THE RESPONSE OF SOUTHERN AFRICAN VEGETATION TO DROUGHTS IN PAST AND FUTURE CLIMATES

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Declaration

I know the meaning of plagiarism and declare that all the work in the thesis, except for that which is properly acknowledged, is my own.

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Abstract

Drought and climate change pose a threat to southern African vegetation. This study examines the response of southern African vegetation to drought in both past and future climates. Multi-year and multi-simulation datasets from three dynamic global vegetation models (DGVMs), namely, Community Land Model version 4 (CLM4), Community Land Model version 4 with Variable Infiltration Capacity hydrology (CLM4VIC), and Organising Carbon and Hydrology in Dynamic Ecosystems designed by Laboratoire des Sciences du Climat et de l'Environnement (ORCHIDEE-LSCE). These three DGVMs and the Community Earth System Model (CESM) were analyzed for the study. The DGVM simulations were forced with the reanalysis climate dataset from the National Centers for Environmental Prediction (NCEP) and the Climatic Research Unit - NCEP (CRUNCEP). The simulated climate results were evaluated with observation datasets from the Climatic Research Unit (CRU), while the simulated vegetation index (i.e. Normalized Difference Vegetation Index, NDVI) were evaluated with NDVI data from the Global Inventory Modelling and Mapping Studies (GIMMS). Meteorological droughts were analyzed at different timescales (1- to 18-month timescales), using two drought indexes: the Standardized Precipitation Evapotranspiration Index (SPEI) and the Standardized Precipitation Index (SPI). The responses of vegetation to drought were quantified by means of Pearson Correlation Analysis. The DGVMs were applied to study the sensitivity of vegetation to fire, while the CESM was used to project impact of climate change on the characteristics of southern African vegetation in the future (up to the year 2100) under the 8.5 Representative Concentration Pathway (RCP8.5) scenario, focusing on impacts at 1.5^{o}C and 2.0^{o}C global warming levels (GWLs).

Analysis of the observed data shows that the spatial distribution of vegetation across southern Africa is more influenced by the rainfall distribution than by the temperature distribution. The observed correlation between drought index and vegetation index is higher than 0.8 over southeastern part of the region at 3-month drought timescale, and there is no difference between the spatial distribution of the correlation between the SPEI and the vegetation index, and between the SPI and the vegetation index. The three DGVMs failed to capture the response of vegetation to drought; however, the CLM4 shows the best performance while ORCHIDEE-LSCE fared the worst of the three. The CLM4 simulation show that fire strongly influences growth of vegetation

over the summer rainfall region but it has weak influence over vegetation in the western arid zone. The CESM strongly captures the spatial patterns of precipitation and the vegetation index across southern Africa, but it overestimates the magnitudes of the vegetation index across the region, except in Namibia and Angola. The CESM also underestimates the correlation between drought indexes with vegetation, and the timescales at which the vegetation respond to droughts.

The CESM projects an increase in the drought intensity as a result of an increased temperature across southern African biomes. However the increase in drought intensity is more pronounced with the SPEI than with the SPI. CESM also projects a future decrease in the vegetation index (i.e. NDVI) in the region except in the dry savanna biome. The impacts of 1.5^{o}C GWLs on the vegetation fluxes vary throughout southern Africa, and the magnitudes of changes in the vegetation fluxes are affected by a further increase in global warming over the region. While there is a good agreement among the CESM simulations on the projected changes in vegetation fluxes across the biomes, the uncertainty in the projections is higher with 1.5^{o}C than with 2.0^{o}C GWL. The results of the study can be applied to mitigate the impacts of climate variability and change on southern African vegetation. Specific mitigation efforts that could be applied to reduce the impacts of droughts and climate change are watershed management, improved vegetation management, impact monitoring, environmental awareness, and remote sensing tools.

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Shakirudeen Abimbola, **Lawal**

April, 2018

Dedication

In memory of my late mother, Alhaja Silifat Lawal.

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List of Abbreviations

AGNPP	Above ground net primary production
AMS	American Meteorological Society
AR	Autotrophic respiration
AVHRR	Advanced Very High Resolution Radiometer
AWC	Available water capacity
BGNPP	Below ground net primary production
CAM	Community Atmospheric Model
CESM	Community Earth System Model
CLM4	Community Land Model version 4
CLM4VIC	Community Land Model version 4 with Variable Infiltration Capacity hydrology
CNVC	Canadian National Vegetation Classification
CORDEX	COordinated Regional Downscaling EXperiment
CRU	Climate Research Unit
DAI	Drought area Index
DD	Dynamical downscaling
DGVM	Dynamic Global Vegetation Model
DJF	December, January and February
DOW	Defenders of Wildlife
DVM	Dynamic Vegetation Model
DWAF	Department of Water Affairs and Forestry
ESM	Earth System Model
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
FGDC	Federal Geographic Data Committee
FPSN	Photosysnthesis
GCM	Global Climate Model
GDP	Gross Domestic Product

GIMMS	Global Inventory Modelling and Mapping Studies
GPP	Gross Primary Production
GWL	Global warming level
HR	Heterotrophic respiration
IISD	International Institute for Sustainable Development
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter Tropical Convergence Zone
IUCN	International Union for Conservation of Nature
JJA	June, July, August
LAC	leaf area cover
LAM	Limited Area Model
LSCE	Laboratoire des Sciences du Climat et de l'Environnement
LSM	Land surface model
MAM	March, April, May
MsTMIP	Multiscale Synthesis and Terrestrial Model Intercomparison Project
NACP	North American Carbon Program
NBP	Net Biome Production
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Predictions
NDMC	National Drought Mitigation Centre
NDVI	Normalized Difference Vegetation Index
NEP	Net Ecosystem Production
NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service
NPP	Net Primary Production
ORCHIDEE - LSCE	Organising Carbon and Hydrology in Dynamic Ecosystems designed by Laboratoire des Sciences du Climat et de l'Environnement
ORNL	Oak Ridge National Laboratory

PDSI	Palmer Drought Severity Index
PET	Potential Evapotranspiration
PHDI	Palmer Hydrological Drought Index
PDSI	Palmer Drought Severity Index
PM	Penman Montheith
RAI	Rainfall Anomaly Index
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RMSE	root mean square error
SADC	Southern African Development Community
SAH	South Atlantic High
SAWS	South African Weather Service
SD	Statistical downscaling /standard deviation
SDGVM	Sheffield Dynamic Global Vegetation Model
SOILC	Soil carbon
SON	September, October, November
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SST	Sea surface temperature
SVAT	Soil-vegetation-atmosphere transfer
SWSI	Surface Water Supply Index
TBM	Terrestrial Biosphere Model
TLAI	Total Leaf Area Index
TTT	Tropical Temperate Trough
UNEP	United Nations Environmental Protection
USAID	United States Agency for International Development
VIC	Variable Infiltration Capacity
VIS	Visible
WMO	World Meteorological Organization

Chapter 1: Introduction

1.1 Vegetation

Vegetation, one of the most obvious features of the earth's landscape, can be defined as a cluster of different plant species (Barbour & Billings, 1999). The characteristics of dominant species usually determine the particular name of an area's vegetation. For instance, a forest vegetation is mainly made up of tree species while a savanna vegetation (also known as a mixed woodland) mostly consists of grasses and few trees. Vegetation can be classified as either natural or cultural, depending on the extent of human influence on it (Efe *et al*., 2009). Natural vegetation refers to vegetation that has developed with little or no human influence, while a cultural vegetation is vegetation that has been altered directly or indirectly by human (NRI, 2003; FGDC, 2008). Natural vegetation is found mostly in uninhabited areas where no deliberate fires are being set by humans to burn areas, and where the removal of plants products such as seeds or leaves, is minimal and is comparable to natural removal by wild animals. The distinction between natural and cultural vegetation depends on interpretation, however, the degree of human influence on vegetation usually varies from slight (e.g. light grazing) to modest (e.g. selective logging), which is also known as semi-natural vegetation, and to heavy (e.g. replacement of natural vegetation with crops). However, even in some densely populated areas, there are likely to be some remnants of natural vegetation. Understanding the characteristics of natural vegetation types is important because they represent a combination of all the physical and biotic attributes of their individual biotypes, thereby revealing the biological potential of an area (Kuchler, 1969). Hence, the focus of the present study is on natural vegetation.

1.2 Spatial and temporal distribution of natural vegetation

The characteristics of natural vegetation vary from one geographical region to another. The world's natural vegetation can be classified into three major groups (or biomes): forest, grassland and desert (Figure 1.1). Forest biome consists of Tropical rain forests (which are found mostly along the equator between 23.5^0 N and 23.5^0 S of the equator), Temperate forests (located farther from the equator between 23.5^0 N and 66.5^0 N and 23.5^0 S and 66.5^0 S) and Coniferous forests (which are dominant in the southern hemisphere, between 50^0 and 60^0 S of the equator). The Grasslands, which are found in every part of the world (except in the Antarctic), occupy 30 - 40% of the earth's land surface, making them the largest single type of biome (White *et al*., 2000). The Grassland biome includes Tropical savannas (also known as mixed woodland) and Temperate grasslands. Tropical savannas are found mainly between 5^o and 15^o north and south of the equator, in the interior of the continents, throughout most of Central Africa, areas of Mexico and northern Australia (McKnight & Hess, 2000). Temperate grasslands are located between 23.5^0 N and 23.5^0 S. The temperate grasslands are situated in colder regions, and generally have hot summers and cold winters (WWF, 2001; Staver *et al*., 2011; DOW, 2018). The Desert biome can be subdivided into the Hot Desert vegetation and the Cold Tundra vegetation. Hot deserts are found on the western coasts of the continents, between 15^0 N and 30^0 N, and 15^0 S and 30^0 S; they include the Namib Desert, the Great Australian Desert, the Iranian Desert, the Thar Desert, the Kalahari Desert, the Peruvian Desert, the Mexican Desert and the Mojave, Sonoran and Californian Desert of the southwestern United States. The Cold Tundra vegetation, which makes up 10% of desert population is located between 60^0 N and 70^0 N. The focus of the present study is on natural vegetation found in the southern African region.

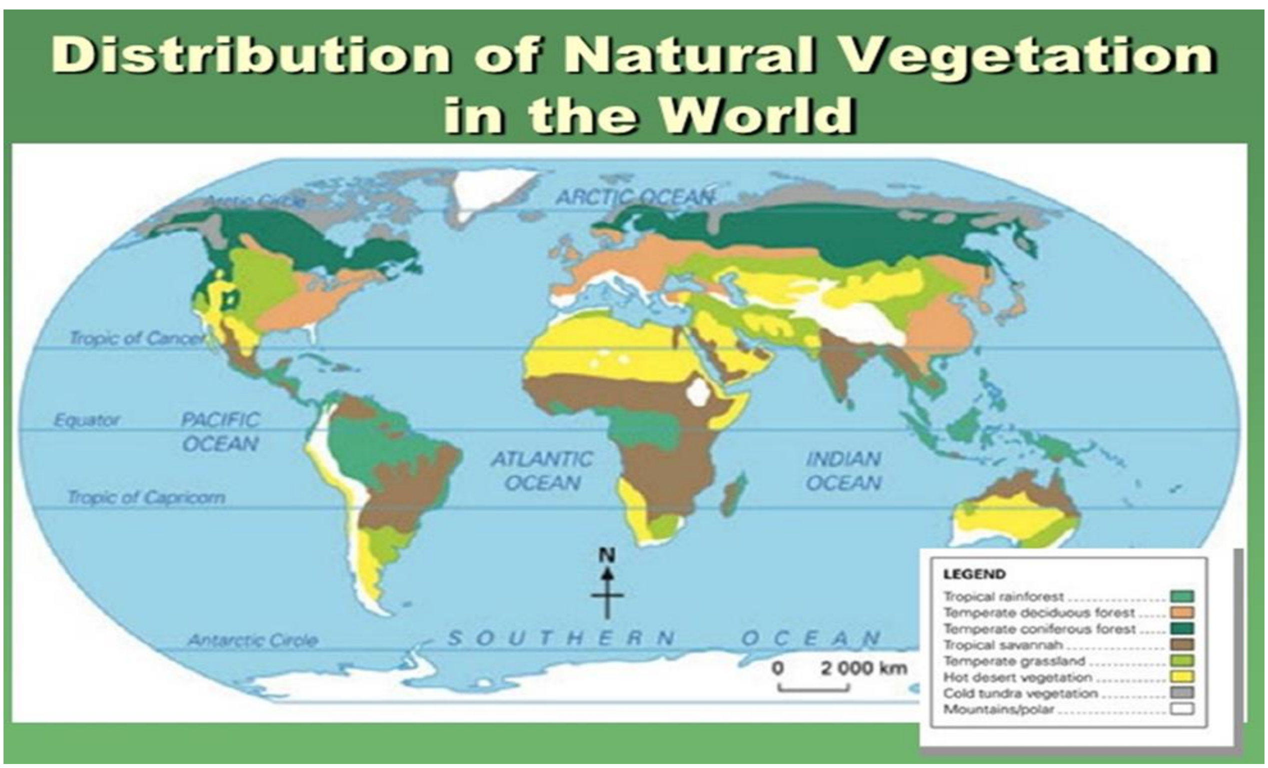

Figure 1.1. Global distribution of vegetation (Source: https://www.slideshare.net/TanBK/chapter-12-natural-vegetation; Assessed on 9 January 2018)

The characteristics of natural vegetation (e.g. the leaf area index) also vary from time to time, depending on vegetation types (i.e. forest or savanna) and the period under consideration (seasonal, annual, or over an even longer period). The temporal distribution of vegetation may change due to natural, anthropogenic and climatic factors (Cahoon *et al*., 1992). For instance, the savanna biome (which has the most temporal variation) naturally burns in summer in order to produce new flushes of more healthy species. Burning can also be prescribed as part of forest management or agricultural practices. Climate-induced temporal distribution of vegetation occurs over a longer timescale than the other two. For example, the results of carbon dating have shown that millions of years ago, the Earth was covered mostly with tropical forest because the Earth was moister and warmer; subtropical palms grew in the Arctic Circle, and tundra was only found on the mountains. However, as the climate changed over time, so did the vegetation (Adams, 1997). In the southern African region too, there is evidence of change (or variability) in vegetation due to natural, anthropogenic and climatic factors (Schulze, 2006; Midgley & Thuiller, 2007; DWAF, 2008). However, the emphasis of the present study is on climate-induced vegetation changes, because such changes are usually widespread and because they have huge impacts on human socio-economic activities (Bellard *et al*., 2012).

1.3 Socio-economic importance of vegetation

Vegetation plays a vital role in the continuous existence of humans and animals worldwide, because of the goods and benefit it provides. For example, vegetation provides watershed protection, erosion control, soil fertilization, habitat for wildlife, ecological productivity and nutrient production in the form of crops, among others (Thackway *et al*., 2006). In Asia, vegetation is a major contributor to foreign exchange earnings and to the gross domestic products (GDP) of some countries (e.g. Nepal, Philippines, Sri Lanka; Keith & Gorrod, 2006). In West and Central Africa, vegetation is essential for social stability because it provides groundwater and food for the population (FAO, 2003). The socio-economic importance of vegetation is even more evident in southern Africa, where a large human population depends directly or indirectly on vegetation products for survival (Twine, 2005).

1.4 Southern African vegetation and their socio-economic importance

Southern African vegetation can be classified into eight biomes (Sinclair & Beyers, 2015), based on the common characteristics that they share in their respective environments. Some of the biomes are either transnational (i.e. extending across national boundaries), and in certain cases, more than one biome is situated within a nation's boundary (Figure 1.2). The characteristics and geographical locations of some of the biomes are briefly described (Low Rebelo, 1996; WWF, 2001; UNEP 2008 & Sinclair & Beyers, 2015) as follows:

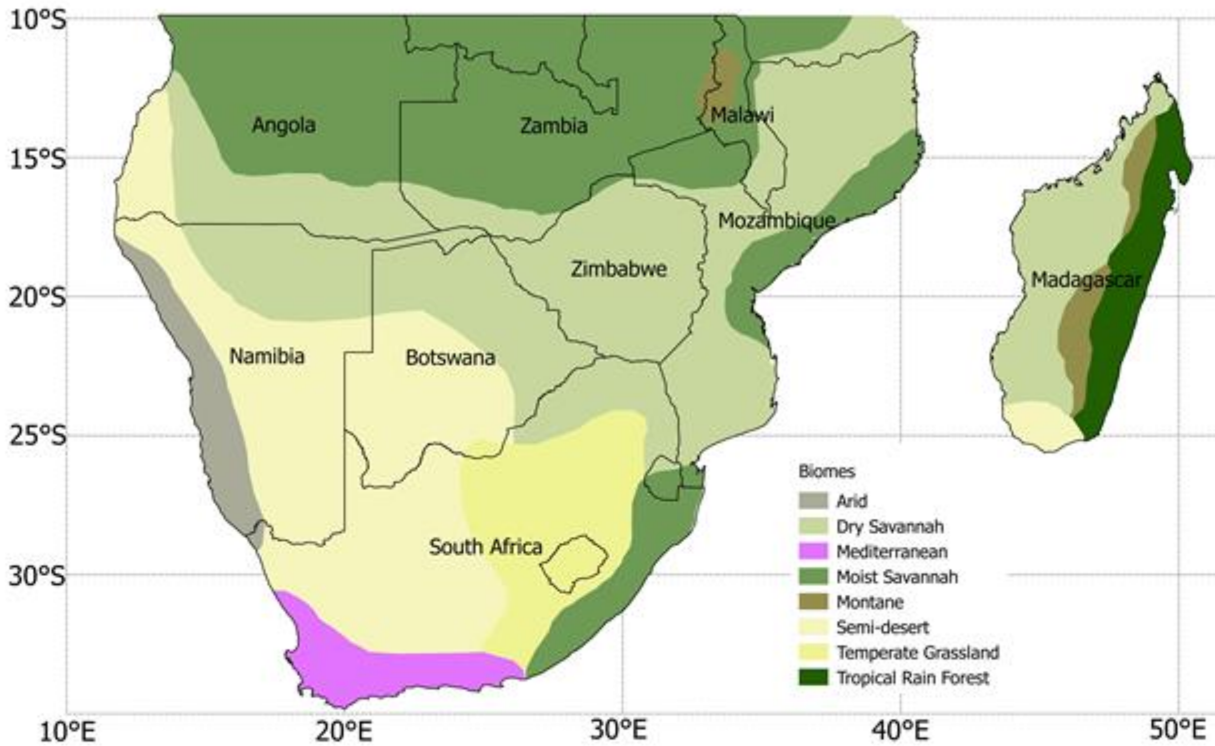

Figure 1.2. Major vegetation biomes in southern Africa (adapted after UNEP, 2008 and Sinclair & Beyers, 2015). The black contours indicate political boundaries. The vegetation biomes are Arid (AR), Dry Savanna (DS), Mediterranean (MT), Moist Savanna (MS), Montane (MA), Semi-desert (SD), Temperate Grassland (TG) and Tropical Rain Forest (TF).

1.4.1 Arid

The arid biome is located along the western coast of Namibia and it penetrates further into the inland part of the country. It is home to more than 5,000 higher plant species, of which 40 percent are endemic and about 18% are under threat of extinction. In addition, it is rich in succulent species, harboring about 10,000 succulent species. The fauna found in this biome are mostly endemic and they include hopliniid beetles, aculeate Hymenoptera, Monkey beetles, Broadley's lance skink, and dwarf leaf-toed gecko among others. Rainfall is reliable and predictable in this biome, falling mostly in winter and prolonged drought are rare. These climatic features distinguish the biome from other arid biomes in other parts of the world. This biome is very important because of its rich biodiversity which is an important source of foreign revenue and also, a potential source of medicine for various ailments.

1.4.2 Dry savanna

The dry savanna biome falls within both Mozambique and Zimbabwe. Although only part of its vegetation is endemic, it is nonetheless rich in flora and fauna (mostly mammals and birds). It is made up of a mix of vegetation types, whose location is mostly determined by elevation. For example, the vegetation found in Mozambique are adapted to a different environment than the Zambezian and Mopane Woodland which are found in low-lying areas. The dry savanna biome also consists of sub-montane and montane grasslands which are situated around hills in the regions. Examples of the common vegetation found in the dry savanna biome are *Exotheca abyssinica*, *Monocymbium ceresiiforme* among numerous others. This biome provide food resources for the human and animal inhabitants of these areas.

1.4.3 Mediterranean vegetation

This Mediterranean vegetation is located between 30^{o} and 40^{o}S; it is found in the Western Cape Province of South Africa. The biome consists largely of evergreen shrubs and sclerophyllous trees which adapt to both dry summer and moist wet winter, similar to the Mediterranean climate. This biome is the most diverse of all southern Africa biomes and, moreover, the smallest of all the natural vegetation biomes in the world. Most of the vegetation in this biome is endemic, with about 70% of the species not found anywhere else in the world. Sadly, however, more than 40% of the species are either threatened or endangered according to the International Union for Conservation of Nature (IUCN). The primary vegetation in this biome is the Fynbos which grows on sandstone acidic soil that is nearly depleted in nutrient. The biome is also home to Spekboom (*Portulacaria afra)*, a species that has been recognized to be important in absorbing atmospheric carbon dioxide.

1.4.4 Moist savanna

The moist savanna biome extends across Angola, Madagascar, Malawi, Mozambique, South Africa and Zambia. Elevation of an environment is the main factor that predetermines the type of moist savanna vegetation found in the region. For example, the vegetation that is found at an elevation of 2200m elevation on the eastern coast is different from the species found in Malawi and Zimbabwe at different elevation. Endemism of the species also varies across latitudes, with endemic species found in narrow bands across Mozambique. The richness of the species is lower for forest species than for savanna woodland. Animals that inhabit the moist savanna biome include elephants, and endemic fauna, such as *Ancylocranium, Chirindia*. The biome is a source of foreign exchange for the regions in which it is located.

1.4.5 Montane

This biome comprises a series of mountains and plateaus which are centered on the shores of Lake Malawi/Nyasa. It is characterized by dominance of trees which include *Brachystegia sp, Isoberlinia sp,* and *Julbernardia sp*; which are endemic to the region. The general climate pattern in this biome is largely influenced by Lake Nyasa from which winds carry moisture. Rainfall in this biome results from surface convection off Lake Malawi and the Indian Ocean, and it is largely confined to the wet season (November – April). However, light rains are experienced at higher altitudes during the dry season (May – August). The montane biome is important for its aesthetics and cultural value.

1.4.6 Semi desert

The semi-desert biome, a part of the larger Kalahari Desert, extends across Angola, Botswana, Namibia, South Africa and Zimbabwe. It covers about 900,000 square kilometers and supports both animal and flora because it is in fact a pseudo desert. It experiences little amount of rainfall and very high summer temperatures. It is a very rich in wildlife species and has one flowing permanent flowing water body (i.e. the Okavango River). Both savanna grasses (e.g. *Aristida sp* and *Schmidita sp*) and trees (mostly *Acacia spp*) are found here. The semi-desert is important because it is home to various biological resources for humans.

1.4.7 Temperate grassland

This biome is regarded to as one of the biggest biomes in South Africa, cutting across many of the provinces in the region. It consists of mostly indigenous species which are very diverse. More than 40 freshwater ecosystems in South Africa fall into this biome, and thus it plays a crucial role in water production for the region. It serves as a rain water storage basin, providing water for the running of Highveld power stations, which generate more than 50% of hydroelectric power in South Africa in the country (Brown *et al*., 2015). The biome is also home to many threatened birds and flora, such as arum lilies, and aloes among many others. In addition, the biome also serve as food source for millions of cattle found in South Africa (Brown *et al*., 2015). Three World Heritage Sites have been established in this biome in recognition of its value and importance.

1.4.8 Tropical forest

The tropical forest biome is located in Madagascar and on the border of Malawi and Zimbabwe. It is made up of vegetation that is characterized by having five layers, namely: overstory, canopy, understory, shrubs and forest floors. Every layer has its own unique attributes and is inhabited by its own unique species of plants and animals, which are mostly endemic to the region. For example, in Madagascar, the tropical forest biome is home to about 50 *Lemur spp*, Herrings, and SeaCatfish, which are among the most threatened animals on Earth (WWF, 2001, Street & Prinsloo, 2013). The biome is regarded to as the 'mother of all biomes" because of its richness in mineral nutrient and biological diversity. It is also described as a major sink of carbon dioxide because of the large concentration of sequestered carbon found in the biome.

Given the socio-economic importance of southern African vegetation, it is crucial to understand the environmental factors that influence the characteristics and distribution of the vegetation in past and future climates. Such an understanding will be helpful guide for sustainably optimizing the socio-economic benefits of the vegetation.

1.5 Factors influencing vegetation

The location and growth of vegetation types can be influenced by a combination of environmental conditions such as organisms, topography, soil parent materials, humans and fire and climate (CNVC, 2013). Brief descriptions of how these environmental factors influence vegetation are given below:

1.5.1 Organisms

These include plants which are the primary organism, as well as animals, fungi and microorganisms. Their influence results in the development of vegetation through several interspecies and habitat relationships. They help in soil formation thus, contributing to humus production by degrading and breaking down organic matter. Humus is very important for the growth of vegetation because is acts as a gluing agent.

1.5.2 Topography

This includes features such as altitudes and slope. Topographic features determine the movement of surface and underground water, the availability of moisture and nutrients, and the creation of microclimates such as aspects and cold air drainage among others. Topographic features also affect vegetation development through temperature effects.

1.5.3 Soil parent materials

These are the materials from which vegetation grow; they include decomposed rocks and other materials that may have been transported and deposited by wind, water or ice. The chemical properties of vegetation are pre-determined by the soil materials from which that they grow. Soil parent materials also have an important primarily influence on the moisture levels and nutrients conditions of the substrates on which plants grow.

1.5.4 Humans and Fire

Humans significantly influence the development of vegetation in a region. One obvious way in which they do this is by means of ‘slash and burn’ method, perhaps for the planting of food crops or for developing housing. While fire is a natural features in the development of vegetation, it may have a negative impact on growth if done artificially or too frequently. This is because humans may burn a plantation either too early or too late. When done too early, it will affect the growth of young plant seedlings and may even destroy the roots; and when done too late, it affects the translocation of food manufactured in the leaves to other parts of the plants.

1.5.5 Climate

This has a primary influence on all the flora (i.e. the plants that make up vegetation). Climate determines the types of vegetation found in a region. For instance, regions of heavy rainfall are associated with forests, while regions of low rainfall induce desert vegetation. Moreover, the influence of climate on vegetation is expressed either in the form of macro-climates or microclimates. Macroclimates are climatic forces acting over a large area such as a country or even a continent, while microclimates occur over an area with fairly uniform conditions that are influenced by the movement of air masses over the earth within certain parameters that characterize specific locations with a geographical scale from $1m^2$ - $100m^2$. The major climatic variables that influence vegetation are precipitation, temperature, precipitation, relative humidity, wind speed and solar radiation (Obi, 2014).

1.6 Climate of Southern Africa

Southern Africa, situated between the Atlantic Ocean and the Indian Ocean, has high pressure zones towards the west and the east (Ker, 1978). The region experiences uneven rainfall distribution and frequent droughts. It has two distinct seasons, namely, the wet and the dry seasons. The wet season occurs when the Inter-Tropical Convergence Zone (ITCZ) moves to the south thus, bringing rainfall. The dry season occurs when the ITCZ moves northward.

The southern African climate is largely influenced by the ocean. Along the east coast, the southward-flowing Mozambique current brings warm water and humid air from the equator thereby creating a warm and humid climate. Conversely, the west coast is influenced by the cold

Benguela current from the Atlantic Ocean, which produces a drier climate. The heaviest and largest amount of rainfall is produced in the interior part of the country i.e. Swaziland and Lesotho. This is because of their high altitude and their exposure to moist air from the Indian Ocean, which creates a strong rainfall gradient from east to west. The amount of rainfall decreases westward, with low and variable rainfall over the central and western regions, which are a semi-arid area. Rainfall in the southern and western parts of South Africa, which experience winter rainfall as part of a temperate climate, is influenced by maritime conditions (Figure 1.3). The interior part of the region experiences rainfall mainly in the summer season in the form of thunderstorms. In the interior part, temperatures also vary with altitudes and continental location. Winters are usually dry and sunny while summers are wet and hot. Furthermore, in areas such as Tanzania and Zimbabwe where the rainy season is influenced by the ITCZ, the 'Botswana High' pressure system sometimes pushes the ITCZ away thus causing drought. Apart from the ITCZ, the other wind systems in the region are the Sub-Tropical Eastern Continental Moist Maritime System, which causes regular cyclones, and the Southeasterly Wind System, which brings rainfall from the Indian Ocean.

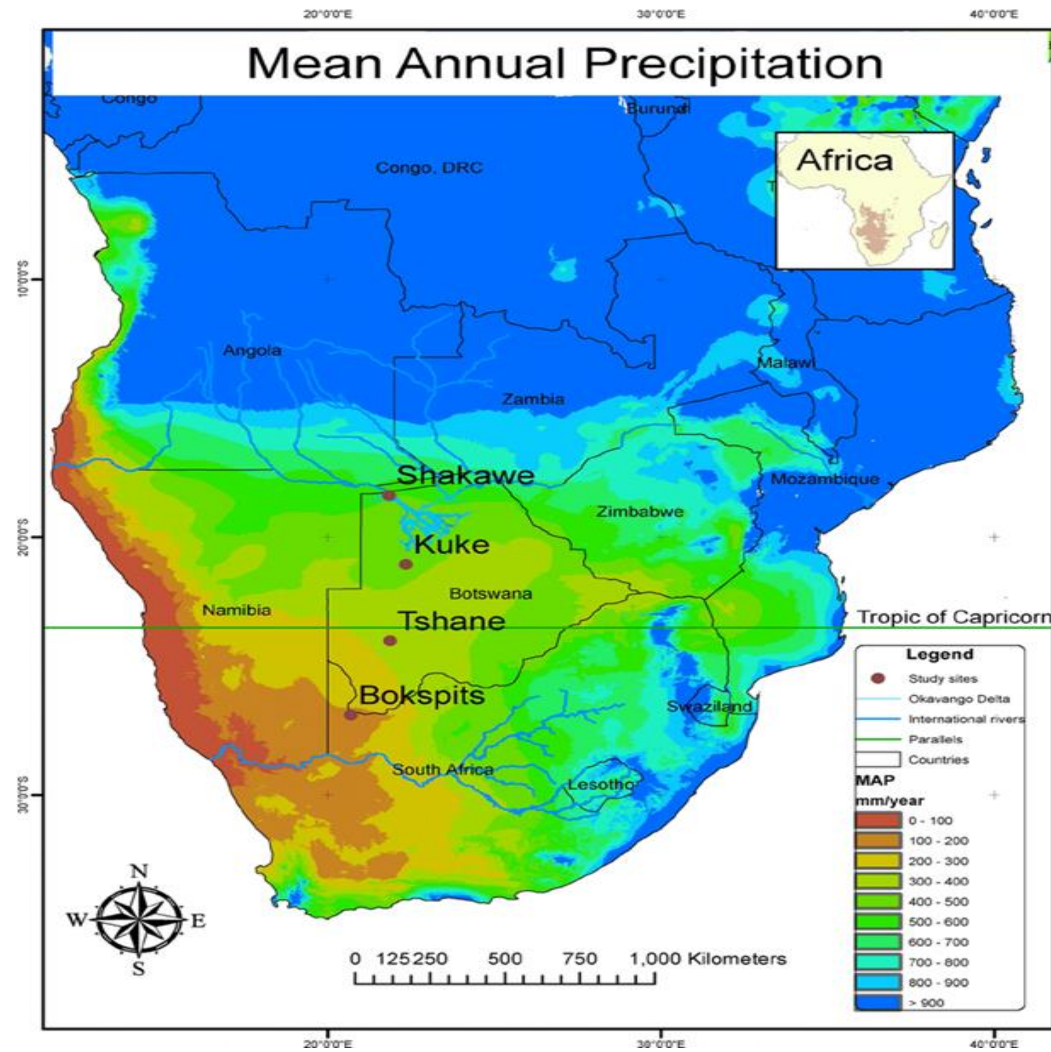

Figure 1.3. Mean annual precipitation in southern Africa (Source: Hijmans *et al., 2005*)

The conditions associated with the austral summer season in the region include the Kalahari Heat Low, the Angola Low, the South Atlantic High (SAH) over western Namibia and South Indian High (SIOH) over eastern Mozambique (Figure 1.4) (Nicholson, 2013). Two other important features of the southern African climate are the Tropical Temperate Trough (TTT), which brings moisture from the tropics to the mid-latitudes and the Limpopo Valley Thermal Trough, which acts as a modulator between the east and west coasts of the sub continents (Kruger, 2004b).

Orography also plays a key role in regulating the southern African climate. It causes a rain shadow over the mountains due to elevation uplifts of the airflow. This brings rainfall to the windward side of the mountain and a scarcity of rainfall on the leeward side (Nicholson, 2011). The Drakensberg

Mountains in Lesotho brings as much as 1400 mm annual rainfall to some locations while other locations that experience lesser rainfall are an example of the role of orography in regulating the southern African climate (Nel, 2005).

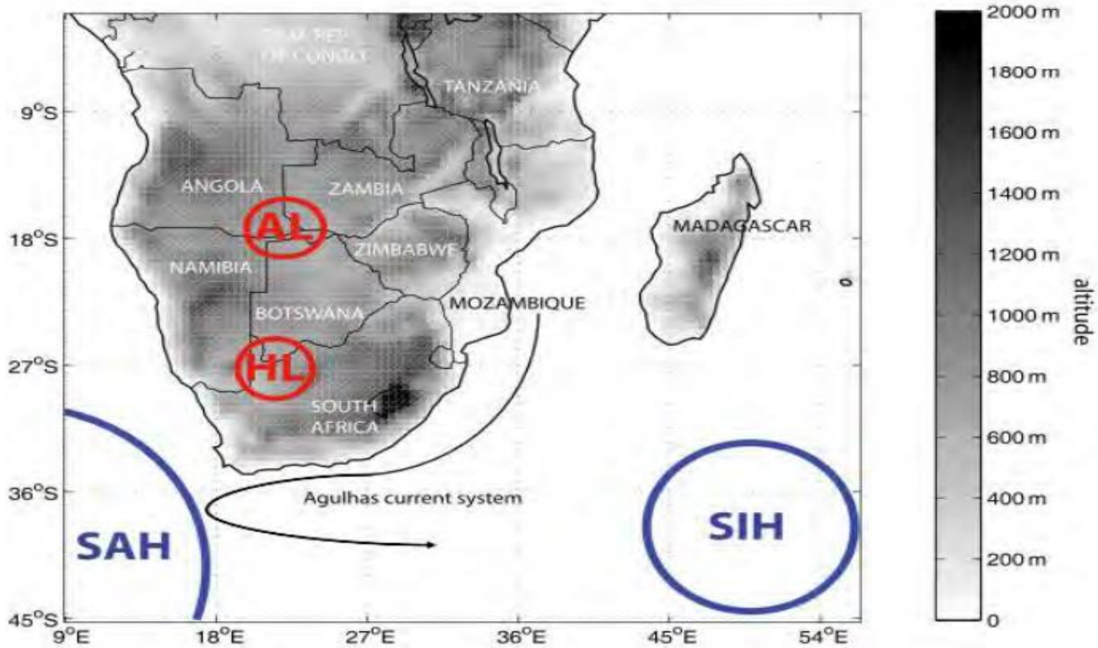

Figure 1.4. Major austral summer synoptic patterns over southern Africa (Source: Macron *et al*., 2014)

1.7 Vegetation-Climate interactions

The interactions between vegetation and climate are two-way. On the one hand, the climate of a region determines the distribution of natural vegetation that grows in that location (Mucina & Rutherford, 2006). For example, forests are found in areas that have between 300 mm to 2000 mm of rainfall, and a temperature of -12 to 30^{0}C. Thus, the distribution of vegetation in a particular location (e.g. southern Africa) is a product of all the climate factors (Kruger, 2004b). On the other hand, vegetation also regulates climate just as its growth is influenced by the climate (Woodward, 1987). One way in which the climate is regulated by vegetation is through the creation of a 'microclimate', which is caused and controlled by the biophysical properties of vegetation such as evapotranspiration, soil moisture content and surface albedo (Adams, 1997; Richard & Poccard, 1998). A combination of microclimates results in a larger climates. Furthermore, the land surface cover and the type of vegetation also affects the net energy balance through the changes to soil moisture, latent heat and sensible heat, among others; these then influence atmospheric temperature and moisture (Zhao and Jack, 2014; Mahmood *et al*., 2014).

1.8 Research rationale

The socio-economic and ecological importance of vegetation in southern Africa is enormous, as discussed in the previous sections (see Sections 1.3 and 1.4). However, the ability of such vegetation to continue be of value is greatly influenced by climate variability and climate change, which are significant in the region (see Sections 1.5, 1.6 and 1.7). One prominent climate event in the region is the incessant drought. In spite of the vegetation-climate interactions in the region, however, there is a dearth of studies and research on how southern African vegetation is affected by climate variability and change. There is thus a need to study the response of southern African vegetation to droughts both in the past and in the future. The results of such a study will help to identify which southern African biomes are the most susceptible to climate variability and change, as well as the time period it may take for such changes to occur.

1.9 Aim and objectives

The goal of the present study is to investigate the response of southern African vegetation to drought in past and future climates. The specific objectives are:

- To examine the observed response of southern African vegetation to drought;
- To assess the performance of the Dynamic Global Vegetation Models (DGVMs) in simulating the response of vegetation to drought in southern Africa;
- To examine the performance of the Community Earth System Models (CESM) in simulating the response of vegetation to drought in southern Africa;
- To investigate the response of vegetation fluxes to climate change at 1.5^{o}C and 2.0^{o}C global warming levels (GWLs).

1.10 Thesis outline

The thesis is divided into eight chapters. The present chapter (Chapter 1) introduces the general concepts and classifications pertaining to vegetation, the distribution of natural vegetation in southern African vegetation and its socioeconomic importance, the climate of southern Africa and, lastly, vegetation-climate interaction during droughts. The general aim and specific objectives of the research, as well as research rationale, are also presented in this chapter.

Chapter 2 reviews the literature relating to the quantification, monitoring and prediction of drought; and the use of vegetation indexes. It also describes the modelling efforts that are aimed at understanding droughts and vegetation, and it provides an insight into vegetation in the semi-arid region of southern Africa. The literature review also discusses the impacts of climate and climate change on southern African terrestrial vegetation. In addition, it reviews the relationship between precipitation and carbon fluxes in a semi-arid environment.

Chapter 3 highlights the study areas that were considered for this particular study. It provides details of the models used in the study. It also describes the datasets and the methodology applied in achieving the objectives.

Chapter 4 presents the results in respect of the observed response of southern African vegetation to drought. It looks at the spatial distribution of the observed climate and vegetation variables across southern Africa, and at the annual cycle of climate variables and vegetation index. It also discusses the spatial and seasonal distribution of the observed response.

Chapter 5 evaluates the performance of DGVMs in simulating the response of vegetation to drought in southern Africa. The chapter evaluates these models in terms of their performance in reproducing the vegetation index, the response of vegetation and the corresponding timescale of such responses. It also examines, by means of simulation, the influence of fire on vegetation in southern Africa.

Chapter 6 present the results on the performance of the ensemble members of the Community Earth System Model (CESM) in simulating the response of vegetation to drought in southern

Africa, specifically with regard to precipitation, temperature and vegetation. The chapter then gives the results of the model on vegetation response to drought.

Chapter 7 discusses how climate change influences the changes in drought indexes and how these changes contribute to the changes in vegetation in southern Africa. It also examines how southern African vegetation fluxes are likely to respond to climate change at 1.5ºC and 2ºC GWLs. The chapter also provides the results of agreement among the ensemble members in the projections of vegetation response under GWLs across the southern African biomes.

Finally, Chapter 8 summarizes the findings of the study and presents concluding remarks. It also makes certain recommendations and sets out the limitations of the current study.

Chapter 2: Literature Review

This chapter reviews the relevant literature on commonly used proxies for quantifying vegetation characteristics and it looks at uniqueness of the southern African vegetation. It also reviews previous studies on the impacts of climate variability and climate change on vegetation in southern Africa, as well as on droughts characteristics and on the simulation of vegetation fluxes. Lastly, it looks at the classification of vegetation into biomes.

2.1 Assessment of vegetation characteristics

Previous studies have employed various proxies to describe the characteristics of vegetation in different parts of the world (Beer *et al*., 2010; Abdi *et al*., 2014; Li *et al*., 2014; Williams *et al*., 2014; Chu *et al*., 2015). For instance, Abdi *et al*. (2014) showed that net primary production (NPP) is suitable for estimating the amount of food exchange as well as the vulnerability of an ecosystem, while Williams *et al*. (2014) found that the gross primary production (GPP) is linearly correlated with biomass of vegetation. Nevertheless, these studies did not take into account the factors that affect these proxies. The use of a proxy depends on the vegetation characteristics under consideration. While some proxies are able to describe only one vegetation characteristic (Pan *et al*., 2014), others can describe more than one vegetation characteristics. This section examines how past studies have used some of the proxies to assess characteristics of the vegetation.

2.1.1 Normalized Difference Vegetation index (NDVI)

The Normalized Difference Vegetation Index (NDVI), defined as the normalized ratio of near infrared and red bands (Rouse *et al*., 1974), is one of the earliest and most widely used proxies for characterizing various aspects of vegetation. Several studies (e.g. Myeni & Williams, 1994; Koide *et al*., 1998; Telesca *et al*., 2006) have shown that the NDVI may be used to estimate vegetation biomass, greenness, primary production, leaf area index and fraction of absorbed photosynthetically active radiation. Huete *et al.* (2002) indicated that the NDVI is good for measuring vegetation because it is sufficiently stable to permit comparisons of seasonal and inter-annual changes in vegetation growth and activity. Hence, the NDVI is one of the proxies used in the present study to investigate response of vegetation to drought. Other studies (Maskova *et al*., 2008; Verhulst & Govaerts, 2010) have shown, however, that the NDVI is limited by its inherent non-linearity and also, that it is influenced by additive noise effects such as atmospheric path radiances.

2.1.2 Net Primary Production (NPP)

Several studies have defined Net Primary Production (NPP) as the amount of plant uptake minus plant respiration. It has been identified as a proxy for estimating more than one characteristic of vegetation. For instance, Pan *et al* (2014) used it to determine the net carbon captured by plants (via photosynthesis) and to evaluate biospheric properties such as fiber, wood productions and food (Pan *et al.*, 2014). Chapin *et al* (2006) showed that NPP can be used to estimate food from plants, because the largest portion of food comes from NPP. Other studies (Melillo *et al.*, 1993; Running *et al.*, 2004 & Shvidenko *et al*. 2008; Zhao and Running, 2006; Pan *et al.*, 2014) have reported that the NPP is also an indicator of ecosystem health and services and thus of a crucial component of the carbon cycle. Nevertheless, NPP is reported to be limited by abiotic components such as temperature and moisture (Tait & Schiel, 2014). While some these of studies have estimated the global NPP to be between 39.9 $PgCyr^{-1}$ and 56.4 $PgCyr^{-1}$ and projected a future reduction in the global NPP due to global warming, there have thus far been no studies showing how NPP across southern Africa may change in the future. For the purposes of this study, however, NPP is a helpful proxy in quantifying the impact of climate change on vegetation in southern Africa.

2.1.3 Gross Primary Production (GPP)

The Gross Primary Production (GPP) has been widely used to estimate the carbon flow in an ecosystem, but with different definitions. For example, while Clark *et al*. (2001) defined GPP as the total carbon retained in a vegetation before autotrophic respiration, Ma *et al*. (2015) describes it as the largest CO_2 flux of the carbon cycle in the terrestrial ecosystems. Various studies have shown that GPP, varies across biomes (with the forest biome having the largest GPP accumulation, viz 48%), that is sensitive to climate change, and that it may thus increase with the global warming. Hence, GPP is one of the proxies used in the present study.

2.1.4 Net Ecosystem Production (NEP)

The Net Ecosystem Production (NEP) is described as the net plant uptake minus the respiration of plants (Pregistzer & Euskirchen, 2004). The use of NEP for evaluating the amount of organic components in a vegetation is well documented in the literature. For example, Fisher *et al*. (2014) used NEP to quantify the accumulation of organic matter fixed by photosynthesis in an ecosystem, and to quantify total ecosystem production. NEP has also been used to assess the organic carbon that is either available for storage or lost from an ecosystem by non-biological oxidation (Lovett *et al*.; 2015). Xiao *et al*., (1998) showed that the forest biome accumulates the largest NEP in the terrestrial biosphere. Climate change is expected to have an impact on global NEP. Boris *et al*. (2010) and Xu *et al*. (2017) found an upward trend in NEP as warming increases. It is projected that there will be a more significant increase in NEP in the northern middle to high latitudes than in other regions as warming increases. This increase in NEP is due to slow decomposition rates of soil organic matter (Prinn *et al*., 1998). Veroustrate *et al* (2002) reported that NEP is limited by temperature and water. The present study focused on the use of NEP over southern Africa.

Other less commonly used proxies for assessing vegetation characteristics in the literature include Net Biome Production (NBP) (Kirschbaum *et al*., 2001; Fisher *et al*., 2014) and Net Ecosystem Exchange (NEE) (Steffen *et al*., 1998; Aubinet *et al*., 2000). For instance, Kirschbaum *et al*. (2001) used NBP to evaluate the net production of organic matter after losses from the decomposition of organic matter, fire, harvesting and land use change while Verlinden *et al*. (2000) used NEE to assess the net CO2 from the ecosystem to the atmosphere.

All of these proxies have been used to study the response of vegetation to climate variability and change. For instance, Chu *et al*. (2015) used NPP to study the influence of climate on an ecosystem, and thus recommends NPP for monitoring the impacts of climate change on vegetation. Li *et al* (2014) used the NDVI to assess dynamic changes in regional vegetation dynamic changes as a result of increasing temperature. However, most of these studies have used these proxies in isolation. Given that some of these proxies measure different characteristics of vegetation, and given that some use different definitions to quantify the same vegetation characteristics, they may have different sensitivities to climate variability and change. Hence, in order to ensure more robust results, the present study has utilized all of the (four) proxies identified in this section to assess the response of vegetation to climate in southern Africa.

2.2 Characteristics of southern African vegetation

The characteristics of southern African vegetation are well documented in the literature. A general description of each type of southern African vegetation is given Chapter 1 (Section 1.4), while a comprehensive descriptions of the vegetation types are contained in Chapter 1 (Sections 1.1, 1.2, 1.3 and 1.5). This section focuses on the characteristics that, according to previous studies, make southern African vegetation unique. However, this uniqueness varies according to the specific location of the vegetation (Driver *et al*., 2011).

2.2.1 Tolerance to water scarcity

Many studies agree that the southern African vegetation have well developed morphological and physiological features that enable them to survive in the semi-arid soils, where water is scarce water. Cowling *et al.* (1997) indicate that Mediterranean vegetation consists of fine-leaved bush which are acclimatized to Mediterranean-type climates and thus, able them to survive on only winter rainfall. Moreover, such fine-leaved bush are well adapted to surviving on low-nutrients substrate/soils. Watkeys (1999) also reported that the root structure of vegetation in the semi desert biome is well suited for shallow and lime-rich soils. Scholes (1997) reported that the vegetation in dry and moist savanna is suited to surviving mostly on water received during the short moist season. However, there is a dearth of information on the degree to which such vegetation can tolerate drought. West *et al*. (2012) showed that the Mediterranean vegetation does have some degree of resilience to drought, while Hoffman *et al*. (2009) indicated that the semi desert biome exhibits resistance to drought. The present study will examine how different levels of global warming may induce drought, which may can stress the vegetation beyond their tolerance level.

2.2.2 Fire tolerance

The tolerance of southern African vegetation to fire has been documented in numerous studies. Fire is a major factor that drives the eco physiological processes of the vegetation, playing a crucial role in determining species composition in a biome (Rutherford and Westfall, 1984; Low &

Rebelo, 1996). Cowling and Hilton-Taylor (1994) reported that the southern African vegetation have unique stem and leaf structures, which allow them to survive fire outbreaks - a frequent occurrence in southern African biomes. For instance, the leaves of temperate grassland vegetation are highly regenerative; this is an adaptive characteristic that species use to survive frequent fire outbreaks. Fire is a common phenomenon and part of the growth process of southern African vegetation; its role is less prominent in the dry and moist savanna biomes, and more prominent in the temperate grassland, savanna and Mediterranean regions (Scheiter *et al*., 2012). Goldammer (2015) noted, however, that the capacity of southern African biomes to tolerate fire might decrease as global warming increases. The sensitivity of the land model (CLM) to fire was thus also investigated in this study.

2.2.3 Plant mobility

Several studies agree that southern African vegetation exhibits different rates of mobility, and that plant mobility differs according to the various biomes. Williams *et al* (2004) reported that proteas which are a Mediterranean species, have a shorter mobility range than other species within the same biome. Cowling *et al*. (1997) showed that the forest biome has a shorter mobility range than do the other southern African biomes. The shorter the mobility range of a vegetation type, the more vulnerable it becomes, as warming increases. In addition, such species are likely suffer from the invasive alien species, which are usually better competitors for growth resources (Macdonald, 1994). Although it remains unclear how the mobility of southern African vegetation might change due to climate change, this issue is not explored in the present study.

2.2.4 Endemism

Southern African vegetation types are reportedly characterized by mostly endemic flora (Scholes *et al*., 1999). The region has been identified as having one of the largest endemic flora in the world (Cowling & Hilton-Taylor, 1994). Russel (1987) found that, of all the Mediterranean vegetation in southern Africa, there are more than 5,780 endemic species, covering an area of 600, 000 square kilometres. In addition, it is estimated that more than 40% of the flora and the majority of the fauna in the semi desert biome are endemic (Vernon, 1999). The enabling climate of southern Africa has been identified as the reason for the high degree of endemism of the vegetation (Cowling *et al*., 1999). However, there is little information on how these vegetation might respond to drought which is expected to increase in the region due to increase warming (Glantz *et al*., 1997). The present study will thus investigate the response of southern African biomes to drought.

2.3 Impacts of climate variability and change on vegetation in southern Africa

Many studies have documented the impacts of climate variability on vegetation in southern Africa. For instance, Ahlstrom *et al.* (2015) noted that there is a positive linear relationship between precipitation and southern African vegetation. It is reported that an increase in precipitation results in a carbon sink for the southern Africa vegetation and vice versa (Poulter *et al.*, 2014). Rowhani *et al*. (2011) reported that the NPP of vegetation in southern Africa is directly linked to rainfall variability. Richard and Poccard (1998) and Chamaille-Jammes *et al*., (2006) also showed that the seasonality of southern vegetation production follows the regional seasonal patterns of precipitation. Variability in temperature also affects the seasonal productivity of vegetation in these southern African biomes (Thornton *et al*., 2011). However, there is little information on how the different biomes might respond to extreme climate variability (like drought). The present study thus examines the response of southern African biomes to droughts in different seasons.

The impacts of climate change on southern African vegetation are well reported in the literature (MA, 2005a; IISD, 2009). Allen *et al.,* (2010) reported that the current die-back of vegetation in the region is the result of changes in temperature and rainfall regimes. Phillips *et al.* (2009) even suggested that this has contributed to a decline in above-ground biomass. Warburton and Schulze (2006) posited that climate change will alter wood and timber production in the region. In addition, it is documented that warming will affect the hydrological cycling in vegetation (Shaver *et al*., 1998). Wan *et al*. (2002) noted that warming leads to increases in evapotranspiration and drying of soil, and thus also to increased stress on vegetation. Heubes *et al* (2012) reported that climate change will lead to biome shifts, threaten biodiversity and reduce the capacity of vegetation to produce food. Furthermore, it is noted that warming will affect plants' phenology, seasonal production and behavioral patterns of plants. For example, Peterjohn *et al*. (1993) and Price and Waser (1998) reported that the flowering time of herbaceous plants might be shortened in response to warming. Nemani *et al*. (2003) also reported that the lengthening of the growing season in the spring and/or later in the autumn was increasing the NPP of plants. Rutherford *et al*. (1999) reported that the existing biomes would shift eastwards becoming more prominent in the eastern part of the region due to warming. It is expected that the southern African biomes will respond differently to climate change. Rutherford *et al*. (1999) reported that the vegetation in the semi desert biome might be the least affected because of their tolerance for hotter and drier land surfaces. However, there is a dearth of studies on the projected impacts of climate change on southern African vegetation at specific warming levels. Consequently, the present study investigates the impacts of climate change on vegetation fluxes in southern Africa at 1.5ºC and 2.0ºC GWLs.

2.4 The description of droughts

Several studies (Palmer, 1965; Tate & Gustard, 2000) have shown that drought can best be described based on the sector or region under focus. For instance, in the agricultural sector, drought is described as the scarcity of water for plant uptake. In hydrology, it is defined as a "period of abnormally dry weather sufficiently prolonged for the lack of precipitation to cause serious hydrological imbalance, carrying connotations of a moisture deficiency with respect to man's usage of water" (McMahon & Diaz Arenas, 1982). In meteorology, drought is defined as a "recurring extreme climate event over land characterized by below-normal precipitation over a period of months to years" (Dai, 2011). However, there is no yet agreed threshold for precipitation, beneath which drought can be said to have occurred in a region (Botterill & Cockfield, 2013). For example, McGuire and Palmer, (1957) noted that drought is sometimes reported to have occurred when the monthly or annual precipitation is less than a particular percentage of normal precipitation for that area. White (1955) stated that drought may be said to have to have occurred when precipitation is insufficient to meet the needs of established human activities.

2.4.1 Types of drought and their impacts

Five types of droughts have been identified and discussed in the literature, namely: meteorological or climatological, agricultural, hydrological, socioeconomic and most recently, ecological droughts (see Figure 2.1; NDMC, University of Nebraska-Lincoln). Meteorological drought is described as the primary form of drought and it culminates in other types of drought over a prolonged period of time (Lake, 2011). Consequently, the impacts of meteorological drought on the different sectors result in the other types of impact, which are illustrated in Figure 2.1 (Fig 2.1; NDMC, University of Nebraska-Lincoln).

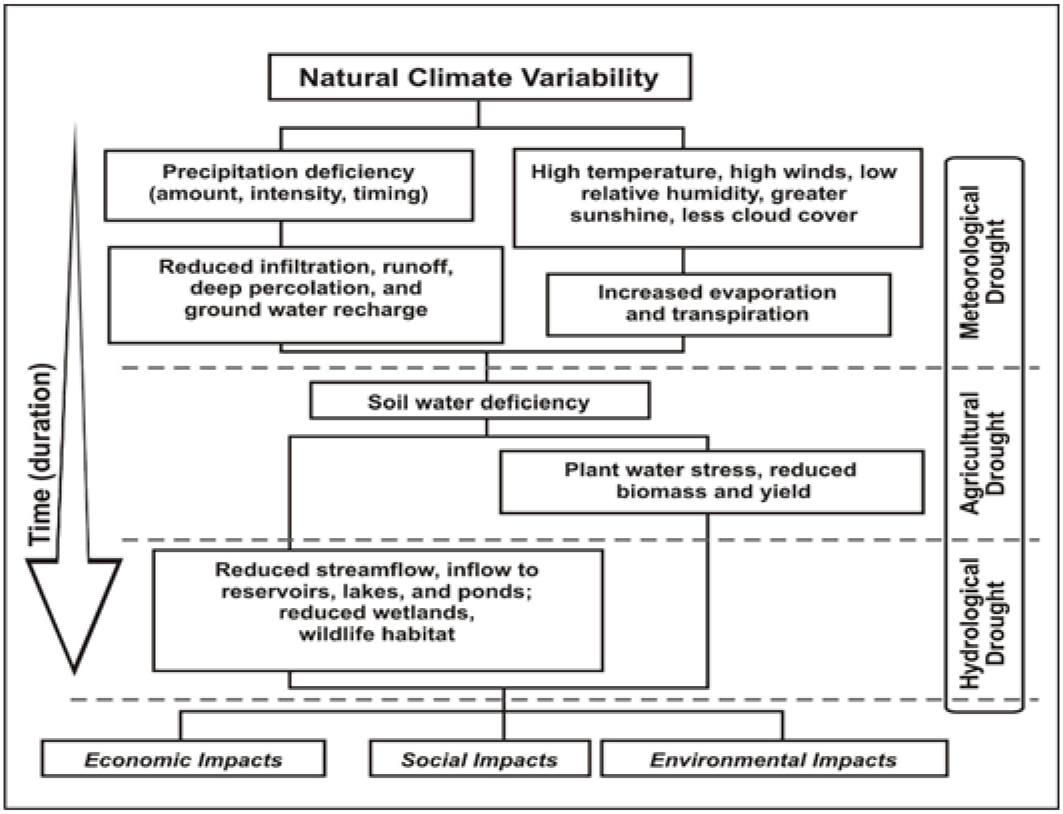

Figure 2.1. Sequence of drought occurrence and impacts for commonly accepted drought types (Source: National Drought Mitigation Center, University of Nebraska-Lincoln, USA).

2.4.1.1 Meteorological or climatological drought

Meteorological drought is reported to occur when the precipitation of a region during a particular period is lower than the average precipitation of same region over a long period of time (Wilhite & Glantz, 1985; Moneo & Iglesias, 2004; AMS, 2016). Wilhite and Glantz (1985) also noted that meteorological drought is region specific because the atmospheric conditions that cause precipitation deficiencies vary from one place to another. For instance, meteorological drought in a tropical climate region (such as Brazil) will be defined according to the number of days with precipitation less than certain specific threshold (AMS, 2016).

2.4.1.2 Agricultural drought

It is well documented that agricultural drought stems from the impacts of various factors such as rainfall deficits, soil water deficits, and reduced groundwater or reservoir levels on agriculture (NWS, 2017). Certain factors have been identified as being responsible for the development of agricultural drought; they include decreases in precipitation, increases in evaporation and transpiration, deficits topsoil and subsurface moisture deficits and reduced groundwater and reservoir levels (WeatherSTEM, 2017). Beaudry (2017) noted that while agricultural drought often occurs when precipitation is low, it sometimes occurs when the periods of average precipitation provides less water than the soil requires. NDMC (2017) reported that agricultural drought causes the failure of crops during different stages of their development, i.e. from emergence to maturity. Depending on the strength of drought, crops may recover or they may be permanently damaged (Manuel, 2008).

2.4.1.3 Hydrological drought

Hydrological drought is reported to occur when there is a precipitation shortfall in the surface or subsurface supply (Tallaksen & van Lanen, 2004). It is also defined as a regionally extensive occurrence of below average natural water availability (Tallaksen & van Lanen, 2004). Wilhite and Glantz (1985) showed that the intensity and frequency of hydrological drought often depends on a river basin scale. Hydrological drought is described to be more complex than meteorological drought because of its impacts on the properties of river basins such as topography and geology, among numerous others. Hydrological drought moreover occurs over extended periods and thus, requires longer periods of recovery (eXtension, 2017). Van Loon (2015) noted that there are several processes that aid both the development and the dissipation of hydrological drought. These include temperature anomalies, such as freezing conditions in winter and low temperatures in summer, atmospheric anomalies, and increased evapotranspiration due to radiation.

2.4.1.4 Socioeconomic drought

Socioeconomic drought is identified as the type of drought that stems from the impacts of meteorological, agricultural or hydrological drought on the supply and demand of economic goods such as fruits, forage, hydroelectric power or vegetables (Wilhite & Glantz, 1985). Moneo and

Iglesias (2004) defined socioeconomic drought as a weather-related deficit in water supply which causes the demand for economic goods to exceed the supply. DroughtFact (2017) found that the factors that are used to assess socioeconomic drought include the severity of crop failures, water and fodder requirements, human and animal population growth rates, industry types and water requirements.

2.4.1.5 Ecological drought

One major shortcoming of the previously discussed drought types is that they have mostly emphasized impacts on humans, without addressing how drought affects vegetation and ecosystems such as the drying up of tree stems. Crausbay *et al*. (2017) argued that the rapidly growing human population, coupled with anthropogenic climate change, has increased the pressure on water supplies, which has affected vegetation and indirectly also the human communities that rely on them for critical services. Recent efforts have thus focused on defining a new type of drought that integrates the agricultural, hydrological, socioeconomic aspects of drought; it is called the ecological drought (Crausbay *et al*., 2017). Ecological drought is defined as "a prolonged and widespread deficit in naturally available water supplies – including changes in natural and managed hydrology – that create multiple stresses across ecosystems" (Wilhite & Glantz, 1985). Hence, the emphasis of the present study is on meteorological and ecological forms of drought.

2.4.2 Characteristics of droughts

The characteristics of droughts are well documented in previous studies (e.g. AMS, 2003; Kain *et al*., 2007). The characteristics of drought identified in the literature include:

- Drought Intensity (I): defined as the magnitude of the precipitation, streams and soil moisture deficit and how quickly it forms. Drought intensity is nearly independent of the duration (Woo & Tarhule, 1994); in fact, it is the ratio of drought magnitude to the duration

- Drought Duration (D): defined as a period of time during which there is a precipitation deficit, followed by a period when there is no deficit (Kain *et al*., 2007). A drought may have a duration of months, seasons or years.

- Drought Magnitude (M): defined as the amount of water available for uses; measures the cumulative water deficit below some threshold during drought period (Santos, 2011; Zargar *et al*., 2011).

- Drought Severity(S): defined as the "threshold level below which the flow of groundwater is regarded as being defined in a drought situation" (Kain *et al*., 2007).

- Spatial distribution (or geographic extent): defined as the area coverage (pixel, watershed or region) of the drought and this differs during drought event (Zargar *et al*., 2011).

- Frequency or return period; defined as the average time from one drought event to the other where severity is equal or greater than threshold (Razmhkah, 2016).

2.4.3 Quantification of droughts

Many studies agree that there is a need to quantify how droughts affect a sector, and that a numerical standard is needed for measuring drought intensity and thus comparing droughts across regions. This standard is known as the 'drought index' and it is defined "as an index, which is related to some of the accumulative effects of a prolonged and abnormal moisture deficiency" (WMO, 1992).

Several drought indices have been developed, based on different variables, to quantify the severity of a drought (Webb, *et al.*, 1983). Friedman (1957), for instance, identified five major criteria that a drought index must meet, namely: (a) an appropriate timescale; (b) a quantitative measure of large-scale, long-continuing drought conditions; (c) applicability to solving a specific problem; (d) availability of long, accurate past records; and (e) computability of the index on a near-real-time basis. Vicente-Serrano *et al*. (2015) identified the most commonly used drought indexes, which are discussed in the sections below.

2.4.3.1 Palmer Drought Severity Index (PDSI)

The Palmer Drought Severity Index (PDSI) created by Palmer (1965) is defined as a soil moisture balance that uses precipitation, evapotranspiration and the soil's available water capacity (AWC) as its primary inputs. The evapotranspiration is computed using Thornthwaite's (1948) formula (Dai, 2011). The PDSI is used mostly in the US and is a dimensionless number varying between 4 and -4 (Table 2.1). It calculates fluctuations in moisture balance and water balance terms for two-layer soil models. The PDSI is a forerunner of similar drought indexes, namely, the Palmer Drought Severity Index (WPLM), the Palmer Hydrological Drought Index (PHDI) and the Palmer Z-Index. The PDHI was derived from the PDSI to measure the long-term impacts of drought on hydrological systems (Karl *et al*., 1987), while the Palmer Z-Index was derived to address shorter term deficiencies than those measured by the PDSI. One key limitation of the PDSI is that it has a fixed temporal scale (Alley, 1984; Karl, 1986, Soule, 1992: Akinremi *et al*., 1986); however, drought is a variable-scalar phenomenon because the periods of time from the water shortages to the actual impacts differ. Another limitation is the PDSI's lack of precision, as it treats all precipitation as rainfall; however, snow does not always become available as water (Alley, 1984; Karl, 1986, Soule, 1992: Akinremi *et al*., 1986).

Table 2.1. Classification of drought intensity based on PDSI classification

PDSI	**Drought Intensity**
> 4.0	Extremely wet
3.0 to 3.99	Very wet
2.0 to 2.99	Moderately wet
1.0 to 1.99	Slightly wet
0.5 to 0.99	Incipient wet spell
0.49 to -0.49	Near Normal
-0.5 to -0.99	Incipient dry spell
-1.0 to -1.99	Mild droughts
-2.0 to -2.99	Moderate droughts
-3.0 to -3.99	Severe droughts
< -4.0	Extreme severe drought

Source: Fuchs *et al*. (2014)

2.4.3.2 Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) developed by McKee *et al.* (1993) is a dimensionless index that is computed as the discrete mean precipitation anomaly of transformed data, divided by the standard deviation, with the mean and standard deviation determined from the past records (Agnew, 2000; McKee *et al.*, 1993). The values of the SPI are calculated for multiple timescales (Maliva, 2012). For the SPI, the precipitation data over the long term are fitted into a probability distribution and then transformed into a normal distribution, such that the mean SPI for a region and time period is zero. Drought is said to have occurred when the SPI is -1.0 or less, and to have ended when the SPI is positive (Table 2.2) (Maliva, 2012). The SPI is the accepted reference drought index of the WMO (WMO, 1992). However, a major limitation of this index is that its calculation is based solely on precipitation data: it does not account for other variables that influence drought, and it also requires less data than the PDSI (Maliva, 2012). Despite these limitations, the present study did use the SPI to quantify the impacts of drought on southern African vegetation.

Table 2.2. Drought Classification based on the SPI

SPI	Drought intensity classification
> 2.0	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to 1.49	Moderately dry
-1.5 to -1.99	Severely dry
< -2.0	Extremely dry

Source: Fuchs *et al*. (2014)

2.4.3.3 Standardized Precipitation Evaporation Index (SPEI)

As reported above, one major limitation of the SPI is that it does not account for other variables that play a crucial role in the intensity of drought in a region (Vicente-Serrano, 2012). This is because the SPI assumes that the variability of precipitation is higher than that of other variables, e.g. temperature and potential evapotranspiration (PET), and that other variables do not have a temporal trend (Vicente-Serrano, 2012). However, it is documented that warming-induced drought does have severe impacts on vegetation (Yang & Liu, 2011). Therefore, any drought index that accounts for the roles of other variables in drought intensity would be preferred over the SPI. Although the PDSI accounts for these other variables, it lacks the multi-scalar character necessary for assessing drought in different hydrological systems and for differentiating among drought types (Vicente-Serrano *et al.*, 2010). Thus, the Standardized Precipitation Evapotranspiration Index (SPEI) was developed. The SPEI (Vicente-Serrano, 2012) is based on precipitation (P) and Potential Evapotranspiration (PET). This combines the sensitivity of the PDSI to changes in evaporation demand as a result of temperature fluctuations and trends with the multi-temporal dimension of the SPI. The SPEI has a considerable advantage over other drought indexes. The SPEI is uniquely important because it identifies the role of PET, precipitation and temperature variability for drought assessment within the climate change context (Abdullah, 2014).

The SPEI is calculated based on the climatic water balance, which is the difference between precipitation and PET (Vicente-Serrano, 2012):

$$D = P - PET,$$

where D values are aggregated at various time scales

These timescales range from 1- to 24-month periods. Vicente-Serrano *et al.* (2012) note that, for the 3-month timescale, there are short dry (i.e. negative SPEI values) and humid (i.e. positive SPEI values) conditions, and that these values alternate continuously. Thus, the highly plastic vegetation that is acclimated to high-frequency variability in moisture conditions in drought-vulnerable areas and the vegetation that is not well suited to drought stress are both expected to respond to these short-term droughts differently. Vicente-Serrano *et al.* (2012) further reported that, at a much longer timescale (i.e.12 to 24 months), droughts are less frequent and have a longer duration. The present study also used the SPEI to quantify the impacts of drought on southern African vegetation. Table 2.3 shows drought intensity based on the SPEI scale.

Table 2.3. Classification of drought intensity based on the SPEI scale

SPEI	Drought intensity
2 or more	Extreme wet
1.5 to 1.99	Severe wet
1 to 1.49	Moderate wet
0 to 0.99	Mild wet
0 to -0.99	Mild drought
-1 to -1.49	Moderate drought
-1.5 to -1.99	Severe drought
-2 or less	Extreme drought

Source: Wang *et al*. (2014)

The SPEI has been recommended for use as a key indicator to measure drought severity and duration across regions with different climatic and hydrological conditions (Vicente-Serrano *et al*., 2010). One key feature of the SPEI is the inclusion of PET (McMahon *et al*., 2013). Various methods have been chosen for calculating PET, including the Thornthwaite method, as developed by Thornthwaite (1948); the Hargreaves method developed by Hargreaves and Samani (1985); the Penman-Monteith commonly known as P-M, which is a derivation of Hargreaves, because it uses the Hargreaves radiation term (Allen *et al*., 1998); the Priestley-Taylor method (Priestley & Taylor, 1972); and the FAO-56 Penman-Montieth method, also known as P-M (FAO-56) (Allen *et al*., 1998). The differences in the calculation of the SPEI, using the five methods highlighted above, are shown in Table 2.4 below.

The use of the SPEI to investigate drought characteristics and its impacts in southern Africa is well documented in literature. For instance, Ujenza and Abiodun (2014) found that about 50% variance in the SPEI can be represented with four major drought patterns in the region. The study also found that about 70% of the global climate models (GCMs) simulate SPEI at 3-month timescale. Furthermore, Araujo *et al* (2014) showed that simulated grape yield are sensitive to drought throughout the growing seasons, however, this intensity varies in different months. In addition, Meque and Abiodun (2014), using SPEI, confirmed that there is strong relationship between drought and ENSO over the region. However, none of these studies examined how southern vegetation may be affected by drought, using SPEI as the drought index, hence, the focus of this study.

Table 2.4. Summary of potential evapotranspiration equations

PET Groups	Group 1 Empirical	Group 2 Temp-Proxy Radiation		Group 3 Observed Radiation	
PET Model	Thornthwaite	Hargreaves	P-M	Priestley-Taylor	P-M (FAO56
Mean temp	X	X	X	X	X
Min/Max temp		X	X		
Wind speed			X		X
Surface pressure					X
Specific humidity					X
Radiation	Tmean	Tmax-min	Tmax-min	WFD	WFD

Source: Stagge *et al*. (2014)

Other less popular indexes have been discussed in several other studies (AMS, 2003; Vincente-Serrano *et al*., 2012); they are outlined below:

- The Drought Area Index (DAI), which is described as a recursive index because the successive calculations are dependent on the prior month's values (Bhalme & Mooley, 1980). This index is mostly tailored towards measuring moisture during the summer Indian monsoon during which some areas may receive 75% or more of the annual rainfall (Bhamlme & Mooley, 1980)
- The Rainfall Anomaly Index (RAI), which is reported to incorporates a ranking procedure to designate magnitudes as positive and negative anomalies (van Rooy, 1965)
- The Hydrological Drought Indexes, which are described as total water deficit and cumulative streamflow anomalies (Heim, 2002)
- The Surface Water Supply Index (SWSI) which measures hydrological droughts for regions e.g. the mountainous southwest, where snow contributes significantly to the annual streamflow (Garen, 1992).

2.4.4 Drought in southern Africa

It is well documented that increasing temperatures are affecting the short-term variability of rainfall and, as a result, reducing the availability of rainfall. Recent climate trends in the southern African region (such as in Mozambique) indicate that the warming trend has risen over the last few decades since the 1970s (Figure 2.2). The Intergovernmental Panel on Climate Change (IPCC) (AR5, 2014) reported that surface temperatures in the region have risen by more than 0.5° over the last century. It has further been reported that the frequency of El Niño events has increased in countries such as South Africa and Mozambique since 1980, and that this has led to frequent drought occurrences (Glantz, 1994). Shinoda *et al*. (2010) also reported that droughts are expected to be exacerbated by the effects of climate change in the semi-arid biomes (Shinoda *et al*., 2010). In addition, in southern Africa (e.g. in Madagascar and South Africa), a significant deficit in precipitation has been observed between 1960 and 2004 (Jury *et al*., 2013; South African Weather Service [SAWS], 2016). Furthermore, below-normal rainfall is becoming more frequent (United States Agency for International Development [USAID], 1992), and from 1988 to 1992, more than 15 droughts have been recorded in the region (Glantz *et al*., 1997).

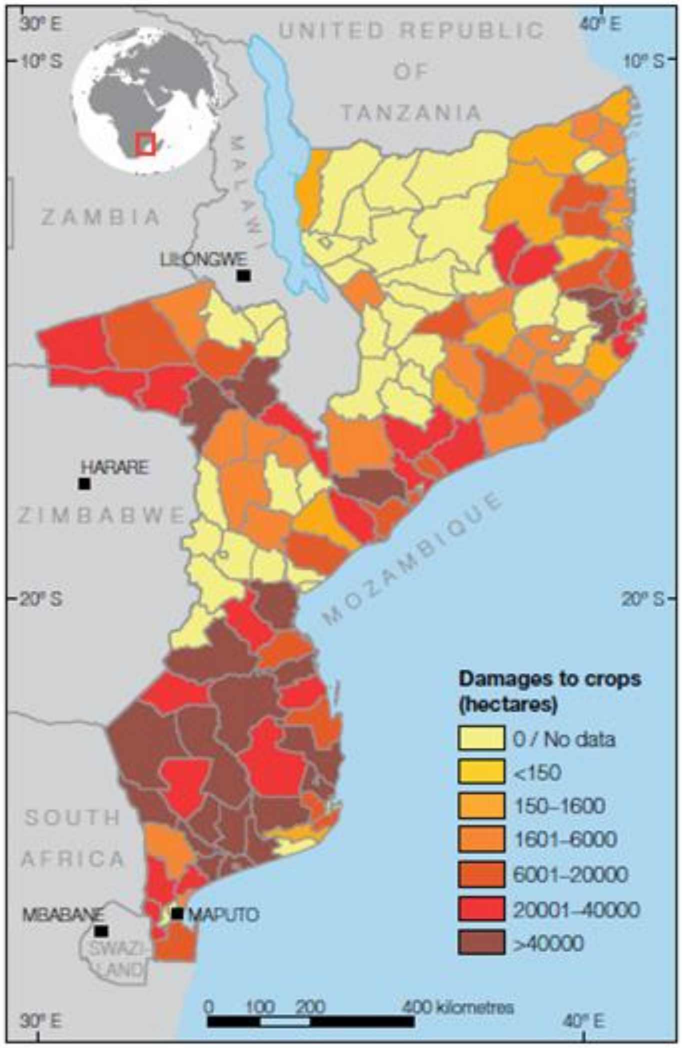

Figure 2.2. Drought-related crop damage in Mozambique, 1990-2009 (Source: Global Assessment Report on Disaster Risk Reduction, 2011).

2.5 Simulating vegetation fluxes

Previous studies have used different methods to quantify carbon fluxes in vegetation. For example, Ryan (1991) used a simple foliage-above-belowground wood empirical relationship to quantify gross carbon budgets in vegetation. Sundarapandian *et al*. (2013) quantified biomass and carbon stock using an allometric equation. Furthermore, carbon bookkeeping models, such as the CO2FIX accounting model, have also been used to quantify carbon fluxes (Schelhaas *et al*., 2004). However, Schelhaas *et al*. (2004) has identified some of the limitations of allometric carbon equations:

- They do not account for the emissions from disturbances and products
- They do not also fully account for the biological processes such as burning or respiration
- They only estimate points/plots of carbon flux and thus, do not account for boundary conditions and
- They fail to account for two-way feedback between climate and vegetation.

Recent studies have shown that terrestrial carbon fluxes are better estimated by means of Dynamic Global Vegetation Models (DGVMs), global climate models (GCMs) and regional climate models (RCMs). For instance, Sitch *et al*. (2008) reported that DGVMs are capable of simulating transient and long-term changes in vegetation characteristics. Meehl *et al.* (2006) also showed that GCMs are able to predict responses of vegetation to climate variation, trend and change. The different models are briefly described in the following sections.

2.5.1 Dynamic Global Vegetation Models (DGVMs)

Numerous studies have used stand-alone Dynamic Global Vegetation Models (DGVMs) to simulate the influence of climate on vegetation (e.g. Heubes *et a*l., 2012; Huntzinger *et al*., 2013). For example Sitch *et al*. (2008) showed that Sheffield Dynamic Global Vegetation Models (SDGVMs), which are standalone biogeochemical and biogeographical models, are capable of simulating the dynamic state and changes of terrestrial vegetation in any location. Furthermore, Friend *et al*. (2007) reported that DGVMs allow for two-way interaction between climate and vegetation, and permit the simulation of biogeochemical processes, such as vegetation and terrestrial ecosystem services, while accounting for future increase in CO_2. Murray *et al*. (2012) noted that DGVMs are suitable for investigating hydrological processes, plant morphology and physiology in different biomes, and for assessing the impacts of climate change on terrestrial ecosystems and their functions, such as nutrient regulation and water regulation. Fisher *et al.* (2012) noted that the Terrestrial Biosphere Model (TBM) is a combination of four simple models, namely:

(a) Plant geography of biography models, which only simulate the spatial distribution of biomes but lack the capacity to account for the biogeochemical cycling of carbon-water-nutrients nexus;

(b) Gap models, otherwise known as vegetation dynamics models, which can only predict the plant succession and behavior within a larger community as well as other ecosystem processes; examples of these models are JABOWA, FORET, HYBRID etc. (Fisher *et al*., 2012). The main limitation of the gap models is their inability to simulate the preservation of the moisture and energy balance. This resulted in the development of the next type of models;

(c) Terrestrial biogeochemistry models, such as BIOME-BGC and CENTURY, which account fully for biogeochemical cycling but do not account for the transfer of moisture between soil and atmosphere;

(d) Biophysics models, which provide a basis for the soil-vegetation-atmosphere transfer (SVAT) mechanisms, otherwise known as fluxes in land surface models (LSMs) or coupled atmospheric global climate models (GCMs).

While there have been studies (e.g. Friend *et al*., 2012; Huntzinger *et al*., 2013) that compared the performance of DGVMs to observation, there is little information on whether DGVMs can correctly simulate the impacts of drought on vegetation. The present study thus examined the capability of three DGVMs to capture the responses of southern African vegetation to drought. The models used were CLM4, CLM4VIC and ORCHIDEE.

2.5.2 General Circulation Models (GCMs)

The capability of GCMs in simulating vegetation fluxes is well documented in the literature. Anderson (2016) showed that GCMs are capable of simulating the interactions between atmosphere and vegetation, such as FPSN and transpiration, among others. Flato (2011) noted that the early versions of the GCMs did not sufficiently capture these interactions, because those models only allowed for one-way interaction between vegetation and atmosphere. However, this limitation has been addressed in the recently developed GCMs (also known as Earth System Models or ESM). Such ESMs incorporate the Dynamic Vegetation Models (DVMs), which are capable of resolving the interaction between biogeochemical processes with physical climate; ESMs also modify its response to climate forcings, such as those associated with human-caused emissions of greenhouse gases (Flato, 2011). A prominent ESM is the Community Earth System Model (CESM). For example, Li *et al.* (2016) showed that, over China, the CESM strongly captures the trends of observed annual mean temperature. In addition, Gadian *et al.* (2018) reported that the CESM replicates observed precipitation changes over Western Europe. Furthermore, Li *et al.* (2017) noted that the CESM captured energy fluxes and modelled fire in the tropical savannas of Australia. However, there is a dearth of studies on the impacts of climate change on vegetation at specific warming levels using the ESM, especially in southern Africa. The present study thus examines the response of southern African vegetation at 1.5°C and 2°C GWLs, using GCM.

2.5.3 Regional Climate Models (RCMs)

Studies have also coupled RCMs with DGVMs to simulate the atmosphere-vegetation interaction at a higher resolution (Notaro *et al*., 2016). The use of RCMs is to address the problem of coarse resolution in typical GCMs, as it limits the capability of the GCM simulation to resolve local scale features and their interactions (Benestad, 2008). Essentially, RCMs address this limitation by downscaling the GCM outputs (Benestad, 2008). Downscaling can be either statistic or dynamic (Benestad, 2008). Wilby *et al*. (2004) described statistical downscaling (SD) as the process of linking large-scale features through the use of advanced statistical methods. Dynamical downscaling (DD) is described as the nesting of a Limited Area Model (LAM) or RCM within GCM (Wilby *et a*l., 2004). However, the present study did not use RCM, because the associated computational demands exceeded the resources available for the study; but this may not substantially affect the results of this study. This is because the main difference between GCMs and RCMs lies mainly in their respective spatial resolutions. The high-resolution of RCM would assist to resolve local-scale atmospheric circulations better than what is obtainable in a low-resolution GCM. However, the focus of the present study is not on local scale features.

2.6 Vegetation classification

The classification of vegetation into separate biomes is well documented in the literature. Early classifications (e.g. Clements 1916; Clements and Shelford, 1939; and 1949; Holdridge, 1947, and 1964) categorized vegetation based on the effects of rainfall and temperature on various life zones. For instance, Holdridge (196747; 1964) classified vegetation into more than 30 life zones across the latitudinal regions and altitudinal belts. However, these classifications failed to account for the influence of soil on vegetation. Other classifications (such as Allee, 1949; Whittaker, 1992, 1970,

1975) have however, revised the classification of biomes based on the influence of soil, moisture and temperature. The present study uses a recent biome classification system that largely takes into accounts the prevailing influence of rainfall and temperature on vegetation growth in southern Africa. Furthermore, the biome classification used in this study also takes into consideration the connectivity between the southern African climate and its vegetation.

Chapter 3: Methodology

This chapter describes the study area (southern Africa), provides detailed information on the datasets used for the study, and explains the methods used in analyzing the datasets. The choice and sequence of the methods is based on the objectives of the study, as outlined in Chapter 1 (Section 1.7).

3.1 Study area

The study area is southern Africa, with an emphasis on southern Africa vegetation (Figure 3.1); this comprises the types of vegetation that fall between Latitudes 10^o and 36^{o}S and Longitudes 9^o and 52^{o}E. The countries in these geographical domains include Angola, Botswana, Lesotho, Madagascar, Malawi, Mozambique, Namibia, South Africa, Swaziland, Zambia and Zimbabwe. The vegetation here ranges from forest to savanna and even desert, as shown in Chapter 1 (Section 1.4), but desert biomes are excluded from the present study. Apart from analyzing the climate and vegetation data in southern Africa, we also analyze the data in each area of the biomes, as shown in Figure 3.1.

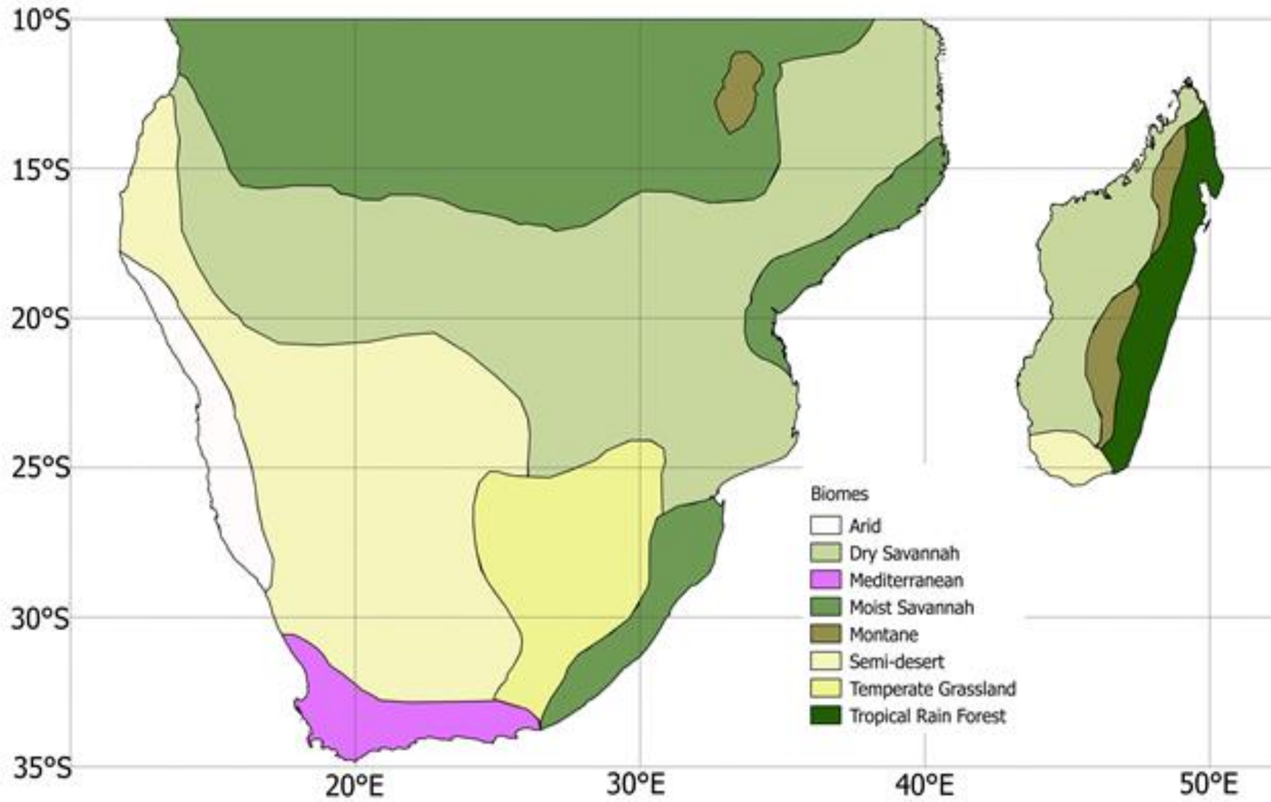

Figure 3.1. Major southern African biomes used (adapted after UNEP, 2008 and Sinclair & Beyers, 2015). The black contours indicate boundaries of the biomes. The vegetation biomes considered in the study are Dry Savanna (DS), Mediterranean (MT), Moist Savanna (MS), Semi-desert (SD), Temperate Grassland (TG) and Tropical Rain Forest (TF). The white patch (arid) indicate that this biome is not analyzed for this study.

3.2 Data

For this study, we analyzed three types of climate and vegetation datasets: observation, reanalysis and model simulations. The datasets are described below.

3.2.1 Observations

3.2.1.1 Climate Research Unit (CRU)

Observed climate datasets were obtained from the Climate Research Unit (CRU TS3.22) (Harris *et al*., 2014; Mitchell & Jones, 2005) at the University of East Anglia. The CRU datasets comprise global monthly observations with a spatial resolution of 0.5^0 x 0.5^0 and cover the period from 1901 to 2015. They include precipitation, mean temperature, and minimum and maximum temperature. The CRU datasets were used to calculate the drought indexes (i.e. SPEI and SPI) for the period 1983 – 2004. The CRU datasets can be freely downloaded from http://badc.nerc.ac.uk/data/cru.

3.2.1.2 Global Inventory Modelling and Mapping Studies (GIMMS)

The observed vegetation dataset – the normalized difference vegetation index (NDVI) - was obtained from the Global Inventory Modelling and Mapping Studies (GIMMS). The GIMMS-NDVI dataset with a spatial resolution of 0.2^0 covers a 25-year period from 1981 to 2006. The product is derived from imagery which was obtained from the Advanced Very High Resolution Radiometer (AVHRR) on board the National Oceanic and Atmospheric Administration (NOAA) Terra satellite (*http://modis.gsfc.nasa.gov/data/dataprod/mod13.php*). The product has been corrected for calibration, view geometry, volcanic aerosols, and other all other effects not related to vegetation change. For more information on the product, see Tucker *et al* (2004). It was freely downloaded from http://glcf/uniacs.umd.edu/data/gimms. The use of the MODIS NDVI was not considered for the study because the products are available later than the GIMMS NDVI datasets.

3.2.2 Reanalysis

The reanalysis dataset used in the study is the CRUNCEP. The product is a combination of two existing datasets: the CRU and the NCEP. The NCEP datasets are globally gridded reanalysis datasets which are joint products of the NCEP and the National Center for Atmospheric Research (NCAR) (Kalnay *et al*., 1996). The NCEP has a temporal and spatial resolutions of 6 hourly and 2.5^0 x 2.5^0 respectively. The reason for merging the two datasets was because of the limitations of CRU and NCEP in terms of temporal and spatial resolutions respectively. On the one hand, CRU has a good spatial resolution which is only available in the monthly mean field, but its temporal resolution is too low for modelling purposes. On the other hand, the NCEP has a temporal resolution of 6 hours, but has a low spatial resolution and, as such, its precipitation outputs are less reliable than the CRU based on station data (*dods, 2015*). Thus, the CRUNCEP has a spatial resolution of 0.5^0 x 0.5^0 and is available 6 hourly. For further reading on the method of generating the CRUNCEP, please see: *dods.extra.cea.fr/data/p529viov/cruncep/readme.htm*. The CRUNCEP datasets were freely obtained from the NACP database (http://dods.extra.cea.fr/data/p529viov/cruncep). The CRUNCEP datasets used are precipitation, mean temperature, minimum and maximum temperature and these datasets were used to compute the drought indexes i.e. SPEI and SPI.

3.2.3 Model

The simulation datasets were obtained from firstly, the climate model and, secondly, Dynamic Global Vegetation Models (DGVMs). They are discussed below.

3.2.3.1 Climate Model

The climate model used for the study is the Large Ensemble from the Community Earth System Model version 1, which has the Community Atmospheric Model version 5 as its atmospheric component (CESM1(CAM5); Hurrell *et al*., 2013). The land model component of the CESM is the Community Land Model version 4.5 (CLM 4.5). Climate and vegetation simulation datasets were obtained from the model. The 40-member ensemble simulation datasets were outputs of the Community Earth System Model version 1 (CESM) (Hurrell *et al*., 2013; Kay *et al.*, 2015). The CESM is a fully-coupled community global climate model maintained by the National Center for Atmospheric Research (NCAR). Several studies have shown that the CESM gives a realistic simulation of southern Africa (Gettelman *et al*., 2013; He *et al*., 2015). For example, Hodnebrog *et al*. (2016) showed that the model captures changes in mean precipitation, while Zhiyuan *et al.* (2015) also showed that the model simulates well the spatial distribution of temperature over the region. Detailed information on this model and the set-up used for the simulations in the present study are presented in Kay *et al*. (2015). Each ensemble member analyzed in this study differs from other members in respect of their initial atmospheric state, which was created by randomly perturbing temperature (Kay *et al*., 2015). The climate simulations obtained from the model are precipitation, the mean temperature, the minimum temperature and the maximum temperature; these were also used to calculate drought indexes (SPEI and SPI), shortwave radiation (in the visible band: 0.38-0.71 μm; hereafter, VIS) and near infrared reflectivities (0.71-4.0 μm; hereafter, NIR) which were used to compute the modeled NDVI.

In addition, twelve vegetation fluxes data were obtained from the model. These are described in Table 3.1 below:

Table 3.1. The name and description of vegetation fluxes and soil moisture used in the study

Vegetation Fluxes / Soil moisture (Codes)	Description
Total Leaf Area Index (TLAI)	Total one-sided area of leaf tissue per unit ground surface area; it is a dimensionless quantity characterizing the canopy of vegetation (Watson, 1947; Breda, 2003)
Autotrophic respiration (AR)	Organic matter metabolism by plants, which involves the absorptions of CO_2 from the atmosphere (Kirschbaum *et al*., 2001)
Heterotrophic respiration (HR)	Consumption of organic matter by plants and it results in the release of CO_2 to the atmosphere (Kirschbaum *et al*., 2001)
Gross primary production (GPP)	Total amount of carbon fixed by plants during photosynthesis (Kirschbaum *et al*., 2001)
Net primary production (NPP)	Net production of organic carbon by plants over a period of a year or more. It is the difference between GPP and autotrophic respiration (Kirschbaum *et al*., 2001)
Above ground net primary production (AGNPP)	Amount of aboveground plant biomass or carbon that is accumulated over a period of time (Bryne *et al*., 2011)
Below ground net primary production (BGNPP)	Amount of biomass or carbon that is assimilated belowground at a particular inter (Sala *et al*., 2000)
Photosynthesis (FPSN)	Physico-chemical process through which plants synthesize organic compounds with sunlight; it results in the release of oxygen and the removal of atmospheric CO2 which is used to produce carbohydrates (Whitmarsh & Govindjee, 1995)
Canopy transpiration (QVEGT)	Complex phenomenon that involves the flow of water vapour from leaves into the atmosphere; this is dependent on radiation

	from the soil, leaf area and amount of water available soil water (Wang *et al*., 2007)
Soil carbon (SOILC)	Amount of soil organic matter in the soil (Ontl, *et al*., 2012)
Ground evaporation (FGEV)	Water loss from the ground surface and ground water table (Tanvir, 2008)

3.2.3.2 Dynamic Global Vegetation Models (DGVMs)

We used three DGVMs in this study, namely, Community Land Model version 4 (CLM4), Community Land Model version 4 with Variable Infiltration Capacity hydrology (CLM4VIC), and Organising Carbon and Hydrology in Dynamic Ecosystems designed by Laboratoire des Sciences du Climat et de l'Environnement (ORCHIDEE-LSCE. They are standalone models, which only simulate vegetation variables. All three have been forced with the CRUNCEP datasets and run under the same experimental protocols. The protocols were the initiative of the North American Carbon Program (NACP) under the platform "Multiscale Synthesis and Terrestrial Model Intercomparison Project (MsTMIP)". None of these DGVMs gives the NDVI as a direct output, and thus we obtained VIS and NIS and calculated the simulated NDVI, as shown below (Oke, 1987). It is important also to note that that only few DGVMs under the MsTMIP protocols have simulated these internal energy parameters, and thus we were constrained to using only the three DGVMs in this study.

Table 3.2. Highlights of DGVMs participating in the MsTMIP activity. The domain of the models is 0.5^{o} x 0.5^{o}.

Model name	Affiliation	Institute ID
CLM4	Oak Ridge National Lab	ORNL
CLM4-VIC	Pacific Northwest National Lab	PNNL
ORCHIDEE-LSCE	Laboratoire des Sciences du Climat et de l'Environnement	LSCE

3.3 Methods

3.3.1 NDVI Simulations

Most studies have mainly used the observed NDVI to investigate the characteristics of vegetation; but, there are no direct outputs of the NDVI simulations from the models. However, Connelly-Brown *et al* (2008) computed the modeled NDVI from NIR and VIS bands, although their focus was neither on the southern African region nor on drought impacts. The present study apply this knowledge to investigate how well models are able to simulate how drought affects southern African vegetation by correlating the modeled NDVI with simulated drought indexes.

The NDVI, as defined by Oke (1987), which is the ratio:

$$NDVI = ((NIR - VIS))/((NIR+VIS)) \quad (1)$$

The NDVI ranges theoretically from -1.0 to 1.0, although the realistic range is from 0.0 to 1.0; because, in the absence of vegetation, NDVI approaches zero (Connelly-Brown *et al*., 2008). Slight negative NDVI values have been shown to depict differences in albedo (Tucker *et al*., 2004); however, they are mostly ignored. We computed the NDVI for each model ensemble member and for future projections, it was computed under the Representative Concentration Pathway 4.5 (RCP4.5) and Representative Concentration Pathway 8.5 (RCP8.5).

3.3.2 Drought identification

The severity of the drought was quantified by computing two drought indexes, i.e. the SPEI and the SPI, from observation and model datasets. For the study, the SPEI was calculated using the potential evapotranspiration obtained from both the Hargreaves (hereafter, SPEI_HG) and the Penman-Monteith (hereafter, SPEI_PM) methods. Thereafter, the SPI (hereafter, SPI) was calculated using precipitation data.

The approaches used to compute the drought indexes are highlighted below:

3.3.2.1 SPEI

The SPEI was computed from the observed (CRU) and the simulations datasets (CESM) at time scales of 1-, 3-, 6-, 9-, 12-, 15- and 18-months. The methods involved computing the SPEI from the difference between precipitation (P) and potential evapotranspiration (PET) as shown thus:

$D = P_i – PET_i$………………………………………………………….. (2)

Where "i" is the month

PET was calculated from the mean temperature, the maximum temperature and the minimum temperature. D values are aggregated to obtain various timescales of the SPEI, which range from 1- to 18-months (Vicente-Serrano *et al*., 2010).

The difference $D^k_{i,j}$ in a given month j and year i is dependent on the chosen time k. For computation of the SPEI at various time scales, a probability distribution of the gamma family was used (i.e. a three-parameter gamma Pearson III distributions).

The probability density function of a three-parameter log-logistic distribution can be expressed as shown below (Vicente-Serrano *et al*., 2010):

F(x)= β/(α) ((x- γ)/α)β-1 [1+((x- γ)/α)β] -2………………………………….…....(3)

where α, β and γ are scale, shape and origin parameters, respectively, for D values in the range (γ > D < ∞). W_0

Parameters of the log-logistic distribution are obtained by using various techniques (Vicente-Serrano *et al*., 2009). The L-moment approach is considered as the most robust (Ahmad *et al*., 1988). The parameters of the Pearson III distribution needed to calculate L-moments can be obtained by following Singh *et al*. (1993):

β = (2W1-W0)/(6W1-W0-6W2)………………………………………………. (4)

$\alpha = ((W0- 2W1)\beta)/(\Gamma(1+1/\beta)\Gamma(1-1/\beta))$………………………………………... (5)

$\gamma = w0- \alpha\Gamma(((1+1)/\beta)\Gamma(((1+1)/\beta)$……………………………………………….(6)

where Γ (β) is the gamma function

The probability distribution function of the D series based on the log-logistic distribution is shown as follows C1W2

$F(x) = [1+(\alpha/(x- \gamma))\beta] -1$……………………………………………………...(7)

The SPEI can then be easily computed as the standardized values of F(x). For instance, Abramowitz and Stegun (1965) used classical approximation to obtain the SPEI as shown thus:

SPEI = W - (C0+C1W +C1W2)/(1+d1w+d2W2 +d3w3)……………………..(8)

where $W = \sqrt{(-2\ln(P))}$ for $P \leq 0.5$

and P is the probability of exceeding a determined D value, P = 1 – F(x). If P > 0.5, then P is replaced by 1 – P and the sign of the resultant SPEI is reversed. The constants are C0 = 2.515517, C1 = 0.802853, C2 = 0.010328, d1 = 1.432788, d2 = 0.189269 and d3 = 0.001308.

The probability density function is given in Figure 3.2 below:

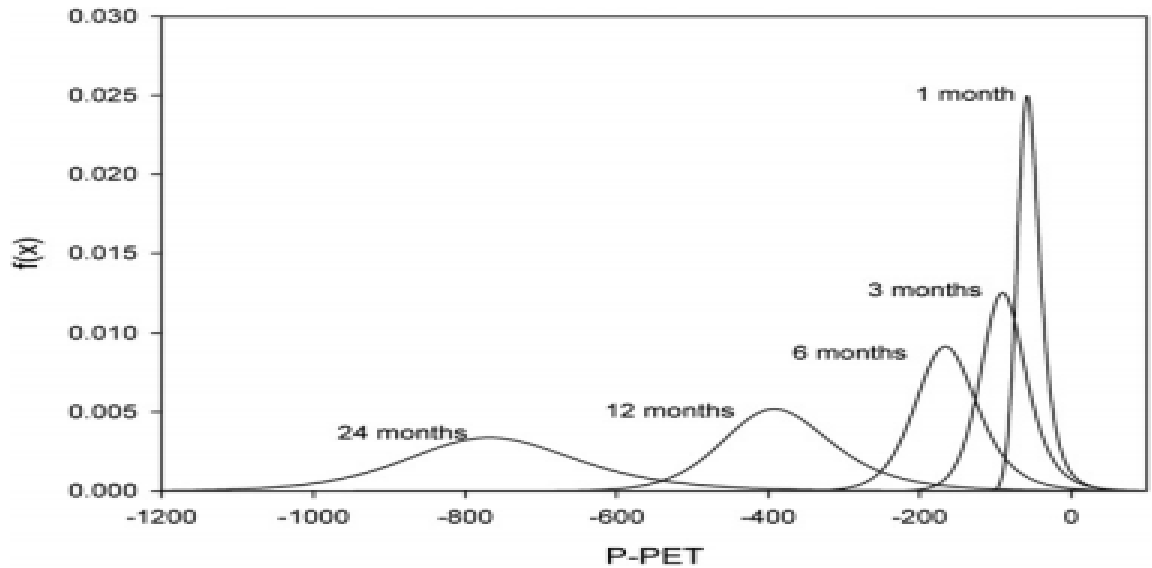

Figure 3.2. Probability density functions of the log-logistic distribution for D series calculated at different timescales over a region

3.3.2.1 SPI

The SPI (sometimes called the *z* score) is the number of standard deviation from the mean at which an event occurs (Guanang *et al*., 2009). For instance, the *n*-month SPI value is the accumulated precipitation over that *n*-period with the precipitation for the same annual period as calculated for the full study period (Guanang *et al*., 2009). High positive SPI values corresponds to wet periods while high negative values correspond to drought (Guttman, 1998). Although there are numerous of wetness and dryness events according to the SPI, for our study, we used the probability density functions to describe dry and wet periods. These are highlighted below.

A two-parameter gamma Person III distributions was used to compute the SPI at different timescales, (Vicente-Serrano *et al*., 2010). The variable *x* in this distribution has a lower boundary zero (i.e. $0 > x < \infty$). The probability density function of the gamma distribution was defined thus (Guanang *et al*., 2009):

$$g(x) = 1+\frac{1}{\beta\alpha\Gamma(\alpha)}\, x\alpha\text{-}1e\text{-}x/\beta \text{ for } x > 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots....(9)$$

where α > 0 is a shape parameter, β > 0 is a scale parameter, x > 0 is the amount of precipitation and Γ(α) is the gamma function.

In order to fit the distribution parameters, α and β were estimated from the sample data and they were estimated using the ML approximation (Thom, 1958):

$$\alpha = \frac{1}{4A}(1 + \sqrt{1 + \frac{4A}{3}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

and

$$\beta = \frac{\ddot{x}}{\alpha} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(11)$$

where ẍ is mean precipitation and *A* is given as

$$A = \ln(\ddot{x}) - n^{-1}\Sigma\ln(x) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(12)$$

For a given month and time scale, the cumulative probability G(x) of an observed amount of precipitation is given by

$$G(x) = \frac{1}{\beta\alpha\Gamma(\alpha)}\int_0^x x\alpha e - \frac{x}{\beta}dx \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(13)$$

By making $\frac{x}{\beta}$= t, the expression may be written as

$$G(x) = \frac{1}{\Gamma}\int_0^x x\alpha - 1 - e - 1dt \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(14)$$

The gamma distribution is not defined for x = 0 and the probability zero precipitation q = P(x=0) being positive, the cumulative probability is

$$H(x) = q + (1-q)(G(x) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(15)$$

3.3.3 Model evaluation

For the study, three broad sets of model evaluation were performed on the climate and vegetation simulations.

First, the capability of the DGVMs in simulating the response of vegetation in southern Africa was evaluated as follows: a) the spatial distribution of climate variables was computed and plotted over a 22-year period (1983 – 2004); b) grid cell correlations of the observed NDVI with the simulated NDVI for the same period. These periods were chosen because of the limited availability of the GIMMS-NDVI datasets (i.e. 1981 – 2006). This was necessary to show how well the models simulate the vegetation index in the region. The spatial distribution of models was then evaluated, to examine how well the models replicate the temporal and spatial variation of vegetation in southern Africa; c) computation of NDVI anomalies for each model were also computed and plotted d) time series distributions of the climatology of the modeled vegetation index over six major biomes in the region for the periods 1983 – 2004 were then calculated and compared with observations. The biomes considered for all these evaluations are: (Dry Savanna: DS; Semi Desert: SD; Mediterranean: MT; Temperate Grassland: TG, Tropical Forest: TF and Moist Savanna: MS).

Secondly, evaluation was performed on forty ensemble members of the CESM. This was done by first computing and then mapping of the spatial distributions of modelled ensemble mean of climate and vegetation variables over a 22-year period (1983- 2004). These distributions were compared with observations for the same period. Thereafter, a time series was plotted of observed and simulated climatology of the climate and vegetation variables over six southern African biomes were then plotted. The purpose of this was to understand how rainfall and temperature variability drive vegetation changes; and how well the model ensemble members captured those patterns.

Thirdly, another evaluation was done on the CESM ensemble members, albeit at different time periods. This was to compare a 30-year historical period to a 30-year future period. Here, the historical period was chosen as 1971-2000. These periods were used because the objective was to investigate how southern African vegetation would be affected by global warming at different global warming levels (GWLs). However, since GIMMS-NDVI does not extend to this start date of the reference period, we chose 1982 as the start time and thus, we selected a 19-year period (1983- 2000) for observed vegetation. Afterwards, the spatial distribution of observed and the model ensemble median of the NDVI were calculated and mapped. In addition, a boxplot of observed and simulated climatology of the NDVI over six southern Africa biomes were then plotted.

The tasks for achieving the objectives of the study (as listed in Chapter 1, Section 1.8) are highlighted thus:

3.3.4 Examining the observed response of vegetation to drought in southern Africa

Here, the spatial distribution of climate and vegetation variables over a 22-year period (1983 - 2004) was computed and mapped. Afterwards, the time series distribution of the climate and vegetation variables over the same periods was calculated and plotted. Hereafter, the computed drought indexes (discussed in Section 3.3.2) were interpolated to a spatial resolution of 0.2^0 to match that of the observed vegetation. The correlations per grid between drought index (CRU) and the GIMMS NDVI over the 22-year period and at the different drought timescales were computed. The drought indexes (Hereafter, SPEI_HG and SPI) were computed by using the Hargreaves method. SPEI (hereafter, SPEI_PM), which was computed using Penman-Monteith method was correlated with the GIMMS NDVI. The spatial distribution of the peak correlations and the corresponding time scales from 1- to 18-months timescales were mapped for observed value.

Furthermore, the seasonal mean was calculated for four seasons i.e. (a) December, January and February (DJF); (b) March, April and May (MAM); (c) June, July and August (JJA); and (d) September, October and November (SON) from monthly correlations. These were computed from correlating monthly series (twelve series per year) per pixel of the GIMMS-NDVI and each monthly series of 1- to 18-months from the drought index (SPEI_HG & SPI) series of the pixel using Pearson correlation (r) for the 22-year period; thereby giving a total of 252 correlation values. The observed peak correlation and observed drought timescales were plotted in different seasons over six biomes in southern Africa namely – Dry Savanna, Semi-desert, Mediterranean Vegetation, Temperate grassland, Tropical forest and Moist Savanna were shown.

3.3.5 Simulating the response of vegetation to drought in southern Africa using Dynamic Global Vegetation Models (DGVMs)

The analyses include the correlation per grid between the droughts indexes computed from the reanalysis data (CRUNCEP) to vegetation index from individual model (i.e. DGVMs). The drought indexes have been computed by using the Hargreaves method. The CRUNCEP datasets was used to calculate drought indexes because it is the dataset that was used to force the DGVMs. The peak correlations and corresponding time scales from 1- to 18-months timescales were mapped for each individual the models. Comparisons between the spatial maps of the drought indexes of the models were shown alongside the observation.

Furthermore, the influence of fire on southern African vegetation fluxes and indexes was determined with CLM which is the model that performs best among the DGVMs. This impact was studied because fire is a frequent occurrence in the savanna and grassland area of the region. In order to achieve this, we performed two experiments over the same reference period (1983 – 2004). These experiments were done as follows: (a) running the CLM with an active fire module and b) simulating the fluxes and index without the prescribing fire. We also mapped the differences between the two experiments.

3.3.6 Simulating the response of vegetation to drought in southern Africa using Community Earth System Models (CESM)

Two drought indexes (SPEI and SPI) were computed from forty ensemble members of CESM using the Hargreaves method over a 22-year period (1983 - 2004). These drought indexes were correlated with NDVI which were calculated for each ensemble member. The ensemble means of the individual correlations and drought timescales (1- to 18-months timescale) were then computed, mapped and compared with observation.

The seasonal mean distribution of correlation and timescales were computed for each ensemble member using the method discussed in Section 3.3.4. Afterwards, the peak correlations and drought timescales of the maximum, minimum and ensemble median were calculated. These were then compared with the observed peak correlations and the observed drought timescales, using box plots for the same six biomes mentioned in Section 3.3.4.

3.3.7 Investigating the response of southern African vegetation to 1.5^{o}C and 2^{o}C global warming levels

Here, the evolution of drought, climate and vegetation variables in past and future climates were investigated. The changes in the SPEI (12-month timescale), the SPI (12-month timescale), the PET and the NDVI were analyzed for the periods, 1972 to 2100. The 12-month timescale was chosen because it is one of the prominent timescales at which southern African vegetation has been found to respond to drought. In addition, following Nikulin (2017), the mean temperature was used to obtain the 30-year window in which the global warming reaches 1.5^{o}C and 2^{o}C global warming level above the pre-industrial levels in the simulations (GWL15 and GWL20). The 30-year windows have different periods for each of the ensemble members and for the GWLs. The period ranges from 2012 to 2041 in some ensemble members to 2048-2077 in other ensemble members. All the simulated climate and vegetation data for historical climates (1971 - 2000) and for GWLs climates under the business-as-usual scenario (i.e. RCP8.5) scenario were extracted from the 40 ensemble members and analyzed for the study. The impact of each GWL on the vegetation fluxes was calculated as the difference between the GWL and the historical vegetation fluxes (i.e. GWL minus historical). These impacts were calculated over Southern Africa and across six biomes on the sub-continent.

Chapter 4: The Observed Response of Southern African Vegetation to Drought

Several studies have shown that southern African vegetation is affected by drought. However, little is known about how fast the vegetation in southern Africa is responding to drought, and how this response varies by season across the biomes. This chapter presents the result of the response of southern African vegetation to drought in observation. It starts by discussing the climatology, in respect of climate and vegetation variables, before discussing the correlation between the vegetation index and droughts, using 1- to 18-month SPEI and SPI timescales. The climate variables were obtained from the CRU, while the vegetation index is the GIMMS-NDVI.

4.1 Spatial distribution of observed climate and vegetation variables over southern Africa

Figure 4.1 presents the spatial distribution of climate variables over Southern Africa. It features a sharp gradient in precipitation distribution over the region. The precipitation amount is higher over the northern and eastern parts of southern Africa than over the southwestern areas. The peak of the precipitation amount (up to 285 mm/month) occurs over eastern Madagascar, while the least precipitation intensity (less than 5 mm/month) is observed over the western parts of Namibia, which is a desert. Pohl *et al* (2007) attributes most of the precipitation over the highland to the tropical temperate troughs (TTT). The sparse precipitation over the southwestern areas can be attributed to moisture loss by the easterly trade winds from the Indian Ocean when rising over the eastern escarpment of the Drakensberg Mountains in South Africa (Jury *et al*., 2013; Richter *et al*., 2006). It can also be attributed to the fact that the air inversion of the southwesterly wind prevents the convectional rise of cool and humid air (Von Willert *et al*., 1992).

Figure 4.1 also shows that southern African temperatures are characterized by marked spatial variability. For instance, the maximum temperature is as high as 34^{o}C over parts of Botswana, Angola and Zambia, and as low as 7^{o}C over eastern South Africa. The mean temperature is between 20 and 28^{o}C over the northern (including the western and central) parts of the region, and between 7 and 15^{o}C in the southern parts i.e. South Africa, Swaziland and Lesotho. Across the northeastern parts of inland southern Africa and across the western areas of Madagascar, minimum temperature is up to 18°C but about 3°C over the southwestern parts of South Africa. The marked difference in temperature between the upper and lower areas of southern Africa may be attributed to the hemispheric climatic influences (Odada & Olago, 2005). For instance, while tropical climatic conditions are experienced in Mozambique and Zambia, a temperate climate prevails further south.

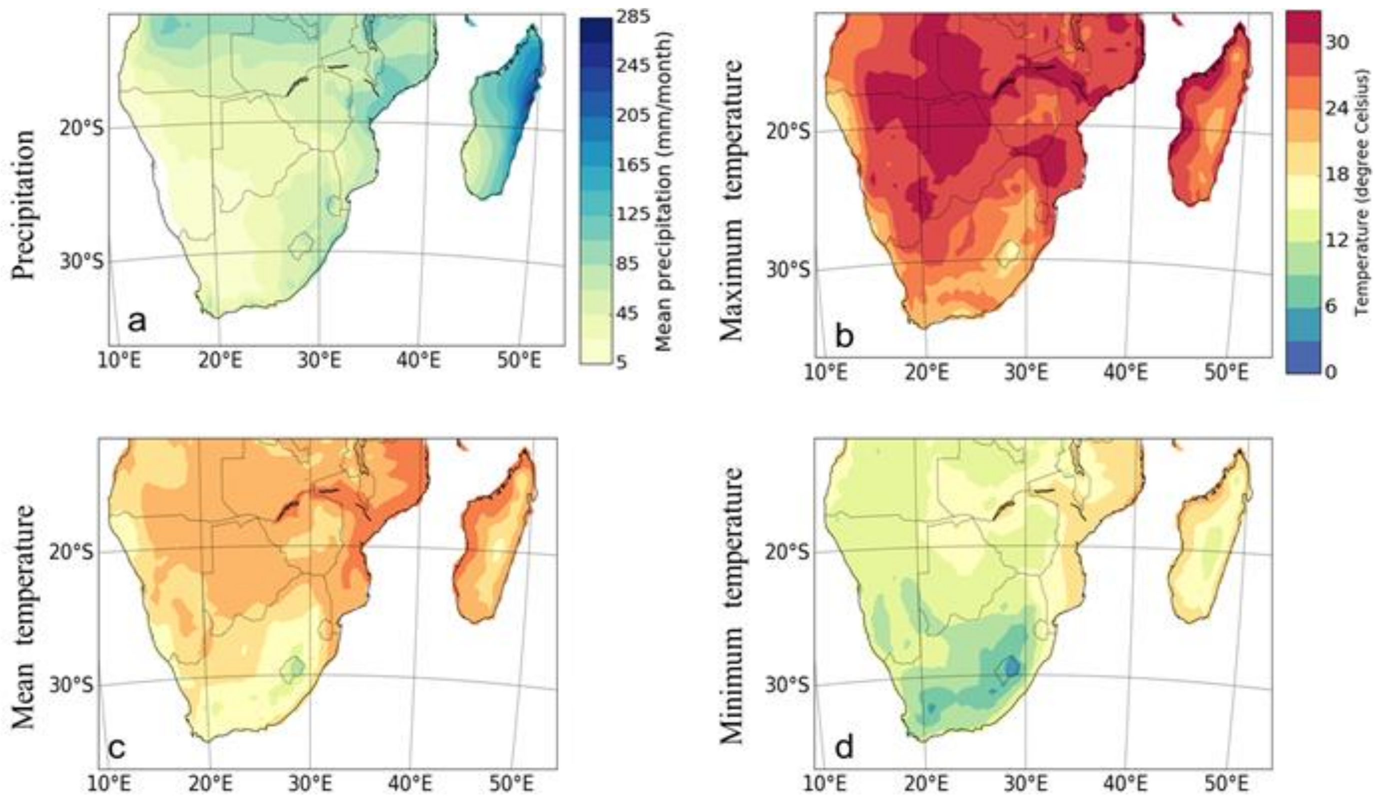

Figure 4.1. The spatial distribution of observed climate variables (rainfall, mean temperature, maximum temperature and minimum temperature) over southern Africa, as depicted by the CRU during the period 1983 – 2004.

The spatial distribution of the NDVI is similar to that of precipitation (Figure 4.2). High NDVI values (about 0.70) are observed over the eastern part of the region (i.e. Zambia, Angola, Mozambique, Zimbabwe, Malawi and Madagascar), while low NDVI values (less than 0.1), and thus depicting small vegetation cover) are observed over western and central parts of the region (i.e. Namibia and Botswana). While the high NDVI over the western part can be attributed to the presence of large vegetation cover (mainly shrubs and trees) in that area, the low NDVI over the western and eastern parts is indicative of a lack of vegetation over area. The gradient in the vegetation distribution is akin that of the rainfall patterns (Kruger, 1984); however, Ward *et al*. (1983) indicated that the aridification of the western part of the sub-continent may be attributed to the influence of cold sea surface temperature (SST), induced by the Namibian upwelling system along the Namibian coasts (Ward *et al*., 1983). The relatively high NDVI over the south-western tip of southern Africa (in comparison to the western and central part of Africa) are due to winter rains, which are produced by the frontal systems.

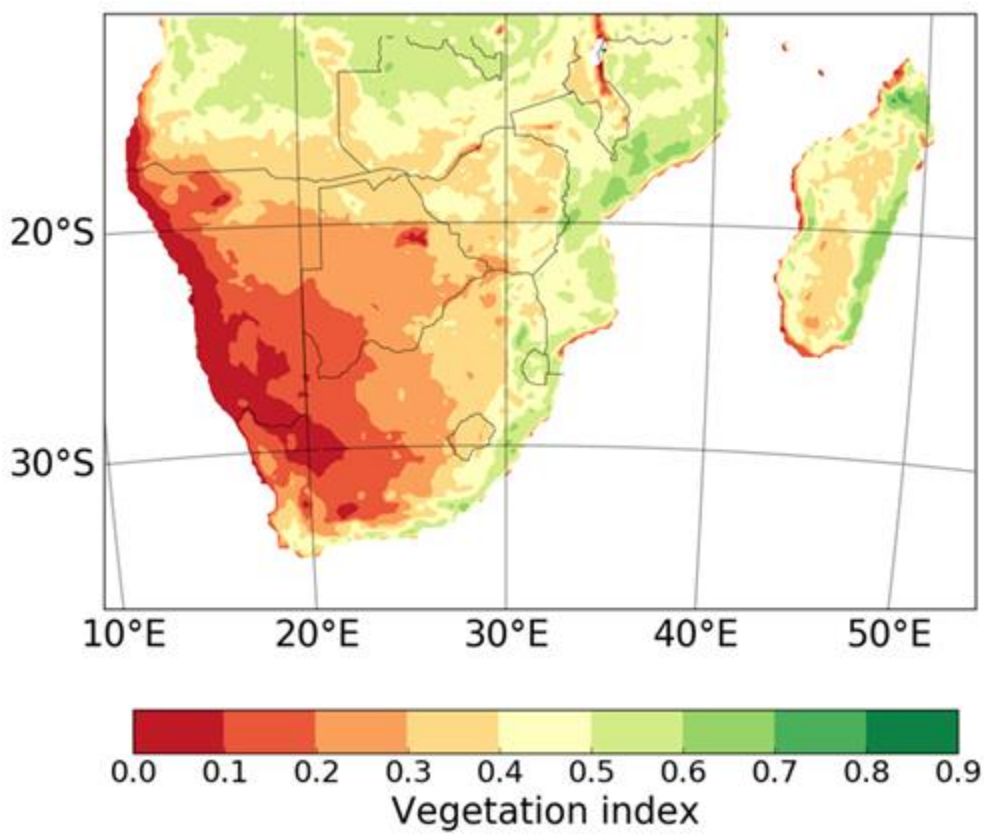

Figure 4.2. Spatial distribution of the observed NDVI over southern Africa during the period 1983 – 2004.

4.2 Annual cycle of climate variables and Vegetation index over the southern African biomes

Figures 4.3 to 4.7 shows the annual cycle of the climate variables and the vegetation index over different southern African biomes. Over most biomes (except over the Mediterranean), the maximum precipitation occur is in the DJF and MAM seasons. In the dry savanna, semi desert, temperate grassland, tropical forest and moist savanna. The wettest season is DJF. The precipitation magnitude is as high as 350 mm during this season in the tropical forest biome. Conversely, there is less rainfall in the JJA season (which is the driest season) over the same biomes. However, June and July months in the tropical forest do experience some precipitation and this may be attributed to rainfall experienced over this biome during this period (Tadross *et al*., 2008). There is less rainfall variability over the Mediterranean biome. It is mostly dry here in the SON and DJF seasons while the wettest season is JJA. This is because the biome experiences winter rainfall, which is not the case in the other biomes (Tadross & Johnston, 2012). This result is in agreement with Klein and Roehrig (2006), who reported that rainfall is highly variable in the semi-arid regions.

There is high seasonal variability in respect of the mean, maximum and minimum temperature in the southern African biomes (Figures 4.4, 4.5 and 4.6). The highest maximum temperature (more than 32^{o}C) is experienced over the semi-desert. The most pronounced seasonal variability in maximum temperature is over the semi desert and in the Mediterranean biomes; with both having standard deviation (SD) values of 4.1. The highest (20^{o}C) and lowest (15^{o}C) magnitudes of minimum temperature are observed over the dry savanna and the Mediterranean biomes. The Semi desert biome has the largest (5.0) seasonal variability in minimum temperature.

Vegetation in the southern African biomes is seasonally variable (Figure 4.7). In the dry savanna, semi desert, temperate grassland and moist savanna biomes, high vegetation is observed in SON and DJF and this is largely due to the suppression of the mid-level subtropical high pressure system which allows monsoon trough to be established and thus resulting in high rainfall, which drives vegetation growth (SADC Rainfall outlook, 2001). The peak of vegetation (as high as 0.6) is observed in April in the tropical forest and moist savanna biomes. However, the least vegetation is in JJA season with the lowest amount (about 0.2) occurring over the semi-desert biome. This may be attributed to the dry conditions experienced during this period, as a result subtropical high pressure system, which suppresses rainfall by shifting the ITCZ (the Inter-Tropical Convergence Zone) away from these regions (Naik & Abiodun, 2016). However, in the Mediterranean vegetation, high vegetation growth is most likely in the JJA season but has reduced during the DJF season. The decrease in greenness over this biome during this season may be due to the thrust of mid-latitude frontal systems which brings rainfall to those regions (Reason & Rouault, 2002). In addition, it can be inferred from the results that vegetation has a stronger relationship to precipitation than it does temperature.

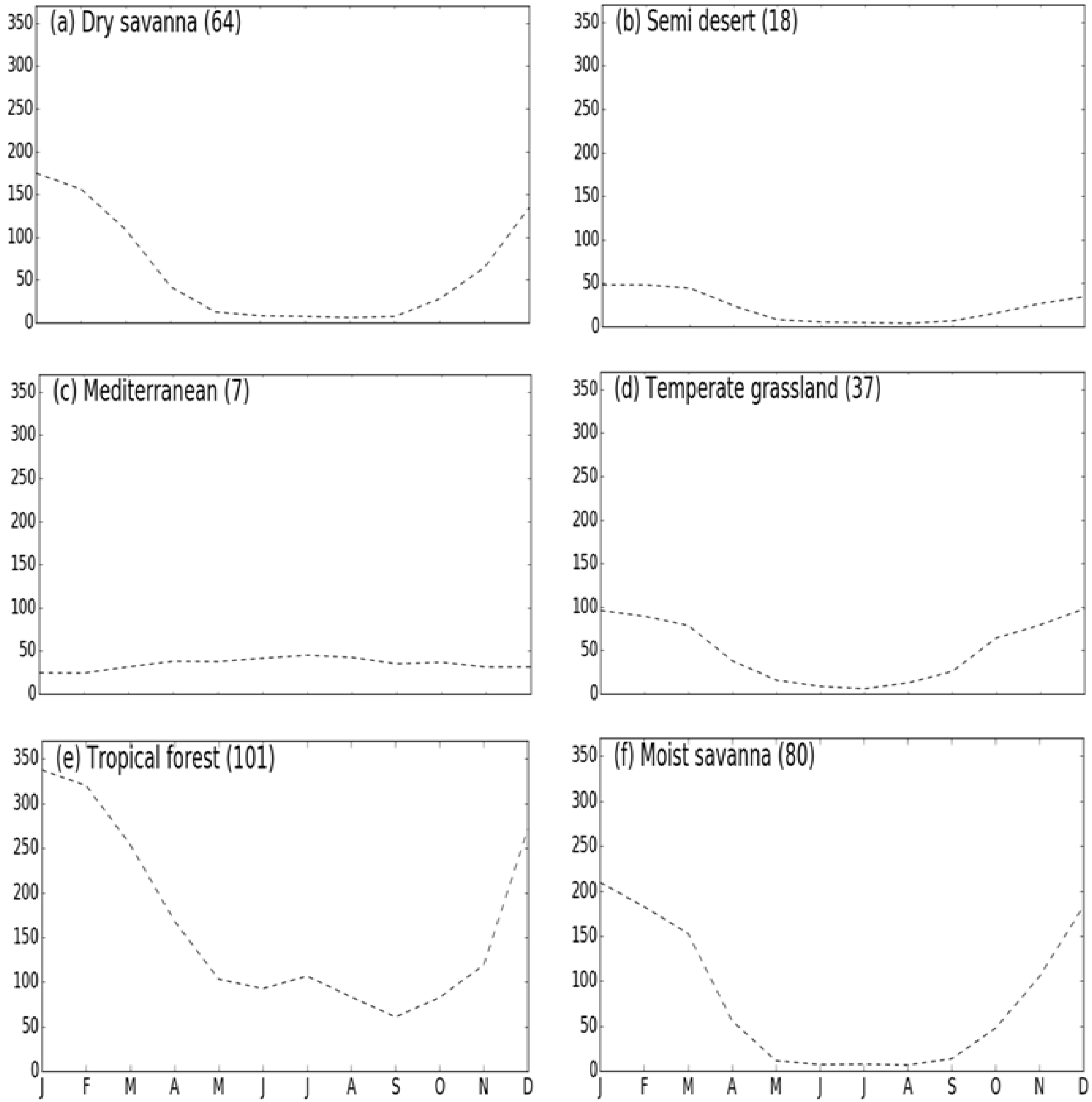

Figure 4.3. Annual cycle of observed rainfall (mm/month) across six biomes in southern Africa during the period 1983 – 2004. The Standard Deviation (SD) values are indicated in the brackets.

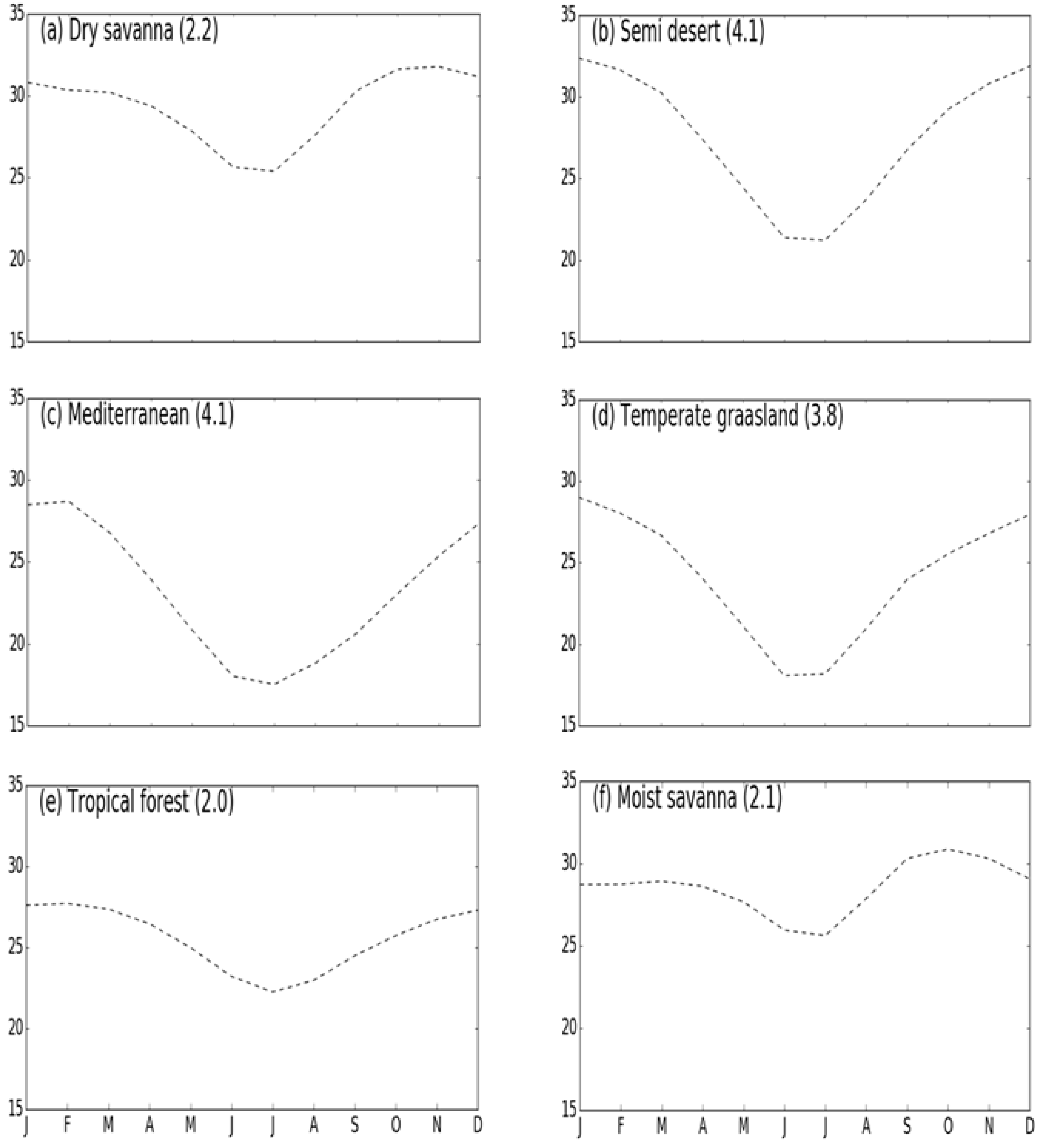

Figure 4.4. As in Figure 4.3 but for maximum temperature (^{0}C).

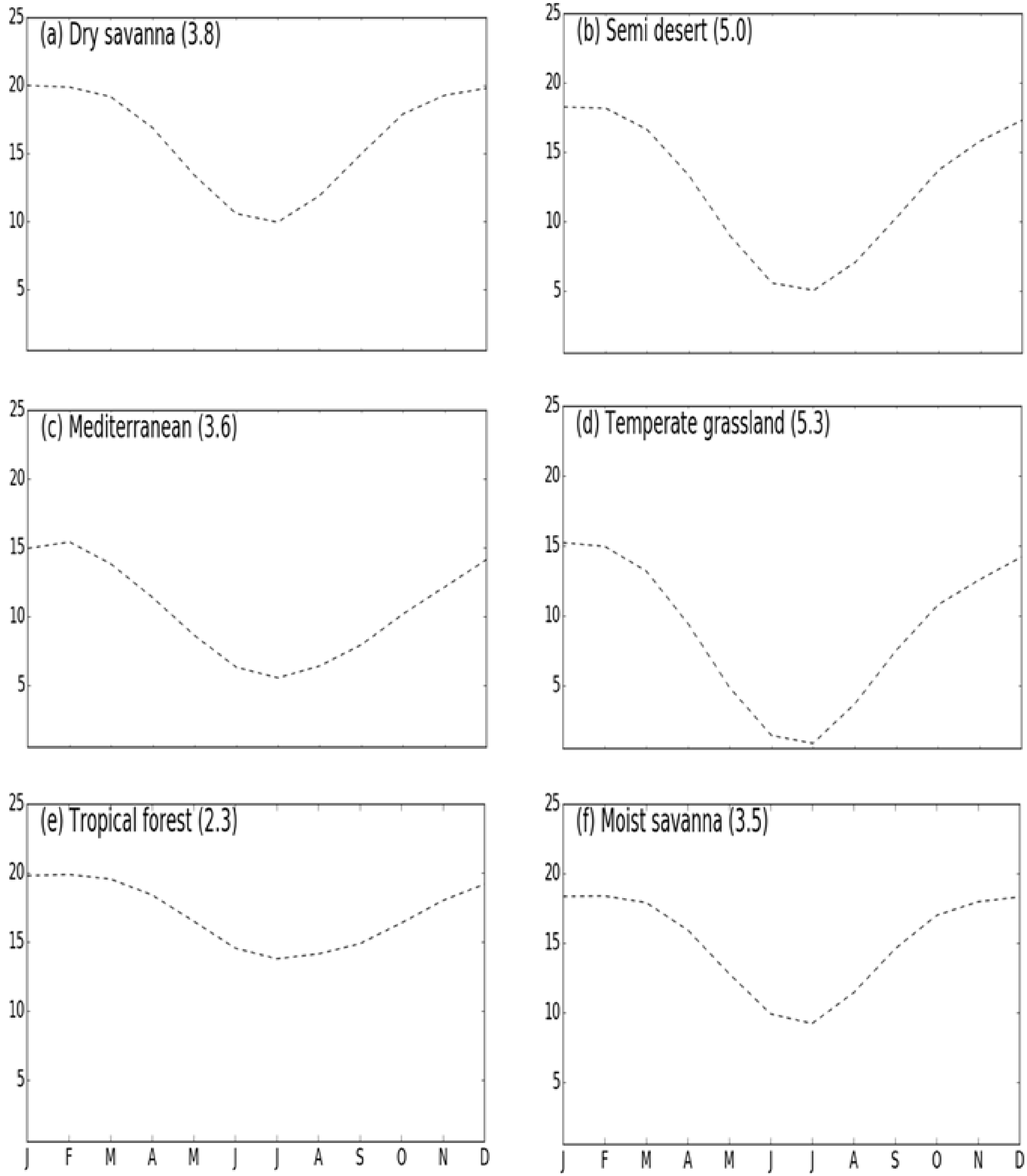

Figure 4.5. As in Figure 4.3 but for minimum temperature (^{0}C).

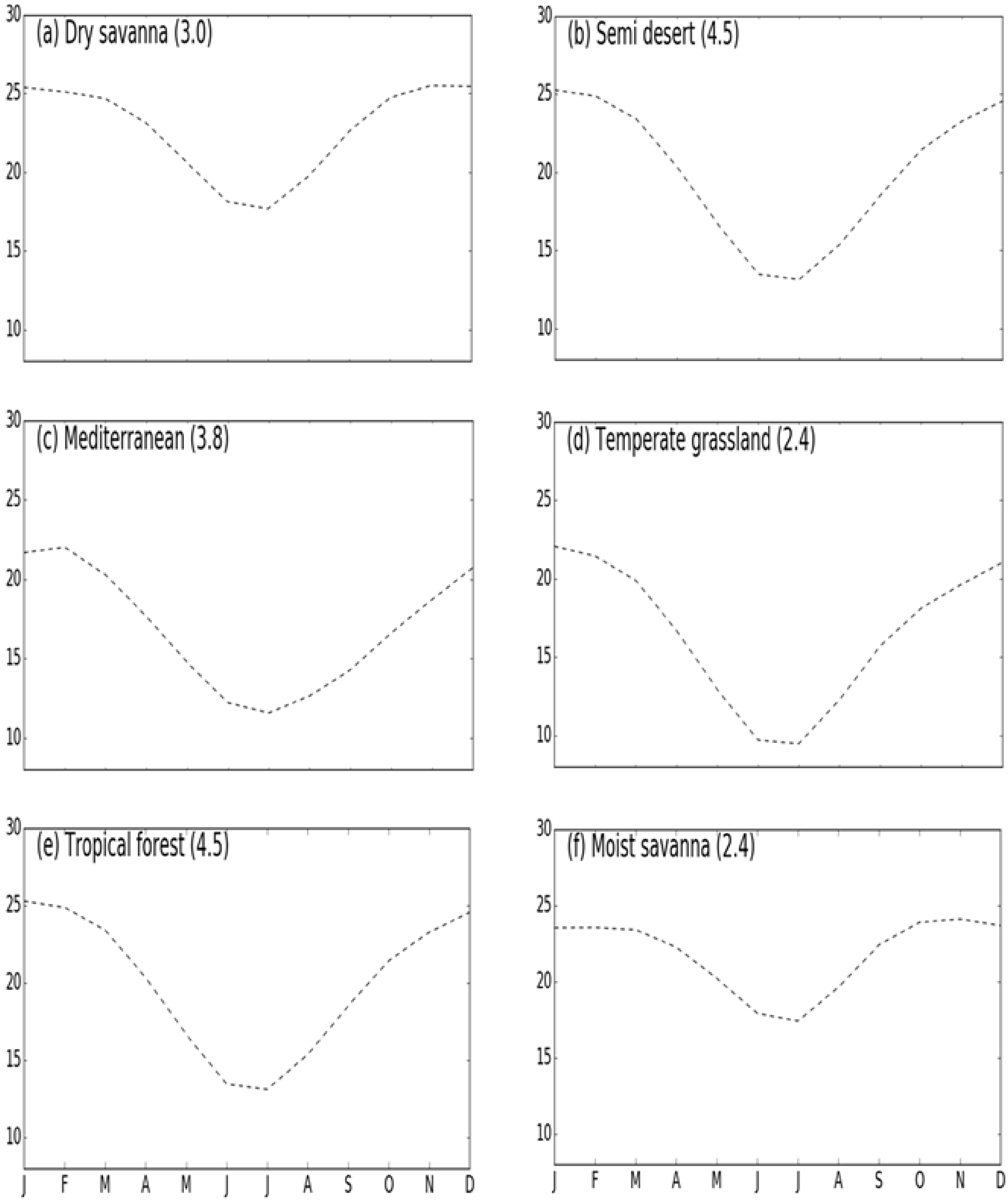

Figure 4.6. As in Figure 4.3 but for mean temperature

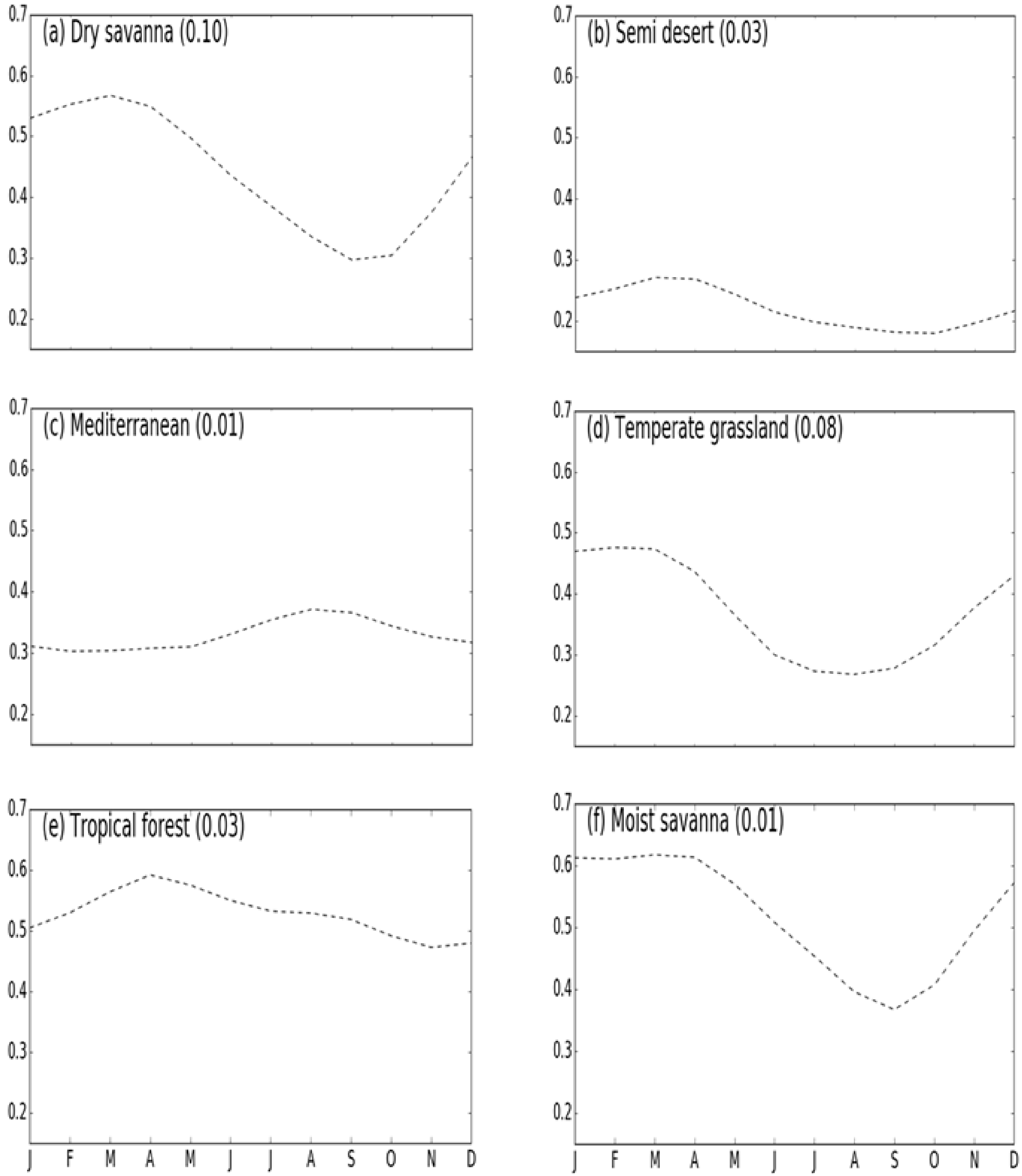

Figure 4.7. As in Figure 4.3 but for vegetation index

4.3 Spatial distribution of observed response and drought timescales of vegetation to droughts

The SPEI_HG shows a strong correlation (i.e. relationship) between drought and vegetation in most parts of southern Africa (Figure 4.8a). There is a high correlation (up to 0.8) over the central parts of South Africa and Namibia, the southern border of Botswana and the western parts of Zambia. The strong correlation may be caused by the dependence of vegetation on precipitation for their ecological functions (Tucker *et al.*, 2009). Therefore, vegetation will show a strong response to droughts in regions where precipitation for their physiological processes is highly limited. The high correlation between vegetation and drought could also be due to sparseness in vegetation cover as a result of low rainfall distribution in such areas - which are mostly semi-arid and desert locations (Anyamba *et al*., 2003). However, the correlation is weaker (less than 0.3) over Angola, Malawi, eastern Zambia and Madagascar. Such a weak relationship between vegetation and droughts indicates that precipitation is not the major limiting factor in the growth of vegetation in these regions (Fuller & Prince, 1996). In addition, a weak response of vegetation to droughts may be because of the vegetation's low water use effectiveness arising from a positive water balance; or from saturation of the water table (Schuur, 2003; Huxman *et al*., 2004). The figure also shows a relatively high correlation (about 0.6) in southeastern parts of South Africa, and on the border on Namibia and Botswana. Our findings are consistent with those of other studies (Rouault and Richard, 2003; Richard & Poccard, 2008) which showed a similar spatial distribution of the correlation between drought and vegetation in southern Africa. This finding is, however, in contrast with those of Vicente-Serrano (2012), which showed a stronger vegetation response to drought in southern Namibia.

The Southern African vegetation responds to drought at different timescales (Figure 4.8b). In some parts of the region, e.g. in South Africa, central Namibia, Botswana, Zimbabwe and southern Angola, the correlation occurs at a drought timescale of 3-month. This implies that this vegetation is responding to drought within a very short time period. However, the response is shorter over eastern Madagascar, i.e. 1-month. Over Mozambique, southern parts of South Africa and Malawi, vegetation responds at 6-month timescales which is also within a short time period. Over the arid parts of Namibia, the northern parts of Angola and central Zambia, as well as in the southern areas of Madagascar, however, it is at a longer period (i.e. 12- to 18-month). These varying timescales over the region may be because the different types of vegetation have different process to minimize the potential damage caused by water deficits; and this thus determines the timescales at which they respond to drought (Chaves *et al*., 2003). For instance, vegetation with physiological and morphological features for adapting to water shortages will take a longer time to respond to drought, and hence, do not quickly shows signs of water stress. Conversely, vegetation may have a short drought timescale because it is relying mostly on precipitation for functioning or because it does not have a strong adaptive capacity to cope with water deficits (Vicente-Serrano *et al*. 2012).

The correlation and drought timescales of the SPEI_HG (Figures 4.8a and 4.8b) are similar to those of the SPEI_PM (Figures 4.8c and 4.8d) over most parts of southern Africa. Both the SPEI_PM and the SPEI_HG show identical correlations (about 0.5) in Angola, Zambia and Malawi; and weak correlations (~0.3) in Madagascar. However, the strong correlation on the border of Namibia- Botswana shown in the SPEI_HG is absent in SPEI_PM. Furthermore, the preponderant spread of strong spatial correlations in central parts of South Africa and Botswana that are observed in the SPEI_HG are absent in the SPEI_PM. There are also a few dissimilarities in the drought timescales of the two observation results. For instance, the 1-month drought timescale over Madagascar that is present in the SPEI_HG is absent in the SPEI_PM. The SPEI_PM also shows more prevalent correlations at the 18-month timescale than is observed in the SPEI_HG. Although the SPEI_HG and SPEI_PM are both observational outputs, the climate variables used in their computation are quite different. In addition to other climate datasets, wind speed is also used in the computation of the SPEI_PM but it is not used in calculating SPEI_HG (Stagge *et al*., 2014). Thus, this is why there are few differences in the correlation and drought timescales of both observations. In addition, we may infer from the results that the SPEI_PM is a better drought index than the SPEI_HG (Bengueria *et al*., 2017). Our findings are consistent with Vicent-Serrano *et al.*, (2012) who found a similar spatial pattern of correlation in southern Africa.

There is a similarity between spatial correlation and drought timescales of the SPI (Figures 4.8e and 4.8f) and those of the SPEI_HG (Figures 4.8a & 4.8b) in most areas of southern Africa. Both the SPI and the SPEI_HG show weak correlations over Madagascar, Zambia and Angola; as well as strong correlations in South Africa and Botswana. The major differences in both observation is in their magnitudes. The correlation magnitude shown in the SPI are lower over Namibia and northern parts of Botswana than in the SPEI_HG. The lower magnitude of correlations shown by SPI may be attributed to the fact that PET is used in the computation of the SPEI_HG but not in the SPI formulation (Vincent-Serrano *et al.,* 2012). The major difference in drought timescales of both the SPEI_HG and the SPI is over Namibia, western Botswana, Zimbabwe and Zambia where SPI shows correlations occurring at an intermediate timescale (9-month) while the SPEI_HG shows a 3- to 6-month timescale. These findings agree with previous studies (Vicent-Serrano *et al*., 2012; Stagge *et al*., 2014).

There is a slight difference in the spatial distribution of vegetation to drought using observed the SPEI and the SPI. Lower magnitudes of correlations are shown by the SPI and this may be attributed to the fact that potential evapotranspiration (PET) is used in the computation of the SPEI while it is absent from computing the SPI (Vicente-Serrano *et al.,* 2012). Therefore, SPEI_HG is a better measure of drought than SPI (Homdee *et al*., 2016). In addition, the differences in correlation magnitude between the SPI and the SPEI become much wider and more pronounced during periods when the temperature difference is between 2 and 4^0C; as is the case with climate change (Mavromatis, 2007).

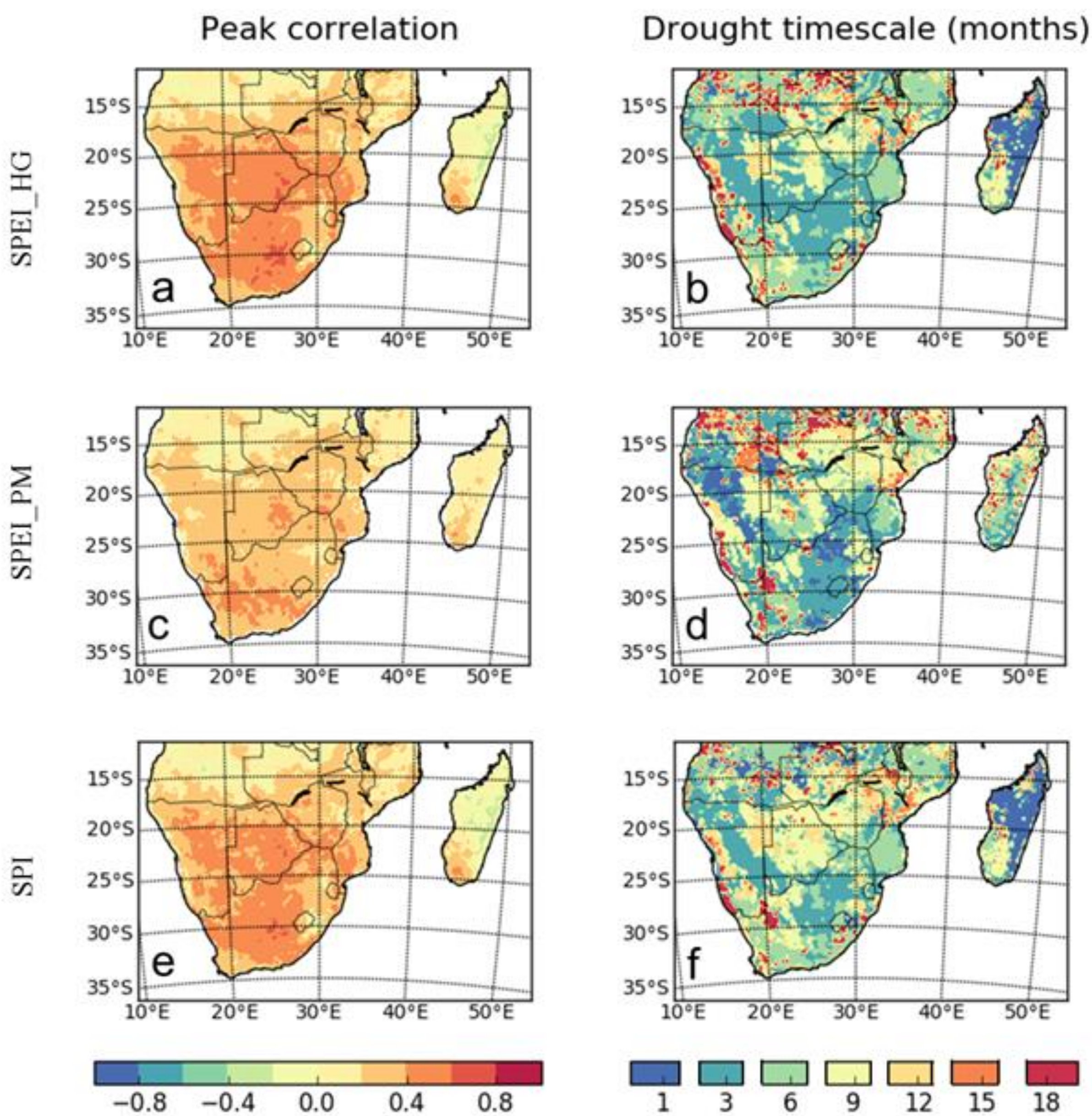

Figure 4.8. Spatial distribution of correlation between drought and vegetation over southern Africa for observations. Panels (a), (c) and (e) show the peak correlations (Pearson coefficient, r) per grid between the CRU - SPEI and the GIMMS - NDVI (SPEI_HG & SPEI_PM) for the period 1983 – 2004; and peak correlations (Pearson coefficient, r) per grid between the CRU - SPI and GIMMS-NDVI ((SPI) for the same period. The corresponding drought time scales at which maximum (or peak) correlation between drought and vegetation is found are shown in panels (b), (d) and (f)

4.4 Seasonal distribution of observed response and drought timescales of vegetation to droughts

Figures 4.9 and 4.10 use bar charts to present the seasonal distribution of observed vegetation responses to the drought as well as the timescales. Observation dataset shows a seasonal distribution of high magnitudes of correlation between vegetation and drought in the biomes, although these correlations are slightly lower over the tropical forest biome. Over the dry savanna, the vegetation response to drought is strong and is as high as 0.83 in MAM season and it occurs at the 3-month timescale. The response is particularly stronger in the MAM season because this is when the vegetation bears fruit, and develops leaves and biomass (Zeppel *et al*., 2014). The reason why these vegetation respond to drought at such a short timescale may be because of the critical water requirements by the vegetation for their developmental activities during the MAM season (Zeppel *et al*., 2014). These findings are in agreement with numerous other studies (Woodward & Lomas, 2004; Desanker *et al*., 1997; Hoffman *et al*., 2009) even though it disagrees with a few others (Vicente-Serrano *et al*., 2010a) especially with regard to the correlation magnitudes in the region. The strongest vegetation response (about 0.92) is observed during the JJA season over the semi desert biome which is in the semi-arid environment. The vegetation here rely heavily on water for all their ecosystems functioning without which they would not survive (New, 2015). The response of tropical forest to droughts is weak compared to all other biomes. The correlation is as low as 0.4 in the DJF season but goes up 0.60 in MAM season. The relatively weaker response of tropical forest to drought may be because this biome can be drought-tolerant, have stronger adaptive capacity and thus, be as severely affected by droughts as do the other biomes (Gilgen *et al*., 2005; Corlett, 2016). The correlations of semi-desert, Mediterranean, temperate grassland biomes occur at either 3-, 6- or 9-month drought timescales. For instance, the semi-desert biome responds to drought at 3-month timescales in the MAM, JJA and SON months; while it takes longer period (9-month) for the same biome to respond in DJF season. The sensitivity of the semi-desert to water shortages makes them show quick response to drought (New, 2015).

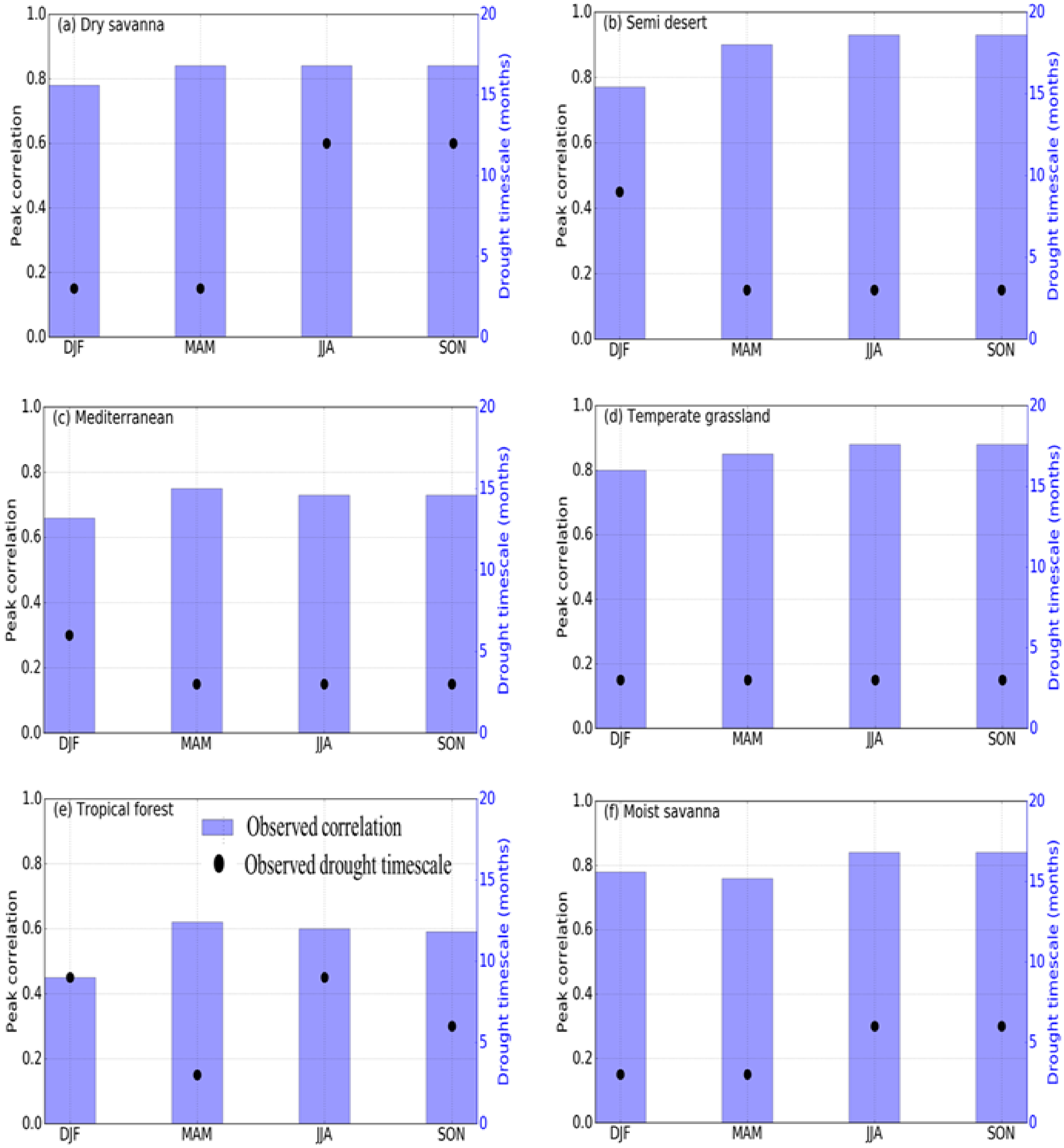

Figure 4.9. Seasonal correlations (Pearson coefficient, r) of drought (SPEI) and NDVI across six biomes. The values on the left axis show the peak correlation values in respect of observation. The values on the right axis show the corresponding drought timescale for the correlation value.

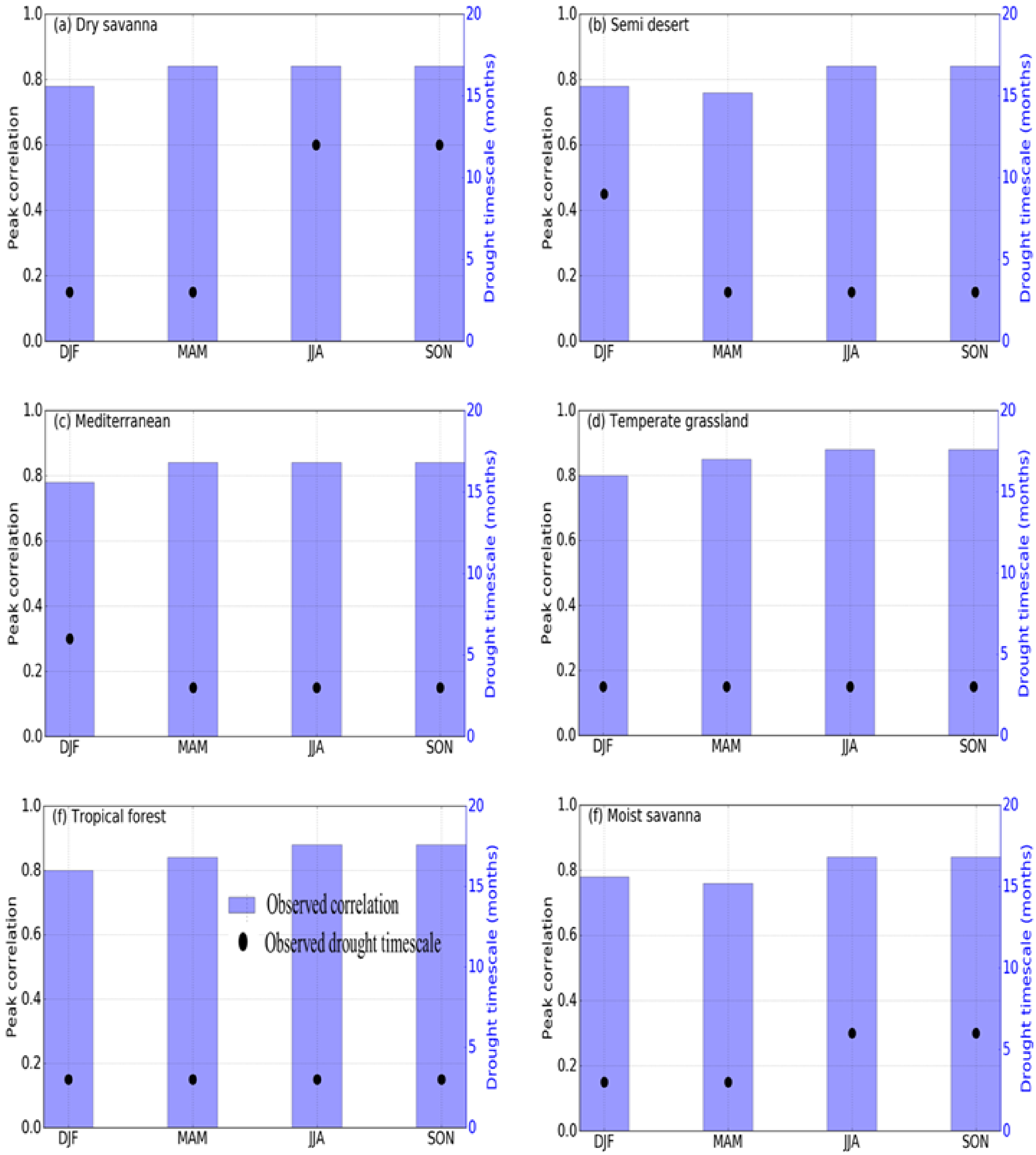

Figure 4.10. Same as Figure. 4.9 but for SPI

4.5 Summary

This chapter investigated the observed response of southern African vegetation to drought over a 22-year period (1983 - 2004). Observed monthly climate data (temperature and precipitation) and vegetation index from the CRU and the GIMMS, respectively, were analyzed for the study. The observed drought indexes (SPEI_HG, SPEI_PM and SPI) at various time scales (1- to 18-month timescales) were obtained from the climate data and correlated with the normalized NDVI. The results from the analysis showed that:

- All the climate variables show large spatial variation over southern Africa and large seasonal variability over the biomes. However, the largest seasonal variability in terms of precipitation and temperature occur over Tropical rainforest and Semi-desert biomes, respectively.

- The vegetation index (NDVI) also exhibits a large spatial and temporal variability, but the spatial variation in the NDVI is more akin to that of precipitation than that of rainfall, suggesting that precipitation may play a more crucial role than temperature in determining the spatial distribution of the vegetation index.

- All the drought indexes (SPEI_HG, SPEI_PM and SPI) show similar pattern of correlation with the vegetation index. A maximum correlation (about 0.8), which is shown by the SPEI_HG, is observed over the southeastern part of the region. This maximum correlation occurs at 3-month drought time scales.

- The correlation of the drought indexes (SPEI_HG & SPI) with the vegetation index varies across the biomes through the different seasons. The maximum seasonal correlation (about 0.92), is with the SPEI_HG and is observed over the semi desert biomes in JJA season, and this occurs at 18-month drought timescales.

- SPEI is a better drought index than the SPI (with the SPEI_PM as a more effective drought index than the SPI). The choice of an appropriate drought index is important for a successful management of plant ecosystems. For example, use of the SPEI_PM will help ecosystems manager to plan and minimize the combined impacts of rainfall, moisture and wind on vegetation, as well as rehabilitate the functioning of their ecosystems, whereas, with SPI, the ecosystems managers would only consider the impacts of rainfall in mitigation measures.

The study has provided several insights into how southern African vegetation respond to drought. It can be inferred from the study that southern African biomes are affected differently by drought. This is perhaps, because vegetation have different levels of need for water, and also divergent morphological and physiological properties that allow them to withstand water scarcity. It will also be interesting to investigate how models (i.e. DGVMs and ESMs) are capable of replicating this response. The next chapter examines the performance of DGVMs in simulating the response of southern African vegetation to drought

Chapter 5: Performance Evaluation of Dynamic Global Vegetation Models in Simulating the Response of Vegetation to drought in Southern Africa

This chapter evaluates the ability of DGVMs to simulate the response of southern African vegetation to drought. These DGVMs are stand-alone process-based models and have been reported (e.g. in Huntzinger *et al*., 2013) to show reliability in simulating the carbon exchange between the atmosphere and vegetation ecosystems. Here we correlated and mapped 1- to 18-month SPEI and SPI with three DGVMs (CLM4, CLM4VIC and ORCHIDEE-LSCE). The correlations were compared with observed responses - which were calculated by correlating the CRU with the GIMMS-NDVI.

5.1 Spatial distribution of precipitation, mean temperature, maximum temperature and minimum temperature over southern Africa

The spatial distribution of the observed and the reanalysis precipitation, maximum, minimum and mean temperature as depicted by the CRU and CRUNCEP datasets is presented in Figure 5.1. While the CRU is an observed dataset, CRUNCEP is a combination of observation and reanalysis data. A detailed description is given in of the Chapter 3 (Section 3.2.2).

The CRUNCEP does not simulate the magnitude of precipitation over some parts of southern Africa well, although it has similar precipitation patterns and magnitudes as the observation (Figure 5.1). CRUNCEP which has a spatial correlation of 0.89 with observation, overestimates the precipitation intensities over some parts of Angola and Madagascar (Figure 5.1b), and underestimates the magnitudes over Botswana and parts of South Africa.

Furthermore, the CRUNCEP weakly simulate the magnitudes of temperature over southern Africa. For instance, it overestimates the magnitude over parts of Mozambique and underestimates it over parts of South Africa. In addition, it also overestimates the maximum temperature over central parts of Botswana but underestimate it over southeastern parts of South Africa. Over the western parts of the region, the CRUNCEP overestimates minimum temperature (Figure 5.1h). The inability of the CRUNCEP to capture the magnitudes of the climatic variables will likely affect the DGVM ability to simulate vegetation response to drought. Nevertheless, CRUNCEP has a high correlations of 0.92, 0.90, and 0.93 with observed mean temperature, maximum and minimum temperature respectively.

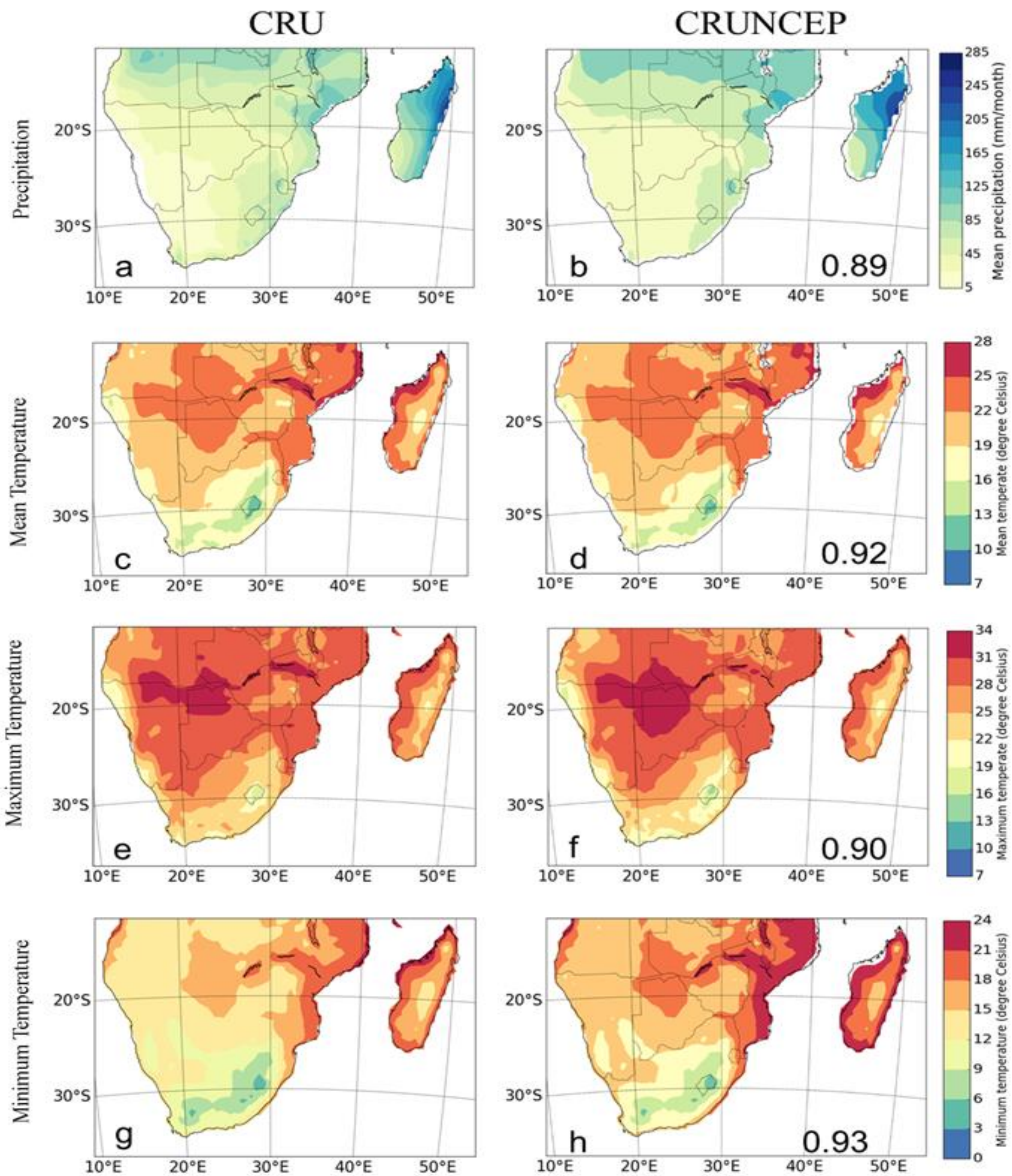

Figure 5.1. Spatial distribution of rainfall, mean temperature, maximum temperature and minimum temperature over southern Africa in observation and reanalysis; for the periods 1983 – 2004. The spatial correlation between observed and reanalysis variables are indicated inside the panels.

5.2 Observed and simulated vegetation index

Figure 5.2 the compares the simulated and observed NDVI by using a scatter-plot with correlations and normalized standard deviation. The observed NDVI was obtained from the satellite dataset described in Section 3, while the simulated NDVI was obtained from the three DGVMs datasets (CLM4, CLMVIC, and ORCHIDEE-LSCE) using the method described in the same section. Since, the figure was generated by using the monthly NDVI data over each grid point over in the Southern African domain, the correlation accounts for both spatial and temporal relationship between the observed and the simulated NDVI. The normalized standard deviation was calculated by dividing the simulated standard deviation (spatial and temporal) by the corresponding observed NDVI.

The DGVMs performs differently in simulating the characteristics of the observed NDVI over southern Africa (Figure 5.2). The simulated NDVIs have different correlation with observed (Fig 5.2). The CLM4 NDVI features the highest correlation ($r = 0.60$) followed by the CLM4VIC NDVI ($r = 0.58$) and ORCHIDEE-LSCE NDVI ($r = 0.47$). For all the DGVMs, the normalised standard deviation of the simulated NDVI is less than 1.0 (i.e. CLM4: 0.6; CLM4VIC: 0.5; ORCHIDEE-LSCE: 0.17), meaning that the spatio-temporal variability of the simulated NDVI is lower than the observed NDVI. They also underestimate NDVI. The above results indicate that CLM4 performs best in simulating the NDVI while ORCHIDEE-LSCE perform worst. Although the performance of CLM4VIC is comparable to that of CLM4 (because CLM4VIC is a modified version of CLM4), the better performance of CLM4 than CLMVIC indicate that modification made in CLM4VIC has deteriorated the simulation of NDVI over southern Africa. In the modification, the soil hydrological scheme was replaced with the scheme used in the Variable Infiltration Capacity (VIC) model (Wang *et al*., 2008). Wang *et al.*, (2008) shows that this modification improved the modelling of land surface hydrological processes, but the present study indicates that there is a need to ensure that the new scheme performs better than CLM4 in simulating the NDVI over southern Africa.

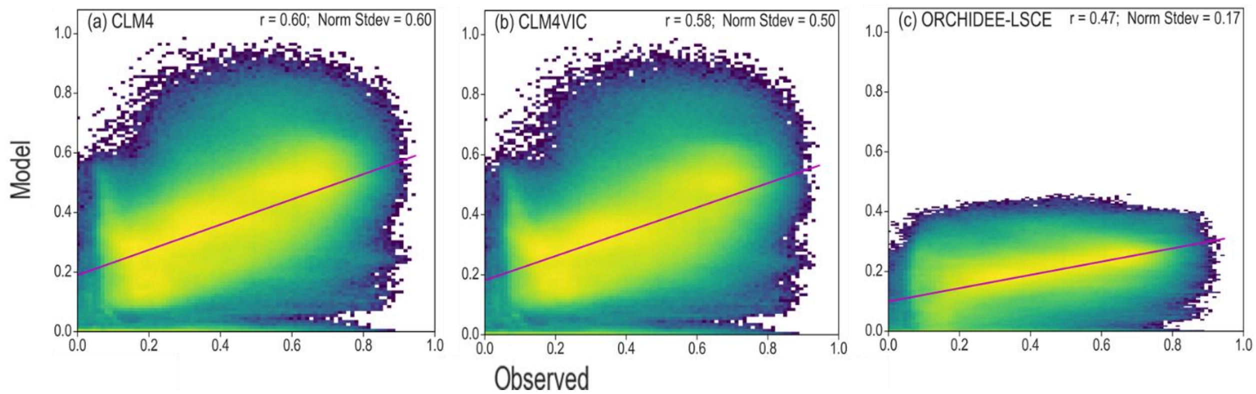

Figure 5.2. Scatter-plots of the observed and the simulated NDVI over Southern Africa. The coefficient of correlation (r) between the observed and the simulated NDVI for each DGVM is shown. The normalized standard deviation (Norm Stdev) of the simulated NDVI is also indicated.

The DGVMs underestimate the NDVI over the eastern part of the over southern Africa; hence, they produce a weaker NDVI gradient than is observed over the sub-continent (Figure 5.3). However, the magnitude of the negative bias varies among the models. CLM4 that perform best has a spatial correlation of about 0.64 with the observed, a maximum bias about -0.2 (along the eastern coastline and over Madagascar) and a normalized standard deviation of 0.85. ORCHIDEE, which performs worst has a correlation of 0.5 and a maximum bias of -0.3 (along the eastern coastline and over Madagascar). However, in all the models, a comparison of performance metrics (bias, correlation, and normalized standard deviation), as illustrated in Figures 5.2 and 5.3, suggest that the model captures the spatial variability of the NDVI better than the temporal variability. For instance, with ORCHIDEE, the correlation of the simulated and observed NDVI increases from 0.47 in the spatial-temporal distribution (Figure 5.2) to 0.5 in the spatial distribution, whereas the corresponding normalized standard deviation increases from 0.17 to 0.47.

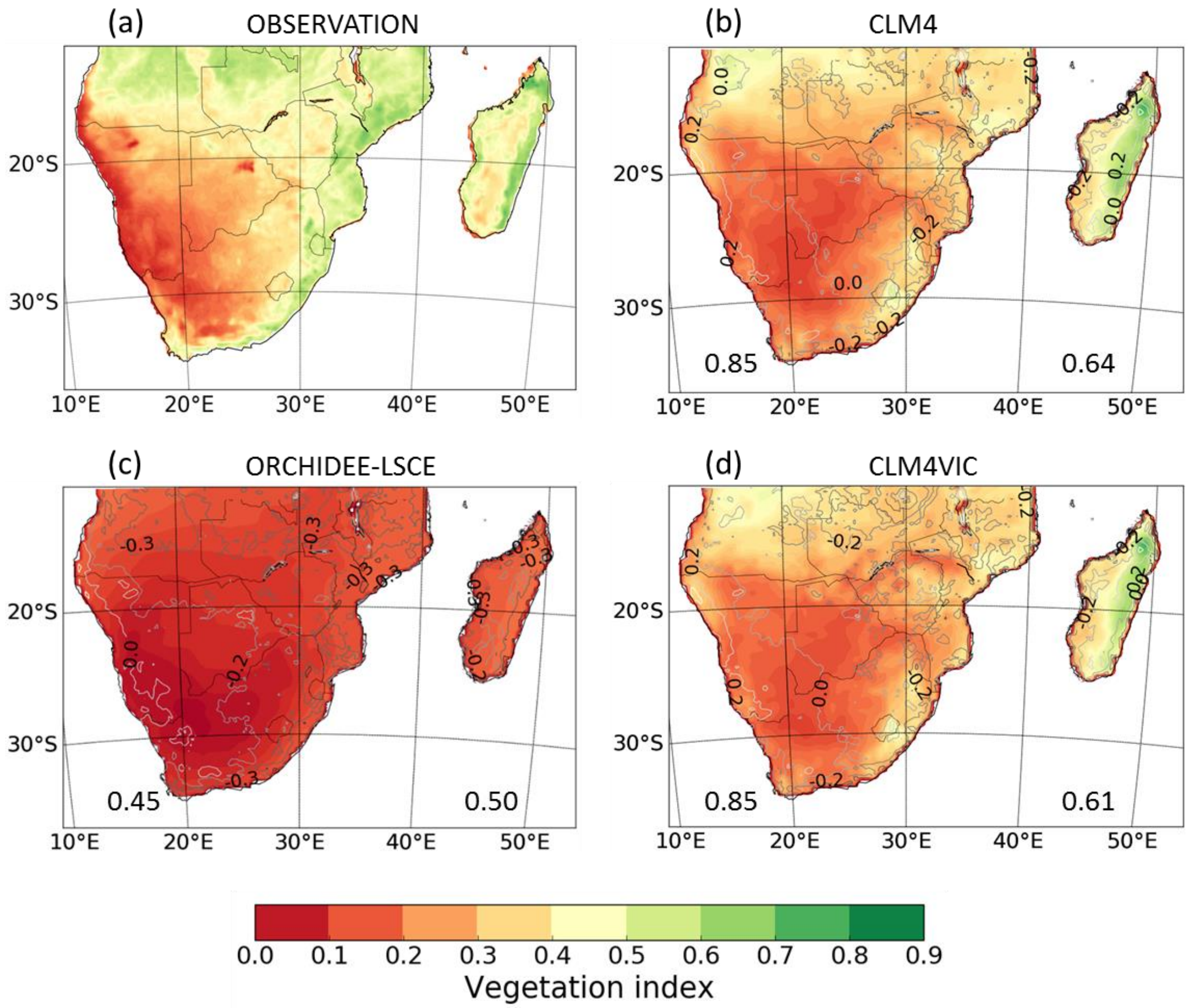

Figure 5.3. Spatial distribution of observed and simulated vegetation indexes over southern Africa; for the periods 1983 – 2004. For panels (b) – (d), the inset values on the right hand side are r values obtained from the spatial correlation between the observed and the modeled NDVI, while the inset values on the left hand side are the normalized standard deviations. The gray contours indicate the vegetation anomalies for each model.

The models do not well reproduce the climatology of the vegetation index over the southern African biomes with a few exceptions (Figure 5.4). For instance, the models poorly simulate the decline in vegetation over the dry savanna, semi desert, temperate grassland, tropical forest and moist savanna biomes during the JJA and SON seasons. Although CLM4 and CLM4VIC reproduces similar patterns as observation dataset, especially over the dry savanna, semi desert, temperate grassland and moist savanna, it lags behind by for two month. This lag may be the reason for the models' underestimation as shown Figure 5.3 above. ORCHIDEE-LSCE perform poorly in replicating of observed vegetation index, as it shows opposing climatology particularly during MAM and JJA seasons. Conversely, ORCHIDEE-LSCE best performs in Mediterranean vegetation and tropical forest biome, while CLM4 and CLM4VIC perform the worst. Both CLM4 and CLM4VIC show the similar climatological patterns over all the biomes, however, the simulated values in CLM4 are generally higher than those of CLM4VIC. In addition, ORCHIDEE-LSCE overlaps CLM4 and CLM4VIC during JJA season except over tropical forest and moist savanna biomes. The highest underestimation is by ORCHIDEE-LSCE over the tropical forest and moist savanna. The poor performance by these models might be caused by the parameterization process in their simulation of energy balances. For example, in CLM4VIC, there are run-off parameterizations of the VIC model and the TOPMODEL-based soil model respectively (Oleson, *et al*., 2004). The failure of DGVMs to sufficiently capture the climatology and magnitudes of the vegetation index will likely affect the models' ability to strongly capture the response of vegetation to drought in different biomes. Thus, the DGVMs, particularly ORCHIDEE-LSCE, may not be a top choice model for simulating the vegetation index and climate-vegetation interaction.

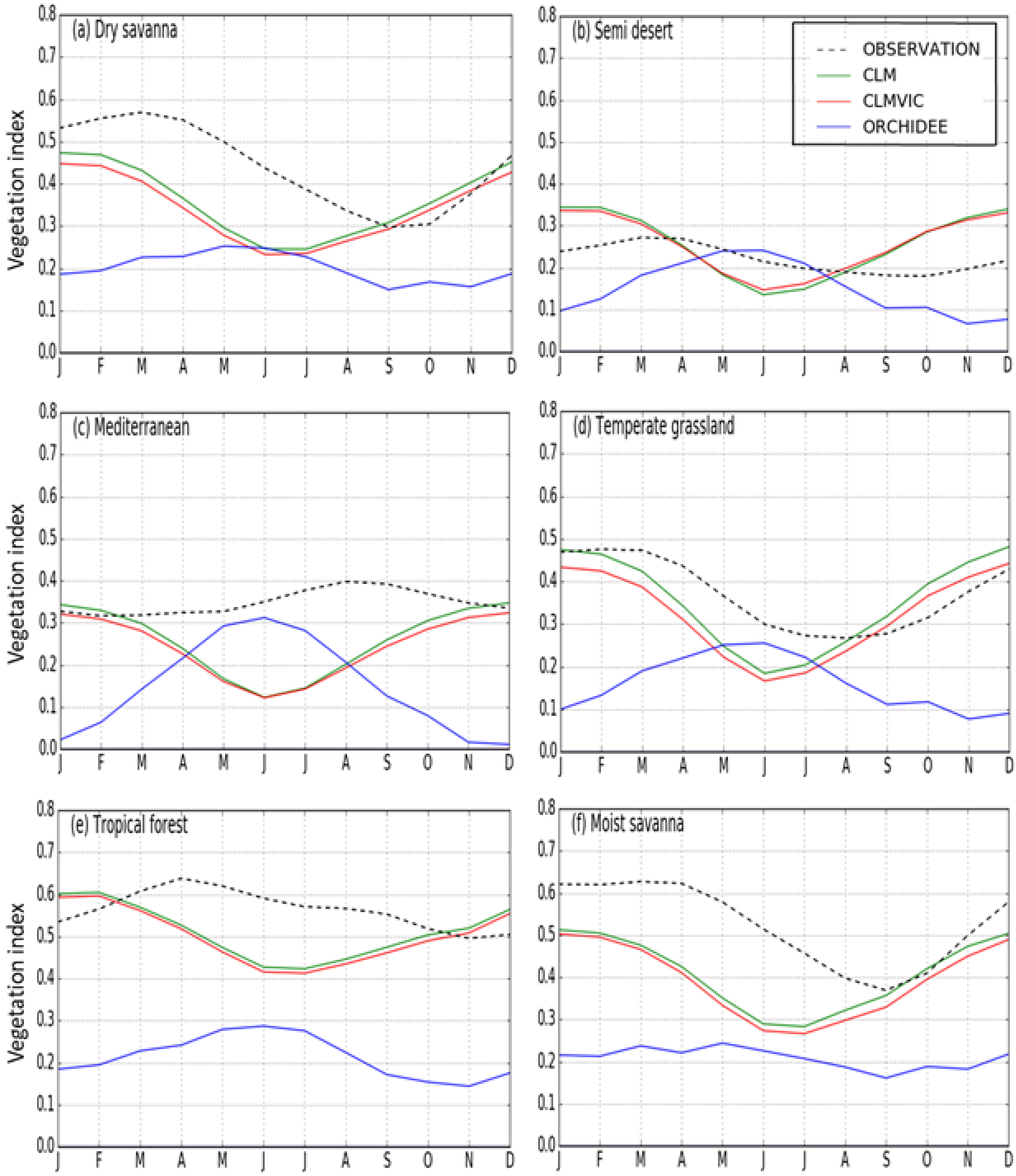

Figure 5.4. Monthly cycle of vegetation index; for observation and models, across six biomes of southern Africa for the periods 1983 – 2004.

5.4 Spatial distribution of observed and simulated vegetation response to drought

The models do not generally show the magnitude and patterns of vegetation response as the observed (Figures 5.5 and 5.6). For instance, in Botswana, Zimbabwe, Zambia, parts of Angola and South Africa, ORCHIDEE_LSCE show a correlation magnitude of about 0.4. The poor replication of drought response by the models may be due to the bias in reanalysis (CRUNCEP) data from which drought is computed (Barman *et al*, 2014). Thus, this bias in variables may have contributed to the models underestimating the vegetation's response to drought. Furthermore, poor replication by models may also be attributed to the fact that they do not well simulate the magnitudes of vegetation index as seen in Figures 5.3 and 5.4. However, there is not much difference in the spatial distributions of the SPEI and SPI of the models. The inability of the DGVMs to adequately simulate vegetation response to drought may also imply that the parameterizations process in the models does not represent the complex processes very well. Hence, there is a need to fix the representation of the vegetation processes in the models.

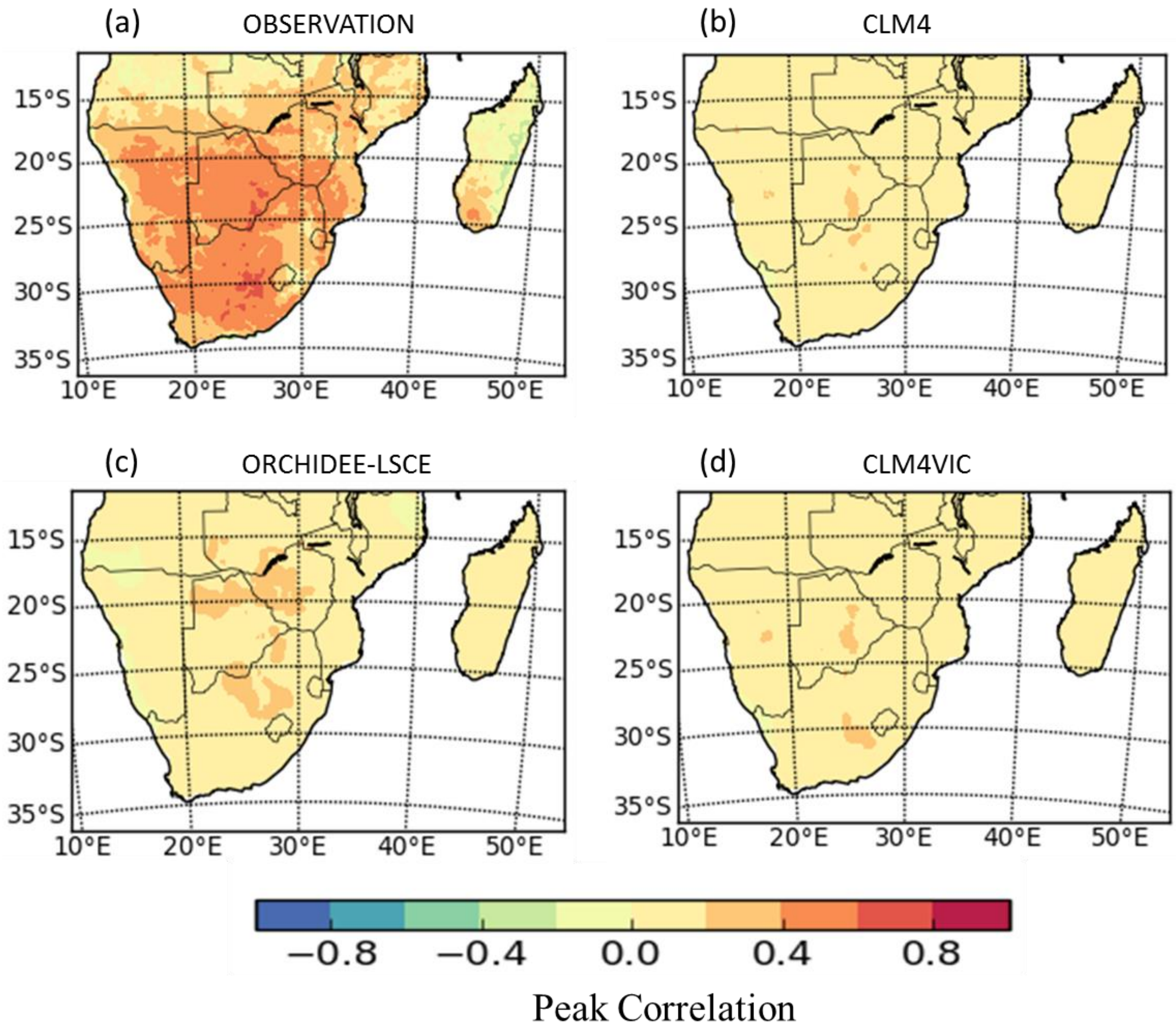

Figure 5.5. Spatial distribution of correlation between drought (SPEI) and vegetation over southern Africa in observation and in the models for the period 1983 – 2004.

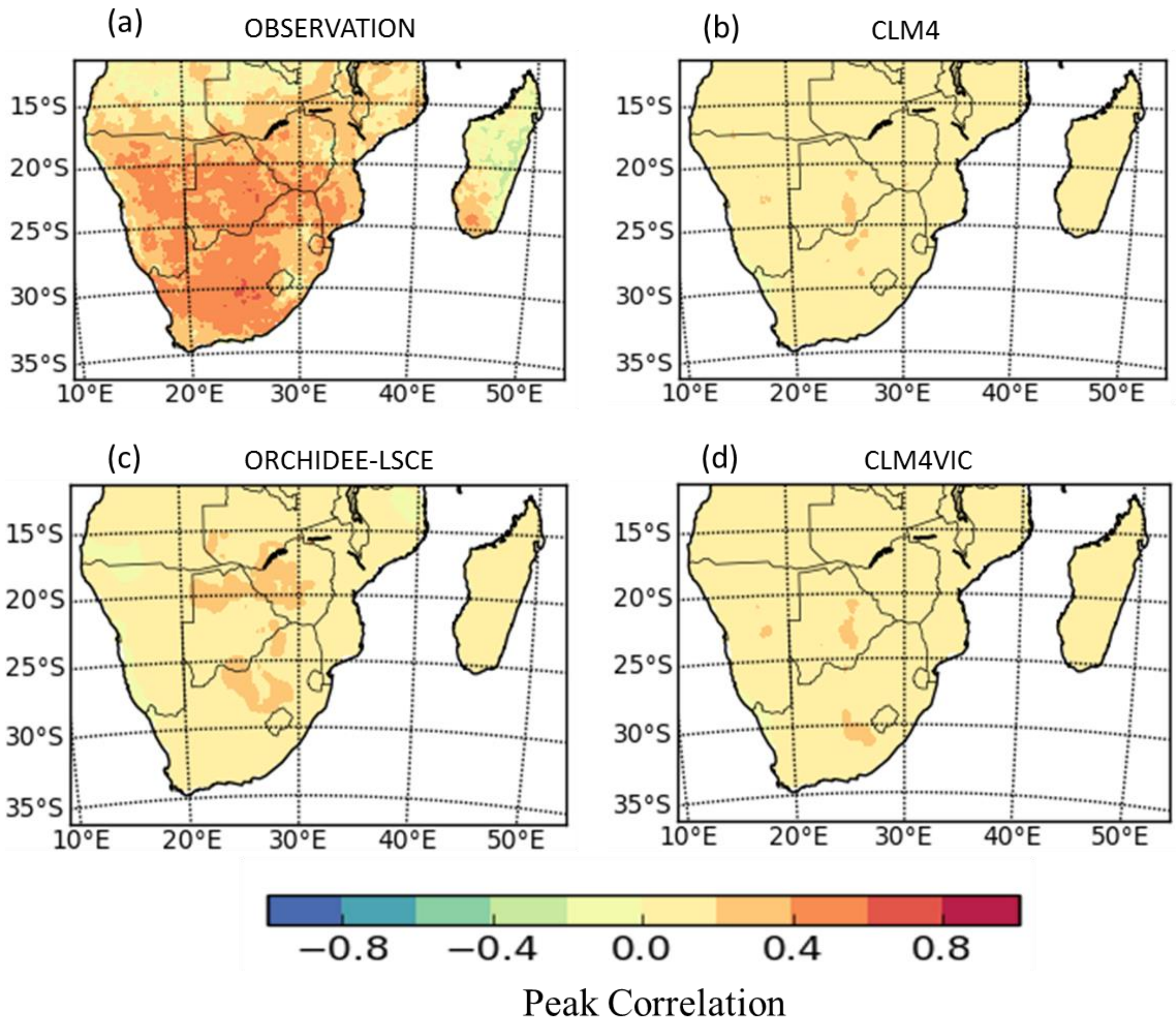

Figure. 5.6. As in Figure. 5.5 but for SPI

5.5 Drought timescales of vegetation response to drought

The simulated timescales of vegetation response to drought do not agree with the observation (Figures 5.7 and 5.8). The models do not reproduce the variability in drought timescale that is shown in the spatial distribution of the observation. The models greatly overestimate the timescale. For example, over the western parts of the region, the models underestimate the timescale by simulating a preponderance of 1-month timescale. Furthermore, the models show some inconsistencies with the observation over eastern parts of Madagascar. The difference in the spatial distribution of timescales in models from observation might be because of the method with which land cover-atmosphere feedback and parameters are represented and estimated in the models. Furthermore, the models are not similar in their simulations of drought timescales. The difference in the energy exchange processes may also be the reason for the difference in the spatial distribution of timescales simulated by the different models. For example, there is less variability in CLM4VIC than in the CLM4 simulations over eastern parts of the region; and there is even less variability shown in ORCHIDEE-LSCE.

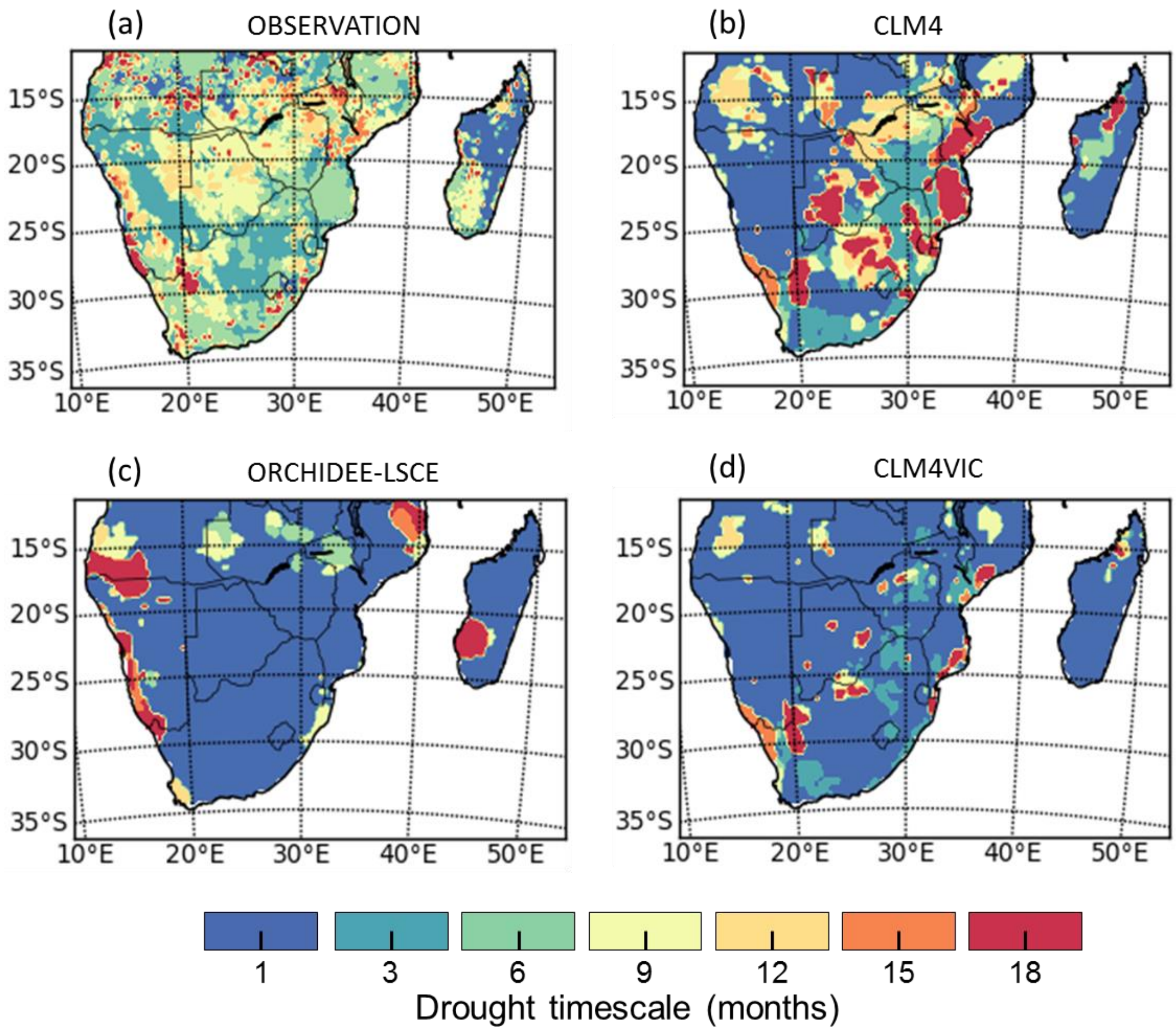

Figure 5.7. Spatial distribution of drought (SPEI) time scales of vegetation response in observation and models; for the period 1983 – 2004.

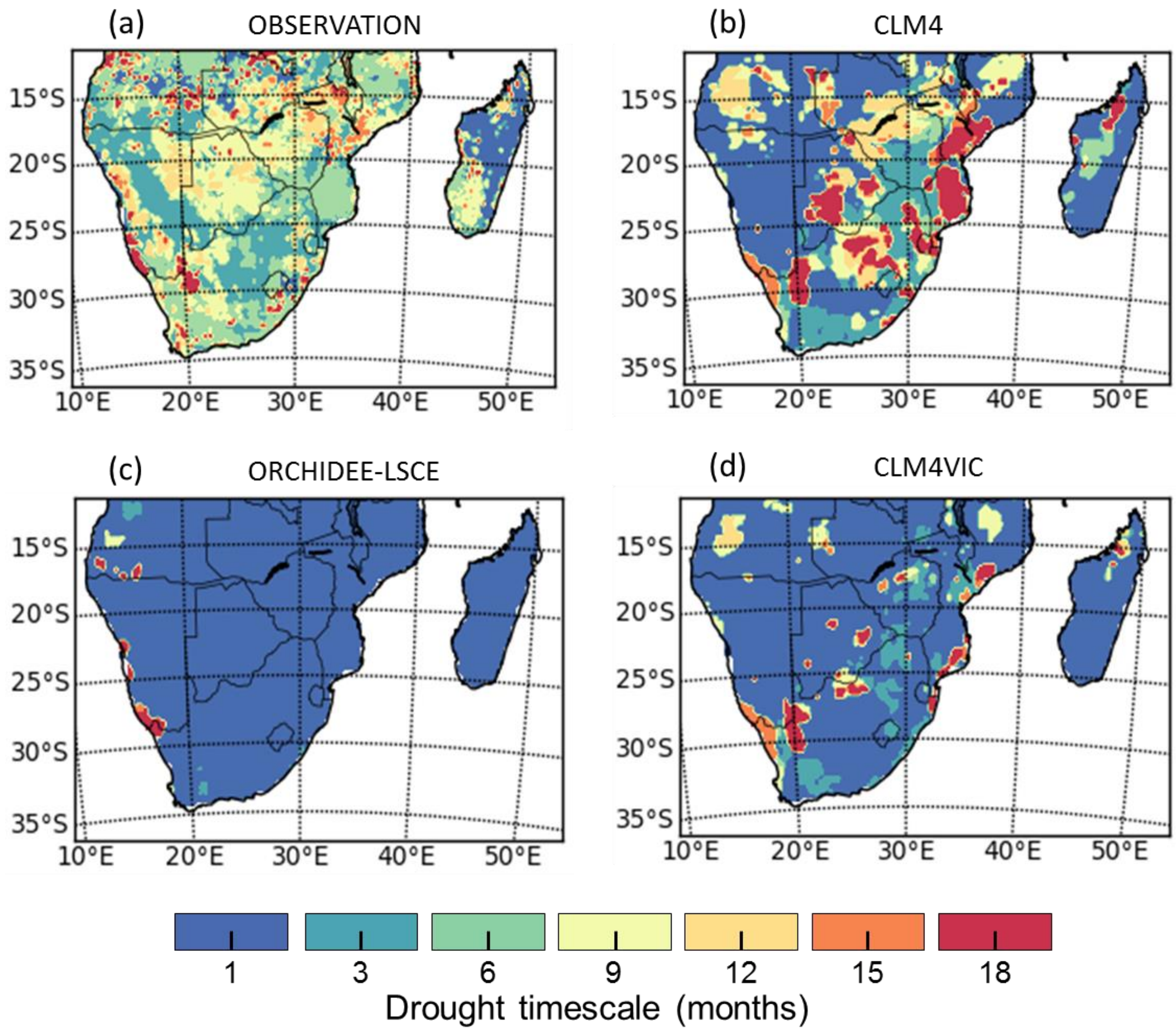

Figure 5.8. As in Figure 5.7 but for SPI

5.7 Influence of fire on biomass and vegetation fluxes over southern Africa

Figures 5.9 to 5.11 show the simulated differences in biomass and vegetation fluxes with and without fire over southern Africa. The effects of fire on fluxes and biomass varies across southern Africa. For example, over parts of Namibia, Botswana, Angola and South Africa, the aboveground and belowground net primary production (AGNPP and BGNPP) decreases with burning (Figures 5.9 to 5.11; f, g). This may be attributed to the fact that both variables are sensitive to fluctuation in temperature (Pricope *et al*., 2015). However, Over same regions, total leaf area index (TLAI) increases in the absence of fire (Figures 5.9 -5.11; a). The implication of these is that while fire may be beneficial to the increase of fluxes in some areas; nevertheless, it is detrimental to other fluxes, particularly those which are sensitive to fluctuations in climate variables such as temperature.

Fire strongly influences changes in biomass (NDVI) over the region (Figure 5.11l). For instance, over the arid zone of Namibia and the tropical biome of Madagascar, NDVI is largely unaffected by fire. However, over the summer rainfall of eastern South Africa, the results of simulation shows that the exclusion of fire resulted in significant changes (increase) of biomass. This is because fire is the main determinant of vegetation over this location, and such ecosystems are fire-dependent for functioning (Bond *et al*., 2002; Staver *et al*., 2011). In addition, the physiological difference in the response of the vegetation in these locations also determine their response to fire. For example, the vegetation in temperate grassland biome of eastern South Africa uses the C_4 photosynthetic pathway which yield to high temperature and low CO_2 while the vegetation in the tropical forest biome over Madagascar uses the C_3 photosynthetic pathway which yield to low temperature and high CO_2 (Higgins & Scheiter, 2012). The implication is that the temperate grassland has high demand for fire in comparison to the tropical forest which has a high demand for CO_2. It should be noted that this is why an increase in CO_2 will benefit tree growth, and a shift in temperature will lead to growth of the grassland (Scheiter & Higgins, 2009). However, fire appears to have no influence on the simulation of AGNPP, BGNPP and FPSN over Namibia, Botswana and eastern parts of South Africa (Figures 5.11f, 5.11g and 5.11h).

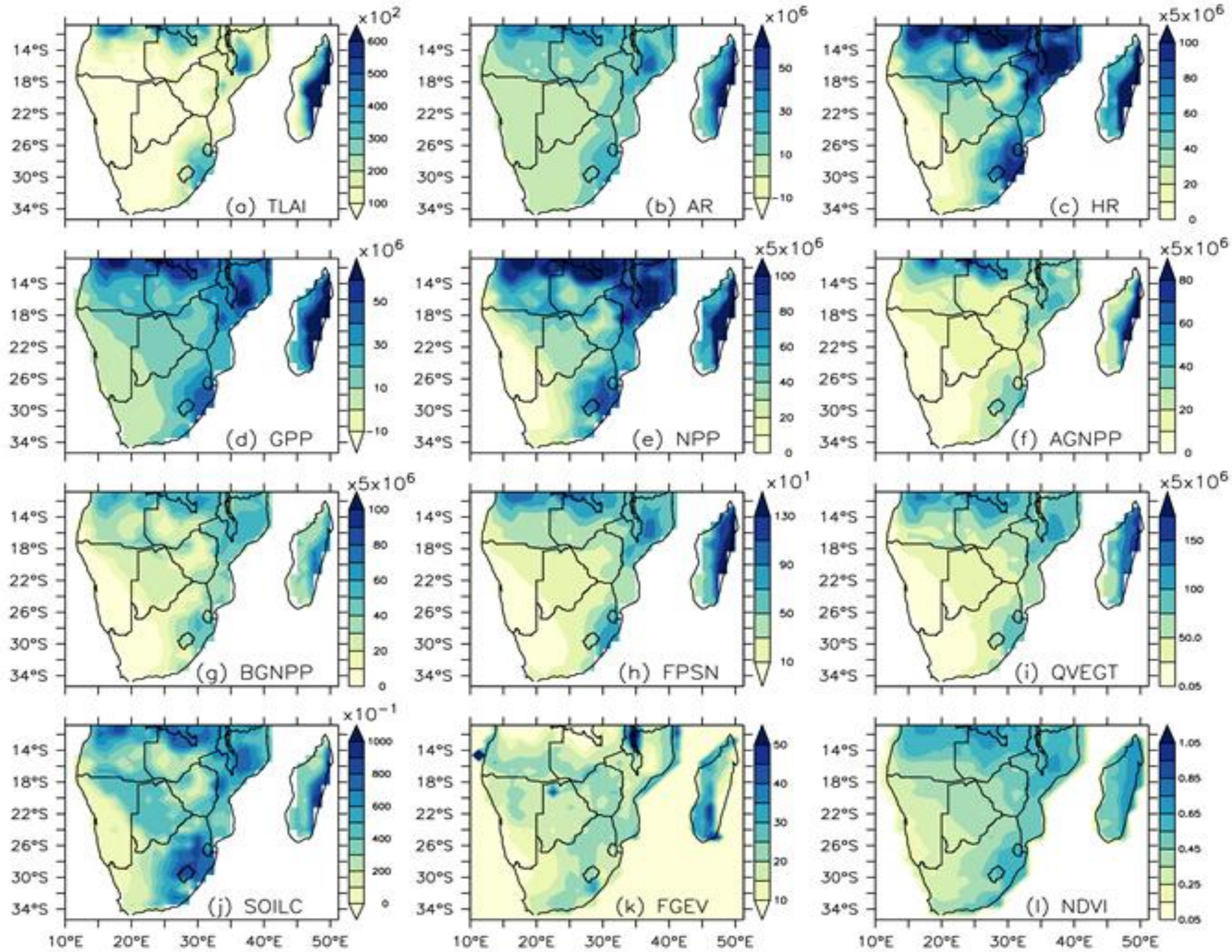

Figure 5.9. The effect of fire on vegetation fluxes and biomass (NDVI) over southern Africa simulated with the Community Land Model (CLM, v4.5). The vegetation fluxes and their units are: total leaf area index (TLAI, gC/m^2/s); autotrophic respiration (AR, gC/m^2/s); heterotrophic respiration (HR, gC/m^2/s), gross primary production (GPP, gC/m^2/s), net primary production (NPP, gC/m^2/s), aboveground net primary production (AGNPP, gC/m^2/s), below ground net primary production (BGNPP, gC/m^2/s), photosynthesis (FPSN, umol/m^{2}s), canopy transpiration (QVEGT, mm/s), soil carbon (SOILC, gC/m^2) and ground evaporation (FGEV, W/m^2).

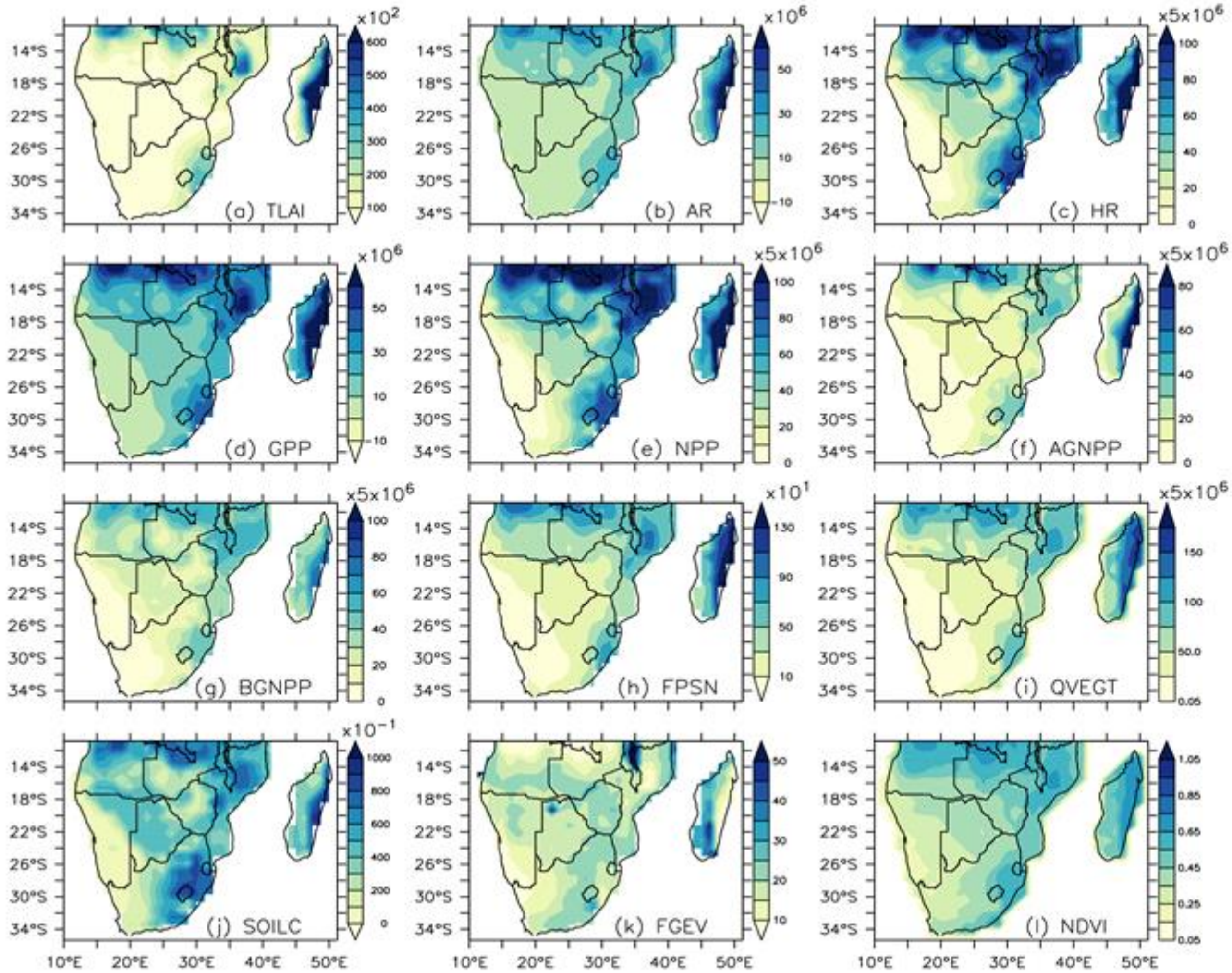

Figure 5.10. As in Figure 5.9 but without fire

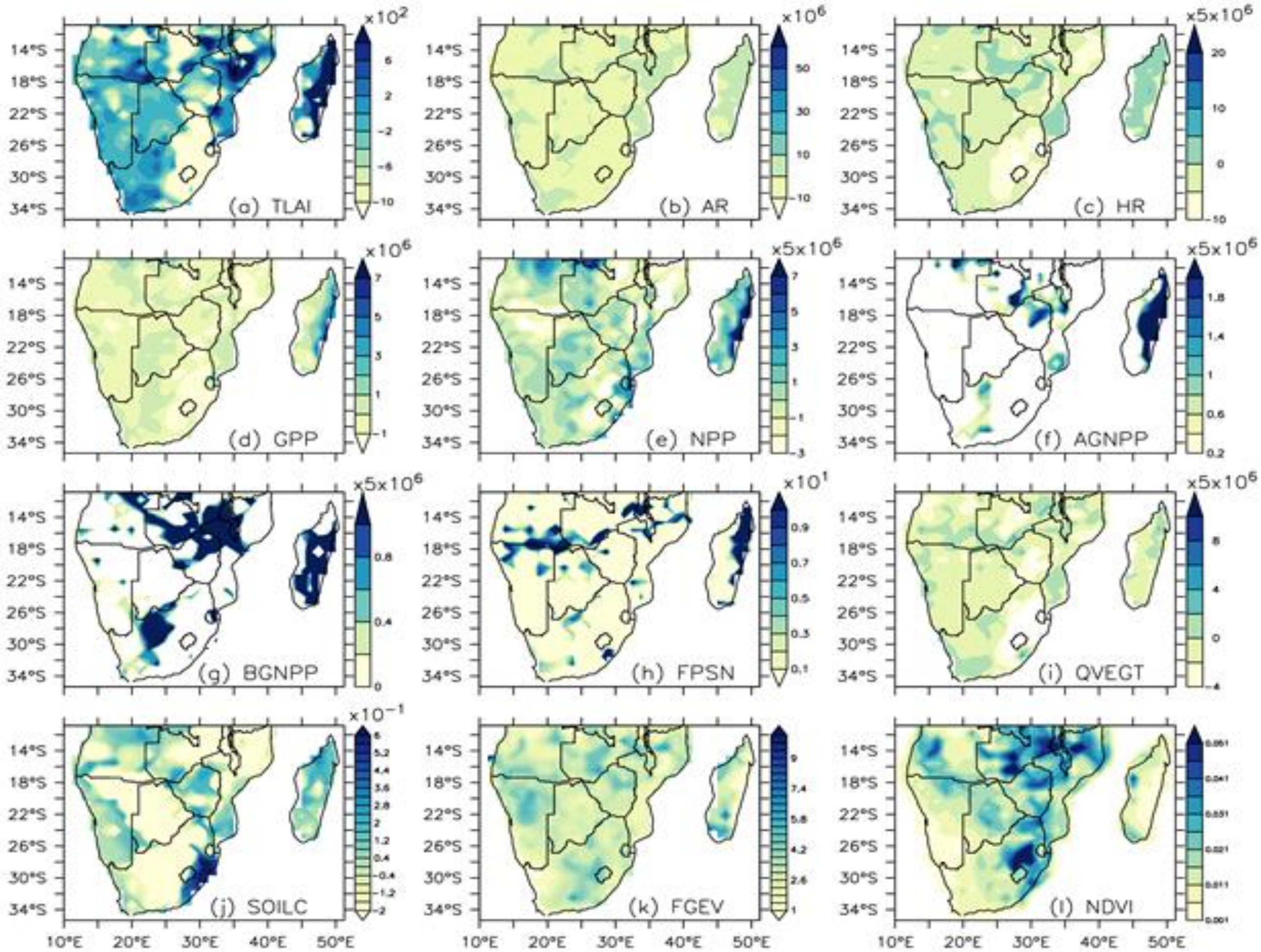

Figure 5.11. As in Figure 5.9 but bias

5.8 Summary

The chapter examined the response of vegetation to drought by using 1- to 18-month SPEI and SPI from the CRUNCEP data. The vegetation datasets used in the study were obtained from CLM4, CLM4VIC and ORCHIDEE-LSCE. The models were evaluated by computing a grid cell correlation of the modeled vegetation indexes with / and the models with observation. We computed and compared the spatial distribution of the modeled vegetation index with the observation. The simulated peak correlations and the corresponding timescales from the models were mapped and compared with the observed correlations and timescales. The results from the studies can be summarized as follows:

- The NDVI from the DGVMs show a fairly high correlation but a linear relationship with the observed NDVI (i.e. GIMMS NDVI). Among the models, CLM4 has the best correlation with observed while ORCHIDEE-LSCE shows the weakest correlation.

- The monthly cycle of the NDVI over southern Africa was not well reproduced by DGVMs. The poorest replication of the cycle is shown by ORCHIDEE-LSCE.

- The models poorly capture the vegetation response to drought as they all underestimate the correlation of the drought indexes (SPEI and SPI) with vegetation. The poorest correlation is simulated by ORCHIDEE_LSCE and this is over the Angola- Namibia border.

- The drought timescales are not well reproduced by the models. The poorest simulation is ORCHIDEE-LSCE while CLM4 performs relatively better, particularly over the eastern parts of the region.

- CLM4 simulations show that the NDVI is unaffected by fire over the arid zone of Namibia and tropical biome of Madagascar. However, over the summer rainfall eastern region of South Africa, fire does not have an influence on the greenness of vegetation. However, the full extent of the impact of fire on southern African vegetation may not have been fully captured by CLM. This is because wildfires occur seasonally in the region. For instance they occur during the dry summer months on the west coast of South Africa and in dry summer months on the east coast of the region. However, in CLM, prescribed fire depends on fuel availability, soil moisture as well as human population among other variables (Thonicke *et al*., 2011). This implies that the length of the fire season in the model might be longer or shorter than normal. Hence, there is a need to adjust fire module in CLM.

- The varied impacts of fire on vegetation fluxes and biomass over southern Africa have implications for mitigation actions over the region. For instance, over the north-western parts of the region, efforts would include minimizing the incidence of fires and their impacts on vegetation, but this may not be necessary in other areas.

The results of the study show that the DGVMs do not adequately capture vegetation response to drought as in the observation (GIMMS NDVI) did. This might be due to the manner in which the parameters (with which NDVI was derived) were run in the models. It may also be because the models are not coupled model. Hence, there is a need to investigate how the response would be captured in a fully coupled model (ESM), which has its own atmospheric component. The next chapter examines the performance of CESM in simulating the response of southern African vegetation to drought.

Chapter 6: Performance Evaluation of the Community Earth System Models in simulating the response of vegetation to drought in southern Africa

The previous study (Chapter 5) has shown that DGVMs do not well capture the response of vegetation to drought, perhaps because they are standalone models. However, little is known about how well earth system models (ESMs) which have atmospheric and land components can simulate this response. This chapter thus examines the response of southern African vegetation to drought in both the observation dataset and the CESM1(CAM5) (hereafter, CESM). Here, drought was computed by using observed climate datasets, which were obtained from the CRU, and the simulated climate data obtained from forty CESM ensemble members. Furthermore, observed vegetation datasets obtained from the GIMMS-NDVI and computed NDVI data for each CESM ensemble member were also analyzed. The climatology of precipitation, vegetation indexes, maximum and minimum temperature across the southern African biomes were also computed. Thereafter, the correlations between drought index and vegetation in both observation (CRU and GIMMS NDVI) and model (CESM) were calculated and mapped.

6.1 Spatial distribution of climate variables and vegetation index over southern Africa

The magnitudes of climate variables and vegetation index over southern Africa are not well replicated by the model (Figure 6.1). For instance, over Angola, South Africa, Mozambique, Zambia and Madagascar, the model overestimates the intensity of precipitation (Figures 6.1a & 6.1b). The biases in the magnitude of rainfall simulated by CESM may be caused by inadequate representation of the diurnal cycle which is due to the choice of the convective parameterization schemes used in the model (Liang et al., 2004). It might also be due to the inability of the model to resolve the moist layer depth, rate of evapotranspiration and deposition of vertical uplift in the heated air as well as the steep topography over some parts of the region (Engelbrecht *et al.*, 2002; Jury, 2012; Dedekind *et al.*, 2016). In addition, model overestimates mean temperature over Namibia and Angola, and underestimates it over the eastern parts of South Africa (Figures 6.1c &

6.1d). Furthermore, the model overestimates the maximum temperature but underestimates the minimum temperature over the region (Figures 6.1e, 6.1f, 6.1g & 6.1h). The biases in the intensity of temperature simulation by CESM may be due to the model's sensitivity to climate (Sanderson *et al*., 2015). The model also overestimates the vegetation index over the region (Figures 6.1i and 6.1j). The model bias in simulating the vegetation index may be attributed to the inability of its land component to resolve the vegetation parameters. However, the simulated climate variables and vegetation index have fairly high correlations of 0.6, 0.7, 0.6, 0.8 and 0.7 with the observed precipitation, mean temperature, maximum temperature, minimum temperature and vegetation index respectively.

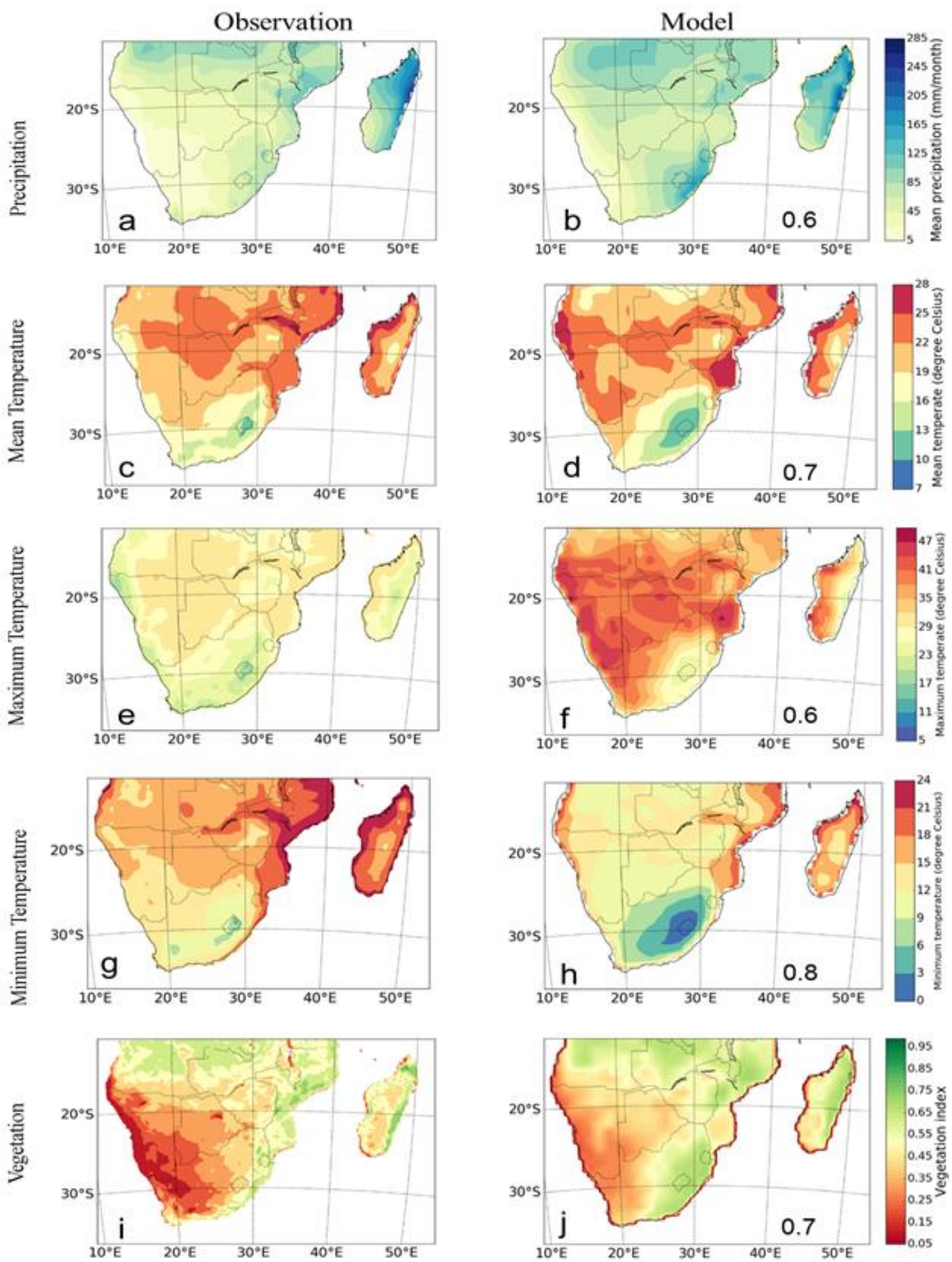

Figure 6.1. Spatial distribution of rainfall, mean temperature, maximum temperature, minimum temperature and vegetation over southern Africa in the observation and the model; for the periods 1983 – 2004. The spatial correlations between the observed and the simulated variables are indicated inside the panels.

6.2 Temporal distribution of climate variables and vegetation index over the southern African biomes

Model ensemble members do not well replicate the climatology of precipitation over southern Africa (Figure 6.2). For instance, over the dry savanna, semi desert, temperate grassland, and moist savanna biomes, ensemble members show higher precipitation magnitudes. Over the Mediterranean vegetation, the ensemble members do not replicate observed pattern in JJA season. However, they simulate close magnitudes with observation over the tropical forest. The model bias might be caused by the addition of convection effects in the CESM model with the aim of improving precipitation events, which were much lower in the previous version (CCSM3) of the model (Richter & Rasch, 2008).

Figures 6.3 and Fig. 6.4 show that model ensemble members underestimate maximum temperature and overestimate minimum temperature over most of the biomes. However, simulated maximum temperature are closer to the observation over the semi desert biome during the JJA and SON seasons. Over the moist savanna, the minimum temperature have close magnitudes with observation. Furthermore, the model reproduces the annual cycle of mean temperature over the southern African biomes (Figure 6.5). However, the magnitudes of these annual cycle are not well replicated by models. For instance, over the dry and the moist savanna, model underestimates the magnitudes but it overestimates the annual cycle over the rest of the biomes.

The model ensemble members replicate the pattern of vegetation climatology over all the biomes in the region (Figure 6.6), but underestimate the magnitudes across most of the biomes. The magnitudes that most closely resemble the observation magnitudes occur in the Mediterranean vegetation biome, where the model overlap observation. However, the model overestimates observation in the temperate grassland biome. In comparison to DGVMs (see Chapter 5; Section 5.2), the CESM produces simulates the temporal pattern better, although its intensity bias is larger than that simulated by the DGVMs.

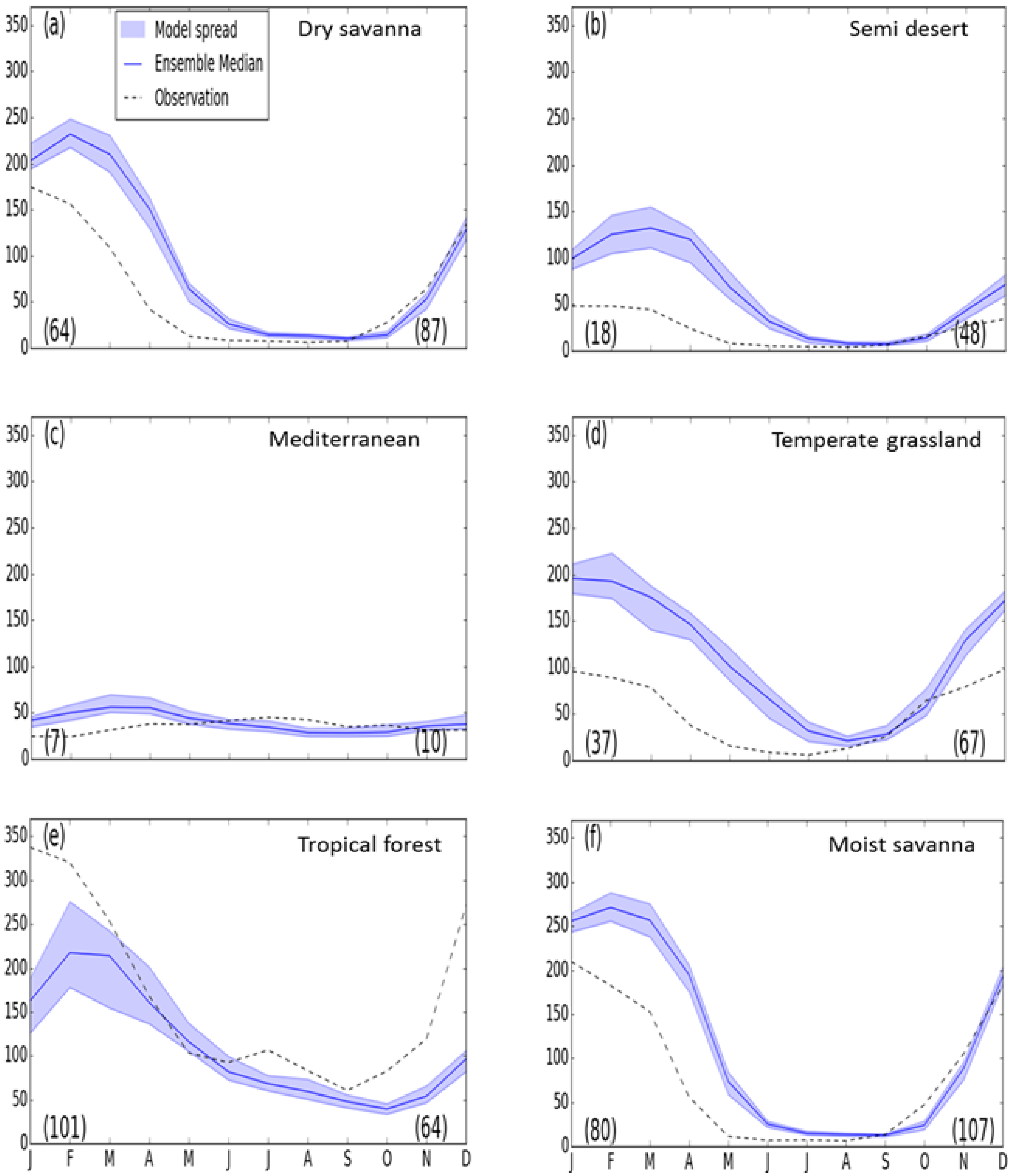

Figure 6.2. Annual cycle of observed and simulated rainfall (mm/month) across six biomes in southern Africa for the periods 1983 – 2004. The inset values at the bottom left and right of the panels indicate the Standard Deviation (SD) of the observed and the ensemble median respectively.

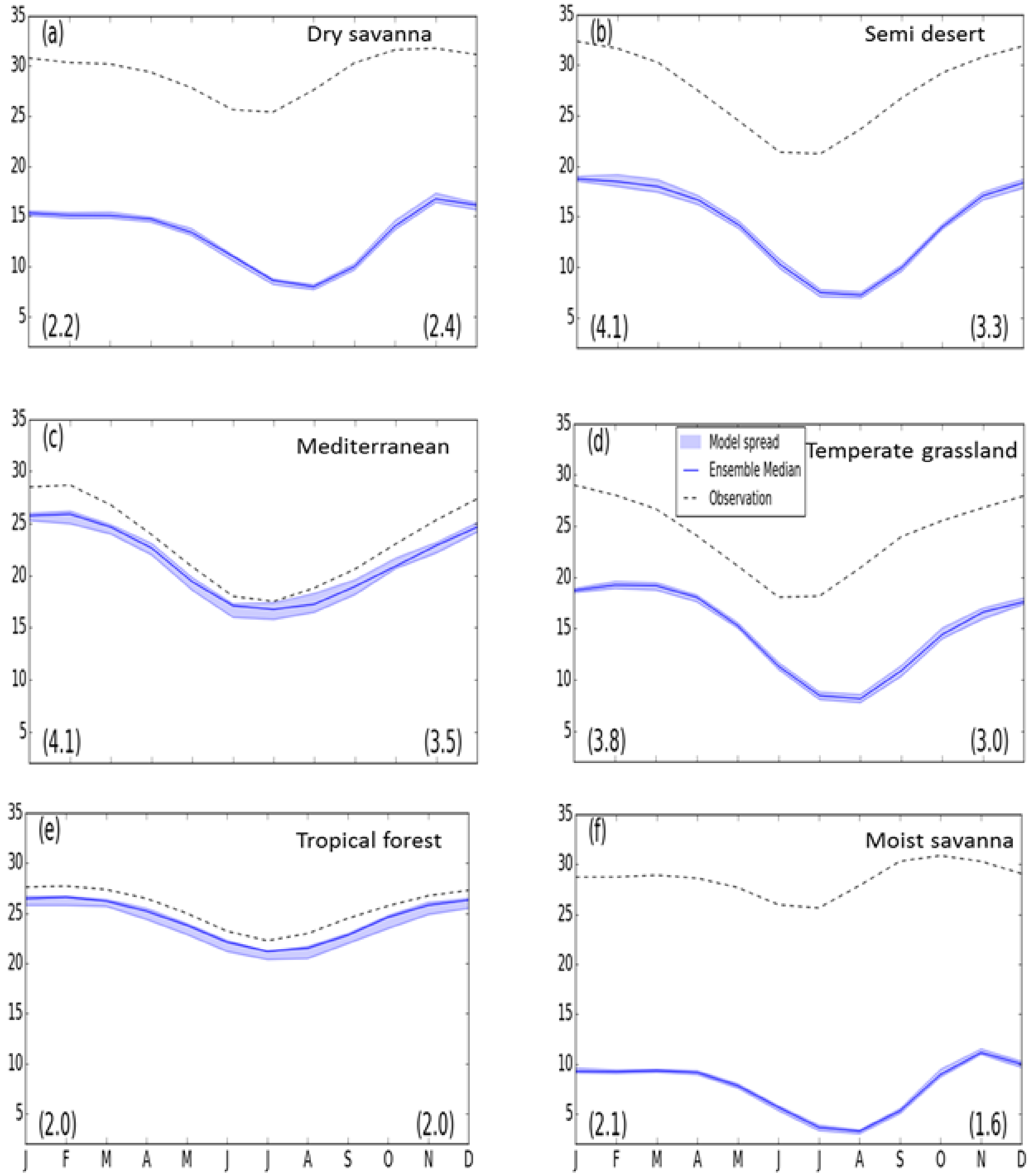

Figure 6.3. As in Figure 6.2 but for maximum temperature (^{0}C).

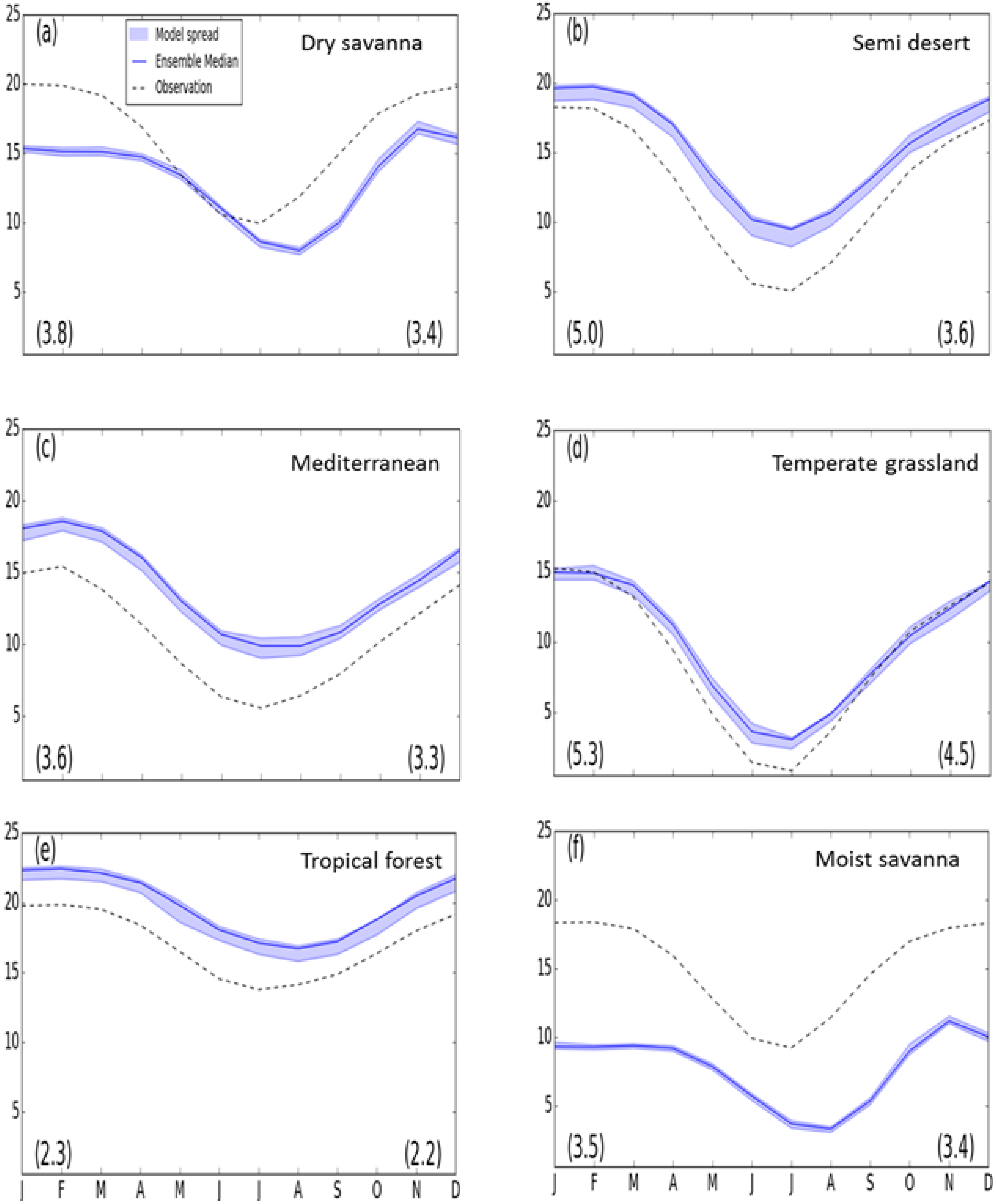

Figure 6.4. As in Figure 6.2 but for minimum temperature (^{0}C).

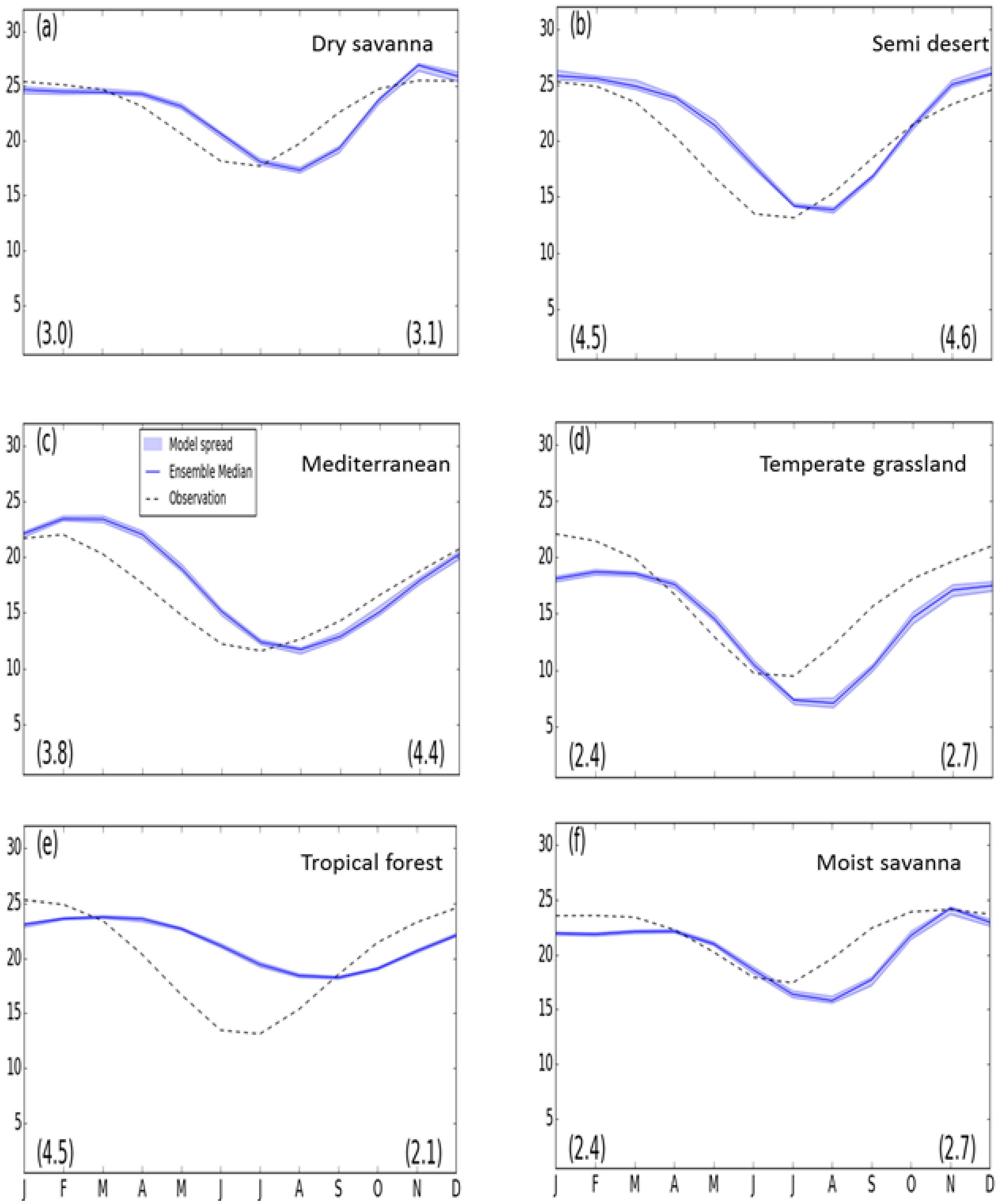

Figure 6.5. As in Figure 6.2 but for mean temperature (^{0}C).

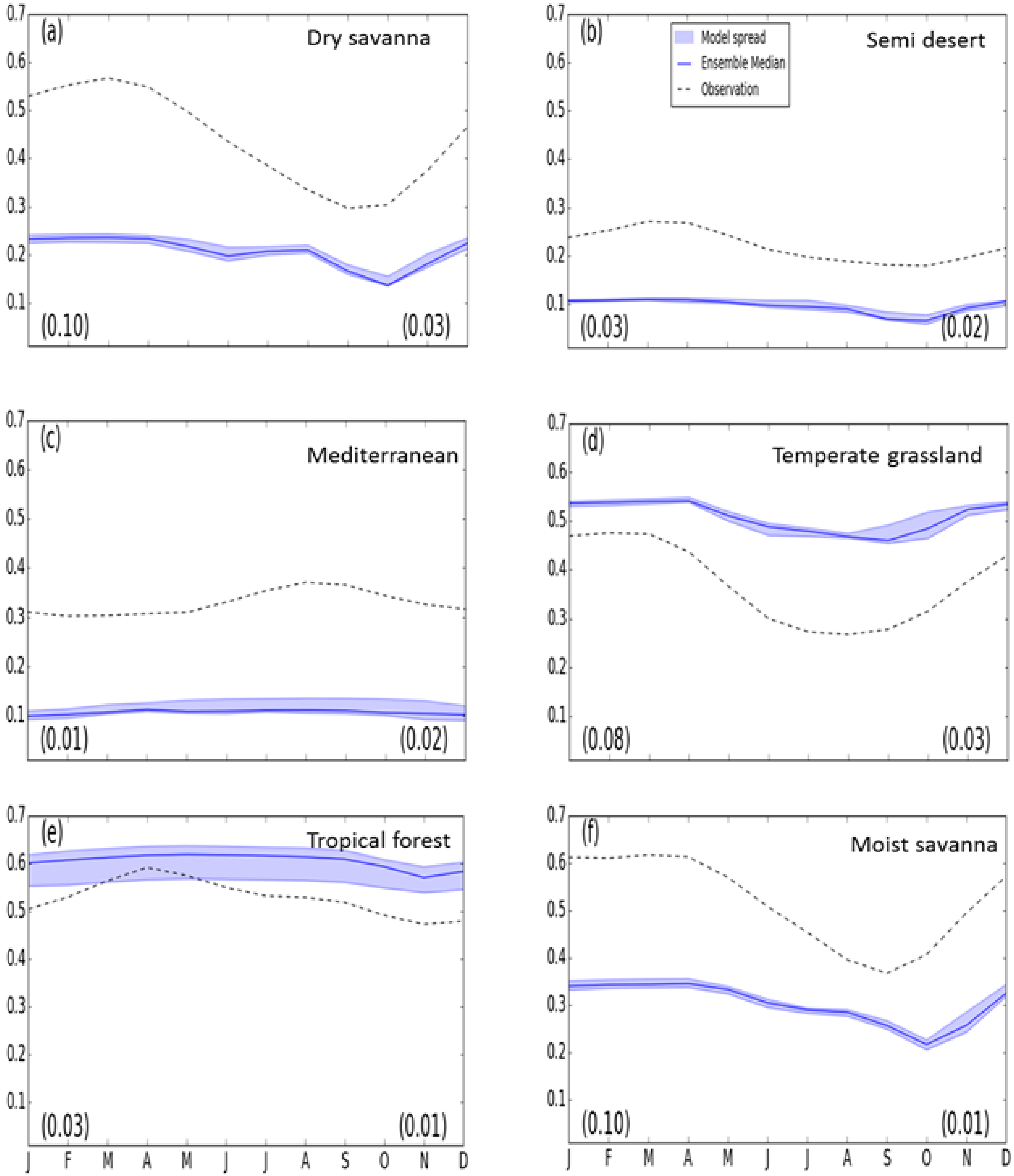

Figure 6.6. As in Figure 6.2 but for vegetation Index

6.3 Spatial distribution of vegetation response to droughts

The CESM underestimates the correlations of the SPEI with the vegetation index and that of the SPI with the vegetation index (Figures 6.7a and 6.8a; Figures 6.7e and 6.8c); and it greatly overestimate the drought timescales (Figures 6.7b & 6.8b; 6.7f and 6.8d) over most parts of southern Africa. Figures 6.8 (a, b, c and d) illustrate the model ensemble’s median of correlation and the timescales for SPEI and SPI. With regard to the SPEI, the peak correlation values shown by the model are about 0.45 which is less than those obtained by means of observation (i.e. SPEI_HG), which is as high as 0.7. The only region where the model correlates with observation is Madagascar. With respect to the drought timescale, the model shows the correlation occurring predominantly at the 18-month timescale while observation shows the correlation occurring mostly at a 3- to 6-month time scale in most parts of southern Africa. Nonetheless, the drought timescale in some parts of Namibia, Angola, Zambia and Madagascar are very much similar for both observation and model. The poor performance of the model in simulating correlation and drought time scale for the SPI may still be attributed to the parameterizations and/or schemes according to which the model computes vegetation variables (Doney *et al*., 2006). However, the CESM is better than the DGVMs (Chapter 5, Section 5.2) at capturing the spatial patterns and timescales of vegetation responses to drought in southern Africa.

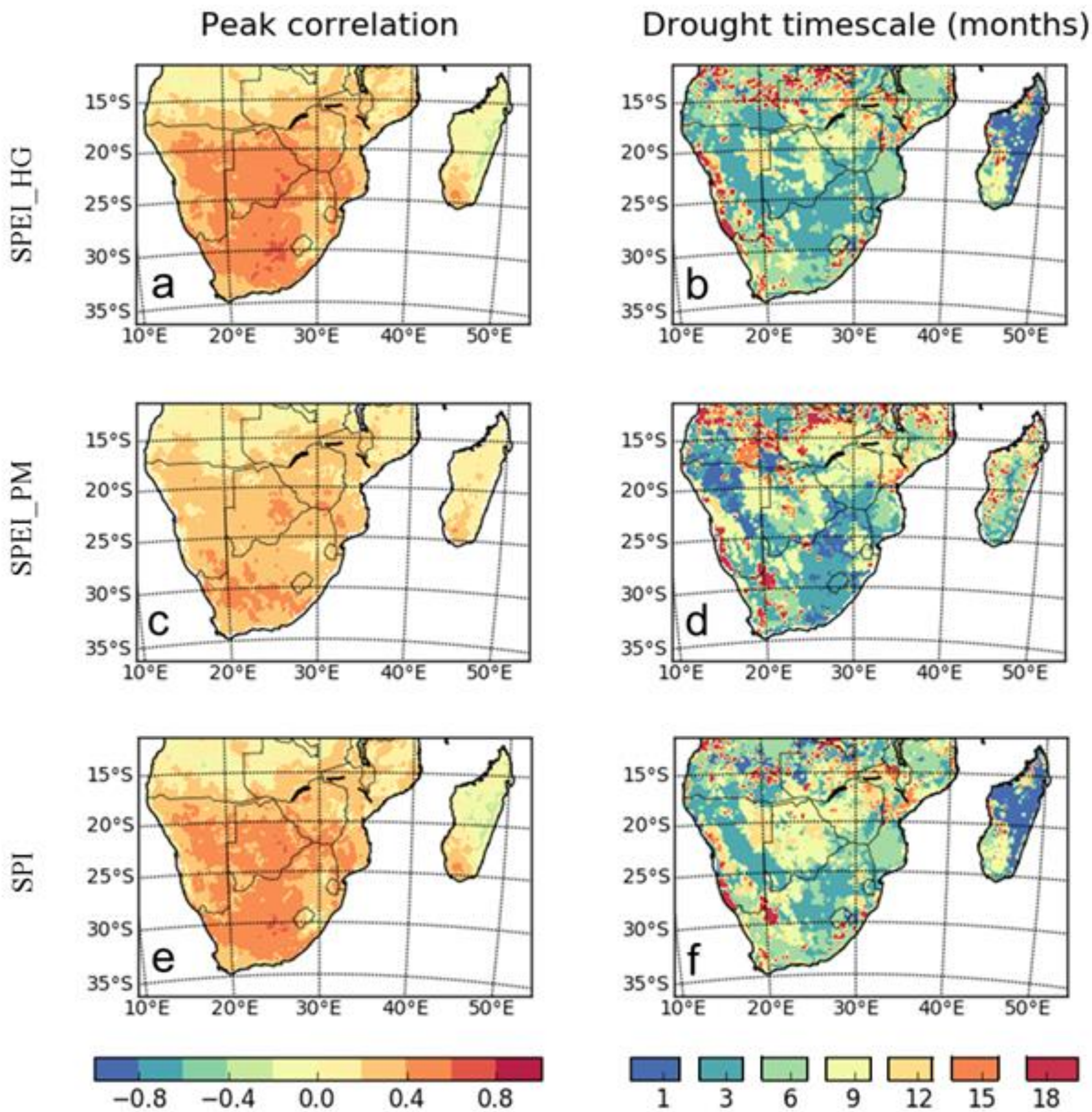

Figure 6.7. Spatial distribution of correlation between drought and vegetation over southern Africa for observations. Panels (a), (c) and (e) show the peak correlations (Pearson coefficient, r) per grid between the CRU - SPEI and GIMMS-NDVI (SPEI_HG & SPEI_PM) for the period 1983 – 2004; and peak correlations (Pearson coefficient, r) per grid between the CRU - SPI and the GIMMS-NDVI ((SPI) for the same period. The corresponding drought time scales at which the maximum (or peak) correlation between drought and vegetation is found are shown in panels (b), (d) and (f)

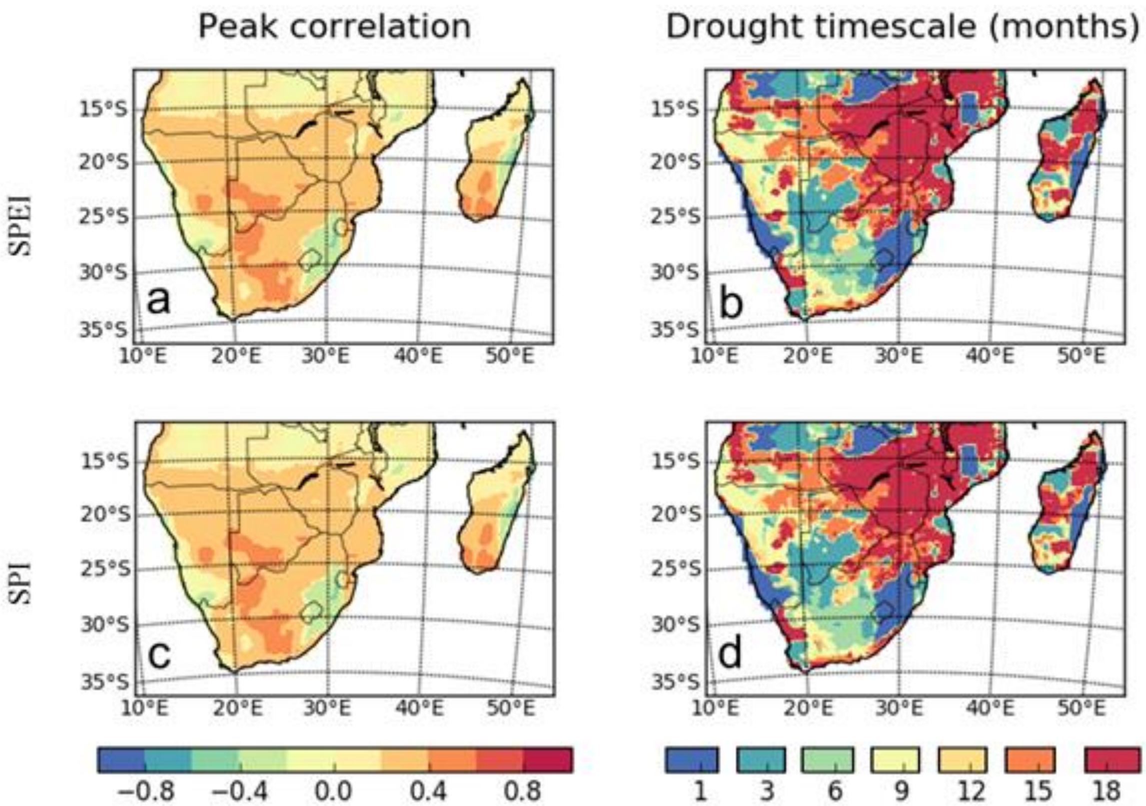

Figure 6.8. Same as Figure 6.7 but for model

6.4 Seasonal distribution of vegetation response to droughts

Model ensemble members do not simulate the magnitudes of vegetation response to drought well; and this differs not only across biomes and seasons but also with drought index (Figures 6.9 and Fig. 6.10). For example, in the dry savanna, most of the model ensemble members underestimate the response of vegetation to drought. Over this biome and for the SPEI, the ensemble members most underestimate observation during the DJF season (Figure 6.9). However, for the SPI, the largest underestimation is during the JJA season (Figure 6.10). In all the biomes (except in tropical forest), the model ensemble members simulate the strongest response during the SON season and lowest response in the DJF season.

The simulated drought timescales also differ with the seasons and across the biomes. In the Mediterranean and temperate grassland biomes, most of the ensemble members overestimate the drought timescales (Figures 6.9 and 6.10). However, in the other biomes, the drought timescales of the ensemble members fall largely within the observed timescales. The ensemble members underestimate the observation drought timescale mostly in JJA and SON seasons.

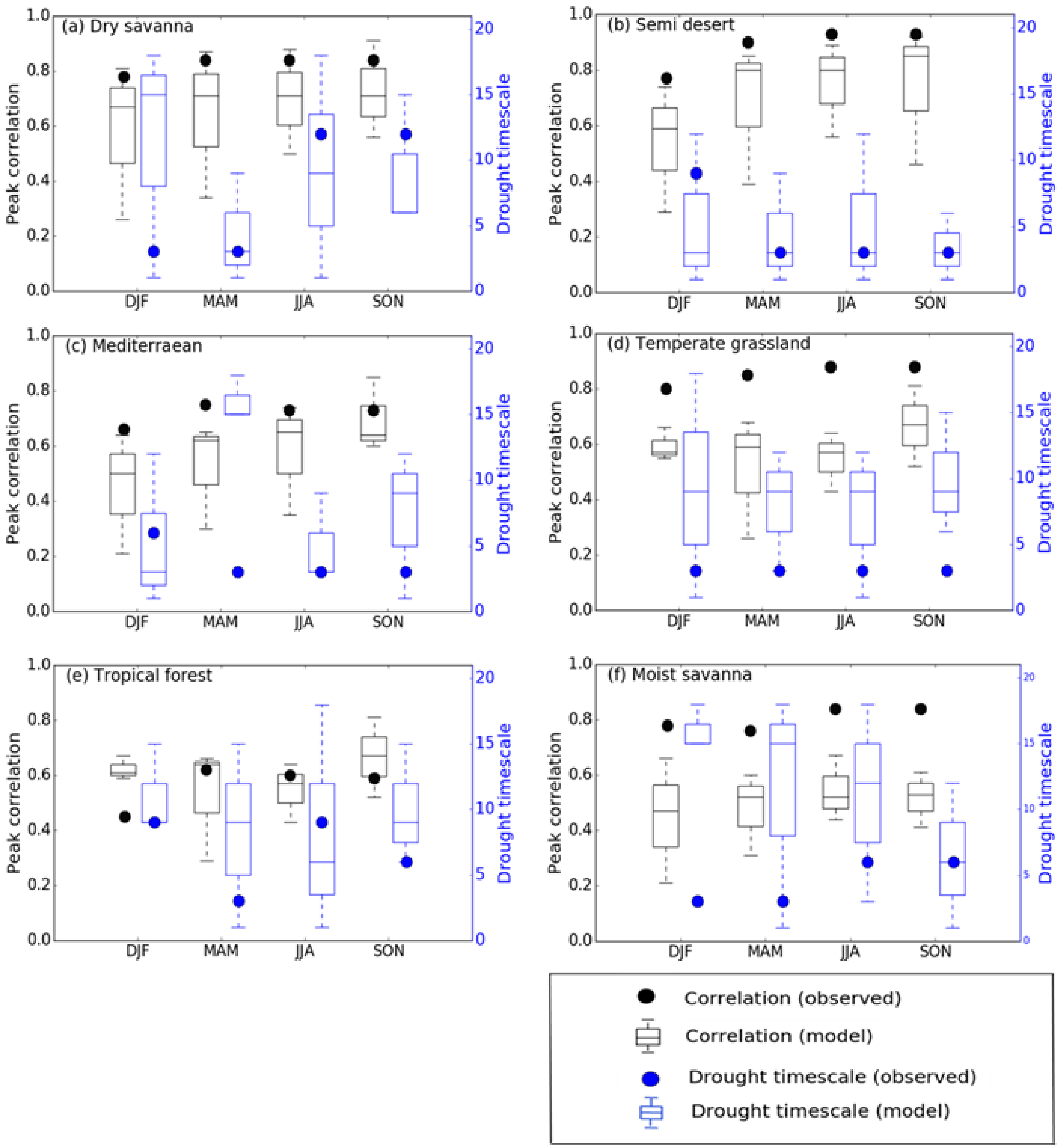

Figure 6.9. Seasonal correlations (Pearson coefficient, r) of drought (SPEI) and the NDVI across six biomes. The values on the left axis show the peak correlation values for the observation and the models (median, maximum and minimum). The values on the right axis show the corresponding drought timescale for the correlation value.

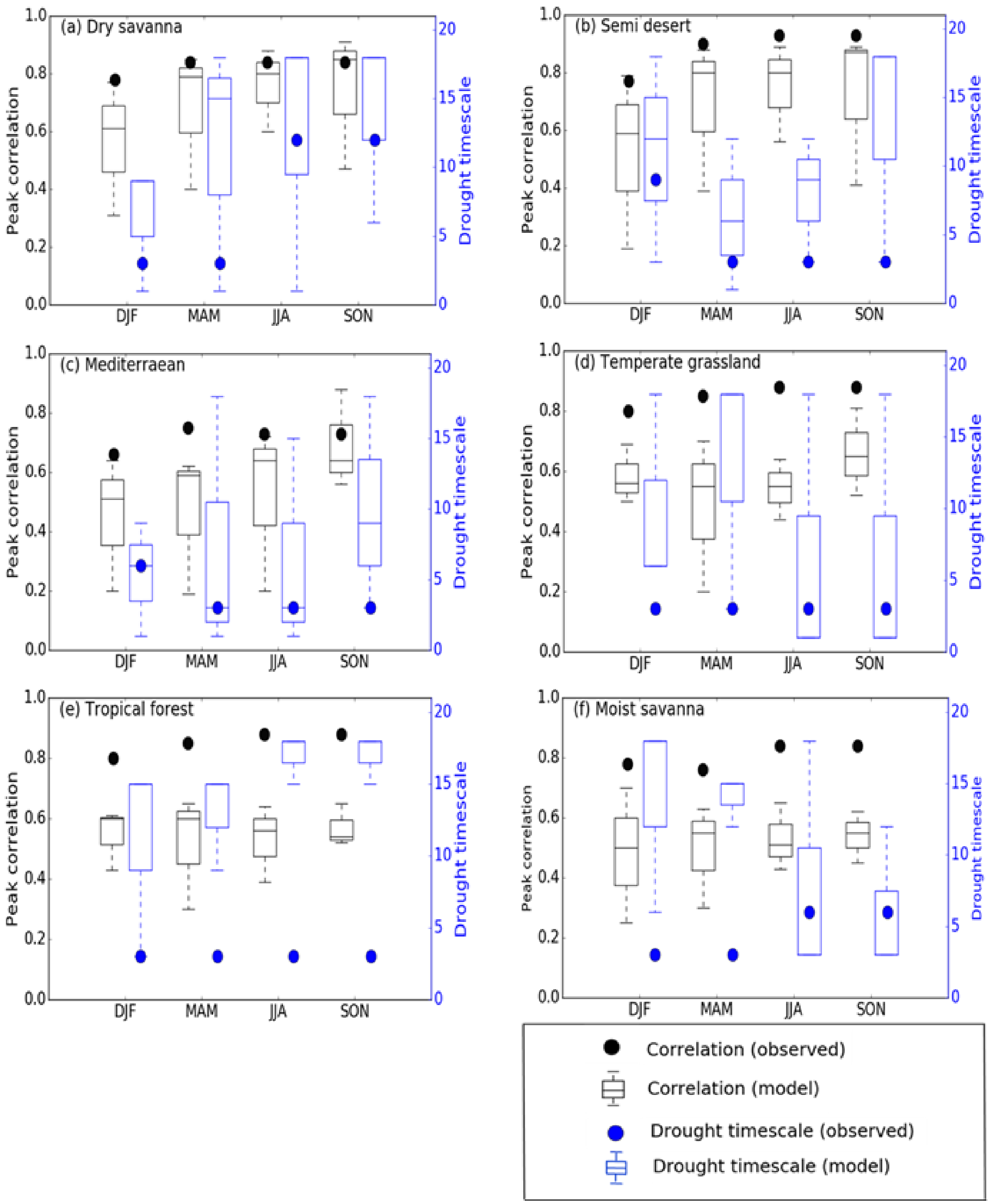

Figure 6.10. Same as Figure 6.9 but for SPI

6.5 Summary

This chapter investigated the response of southern African vegetation to drought in both the observation and the CESM. A spatial distribution of simulated climate and vegetation variables (from the CESM) was compared with observation. Furthermore, the temporal distributions of the observed and simulated variables were also compared. In addition, a comparison was made between observed drought (SPEI_HG and SPI) which had been correlated with GIMMS NDVI at 1- to 18-month timescale, with peak correlations and timescales computed from forty ensemble members of CESM. The results of this chapter can be summarized as follows:

- The intensity of precipitation is captured by the CESM ensemble mean. Although the model captures the monthly cycle of rainfall in the region, it show bias in simulating of the magnitudes

- Over Namibia and Angola, the magnitudes of mean temperature are overestimated by CESM ensemble mean. Over South Africa, however, they are underestimated. The CESM furthermore underestimates maximum temperature but overestimate minimum temperature

- The CESM ensemble mean underestimate NDVI over Namibia and Botswana but overestimates it in other parts of the region. The CESM ensemble mean underestimates vegetation across the biomes.

- CESM underestimates the peak correlation of drought for the SPEI and the SPI. In addition, the seasonal response and drought timescales of vegetation to drought is mostly underestimated by CESM ensemble members. The weakest simulation by the ensemble members is simulated occurs during the DJF season.

- The CESM simulates the temporal distribution of the NDVI better than the DGVMs do. However, its intensity bias is larger than that of the DGVMs. Furthermore, the CESM capture the spatial patterns of vegetation response to drought in southern Arica more closely.

This chapter has shown the capability of CESM to simulate the response of southern African vegetation to drought. In order to obtain a more robust information, the land component of the model (CLM) could be optimized to simulate vegetation changes. This would involve the modification of CLM parameters in order to reduce the root mean squared error (RMSE) between simulations and observation. The parameters could be chosen based on their performance during a sensitivity test. It is worthwhile to examine further how the response of southern African vegetation might be affected by climate changes. The next chapter examines the response of southern African vegetation to drought at 1.5ºC and 2ºC GWLs.

Chapter 7: Response of Southern African vegetation to 1.5^{o}C and 2^{o}C global warming levels

Recent studies have shown that limiting the global mean temperature to well below 2^{o}C above pre-industrial level may reduce the anticipated catastrophic effects of anthropogenic climate change. However, there is a dearth of knowledge on the response of vegetation to climate change at GWLs. This chapter examines how southern African vegetation is likely to respond to climate change at 1.5^{o}C and 2^{o}C GWLs. Ensembles of climate projections from the CESM model were analyzed to determine the timing and magnitudes of changes in vegetation fluxes across southern African biomes for global warming at 1.5^{o}C and 2^{o}C under the RCP8.5 scenario. The CESM was chosen for this study because it gives a realistic simulation of the response of vegetation to drought in southern Africa. The RCP8.5 scenario was used because the earth is already warming as usual and changing beyond what is expected under the other scenarios. Thus, this chapter discusses how southern African vegetation might be affected by the two warming scenarios.

7.1 Characteristics of vegetation in historical climate

The CESM ensemble mean captures the spatial variability of the NDVI over southern Africa. (Figures 7.1a and 7.1b). The correlation between the observed and simulated values is strong ($r = 0.63$). The model captures the high vegetation index over Angola, Madagascar and Mozambique and the low vegetation index over Namibia. It agrees with the observation that the highest vegetation index is over the temperate grassland biome and the lowest index over the semi desert biome (Figure 7.1d). However, there are some notable biases in the model simulations and the magnitude of these biases vary over the domain. The model features positive biases (up to 0.4) over the eastern parts of South Africa and negative biases (up to 0.3) over the eastern coasts of Mozambique, central parts of Angola and the southern tip of South Africa (Figure 7.1c). Among the biomes, the largest model bias occurs over the temperate grassland biome (up to 0.37) where all the ensemble members overestimate the NDVI. However, in the remaining biomes, the observed NDVI falls within the model ensemble's spread. The discrepancy between the model simulation and the observation may be attributed to a number of reasons. It may due to the difference in the climate period between the simulated and observed climate periods, or it may be due to approximations in calculating the simulated NDVI (Gent *et al*., 2011). In addition, the bias may be due to the deficiencies in the model parameterization of certain factors (such as fire) which is a major predictor of vegetation growth, especially in the temperate grassland (TG) biome of the region. Thonicke *et al* (2001) noted that the representation of fire and their burning effects on temperature are usually not well parameterized in models. However, the high level of the agreement between the simulated and observed distribution of the NDVI suggests that the model does reliably capture the relevant processes for reproducing the vegetation dynamics.

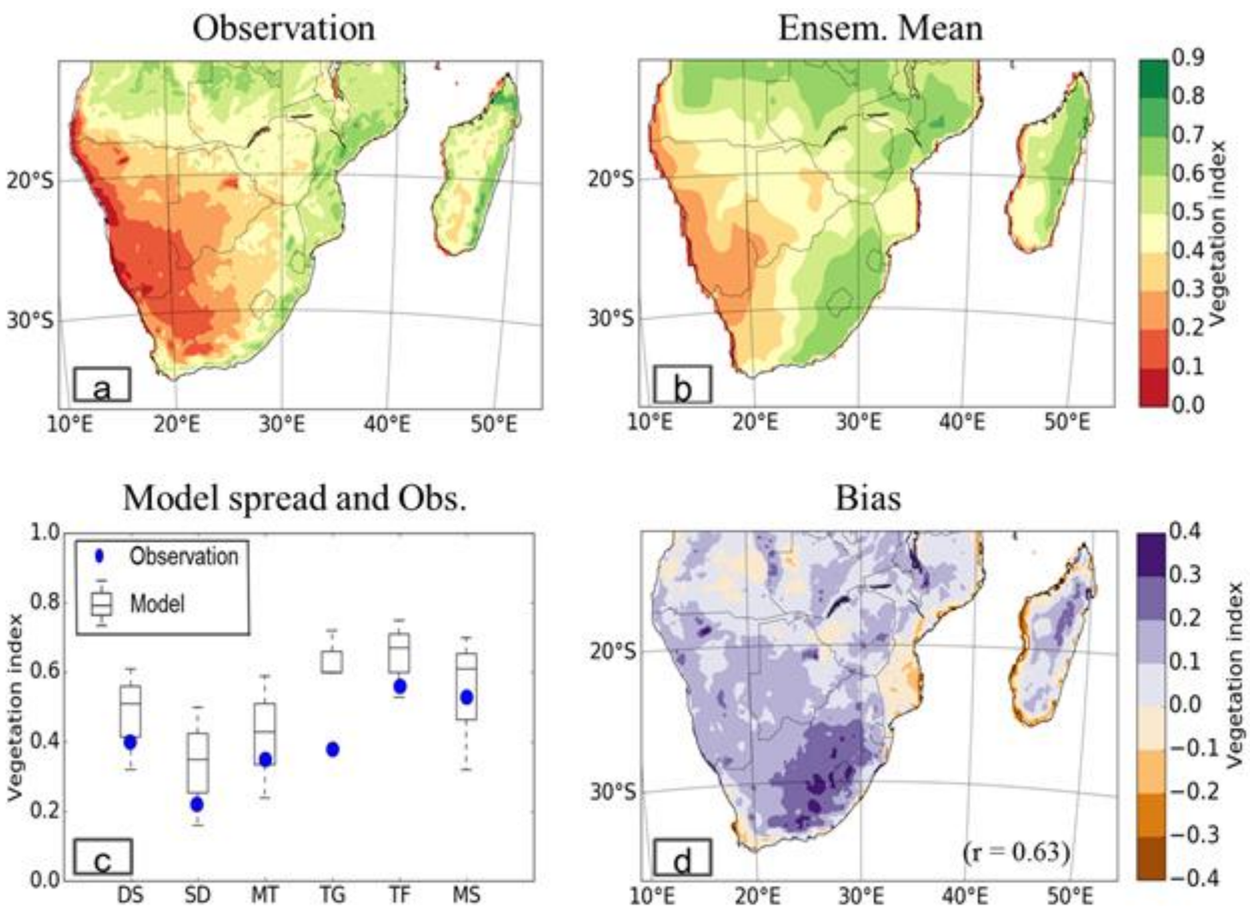

Figure 7.1 Spatial distribution of (a) observed and (b) ensemble median of vegetation index. The inset value is the correlation between observation and the model ensemble median (c) Boxplot of observed and simulated vegetation index over six major southern African biomes (DS: Dry Savanna; SD: Semi Desert; MT: Mediterranean; TG: Temperate Grassland; TF: Tropical Forest; and MS: Moist Savanna) and (d) bias between spatial distribution of observation and simulation

There is a strong relationship between the simulated NDVI and simulated carbon fluxes over southern Africa (Figure 7.2). For instance, over Madagascar where there is high vegetation index, the total leaf area index (TLAI) over the region is high. The high TLAI value indicates the presence of a dense vegetation and thus a large leaf area cover (LAC) over the region. Autotrophic respiration (AR) and heterotrophic respiration (HR) of vegetation increases with broad LAC. This is because there are more stomata openings on the leaves through which carbon dioxide (CO_2) is taken in and released back to the atmosphere (Gratani *et al.*, 2008). The increased turnover of CO_2 in the vegetation will most likely lead to further expansion of leaves, which will enhance the capacity of the vegetation capacity to intercept sunlight (FPSN). With increased FPSN and CO_2, vegetation produces more sugar (GPP) which they use for building their body tissues i.e. their growth processes (NPP) (Weraduwage, *et al*., 2008). Stem volume becomes enlarged when there is improved growth of vegetation as a certain amount of carbon is stored in the aboveground while the rest are accumulated below ground. Furthermore, vegetation increases in density when the aboveground growth improves thereby giving vegetation more capacity to expand (Xue *et al*., 2012). High amounts soil carbon (SOILC) also indicate that there is large undergrowth (e.g. deep roots) of vegetation in this region. We can infer from the above relationship that the healthier the vegetation, the higher the amount of sequestrated carbon. In addition, canopy transpiration generally increases with vegetation growth because there are more pores and vessels through which moisture will be released to the atmosphere.

Nevertheless, the spatial distributions of the simulated NDVI and FGEV differ. The model shows an almost opposite patterns between these two variables. For example, while the vegetation index over the western parts of Namibia is low, there is a high rate of evaporation from the ground. This is because the region has scanty vegetation and hence, low LAC, which could serve as ‘shade’ to minimize the rate of water loss over the area. Conversely, over the east coast of South Africa and Madagascar where there is a high vegetation index, the ground evaporation rates are low due to high levels of LAC.

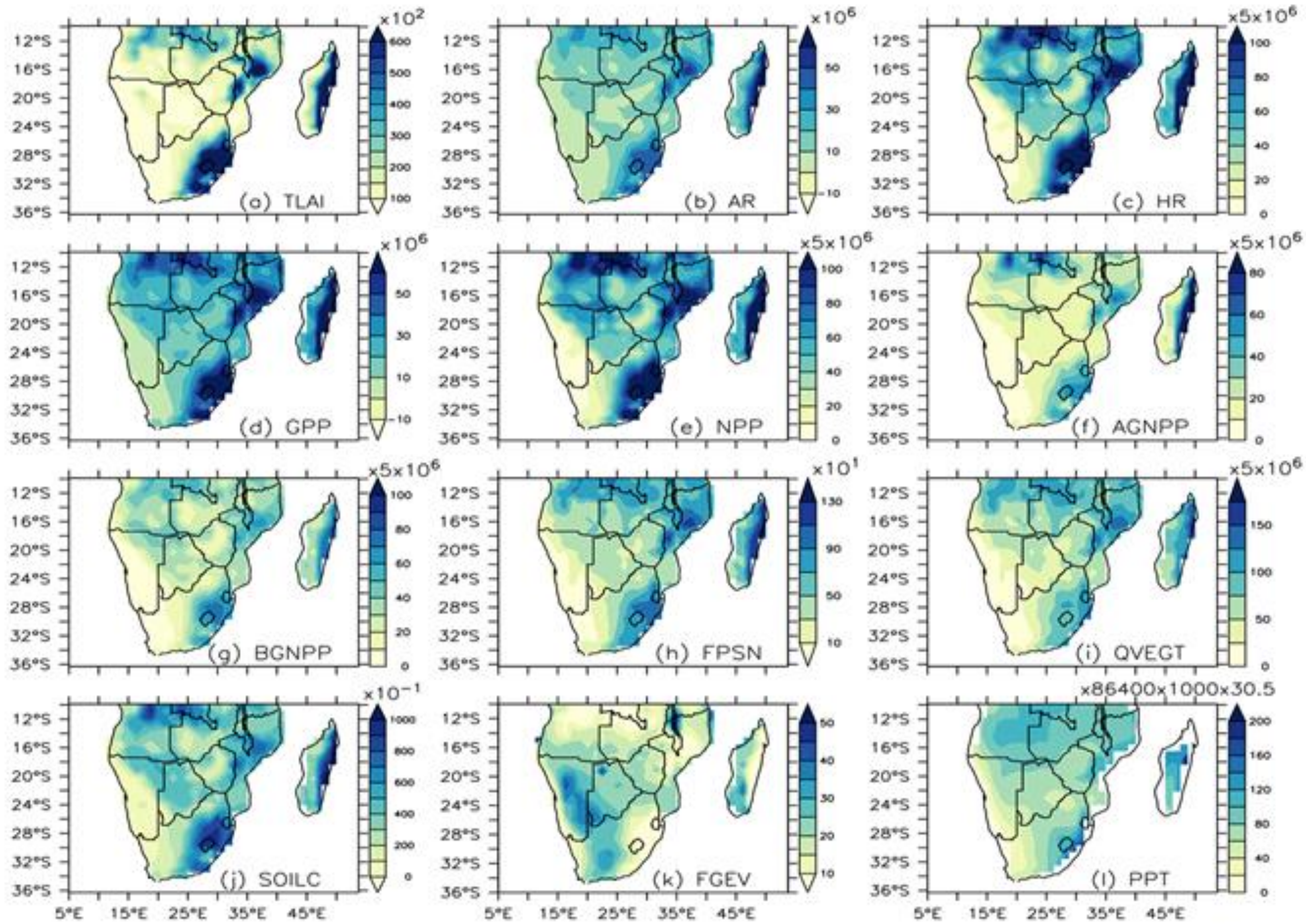

Figure 7.2. Spatial distribution of the simulated vegetation fluxes and soil moisture over southern Africa: total leaf area index (TLAI, gC/m^2/s); autotrophic respiration (AR, gC/m^2/s); heterotrophic respiration (HR, gC/m^2/s), gross primary production (GPP, gC/m^2/s), net primary production (NPP, gC/m^2/s), aboveground net primary production (AGNPP, gC/m^2/s), below ground net primary production (BGNPP, gC/m^2/s), photosynthesis (FPSN, umol/m^{2}s), canopy transpiration (QVEGT, mm/s), soil carbon (SOILC, gC/m^2), ground evaporation (FGEV, W/m^2) and precipitation (PPT, mm/month) over southern Africa for the period 1971 – 2000.

7.2 Evolution of climate and vegetation variables in past and future climates

Figures 7.3 to 7.8 show the time series of the simulated climate variables (Temperature, 12-month SPEI, and 12-month SPI) and the simulated vegetation index (NDVI) from 1972 to 2100 over each of the southern African biomes. The figure shows that global warming may influence the intensity of the drought in the region. Moreover, the magnitude of changes may differ for the drought indexes over each biome. For example, over the dry savanna and tropical forest biomes, global warming is likely to cause a more significant decrease in the SPEI than in the SPI (Figures 7.3 and 7.7). Over the semi-desert and Mediterranean vegetation, although the decline in the SPI is more pronounced, the decrease may not be as low as that of the SPEI (Figures 7.4 and 7.5). Global warming does not seem to affect the magnitude of the SPI changes over the temperate grassland, but it is likely to reduce the SPEI in this biome (Figure 7.6). Over the moist savanna, global warming is likely to increase the SPI and to decrease the SPEI (Figure 7.8). The differences in the level of changes in the drought indexes over the biomes may be because of the changes in PET. For example, in biomes (e.g. semi-desert) where there is likely to be a significant increase in PET, the differences in changes of the SPEI and the SPI are less, than in the case of temperate grassland, where PET changes are not as high. Furthermore, the changes in the drought indexes could have contributed to changes in the NDVI, particularly over the dry savanna where there is an increase in greenness. However, over the other biomes, the changes in the drought indexes may not lead to any significant changes (and sometimes even cause decrease) in the NDVI. These findings are in agreement with Engelbrecht *et al.* (2010) who reported a reduction in future dry spells as well as temperature increases over the region, and Davis *et al.* (2011) who showed that a reduction in drought may not necessarily lead to an increase in vegetation.

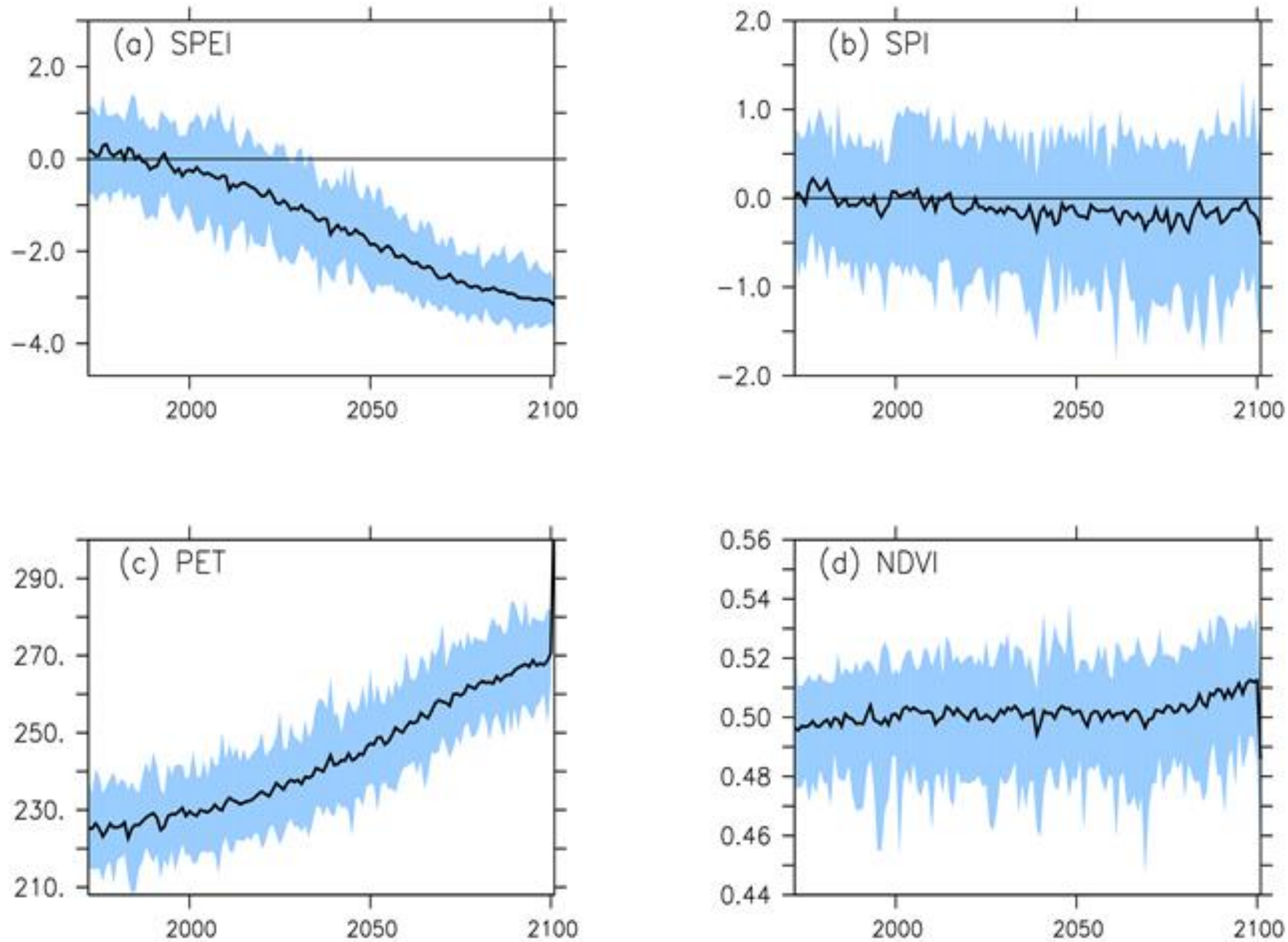

Figure 7.3. Time series evolution of (a) Standardized Precipitation Evaporation Index (SPEI), (b) Standardized Precipitation Index (SPI), (c) Potential Evapotranspiration (PET) and Normalized Difference Vegetation Index (NDVI) over the dry savanna biome for the periods 1972 - 2100. The shaded shows that maximum and minimum values while black line indicates ensemble mean.

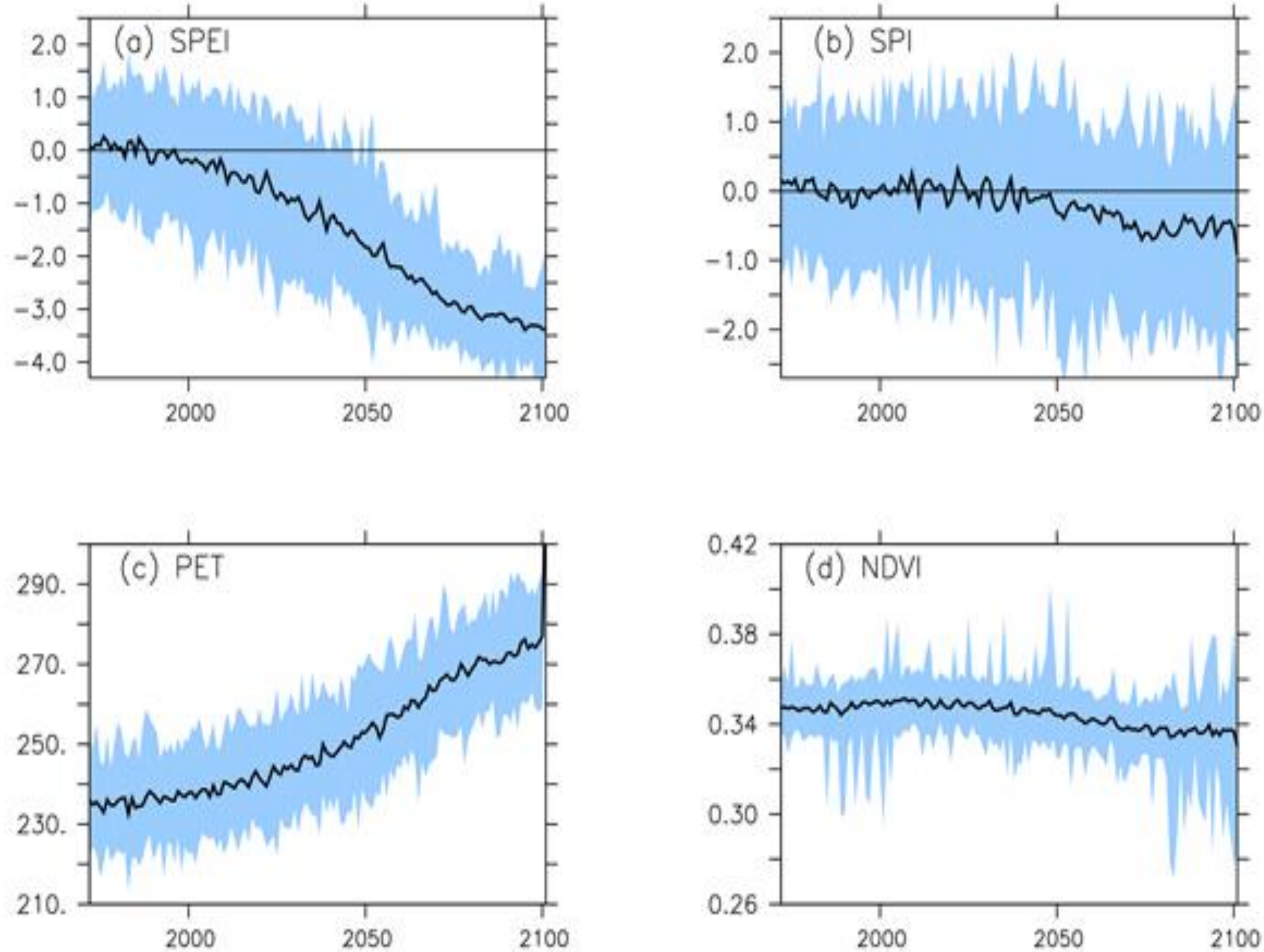

Figure 7.4. As in Figure 7.3 but over semi desert biome

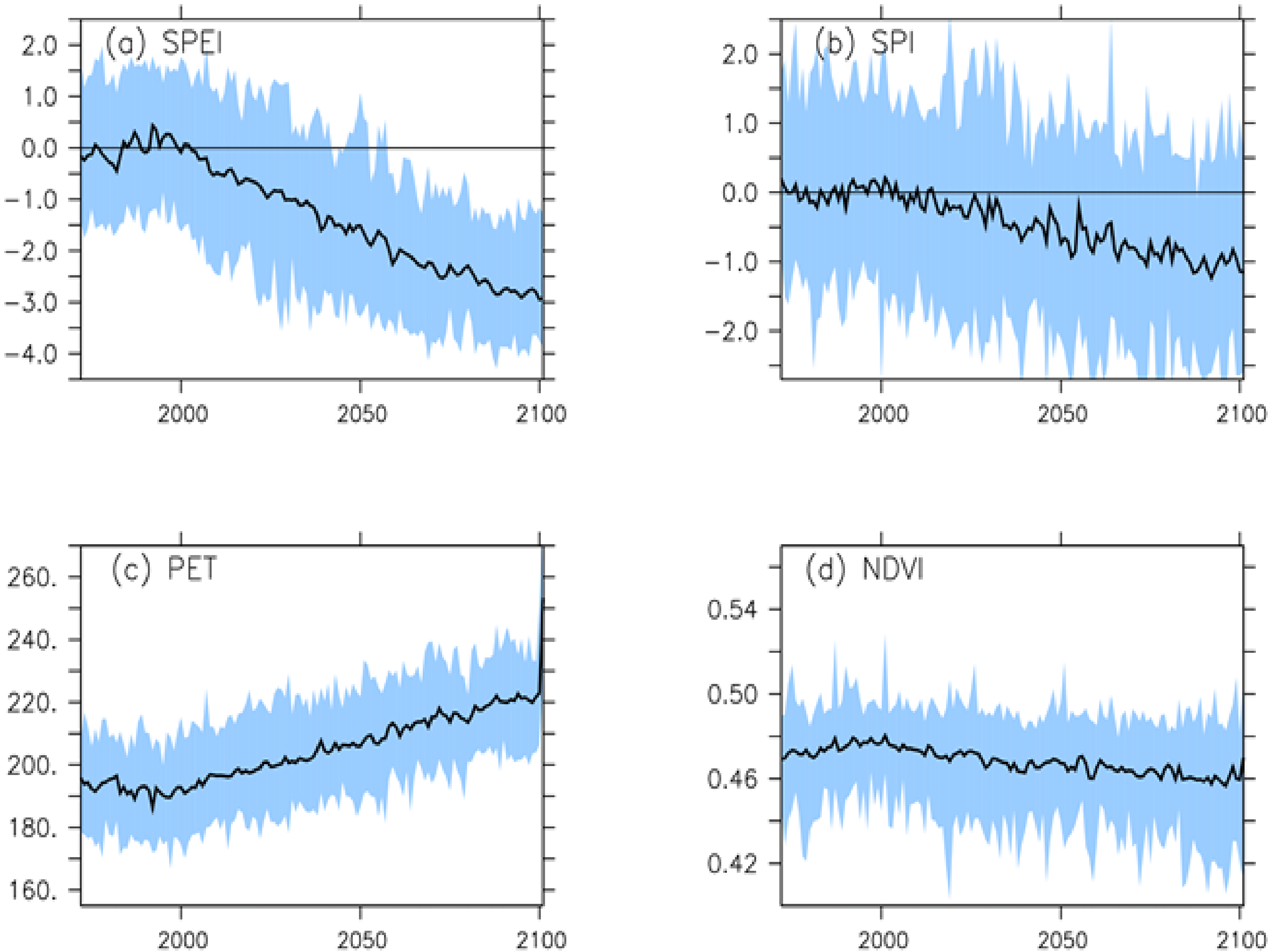

Figure 7.5. As in Figure 7.3 but over Mediterranean vegetation

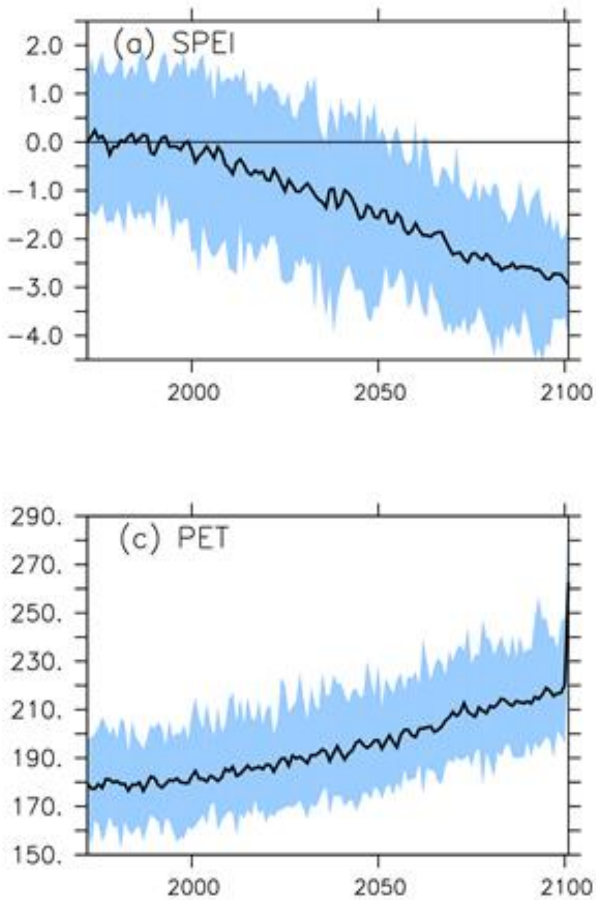

Figure 7.6. As in Figure 7.3 but over the temperate grassland biome

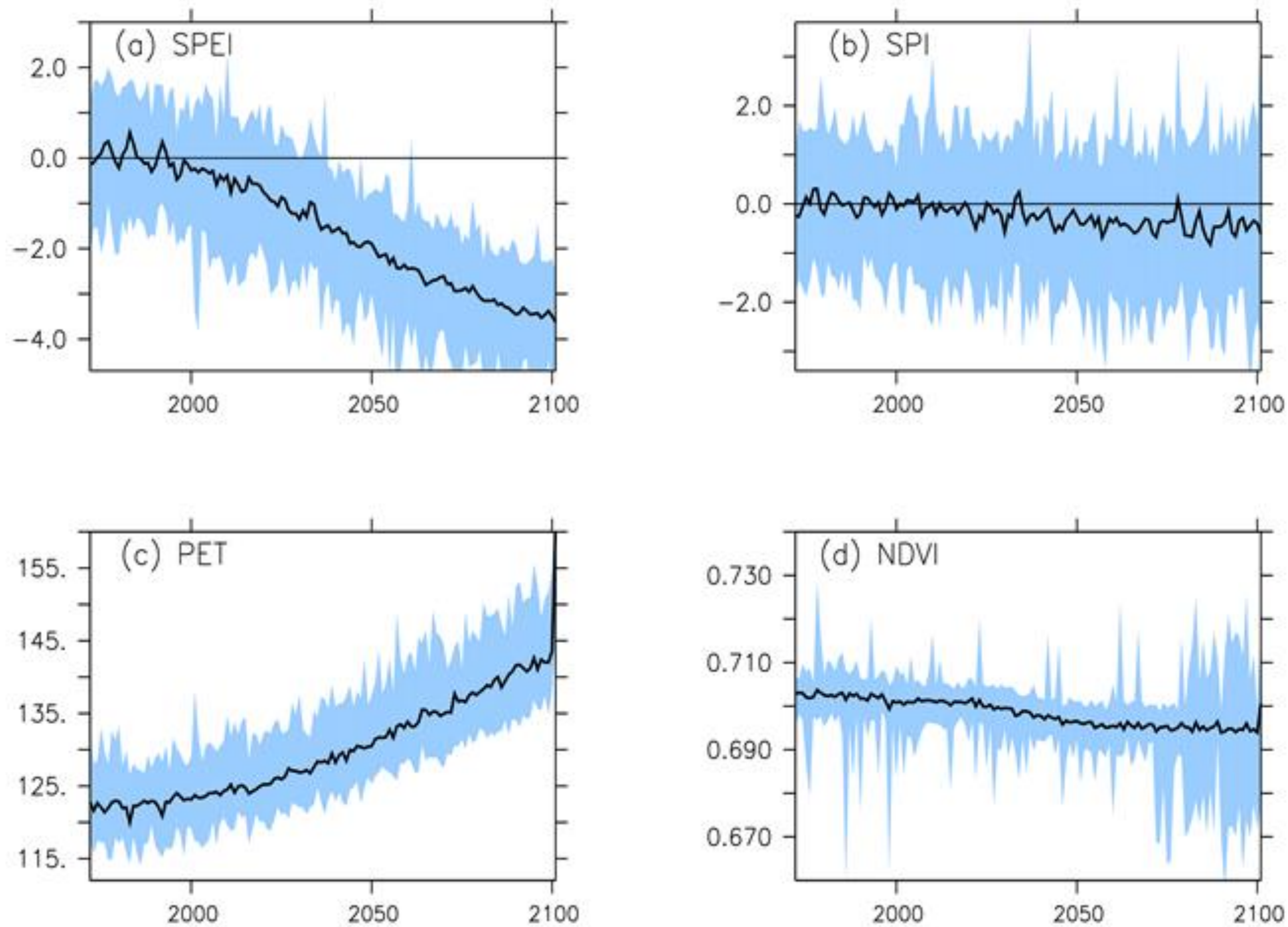

Figure 7.7. As in Figure 7.3 but over tropical forest

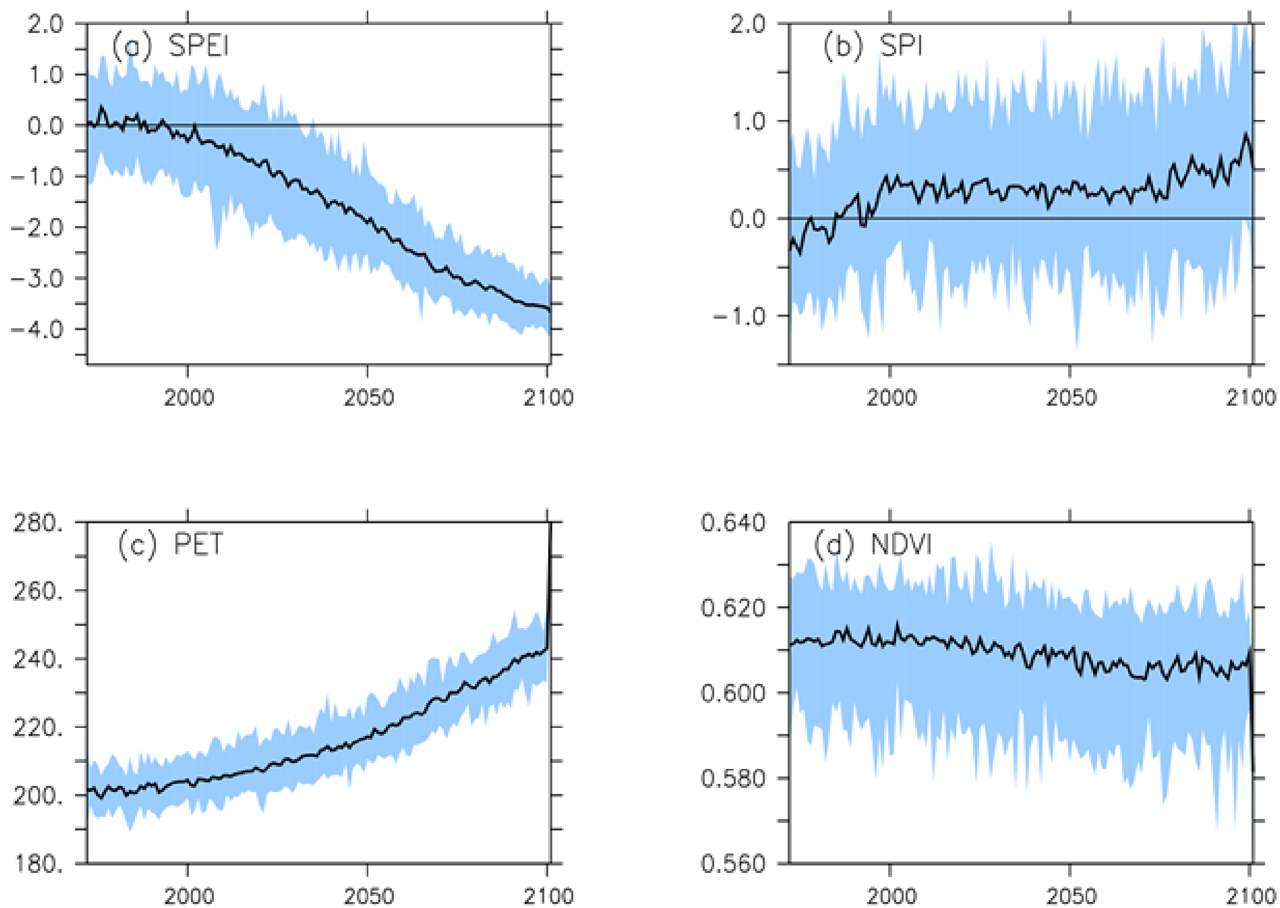

Figure 7.8. As in Figure 7.3 but over moist savanna

7.3 Impacts of 1.5ºC and 2ºC warming on vegetation fluxes

The CESM ensemble projection shows that the impacts of 1.5ºC GWL on vegetation fluxes vary over southern Africa (Fig. 7.9). For example, while it decreases TLAI (by about 0.4) in the Mozambique, Namibia, Botswana, Zimbabwe, Malawi, and in the western parts of South Africa and Madagascar, it increases it (by to 0.3) over Angola, and in the eastern parts of South Africa and Madagascar. These changes suggest a decrease in semi desert, dry savanna and Mediterranean vegetation but an increase in temperate grassland, moist savanna and tropical forest biomes. This pattern of changes agrees with the projected changes in rainfall and potential evaporation which are drivers of vegetation growth in the region (Rutherford *et al*., 1999; Jury, 2013; Engelbrecht *et al*. 2015). The results are consistent with IPCC (2007) projection that the wet region of world would become wetter, while the dry regions will become drier. The projected changes in AR, HR, GPP, NPP and BGNPP are similar to those in TLAI. This is because the leaf area index of vegetation determines the quantities and sizes of stomata pores through which CO_2 is absorbed (autotrophic respiration), and released (heterotrophic respiration) to the atmosphere, and thus, the production of total and net photosynthates (i.e. gross and net primary production). However, the changes in TLAI are not consistent with the remaining vegetation fluxes. For instance, AGNPP is projected to decrease over most parts of southern Africa except over Angola and parts of Namibia. This implies that the increase in TLAI in produces a decrease in AGNPP over South Africa and eastern Madagascar, which may mean that while vegetation in those areas may likely have more biomass (i.e. stem growth), it may also have fewer leaf area cover. Furthermore, FPSN is projected to decrease over eastern parts of South Africa, indicating that vegetation in this region would efficiently utilize the sequestered atmospheric carbon for growth. In addition, canopy transpiration is projected to reduce over eastern parts of South Africa suggesting that the vegetation would produce improved cuticle, boundary layer and more rigid guard cells to prevent water loss from the stomata (Xu & Zhou, 2008). However, over Namibia, canopy transpiration is projected to increase which might indicate weakening of transport vessels in vegetation. Soil carbon is projected to decrease over the northeastern parts of Madagascar which suggests that less organic matter will be stored by vegetation beneath the soil. Over Mozambique, ground evaporation is projected to increase, indicating that while leaf area cover in this region would likely reduce, the vegetation may have better capacity to utilize soil water.

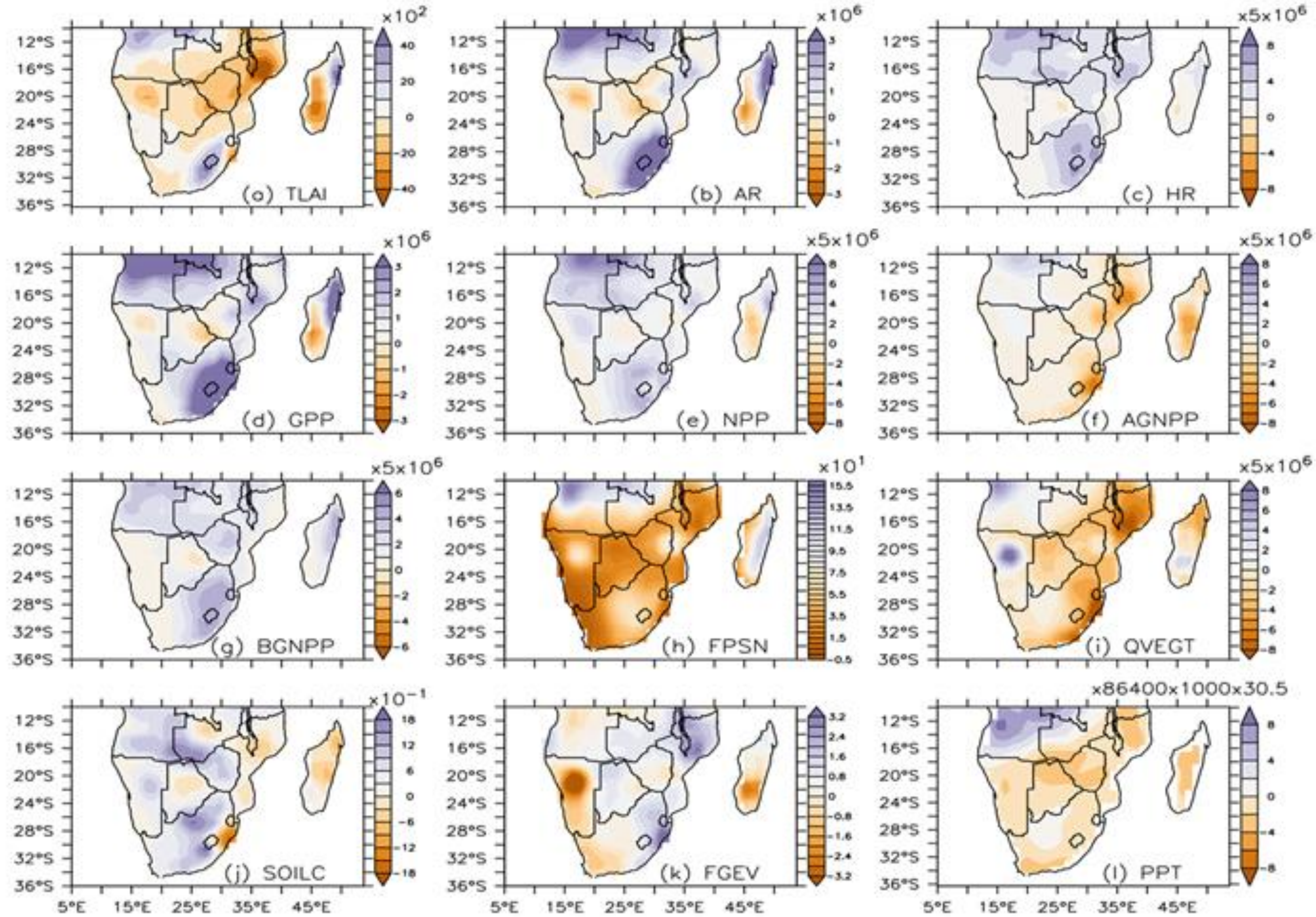

Figure 7.9. Spatial distribution of the simulated vegetation fluxes and soil moisture over southern Africa: total TLAI, AR ($gC/m^2/s$), HR ($gC/m^2/s$), GPP ($gC/m^2/s$), NPP ($gC/m^2/s$), AGNPP ($gC/m^2/s$), BGNPP ($gC/m^2/s$), FPSN ($umol/m^2s$), QVEGT (mm/s), SOILC($/gC/m^2$), FGEV (W/m^2) and PPT (mm/month) under 1.5°C GWL.

A further increase in the global warming (i.e. from GWL15 to GWL20) alters the magnitude and direction of the projected changes in vegetation fluxes (Figure 7.10). For instance, it enhance the increase in TLAI (by up to 14) in Angola and in the eastern parts of South Africa and Madagascar, suggesting that warming favours an increase in TLAI over the temperate grassland, moist savanna and Mediterranean biomes. In addition, it enhances the projected decrease over Botswana, Zimbabwe and Zambia, indicating that increased warming would result in more decline of the semi desert, dry savanna and Mediterranean vegetation. The changes in TLAI are similar to those in AR, HR, GPP, NPP and BGNPP. However, an increase in warming has different impacts on other vegetation fluxes. For example, over the eastern parts of South Africa, the projected decrease in AGNPP is reduced, suggesting that warming would result in less decline of aboveground net primary production. Similarly, it also reduces the projected decrease in FPSN over Zambia, Zimbabwe, Mozambique and South Africa.

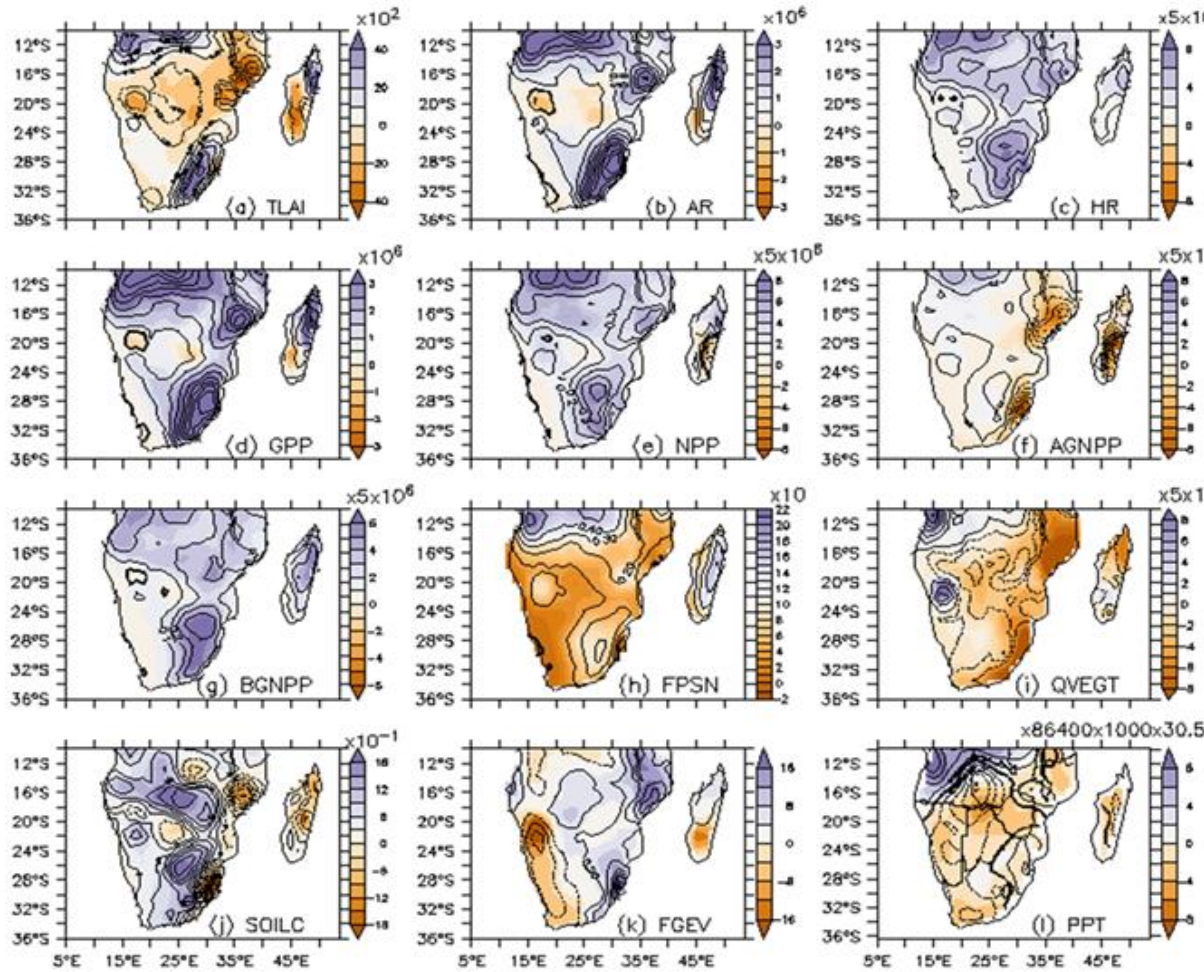

Figure 7.10. Same as fig. 6.6 but for 2°C warming. The contours indicate the difference between the impacts of 1.5°C and 2°C GWL.

There is a good agreement among the CESM simulations on the projected changes in vegetation fluxes over the biomes (Figure 7.11). For most vegetation fluxes (AR, HR, GPP, NPP, AGNPP, BGNPP, FPSN, and SOILC), more than 75% of the simulations agree on the projected changes across all the biomes. For example, all the simulations agree on the increase in BGNPP over all the biomes. They also agree on the decrease in SOILC over Tropical Forest and the increase over other biomes. However, the best agreement among the simulation is in SOILC projection and the least agreement in TLAI. While at least 75% of the simulations agree on direction of changes in TLAI over Dry Savanna, Temperate Grassland and Tropical Forest biomes, there is no agreement on the direction of the changes in TLAI over the other biomes because half of the simulations project an increase and the other half project a decrease. Among the biomes, the simulations feature the best over the Dry Savanna (where at least 75% of simulations agree on the direction of the changes in all the vegetation fluxes); the least agreement relates to the Mediterranean vegetation (over which there is no agreement among the ensemble members regarding the direction of changes in TLAI and AGNPP). However, the level of uncertainty of the projections is lower in the $2^{o}C$ projections than in the $1.5^{o}C$ projections.

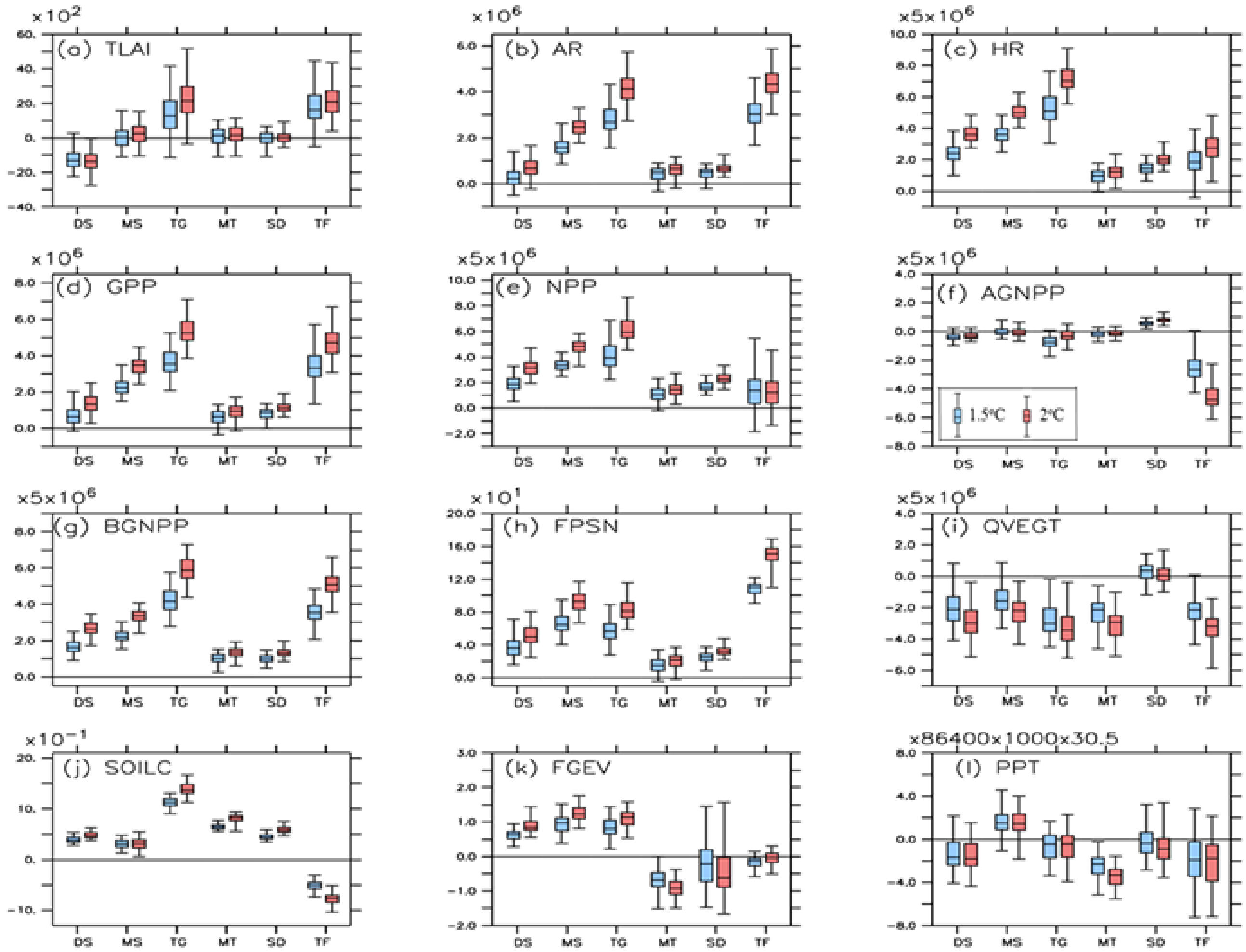

Figure 7.11. Projected changes of vegetation fluxes and soil water over six biomes in Southern Africa (DS: Dry Savanna; MS: Moist Savanna; TG: Temperate grassland; MT: Mediterranean; SD: Semi Desert; and TF: Tropical Forest). The vegetation fluxes are: TLAI, AR ($gC/m^2/s$), HR ($gC/m^2/s$), GPP ($gC/m^2/s$), NPP ($gC/m^2/s$), AGNPP ($gC/m^2/s$), BGNPP ($gC/m^2/s$), FPSN ($umol//m^2/s$, QVEGT (mm/s), SOILC ($gC/m^2/s$), FGEV (W/m^2) and PPT (mm/month) at 1.5^{o}C and 2^{o}C warming.

7.4 Summary

The chapter has investigated the response of southern African vegetation to climate change at 1.5^{o}C and 2^{o}C GWLs. The observation dataset and forty ensemble members from CESM have been analyzed to evaluate the model performance and describe the vegetation index in the historical climate. The model simulations were used to project future changes of vegetation fluxes under the 2^{o} GWL across different biomes. The results of the study can be summarized as follows:

- The CESM simulations give a credible simulation of NDVI variation over southern Africa. Across all the biomes (except TG) the observed NDVI falls within the CESM ensemble spread, and the ensemble mean is comparable to the observed value.

- The model features the relationship between the NDVI and carbon fluxes over southern Africa, as reported in previous studies (e.g. Martiny *et al*., 2006; Zhu & Southworth, 2013).

- There is a decreasing trend of drought (except over moist savanna and temperate grassland biomes) and an increase in temperature over the past and future climates in the region. In the dry savanna biome, there is a corresponding increase in trend of greenness although it decreases over the rest of the other biomes.

- The impacts of 1.5^{o}C GWLs on vegetation fluxes vary across southern Africa. It reduces TLAI over the dry savanna, but increases it over temperate grassland and tropical forest.

- The magnitudes of the changes in vegetation fluxes over southern Africa are affected by further increase in the global warming. It improves the projected increase of TLAI over Angola and in the eastern parts of South Africa, and it also enhances the decline in FPSN in Zimbabwe, Zambia and Mozambique.

- Among the CESM simulations, there is a good agreement on the projected changes in vegetation fluxes across the biomes. The best agreement among the simulations of fluxes is in SOILC, and in respect of the biome it is best in respect of the dry savanna. The uncertainty in the projections is higher with 1.5^{o}C than with 2.0^{o}C GWLs.

In order to obtain more robust information on the impacts of climate change on vegetation at GWLs, there is need for a regional climate simulations of the vegetation fluxes. This is because the resolutions of the CESM simulations are currently too low and thus, not able to resolve smaller certain features. Hence, future work may run simulations using the COordinated Regional Downscaling EXperiment (CORDEX). However, the current work has shown that vegetation fluxes over southern Africa are affected differently by climate change under different GWLs, and that these impacts vary across biomes. This work has application in mitigating the impacts of climate change on southern African vegetation.

Chapter 8: Conclusions and Recommendations

8.1. Summary

Climate variability and climate change pose a threat to the southern African vegetation. The study has used the SPEI and the SPI to characterize drought (1- to 18- month timescale) across southern Africa and investigated the response of southern African vegetation the droughts. It uses the CRU (observation), the CRUNCEP (reanalysis) and the CESM (model) to compute the drought indexes, and examined how well DGVMs (CLM4, CLM4VIC and ORCHIDEE-LSCE) and CESM is able to simulate the vegetation response to drought. Their response is quantified using the Pearson correlation analysis to find the correlation between drought indexes and the vegetation index. Furthermore, it uses the CESM simulations of the RCP8.5 scenario at 1.5^{o}C and 2^{o}C to project future characteristics of vegetation in response to drought.

In Chapter 4, the study shows that, across southern Africa, the spatial distribution of vegetation and precipitation is more similar than that of temperature. The correlation of drought index and the vegetation index is high (up to 0.8) in the southeastern part of the region, and this occurs at 3-month drought timescale. The spatial distribution of the correlation between the SPEI and vegetation index, and between the SPI and the vegetation index, are similar.

In Chapter 5, the study shows that the three DGVMs (CLM4, CLM4VIC and ORCHIDEE-LSCE) failed to capture the response southern African vegetation to drought; nevertheless, of these, CLM4 performs the best, while ORCHIDEE performs least. The simulation of CLM shows that fire has a strong influence on the growth of vegetation throughout the summer rainfall region, but it has a weak influence in the vegetation in western arid zone.

In Chapter 6, the study shows that the spatial patterns of precipitation and vegetation index over southern Africa are strongly captured by CESM. However, the model overestimates the magnitudes of the vegetation index over the region, except in Angola and Namibia, and it underestimates the correlation and the timescales at which vegetation respond to droughts.

In Chapter 7, the CESM projects a decrease in drought intensity (except over the moist savanna and temperate grassland biomes) and an increase temperature, however, the increase in drought intensity is more pronounced with the SPEI than it is with the SPI. There is a projected decrease in vegetation index over the region except the dry savanna biome. There is variation with regard to the impacts of 1.5^{o}C global warming on the vegetation fluxes over the region, and the intensity of changes in the vegetation fluxes are affected by further increase in the global warming over the region. Although there is good agreement among the CESM simulations on the projected changes in the vegetation fluxes over the biomes. The uncertainty in the projections is however, higher with 1.5^{o}C than 2.0^{o}C GWLs.

8.2. Scientific contribution to knowledge

The study has found that drought and climate change have different effects on southern African vegetation. It has discussed out the capabilities and limitations of the CESM and the various DGVMs in simulating climate features, vegetation index and vegetation response to drought. The scientific contribution of this study to knowledge are listed as follows:

- The Dynamic Global Vegetation Models (DGVMs: CLM4, CLM4VIC and ORCHIDEE-LSCE) simulated the spatial patterns of climate variables and vegetation index over southern Africa. However, the models lagged in their replication of the temporal distribution.

- The DGVMs did not replicate both the spatial and temporal distribution of vegetation response to drought. However, they did capture the impacts of fire on the vegetation.

- The CESM ensembles strongly capture (and perform much better than DGVMs) the spatial pattern of the climatic variables although the model's ensembles do have some biases in their replication of magnitudes. The CESM ensembles also capture better the response of vegetation to drought in the region.

- The study also asserts that under RCP 8.5, and at 1.5^{o}C global warming level (GLW), the total leaf area index (TLAI) increases over the forested area and decreases in drier areas, but at 2^{o}C, the forested areas increase more substantially while the drier areas reduce further. This thus, shows that increased warming leads to more rapid decline of TLAI in drier areas but further increase growth in wet areas.

8.3. Study limitations

While the present study provides a robust results with regard to simulating the response of vegetation to drought in past and future climates, the results are not conclusive. This is due to certain limitations. Firstly, the simulations of vegetation response to drought using DGVMs and CESM considered a 22-year period. This might have implications for long term mitigation plans. Secondly, the study used only three DGVMs. There are other DGVMs, which may utilize better climate variables and vegetation indexes, but they were not used in this study. Thirdly, the study used only one type of vegetation index (i.e. the NDVI), but it could have considered other indexes, such as the Enhanced Vegetation Index (EVI). Lastly, the study only considered observed climate variables from the CRU. However, there are other observed datasets from both satellite and weather stations, which may have given different results. Thus, we consider this study to form just a part of broader future study.

8.4. Recommendations

The results of the study can be improved in many ways. Firstly, longer time periods in both observations and simulations should be considered for further studies. In addition, more vegetation fluxes, such as net biome production (NBP) and net ecosystem exchange (NEE) could be considered in studying the impacts of climate change on vegetation characteristics. Furthermore, other vegetation indexes, such as the Enhanced Vegetation Index (EVI) could also be used for a similar type of study. There is a need to improve the land component of the CESM model, so that it can more accurately capture the response of vegetation to drought. Despite these limitations, the present study has shown that southern African vegetation is indeed affected by drought, and that these effects can be simulated with models; moreover, this study can be applied in the mitigation of the impacts of climate variability and change on vegetation in southern Africa. Therefore, there is a need to adopt different drought and climate change mitigation measures in order to lessen the impacts of drought and climate change on vegetation in the region. The mitigation plans could be a mixture of preparedness and response.

8.5. Conclusion

This study has shown that drought and climate change are indeed threats to southern African vegetation. This has significant implications for policy makers who need to make decisions for reducing the impact on the region's rich vegetation. It is suggested that climate mitigation measures in southern Africa should be all-encompassing, ranging from monitoring to impact assessments. Some of the specific mitigation measures that may be adopted include:

- There should be more investment into the prediction and monitoring of droughts in the region. Thus, there is a need for more manpower to monitor the impact of droughts, as well as a greater need for remote sensing tools and satellites.

- Furthermore, the national governments of the various countries in this region should develop a white paper on how the impacts of drought and climate change can be lessened. There should be better intergovernmental cooperation among the Southern African Development Community (SADC) bloc to enhance effective monitoring.

- There is a need for regular assessment of drought impacts, particularly in respect of vegetation. This includes improved watershed protection, improved crop management, water management and enhanced soil quality.

- There is also a need to create public awareness in order to educate the population on the importance of vegetation to human survival, and in order to demonstrate how droughts and climate change could negatively affect the value derived from such vegetation. The public should be made aware of the efforts that they themselves could make in abating the impacts of climate change on their surrounding vegetation. In essence, communities should be made guardians of southern African biodiversity.

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