Meteorological Drought Projections for New Zealand using CMIP5 Data

by

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Thesis

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This thesis is dedicated to my parents
for their love, endless support
and encouragement.

Abstract

Droughts are one of the most damaging natural hazards, and anthropogenic climate change will continue to impact drought sensitive sectors such as primary production, industrial and consumptive water users. Drought monitoring and early warnings are essential for the development of mitigating strategies. The overall aim of this thesis is to develop a methodology to project droughts and its severity in the future through a multi-scenario and multi-model approach using the latest Coupled Model Intercomaprison Project Phase5 (CMIP5) models. All sixteen regions of New Zealand are included in the analysis. To achieve the above objective, the analysis was initially carried out to select the most applicable meteorological drought index – Standardised Precipitation Index (SPI) for New Zealand.

Temporal changes in historic rainfall variability and the trend of SPI were investigated using non-parametric trend techniques to detect wet and dry periods across the regions of New Zealand. The first part of the analysis was carried out to determine annual rainfall trends using Mann-Kendall (MK) and Sen's slope tests for the sixteen regions with long historical records (109 years) of the data set. For SPI trend analysis, it was observed that, results obtained showing significant trends; direction of SPI trends were similar to annual precipitation (downward and upward trends). In addition, the rate of occurrence of drought events were examined in the temporal trends. The fact that all regions showed positive slopes indicated that the intervals between events were becoming longer and the frequency of events was temporally decreasing. From the SPI trends, it was also observed that some of the regions over New Zealand will face more dry periods leading to increased drought occurrence. Information similar to this would be very important to develop suitable strategies to mitigate the impacts of future droughts.

This main objective of this thesis is to assess the drought projections for the regions of New Zealand using General Circulation Models (GCMs) under two emission scenarios – Representative Concentration Pathways (RCP4.5) and RCP8.5 for three future periods (2010-2039, 2040-2069, 2070-2199). Drought severity and spatial extent are analysed for 12-month (SPI12) events.

A novel concept centric on improving the GCM data was successfully derived for the regions using an innovative bias correction algorithm. This algorithm removes errors from climate models in comparison with historical observations. The quantile

mapping bias correction applied to the GCMs improved the rainfall projections thus reliable SPI values for the drought projections were generated.

Drought projections vary substantially depending on the GCM, emission scenario, region, season and definition of drought. Overall, climate change enhances drought conditions across the study region, with marked increases projected for the northern islands under both emission scenarios; reductions in moderate droughts are projected for the regions in the South Island. The interannual variability of precipitation tends to enhance drought conditions caused by mean precipitation changes, or to moderate or reverse their reductions. Greater agreement in the direction of change tends to occur in the northern island regions. Projection ranges tend to increase with time and magnitude of warming. The implications of the large uncertainties include that decision-making should be based on multi-scenario and multi-model results, and with consideration of drought definition.

Many parts of New Zealand have experienced their worst droughts on record over the last decade. With the threat of climate change potentially further exacerbating droughts in the years ahead; a clear understanding of the impact of droughts is vital. The information on the probability of occurrence and the anticipated severity of droughts will be helpful for water resource managers, infrastructure planners and government policy-makers with future infrastructure planning and with the design and building of more resilient communities.

Acknowledgements

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Glossary

Term	*Definition*
Bias Correction	*An approach that corrects the projected raw daily GCM output using the differences in the mean and variability between GCM and observations in a reference period.*
CORDEX	*The Coordinated Regional Downscaling Experiment (CORDEX) is a program sponsored by World Climate Research Program (WCRP) to develop an improved framework for generating regional-scale climate projections for impact assessment and adaptation studies worldwide within the IPCC AR5 timeline and beyond.*
CMIP	*The Intergovernmental Panel on Climate Change (IPCC) gathers and reviews global climate models as part of the international climate change Assessment Reports. The ensemble of the models are called the Climate Model Intercomparison Project.*
CMIP3	*Coupled Model Intercomparison Project Phase 3 is a set of climate model experiments from 17 groups from 12 countries with 24 models. The resulting dataset from the CMIP3 project is the largest and most comprehensive international global coupled climate model experiment.*
CMIP5	*Coupled Model Intercomparison Project Phase 5 is a set of climate model experiments from 23 groups from 12 countries with 64+ models. The experiments are carried out with the latest emission scenarios. This is the most ambitious coordinated multi-model climate data experiment ever attempted.*
CRU	*Climate Research Unit is widely recognised as one of the world's leading institutions concerned with the study of natural and anthropogenic climate change. It houses data at 0.5-degree resolution for parameters such as rainfall, temperature, radiation and cloud fraction for over 100 years.*
Drought	*An insidious hazard of nature that has prolonged period of*

	abnormally low rainfall in a given region leading to a shortage of water supply, whether atmospheric, surface water or ground water.
Drought Severity	*The measure of relative dryness or wetness affecting water sensitive economies. It is categorised based on the index used to calculate the drought - normal, moderate, severe and extreme.*
GCM	*Numerical models (General Circulation Models or GCMs), representing physical processes in the atmosphere, ocean, cryosphere and land surface, are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations.*
GHG	*is a gas in the atmosphere that absorbs and emits radiation within the thermal infrared range. This process is the fundamental cause of the greenhouse effect. The primary greenhouse gases are water vapor, carbon-di-oxide, methane, nitrous oxide and ozone.*
IPCC	*The Intergovernmental Panel on Climate Change is a United Nations body, founded in 1988, which evaluates climate change science. assesses research on climate change and synthesises it into major 'assessment' reports every 5–7 years. The IPCC itself is comprised of representatives from 194 governments who review the contents of reports before publication and have to agree the final text.*
Meteorological Drought	*Is defined usually as a below-normal rainfall over a period of time over a region.*
MK test	*Mann-Kendall test is a non-parametric way to use to detect if there is a monotonic upward or downward trend of the variable of interest over time.*
MME	*A multi-model ensemble, is a large number of climate model simulations created by using many different international Climate model.*
Projection	*An estimate or forecast of a future situation based on the present trends.*
RCP	*Representative Concentration Pathways are four greenhouse gas concentration trajectories adopted by the IPCC for its fifth*

assessment report in 2014.

Regridding *Regridding is the process of interpolating from one grid resolution to a different grid resolution. This could involve temporal, vertical or spatial ('horizontal') interpolations. However, most commonly, regridding refers to spatial interpolation.*

SPI *The Standardized Precipitation Index (SPI-n) is a statistical indicator comparing the total precipitation received at a particular location during a period of n months with the long-term rainfall distribution for the same period of time at that location. SPI is calculated on a monthly basis for a moving window of n months, where n indicates the rainfall accumulation period, which is typically 1, 3, 6, 9, 12, 24 or 48 months. The corresponding SPIs are denoted as SPI-1, SPI-3, SPI-6, etc. It is a widely-used index to characterize meteorological drought on a range of timescales.*

SRES *Special Report on Emission Scenarios were constructed to explore future developments in the global environment with special reference to the production of greenhouse gases and aerosol precursor emissions.*

Chapter 1

Introduction

Extreme weather/climate events have significant environmental and societal impacts, and anthropogenic climate change has and will continue to alter their characteristics. Droughts (e.g. the 2003 European heatwave and drought; Fink *et al.*, 2004; Stott *et al.*, 2004) are one of the most damaging natural hazards in human, environmental and economic terms (Sheffield and Wood, 2008b; Kirono *et al.*, 2011). Regional changes in drought patterns in the 20th century have been observed (see Section 2.3) and their future changes have been simulated (see Section 2.4). Climate change is stimulating demand from public and private sector decision-makers, as well as other stakeholders, for better understanding of potential future drought characteristics. Such knowledge is the initial step to assessing the impacts of drought (Bordi *et al.*, 2009). It also has both strategic and policy implications by informing effective adaptation and planning strategies (Graham *et al.*, 2007) for managing drought risks and impacts.

Until recently, studies on the projections of extreme weather events, such as drought, have often been based upon a few general circulation models (GCMs), regional climate models (RCMs), and/or emission scenarios, partly due to availability. Only a few studies such as Burke, 2011 have considered the changes in drought under a perturbed climate using a large ensemble of simulations. In addition to the uncertainties due to climate modelling, droughts can be represented by a wide range of indices depending on the purpose of application, and events can be quantified in various ways (see Section 2.2). The different concepts and methods of representing drought events applied in different studies make inter-comparing results from different analyses challenging (IPCC, 2012).

Changes in the variability of variables are also an important consideration in a climate change as they may mask/moderate or exacerbate the direction and/or magnitude of an anthropogenic signal. For example, perturbations in interannual climate variability could have implications on the agriculture (Skuras and Psaltopoulos, 2012), food production and forestry (Salinger, 2005); exacerbated precipitation variability could raise drought risks (Bates *et al.*, 2008). Future interannual precipitation variability could enhance or alleviate changes in drought characteristics caused by mean precipitation changes, but their spatial and temporal effects have not been well studied.

Climate Change has the potential to increase drought risk by subjecting regions to levels of drought not previously experienced. Prior drought studies have identified that New Zealand will continue to experience droughts, and with climate change the frequency and length of droughts are likely to increase (National Institute of Water and Atmospheric (NIWA) Research), but have produced conflicting results with regards to future drought severity. Some of these disagreements are likely related to the coarse resolution of a single GCM under the CMIP3 programme and regional averaging tends to smooth extremes. This thesis investigates the problem of projection of drought for the regions of New Zealand using the latest CMIP5 dataset made available by the World Climate Research Programme (WCRP).

As vulnerability to drought has increased globally, greater attention has been directed to reducing the risks associated with its occurrence. The present study therefore seeks to answer the following questions:

- Are there any trends in the climatic data?
- Can we make projections of meteorological drought until 2100 using the most applicable meteorological drought index for the regions of New Zealand?

GCMs are widely applied in climate change studies. In spite of advanced GCMs and improved knowledge, considerable levels of uncertainty remain in climate change projections, particularly in relation to extreme events. Uncertainties arise not only from the various emission scenarios and GCMs, but also from the different classifications of drought (namely meteorological, agricultural, hydrological, socio-economic and ground- water droughts), and a number of indices have been developed to quantify them. This thesis aims to examine the drought projections for the regions of New Zealand using a high resolution (20km x 20km) bias corrected data, We also aim to prove the robustness of these projections by quantifying the effects of using different emission scenarios and GCMs. The aim of the study was achieved primarily by undertaking the following tasks:

1. Reviewing drought index.

2. Analysing the rainfall and drought severity trends for the sixteen regions of New Zealand.
3. Projecting meteorological drought by the end of the century (until 2099) using the Standardized Precipitation Index (SPI) tool for an accumulation period of 12-months.

The above task was executed by regridding the twenty-one (see Table 3.1) GCMs of different resolutions to 20km x 20km. Furthermore, the quantile mapping algorithm was implemented for bias correcting each of the regridded models with respect to observational data. Lastly, Multi Model Ensemble (MME) of GCMs were calculated under two emission scenarios, namely RCP4.5 (moderate emission scenario) and RCP8.5 (high emission scenario). The machine learning language R, ArcGIS and NCAR Command Language (NCL) has been used for calculations, spatial and temporal plots throughout this thesis. The significance of this research and possible outcomes are discussed in this section including its contributions.

Trend analysis facilitates the identification of any possible trends in climatic parameters which directly influences the occurrence of droughts. To date, no comprehensive research has been conducted on drought severity trends in New Zealand. Hence, whether there is a possible trend in the risk of occurrence of drought events will be determined.

Drought information is often too technical and difficult to understand by decision makers and end-users. This study aims to initially derive information about drought using precipitation information which can be understood easily by ordinary users.

The gaps in existing research will be addressed by not only examining the potential changes in drought characteristics due to climate change, but also the associated uncertainties in the projections through the application of a range of emission scenarios and GCMs.

Projecting drought severity in the long term (2070-2099) would provide essential information on drought and help the state/regional based organisations to plan and implement responses and mitigation measures.

1.1 Thesis Structure

This thesis is presented in six chapters, including Chapter 1 which describes the background of the research, the aims and the research significance. Chapter 1 also formulates the research questions to be addressed and provides an overall picture of the research tasks undertaken in the thesis.

Chapter 2 provides an overview of the drought concept, the various classifications of drought and methods for their quantification. It presents the observed and projected changes in drought, along with the drivers of their occurrence. This chapter also discusses the various sources of uncertainties in climate modelling and the challenges in projecting future drought characteristics.

Chapter 3 describes the general methods applied in this study, the approach for identifying and measuring drought, the study area and regions.

Chapter 4 presents the results of preliminary analysis for the climatic data that has paved the way for the assessment of droughts using meteorological drought indices (i.e. Standardised Precipitation Index (SPI).

Chapter 5 investigates the trend by non-parametric tests of rainfall data for longer data lengths. This chapter also examines the spatial and temporal distributions of identified trends. Similar to the above analysis, this chapter provides the trend of dry periods using a selected meteorological drought index, namely the SPI and the temporal trends in drought events.

Chapter 6 explores the spatial effects of climate change on meteorological drought characteristics for 12-month (SPI12) events. It also assesses the uncertainties that arise from emission scenarios and GCMs.

Chapter 7 summarises the key findings revealed from this thesis, and presents some concluding remarks about the policy implications and areas for future research.

Chapter 2

Literature Review

2.1 Introduction

Climate variability and extreme weather/climate events are of great concern as they produce disproportionately large climate-related damages (Katz and Brown, 1992; Easterling *et al.*, 2000; Meehl *et al.*, 2000). Studies have shown that there is growing confidence that human-induced climate change can alter/raise the risk of extreme events, which have implications for regional and local adaptation and risk reduction strategies (Meehl *et al.*, 2000; Smith *et al.*, 2009a; Berrang-Ford *et al.*, 2011). This chapter describes the importance of drought events, and provides an overview of the drought concept, the various classifications of drought and methods for their quantification. The observed and projected drought trends are then presented, along with the drivers of drought and their variations. This chapter also discusses the various sources of uncertainties in climate modelling and the challenges in projecting future drought characteristics.

Drought is one of the most damaging natural hazards, in human, environmental and economic terms (Sheffield and Wood, 2008b; Kirono *et al.*, 2011). It affects agriculture, irrigation and food production. Droughts also have implications for hydrological and ecological systems (Marsh *et al.*, 2007; Vidal and Wade, 2009; Ciais *et al.*, 2005; Gobron *et al.*, 2005; Archer and Predick, 2008). Increasing drought conditions can lead to human health concerns, e.g. famine in northern Nigeria, as they could counteract the effects of the anticipated longer growing seasons (Quevauviller, 2011; Tarhule and Woo, 1997). Droughts can also impact on ecosystem goods and services that include the loss of sequestered forest carbon and associated atmospheric feedbacks (Ciais *et al.*, 2005; Allen *et al.*, 2010). Global wildfire potential may also increase (Liu *et al.*, 2010), e.g. more fires in the eastern Iberian Peninsula with dry summers (Pausas, 2004).

Current management practices may be insufficient to cope with future changes in sustainability, quantity and quality of water resources, and many developments are planned in drought-prone areas (e.g. the Thames Gateway; Walden, 2009; Bates *et al.*, 2008). Drought by itself does not necessarily imply a disaster. While drought risk generally increases with warming and drying, local and global, social and environmental changes influence vulnerability (Dai *et al.*, 2004; Iglesias *et al.*, 2006; García-Ruiz *et al.*, 2011). Human activities such as over farming, excessive irrigation, deforestation, over-exploiting available water and erosion can alter the land's ability to capture and hold water (Mishra and Singh, 2010). Climate change can be incorporated into existing disaster risk reduction and development planning strategies. For instance, improved water management, water pricing and water recycling policies may reduce the population exposed to water stress (Arnell, 2004a; García-Ruiz *et al.*, 2011).

Despite advances in science and improved technology, drought remains one of the major challenges of climate variability worldwide (Piao *et al.*, 2010). Impact assessment and adaptation decisions require specific information about the spatial and temporal characteristics of drought risk (Loukas and Vasiliades, 2008; Mechler *et al.*, 2010). A better understanding of potential future drought evolution could facilitate the implementation of effective adaptation, preparedness and disaster risk reduction measures (Wilhite, 1997).

2.2 Drought

2.2.1 Drought as a Concept

Palmer (1965), Yevjevich (1967), Wilhite and Glantz (1985), Panu and Sharma (2002), Wilhite (2005), Paulo and Pereira (2006), WMO (2006), Mishra and Singh (2010) and Dai (2011) have comprehensively reviewed the concept of drought, which can be defined and understood in many ways. Sections 2.2.1–2.2.7 are based on these and other studies.

Drought is a natural, temporary and recurrent feature of variability, characterised by a cumulative precipitation deficit from the long-term mean (Bordi *et al.*, 2009; Vidal and Wade, 2009). The predominant driver is low precipitation, but high evaporation rates also play a role (van Lanen *et al.*, 2007; Li *et al.*, 2009). This universal phenomenon therefore needs to be considered as a relative, rather than an absolute, condition; its characteristics also vary significantly from one region to another (Mpelasoka *et al.*, 2008). The effects of rainfall deficiency may take weeks or months to become apparent. A prolonged and more spatially extensive meteorological drought may induce other types of drought (see Section 2.2.2).

2.2.2 Drought Classifications, Characterisation and Indices

A single drought event can span across different climate zones and affect various human activities (Fleig *et al.*, 2006). A standard methodology for characterising droughts under different hydroclimatological and hydrogeological conditions would help monitoring and forecasting of regional episodes. However, each event has unique climatic characteristics, spatial extent and impacts. The wide range of geographical and temporal distribution of droughts (thus the varying concepts), their complexity and interdisciplinary nature, and differing perspectives held by various stake-holders, make the onset and end of a drought difficult to determine. Hence, a precise, systematic and universal drought definition is lacking (Heim Jr., 2002; Quiring, 2009a; 2009b). Definitions also vary according to the variable (e.g. precipitation, stream flow or soil moisture) used to describe the drought (Mishra and Singh, 2010).

Conceptually, a drought refers to a water shortage (the demand) relative to the supply that originates from the absence or reduction in precipitation due to atmospheric conditions. Droughts are commonly classified into meteorological, agricultural, hydrological and socio-economic droughts (AMS, 2004; see Sections 2.2.3–2.2.7). Meteorological drought is a more common and natural event, whereas agricultural, hydrological and socio-economic droughts emphasise the human or social aspects (WMO, 2006). The sequence begins with meteorological drought; persistent dry conditions may induce agricultural, hydrological and water resources droughts (Vidal and Wade, 2009).

Mishra and Singh (2011) discussed the various components and methodologies in drought modelling, including forecasting, probabilistic characterisation, spatio-temporal analysis, the use of General Circulation Models (GCMs) and land data assimilation systems. Besides its scientific merits and ability to quantify events at different time scales, which requires a long time series, a "good" indicator should also be valuable and informative to decision makers (Mishra and Singh, 2010; Steinemann *et al.*, 2005; Steinemann and Cavalcanti, 2006).

Many statistical techniques exist for drought analysis (Panu and Sharma, 2002). As different types of drought may not occur simultaneously nor exhibit the same severity, they should be characterised separately (Fleig *et al.*, 2006). Many studies have reviewed and/or evaluated the various indicators; some of these are mentioned in Sections 2.2.3–2.2.7 (e.g. Hayes, 1998; Byun and Wilhite, 1999; Heim Jr., 2002; Steinemann, 2003; Quiring, 2009b). Besides the classical drought definitions, drought analysis methods may be based on frequency/probability, regression and Moisture Adequacy Index (MAI) (Panu and Sharma, 2002).

Drought is generally analysed using a time series of different variables on time scales that vary from months to years based on a threshold approach that originated from the theory of runs (Yevjevich, 1967; Dracup *et al.*, 1980; Hisdal *et al.*, 2003). This allows various statistical drought parameters, including frequency, duration, intensity and severity, to be determined. Figure 2.1 (from Mishra and Singh, 2010) presents a schematic diagram of a drought variable (X_t), which is intersected at several places by the truncation level (X_0) that produces three drought events. A negative (positive) run occurs when all values of the timeseries of a drought variable (X_t) are below (above) the pre-determined threshold (X_0). Drought initiation time (t_i) specifies the start of the deficit period, i.e. when the drought begins; drought termination time (t_e) denotes the time when the drought ends. Drought duration (D_d) is defined as the number of consecutive time-steps with below-threshold values (Byun and Wilhite, 1999), i.e. the time period between the initiation and termination of a drought. While drought severity (S_d) indicates the cumulative departure from a threshold, drought intensity (I_d) represents the averaged cumulative anomaly for that duration, i.e. the average magnitude of an event (Andreadis *et al.*, 2005). With a gridded dataset, the components in Figure 2.1 enable the determination of the areal extent of droughts, which is important as it (together with duration) can influence the range and scale of impacts.

Frequency analysis of critical events helps to determine design criteria in water resource projects (i.e. hydrological drought) and to select a cropping system or pattern (i.e. agricultural drought). Duration strongly correlates to severity, which is important for studying hydrological drought (Bonacci, 1993; Tarhule and Woo, 1997). Critical duration, even with lower severity, is important for agricultural drought (Panu and Sharma, 2002). Droughts can be spatially identified on a local, regional or national scale.

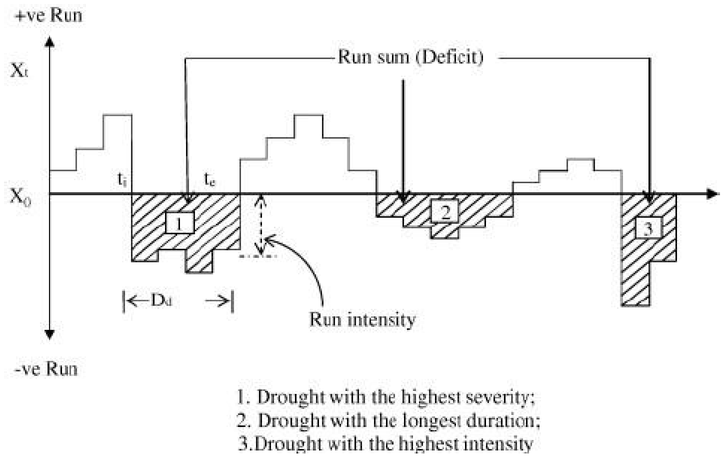


Figure 2.1: Drought characteristics using the run theory for a given threshold level. Source: Figure 1 in Mishra and Singh (2010).

The duration and location of a drought depends on a pre-defined threshold of a sequence (e.g. SPI or runoff time series) below which an event occurs. The threshold, either a constant or a function of time of the year, is of significant importance as it distinguishes the variable time series into “deficit” and “surplus”. It may be in absolute (e.g. deficit volumes in mm) or relative (e.g. the 80th percentile) terms. The former may be more meaningful for practitioners engaged in drought monitoring, forecasting and management operations, whereas the latter enables comparisons with other regions that have different hydro-climatic characteristics. Different thresholds (e.g. mean, median and percentiles) characterise events of different intensities, depending on the needs or applications and location (WMO, 2006).

2.2.3 Meteorological Drought

Meteorological drought typically refers to below-normal precipitation over a period of time over a region; it may also be described by temperature and evapotranspiration. It can develop quickly and end abruptly (Bordi *et al.*, 2009). The high temporal and spatial variability of precipitation and insufficient observation stations can pose analytical challenges.

Meteorological indices include percentile ranking methods (e.g. quartiles and deciles; Gibbs and Maher., 1967), percent of normal precipitation, Consecutive Dry Days (CDD), Rainfall Anomaly Index (RAI; van Rooy, 1965), Effective Drought Index (EDI; Byun and Wilhite, 1999), and Standardized Precipitation Index (SPI; see Section 4.2.2) (Mckee *et al.*, 1993).

2.2.4 Agricultural Drought

Agricultural drought is often characterised by insufficient moisture in the surface soil layers to support crop and forage growth, even with saturated deeper soil layers, through its control on transpiration and thus vegetative vigor (Sheffield and Wood, 2008a), without referring to surface water resources. Factors that cause meteorological (Section 2.2.3) and hydrological (Section 2.2.5) drought events, differences between actual and Potential Evapotranspiration (PET), plant biology and physics, and soil properties (e.g. water-holding capacity), all influence soil moisture, which is determined by the fluxes of precipitation, evapotranspiration and runoff. However, precipitation amounts do not directly relate to soil infiltration.

Agricultural drought indices often combine precipitation, temperature and soil moisture to measure soil moisture and crop yield. Numerous indices exist, including a Soil Moisture Index (SMI), Normalised Difference Vegetation Index (NDVI), water balance, heat stress, Palmer Moisture Anomaly Index (Z-index, which also measures meteorological drought), Crop Moisture Index (CMI), Soil Moisture Anomaly Index and Palmer Drought Severity Index (PDSI) (Hayes *et al.*, 2011; Palmer, 1965; 1968; Bergman *et al.*, 1988).

The PDSI has been widely applied especially in the U.S. (Soulé, 1992; Kangas and Brown, 2007; Gutzler and Robbins, 2011). PDSI, although originally developed to monitor long-term meteorological events, is a soil moisture algorithm calibrated for relatively homogeneous regions, and has been extensively used to describe agricultural droughts (Panu and Sharma, 2002).

2.2.5 Hydrological Drought

Surface waters (e.g. lakes and streams) are used for many purposes, including hydropower, irrigation and drinking water supply. Hydrological drought is generally defined as a period of inadequate surface and subsurface water supplies for use of a given water resource management system (Bordi *et al.*, 2009). Potential triggers include precipitation and/or soil moisture deficits (possibly due to more intense but less frequent precipitation), storage conditions, high evaporative losses, poor water management and erosion (Andreadis *et al.*, 2005). It usually lags behind meteorological and agricultural events, develops slowly as it involves stored water that is depleted but not replenished, and persists longer (Dai, 2011; Hisdal and Tallaksen, 2003; Steinemann *et al.*, 2005).

Although surface and subsurface components recover slowly due to the long recharge periods, runoff may recover in response to precipitation more quickly than soil moisture.

Hydrological droughts may be reflected by the total water deficit or cumulative stream-flow anomaly based on streamflow, reservoir and lake levels. A new "composite index" based on streamflow, precipitation, reservoir levels, snowpack, and groundwater levels have been recommended (Hayes *et al.*, 2011).

2.2.6 Groundwater Drought

Surface water drought may progress to groundwater drought, which is less extensively studied than other drought categories, particularly its spatial distribution (Peters *et al.*, 2005; 2006; Mishra and Singh, 2010). It occurs when groundwater levels, storage and discharge decline with some combination of low precipitation, high evapotranspiration, low soil moisture content and thus reduce groundwater recharge. The propagation of groundwater drought from recharge to discharge and the influence of aquifer characteristics on the propagation has been studied (Peters *et al.*, 2003; Peters and van Lanen, 2003). Abstraction and over exploitation may create/enhance a groundwater drought.

2.2.7 Socio-economic Drought

Socio-economic drought characterises the supply and demand of some precipitation dependent commodity or economic good (e.g. water, livestock forage or hydroelectric power) that may affect society's productive and consumptive activities (Dracup *et al.*, 1980). Supply depends on precipitation or water availability, which fluctuates annually. Demand is a function of human use and often correlates positively with increasing population and development. Temporal and spatial scales of supply and demand should be considered when defining a socio-economic drought. It is worth noting that demand for freshwater resources could change over time even with an unchanged climate. For instance, demand could increase with an increase in development, or the construction of reservoirs could enhance resilience to future climate change.

2.2.8 Discussion

The choice of drought index determines the spatial patterns of drought characteristics (Soulé, 1992). The wide range of drought definitions discussed in this subsection implies that one or more indices may be consulted as each has its own advantages and weaknesses (Bonacci, 1993; Hayes *et al.*, 2007). Drought definitions thus need to be region and application- or impact-specific, with the appropriate time scales chosen (Kangas and Brown, 2007). Nonetheless, few definitions adequately address drought impacts (Wilhite and Glantz, 1985).

2.3 Past Changes in Drought

This subsection presents an overview of the historic changes in drought globally. While long-term global drought trends are complex and there are no emergent coherent patterns of behaviour, there have been regional-scale spatial and temporal variations (IPCC, 2012; Easterling *et al.*, 2000). During the last 500–1000 years, North America, West Africa, and East Asia have experienced multi-year to multi-decade dry periods (Dai, 2011).

Globally, the areas affected by severe drought increased slightly over 1900–1995 (Dore, 2005). PDSI trends revealed drying along the Guinea Coast, southern Africa, parts of Canada, and southern and central Europe during 1900–1949 (Dai *et al.*, 2004).

Global very dry (PDSI<−3.0) areas decreased by 7% over 1950–1972, but have increased by 12–30% since the 1970s, particularly in the early 1980s with an ENSO-induced precipitation decline and surface warming. Since the mid-20th century, increased wetness occurred over the central U.S., Argentina and northern high-latitude areas whereas, in most of Africa, southern Europe, southeast Asia, and eastern Australia, (Dai *et al.*, 2004; Dai, 2011; as shown in Figure 2.2) there were more frequent and intense drought. The U.S. and Europe had both increases in the percentage of areas with severe drought or moisture surplus (Huntington, 2006). Less frequent/intense or shorter droughts have occurred in central North America and northwestern Australia (IPCC, 2012).

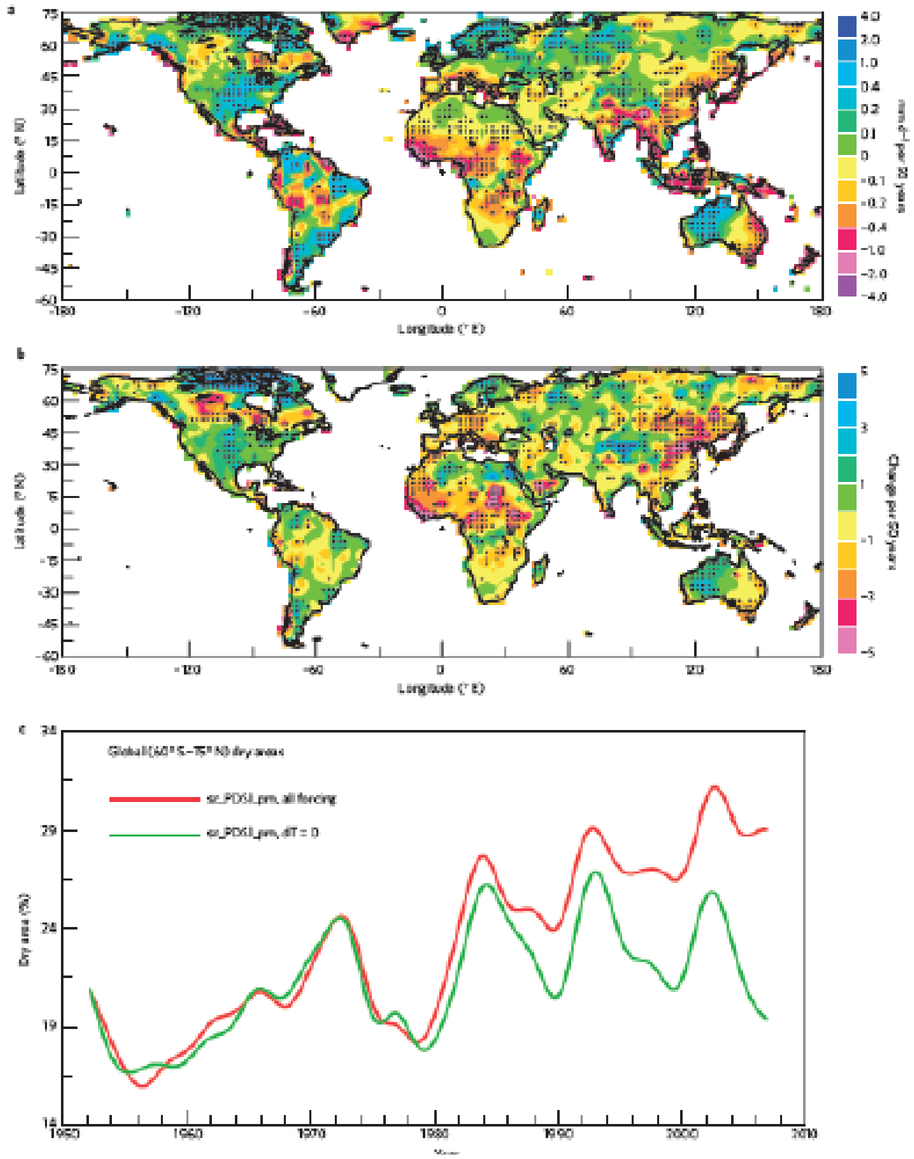


Figure 2.2: Trend maps for precipitation and scPDSI (scPDSI with PET estimated using the Penman-Monteith equation) and time series of percentage dry areas. Long-term trends from 1950-2010 in annual mean a, observed precipitation and b, calculated scPDSI using observation based forcing. The strippling indicates the trend is statistically significant at the 5% level, with the effective degree of freedom computed. c, Smoothed time series of the drought area as a percentage of global land areas based on the scPDSI computed with (red line) and without (green line) the observed surface warming. Source: Figure 1 in Dai (2013).

These studies have reported spatial and temporal variations in the drying and drought trends. Such differences may be associated with the different datasets used for drought analysis. Dai *et al.* (2004) used observed/historical precipitation and temperature datasets, whereas Sheffield and Wood (2008a) used soil moisture simulation from the Variable Infiltration Capacity (VIC) land surface hydrological model driven by a hybrid dataset of precipitation, near-surface meteorological and radiation data derived from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis and a suite of global observation-based products.

In addition, the different definitions and methodologies applied for drought quantification and computation (e.g. in the calculation of PDSI) can also contribute to some of the inconsistencies in the trends. Despite the variations in the trends found in different studies, drying and/or worsening drought conditions have consistently been found in Northern New Zealand.

2.4 Projected Changes in Drought

This subsection presents an overview of the projected changes in drought under future climates globally.

Compared to high precipitation extremes, projected trends for global dry events appear weaker and less consistent (Planton *et al.*, 2008). Due to the range of definitions that correspond to different classifications of drought and inconsistencies in the model projections when based on different dryness indices (e.g. short- vs. long-term events), there is medium confidence in future drought projections (IPCC, 2012). Despite the considerable regional variations, studies generally suggest a net overall global drying trend is projected over the 21st century.

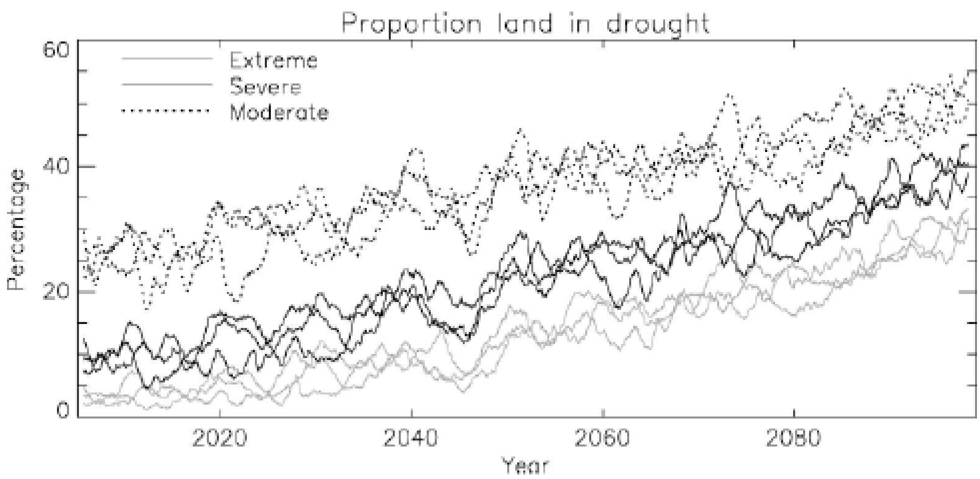


Figure 2.3: The proportion of the land surface in drought each month. Drought is defined as extreme, severe, or moderate, which represents 1%, 5%, and 20%, respectively, of the land surface in drought under present-day conditions. In each case results from the three simulations made using the A2 emissions scenario are shown. Source: Figure 9 in Burke *et al.* (2006).

Over the 21st century, dry day frequency increases under A2 and A1B emission scenarios but varies little under B1 (Tebaldi et al., 2006). The area of land surface in extreme drought increases from 1–30% (present-day) to 30–50% (by 2100) under the A2 scenario, with slightly less frequent but much longer events (Burke et al., 2006; Bates et al., 2008; as shown in Figure 2.3).

Using a drought risk index (based on a revised PDSI) that accounts for the effect of drought-disaster frequency, drought severity, production (yield) and extent of irrigation, results from 20 GCMs indicate that global drought disaster-affected areas increased from 15% (present-day) to 44% (2100) (Li *et al.*, 2009).

The frequency of dry days are projected to increase (decrease) in sub-tropical latitudes of northern and southern hemispheres (high-latitude northern hemisphere), according to nine GCMs (Tebaldi *et al.*, 2006). Future droughts (on the annual time scale and based on both soil moisture anomalies and CDD) will intensify in southern and central Europe, central North America, Central America and Mexico, northeast Brazil, and southern Africa (IPCC, 2012). Decadal-mean scPDSI calculated using the ensemble-means from 22 GCMs suggest increasing aridity between the 1950s and 2090s over most of Africa, southern Europe and the Middle East, most of the Americas, New Zealand, and Southeast Asia; persistent droughts may also occur in the U.S. in the first half of the 21st century (Dai, 2011).

2.5 Causes of Drought and its Characteristics

Meteorological droughts are mainly driven by precipitation and available energy; perturbations in the mean and/or the variability of either, or both, of these drivers can alter drought patterns (Burke, 2011). For instance, decreasing mean precipitation, increasing standard deviation of precipitation, increasing mean available energy and decreasing standard deviation of available energy tends to increase drought. The interactions between perturbations in precipitation, temperature, and hydrologic processes through their frequency, intensity, and seasonality (especially in snow-dominated regions) makes it difficult to assess the relative importance of temperature and precipitation in changes in drought events (Sheffield and Wood, 2008b).

2.5.1 Natural Causes of Drought

Global-scale atmospheric circulation changes can alter large-scale patterns of precipitation, temperature and cloudiness (Dai, 2011). Atmospheric circulation patterns that affect precipitation (which has a notable seasonality) are easier to distinguish than those responsible for spatial variations of drought, which tend to be more continuous (Vicente-Serrano, 2006). Changes in annual/heavy precipitation, or differences between precipitation and evapotranspiration cannot simply explain drought and flood changes, e.g. in some regions, both drought and flood frequencies increase with less frequent precipitation days but more frequent heavy precipitation days (Hirabayashi *et al.*, 2008).

The inter-decadal and multi-decadal climate variability (Dore, 2005) and anomalous tropical sea surface temperatures (SSTs) (Hoerling and Kumar, 2003; Dai, 2011) could weaken the East Asian summer monsoon (EASM) (Li *et al.*, 2010). Some of the effects of the El Niño Southern Oscillation (ENSO), North Atlantic Oscillation (NAO) and other phenomenon are briefly described below.

ENSO is one of the major modes of climate variability. Since the late 1970s, a shift in ENSO towards more warm events, which corresponded with record high global-mean temperatures, has severely altered drought-affected areas (Dore, 2005). More (less) short-term droughts have coincided with El Niño (La Niña) episodes (Sheffield *et al.*, 2009). El-Niño-like conditions promote drought in Australia, New Zealand, Indonesia, East China and South Africa (Salinger, 2005; Collier *et al.*, 2008; Dai, 2011).

2.5.2 Anthropogenic Influences

Although natural causes have contributed to some of the recent regional trends in dryness or drought, anthropogenic influences may have exacerbated or dampened these trends (Sheffield and Wood, 2008a). Human induced rapid warming since the 1970s has increased atmospheric moisture demand and likely altered atmospheric circulation patterns (Schär and Jendritzky, 2004; Dai, 2011). According to the Clausius-Clapeyron relation, warming implies higher atmospheric moisture-holding capacity, and where available, more water vapour for the precipitating weather systems (Alexander *et al.*, 2006). The decreasing ratio between precipitation and precipitable suggests an enhanced global hydrological cycle (Dore, 2005; Huntington, 2006). On a global scale, this could be a result of strengthened horizontal moisture transports, assuming that atmospheric circulation remains constant (Held and Soden, 2006). This occurs as more moisture (with increased atmospheric water vapour concentrations) is transported from areas where evaporation exceeds precipitation (P −E<0; e.g. in the sub-tropical oceans) to areas where precipitation exceeds evaporation (P −E>0; e.g. the higher latitudes) (Hegerl *et al.*, 2013). Therefore, drying intensifies in areas where P −E<0 and wetting amplifies in areas where P −E>0.

Human-induced changes in global land precipitation could be a result of GHG and black carbon/sulphate aerosol emissions (Frieler *et al.*, 2011), which have led to the global drying trend since 1952 (Burke *et al.*, 2006). For instance, the Asian monsoons are affected by black carbon/sulphate aerosols (Ramanathan and Feng, 2009; Kuhlmann and Quaas, 2010). These, together with land use changes, have weakened the East Asian summer and winter monsoon, producing droughts in North China (Ding *et al.*, 2007; Liu *et al.*, 2009). Anthropogenic influences can also alter both runoff volume and distribution. Relatively small temperature/precipitation changes can have large impacts on runoff (Frederick and Major, 1997).

2.5.3 Summary

This subsection has discussed some of the natural and anthropogenic drivers that can alter precipitation, temperature and runoff characteristics, thus modifying drought conditions. Natural causes of drought include changes in atmospheric circulation and modes of climate variability (e.g. ENSO and NAO) — the characteristics of which may also be modified by human activities. Humans can also influence drought patterns through greenhouse gas (GHG) and black carbon/sulphate aerosol emissions, as well as changes in land use and land cover, population and socio-economic activities. However, it may be difficult to distinguish between the effects of climate change and human activities. Furthermore, droughts have been produced by past large, widespread, abrupt climate changes, which may be triggered by human influences (Alley *et al.*, 2003). Therefore, drought occurrence and changes in their characteristics can be a result of any combination of climatic and hydrological elements, land surface conditions, and anthropogenic activities.

2.6 Uncertainties in Climate Modelling

Despite advanced climate models and improved knowledge, considerable levels of uncertainty remain in climate change projections, particularly in relation to extreme events such as future drought characteristics. Uncertainties on large spatial and longer temporal scales may be estimated (Vasiliades *et al.*, 2009; Knutti, 2008). Uncertainties arise from future human activities and the associated response of the climate system. The former are represented by future GHG and aerosol emissions (Section 2.6.1); the latter are explored with different climate model parameters and structures (Sections 2.6.2–2.6.11) and include natural climate variability (Section 2.6.12) (Seneviratne *et al.*, 2012).

2.6.1 Forcing Uncertainty

Human activities have influenced 20th-century temperature and precipitation trends (Stott, 2003; Zhang *et al.*, 2007). Forcing uncertainty arises from non-climate factors that affect the climate system e.g. population changes (Arnell, 2004a). It is often examined by applying various scenarios of prescribed atmospheric GHG concentrations that may contain assumptions about future world economic and social development, and political decisions. A range of emission scenarios — notably the IPCC SRES (Nakicenovich and Swart, 2000) and Representative Concentration Pathways (RCPs; Moss *et al.*, 2010) (see Section 3.4) — have been developed. The relative likelihood of these is difficult to determine (Tebaldi and Knutti, 2007; Knutti *et al.*, 2010). Temperature-related impacts tend to scale with the amount of anthropogenic emissions and the associated global-mean temperature change (Arnell, 2003a; Tebaldi *et al.*, 2006; Sheffield and Wood, 2008b).

2.6.2 Initial Condition Uncertainty (ICU)

ICU arises from the initialisation of models (the initial state, or ensemble of states) from which they are integrated forward in time (Stainforth *et al.*, 2007a). The incomplete knowledge of the current state of the system introduces macroscopic ICU, which affects the predicted state variable distributions that have relatively “large” slowly mixing scales; microscopic ICU is due to the imprecise knowledge of “small” rapidly mixing scales. While ICU may affect modelled climate distributions, it is the primary error source in weather forecasting (Collins and Allen, 2002). The initial ocean state provides the “memory” of the system, which may be useful on interannual time scales (e.g. the forecasting of ENSO), but it is less relevant for longer-term (decadal) climate projections and multi-model simulations (Tebaldi and Knutti, 2007; Knutti *et al.*, 2010).

2.6.3 Boundary Condition Uncertainty (BCU)

Boundary conditions are prescribed externally to the model, experiments of which are otherwise self-contained (Tebaldi and Knutti, 2007). External influences can cause climate change beyond the "noise" of climate variability (Collins and Allen, 2002). These can be natural (the solar cycle or volcano eruptions; see Section 2.6.12), which may not be predictable in a deterministic sense or anthropogenic (GHG emissions; see Section 2.6.1).

2.6.4 Model Imperfections

Model imperfection results from our limited understanding of, and ability to simulate the Earth's climate (Stainforth *et al.*, 2007a). Model imperfection takes two forms: inadequacy and uncertainty.

2.6.4.1 Model Inadequacy

Even the most sophisticated models are unrealistic representations of many relevant aspects of the climate system (Stainforth *et al.*, 2007a). Model inadequacy (structural uncertainties) relate to grid resolution (therefore particularly relevant for regional simulations) and missing/approximated processes that cannot be accurately described in the model (Knutti *et al.*, 2010). Different choices made by modeling groups may be due to limited knowledge that includes incomplete understanding of deterministic processes, and limited resources to measure and obtain empirical information (see van Asselt and Rotmans, 2002). For example, the simulation of convection and its effect on the water vapour and cloud distribution within the atmosphere, feedback from vegetation change to climate change and land cover changes, aerosol (e.g. black carbon) effects on clouds and precipitation are often omitted or implicitly represented in climate models (Bates *et al.*, 2008; Knutti *et al.*, 2010). In addition, climate models exclude some natural processes (e.g. vegetation dynamics and wildfire) and anthropogenic forcing (e.g. irrigation, water diversion and land use that directly affect drought occurrence), which are difficult to quantify, even historically (Sheffield and Wood, 2008b).

2.6.4.2 Model Uncertainty

Model (parameter) uncertainty represents the impact of known uncertainties (Stainforth *et al.*, 2007a). Processes to be included in a model and their parameterisation may be subjectively chosen based on expert knowledge and experience (Tebaldi and Knutti, 2007). Similar sets of primitive dynamical equations may be solved by different numerical algorithms. Different parameterisations contribute to diverging model responses due to different realisations of a given forcing scenario (Goodess *et al.*, 2003a; Parker, 2010b), e.g. the grand ensemble of climateprediction.net (Stainforth *et al.*, 2004) reveals climate sensitivities that range from below 2 K to over 11 K (Stainforth *et al.*, 2005).

2.6.5 Multi-Model Ensembles (MMEs)

Simplifications, assumptions and parameterisation choices made during model construction lead to model and projection errors (Tebaldi and Knutti, 2007). Thus, it is impossible to designate a “best model” when simulation skill for mean precipitation, for instance, varies both temporally and spatially (Blenkinsop and Fowler, 2007a). Since each simulation provides a projected distribution, a multi-model approach can present the range of behaviour in the variables of interest across different models, and enables sensitivity analysis of the models’ structural choices (Stainforth *et al.*, 2005; 2007b; Knutti *et al.*, 2010). This may capture much of the uncertainty, and multi-model mean implicitly imply improved skill, reliability and consistency of model projections (CCSP, 2008; Tebaldi and Knutti, 2007; Knutti *et al.*, 2010). An ensemble of different models or model versions, MMEs, refers to a set of model simulations from structurally different models where each model has one or more initial condition ensemble (Tebaldi and Knutti, 2007). A multi-model approach has been recommended, possibly due to cancelling the offsetting errors in the individual GCMs although the exact reason remains unclear (Pierce *et al.*, 2009; Reichler and Kim, 2008; Vrochidou *et al.*, 2013). Stainforth *et al.* (2007b) provided an analysis pathway for how climate model ensembles may inform decisions.

MME mean is often used and uncertainty is often represented by the standard deviation or some other measure of spread of individual model results; ensemble median may outperform ensemble mean (Gudmundsson *et al.*, 2012a). Models can also be weighted; weighted averages may perform better if there is sufficient available information to derive the weights (Knutti *et al.*, 2010).

2.6.6 Challenges in Interpreting Multi-Model Projections

It is tempting to infer more from ensemble results as outcomes that are not simulated are similarly plausible (Parker, 2010a; 2010b). Since uncertainty in multi-models are expected to widen with model development, increased physical realism and incorporation of additional processes or methods, current ensembles provides a lower bound on the maximum range of uncertainty, which may be constrained by the methods used to assess a model's ability to inform us about real-world variables (Stainforth *et al.*, 2007a; Stainforth *et al.*, 2007b).

Therefore, when constructing and interpreting MME climate results (in the form of climate change probability distributions or averages and measures of variability across models), a number of issues need to be considered (Stainforth *et al.*, 2007a), as discussed below.

2.6.7 Interpreting Multi-Model Ensemble (MME) Results

The ensemble mean could outperform single model results, can demonstrate characteristics that are not reflected in any single model, and may cause a loss of signal that has barely been addressed (Knutti *et al.*, 2010). Uncertainty is often not adequately characterised (e.g. by standard deviation) due to the same biases in groups of GCMs (Chiew *et al.*, 2009). Nevertheless, ensembles are valuable for understanding present-day limitations (Stainforth *et al.*, 2007a).

2.6.8 Discussion

Model simulations have a number of limitations. GCMs generally reproduce the overall and broad geographic (e.g. spatial mean annual) patterns of observed climate trends (Arnell, 2004a; Milly *et al.*, 2005). However, models may accurately simulate one metric but not another (Brekke *et al.*, 2008; Foley, 2010). Projected precipitation changes, which are important for impact modelling, are less spatially coherent weaker and more uncertain than temperature. Models have difficulties simulating precipitation response to large-scale climate variability.

Models that reproduce the mean climate can necessarily perform well at replicating the observed climate extremes (McCrary and Randall, 2010; Williams *et al.*, 2010). A climate model that reasonably simulates present-day regional precipitation variability may produce less uncertain future drought projections (Burke, 2011).

2.7 Challenges in Projecting Future Drought Conditions

Droughts are one of the most damaging natural hazards in human, environmental and economic terms. Anthropogenic climate change has and will continue to alter their characteristics. A better understanding of potential future drought characteristics and the uncertainties associated with the various methodologies to derive them are vital for identifying effective measures to manage drought risks and any direct/indirect impacts. However, confidence in drought projections is constrained by definitional issues (see Section 2.2), lack of observational data and the limitations of climate models (IPCC, 2012). Some of the uncertainties associated with drought identification and quantification are presented in Section 2.2; those related to climate modelling are discussed in Section 2.6. Hence, it is important to characterise the uncertainties associated with future drought simulations (Vasiliades *et al.*, 2009).

Projecting future climate remains very challenging. Present-day climate and its natural variability, climate change, and the sensitivity of drought metrics to these changes all define future drought changes. The strength of the change (signal) against the background of natural variability (noise) governs the detectability of any changes, and hence their statistical significance. A future shift in modes of climate variability remains uncertain. Moreover, climate change effects may not be felt in the near future at regional scales (Sheffield and Wood, 2008b).

Despite the limitations discussed in Section 2.7, GCMs are valuable tools for studying climate change and the related impacts as each simulation presents a “what-if” scenario (Stainforth *et al.*, 2007a). However, GCMs were originally constructed for assessing the global climate system response to varying emissions and facilitating mitigation efforts, rather than informing an adaptation-type analysis (Kundzewicz and Stakhiv, 2010). They also differ in their design and outcomes. Since each model has its own set of strengths and weaknesses, no one model is particularly good or bad, and a multi-model approach is desirable (Knutti, 2008; Alexander and Arblaster, 2009).

To evaluate the robustness of projections of Meteorological drought in New Zealand under climate change, the effects of applying different emission scenarios and GCMs from the Coupled Model Intercomparison Project (CMIP5) are explored in this thesis (particularly Chapter 3 and 6). In most cases, however, resource constraints have prevented the running of large ensembles of GCM experiments.

Chapter 3

Methodology

This chapter presents the general methodology, including the GCMs, bias correction algorithm, study area and drought identification, applicable to Chapters 4–6. More specific details are elaborated in the individual sections.

3.1 General Circulation Models (GCMs)

General Circulation Models or GCMs are Numerical models, representing physical processes in the atmosphere, ocean, cryosphere and land surface, are the most advanced tools currently available for simulating the response of the global climate system to increasing greenhouse gas concentrations. While simpler models have also been used to provide globally- or regionally-averaged estimates of the climate response, only GCMs, possibly in conjunction with nested regional models, have the potential to provide geographically and physically consistent estimates of regional climate change which are required in impact analysis. (IPCC Data.org). GCMs and global climate models are used for weather forecasting, understanding the climate and forecasting climate change.

GCMs depict the climate using a three dimensional grid over the globe (see below), typically having a horizontal resolution of between 250 and 600 km, 10 to 20 vertical layers in the atmosphere and sometimes as many as 30 layers in the oceans. Their resolution is thus quite coarse relative to the scale of exposure units in most impact assessments. Moreover, many physical processes, such as those related to clouds, also occur at smaller scales and cannot be properly modelled. Instead, their known properties must be averaged over the larger scale in a technique known as parameterization. This is one source of uncertainty in GCM-based simulations of future climate. Others relate to the simulation of various feedback mechanisms in models concerning, for example, water vapour and warming, clouds and radiation, ocean circulation and ice and snow albedo. For this reason, GCMs may simulate quite different responses to the same forcing; simply because of the way certain processes and feedbacks are modelled.

From amongst 64 models, only 21 GCMs are used from the Coupled Model Intercomparison Project (CMIP5) to measure the projected change in temperature, precipitation and drought over New Zealand during the next century at a fine gridded scale. CMIP5 provides nearly 64 models (for temperature and precipitation) contributed by ~ 20 countries around the world (Taylor, 2012). These models are at a coarse resolution ranging from 0.9 (90 km) to 3.625 (362 km). The historical simulations start from 1950-2005 while the scenarios from 2006 to 2100. Numerous parameters are available for analysing, the only parameters considered for analysing the meteorological are temperature and precipitation. 21 models for precipitation are considered for the analyses in this study (see Table 3.1).

Table 3.1: List of CMIP5 models and their spatial resolution

Model	Modeling Center	Latitude Resolution(degree)	Longitude Resolution (degree)
bcc-csm1-1	Beijing Climate Center, China Meteorological Administration	2.812	2.812
bcc-csm1-1-m	Beijing Climate Center, China Meteorological Administration	2.812	2.812
CCSM4	National Center for Atmospheric Research, USA	0.942	1.250
CESM1-CAM5	Community Earth System Model, USA	0.937	1.250
CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization, Australia	1.895	1.875
FIO-ESM	The First Institute of Oceanography, China	2.812	2.812
GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.000	2.500
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.000	2.500
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.000	2.500
GISS-E2-H	NASA Goddard Institute of Space Studies, USA	2.022	2.517
GISS-E2-R	NASA Goddard Institute of Space Studies, USA	2.022	2.517
HadGEM2-AO	Met Office Hadley Centre, UK	1.241	1.875
HadGEM2-ES	Met Office Hadley Centre, UK	1.241	1.875
IPSL-CM5A-LR	Institute Pierre-Simon Laplace, France	1.897	3.750
IPSL-CM5A-MR	Institute Pierre-Simon Laplace, France	1.897	3.750
MIROC5	The University of Tokya, National Institute	1.417	1.406

	for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan		
MIROC-ESM	The University of Tokya, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	2.857	2.813
MIROC-ESM-CHEM	The University of Tokya, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	2.857	2.813
MRI-CGCM3	Meteorological Research Institute, Japan	1.132	1.125
NorESM1-M	Norwegian Climate Centre, Norway	1.875	2.500
NorESM1-ME	Norwegian Climate Centre, Norway	1.875	2.500

3.2 Emission Scenarios

This thesis has examined the effects of a range of emission scenarios including the IPCC RCPs, as outlined below.

3.2.1 Representative Concentration Pathways (RCPs)

The Representative Concentration Pathways (RCPs; Moss *et al.*, 2010) represent the full range of potential future radiative forcing pathways that are considered to be feasible, which are compatible with the full range of stabilisation, mitigation and baseline emission scenarios available in the scientific literature. Unlike the SRES scenarios that were developed sequentially (i.e. from detailed socio-economic storylines which determine GHG emissions to radiative forcing), the RCPs were developed through the parallel approach, where important characteristics for scenarios of radiative forcings, such as the level of radiative forcing in the year 2100, was first identified.

Four individual modeling groups developed four independent pathways for the RCPs (Table 3.2) using integrated assessment models that combine economics, technology, and physical processes. The scenarios include a full suite of GHG concentrations, spatially explicit emissions for pollutant gases and aerosols, and spatially explicit land-use and landuse change information. The differences between the RCPs may be partly attributable to differences between models and scenario assumptions (scientific, economic, and technological), but cannot directly be interpreted as a result of climate policy or particular socioeconomic developments.

Although the RCPs were not developed to mimic specific SRES scenarios, temperature projections for RCP8.5, RCP6 and RCP4.5 are similar to those for the SRES A1FI, B2 and B1 scenarios, respectively. Temperature estimates for the RCPs span a larger range than for the SRES scenarios, as the former span a large range of stabilisation, mitigation and non-mitigation pathways while the latter covers only non-mitigation scenarios (Rogelj *et al.*, 2012).

Table 3.2: Representative Concentration Pathways (RCPs)

RCP	Description	Developed by
RCP 2.6	Peak in radiative forcing at ~ 3 W/m2 before 2100 and decline	IMAGE
RCP 4.5	Stabilization without overshoot pathway to 4 W/m2 at stabilization after 2100	GCAM (MiniCAM)
RCP 6.0	Stabilization without overshoot pathway to 6 W/m2 at stabilization after 2100	AIM
RCP 8.5	Rising radioactive forcing pathway leading to 8.5 W/m2 in 2100.	MESSAGE

There is no single "best model" for reproducing mean precipitation and drought statistics across New Zealand; model skills also vary temporally, even on the catchment scale (Blenkinsop and Fowler, 2007b). Projections of future climate inevitably contain uncertainty that is typically addressed by using a variety of scenarios to generate a range of possible outcomes.

Since there is no universal definition of drought (Section 2.2), one of the classifications studied in this thesis are meteorological events. Meteorological droughts have been quantified by the precipitation-only Standardised Precipitation Index (SPI; see Section 4.4.1)

3.3 Bias Correction Algorithm

Global Climate Models (GCMs) have been the primary source of information for constructing climate scenarios, and they provide the basis for climate change impacts assessments at all scales, from local to global. However, impact studies rarely use GCM outputs directly because climate models exhibit systematic error (biases) due to the limited spatial resolution, simplified physics and thermodynamic processes numerical schemes or incomplete knowledge of climate system processes. Errors in GCM simulations relative to historical observations are large (Ramirez-Villegas *et al.*

2013). Hence, it is important to bias-correct the raw climate model outputs in order to produce climate projections

Bias-Correction removes errors from data from climate models in comparison with historical observations. It relies on computation of differences between RCM/GCM and satellite-based estimates in regions with limited rain gauges. A more sophisticated approach for bias-correcting is needed for stochastic variables such as precipitation and solar radiation. This is because for example, GCM outputs are known to have a "drizzle problem", that is, too many low-magnitude rain events as compared to observations (Gutowski *et al*., 2003).

In order to appropriately bias-correct GCM output for monthly totals and wet-day frequency, while ensuring realistic daily and interannual variability, we implemented the Quantile Mapping (QM) algorithm approach with the qmap library written for R statistical software (Gudmundsson, 2014). The quantile mapping algorithm removes the systematic bias in the GCM simulations and has the benefit of accounting for GCM biases in all statistical moments, though, like all statistical downscaling approaches, it is assumed that biases relative to historical observations will be constant in the projection period (Thrasher *et al.*, 2013).

The so-called quantile-based mapping method (CDF matching) maps the cumulative distribution function (CDF) of the biased model outputs onto the distribution of observations. The approach imposes the following equivalence:

$$F_{OBS}(y) = F_{MOD}(x) \qquad (3.1)$$

where $F(\cdot)$ denotes the CDF of the observations (OBS) and the modeled (MOD) outputs. From where the bias corrected model output is obtained:

$$X_{adj} = F_{OBS}^{-1}(F_{MODh}(x)) \qquad (3.2)$$

where X_{adj} is the bias-corrected model output while denotes F_{MODh} the CDF of the historical modeled simulations. Figure 3.1 illustrates a schematic of the CDF method for correction of the bias at an arbitrary point (x = 3.5, solid circle, selected for illustration purposes).

The CDFs and their inverse can be estimated by fitting a distribution function to the data empirically or theoretically through parameter estimation. The theoretical distribution function fitted to the historical data is more likely to capture the extreme values of the projection compared to the empirical one.

This study thereby enhanced the dataset of 21 CMIP5 GCMs by using a quantile mapping bias correction algorithm and the improved datasets were used for drought projections over the regions of New Zealand.

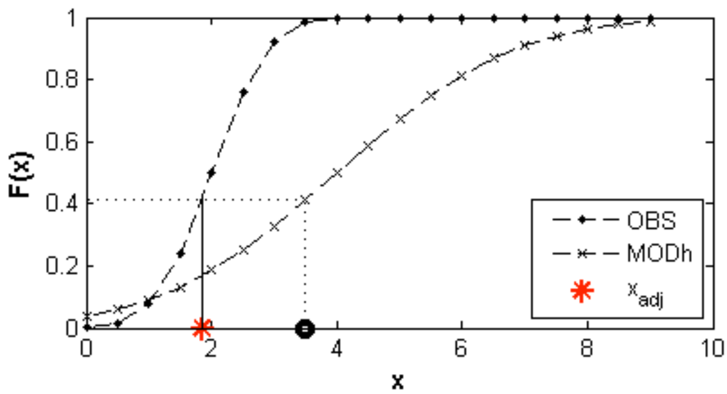


Figure 3.1: Illustration of the CDF method for correction of the bias at x=3.5 (solid circle). Dashed line is the cumulative distribution function (CDF_{OBS}) for the observation, cross-dashed line is the cumulative distribution function (CDF_{MODh}) for the historical modeled variable, and solid star is an adjusted value (x_{adj}) based on the CDF method. Source: Figure 2 in Moghim, 2015.

3.4 Time scales and Study Periods

Different time scales may be useful for monitoring different drought classifications. A 3–6 month drought describes a surface water drought, whereas a 6+ month drought represents a water resource drought that could affect groundwater resources (Fowler and Kilsby, 2004; Blenkinsop and Fowler, 2007a). For meteorological events, SPI time scales of 7–12 months better represent river discharges.

Short (3-month), medium (6-month) and long (12-month) droughts were studied here; meteorological events were denoted by SPI3, SPI6 and SPI12, respectively for the temporal characteristics of drought. Prior to SPI computation (for meteorological drought; Section 4.2.2) quantification (for hydrological drought; Section 5.3), a 3/6/12-month lagged moving average of the raw monthly precipitation timeseries was derived. This accounts for conditions in the preceding months, as a drought is a cumulative precipitation deficit.

Drought projections were characterised for the baseline period (1971–2000), and three future periods (2010-2039, 2040-2069, 2070-2199). The 30-year period was chosen in order to sample a range of (e.g. multi-year) events and a range of natural variability; a shorter time scale may result in zero drought events being identified in some cells of the study region (see Section 3.9) during 1971–2000, thus the percentage change in future events would not be able to be determined. Hence, SPI time scales of 12 months (SPI12) were studied for future drought projections.

3.5 Drought Identification

Meteorological droughts were characterised using a threshold approach (see Section 2.2.2): a meteorological event occurs when the value of the lagged moving average SPI series falls below the threshold. For meteorological events, the focus is on the severely or extremely dry conditions (see Table 4.1) — i.e. a drought was considered to begin when SPI≤−1.5. For SPIm (where m represents the time scale concerned), when the SPI values of over m consecutive months remained SPI>−1.5, an event terminated in the first month when the SPI value rises above SPI−1.5. Hence, two separate events occurred only when there were over m months of SPI>−1.5; persisting dry conditions (e.g. several years) with occasional wet periods that could only temporarily alleviate the drying were regarded as a single event, i.e. lower frequency despite extensive drought conditions.

3.6 Drought Parameters

As discussed in Section 2.2.2, precipitation deficit has been characterised by different parameters. This thesis has quantified meteorological and hydrological droughts by considering their severity and spatial extent. Drought severity for cell *i* represent the cumulative deficit from the threshold over a 30-year period, and is given by:

$$\text{Severity} = \sum_{t=i}^{t=e} X_o - X_t \tag{3.3}$$

where X_0 is the threshold, X_t is the drought variable at month t, and $t = i$ and $t = e$ represents the start and the end of the drought event, respectively (c.f. Figure 2.1). Severity provides no information on the timing of the events. For hydrological events, severity is equivalent to deficit volume in units of mm. Therefore, drought intensity represents the averaged magnitude and is denoted by:

$$Intensity = \frac{Severity}{t_e - t_i + 1} \tag{3.4}$$

3.7 Drought Projection Procedure

Climate change will create many challenges and opportunities for New Zealand's agriculture and forest industries. Productivity will increase in some areas and a wider selection of species will become suitable, but at the same time an increase in a number of potential threats could occur: high temperatures, drought, wind damage, fire risk, and increased insect and plant disease damage. Of these various threats, drought is the hazard that could have the largest effect on the New Zealand economy, and changes in extreme winds is the factor least understood at this time.

Projection of droughts for the future would point to a number of areas where future adaptation analysis and responses might be targeted. The changing nature of drought through the 21st century highlights that basing response on a historically determined understanding of what is normal will increasingly put Governments and farm managers in a weakened position to manage drought risk. As discussed in Section 2.2, precipitation is the solo parameter of consideration for SPI. This study has implemented the following procedure for projecting droughts through the 21st century.

Initially, projections are made for the bias-corrected MME precipitation under two emission scenarios for the periods mentioned in Section 3.4.

> Regridding the bias corrected models to 20kmx20km and Ensemble of 21 models is calculated using NCL code; This code also writes out the Precipitation for three future periods along with the baseline.
>
> $Precip_{(sc,\ tp)}$, $Precip_{(bl)}$
>
> Where, $Precip_{(sc)}$ is the precipitation for the scenarios and $Precip_{(bl)}$ is the baseline precipitation
>
> tp = 1971-2000, 2010-2039, 2040-2069, 2070-2199
>
> sc = rcp4.5, rcp 8.5

SPI12 for the baseline and future periods under RCP4.5 and RCP8.5 scenarios were generated for the calculation of change in drought projection in percent. The outcome of this procedure is detailed in Chapter 6.

SPI tool calculates the drought for 3, 6, 12 and 24 month timescale for both baseline period and future periods, under RCP4.5 and RCP8.5. Only 12month time scale (SPI12) is used for projection of droughts. Projection of droughts is calculated as follows

$$\frac{SPI12_{(sc,\,tp)} - SPI12_{(bl)}}{SPI12_{(bl)}} = SPI12_{ch\ (\%)}$$

Where, $SPI12_{ch\ (\%)}$ is the change in drought projection, SPI12 (sc,tp) is the 12month timescale SPIvalues for the scenarios and future time periods and $SPI12_{(bl)}$ is the 12month timescale SPIvalues for baseline
tp = 1971-2000, 2010-2039, 2040-2069, 2070-2099
sc = rcp4.5, rcp 8.5

3.8 Study Area and Regions

The study area defines a region at 41 ^{o}S 174 ^{o}E. New Zealand is in Oceania, in the South Pacific Ocean. New Zealand's climate is complex and varies from warm subtropical in the far north to cool temperate climates in the far south, with severe alpine conditions in the mountainous areas. Most areas of New Zealand have between 600 and 1600 mm of rainfall, spread throughout the year with a dry period during the summer. Over the northern and central areas of New Zealand more rainfall falls in winter than in summer, whereas for much of the southern part of New Zealand, winter is the season of least rainfall.

Mean annual temperatures range from 10°C in the south to 16°C in the north of New Zealand. The coldest month is usually July and the warmest month is usually January or February.

In New Zealand generally there are relatively small variations between summer and winter temperatures, although inland and to the east of the ranges the variation is greater (up to 14°C). Temperatures also drop about 0.7°C for every 100 m of altitude.

There are 16 regions in New Zealand (see Figure 3.2). Seven regions namely – Canterbury, Marlborough, Nelson, Otago, Southland, Tasman and West Coast fall into the Sothern Part of the New Zealand while the remaining regions – Auckland, Bay of Plenty, Gisborne, Hawke's Bay, Manawatu-Wanganui, Northland, Taranaki, Waikato and Wellington belong to the Northern Island of New Zealand.

Monthly data obtained on a global scale is regridded to 20km x 20km resolution and are further processed in ArcGIS to truncate the dataset only for the region of study, shown in Figure 3.3.

Figure 3.2: Study area and regions.

Our region for truncation: 48 degrees south to 34 degrees south, 166 degrees east to 180 degrees east. Total 721 grids points are considered over the study region.

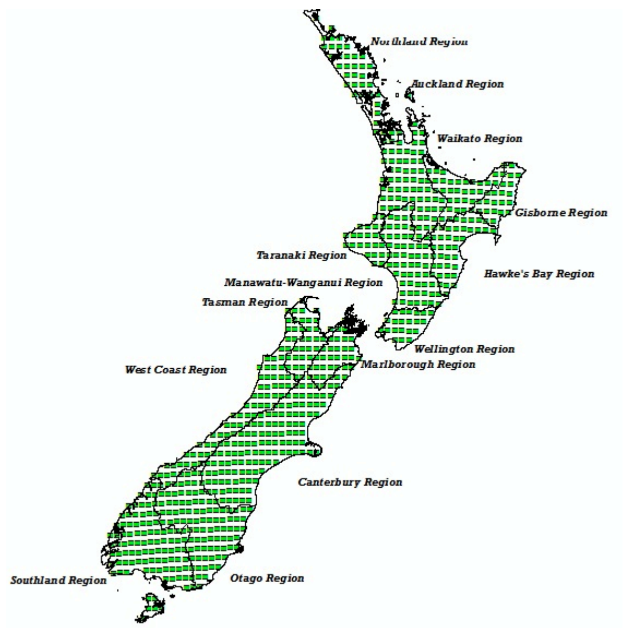


Figure 3.3: Grid points considered in the study area.

3.9 Summary

This chapter has outlined the emission scenarios, models, bias correction algorithm, projection procedure, drought identification, time scale and study area used in this thesis for generating rainfall and temperature timeseries. It has also described the identification and quantification of droughts as applied in Chapter 6.

As this study concerns drought monitoring and early warning, the meteorological drought index provides the best initial evaluation. Rainfall, evaporation, temperature, soil-moisture and other indicators have been used to calculate drought indices, but there is no doubt that the most useful and convenient single indicator is rainfall. Therefore, in Chapter4; Standardised Precipitation Index (SPI) is assessed to further investigate how well this index reflects drought conditions in the regions of New Zealand and to analyse temporal and spatial variation of drought characteristics.

Chapter 4

Preliminary analysis of climatic data

4.1 Introduction

As discussed in the previous chapter, drought indices (DIs) have been commonly used to quantify rainfall deficits, soil moisture and water availability and to assess drought severity (Morid *et al.*, 2006; Mishra and Singh, 2010). New Zealand still lacks an appropriate drought assessment tool that can be used to define drought conditions and to predict future droughts. Therefore, this chapter focusses on the usage of drought index – SPI for use in this study in terms of how well it reflects drought conditions in New Zealand. A description of the data used and some preliminary analysis of the data are also presented in detail. As mentioned in Chapter 2, meteorological DI provide the best initial assessment for drought monitoring and early warning. For that reason, the Standardised Precipitation Index (SPI) was applied to the study area and the results evaluated (McKee *et al.*, 1993).

The SPI was chosen due to its widespread application for describing and comparing actual drought events in other parts of the world.

4.2 Spatial and Temporal Variation of Annual Climatic Data

The study uses 109 years of monthly rainfall and temperature data from Climate Research Unit (CRU). The CRU data has been validated over the study region.

Figure 4.1 shows characteristics of annual rainfall over New Zealand for the period 1901-2009. Annual rainfall over New Zealand varies from 1400 mm to 1900 mm. Table 4.1 and Figure 4.2 demonstrate the descriptive statistical analysis of annual rainfall data (y) for all 16 regions of New Zealand to examine its central tendency (mean) and variability (standard deviation). Standard deviation is an indicator of the variability of data around the mean. The coefficient of variation (CV) is the statistical measure of the dispersion of data points in a data series around the mean. The *CV* is the ratio of the standard deviation to the mean of the data.

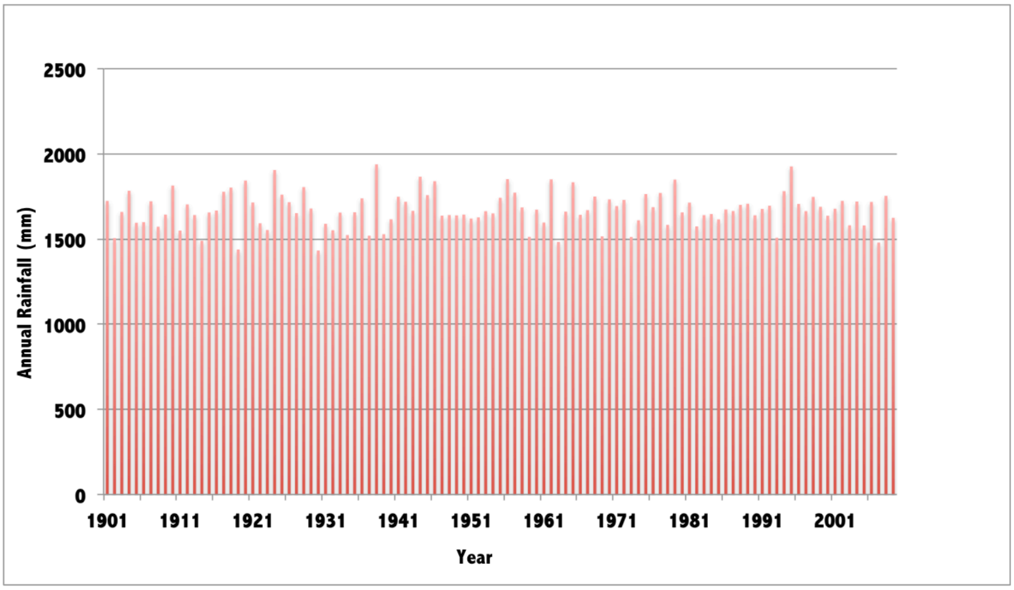


Figure 4.1: Characteristics of observed annual rainfall (mm) over New Zealand (1901-2009).

The various statistical moments used are given below:

First moment (mean):

$$\bar{y} = \frac{\sum y_i}{n} \tag{4.1}$$

Second moment (variance):

$$s^2 = \frac{\sum (y_i - \bar{y})^2}{n-1} \tag{4.2}$$

n = number of years of record

$\bar{y}$ = mean annual precipitation data

y = annual precipitation data

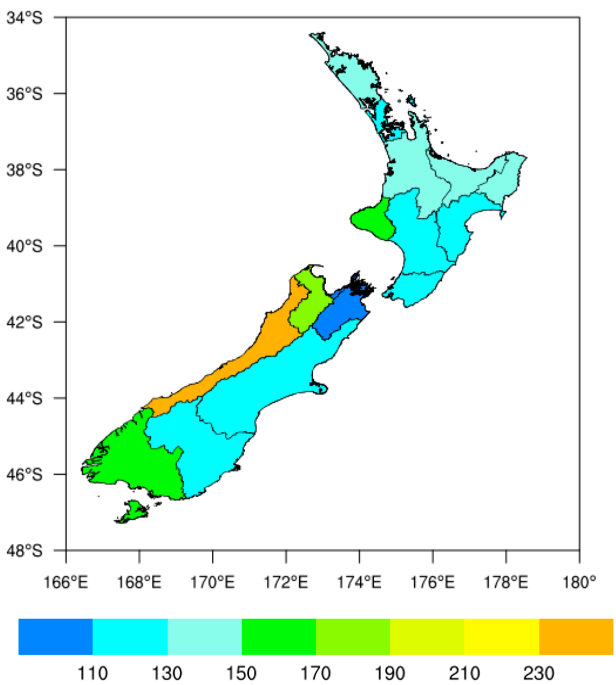
s = standard deviation

It is observed that the West Coast region receives the highest mean annual rainfall of 269 mm; while the lowest mean annual rainfall of 104 mm is noted over the Nelson and Marlborough regions (see Table 4.1)

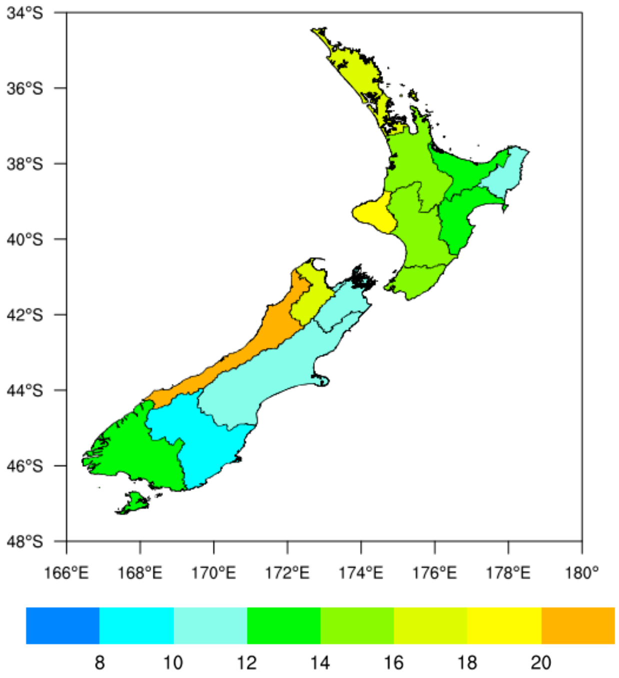
Table 4.1: Descriptive statistics of annual rainfall

Regions	Mean(mm)	Annual rainfall Standard deviation (mm)	Coefficient of variation
Auckland	117.67	17.96	0.15
Bay of Plenty	144.14	13.29	0.09
Canterbury	118.06	10.33	0.09
Gisborne	147.90	11.52	0.08
Hawke's Bay	127.62	12.47	0.09
Manawatu	124.45	14.52	0.12
Marlborough	104.71	11.86	0.11
Nelson	104.6	11.86	0.11
Northland	138.61	17.63	0.12
Otago	116.82	9.14	0.08
Southland	168.34	12.87	0.08
Taranaki	152.68	19.59	0.13
Tasman	179.40	17.42	0.09
Waikato	136.56	15.63	0.11
Wellington	117.46	15.93	0.14
West Coast	268.71	25.01	0.09

Figure 4.2 depicts the spatial variations of annual rainfall over the regions of New Zealand. Standard Deviation over the regions vary from 9 to 25 (Figure 4.2(b)) with *CV* ranging between 8 to 15%.



a) Mean annual rainfall (mm)



(b) Standard deviation (mm)

Figure 4.2: Spatial variations in statistical parameters of annual rainfall across the regions of New Zealand.

Yearly average temperature over New Zealand is demonstrated in Figure 4.3. Annual mean temperature over New Zealand varies from 13.3 to 15.5 ^{o}C (see Figure 4.3).

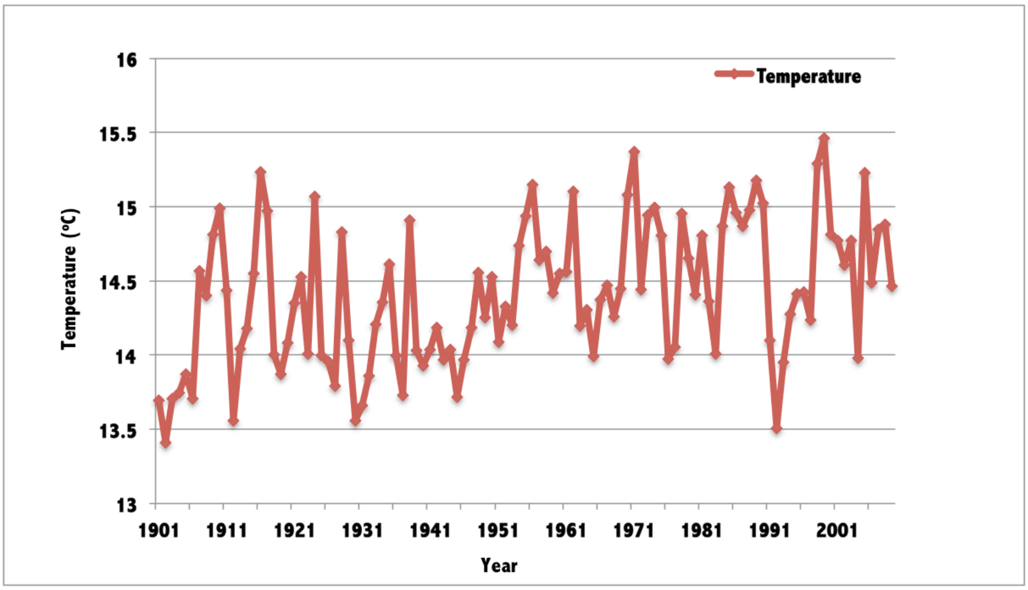


Figure 4.3: Observed annual average temperature (^{o}C) over New Zealand (1901-2009).

4.3 Preliminary Analysis: Assessing Droughts Using Meteorological Drought Index – SPI

The climate of New Zealand has a strong maritime influence. Due to highly varied topography, climate is varied across the country. This part of the globe precipitates throughout the year except during summer months. On an average most of the regions receive between 620 mm to 1317 mm of precipitation annually. Since it is an island, the influence of Ocean curtails extremes in coastal temperature. High humidity is experienced especially in the upper North Island and many parts of the country throughout the year making summer feel warmer and winters cooler. (Source: Wikipedia).

Mean monthly rainfall over New Zealand for a period of 109 years (1901-2009) is demonstrated in Figure 4.4.

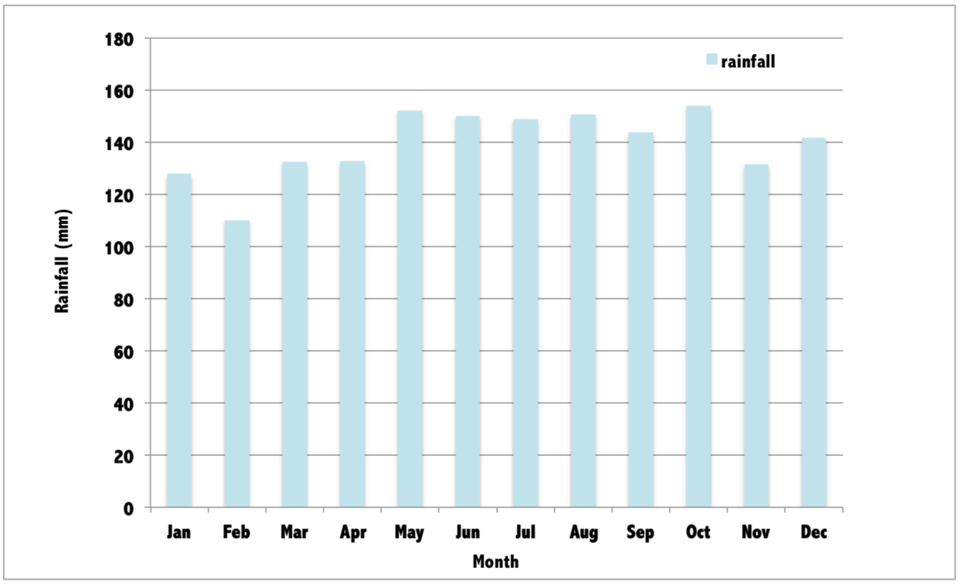


Figure 4.4: Observed mean monthly rainfall over New Zealand for the period 1901-2009.

Overall, rainfall is at a maximum in late winter and early spring (i.e. May - October) and a minimum in summer or early autumn (i.e. December – March). Mean monthly rainfall recorded over the 109 years is between 110 mm to 150 mm; with a maximum of 150mm in October and May. Except for February, the rest of the months receive a reasonable quantity of rainfall indicating the region to be mostly wet throughout the year. Thus, drought index is calculated based on the annual time period.

4.4 Drought Index

4.4.1 Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) is one of most widely used drought indices in drought assessment. It has been applied to Africa, Australia, Europe , Central and North America, the Middle East and other regions (e.g. Rouault and Richard, 2005; Bordi *et al.*, 2001; López-Moreno and Vicente-Serrano, 2008; Bordi *et al.*, 2009; Méndez and Magaña, 2010; Motha and Baier, 2005; Kangas and Brown, 2007; McCrary and Randall, 2010; Raziei *et al.*, 2010).

The SPI was developed at Colorado State University in 1993 as an alternative to Palmer's index (see Section 2.2.3), which addresses many of the PDSI's weaknesses (Mckee *et al.*, 1993; 1995). It measures meteorological events and is normalised to identify both dry and wet periods (Bordi *et al.*, 2009) for any location with a long-term precipitation record (typically ≥30 years). Dry (wet) spells, represented by negative (positive) SPI values, are expressed in terms of precipitation deficit (surplus), percent of normal and probability of non-exceedance (Heim Jr., 2002), with one/two/three standard deviations occurring approximately 68%/95%/99% of the time (Hayes *et al.*, 1999).

A probability density function (PDF; e.g. Pearson Type III or Gamma) is fitted separately for each month of the lagged moving average precipitation timeseries to the frequency distribution of precipitation summed over the time scale concerned. Each PDF is then transformed into a standardised Gaussian distribution (Edwards and McKee, 1997). Therefore, a percentile on the fitted distribution corresponds to the same percentile (Z-score) on the standard Gaussian distribution and the SPI value; the SPI represents a cumulative probability in relation to a reference period for which the probability distribution parameters are estimated (Wilhite, 2005). SPI normalises an anomaly both spatially (by considering the precipitation frequency distribution and the accompanying variation at the location) and temporally (as it can be computed at any time scale). The SPI for any given location (and duration) is expected to have a mean of zero and a variance of one, at least during the calibration period. Table 4.2 shows the categories of drought intensities; a drought is generally defined when SPI≤−1.0 and to end when the SPI becomes positive (Mckee *et al.*, 1993).

The SPI is basically the transformation of the precipitation time series into a standardized normal distribution. The computation of the SPI index requires the following steps (McKee *et al.*, 1993; Wu *et al.*, 2007):

1. Fit a cumulative probability distribution function (PDF) (gamma distribution) on aggregated monthly (k) precipitation series (say $k = 12$ months in this study). The gamma PDF ($g(x)$) is defined as:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)}\, x^{\alpha-1}e^{-x/\beta} \tag{4.3}$$

where β is a scale parameter; α is a shape parameter, which can be estimated using the method of maximum likelihood; x is the precipitation amount; and $\Gamma(\alpha)$ is the gamma function at α. The estimated parameters can be used to find the cumulative probability distribution function of observed precipitation events for the given month and particular. The cumulative distribution function (CDF), $G(x)$ is obtained by integrating Equation 4.3 and given in Equation 4.4.

$$G(x) = \int_0^x g(x)dx = \int_0^x \frac{1}{\hat{\beta}^{\hat{\alpha}}\Gamma(\hat{\alpha})}\, x^{\hat{\alpha}-1}e^{-x/\hat{\beta}} \tag{4.4}$$

where,

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \tag{4.5}$$

$$\hat{\beta} = \frac{\hat{x}}{\hat{\alpha}} \tag{4.6}$$

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \tag{4.7}$$

n = number of precipitation observations and $\bar{x}$ refers to the sample mean of the data.

2. Transform the cumulative distribution function (CDF) to the CDF of the standard normal distribution with zero mean and unit variance, which is given as follows (Equation 4.8):

$$SPI = \psi^{-1}[G(x)] \tag{4.8}$$

This transformed probability is the SPI (see Figure 4.5). A positive value for SPI indicates that precipitation is above average and a negative value denotes below average precipitation.

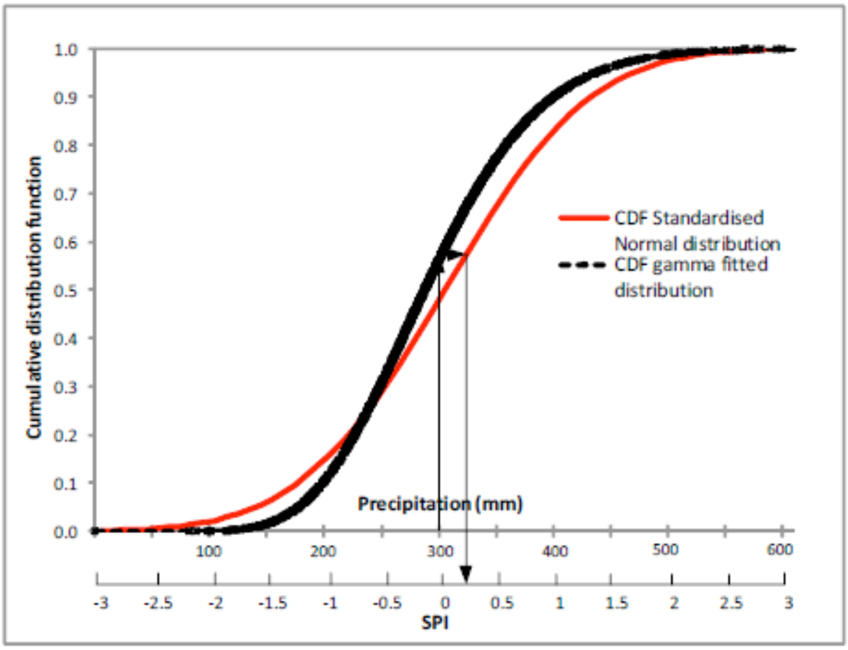


Figure 4.5: Example of equiprobability transformation from fitted gamma distribution to the standard normal distribution.

A drought event is defined as a period in which the SPI is continuously negative and reaching a value of -1.0 or less (McKee *et al.*, 1993; Paulo and Pereira, 2006). Figure 4.6 presents a pictorial description of drought characteristics. McKee *et al.* (1993) used a classification system using SPI values as depicted in Table 4.2 to define drought intensities.

The duration (d) is defined by the time between the beginning and the end (of negative SPI values); the drought severity (s) is the cumulative value of SPI within the drought duration, the intensity is the ratio between the magnitude and the duration of the event and lead-time is the number of months within a drought event before SPI $\leq$ -1 is reached.

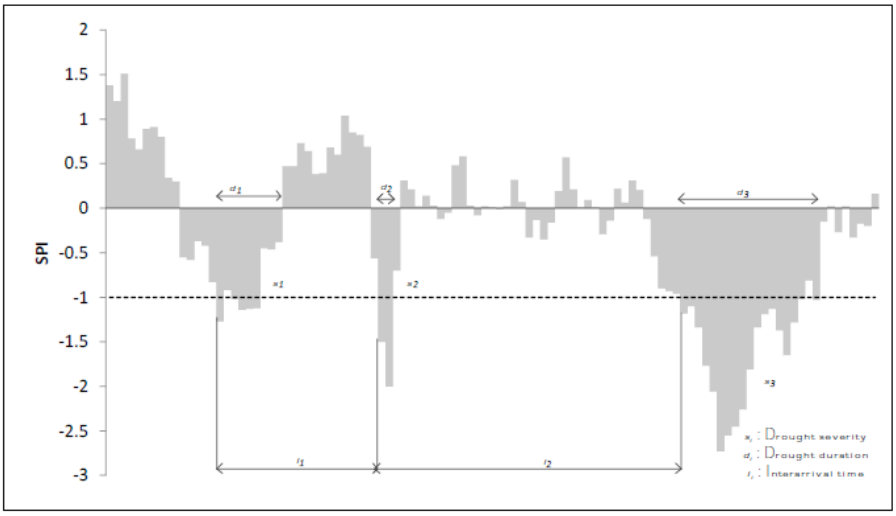


Figure 4.6: Depiction of drought characteristics using the Standard Precipitation Index (SPI). Source: Figure 1 in Ganguli P and Reddy M J (2013).

Table 4.2: Classification scale for SPI values

SPI Values	Category/Intensity	Cummulative Probability
0 to -0.99	Normal	0.159-0.841
-1.0 to -1.49	Moderate drought	0.067-0.159
-1.5 to -1.99	Severe drought	0.023-0.067
-2 and less	Extreme drought	0.00-0.023

4.5 Temporal Characteristics of Droughts in New Zealand

Drought index SPI was applied to all 16 regions of New Zealand covering 3-month, 6-month and 12-month time scales. Rainfall from 1901 to 2009 is considered for this method. Drought events are identified for all three time scales. The below panels depict the drought events for 3-month, 6-month and 12-month time scales over the Wellington region of New Zealand.

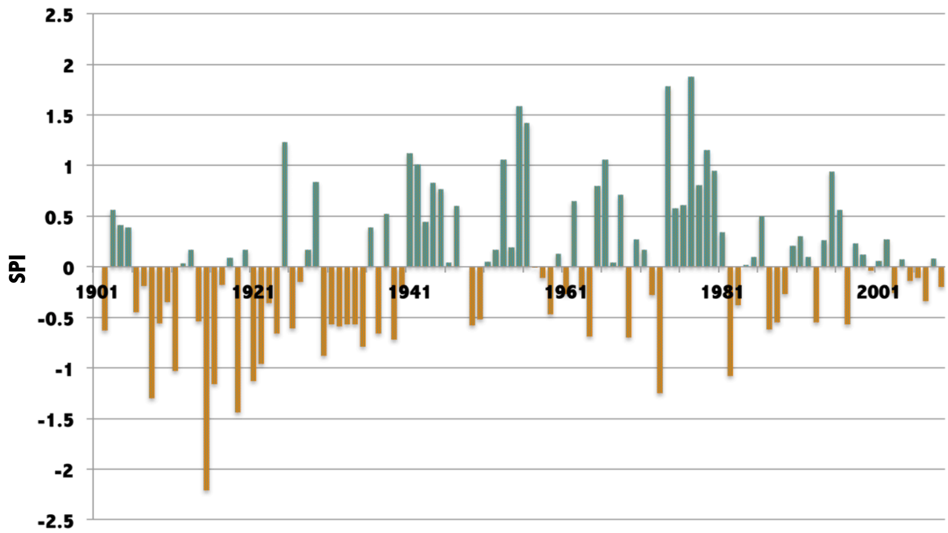


Figure 4.7: Drought events identified using SPI on a 3-month time scale for the Wellington Region.

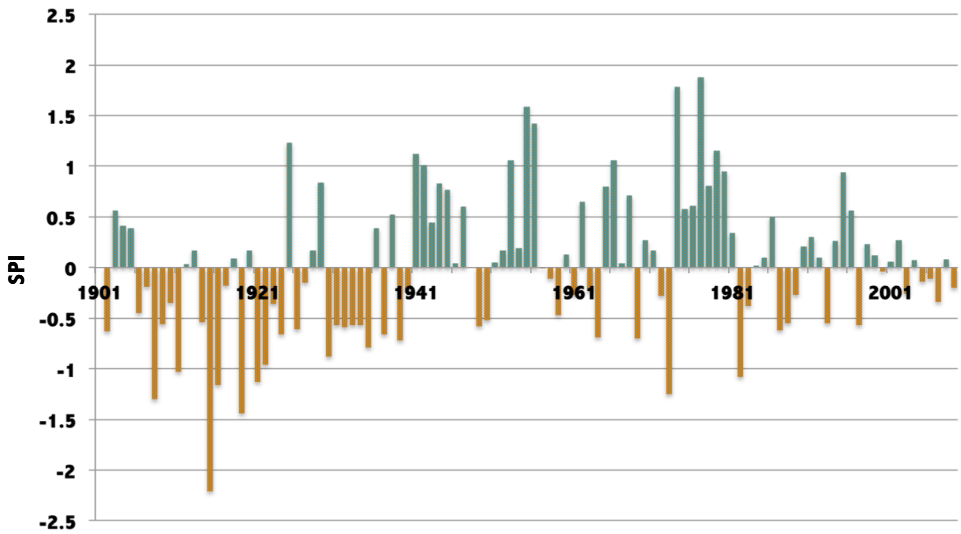


Figure 4.8: Drought events identified using SPI on a 6-month time scale for the Wellington Region.

For the 12-month time scale the total number of drought events identified for each of the regions is demonstrated as a bar graph in Figure 4.10. Taranaki region has the maximum number of drought events (14) followed by Auckland with 12; Tasman region stands last with the least number of droughts events (6).

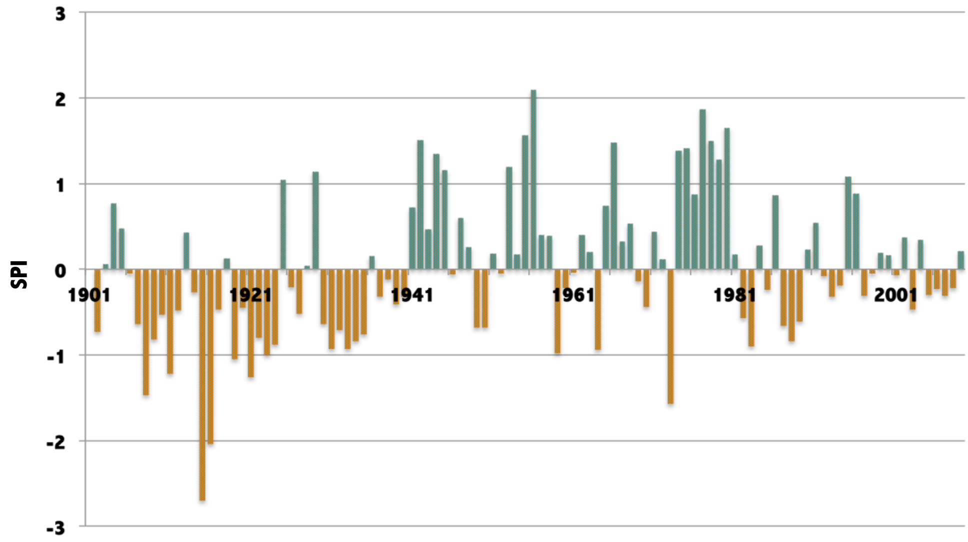


Figure 4.9: Drought events identified using SPI on a 12-month time scale for the Wellington Region.

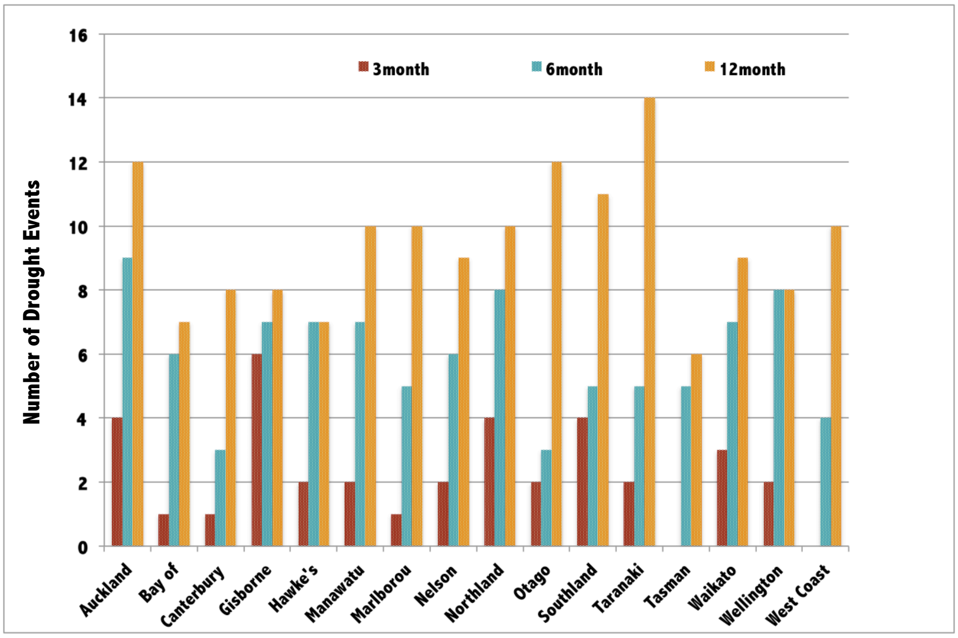


Figure 4.10: Total number of drought events identified on a 12-month time scale for each region.

4.6 Spatial patterns of droughts identified using the SPI

As the SPI provide a standardized classification of severity, this index was used to examine the severity of droughts for the historical data which spans over 109 years (1901-2009). The time series of the SPI is calculated on a time scale of 12 months.

According to the criteria of McKee *et al.* (1993), moderate, severe and extreme droughts correspond to the categories of -1.5 < SPI ≤ -1.0, -1.99 < SPI ≤ -1.5 and SPI ≤ -2.0, respectively.

Figure 4.11 shows the spatial distribution of percentage of drought severity for the regions of New Zealand. Maximum probability of moderate drought is in Taranaki region (10% probablity), while Gisborne, Manawatu, Wanganui, Northland, Southland, Otago and West Coast show a probability of severe drought of 2%. Probability of extreme drought is more prominent in the Bay of Plenty, Gisborne, Hawke's Bay, Waikato and the Wellington regions (4%).

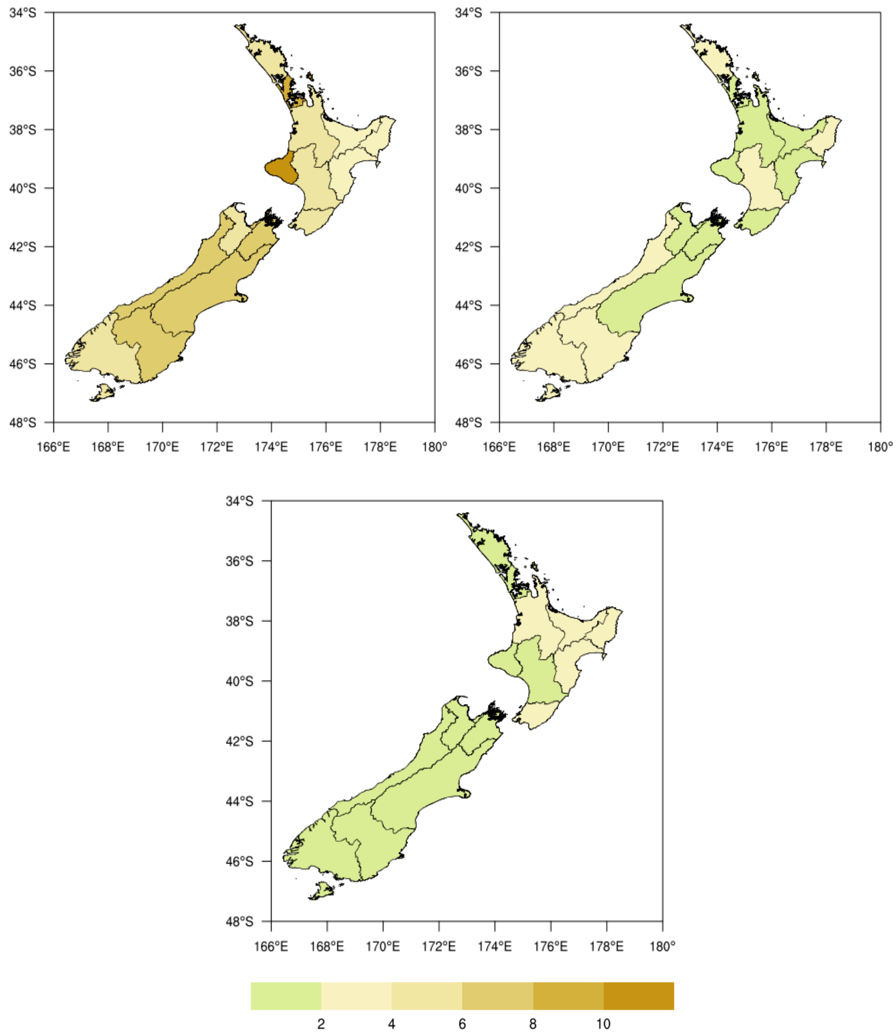


Figure 4.11: Spatial distribution of drought severity in percentage; moderate drought (top left panel), severe drought (top right panel) and extreme drought (bottom center panel).

4.7 Summary

This chapter has presented details of the spatial and temporal variation of annual climatic data and results from the preliminary analysis of the assessment of the droughts using a meteorological drought index. An analysis was carried out to evaluate and validate the method for the assessment of drought occurrences using data over sixteen regions of New Zealand. The SPI requires only rainfall data, which are usually available in most countries for many locations.

SPI do not rely on the arbitrary selection of threshold values and the classification of drought occurrence is clear and objective. They are also applied consistently across jurisdictions as the methodology has inbuilt standardisation of the specific indices. The SPI is able to identify the dry events of meteorological droughts successfully when applied to the data. It has been shown to be a good indicator and worthy of further examination for its use for drought monitoring, early warning and projection in the future.

Therefore, the SPI will be used for further analysis in this study (1) to analyse temporal and spatial trends in rainfall and drought characteristics in Chapter 5 and drought projections until the end of the century in Chapter 6. As meteorological drought drives agricultural and hydrological droughts, the focus in this study will be on the former.

It is important to identify trends in climatic variables as extreme events are becoming more common and severe due to climate change. Trend analysis will be carried out to determine any trend in annual rainfall which also includes the recent years' conditions. It is important to determine any possible causes or explanations of increasing or decreasing trends that are observed. Therefore, the trend analysis of droughts using appropriate indices will be carried out in this current study. Chapter 5 examines the trend in climatic parameters and drought using SPI.

Chapter 5

Trend analysis of Rainfall and the Standardised Precipitation Index (SPI)

5.1 Introduction

In recent years, a few studies have evaluated and assessed long-term trends in rainfall over New Zealand. They identified long-term decreases in rainfall over New Zealand for the period 1951-1996. This study however was one of the first national analyses of trends which concluded that 46 years was too short a period for measuring climate trends, particularly for rainfall (Salinger and Griffiths, 2001; Tommaso, 2015).

New Zealand rainfall is more variable than would be expected from similar climates elsewhere in the world (Salinger and Griffiths, 2001). Therefore, the aim of this chapter is to analyse the temporal changes in historic rainfall variability across the regions of New Zealand using data spanning over 109 years (1901-2009). To examine the recent trends and to assess the sensitivity of trends to the length of the time periods considered, the annual rainfall analysis was repeated using more recent data. The sequential Mann-Kendall test was applied to detect abrupt change in the annual rainfall series. Graphical outputs from this test give a visual observation of the trend's beginning year. It is important to investigate the change of dry or wet conditions and the adaptive responses to extreme rainfall events within the context of climate change. Ganguli and Reddy (2014) performed a trend analysis of droughts based on SPI time series using non-parametric trend tests in western India. Subash and Ram Mohan (2011) investigated possible trends in monsoon rainfall and frequency of droughts using SPIs spanning 100 years (1906-2005) of records to assess rice and wheat productivity in India. This chapter will focus on the drought severity time series trend computed using the SPI.

Numerous approaches are used for analysing trends. Tests for the detection of significant trends in climatologic time series can be classified as either parametric or non-parametric methods (Tabari *et al.*, 2012). The purpose of trend tests is to determine if the values of a random variable generally increase (or decrease) over some period of time in statistical terms. As many climate time series data are not normally distributed, non-parameter tests are preferred over parameter tests (Karpouzos *et al.*, 2010). One advantage of these tests is that the data do not have to fit any particular probability distribution to validate the tests. To name a few, the Mann-Kendall (*MK*), Spearman's Rho (*SR*), Sen's Slope Estimator, Seasonal Kendall and Sen's T statistical tests are examples of non-parametric tests that have been applied to detect trends (Drapela and Drapelova, 2011; Paulo *et al.*, 2012).

5.1.1 Non-parametric tests

The Mann-Kendall (*MK*) test is used for determining monotonic trends and is based on ranks taking seasonality into account. This is a test for the correlation between a sequence of pairs of values. The significance of the detected trends can be obtained at different levels of significance (generally taken as 0.05). This technique has been widely used in rainfall, runoff and air temperature time series trend detection (Tabari *et al.*, 2011; Soltani *et al.*, 2012; Croitoru *et al.*, 2012). The *MK* test is also recommended by the World Meteorological Organization (WMO) for non-parametric analysis of the significance of monotonic trends of hydrological or climatological variables (WMO, 1988).

Sen's slope (*Q*) estimator method accounts for the seasonality of the precipitation data. This method uses a simple non-parametric procedure developed by Sen (1968) to estimate the slope. The non-parametric tests are used to detect trends but do not quantify the size of the trend or change. Hence, the magnitude of the observed trend can be estimated with Sen's slope estimator when significant (Helsel and Hirsch, 2002; Paulo *et al.*, 2012).

Several studies have used the Mann-Kendall test and Sen's slope estimator to analyse trends and quantify the magnitude of change. These include Tabari *et al.* (2011), who examined the seasonal and monthly trends in the Penman-Monteith in Iran, Drapela and Drapelova (2011), who analysed the composition of precipitation in the north-eastern part of the Czech Republic and Croitoru *et al.* (2012), who analysed air temperature variability and trends in Romania.

5.1.2 Framework

The main objective of this chapter is to determine the long-term trends of rainfall and SPI related to the risk of occurrence of a drought event. The identification of long-term trends in climatic variables is important in planning climate change adaptation measures and infrastructure design. The outline of the trend tests used in this current study is shown in Figure 5.1. The analyses were carried out using more than 100 years of precipitation data. The *MK* test and Sen's slope were applied to identify gradual trends in rainfall series. As for the SPI - time series trend, the MK test and Sen's slope were used.

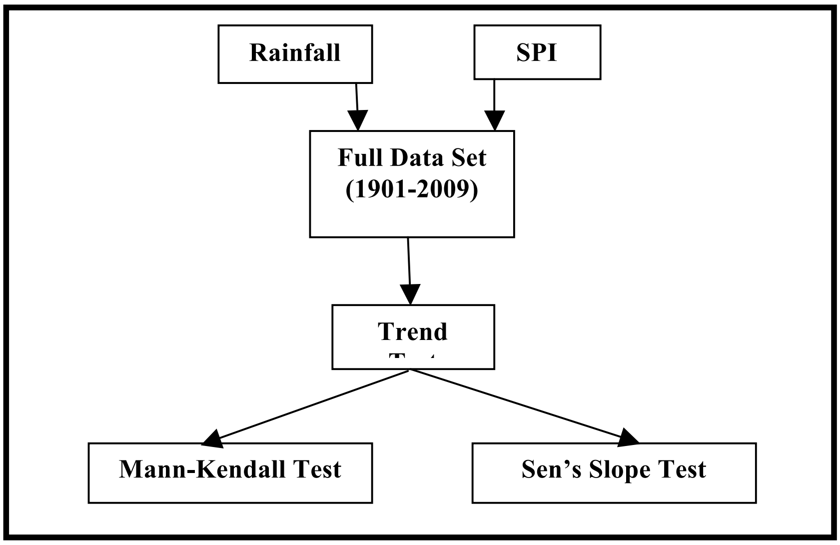


Figure 5.1: Trend analysis framework

5.2 Preliminary Trend Analysis of Annual Precipitation

The climate of New Zealand has a strong maritime influence. Due to highly varied topography, climate is varied across the country. This part of the globe precipitates throughout the year except during summer months. On average most of the regions receive between 620 mm to 1317 mm of precipitation annually. Since it is an island, the influence of Ocean curtails extremes in coastal temperature. High humidity is experienced especially in the upper North Island and many parts of the country throughout the year making summer feel warmer and winters cooler. (Source: Wikipedia).

Information on spatial and temporal variations of precipitation is essential in understanding the hydrological balance on a global or regional scale. The distribution of precipitation is extremely essential for water management in agriculture, power generation and drought-monitoring. The long-term precipitation patterns impacting availability of water with the possibility of increasing occurrences of droughts and floods may be influenced by the global climate changes (NIWA, 2016).

A preliminary trend analysis was carried out over the region selected for this study. The CRU data was chosen for this trend analysis as a long rainfall data record was available spanning a period of 109 years.

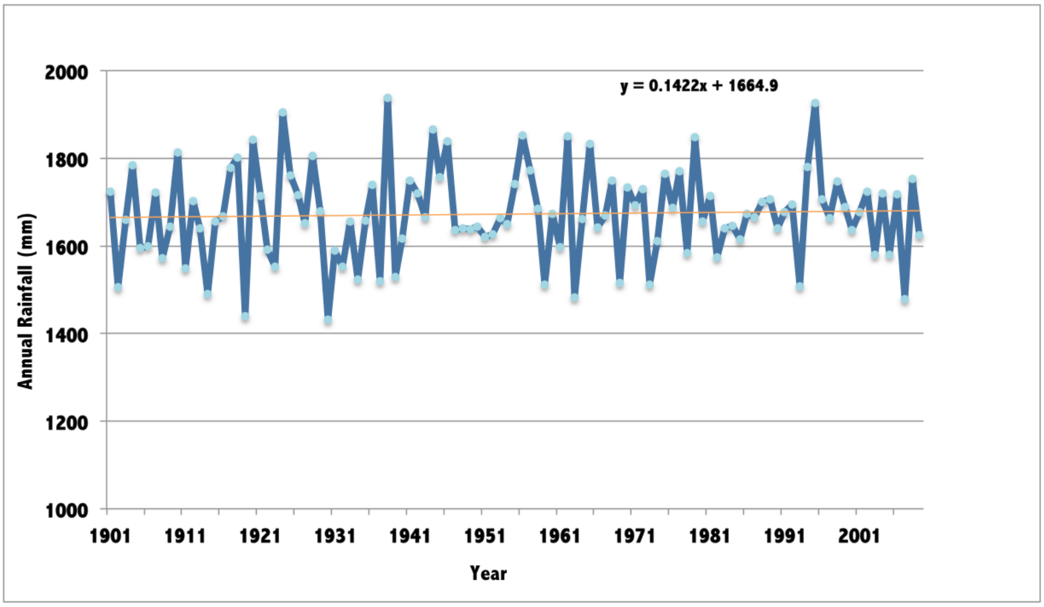


Figure 5.2: Trend in annual rainfall over New Zealand.

Trends in annual rainfall series (more than 100 years of data) are determined by using two nonparametric trend tests (*MK* and Sen's slope (*Q*)). Figure 5.2 presents the time series data of annual rainfall over New Zealand. Trend line (red dotted line) along with the linear trend equation is mentioned in the figure. Fitting a liner regression curve, the trend of rainfall over 109 years is 0.142mm. The positive sign indicates an increase in the rainfall trend over New Zealand. This finding further leads to investigate which of the sixteen regions show a significant trend.

5.3 Non-parametric Trend Tests

5.3.1 Mann-Kendall (MK) Test

The *MK* test is used for determining monotonic trends and is based on ranks. This is a test for correlation between sequences of pairs of values. The significance of the detected trends can be obtained at different levels of significance (generally taken as 0.05). This has been suggested by the World Meteorological Organisation to determine the existence of statistically-significant trends in climate and hydrologic data time series. The *MK* test statistics and the sign function are calculated using the formula:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i) \tag{5.1}$$

$$sign(x_j - x_i) \begin{cases} +1 & x_j > x_i \\ 0 & x_j = x_i \\ -1 & x_j < x_i \end{cases} \tag{5.2}$$

where n is the number of data, x is the data point at times i and j $(j > i)$. The variance of S is as follows

$$VAR(S) = \left[n\ (n-1)(2n+5) - \sum_{i=1}^{m} t_i i\ (i-1)(2i+5) \right] /18 \tag{5.3}$$

where t_i is the number of ties of extent i and m is the number of tied groups. For n larger than 10, the standard test statistic Z is computed as the *MK* test statistic as follows

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{VAR(S)}} & if\ S > 0 \\ 0 & if\ S = 0 \\ \dfrac{S+1}{\sqrt{VAR(S)}} & if\ S < 0 \end{cases} \tag{5.4}$$

The presence of a statistically significant trend is evaluated using the Z value. Positive values of Z indicate increasing trends, while negative values show decreasing trends. To test for either increasing or decreasing monotonic trend (a two-tailed test) at α level of significance, H_0 should be rejected if $|Z| > Z_{1-\alpha/2}$, where $Z_{1-\alpha/2}$ is obtained from the standard normal cumulative distribution tables. For example, at the 5% significance level, the null hypothesis is rejected if $|Z| > 1.96$. A higher magnitude of Z value indicates that the trend is more statistically significant.

5.3.2 Sen's estimator of slope

Sen's slope estimator method accounts for the seasonality of the precipitation data. This method uses a simple non-parametric procedure developed by Sen (1968) to estimate the slope. The variance of the residuals should be constant in time. The equation used for calculating the slope of two rainfall records is as follows:

$$Q_i = \frac{(x_j - x_k)}{j - k} \quad \text{, for all combinations of } j > k \qquad (5.5)$$

where, x_j and x_k are the rainfall values at times j and k, respectively, and Q_i is the slope between data points x_j and x_k .

Sen's estimator of slope is the median of these N values of Q_i. The N values of Q_i are ranked from the smallest to the largest and the Sen's estimator is computed by

$$Q = \begin{cases} Q_{\frac{N+1}{2}}, & if\ N\ is\ odd \\ \frac{1}{2}\left(Q_{\frac{N}{2}} + Q_{\frac{N+2}{2}}\right), & if\ N\ is\ even \end{cases} \qquad (5.6)$$

A 100(1-α)% two-sided confidence interval for the slope estimate is obtained by the non- parametric technique based on the normal distribution (Drapela and Drapelova, 2011).

5.4 Trend Analysis of Annual Rainfall

The Z and Q statistics obtained from MK and Sen's slope tests using the annual rainfall data are presented in Table 5.1. Overall no significant trends are shown for any of the regions except for Wellington. The regions namely – Bay of Plenty, Hawke's Bay, Manawatu Wanganui, Marlborough, Nelson, Otago, Southland and Waikato show statistically insignificant increasing annual precipitation trends with Z values ranging from 0.01 to 0.49. The slopes (mm/year) of the upward trend obtained for these regions are as tabulated in Table 5.1. Some of the regions such as Auckland, Canterbury, Gisborne, Northland, Tranaki, Tasman and West Coast show statistically insignificant decreasing trends in annual rainfall. The only region with an upward statistically significant trend with the *Z* values 1.14 is Wellington.

Table 5.1: *Z* statistic values from *MK* and *Q* tests

Regions	1901-2009	
	Z	***Q (mm/year)***
Auckland	-1.156	0.098
Bay of Plenty	0.461	0.276
Canterbury	-0.095	0.856
Gisborne	-0.201	0.183
Hawke's Bay	0.490	0.231
Manawatu	0.772	0.142
Marlborough	0.369	0.485
Nelson	0.369	0.485
Northland	-0.997	0.146
Otago	0.086	0.779
Southland	0.230	0.688
Taranaki	-0.618	0.388
Tasman	-0.564	0.380
Waikato	0.158	0.765
Wellington	1.141	**0.050**
West Coast	-0.616	0.491

*Results in boldface indicate significant trends

Figure 5.3 demonstrates the spatial variation of trend in annual rainfall over New Zealand. A non-parametric trend analysis using the Mann-Kendall rank statistic is determined. Regions namely – Wellington, Manawatu-Wanganui, Hawkes Bay, Bay of Plenty, parts of Waikato, Marlborough and Southland show an increasing trend of annual rainfall. A trend test is performed at the 5% level of significance to signify the presence of a statistically significant trend.

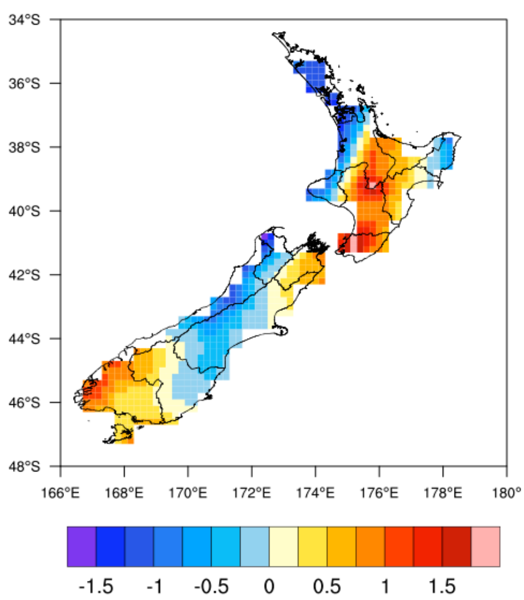


Figure 5.3: Spatial trend in observed annual rainfall over New Zealand (1901-2009).

It could therefore be said that the reduction at most of the regions is part of a short-term climatic cycle and not a decline in long-term rainfall. Therefore, it is difficult to predict whether extreme events or droughts will occur more frequently in the future, and great care is needed when interpreting results. For example, with short rainfall data series there may be a statistically significant trend, but the trend might not have been detected if a longer record had been considered.

5.5 Discussion of Rainfall Trend Analysis

It was found that for any given long term trend study; a dataset of more than 30years is essential (WMO, 1988; Salinger and Griffiths, 2001). A longer time scale would be useful for assessing climate variability and change and for studying slow responding receptors such as the impact on flora and fauna. Salinger *et al.* (2001) concluded that most of the regions of New Zealand show a decreasing trend except for Wellington, Blenheim, Timaru and Dunedin which correlates with the results of this thesis. In order to identify possible dry trends in the regions of New Zealand, a study using SPI for the same location is carried out. The SPI uses rainfall data and provides a normalised system to classify and represent dry and wet climates in the same manner as Sirdas and Sen (2003). Positive values imply that the observed rainfall is larger than the mean precipitation and vice versa (Morid *et al.*, 2006).

As mentioned in Section 5.1.1, the *MK* test was developed to detect monotonic change. When annual rainfall was analysed with the *MK* and *Q* tests for 109 years of data, only the Wellington region showed a significant positive trend.

Although this study did not seek to determine any possible causes or explanations for the increasing or decreasing trends that were observed, the results presented herein will be useful as a benchmark for further analysis of the effect of climate change.

5.6 Preliminary Trend Analysis of Drought Severity

To determine whether this region has experienced a wet or dry period, the trend analysis technique for the time scale 12-months of SPI was applied to all the regions considered in this study and the results are given in Figure 5.4 - Figure 5.8.

Figure 5.4 – 5.8 shows the time series of SPI for each region on a 12-month time scale and the trend lines (red) for the period 1901-2009. Seven regions out of sixteen show a decreasing trend. The slopes (*Q*) were computed and the results are consistent with the results of the *MK* test. The values of the slope range from -0.001 to -0.004. The range of slope varies from 0.001 to 0.007 for the regions with an increasing trend.

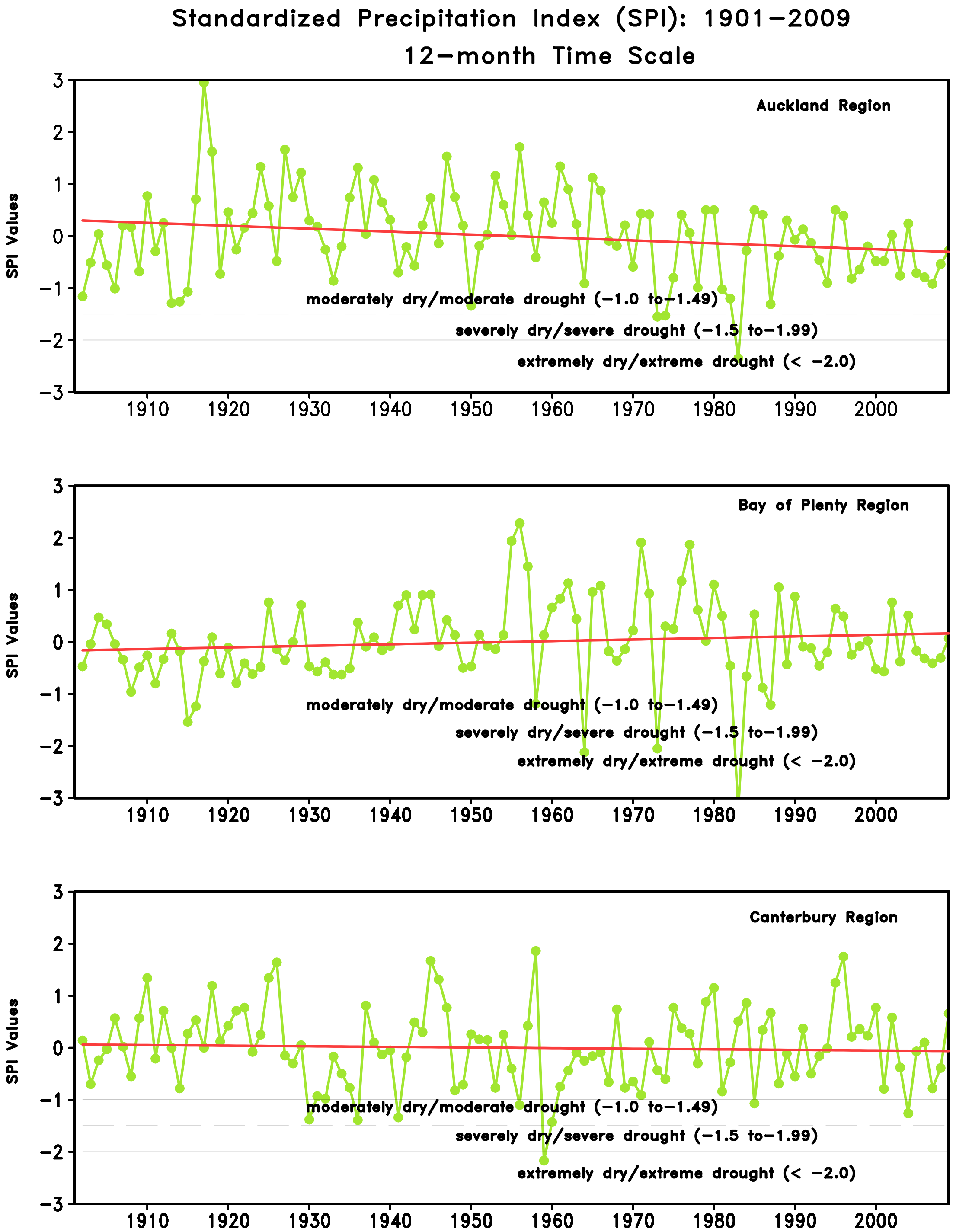


Figure 5.4: Time series of SPI on a 12-month time scale and the trend line in red for Auckland (top panel), Bay of Plenty (center panel) and Canterbury (bottom panel) regions.

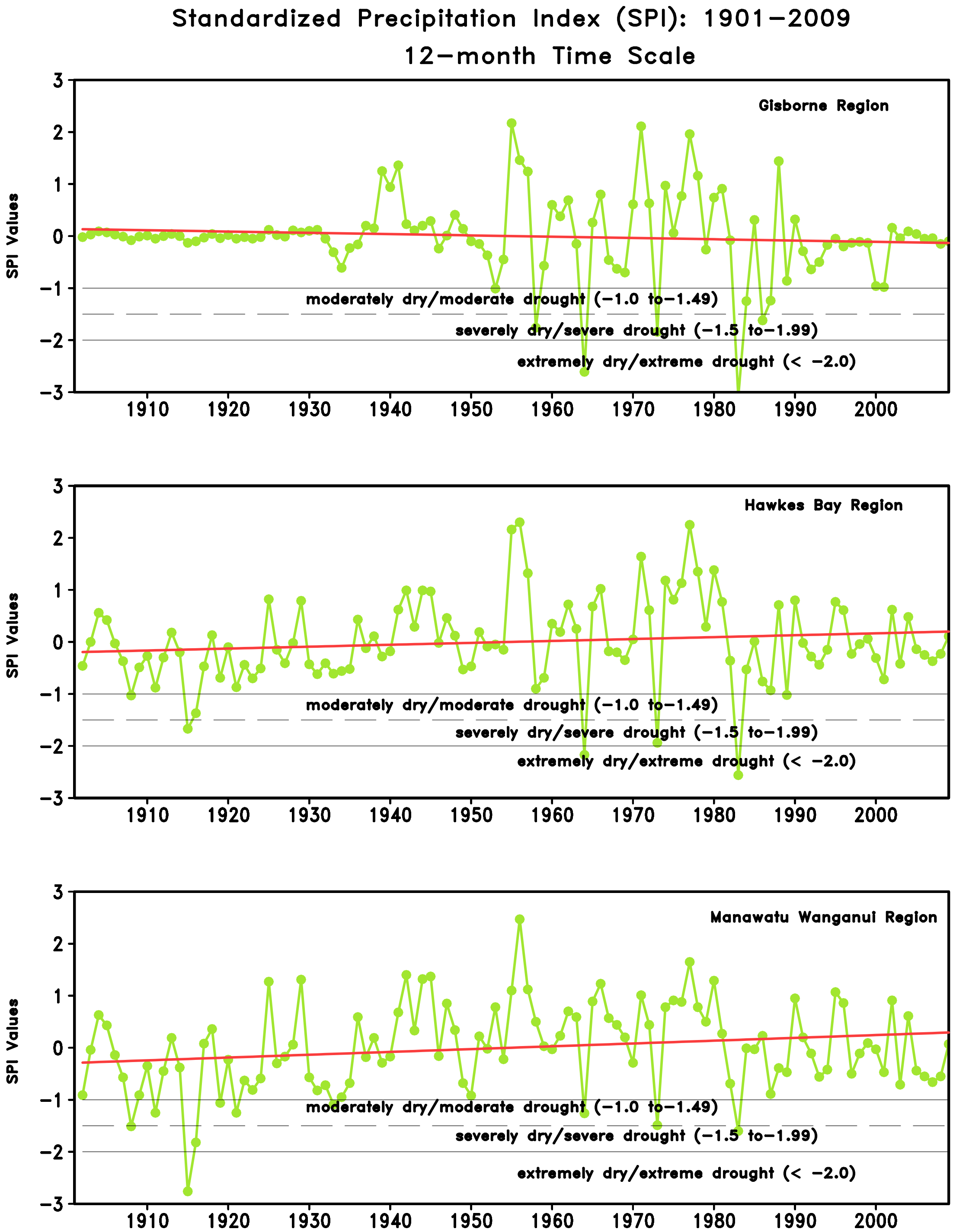


Figure 5.5: Time series of SPI on a 12-month time scale and the trend line in red for Gisborne (top panel), Hawkes Bay (center panel) and Manawatu-Wanganu (bottom panel) regions.

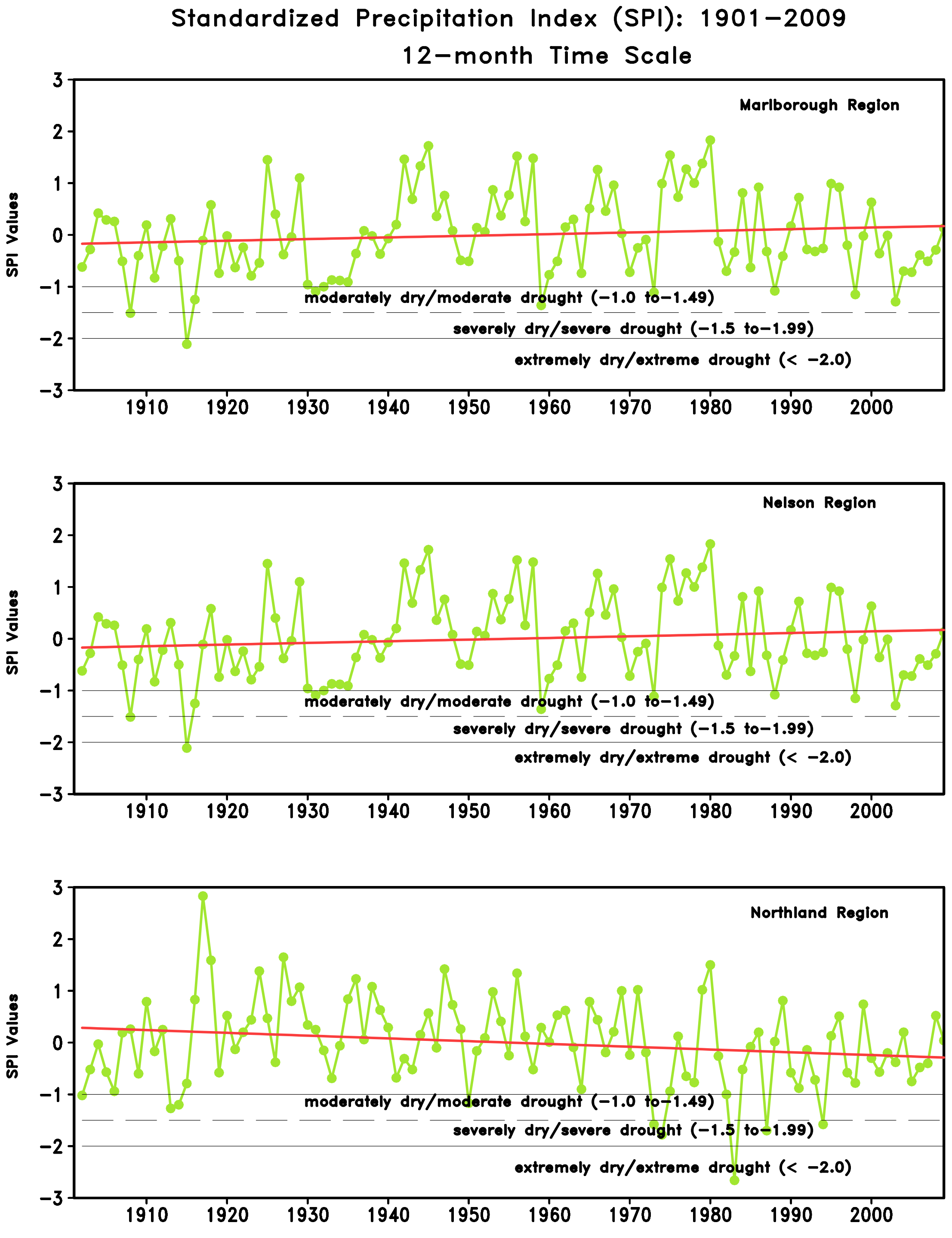


Figure 5.6: Time series of SPI on a 12-month time scale and the trend line in red for Marlborough (top panel), Nelson (center panel) and Northland (bottom panel) regions.

In Figure 5.6, Northland region shows three severe and one extreme drought events. The region was hit by an extreme drought in the year 1982. Over the 109 years (1901-2009) drought events show a decreasing trend. The Marlborough and Nelson region show an upward trend but the intensity of drough is far below that of Northland.

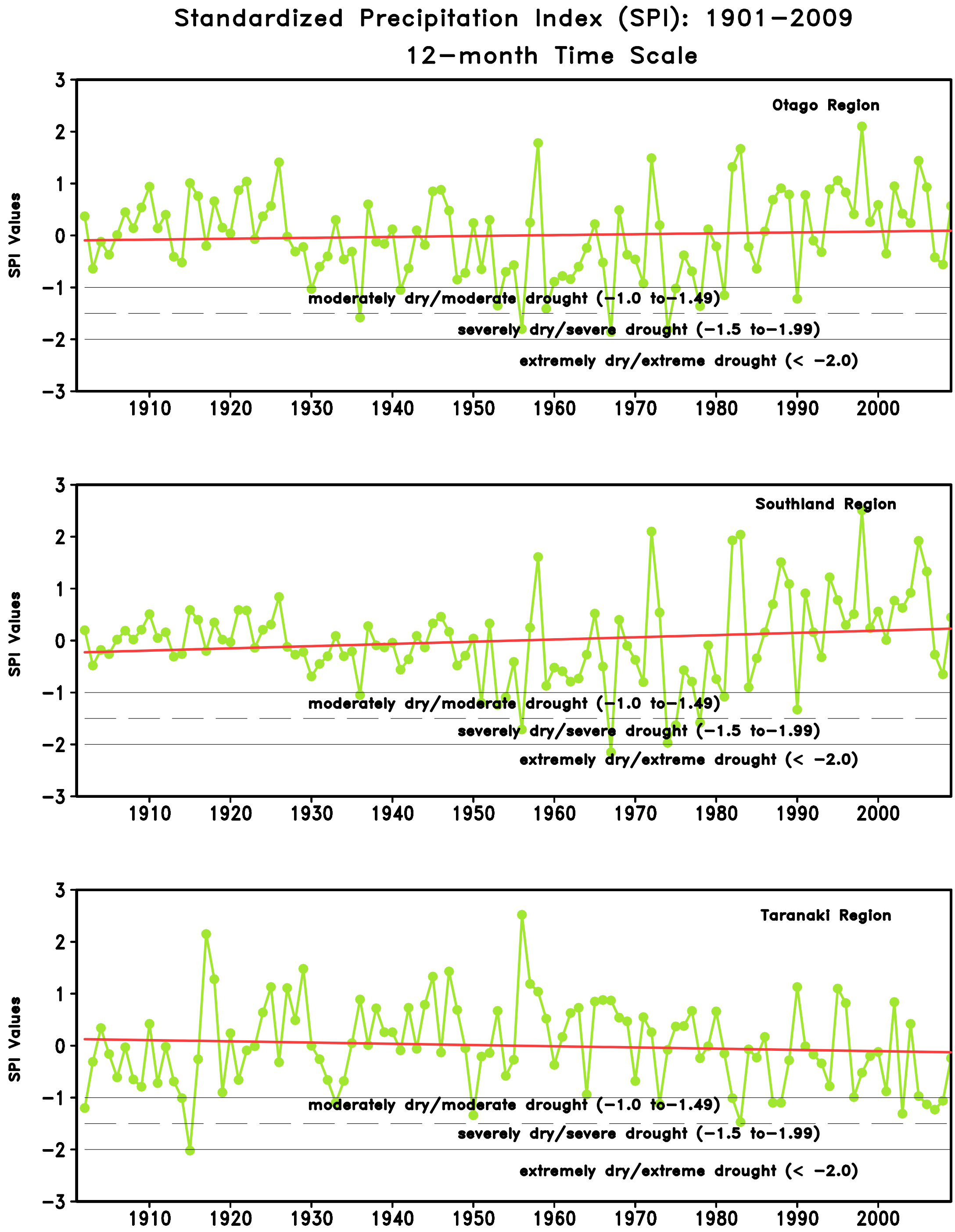


Figure 5.7: Time series of SPI on a 12-month time scale and the trend line in red for Otago (top panel), Southland (center panel) and Taranaki (bottom panel) regions.

The Southland region was hit by an extreme drought event in the year 1968 which is well captured in the observational (CRU) data. (Figure 5.7). Severity of drought events in this region falls into the second category (-1.99 < SPI ≤ -1.5). The Taranaki region experienced 14 drought events of which only one was a severe drought in the year 1916, the rest of the events are moderate drought.

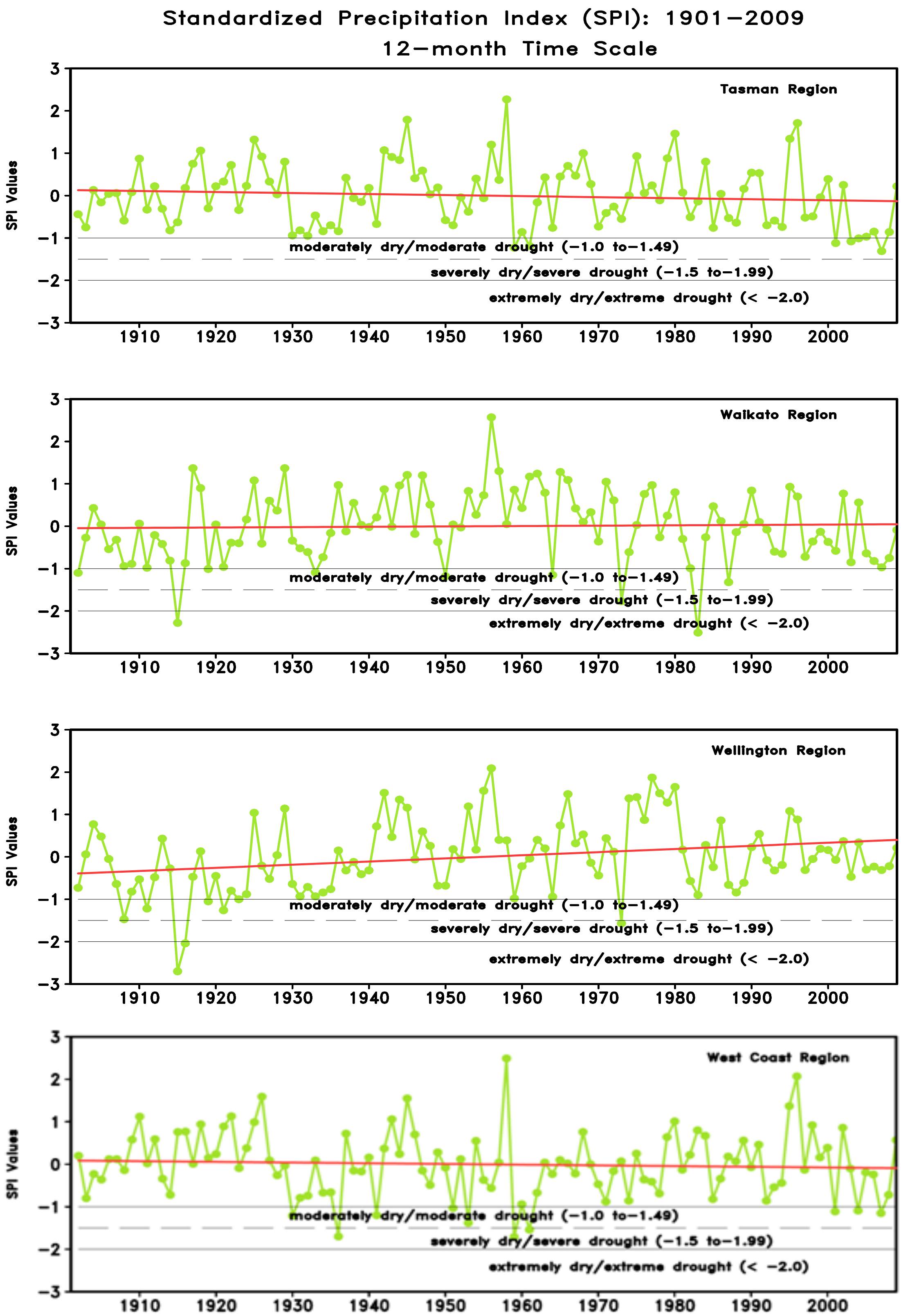


Figure 5.8: Time series of SPI on a 12-month time scale and the trend line in red for Tasman (topmost panel), Waikato (top panel), Wellington (center panel) and West Coast (bottom panel) regions.

Temporal trends shown in Figure 5.4 – Figure 5.8 also examine the rate of occurrence of drought events. The regions showed positive slopes indicating that the intervals between events are becoming longer and the frequency of events were temporally decreasing.

Similar to annual rainfall, trends in drought severity series were determined by using the *MK* and Sen's slope (*Q*) tests. The Z statistics obtained from the *MK* and *Q* tests on a 12-month time scale of SPI for all the regions are presented in Table 5.2 and Figures 5.9.

Table 5.2: *Z* statistic values from *MK* and *Q* tests

	1901-2009	
Regions	***Z***	***Q (mm/year)***
Auckland	-0.0048	0.075
Bay of Plenty	0.0040	**0.041**
Canterbury	-0.0003	0.879
Gisborne	-0.0008	0.421
Hawke's Bay	0.0044	**0.034**
Manawatu	0.0057	**0.026**
Marlborough	0.0037	0.143
Nelson	0.0037	0.143
Northland	-0.0041	0.119
Otago	0.0018	0.507
Southland	0.0030	0.260
Taranaki	-0.0018	0.442
Tasman	-0.0021	0.378
Waikato	0.0015	0.533
Wellington	0.0077	**0.001**
West Coast	-0.0015	0.521

*Results in boldface indicate significant trends

Four of the regions, namely – Bay of Plenty, Hawkes's Bay, Manawatu-Wanganui and Wellington display a significant increasing trend. However, Auckland, Canterbury, Gisborne, Northland, Taranaki, Tasman and West Coast regions show a decreasing trend with no significance. The slope of the SPI trend is estimated by the application of a *Q* test. The slope value ranges from 0.001 to 0.879 (Table 5.2). The results are consistent with Figure 5.3, where Northand also exhibits the highest decreasing trend.

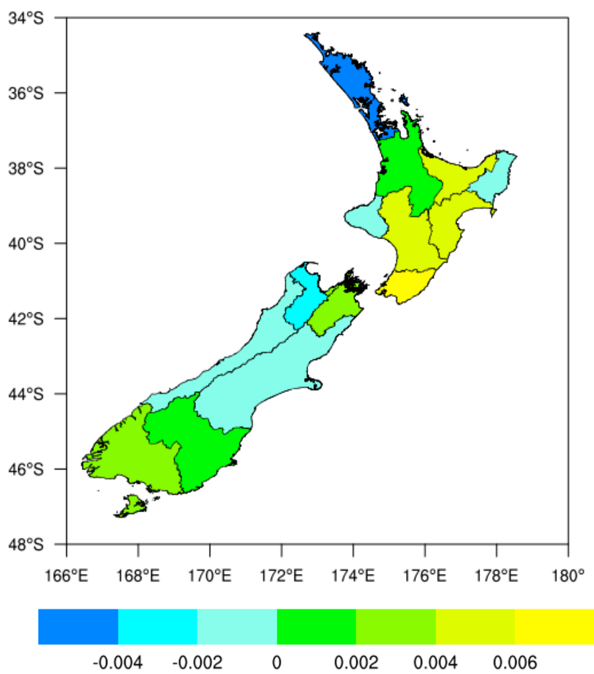


Figure 5.9: Spatial distribution of trend for the regions of New Zealand.

5.7 Summary

The objective of this chapter was to analyse the temporal changes in historic rainfall variability and the trend of SPI values across sixteen regions in New Zealand. The first part of the analysis was carried out to (1) determine annual rainfall trends using the non-parametric Mann-Kendall (*MK*) trend test with long historical records.

The second part of the analysis included a trend analysis of dry/wet periods based on a SPI time series using more than 100 years of data. Using a full data set the result obtained was - out of sixteen regions seven showed decreasing trends. However, The SPI time series analysis gave similar trend direction to the annual precipitation time series analysis in showing downward and upward trends.

It should be noted that, for the annual precipitation trend analysis, it was the accumulation of rainfall amount for the twelve months of each year. In this study, more than 100 values in the annual time series were used for each region. In contrast, SPI is a continuing index of certain duration (in this case the duration was selected to be 12 months) using a monthly precipitation data set. This monthly precipitation data set varies with time; that is, in each month, a new value is determined from the previous *i* months (where *i* in this study was 12 months). Hence, the results for annual precipitation trend provide information on whether rainfall patterns show an increase or decrease at a particular region. On the other hand, the SPI trend identifies wet (increase) or dry (decrease) conditions with a single index. Therefore, it is essential to use an appropriate methodology to develop suitable strategies to mitigate the impacts of future droughts and properly understand past droughts to be able to project the future wherever possible. Chapter 6 attempts to examine the projection of meteorological drought over New Zealand using a higher resolution data and the associated uncertainties in the projections.

Chapter 6

Projections of meteorological droughts and uncertainties

6.1 Introduction

Over the 20th century, climate change could shift and widen the precipitation distribution, increasing the risk of both flood and drought events, and may alter the characteristics of future dry and wet spells in New Zealand. The common view is that precipitation will decrease (increase) in New Zealand (Salinger and Griffiths , 2001; Gao *et al.*, 2006; NIWA, 2016).

Warming may increase the drought-affected area globally, including more severe events. Although there are different classifications of drought (Section 2.2) depending on the nature of the water deficit and the study objective, precipitation is the fundamental driver of drought and analysing future precipitation characteristics is crucial in drought risk assessment, especially when considering meteorological droughts (Bordi *et al.*, 2009; Panu and Sharma, 2002; Osuch *et al.*, 2016). Many studies have focused on the hydrological aspects (such as river discharge and low flow regimes) rather than assessing meteorological events (Vasiliades *et al.*, 2009). Yet, the application of meteorological drought indices require less input data, which in turn limits the additional uncertainties arising from the availability, quality, resolution and parameterisations of data/models. Furthermore, Hisdal *et al.* (2001) found good agreement between precipitation deviations and drought trends. Therefore, this chapter focuses on meteorological drought assessment.

Our incomplete understanding of the behavior of the climate system has led to the development of various emission scenarios and GCMs. Studies with equally weighted multi-models generally outperform the single models (Weigel *et al.*, 2010). However, projections for both mean and extreme precipitation are often uncertain in both the direction and magnitude of change (Kjellström *et al.*, 2011; Blenkinsop and Fowler, 2007a;b; Burke and Brown, 2008). Changes in the seasonal distribution of precipitation and drought occurrence will significantly affect water resource management. Although drought studies (e.g. NIWA, 2016) have attempted to address this through a multi-model and multi-scenario analysis using the CMIP3 models, the number of climate models and emission scenarios applied are often limited, and few have explored uncertainty in drought projection using large simulation ensembles (e.g. Burke and Brown, 2008).

Using the SPI (Section 4.4.1), this chapter examines the drought projections under climate change on New Zealand's meteorological drought on a 12-month (SPI12) events, and assesses their robustness based on precipitation scenarios simulated using two emission scenarios and twentyone GCMs (Sections 3.1– 3.2).

6.2 Methodology

6.2.1 Standardized Precipitation Index (SPI)

Vicente-Serrano *et al.* (2010) proposed the multi-scalar Standardised Precipitation Evapotranspiration Index (SPEI), the computation of which is mathematically similar to the SPI. The SPEI uses precipitation and temperature data, and can be compared to the self-calibrated Palmer drought severity index (sc-PDSI) as it is based on a normalisation of the simple water balance developed by Thornthwaite (1948). The SPI, rather than the SPEI, has been adopted in this thesis as a measure of meteorological drought (which typically refers to rainfall deficit).

In summary, the SPI is useful for monitoring drought (and wetness) on multiple time scales and comparing climatic conditions of areas governed by different hydrological regimes (Bordi *et al.*, 2009; section 4.4.1)

6.2.2 Taylor Diagram

Multiple models considered in this study are evaluated with the Taylor diagram. The closeness of a pattern (or a set of patterns) matching observations is well illustrated by Taylor (2001). One can quantify the similarities between two patterns in terms of statistical measures, such as – their correlation, centred root-mean-square difference and the standard deviation at a glance. Taylor diagram for rainfall is shown in Figure 6.1. Colour circles represent the 21 CMIP5 models while the ensemble of these models (MME) is represented by a star sign, the observed data (CRU) lie at the point marked.

Models with higher correlation, least RMSE and with much variance (standard deviation) as observed are considered as the best performing models.

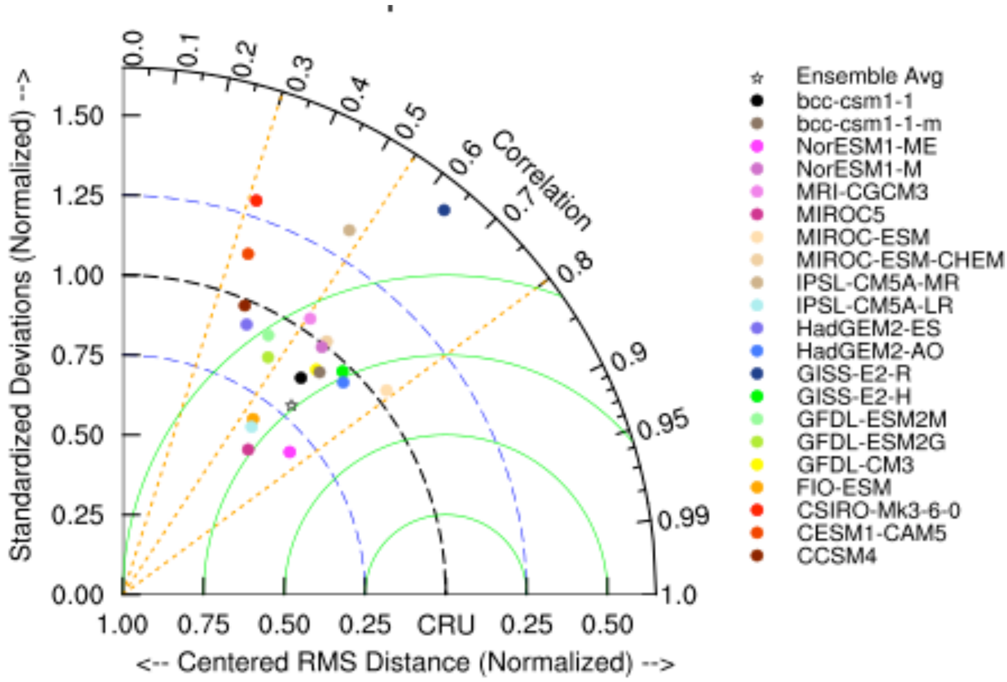


Figure 6.1: Taylor diagram for rainfall spanning the period (1901-2009) for New Zealand. Colour circles represent models while the star represents the ensemble of 21 models.

Figure 6.1 suggests that the models are spread with higher RMSE and lower correlation between 0.3 to 0.8. However, the ensemble of the models seems to be close to the observation. Thus, we consider the multi-model ensemble (MME) for projecting droughts over New Zealand by the end of the century (2099).

6.2.3 Bias Correction

The quantile mapping bias correction (Section 3.3) was applied for improving the CMIP5 rainfall projections which serves as the input data for the SPI calculation and thereafter projection of droughts.

A quantile mapping bias correction algorithm was applied to all twenty-one models. Figure 6.2 shows the CDF for observation, GCM historic and GCM future precipitation data. The Bias for each of the 21 models is tabulated in Appendix A, Table A1.

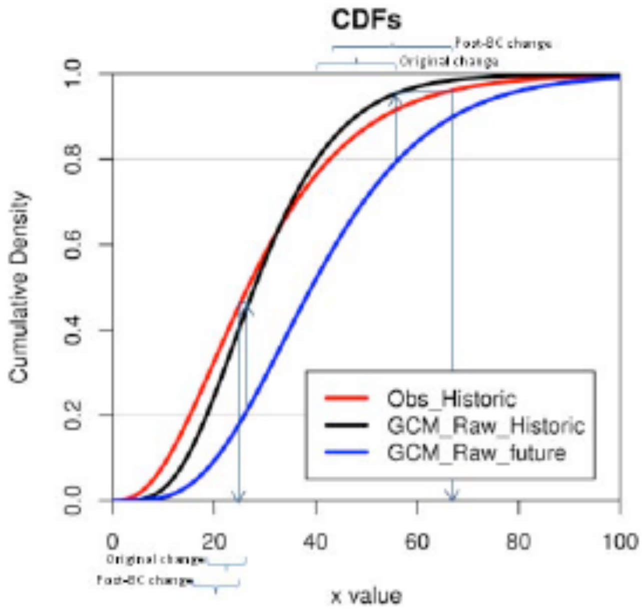


Figure 6.2: Cummulative distribution functions for a set of observed, GCM simulated historic, and GCM projected future precipitation data.

6.3 Drought Analysis

Drought identification, the parameters (i.e. drought severity) used and the time scales considered, along with study area/regions are detailed in Sections 3.6–3.9. Long (SPI12 time scale) droughts, defined as SPI≤−1.0 (a moderate/severe/extreme drought, Table 4.1), were studied. Climate change effects were determined by comparing results in 2010–2039, 2040-2069 and 2070–2099 to those in 1971– 2000. Drought severity was derived for each of the regions within the study area. Regional severities are presented for analysis in Sections 4.4–4.6.

6.4 Future Changes in Drought: Spatial Variation

This section presents the projected changes in drought parameters until the 21st century climates. Firstly, the moderate and higher emission scenarios - RCP4.5 and RCP8.5 is used to demonstrate the spatial variations in the simulated changes in drought severity across the study region.

Figures 6.3 to 6.6 show the drought severity on a 12-month time scale, along with their percentage changes until the 21st century projected by the MME for two scenarios – RCP4.5 and RCP8.5. Midterm (2040-2069) and longterm (2070-2099) projections are shown in Figures 6.3 – 6.6, while for the shorterm (2010-2039) under both moderate and higher emission scenarios are given in Appendix A, Figure A2 and A3.

Under the moderate emission scenario (RCP 4.5) the projected change in drought severity over New Zealnd and it's regions by midterm (2040-2069) is as seen in Figure 6.3. The southern tip of NewZealand is more prone to moderate and severe drought events and the probability of its occurrence is projected to be in the range of 100 to 300 %. Northernmost regions such as Auckland, Bay of Plenty, Gisborne, Northland and Waikato are projected to experience a decrease in the occurances of moderate as well as severe drought (Figure 6.3; top left and right panels)

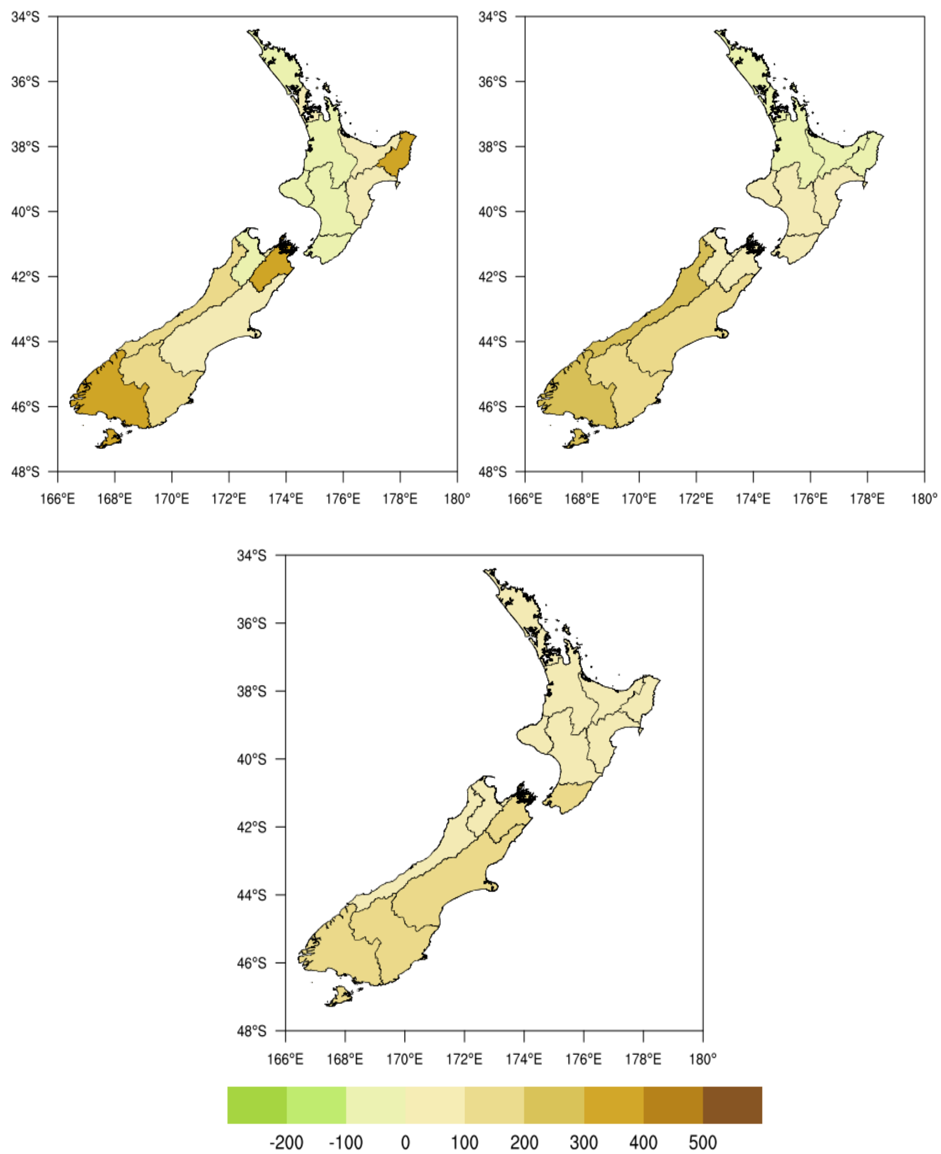


Figure 6.3: Projected change in drought severity on a 12-month time scale (top left panel – moderate drought, top right panel – severe drought and bottom center panel – extreme drought) for 2040-2069 w.r.t baseline period (1971-2000) under moderate emission scenario, RCP 4.5.

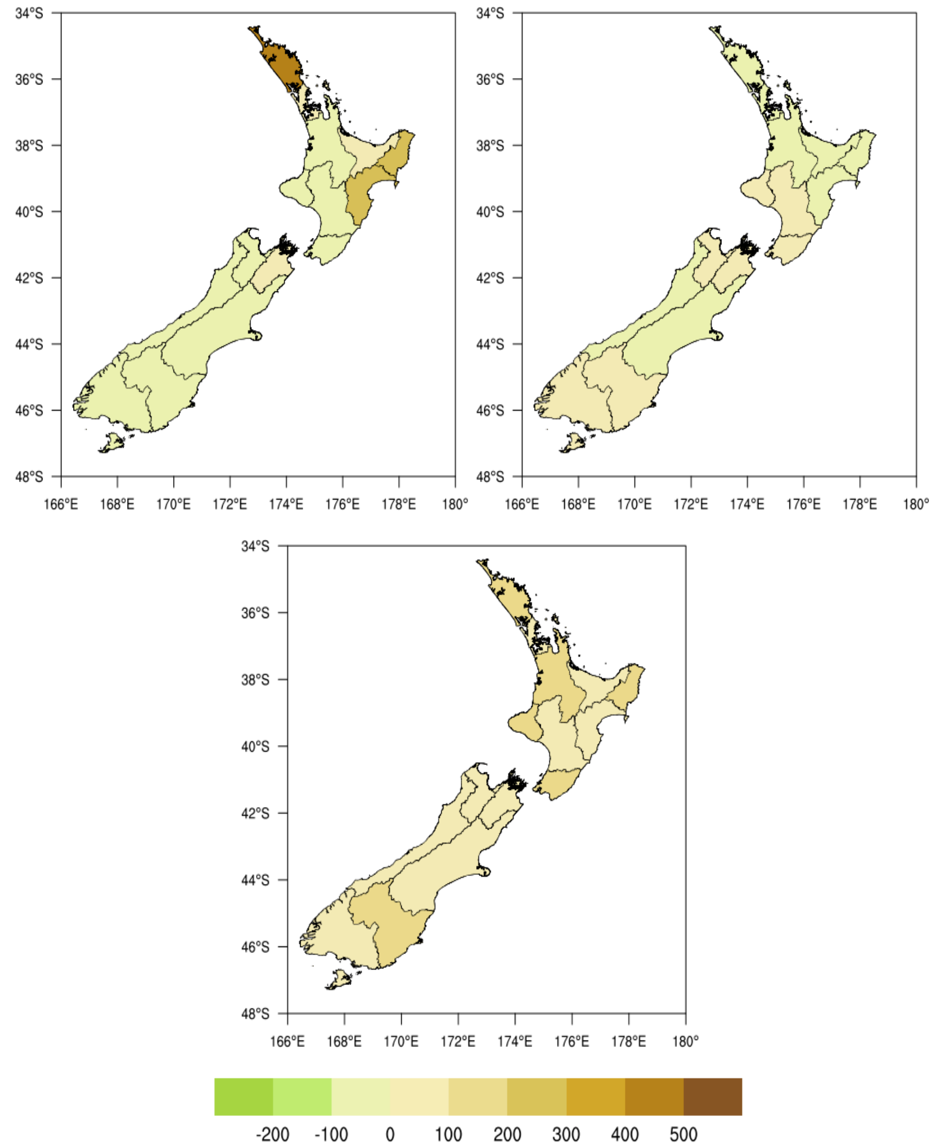


Figure 6.4: Projected change in drought severity on a 12-month time scale (top left panel – moderate drought, top right panel – severe drought and bottom center panel – extreme drought) for 2070-2099 w.r.t baseline period (1971-2000) under moderate emission scenario, RCP 4.5.

In contrast to the projected change in drought severity over New Zealnd and it's regions by midterm (2040-2069), in the longterm (2070-2099) shown in Figure 6.4, the southern tip of NewZealand are projected to experience a low probabilty of moderate and severe drought event occurance. Northland would be vulnerable to moderate droughts with a probabilty of 500%. Projected droughts in the extreme category is largely seen to occur in the Northern region – Northland, Auckland, Bay of Plenty, Gisborne, Waikato and Wellington (Figure 6.4; bottom center panel).

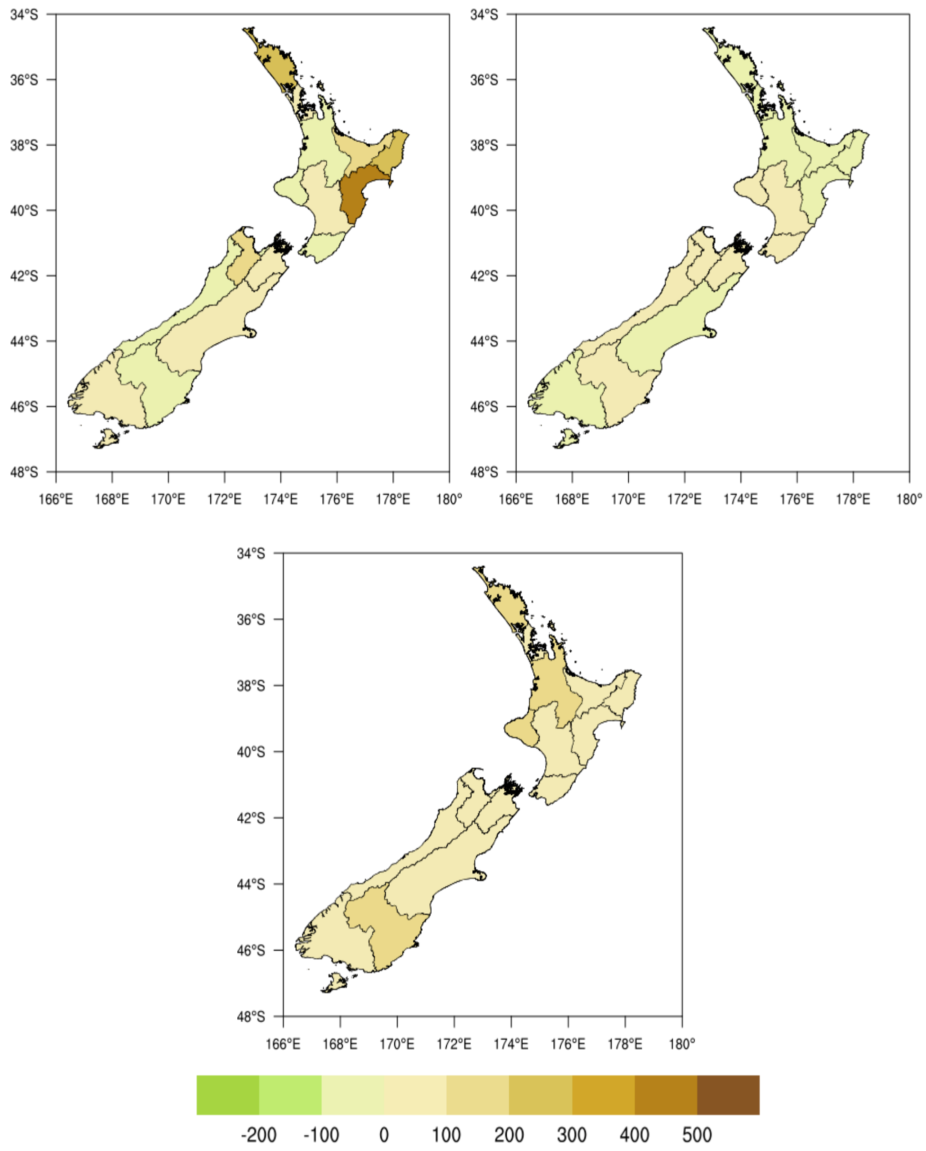


Figure 6.5: Projected change in drought severity on a 12-month time scale (top left panel – moderate drought, top right panel – severe drought and bottom center panel – extreme drought) for 2040-2069 w.r.t baseline period (1971-2000) under moderate emission scenario, RCP 8.5.

From the above series of figures, it is evident that the moderate droughts are increasing as compared to severe and extreme. This result correlates very well with the global trend shown in Figure 2.3 (Bruke et.al (2006)). Under the moderate emission scenario (RCP4.5) – Northland region shows a 400% increase with respect to baseline period by the end of century (2070-2099). Under the higher emission scenario (RCP 8.5) – Northland and Hawke’s Bay project higher percentage increase in moderate drought. Projected extreme drought is the highest for Northland region, this result is an important finding of this work. NIWA (2016) has considered evapotranspiration and soil moisture in their study which also has pointed the same region to be vulnerable to drought by 2099.

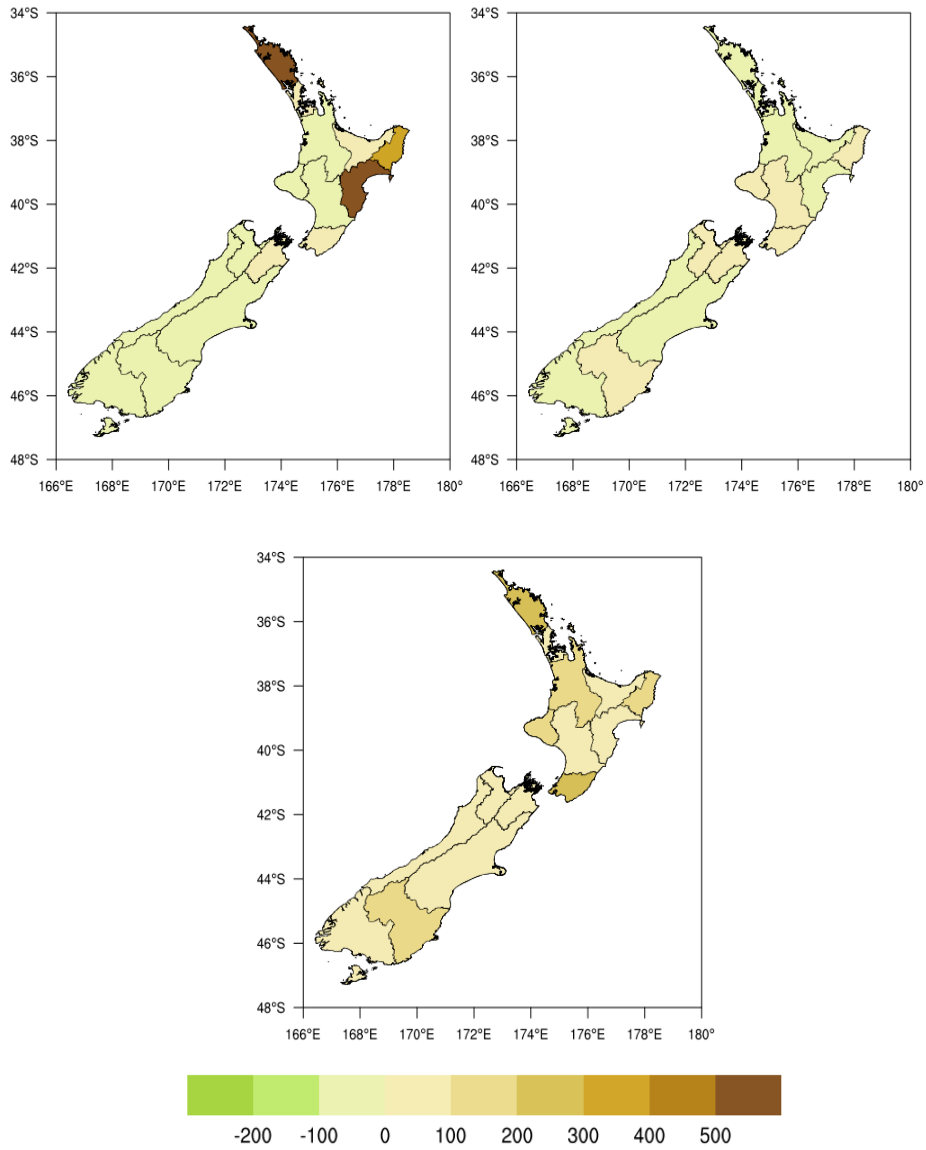


Figure 6.6: Projected change in drought severity on a 12-month time scale (top left panel –moderate drought, top right panel – severe drought and bottom center panel – extreme drought) for 2070-2099 w.r.t baseline period (1971-2000) under RCP8.5.

6.5 Projection Range

Uncertainties in climate change projections create a significant challenge to how scientific information can be used in practical applications (Blenkinsop and Fowler, 2007a). As the Figures suggest, projected drought characteristics and changes are highly influenced by the choice of emission scenario and GCM but they also enable some generalisations to be made.

6.6 Sources of Uncertainty

The range of emission scenarios and GCMs applied in the present study has enabled the assessment of their relative contribution in the total variance of the drought projections. Emission scenario uncertainty produces varying degrees of future radiative forcings. GCM uncertainty arises when different GCMs respond differently to the same radiative forcings, producing a range of global temperature warming and a range of geographical and seasonal patterns of precipitation changes.

Burke and Brown (2010) reported that simulated warming-induced meteorological drought changes for the UK are indistinguishable from natural variability or projection uncertainty. Nevertheless, similar to the present findings, many studies also found climate model (GCM/RCM) uncertainty (particularly GCM and their representation of changes in the large-scale circulation) to dominate in all lead times, especially for precipitation (Orlowsky and Seneviratne, 2013). Variance due to natural internally-generated variability and emission scenarios in precipitation projections are more important for the first and last few decades, respectively (e.g. Dubrovsky *et al.*, 2005; Lioubimtseva and Cole, 2006; Beniston *et al.*, 2007; Blenkinsop and Fowler, 2007a;b; Giorgi and Lionello, 2008; Vidal and Wade, 2009; Burke *et al.*, 2010; Kyselý *et al.*, 2010).

In the baseline for instance, different combinations of emission scenario and GCM patterns may generate different precipitation decline rates with warming. Greater warming could produce a larger discrepancy in the exponential/linear functions. Nevertheless, the fractional contribution of this element remains small.

6.7 Summary

This chapter has projected drought as well as characterised the spatial changes in meteorological drought over the regions of New Zealand for the baseline period 1971–2000 and three future periods, 2010–2039, 2040-2069 and 2070–2099 with a higher resolution data (20km x 20km). Firstly, the CMIP5 model data was regridded to 20km x 20km using the bilinear interpolation method. Secondly, the regridded data was bias corrected using the quantile mapping algorithm. Further on, drought was measured by the SPI, which involves relatively simple calculations and data requirements; drought was defined as SPI≤−1.0. Precipitation scenarios, simulated by MME (twenty-one

GCMs) under 2 emission scenarios were used. Geographically- and climatically-averaged drought severity and spatial extent for 12-month events were analysed.

The projected drought changes generally reflect the precipitation changes simulated as seen in Appendix A, Figure A1. Since SPI is transformed from precipitation accumulated over a given period. Results vary substantially depending on the GCM, emission scenario and region. Projected changes increase with larger forcing.

Neither the emission scenarios nor the models were weighted, and each emission scenario and model pattern was assumed to be independent and equally plausible. The assumption that all the emission scenarios were equally likely is due to the difficulty in estimating the levels of emissions in future, as well as the incomplete understanding of how the climate system would respond to these emissions.

One of the most striking findings of this study was the vulnerability of the Northland and Hawke's Bay regions to moderate droughts under the high emission scenario (RCP8.5) for all three future periods, 2010–2039, 2040-2069 and 2070–2099. These regions need a comprehensive risk management strategy for dealing with drought.

It is worth noting that increasing drought conditions in regions that already suffer from the hazard maybe of less concern compared to regions that do not currently experience their effects. Since orographically-induced fine scale structures are often absent in GCM-simulated precipitation scenarios, detailed climate change impact studies would require high resolution models with a better representation of topography (Giorgi and Lionello, 2008; Räisänen *et al.*, 2004; Gao *et al.*, 2006; NIWA 2016). Local/regional drought impact assessments would require the use of locally appropriate drought indices and consideration of processes and practices currently excluded from the climate models (e.g. irrigation). The diverse meteorological drought response to climate change found here implies the need for policy-relevant research on climate change impacts and robust adaptation decisions that consider a wide range of expression of modeling uncertainty, or risk-based information (e.g. by considering frequency distributions of climate change impacts) rather than deterministic information.

Chapter 7

Conclusion and Future Work

Drought is a routine and dominant feature of the New Zealand climate and many parts of the country suffer from frequent droughts. Significant droughts have occurred in the past years. These frequent droughts have severely stressed water supply systems and the communities that depend on them, and adversely impacted the economy by affecting primary production. The frequency, intensity and duration of droughts may increase due to anthropogenic climate change, emphasising the need for drought management and mitigation. As vulnerability to drought increases, greater attention should be directed to reducing the impacts and risks associated with its occurrence.

The frequently used drought index was first reviewed in this study in Chapter 4. As the aim of this study was drought projection and early warning, the meteorological drought index was chosen as the prime indicator of drought. An assessment of the popular meteorological drought index was conducted to investigate how well these drought indices replicate historical droughts in the regions of New Zealand. This initial study used monthly precipitation data from CRU. Based on this study, a meteorological drought index, namely the Standardised Precipitation Index (SPI), was selected for further scrutiny.

Precipitation or rainfall is the primary factor which controls the formation and persistence of droughts and floods. Therefore, the interpretation and understanding of the trend behaviour of rainfall and dry/wet events are important. The first part of the analysis was carried out to determine annual rainfall trends using non-parametric tests, namely the Mann-Kendall (*MK*) and Sen's estimator of slopes with long historical records (more than 100 years) of the data set as in Chapter 5. Further, the same data was used to investigate the sensitivity of trends to the length of the continuous time period considered. This information is vital for climate change authorities in New Zealand to determine any shift in climatic patterns, and is also important when planning climate change adaptation measures and civil infrastructure design. The second part of the analysis was carried out to perform a trend analysis of wet and dry periods based on the SPI time series.

This thesis aimed to project drought over New Zealand by the end of the century, as well as the associated uncertainties in the methodologies for drought quantification and climate change projection, through a multi-scenario and multi-model approach. In this study, droughts are characterised by drought severity. This chapter highlights the main results, their policy implications and knowledge gaps.

This thesis builds on existing literature by systematically analysing some of the uncertainties in drought projections under a changing climate. As discussed in Section 1.1, few studies have examined the climate-change-induced changes in drought using a large ensemble of simulations; the meteorological drought analysis in Chapter 6 is based on simulations projected by two emission scenarios and 21 general circulation models (GCMs).

7.1 Key Findings

Drought characterization using SPI provides a standardized classification of severity, thus exhibiting advantages over other indices. The use of the SPI is satisfactory for assessing and monitoring meteorological droughts in the regions of New Zealand. Given the importance of rainfall and its criticality in assessing droughts, the SPI was selected for further analysis of its use in drought assessment.

There is long-term temporal variation of climatic data over New Zealand. A few conclusions based on the trend analysis techniques applied to rainfall data and the SPI values calculated:

Trend analysis is performed at a 5% level of significance to signify the presence of a statistically significant trend. The analysis resulted in an overall non-significant trend for most of the regions except for Wellington. Regions namely – Bay of Plenty, Hawke's Bay, Manawatu Wanganui, Marlborough, Nelson, Otago, Southland and Waikato show statistically insignificant increasing annual precipitation trends.

Similar to rainfall, when SPI trends were analysed using *MK* and Sen's slope - Four of the regions, namely – Bay of Plenty, Hawkes's Bay, Manawatu-Wanganui and Wellington display a significant increasing trend. However, Auckland, Canterbury, Gisborne, Northland, Taranaki, Tasman and West Coast regions show a decreasing trend with no significance.

Under the moderate emission scenario (RCP4.5) – Northland region showed a 400% increase with respect to baseline period by the end of century (2070-2099). Under the higher emission scenario (RCP 8.5) – Northland and Hawke's Bay project higher percentage increase in moderate drought. Projected extreme drought is the highest for Northland region, this result is an important finding as a study of NIWA (2016) also has pointed the same region to be vulnerable to drought by 2099.

7.2 Policy Implications

This study seeks to develop an improved understanding of potential changes in drought under future climates, which could facilitate the development and implementation of more effective drought management and climate change adaptation measures.

The diverse meteorological drought response to climate change simulated in this study implies that findings based on a single scenario/model could be highly misleading. Substantial research and considerable improvements in climate models are needed before climate projections can be applied directly and effectively in adaptation planning and design, e.g. water management, as suggested by the range of projected changes in drought characteristics found in this thesis. Uncertainties in climate change projections or the risk information supplied to decision-makers are unlikely to decrease in the near future (Knutti, 2008; Todd *et al.*, 2011). Even with a perfect climate model, future changes in non-climatic pressures such as demographic and economic development, natural forcings (solar and volcanic activity), and natural internal variability mean that climate change and meteorological projections would remain highly uncertain, especially at the regional scale. Therefore, policy relevant research on climate change impacts and robust adaptation decisions should be based on a multi-scenario and multi-model approach; they also need to consider a wide range of expressions of modeling uncertainty, or risk-based information (e.g. by considering frequency distributions of climate change impacts) rather than deterministic information (Gosling *et al.*, 2011a).

Although the degree of uncertainty in future projections of drought, for example, may create challenges in the development of appropriate adaptation measures, many organisations have experience in working in the face of various kinds of uncertainty (Todd *et al.*, 2011; Stainforth *et al.*, 2007a).

Despite the limitations, climate models simulate numerous processes and feedbacks; large ensembles, as applied in this study, enhance our understanding of the range of possible model behaviour in response to different emission scenarios (Stainforth *et al.*, 2007b). They can also help to identify the areas where results depend strongly on model assumptions, thus providing guidance for future model development Much resources have been allocated to climate research and model development, such as the variables and spatial/temporal scales of interest, but these should be shaped by the needs of the end users and policy-makers if the goal is to benefit society. More emphasis is needed on extracting the data and information that is decision and policy-relevant, and to explore how to make the best use of the model results so that they add value to decision making, e.g. by working with stakeholders and to provide guidance on how to use/interprete the data and information (Knutti, 2008). Each simulation presents a "what-if" scenario; appropriate interpretation and accurate communication of such information and uncertainties, even in qualitative terms, is therefore crucial and can have substantial value in the design of robust adaptation strategies that reduce vulnerability to both climate variability and change (Pappenberger and Beven, 2006; Stainforth *et al.*, 2007a;b).

7.3 Limitations and Further Work

Specific limitations and areas for further research are presented in the relevant chapters. This subsection outlines some of the limitations of the study approach adopted in this thesis and provides some general directions for future work.

Analysis in this thesis has focused on relative drought. Given that drought is a phenomenon relative to the local conditions that can occur in virtually all climate regimes, including in cold regions, it needs to be considered in a relative, rather than an absolute, sense. Nevertheless, the application of a fixed absolute drought threshold (say, 20 mm of precipitation) for the entire study region would allow the identification of the more "drought-prone" areas. Therefore, an absolute drought analysis could provide useful information for large-scale management practices and could aid resource allocation. Also, the projected changes in drought characteristics presented here, as well as the SPI computation, are based on the reference period of 1971–2000; the choice of another baseline (e.g. 1961–1990) could lead to different results.

A caveat of this study is the separate characterisation of drought severity and spatial extent. This could be improved in future work by assessing the spatio-temporal characteristics of droughts simultaneously through a severity–area–duration analysis, which relates the area of each drought to its severity (Andreadis *et al.*, 2005; Sheffield *et al.*, 2009; Philip *et al.*, 2015). Alternatively, Perez *et al.* (2011) presented two methodologies (non-contiguous and contiguous drought area analyses) for analysing the spatio-temporal development and characteristics of large-scale meteorological droughts using gridded timeseries of meteorological data.

This study could therefore be extended to investigate the effects of climate change in relation to specific impact sectors such as agriculture, using locally appropriate drought indices such as those covered in Section 2.2. Such analysis may need to be carried out on a local or regional scale with the aid of higher resolution models that have better representation of topography; processes and practices that are often excluded from the climate models (e.g. irrigation) may also need to be considered (Räisänen *et al.*, 2004; Gao *et al.*, 2006).

Although this thesis has explored the effects of several sources of uncertainty on drought projections under future climates, results obtained here under-represent the true uncertainty as other sources of uncertainty have not been examined. For example, meteorological droughts have only been represented by the precipitation only Standardised Precipitation Index (SPI); the application of another meteorological drought index may produce different results.

A study by Huntingford *et al* (2009) states that the source of uncertainty has been estimated to be ˜40% of that of the physical climate properties (e.g. equilibrium climate sensitivity and global heat capacity), thus could be explored further in the meteorological and hydrological drought analyses.

The application of gridded outputs at 0.2^{o} x 0.2^{o} resolution has been investigated in this thesis. Hence, results presented in this thesis could be compared to those based on regional climate change simulations such as the CORDEX (Coordinated Regional Climate Downscaling Experiment) initiative from the World Climate Research Program (http://www.meteo.unican.es/en/projects/CORDEX). Drought analyses carried out here have been based on the monthly precipitation timeseries. However, the daily resolution is important in operational monitoring of drought development and decision-making in agriculture and water resource management (Lu, 2011), especially on a local or regional scale, as a drought-affected region may return to normal condition with only one day of intense rainfall. Another area of further research could be to compare the meteorological drought results to those derived from the Palmer Drought Severity Index (PDSI), as well as the standardised precipitation evapotranspiration index (SPEI), for instance, as both of these methods account for temperature effects. Moreover, both meteorological and hydrological drought events have been defined based on the threshold of SPI−1.5; this study could be extended by studying the changes in drought for a more extreme SPI category (e.g. SPI−2.0) and compared with the results obtained here.

Given that the uncertainties associated with future drought projections are unlikely to be constrained in the near term, it is worth exploring how the findings in this study could contribute to the development and implementation of drought risk assessment and management practices, as well as societal vulnerability assessments, to reduce the adverse impacts of droughts under a changing climate. Working closely with stakeholders, such as policymakers, water resource managers and others, would help to determine how this study could be further developed to address the drought/water resource issues within an integrated framework, based on their needs.

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APPENDIX A

Table A1. Bias of CMIP5 models with respect to CRU

Model	Bias
bcc-csm1-1	0.95
bcc-csm1-1-m	0.96
CCSM4	1.08
CESM1-CAM5	0.93
CSIRO-Mk3-6-0	0.9
FIO-ESM	0.84
GFDL-CM3	0.89
GFDL-ESM2G	1.01
GFDL-ESM2M	1.02
GISS-E2-H	0.94
GISS-E2-R	0.93
HadGEM2-AO	0.87
HadGEM2-ES	0.89
IPSL-CM5A-LR	0.80
IPSL-CM5A-MR	0.82
MIROC5	0.97
MIROC-ESM	1.10
MIROC-ESM-CHEM	1.08
MRI-CGCM3	0.76
NorESM1-M	0.82
NorESM1-ME	0.85

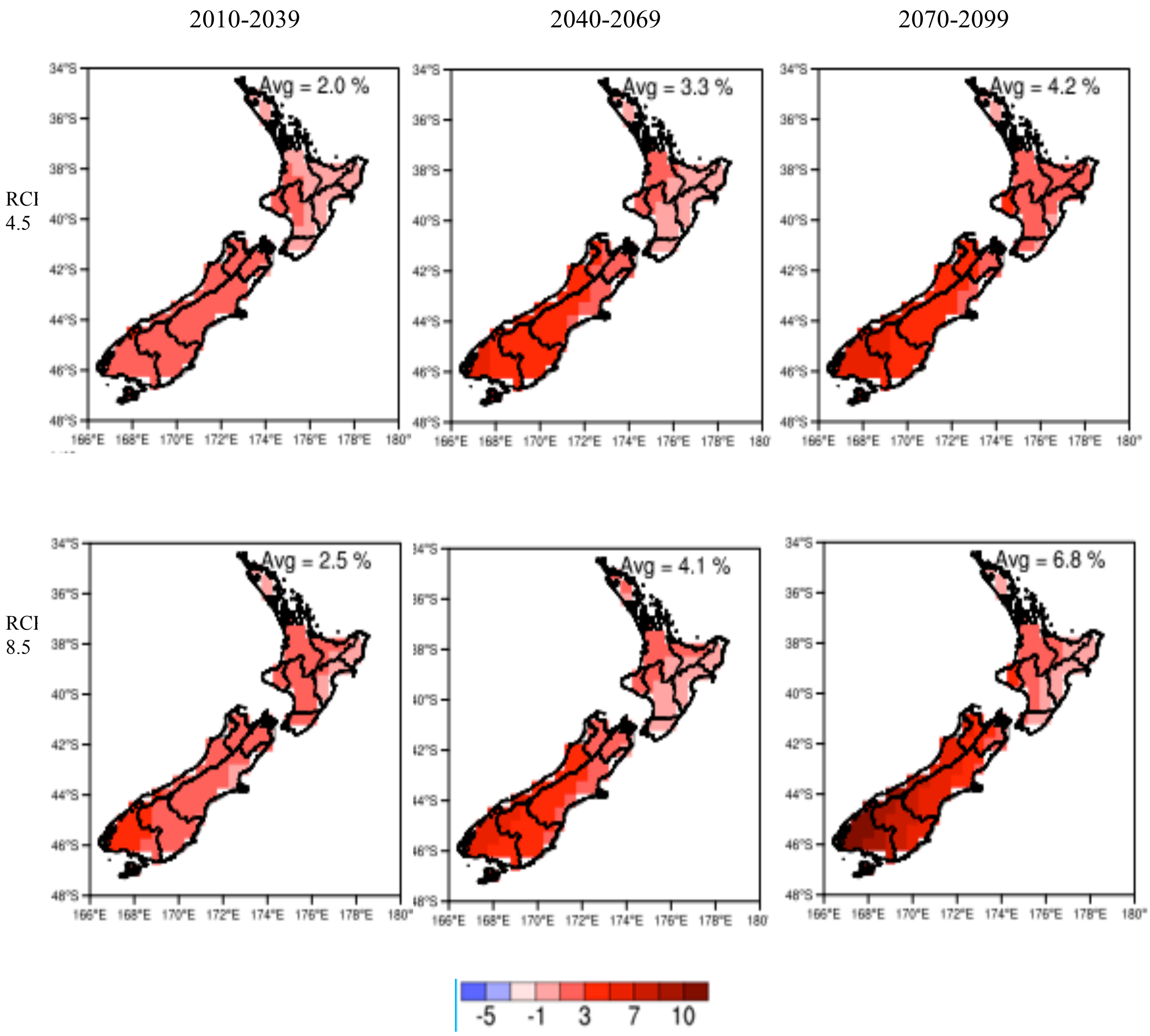

Figure A1. CMIP5 model ensemble Annual precipitation change (%) projected over New Zealand for 2010-2039, 2040-2069 and 2070-2099 with respect to the baseline period (1971-2000) for RCP 4.5 and RCP 8.5 emission scenarios.

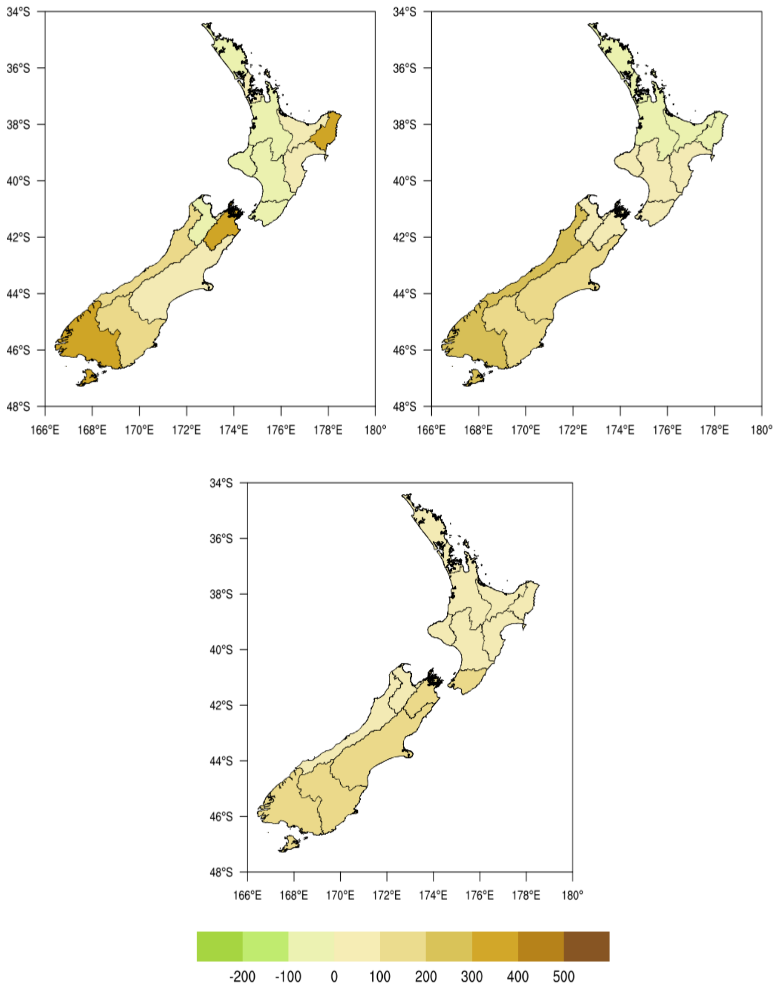

Figure A2. Projected change in drought severity on a 12-month time scale (top left panel – moderate drought, top right panel – severe drought and bottom center panel – extreme drought) for 2010-2039 with respect to baseline period (1971-2000) under moderate emission scenario, RCP 4.5.

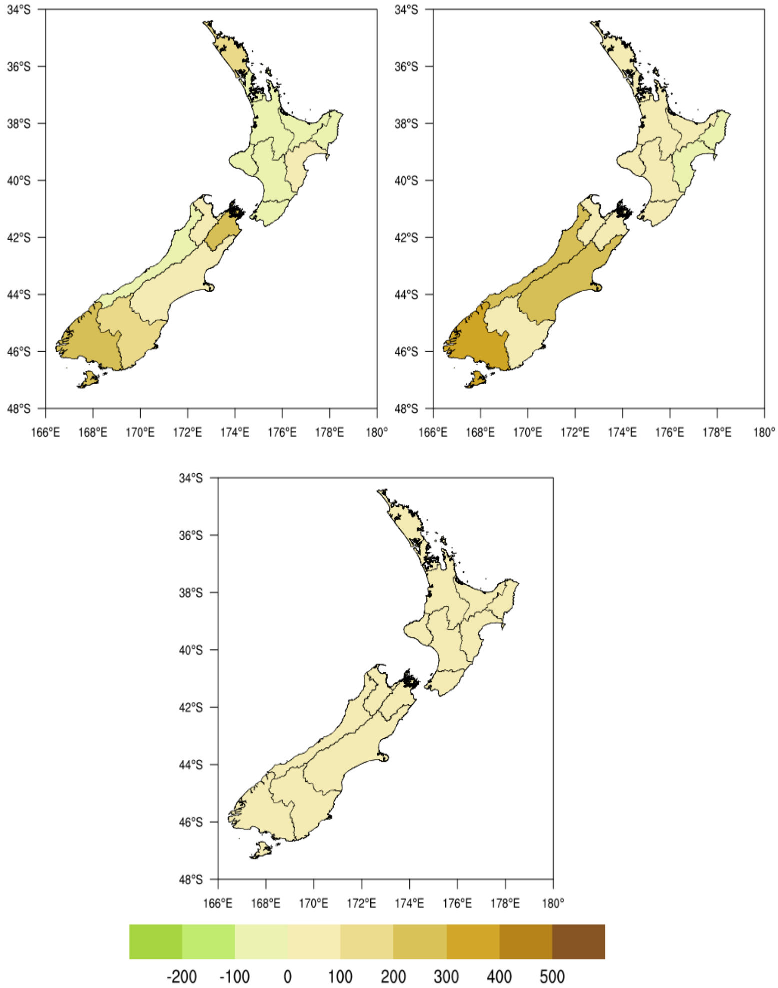

Figure A3. Projected change in drought severity on a 12-month time scale (top left panel – moderate drought, top right panel – severe drought and bottom center panel – extreme drought) for 2010-2039 with respect to baseline period (1971-2000) under moderate emission scenario, RCP 8.5.