Influences of Rainfall Pattern Changes on Vegetation Dynamics of Savanna Ecosystems in Australia under Climate Change

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Certificate of Authorship

I, Jie He, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Life Sciences/Faculty of Sciences at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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CONTENTS

Abstract

Climate change has significantly influenced the global hydrological processes with rising temperature and elevated CO_2. Rainfall is the most active factor to influence the terrestrial ecosystems, especially with frequent heavy rainfall events in recent decades. Although much research has addressed the relationship between rainfall and vegetation under climate change, the impacts of rainfall pattern changes on terrestrial ecosystems have still not been stated clearly. In this project, we attempted to explore the mechanism of how rainfall pattern changes driving vegetation dynamics of savanna ecosystems in Northern Territory, Australia, where a well-known rainfall gradient is located and provides a natural laboratory for climatic analysis. To investigate rainfall pattern changes, we diagnosed the long-term rainfall pattern changes by analyzing trend, periodicity, abrupt change, and extreme rainfall events based on long-term rain gauge data, describing rainfall conditions over the sub-continent. The findings supported the view that rainfall pattern has significantly changed and especially occurred after the 1970s, illustrated by showing more frequent hydroextremes. We explored the sensitivity of vegetation phenology to rainfall variations from the wet coastal regions to the dry inland regions over different savanna vegetation biomes by retrieving phenological metrics from MODIS enhanced vegetation index (EVI). Results revealed maximum EVI was the most appropriate proxy to represent vegetation growth status and also be sensitive to rainfall variations, even if the sensitivity declined in water sufficient regions. Afterwards, we demonstrated the dominating roles of rainfall patterns in driving vegetation dynamics by evaluating the relative importance between maximum EVI and three decomposed rainfall pattern components, namely, intensity, duration, and frequency. Surprisingly, we noticed the roles of three factors varied along with rainfall gradient, and frequency become the most dominating factor in controlling vegetation dynamics in semi-arid and semi-humid regions. Eventually, we extended our research from ground rain gauge measurements to TRMM satellite precipitation observations to investigate the spatiotemporal variations of rainfall patterns and its influences. We found savanna biomes in semi-humid regions responded to rainfall changes mostly, and the relative importance of rainfall pattern component followed the consistent spatial regime, which has been illustrated by meteorological data. In summary, this study contributes to the deeper understanding of the roles of rainfall pattern changes in dominating vegetation dynamics under different rainfall conditions, and the findings benefit projection and modelling to mitigate the impacts of climate change.

Keywords: Rainfall pattern changes, vegetation dynamics, savanna ecosystems, climate change, Northern Territory, Australia

Chapter 1: Introduction to the research

1.1 Brief research background

Climate change has been widely pronounced to influence the atmosphere, lithosphere, biosphere, and our society. It is unavoidable that we have to face climatic change with more and more hydroextremes. Globally, the changes in the spatiotemporal regime of rainfall have been pronounced by many studies. Consequently, the uneven distribution of rainfall at spatial and temporal scales incurs the issue on water availability, which also definitely influences terrestrial ecosystems. Under the pressure of frequent hydroextremes, terrestrial ecosystems are pivotal to adapt to climate change because of links among water, carbon and energy balance. Hence, there is an urgent need to understand the influences of rainfall pattern changes on terrestrial ecosystems at spatial and temporal scales.

Although a great deal of research has addressed the relationship between water and vegetation from cell scale to ecosystems scale, covering filed experiments, ground measurements, and remote sensing observations, the mechanism of the influences of rainfall pattern changes on vegetation dynamics has still received less clear statement. In this study, we attempted to explain the role of rainfall pattern in controlling vegetation growth of savanna ecosystems in Australia at biomes or ecosystems scale via using remote sensing. The results are expected have a further understanding of the interaction between rainfall and vegetation. In addition, the work is also expected to be a benchmark to benefit the climate assessment on terrestrial ecosystems, contributing to monitoring, modelling, and prediction.

1.2 Aim and objectives

The primary aim of this study is to understand the mechanism of how rainfall pattern changes influence vegetation dynamics under climate change. To achieve this aim, the research project related to rainfall patterns and savanna ecosystems in Northern Australia will be conducted based on multiple data sources, including ground measurements and remote sensing observations. Here, we confined our research topic within savanna ecosystems, which are sensitive to rainfall variation. In addition, the objectives contributing to the further understanding of our aim are listed as follow,

1) To identify and characterize rainfall pattern changes based on long term historical observations;

2) To explore the spatial regime of rainfall pattern on vegetation dynamics with respect to the rainfall pattern factors as amount, intensity, duration, and frequency;

3) To identify and analyse the critical factors in dominating vegetation responses to rainfall pattern changes.;

4) To quantify and evaluate vegetation dynamics under rainfall pattern variation at spatial scale.

1.3 Outline of the thesis

To achieve the abovementioned aim and objectives, each chapter addressed the specific issue to improve our understanding of the influences of rainfall pattern on vegetation growth. The outline of the thesis is listed below.

Chapter 1: This chapter is a brief introduction to our research question. It is to clarify the scope of our work with clear statement of aim and objectives.

Chapter 2: This chapter is literature review, enhancing the understanding of research background, which covers the significance of study, potential data sources and applications, climatic conditions on the study area.

Chapter 3: This chapter mainly focuses on the identification of rainfall pattern change based on long-term meteorological recording. In this chapter, we confirmed rainfall pattern has presented significant changes in terms of trend, periodicity, abrupt change, probability distribution, and rainfall extremes. This chapter provides a deeper understanding of rainfall pattern changes and also indicates the urgent need to evaluate the impact of rainfall pattern changes.

Chapter 4: This chapter is mainly to explore the sensitivity of phenological metrics to rainfall variation. The primary purpose of this chapter is to characterize vegetation dynamics with an appropriate proxy. The findings in this chapter enhance our understanding of how vegetation responds to rainfall variation, and it is also the fundamental work for further research on issues related to vegetation phenology and rainfall variations.

Chapter 5: This Chapter is mainly to explore the dominating roles of rainfall pattern in driving vegetation dynamics. This chapter was based on the findings in the previous chapters and combined ground rainfall gauge data with remote sensing vegetation index to explore the influences of rainfall pattern changes. To highlight, the method we proposed in this chapter is suitable in analyzing the contribution of the rainfall pattern components to vegetation dynamics, which could improve the understanding of the impacts of climate change and benefit projection in the future.

Chapter 6: This chapter extends the spatial scale of research by introducing TRMM precipitation satellite into rainfall pattern analysis. With validation of the applicability of TRMM satellite data, it is potential to explore the impacts of rainfall pattern changes at a larger spatial scale, or even at global scale. Presently, we obtained the consistent results compared with findings in Chapter 5 to support the effectiveness of TRMM data. We also obtained the spatial regime of the influences of rainfall pattern on vegetation along a rainfall gradient at a sub-continent scale.

Chapter 7: This chapter provides a retrospect on our research. A general understanding of the role of rainfall pattern in vegetation growth is expected to benefit and improve the relevant research. Besides, the limitations of this research were also stated to guide the future study.

Chapter 2: Literature review

2.1 Climate change

2.1.1 Global warming

Anthropogenic emissions of greenhouse gases, including carbon dioxide CO_2, methane, and nitrous oxide caused by human being activities, such as transport fuel burning and livestock industry, leads to global warming compared to the pre-industrial era (Lashof et al. 1990; Reid et al. 2014; Satterthwaite 2008). The impacts of greenhouse gases associated with other anthropogenic activities, such as deforestation, have been detected throughout the climate system and are likely to be the major cause of noticeable climate change (Lashof et al. 1990). With greenhouse emissions increase dramatically, the climate has changed significantly, and many climatic observations, including CO_2 concentration, temperature, extreme rainfall events, and biodiversity, have a distinct shift since the 1950s (IPCC 2013). Globally, averaged temperature has increased by 0.8 °C since 1880, the anomaly of globally averaged combined land and ocean surface temperature presents a steeper increasing trend in the recent 30 years (in Figure 2-1). The rising temperature not only causes snow and ice melting and the rising sea level to influence marine and terrestrial ecosystems and biodiversity, but also threatens human health and society with more and more frequent extreme events (Botkin et al. 2007; Desmet et al. 2015; García Molinos et al. 2015; King et al. 2018; Piao et al. 2010).

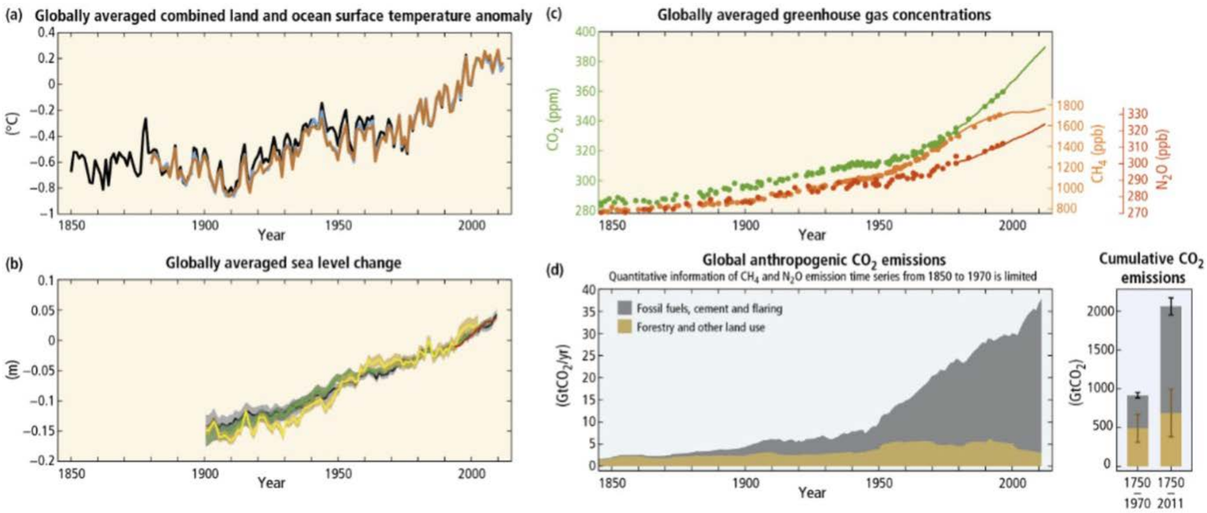

Figure 2-1. The complex relationship between the observations. (a) Globally averaged combined land and ocean surface temperature anomalies. Colors indicate different data sets. (b) Globally averaged sea-level change. (c) Atmospheric concentrations of

the greenhouse gases (d) Global anthropogenic CO_2 emissions from forestry and other land use as well as from the burning of fossil fuel, cement production and flaring (IPCC 2013).

Since recent decades, a great deal of research has focused on climatic modellings and their influences under future scenarios (Oerlemans et al. 1998). For instance, Wang et al. (2014) applied 35 climate models to predict annual average temperature will increase by 0.8 to 1.6 °C (0.8 to 1.7 °C), 1.5 to 2.7 °C (2 to 3.7 °C), and 1.9 to 3.3 °C (3.4 to 6 °C) under greenhouse gases emission scenarios of RCP4.5 and RCP8.5 in three time periods (2010–2039, 2040–2069, and 2070–2099) over China, respectively. If we continue to execute the current trajectory of gases emissions, there is a challenge for us to hole global average temperate increasing below 2°C above pre-industrial levels, which was proposed in Paris Agreement for future aim (Peters et al. 2012; Rogelj et al. 2016). Hence, we should have a better understanding to realize climate change based on current observations and projected modelling, and meanwhile to assess climatic impacts associated with feasible methods to take measures by involving more resources of up-to-date technologies, breakthrough social and political regimes and innovation for the mitigation and adaptation of climate changes (Mi et al. 2017).

2.1.2 Hydrological variation under climate changes

Water is at the heart of both the causes and effects of climate change. With continuous water cycle, atmosphere, biosphere, and lithosphere are connected, so that energy, carbon, and materials can be transported to change the stuffy and rigid world into the animated and vivid world (Martin-Ortega et al. 2015).However, present observations demonstrate the hydrological cycle has been influenced by climate change. Intergovernmental Panel on Climate Change (IPCC 2013) reported that the observed global warming has presented changes in the global water cycle, snow and ice melting, sea-level rising, and also extreme events since the mid-20th century. The evidence of increasing greenhouse concentration observed in the atmosphere shows human beings' influences on climate change explicitly via hydrological variations (AghaKouchak et al. 2015; Allan et al. 2008; Fischer et al. 2015).

Under the background of an increasing trend in temperature and potential changes in synoptic circulation patterns, the intensities and frequencies of precipitation are expected to be changed and show an accelerated cycle in future. Global warming influences the hydrological cycle and causes heavy rainfall, and the intensification is expected to follow the law of thermodynamics at a rate of 6.5 % $^{o}C^{-1}$, namely Clausius-Clapeyron rate (Allan et al. 2008). With the temperature increasing, many observations have reported increases in daily rainfall extreme (Donat et al. 2013). Also, hourly rainfall extremes have been detected even at a continental scale in Australia (Guerreiro et al. 2018). Furthermore, the future projection showed extreme hourly rainfall was increasing with temperature in moist, energy-limited environments (Bao et al. 2017). Li et al. (2016) found that the total number of extreme rainfall events presented a positive trend under a warming climate, and the small-scale extreme rainfall events happened more frequently than the large-scale extreme rainfall events. Those studies provide a better understanding to characterize frequency and intensity increases, which promotes societal resilience to future extreme precipitation events.

Similarly, the consistent finding also showed that the convective precipitation was sensitive to temperature increases with more extreme events in south-western Germany (Berg et al. 2013). Increasing rainfall variability leads to not only more frequent extreme rainfall events, but also the deficiency of expected valid rainfall amount when considering soil penetration with sparse vegetation cover (Magliano et al. 2015). The imbalance of water distribution at a spatial scale and temporal scale also causes drier regions becoming drier (Chou et al. 2009; Durack et al. 2012; Held et al. 2006). Modarres et al. (2016) applied the Mann-Kendall test to demonstrate Iran experiences both floods and droughts, which challenge future water management. Due to regional long-term warming, soil moisture decline and intensified evaporation, the rapidly developing drought events have increased 109% averaged over China from 1979 to 2010, especially in the southern and north-eastern China (Wang et al. 2016). Hence, with temperature increase globally, variations of the hydrological cycle not only simply performed as increase precipitation amount in some regions, but also associated with more frequent extreme rainfall events and higher uncertainty of rainfall pattern than before. That is the core issue we have to face and evaluate its influences on our living environments.

2.1.3 The impacts of hydrological variations

Climate change and increased anthropogenic activities noticeably play a key role in rising hydrological variability by affecting water availability, quality, and other hydrological processes, such as evapotranspiration, infiltration, and watershed yield at a regional, continental and even global scale (Blöschl et al. 2010; Huo et al. 2013; Milly et al. 2005; Semadeni-Davies et al. 2008; Whitehead et al. 2009). Those impacts on hydrological variation certainly influence the environment we depend on and transfer climatic pressure on both natural ecosystems and human being's society (AghaKouchak et al. 2015; Kjerfve et al. 1999; Praskievicz et al. 2009; Richter et al. 1996). Therefore, climate change induces a series of water-related issues we have to face and take measures for adaptation and sustainable development.

Compared to other hydrological processes, precipitation can be the most critical hydrological process and acts as an indicator to reflect climatic element fluctuation (Chiew et al. 2003). The most direct influences resulting from rainfall pattern changes can be water availability (Rosengrant et al. 2001). Rainfall variability leads to soil water availability becoming limited, and rainfall dependent ecosystems becoming more vulnerable, as water content decreases in soil (Tietjen et al. 2017). In addition, the continuously increasing temperatures in most parts of the world cause water distribution at both spatial and temporal scale more unevenly and irregularly than before, and the increasing extreme climate events, such as drought, heatwave, and flooding, cause economic loss and threaten life safety at an extensive scale (Arnell et al. 2016; Mitchell et al. 2016; Serdeczny et al. 2017). Furthermore, many freshwater, marine, and terrestrial species have changed their geographic ranges, seasonal activities, migration patterns, abundances and species interactions to respond current ongoing climate change (Burrows et al. 2011; IPCC 2013; McCluney et al. 2012; Occhipinti-Ambrogi 2007; Poloczanska et al. 2013).

2.2 Precipitation measurements

The observations of precipitation are essential for monitoring of hydrological processes and climate assessments (Bárdossy et al. 2008). Ground precipitation measurements would be the most direct method to obtain rainfall data in first hand as well as keep long term recording. Usually, rain gauge measurements provide rainfall data with a high quality of accuracy, which is able to analyze rainfall characters in some specific spots (Villarini et al. 2008). On the other hand, rainfall monitoring from satellite offers a board view on a larger spatial scale while at the expense of data accuracy (Maggioni et al. 2016). Multiple rainfall monitoring satellites were combined with ground observations before the products can be applied in the fields of hydrological application, climate study, and water resources management (Bajracharya et al. 2015; Bayissa et al. 2017). Further, projected datasets of precipitation derived from multiple data sources also provide new insight into the analysis of climate changes in future scenarios (Dowdy et al. 2015; Grose et al. 2015). Since then, many institutes and organizations have reinforced the monitoring and modelling of rainfall variability. The Global Energy and Water Cycle Experiments (GEWEX) has been conducted since 1988 to understand the prediction of precipitation and evaporation processes at a global scale by the World Climate Research Program (Chahine 1992). The Coordinated Enhanced Observing Period (CEOP) is designed to collect various hydrological datasets from observation, satellite and model sources (Randall et al. 2003).

2.2.1 Ground Observation

Actually, the type of rainfall products we selected is dependent on the specific research purposes and products itself attributes. Weather datasets from gauging stations are applied easily and widely over the world. The rainfall measurement is typically dependent on rain gauge instruments. Although this method is directly getting rainfall information via recording in time, the accuracy and data quality is influenced by various types of instruments, temporal sampling resolution, and locations of gauges (Villarini et al. 2008). The advantage of gauge monitoring is long-term recording over several decades, contributing to global networks from private or public owners and organizations (Kidd 2001). The shortcoming is also obvious that gauge stations are only able to applied in some areas, and the density of spatial distribution and data reliability are also associated with consideration of topography, regional politic stability, and regional financial supports (Sun et al. 2018). Therefore, the gauge stations may not always cover the regions for some specific regions. However, with sufficient observation networks, ground precipitation measurements certainly would be a good source to support the investigation on climate change.

2.2.2 Spatial Observation

Precipitation is spatially and temporally highly variable. Satellite observations of rainfall provide a holistic view of weather and climate at a large quasi global scale and contribute to earth processes and changes monitoring (Anagnostou et al. 2009; Hou et al. 2014; Petty 1995). The first meteorological satellite was Television and Infrared Observation Satellite (TIROS-1) launched in April 1960 (Yevjevich 1992). Afterwards, the development of a satellite monitoring system promotes rainfall observation at a larger scale (Kidd 2001). However, extended spatial range against coarse spatial resolution limited its application in some meteorological areas. Presently, the Tropical Rainfall Measuring Mission (TRMM) is widely applied in meteorological research according to its leading retrieval algorithms for rainfall estimates and long-term observations since 1997. TRMM is in a low Earth, non-sun-synchronous orbit with sensors of Microwave Imager (TMI), Visible and Infrared Scanner (VIRS) and the active microwave Precipitation Radar (PR) scanning the global range from 40°N to 40°S for a better understanding of rainfall. TRMM serviced for over 17 years retrieving data at 0.25° spatial scale, and temporal resolution can reach the finest level as 3-hour real time (Maggioni et al. 2016; Veloria et al. 2019). However, applications reported by many researchers revealed that composited monthly datasets have satisfied correlation with ground measurements of rainfall, but low correlation at daily scale (Sorooshian et al. 2002). Usually, TRMM also underestimates heavy rainfall events but has a better estimate result in the ocean than in the land (Jiang et al. 2018; Maggioni et al. 2016).

2.3 Vegetation responses to climate changes

2.3.1 The role of climatic factors in vegetation dynamics

Global change links the interactions among the lithosphere, atmosphere, and biosphere via the materials cycle and energy balance. The activities of vegetation reflect the responses to variations of climatic factors, which involve the complicated processes and mechanisms related to water and energy transport (Fang et al. 2004; Raich et al. 1992). Furthermore, those influences derived from climatic variation has a distinct regional difference among various ecosystems (de Jong et al. 2013; Lucht et al. 2006). Usually, the coupling of vegetation behaviours and the fluctuation of climatic conditions is to build relationships in aspects of radiation, temperature, and water. Those three factors are regarded as the most important elements in influencing vegetation distribution, dynamics and structure changes (Knapp et al. 2002; Seddon et al. 2016). The driving factors to vegetation dynamics is easier to be listed, but the mechanism is still not very clear. The impacts of climate change involve many closely related and interactively physical, chemical and biological processes such as photosynthesis, respiration and transpiration, and the responding processes of vegetation activities to climate factors reflects the comprehensive characteristics of multi-factor and multi-process, forming a climate-vegetation relationship with complex interactive processes and spatial differentiation. Those complex processes and interactions between climate factors and vegetation require an integrated and complicated system to reveal the vegetation response to climate stress and adaptation to climatic variability.

Vegetation is always continuously adapting to environmental conditions to make its own activities more beneficial (Krishnaswamy et al. 2014). With environment changes, the behaviors of vegetation also responses from micro stoma scale to larger regional scale. As for temperature, moderate warming can play a positive role in enhancing vegetation growth (Peng et al. 2011). The fifth IPCC report pointed out that the global temperature is about 0.8 ℃ in the 20th century, while the global total potential net primary productivity (NPP) was estimated with an increment by 13% in the warmer environment (Del Grosso et al. 2008). The responding mechanism of vegetation activities to temperature mainly reflected the degree of influence of warming on photosynthesis, respiration and other processes at different time scale.

However, excessive warming can adversely affect the processes of vegetation activities (Chen et al. 2014). High temperature may accelerate soil moisture evaporation and cause the drought trend, which is prone to occurrence in parts of low latitudes in the southern hemisphere and northern hemisphere. Vegetation prevents water loss by reducing leaf area or closing stoma which cuts down CO_2 supply, limits photosynthesis rate, and affects the synthesis of organic matter. Besides, the rising temperature increases the rate of autotrophic respiration and transpiration, accelerates the consumption of organic matter, and reduces the net productivity of vegetation, thus inhibiting vegetation activities. For instance, Gu et al. (2017) investigated the response of NPP to warming at both national and subregional scales during 1961–2010. The results indicated that a 1.3°C increase in temperature stimulated the positive changing trend in NPP at national scale during the past 50 years. However, the positive trend of NPP decreased when warming exceeded 2°C, regardless of whether precipitation increased or decreased.

Apart from temperature, climate change can cause significant changes in rainfall patterns in aspects of intensity, duration, frequency, and extremes, which will have a great hydrological impact on terrestrial ecosystems and vegetation productivity and coverage (Fay et al. 2003a; Fensham et al. 2005; Heisler-White et al. 2009; Knapp et al. 2008; Knapp et al. 2002; Nicholson et al. 1990). Water is involved in physiological and biochemical processes such as photosynthesis and transpiration of vegetation, and many nutrients and minerals in soil can only be absorbed by plants under the condition of water solubility. Therefore, when water decreases, the photosynthesis rate of vegetation will decrease, organic matter yield will decrease, and as well as vegetation activities such as growth and coverage will be inhibited (Angelopoulos et al. 1996; Behboudian et al. 1994; Chaves et al. 2002). However, when the increase of precipitation exceeds the requirement of vegetation, it may indirectly cause adverse effects on vegetation activities such as growth and development by reducing radiation and increasing relative humidity (Srivastava et al. 1998). In areas where the average annual precipitation is sufficient for water demand, vegetation is more sensitive to the change of heat factor, and a slight decrease in precipitation may indirectly promote vegetation activities. In semi-arid regions with insufficient water supply, precipitation becomes a limitation to vegetation activities (Rodriguez - Iturbe 2000).

Field experiment results showed that the concentrated precipitation increased the above-ground NPP of the grassland ecosystem in the semi-arid region by 70%, and decreased it by 18% in the humid region (Heisler-White et al. 2009). Many studies compare the different effects of precipitation increase and decrease on vegetation activities. For example, when summer precipitation increases by 50% in the mixed grassland of Wyoming, biomass increases by 44%, while decreases by 18% when precipitation decreases by 50% (Chimner et al. 2010).

Besides, radiation is also a necessary climatic factor for vegetation, which affects vegetation activities together with temperature, precipitation and other climatic conditions (Dymond et al. 2002). Light intensity directly affects the intensity of photosynthesis of vegetation (Peeters et al. 1978; Ye et al. 2014). When the light intensity exceeds the saturation point of photosynthesis, chlorophyll decomposition will occur, or water loss of cells will lead to stomatal closure, inhibiting or even stopping photosynthesis (Ye et al. 2010). Generally, the light is closely related to the temperature in spring and autumn, and the temperature will rise for a short time under the condition of strong light. In summer, precipitation is relatively large, water vapour in the atmosphere is sufficient, cloud cover is abundant and thick, and the influence of precipitation on light exceeds temperature and presents a negative correlation (Bradley et al. 2011). It can also be seen that in areas with abundant water, light has become a major limiting factor for vegetation activities (Gentine et al. 2012; Zhuang et al. 2016).

2.3.2 Remote sensing monitoring of vegetation

Vegetation is a sensitive indicator of global climate change. The hydrothermal conditions in the climatic environment determine the vegetation phenology, productivity, distribution pattern, and its dynamic changes. Therefore, monitoring the vegetation dynamics with effective long-term observations over multi-ecosystems and different climatic conditions is important to study the impacts of climate change on vegetation and ecosystems. With the development of remote sensing spectrum observation, vegetation indices have been widely applied to address issues on spatial and temporal variations of terrestrial photosynthetic activities, which are based on the mechanism of spectral signature of healthy vegetation (Huete et al. 2002; Ma et al. 2013; Piao et al. 2008).

The moderate-resolution imaging spectroradiometer (MODIS) provides a global Earth observation from Terra and Aqua satellites. MODIS provides many products, which are accessible from Land Processes Distributed Active Archive Centre (LPDAAC). Besides, the quality assessment is controlled by the MODIS Land Data Discipline Team(Paget et al. 2008). The relevant data products include vegetation index products such as EVI, leaf area index (LAI), gross primary production (GPP), and evapotranspiration (ET). Those products offer a continental view to observe vegetation and water variation as well.

2.4 Ecological sensitivity to hydrological variability

2.4.1 Ecological sensitivity to water

Seddon et al. (2016) identified the relative sensitivity of global ecosystems to climate variability considering climatic drivers as air temperature, water availability and cloud cover. According to the assessing results, the most influential variable is heterogeneous at a global scale. However, according to the global vegetation sensitivity index, water availability was identified as the highest percentage of the most influential factors compared to the other two major factors, temperature and radiation, globally. As for the specific case, the focused study area in this thesis, Australia, is also dominated by the factor of water availability.

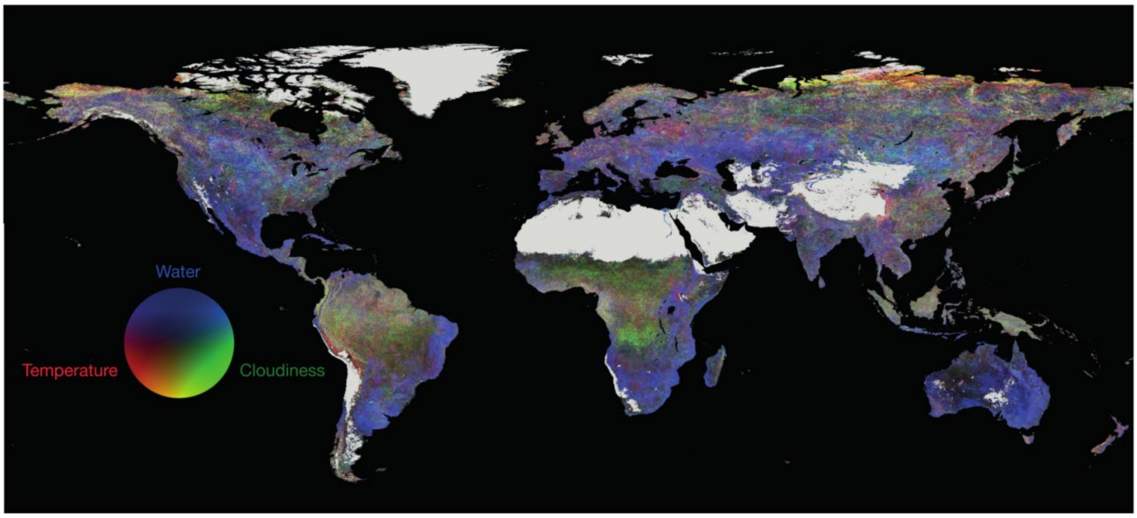

Figure 2-2.RGB composite of the global contribution of three climate variables to vegetation sensitivity index. Red is for temperature; blue is for water availability; green is for cloudiness, and white is for barren land. (Seddon et al. 2016)

Rainfall, as the core process of the hydrological cycle, stimulates vegetation activities mostly, and cause vegetation responses sensitively. The increasing intensity of rainfall is an important factor for niche partitioning. A higher intensity of precipitation facilitates the growth of a woody plant and meanwhile decreases grass plant growth, as the increasing intensity can push water into deeper soil for a woody plant with deeper root depth. (Kulmatiski et al. 2013). Huxman et al. (2004) summarized the timing and magnitude of precipitation pulses play an important role in C exchanges of arid and semiarid ecosystems. The precipitation pattern related to precipitation amount, infiltration depth, soil microbial fauna, and response time could be critical to influence the available water for plants, rather than considering annual or seasonal rainfall amount as water limitation simply (Fay et al. 2003a; Knapp et al. 2002). Small precipitation pulse primarily increases microbial respiration while larger precipitation pulses trigger C accumulation as water infiltration into deep soil for plant use.

2.4.2 The relation between water and vegetation

Water resources are critically important to human beings as well as vegetation (Kundzewicz 1997). It not only means water supports vegetation survival, but also water nurtures vegetation to maintain ecological functions, contribute to biodiversity, supply foods, conserve water and soil, and alleviate the impacts of climate change

(Abbaspour et al. 2009; Oki et al. 2006; Vörösmarty et al. 2010). Besides heat energy, water condition is one of the most crucial elements to dominate the distribution and type of vegetation (Stephenson 1989; Stephenson 1990). Hence, understanding the mechanism of vegetation responses to water, especially under the background of global change, is essential for human beings' sustainable development.

In ecology, usually, an isolated rainfall event is considered as a signal of pulse, which drives episodes of elevated biological activity (Dunkerley 2013). Extensive studies have addressed the relationships between vegetation and water across the world to demonstrate its significance. Stephenson (1990) employed the normalized difference vegetation index (NDVI) to explore a good relationship between rainfall variations and vegetation in East Africa and the Sahel. Suepa et al. (2016) also applied remote sensing observations of vegetation to monitor the phenological changes along with the monsoon climate in Southeast Asia to present a strong correlation between vegetation phenology and seasonal rainfall. The spatial and temporal features of rainfall greatly influence vegetation variation, and this relation is more distinct in arid regions, where water is regarded as a limitation.

Various studies have demonstrated the relationship between vegetation and rainfall regimes. However, the water content in soil is the direct factor influences vegetation ultimately. The combined effects of soil characteristics and rainfall patterns should also be considered when studying the dynamics of vegetation (Ursino et al. 2006). Zhou et al. (2015) demonstrated the temporal stabilities of soil moisture presented differences with different types of vegetation in the arid and semi-arid ecosystems. Meanwhile, vegetation also interacts with soil moisture in the spatial pattern (Yang, Chen, et al. 2015).

Although the response of vegetation to rainfall is certain, this effect may have time lag to reduce the year-to-year variability (Zeng et al. 1999). By assessing satellite data of vegetation with ground observation verification, it can be found that the highest vegetation index presented a few weeks later after the main rainfall event happened in a semi-arid environment (Schmidt et al. 2000). Relatively, the influence of time lag is more detectable in arid regions than in humid regions. In addition, compared with other ecosystems, groundwater dependent ecosystems (GDEs) absorb water from the near surface groundwater. Therefore, the responses of those ecosystems to variability of precipitation is stable, especially for the ecosystems highly dependent on groundwater (Eamus 2006).

2.4.3 The significance of vegetation response to hydrological variation

As we know, there is a strong bond between water and vegetation. Under the climate changes, vegetation is influenced by hydrological variation, including changing rainfall patterns, intensive evapotranspiration, and other hydrological processes. The hydrological variation influences both water availability to vegetation and water use efficiency to vegetation. Since both annual rainfall amount and the distribution frequency of rainfall events contribute to actual available water for plants, which controls vegetation dynamics (Guan et al. 2015). On the other hand, vegetation phenology is a sensitive indicator to reflect the climate changes (Schmidt et al. 2000). In terms of vegetation phenology, the seasonal life cycle of plants presents its variation via the changes of onset of the growing season, the end of senescence and the timing of peak greenness. Hence, the response of vegetation to climatic factors could be applied for long-term environment monitoring.

According to ground observations and mechanisms of vegetation to climatic factors, the approaches to future scenarios analysis benefit a deep understanding of climate change. Many studies have been conducted to improve the application. For instance, BureauofMeteorology (2015) simulated net primary productivity (NPP) increased by 79% and 134% under the scenarios with increasing temperature as 1.3℃ and 4.2℃. In addition, the spatial responses of vegetation are also observable. With increasing rainfall, sufficient water supports the expansion of the oasis belt in arid regions (Martin-Ortega et al. 2015). In conclusion, understanding the responses of vegetation to hydrological variation benefits the adaptation to climate changes.

The significance of research on the responses of vegetation to hydrological variation is not only monitoring the ecosystem to maintain the ecological health, but also it is beneficial to enhance the adaption to climate change. For instance, Guan et al. (2015) applied two validated models to assess the sorghum yield under the possible variation in seasonal rainfall in west Africa. Considering the shifts in rainfall intensity, frequency, the duration, and timing of the rainy season, the modelling result showed that intensive rainfall events have a greater benefit to yield than frequency, though total rainfall amount should always take into account first. The strategic adaption to future rainfall changes could be planned based on relevant research.

2.5 Impacts of climate changes in Australia

2.5.1 Climatic conditions in Australia

Australia is the driest hinterland in the world, where the annual precipitation is below 500 mm over the whole continent based on long-term records (Nicholls et al. 1997). Water resources are scarce in the majority of land, excluding the coastal regions with plentiful water supply. In northern Australia, the dominant climate is tropical, but the annual precipitation varies from 2000 mm in coastal regions to 200 mm towards inland, while the monsoonal season begins in November, increasing the climatic variation. In the western and eastern Australia, the climatic type is mainly Mediterranean and subtropical, where the annual rainfall can reach 1000 mm. However, periodic droughts can occur and be severe. In the Mediterranean and subtropical regions, usually, the temperature is high, and coastal areas are frost-free. The rest inland regions are dominated by arid and semi-arid climate, where annual rainfall is less than 300 mm and 350 mm on average in arid and semi-arid regions, respectively (Sturman et al. 2006). The yearly rainfall is exceptionally low and the distinctive rainy season aggravates the uneven water distribution and water scarcity. Besides, severe droughts happen commonly.

The Australian mainland is also characterized by the strongest climatic variations compared with other continents. The intrinsic rainfall variability is varying largely from year to year and even decades to decades (Karl Braganza et al. 2015). Besides, the

Australia continent spans over 30°of altitude, which expends from tropical weather systems to temperate weather systems. Due to climatic variability, the energy and water present a distinct fluctuation at both spatial and temporal scale. In northern Australia, the two distinct seasons divide the annual water distribution. The wet season usually starts from November and lasts until April, while the dry season is from May to October. In southern part of regions, as the influence of tropical weather system decreases, the annual cycle of rainfall becomes weaker, and the differences in temperature in winter and summer are larger than northern Australia, so the distinct four seasons are clear.

The extreme weather in Australia is influenced by both intrinsic natural variability and comprehensive climatic modes. The variability of rainfall from the north to the south cannot be explained by intrinsic modes alone, and also multiple climatic modes and factors have an interactive effect in Australia land, including the El Niño-Southern Oscillation (ENSO), the Indian Ocean Dipole (IOD), the Southern Annual Mode (SAM), Madden–Julian oscillation (MJO) and other critical modes (Risbey et al. 2009).The interactions among those climate systems aggravate the uncertainty and variation of climate and influence the hydrological processes (Cleverly, Eamus, Luo, et al. 2016; Xie et al. 2019), which may cause water issues in human society and ecosystems.

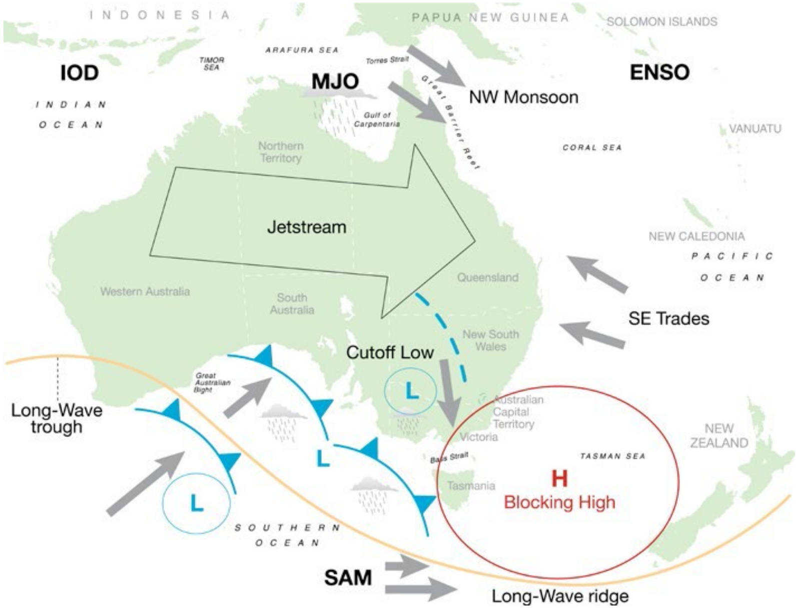

Figure 2-3 Schematic showing the main weather and climate features affecting Australian climate variability (Jeffrey et al. 2001).

In particular, ENSO is regarded as the major driver of the interannual and decadal climate variability of Australia (Dijk et al. 2013; Dore 2005; McMichael et al. 2006; Nicholls et al. 1997). The Southern Oscillation Index (SOI) and rainfall present a strong positive relationship indicates ENSO is the dominant driver of variation in extreme rainfall event in Australia (Dunkerley 2013). Kamruzzaman et al. (2011) presented evidence that monthly rainfall is decreased during the negative period of the Southern Oscillation Index (SOI) in eastern Australia. The widely reported “Millennium Drought” from late 1996 to mid-2010 can be explained by association with SOI in northeast Australia. The following “big wet” from 2010 to 2012 also presents a strong relationship with positive SOI (indicating La Niña event). Jeffrey et al. (2001) also indicates IOD is the most important factor for precipitation during the period from June to October. Specifically, a notable lack of negative IOD events, as a contributing factor, has been related to the drought in the southeast of Australia since the 1990s to be expressed for identification (Harmsen et al. 2016).

In general, under the interplay of intrinsic natural variability and complexity of climatic modes, Australia experiences both interannual and inter-decadal changes in rainfall. The hydrological variation not only intensifies the uncertainty of water distribution at spatial and temporal scale but also causes a series of adverse influences, including heavy rainfall, long-term drought, fire weather, and ecological degradation. It is essential to evaluate the impacts of hydrological variations over Australia for ecological conservation.

The impacts of climate change presented a higher uncertainty of hydrology. According to both observations and model simulations, a general increasing trend in rainfall intensity and on a global scale is discernible (Li et al. 2016). Rainfall in Australia also presents an obvious increasing trend in most parts since the 1900s. Especially, the average annual rainfall over the entire continent has increased by about 50 mm, comparing the period 1900 to 1960 with the period 1970 to 2013 (BureauofMeteorology 2015). However, the rainfall also declines as much as 40% in the southwest of Australia over the last fifty years (Sturman et al. 2006; Wallace 2007). The uneven spatiotemporal distribution of rainfall increases the risk of water security for both ecology and society.

2.5.2 Eco-hydrology in Australia

Ecosystems in Australia are highly related to water, as it is the major limitation to vegetation type and distribution in Australia (Wallace 2007). Rainfall patterns in Australia present a high variability compared to other continents. The interannual rainfall difference between a wet year and a dry year can be as much as twice in Australia. Meanwhile, a distinct rainfall gradient is from coast to inland central. The uneven spatial distribution of water also classifies several different ecosystems in Australia (Figure 2-6). During a relative wet year, rivers are wide, deep, and fast flowing, but when suffering drought, less than one fifth of rainfall ends up in rivers in Australia. Hydrological variation aggravates the vulnerability of ecosystems in Australia.

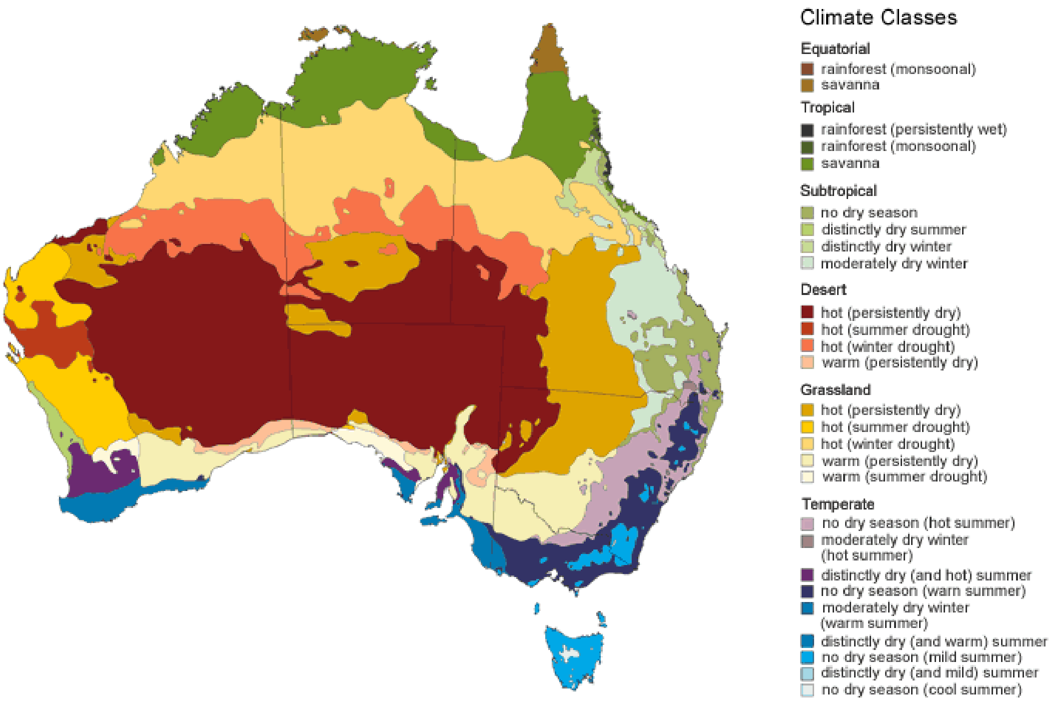

Figure 2-4. Australian climate classes based on a modified Köppen classification system (http://www.bom.gov.au/iwk/climate_zones/).

In addition, extreme hydrological events happened more frequently than before under climate change. Heavy rainfall changes its rainfall pattern from duration, intensity, and frequency, which has a great impact on the entire hydrological cycle, including penetration, runoff generation, and evaporation (Dore 2005; McMichael et al. 2006). Ecosystems will be influenced by water conditions certainly. From 1995 to 2010, the Millennium Drought is widely spreading over Australia. The water restriction is also accompanied by ENSO events associated with high temperature (Dijk et al. 2013; Heberger 2012). Bushfire happened frequently in the case of long-term water deficit (Lucas et al. 2007). Ecosystems over Australia are influenced intensively, and also including agricultural ecosystems. For instance, Australia's cotton production had dropped, with the smallest area planted in 20 years, a 66% reduction compared to five years earlier, which was considered a "normal" year. The crop had been half its usual size for three of the previous five years (BureauofMeteorology 2015). Hence, hydrological variations present more and more influences on vegetation in Australia.

Ecosystems in Australia are highly dependent on water. The major factor contributing to the persistence and resilience of ecosystems is water rather than light and temperature over the entire Australian continent based on the research on vegetation sensitivity index at a global scale (Seddon et al. 2016). Although approximately 70% of land cover in Australia is arid and semi-arid zones, the native vegetation has well adapted to low average rainfall and cyclical drought (Pudmenzky et al. 2015). However, under extreme climatic conditions and influences from land practice for production, vegetation also indicates changes along with hydrological variation. The observations satellite imagery of NDVI from 1982 to 2010 indicates the sub-humid and sub-arid of Australia become greening with an increasing trend of precipitation and increasing release of CO_2 fertilization (Luce 2014). However, the greening vegetation also consumes more water to influence the hydrological processes by reducing stream flow.

Actually, there is a rainfall gradient in north Australia to examine the impacts of water conditions on ecosystems. From the north to the central Alice spring with more than 1100 mm annual rainfall gradient, above-ground woody biomass, stem density, overstorey LAI, and canopy height all present a declined trend (Hutley et al. 2011). Similarly, the phenology alone with rainfall gradient was analyzed combining MODIS satellite data to investigate biogeographical and inter-annual patterns in savanna phenology. The results support that the variances of the period over greening season across the major vegetation groups could be explained as much as 80% by the variances in annual precipitation alone (Kelley et al. 2015).

The intrinsic sensitivity of ecosystems to water availability can also indicate changes in greenness interannually and seasonally. By applying the observed total water storage anomaly (TWSA) from the Gravity Recovery and Climate Experiment (GRACE), the greenness, represented by NDVI, fluctuated along with changes in water storage in different years and seasons. Besides, during the period of “Millennium Drought”, a distinct decline in annual mean NDVI was displayed as well (Yang et al. 2014).

Variation in water can explain the majority of variations in vegetation across Australia mainland. However, the temporal characteristics of vegetation response to water present variability in regional distinction. Dry regions with low vegetation density are more sensitive to water for the high end of the distribution of NDVI than wet regions, suggesting that water enhances vegetation growth in dry regions, and water use efficiency usually is higher in the dry region (Feng et al. 2013).

In conclusion, Australia is a water-limited continent accompanying with complex climatic modes and hydrological variations. Australia is also a mainland where a large variety in ecosystems contributes to a large part of the global terrestrial carbon sink. The availability of water influences over half of the primary productivity of the world's terrestrial ecosystems (McMahon et al. 2013) and influences present more intensively in Australia as its water sensitivity. Hence, the research on the relation between water and vegetation in Australia not only benefits indigenous ecosystems but also contributes to global carbon, water, and energy circulation.

Chapter 3: Hydrological diagnosis of rainfall pattern changes in Northern Australia with long term observations

Abstract

Climate change has had noticeable impacts on the hydrological cycle and has influenced the variability of rainfall patterns at both spatial and temporal scales in recent decades. The diagnosis of rainfall pattern changes is essential for a deeper understanding of how climate change produces variation in hydrological processes, including changes to rainfall patterns. Although a great deal of research has identified rainfall abnormalities as impacts of climate change, the effects of climate change on rainfall pattern changes has not been systematically studied. The objective of this study was to identify rainfall pattern changes under climate change at a sub-continental scale by analyzing long-term rain gauge data from 1910 to 2017 in the Northern Territory of Australia. Analytical methods, including linear regression, Morlet wavelet analysis, Mann-Kendall testing, probability density analysis, and determining the frequency of heavy rainfall events, were applied to metrological sites located within the study area. Changes in rainfall patterns were characterized by considering aspects of trends and periodicity of annual rainfall, abrupt changes in annual rainfall, rainfall distribution, and extreme rainfall events. Our results confirmed that rainfall patterns in Northern Australia have changed significantly compared with the early period of the 20th century. Specifically, a noticeable increasing trend in annual precipitation associated with more frequent extreme heavy rainfall events was observed over the entire study area which encompassed wet to dry conditions. An abrupt change of annual rainfall amount occurred during the 1965-1975 period. Additionally, the finding that the mean rainfall periodicity was 27 years supported the temporal identification of rainfall pattern changes. The study also determined that rainfall variability has increased in recent decades along the north-south rainfall gradient. This finding also supported the conclusion that rainfall patterns have changed. The findings of this study provide an up-to-date perspective on climate change impacts on rainfall patterns. The results will facilitate further studies on climate change impacts on rainfall and other hydrological processes.

Keywords: rainfall pattern, trend, period, abrupt change, extreme rainfall event, Northern Territory

3.1 Introduction

Hydrological processes have have been influenced by global climate change due to increasing temperatures and elevated CO_2 concentrations (Allan et al. 2008; Ma et al. 2016; Ukkola et al. 2015). The major impacts of global warming include the acceleration of the hydrological cycle, more hydroclimatic extremes, and high variability in the water balance at both spatial and temporal scales (Guerreiro et al. 2018; Wasko et al. 2015). Rainfall is the most sensitive hydrological process responding to natural climate changes and anthropogenic influences. As such, there is an ongoing interest in characterizing abrupt climatic changes and shifts. Climatic systems have major impacts on rainfall intensity and timing (Chen et al. 2013; Cook Garry et al. 2001; Fu et al. 2010; Huang et al. 2013; Piechota et al. 1996; Ranatunge et al. 2003; Yilmaz et al. 2014). Rainfall influences ecosystems, agriculture, society, and human activities (Guan, Good, et al. 2014; Guan et al. 2018; Heisler-White et al. 2009; Huxman et al. 2004; Kanniah et al. 2011; Ponce Campos et al. 2013; Shen, Huete, et al. 2018). Because of interactions among the water cycle, the carbon cycle, and the global energy balance, rainfall pattern analysis is fundamental and crucial for identifying and quantifying climate influences. Hence, the diagnosis and characterization of changes in rainfall patterns, variability, and distribution in space and time can provide insights into the functioning of climatic systems and the degree of their impact over multiple space and time scales.

Currently, a great deal of rainfall pattern research based on reliable observations and model projections has concluded that extreme rainfall intensity has increased in many regions (Kulmatiski et al. 2013; Wasko et al. 2017; Zhang & Cong 2014). A prevalent finding is that climate change has intensified the water cycle, which has caused wet regions to become wetter, leading to more imbalanced distributions of rainfall (Feng et al. 2015; Oki et al. 2006). However, those previous studies mainly reported rainfall changes based on isolated and limited perspectives. Therefore, a deeper analytical and comprehensive understanding of rainfall patterns and behaviors is needed to explore the modes of rainfall pattern change in response to climate change.

Numerous studies characterize rainfall pattern changes by analyzing variations in observations and model scenario simulations. Generally, trend analysis is a widely used and straightforward method to present variations of rainfall amount over time (Haylock et al. 2006; Makuei et al. 2013; Suppiah et al. 1998; Syafrina et al. 2015). In addition, temporal rainfall analysis builds the linkage between variations in magnitude and timing of rainfall (Fu et al. 2010; Montazerolghaem et al. 2016a; Panagos et al. 2017). Rainfall patterns have also been characterized by climatic indexes that represent the fluctuation of rainfall and extremes by extracting the features of rainfall variability (Haylock et al. 2000; Montazerolghaem et al. 2016b; Rouillard et al. 2015). Furthermore, rainfall modelling provides an approach for analyzing rainfall pattern changes under different scenarios and environments (Chadwick et al. 2015; Raut et al. 2017; Wang et al. 2014).

The findings of these studies have demonstrated the systematic and clear changes on rainfall patterns. However, only some specific characteristics of the many features of rainfall patterns have been identified, and derived insights and knowledge have been limited. The main reasons leading to a lack of comprehensive understanding of climatic impacts include limited and one-sided approaches, restricted regional representation, and the lack of integrated analysis. Hence, a systematic diagnostic framework of rainfall patterns is required to analyze aspects of trends and periodicity of rainfall, abrupt rainfall changes, and extreme rainfall events observed in long-term rainfall records.

Many studies have addressed the issue of rainfall pattern variations and changes in Australia by methods ranging from rain gauge data analysis to monitoring hydroclimatic extremes via remote sensing (Haylock et al. 2000; Spessa et al. 2005; Suppiah et al. 1998; Xie, Huete, Ma, et al. 2016; Xie, Huete, et al. 2016b). Australia is the continent most sensitive to water conditions (Seddon et al. 2016; Suppiah 2004). Rainfall patterns show high interannual variability driven by multiple complex climatic systems (Forootan et al. 2016b; Risbey et al. 2009; Wang et al. 2007). Specifically, climatic variability in Australia is mainly influenced by the El Niño-Southern Oscillation (ENSO), the Indian Ocean dipole (IOD), and the Southern Annular Mode (SAM), which have been shown to have a strong and complex effect on rainfall variations due to the synchronization of three climate modes (Cleverly, Eamus, Luo, et al. 2016; Xie et al. 2019). Due to the extensive scope of the continent and the different degree of climatic impacts on rainfall, interannual precipitation variability is large and rainfall conditions vary across Australia from coastal areas to central areas. These conditions have created interest in rainfall pattern analysis in Australia under different wetness conditions. Although many studies have attempted to characterize rainfall variation and establish the relationship between climate change and rainfall patterns in Australia, a comprehensive understanding of rainfall pattern changes has not yet been established. Australia is an ideal natural laboratory for rainfall analysis to reveal various aspects of climatic influences and the driving mechanism of rainfall pattern changes.

In this study, we analyzed long-term rain gauge data from 1910 to 2017 at a sub-continental scale in the Northern Territory of Australia, which is well-known as a north-south rainfall gradient transect varying from wet to dry rainfall conditions (Hutley et al. 2011). We used analytical methods to systematically and comprehensively diagnose rainfall pattern changes to reveal climatic influences on the water cycle, including rainfall trend, periodicity, abrupt change timing, rainfall probability density changes, and extreme rainfall events. The objectives of this study were to (1) identify whether rainfall patterns have changed under climate change along the rainfall gradient; (2) characterize rainfall pattern changes quantitatively at spatial and temporal scales; and (3) assess the impacts of climate changes on extreme rainfall events. Results from this study will be useful in illustrating climate change impacts on rainfall patterns according to long-term historical records. The results will also improve understanding of interactions between hydrological dynamics and climate variation, resulting in the capacity to design strategies for adapting to and mitigating the negative impacts of climate change.

3.2 Data and methods

3.2.1 Study area

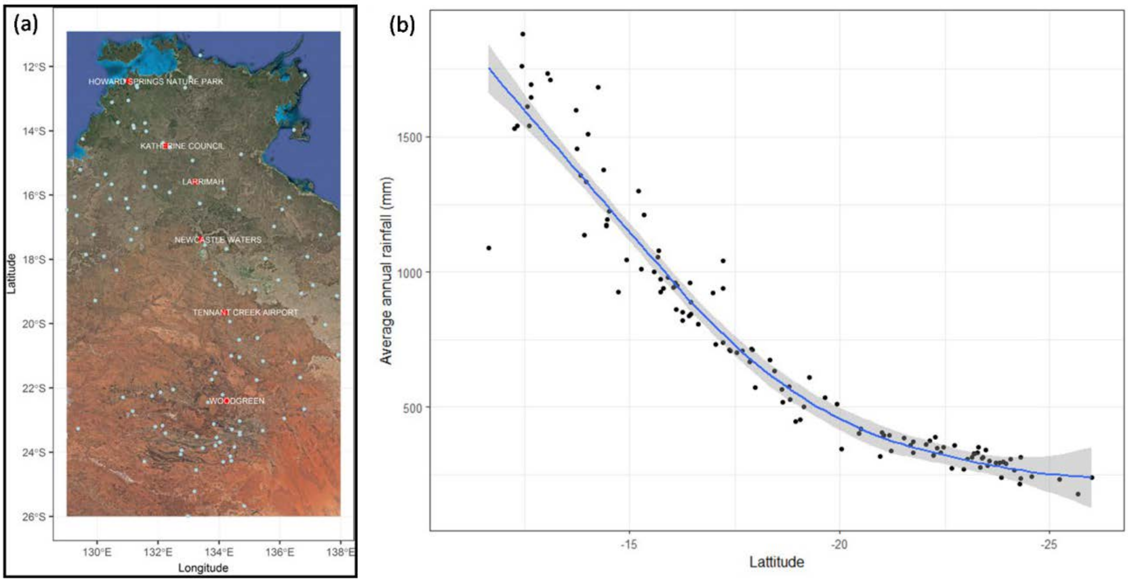

Figure 3-1. Study area and the spatial distribution of rain gauge sites, in the Northern Territory, Australia. (a) satellite image with rainfall gauge sites; (b) Rainfall gradient along latitude. Six sites (red dots) were selected as representative of different rainfall conditions.

In this study, the Northern Territory of Australia (ranging from 128°E to 138°E and from 11°S to 26°S) was selected as the study region (Figure 3-1). The entire area can be divided into two zones according to two distinctive climatic conditions: 1) the coastal wet region and 2) the hinterland dry region. In the northern coastal region, two seasons are seen in the monthly rainfall distribution, namely the wet season from October to April and the dry season from May to September. This seasonal precipitation pattern is also associated with tropical cyclones and monsoonal activity (Williams et al. 1996). The annual average rainfall ranges from 1800 to 2100 mm/yr near the coastal regions. The Northern Territory is also well-known as a natural laboratory because of its north-south rainfall gradient. Average annual rainfall decreases at a rate of about 1 mm per 1 km from the northern coast (1800 mm/yr) to the inland area (200 mm/yr) (Hutley et al. 2011). Hence, the central hinterland region is semi-arid or desert with the lowest water supply and the driest region receives annual rainfall of less than 200 mm/yr. Additionally, the interannual variability of rainfall in this region is large, with the difference in rainfall amount between wet years and dry years reaching up to 1000 mm. In terms of rainfall gradient associated with rainfall variability, the Northern Territory is a suitable area for accomplishing the research aims of this study (Koch et al. 1995).

3.2.2 Rainfall data

In the Northern Territory of Australia, annual rainfall varies from the coastal regions to the central inland. To analyze long-term rainfall pattern variations at this sub-continental scale, high-quality meteorological data were obtained from the Scientific Information for Land Owners (SILO) database, which included gauge-based daily rainfall data from 1910 to 2017 with quality assurance (http://www.bom.gov.au/silo/). A total of 230 sites were located in our study area. The spatial distribution of those sites covered regions evenly from the coastal wet rainfall condition to the central dry rainfall condition in the Northern Territory of Australia, except for the western mountainous region between 20 °S and 22 °S that had few established observation sites (Figure 3-1). We desired to analyze the historical changes of rainfall patterns at sites with the longest qualified records. However, because rainfall records prior to 1910 were not quality-checked (Lavery et al. 1992), we used only the rainfall records from 1910 to 2017. The annual rainfall at each site was determined from daily rainfall amounts. A single rainfall event was defined as the period of consecutive rainy days from the beginning to the end of a rain period in order to analyze variations in rainfall magnitude.

3.2.3 Trend analysis

Trend analysis is one of the most prevalent methods used to identify the overall changes of time series data, which may be partly hidden by noise (Longobardi et al. 2010; Partal et al. 2006). We used linear regression to examine changes in rainfall patterns and long-term variations, and to identify the long-term trend of annual rainfall in the Northern Territory of Australia. Rainfall data from a total of 230 sites were used from 1910 to 2017 (108 years). Additionally, six representative sites (shown as red dots in Fig. 3-1 and listed in Table 3.1) were selected to represent long-term rainfall trends under different rainfall conditions. The spatial pattern of long-term rainfall trends was produced by spatial interpolation of trends at all sites via Kriging interpolation (Oliver et al. 1990). All calculation processes for the trend analysis were completed via R programming (Ihaka et al. 1996).

Table 3-1. Representative rainfall sites in the Northern Territory, Australia.

Site	Longitude	Latitude	Rainfall (mm)	Temperature (°C)	Biomes
Howard Springs Nature Park	131.05	-12.46	1700	27.58	Tree open
Katherine Council	132.25	-14.46	1000	27.32	Tree open
Larrimah	132.21	-15.57	797	26.83	Tree sparse
Newcastle Waters	133.41	-17.38	515	26.72	Tussock grasses closed
Tennant Creek Airport	134.18	-19.64	396	25.78	Shrubs and grasses sparse scattered
Woodgreen	134.23	-22.40	287	22.39	Shrubs and grasses sparse scattered

3.2.4 Periodicity analysis

The periodicity of a hydrological phenomenon refers to its periodic variation over time. Due to the influence of meteorological factors, rainfall presents the regularity of alternating periods of wet and dry states. In this study, wavelet analysis was employed to analyze rainfall periodicity, which has been widely applied to analyze periods for stationary and nonstationary features of time series in meteorology (Beecham et al. 2010; Nakken 1999; Rashid et al. 2015).

Wavelet transform analysis is similar to Fourier transform analysis. Fourier transform is one of the most widely used methods in signal processing, and is able to transfer time series from time scale to frequency scale. However, the disadvantage of Fourier transform analysis is a lack of capability for nonstationary signals and localized variation. Although the short-time Fourier transform (STFT) has improved this issue by determining the sinusoidal frequency and phase content of local sections of a signal as it changes over time, the fixed window function is still a limitation for localized analysis (Addison 2017; Torrence et al. 1998). Compared with Fourier transform, wavelet transform is a local time-frequency domain transform. It can effectively extract information from signals and perform multi-scale analysis on signals through operations including scaling and translation. It inherits and develops the idea of localization of short-time Fourier transform, and overcomes the shortcomings of window size not changing with frequency. Wavelet transform analysis can provide a "time-frequency" window that varies with frequency, and it is used as an ideal tool for signal time-frequency analysis and processing. Therefore, we adopted wavelet transform to analyze annual rainfall variation at both time and frequency scales. More information on wavelet analysis applications is also available (Addison 2017), and this study mainly focused on the application of wavelet analysis in the long-term period diagnosis of rainfall patterns.

Wavelet transform was applied to the annual rainfall time series to identify rainfall period pattern with temporal variations. The continuous wavelet transform (CWT) is expressed as:

$$\mathrm{W(a,b)}=\frac{1}{\sqrt{\mathrm{a}}}\int_{-\infty}^{\infty} f(t) * \psi_{a,b}(\frac{t-b}{a})\, dt \qquad (3-1)$$

where W is the wavelet transform coefficient with “a” scale parameter and “b” time position parameter. $1/\sqrt{\mathrm{a}}$ is used to normalized wavelet energy. $f(t)$ is time series or signals to be analyzed. $\psi(t)$ is the mother wavelet complex conjugate. In this study, Morlet wavelet was selected as the mother wavelet function for rainfall period analysis, which has been widely applied in hydrological and meteorological time series analysis (Martínez et al. 2009; Moreira et al. 2019; Nakken 1999). The expression of Morlet wavelet is presented as:

$$\psi(t) = \pi^{-\frac{1}{4}} * e^{i\omega_0 t} * e^{-\frac{1}{2}t^2} \int_{-\infty}^{\infty} f(t) * \psi_{a,b}(\frac{t-b}{a})\, dt \qquad (3-2)$$

where ω_0 is frequency and t is time. When considering periodical analysis, setting ω_0 as 6 is an appropriate choice to balance time and frequency.

In this study, we first calculated wavelet coefficients for the six representative sites from the coastal area to the central region in the Northern Territory, and then plotted wavelet power spectrum of annual rainfall at the time-frequency domain. Afterward, the same Morlet wavelet method was applied to all 230 sites located in the study area and the major period was extracted at each site to get an overall mean value of period for rainfall pattern analysis. All calculation processes were completed using R programming via the WaveletComp package developed by Roesch et al. (2014)

3.2.5 Abrupt change analysis

In this study, the Mann–Kendall test (Kendall 1948; Mann 1945) was applied to diagnose abrupt changes in rainfall patterns and to identify the timing of abrupt rainfall changes. This method has been extensively used in meteorology and hydrology for diagnosis of abrupt changes (Douglas et al. 2000; Du et al. 2015; Gocic et al. 2013; Shen, Bao, et al. 2018). We used the Mann–Kendall test at the six representative sites to first identify the timing of shifting rainfall patterns under different water conditions, and then to summarize the major times of abrupt changes in regional rainfall patterns by analysing statistical values at all sites.

The statistical rank series S_k is constructed as:

$$S_k = \sum_{i=1}^{k} r_i, k = 2,3, \dots, n \qquad (3-3)$$

where

$$r_i = \begin{cases} 1, X_i > X_j \\ 0, X_i \le X_j \end{cases} \quad 1 \le j \le i \qquad (3-4)$$

The statistical series is defined as

$$UF_k = \frac{S_k - E(S_k)}{\sqrt{var(S_k)}}, \qquad k = 2,3, \dots, n \qquad (3-5)$$

where $UF_k = 0$ is given, $E(S_k)$ and $var(S_k)$ are the mean and variance of the rank series respectively, which can be calculated as

$$E(S_k) = \frac{k(k-1)}{4} \qquad (3-6)$$

$$var(S_k) = \frac{k(k-1)(2k+5)}{72} \qquad (3-7)$$

Then the original time series, $X_1, X_2, \dots, X_n$, is reversed and the above steps repeated to calculate UF_i. Following this, the process shown below was used to obtain the rank series UB_k

$$UF_1 = 0 \qquad (3-8)$$

$$UB_k = -UF_i\,, \qquad i = n, n-1, \ldots, 1 \qquad (3-9)$$

The abrupt change point was determined as the intersection point of the UF_k and UB_k sequences. If the intersection point existed and was also within the confidence interval [-1.96, 1.96], then we could identify the timing of the occurrence of the abrupt change in rainfall.

3.2.6 Probability density distribution

To explore rainfall pattern changes through time, we analyzed the changes in rainfall probability density distribution. The six representative sites were used to illustrate rainfall pattern changes under different rainfall conditions. In order to validate that rainfall patterns had changed distinctively, we divided the time series into four periods, namely 1910 to 1935, 1936 to 1962, 1963 to 1989, and 1990 to 2016. These partitioning times were determined by the results of the mean major period determination (described in Results Section 3.3.2) and the abrupt change times described in Results Section 3.3.3). Then the rainfall probability density distribution for each period was calculated and overlayed together for comparison. Annual rainfall amounts greater than the 95th percentile (described below) were considered to be extremely wet years (Haylock et al. 2000; Shahid 2011). Mean precipitation and standard deviation values for each period at each of the six sites were also calculated for illustration. This work was also done with R programming.

3.2.7 Extreme rainfall event analysis

In addition to annual rainfall amounts, the rainfall amount of each individual rainfall event is also a critical element for analyzing the impacts of climate change on rainfall patterns (Boers et al. 2013; Jung et al. 2011). In this study, the total rainfall amount of consecutive rainy days was considered to be the rainfall amount of one single rainfall event. We defined an extreme rainfall event as one that exceeded the 95th percentile from the historical record at the six sites. The frequency of extreme rainfall events was counted every ten-year interval. The influence of climate change was assessed from the trends of extreme rainfall events. The rainfall events were ordered from smallest to largest values, and then the percentile formula was used to identify the extreme rainfall event threshold as

$$R = \frac{P}{100} \times (N + 1) \qquad (3-10)$$

where R is the rank for the specific percentile; P is the desired percentile (P=95 in this analysis); N is the number of total rainfall events.

3.3 Results

3.3.1 Trends of long-term annual rainfall

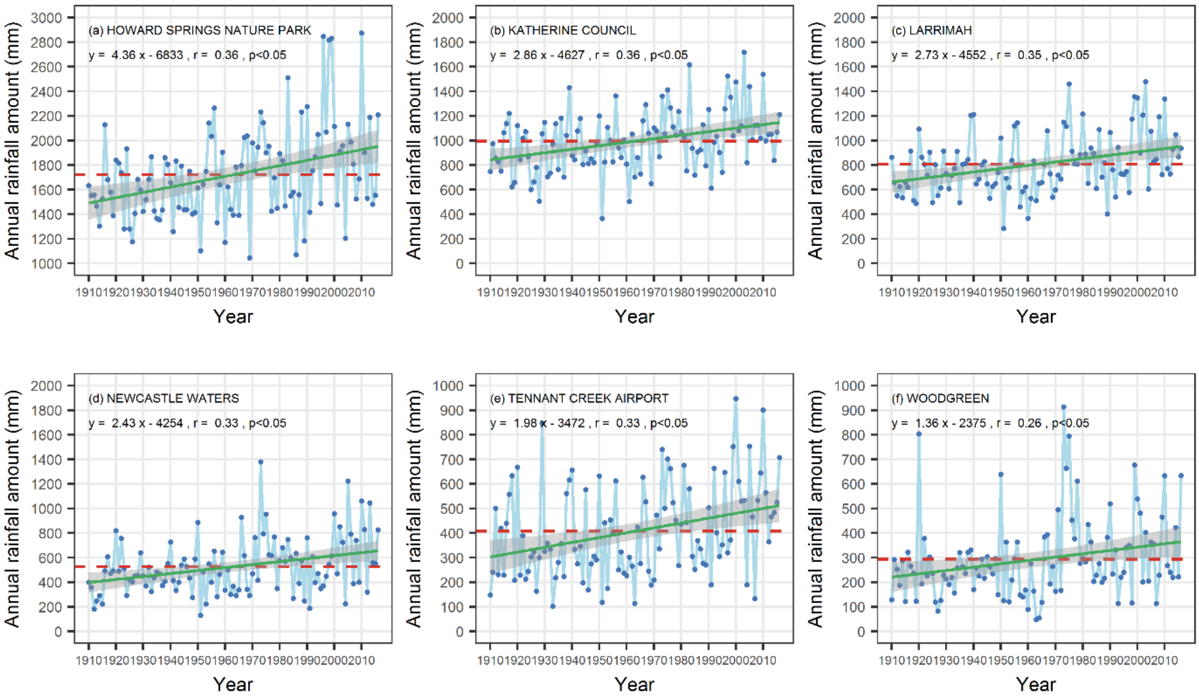

Figure 3-2. Long term annual rainfall trends at six selected sites in the Northern Territory, Australia, from wet coastal regions to dry central regions. The red dashed lines show the average annual rainfall for each site. The green line indicated the linear regression, and the grey areas denoted the confident intervals.

The long-term annual rainfall time series showed both noticeable decadal trends and interannual variability at all six selected sites from the wet coastal region to the dry central region in the Northern Territory (Figure 3-2). We found that all six representative sites exhibited a significant increasing trend ($p<0.05$) from 1910 to 2017 across the regional rainfall gradient. The coastal site (Howard Springs Nature Park), was the wettest site with mean annual rainfall around 1700 mm/yr. At this location, annual rainfall increased at a rate of 4.36 mm/yr. Mean annual rainfall declined as distance from the coast increased towards the central areas. The rate of rainfall increase over time declined to 1.36 mm/yr ($P<0.05$) at the driest site (Woodgreen) where mean annual rainfall was 300 mm/yr. Although a consistent increasing rainfall trend was observed under the different annual rainfall conditions seen at the six sites, a striking finding was that the annual rainfall amount increased unstably with higher rainfall variation in recent decades. Starting with the 1970 to 1990 period, the fluctuations of annual rainfall became larger than observed in previous decades at all six selected sites. The wettest representative site showed rainfall amounts varying from around 1000 mm/yr to as much as 2800 mm/yr, and even the driest site had an annual rainfall observation reaching as high as 900 mm/yr after 1970, which was triple the mean annual rainfall amount. The detectable rainfall pattern changes could be characterized not only as consistently increasing trends, but also as having higher rainfall variation according to the rain gauge data at the six sites.

The spatial pattern of annual rainfall trend in the study area (Figure 3-3) was determined by interpolation of data from the 230 rain gauge sites. The rainfall trend across the region was in line with the consistent increasing trend at the six selected sites. On average, precipitation for the coastal region increased at a rate of 45-65 mm per 10 years, whereas precipitation in the central region increased at a rate of only 5 mm per 10 years. As latitude increased towards the central hinterland, annual rainfall amount decreased following the rainfall gradient. However, the increasing trend of annual rainfall over time was seen over the entire Northern Territory of Australia.

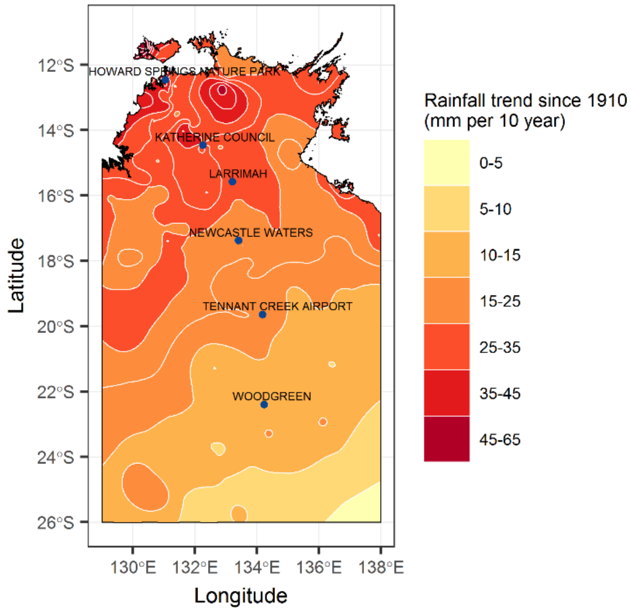

Figure 3-3. The spatial pattern of annual rainfall trend in the Northern Territory, Australia.

3.3.2 Periodicity of long-term rainfall patterns

The decadal periods of rainfall pattern were diagnosed via Morlet wavelet analysis for the six representative sites using the annual rainfall time series from 1910 to 2017. The results shown in Figure 3-4 are wavelet power spectra in the time-frequency domain. The area within the thick white contours in Figure 3-4 indicated that wavelet power spectra were statistically significant at the 95% confidence level, and black dashed lines denote the main detected periods of rainfall pattern in the frequency domain. When focusing on long-term decadal periods greater than ten years, a striking finding was that all six selected sites presented a consistent period around 27-30 years, which indicated temporal variations in rainfall patterns that represented a corresponding 27-30 year interval for rainfall cycle or shift from one rainfall condition to another rainfall condition. Additionally, those periods of rainfall pattern appeared in a concentrated time across regions from wet to dry. Concerning the timing, this period shift mainly happened during the 1970s except at the Newcastle Waters site where the rainfall pattern period changed in the 1950s. The shift occurred in the 1940s at the Woodgreen site in the drier region.

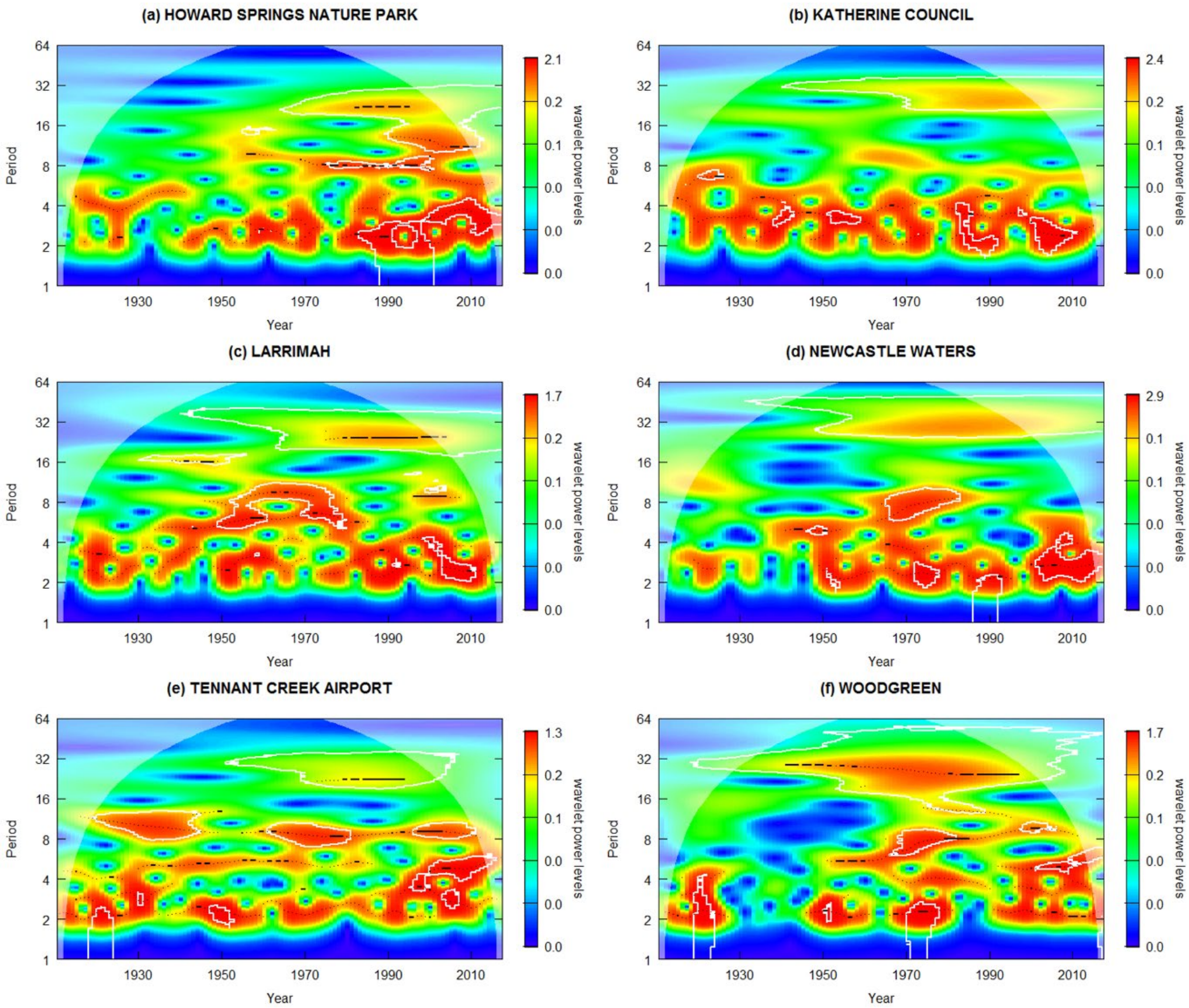

Figure 3-4. Wavelet power spectra using Morlet wavelet analysis for six representative sites in the Northern Territory, Australia.

The peaks of the average wavelet spectra across period scale indicated the main period for time series. After removing short-term period disruptions and illustrating the long-term periods for the 230 sites in our study area, the results revealed that 27 years was the mean long-term period for the entire study area. This result indicated that a noticeable rainfall pattern shift could be part of the reason attributed to a periodical cycle of about every 27 years (Figure 3-5). Those period changes were relatively consistent, and the value of the main period became less variable (with a temporal interval of 26-30 years) in the drier regions where annual rainfall was below 600 mm/yr. In addition to the main period of 27 years, a second period at the spatial scale was found at 20 years, which was found from wet regions to dry regions at some specific sites.

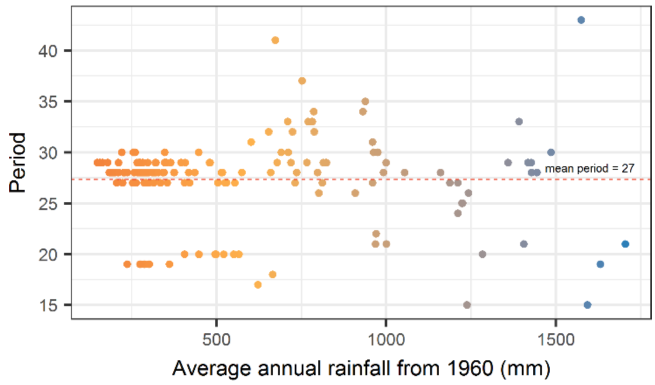

Figure 3-5. Diagnosis of the major long-term period for all rainfall sites in the Northern Territory, Australia. The major period was extracted from the wavelet power average across the time of a single time series at each site. The dashed line denotes the mean value for all sites, which was 27 years. The color indicates different rainfall conditions from dry to wet.

3.3.3 Abrupt changes in long-term rainfall patterns

The observation of an abrupt change in the rainfall pattern (i.e., rainfall amount increasing steeply or decreasing dramatically) indicates the time of a major change in rainfall pattern, and may also be associated with greater rainfall variation. In this study, the abrupt changes in the annual rainfall time series retrieved from the six selected sites located from wet coastal regions to dry hinterland regions were detected by the Mann-Kendall test. This test indentifies the year of the abrupt change by testing whether the intersection point of Mann-Kendall statistical sequences from the original time series and reversed time series is within the 95% confidence interval. Figure 3-6 shows that all six selected sites identified the abrupt change in precipitation to occur in the period between 1965 and 1975 (see the point at which the blue and red lines intersect in Figure 3-6), except at Tennant Creek Airport where the intersection point occurred in 1989. We found the times of the abrupt change in rainfall pattern at different rainfall levels (from wet to dry) across the region pointed out a relatively distinct and temporally consistent shift. The annual rainfall time series shown in Figure 3-2 clearly shows an increase after the 1970s. Furthermore, the detected time of abrupt rainfall change was also consistent with the timing of wavelet power spectra for most sites, which showed apparent higher values within the 95% confidence contour after the 1970s (Figure 3-4). The time of change in rainfall pattern was not distinctly different for the six selected representative sites across the rainfall gradient, and the changes of rainfall pattern remained relatively uniform at the temporal scale irrespective of rainfall conditions.

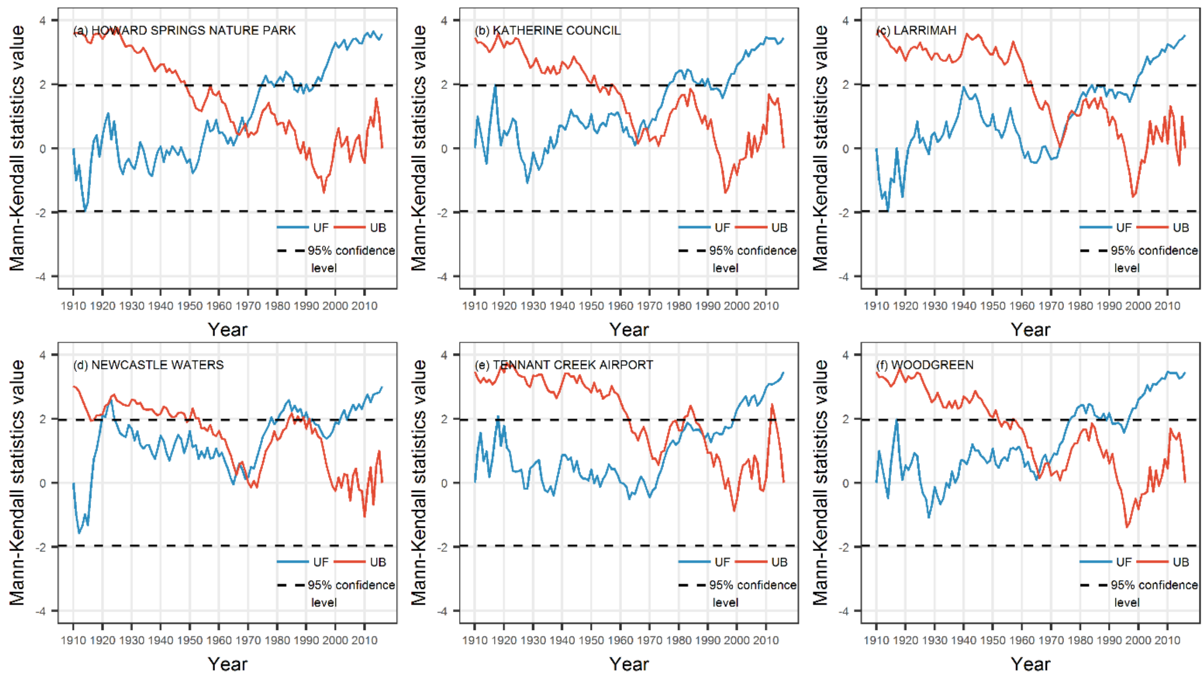

Figure 3-6. Diagnosis of the time of abrupt change in annual rainfall for six representative sites in the Northern Territory, Australia as determined by the Mann-Kendall test. The blue line (UF) denotes the statistical series from the original time series, and the red line (UB) denotes the statistical series from the reversed time series. The intersection point within the 95% confidence interval (dashed lines) indicates the year of the abrupt change in rainfall.

The times corresponding to the abrupt change in rainfall for the 230 sites over the entire study area were divided into four groups according to average rainfall amounts (Figure 3-7). We found two apparent timing points for abrupt changes in rainfall (i.e., 1970 and 1990), which indicated that the rainfall pattern shifted dramatically primarily during the periods of 1966 to 1975 and 1986 to 1995. Most of the sites classified as wet (humid) or dry (arid) rainfall conditions were found to have the abrupt rainfall change occurring in 1970, but sites classified as medium dry (semi arid and semi humid) were found to have the highest frequency of time of abrupt rainfall change close to 1990. Overall, 73% of the sites presented the time of abrupt rainfall change after 1965, which showed that the regional rainfall pattern had an apparent shift in recent decades.

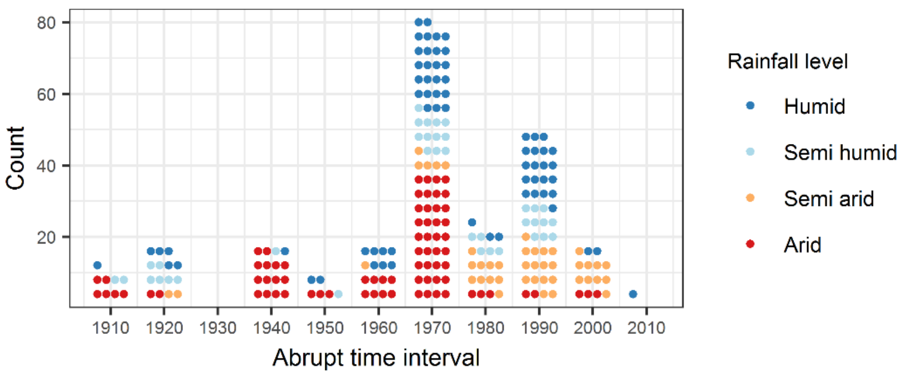

Figure 3-7. The statistical frequency of the year of abrupt change in rainfall for 230 sites across the Northern Territory, Australia. Each single dot represents the time of abrupt change for one site. The colors denote the mean annual rainfall (i.e., dark blue: <400 mm/yr; light blue: 400-800 mm/yr, orange: 800-1200 mm/yr; red: >1200 mm/yr).

3.3.4 Density distribution of rainfall patterns and extreme rainfall

We compared the density distribution curves of rainfall pattern at the six selected sites (Figure 3-8) by analyzing annual rainfall time series from 1910 to 2016. Each time series was divided into four periods according to the 27-year mean cycle period and two timing points, 1970 and 1990, for abrupt changes in rainfall pattern to guide our selection of the four time intervals to be used for analysis. Following this, the changes in rainfall pattern were determined for four phases, namely 1910 – 1935, 1936 – 1962, 1963 – 1989, and 1990 – 2016. The distributions clearly showed that the mean values of annual rainfall had continuously increased over time across the wet regions to the dry regions. Although mean annual rainfall at Woodgreen (representing the driest rainfall condition) was not different between the period from 1990 to 2016 and the period from 1963 to 1989, mean annual rainfall was almost 100 mm greater after 1963 than before 1963. As for the Howard Springs Nature Park site located in the wet coastal region, mean annual rainfall increased 390 mm from the earliest period to the latest period. The significant increasing rainfall trend over time was observed at the other sites towards the central hinterland, but the increases over time became less as annual rainfall decreased. Although all six representative sites presented an increasing trend in rainfall over time, we noticed that the timing of a larger increment shift coincided with the timing of the abrupt change in rainfall amount. Furthermore, not only rainfall pattern changed (increasing values of mean annual rainfall), but also the variation of annual rainfall became larger throughout the study area. The standard deviation of annual rainfall at the wettest location increased by 240 mm from 227 mm to 467 mm, and increased by about 30 mm for the two driest sites. The density distribution curves appeared to become flatter over time as a result of the higher variability. The black dashed lines in Figure 3-8 are the 95th percentile values of annual rainfall that were used as the threshold values to represent the extreme annual rainfall condition at the six sites. We found that all six sites showed that the highest density of extreme annual rainfall occurred after 1990, indicating that rainfall patterns had changed to be wetter along with greater frequencies of wet year in recent decades.

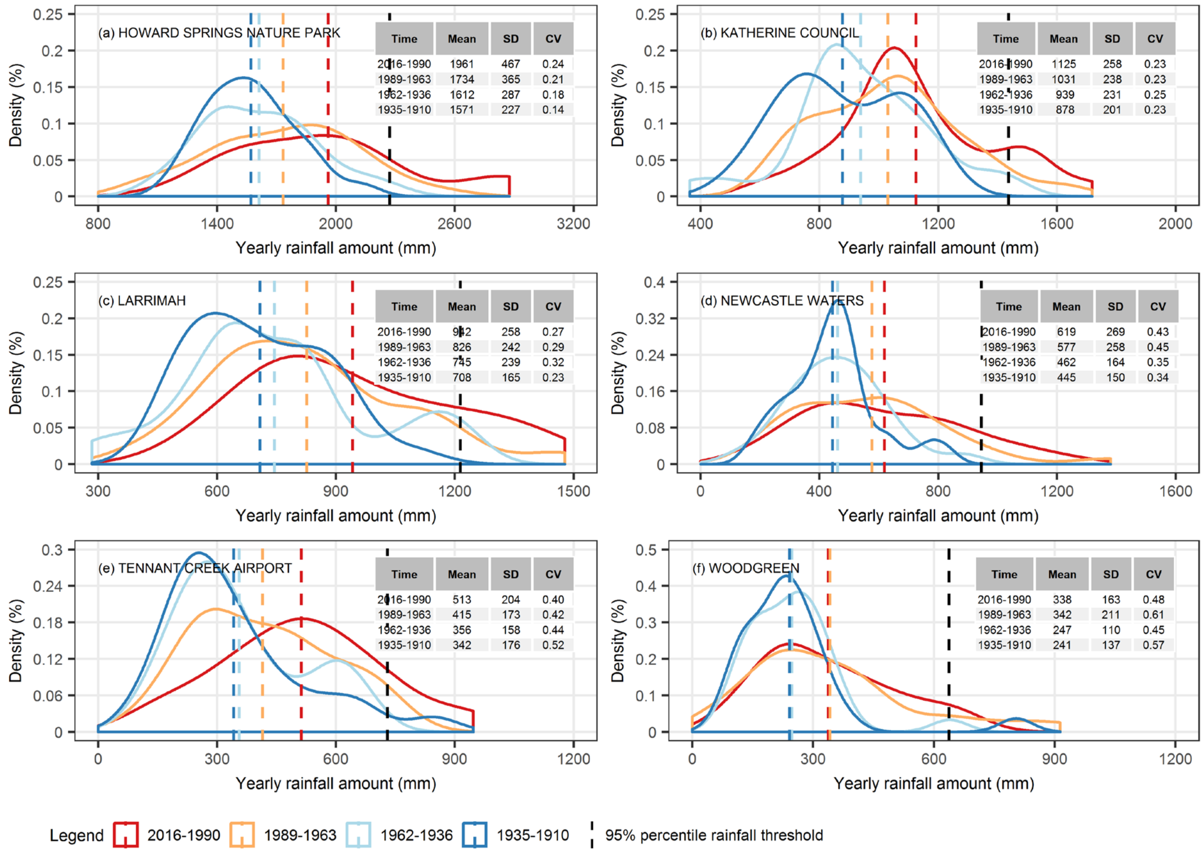

Figure 3-8. Changes in the probability density of rainfall for six locations in the Northern Territory, Australia. Each time series was divided into four periods for comparison. The mean value for each period was shown with the corresponding dashed color line. The dashed black line denotes the 95th percentile (i.e., rainfall amounts greater than this line were considered extreme rainfall amounts).

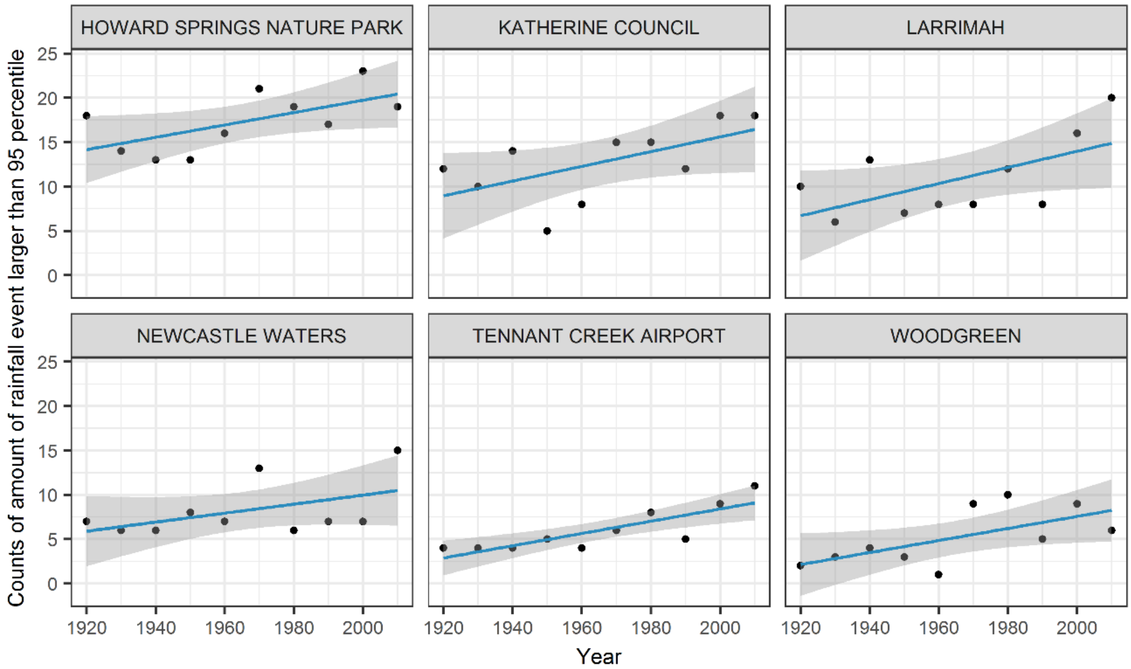

Figure 3-9. The tendency of extreme rainfall events at six representative sites in the Northern Territory, Australia. The blue lines are linear regressions applied to the data points. The blue shaded area represents the 95% confidence interval of the regression.

In addition to the increase in annual rainfall amount over time, we also observed that the frequency of extreme rainfall events increased with time (Figure 3-9). We counted the number of times that rainfall events occurred with accumulated rain amount greater than the 95th percentile of the long-term historical values at each site and found all six sites exhibited an increasing trend of the frequency of extreme rainfall events throughout the entire rainfall gradient region. Meanwhile, the sites located under medium rainfall condition, such as Larrimah and Newcastle Waters, presented a higher variation of the frequency of extreme rainfall events than observed at the other sites. The changes in rainfall pattern, therefore, exhibited not only increasing amounts of rainfall over time, but also had more extreme rainfall events and larger variation in rainfall over the entire study region from wet to dry rainfall conditions.

3.4 Discussion

3.4.1 Significant rainfall pattern changes over a sub-continental region

Our study confirmed that rainfall patterns had already been influenced by climate change with respect to the trend and periodicity of annual rainfall, and abrupt changes of long-term rainfall observations. The analytic results, derived from rainfall observations at 230 sites covering an extensive sub-continental region from 1910 to 2017, revealed distinct rainfall pattern changes in recent decades and represent the impacts of climate change on the hydrological cycle and water distribution. With measurable global warming (Chou et al. 2013; Chou et al. 2009; Held et al. 2006; IPCC 2013), hydrological processes have been accelerated, and the intensification is expected to follow the law of thermodynamics at a rate of 6.5% $°C^{-1}$ according to the Clausius-Clapeyron rate (Allan et al. 2008), which results in greater atmospheric moisture and causes more frequent rainfall events. Our findings also confirmed that climate change had a distinctive climatic impact on annual rainfall amount, and were in line with results of previous studies (Haylock et al. 2000; Suppiah 2004).

Our study showed the rainfall pattern not only changed in terms of quantitative variation, but also presented a temporal shift in rainfall. Northern Australia has seen a relatively stable increasing trend in rainfall amount over time, with noticeable fluctuations or oscillations in rainfall since 1910. However, in latter decades, rainfall pattern shifted from a stable but small increasing state to a state of larger rainfall increase over time with higher variability. We characterized the impacts of climate change on rainfall pattern from the aspects of trend and periodicity of annual rainfall, and time of abrupt change in annual rainfall. It is worth nothing that the rainfall pattern shift appeared to happen within a specific period around 1970. We not only detected the convergence of the timing of the abrupt change in rainfall amount at 1970 via the Mann-Kendall test, but also found that annual rainfall amount showed a dramatically increasing trend since 1970. The wavelet power spectrum, which indicated temporal variations, was observed to increase since 1970 as well. Those shifts and changes were all consistent at temporal scale. Hence, the interactions and changes in rainfall patterns help to explain some of the pressure felt from changing climatic factors that had occurred since 1970. Much research has observed and reported the rainfall pattern changes in the 1970s, and related the rainfall anomalies to modes of the El Niño-Southern Oscillation (ENSO) (Cook Garry et al. 2001; Forootan et al. 2016a; Grimm et al. 2009; Watterson 2009). This research pointed out that frequent strong El Niño events occurred around 1970 (Yu & Zou 2013), which coincided with the time of observed rainfall pattern changes in our study. These findings supported the potential climatic drivers of rainfall pattern changes (King et al. 2014; Risbey et al. 2009).

According to a systematic diagnosis of rainfall pattern, we obtained a further understanding of how climatic factors influenced rainfall pattern behaviors. Meanwhile, we cannot ignore that anthropogenic activities have intervened in natural processes in recent decades, which has been a potential factor affecting rainfall. Further discussion on the connections between those natural and anthropogenic factors is beyond the scope of this study. However, we realize that rainfall patterns had distinctive changes in both annual amount and variability since 1970, and this would be a sensitive factor influencing society and dependent ecosystems.

3.4.2 The modes of rainfall pattern changes

We also found that the degree of rainfall pattern changes varied along with different rainfall conditions, but the mode of rainfall pattern changes did not present a distinct difference between wet regions and dry regions. Annual rainfall maintained a continuously increasing trend over the entire Northern Territory from the early period of record to the most recent period, irrespective of the different rainfall conditions across the region. According to the long-term observations, the entire region was getting wetter under climate change. Additionally, the entire region showed a relatively consistent time regarding the shifting of rainfall amount. The highest frequency of the time in which rainfall amount was shifting was around 1970, and then in 1990 for both humid and arid areas. Hence, although rainfall amounts were clearly different along the regional rainfall gradient from wet to dry, the abrupt change in rainfall amount mainly occurred around 1970 over the entire area. Also, this shift was monotonic for most sites, rather than a decadal oscillation. This means only one single abrupt change point was determined for the majority of sites by using the Mann-Kendall test. Furthermore, the time of this abrupt change was also captured by using wavelet analysis to extract time-frequency variations. We found the stable long-term cycle also appeared around 1970 for all of the sites (wet to dry) by using Morlet wavelet analysis, which also corresponded to the time of an abrupt change. The impacts of climate change on rainfall pattern have increased since 1970, and the intensity of these impacts has covered the extensive sub-continental area from coastal regions to hinterland in the Northern Territory.

Although the entire region presented a consistent shift of rainfall pattern from a stable state to a complex and variable state under climate change, the degree of impacts was different along the rainfall gradient. Mean annual rainfall amount increased by 25% at the coastal site. In contrast, mean annual rainfall increased by as much as 50% at inland locations. The standard deviation of annual rainfall amount also revealed the higher variability of rainfall observed in drier regions. The changes in rainfall patterns were more intense in water-limited regions. Water is not a major restriction to vegetation or ecosystems in wet regions, so the impacts of rainfall fluctuations in such regions are limited. However, intense fluctuation of rainfall patterns is strongly linked to water availability and water distribution in arid or semi-arid regions, and the higher variability can influence vulnerable ecosystems (Thornton et al. 2014).

3.4.3 The challenge of rainfall pattern changes with frequent extreme events

Apart from the findings of rainfall pattern changes with regard to trend, periodicity, and abrupt changes, we also noticed that more extreme rainfall appeared in forms of both annual accumulated amounts and single rainfall events. Considered over the 1910-2017 historical rainfall record, annual rainfall exhibited an apparent increasing trend, as did extreme annual rainfall, defined as precipitation greater than the 95th percentile in the historical rainfall record (shown in Figure 3-8), and higher rainfall amounts had a higher probability of occurring in the most recent 30 years. This same shifting of probability covered the entire region from wet to dry. Additionally, the amplitude of annual rainfall was higher in drier regions. More annual rainfall appeared to bring more potential water supply for regional water demands, but the shift of rainfall pattern was not a stationary process. The rainfall events became more frequent during wet years, while frequent extreme rainfall events possibly resulted in a series of responses of hydrological processes, including soil water content, evapotranspiration, and runoff generation (Fay et al. 2008; Mpelasoka et al. 2009; Wei et al. 2009). More frequent heavy rainfall can cause a series of undesirable consequences, including soil erosion, flooding, and negative impacts on water availability (Fay et al. 2003b; Johnson et al. 2016; Knapp et al. 2002; Zhu et al. 2019), that can ultimately result in more uncertainty and risks to ecosystems(Knapp et al. 2008).

Complex climatic systems may contribute to extreme events via multiple hydrological processes. The Bureau of Meteorology (2012) also reported a strong relationship between La Niña events and frequent extreme rainfall events. Furthermore, combined with the impacts of global warming, extreme rainfall events are expected to become more frequent with accelerated hydrological cycle impacts (Huang et al. 2015). Rainfall, as one of the most sensitive factors, also responds to climate changes rapidly at both spatial and temporal scales. In this study, we found that although the magnitude of rainfall events was not uniform over different rainfall conditions, the increasing trends of extreme rainfall events were consistent under the current climatic environment. The impacts of climate change were considered to produce extremes in both coastal and central areas. The increasing trend in annual rainfall amount appeared to be continuous since 1970 rather than fluctuating. We must acknowledge the prospect that extreme rainfall events will happen more frequently if global warming is not alleviated. Frequent extreme rainfall events also play a critical role in climatic systems by influencing water distribution at spatial and temporal scales, which can further threaten biospheres, vulnerable ecosystems, and our society (Barron et al. 2012; Greenville et al. 2012; Heisler-White et al. 2009; Vörösmarty et al. 2013; Wilhelmi et al. 2013). Hence, our research serves a supporting role in assessing the impacts of climate change in future scenarios.

3.5 Conclusions

Diagnosing rainfall pattern changes is urgently needed to investigate the impacts of climate change on the hydrological cycle and hydroclimatic extremes. Our study established a framework to assess rainfall pattern changes under climate change by analyzing long-term rain gauge data in the Northern Territory of Australia. The findings resulting from diagnosing rainfall pattern variations from the aspects of trend, periodicity, time of abrupt changes in rainfall amount, rainfall probability density distribution, and frequency of extreme rainfall events supported the conclusion that rainfall patterns have changed significantly and were associated with higher variability. Annual rainfall amounts across the study area were seen to consistently increase over time, but the interannual fluctuation of annual rainfall also had increased in recent decades (since about 1970). Due to the analytical findings derived over a rainfall gradient varying from 1800 mm/yr to 200 mm/yr, the magnitude and variation of rainfall pattern changes showed distinct differences from wet to dry environments. However, the modes and shifting time of rainfall pattern changes were shown to be similar across different annual rainfall conditions. We also confirmed that the frequency of extreme rainfall events had increased significantly across all sites in this sub-continental scale region. The study characterized the changes in rainfall patterns and analyzed shifting modes by considering the factors of space-time and magnitude, which improves our understanding of rainfall pattern changes and improves opportunities to mitigate negative impacts of climate change.

Chapter 4: Vegetation phenology and growth responses to rainfall variations in savanna ecosystems in Australia

Abstract

Vegetation phenology responding to climatic variables are pivotal indicators for monitoring biosphere processes and terrestrial ecosystem functioning. In recent years, rainfall variability has become larger with more frequent hydroextremes. Therefore, the sensitivity of vegetation to rainfall is critical for investigating vegetation responses to climate change. Although many studies have focused on characterizing vegetation phenology based on multiple sources and observations, the sensitivity of vegetation phenology to rainfall has not been clearly identified and quantified. The objective of this study was to determine vegetation phenology sensitivity to annual rainfall variations over different savanna ecosystems by comparing two proxies [maximum enhanced vegetation index (EVI) and length of the growing season (LGS)] in the Northern Territory of Australia. We established relationships between vegetation metrics determined from MODIS satellite data and annual rainfall amount obtained from rain gauge data by using smooth regression and correlation analysis. Maximum EVI was found to be more sensitive to rainfall than LGS, and maximum EVI provided a better representation vegetation growth over the entire growing season. Temporal phenology metrics were not sensitive to rainfall amount. The results of this study improve the understanding of eco-hydrological processes and will facilitate terrestrial ecosystem modelling and forecasting in future studies.

Keywords: phenology, sensitivity, rainfall, maximum EVI, length of growing season, savanna ecosystems

4.1 Introduction

Vegetation phenology reflects ecosystem responses to inter- and intra-annual environmental variability (Fu et al. 2015; Peñuelas et al. 2004), and also plays an important role in monitoring terrestrial ecosystems for assessment of climatic influences (Zhang et al. 2003). Recently, with multiple improvements in phenological measurements from leaf to satellite scale, vegetation phenology analysis is regarded as an effective approach for detecting the driving factors of sensitive vegetation life rhythms (Nagai et al. 2016). Hence, under the pressure of global warming and increasingly extreme meteorological events (Allan et al. 2008), a great deal of research on vegetation phenology has been conducted to support environmental risk assessments.

Phenology studies link changes in vegetation growth seasonality, dormancy onset date, flowering date, leaf browning date, growing season length, and relevant phenological metrics (Craine et al. 2012; Jeong et al. 2011; Visser et al. 2010; Yang, Guan, et al. 2015) to dynamic changes in environmental parameters. These parameters include temperature, radiation, precipitation, and natural or anthropogenic disturbances (Bradley et al. 2011; Chen et al. 2012; van Leeuwen et al. 2013; Villegas et al. 2016; Yu et al. 2010; Zeng et al. 2013). Vegetation phenology responses to water availability in arid and semi-arid regions is a topic that continues to receive great interest (He et al. 2018; Xia et al. 2012). For example, rainfall timing and amount trigger the vegetation greening season, and rainfall pattern plays a dominant role in controlling when and how much vegetation growth occurs (Travers et al. 2013; Whitecross et al. 2017). Additionally, because rainfall is a critical factor influencing crop growth from germination to harvest, it has consequential impacts on our society (Sakamoto et al. 2006). Moreover, rainfall presents a high variability to reflect climate change, especially in water-limited regions, resulting in more extreme events (Donat et al. 2016). Therefore, monitoring vegetation phenology responses to rainfall variations is urgently needed to guarantee an effective strategy for dealing with climate change.

Phenological measurements of vegetation have developed from in-situ field monitoring at different vegetation stages to remote sensing observations over landscape, continental, and even global scales (Balzarolo et al. 2016; Jeong et al. 2013; Maignan et al. 2008). Originally, in-situ measurements of vegetation growth provided direct data on phenoloical traits leading to an understanding of seasonality and responses to climatic variations (Primack et al. 2015). In more recent times, a number of studies have presented biophysical and biochemical measurements of vegetation phenology by using satellite observations (Gitelson et al. 2015; Walther et al. 2018; Walther et al. 2016; Zhang et al. 2006). Phenology metrics retrieved from space with satellite sensors provide an extensive insight into land surfaces, and even capture daily terrestrial dynamics (Zhang 2015). Compared with ground observations (such as those obtained with digital cameras and flux tower measurements), observations from remote sensing are too coarse to reflect the influences of complex topography and heterogeneous land cover (Nagai et al. 2016). However, the application of remote sensing extends our understanding of terrestrial ecosystem activities to larger scales.

In recent decades, a number of studies have developed approaches to determine vegetation phenology from satellite observations. Time series of normalized difference vegetation index (NDVI) data produced by the Advanced Very High Resolution Radiometer (AVHRR) (Reed et al. 1994; White et al. 1997) and enhanced vegetation index (EVI) derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) products have been widely used in tracking vegetation dynamics at a large spatial scale (Cuba et al. 2013; Ma et al. 2013; Reed et al. 2009; Testa et al. 2018; Zhang et al. 2006; Zhang et al. 2017). A great deal of research has characterized the phenological dynamics of terrestrial ecosystems by detecting changes in the timing of the vegetation greening season and senescence, including the starting and ending dates of the growing season (Doi et al. 2008; Keenan et al. 2015; Mugalavai et al. 2008). Furthermore, a measure of the magnitude of vegetation growth, such as maximum EVI, has also been regarded as a proxy to represent vegetation productivity (Santos et al. 2016). Increased use of remote sensing for vegetation monitoring since the beginning of the 21st century has allowed the capture of spatiotemporal variations of ecosystems for analysis of photosynthetic activities (Sun et al. 2015; Wu et al. 2014; Yang, Guan, et al. 2015). In particular, extensive coverage and real-time monitoring of land surface phenology can significantly improve land management and mitigate ecological hazards.

Although a great deal of research on the relationship between phenology dynamics and rainfall variations has been conducted, the sensitivity of vegetation phenology is still has a demand to to be discussed further. In particular, a comprehensive understanding of vegetation phenology determined from remote sensing data is required to apply effective and sensitive proxies that will accurately reflect terrestrial ecosystem responses to environmental changes.

In this study, we identified the sensitivity of vegetation phenology to annual rainfall variations in the Northern Territory of Australia, where various savanna ecosystems cover the three major vegetation biome categories of grasses, shrubs, and trees. The study area (from the northern coastal area to the central dryland area) provides a natural rainfall-controlled condition for analyzing phenological responses to varying wetness conditions. We evaluated phenology sensitivity by determining correlations between annual rainfall amount and phenology metrics, including the length of the growing season (LGS); maximum EVI; and the timing of the start of the growing season (SGS), the peak of the growing season (PGS), and the end of the growing season (EGS), all of which were retrieved from MODIS satellite data. The objectives of this study were to (1) determine the sensitivity of vegetation phenology and growth to rainfall variation under different wetness conditions; (2) analyze phenological and growth responses of different ecosystems to rainfall variation; and (3) compare the sensitivity of phenology metrics and identify which proxies best reflected the responses of vegetation phenology and growth to rainfall. The results obtained from this study will improve our understanding of the sensitivity of vegetation phenology and growth to rainfall variability, especially in water-limited regions. The results will also facilitate the application of remote sensing monitoring of terrestrial ecosystems changes that result from climate change.

4.2 Data and Methodology

4.2.1 Study Area

The Northern Territory of Australia covers 1,420,968 square kilometers ranging from the coastal area to the inland central area. The area is characterized by a north-south rainfall gradient, decreasing toward the hinterland and ranging from 1800 mm/yr to 200 mm/yr with high interannual rainfall variability. The distinctive spatial variability of rainfall results in various savanna ecosystems comprised of grasses, shrubs, and trees, which occupy 32.6% of the total savanna cover in the Northern Territory of Australia. In contrast to rainfall and vapor pressure deficit (VPD), both temperature and solar radiation presents an expectable but limited changes with latitude (Kanniah et al. 2011). Hence, the Northern Territory is an ideal region to explore the sensitivity of vegetation to rainfall variations with other meteorological factors controlled naturally (Hutley et al. 2011).

4.2.2 Rainfall data

Meteorological data were obtained from the Scientific Information for Land Owners database (SILO, http://www.bom.gov.au). Because of the temporal length of satellite observations, the time series of rainfall data were extracted starting from 2000 and ending in 2017. Following quality control protocols with consideration of land cover types and cloud conditions of pixels of remote sensing data to remove unsatisfactory sites, 119 rain gauge sites were selected to build the relationship between rainfall variation and vegetation dynamics at a sub-continent scale. The spatial distribution of these sites covered different savanna ecosystems in the Northern Territory. In this study, the annual rainfall was calculated based on a hydrological year (starting from July and ending in June of the following year. Furthermore, the wetness conditions at each site were classified into four groups according to average annual rainfall. The classifications were semi-arid (less than 400 mm/yr), semi-humid (between 400 mm/yr and 800 mm/yr), semi-humid and humid (between 800 mm/yr and 1200 mm/yr), and wet (greater than 1200 mm/yr).

4.2.3 Land cover data

The land cover data used in this study were retrieved from the Dynamic Land Cover Dataset (DLCD) developed by Geoscience Australia. The land cover map was identified according to the latest DLCD 2.1 version (published in 2015). The DLCD was produced from MODIS EVI time-series data with spatial resolution of 250 m (http://www.ga.gov.au/). Three major types of vegetation were included in this study (grasses, shrubs, and trees), while other land types (e.g., urban areas or water bodies) were eliminated.

4.2.4 Vegetation data and Index

Moderate Resolution Imaging Spectroradiometer (MODIS) provided the remote sensing product MOD09A1 with 8-day temporal resolution and 500 m spatial resolution. Spectrum band pixels marked with the percentage of NA values greater than 5% were eliminated according to the quality assurance (QA) flag. Enhanced Vegetation Index (EVI) is one of the well-known greenness indexes, derived from the reflectance of red, blue, and near-infrared spectrum bands, was used to describe the "greenness" of vegetation dynamics (Figure 4-1). In contrast to other vegetation indexes, such as Normalized Difference Vegetation Index (NDVI), EVI can eliminate soil background and atmospheric noise, even for non-saturated soil, which can be a typical problem for NDVI (Huete et al. 2002). EVI was calculated as:

$$EVI = \mathrm{G}\frac{\rho_{nir}-\rho_{red}}{\rho_{nir}+\mathrm{C1}\rho_{red}-\mathrm{C2}\rho_{blue}+\mathrm{L}} \qquad (4-1)$$

where ρ_{NIR}, ρ_{red} and ρ_{blue} are atmospherically corrected or partially corrected surface near-infrared (NIR), red and blue spectral reflectance, G is the gain factor, L is the canopy background adjustment, and C_1, C_2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients used in the MODIS-EVI algorithm are G=2.5, L=1, C1 = 6, C2 = 7.5(Huete et al. 2002; Huete et al. 1994; Huete et al. 1997). The numeric values of coefficients used in the equation are aerosol resistance terms, which are also the same as the values in other MODIS-EVI products distributed by the Land Processes Distributed Active Archive Center (https://lpdaac.usgs.gov/). Presently, the global satellite product of EVI is provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) launched in Feb. 2000. This optimized vegetation index improves vegetation monitoring and enhances the observation of terrestrial ecosystems, facilitating the global carbon cycle researches.

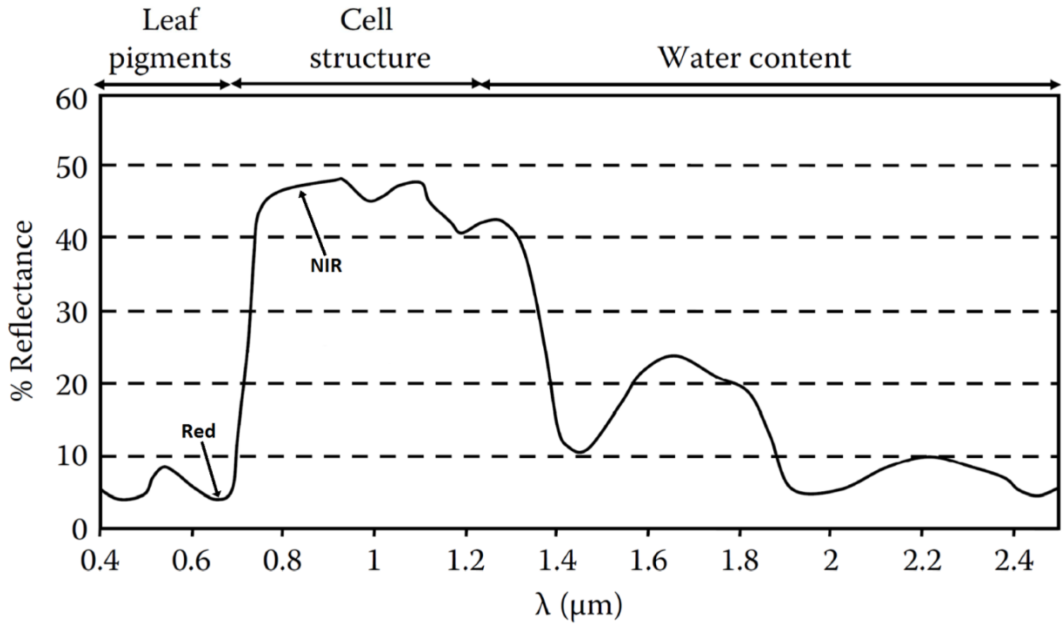

Figure 4- 1. Spectral signature of healthy vegetation (Chuvieco et al. 2009).

The Singular Spectrum Analysis (SSA) has been widely applied to analyze non-linear time series in geophysical studies (Golyandina et al. 2005; Ma et al. 2013). The method has been developed to effectively solve issues such as decomposition, filtration, and forecasting for non-parametric time series (Golyandina et al. 2013). In this study, we applied an R package named “Rssa” to reduce noise and uncertainties, and gap filling of EVI time series (Golyandina et al. 2014; Golyandina et al. 2013). Afterwards, the reconstructed EVI time series were interpolated by using local polynomial regression fitting, and then the span parameter was set as 0.02 based on iteration fitting results to obtain daily EVI time series for extraction of vegetation phenology metrics.

4.2.6 Phenology metrics retrieval

Vegetation dynamics can be reflected by phenology variations, which are affected by multiple climatic conditions. Here we retrieved phenological metrics from interpolated daily EVI time series data according to five key points that defined the growing season, and partitioned the growth stages as shown in Figure 4-2. Three of the key points were defined as the minimum EVI before the growing season, the minimum EVI after the growing season, and the maximum EVI during the growing season. The other two key points were derived from the first derivative of the EVI time series, including the fastest greening date and the fastest browning date. Following the determination of these five points, phenology metrics could be calculated. We assumed the SGS was halfway between the minimum EVI date before the growing season and the fastest greening date. Similarly, EGS was defined as the date halfway between the minimum EVI date after the growing season and the fastest browning date (Ma et al. 2013). Therefore, LGS was defined as the length of the period between SGS and EGS. Furthermore, maximum EVI was selected to depict the magnitude of vegetation growth, and the corresponding date of maximum EVI defined PGS. Maximum EVI was then used to represent the vegetation sensitivity of amplitude to rainfall variations. In contrast, LGS was used to determine temporal sensitivity of vegetation development. SGS, PGS, and EGS were used to represent the influence of rainfall amount on the timing of the growing season. We also used average growing season EVI to make comparisons applicable to the entire growing season.

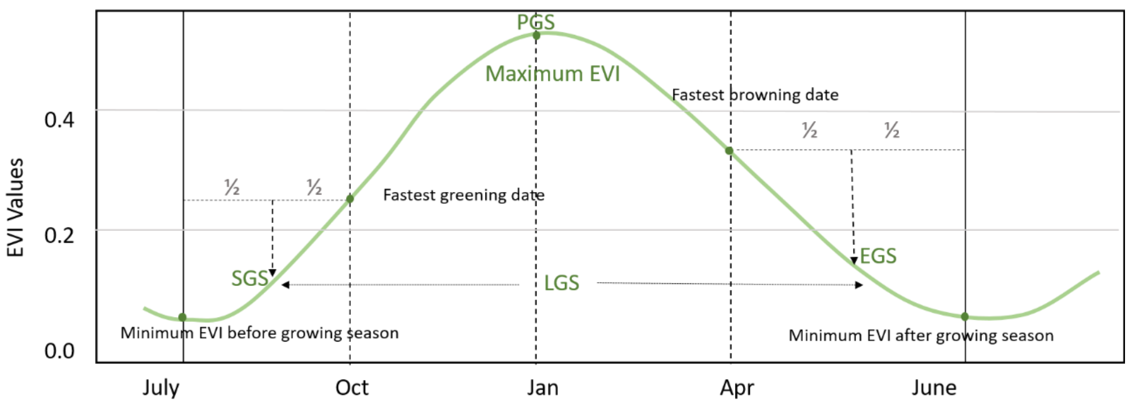

Figure 4-2. Schematic diagram of vegetation phenology. EVI is enhanced vegetation index; SGS is the start of the growing season; PGS is the peak of the growing season; EGS is the end of the growing season; LGS is the length of the growing season.

Finally, we classified the 119 sites according to rainfall conditions and land cover types, and retrieved phenological metrics from the corresponding remote sensing pixels. The grouped points were combined to assess the sensitivity of phenology and growth to rainfall amount.

4.3 Results

4.3.1 Sensitivity of LGS and maximum EVI to rainfall in different ecosystems

The sensitivity of LGS to rainfall variations under different rainfall conditions is illustrated in Figure 4-3. We processed rainfall and EVI time series data, and presented the statistical information by using smooth regression. We found clearly different responses of LGS to rainfall for ecosystems under water-limited conditions compared with water-sufficient conditions. In semi-arid regions where the average annual rainfall was below 400 mm/yr, grass, shrub, and tree biomes all exhibited a similar response of LGS to rainfall variations. LGS increased as rainfall increased until reaching a threshold rainfall of about 300 mm/yr. At greater rainfall amounts the facilitating effect of rainfall on LGS became weak, and the regression curve became flatter. The LGS response to annual rainfall variations in semi-humid regions was also similar to the response observed in semi-arid regions, but the sensitivity became weaker with greater precipitation. In contrast, the relationship between LGS and annual rainfall was essentially flat in semi-humid and humid regions. LGS was only sensitive to annual rainfall under water-limited circumstances, and the sensitivity became low under sufficient-water circumstances. Therefore, LGS did not reflect vegetation responses to annual rainfall amount in wet regions.

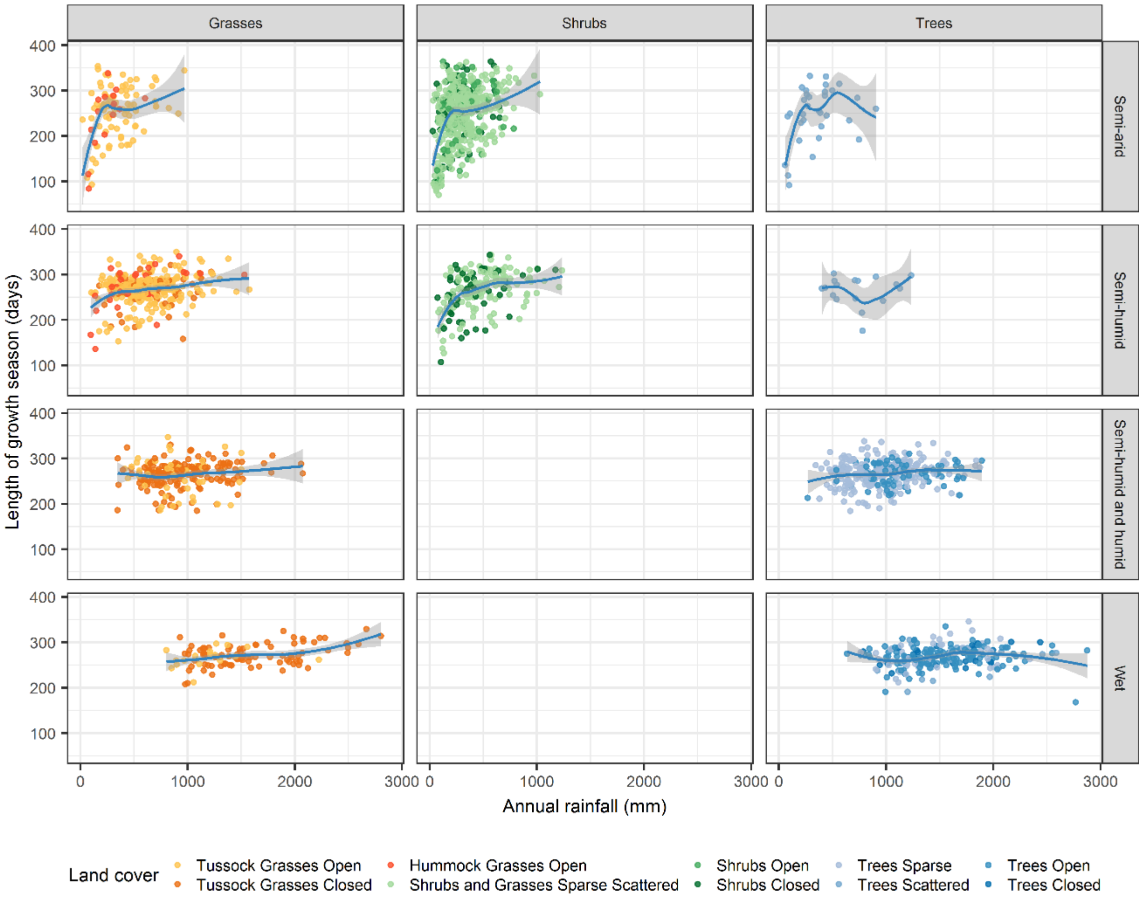

Figure 4-3. Sensitivity of length of growing season to annual rainfall amount for three vegetation types and four wetness regions in the Northern Territory, Australia.

The sensitivity of the maximum EVI to rainfall variation under different rainfall conditions is presented in Figure 4-4. Similar to the results observed for LGS, there also existed clearly different responses of maximum EVI to rainfall for ecosystems under water-limited conditions compared with ecosystems in water-sufficient regions. Maximum EVI increased approximately linearly with increasing annual rainfall in semi-arid and semi-humid regions. The observations showed that the response of maximum EVI to rainfall for the grass biome remained linear until annual rainfall exceeded around 800 mm/yr. With greater rainfall amounts, the response became flat and then decreased with even greater rainfall amounts.. The response generally became flatter as ecosystems changed from grasses and shrubs to trees. When rainfall was greater than 1200 mm/yr in water-sufficient regions, there was no observable linear response of maximum EVI to rainfall. In wet regions, only the regression curve for grass ecosystems exhibited a limited sensitivity to annual rainfall during dry years.

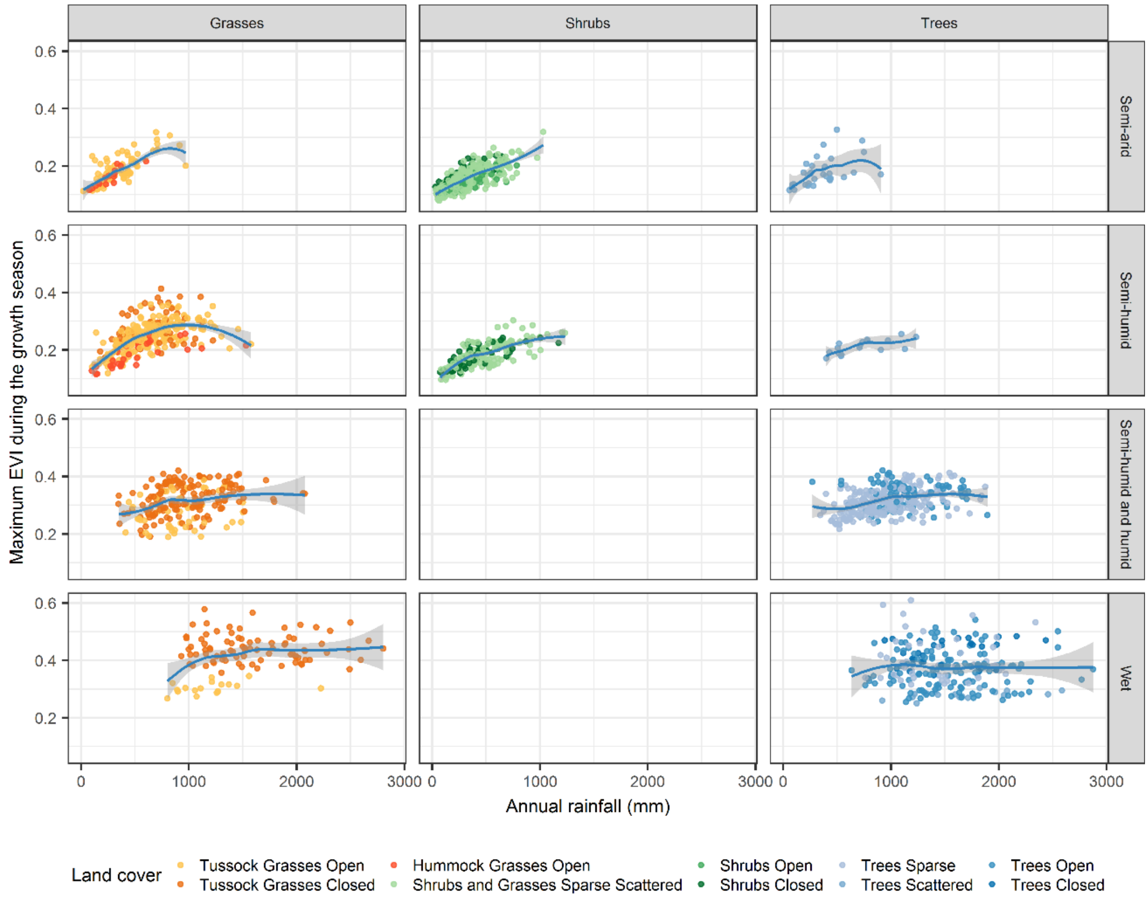

Figure 4-4. The sensitivity of maximum enhanced vegetation index (EVI) to annual rainfall amount for three vegetation types and four wetness regions in the Northern Territory, Australia.

In summary, the influence of rainfall amount on the response of both LGS and maximum EVI was evident. Positive responses of these two phenological proxies to rainfall were observed in drier regions. Maximum EVI was more sensitive than LGS in reflecting the impacts of rainfall variation on vegetation growth.

4.3.2 Representation of vegetation growth

In this study, we used average EVI during the growing season to represent the vegetation growth status. The relationship between LGS and average EVI during the growing season is shown in Figure 4-5. The observations showed that there was essentially no useful relationship between vegetation growth status and LGS for any of the three ecosystem types under the four different rainfall conditions. Only limited dynamics were observed in the drier regions. However, the magnitude of change was limited in distinguishing the fluctuations of vegetation dynamics. Hence, we did not use LGS to represent average vegetation growth status.

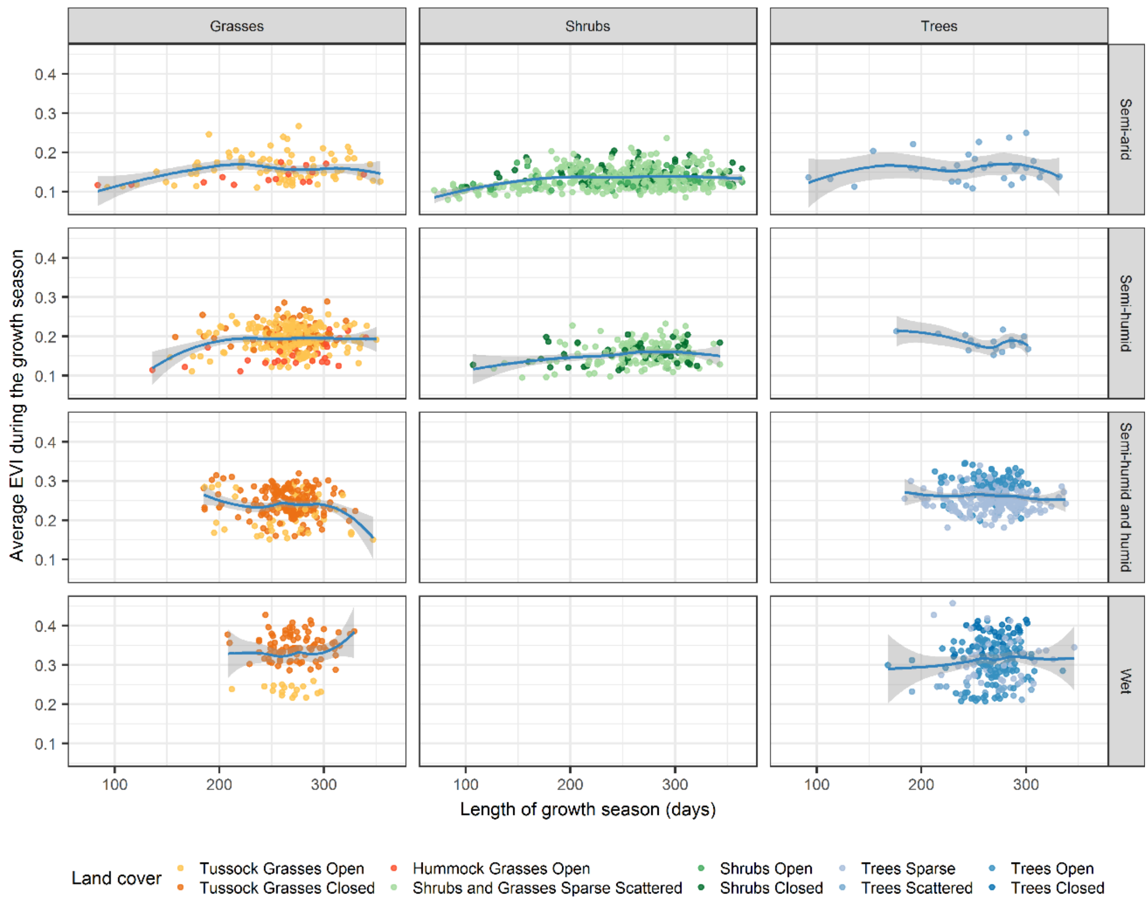

Figure 4-5. Relationship between length of growing season and average enhanced vegetation index (EVI) during the growing season for three vegetation types and four wetness regions in the Northern Territory, Australia.

We also established the relationship between maximum EVI and average EVI during the growing season for all three ecosystems under the four different rainfall conditions (Figure 4-6). In contrast to the poor relationship between LGS and average EVI, a strong positive relationship between average EVI and maximum EVI was observed under all circumstances. The observations were fitted with smooth regression to display the relationships. According to the shape of the curve, we were able to infer that the relationship between maximum EVI and average EVI was approximately linear, as shown in Figure 4-6. A striking finding was that similar linear relationships were found for grass, shrub, and tree ecosystems across all four wetness regions. Hence, we were confident in being able to use maximum EVI to describe the vegetation growth status for the entire growing season.

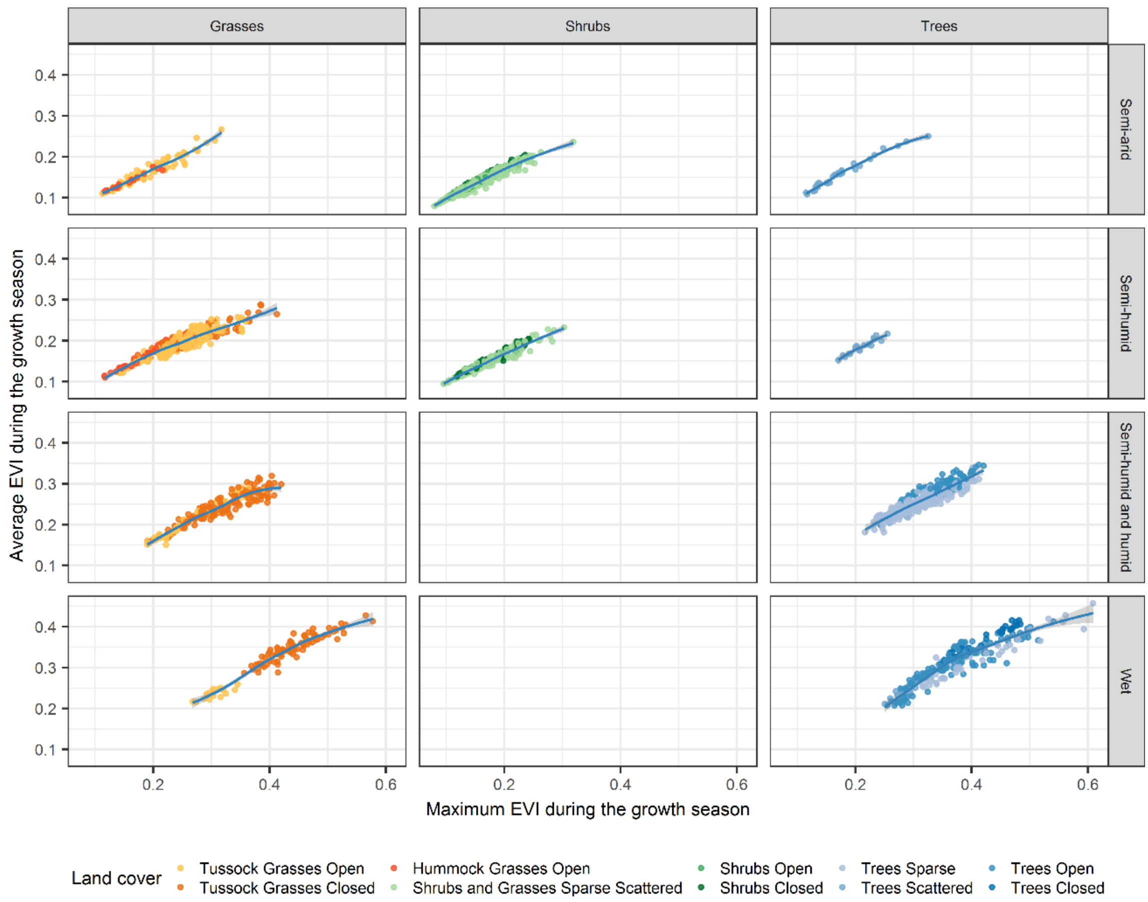

Figure 4-6. Relationship between maximum EVI and the average EVI during the growing season for three vegetation types and four wetness regions in the Northern Territory, Australia.

4.3.3 Comparison of rainfall-sensitive proxies

Maximum EVI and LGS are two phenological proxies that reflect vegetation growth status. The above results demonstrated the relationships of these two proxies to rainfall and vegetation growth, respectively. Figure 4-7 shows the relationship between maximum EVI and LGS. As we expected, the relationships were all flat with little fluctation for all ecosystems. Even for the grass ecosystems in the drier regions, the limited responses indicated that maximum EVI and LGS were essentially not related and were independent of each other.

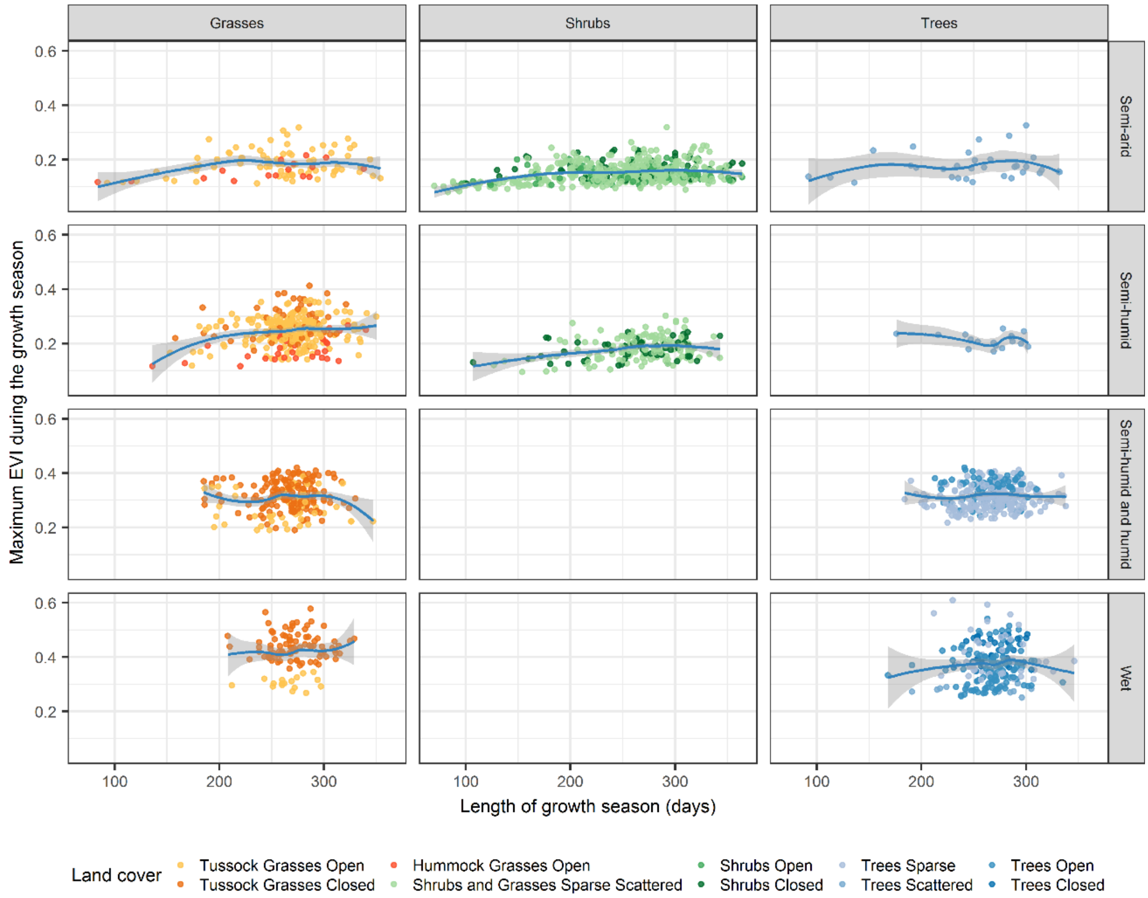

Figure 4-7. Relationship between maximum EVI and LGS for three vegetation types and four wetness regions in the Northern Territory, Australia.

To more clearly show this result, the Pearson correlation matrices among annual rainfall, LGS, maximum EVI, and average EVI was constructed for the four wetness regions (Figure 4-8). The correlation coefficients between maximum EVI and LGS were all below 0.27, with values as low as 0.04 in humid regions. Therefore, we are able to conclude that LGS and maximum EVI can be regarded as two independent phenological proxies.

Furthermore, the sensitivity of maximum EVI and LGS were able to be compared quantitatively based on correlation coefficients. In semi-arid and semi-humid regions, the correlation coefficient between maximum EVI and annual rainfall was above 0.6, which was much higher than the correlation coefficient between LGS and annual rainfall of about 0.3. In humid regions, the influence of rainfall variation on phenology weakened, and correlation coefficients were lower. In summary, it was clear that the sensitivity of maximum EVI to annual rainfall was higher than the sensitivity of LGS to annual rainfall, except in wet regions, where the impacts of rainfall on vegetation were limited.

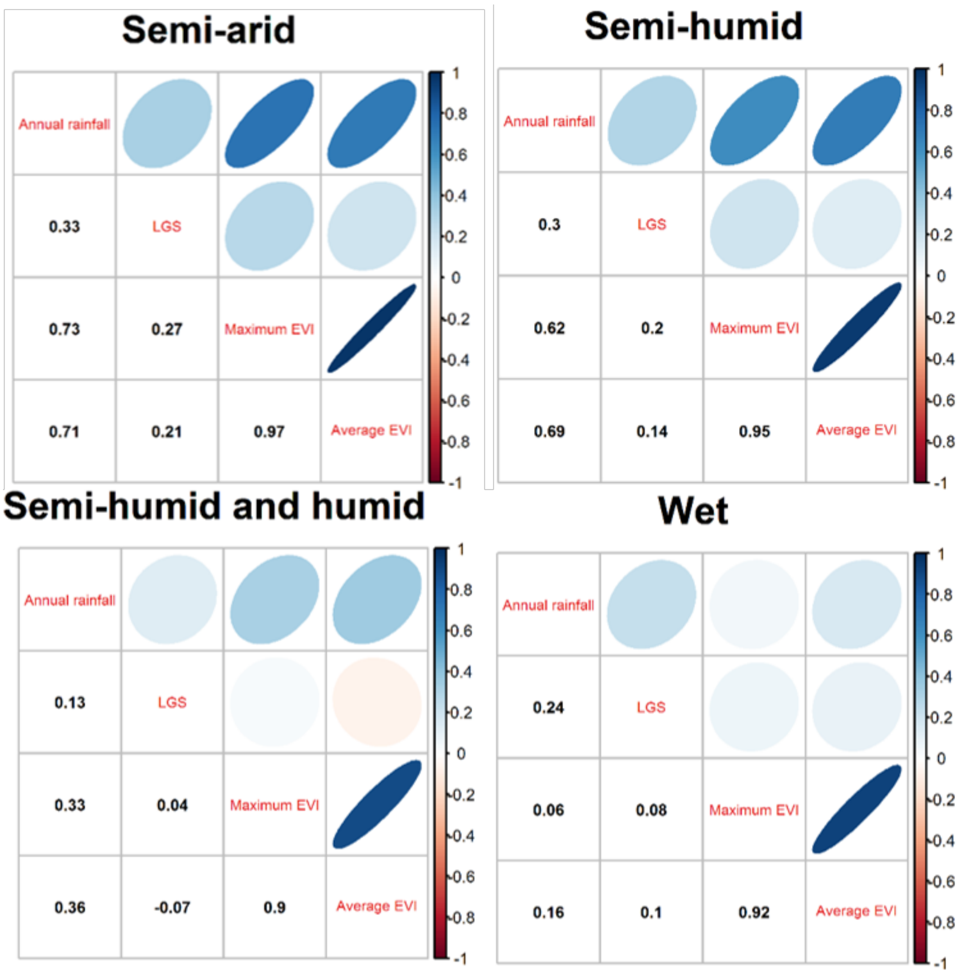

Figure 4-8. The Pearson correlation matrices of phenology metrics and annual rainfall for four wetness regions in the Northern Territory, Australia.

In addition, maximum EVI and average EVI were highly correlated in all four regions (semi-arid to wet). The correlation coefficient between maximum EVI and average EVI was 0.97 in the semi-arid regions, but was only 0.21 between LGS average EVI. Moreover, the correlation coefficients between annual rainfall and average EVI were closer to the correlation coefficients between maximum EVI and average EVI than the correlation coefficients between annual rainfall and LGS. Hence, maximum EVI was a better phenological proxy to represent the entire vegetation growth status.

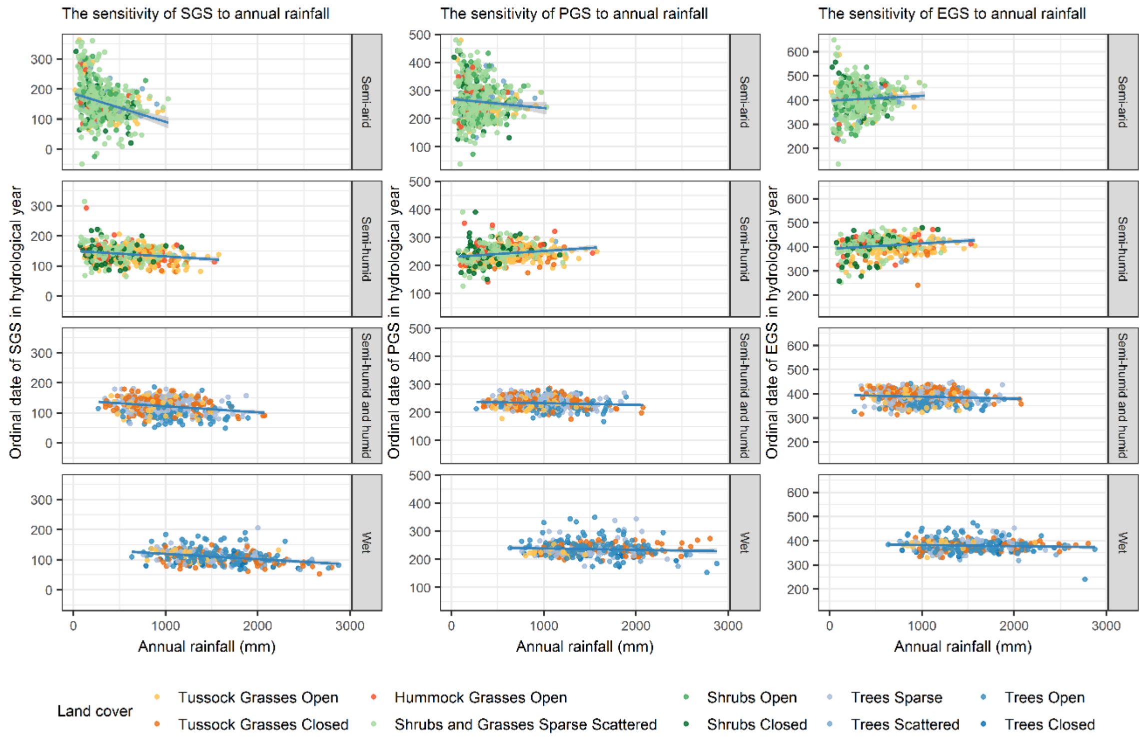

Figure 4-9. The sensitivity of the start of the growing season (SGS), peak of the growing season (PGS), and end of the growing season (EGS) to annual rainfall amount for grasses, shrubs, and trees for four wetness regions in the Northern Territory, Australia.

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4.3.4 Sensitivity of other temporal metrics to rainfall variations

In addition to LGS and maximum EVI, we also evaluated the sensitivity of three other phenological proxies (SGS, PGS, EGS) to annual rainfall variation (Figure 4-9). The findings were expected to demonstrate the temporal impacts of rainfall on vegetation growth. For SGS, only the ecosystems in semi-arid regions exhibited a distinctive trend, with SGS moving to earlier dates as annual rainfall increased. However, the sensitivity of SGS dropped as rainfall supply increased in wetter regions. Additionally, the sensitivity of PGS and EGS to annual rainfall was low, even though a slight response (later date with increasing rainfall) could be detected in the semi-arid and semi-humid regions. In light of these results, we conclude that SGS, PGS, and EGS were not sensitive enough to reflect phenological responses to variations in rainfall amount in savanna ecosystems in Australia.

4.4 Discussion

4.4.1 Comparing the temporal proxy (LGS) to the magnitude proxy (maximum EVI)

In order to explore the response of vegetation dynamics to rainfall variation, we concentrated on two phenological proxies, namely LGS and maximum EVI. LGS is a parameter related to SGS, EGS, and the rainy duration. The spatiotemporal variation of LGS has been found to be closely related to rainfall seasonality (Suepa et al. 2016). The inter-annual variations of phenology also were found to produce changes in LGS along with the rainfall gradient (Ma et al. 2013). However, according to our results, the sensitivity of LGS response to annual rainfall amount limited its application in monitoring ecosystems' productivity. In semi-arid regions, LGS was lengthened as annual rainfall increased but this response only occurred during the dry rainfall season. Once rainfall amount satisfied a certain vegetation demand, such as 300 mm/yr, LGS did not increase with increasing rainfall amount (Figure 4-3). An explanation for this observation may be that LGS indicated a capacity for a normal vegetative growth level sustained by a certain amount of water, but it did not indicate that vegetation productivity could be maintained at a normal level with limited rainfall amount. In addition, the sensitivity of LGS to rainfall became weaker in wetter regions, with all correlation coefficients below 0.3. We conclude that LGS does not adequately reflect vegetation dynamics in response to annual rainfall variations. Our results are also supported by previous work with phenological models that found that simulating vegetation onset date was more difficult in water-limited regions (Botta et al. 2000).

In contrast, maximum EVI is a better proxy to represent vegetation growth. In semi-arid and semi-humid regions, we observed that maximum EVI increased with anuual rainfall amount, and that this response was approximately linear. Although the sensitivity decreased in wetter regions, maximum EVI reflected dynamic vegetation responses to rainfall variations in water deficit regions. Additionally, maximum EVI represented growth for the entire growing season. Vegetation growth is a series of continuous biophysical and biochemical processes including germination, leaf emergence, stem elongation, flowering, and harvest. Maximum EVI could be regarded as a final accumulated growth status resulting from the previous growth stages. In our study, the high correlation coefficient between maximum EVI and average EVI during the growing season (above 0.9 in all ecosystems) indicated that maximum EVI is a reasonable proxy for vegetation growth status.

4.4.2 Phenological sensitivity across different savanna ecosystems

Maximum EVI also performed better than LGS with regard to dynamic vegetation response to rainfall changes across different ecosystems. For the grass biome, maximum EVI detected water deficit influence on vegetation growth, even in wet regions. However, changes in vegetation growth were difficult to distinguish using LGS. Similarly, although we only obtained phenological observations of the shrub biome in semi-arid and semi-humid regions, we found that the deviation of the regression between maximum EVI and annual rainfall amount was also smaller than that of LGS, indicating that maximum EVI of shrub ecosystems is more sensitive to rainfall than LGS. In contrast, the tree biome is a more stable ecosystem. The response of vegetation growth to rainfall was limited, especially in wetter regions. However, in semi-arid and drier regions, annual rainfall cannot sustain a large coverage of woody vegetation, so trees are generally distributed sparsely. Both LGS and maximum EVI indicated the response of sparse tree growth to rainfall variation in semi-arid regions, but LGS did not quantify this response as well as maximum EVI during wet years.

4.4.3 Limitations and perspectives

In this study, we concluded that maximum EVI was a better representative of vegetation growth because of its higher sensitivity to rainfall amount. However, this conclusion was only determined from the viewpoint of vegetation growth and quantitative production.

On the other hand, we may have underestimated the temporal variability in vegetation phenology. LGS and other temporal proxies (including SGS, PGS, and EGS) were not sensitive to rainfall amount, but the synchronization between vegetation growing season and the rainy season has been addressed in many previous studies (Guan, Wood, et al. 2014; Mugalavai et al. 2008; Zhang et al. 2005). Additionally, we applied annual rainfall amount as a wetness proxy to simplify the precipitation process, and this methodology leads to underestimation of the impacts of real-time rainfall events and temporal distribution of rainfall. In addition, vegetation growth stages, such as leaf bud and flowering, are also strongly related to temperature and radiation, and these meteorological parameters were not considered in this study. Hence, temporal phenology metrics could be more sensitive to the timing of meteorological conditions than to the magnitude of rainfall variations.

Our study provides a fundamental basis for understanding the sensitivity of vegetation growth to rainfall amount. The results support the application of maximum EVI for detecting terrestrial responses to rainfall amount. Maximum EVI not only presents a good relationship for the entire vegetation growing season over all savanna ecosystems, but also provides an approach for investigating the impacts of rainfall variations before the time of the peak of the growing season.

4.5 Conclusions

This study evaluated the sensitivity of vegetation phenology to annual rainfall amount along a rainfall gradient in the Northern Territory, Australia. Two major phenological proxies, LGS and maximum EVI, retrieved from MODIS satellite data, were compared for different ecosystems and rainfall conditions. Using the average EVI during the growing season as a proxy for vegetation growth, we concluded that maximum EVI was superior to LGS for representing vegetation dynamics. Maximum EVI was highly correlated with average EVI for grass, shrub, and tree ecosystems. Furthermore, the relationship between maximum EVI and annual rainfall amount was linear in water-limited regions. EVI was more sensitive to annual rainfall than LGS. Because of climate change, inter- and intra-annual variability of rainfall patterns has increased. Determining the sensitivity of phenology metrics to rainfall is urgently needed. The fundamental work of investigating the responses of phenological proxies to rainfall variations based on satellite observations enhances our understanding of eco-hydrological processes, and also facilitates terrestrial ecosystem monitoring and modelling via the application of remote sensing.

Chapter 5: Dominating roles of rainfall pattern in driving vegetation dynamics in savanna ecosystems under climate change

Abstract

Global warming accelerates the hydrological cycle in recent decades, leading to observable rainfall pattern changes at spatial and temporal scales globally. As rainfall is one of the most influential and active factor to influence terrestrial ecosystems, many studies have focused on the relationship between rainfall and vegetation under climate change. However, the roles of rainfall pattern in driving vegetation dynamics have still not been stated clearly. Hence, in this study, we explored the mechanism of how rainfall pattern changes dominate the vegetation growth in savanna ecosystems of the Northern Territory, Australia, where a rainfall gradient is located and appropriate for rainfall variability analysis. The relative importance method and spatial correlation were mainly applied to the responses of savanna biomes to rainfall pattern changes under different rainfall conditions, based on the coupling of ground rain gauge measurements and remote sensing observations of vegetation. According to the roles of rainfall pattern and responses of ecosystems to rainfall variations, we found the study area was partitioned into three zones by two rainfall isohyets, 400 mm and 900 mm. Besides, frequency is the most dominating factor to influence vegetation dynamics, especially in semi-humid regions where average annual rainfall is between 400 mm and 900 mm. the other two factors, intensity and duration, have stronger influences in humid regions. In semi-arid regions, the relative importance of the frequency component declined but still played a controlling role in vegetation growth. Eventually, our study improves the understanding of the influences of rainfall pattern changes on savanna ecosystems, and also provides an approach to evaluate ecosystems' responses to rainfall pattern changes in terms of amount, intensity, duration, and frequency.

Keywords: rainfall pattern, vegetation dynamics, savanna ecosystems, MODIS EVI, Northern Australia

5.1 Introduction

Climate change predicts the substantial changes in rainfall globally with continuous warming (Alexander et al. 2006; Allan et al. 2008; IPCC 2013; Trenberth 2011). Because the rising temperature accelerates the hydrological cycle and causes frequent hydrological extremes, spatiotemporal water distribution has also been influenced significantly (Donat et al. 2013; Donat et al. 2016; Guerreiro et al. 2018; Min et al. 2011). With changes in rainfall patterns, terrestrial ecosystems are sensitive to respond to the rainfall variations by influencing its photosynthesis and interactive processes of water and carbon exchange (Fay et al. 2003a; Guan, Wood, et al. 2014; Huxman et al. 2004; Peñuelas et al. 2004). Consequently, there is an urgent need to explore the mechanism of how rainfall pattern drives vegetation dynamics under the pressure of global warming. Particularly, it is more important for water sensitive ecosystems (Guan et al. 2018; Seddon et al. 2016), including savanna biome which covers 20% of the Earth's land surface and contributes 30% of terrestrial net primary production(Grace et al. 2006; Lipsett-Moore et al. 2018), to investigate the impacts of climate change. Although many studies have noticed rainfall regimes play an influential role in vegetation activities and distribution (Kulmatiski et al. 2013; Radu et al. 2018; Shen et al. 2008), the role of rainfall pattern changes in vegetation dynamics have not been stated clearly. In this study, we focused on the role of rainfall pattern changes in controlling vegetation growth of savanna ecosystems for obtaining a further understanding of the relationship between vegetation and rainfall.

Although a great deal of research has attempted to explore the relationship between rainfall and vegetation(Fay et al. 2003a; Guan, Wood, et al. 2014; Peñuelas et al. 2004), the issues on how to characterize rainfall pattern changes and how to express the driving mechanism of rainfall patterns on vegetation dynamics systematically have received less attention. According to physiology and the growing stages of vegetation, the rainfall effectiveness is changing along with growth timing and also varies in terms of different rainfall event types (Ponce Campos et al. 2013; Yang et al. 2016; Zhang, Ju, et al. 2014). Therefore, the temporal changes in rainfall patterns associated with varying rainfall amounts in each event can lead to different effects in nurturing vegetation growth. The impacts of temporal rainfall variations on vegetation dynamics are difficult to be characterized by using total rainfall amount merely because many detail temporal features related to rainfall events, including timing, intensity, duration, and frequency, are neglected. Hence, to characterize rainfall pattern appropriately is critical to evaluate the influences of changes to rainfall pattern.

Some studies also explored the impacts of rainfall patterns by using in-suite experiments to control rainfall conditions (Radu et al. 2018). The in-situ approaches are beneficial in terms of purpose-designed experiments and first-hand data for analysis. However, the limited number of experiments and the requirements for facilities confines the application in consideration of extensive spatial scope. Thereby, the spatial impacts of rainfall pattern changes are also difficult to describe.

With decades of the retrieved remote sensing imagery, the approach of vegetation index derived from the reflectance spectra is available to monitor vegetation dynamics and record the vegetation responses to the changes in climatic conditions (Zhang et al. 2003). The sensitive and effective vegetation index is an appropriate indicator to demonstrate the influences of climate change on terrestrial ecosystems (Huete et al. 2002). MODIS enhanced vegetation index (EVI) is one of the widely-used index to characterize vegetation phenology and dynamics (Ma et al. 2013; Shi et al. 2017; Zhang et al. 2003). In addition, many studies also improve the application of remote sensing by coupling with ground measurements (Bobée et al. 2012; Sepulveda et al. 2018).

With the above context, we attempted to explore the dominating role of rainfall pattern changes in driving vegetation dynamics in savanna ecosystems of the Northern Territory, Australia, where a rainfall gradient is located and appropriate for rainfall variability analysis. We took advantage of remote sensing to investigate extensive area of vegetation growth, and also benefited ground rain gauge data to analyse rainfall pattern changes based on rainfall events statistics. We tried to improve the understanding of how rainfall pattern changes influence vegetation growth at large spatial scale. Our primary objectives are to 1) establish the relationship between characterized rainfall pattern and delineated vegetation dynamics; 2) evaluate the roles of rainfall pattern factors in controlling vegetation growth, in terms of rainfall amount, intensity, duration, and frequency; 3) assess the savanna ecosystems' responses to rainfall pattern changes under different rainfall conditions.

5.2 Data and Methodology

5.2.1 Study Area

The Northern Territory of Australia was selected as our study area, because of the North Australian Tropical Transect (NATT), as it is a sub-continental scale living laboratory to research climatic variability and spatial pattern of savanna vegetation across a rainfall gradient (Hutley et al. 2011). Furthermore, limited topographic changes are suitable to focus on the impacts of rainfall patterns on vegetation biophysical and biochemical responses over different rainfall levels involving rainfall interannual variability and seasonality. Presently, extensive studies have focused on this transect to explore the influences of climate drivers on vegetation structural and floristic changes of savanna ecosystems (Eamus et al. 2000; Kanniah et al. 2011; Ma et al. 2014).

Based on the land cover dataset we used, biomes in our sampling sites are mainly classified as nine groups totally considering the land cover composition and vegetation structure, including trees-closed, trees-open, trees-sparse, tussock grasses-closed, tussock grasses-open, shrubs and grasses sparse-scattered, shrubs-closed, shrubs-open, and hummock grasses-open. Along rainfall gradient towards inland, savanna ecosystems transfer from mesic ecosystems to xeric ecosystems. The biomes structure change from trees and grasses coexistence to shrubs and grasses coexistence and tree biomes transit from tree closed type to tree sparse type or tree scattered type.

5.2.2 Data sources

The land cover data was available from the Dynamic Land Cover Dataset (DLCD) produced by Geoscience Australia (http://www.ga.gov.au). The dataset version 2.1 was used in this study to identify land cover types at 250m spatial resolution covering the period from2001 to 2015.

In this study, vegetation proxies were obtained from remote sensing observations. The Enhanced Vegetation Index (EVI) was adopted to illustrate the dynamic of vegetation based on spectrum bands retrieved from Moderate Resolution Imaging Spectroradiometer (MODIS). The MODIS Surface Reflectance product MOD09A1 provided by NASA Land Processes Distributed Active Archive Center (LP DAAC) was used for EVI calculation. The spatial resolution and temporal resolution of MOD09A1 product are 500m and 8-day, respectively. The retrieved remote sensing observations covered the period from 2000 to 2017.

The meteorological data were obtained from the Scientific Information for Land Owners (SILO), and gauge-based daily rainfall records were retrieved from 2000 to 2017 under quality assurance (http://www.bom.gov.au). The spatial distribution of those sites covers wet regions and dry regions evenly from the coastal to central inland areas in northern Australia, except western mountainous regions with seldom sites established between 20 °S and 22 °S.

5.2.3 Vegetation index calculation and pre-process

In this study, MODIS product MOD09A1 was used to couple ground rain gauge measurements. The spatial and temporal resolutions of satellite imagery were 500 m and 8 days, respectively. The spectrum bands were pre-processed by using quality assurance (QA) flag of products. We remained those pixels with NA value less than 5% for vegetation index calculation. EVI was applied to represent the "greenness" of vegetation dynamics according to those spectrum bands, and the calculating processes referred to Section 4.2.4.

5.2.4 Phenology metrics retrieval

Vegetation dynamics can be reflected by variations of phenology, which are affected by multiple climatic conditions. Here we retrieved phenological metrics mainly referred to Section 4.2.6. Afterwards, we partitioned the growing stages and found that the period between the fastest greening date and the date with maximum EVI was much more sensitive to rainfall amount, where time window were used in this study to investigate impacts of rainfall pattern changes. In the following context, we referred to this span of time as the growth season, which is the primary period we concerned about.

5.2.5 The definition of rainfall pattern

Daily rainfall observations in Northern Territory were processed by removing some gauge sites according to land cover types classified as urban or lake area, and quality control. The rain gauge sites marked as good quality but the corresponding EVI pixels' quality evaluated as unsatisfied were also dropped. Eventually, 119 out of 230 in total sites in the Northern Territory were selected to analyse the influences of rainfall pattern.

As we wanted to explore what is the dominating factor to influence vegetation dynamics along with rainfall processes during the growth season, we applied a rainfall event based method by characterizing rainfall pattern according to amount, intensity, duration, and frequency. Unlike traditional definition in hydrology, here we defined the conceptions of amount, intensity, duration, and frequency in consideration of biophysical water demand. The definition of formula is explained as follow,

$$P = IDF \qquad (5-2)$$

where P is total rainfall amount within the growth season (mm), which represents amount factor of rainfall pattern; I is average daily rainfall amount within the rainy days of the growth season (mm/day), representing intensity of rainfall pattern; D is average days for the lasting time of one rainfall event (day) in the growth season, representing duration of rainfall pattern; F is the total number of rainfall events during the growth season (non-dimensional), which shows the frequency of rainfall pattern.

The definition for one rainfall event is counted from the starting date to the ending date with continuous rainy days. Only valid rainfall amount larger than 5 mm/day will be accounted, considering vegetation responses to rapid rainfall pulse as small as 5 mm (Huxman et al. 2004). Otherwise, the day with daily rainfall amount less than 5 mm was not regarded as a rainy day for rainfall event analysis.

5.2.6 Changes in rainfall pattern

In this study, rainfall pattern variation was characterized by changes in amount, intensity, duration, and frequency of rainfall events. Total differential of rainfall amount during the growth season was applied with respect to intensity, duration and frequency factors. The method initially only define rainfall pattern with intensity and frequency, but here we redefine the rainy days separated by duration and frequency to reflect consecutive rainfall events (Karl et al. 1998; Song et al. 2015). The changes in rainfall pattern were evaluated as follow,

$$\frac{dP}{dt} = \frac{dI}{dt}DF + \frac{dD}{dt}IF + \frac{dF}{dt}ID \qquad (5-3)$$

where, P denotes rainfall amount (mm), I denotes rainfall intensity (mm/d), D denotes duration of one rainfall event (d), F denotes the number of rainfall events during the a certain period (dimensionless), t denotes a certain period.

In this study, the average period of the growth season (stage 2) over 119 sites in NATT was 66 days. In addition, rainfall also has the lagging effect on vegetation growth, so we estimated time lag by using cross correlation regression. The lagging period was determined by the highest cross correlation coefficient. Afterwards, we obtained the time lag was 28 days in our study. Hence, we applied the period as 100 days prior to the date of maximum EVI as our time window to analyze the growth season.

The discrete formula of changes in rainfall pattern was described as follow.

$$\Delta P_t = \Delta I_t \bar{D}_t \bar{F}_t + \Delta D_t \bar{I}_t \bar{F}_t + \Delta F_t \bar{I}_t \bar{D}_t + \varepsilon \qquad (5-4)$$

where, ΔP_t denotes change in rainfall amount during the growth season t; it is similar to the meaning of ΔI_t, ΔD_t, and ΔF_t; $\bar{I}_t$ denotes the mean intensity of rainy days during the growth season (mm/day); $\bar{D}_t$ and $\bar{F}_t$ also denotes the similar meaning during the growth season. ε denotes error term as $-\frac{3}{4}\Delta I_t \Delta D_t \Delta F_t$, which is small and can be eliminated.

Here we regarded $\Delta I_t \bar{D}_t \bar{F}_t$ as the intensity component of rainfall pattern change, which indicates the portion of change in rainfall amount caused by change in intensity. $\Delta D_t \bar{I}_t \bar{F}_t$ and $\Delta F_t \bar{I}_t \bar{D}_t$ are similar to express the duration component of rainfall pattern change and the frequency component of rainfall pattern change. Hence, we were able to decompose change in rainfall amount into three critical rainfall components. Also, this method provided an approach to evaluate and compare the impacts of each component quantitatively in the same dimensional unit (mm).

5.2.7 Correlation analysis between vegetation and rainfall pattern

To evaluate impacts of rainfall pattern on vegetation dynamics, the correlation between ΔEVImax representing vegetation dynamics, and changes in rainfall pattern, including amount, intensity, duration, and frequency, was established by linear regression, respectively. In addition, the Pearson's r and p-value were used to state correlation and statistical significance. Regression coefficient was used to reflect parameter sensitivity.

5.2.8 Relative importance analysis of rainfall pattern factors.

To evaluate the dominating roles of rainfall pattern in driving vegetation dynamics, we applied the relative importance method to estimate and compare the impacts of different rainfall pattern components under different rainfall conditions spatially. We calculated the relative importance by using an R package "relaimpo" (Grömping 2006)and then established the contributions of three rainfall pattern components to vegetation dynamics. The factor with a higher relative importance value was regarded as a dominating factor in controlling vegetation growth.

5.3 Results

5.3.1 Spatial relationship between rainfall amount and vegetation

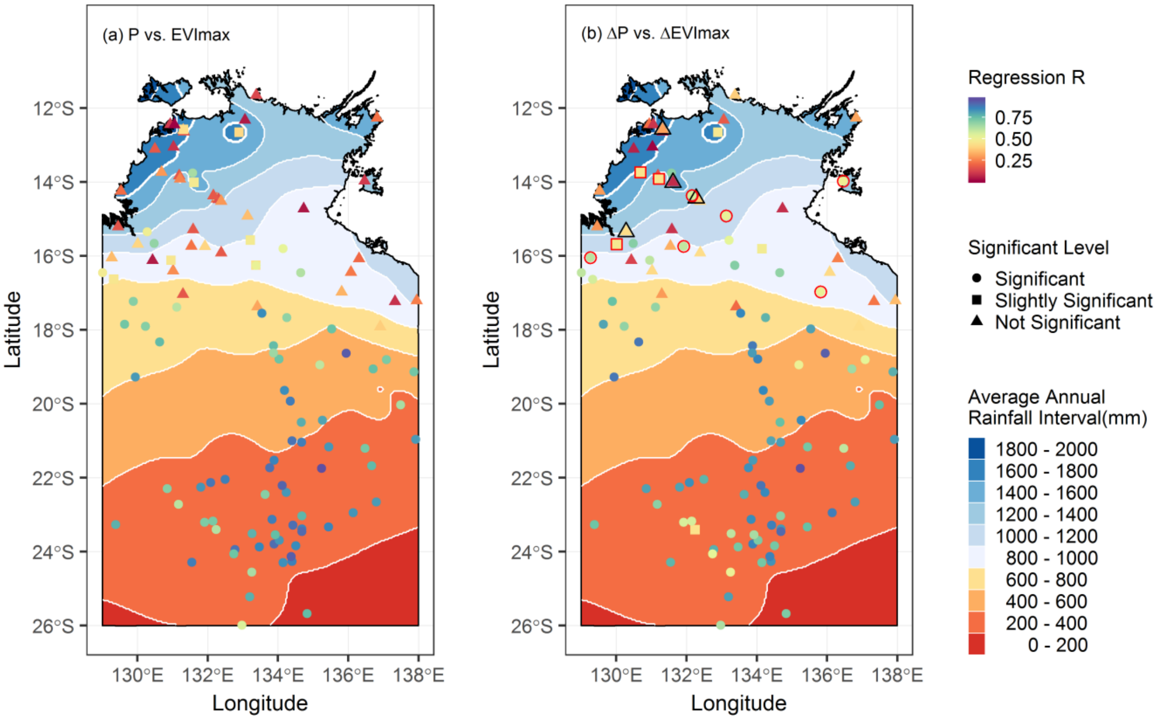

Figure 5-1. The spatial impacts of rainfall amount on vegetation growth. (a) spatial correlation between rainfall amount (P) during the growth season and maximum EVI (EVImax) from 2001 to 2017. (b) spatial correlation between change in rainfall amount (ΔP) during the growth season and change in maximum EVI (ΔEVImax) from 2001 to 2017. The color of points denoted Pearson's r values in regression. The shapes of points including circle, rectangle, and triangle represented different significant levels of regression, where p-value <0.05 was classified as "significant", p-value between 0.05 and 0.1 was classified as "slightly significant", and p-value >0.1 was classified as "not significant". The points outlined with the red line defined significant or slight significant in the correlation between ΔP and ΔEVImax but not significant in the correlation between P and EVImax, and vice versa for points outlined with the black line. The background illustrated the isohyet of average annual rainfall.

The spatial impacts of rainfall were illustrated by the correlation between rainfall amount (P) and maximum EVI (EVImax), as well as the correlation between change in rainfall amount (ΔP) and change in maximum EVI ($\Delta \mathrm{EVImax}$). Figure 5-3 (a) represented rainfall amount has a significant impact from the central inland area towards the northern areas until reaching to a transition boundary near latitude 17 °S, where the average annual rainfall amount is larger than 900 mm, and water becomes a weak controlling factor to constrain vegetation growth. The Pearson's r which represents relativity between rainfall and vegetation also declined along with the annual rainfall increases from the central areas to the coastal areas. A similar spatial pattern was demonstrated by the correlation between ΔP and $\Delta EVImax$. The correlation between ΔP and $\Delta EVImax$ was "significant" in arid or semiarid regions, while correlation became weaker as the significant level turned to "slight significant" and then "not significant" towards the humid coastal areas. The major difference between two spatial regimes was nine points outlined with red color in Figure 5-3 (b). The red outlined sites located in the regions with annual rainfall ranging from 800mm to 1600mm presented "significant" or "slight significant" change of rainfall amount but "not significant" to rainfall amount. The other four points outlined with black color demonstrated the opposite results merely showing a significant correlation between P and EVImax. However, both two spatial regimes showed "not significant" in most humid regions, where the average annual rainfall amount is higher than 1600 mm.

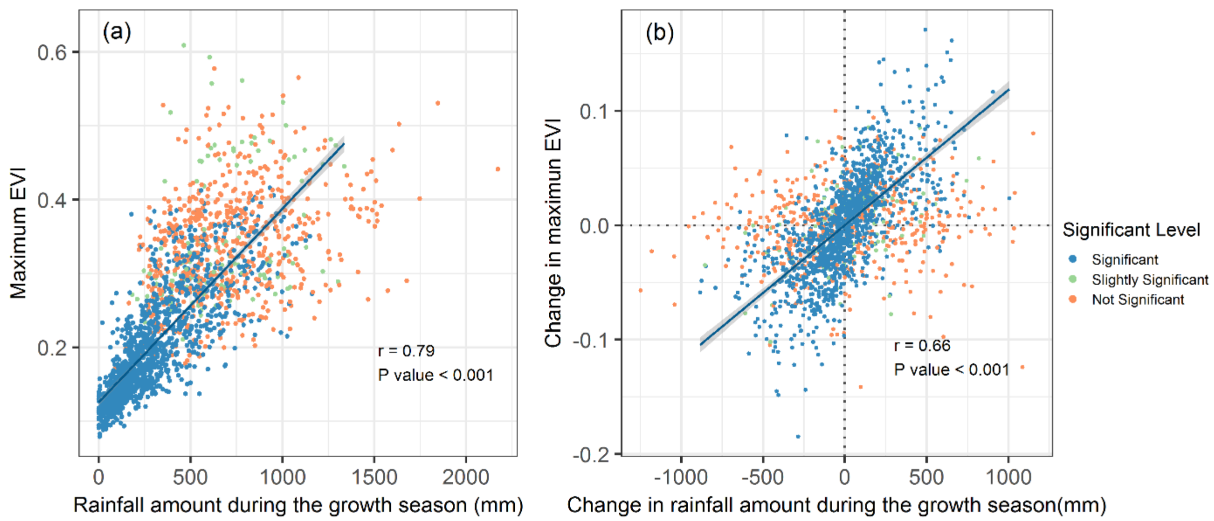

Figure 5-1. Scatter plots of the relativity between rainfall amount and maximum EVI. (a) Regression between P and EVImax. (b) Regression between ΔP and $\Delta EVImax$. The points with different colors were categorized by the significant level calculated from multiple-year regression, implying the level of rainfall constrains vegetation in the spots of corresponding sites. The regression line was drawn by using all points instead of only significant points.

Figure 5-4 presented scatter plots of the regression between rainfall amount and maximum EVI and the regression between change in rainfall amount and change in maximum EVI. Both two regressions presented a highly significant correlation with

Pearson's r value as 0.79 and 0.66, respectively. EVImax increased with rainfall amount during the growth season, while variations became larger when rainfall amount was larger than 500 mm, where the regression between P and EVImax transited to "not significant" implying the constraint of water was weakened. Meanwhile, in the holistic study area, ΔEVImax also responded to ΔP positively, except for the points located in the coastal regions with less water constraint.

5.3.2 Spatial regime of change in rainfall pattern

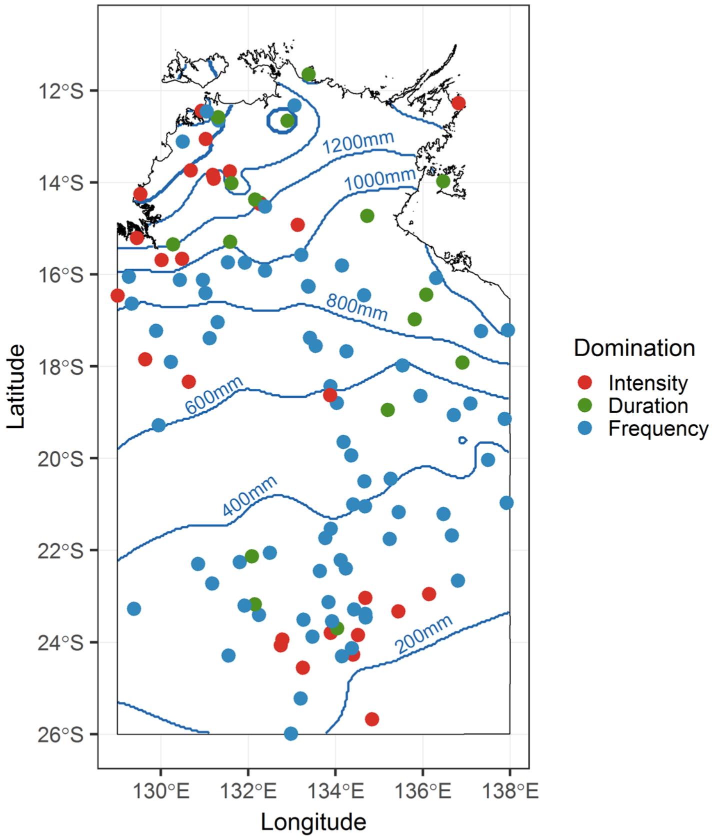

Figure 5-2. The spatial regime of the dominating component of rainfall pattern in influencing vegetation. The components were shown according to the highest relative importance value indicating the most influential factor to vegetation growth. The blue annual average rainfall isohyet was drawn to illustrate the spatial rainfall conditions.

The relative importance method was applied to evaluate the dominating drivers of rainfall patterns to vegetation dynamics. The dominating components of rainfall patterns presented the spatial patterns in controlling vegetation growth along with rainfall gradient from the coastal area to the central area in Figure 5-5. In low latitude coastal areas with the average annual rainfall amount larger than 900 mm, the dominating components were both intensity and duration, instead of frequency. The spatial pattern shifted to the frequency component as the dominator controlling vegetation dynamics in the region where rainfall amount was within 400mm to 900mm between 15°S to 22°S. Only several sites presented the dominator as intensity or duration in the mid-latitude areas. Although the frequency component was still the dominator to vegetation dynamics in the semi-arid region, where the average annual rainfall is below 400 mm, and the relative importance of frequency was weakened by enhanced the impacts of intensity and duration.

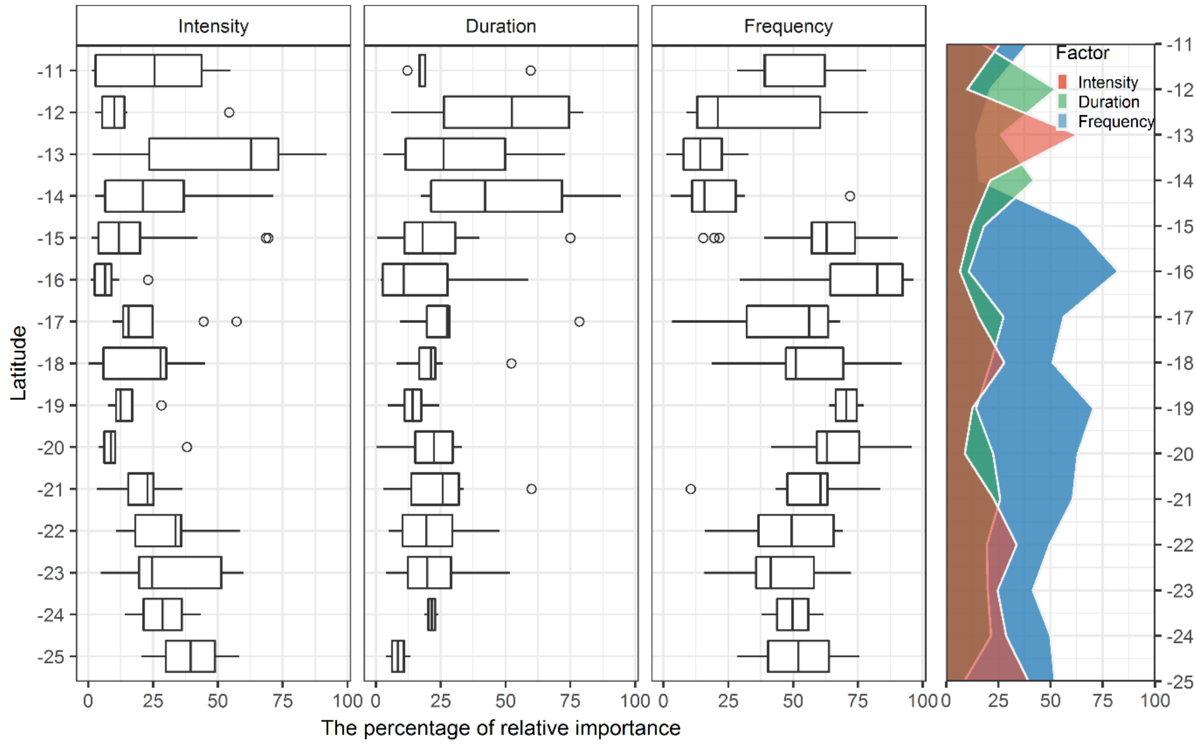

Figure 5-3. The boxplot of variation of rainfall change by the components of intensity, duration, and frequency alone with latitude. The left color panel overlaps the median values of the relative importance of each component.

The relative importance of the components of rainfall pattern changes, including intensity, duration, and frequency, were grouped by latitude to illustrate the rainfall pattern shift at spatial scale (Figure 5-6). The variation of the relative importance was larger in the lower latitude wetter areas than in the higher latitude drier areas for the components of intensity and duration. On the other hand, the higher variability was also presented in the low latitude areas in terms of the frequency component, but the deviation was not as large as the intensity component or the duration component. The right-side colored panel illustrated the dominating component shift alone with latitude via overlapping the median relative importance values of intensity, duration, and frequency components (Figure 5-6). In the low latitude coastal regions, both the relative importance of intensity and duration components were larger than the frequency component. As latitude increases along with rainfall amount declines, frequency started to control vegetation dynamics showing the relative importance weighted more 50% near 15°S where the average annual rainfall amount is around 400 mm. The frequency component maintained as the dominator until the latitude reaching to 22°S, where the relative importance of the frequency component dropped below 50% and an obvious valley near 23°S with the relative importance of the other two components enhanced, particularly the intensity component. In the regions dominated by the frequency component, the outliers of the intensity and duration components shown in Figure 5-6 were larger than their corresponding median values, but the opposite results that the outliers were smaller than their corresponding median values were shown for the frequency component.

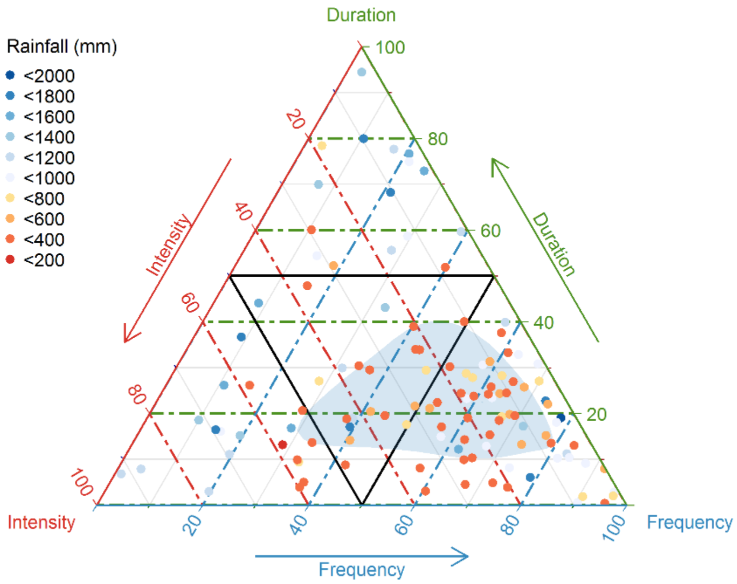

Figure 5-4. The ternary diagram of rainfall pattern change determined by the components of intensity, duration, and frequency. The black lines denote 50% boundaries for each component. The shadow area encircled the major distribution area of the rainfall pattern change cluster.

The impacts of rainfall components on vegetation were also strongly related to the annual rainfall amount. The rainfall pattern showed the frequency components overweighted the intensity and duration components in the semi-arid and sub-humid areas, and the major distribution of rainfall pattern change was closed to frequency direction in Figure 5-7 within an encircled shadow area. The ternary diagram of rainfall pattern change was partitioned into four sections by 50% percentage black lines, which indicated the intensity and duration component became the dominating factors to vegetation in wet regions, but most sites controlled by the frequency component were located in semi-arid areas or even drier regions.

5.3.3 Vegetation responses to rainfall pattern changes

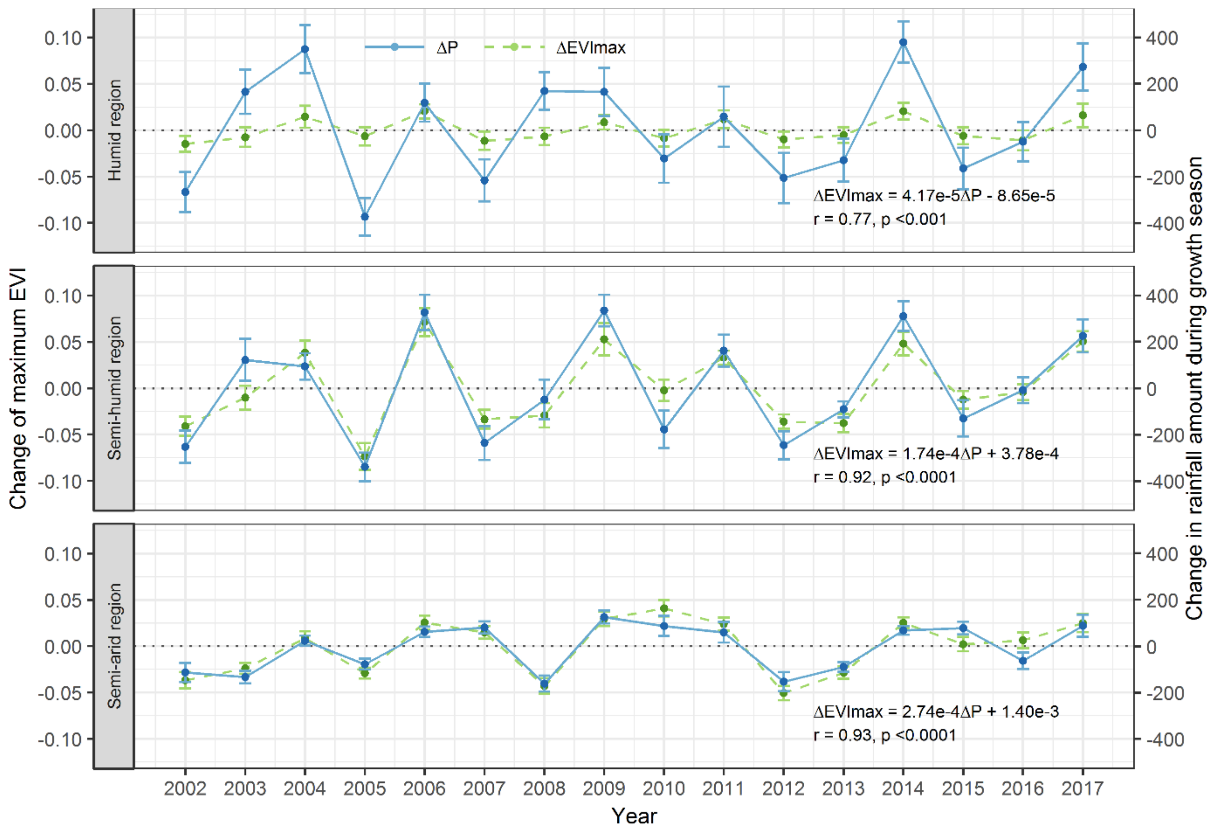

Figure 5-5. Vegetation responses to rainfall amount change over different rainfall conditions. The regression formula of ΔEVImax and ΔP was shown in panels, and Pearson's p-values were also listed. The error bar represented the standard deviation.

The vegetation responses to rainfall amount changes during the growth season had noticeable differences among semi-arid, semi-humid, and humid regions (in Figure 5-8).

The regions were partitioned according to the rainfall constraints and the impacts of rainfall pattern components. Firstly, all biomes were shown a significant response to rainfall variation with representing the Pearson's r as 0.77, 0.92, and 0.93 in humid regions, sub-humid regions and semi-arid regions, respectively. The highest sensitivity to rainfall variation was captured in semi-arid regions with the fluctuation of *Δ*EVImax as 0.05. However, the limited responses of vegetation (as *Δ*EVImax varied within 0.025) to rainfall variation were observed in humid regions, where even if *Δ*P could be the largest change reaching up to 400mm. Vegetation in the sub-humid region demonstrated a synchronize response to rainfall fluctuation with the maximum magnitude of *Δ*EVImax compared to vegetation in the other two regions, which could be as large as 0.075.

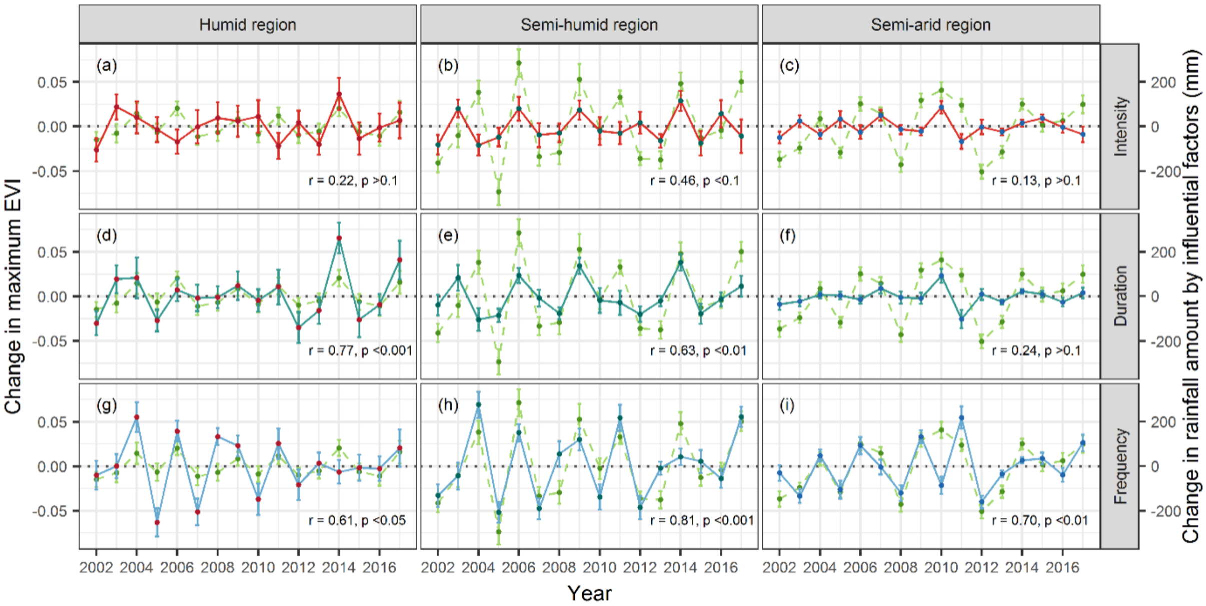

Figure 5-6. Vegetation responses to the rainfall change components of intensity, duration, and frequency over semi-arid, sub-humid and humid regions. Pearson's r denoted correlation between *Δ*EVImax and the corresponding rainfall pattern component under three different rainfall conditions.

The impacts of intensity, duration, and frequency of rainfall pattern on vegetation dynamics were varying under different water conditions illustrated by the correlation between the mean value of *Δ*EVImax and the mean value of *Δ*P by each component over 16 years in Figure 5-9. Above all, only the duration and frequency components were significantly correlated with vegetation dynamics in humid regions, and Pearson's r values were shown as 0.77 and 0.61, respectively.

However, the intensity component was not significant in humid regions, because some specific years were out-of-phase. In sub-humid regions where rainfall could be a critical climate factor for biomes, the duration and frequency components were shown significant impacts on vegetation dynamics with Pearson's r values as 0.63 and 0.81, respectively. In addition, the intensity component was shown slightly significant with Pearson's r values as 0.46. Especially, the correlation between the frequency component and ΔEVImax were in-phase over study years. Whereas, only the frequency component was significantly correlated with ΔEVImax, and the p-value was less than 0.01in semi-arid regions. The intensity and duration components were out-of-phase in most years except in 2010, where increasing rainfall amount contributed by intensity and duration may offset the declined rainfall amount by frequency to maintain increment of EVI.

5.4 Discussion

5.4.1 The spatial regime of the impacts of rainfall pattern changes

We observed the impacts of rainfall pattern changes have a distinct spatial partitioning regime from the coastal humid regions to the central semi-arid regions. The Northern Territory was divided into three zones by two rainfall isohyets around 900 mm and 400 mm located near 15 °S and 22 °S. The influences of rainfall pattern changes on vegetation dynamics were characterized heterogeneously.

In humid regions where the average annual rainfall was above 900 mm, rainfall was not a constraint to vegetation growth, and changes in rainfall amount during the growth season caused few vegetation responses by showing "slightly significant" or "not significant" correlation between ΔP and ΔEVImax in Figure 5-3(b). However, the rainfall change components of intensity and duration became the controlling factors to vegetation dynamics in rainfall sufficient regions by showing a higher value of the relative importance than that of frequency. The reasonable explanation could be the lasting time and intensity of one rainfall event in wet regions have more influential effects on deeper soil infiltration and soil water maintenance.

However, with rainfall declined from the northern coastal regions towards the inland regions, vegetation becomes more and more sensitive to rainfall pattern variations, and frequency becomes the dominating factor that influences vegetation dynamics mostly by showing more than 50% of the relative importance of the frequency component compared with the other two rainfall pattern factors in the sub-humid regions, where the average annual rainfall ranges from 400 mm to 900 mm. In semi-humid regions, increasing the number of rainfall events may produce more positive responses of vegetation, rather than heavy rainfall events or a longer continuous rainy period. This result showing the frequency of rainfall pattern was the critical factor influencing on vegetation dynamics are also in line with many previous studies, including field experiments and statistical analysis of meteorological time series (Guan et al. 2018; Sepulveda et al. 2018). Our results confirmed the view that frequency is the dominating factor to influence vegetation growth in water-limited regions.

In semi-arid regions, we observed that the frequency factor still played a role in controlling vegetation dynamics compared with the intensity and duration factors. The relative importance of frequency declined below 50%, because the impacts of the intensity and duration factors increased in drier regions. This implied the biomes in dry land enhanced its responses to rainfall pulses, in terms of intensity and duration, to utilize the limited water resources. Because frequent rainfall events are not always expected in dry regions, so vegetation changes its behaviours, structure and strategies to adapt to environments and climate change.

5.4.2 Dominating factors of rainfall pattern controlling vegetation dynamics

We found that the frequency was the most importance factor in driving vegetation dynamics in water limited regions, including in sub-humid regions and semi-arid regions. Generally, higher frequency of rainfall events contributes to the increment of total rainfall amount and lower frequency of rainfall events causes drought or water deficit with long-term dry days. Soil moisture content hardly maintains enough water for plants with lower frequency of rainfall events, because soil water can be evaporated, and soil water content drops incurring drought until next valid rainfall comes. This may explain the reasons that the frequency was a more important factor than intensity and duration in drier regions.

Although frequency, as a more critical factor compared with intensity and duration, dominated the vegetation growth in most semi-arid regions, our studies also illustrated that the relative importance of frequency declined in some specific spots located in desert regions (Figure 5-5). In addition, frequency was not a dominating factor to vegetation in humid regions in our study area, where limitations could mainly be temperature and radiation (Beringer et al. 2011; Whitley et al. 2011). In water sufficient regions, vegetation dynamics was prone to be stimulated or influenced by an intensified rainfall event or longer rainy period rather than fluctuation of rainfall frequency.

Overall, our results revealed that the relative importance of frequency controlling vegetation dynamics was highly linked to rainfall amount level (Figure 5-7). Frequency, as the dominating factor of rainfall pattern, controlled vegetation dynamics in semi-humid regions and strongly influenced vegetation growth in semi-arid regions. Compared with frequency, intensity and duration only play a dominating role in wet regions. This hints changes in rainfall patterns caused by frequency variation may have higher correlated responses for xeric ecosystems rather than mesic ecosystems.

5.4.3 Vegetation responses to variations of rainfall patterns differently under different rainfall conditions

We found that the responses of savanna biomes to changes in rainfall amount under different rainfall conditions presented a clear distinction (Figure 5-8). In humid regions, the biomes, comprising of trees and grasses, was the most stable ecosystems compared with biomes located in drier regions. Although the amplitude of ΔP were able to vary from -400mm to 400mm, ΔEVImax which represents yearly vegetation dynamics only presented a limited fluctuation within 0.025. It denoted the impact of rainfall amount on savanna ecosystems was tiny when rainfall was enough and no longer as a constraint on controlling vegetation dynamics.

However, in sub-humid regions with the average annual rainfall between 400mm and 900mm, vegetation dynamics (ΔEVImax) responded to ΔP mostly, ranging from as low as -0.075 to as high as 0.075. The fluctuation of rainfall amount only weakened slightly compared with rainfall in humid region, vegetation response to variation changes was significant by showing Pearsons'r as 0.92 and p-value less than 0.0001. The biomes in sub-humid regions showed a higher resilience compared to the biomes in humid regions or in semi-arid regions. For instance, biomes suffered from a drought in 2005, but it recovered in 2006 immediately with rainfall increased. In semi-arid region, vegetation dynamics was highly correlated to the variation of rainfall amount. In addition, it showed ΔEVImax was the most sensitive proxy to ΔP, showing the changing rate as 0.0274 per 100 mm.

Apart from the vegetation dynamics influenced by change in rainfall amount, our results also revealed that rainfall patterns changes determined by different components, including intensity, duration, and frequency, drove vegetation dynamics of savanna ecosystems differently under different rainfall conditions.

In humid regions, biomes, comprising of both trees and grasses, were not sensitive to rainfall variation, because rainfall amount has already reached up to a certain level to satisfy water demands. However, the duration component of rainfall pattern determined by the consecutive rainy days still has a distinct impact on driving vegetation dynamics (Figure 5-9). Frequency also play a role in affecting vegetation dynamics, but vegetation responses was limited in humid regions. In terms of the intensity component of rainfall pattern, vegetation responses were liable to correlate with strong pulses, but vegetation dynamics was confined or out-of-phase when rainfall intensity was limited.

In sub-humid regions, vegetation dynamics was highly correlated to the variations of the frequency component, and also showed "slightly significant" or "significant" correlated with intensity and duration by showing p-value less than 0.1 and 0.01, respectively. Vegetation growth under this rainfall condition is mainly constrained by water, and frequency is the most dominating factor to govern rainfall amount change. Therefore, a quite good fitting relation can be obtained between vegetation and the frequency component. Meanwhile, biomes performed a really good resilience in sub-humid region. In our case, the vegetation dynamics was mainly controlled by the variation of the frequency component from 2002 to 2013, and the study area suffered from a severe drought in 2005, but vegetation growth bounced strongly in 2006 when the components of rainfall pattern also increased (Figure 5-9).

In semi-arid region, vegetation dynamics was also governed by frequency but the correlation between the frequency component and vegetation dynamics declined compared with that in semi-humid regions. In drier region, where the average annual rainfall is below 400 mm, the contribution of intensity and duration to changes in rainfall amount was tiny. However, this not denoted vegetation in drier region was not sensitive to changes in intensity and duration of rainfall pattern, but vegetation links to frequency strongest because changes in frequency of rainfall pattern contributed to changes in rainfall amount mostly. Besides, in semi-arid or even drier regions, ground-water dependent ecosystems also weakened the dependence on rainfall (Eamus 2006), so the sensitivity of vegetation dynamics to changes in rainfall pattern also declined.

5.4.4 Implications of rainfall pattern analysis and its uncertainties

Assessing the impacts of rainfall pattern variations on vegetation dynamics is critical to understand the influences of climate change, especially in water-sensitive regions and for vulnerable xeric ecosystems. In this study, we decomposed the change of rainfall amount during the period prior to the date of maximum EVI to attribute the change in rainfall amount into three major factors of rainfall, namely intensity, duration, and frequency. This approach is a method based on the statistical information of rainfall events during the growth season, which is the most water-sensitive period for vegetation growth and also consider the impact of rainfall timing on vegetation dynamics. We characterized the variability of rainfall patterns by using the total differential of rainfall amount with respect to rainfall factors of intensity, duration, and frequency. Therefore, the impacts of rainfall change produced by different components could be evaluated and compared quantitatively in the same dimensional unit.

The uncertainty of this study was mainly caused by rainfall event measurements because missing observations and interpolation of rainfall can introduce errors into statistical processes of counting intensity, duration, and frequency. However, the abovementioned results showed that we captured the features of rainfall pattern to obtain the explainable correlations with vegetation dynamics, which indicated our method is effective to analyze the impacts rainfall pattern changes on savanna ecosystems.

5.5 Conclusions

In this study, we fulfilled our research to explore the dominating roles of rainfall pattern changes in driving savanna ecosystem under climate change. The study area was in the Northern Territory where a well-known rainfall gradient is appropriate to analyze the impacts of rainfall variability. Our results revealed the roles of intensity, duration and frequency to vegetation dynamics could shift from humid regions to semi-arid regions, which partitioned our study area into three zones by two rainfall isohyets, 400 mm and 900 mm. We also found frequency was more critical to vegetation growth in water-limited regions overweighting the impacts of the other two factors, intensity and duration. Savanna ecosystems under different rainfall conditions responses to the components of rainfall pattern differently. However, vegetation biomes in semi-humid regions represented the highest correlation with all three rainfall factors, intensity, duration, and frequency. Besides, we found savanna ecosystem in humid regions was the most stable ecosystems with limited responses to rainfall variations; savanna ecosystem in semi-humid regions was the most resilient to rainfall abnormality; and savanna ecosystems in semi-arid regions was the most sensitive to changes in rainfall amount.

In perspective of climate change, vegetation resilience probably benefits from increasing frequency of rainfall instead of extreme heavy rainfall event but a long spell of drought. This research contributes to further understanding of rainfall pattern influences on vegetation via solid data supports. In addition, the results associated with rainfall gradient can be a benchmark for further studies of vegetation responses to rainfall pattern changes in water-sensitive regions. The approach applied in this study also provided a perspective upon estimating impacts of rainfall factors, which could also contribute to our understanding of climatic influences and analysis of future climate projections.

Chapter 6: Analyzing the influences of rainfall pattern changes on savanna ecosystems in Northern Australia via combining TRMM and MODIS satellite observations

Abstract

Climate change has influenced extensive areas with a significant temperature rising, thereby the accelerated hydrological processes incurs rainfall pattern changes at a large spatial scale. Although the impacts of rainfall variability and hydrologic extremes on ecosystems has been addressed mostly to investigate climate change, the spatiotemporal influences of rainfall regimes on ecosystems have still received less attention, especially in consideration of analyzing the impacts of rainfall pattern changes at a large spatial scale. Here we explored the relationship between rainfall pattern and vegetation growth of savanna ecosystems by combining TRMM precipitation satellite observations and MODIS satellite data to analyze the impacts of rainfall pattern changes in northern Australia with our purpose to demonstrate that whether TRMM is applicable to describe changes in rainfall patterns at a large spatial scale. Our results showed that the correlation coefficient is 0.76 between hydrological yearly rainfall and maximum EVI values, and also illustrated a significant correlation between the interannual variation of rainfall and vegetation dynamics. Taking advantage of TRMM with an extensive monitoring scope, we found the roles of rainfall patterns in influencing the vegetation dynamics were changing along with rainfall gradient from the humid coastal regions to the semi-arid inland regions. Surprisingly, our results also support the view that the frequency factor of rainfall patterns influences the vegetation growth mostly in water-controlled regions, compared with the other two factors, namely intensity, and duration. Besides, the savanna biomes in semi-humid regions were more sensitive to respond to rainfall variations by showing the highest percentage of the changed maximum EVI value. Our findings suggest that the applicability of TRMM satellite data is appropriate in analyzing rainfall pattern changes and its coupling influences on vegetation growth at a large spatial scale. The consistent findings of the dominating roles in driving vegetation dynamics also reinforce our understanding of the relationship between water and vegetation under climate change and support the prediction of vegetation responses to hydroextremes.

Keywords: TRMM, MODIS, rainfall pattern, savanna ecosystem, northern Australia

6.1 Introduction

Global warming has accelerated the hydrological cycle significantly following the consequences that heavy rainfall events becomes more frequent and rainfall pattern also enlarge its variability at both spatial and temporal scales (Allan et al. 2008; Asadi Zarch et al. 2015; Guerreiro et al. 2018). Terrestrial ecosystems have suffered the pressure of climate change by changes in the processes of photosynthesis, transpiration, biomes structure, and regional distribution (Barron et al. 2012; Cleverly, Eamus, Van Gorsel, et al. 2016; Eamus 2006). Rainfall, as one of the most critical and variable factor, links water, carbon, and energy together to influence terrestrial ecosystems directly and indirectly, especially considering savanna ecosystems, which was reported as the major ecosystem contributing to 20% of the global land area (Eamus et al. 2013). However, with the dramatic changes in rainfall patterns globally, there is an urgent need to assess the influences of rainfall patterns changes on water-sensitive ecosystems in large extensive spatial regions.

Indeed, a great deal of research has pay attention to the impacts of the spatiotemporal variations of rainfall regimes on ecosystems (Fensham et al. 2005; Peng et al. 2013; Peñuelas et al. 2004). Field experiments, rainfall gauge data, and flux tower observations were applied to identify the influences of rainfall variability on ecosystems, in aspects of productivity, distribution, and structure(Huxman et al. 2004). For instance, Radu et al. (2018) designed the experiments to illustrate that changes to rainfall frequency will lead to the increasing coverage of vascular plant in peatlands, and influence carbon sink metabolism. Petrie et al. (2018) investigated the relationship between net primary productivity and precipitation by compiling dataset of eight North American grasslands sites. The results emphasize the importance of legacy effects on productivity.

Although the previous studies stated the significant influences of rainfall variations on ecosystems, it is still difficult to present the spatial pattern of influences of rainfall. The conventional ground rain gauge data are able to provide the features of rainfall pattern by recording each rainfall event precisely but was limited on its applicability considering the extrapolation in large areas (Villarini et al. 2008). With the developing of remote sensing imagery, the available space-borne precipitation measurements are capable to monitor rainfall regimes coupling with vegetation indices by using TRMM satellite (Sorooshian et al. 2002). Zhang et al. (2005) pioneered to demonstrate the application of TRMM data coupled with MODIS observations of vegetation in monitoring the response of vegetation phenology to precipitation in Africa. Afterwards, the precipitation indices derived from the TRMM data were also developed to represent the interannual variability of spatial rainfall regimes (Du et al. 2013; Weber et al. 2009).

With the continuous collections of TRMM imagery, TRMM instruments have been demonstrated to represent rainfall variability at spatial and temporal scales effectively (Maggioni et al. 2016). Many studies also related TRMM observations to ecosystems to research the impacts of the spatial rainfall variations on vegetation (Ma et al. 2018; Suepa et al. 2016; Zhang et al. 2005). However, there is less research addressing on the issue that the ecohydrological impacts of rainfall pattern changes in perspective of rainfall event-based analysis. Monthly and yearly TRMM observations have illustrated a positive correlation with vegetation, but daily TRMM product 3B42 has a higher error in comparison with the ground rain gauge measures, which is mainly induced by the coarse spatial resolution and underestimation of heavy rainfall (Chokngamwong et al. 2005). However, it is still worthy of the practice in characterizing the rainfall pattern changes by utilizing daily TRMM products to retrieve information on rainfall events, because we are urgent to evaluate the substantial impacts of rainfall pattern at a large regional, continental, and even global scales.

Referring to the above context, we intended to demonstrate the applicability of daily TRMM measurements in analyzing the spatiotemporal variations of rainfall pattern, and establish the relationship with vegetation dynamics to investigate the spatial influences of rainfall pattern by applying the approach of rainfall pattern analysis proposed in the previous chapter. In this study, our objectives were to: 1) explore the correlation between rainfall and vegetation at spatial and temporal scales; 2) illustrate the spatiotemporal responses of savanna ecosystems to rainfall pattern changes; 3) demonstrate the mechanism of rainfall pattern changes in driving vegetation dynamics via coupling the TRMM precipitation observations and vegetation index measurements. Our study is expected to provide insight into the applicability of remote sensing in rainfall pattern analysis at large spatial scale, and reveal the spatiotemporal impacts of rainfall pattern on terrestrial ecosystems.

6.2 Data and Methods

6.2.1 Study area

We conducted this study in the Northern Territory, Australia, which is the same study area for the previous chapters. Hence, the findings in this study could also relate to the results in the previous chapters for supports and comparison. The detail description of study area was introduced in section 3.2.1, section 4.2.1, and section 5.2.1.

6.2.2 TRMM rainfall observations

TRMM satellite was launched in 1997 with the primary purpose to measure precipitation in tropic areas. The coverage of TRMM data is 180°W -180°E and 40°S-40°N, which covers our study area. In this study, we adopted the daily precipitation product 3B42 to obtain rainfall event estimates at spatial scale. The spatial resolution of 3B42 is 0.25°, and the period we collected data was from 2000 to 2017, which is corresponding to the length of MODIS data we used.

6.2.3 Vegetation Index

In this study, we also used MODIS product MOD09A1 to represent vegetation dynamics. The detail description of data and processes was introduced in section 4.2.4. The only extra process was to resample satellite imageries for upscaling the spatial resolution from 500 m to 0.25 degree for matching the spatial resolution of TRMM satellite product.

6.2.4 Phenology metrics from MODIS EVI

We used the same definition and phenological metrics to characterize vegetation dynamics. The detail description was introduced in section 5.2.4.

6.2.5 Changes in rainfall pattern and its components

We used the same method to analyze changes in rainfall pattern by replacing ground rain gauge data with TRMM precipitation satellite observations. The detail method was described in section 5.2.5 and section 5.2.6.

6.2.6 Analysing approaches

In this study, we applied spatial correlation, linear regression to evaluate the validation of TRMM data for characterizing rainfall pattern. Besides, we also use the relative importance to analyse the dominating role of rainfall pattern and the spatial regime of rainfall pattern. The more details were referred to section 5.2.7 and section 5.2.8.

6.3 Results

6.3.1 The Correlation between TRMM rainfall measurements and MODIS vegetation observations

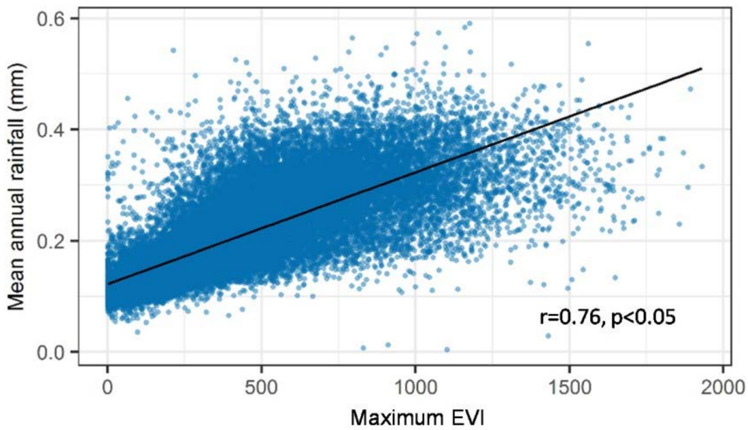

Figure 6-1. The correlation between maximum EVI values and annual rainfall amount retrieved from TRMM satellite imagery in the Northern Territory Australia. The correlation coefficient is 0.76 and p-value is significant (<0.05).

The relation between rainfall represented by TRMM observations and vegetation represented by MODIS maximum EVI values was shown in Figure 6-1. The annual rainfall amounts calculated based on daily measurements and hydrological year were linked to vegetation dynamics significantly (r=0.66, p-value < 0.05). In addition, the deviations were smaller in drier regions compared with that in wetter regions.

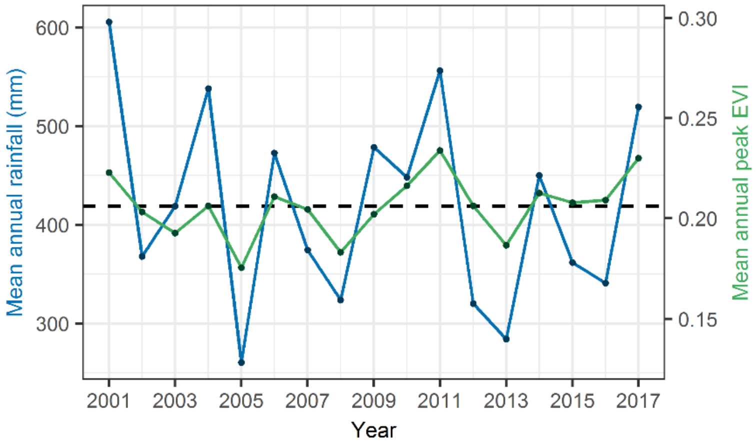

Figure 6-2. The internanual variations of mean annual rainfall and mean maximum EVI in the Northern Territory, Australia. The black dashed line indicates the mean values for rainfall in the left y-axis and the mean values for EVI in the right y-axis.

Besides, the fluctuations of interannual changes in rainfall and vegetation can also reflect the significant correlation between TRMM precipitation measurements and MODIS vegetation observations (Figure 6-2). The changes in the spatial mean value of maximum EVI was in phase with the changes in the spatial mean value of annual rainfall by showing that the peak value of EVI was sensitive to the wet year, and the bottom value of EVI was also accompanied with water deficit.

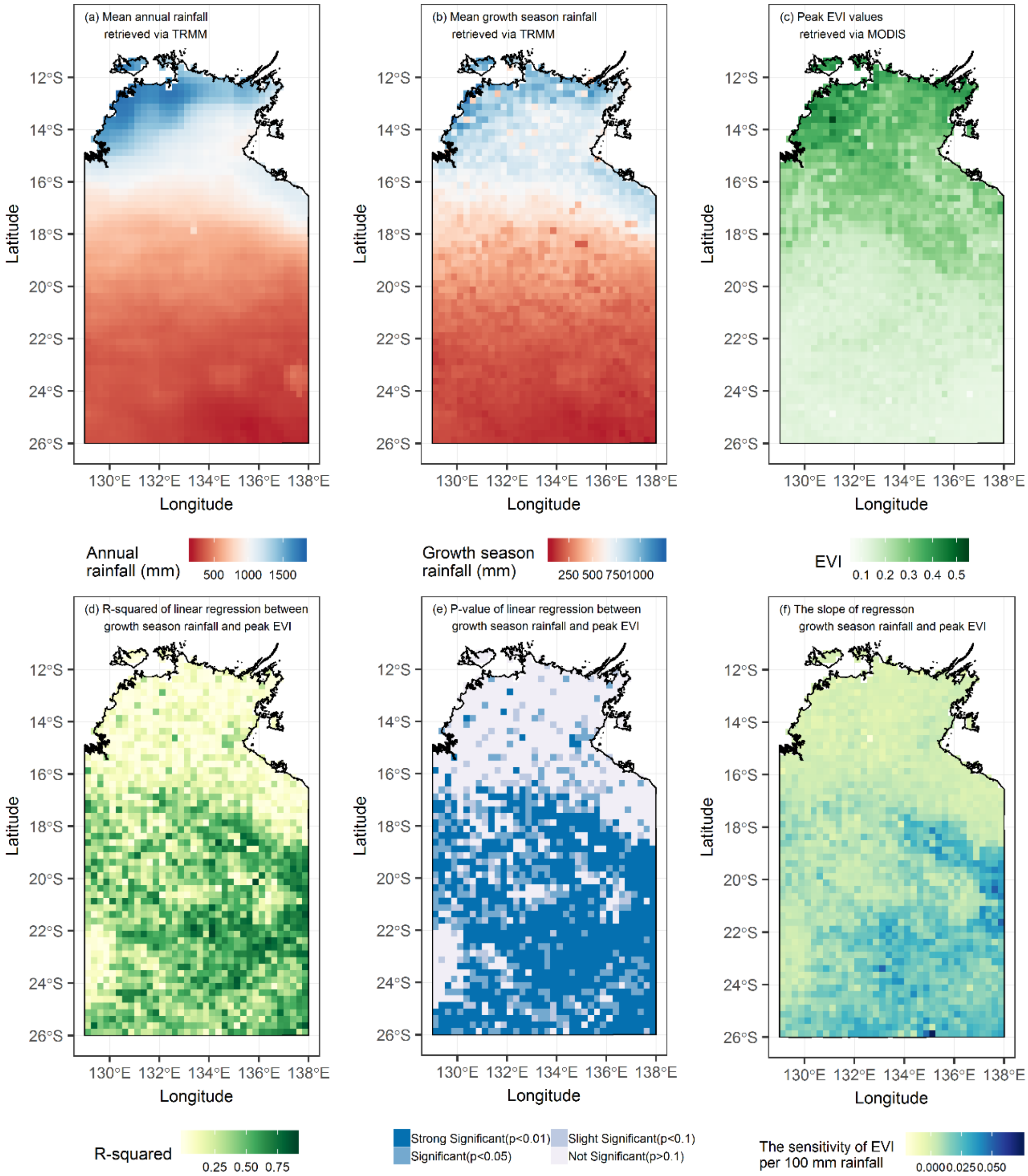

Figure 6-3. The spatial patterns and the spatial linear regression between rainfall and vegetation in the Northern Territory, Australia. a) The spatial pattern of annual rainfall retrieved from TRMM according to the daily product; b) The spatial pattern of rainfall during the growth season; c) The spatial pattern of maximum EVI; d) R-squared values of the spatial linear regression; e) P-values of the spatial linear regression; f) The slope coefficients of the spatial linear regression.

The spatial regimes of rainfall and vegetation were distinctive partitioned along with the rainfall gradient from the coastal regions to the central inland regions (See Figure 6-3). The annual rainfall declined from 2000 mm in the northern regions to 200 mm in the hinterland, with a clear partitioning line near 17 °S latitude to indicate humid and semi-humid boundary (Figure 6-3.a). The spatial pattern of rainfall amount during the growth season was also similar to the spatial pattern of annual rainfall amount, indicating the spatial variations were controlled by rainfall conditions (Figure 6-3.b).

The maximum EVI values also showed a distinctive difference between wet coastal regions and dry inland regions (Figure 6-3.c). The average maximum EVI values in northern regions were above 0.3, and the average maximum EVI values in central regions were below 0.2. The mean value in water sufficient regions was statistically higher than that in water deficit regions. The savanna biomes consists of trees and grasses mainly with sufficient water supply, but the biomes are mainly grasses and shrubs, coexisting with sparse trees, which lead to the significant difference of EVI values.

The spatial linear regression between maximum EVI values and rainfall amount during the growth season was established over the study area to explore the spatial regime of savanna ecosystems responding to rainfall variations (Figure 6-3. d&e). Although the coastal regions showed higher maximum EVI values, the inland regions in semi-arid and semi-humid water conditions presented a significant correlation between rainfall variation and vegetation dynamics illustrated by higher R-squared values of linear regression than the coastal regions and extensive strong significant p-values (<0.01). There is a clear transit boundary near 17 °S in western 130 °E and dropping to 18 °S in eastern 138 °E, to partition the Northern Territory into water-controlled region and non water-controlled region. In addition, the spatial pattern of the slope coefficients also indicated the most sensitive biomes responding to rainfall variations were distributed in eastern semi-arid and semi-humid regions between 18 °S to 24 °S.

6.3.2 Ecosystems responses to changes in rainfall pattern considering extremes

According to the results shown in Figure 6-2, we noticed the driest year and wettest year for our study area were 2005 and 2017, respectively, which were also referred as "big dry" and "big wet" (Xie, Huete, et al. 2016a). In order to represent the responses of savanna ecosystems to rainfall distinctively, we described the spatial regimes of the changes in maximum EVI and changes in rainfall patterns.

As for the driest scenario in 2005, maximum EVI was changed mostly in semi-humid regions near 18 °S, where annual rainfall was 1000 mm (Figure 6-4). Considering the relative changed percentage, not only the semi-humid regions showed the distinctive decrease in maximum EVI, but also the drier inland presented a noticeable decrease in maximum EVI. Compared to the changes in vegetation growth, rainfall declined extensively in the Northern Territory. Besides, the strongest decrease in rainfall amount during the growth season was showed in coastal regions between 14°S and 16°S. We decomposed the change in rainfall amount by attributing the changed amount into three components, namely intensity, duration, and frequency of rainfall pattern. We found that only the spatial regime of rainfall changes by frequency component showed a similar spatial rainfall pattern to the spatial rainfall pattern, which denoted the decreased rainfall amount was mainly resulted from the decreasing change in frequency component, rather than the other two components (Figure 6-4. d-f). To claim the difference clearly, the spatial regime of the intensity component of rainfall change showed a certain increase in western coastal areas and south-eastern inland areas, which hinted that the heavier intensity of rainfall event could alleviate the severity of the drought in those regions. In addition, the spatial regime of the duration component of rainfall change mainly represented the obvious decrease in the coastal regions. In summary, compared among three rainfall pattern components, the frequency was the determining factor to influence the spatial pattern of rainfall changes.

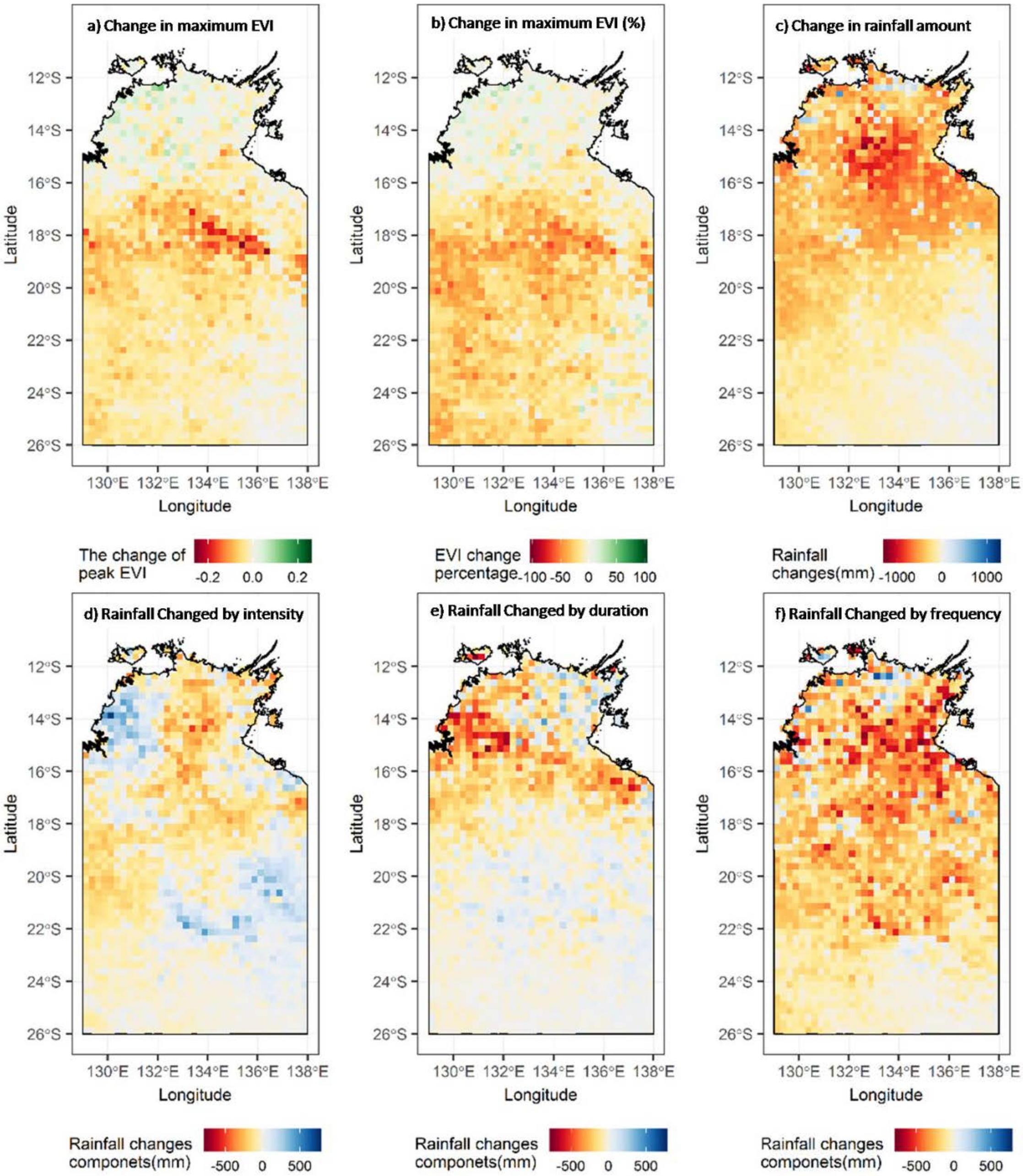

Figure 6-4. The spatial pattern of savanna ecosystems responding to driest scenario in 2005. a) The changed maximum EVI values compared with last year; b) The percentage of changed maximum EVI values compared with last year; c) The changed rainfall amount during the growth season compared with last year; d) The spatial pattern of the intensity component of rainfall changes; e) The spatial pattern of the duration component of rainfall changes; f) The spatial pattern of the frequency component of rainfall changes.

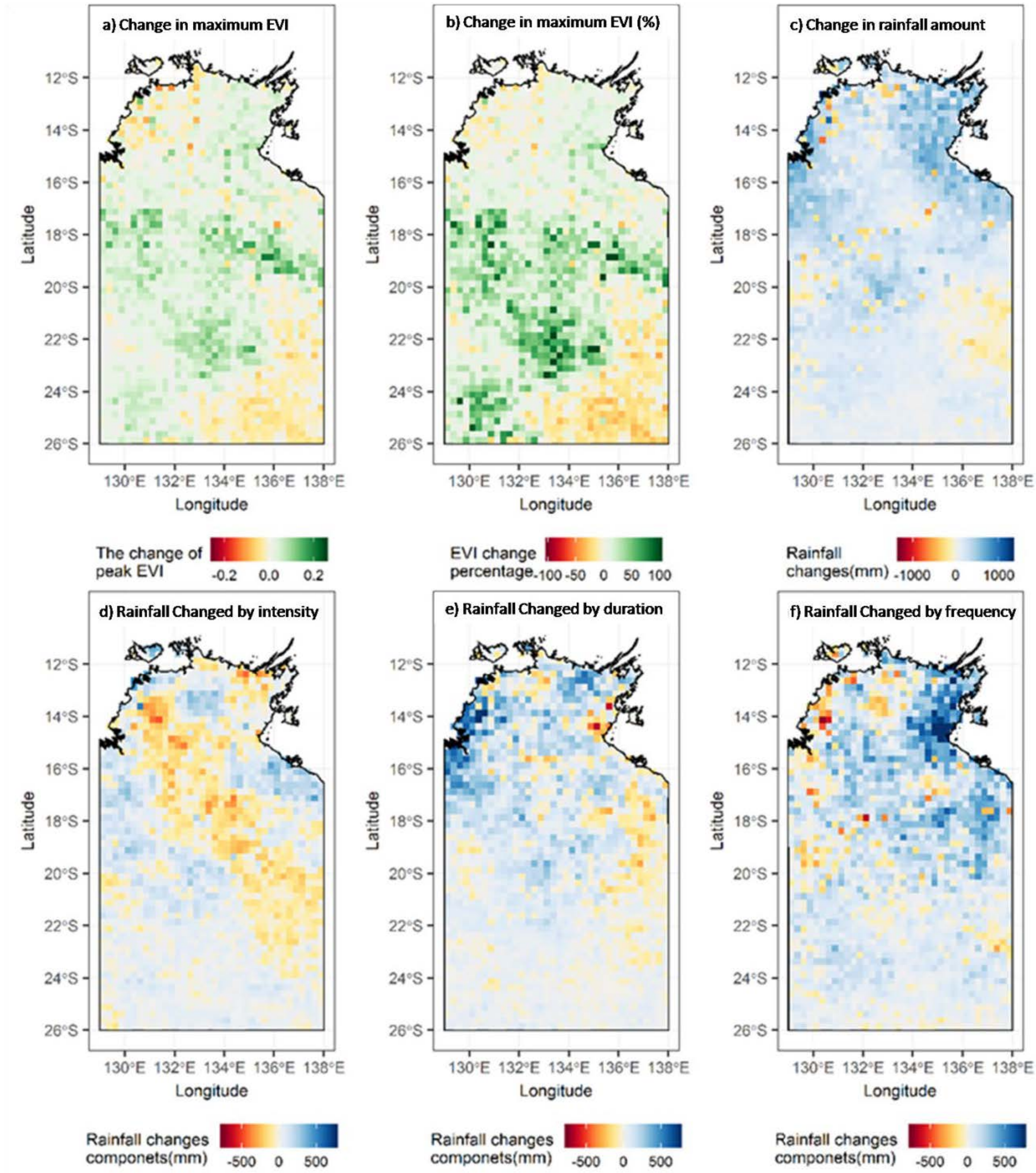

Figure 6-5. The spatial pattern of savanna ecosystems responding to wettest scenario in 2017. a) The changed maximum EVI values compared with last year; b) The percentage of changed maximum EVI values compared with last year; c) The changed rainfall amount during the growth season compared with last year; d) The spatial pattern of the intensity component of rainfall changes; e) The spatial pattern of the duration component of rainfall changes; f) The spatial pattern of the frequency component of rainfall changes.

By contrast, we considered the wettest scenario in 2017 to investigate the savanna ecosystems responding to water sufficient conditions (Figure 6-5). Similar to the driest scenario, the most sensitive biomes to rainfall changes were also located in semi-humid regions between 18 °S and 23 °S. However, the entire Northern Territory showed the increase in rainfall amount approximately, except parts of regions in the south-eastern showing the decrease in rainfall amounts. Both the frequency component of the rainfall change and the duration component of the rainfall change demonstrated the contribution to the spatial rainfall increases. Specifically, the prolonged duration of rainfall events mainly had a positive effect on the western coastal areas mostly (14 °S- 16 °S, 130 °E- 132 °E) to increase water availability. Similarly, the more frequent rainfall events contributed to the eastern coastal areas mostly (14 °S-16 °S, 134 °E-136 °E). Surprisingly, we noticed the intensity component of the rainfall change showed a large area of decreasing changes even during the wettest year, covering areas starting from north-western coastal regions (14 °S,131 °E) and stretching towards south-eastern inland areas (22 °S,137 °E).

6.3.3 Rainfall pattern changes in driving

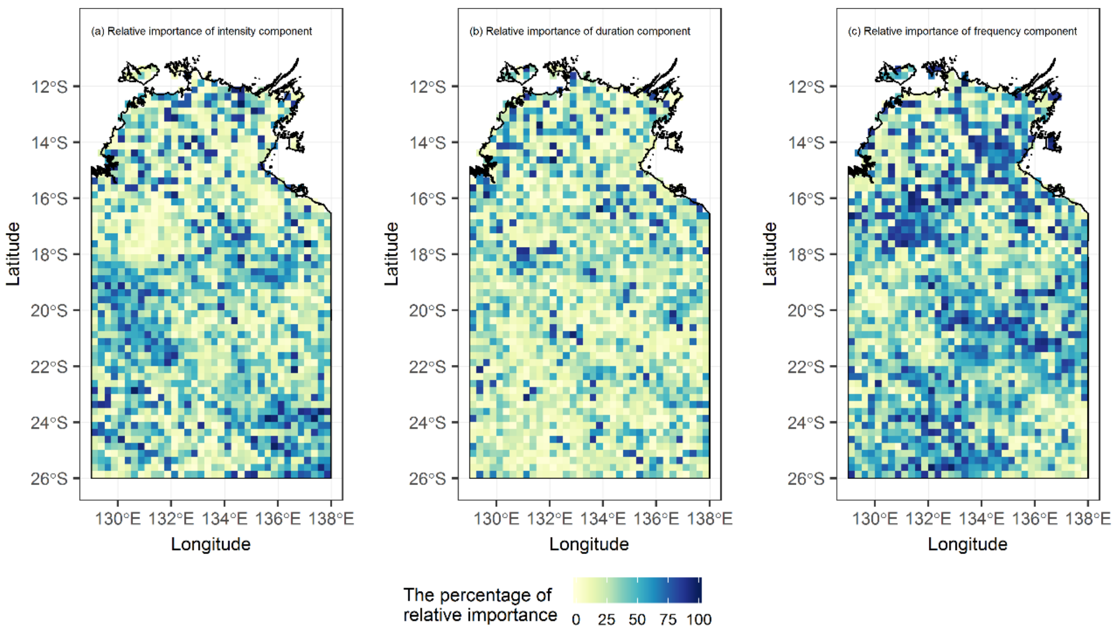

Figure 6-6. The spatial regimes of the relative importance of rainfall pattern changes. Panel a, panel b, and panel c denotes intensity component, duration component, and frequency component, respectively.

We investigated the dominating factors to drive vegetation responses by using relative importance method to evaluate the influences of three decomposed rainfall pattern components, namely intensity, duration, and frequency, in Northern Territory, spatially

(Figure 6-6). Compared among three factors, the frequency component had the highest percentage of the relative importance overall the spatial scope, followed by intensity component, and then duration component. From the coastal regions to inland regions, frequency strongly controlled some specific regions along with rainfall gradient (Figure 6-6.c). In addition, the spatial regime of the relative importance of intensity component seemed to present a spatial complementary relationship with that of frequency component. The two embedded spatial regimes of intensity component and frequency component controlled the most regions, whereas only sparse pixels in our study region represented the high percentage of relative importance of duration component.

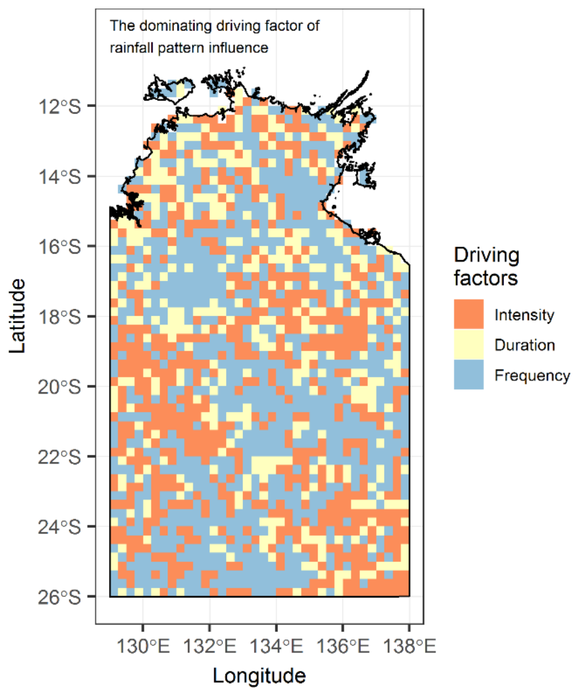

Figure 6-7. The spatial pattern of dominating factor in driving vegetation dynamics. Each pixel value was determined by the maximum relative importance of the component of the rainfall pattern change.

In order to highlight the dominating role of rainfall components in driving vegetation growth, we composited the spatial regime by showing the driving factor with the highest percentage of the relative importance of rainfall pattern components (Figure 6-7). In general, the frequency factor controlled the vegetation dynamics mostly distributing consecutively from the coastal regions to the inland regions. Besides, three zones were mainly dominated by the intensity factor. One zone was located in semi-humid region near 18 °S; one was located in eastern mountainous areas between 18 °S latitude and 22 °S latitude; the other one zone was in south-eastern semi-arid area. The duration factor presented the weakest controlling in vegetation growth by showing only scattered pixels marked as duration.

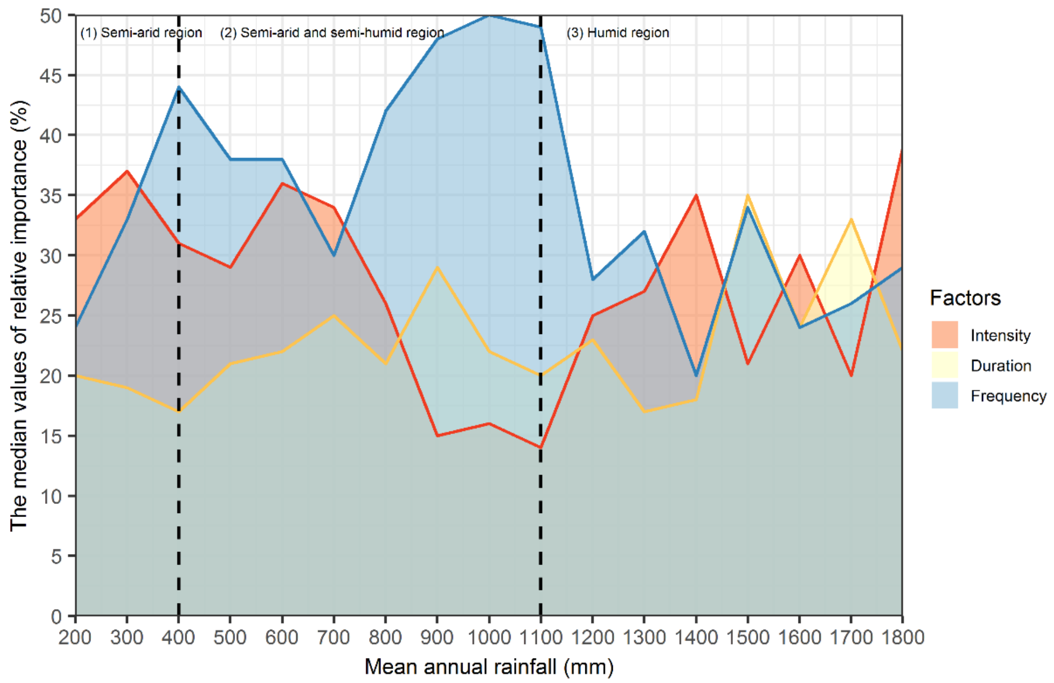

Figure 6-8. The role of rainfall pattern components along with rainfall gradient. The pixels were grouped by the average annual rainfall with 100 mm interval firstly, and then plotted the median values of relative importance of three rainfall pattern components together to demonstrate the fluctuation of rainfall pattern impacts along with rainfall gradient.

The impacts of changes in intensity, duration, and frequency of rainfall pattern varied along with rainfall gradient (Figure 6-8). The spatial regime was prone to be determined by the interactions among three rainfall components. In humid regions, the relative importance of intensity, duration, and frequency were almost equivalent with alteration among each component. There was no distinct dominating factor in humid region. With rainfall declined, the relative importance of frequency had increased dramatically rising up to as high as 50%, and the frequency became the dominating factor in driving vegetation dynamics in the semi-arid and semi-humid regions. Two boundary rainfall lines, 400 mm/yr and 1100 mm/yr, partitioned the Northern Territory clearly considering the varying relative importance of rainfall pattern components. When rainfall decreased below 400 mm/yr in semi-arid regions, the controlling role of frequency factor was weakened, and the relative importance of intensity component was weighted instead. In addition, the results based on TRMM satellite observation indicated the role of rainfall pattern changes along with rainfall gradient, which was consistent with our findings based on ground rain gauges stated in the previous chapter.

6.4 Discussion

6.4.1 The applicability of TRMM precipitation observations in analyzing the influences of rainfall pattern

In this study, we applied TRMM daily product 3B42 to explore the impacts of rainfall pattern changes at a large spatial scale. We obtained a board view on a sub-continental rainfall pattern at expense of finer resolution compared with the ground rain gauge data. At beginning, we have some doubt in using space-borne rainfall estimate to analyze rainfall variation based on rainfall events. The precision of the spectrum measurement could lead to errors of statistical information on rainfall event directly. For instance, the underestimating of TRMM could weaken the impacts of the intensity component on ecosystems (Chokngamwong et al. 2005; Maggioni et al. 2016). Surprisingly, we found the accumulated annual rainfall amount derived from daily product was effective to express the relationship between water and vegetation. In addition, TRMM data was also able to reflect interannual variability coupling with vegetation dynamics.

To further explore the applicability of TRMM in rainfall pattern analysis, we established the spatial regression between rainfall amount during the growth season and maximum EVI. The spatial regime of correlation was in line with rainfall conditions along rainfall gradient from the coastal regions to the inland regions. Furthermore, we reinforced our confidence on the applicability of TRMM daily product in analyzing rainfall pattern by applying the analytic method of rainfall pattern (proposed in Chapter 5) with TRMM data. The consistent results support the effectiveness of TRMM data but also expand our perspectives on the spatiotemporal variations in rainfall pattern.

In summary, TRMM daily product is able to characterize rainfall event at a large spatial scale for climatic assessment. Although this issue has received less statement, it is worthy of understanding the scope of application, especially considering the extensive spatial impacts of climate change.

6.4.2 The spatial regime of rainfall pattern and its impacts on savanna ecosystems

Taking advantage of TRMM, we acquired a board view on the spatiotemporal variations of rainfall pattern. Considering two scenarios, the driest year in 2005 and the wettest year in 2017, we found the changes in rainfall amount also presented a gradient from the coastal regions to the central regions. Actually it is understandable that average annual rainfall is much higher in humid regions than that in semi-arid regions, which causes larger fluctuation of rainfall amount in humid regions. However, we noticed the frequency component contributed to the change in rainfall amount mostly under both dry and wet scenarios (Figure 6-4 & Figure 6-5). The spatial outlines of change in rainfall amount and change in frequency component were similar. Because our results indicated the variations of rainfall amount were mainly derived from variations of rainfall frequency, this finding provides us a hint that we may pay more attention to variations of rainfall frequency when assessing the impacts of climate change, rather than intensity or duration.

We also noticed although change in rainfall amount was large in humid coastal regions, vegetation in semi-humid regions (latitude between 18°S and 22°S) responded to rainfall variations mostly. In addition, the spatial responding pattern stretched towards the drier semi-arid regions, even if the change in rainfall amount was tiny in semi-arid regions. This result was consistent with the findings in chapter 5 that ecosystems in semi-humid regions has the largest fluctuation of maximum EVI, and also indicated the resilience of ecosystems was stronger than ecosystems in humid or semi-arid regions. Furthermore, we found the ecosystems during the dry year have a larger responding area than the responding area during the wet year, indicating ecosystems in water-limited regions were more sensitive to drought. In summary, our results suggest that changes in rainfall pattern have the most influences on ecosystems in semi-humid regions than in other water conditions.

6.4.3 The spatial regime of the dominating roles of rainfall pattern in influencing vegetation growth along rainfall gradient

Eventually, we investigated the spatial regime of the dominating factors of rainfall pattern in influencing vegetation growth along rainfall gradient. We found that frequency was the most influential factor, which has the observable controlling over rainfall gradient regions. Intensity was the second influential factor but only showed higher relative importance in water-limited regions, including in semi-humid and semi-arid areas. Duration presented its influence only in some specific spots. Regionally, the areas controlled by different rainfall components followed the order by frequency, intensity, and duration (Figure 6-7). This result was in line with our previous findings in chapter 5 to support that frequency is the critical factor to influence vegetation dynamics mostly.

The overlapped median values of relative importance of each rainfall pattern component illustrated the interaction among vegetation dynamics, rainfall gradient level and rainfall factors (Figure 6-8). Indeed, the dominating role of rainfall factor was not constant, but the effect of rainfall component on vegetation dynamics was changing and shifting along rainfall gradient. For instance, it is clear that we hardly determined the most influential factor in humid regions according to Figure 6-8. Firstly, the altering relative importance values among three components of rainfall pattern were observed in humid regions. Secondly, although we noticed the frequency occupied a higher proportion of areas as the dominating regions than the other two factors in coastal areas (Figure 6-7), we have to realize water is not the constraint in humid region. Hence, even if the specific factor has a higher relative importance, it still has a limited impact on vegetation dynamics in humid regions.

Along the rainfall gradient, water constraint on vegetation growth is enhanced. Clearly, the relative importance of the frequency component increased dramatically in semi-humid regions (Figure 6-8), which represented a similar spatial regime to our previous findings in Chapter 5. Here, two annual rainfall isohyets boundaries were 400 mm/yr and 1100 mm/yr to partition the study area into three zones according to the relative importance of the rainfall component. Compared with the results in Chapter 5, the boundary for dividing the humid region and semi-humid region has risen up from 900 mm/yr to 1100 mm/yr, but both results and findings supported the view that the dominating role of rainfall pattern varied under different rainfall levels. However, in semi-arid or drier regions, considering the intense evapotranspiration, the impacts of frequency weakened, but the role of intensity and duration in rainfall infiltration into deep soil enhanced their impacts on vegetation growth.

6.5 Conclusions

In this study, we contributed to the further understanding of the influences of rainfall pattern on vegetation dynamics at a sub-continental scale by coupling TRMM precipitation measurements and MODIS vegetation observations. Our results supported the applicability of TRMM data in analyzing rainfall pattern by showing the consistent findings compared with the results based on ground rain gauge data. In addition, taking advantage of TRMM products with an extensive scanning extent, we noticed the ecosystems in semi-humid regions responded to changes in rainfall pattern mostly. Considering the roles of rainfall pattern components in controlling vegetation dynamics, the semi-humid region in our study area was dominated by frequency. The impact of the frequency component declined but still act as a controlling factor in semi-arid region. As for humid regions, the impacts of intensity, duration, and frequency were equivalent according to the median values of relative importance. Our study provides a feasible approach to analyze the impacts of rainfall pattern at a large spatial scope or even in ungauged regions, which improves our understanding of the spatiotemporal variations in rainfall patterns and benefits the prediction of terrestrial ecosystems to mitigate the effects of climate change.

Chapter 7: Final conclusions

7.1 Summaries

In this study, we mainly explored the relationship between rainfall pattern and vegetation dynamics under climate change. Our hypothesis was rainfall pattern could certainly be influenced by climate change, and afterwards had an impact on terrestrial ecosystems. To investigate the impacts of rainfall pattern changes, we analyzed rainfall variations coupling with vegetation dynamics via multiple data sources, including ground rain gauge data, remote sensing observations for precipitation and vegetation. The main findings were summarized as follow:

1) We diagnosed rainfall pattern variations from the aspects of trend, periodicity, time of abrupt changes in rainfall amount, rainfall probability density distribution, and frequency of extreme rainfall events based on long-term rain gauge data. The results supported the view that rainfall patterns have changed significantly and accompany with higher variability. Above all, we noticed annual rainfall amounts in our sub-continental region were seen to consistently increase over time, but the interannual fluctuation of annual rainfall also had increased in recent decades (since about 1970). Due to the analytical findings derived over a rainfall gradient varying from 1800 mm/yr to 200 mm/yr, the magnitude and variation of rainfall pattern changes showed distinct differences from wet to dry environments. However, the modes and shifting time of rainfall pattern changes were shown to be similar across different annual rainfall conditions. We also confirmed that the frequency of extreme rainfall events had increased significantly across this sub-continental region.

2) We evaluated the sensitivity of vegetation phenology to annual rainfall amount along a rainfall gradient in the Northern Territory, Australia. Two major phenological proxies, LGS and maximum EVI, retrieved from MODIS satellite data, were compared for different ecosystems and rainfall conditions. Using the average EVI during the growing season as a proxy for vegetation growth, we concluded that maximum EVI was superior to LGS for representing vegetation dynamics. Maximum EVI was highly correlated with average EVI for grass, shrub, and tree ecosystems. Furthermore, the

relationship between maximum EVI and annual rainfall amount was linear in water-limited regions. We concluded that maximum EVI was more sensitive to annual rainfall than LGS, which we can apply to characterize vegetation responses to rainfall variations.

3) We explored the dominating roles of rainfall pattern changes in driving savanna ecosystem under climate change. The results revealed the roles of intensity, duration and frequency to vegetation dynamics could shift from humid regions to semi-arid regions, which partitioned our study area into three zones by two rainfall isohyets, 400 mm and 900 mm. We found the frequency was more critical to vegetation growth in water-limited regions overweighting the impacts of the other two factors, intensity and duration. Savanna ecosystems under different rainfall conditions responses to the components of rainfall pattern differently. However, vegetation biomes in semi-humid regions represented the highest correlation with all three rainfall factors, intensity, duration, and frequency. Besides, we found savanna ecosystem in humid regions was the most stable ecosystems with limited responses to rainfall variations; savanna ecosystem in semi-humid regions was the most resilient to rainfall abnormality; and savanna ecosystems in semi-arid regions was the most sensitive to changes in rainfall amount.

4) We also contributed to the further understanding of the influences of rainfall pattern on vegetation dynamics at a sub-continental scale by coupling TRMM precipitation measurements and MODIS vegetation observations. Our results supported the applicability of TRMM data in analyzing rainfall pattern by showing the consistent findings compared with the results based on ground rain gauge data. In addition, taking advantage of TRMM products with an extensive scanning extent, we noticed the ecosystems in semi-humid regions responded to changes in rainfall pattern mostly. Considering the roles of rainfall pattern components in controlling vegetation dynamics, the semi-humid region in our study area was dominated by frequency. The impact of the frequency component declined but still acted as a controlling factor in semi-arid regions. As for humid regions, the impacts of intensity, duration, and frequency were equivalent according to the median values of relative importance. Our

study provides a feasible approach to analyze the impacts of rainfall pattern at a large spatial scale or even in ungauged regions, which improves our understanding of the spatiotemporal variations in rainfall patterns and benefits the prediction of terrestrial ecosystems to mitigate the effects of climate change.

7.2 Limitations and uncertainty

In this study, we mainly concentrated the impacts of rainfall pattern changes on vegetation growth, namely represented by the changes in maximum EVI. However, the timing of each rainfall event and rainy season is also critical and related to the timing of the growing season, which we have not addressed deeply to explore the temporal impacts of climate change. In further study, we should conduct a project to cover this research aim to reinforce a comprehensive understanding of the interactions between rainfall pattern changes and vegetation responses.

Apart from rainfall, temperature and radiation are the other two critical climatic variables to influence terrestrial ecosystems. However, we analyzed rainfall pattern changes regardless of influences resulting from temperature and radiation, because we conducted the research in the Northern Territory, Australia, where the climatic type mainly belongs to tropic climate. Thereby, we did not consider the impacts of variations in temperature and radiation. Actually, the interaction among those three factors is strongly related to photosynthesis and evapotranspiration, which also have effect on the relation between water and vegetation directly or indirectly. Hence, as for further research, we may continue our research to evaluate the influences of climate change on terrestrial ecosystems by involving rainfall, temperature, and radiation together.

The uncertainty of this study was mainly incurred by ground observations and remote sensing data. The SILO meteorological data for rainfall pattern analysis have some missing records. Although gaps are processed by rigid interpolation, the uncertainty of rainfall events retrieval could also induce error and cause misleading results in some sites. Besides, the remote sensing observations of TRMM and EVI also have uncertainty considering spatial scale and temporal interpolation. To minimize those impacts, the validation supported by ground observations could reduce the uncertainty from satellite measurements, which should be considered in further study. However, according to the results presented in this study, the analysis of rainfall pattern changes and its influences on vegetation were still valuable to shed light on the dominating role of rainfall pattern on vegetation dynamics under climate change.

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