effects of future drought events. In order to do this the following chapter sets out to identify and quantify drought events and their magnitude in the first half of the 21st century, under various climate change scenarios.

4. Projections of Drought under Future Climate Change

Climate change is expected to affect the frequency and intensity of drought events in the future, potentially increasing the social and economic effects felt (IPCC, 2007b). The previous section linked the drought magnitude of historical events to reported data on the economic and social effects to create drought damage functions. Therefore, a first step in estimating the future economic damages of drought events is to make projections of future drought events under climate change and quantify the magnitude of events. Section 4.1 describes the modelling tools used to project future climate change, and consequences for precipitation, and changing drought patterns. The section also describes the different emission scenarios and climate models utilised. Section 4.2 describes the methodological approach devised for identifying future drought events and quantifying the magnitude to allow a comparison against past observations. Results, a discussion of main findings, and a summary of the chapter are presented in sections 4.3, 4.4 and 4.5.

4.1 The Community Integrated Assessment System (CIAS)

In order to assess how climate change could affect the global precipitation regime and subsequently the magnitude of drought events the IAM CIAS is used. CIAS is a third generation IAM designed to assess policy options, avoided damages and uncertainties associated with climate change (Warren et al., 2008). The main distinction between a third generation IAM and a second generation IAM is the way in that the model is implemented. A second generation IAM is typically modelled as a monolithic whole, incorporating various modules that are constrained by the model in which they function. A third generation IAM has a conceptual modular structure in which existing modules can be coupled. Modules can be changed or switched to allow multiple couplings to be run in order to address uncertainties (Hulme, 2001). Figure 4.1 shows a schematic of the CIAS model components used in this study[13].

[13] CIAS also incorporates a global impacts module for biome shifts and a hydrological module. For more details see Warren *et al.,* (2008).

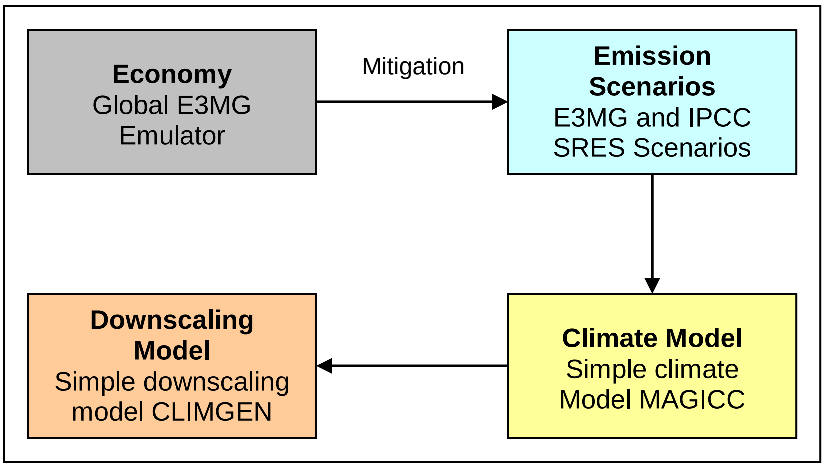


Figure 4.1: Schematic of the model components of CIAS used in this study

CIAS can either be driven by stabilisation scenarios provided by an economy component which emulates the econometric model E3MG (Energy-Environment-Economy Global Model), or by exogenous emission scenarios. E3MG is a macro-scale dynamic simulation model developed by teams at Cambridge Econometrics and the University of Cambridge as a contribution to the work of the Tyndall Centre for Climate Change Research (Barker et al., 2006b). It is an estimated model of demand-led growth encompassing both long-term behaviour and year-to-year fluctuations. This means it can be used for dynamic policy simulation and for forecasting and projecting over the medium and long term. As noted by Kemfert (2002) economic modelling approaches in IAMs tend to follow one of two patterns in that models either run over long time periods but are highly aggregated so do not cover sectoral effects, or they are disaggregated but limited in their time-frames. E3MG is able to model the long-term changes to 2100 required for a comprehensive study of the impacts of climate change but it is also highly disaggregated covering 20 regions and 42 sectors. E3MG is also novel in that it does not necessarily assume equilibrium between supply and demand in all markets as most traditional economic models do (discussed in section 2.2.2). Within CIAS E3MG provides stabilisation scenarios, which explicitly assume climate change mitigation, for 550, 500 and 450ppm CO_2 by 2100 (Barker et al., 2006a). E3MG outputs global emissions of CO_2 on a five yearly basis from 2000 to 2100 which are stored in the emission scenario database.

The emissions scenario database in CIAS also includes an alternative set of exogenous emission scenarios. These scenarios are representations of the standard IPCC Special Report on Emission Scenarios (SRES) interpreted and modelled using different IAMs[14]. The

[14] The data is available at: http://sres.ciesin.org/final_data.html

IPCC SRES scenarios provide a range of storylines about how future GHG emissions might unfold with changing populations, socio-economic development, and technological change, to assist in climate change analysis (Nakicenovic and Swart, 2000). The SRES scenarios assume no climate change mitigation. Figure 4.2 shows the projected range of CO_2 concentrations from 1990-2100 relative to 1990 for the six SRES scenarios and for the E3MG 450ppm stabilisation scenario.

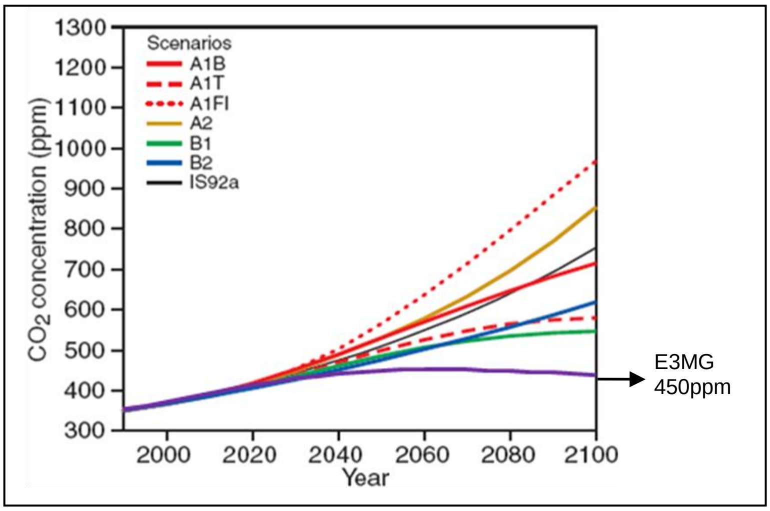


Figure 4.2: Projected CO_2 concentrations using the SRES scenarios for 1990-2100 relative to 1990. The purple line illustrates the projected CO_2 concentrations resulting from the E3MG 450ppm stabilisation scenario. Source: Modified from IPCC (2001, p.14).

The emission scenario database in CIAS provides a link between the stabilisation and emission scenario data and the simple climate model (SCM) MAGICC (Model for the Assessment of Greenhouse-gas Induced Climate Change). MAGICC is a well-known and widely used climate model consisting of a set of linked reduced form models (gas-cycle, radiative forcing, climate, and ice-melt). MAGICC has been tuned to emulate seven Atmosphere-Ocean General Circulation Models (AOGCMs) used within the IPCC Third Assessment Report (TAR) so that the user can force the model to emulate the behaviour of any of these (Warren et al., 2008). MAGICC also includes climate feedbacks on the carbon cycle and natural climate emissions. The model produces changes in global mean surface temperature, and sea level between 2000 and 2100 resulting from anthropogenic greenhouse gases.

In order to assess regional patterns of climate change CIAS incorporates the statistical downscaling model ClimGen (Climate Generator) developed by Tim Mitchell and Tim

Osborn at the University of East Anglia. ClimGen provides monthly climate variations for eight climate variables, including precipitation, at a 0.5° x 0.5° resolution for the entire terrestrial land surface (excluding Antarctica) for observed climate (1901-2002 based on the 0.5° x 0.5° resolution dataset of Mitchell and Jones (2005)) and for future climate (2001-2100). The model outputs can be annual, seasonal, or monthly. ClimGen uses the simple statistical method of ‘pattern scaling’ to generate the spatial climate change information for a given change in global mean temperature, based on output from MAGICC. Pattern scaling involves normalising GCM response patterns, at the resolution of the GCM, according to the global mean temperature change of the respective GCM to give the change in temperature per degree of global warming. These patterns can then be rescaled using a scalar derived from a SCM (e.g. MAGICC) to represent the particular emission scenario under consideration (IPCC, 2007b). Pattern scaling is based on the assumptions that the spatial pattern of change remains constant over time, that climate responses will be the same for all greenhouse gases, and critically that there is a linear relationship between annual global mean temperature and local climate change (Goodess et al., 2003a). With regards to precipitation Mitchell (2003) finds that although slight non-linearity’s arise estimates of future change in precipitation patterns made using pattern scaling accurately represent the modelled changes well. Similarly, Cabré et al., (2010) found that for southern South America for the 2020s and 2050s the spatial patterns of precipitation change obtained via the scaling technique were reasonable. Although, when comparing scaled and simulated patterns of change under the B2 scenario for the end of the 21st century results for southern Brazil in DJF were of opposite signs. The errors of estimating precipitation changes were considered comparable to those inherent to the regional model and to the projected changes themselves. Thus, the uncertainties introduced by the scaling technique can be large for precipitation, especially for certain regions, and these uncertainties must be considered when interpreting the results.

ClimGen uses simulations from five GCMs (HadCM3, CSIRO2, ECHAM4, PCM2 and CGCM2), each run with up to four SRES scenarios. The different patterns generated allow the range of uncertainty related to the use of different GCMs and emission scenarios to be investigated. This is beneficial as due to the complexity and computational costs of running GCMs most GCMs only consider a few emission scenarios. In contrast, SCMs demand fewer computational resources but are not are able to provide spatial patterns of climate change. Thus, the ‘pattern scaling’ approach allows the computational simplicity of SCMs and the spatial patterns of GCMs to be combined (Mitchell, 2003).

At this stage, the climate change data is still at the coarse resolution of the original GCM. ClimGen interpolates the grid data of the GCM using distance-weighted averaging and combines the climate change pattern from the GCM with the observed climate data of Mitchell and Jones (2005) to simulate absolute climate change at a spatial resolution of 0.5° x 0.5°. In addition, the observed deviations in the monthly mean climate are combined to represent inter-annual variability in the future time-series, assuming that the magnitude of inter-annual variability will not change in the future (Osborn and Mitchell, 2005). The pattern of mean climate change is simply added to the observed data however, ClimGen includes additional options for downscaling precipitation. The 'ratio-method' expresses the precipitation changes seen in the GCM pattern as a fractional change from present day precipitation rather than an absolute change. The fractional change in precipitation generated from the pattern-scaled GCM is combined with the observed precipitation data and the observed deviations in the precipitation data by multiplication. This method assumes that the ratio of precipitation change is more important than the absolute change and that the inter-annual variability will increase in magnitude by the same ratio (*ibid.*). A third option, the 'gamma-method' (described by Goodess et al., 2003b), models changes in mean precipitation in the same way as the ratio-method but considers inter-annual variability independently of the mean precipitation changes. This is particularly important for addressing extreme weather events, which will be affected by a change in the variance of the distribution. The method uses the gamma shape parameter, which provides a measure of the skewness of the distribution, to change the precipitation distribution as well as changing the mean. In ClimGen the observed inter-annual variability is modified according to changes in the shape parameter of the gamma distribution derived from the selected GCM simulation (Warren et al., In review). The gamma method is used in this study to downscale precipitation patterns to 0.5° x 0.5°.

4.1.1 Timeframe of projections

CIAS is able to provide projections of monthly precipitation, at a 0.5° x0.5° resolution for the period 2001-2100. In this study it was decided to focus on the first half of the 21st century (2003 to 2050) which will be compared to observed data from 1955-2002. Although short-term projections (e.g. to 2015) may provide information on a timescale useful for policy makers there may be very little change in the frequency of drought events in such a short space of time limiting the usefulness of this assessment. It would be expected that more drought events would show up in medium-term projections due to stronger climate forcing and give a better indication of potential effects that may occur under future climate change. However, it is also important to bear in mind that in the medium-term there may also be changes in the socio-economic structures of the eight countries considered here. In the second half of the 21st century greater changes in the frequency and intensity of drought events would be expected, however, it was felt that the socio-economic conditions of countries would be significantly different by 2100 making the application of the drought-damage functions less robust. By focusing this study on the first half of the 21st century it is hoped that the damage estimates will remain robust, issues related to changing socio-economic situations will be minimised, and the outputs generated will still be of value to policy makers.

4.1.2 Emission and stabilisation scenarios

As mentioned previously in making projections of future climate change there are many sources of uncertainty. Given the sheer number and variety of future global scenarios of climate change it is impossible to predict with any certainty which scenario is most likely. In order to address this uncertainty a variety of scenarios can be used so that a range of outcomes and results can be provided. Two different emission scenarios are used in this study. Firstly, the A1FI emission scenario is used from the IPCC SRES emission database. The A1FI scenario is part of the A1 group of emission scenarios, which have the highest rates of technological change and assume rapid economic growth. The A1FI scenario assumes a fossil intensive future resulting in 573ppm CO_2 by 2050 and 976ppm CO_2 in 2100. The population projection follows the lowest trajectory, increasing to 8.7 billion people by 2050 and declining towards 7 billion people by 2100. Additionally, the E3MG emulator 450ppm CO_2 stabilisation scenario is used as it explicitly assumes mitigation and provides a lower stabilisation target than covered by the IPCC scenarios. The scenario projects that CO_2 emissions will stabilise around 2050 at ~455ppm, declining to ~450ppm CO_2 by 2100. The population scenario is based on the long-term medium range UN projections from 2030 onwards, with global population reaching 8.7 billion people by 2050 and 9.1 billion people by 2100. These emission scenarios were selected as they encompass the full range of the IPCC scenarios, and represent different populations, economic output, land use, and technology and energy use. The decision to use just two scenarios was due to the focus of the study on the first half of the 21st century as projections of CO_2 concentrations, and subsequently global temperatures, are relatively comparable up to 2030 for all scenarios, with only slight divergence by 2050 (highlighted in figure 4.2).

4.1.3 Climate models

CIAS also enables different climate models and their underlying assumptions to be assessed. This is important as different GCMs can project diverse patterns of future climate variables, often showing opposite signs of change (IPCC, 2007b). Particularly for the early 21st century inter-model variability tends to be greater than inter-scenario variability (Goodess et al., 2003b). Blenkinsop and Fowler (2007) attribute this divergence and uncertainty in GCM performance to the parameterization of small-scale physical processes as well as uncertainties in the structures used to represent large-scale climate processes. Therefore, any one single model projection provides just one of many possible future scenarios. Whilst Blenkinsop and Fowler (*ibid.*) note the importance of using multiple GCMs to provide probabilistic projections of future climate change this has generally been applied to studies of mean temperature change at the global scale and the authors note that assessments of future drought events have traditionally only used one climate model to assess possible impacts. In this study the GCMs HADCM3, CSIRO2, and ECHAM4, which are available in both MAGICC and ClimGen, are used. In general, compared to the full range of climate models used by the IPCC in the TAR the three models are considered to provide medium range projections of future global temperature change. However, the models show more pronounced differences for global precipitation with ECHAM4 at the low end of the model range, CSIRO2 at the high-end of the model range, and HADCM3 towards the middle of the range (IPCC, 2001, figure 9.3). In summary, six scenarios will be investigated using the A1FI emission scenario and the 450ppm stabilisation scenario for each of the climate models HADCM3, CSIRO2, and ECHAM4.

4.2 Modelling future drought events

Projections of gridded monthly precipitation data for the period 2003-2050 were derived for each of the six scenario runs. The precipitation data was transformed to the SPI following the method described in section 3.1.2, for both SPI-6 and SPI-12 time periods. As described in section 4.1 observed precipitation data from 1955-2002 were used to create the future precipitation time-series data in ClimGen, with the mean monthly precipitation trends for 1955-2002 assumed unchanged for the period 2003-2050. Consequently, any changes seen in the precipitation distribution and subsequently SPI data can be linked to anthropogenic climate change.

In creating the drought damage functions bar graphs of the average monthly SPI were created for each reported drought event, at SPI-6 and SPI-12 time periods (demonstrated in figure 3.2). However, the methodology devised in section 3.2 to identify historic drought events was based on reported information on the specific states/regions affected as reported in the EM-DAT database. Such spatial boundaries were not available for future projections of drought events. Consequently, an approach similar to that of Giorgi and Francisco (2000) has been adopted. In order to look at regional changes in climate change Giorgi and Francisco (2000) divided all land areas in the World into 21 regions. These regions were selected in order to represent different climate regimes with a manageable number of regions of similar shape. This approach has been widely used (e.g. Ciscar et al., 2011, Giorgi, 2006, IPCC, 2007b, Ruosteenoja et al., 2003, Sheffield and Wood, 2008) in order to encompass specific climate regimes and provide robust statements of regional climate change. The regions used in this study for the eight countries of interest were based primarily on those defined in the above studies. However, as some of these regions were still very large they were further divided based on country specific climate change reports and information on particular precipitation regimes of the countries. This enabled a more disaggregated study of drought events to be conducted and aimed to minimise biases in spatial averaging when identifying drought events. The country regions used in this study are illustrated in figure 4.3 and defined in table 4.1.

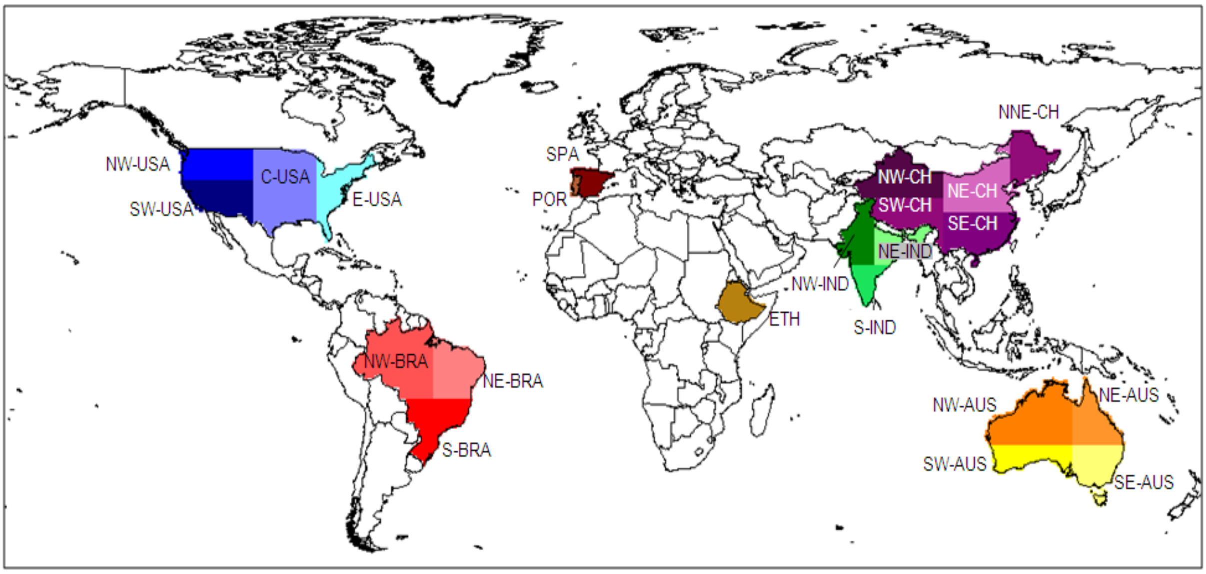


Figure 4.3: The country regions used in this study (defined in table 4.1)

Name	Acronym	Latitude (°)	Longitude (°)
Northwest Australia	NW-AUS	27.75S – 10.25S	112.75E – 138.25E
Southwest Australia	SW-AUS	43.75S - 28.25S	114.25E – 138.25E
Northeast Australia	NE-AUS	27.75S – 10.25S	138.75E – 153.75E
Southeast Australia	SE-AUS	43.75S - 28.25S	138.75E – 153.75E
Northwest Brazil	NW-BRA	15.75S – 4.25N	73.75W – 50.25W
Northeast Brazil	NE-BRA	15.75S – 0.25N	49.75W – 34.75W
Southern Brazil	S-BRA	33.25S – 16.25S	57.75W – 38.75W
Northwest China	NW-CH	36.25N – 49.25N	74.25E – 100.25E
Southwest China	SW-CH	22.25N – 35.75N	79.25E – 100.25E
Northeast China	NE-CH	32.75N – 50.75N	100.75E – 119.75E
Southeast China	SE-CH	18.25N – 32.25N	100.75E – 122.75E
North-Northeast China	NNE-CH	38.75N – 53.25N	120.25E – 134.75E
Ethiopia	ETH	3.75N – 14.25N	33.75E – 47.75E
Northwest India	NW-IND	18.75N – 35.75N	68.25E – 79.75E
Northeast India	NE-IND	18.75N – 35.75N	80.25E – 97.25E
Southern India	S-IND	8.25N – 18.35N	72.75E – 84.25E
Spain	SPA	36.25N – 43.75N	9.25W – 3.25E
Portugal	POR	36.75N – 42.25N	9.25W – 6.75W
North-West USA	NW-USA	40.75N – 48.75N	124.75W – 103.25W
South-West USA	SW-USA	29.75N – 40.25N	124.25W – 103.25W
Central USA	C-USA	26.25N – 48.75N	102.75W – 84.75W
Eastern USA	E-USA	24.75N – 47.25N	84.25W – 66.75W

Table 4.1: Definition of regions used in this study

Bar charts of the average monthly SPI were created for each of the regions for future SPI data (2003-2050), for each scenario and for both SPI-6 and SPI-12 time periods, so that drought events could be visually identified. The same methodology was also applied to the observed data for the baseline period (1955-2003) so any changes in future drought characteristics could be compared to historic characteristics. This ensured that the results could be comparable over time as they were generated using the same methodology. As in section 3.2, a drought was recorded as starting when the SPI value fell below zero, and ended when the SPI value exceeded zero, and where the SPI reached a minimum threshold. In creating the drought damage functions drought was defined as a period where negative SPI values could be identified which coincided with the drought details reported in EM-DAT, in order to identify and quantify reported historical events. However, in order to compare past drought events to future drought events under climate change the threshold was set at SPI -1.50, representing drought events that are either severely or extremely dry (see table 3.2). Setting a standard threshold allowed consistency in modelling drought parameters across the different countries, regions and scenarios. In addition, the pre-defined threshold was used so that the emphasis of the study was on the effects of severe and extreme drought events for the following reasons:

- It is assumed that larger magnitude events will result in the most severe consequences for economies and society.
- The NDMC (2006b) state that for longer time-periods, such as SPI-12, SPI values below -1.50 are usually a good indicator that fairly significant impacts are occurring in agriculture and potentially other sectors.
- It is assumed that these events will be difficult to cope with compared to more moderate drought events, even if future adaptation takes place.
- There is some evidence to suggest that at a global level the frequency of severe and extreme drought events will increase whilst the number of moderate drought events will remain stable (Burke et al., 2006).

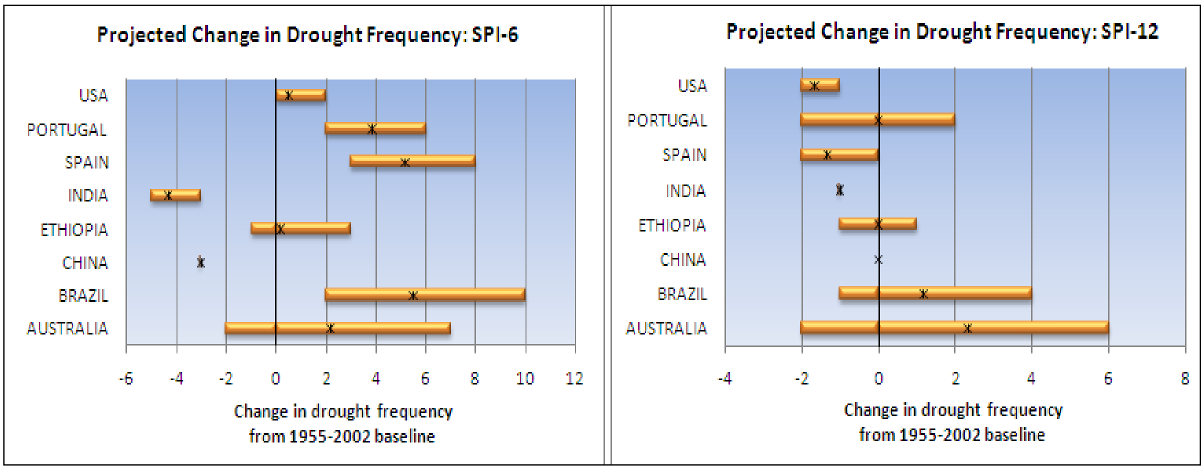
Once the drought start and end months (and duration) were identified, each drought event was quantified using the methodology described in section 3.2 (equations 3.13-3.15). Where countries are divided into multiple regions (e.g. the USA, Brazil, China, India and Australia) the same drought event could potentially encompass two or more regions resulting in a large-scale drought being counted as multiple, smaller events. In order to avoid this issue when regional drought dates coincided for a given country maps were created using DIVA-GIS to identify visually if they were separate drought events or a single event encompassing multiple regions.

4.3 Results

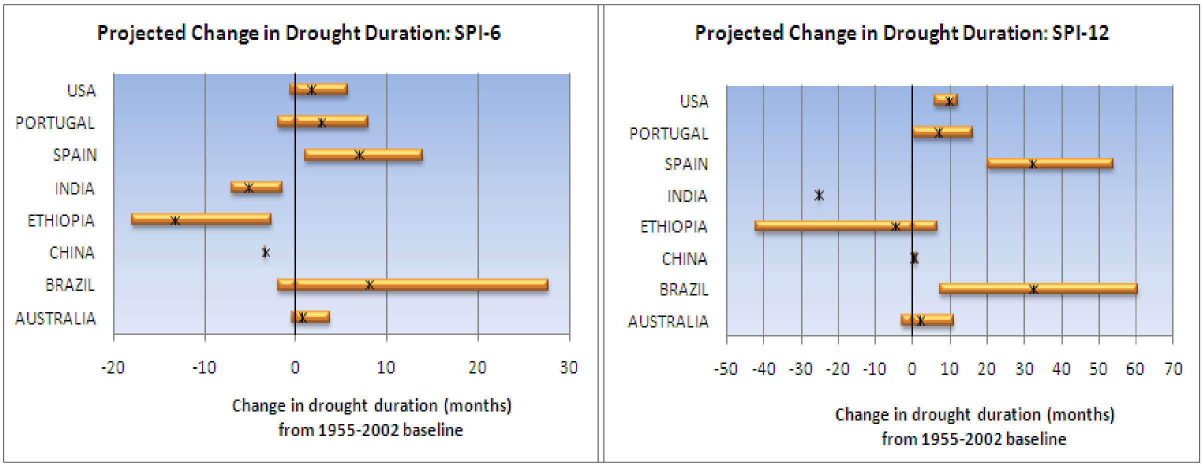
Drought parameters computed for each country and scenario were averaged for the 1955-2002 and 2003-2050 periods. Results are presented in this manner, as although the method provides quantitative estimates of individual drought characteristics it does not aim to explicitly present projections of individual events, their exact timing, or location. Instead, the results reflect a broader picture of changes that may occur under future climate change. However, it is important to bear in mind that this averaging can mask some large variability in the characteristics of individual drought events. The study does however help to identify 'hot-spot' regions, which may be particularly vulnerable to drought in the first half of the 21st century. The reported changes in drought characteristics, at a national and regional level, are reported and reviewed in light of other modelling studies.

Figure 4.4a-d displays the projected change in drought frequency, average duration, magnitude, and peak intensity for 1955-2002 to 2003-2050 for the eight countries studied. The range represents the results generated under the six climate/emission scenarios and highlights how drought characteristics can vary, even being of a different sign, depending on the particular scenario used. The results used to create figure 4.4 and subsequently discussed in this section are presented in tables 4.2 and 4.3 at the end of this section. Country results are reported and discussed in turn below, including regional findings.

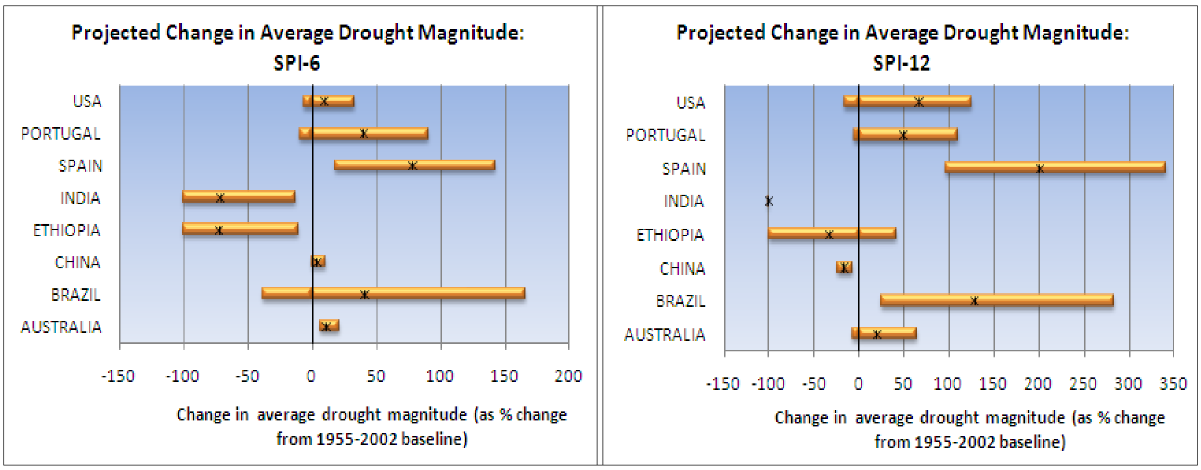
a. Projected Change in Drought Frequency



b. Projected Change in Drought Duration



c. Projected Change in Drought Magnitude



d. Projected Change in Peak Intensity

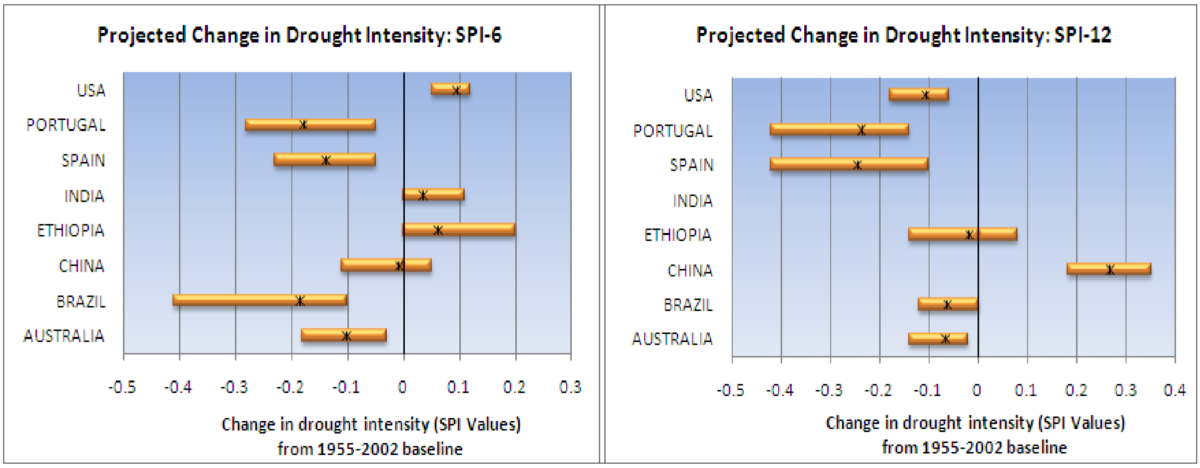


Figure 4.4 a-d: Change in drought characteristics for 2003-2050 compared to 1955-2002 using ECHAM4, HADCM3 and CSIRO2 and the A1FI and 450ppm scenarios for a) change in drought frequency, b) change in drought duration, c) percentage change in average TDM, and d) change in PI. Black crosses indicate mean values (left: SPI-6 drought events, right: SPI-12 drought events).

Results for Australia highlight that on average drought frequency is expected to increase for both SPI-6 and SPI-12 drought events, drought duration increases slightly, and drought magnitude also increases. Average drought magnitude was projected to increase by 6-21% for SPI-6 droughts. Projected changes in average drought magnitude were more mixed using SPI-12, ranging from -6% to +64% depending on the GCM used. In all scenarios the average peak intensity was projected to increase (i.e. the SPI value became more negative), suggesting the potential for more intense droughts in the future. Based on the country regions, projections using ECHAM4 and HADCM3 suggested an increase in drought events in south and west Australia, particularly the south-west. This finding is in agreement with Christensen et al., (2007) who project increased drought in Southern Australia, and a report by CSIRO and the Australian BoM (2007) who projected an increase in drought events, particularly in the south-west. Conversely, results of this analysis simulated with CSIRO2 suggested a decline in drought events in south-west Australia.

The general pattern of change for Brazil is for an increase in drought frequency, drought duration and drought magnitude. Average drought magnitude is projected to change by between -38% to +165% for SPI-6 drought events and by 25% to 282% for SPI-12 drought events. This suggests that long-term SPI-12 drought events are likely to become more severe under climate change compared to medium-term SPI-6 drought events. All the models consistently projected that average peak intensity of drought events would increase or stay the same. Whilst there was some variability in scenario results the general picture is one of worsening drought conditions for Brazil. Furthermore, the average drought duration of SPI-12 events is projected to increase by 30 months, with some drought events projected to last over seven years. Therefore, even in the first half of the 21st century climate change may induce multi-year drought events. Regionally, projections using ECHAM4 showed an increase in drought events in northern Brazil, particularly the northeast with little change seen in the south. Similar projections were seen using HADCM3 although a greater increase in drought events was seen in the northwest compared to northeast Brazil. Whilst there are few regional precipitation studies for Brazil these findings are consistent with those of Marengo et al., (2009) who used the comprehensive Hadley Centre regional model PRECIS (Providing Regional Climates for Impacts Studies) to look at changing extreme climate conditions from 1961-1990 to 2071-2100. Results suggest that northeast Brazil and eastern Amazonia could suffer drier conditions due to increased temperatures and reduced precipitation. Likewise, under the A1B scenario Li et al., (2008) highlighted a move towards more negative SPI values in the future suggesting more intense effects of anthropogenic climate change on Amazon drying, with the potential for a 16% increase in dry events and the possibility of more extreme dry events in the 21st century.

Results for China suggest a decline in the frequency and severity of drought events in the first half of the 21st century. The results indicate that the average drought frequency and drought duration may well decrease for SPI-6 drought events whilst there is little change in the intensity and magnitude of events. For SPI-12 drought events drought frequency and duration remained stable and drought magnitude and drought intensity decrease. These broad findings are consistent with those of other published studies. For example, Christensen et al., (2007) report that precipitation is likely to increase in east China in all seasons and increase in the Tibetan Plateau, with most models projecting an increase in precipitation in all seasons. Kim and Byun (2009) also projected increases in precipitation for most parts of Asia leading to a decrease in drought frequency and duration. Unfortunately, as there were so few severe drought events visible in the future projections it is difficult to make a robust statement about the spatial pattern of change in drought events for China. However, the average drought frequency across the six scenarios declined for all of the regions assessed, indicating China is likely to become wetter in the first half of the 21st century. In comparison, at a regional scale Chen and Sun (2009) project a consistent enhancement in summer precipitation in China in the 21st century, with greater increases projected for the southern coast of China and north China. Other studies suggest that there will be a north-south divide with southern China becoming drier and northern china becoming wetter by the 2050s or later (Gao et al., 2008, Hirabayashi et al., 2008, Xiong et al., 2008).

Results for Ethiopia suggest that drought frequency remains relatively stable in the first half of the 21st century although drought duration and magnitude are projected to decrease. Drought intensity is likely to become less severe for SPI-6 drought events, although slightly more severe for SPI-12 drought events. The range in results for some drought characteristics were large depending on the GCM used, and particularly for SPI-12 drought events where there was less consistency in the direction of change. For example, for some scenarios there is an increase in drought frequency although average drought characteristics are less severe. In other cases, drought events occur less frequently but when they do occur, they are projected to be of greater magnitude than historic drought events. Therefore, it is difficult to ascertain any clear trends for changing drought characteristics in Ethiopia. However, the general trend for declining drought duration and magnitude are consistent with the findings of Christensen et al., (2007) who state that there is likely to be an increase in annual mean rainfall in east Africa in the 21st century, particularly in the dry season. These findings for East Africa are quite robust across the suite of IPCC models used with 18 out of 21 models predicting an annual increase in precipitation in the core of this region. Model projections also suggest an increase in the intensity of extreme rainfall events (*ibid.)*, although regional trends are less clear. As drought events were identified and quantified at a country level for Ethiopia no information on regional characteristics were obtained.

Results for India showed a consistent trend in the sign of change for projections of drought characteristics across the six scenarios. Average drought frequency, duration, magnitude and intensity were projected to decline. The only scenario where severe/extreme drought events occurred was for SPI-6 drought events using CSIRO2 suggesting an increase in precipitation over India in the first half of the 21st century. These results are consistent with the findings of Christensen et al., (2007) for South Asia who project a slight decrease in precipitation in DJF (the dry season) but an increase in precipitation for the rest of the year, with only three out of the 21 GCMs used projecting an annual decrease in precipitation. In a review of GCM output for India Rupa Kumar et al., (2006) also report an increasing trend in precipitation, particularly enhanced from the 2040s onwards. At a regional scale, a decrease in drought events was projected for all regions of India analysed in this study. However, as so few events were visible, including in the observed data, it is hard to make any robust statement on the regional affect of climate change on drought events. Rupa Kumar et al., (2006) found increasing precipitation trends for India, particularly over the west coast and northeast India using the regional PRECIS model. However, at a state level they find that central Indian states are more prone to severe rainfall activities whilst there are slight declines in annual rainfall for three states in southern and northeast India.

Results for Spain highlight a general decline in precipitation as average drought duration, magnitude, and intensity all increase. There is good consistency in the model results for SPI-6 and SPI-12 drought events with most scenarios agreeing on the sign of change. However, for SPI-12 drought events a slight decline in the frequency of drought is projected. For SPI-6 drought events average drought magnitude is projected to increase by 18 to 143% in the first half of the 21st century. For SPI-12 drought events the average drought magnitude is projected to increase by 96 to 341%, highlighting that both medium and longer-term drought events are likely to become more severe under future climate change. The effect of climate change on drought trends in Portugal was less consistent with more variability in the direction of change. However, average results suggest that drought duration, magnitude and intensity all increase in the future. As with Spain, drought frequency was projected to increase for SPI-6 drought events but results for SPI-12 drought events suggested no change on average. The findings for Spain and Portugal are consistent with those reported by Christensen et al., (2007) who project that annual precipitation is very likely to decrease in most of the Mediterranean area with a decline in the annual number of precipitation days and an increase in the risk of summer drought. In addition, numerous other modelling studies have focused on the Mediterranean region or the larger European region. There is good consensus in modelling studies for a decline in precipitation in the Mediterranean and increased drought frequency and duration (e.g. Beniston et al., 2007, Blenkinsop and Fowler, 2007, Frei et al., 2006, Lehner et al., 2006, Warren et al., In review). Results were estimated for Spain and Portugal at the country level and so no assessment of regional drought trends were made.

For the USA the general findings of this analysis were mixed with less model consistency seen in the direction of change in trends. Using SPI-6 there was only a slight increase in drought frequency and duration projected. For SPI-12 drought events drought frequency was projected to decline slightly whilst drought duration was projected to increase on average by 10 months. The change in average drought intensity also varied depending on the SPI time period used with a decrease in intensity seen for SPI-6 drought events and an increase in intensity for SPI-12 drought events. Drought magnitude was projected to increase on average by 10% for SPI-6 drought events and by 66% for SPI-12 drought events. Different regional trends were seen depending on the scenario used, with no consistent pattern seen. For example, using SPI-6 droughts increased in northwest USA using ECHAM4 and HADCM3, whilst projections using CSIRO2 highlighted an increase in drought frequency in southwest and central USA with no change in the northwest. For SPI-12 droughts the general trend suggested a decline in drought frequency in western USA although the magnitude of the events that did occur increased. Inter-model uncertainties have been highlighted by other regional studies conducted for the USA. The North American Regional Climate Change Assessment Program (NARCCAP) provides precipitation data for North America based on a variety of regional and global climate models. Using the A2 IPCC SRES scenario seasonal precipitation maps are constructed for the period 2041-2070 and displayed online (NARCCAP, 2007). Although the precipitation maps highlight regional uncertainties, some common features are visible including a general drying trend in the south-west in DJF, wetter conditions in the NE, and drying across western USA during JJA.

The above results highlight that climate change could have large repercussions for future drought regimes however the uncertainty seen when using different scenarios can be large. Interestingly, it was found that this uncertainty increases as the SPI time period increases from SPI-6 to SPI-12. Additionally, whilst the frequency of SPI-12 droughts generally decrease climate change is likely to have a larger effect on their duration and magnitude, and for Portugal, Spain and the USA their intensity. As SPI-12 can be tied to hydrological drought it suggests that water resources will be very vulnerable to climate change. This finding is in agreement with that of Vasiliades et al., (2009) who also used downscaled monthly precipitation data, converted to the SPI to assess drought. Furthermore, results indicate an increase in multi-year drought events in Australia, Brazil, Spain, Portugal and the USA. Multi-year drought events will be harder to cope with due to their compounding effects and continued drain on resources and adaptive strategies (Wheaton et al., 2008).

As mentioned, for some of the countries there were significant differences in the direction of change in the trend of drought parameters from the 1955-2002 observed data. It was assumed that as the time period of the study was for the first half of the 21st century there would be little difference in future precipitation projections using different emission scenarios as CO_2 concentrations, and subsequently temperature change, is relatively comparable up to 2030 for all scenarios (figure 4.2). This is confirmed in figure 4.5 which presents the average drought magnitude of SPI-6 droughts for Spain calculated by this study, using the A1FI, A2, B2 and B1 SRES scenarios and the E3MG 450ppm emission scenario for 2003-2050 and 2051-2098. Results are generated following the above methodology and using the GCM ECHAM4.

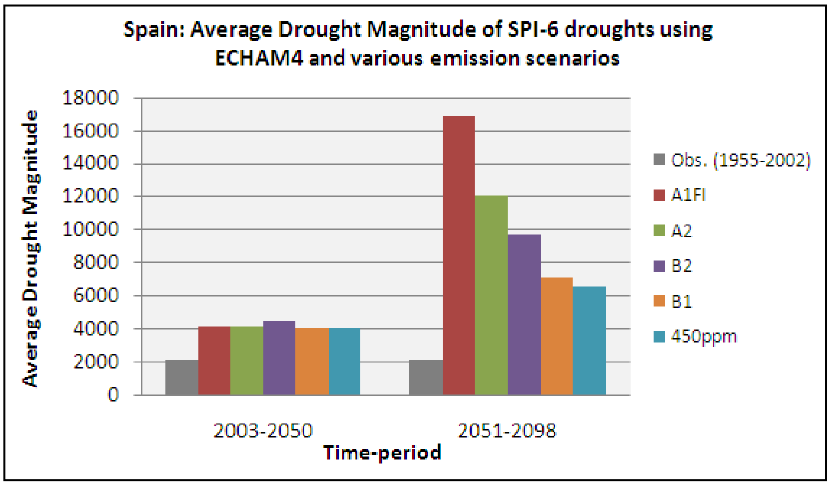


Figure 4.5: Average drought magnitude of SPI-6 drought events in Spain for 1955-2002 compared to 2003-2050 and 2051-2098. Results are generated using the GCM ECHAM4 and various emission/stabilisation scenarios.

The similarity between scenarios for the first half of the 21st century is illustrated in the graph. In comparison, average drought magnitude in the period 2051-2098 varies widely depending on the particular emission/stabilisation scenario used. As expected the largest increase in average drought magnitude in the second half of the 21st century occurs under the A1FI scenario with average drought magnitude projected to increase by 690%. The 450ppm scenario results in the smallest increase in average drought magnitude, although even with this stringent stabilisation target the average drought magnitude is still projected to increase by 206% in Spain.

Results for 2003-2050 generated using different GCMs exhibit much larger variability than that seen using various emission/stabilisation scenarios. Figure 4.6 shows the average drought magnitude calculated for the first half of the 21st century for each of the six scenarios using SPI-6 and SPI-12. Graphs are presented for Australia, Brazil, China, Portugal, Spain and the USA as drought events were visible for these countries across all six scenarios for comparison.

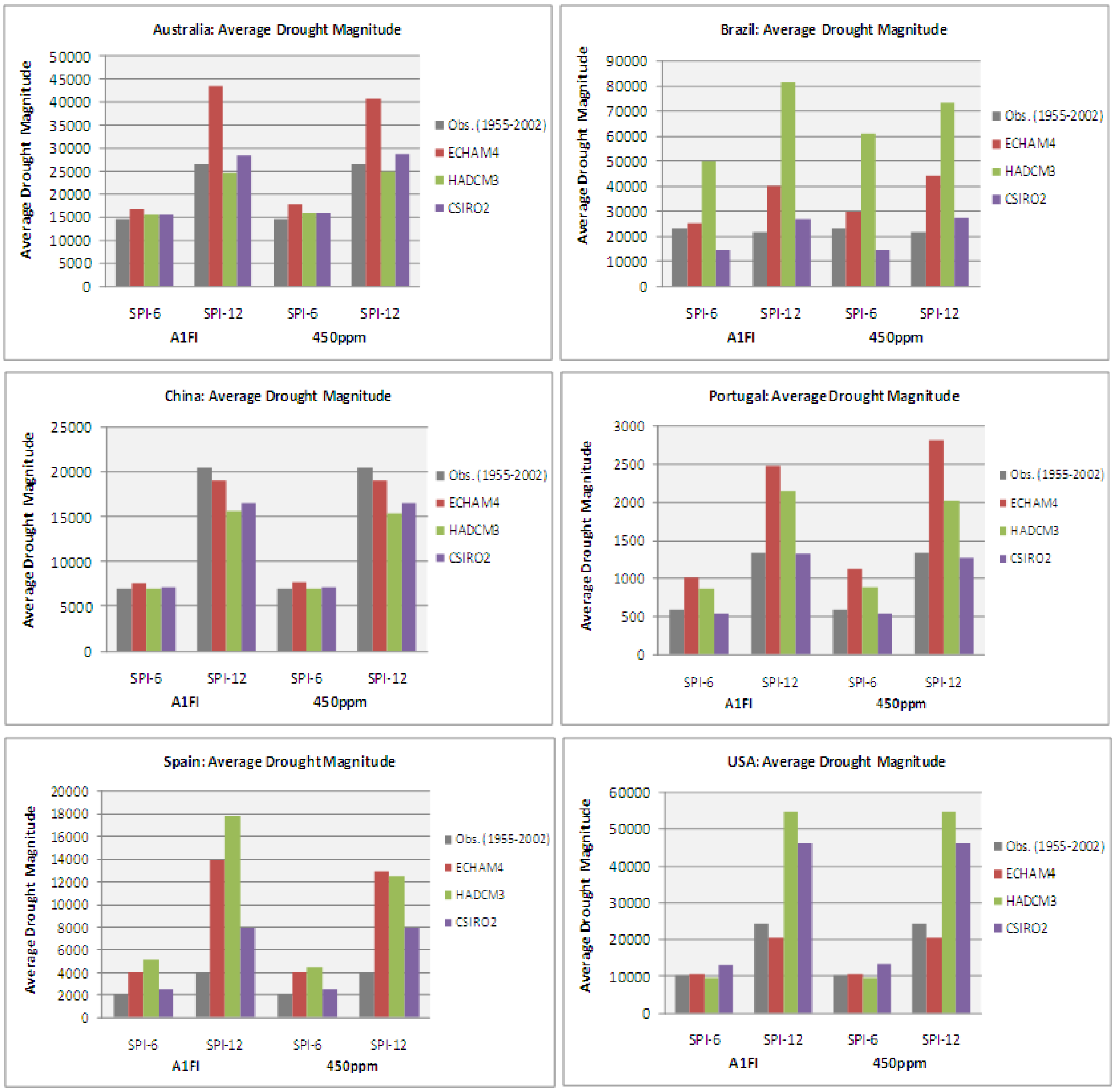


Figure 4.6: Average drought magnitude for the observed period 1955-2002 and future period 2003-2050. Results are generated for the SPI-6 and SPI-12 time-periods using the A1FI and 450ppm scenarios and the GCMs ECHAM4, HADCM3 and CSIRO2.

The graphs highlight the large range in results gained using different GCMs compared to the similarities in results using the different emission and stabilisation scenarios. As such, much of the uncertainty in the results can be attributed to the GCM used and their underlying assumptions. As discussed previousy the graphs also highlight the larger effect of climate change on magnitude of SPI-12 droughts, and the larger range of results.

The results shown in figure 4.4a-d and discussed above are detailed in tables 4.2 and 4.3 below. The data tables present the results of the drought analysis for the observed data

(1955-2002) and for the future projections (2003-2050) for each country and scenario. The tables display the number of drought events identified, average duration, peak intensity, magnitude, and the percentage change in drought magnitude from 1955-2002 to 2003-2050. Table 4.2 presents results for SPI-6 drought events and table 4.3 presents results for SPI-12 drought events. Shaded columns indicate that country trends projected under the six scenarios are all of the same direction. Orange shading indicates enhanced drought conditions (i.e. reduced precipitation) and blue shading indicates improving drought conditions (i.e. increased precipitation).

Country	Emission Scenario	GCM	Drought Frequency	Average Duration (months)	Average Peak Intensity[a]	Average Magnitude[b]	% Change in Average Magnitude from Observed
Australia	Observed	--	10	17.2	-1.78	14,628	--
	A1FI (2003-2050)	ECHAM4	16	18.9	-1.83	16,793	14.8
		HADCM3	12	16.8	-1.87	15,562	6.4
		CSIRO2	8	17.0	-1.95	15,695	7.3
	450ppm (2003-2050)	ECHAM4	17	21.0	-1.81	17,708	21.0
		HADCM3	12	16.8	-1.87	15,873	8.5
		CSIRO2	8	17.0	-1.96	15,760	7.7
Brazil	Observed	--	3	25.7	-1.77	22,979	--
	A1FI (2003-2050)	ECHAM4	8	29.1	-1.87	25,388	10.5
		HADCM3	9	39.0	-2.09	49,596	115.8
		CSIRO2	5	23.8	-1.88	14,224	-38.1
	450ppm (2003-2050)	ECHAM4	11	33.5	-1.92	29,685	29.2
		HADCM3	13	53.5	-2.08	61,048	165.7
		CSIRO2	5	23.8	-1.89	14,314	-37.7
China	Observed	--	4	11.3	-1.76	6,976	--
	A1FI (2003-2050)	ECHAM4	1	8.0	-1.85	7,627	9.3
		HADCM3	1	8.0	-1.71	6,971	-0.1
		CSIRO2	1	8.0	-1.73	7,133	2.3
	450ppm (2003-2050)	ECHAM4	1	8.0	-1.87	7,703	10.4
		HADCM3	1	8.0	-1.72	6,996	0.3
		CSIRO2	1	8.0	-1.73	7,128	2.2
Ethiopia	Observed	--	1	18	-1.86	6,304	--
	A1FI (2003-2050)	ECHAM4	0	0	0	0	-100.0
		HADCM3	0	0	0	0	-100.0
		CSIRO2	3	15.3	-1.69	5,615	-10.9
	450ppm (2003-2050)	ECHAM4	0	0	0	0	-100.0
		HADCM3	0	0	0	0	-100.0
		CSIRO2	4	13.3	-1.66	4,910	-22.1
India	Observed	--	5	7	-1.70	3,938	--
	A1FI (2003-2050)	ECHAM4	0	0	0	0	-100.0
		HADCM3	0	0	0	0	-100.0
		CSIRO2	2	5.5	-1.59	3,406	-13.5
	450ppm (2003-2050)	ECHAM4	0	0	0	0	-100.0
		HADCM3	0	0	0	0	-100.0
		CSIRO2	2	5.5	-1.60	3,427	-13.0
Portugal	Observed	--	13	12	-1.83	589	--
	A1FI (2003-2050)	ECHAM4	19	17	-2.09	1,008	71.1
		HADCM3	18	16	-2.02	875	48.6
		CSIRO2	15	11	-1.88	535	-9.2
	450ppm (2003-2050)	ECHAM4	17	19.5	-2.11	1,120	90.2
		HADCM3	17	16	-2.07	886	50.4
		CSIRO2	15	11	-1.88	535	-9.2
Spain	Observed	--	4	11	-1.72	2,143	--
	A1FI (2003-2050)	ECHAM4	12	19	-1.87	4,085	90.6
		HADCM3	9	25	-1.88	5,196	142.5
		CSIRO2	7	12	-1.77	2,538	18.4
	450ppm (2003-2050)	ECHAM4	11	19	-1.90	4,082	90.5
		HADCM3	9	25	-1.95	4,454	107.8
		CSIRO2	7	12	-1.78	2,534	18.2
USA	Observed	--	5	13.0	-1.92	10,127	--
	A1FI (2003-2050)	ECHAM4	5	14.0	-1.80	10,452	3.2
		HADCM3	5	12.4	-1.81	9,472	-6.5
		CSIRO2	7	16.9	-1.83	13,152	29.9
	450ppm (2003-2050)	ECHAM4	5	14.0	-1.81	10,548	4.2
		HADCM3	5	12.4	-1.83	9,488	-6.3
		CSIRO2	6	18.7	-1.87	13,461	32.9

Table 4.2: SPI-6 Drought characteristics quantified from observed data (1955-2002) and future projections (2003-2050). Shading indicates results are all of the same sign (orange for worsening drought conditions and blue for improving drought conditions).[a] Peak Intensity is inferred directly from the SPI values (see table 3.2) and defined in equation 7.15. [b] Drought Magnitude is defined in equation 7.14.

Country	Emission Scenario	GCM	Drought Frequency	Average Duration (months)	Average Peak Intensity[a]	Average Magnitude[b]	% Change in Average Magnitude from Observed
Australia	Observed	--	5	32.8	-1.70	26,524	--
	A1FI (2003-2050)	ECHAM4	11	43.8	-1.73	40,624	64.0
		HADCM3	8	30.9	-1.72	24,465	-7.8
		CSIRO2	3	30.0	-1.82	28,423	7.2
	450ppm (2003-2050)	ECHAM4	11	43.9	-1.75	40,810	53.9
		HADCM3	8	31.4	-1.74	24,925	-6.0
		CSIRO2	3	30.0	-1.84	28,756	8.4
Brazil	Observed	--	3	26.7	-1.73	21,328	--
	A1FI (2003-2050)	ECHAM4	4	54.8	-1.83	39,956	87.3
		HADCM3	4	87.3	-1.73	81,634	282.7
		CSIRO2	2	34.0	-1.78	26,652	25.0
	450ppm (2003-2050)	ECHAM4	6	61.8	-1.85	43,934	106.0
		HADCM3	7	82.1	-1.79	73,186	243.1
		CSIRO2	2	35.0	-1.78	27,091	27.0
China	Observed	--	1	22.0	-2.11	20,499	--
	A1FI (2003-2050)	ECHAM4	1	23.0	-1.92	19,052	-7.1
		HADCM3	1	22.0	-1.76	15,703	-23.4
		CSIRO2	1	22.0	-1.84	16,606	-19.0
	450ppm (2003-2050)	ECHAM4	1	23.0	-1.93	19,135	-6.7
		HADCM3	1	21.0	-1.77	15,440	-24.7
		CSIRO2	1	22.0	-1.84	16,583	-19.1
Ethiopia	Observed	--	1	42.0	-1.67	12,457	--
	A1FI (2003-2050)	ECHAM4	0	0	0	0	-100.0
		HADCM3	1	27.0	-1.59	7,594	-39.0
		CSIRO2	2	48.5	-1.80	17,422	39.9
	450ppm (2003-2050)	ECHAM4	0	0	0	0	-100.0
		HADCM3	1	26.0	-1.59	7,436	-40.3
		CSIRO2	2	48.5	-1.81	17,619	41.4
India	Observed	--	1	25.0	-2.01	13,853	--
	A1FI (2003-2050)	ECHAM4	0	0	0	0	-100.0
		HADCM3	0	0	0	0	-100.0
		CSIRO2	0	0	0	0	-100.0
	450ppm (2003-2050)	ECHAM4	0	0	0	0	-100.0
		HADCM3	0	0	0	0	-100.0
		CSIRO2	0	0	0	0	-100.0
Portugal	Observed	--	6	26	-1.80	1,346	--
	A1FI (2003-2050)	ECHAM4	7	37	-2.13	2,472	83.6
		HADCM3	6	37	-2.01	2,143	59.2
		CSIRO2	4	25	-1.94	1,321	-1.86
	450ppm (2003-2050)	ECHAM4	7	42	-2.22	2,820	109.5
		HADCM3	8	34	-1.98	2,014	49.6
		CSIRO2	4	23	-1.94	1,270	-5.65
Spain	Observed	--	4	22	-1.69	4,039	--
	A1FI (2003-2050)	ECHAM4	3	56	-2.00	13,917	244.6
		HADCM3	2	76	-2.11	17,811	341.0
		CSIRO2	2	42	-1.80	7,925	96.2
	450ppm (2003-2050)	ECHAM4	4	55	-1.95	12,914	219.7
		HADCM3	3	52	-1.96	12,468	208.7
		CSIRO2	2	42	-1.79	7,904	95.7
USA	Observed	--	4	24	-1.67	24,321	--
	A1FI (2003-2050)	ECHAM4	2	30.0	-1.82	20,471	-15.8
		HADCM3	2	35.5	-1.75	54,589	124.5
		CSIRO2	3	36.0	-1.73	46,092	89.5
	450ppm (2003-2050)	ECHAM4	2	30.0	-1.85	20,594	-15.3
		HADCM3	2	35.5	-1.77	54,708	124.9
		CSIRO2	3	36.0	-1.74	46,245	90.1

Table 4.3: As Table 4.2 but for SPI-12 drought events.

4.4 Discussion

The study utilised the IAM CIAS to make future projections of precipitation at a 0.5° x 0.5° resolution for the first half of the 21st century. The projections of precipitation represent a high emission scenario (without mitigation) and stringent stabilisation scenario (with mitigation), and three GCMs. Precipitation data was converted to the SPI in order to identify individual drought events and quantify their magnitude, intensity and duration. The projections of drought magnitude will be directly used to determine the economic and social drought effects, via the drought damage functions. Therefore, it is important to determine the robustness of the results presented.

In order to test the methodological approach the frequency, magnitude, intensity and duration of drought events were quantified for each country, scenario and SPI time period. The results suggest that climate change in the first half of the 21st century could result in worsening drought regimes in Australia (particularly in the south-west), Brazil (particularly in the northeast and northwest), Portugal, and Spain. The effect of climate change on average drought conditions in the USA was more variable depending on the region and the climate scenario used. However, results suggest that changing trends in drought characteristics, particularly for long-term drought events, are likely to be negative. Conversely, results for China, Ethiopia and India suggest that climate change may well cause increased precipitation which could mitigate the frequency and severity of droughts, with very few, if any, severe and extreme drought events projected for 2003-2050. The results also highlighted that climate change is likely to have a larger effect on the duration and magnitude of long-term SPI-12 droughts, with an increase in multi-year drought events projected in Australia, Brazil, Spain, Portugal and the USA. Reported changes in drought characteristics, at a national and regional level, were presented in section 4.3 and reviewed in light of other modelling studies. The results highlighted that the average change in drought trends projected for Australia, Brazil, China, Ethiopia, India, Portugal, Spain and the USA were in line with projections reported by the IPCC (Christensen et al., 2007), as well as other modelling studies reviewed. This is a promising result as it suggests that the SPI and the methodology devised to identify and quantify drought events can accurately capture precipitation change over the first half of the 21st century.

The study also aimed to address some of the uncertainties that arise when modelling future precipitation due to the use of different emission/stabilisation scenarios and climate models. As the study focuses on the first half of the 21st century there was little variability seen between results generated using the A1FI and 450ppm scenarios. As such, the implementation of a stringent mitigation policy is projected to have limited effect on worsening drought conditions from 2003-2050 compared to the A1FI scenario with no mitigation. However, the choice of emission scenario will have a larger effect on drought conditions in the latter half of the 21st century as demonstrated for Spain in figure 4.5. However, even though drought magnitude was significantly reduced after 2050 when assuming stringent mitigation compared to the A1FI scenario, drought magnitude was still notably affected. This finding is in agreement with Warren et al., (In review) who project that even under stringent mitigation scenarios significant increases in drought events may be unavoidable for Spain in the second half of the 21st century.

The study also provided a range of results based on the use of three GCMs. Much of the uncertainty in future projections of drought events, including the direction of change, can be linked to the GCM used (figure 4.6). This finding is consistent with Goodess et al., (2003b) who reports that for the early 21st century inter-model variability tends to be greater than inter-scenario variability. Interestingly, this study found that the uncertainty increased as the SPI time period increased from SPI-6 to SPI-12. The three GCMs used in this study (ECHAM4, HADCM3 and CSIRO2) lie in the low, medium and high range of changes in global average precipitation projections relative to the larger suite of IPCC models used in the IPCC TAR (IPCC, 2001, figure 9.3). As such, it is anticipated that they provide a good representation of the scale of model uncertainty. Whilst the use of three GCMs in this study is an advantage as assessments of future drought events have traditionally only used one GCM (Blenkinsop and Fowler, 2007), they cannot be assumed to fully address uncertainty and a larger range would be required to provide more robust or probabilistic projections.

The study used pre-defined country regions to overcome issues of spatial averaging when assessing future drought events. In order for drought projections in the 21st century to be comparable to past projections, this method was also applied to observed precipitation data from 1955-2002. The method of using pre-defined country regions to identify and quantify regional drought parameters differed from the method used to create the drought damage functions, where past historical droughts were identified and quantified based on information from EM-DAT on the specific states affected. As projections of drought magnitude will be correlated to the drought damage functions, to estimate economic and social effects, it is important to establish if this difference in methodology has a substantial impact on the frequency and characteristics of drought events identified. The frequency of drought events in 1955-2002 generated using the coarse country regions (defined in figure 4.3 and table 4.1), and the frequency of drought events in 1940-2002 generated based on information on the affected states from EM-DAT were compared. Whilst the results were found to be comparable, fewer drought events were identified in the SPI time-series data using the coarse country regions. This result is to be expected as in many cases the coarse country regions encompassed larger areas than the specific states analysed in creating the drought damage functions.

This finding can also be explained by the difference in the SPI threshold used to define a drought (detailed in section 4.2). That is, in creating the drought damage functions the threshold was zero as long as there was a period where negative SPI values could be identified which coincided with the drought details reported in EM-DAT. However, in modelling past and future drought events using the coarse country regions the SPI threshold was set at -1.50, representing severe and extreme drought events, and so some smaller magnitude events that only affected a single state or very small regions of a country were not captured. Conversely, for SPI-6 drought events the use of coarse country regions actually resulted in an increase in drought frequency for Australia and Portugal. For Australia, this was linked to the identification of drought events that occurred prior to 1965 as EM-DAT only reported drought events and impacts from 1967 onwards. For Portugal, it is postulated that the additional drought events that were identified may not have caused significant economic or social losses to meet the EM-DAT criteria or data may not have been available for the event to be included in the database. It is concluded that the use of the coarse country regions enables the largest scale drought events in 1955-2002 and 2003-2050 to be identified. As the focus of this analysis was on severe and extreme drought events only, this methodology is assumed robust. Additionally, future projections of drought trends were in agreement with projections made by the IPCC and other published studies, for all countries assessed. This suggests that the coarse country regions used were effective at capturing spatial patterns of severe and extreme drought.

The methodology also enabled a rudimentary assessment of regional changes in drought trends in the first half of the 21st century. Whilst the use of the coarse regions may not be as accurate as focusing on individual states, as was the case in creating the drought-damage functions, results were promising. Findings for Australia, Brazil, and India were consistent with other published studies whilst results for China and the USA were more uncertain. However, the coarse regions are still relatively large and in the case of Ethiopia, Portugal, and Spain results were analysed at a country level only. Future research may benefit from using smaller, pre-defined geographical regions or state boundaries. This would be particularly beneficial for countries that have varying regional precipitation regimes such as China and the USA. However, it is important to note that the methodology would be less beneficial for identifying drought at smaller spatial and temporal scales as it does not represent small-scale weather processes, local topography, land-use, or hydrological systems such as rivers, catchment areas, dams, or reservoirs that would be required for a study of hydrological drought impacts on this scale. Although precipitation data has been downscaled it is important to note that simply interpolating GCM output to the spatial scale of the higher resolution observed climatology data does not add any information about smaller scale physical processes (Goodess et al., 2003a).

In order to assess drought characteristics the monthly precipitation data was converted to the SPI. The SPI is a relatively simple index, which can be applied universally, and to various time periods to assess the dynamics of different types of drought. The SPI was also considered advantageous for this study as it provides a method for analysing not only the frequency of drought events but also the duration, intensity, and magnitude. Magnitude was found to be a valuable parameter providing a comprehensive measure of drought by combining information on intensity, duration and area affected. The analysis also highlighted that drought magnitude may be a better parameter to use for identifying severe or extreme droughts, rather than using intensity alone. By setting the drought threshold at a SPI value of -1.50 a very slight change in the average SPI value generated by using different emission scenarios could result in a drought being recorded in one case and excluded in the other. For instance, using the same GCM the SPI value could be very low but not exceed the threshold (i.e. a SPI value of -1.49) using one emission scenario, but could fall just on the threshold (i.e. -1.50) using the other emission scenario. Therefore, whilst there was minimal difference in the SPI value one event would be included in the analysis whilst the other would not. Furthermore, it was postulated that the use of the pre-defined SPI threshold would result in only severe and extreme drought events being detected. Yet, the method of setting a pre-defined threshold may limit the definition of a drought event too much to the intensity of drought in a single month and less on the overall magnitude of an event. Thus, an interesting finding is that the use of SPI categories could actually be misleading in some cases when analysing drought events over spatial and temporal scales.

Another advantage of using drought magnitude in this study is that it can avoid the misrepresentation of results seen when focusing on drought frequency or drought duration alone. For example, if future drought events occur over increasingly long periods then the number of events within a fixed time-period may well decrease. For Spain and Portugal, it was projected that there would be almost no change or even a decline in the frequency of SPI-12 drought events in 2003-2050 compared to 1955-2002 (figure 4.4a). This result alone suggests that climate change does not have a large influence on drought frequency in these countries. However, drought duration and intensity are projected to increase substantially during 2003-2050. Warren et al., (In review), who used a similar approach to this study to assess the consequences of climate change on drought frequency and duration in Europe, also highlighted misleading results when using drought frequency alone to assess SPI-12 drought events. Therefore, it is important to view changes in drought frequency and magnitude together to understand the actual trends taking place.

The SPI is advantageous as it is simple to calculate as it is based on precipitation data alone (discussed in section 3.1.1). However, in applying the SPI to future projections of precipitation and drought it is also important to consider the specific case of climate change. Whilst precipitation may be the primary factor in drought occurrence, under climate change high temperatures may have an increasingly large effect on drought events. This is a particularly important issue as it is projected that annual average temperatures increase in all of the countries assessed in this study in the 21st century (IPCC, 2007c). Wilhite (2005) agrees that the effects of future climate change on temperature means that future drought projections will require temperature and precipitation data, even where precipitation was commonly the main variable causing drought. This already appears to be the case in Australia where recent drought events have not been drier than recorded 20th century droughts, but they have reportedly been accompanied by higher temperatures (CSIRO and Australian BoM, 2007).

Changes in temperature, radiation, atmospheric humidity, and wind speed can also affect the amount of evaporation and further exaggerate effects of decreased precipitation on surface water and run-off (IPCC, 2007c, Ch 3). CSIRO and the Australian BoM (2007) state that a drought index based on rainfall deficiency alone will fail to account for the effect of projected increases in potential evaporation, and interactions between precipitation and the water holding capacity of soils, something which is particularly important for assessing agricultural drought and its consequences. Other studies also note the importance of evaporation for future drought projections particularly where the effects of increased temperatures are not offset by increased precipitation (e.g Blenkinsop and Fowler, 2007). However, evaporation over land will also depend largely on the moisture supply and as such is thought closely related to variations in precipitation and run-off at a global scale (IPCC, 2007b). The results from this study are based on precipitation data only and as such, drought parameters for the first half of the 21st century may well be underestimated.

A further advantage of using the SPI is the ability to use different time periods so that the effects of climate change on different types of drought can be assessed. Results of this analysis were presented for two different SPI time-periods: the SPI-6 time-period allowed an assessment of medium-term drought events and is effective at showing changes in precipitation over distinct seasons. The SPI-12 time-period allowed an assessment of long-term drought events and is effective at highlighting specific trends and long term changes in annual precipitation patterns (NDMC, 2006b). As previously mentioned the results highlighted that climate change is likely to have a larger effect on the duration and magnitude of long-term SPI-12 droughts representing greater risk to hydrological systems and water resources. For example, in the USA the effect of climate change in the first half of the 21st century on the average magnitude of SPI-12 droughts was much greater than that seen for SPI-6 drought events. Likewise, the change in average drought magnitude for Brazil was more than three times as great using SPI-12 compared to SPI-6. One explanation may be that the SPI-12 results reflect an average annual decline in precipitation, although this decline may not be evenly distributed over seasons. In comparison, the SPI-6 index will be more sensitive to short-term variability in the volume and intensity of precipitation. Importantly, the averaging of the drought parameters masks large variability in individual drought events.

This is an important issue to consider as increased variability in precipitation is an expected consequence of climate change due to increasing temperature, increases in the water holding capacity of the atmosphere, and increased evaporation affecting and altering the hydrological cycle (discussed in section 1.2). Climate change can also enhance seasonality with precipitation increasing in one season and declining in another (IPCC, 2007c). Areas projected to suffer more drought events in the future may also be at risk from heavy precipitation or flood events. This issue has been highlighted by the IPCC (2007b), and more recently by Hirabayashi et al. (2008) who modelled the change in return period of 110-year flood events from the 20th century to 2001-2031 and 2071-2100. The study showed that some areas including Eastern Europe to central Eurasia, inland China and northern North America showed an increase in drought events and an increase in annual precipitation.

The timing of drought events is also an important factor to consider when assessing the type and scale of effects that may occur. This study did not take into consideration particular seasons affected by drought, or indeed, if there were seasonal changes in the timing of drought events. Additionally, large-scale atmospheric processes such as monsoon rainfall and ENSO events are not well covered by the GCMs or by ClimGen. Consequently, it is important to remember that there are many modelling uncertainties and unknown parameters in projecting future precipitation regimes. For example, uncertainties in future precipitation projections can be caused by a lack of observational data; a lack of regional assessments; complexities in understanding and modelling the influence of large-scale atmospheric processes such as the ENSO, NAO, or tropical cyclone behaviour on precipitation; difficulties in modelling changes in monsoons; uncertainties over feedback processes, e.g. how feedbacks between the Amazonia basin and land use and land-use change could affect regional precipitation; and the success of downscaling techniques for representing precipitation in certain regions (IPCC, 2007c). As such, it is found that precipitation is not well simulated in present GCMs (Kundzewicz et al., 2008).

Finally, it is important to reiterate some of the caveats raised in section 3.4 when creating the drought-damage functions. Namely, that the study assesses meteorological drought only and does not consider other external socio-economic factors that may change in the first half of the 21st century, e.g. increasing populations, increasing demand for water, or increased extraction of groundwater. Likewise, whilst increased water consumption may affect future droughts it is also important to remember that future adaptation to drier conditions (i.e. improved water management systems, increased water storage capacity, and extraction of ground water) may offset some of the threat. As stated previously adaptation is not explicitly modelled. Instead, the analysis focuses on severe and extreme drought only assuming that society will be better able to cope and adapt to moderate drought events.

4.5 Summary

The above chapter has outlined a novel methodological approach for identifying and quantifying SPI-6 and SPI-12 drought events under various scenarios of climate change. The results of the analysis suggest that climate change in the first half of the 21st century could severely affect drought conditions in Australia (particularly in the south-west), Brazil (particularly in the northeast and northwest), Portugal, and Spain. The effect of climate change on average drought conditions in the USA was variable depending on the region and the climate scenario used. However, results suggest that changing trends in drought characteristics, particularly for long-term drought events, are likely to be negative. Conversely, results for China, Ethiopia and India suggest that increases in precipitation may well mitigate the frequency and severity of droughts, with very few, if any, severe and extreme drought events projected during 2003-2050. The results highlight that long-term SPI-12 droughts are particularly vulnerable to climate change. Whilst many modelling uncertainties remain the modelled drought regimes are in line with projections reported by the IPCC (Christensen et al., 2007), as well as other modelling studies reviewed. The use of magnitude as a drought parameter has proved to be highly advantageous. The estimates of drought magnitude will be used in the following chapter to estimate social and economic effects of drought events using the country specific drought damage functions.

5. Economic and Social Drought Effects under Future Climate Change

The previous chapter highlighted how climate change in the first half of the 21st century can affect the frequency, duration, magnitude and intensity of drought events. The following chapter focuses on estimating the economic and social effects that could occur, given such changes in drought characteristics, for the first half of the 21st century. The estimates of economic and social drought effects form a major output of this study. Section 5.1 outlines the methodological approach for estimating future economic damages and social effects of drought events via the novel drought damage functions. Section 5.2 presents the results of the analysis for economic damages (5.2.1) and social effects (5.2.2). Section 5.3 provides a discussion of the main findings and the chapter is summarised in section 5.4.

5.1 Estimating future economic and social effects of drought

Estimates of direct economic drought damages are made using the drought damage functions presented in chapter three. The country specific drought damage functions link the magnitude of individual drought events to reported impact data on economic damages, and the number of lives lost and affected. The magnitude of individual drought events, identified in the 1955-2002 and the 2003-2050 time periods (chapter four), can therefore be used to estimate the direct economic costs of each individual drought event and the consequences that such an event would have on society.

In order to compare historical drought events economic damages were normalised to 2002 US$ when creating the damage functions. Consequently, future estimates of drought costs based on the drought damage functions are presented in the same metric and the estimation of future economic losses is based on the assumption of a static economy. This is a similar approach to that used in impact analysis studies which focus on the damage costs of climate change, both for direct (e.g. Ciscar et al., 2011, Nordhaus, 1991, Tol, 2002a), and indirect economic loss estimation (e.g. Hallegatte, 2007, Hallegatte et al., 2011, Ranger et al., 2011). Similarly, the 14 peer-reviewed studies of global costs of climate change reviewed by Tol (2009) assume static socio-economic conditions. As such, the economic estimates presented do not have a time dimension but are related to a change in global mean warming. Using a standard metric across time is beneficial as it avoids the need for economic costs to be discounted (as discussed in section 2.2), and means the focus of the economic analysis will be on changing economic costs due to climate change rather than effects of changing socio-economic conditions. Thus, normalised damages remove the influence of economic growth and allow the results to be interpreted in terms of changing climate only. Similarly, the effects of drought events on lives lost and lives affected are assumed to affect countries with static populations at 2002 levels.

However, as discussed in section 3.2 normalising economic data by adjusting for inflation based on a countries changing GDP is a relatively simple way to account for changing economic conditions which does not take into account changes in wealth, assets at risk, or changing populations. As the drought damage functions will be applied to drought events occurring in the future the countries studied may have undergone further changes in their socio-economic structure. There are merits to using future economic scenarios of GDP to estimate the changing assets at risk. However, uncertainties over such changes are extremely high as GDP trends will depend on specific economic assumptions made about growth and the implementation of technological changes; the characteristics of the economic model used to project GDP; and assumptions about future exchange rates (Arnell et al., 2004). To address the sensitivity of results to different GDP projections numerous economic scenarios of annual GDP would also be required for each individual country. Additionally, whilst increased economic growth may increase assets at risk and exposure it can also lead to an increase in resilience in the affected economy so a country is more able to cope in the disaster aftermath (Benson and Clay, 2004). Such complex issues are extremely difficult to model, project and quantify.

Whilst the assumption of a static economy and population in the future is improbable, the method does allow a first estimate of drought damages under future climate change to be made. As noted by Tol (2002a) this is a necessary first step in estimating future impacts of climate change. As well as assuming that the economy and population of countries assessed is static, and socio-economic vulnerability will remain constant over time, the study also assumes no change in adaptation to drought events. Mitigation is explicitly considered in the E3MG 450ppm scenario.

5.2 Results

5.2.1 Direct economic drought costs

Direct economic damages from drought events were estimated based on the magnitude of individual drought events identified in the SPI time-series data, for each SPI time-period, country and scenario. Direct economic damages are presented as average annual costs for the observed data (1955-2002) and future data (2003-2050), for each scenario. Results are presented as *annual* costs (i.e. the sum of economic damages from all drought events reported divided by the *number of years*) as the methodology does not aim to explicitly present projections of economic damages of individual events for a given time and region. It is important to distinguish the difference from the drought characteristics reported in chapter four (section 4.3) that were presented as *average* changes (i.e. the sum of the drought parameters form all drought events reported divided by the *number of drought events*).

Figure 5.1 presents the percentage change in annual direct economic damages from 1955-2002 to 2003-2050 comparing results for the countries assessed and based on the SPI time periods. As the results are derived from the drought magnitude data the general trends reflect those previously reported, and while results are presented at a country level the economic effects are centred on the regions highlighted as ‘hot spots’ (section 4.3). Figure 5.1 highlights how the range of economic estimates can vary significantly, even being of a different sign, depending on the particular scenario used. It also presents the average result (black cross) of the six scenario runs for each country. No estimates are provided for Ethiopia, as it was not possible to create a drought damage function due to a lack of historical economic data, or Brazil, due to the very weak trend seen in the economic drought damage function. The results used to create figure 5.1 and subsequently discussed in this section are presented in tables 5.1 and 5.2 below. Economic damages are reported in 2002 US$ (000’s) and are representative of direct damage from droughts categorised as severe and extreme only.

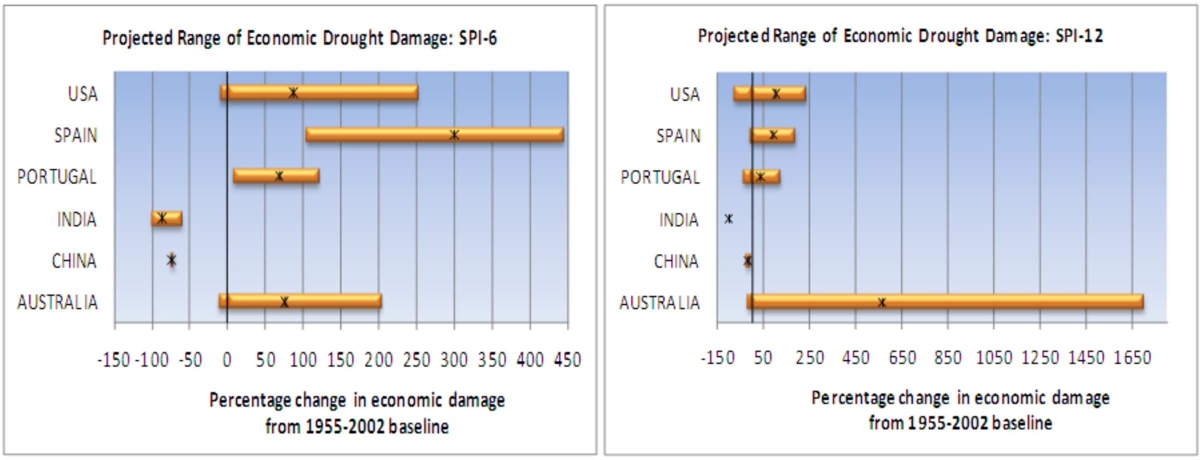


Figure 5.1: Percentage change in annual economic damages for 2003-2050 compared to 1955-2002 modelled using the GCMs ECHAM4, HADCM3 and CSIRO2 and the A1FI and 450ppm scenarios. Black crosses indicate average values (left: SPI-6 drought events, right: SPI-12 drought events).

Figure 5.1 indicates that average annual economic drought damages are projected to increase for both SPI-6 and SPI-12 drought events in Australia. Across the range of scenarios, the mean percentage change in economic damages is estimated to increase by 76% and 565%, for SPI-6 and SPI-12 drought events in 2003-2050. In a worst-case scenario the results suggest that annual drought losses may increase three-fold from 1.0bn US$ in 1955-2002 to 3bn US$ in 2003-2050 for SPI-6 drought events. For SPI-12 droughts losses would be particularly devastating, increasing from 1.95bn US$ to 35bn US$ in 2003-2050. Figure 5.1 shows that the percentage change in annual economic damages for SPI-12 drought events has an extremely large range depending on the scenario used. This range reflects the extremely large drought magnitude of individual events projected using the GCM ECHAM4 and the projected decline in magnitude of drought events using HADCM3 (highlighted in table 4.3). As the economic drought damage function for Australia is exponential, the costs estimated for exceptionally large drought events have a big effect on the annual estimates.

Presenting results as annual losses masks the variability in the scale of individual drought events. The analysis highlights that the largest magnitude individual drought events could cost the Australian economy 37bn US$ for SPI-6 droughts alone. To put this into perspective the 1981-1982 and 2002-03 drought events were estimated to cost ~12.9bn and ~7.9bn US$ respectively (CSIRO and Australian BoM, 2007, EM-DAT, 2010) hence the cost of individual drought events are projected to rise dramatically in the future. More importantly, the largest magnitude SPI-12 drought event was projected to cost 701bn US$. This value is greater than the entire Australian Economy in 2002 and highlights a serious problem with over-estimating economic damages of drought events at the extreme end of the range. This can be linked to the shape and scale of the exponential damage function used, which in turn was based on limited data points, and the assumption that the trend identified would remain constant for drought events outside the range of historical experience. To demonstrate this issue, economic drought damages were also estimated for Australia assuming a linear damage function. Whilst this had limited effect on estimates of damages from SPI-6 drought events, damages caused by large magnitude SPI-12 droughts were substantially less. For example, the largest magnitude SPI-12 drought event was projected to cost 31bn US$ assuming a liner damage function compared to 701bn US$ estimated using the exponential damage function.

In China average annual economic drought damages were projected to decrease in the first half of the 21st century, declining by 74% and 17% for SPI-6 and SPI-12 drought events respectively. This represents an annual decline in drought losses from 883 million US$ in

1955-2002 to 220-245 million US$ in 2003-2050 for SPI-6 drought events, and from 579 million US$ in 1955-2002 to 436-540 million US$ in 2003-2050 for SPI-12 drought events. There is good consistency across the six scenarios for both SPI-6 and SPI-12 drought events, with all scenarios resulting in a decline in economic damages. Figure 5.1 shows that the range in results is also very small which can be explained by the fact that only one future drought event was visible in the SPI-6 and SPI-12 data for all scenarios (shown in tables 4.2 and 4.3). Similarly, mean precipitation was projected to increase in India in the first half of the 21st century with drought events projected to decline. Drought events of a severe or extreme nature were only projected to occur using the GCM CSIRO2 and for the SPI-6 time-period (tables 4.2 and 4.3), hence the small range seen in figure 5.1. Average annual economic drought damages in India were projected to decrease by 87% and 100% for SPI-6 and SPI-12 drought events respectively. This represents a decline in annual drought losses from 71 million US$ in 1955-2002 to between 0-28 million US$ in 2003-2050 for SPI-6 drought events, and from 16 million US$ in 1955-2002 to zero costs in 2003-2050 for SPI-12 drought events.

Results for Spain suggest that average annual economic drought damages could increase by 300% for SPI-6 droughts and by 92% for SPI-12 droughts. In a worst case scenario annual drought losses may increase from 330 million US$ in 1955-2002 to 1.8bn US$ in 2003-2050 for SPI-6 drought events, and from 375 million US$ in 1955-2002 to 1.1bn US$ in 2003-2050 for SPI-12 drought events. There is good consistency across the six scenarios for both SPI-6 and SPI-12 drought events, with all scenarios resulting in an increase in economic damages for the region. The use of annualised data hides some significant variability in the economic damages of individual drought events. For example the largest magnitude events identified in the SPI data were estimated to cost Spain 25.5bn US$ for SPI-6 droughts and 26.9bn US$ for SPI-12 droughts, reflecting approximately 4% of the country's GDP (in 2002). These values are significantly larger than the historic estimates of drought damages reported by EM-DAT, with the most expensive drought on record estimated to have cost Spain 5.9bn US$. Similarly, average annual economic damages are projected to increase in Portugal by 69% for SPI-6 droughts and by 38% for SPI-12 droughts. The average percentage change in annual drought damages are higher for SPI-6 drought events for both Spain and Portugal, compared to SPI-12 drought events, due to the higher frequncy of SPI-6 drought events.

In the USA, average annual economic damages are projected to increase for both SPI-6 and SPI-12 drought events, increasing by 87% and 105% respectively. In a worst-case scenario the results suggest that annual drought losses may increase from 5bn US$ in 1955-2002 to

17.5bn US$ in 2003-2050 for SPI-6 drought events, and from 35bn US$ in 1955-2002 to 119bn US$ in 2003-2050 for SPI-12 drought events. Additionally, as the shape of the drought damage function for the USA was non-linear the costs estimated for exceptionally large magnitude events have a big effect on the annual estimates. Presenting results as annual losses masks such variability in the scale of individual drought events. The analysis highlights that the largest magnitude individual drought events could cost the US economy around 392bn US$ for SPI-6 drought. In comparison, the drought event in 1980-81 which affected central and eastern parts of the USA resulted in estimated economic losses of ~208bn US$ (EM-DAT, 2010). Thus, economic damages of individual drought events may be devastatingly high under future climate change. The largest magnitude SPI-12 drought event was projected to cost 5,455bn US$, equivalent to 50% of US GDP. In contrast the same drought event was estimated to cost 920bn US$ if a linear damage function was assumed. As was the case for Australia, this suggests that economic damages of drought events at the extreme end of the range may be over-estimated. This issue appears particularly pronounced when using a non-linear damage function as it is assumed that the trend identified would remain constant for drought events outside the range of historical experience.

Tables 5.1 and 5.2 show the estimated annual SPI-6 and SPI-12 drought costs for the observed (1955-2002) and future (2003-2050) periods, for each country and climate/emission scenario. Results in orange font highlight an increase in drought costs from the baseline period and results in blue font highlight a decrease in drought costs from the baseline. The tables highlight the large range in results gained using different GCMs compared to the similarities in results across the two emission/stabilisation scenarios.

Country	Emission Scenario	GCM	Estimated Annual Drought Cost (2002 US$ 000's)	Absolute Change in Annual Drought Cost from observed to 2003-2050 (2002 US$ 000's)	Percentage change in Annual Drought Cost from observed to 2003-2050 (2002 US$ 000's)
Australia	Observed	--	1,030,619	--	--
	A1FI (2003-2050)	ECHAM4	2,691,787	1,661,167	161%
		HADCM3	1,597,934	567,315	55%
		CSIRO2	905,399	-125,220	-12%
	450ppm (2003-2050)	ECHAM4	3,123,693	2,093,074	203%
		HADCM3	1,626,592	595,973	58%
		CSIRO2	910,129	-120,490	-12%
China	Observed	--	882,617	--	--
	A1FI (2003-2050)	ECHAM4	242,293	-640,324	-73%
		HADCM3	220,506	-662,111	-75%
		CSIRO2	225,876	-656,740	-74%
	450ppm (2003-2050)	ECHAM4	244,817	-637,799	-72%
		HADCM3	221,337	-661,279	-75%
		CSIRO2	225,726	-656,891	-74%
India	Observed	--	70,720	--	--
	A1FI (2003-2050)	ECHAM4	0	0	-100%
		HADCM3	0	0	-100%
		CSIRO2	28,011	-42,710	-60%
	450ppm (2003-2050)	ECHAM4	0	0	-100%
		HADCM3	0	0	-100%
		CSIRO2	28,022	-42,698	-60%
Portugal	Observed	--	376,195	--	--
	A1FI (2003-2050)	ECHAM4	824,232	448,037	119%
		HADCM3	698,521	322,325	86%
		CSIRO2	406,433	30,237	8%
	450ppm (2003-2050)	ECHAM4	802,666	426,470	113%
		HADCM3	665,850	289,655	77%
		CSIRO2	406,173	29,978	8%
Spain	Observed	--	329,655	--	--
	A1FI (2003-2050)	ECHAM4	1,790,998	1,461,343	443%
		HADCM3	1,678,716	1,349,061	409%
		CSIRO2	672,134	342,479	104%
	450ppm (2003-2050)	ECHAM4	1,640,530	1,310,875	398%
		HADCM3	1,457,221	1,127,566	342%
		CSIRO2	671,118	341,463	104%
USA	Observed	--	5,011,213	--	--
	A1FI (2003-2050)	ECHAM4	6,340,576	1,329,363	27%
		HADCM3	4,511,781	-499,432	-10%
		CSIRO2	17,558,660	12,547,447	250%
	450ppm (2003-2050)	ECHAM4	6,569,432	1,558,219	31%
		HADCM3	4,494,265	-516,948	-10%
		CSIRO2	16,774,378	11,763,165	235%

Table 5.1: Economic estimates of future SPI-6 drought events. Results in orange symbolise an increase in drought costs, results in blue symbolise a decrease in drought costs from the baseline. Economic damages are in 2002 US$ (000's).

Country	Emission Scenario	GCM	Estimated Annual Drought Cost (2002 US$ 000's)	Absolute Change in Annual Drought Cost from observed to 2003-2050 (2002 US$ 000's)	Percentage change in Annual Drought Cost from observed to 2003-2050 (2002 US$ 000's)
Australia	Observed	--	1,956,644	--	--
	A1FI (2003-2050)	ECHAM4	33,717,025	31,760,381	1623%
		HADCM3	2,877,107	920,463	47%
		CSIRO2	1,560,497	-396,147	-20%
	450ppm (2003-2050)	ECHAM4	35,152,379	33,195,735	1697%
		HADCM3	3,132,850	1,176,207	60%
		CSIRO2	1,623,617	-333,027	-17%
China	Observed	--	578,869	--	--
	A1FI (2003-2050)	ECHAM4	537,897	-40,972	-7%
		HADCM3	443,118	-135,751	-23%
		CSIRO2	468,667	-110,202	-19%
	450ppm (2003-2050)	ECHAM4	540,264	-38,605	-7%
		HADCM3	435,655	-143,214	-25%
		CSIRO2	468,028	-110,840	-19%
India	Observed	--	16,111	--	--
	A1FI (2003-2050)	ECHAM4	0	0	-100%
		HADCM3	0	0	-100%
		CSIRO2	0	0	-100%
	450ppm (2003-2050)	ECHAM4	0	0	-100%
		HADCM3	0	0	-100%
		CSIRO2	0	0	-100%
Portugal	Observed	--	213,635	--	--
	A1FI (2003-2050)	ECHAM4	306,042	92,407	43
		HADCM3	316,702	103,067	48
		CSIRO2	140,271	-73,364	-34
	450ppm (2003-2050)	ECHAM4	471,563	257,928	121
		HADCM3	400,069	186,434	87
		CSIRO2	135,873	-77,762	-36
Spain	Observed	--	374,575	--	--
	A1FI (2003-2050)	ECHAM4	919,643	545,068	146
		HADCM3	780,950	406,375	108
		CSIRO2	354,799	-19,776	-5
	450ppm (2003-2050)	ECHAM4	1,071,282	696,707	186
		HADCM3	825,978	451,404	121
		CSIRO2	353,915	-20,660	-6
USA	Observed	--	35,811,162	--	--
	A1FI (2003-2050)	ECHAM4	7,243,484	-28,567,678	-80%
		HADCM3	93,896,437	58,085,275	162%
		CSIRO2	118,451,286	82,640,124	231%
	450ppm (2003-2050)	ECHAM4	7,243,078	-28,568,085	-80%
		HADCM3	93,961,890	58,150,728	162%
		CSIRO2	119,463,443	83,652,281	234%

Table 5.2: As table 5.1 but for SPI-12 drought events.

Table 5.3 presents average annual economic drought damages as a percentage of each country's GDP (with minimum and maximum values in brackets), based on economic data from the World Bank (2010). Losses are particularly severe for SPI-12 droughts in Australia, which cause average losses equivalent to 3.38% of the country's GDP, or 9.13% of GDP in a worst-case scenario. Losses in Portugal are projected to be large, costing on average 0.53% and 0.25% of GDP annually for SPI-6 and SPI-12 droughts respectively. Losses for the USA differ between SPI time-periods with average economic losses of 0.09% for SPI-6 droughts and 0.71% for SPI-12 droughts. Losses that are more substantial are seen using the SPI-12 time-period with losses in the worst-case scenario reaching 1.15% of the country's GDP. However, projected economic losses for SPI-12 droughts in Australia and the USA must be used with caution due to the potential issues of over-estimation of damages as mentioned above. For comparative purposes, estimates for the USA and Australia generated using hypothetical linear damage functions are also displayed in table 5.3.

Country	**Average annual % loss of GDP from future drought events (*min, max*)**	
	SPI-6	**SPI-12**
Australia	0.47 (*0.24, 0.81*)	3.38 (*0.41, 9.13*)
Australia (linear)	0.43 (*0.27, 0.65*)	0.46 (*0.16, 0.85*)
China	0.02 (*0.02, 0.02*)	0.03 (*0.03, 0.04*)
India	0.002 (*0.00, 0.01*)	0.00 (*0.00, 0.00*)
Portugal	0.53 (*0.34, 0.69*)	0.25 (*0.11, 0.34*)
Spain	0.20 (*0.10, 0.27*)	0.11 (*0.05, 0.16*)
USA	0.09 (*0.04, 0.17*)	0.71 (*0.07, 1.15*)
USA (linear)	0.10 (*0.07, 0.16*)	0.16 (*0.06, 0.23*)

Table 5.3: Average annual economic drought damages in 2003-2050 as a percentage of country GDP (in 2002 US$). Numbers in brackets represent the minimum and maximum range. Results in green font for Australia and the USA are estimated using linear, rather than non-linear, damage functions.

Additionally, the average annual economic drought losses are summed across the six countries analysed and compared to *global* GDP. Figure 5.2 displays the losses from the six countries as a percentage of global GDP for SPI-6 and SPI-12 droughts, and for each of the scenarios. For comparison, the dotted lines represent the average annual drought losses as a percent of global GDP calculated for 1955-2002 for SPI-6 and SPI-12 drought events. The graph shows that for SPI-6 droughts economic losses in the six countries assessed, for 1955-2002, are equivalent to 0.02% of global GDP. This increases under all the climate change scenarios, ranging from 0.03% to 0.06% of global GDP in 2002. Economic costs for SPI-12 drought events during 1955-2002 are equivalent to 0.12% of global GDP. This also increases under the climate change scenarios ranging from 0.13% to 0.37% of global GDP in the future. The results highlight that drought events across the six countries are expected to have an increasingly negative impact on global GDP in the first half of the 21st century, potentially costing 122bn US$ on average a year in a worst case scenario. The benefits of reduced drought effects seen in India and China are outweighed by the increasing economic damages in Australia, Spain, Portugal and the USA, with all scenarios resulting in greater losses as a proportion of global GDP compared to the 1955-2002 period.

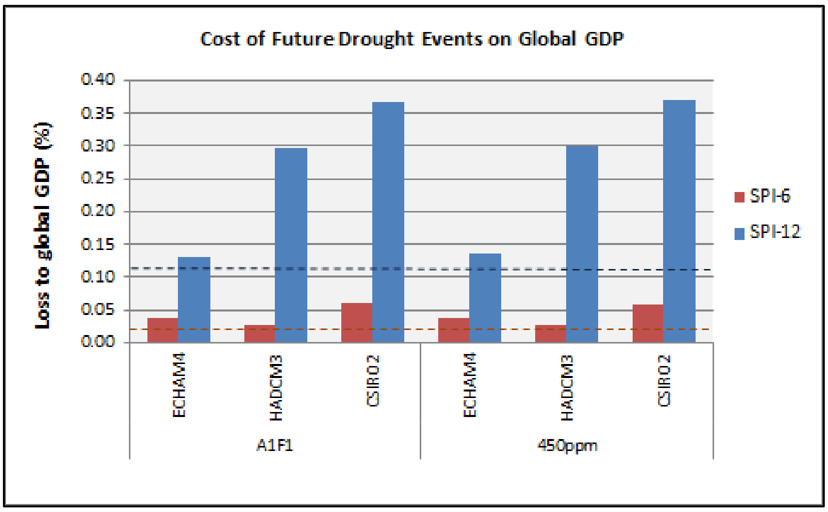


Figure 5.2: Average annual direct economic costs of SPI-6 and SPI-12 drought events in Australia, China, India, Portugal, Spain, and the USA presented as a percentage of global GDP (2002 US$), for various scenarios. The dotted lines represent the 1955-2002 losses for both SPI-6 (red) and SPI-12 (blue) drought events as a comparison.

Importantly, figure 5.2 represents economic drought losses for six countries *only* as a proportion of *global* GDP. It was not considered feasible to extrapolate the estimates of economic drought costs for the six countries assessed to other countries to provide a truly global estimate as the above results were generated based on country specific drought impact data, and regional projections of future precipitation. Nevertheless, considering drought effects under future climate change to just a handful of countries still results in noticeable effects on global GDP.

Whilst few studies aim to assess the global economic effects of climate change on extreme weather events, Stern (2007) reported that extreme weather events would cause additional losses of 0.5-1.0% of world GDP by 2050 (above changes in wealth and inflation). This estimate was assumed to cover all types of extreme weather events across the entire globe. Whilst there is much argument as to the validity of this estimate (see section 2.4.2), it is used for comparative reasons in this study due to a lack of other global indicators specifically focused on extreme weather events. In comparison, the results presented in figure 5.2 indicate that severe and extreme SPI-6 and SPI-12 drought events alone could cause additional losses to global GDP of 0.01% to 0.25% annually. These losses are lower than estimated by Stern, but they reflect drought losses only (compared to multiple extreme weather types), and as discussed above they reflect losses to six countries only (compared to Stern who provided a global estimate). As such, it is highly possible that if the estimates of economic drought damages were made for more countries then this could substantially increase the estimate of Stern for total global costs of extreme weather events under future climate change. The limitations of the methodology in terms of estimating global economic drought damages are discussed in more depth in section 5.3 below.

Comparatively, figure 5.3 displays the losses from the six countries as a percentage of global GDP for SPI-6 and SPI-12 droughts, for each of the scenarios, using the damages estimated for Australia and the USA using the hypothetical linear drought damage functions. In this example, losses as a proportion of global GDP still increase from 1955-2002 to 2003-2050 for SPI-6 droughts under all scenarios. Economic costs for SPI-12 drought events also increase in the future using the GCMs HADCM3 and CSIRO2, although costs are less significant than presented in figure 5.2. However, estimated losses from SPI-12 drought events in 2003-2050 actually decrease compared to 1955-2002 using the GCM ECHAM4. This again highlights the importance of the shape of the drought damage function when estimating future drought costs, as well as the variability in results generated using different climate change models. Implications for this study of the shape of the damage functions and the assumption that the trends will remain unchanged over time are discussed in more detail in section 5.3 below.

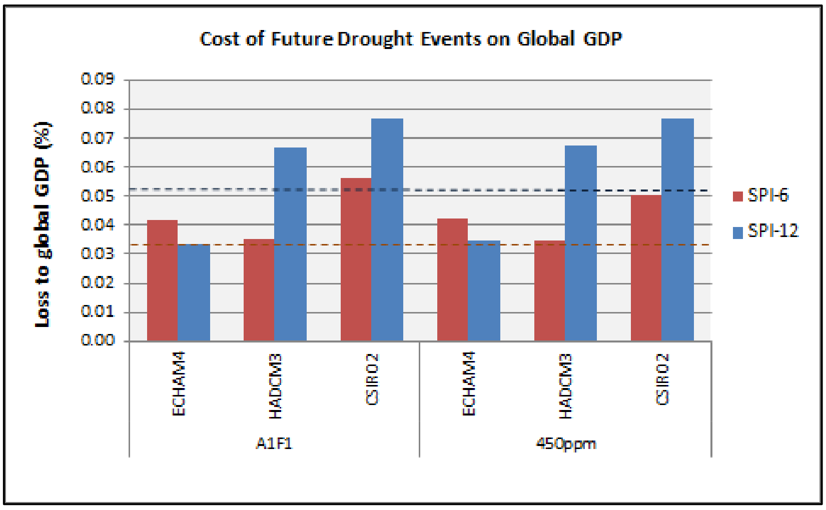


Figure 5.3: As figure 5.2 but economic damages for Australia and the USA are estimated using linear rather than non-linear damage functions.

5.2.2 Social drought effects

The social drought damage functions presented in chapter three for lives affected and lives lost (figures 3.4 and 3.5) were generally not as robust as the economic damage functions. Less social impact data was available in EM-DAT on which to base trends and for Australia, Portugal and Spain no social damage functions were created at all. It was also hypothesised that external factors would be influential on the numbers of lives affected and lost during a drought, in addition to the magnitude of the event. However, this section aims to provide an illustrative example of the potential application of the social drought damage functions for those countries where relationships between drought magnitude and social impact data were identified. Estimates of the numbers of lives affected by drought under future climate change are presented for Brazil and Ethiopia. Estimates of the numbers of lives lost due to drought under future climate change are provided for the USA. Additionally, as estimates of economic drought damages could not be made for Brazil and Ethiopia it is interesting to assess the social consequences for these countries, and provide some indication of the effects that may be felt using different metrics.

Figure 5.4 presents the average annual number of people affected by severe and extreme drought events in Brazil and Ethiopia estimated for 1955-2002 and 2003-2050. The results presented for 2003-2050 are representative of the average value taken across the six climate/emission scenarios. The results used to generate figure 5.4 and discussed below are presented in tables 5.4 and 5.5 for SPI-6 and SPI-12 droughts respectively. The data tables provide the estimated annual numbers of lives affected, the absolute change in the number of lives affected from 1955-2002 to 2003-2050, and the percentage change in lives affected.

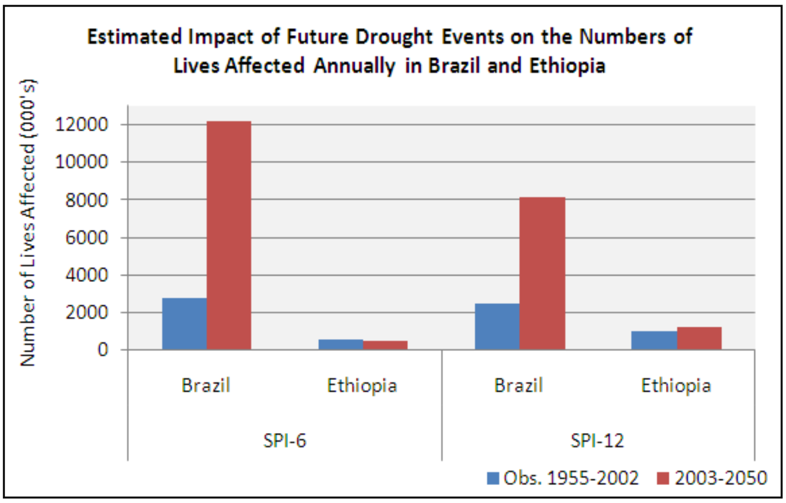


Figure 5.4: Estimates of the annual number of people affected by SPI-6 and SPI-12 drought events in 1955-2002 and 2003-2050 for Brazil and Ethiopia.

In Brazil under future scenarios of climate change there is a large increase in the number of lives affected annually by drought. For SPI-6 the number of lives affected annually increases from 2.8 million people to 12.2 million people, an increase of 334%. For SPI-12 the number of lives affected annually increases from 2.5 million people to 8.1 million people, an increase of 230%. Whilst the changes in drought characteristics for Brazil presented earlier (tables 4.2 and 4.3) showed a larger increase in the magnitude of SPI-12 droughts compared to SPI-6 droughts, SPI-6 droughts are projected to occur more frequently which results in a larger number of lives being affected annually. The population of Brazil in 2002 was ~179 million (World Bank, 2010), as such *ceteris paribus* the effect of climate change on future drought events in the first half of the 21st century could potentially affect 4.5 to 6.8% of Brazils population annually.

The social effects of drought events projected for Ethiopia are less severe compared to those seen in Brazil, as precipitation in Ethiopia is projected to increase rather than decrease in the first half of the 21st century. Results indicate different directions in the change in trends depending on the SPI time-period used. For SPI-6 droughts less people are affected annually in the first half of the 21st century with 506,000 people affected compared to 548,000 people in 1955-2002. For SPI-12 droughts 1.2 million people are affected annually compared to 1 million people in 1955-2002. Ethiopia's population in 2002 was reported as

~69 million (World Bank, 2010) therefore *ceteris paribus* drought events in the first half of the 21st century could potentially affect 1.7% of Ethiopia's population annually in a worst-case scenario.

Country	Emission Scenario	GCM	Estimated number of lives affected annually (2002 population) (000's)	Absolute change in number of lives affected annually from observed to 2003-2050 (2002 population) (000's)	Percentage change in number of lives affected annually from observed to 2003-2050 (2002 population) (000's)
Brazil	Observed	--	2,810	--	--
	A1FI (2003-2050)	ECHAM4	8,157	5,347	190%
		HADCM3	16,683	13,873	494%
		CSIRO2	3,175	365	13%
	450ppm (2003-2050)	ECHAM4	12,844	10,034	357%
		HADCM3	29,227	26,417	940%
		CSIRO2	3,190	380	14%
Ethiopia	Observed	--	548	--	--
	A1FI (2003-2050)	ECHAM4	0	-548	-100%
		HADCM3	0	-548	-100%
		CSIRO2	1,428	880	160%
	450ppm (2003-2050)	ECHAM4	0	-548	-100%
		HADCM3	0	-548	-100%
		CSIRO2	1,607	1,059	193%

Table 5.4: Number of lives affected annually by SPI-6 drought events. Results in orange symbolise an increase in drought effects, results in blue symbolise a decrease in drought effects from the baseline. Lives affected are in 000's normalised to 2002 population.

Country	Emission Scenario	GCM	Estimated number of lives affected annually (2002 population) (000's)	Absolute change in number of lives affected annually from observed to 2003-2050 (2002 population) (000's)	Percentage change in number of lives affected annually from observed to 2003-2050 (2002 population) (000's)
Brazil	Observed	--	2,462	--	--
	A1FI (2003-2050)	ECHAM4	5,802	3,340	136%
		HADCM3	11,439	8,977	365%
		CSIRO2	2,002	-461	-19%
	450ppm (2003-2050)	ECHAM4	9,511	7,048	286%
		HADCM3	18,019	15,557	632%
		CSIRO2	2,031	-431	-18%
Ethiopia	Observed	--	1,022	--	--
	A1FI (2003-2050)	ECHAM4	0	-1,022	-100%
		HADCM3	553	-469	-46%
		CSIRO2	3,167	2145	210%
	450ppm (2003-2050)	ECHAM4	0	-1,022	-100%
		HADCM3	539	-484	-47%
		CSIRO2	3,217	2195	215%

Table 5.5: As table 5.4 but for SPI-12 drought events.

Secondly, the effect of climate change on drought regimes and the numbers of lives lost are investigated for the USA. The social drought damage function created for the USA highlighted very good correlation between the number of lives lost and the drought magnitude of historical events (figure 3.5c) suggesting that drought magnitude has historically had a large influence on the number of lives lost. Figure 5.5 presents the average annual number of lives lost from drought events in the USA for 1955-2002 and for 2003-2050. The results presented for 2003-2050 represent the average value taken across the six emission/climate scenarios. The results used to generate figure 5.5 and discussed below are presented in tables 5.6 and 5.7 for SPI-6 and SPI-12 droughts respectively.

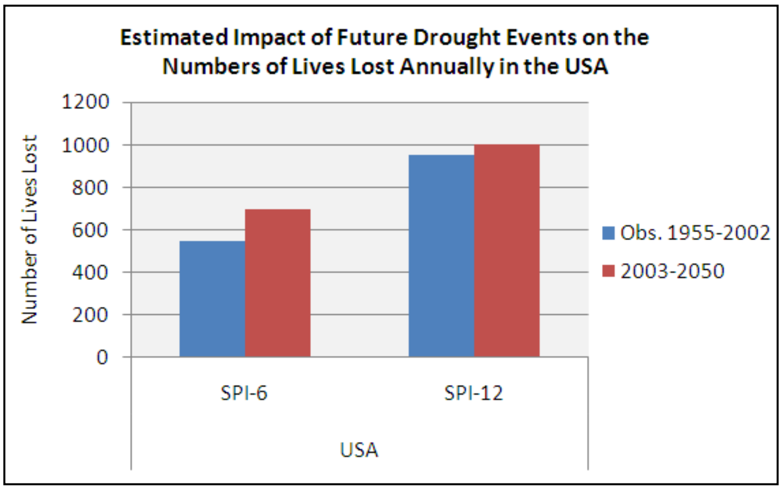


Figure 5.5: Estimates of the average annual number of lives lost from SPI-6 and SPI-12 drought events in the USA for 1955-2002 and 2003-2050.

Figure 5.5 indicates that effects of climate change on drought events may cause an increase in drought related deaths in the USA in 2003-2050 for both SPI-6 and SPI-12 droughts. The annual number of lives lost is projected to rise from 550 people per year to 701 people per year using SPI-6, and from 951 people per year to 1,002 people per year using SPI-12. This represents an increase of 27% and 5% respectively. Compared to the size of the population of the USA (reported as ~304 million people in 2002 (World Bank, 2010)) this change may seem negligible, however it still represents an additional 50 to 150 deaths per year over 2003-2050 due to the effects of climate change on drought regimes. It is very difficult to clarify from the EM-DAT database, and wider literature, the specific circumstances for lives lost during drought in the USA. As previously discussed in section 3.3 primary factors appear to be deaths due to heat stress, or indirectly due to wildfires. Therefore estimates of drought related deaths are likely to represent more complex interactions between drought, heatwaves, forest fires, air quality, society and environmental conditions. Although potentially confounding events such as more intense or frequent heatwaves are not specifically modelled here Meehl and Tebaldi (2004) highlight that many areas currently susceptible to heatwaves are likely to experience the greatest increases in heatwave severity in the future. Additionally, areas not currently susceptible to heatwave, which are at risk in the future, may be more vulnerable as they are not currently so well adapted to heatwaves. As such, these issues may exaggerate the above estimates of drought effects on society.

Conversely, it was stated in the introduction that global trends in the numbers of lives lost from drought events have been steadily declining over the 20th and early 21st century (EM-DAT, 2010). This decline may in part be related to adaptive capacity of society, possibly due to greater wealth, increasing technological options such as early warning systems and drought resistant crops, and quick government, international and aid agency responses in the event aftermath. Such issues are not considered here which may result in the overestimation of losses to life. However, it is also important to consider that climate change may cause increases in drought magnitude beyond current levels of human experience, which could surpass current levels of resilience and adaptability.

Country	Emission Scenario	GCM	Estimated number of lives lost annually (2002 population) (000's)	Absolute change in number of lives lost annually from observed to 2003-2050 (2002 population) (000's)	Percentage change in number of lives lost annually from observed to 2003-2050 (2002 population) (000's)
USA	Observed	--	550	--	--
	A1FI (2003-2050)	ECHAM4	575	25	5%
		HADCM3	502	-48	-9%
		CSIRO2	1,085	535	97%
	450ppm (2003-2050)	ECHAM4	582	32	6%
		HADCM3	503	-47	-9%
		CSIRO2	958	408	74%

Table 5.6: Annual number of lives lost from SPI-6 drought events. Results in orange symbolise an increase in drought effects, results in blue symbolise a decrease in drought effects from the baseline. Lives lost are in 000's normalised to 2002 population.

Country	Emission Scenario	GCM	Estimated number of lives lost annually (2002 population) (000's)	Absolute change in number of lives lost annually from observed to 2003-2050 (2002 population) (000's)	Percentage change in number of lives lost annually from observed to 2003-2050 (2002 population) (000's)
USA	Observed	--	951	--	--
	A1FI (2003-2050)	ECHAM4	388	-563	-59%
		HADCM3	1,160	209	22%
		CSIRO2	1,452	501	53%
	450ppm (2003-2050)	ECHAM4	391	-560	-59%
		HADCM3	1,163	212	22%
		CSIRO2	1,457	506	53%

Table 5.7: As table 5.6 but for SPI-12 drought events

5.3 Discussion

The chapter presents estimates of the economic and social effects of severe and extreme drought events under future climate change, based on the drought damage functions and future drought magnitude presented in chapters three and four. Economic damages were estimated for Australia, China, India, Portugal, Spain and the USA. The results suggest the effects of climate change on drought events are likely to cause negative economic damages for Australia, Portugal, Spain and the USA. Economic estimates for China and India suggest that both countries would benefit economically from a reduction in drought frequency and magnitude due to an intensification of their precipitation regimes. The effect of climate change on precipitation regimes in China is beneficial in regards to the mitigation of severe and extreme drought events and the economic damages they impose, which has also been noted by other authors (e.g. Chen and Sun, 2009). However, when damages are summed across the six countries and represented as a percentage of global GDP the reduction in economic damages seen in China and India are outweighed by increasing costs in other countries. There is consensus across the six scenarios, and for both SPI-6 and SPI-12 time-periods, that climate change in the first half of the 21st century results in greater annual losses to global GDP due to drought than during 1955-2002. The results presented in figure 5.2 indicate that severe and extreme SPI-6 and SPI-12 drought events could cause additional losses to global GDP of 0.01% to 0.25% annually.

Whilst economic benefits from climate change, in the context of drought mitigation, are projected for China and India, the study also highlights the increased likelihood of heavy precipitation events for these countries. This study does not directly aim to analyse or quantify heavy precipitation events but the SPI does provide a measure of above average precipitation. Therefore, for these countries it could be postulated that under future climate change increased precipitation and increased variability of precipitation may lead to more frequent and/or severe flood events, causing increased economic damages. Some studies do present evidence of an increased risk of flooding under future climate change (Milly et al., 2002, Pall et al., 2011). However, to address flood events in detail would require a more spatially explicit assessment of changes in precipitation regimes, regional topography, catchment areas, river characteristics, and land-use types. Such a methodology could form a useful extension to this research in the future. Consequently, the economic estimate presented above do not incorporate the possibility that a region or country may become increasingly vulnerable due to compounding impacts from interactions with other extreme weather events such as floods. For example, a flood event may precede a drought event, so that the drought will affect an already vulnerable society potentially resulting in larger damages, or a flood may follow a drought event affecting the ability and time-scale of the region to recover from the drought in the longer-term.

The findings suggest that in the USA the number of people killed annually by drought events, and their compounding effects, is set to increase over the first half of the 21st century. Based on past trends the effect of worsening drought conditions on lives lost would be expected to be greater for less developed countries, but unfortunately, a lack of historical impact data impeded such an assessment. Importantly the result illustrates that increasing drought magnitude can cause additional loss of life even in developed countries. Similarly, whilst economic costs could not be estimated for Brazil the effect of changing drought magnitude on the number of people affected annually was projected to increase significantly. The analysis suggests that 4-6% of Brazil's population could be affected annually by drought under future scenarios of climate change. This has major implications for the future assessment and management of drought risk in Brazil, especially as the largest effects to society are likely to be felt in the poorer northeast region, where people are more dependent on subsistence farming and agriculture. These results highlight an interesting dichotomy in the risk of future drought depending on whether an economic or social metric is used. The metric used to quantify the effects will also have implications for the type of drought response or adaptation measures suggested.

The effect of climate change on future drought magnitude and subsequently the number of people affected in Ethiopia was more variable. It was projected that Ethiopia would suffer smaller magnitude drought events, on average, under future climate change with SPI-6 droughts projected to affect less people annually. SPI-12 droughts were projected to affect slightly more people annually due to larger variability in the magnitude of individual drought events. Consequently, changes in the variability of precipitation can result in large drought effects even when mean precipitation is expected to increase. As such, certain countries and regions may become more vulnerable to both drought and heavy precipitation events.

The range in economic costs estimated for each country (figure 5.1) is attributed to the different GCMs used. Whilst there was some uncertainty in the direction of the trend for SPI-6 and SPI-12 droughts in Australia and the USA, and for SPI-12 droughts in Portugal, the size of potential economic losses seen outweigh any potential benefits. This suggests that if these losses are to be avoided, a precautionary approach should be taken towards mitigating and adapting to future drought events. Although, it should be noted that the average drought effects estimated for each country (represented in figure 5.1 by black crosses) can be significantly different from the median value as a small number of events of large magnitude can skew the average and make it appear much higher. Figure 5.2 also highlights that annual losses to global GDP from drought events in Australia, China, India, Portugal, Spain and the USA increase under climate change in 2003-2050, even considering the positive benefits seen in India and China. Conversely, the use of different emission scenarios has less influence on the economic estimates for the first half of the 21st century. Stringent mitigation, as implied by the use of the 450ppm CO_2 scenario, does not reduce economic costs of drought events in the short to medium term. Although It is difficult to establish the water related consequences of climate policies and emission scenarios with high accuracy and credibility (Kundzewicz et al., 2008), this will have consequences for the way in which countries adapt to, and manage, future drought risk. It suggests a need for drought adaptation strategies to be implemented urgently to deal with unavoidable consequences. This urgent call for adaptation is also echoed by Kleinen and Petschel-Held (2007) when regarding impacts of climate change on future large scale flood events.

Whilst the drought damage functions have proven to be functional tools in the estimation of economic and social drought effects it is very difficult to accurately assess the robustness of the results. Economic damages were estimated for 1955-2002 using the drought damage functions and could be compared to the economic data reported in EM-DAT. In total, the damage functions produced higher economic damages than suggested by EM-DAT data alone. This is not surprising as economic data was only available for 56% of the drought events reported in EM-DAT and used in this study. Furthermore, not all drought events seen in the precipitation record were included in EM-DAT due to the constraints of the database recording procedure (discussed in section 3.1.4). Alternatively, these results may also suggest that the method overestimates the potential economic damages in the baseline period, and future period. The study aimed to overcome this issue by ensuring that the same methodological approach was used for estimating drought damages from 1955-2002 and from 2003-2050, so that the estimates are comparable over time. It would be interesting to evaluate how results of this study compare to loss estimates made using different methodologies. However, this requires more quantitative studies on future drought effects to be undertaken, contributing to this sparse area of research.

The projected drought damages also differed depending on the SPI time period used. For example, for the USA annual economic damages of ~5bn US$ were projected for 1955-2002 for SPI-6 drought events. This result is consistent with the estimate made in 1995 by FEMA that drought events resulted in average annual losses of 6-8bn US$ nationally (FEMA, 1995). Conversely, annual economic losses estimated using SPI-12 were 36bn US$ for 1955-2002, over four times greater than the FEMA estimate. The FEMA estimate is reported to be very rough, based mainly on agricultural drought losses, and is likely to exclude economic losses associated with mega-drought events like that of the 1950s (Hayes et al., 2004). Hence, even where quantitative estimates are provided in the literature there can still be much uncertainty over their reliability and robustness for validating projected estimates. However, it was found that for the largest magnitude SPI-12 drought events seen in the USA and Australia estimated damages were exceptionally high. This was linked to the use of non-linear drought damage functions, resulting in drought damages rising disproportionally as drought magnitude increased. The influence of the shape of the drought damage function on economic estimates was illustrated in table 5.3, which provided comparative results for Australia and the USA assuming a linear damage function. This resulted in a lower estimate of future average annual drought damages for SPI-12 drought events in these countries.

An important feature of this study was that the shape and scale of the damage functions were fitted to actual historical impact and climate data. Whilst this method has advantages, one drawback is that whilst projected drought magnitude and economic damages can increase indefinitely under the damage functions, in reality actual drought damages may be restricted by the specific characteristics of a region and the total value of assets at risk (Hallegatte, 2007). Furthermore, a key assumption in the analysis was that the shape and scale of the damage functions, calibrated to historical events, would remain unchanged when applied to future drought projections. However, the results presented in chapter four illustrated that the projected magnitude of individual drought events has the potential to exceed the range of magnitude seen for historical events. Thus, projections of future climate change, and increases in the magnitude and frequency of drought events, may cause socio-economic thresholds to be exceeded, beyond which the magnitude of drought effects may increase rapidly (IPCC, 2007c). Consequently, past a certain threshold a linear damage function, for example, may become non-linear, causing substantially larger losses than estimated in this study using the stationary drought damage functions. The results of using different shaped damage functions for Australia and the USA, discussed above, highlight how influential the shape of the drought damage functions are in terms of the estimates of economic and social losses.

Similarly, tipping points may exist beyond which the magnitude of a drought is so severe that there is irreversible or systemic collapse of economies or catastrophic consequences for society. For example, a series of severe droughts may be so destructive to agriculture that the economy passes a threshold where agriculture is no longer a viable market. It is reported that subsistence farming in Africa could go from a meagre livelihood to no livelihood at all if temperature and evapo-transpiration increases, precipitation decreases or increased inter-annual variability including extremes such as drought increase (IPCC, 2007c). As such, countries that already operate close to the threshold limit for agriculture may find themselves unable to grow crops in the future resulting in a complete shift in their economic structure. The economic structure of region or country may also change as farmers are force to switch farming practices, or the types of crops or cattle in which they may specialise, becoming more integrative or diverse (Seo, 2010). The existence of such thresholds and tipping points, which are not considered in this analysis, would have large consequences for the scale of economic and social drought effects. As mentioned previously (section 3.4) there is the potential for estimates of tipping points, in terms of socio-economic effects, to be hypothesised from the existing drought damage functions. For example, the level of drought magnitude, above which would result in economic losses of a given percentage of a countries' GDP deemed as unsustainable or unacceptable, could be used to define the tipping point for unacceptable drought risk.

A second key assumption in the analysis was that socio-economic conditions also remained static for future projections. Whilst the justification for this methodological approach was discussed previously (section 5.1), there are also implications in terms of future tipping points as human interactions alone, which may change under future socio-economic development, can increase vulnerability to drought. For example, simulations of Amazon deforestation typically generate a decline in precipitation of ~20-30%, lengthening the dry season and increasing summer temperature as a large fraction of the precipitation in the Amazon basin is recycled (Lenton et al., 2008). Indeed, Lenton et al., (2008) note that land-use change alone could potentially bring the forest cover to a critical threshold. Thus, there is a complex interplay between society, economic development, land use change and the response of regional precipitation to anthropogenic climate change. Such complex interactions are not reflected by the drought damage functions. Likewise, economies and the economic structure of regions and countries can also evolve over time, dependently and independently of climate. For example, Marangos and Williams (2005) note that drought in Australia has influenced the operations of primary producers and strongly impacted upon agricultural investment, with the government investing little in agricultural infrastructure to help restore the sector and return it to pre-drought conditions. Thus, future vulnerability to drought will be related to the specific characteristics of a region's economy at a given point in time, which may be very different from today. However, the potential implications of changing economic conditions and structures are not reflected in the estimates made using the drought damage functions.

Furthermore, the study does not consider the levels of socio-economic interferences such as irrigation, extraction of groundwater, or other drought management or adaptation strategies that may have mediated drought effects in some countries in the past, or how these may change in the future and influence drought effects on economies and society (as previously discussed in section 3.4). Whilst government and institutional intervention may reduce drought losses (e.g. Buizer et al., 2000) there is also the potential for an additional threshold to exists in terms of adaptability. For example, in the short-term effects of drought may be mitigated through increased used of ground water or irrigation systems. Yet, the ability to use such mechanisms under increasingly severe and frequent droughts may reach a threshold in the future beyond which the processes themselves, or the levels of investment, are no longer viable or sustainable (Sheffield and Wood, 2011).

Other limitations to consider when interpreting the economic estimates include the potential for certain countries (e.g. Spain and Portugal) to suffer from increasingly long duration and successive drought events. As such, the effect of successive drought events on an economy that may already have been weakened by preceding events has the potential to be larger than the economic estimates of this study, which focuses on the effects of individual drought events on a static economy assumed to be in equilibrium prior to drought. The exclusion of such dynamics is likely to result in an underestimation of the economic estimates reported above. Additionally, the results presented in this chapter represent direct economic losses only (the type and potential severity of indirect economic drought losses are explored in more detail in the following chapter). Whilst effects of drought on society have been quantified, they have not been monetised or incorporated within the economic estimates and the potential for social effects to interact with and compound economic losses (e.g. through migration of labour or reduced productivity) has not been analysed. In estimating socio-economic drought risk, it is also assumed that the drought magnitude is the only factor involved (i.e. the spatial and temporal drought extent and intensity). Yet, many other factors, sensitive to climate change in their own right, can influence the type and severity of drought related effects such as temperature; preceding soil moisture levels; land-use; the type of agricultural crops grown in the affected area; and as mentioned above pre-existing societal and economic vulnerabilities.

5.4 Summary

The chapter presents estimates of the economic and social effects of drought events for various countries in the first half of the 21st century. The frequency and magnitude of drought events is projected to increase for certain countries, increasing the likelihood of events causing severe economic costs. Australia, Portugal, Spain and the USA were all highlighted as countries at risk from increasingly high drought damages. In Brazil, the number of people affected annually by drought is likely to rise considerably under future projections of climate change. The number of annual drought related deaths is set to increase in the USA. Even countries that are projected to benefit economically and socially from changing drought regimes are not risk free, as the analysis suggests that these areas are likely to be affected by heavy precipitation events, and potentially increased flood risk, in the future. This could cause equally disastrous consequences although these losses have not been quantified by this study.

Total economic damages from drought in Australia, China, India, Portugal, Spain and the USA, as a proportion of global GDP, are projected to increase under all scenarios for the first half of the 21st century compared to 1955-2002. The results presented in figure 5.2 indicate that severe and extreme SPI-6 and SPI-12 drought events could cause additional losses to global GDP of 0.01% to 0.25% annually. Whilst the cost of drought to global GDP may appear small, it is important to remember that these damage estimates are considered conservative as the analysis is representative of six countries only; the estimates do not incorporate the possibility of successive drought events, or compounding effects on vulnerability from interactions with other extreme events such as floods. Additionally, the global economic estimates exclude indirect economic effects, and social and environmental consequences; the possibility of increasing vulnerability due to changing socio-economic conditions; and the possibility of irreversible or systemic collapse of economies as, under future climate change, drought magnitude may exceed current experience and surpass thresholds of social and economic resilience.

Yet, even just considering the direct economic damages from individual drought events on a handful of countries under future climate change still resulted in a noticeable effect on global

GDP. Furthermore, changes in drought magnitude and economic losses in the latter half of the 21st century would be expected to be significantly higher. Crucially, stringent mitigation does not reduce the projected effects of drought events on economies and societies in the first half of the 21st century. This is not to say that stringent mitigation is not effective in reducing the risk of climate change on drought, as it is likely to reduce future drought effects in the second half of the 21st century. However, this study does highlight the need for investment in adaptation strategies in the short to medium term to deal with drought risk in the most vulnerable areas. The study has highlighted that drought risk needs to be measured and understood in terms of both economic assets and effects on populations.

6. Indirect Economic Drought Costs

The economic consequences of extreme weather events can be both direct and indirect. However, reported data on the costs of extreme weather events tend to reflect the more visible direct economic costs only. Consequently, damage estimates from extreme weather events are likely to underestimate the total economic cost to society. The literature review has highlighted that indirect economic drought costs have the potential to be large and widespread even if the initial event is localised and direct damages are modest. The above chapter has demonstrated a novel methodology for estimating the future direct economic damages of drought events. This chapter provides a preliminary investigation of the potential indirect economic effects that may occur during such drought events, through the application of a pre-existing I-O model to a case study of Spain. As such, the chapter aims to illustrate the importance of considering indirect drought effects within cost assessments, rather than providing a precise quantitative assessment.

Section 6.1 outlines the Adaptive Regional Input-Output Model (ARIO) used. Section 6.2 provides a description of the methodological approach for modelling indirect economic drought damages. It outlines the main issues considered when applying ARIO specifically to drought events, the modifications introduced to the ARIO model especially for this study, and the direct drought impact data and scenarios used. Section 6.3 presents the results of the exercise, including validation of the model output and a sensitivity analysis. Section 6.4 discusses the main findings, and section 6.5 provides a summary of the chapter.

6.1 The Adaptive Regional Input-Output Model (ARIO)

Section 2.5 of the literature review identified I-O analysis as one of the main tools used in the assessment of indirect economic costs caused by sudden shocks to the economic system. The literature review highlighted that this methodological approach is advantageous due to its simplicity, and the explicit distinction made between direct and indirect economic costs. I-O analysis has already been applied to the study of indirect costs from natural disasters, and more recently, extreme weather events. Numerous modifications have been documented within the published literature to address model limitations and account for the particular characteristics of natural disasters and the economic shocks they cause.

To investigate the potential importance of indirect economic losses caused by drought under future scenarios of climate change this study utilises the ARIO Model[15], in a similar approach to that of Hallegatte et al., (2011) and Ranger et al., (2011). The ARIO model is able to capture the direct impact of a disaster on an economy by accounting for interactions between industries through supply and demand of intermediate consumption goods (Hallegatte, 2008). In equation 6.1, the I-O matrix is represented by *A*, which shows the quantity each sector is providing or buying from other sectors. Assuming equilibrium, production (*Y*) will be equal to the demand for intermediate goods and final demand (*C*).

$$Y = AY + C$$

Eq.6.1

In I-O analysis, direct and indirect effects on sectoral output caused by changes in final demand can be estimated using equation 6.2, termed the Leontief inverse matrix. The parameter *Y* would be the new production level, taking into account backward propagation as sectoral output is affected by a change in demand and assuming no constraints on production.

$$Y = (1 - A)^{-1}C$$

Eq.6.2

In the ARIO model direct effects on production capacity can also be modelled, as well as reconstruction of productive capital, which can cause additional demand to the manufacturing and construction sectors. The ARIO model also allows flexibility following a disaster as producers can increase production capacities; producers can import goods from regions outside the affected area when supply is limited; and goods can be rationed with intermediate consumers taking priority over final users. The ARIO model has also been recently extended to incorporate the use of inventories (i.e. goods and materials held in stock) to allow additional flexibility following a disaster. As such, the ARIO modelling approach provides a middle ground between I-O models and CGE models (Hallegatte, 2011). Full details of the model structure, equations, and parameter values are described in Hallegatte (2008, pp.794-798), and Hallegatte (2011).

The ARIO model has previously been used to assess the effects of Hurricane Katrina on the economy of Louisiana (Hallegatte, 2008); to assess coastal flood risk in Copenhagen under

[15] A copy of the ARIO model (version 3.6) was kindly provided by Stéphane Hallegatte, Météo-France.

future climate change (Hallegatte et al., 2011); and to assess terrestrial flood risk under future climate change in Mumbai (Ranger et al., 2011). Compared to actual economic data on production loss in the aftermath of Hurricane Katrina ARIO has been shown to provide realistic results, although it underestimates production losses in some sectors. This underestimation is linked to the fact that ARIO cannot accurately reproduce the economy in the immediate aftermath of a disaster. The ARIO model was also able to represent changes in employment, which is assumed proportional to production in each sector, in the disaster aftermath. This was verified by comparing the model results to actual labour statistics in Louisiana for 2005 and 2006. However, whilst the order of magnitude of results were realistic large uncertainties still surround the quantitative results due to limitations in the I-O modelling framework, and uncertainties over parameter values used to model adaptation and flexibility in the disaster aftermath (Hallegatte, 2008). A sensitivity analysis highlighted that model results were especially sensitive to the maximum overproduction capacity allowed (α), and the timescale for overproduction to reach this level (τ_{α}).

The ARIO-Inventory model has been used to re-assess the economic effects of Hurricane Katrina in Louisiana and compared to earlier results from ARIO, which did not include inventories. In the ARIO-Inventory model, it is assumed that each sector produces commodities by drawing on their inventories. The optimal inventory size is estimated as the amount of goods needed to satisfy production demand for a given number of days of intermediate consumption (n_j^i). Some commodities, such as electricity, cannot be stocked and so if a disaster affects these sectors production will stop, reflecting disruption of lifelines and causing additional bottlenecks to the system. Results were found to be similar for both approaches with indirect losses of $72 billion (in 2000 US$) using the ARIO-inventory model and $69 billion using the initial model, for direct losses of $97 billion (Hallegatte, 2011). The dynamics of the two models are similar although in the short-term the economic losses were smaller using the inventory model due to the smoothing effect of inventories in the immediate disaster aftermath. Hence, inventories can provide flexibility following an economic shock, as production interruptions to sectors with stockable goods do not have immediate impacts on other sectors. However, even though inventories can increase robustness in the short-term, in the longer-term if inventories deteriorate this can becomes a limiting factor for production. This is because in the ARIO-inventory model production is reduced when inventories fall below their optimal level due to supply side constraints, even though production may remain possible.

In this study, the ARIO-inventory model is used for the assessment of indirect drought costs in Spain. The incorporation of inventory dynamics is beneficial as inventories can be important when investigating the resilience of the agricultural sector to drought (Diersen and Taylor, 2003, Wheaton et al., 2008). However, as with the studies of Hallegatte et al., (2011) and Ranger et al., (2011) there are many modelling uncertainties surrounding the quantitative estimates presented below, and results should not be interpreted literally. However, the exercise is important for investigating the feasibility of applying drought damage functions to an I-O model; to demonstrate the advantages of using I-O techniques for climate change and drought cost assessments; to highlight the potential issue of underestimation of drought damages based on direct economic costs only; and to highlight future research questions which will need to be investigated in order to develop a more robust methodology for modelling the indirect economic costs of drought events.

6.2 Representing indirect drought damages in Spain using ARIO

This study focuses on the indirect economic costs of drought at a country scale for Spain. The study focused on Spain as: there was good consistency in the direction of drought trends modelled (chapter 4); Spain was identified as being at high risk from increasing economic losses from future drought events (chapter 5); and drought events affect a large proportion of Spain meaning that effects would be relatively homogenous across the country. The ARIO model is run at a daily time step assuming that production is constant over the year. The ARIO model is based on annual economic data from I-O tables. The I-O tables for Spain were publicly available from Eurostat (2010b) for 2005, with values given in millions of Euros. The data was converted to 2002 US$ in line with the economic metric used throughout this study. Data was available for 59 sectors and was aggregated to the following 15 sectors used in ARIO: (1) agriculture, forestry, fishing and hunting; (2) mining and extraction; (3) utilities; (4) construction; (5) manufacturing; (6) wholesale trade; (7) retail trade; (8) transportation and warehousing; (9) information; (10) finance, insurance, real estate and leasing; (11) professional and business services; (12) educational services, health care, and social assistance; (13) arts, entertainment, recreation, accommodation and food services; (14) other services, except government; and (15) government.

The baseline parameter values for inventory and adaptation dynamics were unchanged from those used by Hallegatte (2011) in this first application of the model to drought, as outlined in table 6.1 below. The sensitivity of model results to these parameters and consequences for future research are discussed in sections 6.3.3 and 6.4 below. In the below analysis direct economic effects of drought are defined as physical damages to capital which result from the drought, and which are reflected in the ARIO model in terms of reduced production capacity to the affected sector (discussed below). The direct economic costs of individual drought events in Spain, estimated using the drought-damage functions (chapter 5), are used as input for this analysis. The indirect economic losses estimated using the ARIO model, and presented here, are defined as losses to the economy due to a change in the flow of goods and services resulting from the direct effect of changed production capacity of an affected sector (e.g. business interruptions).

Description	Parameter	Value
Number of days (n_j^i) of intermediate consumption used to define optimal inventory size	(n_j^i)	30 days
The time it takes for inventories to be restored to their optimal level	τ_s	60 days
Baseline production capacity (i.e. that achievable prior to the disaster occurring)	P^{ini}	100%
Maximum over-production capacity	α	125%
The time it takes for production capacity to increase to its maximum level	τ_α	1 year

Table 6.1: ARIO model parameters used. Source: Hallegatte (2011)

Before applying the ARIO model to drought two important issues were considered. Firstly, the ARIO model has only previously been applied to hurricane and flood events. As the time-scale of these events are relatively short, direct damages can be imposed on the I-O model at a single point in time. Drought events and their direct effects may affect a region over many months to years, with impacts growing gradually over time, and evolving with the duration and severity of the event. It has been postulated that for the same direct damages, an economic shock spread over many months to years would result in smaller indirect economic losses than the same size shock imposed instantaneously on the economy. This is supported by Hallegatte (2005) who found that modelling a productivity decrease over 20 years with the NEDyM model resulted in lower damages than if the same productivity decrease was imposed on the model instantaneously. Indirect economic damages were found to decline as the duration of the economic shock increased.

Secondly, the ARIO model has been designed to represent particular recovery characteristics linked to hurricanes and floods. For example, floods and hurricanes are known to cause direct damages to buildings, property, and infrastructure directly affecting sectors, as well as resulting in large reconstruction costs. The ARIO model can capture the increasing demand to the construction and manufacturing sectors following a disaster, and the reconstruction of productive capital over time. Conversely, droughts events are not associated with large direct effects to buildings, property, and infrastructure (although prolonged effects of droughts on soil moisture conditions can cause subsistence in buildings). Therefore, drought events are expected to affect different sectors to different degrees. To address these issues four modifications were made to the ARIO-inventory model:

1. In ARIO direct economic costs from hurricanes and floods are assumed to affect all sectors of the economy. When specific information on sectoral damages of historic events was not available direct damages were disaggregated based on the proportion of each sectors value-added (VA)[16]. The literature review highlighted that agricultural, industrial, energy, and water sectors are most at risk during drought events. This is linked to water-use demand with water abstraction in the European Union primarily used for energy production (mainly for cooling water) (44%), agriculture (24%), public water supply (21%), and industrial purposes (11%) (European Environment Agency, 2009). However, this differs across countries in the EU with countries such as Spain using abstracted water predominantly for agriculture, specifically irrigation (*ibid.*). It was therefore assumed that a drought event would affect certain sectors directly, and others only indirectly. For Spain direct economic costs from each drought event were disaggregated between agriculture, forestry, fishing and hunting (65%); utilities (31%); and manufacturing (4%). This disaggregation was based on country specific data on each sector's share of water abstraction from surface water (Eurostat, 2010a). The focus of the study on these sectors is supported by reported drought data from historic drought events in Spain from the literature review. Additionally, the 1990-95 and 2005 drought events in Spain were reported to have caused large costs to agriculture, as well as to the energy sector and public water supply (European Commission, 2007).

2. Direct economic drought damages were imposed on the economy over the duration of the drought event rather than as an instantaneous shock. The direct economic damages were distributed across the drought duration based on the peak intensity of the drought event in each month. This information was determined based on the average SPI time-series data for each drought event analysed (described in chapter 3). It was assumed that the more severe the drought became the higher the direct economic damages would be in that month. As the ARIO model used a daily time-step

[16] Value added per unit is the difference between the sale price and the production cost of a product

the monthly drought damages were disaggregated equally across each day per month. For the first day in which the drought is imposed on the ARIO model the production capacity of affected sectors is reduced from the pre-event baseline, based on direct daily drought damages to each sector (outlined in point one). The initial production capacity is defined as the pre-event production of each sector (P_i^{ini}). In ARIO it's assumed that if a disaster reduces the productive capital of a sector by *x* percent, then the production capacity of the industry will also be reduced by *x* percent. Independently of its suppliers, the production capacity P_i^{cap} of the i^{th} sector reads:

$$P_i^{cap} = \propto_i (1 - \Delta_i) P_i^{ini}$$

Eq. 6.3

The variable Δ_i is the reduction in productive capacity due to the direct consequences of the drought.

$$\Delta_i = \frac{L_i}{K_i}$$

Eq. 6.4

Where:

K_i = stock of productive capital in sector *i*

L_i = amount of damage to the sectors productive capital

After the initial drought shock, the production capacity of affected sectors is reduced from the previous day's production level rather than the pre-event baseline. This represents the cumulative effect of the drought on the economy over time. At the end of the drought, production capacity is assumed to return to the pre-event baseline (justified in point four below).

3. For the agricultural sector alternative scenarios were also considered. The first scenario assumed that direct economic costs of drought on agriculture would affect production capacity in a cumulative fashion as described above. However, as agricultural goods are not a marketable commodity until harvested the second scenario assumed that economic drought damages would occur during four months per year, for each drought year. This aims to represent approximately losses over a summer harvest season. The third scenario assumed that drought would cause a sudden shock to the agricultural sector, with losses occurring over one month per drought year only. This scenario is

used to represent a sudden failure of a key harvest. Direct economic losses to utility and manufacturing sectors were assumed to happen in a cumulative fashion during drought under all scenarios.

4. The ARIO model assumes that direct damages to capital are fully repaired. This results in additional demands from each industry to the construction and manufacturing sectors. In this analysis, it is assumed that there will be no destruction of capital and so no additional reconstruction demand. This modelling approach represents a temporary retirement of productive capital, as production capacity declines, which can be returned to full usage without the need for reconstruction, additional investment, or delays following the end of the drought. This method is also used by Wittwer and Griffith (2010) when analysing the consequences of drought on agriculture in Australia.

The analysis considers both SPI-6 and SPI-12 drought events in Spain in 1955-2002 and 2003-2050, so that the effects of climate change on indirect drought costs can be assessed. Quantitative estimates are generated using the GCM ECHAM4 and the climate scenarios A1FI and 450ppm to provide a range of illustrative results. The GCM ECHAM4 resulted in the highest economic damages to Spain compared to results generated using CSIRO2 and HADCM3 (see chapter five). In addition, in order to assess the importance of the emission scenarios on indirect economic drought costs, and consequences of mitigation, results for SPI-6 drought costs in the latter half of the 21st century (2051-2098) are also provided.

6.3 Results

6.3.1 Validation of the ARIO model

To test the model modifications and attempt to validate the estimates of indirect economic drought costs, simulations were carried out for three historic drought events that affected Spain in 1980-1982, 1990-1995, and 1998-2000. The drought in 1980-82 caused direct economic damages of 5.1bn US$ (EM-DAT, 2010). Figure 6.1 illustrates the indirect economic drought costs, as a percent of VA, estimated for the three agricultural scenarios. The results are presented for SPI-6 and SPI-12 droughts. The graphs differ due to the different SPI time-periods used to model the drought event as this effects the duration and monthly severity of the drought. Figure 6.1 demonstrates that during drought VA declines by around 0.20 to 0.25% using SPI-6 and by 0.20 to 0.35% using SPI-12. The differences in the evolution of VA losses for each time-period are related to the agricultural scenarios used. Losses occur more gradually in scenario one, which assumes cumulative losses to agricultural. Under scenarios two and three VA losses are stepped due to agricultural effects occurring more suddenly.

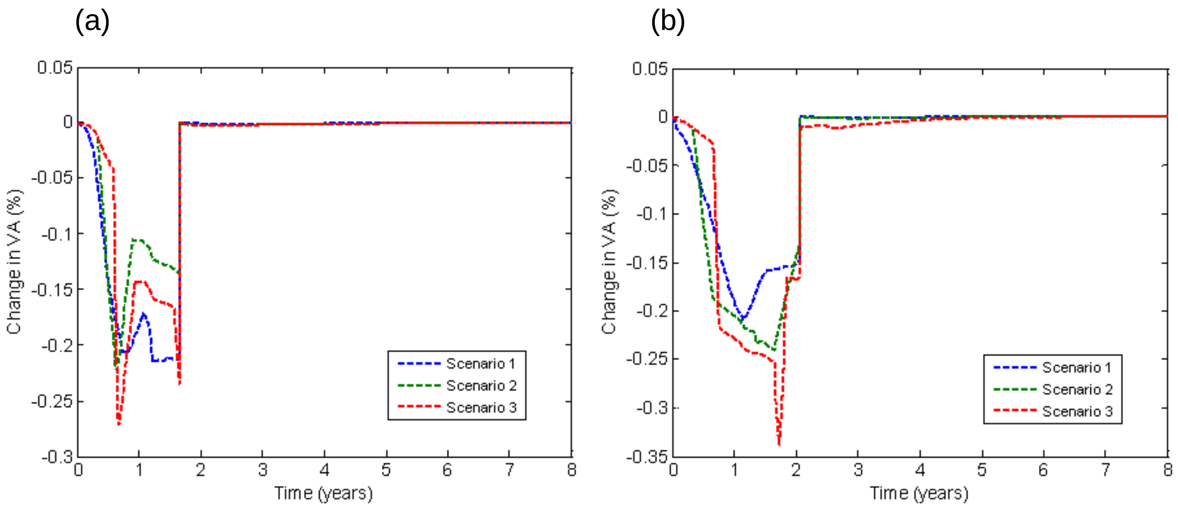


Figure 6.1: Simulated change in VA of Spain's economy during the 1980-1982 drought modelled using (a) SPI-6 and (b) SPI-12 for cumulative drought effects on agriculture (scenario one), seasonal drought effects on agriculture (scenario two), and sudden drought effects on agriculture (scenario three).

In figure 6.1a, a period of mid-term recovery is seen which coincides with a decline in drought severity to near normal conditions, and hence direct economic losses. Interestingly, whilst cumulative drought losses modelled in scenario one do not cause such drastic reductions to VA the sustained reduction in production capacity constrains the recovery of the economy. In scenarios two and three direct drought losses are confined over fewer months for agriculture causing more drastic declines in VA when they do occur. In intermittent periods production capacity of the agricultural sector remains stable (albeit lower than its pre-event level). This coincides with a decline in drought severity so the economy is able to respond and recover more readily to the economic shock by increasing production capacity and imports. Indirect losses were estimated to be 2.35bn, 1.67bn, and 1.86bn US$ for scenarios one, two, and three respectively.

Figure 6.1b illustrates the specific drought characteristics modelled using SPI-12, and the effect of the agricultural scenarios, on VA. At first glance, this graph appears to be contradictory to that shown for SPI-6. Scenario one shows that recovery begins to occur after the first year of drought, although it slows as the drought intensity increases in severity again. Yet, using scenarios two and three mid-term recovery does not happen until the end of the second year, even in the intermittent months when agricultural production capacity is stable. This is explained by the drought event becoming particularly severe in the months following the sudden shock to agricultural production capacity in scenarios two and three. The production capacity of the manufacturing and utilities sectors decline steeply and this, in tandem with the agricultural effects, causes a decline in production capacity and the depletion of inventories which place further restraints on production. In scenario three, the bottleneck that occurs due to inventory constraints following the termination of the drought and increased demand, is so severe that full recovery does not occur until 3 years later. Indirect losses were estimated to be 3.1bn, 3.3bn and 3.2bn US$ for scenarios one, two, and three respectively.

These findings highlight the importance of the specific drought characteristics and evolution of drought effects when assessing the indirect costs of drought, and the ability of the economy to recover from drought. During the drought Spain's actual GDP declined by 0.13% representing ~2bn US$ (2002) (The World Bank, 2010). Reported losses were mainly due to losses in the agricultural sector with a decline in agricultural value added of 1.5bn US$ (*ibid.*). In this study, for SPI-6 drought events, the change in value added of the agricultural sector was estimated to be 1.28bn, 450 million, and 380 million US$ for scenarios one to three respectively. Comparatively, results for SPI-12 droughts were estimated to be 1.3bn, 1.6bn, and 1.5bn US$ for scenarios one to three respectively. Hence, the results highlight that for agriculture the use of SPI-12 drought data, and specifically scenario three, represents the actual historical agricultural situation most accurately. Results using SPI-6 vary widely, with scenario one providing the most robust estimate.

Figure 6.2 displays results for the 1990-1995 drought in Spain, which was estimated to have cost 5.9bn US$ (EM-DAT, 2010). Results are presented for SPI-12 only as the drought was not visible using SPI-6. In scenario one, the decline in VA is smoother as damages accumulate gradually over the drought duration. There is limited recovery during years three and four coinciding with a decline in the severity of the drought event. However, the ability of the system to over-produce is counteracted by continually decreasing production capacity levels and the depletion of inventories below optimal levels. Using scenarios two and three the decline in VA is more stepped representing the larger short-term shocks to agricultural production capacity. However, during years three and four economic recovery is more pronounced when agriculture is not affected and production capacity is relatively stable. As previously described, a decline in drought severity coinciding with stable agricultural production capacity appears to allow the economy time to recovery.

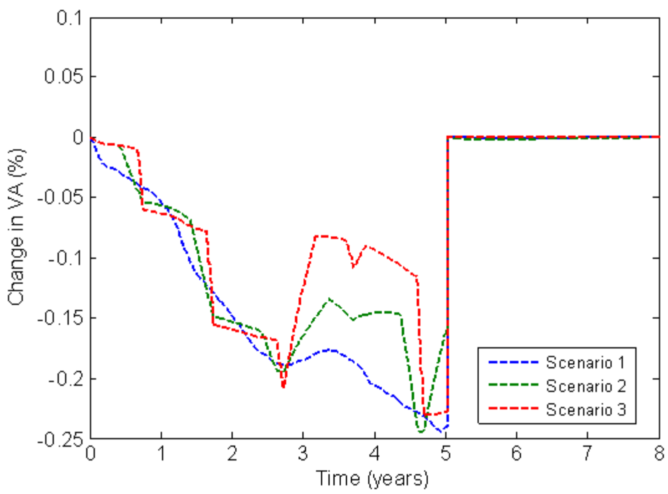


Figure 6.2: Simulated change in VA of Spain's economy during the 1990-1995 drought modelled using SPI-12 for the three agricultural scenarios

Indirect economic losses were estimated to be 6.9bn, 5.9bn and 5.0bn US$ for scenarios one, two, and three respectively. The drought event correlates well to economic time-series data which highlights a decline in Spain's GDP of approximately 5.9bn US$ (2002), in 1994 and 1995 (The World Bank, 2010). The majority of drought damages were reported to have affected the agricultural sector, public water supply and energy industries (European Commission, 2007). Economic data highlighted a decline in agricultural value added of 2.1bn US$ during the drought (The World Bank, 2010). Comparatively, the model estimates losses to value added in the agriculture sector of 4.2bn, 3.2bn, and 2.0bn US$, for scenarios one, two and three respectively. As was the case in the previous example for SPI-12 the third scenario best represented the actual historical trends in agricultural VA. The economic amplification ratio (EAR), defined in section 2.5 as the ratio of the total production losses caused by the disaster to its direct losses, for each of the three scenarios is 2.17, 2.0, and 1.85 respectively, highlighting the potential severity of the drought event in terms of indirect economic losses.

Figure 6.3a-b presents results for the 1998-2002 drought in Spain estimated to have cost 3.55bn US$. Similar trends are seen to those in figures 6.1 and 6.2 discussed above. Indirect economic losses were estimated to be 1.3bn, 1.0bn, and 0.96bn US$ for SPI-6 drought events, and 2.74bn, 2.69bn, and 2.72bn US$ for SPI-12 drought events for the three scenarios respectively. During the drought actual agricultural value added was reported to have declined by ~300 million US$ (The World Bank, 2010). Comparatively, the model estimates losses to value added in the agriculture sector of 745 million, 445 million, and 332 million US$, for scenarios one, two and three respectively using SPI-6. The results generated using the third agricultural scenario again appear most accurate. However, results generated using SPI-12 overestimated the losses on the agricultural sector with VA losses ranging from 1.3bn to 1.7bn US$.

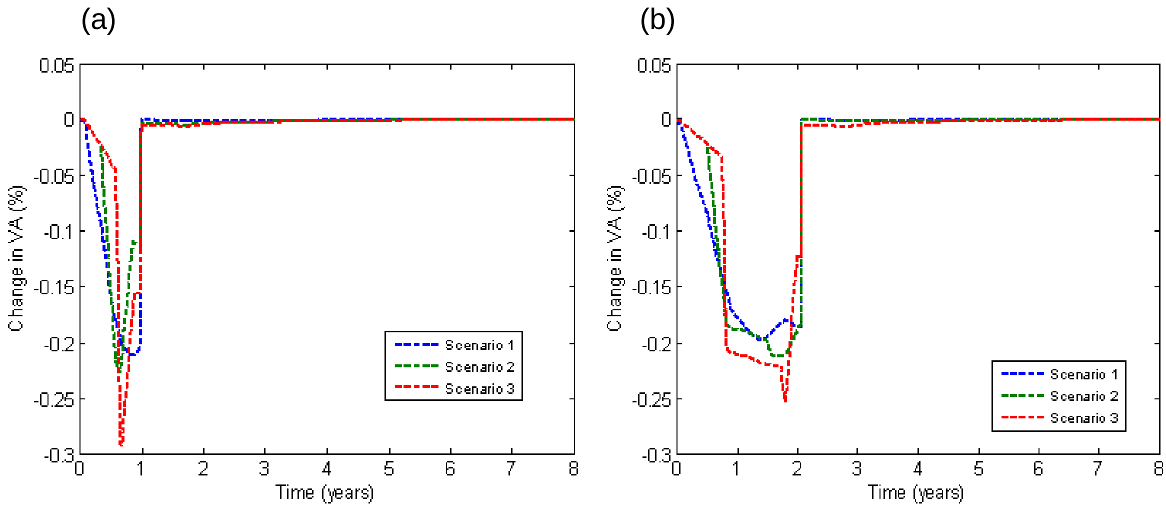


Figure 6.3: Simulated change in VA of Spain's economy during the 1998-2002 drought modelled using (a) SPI-6 and (b) SPI-12 for the three agricultural scenarios

For the three drought events considered, the results suggest that the third scenario represents the effects of drought on agricultural VA most accurately. Ding et al., (2010) notes that as agriculture is highly sensitive to weather variability drought effects can be immediate, which may explain the above finding. Similarly, in a study of macroeconomic implications of drought in Southern Spain Mechler et al., (2009) also suggest that drought effects on agriculture would occur over a limited time period and so responses in the form of reallocation of resources, such as natural resources, labour, and capital, would be limited. As such, the third agricultural scenario is used for investigating future indirect drought losses for Spain in section 6.3.2. The above analysis highlights the importance of the unique characteristics of each drought event, specifically the monthly evolution of drought severity, the duration of the event, and the timing of the shock to the agricultural sector. Additionally, the use of different SPI periods results in different drought characteristics and consequently different loss estimates. The above results suggest particular SPI time-periods may reflect specific historic drought events better than others may. This uncertainty is addressed in this study by providing a range of results for both SPI-6 and SPI-12 time periods.

6.3.2 Applying ARIO to future projections of drought in Spain

Indirect economic costs associated with drought events in Spain were assessed using the methodology outlined in section 6.2 and the assumption that agricultural losses will occur during one month per drought year only. Results are presented for both SPI-6 and SPI-12 drought events in 1955-2002 and 2003-2050. Additionally, for analysis purposes results are also presented for SPI-6 droughts in 2051-2098. Results for 2003-2050 and 2051-2098 were based on estimates of the direct economic costs of individual drought events modelled and quantified in chapter five using the GCM ECHAM4 and the emission scenarios A1FI and 450ppm. As stated previously, economic estimates are presented to illustrate the importance of indirect economic drought costs, and should not be interpreted as precise quantitative estimates.

Figure 6.4a-b present results for SPI-6 and SPI-12 drought events. The graphs illustrate the scale of direct to indirect losses estimated for each individual drought event. The indirect economic losses are significant compared to the direct losses. Both figures highlight that indirect losses increase as direct losses increase. Whilst the trends in losses appear linear, closer inspection reveals that on average indirect losses increase in a slightly non-linear fashion to direct losses for both SPI-6 and SPI-12 droughts. For example, for SPI-6 droughts, as direct losses double from 2bn to 4bn US$ indirect losses increase from 1/6th to 1/5th of direct losses. As direct losses again double to 8bn US$ indirect losses are equal to 1/3rd of direct losses. Figure 6.4a-b also suggests that for smaller magnitude drought events, which cause smaller scale direct damages, there may also be a threshold below which indirect losses are non-existent.

(a) (b)

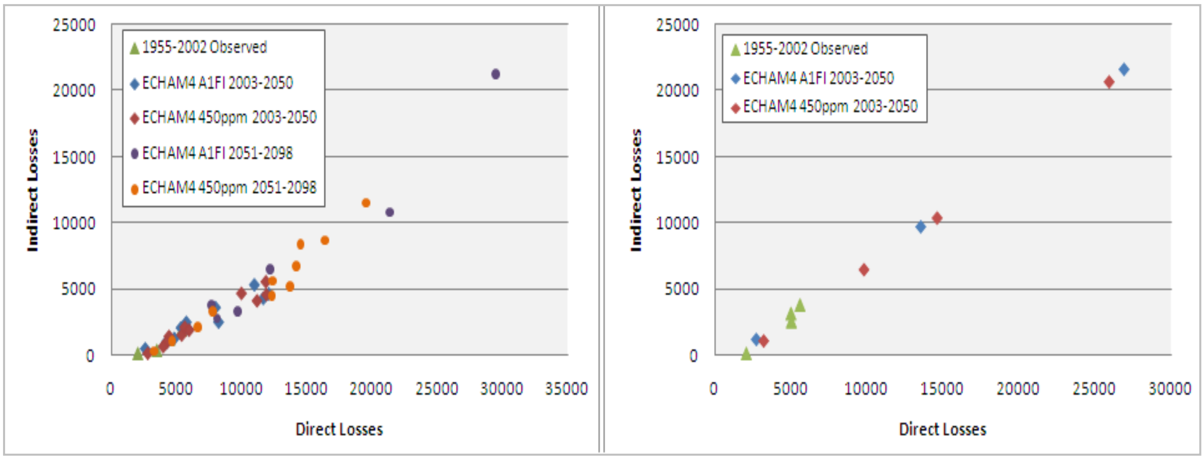


Figure 6.4: Relationship between direct and indirect economic drought losses in Spain for (a) SPI-6 and (b) SPI-12. Losses are in millions of US$ (2002).

Table 6.2 presents the average annual direct, indirect, and total drought losses projected, and the EARs. Results are given for SPI-6 and SPI-12 drought events, for each scenario, and time-period. Table 6.2 highlights the potential significance of indirect economic drought losses for Spain. Previous results presented in section 5.2.1 for direct drought costs highlighted that in a worst case scenario annual SPI-6 drought losses could increase from 330 million US$ in 1955-2002 to 1.8bn US$ in 2003-2050. Using SPI-12 annual drought losses could increase from 375 million US$ in 1955-2002 to 1.1bn US$ in 2003-2050. Table 6.2 illustrates that if indirect economic losses were also considered then future losses would be even more severe.

	SPI-6				SPI-12			
Scenario	**Direct losses**	**Indirect Losses**	**Total Losses**	**EAR**	**Direct losses**	**Indirect Losses**	**Total Losses**	**EAR**
1955-2002 observed	330	76	406	1.23	375	207	582	1.55
2003-2050 ECHAM4 A1FI	1791	645	2436	1.36	920	692	1612	1.75
2003-2050 ECHAM4 450ppm	1641	592	2233	1.36	1140	822	1962	1.72
2051-2098 ECHAM4 A1FI	4136	3155	7291	1.76	--	--	--	--
2051-2098 ECHAM4 450ppm	2811	1268	4079	1.45	--	--	--	--

Table 6.2: Projections of annual drought losses in Spain in million US$ (2002).

Total annual economic losses could reach 2.4bn US$ in 2003-2050 for SPI-6 droughts, and $2.0bn US$ for SPI-12 droughts. Table 6.2 also reiterates the finding that indirect losses increase non-linearly with direct losses. For 1955-2003 the EAR is 1.23 for SPI-6 droughts and 1.55 for SPI-12 droughts, reflecting the different drought characteristics and scale of direct losses seen using the different time periods. For projections of drought in 2003-2050, the increase in direct drought losses causes an increase in the EAR to 1.36 for SPI-6 and 1.72-1.75 for SPI-12. The results for SPI-6 droughts in 2051-2098 highlight that the EAR again increases. Under the high emission scenario the average EAR increases to 1.76, i.e. total damages are 76% higher than direct damages alone. This is restricted to 45% when the 450ppm stringent mitigation scenario is used. Yet, even assuming stringent mitigation, the ratio of indirect to direct losses still increases from that estimated for 1955-2002. Importantly, the results for drought events in 2051-2098 highlight that stringent climate change mitigation could have additional benefits in terms of avoided indirect economic costs, which may be larger than the benefits seen in avoiding direct damages. For example, table 6.2 suggests that stringent climate change mitigation could reduce direct damages by 32% when compared to the high emission scenario, whilst indirect losses are reduced by 60%.

6.3.3 Sensitivity analysis

The sensitivity of the model results to the values of the inventory parameters and adaptive over-production parameters were analysed, using the historic 1990-1995 SPI-12 drought as a case study. The value of the parameter n_j^i, which defines the optimal inventory level in number of days of demand, was shown to have a significant influence on model results as highlighted in figure 6.5a. Indirect drought costs were estimated to increase from 4.7bn to 7.0bn US$ as the value of n_j^i increased from 15 to 60 days (with τ_s = 60). When the parameter was set to 80 days indirect losses increased substantially to 24.8bn US$, and for parameter values of 90 and above (not shown in figure 6.5a) total economic collapse occurred. This finding differs from results of the sensitivity analysis of Hallegatte (2011) for Hurricane Katrina in Louisiana, which reported that the parameter n_j^i had a limited effect on results for a range of 3 to 120 days. However, the direction of the trend, showing that indirect economic losses increase with inventory size, agrees.

It would seem intuitive that smaller stocks of inventories would make sectors more vulnerable to economic shocks in the short-term. However, conversely figure 6.5a also suggests that if optimal inventory levels are too large then inventories can later become a constraining factor on production. This can be linked to the additional demand that results as sectors try to replenish their depleted inventories to their optimal levels. If the demand is too large then it will not be met and production will be limited. Additionally, the timescale of inventory restoration (τ_s) was considered as shown in figure 6.5b.

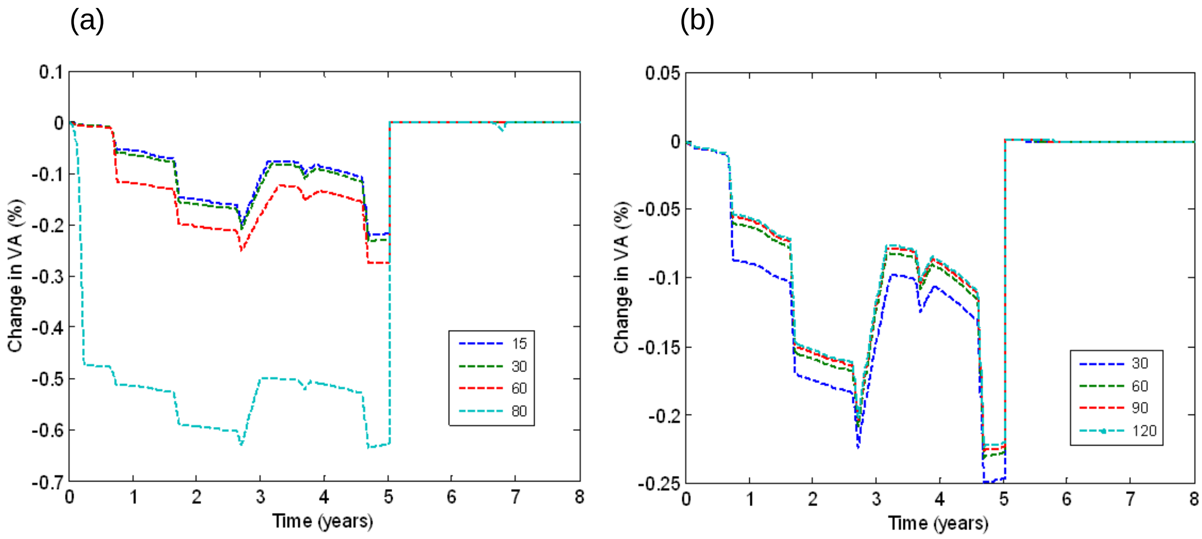


Figure 6.5: Sensitivity analysis of inventory parameters for the 1990-1995 SPI-12 drought in Spain for (a) results generated using different values of n_j^i and (b) results generated using different values of τ_s.

The sensitivity of model output to the timescale of inventory restoration (τ_s) was very limited. Indirect economic losses ranged from 5.8 to 4.7bn US$ for a parameter range of 30 to 120 days. Output losses increased as the inventory restoration time decreased. This is in contrast to Hallegatte (*ibid.*) who found that not only was the parameter more sensitive than n_j^i, but that output losses increased as the inventory restoration time increased. The finding from this study may relate to the long-term shock imposed on the economy by drought, compared to a sudden shock from a hurricane. Using a short restoration time means that sectors are able to increase their demands rapidly if inventories are below optimal levels. Although increased demand may trigger adaptation in the economy, if the demands are very high and happen too quickly, then they cannot be met due to continued constraints on production capacity from drought. Inventories cannot be replenished which further slows the recovery process. As such, both the size of the optimal inventory and the timeframe for inventory restoration should be considered in unison. For example, it was reported above that if n_j^i was greater than 90, with a restoration time of 60 days, total economic collapse occurred. However, when the value of τ_s was increased to 90 days, spreading the additional demand over a longer time-period, then the economy was able to cope much more readily. Therefore, this assessment suggests that resilience of the economy to drought is not only related to the size of inventories available, but also the speed in which they need to be restored for industries to keep functioning.

Sensitivity analysis of the adaptation parameter $\propto_i$, which defines the maximum overproduction capacity, showed that indirect losses would be substantially higher with no over-production, rising to 10.1bn US$ compared to 5.0bn US$ in the reference scenario (figure 6.6a). This highlights the importance of the parameter to the model results, and the important role that such resilience could play in the aftermath of a drought event for minimising indirect losses. Assuming that τ_α=1.0, over-production capacities of 1.25, 1.5, and 2.0 resulted in indirect economic losses of 5.0bn, 4.9bn and 4.8bn US$ respectively. Indirect economic losses declined as the parameter value increased, as higher over-production capacity makes it easier for the economy to keep producing in the disaster aftermath. The importance of the timescale for over-production (τ_α) was also assessed assuming that $\propto_i$ = 1.25. Figure 6.6b illustrates that indirect economic losses are lower where production capacity can be increased quickly, ranging from 5.0bn to 5.2bn US$ as the timescale increases from three months to two years. The trends seen for the adaptation parameters are consistent with those reported by Hallegatte (2008, 2011).

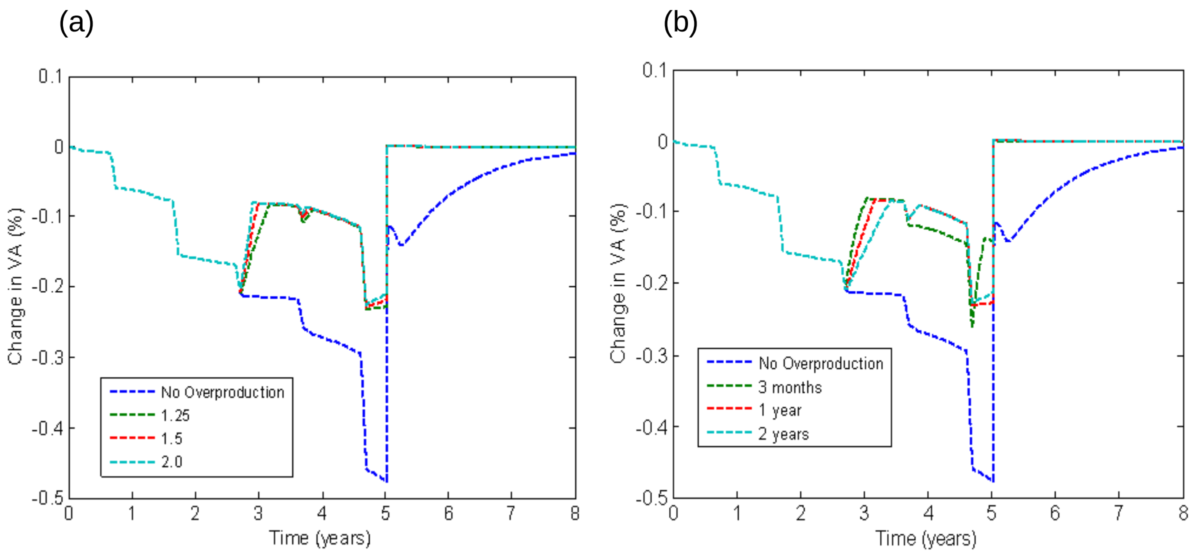


Figure 6.6: Sensitivity analysis of adaptation parameters for the 1990-1995 SPI-12 drought in Spain for (a) different levels of maximum over-production capacity ($\propto_i$), and (b) different response times for over-production (τ_α).

The results for the adaptation parameters suggest that whilst model results are sensitive to the inclusion of over-production they are not sensitive to the level of over-production. As such, a small amount of adaptive capacity could substantially reduce damages in the aftermath of a drought event of similar magnitude to that seen in 1990-1995 in Spain. In order to investigate the above findings further a sensitivity analysis was also carried out for a much larger magnitude SPI-6 drought event, projected to occur in the latter half of the 21st century. The drought event was estimated to cause direct damages of 30bn US$ and last for 84 months. Assuming that τ_α=1.0, over-production capacities of 1.25, 1.5, and 2.0 resulted in indirect economic losses of 21bn, 20bn and 18bn respectively, compared to 93bn US$ when no over-production was modelled. No differences in trends were seen for the parameters $\propto_i$ and τ_α when estimated for the larger magnitude drought (graphs not shown) compared to the results presented above. Similarly, no differences in trends were seen for the inventory parameters n_j^i and τ_s. This suggests that the values of the inventory and adaptation parameters used are not sensitive to the scale of the direct drought damages.

6.4 Discussion

The analysis aimed to illustrate the importance of modelling indirect economic drought costs within climate change cost assessments, by providing a preliminary investigation of potential total economic drought losses in Spain. The chapter applies the technique of I-O analysis, using the pre-existing ARIO model, to drought events. The modifications made to the ARIO model represent a first attempt at capturing specific drought characteristics to assess the scale of indirect economic drought costs under various scenarios of climate change. The model was validated by running scenarios of three historic drought events in Spain (section 6.3.1) and comparing model output to past economic data. In addition, the evolution of direct drought effects on the agricultural sector, and consequences for indirect losses, was assessed. Direct economic costs of drought were modelled to affect agricultural productivity cumulatively, seasonally, and as a sudden shock. Sudden shocks to agricultural production caused quick and steep declines in agricultural and total VA (see figures 6.1, 6.2 and 6.3). Inter-industry multiplier effects were also larger than seen for the other scenarios, particularly for manufacturing which processes agricultural goods. However, the results showed that over the duration of the drought the largest indirect economic costs to the economy and agricultural VA occurred when agricultural damages were modelled in a cumulative fashion or seasonally.

This is explained by the ability of the ARIO model to allow adaptation and recovery following an economic shock. Whilst cumulative drought effects do not cause such drastic and sudden reductions in VA, the continued constraint on production capacity and restricted inventories mean that recovery during the drought is limited. When damages to agriculture occur suddenly the shocks to VA are more sudden and severe however, in the intermittent months that are not affected the production capacity of the agricultural sector remains constant (unless restricted by inventories). During this time, two different dynamics were identified for Spain depending on the specific drought characteristics. If the drought event was particularly severe in the months following the shock to agriculture then the continued effects on the manufacturing and utility sectors meant that recovery was very limited or did not occur (e.g. figure 6.1b). Alternatively, if the drought event became less severe in the intermittent months when agricultural production was not affected, then increased production capacity and the use of inventories resulted in an increase in production (e.g. figure 6.1a). Consequently, economic recovery can begin to occur during a drought event where a decline in drought severity coincides with stable agricultural production capacity. Over the duration of the drought event this can cause substantial reductions in the scale of indirect economic losses. This emphasises the importance of drought characteristics, which will be unique for each individual event, when modelling indirect economic costs of drought and adaptation policies. It also highlights the different pattern of losses economies may face if they suffer from long-term shocks compared to a sudden, short economic shock. To date most I-O analysis studies investigating indirect economic costs of weather extremes have focused on the latter.

A main aim of this chapter was to highlight the application of the direct drought costs, made in chapter five, to the ARIO model to illustrate the potential scale of indirect losses that may occur under future scenarios of drought. The model was used to examine indirect drought costs in Spain for various SPI time periods and emission scenarios. Estimated annual drought losses in Spain in 2003-2050 were found to be 36% higher for SPI-6 droughts if indirect economic costs are considered, and up to 75% higher for SPI-12 droughts. The results highlighted a non-linear relationship between direct and indirect economic costs. The EARs presented in table 6.2 also highlight this trend as direct drought costs become more severe under future scenarios of climate change. This is in agreement with findings of non-linearity reported by Hallegatte (2008), Hallegatte et al., (2011) and Ranger et al., (2011) for hurricane and flood events. Additionally, figure 6.4a-b suggests that for smaller magnitude drought events, which cause smaller scale direct damages, a threshold may exist beyond which indirect losses do not occur. This is also corroborated by Hallegatte (2008) who modelled the effects of varying sized shocks to the economy for the US state of Louisiana, and found that the economy could cope with natural disasters causing direct damages of up to 50bn US$ with little or no indirect effects. However, above this threshold indirect effects appeared and became rapidly larger.

Crucially, the projections of annual SPI-6 drought costs in 2051-2098 highlight drought losses may be 45% higher under a stringent mitigation scenario and 75% higher with no mitigation. Stringent climate change mitigation, (also discussed in chapter four for Spain), is shown to substantially reduce direct economic drought costs. Importantly, due to the non-linearity seen the benefits in terms of avoided indirect losses may be more substantial than for direct losses in the latter half of the 21^{st} century. In addition, the EARs presented for Spain are for average annual drought losses and this averaging can mask the variability in the size of losses of individual drought events. For the largest droughts identified in 2003-2050 EARs were 1.48 and 1.80 for SPI-6 and SPI-12 droughts respectively. For the most severe SPI-6 drought in 2051-2098 the EAR was 1.94, i.e. almost doubling direct losses.

It is very difficult to extrapolate the illustrative findings for Spain to other countries. The scale of indirect economic effects will depend on the specific economic structure of a country, the economic importance of industries at risk from drought, and the particular drought characteristics. However, the study does highlight the likely underestimation of economic costs of climate change on drought, and other extreme weather types, which are based on direct damages only. As touched upon in the literature review (section 2.5) there is some uncertainty over the importance of indirect economic losses. Albala-Bertrand (1993, p.104) claims indirect effects are '*often unimportant for the economy and society as a whole and are rapidly counteracted within the disaster area*' (quoted in Okuyama, 2007). For example, following a disaster the area may benefit from an influx of financial aid, investment for reconstruction, and expansion of manufacturing and construction sectors. Such a surge in economic activity was seen following Hurricane Andrew in the US in 1992, driven by reinvestment of private and public insurance payments (Baade et al., 2007). However, this judgment is disputed by Brookshire et al (1997) who argue that short-term benefits such as increased investment of savings will dampen the economy in the long-term, and inflow of government aid will reduce the financial resources of a nation as a whole. The results of this analysis found that all drought events modelled for Spain resulted in negative indirect economic costs. Importantly, a surge in reconstruction is not commonplace following drought, as with other natural disasters, which further limits the possibility of beneficial economic effects. Benefits may occur for certain region and sectors, for example due to increasing prices of agricultural goods, although there is likely to be disparity between the economic winners and losers of drought (Diersen and Taylor, 2003).

The modelling exercise illustrates how I-O modelling could be used to facilitate climate change cost assessments, and investigate specific adaptation and mitigation policies, with regard to drought. As such, the study presents some very interesting findings. However, the quantitative estimates presented are illustrative only and there is much uncertainty surrounding the results of this analysis, with further research needed to quantify and handle the considerable uncertainties. In addition to the uncertainties in the specific modelling framework of ARIO (discussed in Hallegatte, 2008, 2011), when interpreting the drought results it is also important to consider some of the specific assumptions made here, and highlight caveats of the study. For example, it was assumed that following the end of each drought event the production capacity of affected sectors (agriculture, utilities and manufacturing) immediately returned to the pre-event baseline. The approach assumed a temporary retirement of productive capital as production capacity declined, allowing it to be returned to full usage without the need for reconstruction, additional investment, or delays following the end of the drought. Yet, whilst productive capital may be directly unaffected it may take multiple seasons or even years for the productive capacity of agriculture to recover from drought. Wittwer and Griffith (2010) found that for agriculture in Australia not only did recovery exceed the end of the drought event but that affected areas did not always recover to pre-event levels. This may reflect disinvestment in agriculture resulting in overall reductions in output; reduced stocks e.g. due to the sale or slaughter of cattle; reduced water availability for irrigation, which can last beyond the drought event even if rainfall returns to normal levels; or increasing costs of irrigation water, which can become more valuable even when drought conditions have ended. Additionally, delays in recovery of agricultural yields can have knock-on effects for supply for the following years feedstock, reducing inventory levels (Diersen and Taylor, 2003), and potentially increasing vulnerability. Similarly, in Canada two years of severe drought in 2001 and 2002 resulted in significant reductions in herd stocks which require a long-term recovery period (Wheaton et al., 2008).

In certain cases for Spain, prolonged recovery periods were modelled following drought termination (e.g. figure 6.1b). This can be linked to the sudden jump in demand, which occurs as production capacities increase, which can strain inventories causing additional production constraints. The research would benefit from a more detailed analysis of specific production bottlenecks caused during drought that may limit economic recovery both temporarily and permanently. Detailed data on the effects of historic drought events on specific economic sectors would be advantageous for such a study. Unfortunately, such data appears very challenging to find.

It was also assumed that direct economic drought damages would affect agriculture, utilities and manufacturing sectors only. This assumption was based on past impact data on droughts in Spain. Disaggregating the direct economic drought costs between these three sectors was more complex as the scale of sectoral losses of drought events are very difficult to distinguish and quantify, and are rarely reported in the literature. It was assumed that the share of sectoral losses would be proportional to each sectors reported share of water abstraction from surface water (i.e. drought would have the largest effects on sectors most reliant on water). This assumption is basic especially as, unlike other natural disasters that have clear direct economic consequences on infrastructure, direct and indirect effects of drought are very hard to distinguish clearly. Furthermore, the direct economic damages to utility and manufacturing sectors were assumed to occur over time in a cumulative fashion, linked to the specific drought intensity of each month. For agriculture, three scenarios were investigated: the effect of cumulative losses, seasonal losses and sudden losses to production capacity. Assuming that direct losses to agriculture occurred suddenly provided the most robust results. For each drought event studied, the model could reproduce reported economic losses to agricultural VA for at least one of the scenarios and SPI time-periods used. However, as the evolution of direct drought damages affecting economic sectors is theoretical a caveat must be placed here. The modelling approach would benefit from a more detailed calibration of the specific evolution of drought losses for each economic sector based on actual historic events. Yet as noted above, the availability of such detailed data is a major constraint.

Additionally, drought can cause varying degrees of damage to crop yields depending on the particular season/seasons in which it occurs. Whilst the above agricultural scenarios attempted to represent this in a simple fashion via the three agricultural scenarios, the model itself does not account for the seasonal production dynamics of agriculture. Daily production in the agricultural sector was assumed constant over the year, whereas in real life production is often concentrated over certain time-periods or seasons depending on the agricultural goods being produced. As such, monthly agricultural production dynamics need to be considered in more detail for the indirect effects of drought on agriculture to be modelled in a more realistic manner.

The direct economic costs used as input to the ARIO model were based on the economic drought damage functions, calibrated to historic economic impact data from EM-DAT. It was assumed that data reported by EM-DAT reflected direct economic damages only. Yet particularly for more recent drought events this data may be more comprehensive and include both direct and indirect losses. As a result, there may be some double counting of indirect economic costs due to uncertainties surrounding the direct economic data. The direct economic drought damages for Spain were considered to affect a static economy and as such, the I-O coefficients also remain static over time. However, the study analysed changing drought trends in 2003-2050 and 2051-2098, which would affect an economy potentially very different from that of 2002, and I-O coefficients will also evolve slowly over time due to changes in technology, demography, prices, demand, and social and political change external from any weather related shocks (Hallegatte, 2008). Future drought trends modelled in section 4.3 also suggest that for Spain drought events increase in frequency and duration over the 21st century. This study has considered the indirect costs of individual drought events on a stable economy in equilibrium, and assumed that following the event the economy will return to its pre-event baseline. The indirect economic costs that may occur if successive drought events affected an already vulnerable economy, still recovering from previous drought episodes, may be much more severe. Future research focusing on economic effects of successive drought events would be interesting for countries such as Spain. The sectoral split of direct drought damages is also assumed to remain static although the importance of certain economic sectors may change over time. For example, as economies develop they may become less reliant on vulnerable sectors such as agriculture (Benson and Clay, 2004) and effects of drought might be more heavily felt by e.g. industries and public services. Conversely, the transition of developing economies to intermediate and developed stages can also increase the inter-sectoral linkages and make systems more vulnerable to indirect economic losses (Benson and Clay, 2004, Bočkarjova, 2007).

The study utilised the pre-existing ARIO-inventory model. The model structure, equations and assumptions have been well documented and the code was freely available to use. The use of the ARIO model was also beneficial in the context of this study as it allowed some flexibility in the economy following the onset of drought and incorporated inventory dynamics. Adaptation was explicitly considered through increases in production capacity, and the ability of producers to switch to suppliers outside the affected area, when supply was constrained. The sensitivity analysis showed that the results were not highly sensitive to the level of over-production when modelled (figure 6.6a-b), however, costs increased substantially when over-production was excluded. The increase in indirect economic costs seen when over-production was completely excluded highlights the role that autonomous and planned adaptation could have in mitigating indirect drought costs. However, the adaptation parameters considered here were applied homogeneously across economic sectors. In reality, different sectors may have different adaptive capacities and options available to them. Areas that suffer worsening or successive drought events in the future may also increase their resilience over time through learning and the implementation of risk management strategies. However, as the analysis considered economic costs of individual drought events affecting a static economy, such dynamic changes were not considered. Further investigation into historic drought events and any specific autonomous or planned adaptations that occurred at a sectoral level, and the effect of this, would be beneficial. This would improve the robustness of the modelling exercise and results generated.

The chapter highlights that each individual drought event is unique and the economic losses caused will depend upon on the timing, duration, and magnitude of the event, as well as the economic structure and social conditions of the affected region. The methodology developed was able to capture some of these specific characteristics to help illustrate the potential full economic costs of drought. The study also highlights how drought damage functions can be linked with an I-O model to capture indirect economic costs. Importantly, the methodology was developed in such a way that it can be applied to other countries or states. Direct drought damages can be imposed on high-risk sectors identified in the literature and direct losses disaggregated based on the specific water use of sectors in the affected area.

6.5 Summary

The application of I-O analysis to investigate the indirect costs of weather extremes and natural disasters on the economy is a relatively new and developing area of research. The application of I-O analysis specifically to drought events is even more limited with only a handful of studies existing. The chapter demonstrates how I-O analysis could be used to capture some of the specific characteristics of drought in order to investigate potential indirect economic costs. The simple modifications made to the ARIO model represent a first step in modelling indirect economic drought costs under future scenarios of climate change by incorporating direct drought losses estimated via the drought damage functions.

The preliminary investigation for Spain suggested that for SPI-6 droughts total annual drought losses in 2003-2050 could be 36% higher than direct losses alone. Total annual drought losses in 2003-2050 could be up to 75% higher for SPI-12 droughts compared to direct losses alone. In the latter half of the 21st century, average annual indirect losses for SPI-6 droughts were estimated to rise to 76% of direct costs under the A1FI emission scenario. However, these indirect costs were restricted to 45% assuming stringent mitigation. Importantly the non-linearity seen between direct and indirect economic costs suggests that the benefits of stringent mitigation policies, in terms of avoided indirect losses, could potentially be more substantial than for direct losses in the latter half of the 21st century. The dynamics of the economy following direct drought effects, the scale of indirect losses, and ability of the economy to recover were linked to the evolution of each drought event and the manner and timescale in which direct damages were assumed to occur. Interestingly the results highlighted that *ceteris paribus* long-term versus sudden drought impacts did not necessarily cause lower indirect losses.

However, the quantitative results presented in this chapter should not be interpreted literally, as they are highly uncertain and dependent on a range of simple assumptions that would benefit from a more detailed analysis. Namely, better calibration of the model to account for the size of inventories and their restoration times; better representation of agricultural production dynamics; consideration of specific adaptation and recovery options available for sectors following drought; consideration of potential bottlenecks which may limit economic recovery; and more detailed information on the way in which drought will effect specific sectors. Despite such limitations, the modelling exercise does highlights how valuable I-O analysis could be for providing more comprehensive estimates of drought damages under future climate change; for investigating economic scenarios of drought effects on agriculture; and for assessing specific mitigation and adaptation policies, and implications for the wider economy following drought. Consequently, there are many gains to be seen from the continued development of this research methodology for drought.

7 Discussion and Conclusions

Drought can affect virtually any region of the world, regardless of precipitation or temperature regime, posing a significant risk to both developed and developing countries. The complex nature of drought events such as their slow onset, and large spatial and temporal extent, make them difficult to analyse and plan for (Wilhite et al., 2007). Historically, drought events have had one of the largest effects on society of all extreme weather events, and have the ability to cause significant disruption to economic systems. Evidence suggests that the number of people affected by drought events and their economic consequences have been increasing over the 20th century and early 21st century (EM-DAT, 2010), primarily due to changing socio-economic conditions. Therefore, irrespective of any future changes in climate, drought events and their effects already pose a considerable problem for governments, businesses and individuals.

Superimposed on this risk is the danger that future anthropogenic climate change poses. Evidence suggests that climate change has begun to influence the hydrological cycle, and that drought events have been increasing in frequency and intensity in some regions over the latter half of the 20th century (Dubrovsky et al., 2009, Easterling et al., 2000b, IPCC, 2007b, Lynch et al., 2008, Zhang et al., 2007, Zou et al., 2005). Future projections of climate change suggest that this situation is likely to be exacerbated in certain regions of the world (e.g. Burke et al., 2006, IPCC, 2007b, Sheffield and Wood, 2008, Warren et al., In review). Climate models are increasingly being used to model and understand how climate change may affect future drought patterns and the countries and regions at risk. However, the literature review emphasised that quantitative estimates of the type and scale of social and economic effects that could occur under these future scenarios are virtually non-existent and clear methodologies are still being developed (Changnon, 2003b, Hallegatte et al., 2007b, Mendelsohn and Williams, 2004, Pielke, 2007).

This study aimed to develop a methodology to estimate economic losses and social drought effects under future scenarios of climate change. A summary of the research objectives, methodologies developed and employed, and key findings is presented below. Following this section 7.2 discusses the overall success of the study to address the research aim. Limitations, caveats and uncertainties are revisited in section 7.3. To conclude, future research avenues are discussed in section 7.4.

7.1 Summary of thesis

7.1.1 Creating drought damage functions

The first research objective was to investigate the relationship between historic drought events and their economic and social effects, in order to establish a link for creating drought damage functions. Historical drought events reported in EM-DAT from 1940-2002 were modelled for Australia, Brazil, China, Ethiopia, India, Portugal, Spain and the USA. The drought events were modelled using monthly gridded precipitation data converted to the SPI. The SPI was developed by McKee et al., (1993) and has been found to perform favourably compared to other drought indices (Guttman, 1998, 1999, Keyantash and Dracup, 2002, Lloyd-Hughes and Saunders, 2002, Redmond, 2002). Importantly, The SPI is beneficial for this study as it requires precipitation data only and provides a method for analysing not only the occurrence of drought events but also for defining drought start and end months, intensity, and magnitude for a variety of time periods. Two SPI time periods were used to represent medium-term (SPI-6) and long-term (SPI-12) drought events and their effects, and provide a range of results. A methodology was devised to first assess whether each drought event reported in EM-DAT correlated to the SPI data, and secondly to quantify each drought in terms of its duration, magnitude, and intensity. The relationship between the characteristics of individual drought events and their economic and social effects were investigated using regression analysis. The most robust trends were identified using magnitude, which represents the duration, intensity, and spatial extent of each drought event in a single indicator.

The results highlight that for Australia, China, India, Portugal/Spain and the USA, the magnitude of historic drought events could account for a large proportion of the variance seen in the direct economic losses reported (figure 3.3a-f). Furthermore, where impact data was sufficient social damage functions were created for the numbers of lives affected and the numbers of lives lost. The correlation seen between drought magnitude and social drought effects was generally less robust suggesting that external factors may be more influential when considering social drought effects, for example pre-existing food or water scarcity issues, or high levels of poverty. However, the creation of social drought damage functions highlighted the different vulnerabilities of regions to drought and the particular consequences they may face, and could help inform decisions on the priority of adaptive measures. Vitally, economic metrics alone may not always be representative of the full effects of a drought event.

It is widely reported that the availability of relevant data on extreme weather events is a major limiting factor in their study (Easterling et al., 2000a, IPCC, 2002). Indeed, the availability of data was a large obstacle in creating robust drought damage functions, severely restricting the number of data points on which the trends were based. As such, issues of sampling uncertainty remain large. For the drought events quantified by this study only 56%, 52%, and 26% had available impact data on economic damages, lives affected, and lives lost, respectively.

However, the methodological approach and results were extremely encouraging, facilitating the research objective and enabling the creation of country specific drought damage functions. The methodology for modelling and identifying drought events by applying the SPI to spatial and temporal data was novel. In addition, the drought damage functions are, to the best of the authors knowledge, the only country specific drought damage functions created to date. The drought damage functions improve on many of the current limitations found with climate damage functions (Dietz et al., 2007, Smith et al., 2001, Stern, 2007). Namely, the drought damage functions and their shape and scale are empirically grounded, calibrated to historical event data and precipitation data. The methodology can be used to quantify drought magnitude across different countries, regions and time-scales; can capture the vulnerabilities of regions with different socio-economic characteristics; and can be applied to both market and non-market effects (where sufficient data exists). Importantly, the damage functions enable economic and social effects of drought events of a given magnitude to be estimated, and can be applied to future projections of drought under climate change.

7.1.2 Projections of drought under future climate change

The second research objective was to model and quantify the effect of climate change on future drought regimes. IAMs are considered one of the best tools available for assessing climate change impacts, the global costs of climate change, and risks (Stern, 2007). The IAM CIAS (Warren et al., 2008) was used to create future projections of monthly, gridded precipitation. In order to address modelling uncertainties precipitation data was modelled emulating three different GCMs, each run using a high emission scenario (A1FI) and a stringent stabilisation scenario (450ppm). The ability of the IAM CIAS to run scenarios of precipitation emulating different GCMs builds upon many existing studies of future drought events which have utilised one GCM only. The SPI was used to identify severe and extreme drought events and quantify their frequency, duration, intensity and magnitude, for pre-defined country regions. Drought events were modelled using observed data from 1955-

2002, and projections of precipitation from CIAS for 2003-2050 to allow a comparison of drought characteristics over time.

Results show that south-west Australia, northeast and north-west Brazil, Portugal, and Spain are particularly at risk from worsening drought conditions in the first half of the 21st century. The effect of climate change on average drought conditions in the USA was more variable depending on the region and the climate scenario used. However, changing trends in drought characteristics, particularly for long-term SPI-12 droughts, are likely to be negative. Projections for China, Ethiopia and India suggest that climate change may well increase precipitation over the first half of the 21st century, mitigating the frequency and severity of drought events. Climate change is also likely to affect the variability of precipitation and it was found that drought events may still be severe when they do occur, even if mean precipitation is increasing, agreeing with findings of the IPCC (2007b) and Hirabayashi et al., (2008). The results also highlight that climate change is likely to have a larger effect on the duration and magnitude of long-term SPI-12 droughts, representing increased risk to hydrological systems and water resources. Australia, Brazil, Spain, Portugal and the USA were shown to be particularly vulnerable to multi-year drought events.

The average change in drought trends projected for Australia, Brazil, China, Ethiopia, India, Portugal, Spain and the USA were in line with projections reported by the IPCC (Christensen et al., 2007), as well as other modelling studies reviewed in section 4.3, supporting the robustness of the methodology. However, whilst some general trends emerged the use of six emission/climate scenarios highlighted the large uncertainty that exists (figures 4.4a-d). Most of the uncertainty was attributed to the specific GCMs used. There was little variability seen between results generated using the A1FI emission scenario and the 450ppm stabilisation scenario. This finding is consistent with Goodess et al., (2003b) who reports that for the early 21st century inter-model variability tends to be greater than inter-scenario variability. As such, the implementation of a stringent mitigation policy is projected to have limited effect on drought and its effects in 2003-2050. The choice of emission scenario is much more influential in the latter half of the 21st century, as demonstrated for Spain (figure 4.5).

7.1.3 Economic and social drought effects

The third research objective was to apply the estimates of drought magnitude, for 1955-2002 and 2003-2050, to the social and economic drought damage functions to estimate the scale of additional drought effects under climate change. The modelling approach is static in that economic losses and social effects were normalised to country GDP in 2002 US$ and population levels in 2002 to allow comparison over time. This approach follows the method of other assessment studies that focus on the costs of climate change (e.g. Hallegatte, 2007, Hallegatte et al., 2011, Nordhaus, 1991, Ranger et al., 2011, Tol, 2002a, Tol, 2009). Whilst the assumptions of stationarity ultimately reduce the robustness of estimates made for future drought risks one benefit of using a standard metric across time is that the focus of the analysis will be on changing economic and social conditions due to climate change rather than consequences of changing socio-economic conditions.

The drought damage functions facilitated quantitative estimates of drought effects in terms of direct economic losses, the number of lives affected, and the number of lives lost. Results were presented as annual average losses for each SPI time period and climate/emission scenario. The effect of climate change on future drought events resulted in negative economic costs for Australia, Portugal, Spain, and the USA. Average annual losses increased by 76%, 69%, 300% and 87% for SPI-6 droughts, and by 565%, 38%, 92%, and 105% for SPI-12 droughts for Australia, Portugal, Spain, and the USA respectively. Economic estimates of average annual drought costs for China and India suggested that both countries would benefit from a reduction in drought frequency and magnitude. However, it was consistently found that effects of climate change on drought resulted in greater annual losses to global GDP in 2003-2050 compared to 1955-2002 when losses were aggregated across the countries analysed, particularly for long-term drought. Hence, the potential economic benefits seen in some regions are outweighed by the scale of negative damages in others. The results indicate that severe and extreme SPI-6 and SPI-12 drought events could cause additional losses to global GDP of 0.01% to 0.25% annually. Whilst this effect on global GDP may appear small it is considered a conservative estimate as the analysis represents six countries only, for the first half of the 21st century. The estimates do not incorporate the possibility of successive drought events, or compounding effects on vulnerability and socio-economic conditions from interactions with other extreme weather events such as floods. The global economic estimates exclude indirect economic and potential social effects. Additionally, possibilities of irreversible or systemic collapse of economies, due to passing natural thresholds, are not considered. Consequently, under future climate change, drought magnitude may exceed current experience and surpass thresholds of social and economic resilience causing unprecedented economic losses.

The study also highlighted that annually drought related deaths are set to increase slightly over the first half of the 21st century in the USA. Similarly, the number of people affected by drought was projected to increase severely in Brazil for both SPI-6 and SPI-12 droughts, with drought potentially affecting 4.5 to 6.8% of the population annually. Estimates of the number of lives affected by drought in Ethiopia varied depending on the SPI time period used, with SPI-6 drought events projected to affect less people annually whilst SPI-12 drought events were projected to affect more people annually.

Large variability in the economic and social consequences of individual drought events was seen. It was projected that the effects of some individual drought events will rise dramatically in the future, exceeding historic losses reported by EM-DAT. For economic damages, this was particularly prominent for Australia and the USA due to the use of non-linear drought damage functions. The size of economic losses estimated for some individual drought events of severe magnitude were found to be unrealistic and overestimated. Consequently, more consideration needs to be given to the evolution of the shape and scale of the damage functions as future drought events may exceed historical ranges on which they are based. However, this finding also supports the argument that current thresholds of resilience to climate change may be exceeded in the future (IPCC, 2007c). If socio-economic drought thresholds are exceeded the magnitude of losses may increase rapidly, potentially resulting in irreversible or systemic collapse of economies.

The study established the application of drought damage functions as tools for the estimation of economic and social drought effects across various countries and timescales. The economic and social drought effects were representative of the likely changes in drought regimes modelled under future climate change. By modelling individual drought events the effects of climate change on the variability of future precipitation and drought events was also highlighted. However, it is very difficult to assess the robustness of the future projections of economic and social effects as there is limited data and literature on which to base comparisons. Consequently, many caveats and limitations were highlighted and uncertainties remain large.

7.1.4 Estimates of indirect economic drought costs

The fourth objective was to model and quantify the indirect economic costs of drought events. Improved understanding and validation of indirect damages from past weather extremes is crucial to help improve the estimation of future losses in the context of climate change analysis. This is particularly important when analysing drought events as they are commonly associated with large indirect losses (Wilhite et al., 2007). Crucially, most existing IAMs omit not only extreme weather events but also factors such as cross-sectoral impacts, and effects on businesses productivity (Stern, 2007).

I-O analysis was highlighted as a promising tool for the estimation of indirect losses from natural disasters and extreme weather events (Rose, 2004). However, studies focusing explicitly on the quantitative estimation of indirect economic drought costs are scarce (Ding et al., 2010). In order to explore this issue further the ARIO Model (Hallegatte, 2011) was utilised and calibrated to Spain. The study focused on Spain as there was good consistency in the direction of drought trends modelled (chapter 4); Spain was identified as being at high risk from increasing economic drought losses (chapter 5); and drought events affect a large proportion of the country meaning that effects would be relatively homogenous across Spain. The shock to the economy during drought was based on the direct economic losses estimated previously for Spain.

The ARIO model was modified so that direct economic losses accumulated gradually over the drought duration; direct losses were disaggregated between high-risk sectors based on historical data on drought impacts and water use; and as it was assumed there was no direct damages to infrastructure, production capacity returned to the pre-event level when the drought event terminated. In addition, for the agricultural sector three scenarios were investigated: the effect of cumulative losses, seasonal losses and sudden monthly losses to production capacity. The model was validated by running scenarios for three historic drought events in Spain and comparing model output to actual economic data. Assuming that direct losses to agriculture occurred suddenly provided the most robust results, which may reflect the fact that as agriculture is highly sensitive to weather variability drought losses may be immediate (Ding et al., 2010). Contrary to other studies (e.g. Hallegatte, 2005) it was found that *ceteris paribus* modelling direct drought damages as gradual shocks rather than sudden shocks did not necessarily cause lower indirect losses.

The model was used to illustrate the potential indirect economic drought costs which could occur in Spain for SPI-6 and SPI-12 drought events using ECHAM4 and the A1FI and 450ppm emission/stabilisation scenarios. Estimated annual drought losses in Spain for 2003-2050 were found to be 36% higher for SPI-6 droughts if indirect economic losses were considered, and up to 75% higher for SPI-12 droughts. The results suggested a non-linear relationship between direct and indirect economic costs, in agreement with Hallegatte (2008) and Ranger et al., (2011). The results for SPI-6 droughts in 2051-2098 highlighted that under a high emission scenario total economic losses could be up to 76% higher than direct economic losses alone (table 6.2). This was restricted to 45% when the 450ppm stringent mitigation scenario was used. Importantly, the findings highlighted that stringent mitigation could have large benefits in terms of reducing indirect economic effects. Stringent climate change mitigation was shown to reduce direct economic losses by 32% when compared to the high emission scenario, whilst indirect losses were reduced by 60%.

The analysis emphasised the unique nature of individual drought events. The specific losses caused will depend upon the timing, duration, and magnitude of the event, as well as the economic structure and social conditions of the affected region. The application of the ARIO model was also advantageous at it allows flexibility in the economy following an economic shock by drawing on inventories, and adaptation in the form of over-production or increased imports. It was found that indirect costs of drought in Spain increased substantially when over-production was completely restricted highlighting the role that autonomous or planned adaptation could have in reducing future indirect drought costs. However, the modifications made to the ARIO model represent a first effort at modelling indirect economic drought costs under future scenarios of climate change and quantitative results are illustrative only. In interpreting the results it is important to consider some of the specific assumptions made and caveats of the study, as well as methodological and data issues which would benefit from further research to improve the robustness of the study. Importantly though, the methodology has illustrated that drought damage functions can be linked to an I-O model to provide estimates of indirect economic costs of drought. Consequently, there are many gains to be seen from the continued development of this research methodology for drought.

7.2 Achieving the research aim

The summary of research presented in section 7.1 highlights that the methodology devised, and the modelling tools utilised, have been beneficial for addressing the overall research aim of estimating future economic and social drought effects under various climate change scenarios. The approach has also addressed many of the current methodological issues seen in cost assessment studies of extreme weather events, as identified in chapter two (section 2.6). Namely, the methodology is not case specific and is general enough to apply to drought events universally at an international, national and sub-regional level. Yet, it is not so generalised that it fails to capture spatial variations in drought and its effects. The creation of country specific drought damage functions enables the specific characteristics and vulnerabilities of individual countries and states to be identified and as such can be applied to both developing and developed countries. The damage functions consider the specific characteristics of individual drought events by focusing on drought magnitude, which reflects the intensity, duration and spatial extent of droughts. The damage functions have been applied to market and non-market effects, using various metrics, and empirically calibrated to historic precipitation data and impact data. Finally, a novel methodology to assess indirect economic drought costs has been illustrated for Spain. In investigating indirect losses, the onset time and evolution of direct damages was considered for agriculture, manufacturing and utility sectors.

As discussed a major omission in studies that focus on the costs of climate change are the economic damages and social effects associated with extreme weather events (Buchner et al., 2006, Tol, 2002a, Tol, 2009). The exclusion of extreme weather events from climate change cost assessments leads one to question the comprehensiveness and utility of such assessments for informing climate change policies. Therefore, it was also recommended in section 2.6 that the research should be policy relevant, providing outputs that are useful and understandable to policy makers; which can be incorporated into wider climate change cost assessment studies; and which can help to drive decision-making. The importance of designing a methodology to help address these factors ultimately drove the research and underpinned its aim and objectives.

The effects of future drought events on national and global GDP were provisionally addressed in chapter five (section 5.2.1). The results highlighted that the effect of climate change on drought regimes in the first half of the 21st century was likely to have a significant effect on annual average GDP in Australia, Portugal and the USA. Additionally, the results highlighted that direct economic damages from severe and extreme drought events were expected to have an increasingly negative effect on global GDP in the first half of the 21st century (figure 5.2). Although not directly comparable, results were also presented in light of the estimates made by Stern (2007). This suggested that the findings of Stern that extreme weather events would cause additional losses of 0.5-1.0% of world GDP by 2050 (above changes in wealth and inflation) could well be underestimated when considering the conservative estimates of direct economic losses from severe and extreme drought events to just a handful of countries. Crucially, this highlights how results could be incorporated within climate change cost assessment studies, at either a national or a global scale. Additionally, there is potential for the damage functions to be integrated into CIAS or incorporated within economic models that currently use the economic damage functions of Tol (2002a, b) and Nordhaus and Boyer (2000) to explicitly consider drought. These issues are discussed in more detail in section 7.4 below.

Concerning climate change policy the study emphasised that stringent mitigation (implied by the 450ppm scenario) will be critical for reducing the effects of climate change on drought regimes and socio-economic consequences in the long-term (2051-2098). However, even under stringent mitigation economic and social drought effects were not reduced in the short to medium term (2003-2050), when compared to a high emission scenario. Society is already committed to a certain degree of climate change in the first half of the 21st century, and changes in future drought regimes and socio-economic consequences cannot be entirely avoided. Therefore short-term adaptation will be necessary to address impacts linked to changing timing, volume, and quality of water (Kundzewicz et al., 2008). This will have consequences for the way in which countries manage future drought risk as drought adaptation strategies and water management strategies need to be created using a dynamic framework, which considers future impacts of climate change.

This is an important issue as to date there has been relatively little evidence of downscaling exercises of climate change impacts specifically linked to adaptation assessment (Wilby and Fowler, 2011). However, the major driving factor behind this research was the development of a methodology to quantify drought effects for inclusion within climate change cost assessments in the form of avoided damages, to represent benefits of mitigation in a more comprehensive fashion. Whilst downscaled projections of precipitation were utilised here, and illustrate how such techniques can be used to detect future drought trends and potential socio-economic effects, making a link to specific adaptation planning is difficult. Decisions regarding adaptation are often made on much smaller spatial scales than covered here and for specific businesses or sectors. Additionally, the uncertainties that surround the estimates of drought and its socio-economic consequences, as with any climate change projections, make it hard for robust decisions to be made. This can be especially problematic where there is uncertainty over the general direction of trends using different scenarios (Economics of Climate Adaptation Working Group, 2009). For example, the range of results illustrated in figure 4.4a-d, which in some cases differed in direction of change depending on the climate scenario used.

Whilst the results of this study may be useful for assessing the costs and benefits of adaptation overall, it will be less applicable for informing local adaptation strategies and decision-making. Results focus on aggregate effects to economies and society, however the specific, and numerous, manifestations these effects can take are not specifically addressed. For example, reduced water supply, affected water quality, availability of water for industry and energy generation, effects on water-borne transport, increased incidence of water-related disease, effects on water based tourism and recreation, degradation of aquatic ecosystems, reduced sanitation, consequences for agriculture, implications for insurance industries, and effects on human health and mortality rates. However, this study does identify areas of high drought risk, which are likely to be particularly vulnerable in the future, as well as highlighting the types of damages which regions may be more sensitive too. This information can still be useful for identifying areas where adaptation and drought risk management will be especially important in the short-term. As noted by Wilby and Fowler (2011) simply having information on the trends of climate change and drought events may be sufficient to raise awareness of risks and motivate low regret adaptation options.

7.3 Limitations, caveats and uncertainties

The achievements of the above analysis are considerable. The data sources, methodology, modelling techniques and results have all been selected and utilised in order to make the results as robust as possible. However, as with any studies that involve making future projections there are many limitations, caveats and uncertainties that have been raised and discussed in chapters three, four, five, and six. In interpreting the results of the study, it is important to be aware of such limitations in the methodology and data. As previously noted, as model complexity grows and linkages are made between different components uncertainties will cascade through the modelling chain and increase (Wilby and Fowler, 2011). In this case, it is important to reiterate that modelling limitations and uncertainties exist due to:

- modelling drought using the SPI, related to the specifics of the index itself and the quality of the historic precipitation data
- the quality of data available in EM-DAT, specific issues related to its cataloguing, the assumption that economic damages reflect direct losses only, and the limited availability of the data restricting the data points on which trends were based
- the focus on drought magnitude only although other socio-economic variables, such as increased water demand, can affect the scale and type of drought effects
- the focus on historic drought events until 2002 only, excluding more recent events
- the ability of GCMs to model precipitation accurately, for example linked to difficulties in modelling large-scale atmospheric processes, monsoons and feedback processes
- the robustness of the downscaling technique used, and that only three GCM patterns were used in downscaling
- the coarse country regions defined and the spatial scale of the analysis
- the exclusion of climate variables other than precipitation, e.g. temperature, which may affect future drought regimes and the subsequent consequences of drought
- the implicit treatment of adaptation only, by assuming that society will be more resilient and adapt more readily to moderate drought events which were excluded

from the analysis (although adaptation options were explicitly modelled for indirect economic costs in chapter five)

- modelling the effects of individual drought events on static economic and social systems assumed to be in equilibrium
- the assumption that the shape and scale of drought damage functions will remain valid for future events which exceed historical thresholds
- the exclusion of indirect social effects, such as increased risk of conflict or migration, and environmental effects from the analysis
- the modelling framework and assumptions which underlie the ARIO model, the manner in which direct drought damages were modelled in this study, and the sensitivity of the results to the adaptation and inventory parameters used.

7.4 Further research

This study is unique in its development of a methodology and subsequent creation of country specific drought damage functions, contributing to an area of relatively new and developing research. It is hoped that the drought damage functions, modelling approaches, and outputs of this research will contribute to the current gaps in knowledge highlighted in chapters one and two, and due to the interdisciplinary nature of the research will be beneficial to various parties. The literature review highlighted some important issues to consider when devising a methodology for estimating future economic and social drought effects under future climate change (listed in section 2.6). However, some of these issues, such as modelling drought effects as part of a dynamic system, have not been addressed by this study, and limitations and uncertainties remain large (as discussed in section 7.3). Accordingly, there are many potential extensions to this research, which would be useful for enhancing the robustness of the methodology and for increasing the applicability of the outputs for climate change analysis. Primary areas for further research are outlined below.

Presently, the economic and social drought damage functions have been created for eight countries only. It would be useful to create damage functions for other countries, where sufficient impact data is available, to facilitate a better estimate of global drought effects. The methodology devised is also beneficial as damage functions could also be created for use in specific national studies. Likewise, the potential for creating similar damage functions for heatwaves or heavy precipitation events would be an interesting avenue to explore. However, as a major constraint of this analysis has been the availability of data on drought events and their economic and social consequences it may not be possible to provide a truly global estimate in this manner. One alternative would be to use countries where damage functions can be created as proxies for countries with similar geographical, climatological and economic characteristics. A second alternative, as mentioned in section 3.4, would be to devise more conceptually based damage functions centred on the results of this assessment, but also incorporating information on the effects of other socio-economic criteria on drought related losses, perhaps through a ranking or weighting based framework.

The research would also benefit from temporal extensions. Historical precipitation data was available until the end of 2002 only at the beginning of this study, limiting the historical analysis of event and climate data to this time. From 2002 until present there have been some increasingly severe drought events affecting the countries studied that are not incorporated in the drought damage functions. The damage functions could be updated to 2006 using an extended version of the observed gridded precipitation data recently released by the CRU (CRU TS 3.0) [17] and currently being documented. This would help increase the number of data points on which the trends are based. It would also provide an interesting test of the shape and scale of the damage functions to see how robust they are to the addition of new data points, and whether the trends highlighted remain accurate. Furthermore, the future drought projections could also be improved as CIAS is currently being updated to incorporate the latest version of the SCM MAGICC and the nineteen GCMs used in the 2007 IPCC reports.

The drought damage functions are based on economic losses that have been normalised for each country based on inflation only. Changing socioeconomic conditions which can affect overall societal and economic vulnerability were not considered. This is a major caveat as *inter alia* Crompton and McAneney (2008) and Muir-Wood et al., (2006) have argued that a defensible normalisation procedure must also account for changes in population, assets, and wealth, not just inflation. The drought damage functions would benefit from more comprehensive normalisation techniques. This would increase the robustness of the damage functions and make them more amenable to use in other academic studies. In addition, the losses could be normalised based on regional economic data, as economic damages from drought events are often heavily related to the value and type of regional economic activity. Similarly, regional population statistics could be used to account for the varying exposure of populations in different regions.

An investigation of whether sub-national damage functions are necessary in some areas would also be interesting. For Brazil, the economic drought damage function could not be

[17] Available to download at: http://badc.nerc.ac.uk/data/cru/

utilised in this study due to the very weak correlation seen between drought magnitude and economic damages. Reported drought effects in Brazil were strongly related to the location where they occurred. Drought in south and central Brazil affected coffee crops, a main export for Brazil, resulting in high economic losses. Drought in the arid northeast affected a poorer region dominated by subsistence farming, and so economic losses were smaller regardless of the magnitude of the drought. Alternatively, losses in the northeast were much more significant in terms of social effects. Unfortunately, a major restraint for creating regional/state level drought damage functions is the availability of sufficient drought impact data at this scale. Promisingly, the above issues may be reduced if the economic and social impact data is normalised based on regional statistics as mentioned above.

As a first step, the study has modelled drought effects on a static system rather than a dynamic system. Yet, drought events occurring in the future may affect countries that have undergone large changes in their socio-economic structure, which can affect the vulnerability, resilience and exposure of regions. Unfortunately, such complex issues are extremely difficult to project and available data on future economic scenarios, and assets at risk were not consistently available across all countries studied. There are merits to using future economic scenarios of GDP to estimate changing assets at risk. However modelling uncertainties will also increase as GDP trends will depend on specific economic assumptions made about growth and the implementation of technological changes; the characteristics of the economic model used to project GDP; and assumptions about future exchange rates (Arnell et al., 2004). Such complex issues are extremely difficult to model and quantify.

Additionally, whilst increased economic growth may raise assets at risk and exposure it can also lead to an increase in resilience in the affected economy so a country is more able to cope in the disaster aftermath (Benson and Clay, 2004). For example, in the future there may be increased adaptation, especially in high-risk areas suffering from increasingly frequent and severe drought events. Planned and autonomous adaptation was not explicitly modelled in this study, although it could reduce future effects of extreme weather events (Adger and Brooks, 2003, Wreford et al., 2007). Instead, adaptation was treated implicitly by presenting results for severe and extreme drought events only, and assuming that moderate drought events that occur more frequently would be likely to cause smaller scale effects and would be easier to cope with and adapt to in the future. For future research, it would be beneficial to model explicitly an adaptation coefficient to adjust the estimates accordingly. This would require more research into the specific adaptation measures undertaken during past drought events as well as any implementation costs. The ARIO model did explicitly include basic adaptation options when investigating indirect drought costs for Spain. However, the adaptation parameters considered were applied homogeneously across economic sectors. In reality, different sectors may have different adaptive capacities and options available to them. Therefore, investigation into historic drought events and specific autonomous or planned adaptations that occurred at a sectoral level, and the effects of this, would also be beneficial for the I-O analysis. This would improve the robustness of the modelling approach and results generated.

It was also noted in chapters five and six that the projected economic and social drought effects presented here may be underestimated as the effects of successive drought events, affecting already stressed societies and economies in disequilibrium, were not considered. The future drought projections suggest that in the first half of the 21st century an increase in the frequency and duration of drought events in Australia, Brazil, Portugal, Spain and the USA cause more drought months per year resulting in less recovery time in intervening months. Research would benefit from an analysis of successive drought effects over time. Again, this would be benefitted by undertaking a second phase of research to assess future drought effects in a dynamic manner, using future economic scenarios.

The dominant focus of this research has been on direct and indirect economic drought effects. The effects of drought on the numbers of lives affected and lives lost was illustrated for Brazil, Ethiopia, and the USA, however, the trends between drought magnitude and social effects were less robust and the scope of the study was smaller. It would be useful to extend this analysis to focus more on the social effects of drought, especially for developing countries that are already facing water scarcity issues. Important interactions exist between society, the environment and water. Therefore, any future changes to hydrological systems, such as those caused by drought, could pose a significant risk to society (e.g. Arnell, 2004, Parry et al., 2004). Furthermore, the study has highlighted the importance of indirect effects of drought. Further investigation into the scale of indirect social effects that may occur under future scenarios of climate change, such as the scale of people facing water and food shortages or consequences for migration would be interesting. This type of extension could also provide a connection to secondary economic losses via linkages to increased humanitarian spending and relief aid from the international community. For example, drought damage functions could be created by establishing relationships between drought magnitude and data on humanitarian spending as used by Webster et al., (2008). The study by Webster et al., on the humanitarian costs of climate change, did not consider future effects of changing drought frequency and severity on humanitarian spending and so this could form a useful extension to the research.

If the robustness of the drought damage functions were improved and economic damages estimated based on various socio-economic scenarios it would also be beneficial to extend the analysis to 2100, to assess a wider variety of mitigation strategies. The research outputs could be included within climate change cost assessments to help guide appropriate levels of climate change mitigation, based on more comprehensive estimates of economic costs, as well as helping to gauge the vulnerability of communities to future drought events and guide drought risk management. Economic costs of drought events could be incorporated by relating the average annual economic costs of drought to the change in global temperature projected by 2050 and 2100 under the specific emission/stabilisation scenarios used. In this study, the economic and social drought damage functions have been created offline. Ultimately, they could be incorporated into CIAS, which would also enable more detailed uncertainty analysis to be conducted. There is also potential for the drought damage functions to be incorporated into other economic models, which excluded extreme weather events, to provide a more comprehensive estimate of the total costs of climate change.

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Appendix A: Characteristics of 13 Integrated Assessment Models

Model	Spatial Detail	Model Details	Model Components	Measurement of Impacts	Weather Extremes Modelled	Damage costs of Extreme Weather Modelled	Reference
AIM (Asian-Pacific Integrated Model)	Global and National for Asia-Pacific region.	Large scale simulation model which aims to assess policy options for stabilising global climate. Looks at regional adaptation and mitigation strategies for the Asia-Pacific region. Biophysical Impacts Model	Emissions - Climate Model (GCM) - Impact Modules (water, agriculture, forestry, natural vegetation, malaria)	Biophysical units/Monetary Units	✓ Drought risk	×	(Matsuoka et al., 2001)
CIAS (Community Integrated Assessment System)	Global and regional.	Deterministic simulation model which aims to provide robust estimates of avoided damages and mitigation costs through comparison of climate policy scenarios compared to no policy scenarios.	Economy/Emissions - Simple Climate Model – downscaling model - impact Modules (biome shifts, hydrological model) Plans to include coastal flooding, agriculture and incidence of extreme weather events.	Biophysical units	× (Plans to include incidence of extreme weather events for flood/droughts)	× (Plans to quantify drought damage costs)	(Warren et al., 2008)
CLIMPACTS (Climate Impacts)	Global and New Zealand	Simulation based model used to evaluate policy scenarios in response to climate change including an evaluation of adaptation. Biophysical Impacts Model	Simple Climate Model – New Zealand climate scenario generator – Impact modules for Agriculture and Horticulture (arable crops, fruit crops, grasslands, soils)	Biophysical Units	✓ Scenario generator is linked to an extreme event analysis tool to estimate return periods of extreme events under climate change.	×	(Warrick et al., 2001)
DICE-2007** (Dynamically Integrated Climate	Global	Neo-classical optimal growth model of the global economy that can be used to assess different policy options for reducing greenhouse gas emissions.	GHG Emissions - simple carbon-cycle and climate model - Impacts Module (Agriculture, Sea Level Rise, Health, non-market damages, and	Monetary Units Damage function based	×	×	(Nordhaus, 2007)

Economy Model)		Policy Optimization/CBA model (Also related is RICE a regionalised version of DICE)	catastrophic events)	on Nordhaus and Boyer, 2000.			
ESCAPE (Evaluation of Strategies to address Climate change by Adapting to and Preventing Emissions)	4 world regions including the EU.	A quantitative computational model to investigate policy options concerned with the greenhouse effect. It was the first spatially detailed model for Europe, extending components of IMAGE to look at European policies and impacts. Biophysical Impacts Model	Emissions Model – 2 Climate Models – Impacts Model (range of ecosystem and economic indicators)	Biophysical units/Monetary Units	✗	✗	(Hulme et al., 1995)
FUND 2.8** (Framework for Uncertainty, Negotiation and Distribution)	Global and 16 regions	A computational economic CBA Model which can be used for studying impacts of climate change in a dynamic context, and to perform cost-benefit and cost-effectiveness analysis of greenhouse gas emission reduction policies.	FUND links scenarios and simple models of Population - Technology – Economics – Emissions - Atmospheric chemistry – Climate - Sea level –Impacts (Agriculture, forestry, water resources, energy consumption, sea-level rise, ecosystems, human health (diarrhoea, vector borne diseases, cardiovascular and respiratory disorders)	Monetary Units Damage functions from Tol, 2002b (biophysical units included but monetised)	✗	✓ Damage Functions (human health effects on mortality include impacts of heat and cold stress)	(Tol and Fankhauser, 1998)
ICAM (Integrated Climate Assessment Model)	Global and 17 regions	A simulation impact-centred model, analysing uncertainty and climate change impacts. It was designed to help explore and understand these interactions and evaluate ways to avoid, mitigate, or adapt to global climate change. CBA Model	Links models of demographics and economics – Energy and Emissions – Atmospheric composition and climate model based on SCM output – Impacts (sea-level rise, other market impacts, ecosystems, other non-market impacts, health)	Monetary and Biophysical units	✗	✗	(Dowlatabadi and Granger Morgan., 1993)
ICLIPS (Integrated assessment of Climate Protection	Global and 11 regions	A computational, conceptual model. It seeks to provide Integrated Assessment of Climate Protection Strategies. A new approach, the Tolerable Windows Approach consists of a separation	Climate Model (Energy Balance Model) – Socio-economic model – Climate Impact Models (natural vegetation, agricultural production, fresh-water availability)	Biophysical Units	✗	✗	(Toth, 2003)

Strategies)		of normative settings for "tolerable windows" on climate impacts, negotiable allowances for greenhouse gas emissions, and desirable socioeconomic development scenarios.	Uses climate impact response functions				
IMAGE 2.4 (Integrated Model for the Assessment of the Greenhouse Effect)	Global and 24 regions (plus Antarctica and Greenland)	An ecological-environmental framework. It represents interactions between society, the biosphere and the climate system to assess sustainability issues like climate change, biodiversity and human well-being. The objective of IMAGE (version 2.4) is to explore the long-term dynamics of global change as the result of interacting demographic, technological, economic, social, cultural and political factors.	Socio-economic Models – Land Allocation and Land Emissions Models – Earth System Modules including SCM – Impacts Modules (Sea Level Rise, terrestrial ecosystems, crop distribution and productivity, biodiversity, water availability, energy supply-demand, distribution of disease vectors) – Policy Module	Biophysical units	× SCM used cannot address extremes but a GCM of immediate complexity coupled to a Dynamic Global Vegetation Model has looked at complex feedbacks from land use change on climate and extremes	×	(Bouwman et al., 2006)
MERGE (Model for Evaluating Regional and Global Effects)	Global and 9 regions	A general equilibrium model of the global economy. The model is sufficiently flexible to explore alternative views on a wide range of contentious issues: costs of abatement, damages from climate change, valuation and discounting.	Detailed energy-Economy Model – simple carbon and climate modules – Damage Functions (farming, energy, coastal activities, 'other' non-market impacts)	Monetised Damage function (adjusted from Nordhaus, 1991)	×	×	(Manne and Richels, 2005)
Mini-CAM (Mini-Climate Assessment Model)	Global and 14 regions	A highly aggregated integrated assessment model that focuses on the world's energy and agriculture systems, atmospheric concentrations of greenhouse gases and consequences regarding climate change and sea-level rise. CBA Model	Energy and Land Use Modules – SCM – DSM – Damage Module (non-market impacts linked to Land Use model)	Monetary and Biophysical units	×	×	(Brenkert et al., 2003)
PAGE-2002** (Policy Analysis of the Greenhouse Effect)	Global and 8 regions	A probabilistic optimisation model which allows extensive specification and propagation of uncertainties. Follows a stochastic approach by producing estimates based on Monte Carlo simulation to generate a probability	Economics Model – Mitigation and Adaptation Costs – Impacts (Market and non-market sectors and catastrophe)	Monetary units (Damage Functions linked to 2.5° temperature rise)	×	×	(Hope, 2006)

		distribution rather than a single point estimate. CBA Model					
WIAGEM (World Integrated Assessment General Equilibrium Model)	Global and 25 regions	An integrated economy-energy-climate model to evaluate market and nonmarket costs and benefits of climate change	Economic Module - Energy Module – Climate Module – Impacts (market and non-market including forestry, agriculture, energy demand, water resources, ecosystem changes, mortality due to vector borne diseases and cardiovascular and respiratory disorders)	Moneary Units (Based on damage functions from Tol, 2002b)	✗	✓ Damage Functions (human health effects on mortality include impacts of heat and cold stress)	(Kemfert, 2002)

*Table A.1: Characteristics of 13 Integrated Assessment Models (** indicates most widely used IAMs)*

Appendix B: Validation of the SPI calculations

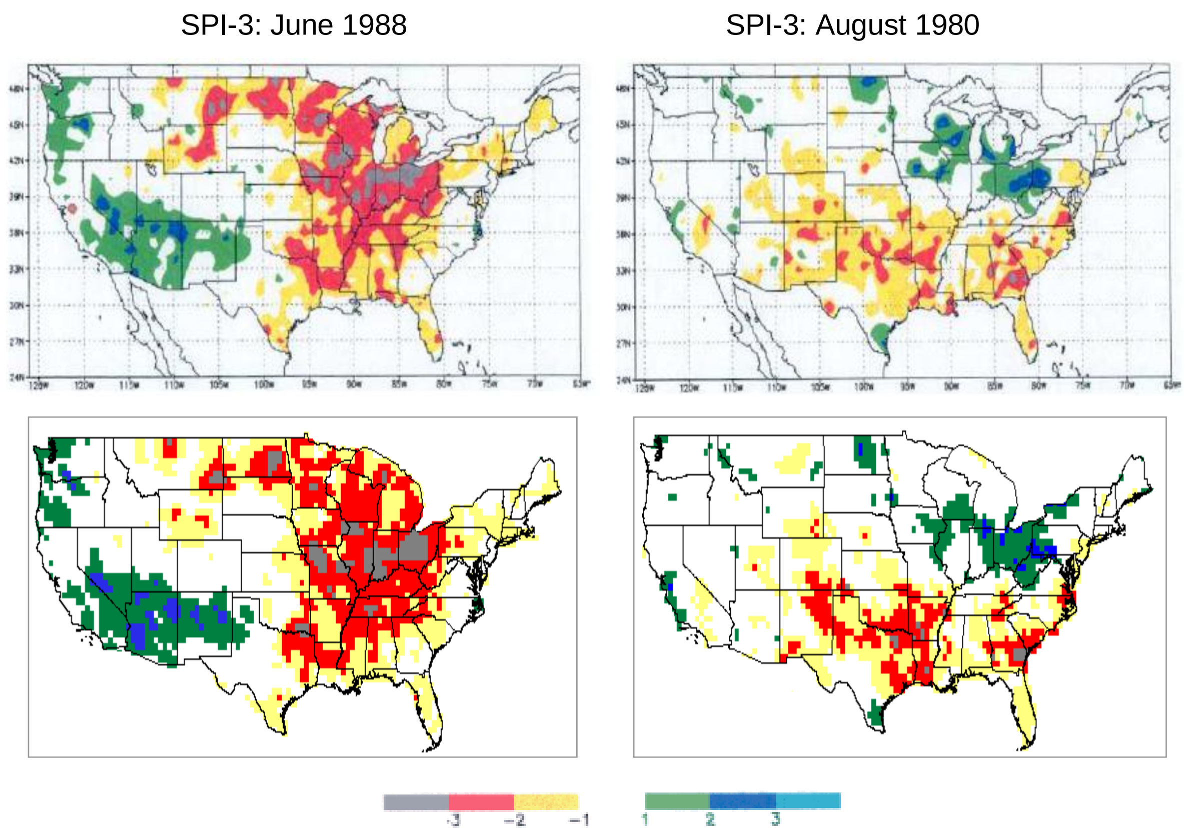

Figure B.1: Validation of SPI code for the 1988 and 1980 US droughts. (Top panels show results from Edwards and McKee (1997). Bottom panels show results from this study mapped using DIVA-GIS)

Appendix C: Country Drought Characteristic and Parameter Tables

AUSTRALIA (States Affected)	Year	Lives Lost (normalised to 2002)	Lives affected (,000) (normalised to 2002)	Inflation Adjusted Damage (US$ 2002) (,000s)	Notes	Sector Specific Impacts
South-East (New South Wales, Victoria and Tasmania)	1967-69	999	--	7921996	Affected wheat yields and almost wiped out entire oat crop. Bush fires and dust storms. Loss of 20 million sheep across Australia	Agriculture
New South Wales (central)	1974-75	--	--	--	Short-term drought	--
Western NSW, Victoria and South Australia	1976	--	--	--	Drought linked to El Nino and failure of autumn/winter rains. 40,000 cattle shot in Victoria. Natural disaster assistance required to provide cattle fodder and disposal. Also affected diary and fruit industries.	Agriculture and Farming
Western Australia (South West Region)	1976	--	--	--	Drought linked to El Nino. Affected the wheat belt area of Western Australia and diary and fruit industries. Natural disaster assistance required to provide cattle fodder and disposal. Bush Fires occurred in 1978.	Agriculture and Farming
Queensland, NSW, Victoria Tasmania	1978	--	--	--	South-east Australia heavily affected despite intermittent heavy rain. Developed through 1977-78 and again worsened in 1979. Affected wheat belt area.	Agriculture
Queensland, New South Wales, Victoria, South Australia	1981-82	--	5263	12856840	Drought linked to high temperatures and reduced rainfall from 1981 to 1982. Many wheat crops failed completely and Queensland saw a 10% reduction in agricultural production. Linked to El Nino. Bush fires and dust storms.	Agriculture
Western Australia (South)	1991	--	--	618520	Agricultural production affected, cattle killed or died. Bush fires. Linked to significant El Nino phase.	Agriculture and Farming
Queensland	1992-95	--	7859	5015596	Agricultural production cut by 8%. Many cattle either died or shot. Bush fires. Winter crops reduced by 50% in 1994. Affected wheat and barley so much that grain was imported to Queensland from other states. Affected Darling river system and led to the loss of irrigation systems in some towns. Linked to a significant El Nino event.	Agriculture, Farming, Water Supply

Table C.1: Drought Characteristics and Impacts for Australia from 1940-2002. Source: EM-DAT (2010), Australian Bureau of Meteorology (2010), and Literature review.

AUSTRALIA (States Affected)	SPI-6						SPI-12					
	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)
South-East (New South Wales, Victoria and Tasmania)	1965-68	01	04	40	-2.16	14992	1965-68	02	11	46	-1.74	17571
New South Wales (central)	1975	04	08	5	-0.92	838	--	--	--	--	--	--
Western NSW, Victoria and South Australia	1976	06	10	5	-1.48	3247	--	--	--	--	--	--
Western Australia (South West Region)	1976-77	05	12	20	-1.58	17254	1976-78	10	06	21	-1.45	17955
Queensland, NSW, Victoria Tasmania	1977-78	08	04	9	-1.45	7044	1978	02	08	7	-0.87	4670
Queensland, New South Wales, Victoria, South Australia	1982-83	01	04	16	-2.07	26252	1982-83	05	10	18	-1.76	28560
Western Australia (South)	1990-91	07	08	14	-1.17	8199	1990-92	05	02	22	-1.10	13448
Queensland	1991-95	08	09	50	-1.78	22070	1992-95	01	12	48	-1.22	23583

Table C.2: Drought Parameters for Australia at SPI-6 and SPI-12. Source: Own calculations

BRAZIL (States Affected)	Year	Lives Lost (normalised to 2002)	Lives affected (,000) (normalised to 2002)	Inflation Adjusted Damage (US$ 2002) (,000s)	Notes	Sector Specific Impacts
Amazon Basin (Acre, Amazonas, Roraima, Amapá, Pará, Rondônia, Mato Grosso)	1963-64	--	--	--	Record levels of low rainfall in 1963 and 1964. Linked to warming of tropical Atlantic rather than El Niño. Reports of severe socio-economic impacts but no data reported.	Agriculture, water resources.
North-East (Maranhão, Piaui, Bahia, Ceará, Rio Grande do Norte, Paraiba, Pemambuco, alagoas, Sergipe)	1970	--	18637	1195	Reports of 200,000 people without jobs due to agricultural employment falling. Cattle industries affected as livestock died or prematurely slaughtered. Food shortages in some areas.	Farming, Agriculture, Employment, Food Supply.
Central/Southern (Rio Grande do sul, Santa Catarina, São Paulo, Paraná, Minas Gerais, Mato Grosso do sul, Rio de Janeiro, Espirito Santo)	1978	--	--	5794688	High crop losses reported, especially coffee beans. Drought affected crop production of 1977/78 coffee bean harvest. More than 10% of coffee crop destroyed in São Paulo and Paraná pushing international coffee prices up.	Agriculture
North-East (Piaui, Bahia, Ceará, Rio Grande do Norte, Paraiba, Pemambuco, Alagoas)	1983	27	27456	4479	Most severe drought to hit Brazil. Rainfall 40% below average in rainy season. Linked to El Niño. Reduction in agricultural production of 16%. Subsistence farmers hit, high levels of unemployment, and rising food prices.	Farming, Agriculture, Employment, Food Supply.
Rio Grande do Sul	1985	--	--	1477254	Slight loss to coffee crops in region.	Agriculture
North East and Minas Gerais	1987-88	--	948	--	Reported rainfall deficiency of 19%, which affected up to 60% of crops in area.	Agriculture
Rio Grande do Sul, Santa Catarina	1988	--	--	1531200	Affected sugar crop and world sugar prices. Drought continued into 1989 affecting grain and coffee crops. 35,000 cattle reported as slaughtered. Reports of unusually high temperatures.	Agriculture, Farming
Rio Grande do sul, Santa Catarina, São Paulo, Paraná, Minas Gerais	1994-95	--	--	231543	Destroyed half of coffee crop leading to a doubling in coffee prices compared to 1993. Affected cattle, milk production, soybean, rice, snap bean and sugar cane crops. Reduces water supply affected the natural environment and tourism.	Agriculture, Farming, Water Supply, Tourism
Piaui (North East)	1998-99	--	10597	73143	Caused climate refugees, Fires killed cattle and crops, affected agriculture and farming. Severe drought linked to El Niño.	Agriculture, Farming
Pernambuco (North East)	2001	--	1014	--	Reduced rainfall affected reservoir levels and generation of hydroelectric power.	Hydro-electricity generation

Table C.3: Drought Characteristics and Impacts for Brazil from 1940-2002. Source: EM-DAT (2010) and Literature review.

BRAZIL (States Affected)	SPI-6						SPI-12					
	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)
Amazon Basin (Acre, Amazonas, Roraima, Amapá, Pará, Rondônia, Mato Grosso)	1963-64	03	09	19	-1.52	23099	1963-65	01	02	26	-1.52	29939
North-East (Maranhão, Piaui, Bahia, Ceará, Rio Grande do Norte, Paraiba, Pemambuco, alagoas, Sergipe)	1970	02	10	9	-1.06	2865	1970-71	03	03	13	-0.92	3588
Central/Southern (Rio Grande do sul, Santa Catarina, São Paulo and Paraná, Minas Gerais, Mato Grosso do sul, Rio de Janeiro, Espirito Santo)	1977-78	12	08	9	-1.73	4876	1977-78	12	11	12	-1.24	5856
North-East	1981-84	09	04	32	-1.44	13686	1982-84	03	09	31	-1.56	13966
Rio Grande do Sul	1985-86	11	03	5	-0.70	194	--	--	--	--	--	--
North East and Minas Gerais	1987-88	--	--	--	--	--	1987-88	02	02	13	-0.75	4077
Rio Grande do Sul and Santa Catarina	1988-90	06	01	20	-1.33	2281	1988-90	07	02	20	-1.32	2644
Rio Grande do sul, Santa Catarina, São Paulo, Paraná, Minas Gerais	1994-95	09	02	6	-1.14	2315	1994-95	10	08	11	-1.06	2523
Piaui (North East State)	1997-99	11	09	23	-2.22	2208	1997-00	11	01	27	-1.97	2850
Pernambuco (North East)	2001	03	07	5	-0.44	52.6	--	--	--	--	--	--

Table C.4: Drought Parameters for Brazil at SPI-6 and SPI-12. Source: Own calculations

CHINA (States Affected)	Year	Lives Lost (normalised to 2002)	Lives affected (,000) (normalised to 2002)	Inflation Adjusted Damage (US$ 2002) (,000s)	Notes	Sector Specific Impacts
Tibet, Sichuan, Yunnan, Guizhou, Chongqing, Guangxi, Guangdong, Hunan, Hubei, Henan	1965	--	--	565565	Reduction in summer precipitation caused by a weakening of summer monsoon and an displacement of the western Pacific subtropical high.	--
Anhui, Jiangsu	1978	--	8035	--	Over 90% of cultivated land destroyed in Anhui.	Agriculture
Tibet	1983	--	--	--	One of the worst droughts recorded in Tibetan history	--
Hubei, Jiangsu, Henan, Anhui, Shandong, and Zhejiang	1988	1627	56952	4462714	Drought affected central and southern grain belts. Millions of acres of crops destroyed with over ½ arable land in Hubei destroyed and 2/3rds of peanut and sesame crop lost. Heatwave and temperatures over 100°C reported.	Agriculture and Farming
Jiangxi, Hunan	1991	2225	5563	--	~1.44 million hectares of farmland were destroyed and in Hunan rivers, lakes and dams ran dry.	Agriculture, Farming, Water Supply
Hunan	1992-93	--	--	184953	At least 316,000 farmers short of drinking water.	Agriculture, water supply
North (Inner Mongolia, Shanxi, Hebei, Beijing, Tianjin, Shanxi)	1992	--	13189	--	Water restrictions in north affected 5.8 million people. Water levels in dams and reservoirs dropped significantly following 1993. Dust storms and forest fires. Average temperatures 2-4°C above normal. Affected grain production.	Agriculture, Farming, Water Supply
Shandong	1997	--	--	258061	Most severe drought in 30 years. Water in reservoirs dried up and 2 million people left short of drinking water. Crops were water stressed.	Agriculture, Water Supply
North China Plain (Liaoning, Hebei, Shanxi, Henan, Shandong, Jiangsu, Anhui)	1999	--	19404	--	Affected wheat growth in North China Plain. 1999 Summer temperatures 1-2°C higher than average. Dry soil conditions.	Agriculture
Anhui, Henan	2000	--	15211	965737	Affected crops and soil and caused major water shortages	Agriculture, Water Supply
Inner Mongolia Autonomous Region	2000	--	5070	--	Sharp drop in grain production with 2/3rds of the regions planting area affected. 600,000 cattle dead and 40 million in poor condition due to lack of grass.	Farming, Agriculture, Water Supply, Food shortages
Inner Mongolia Autonomous Region	2001	--	534	--	Continuation from drought of 2000.	Farming, Agriculture, Water and Food Supply
Sichuan, Yunnan	2001	--	15906	--	High temperatures and low rainfall. Lack of water supplies for people and animals, decrease in production of crops. Over 3000 industrial factories closed in Sichuan	Farming, Agriculture, Water Supply
Guangdong, Fujian, Guangxi	2002	--	60000	--	Precipitation from Jan-Mar reduced in South China by 40% and above average temperatures. Affected farming and rice crop, water shortages, farmland scorched.	Agriculture, Water Supply

Table C.5: Drought Characteristics and Impacts for China from 1940-2002. Source: EM-DAT (2010) and Literature review.

CHINA (States Affected)	SPI-6						SPI-12					
	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)
Tibet, Sichuan, Yunnan, Guizhou, Chongqing, Guangxi, Guangdong, Hunan, Hubei, Henan	1964-65	12	11	12	-1.38	10282	1965-67	04	05	26	-1.21	19577
Anhui, Jiangsu	1978-79	03	03	13	-2.49	2030	1978-79	04	06	15	-2.63	2801
Tibet	1983-84	08	06	11	-1.45	4762.15	1983-85	08	05	22	-1.55	6507
Hubei, Jiangsu, Henan, Anhui, Shandong, and Zhejiang	1988-89	04	03	12	-1.29	3193	1988-89	06	07	14	-1.11	3331
Jiangxi, Hunan	1991-92	05	02	10	-1.26	962	1991-92	04	04	13	-0.95	855
Hunan	1992-93	11	06	8	-1.54	591	1993	04	10	7	-1.41	395
North (Inner Mongolia, Shanxi, Hebei, Beijing, Tianjin, Shanxi)	--	--	--	--	--	--	1992-93	06	06	13	-1.01	4182
Shandong	1997	04	12	9	-2.14	665	1997-98	06	04	11	-1.20	666
North China Plain (Liaoning, Hebei, Shanxi, Henan, Shandong, Jiangsu, Anhui)	1999-00	01	10	22	-1.71	7025	--	--	--	--	--	--
Anhui. Henan	2000	03	08	6	-1.48	643	2000	04	09	6	-0.44	218
Inner Mongolia Autonomous Region	2000	07	02	8	-0.94	2186	--	--	--	--	--	--
Inner Mongolia Autonomous Region	2001-02	04	02	11	-1.90	8022	--	--	--	--	--	--
Sichuan, Yunnan	2001	02	07	6	-1.06	1396	2001	01	08	8	-0.73	976
Guangdong, Fujian, Guangxi	2002	02	07	6	-1.40	923	--	--	--	--	--	--

Table C.6: Drought Parameters for China at SPI-6 and SPI-12. Source: Own calculations

ETHIOPIA (States Affected)	Year	Lives Lost (normalised to 2002)	Lives affected (,000) (normalised to 2002)	Inflation Adjusted Damage (US$ 2002) (,000s)	Notes	Sector Specific Impacts
Nationwide	1965	5422	3968	--	Linked to El Niño	Agriculture
North Ethiopia (Tigray, Afar, Amhara)	1983-84	1794780	12709	--	1984-85 Famine. 1 million people died of starvation. Killed crops and cattle. Famine affected most of the country. Started in northern Ethiopia and spread by 1986 to parts of the Southern Highlands.	Agriculture and Farming
Tigray, Afar, Amhara, Oromia, SNNPR	1987-88	579	10209	--	Failure of rains in main rainy season, however, linked to El Nino conditions and so governments were pre-warned of potential drought which reduced Deaths. Up to 100% crop failure in some states including Tigray.	Agriculture, Food and Water Supply
Borena, Bale, South Ome zone, Somali state	1997-98	--	1109	--	Rainfall in East and North-east Ethiopia below average in August. Food security issues. Links to El Nino.	Agriculture. Food and Water Supply
Southern and South-Eastern	2000	--	8468	--	Reduced rains in main growing season caused food shortages. Forest Fires in South of Country. Approximately 3 million cattle died.	Agriculture and Farming

Table C.7: Drought Characteristics and Impacts for Ethiopia from 1940-2002. Source: EM-DAT (2010) and Literature review.

ETHIOPIA (States Affected)	SPI-6						SPI-12					
	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)
Nationwide	1965	03	10	8	-1.3	2494	1965-66	06	04	11	-1.0	2423
North Ethiopia (Tigray, Afar, Amhara)	1983-85	07	03	21	-1.66	2314	1982-85	07	07	37	-1.74	3801
Tigray, Afar, Amhara, Oromia, SNNPR	1987-88	09	08	12	-1.28	2087	1987-88	07	08	14	-1.39	2079
Borena, Bale, South Ome zone, Somali state	1996-97	11	09	11	-0.91	901	1997	04	10	7	-0.90	655
Southern and South-Eastern	1999-00	04	10	19	-1.30	3962	1999-01	05	02	22	-1.06	3750

Table C.8: Drought Parameters for Ethiopia at SPI-6 and SPI-12. Source: Own calculations

INDIA (States Affected)	Year	Lives Lost (normalised to 2002)	Lives affected (,000) (normalised to 2002)	Inflation Adjusted Damage (US$ 2002) (,000s)	Notes	Sector Specific Impacts
West Bengal/Calcutta	1942	4977662	--	--	Pre-monsoon event.	--
Rajasthan	1964	--	1127	--	Linked to winter rains	--
Karnataka	1964	--	366	--	--	--
Nationwide	1965-67	3227752	215184	863336	Deficiency in monsoon – late season drought. Affected relatively high rainfall region	--
Central (Madhya Pradesh, Maharashtra & Goa)	1972-73	--	365935	714090	Reduced monsoon rains – early season drought. Affected low rainfall region	Agriculture, Farming
Nationwide	1979-80	--	15604	673386	Deficiency in monsoon – late season drought. Affected relatively high rainfall region	Agriculture
Rajasthan, Haryana, Himachal Pradesh & Punjab, Kerala & Tamil Nadu	1982-83	--	145964	--	Link to deficiency in monsoon rains	Agriculture
Gujarat, Rajasthan, Orissa, Madhya Pradesh Andhra Pradesh, Maharashtra	1987-88	394	393890	--	Reduced monsoon rains – early season drought. Affected low rainfall region. Affected 60% of crop area and affected cattle	Agriculture, Farming
Bihar, Orissa, Andhra Pradesh, Maharashtra, Gujarat, Madhya Pradesh, Uttar Pradesh, Karnataka	1993	--	1422	--	--	--
Gujarat, Rajasthan, Madhya Pradesh, Andhra Pradesh, Orissa, Maharashtra, New Delhi	2000-01	21	51610	648977	The worst drought in 100 years in India. Agriculture and cattle affected. Water shortages	Agriculture, Farming, Water Supply

Table C.9: Drought Characteristics and Impacts for India from 1940-2002. Source: EM-DAT (2010) and Literature review.

INDIA (States Affected)	SPI-6						SPI-12					
	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)
West Bengal/Calcutta	1942	5	8	4	-1.48	157	1942	--	--	--	--	--
Rajasthan (central)	1963-64	3	6	16	-1.56	1617	1962-1964	9	6	22	-1.14	1868
Karnataka	1964	4	6	3	-1.9	321	1964	3	6	4	-0.71	128
Nationwide	1965-67	3	2	24	-1.24	19762	1965-67	7	7	25	-1.28	22826
Central (Madhya Pradesh, Maharashtra & Goa)	1972-73	4	6	15	-1.86	4280	1971-73	8	7	24	-1.71	5403
Nationwide	1979-80	6	2	9	-1.24	6820	1979-80	7	6	12	-1.03	8963
Rajasthan, Haryana, Himachal Pradesh & Punjab, Kerala & Tamil Nadu	1982-83	7	2	8	-1.21	1550	1982-83	8	5	10	-1.25	1834
Gujarat, Rajasthan, Orissa, Madhya Pradesh Andhra Pradesh, Maharashtra	1987-88	6	2	9	-1.6	6340	1986-88	7	8	26	-1.58	13999
Bihar, Orissa, Andhra Pradesh, Maharashtra, Gujarat, Madhya Pradesh, Uttar Pradesh, Karnataka	1991-94	7	1	31	-1.62	13966	1991-94	8	6	35	-1.67	17483
Gujarat, Rajasthan, Madhya Pradesh, Andhra Pradesh, Orissa, Maharashtra, New Delhi	2000-01	9	4	8	-1.75	4547	2000-01	9	12	16	-0.98	6438

Table C.10: Drought Parameters for India at SPI-6 and SPI-12. Source: Own calculations

SPAIN & PORTUGAL (States Affected)	Year	Lives Lost (normalised to 2002)	Lives affected (,000) (normalised to 2002)	Inflation Adjusted Damage (US$ 2002) (,000s)	Notes	Sector Specific Impacts
Southern Spain (Andalucía, Extremadura, Castile la Mancha)	1980-83	--	--	4554676	Linked to Azores high. Reservoirs dried up, exceeded water availability. Affected Cereal Crop and natural pasture	Agriculture, Farming
Portugal (Alentejo and Beja community)	1983	--	--	5088087	Linked to Azores High and reduced winter precipitation	Agriculture
Spain (Nationwide)	1981	--	--	464825	Linked to Azores high. Extension of the 1980-83 drought.	Agriculture, Farming, Water Supply
Southern Spain (Andalucía, Extremadura, Castile la Mancha), Portugal	1990-95	--	6383	5927641	Linked to Azores high and potentially El Nino. Water reservoirs were very low or empty leading to water scarcity issues. Desertification and vegetation loss. Forest Fires. Water supplies cut in some areas and hydro-electric power suspended from 1994-95	Agriculture, Tourism, Water Supply, Hydroelectric power
Spain (Andalucía, Extremadura, Castile la Mancha, Murcia, Valencia, Catalonia, Aragon)	1998-99	--	--	3554073	Worst drought in 50 years from reduced rainfall and high temperatures. Led to large-scale debt requiring large bank loans. Crop failure, farmer protests over lack of water for irrigation.	Agriculture, Farming

Table C.11: Drought Characteristics and Impacts for Spain & Portugal from 1940-2002. Source: EM-DAT (2010) and Literature review.

SPAIN & PORTUGAL (States Affected)	SPI-6						SPI-12					
	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)	Event Year/s	Start month	End month	Duration (months)	Peak Intensity (PI)	Total Drought Magnitude (TDM)
Southern Spain (Andalucía, Extremadura, Castile la Mancha)	--	--	--	--	--	--	1980-84	02	02	49	-2.05	4249
Portugal (Alentejo and Beja community)	1982-83	12	08	9	-1.76	182	1982-83	12	12	13	-1.70	292
Spain (Nationwide)	1980-82	09	04	20	-1.57	3048	1980-82	10	10	25	-1.66	4471
Southern Spain (Andalucía, Extremadura, Castile la Mancha)	--	--	--	--	--	--	1990-95	12	12	61	-2.18	5785
Spain (Andalucía, Extremadura, Castile la Mancha, Murcia, Valencia, Catalonia, Aragon)	1998-99	10	09	12	-1.48	1645	1998-00	11	11	25	-1.40	3011

Table C.12: Drought Parameters for Spain & Portugal at SPI-6 and SPI-12. Source: Own calculations

USA (States Affected)	Year	Lives Lost (normalised to 2002)	Lives affected (,000) (normalised to 2002)	Inflation Adjusted Damage (US$ 2002) (,000s)	Notes	Sector Specific Impacts
Central and Eastern USA	1980	12666	--	208434772	Heatwaves (Deaths include those from heat stress). Loss to agricultural.	Agriculture, Industry
Central and Eastern USA	1987-88	8909	--	157745076	Heatwaves and Forest Fires. Drought affected 36% of US. Costliest drought in the US. Affected agriculture and related industries and water supply.	Agriculture, Industry, Water Supply
California	1991	--	--	1751770	Reduced run-off from winter snowpack. Linked to deficient rainfall since late 1980s. Affected agriculture and reduced crop yields.	Agriculture, Farming, Hydroelectric Power
Pennsylvania & Maryland	1991	--	--	586843	--	--
South Eastern US: Alabama, Georgia, North Carolina, South Carolina, Tennessee & Virginia	1993	18	--	2208355	Less than 50% annual rainfall recorded and temperature 1.5-3.5°C higher than normal. Potential link to El Nino. Heatwaves	Agriculture, Farming
Texas, New Mexico, Arizona, California, Nevada, Utah, Colorado, Oklahoma & Kansas	1995-96	--	--	14188470	Affected water supply, wheat crop and caused soil degradation. Forest fires.	Agriculture, Farming, Water supply
Kentucky, Maryland, Ohio, Pennsylvania, Virginia & West Virginia	1999	518	--	1243393	Heatwaves and Wildfires. Record & near-record short-term precipitation deficits on a local and regional scale	Agriculture, Farming, Water supply
South Carolina, Georgia, Alabama, Florida, Gulf Coast Louisiana, West Texas	2000-02	143	--	4480780	Precipitation deficits since mid-1998. Wildfires and Severe Heatwaves. Soil condition in very poor state due to dryness	Agriculture, Water Supply
Midwest	2002	--	--	3300000	Dust Storms and Wildfires. Long-term drought reported to last 37 months (calculated using the PDSI). Drought rapidly expanded during early 2002 to affect 39% of the country by July.	Agriculture, Water Supply

Table C.13: Drought Characteristics and Impacts for the USA from 1940-2002. Source: EM-DAT (2010) and Literature review.

USA (States Affected)	SPI-6						SPI-12					
	(a) Event Year/s	(b) Start month	(c) End month	(d) Duration (months)	(e) Peak Intensity (PI)	(f) Total Drought Magnitude (TDM)	(a) Event Year/s	(b) Start month	(c) End month	(d) Duration (months)	(e) Peak Intensity (PI)	(f) Total Drought Magnitude (TDM)
Central and Eastern USA	1980-81	01	06	18	-1.36	19416	1980-81	04	11	20	-1.25	20469
Central and Eastern USA	1988	02	11	10	-1.65	14560	1987-89	10	05	20	-1.39	23159
California	1990-91	11	05	7	-1.95	1439	1988-92	02	01	48	-1.90	7568
Pennsylvania & Maryland	1991-92	06	06	13	-1.80	975	1991-92	08	10	15	-1.74	1050
South Eastern US: Alabama, Georgia, North Carolina, South Carolina, Tennessee & Virginia	1993	06	12	7	-1.09	1222	1993-94	08	05	10	-0.78	1035
Texas, New Mexico, Arizona, California, Nevada, Utah, Colorado, Oklahoma & Kansas	1995-96	11	08	10	-1.47	10101	1996	01	12	12	-1.24	9395
Kentucky, Maryland, Ohio, Pennsylvania, Virginia & West Virginia	1999-00	07	04	10	-1.24	1849	1999-00	02	06	17	-1.57	3382
South Carolina, Georgia, Alabama, Florida, Gulf Coast Louisiana, West Texas	1999-01	07	01	19	-1.38	8405	1999-01	08	04	21	-1.36	10362
Midwest	2002	02	07	6	-1.23	2905	--	--	--	--	--	--

Table C.14: Drought Parameters for the USA at SPI-6 and SPI-12. Source: Own calculations.