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Identifying potential critical transitions in a forest ecosystem using satellite data

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Identifying potential critical transitions in a forest ecosystem using satellite data

by

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Abstract

Ecosystems can undergo changes that are slow and gradual, or an abrupt change - a sudden nonlinear dynamics that can bring catastrophic changes and ultimately leads to the change in the structure and functioning. Non-linear and discontinuous changes sometimes may cause the system to shift into another undesirable state, called 'regime shifts' or 'critical transition'. Recent model based and simulation studies have identified indicators of impending regime shifts that can be used to provide early warning signals of a critical transition or tipping points. However, these studies lack an empirical base and studies in real world ecosystems are largely missing. Therefore, this study attempted to identify potential critical transitions and tipping points in a Mediterranean type forest ecosystem. In this study, we argue that time series of enhanced vegetation index (EVI) derived from MODIS satellite images can help to identify potential tipping points and critical transitions. The long term increasing trend and changes in the statistical properties of the observed time series of metric-based early warning indicators of critical transition and tipping points - autocorrelation-at-lag-1, standard deviation and skewness are used to identify the potential transitions and tipping points. The study quantified early warning indicators for the Northern Jarrah Forest (NJF) ecosystem, but the strongest signals did not flag any forest that showed any signs of an impending shift. In contrast, it largely identified the areas that were mined in the past and are susceptible to human interference and land use change. Some forest pixels are identified but it did not show any collapse while monitored using imagery from Google Earth at different time. There might be several possible reasons why the results indicated a non-tipping forest. The possible false indication of tipping points could be possibly due to the environmental and climatic variability that might have triggered the rise in indicators to act as a source of false alarm of impending critical transition or tipping point. On the other hand, it could also be that the NJF forest ecosystem is not yet close to tipping points. This study shows that detecting critical transitions and tipping points in real world ecosystems remains challenging and may not be as promising and straightforward as suggested by simulation studies. The gaps in evidences of tipping points in real world examples could be filled by analyzing high resolution and high frequency data, integrating remote sensing with process based approach dynamic vegetation models and validate the results with ground observations.

Keywords: critical transition, tipping point, early warning, EVI, time series

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Chapter 1. Introduction

1.1 Ecosystem States and Tipping Points

Ecosystems are dynamic entities that change over varying time scales. Often, the dynamic interactions that occur within or among ecosystems and environmental conditions are numerous and very complex. These interactions lead to the modifications in the structure and functions of the ecosystems. Many ecosystems are subject to slow and gradual or sudden and abrupt changes that are influenced by the disturbances and variations in climate and environmental parameters (Scheffer et al. 2001). As a consequence, the ecosystem switches from one state to another state, and can exist in two or more alternative states that differ in composition of the species, ecological processes and ecosystem services provided by them (Beisner et al. 2003; Suding et al. 2004). The sudden and unprecedented shifts in the ecosystem are expected to be more common as variations in climate and depletion of natural resources accelerate (Bestelmeyer et al. 2011). The systems that have two alternative stable states for a given combination of parameters switch from one state to another state at tipping points. Tipping points are defined as the ecological threshold beyond which a relatively small change in external conditions may cause the system to shift abruptly from one state to another unforeseen, undesirable and contrasting state, which may be largely irreversible (Scheffer et al. 2009; Bestelmeyer et al. 2011; Laurance et al. 2011). According to (Jax 2014), a tipping point is defined as “a point at which ecological system experiences a qualitative change, mostly in an abrupt and discontinuous way”.

The fundamental concept of a tipping point, where ecosystems respond differently to changing external conditions, is shown in Figure 1. Ecosystems respond either linear or gradual and non-linear. In Figure 1(a), there is a gradual response to gradual changes in external conditions. However, in Figure 1(b) and 1(c), the response of the ecosystem state can be abrupt even with a small change in external condition, and we can see a non-linear response. The ecosystem state in 1(a) and 1(b) are reversible to initial states, if the magnitude of external condition is reduced. However, the ecosystem responds completely differently in 1(c), where the equilibrium curve folds backwards (fold bifurcation) and there occurs a situation where a very small change in external conditions may trigger an extreme discontinuous response, and the system abruptly shifts towards a contrasting state. In Figure 1(c), T1 and T2 represent two threshold positions and within the range of environmental conditions between them, the ecosystems can occur in two contrasting states. It explains the threshold dependent transitions and alternate states in the ecosystem. In case of two alternative stable states 1(c), reversal of an ecosystem to its original state is very difficult or even impossible.

Tipping points are commonly discussed as the existence of multiple states in an ecosystem and their functioning (Andersen et al. 2008). The concept of tipping points is typically used with respect to complex systems like ecosystems and climate, but sometimes also for financial markets, economics, anthropology and ecology (Scheffer et al. 2009; Barnosky et al. 2012). In ecology, various terms have been used to explain abrupt and undesirable changes in the ecosystem states. The concept of tipping points and sudden shifts in ecosystem states are related to other concepts like ecosystem collapse (MacDougall et al. 2013; Lindenmayer et al. 2016), ecological transitions (Kéfi et al. 2014), critical threshold (Wissel 1984), regime shifts or state shifts (Scheffer et al. 2001; Biggs et al. 2009; Guttal and Jayaprakash 2009), critical

transitions (Scheffer et al. 2009; Dakos et al. 2012), alterations in ecosystem state and functions (Pulsford et al. 2016) and resilience (Walker and Salt 2012; Dakos et al. 2015).

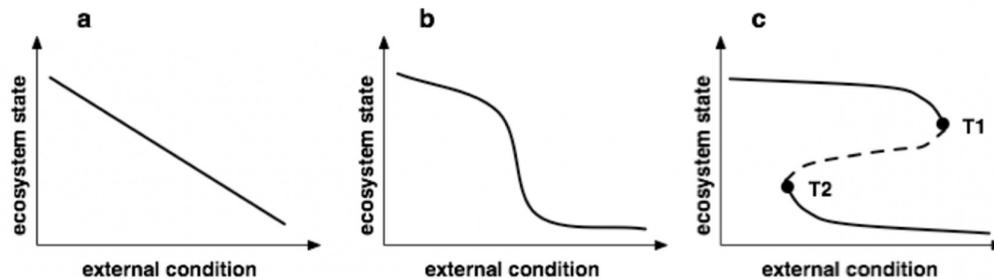


Figure 1. Schematic representation of the concept of tipping point. (adapted from Scheffer and Carpenter (2003))

1.2 Forest Ecosystem and Tipping Points

The forest ecosystem is a significant carbon pool (Bonan 2008) and ecosystem service provider (Betts et al. 2008). In addition, forests have a central role in maintaining local climate (Nobre et al. 1991), biodiversity conservation (Dirzo and Raven 2003) and global biogeochemical cycles (Bonan 2008). However, the ecosystem of such critical importance is subjected to cumulative pressure due to environmental changes and variations at different levels and scales. Increased human population, global climate change (Dale et al. 2001), forest fires (Nepstad et al. 2008) and drought (Klos et al. 2009) are common factors affecting forest ecosystems around the globe. Diebacks, changes in composition and structure of the forest, and loss of biodiversity are the increasing impacts due to those factors (Clark et al. 2016). On the other hand, land-use changes, invasive species and deforestation are putting extra pressure on ability of forest ecosystems to adapt to those impacts (Reyer et al. 2015). This has resulted in a change of structure and function of forest ecosystem that are observed in different parts of the world. For example, forest die back and sudden canopy collapse are reported in Arizona, USA (Ganey and Vojta 2011), Eastern Nicaragua (Granzow-de la Cerda et al. 2012), South Africa and Asia (Steinkamp and Hickler 2015) and Australia (Matusick et al. 2013; Steinkamp and Hickler 2015). Such sudden forest collapse leads to substantial changes in the structure and function of forest ecosystem with several repercussions. It is argued that these changes may ultimately lead to decreased resilience of forest ecosystem (Laurance 2004; Lenton et al. 2008), and can even lead the system into different state (Scheffer et al. 2001).

The occurrence of different alternative states in tropical forest ecosystem e.g. forest, savanna, and treeless state (Hirota et al. 2011) are governed by a feedback mechanism between vegetation and climate (Van Nes et al. 2014), biomass, herbivory and fire intensity (Van Langevelde et al. 2003). A positive feedback between vegetation and climate leads to a wetter and greener state compared to a state without the vegetation (Zeng et al. 2002). Empirical evidence suggest that such alternative states of the ecosystem are the response to climate variability, precipitation changes, external drivers and the historical state of the system (Hirota et al. 2011; Staver et al. 2011). Though evidence of forest state changes due to drought, fire and climate variability exist, unfortunately, the theory of tipping points and state shift is rarely tested for

forest ecosystems. The reason might be that detecting critical transitions and tipping points in complex real ecosystems is very difficult (Eslami-Andergoli et al. 2014).

1.3 Early Warning Indicators of Tipping Points

It is often difficult to predict whether an ecosystem is close to a tipping point (Clark et al. 2001). However, recent studies suggest the use of generic leading indicators - which are also called early warning signals to detect an approaching tipping point (Scheffer et al. 2009). It is often argued that tipping points are associated with fold bifurcations in which the ecosystems have two alternative stable states for the given combination of the parameters (Hastings and Wysham 2010), and small disturbances can switch a system from one state to another (Scheffer et al. 2001; Beisner et al. 2003). As bifurcation approaches, a phenomenon called ‘critical slowing down (CSD)’ occurs (Strogatz 2000) that provides early warning signal about the change that is going to happen in the ecosystem (Van Nes and Scheffer 2007). This critical slowing down is expected due to the tendency to have a decrease in the recovery rates in less resilient systems after a disturbance (Scheffer et al. 2009). In addition, signals that can be either totally or partially explained by CSD are an increase in autocorrelation-at-lag-1, an increase in the variance and an increase in the skewness of the system’s state variable (Eslami-Andergoli et al. 2014).

The use of general early warning signals and leading indicators have been suggested to test whether these approaches can detect approaching critical transitions and tipping points in a system (Scheffer et al. 2009). The early warning indicator of CSD, and hence critical transition and tipping points can be grouped into two broad categories: metric-based and model based indicators (Dakos et al. 2012). Metric-based indicators are developed to quantify changes in statistical properties of a time series - including autocorrelation-at-lag-1, standard deviation, and skewness, and model based indicators attempt to fit a model to the time series data in order to quantify the changes (Dai et al. 2012; Dakos et al. 2012). Early warning signals of CSD can be explained by analyzing the long-term changes in the statistical properties of the observed time series. Ecosystems approaching tipping points show an increase in autocorrelation (Dakos et al. 2009), variance (Carpenter and Brock 2006; Guttal and Jayaprakash 2009), and skewness of the studied variable and a slow recovery from disturbances (Van Nes and Scheffer 2007). The statistical analysis of early warning signals of CSD helps to detect tipping points and critical transitions in time series because it is often argued that long term trends in early warning signals or indicators increase in characteristic ways prior approaching tipping points or a critical transition.

The critical slowing down can be detected by the changes in correlation structure in the time series of the state variable (Dakos et al. 2012). It is found that if the system is approaching a critical transition or a tipping point, there is a noticeable increase in the autocorrelation that builds up long before the critical transition occurs (Scheffer et al. 2009). An increase in autocorrelation at lag-1 indicates that the state of a system becomes more similar between consecutive observations (Dakos et al. 2008), and is one of the simplest form to measure critical slowing down (Held and Kleinen 2004).

Slow return rates to the stable state can force the system state drift widely around the stable state and will cause variance to increase prior to the critical transition (Dakos et al. 2008; Scheffer et al. 2009).

The disturbances can sometimes push the state of the system close to the boundary between the alternate states (Dakos et al. 2012). Due to this, the time series becomes asymmetric and the dynamics in the boundary becomes slow (Scheffer et al. 2009). An increase in asymmetry of fluctuations may happen because of unstable equilibrium close to a tipping point (Scheffer et al. 2009), and we may observe a rise in the skewness of a time series (Dakos et al. 2012).

1.4 Ecosystem Variables

An ecosystem state variable is any characteristic number or quantity that changes over time and scale, for example net primary productivity and standing biomass. Ecosystem state variables are used to describe the state of the ecosystem. Ecosystem variables thus help to compare ecosystems and changes in state variables explain the behavior of ecosystem at different times and under different external conditions. Ecosystems respond differently to different external environment. Disturbances like drought, fire, etc. of significant magnitude and duration have influence on the ecosystem state variables. Examples of forest ecosystem variables include biomass and vegetation index - an indicator that describes the greenness, relative density and health of vegetation derived using the reflectance properties of vegetation, net primary productivity, etc. In this research, enhanced vegetation index (EVI) is taken into consideration as forest ecosystem variable that is acquired through remotely sensed satellite imageries. Using EVI values, we can accentuate a vegetation property and explain the behavior of a forest ecosystem because decrease in EVI value indicate a decline in greenness, and hence biomass and productivity.

1.5 Remotely Sensed Ecosystem Variables for Identifying Tipping Points

Earth observation (remote sensing) data play an important role in mapping, monitoring and understanding dynamics of forest ecosystem. Successful monitoring of ecosystems requires frequent and consistent spatio-temporal datasets (Tarnavsky et al. 2008). Satellite Image Time Series (SITS) offer opportunities to map, monitor and understand how ecosystems are changing over time and space at different scales, and formulate appropriate strategies for its sustainable management and use. SITS are becoming increasingly popular and available (Petitjean et al. 2012), and this has drawn interests to test their applicability in various fields from ecosystem and vegetation monitoring to climate change modeling. Examples of applications of Earth observation and time series analysis include climate monitoring (Wentz and Schabel 2000), vegetation dynamics (Martinez and Gilabert 2009), modeling forest biomass dynamics (Gómez et al. 2014), monitoring vegetation phenology phenomena (Reed et al. 1994; Zhang et al. 2003), mapping and monitoring of land use and land cover changes (Wu et al. 2006; Shalaby and Tateishi 2007), mapping and monitoring deforestation and forest degradation (Margono et al. 2012), monitoring fire events and post fire dynamics (Röder et al. 2008), and crop phenology and crop classification (Wardlow et al. 2007; Zheng et al. 2016).

Remote sensing has the capacity to describe vegetation conditions, and provide more direct estimates of ecological variables like biomass and biodiversity (Andrew et al. 2014). Since tipping points are often led by increased variability of ecosystem variables (Scheffer et al. 2009), we can assume that SITS can provide a realistic estimate on how the variables are changing over time. Satellite derived vegetation indices are generally used for vegetation mapping and monitoring. One common vegetation index is the Normalized Difference Vegetation Index (NDVI) - the most

often used vegetation index – which is a measure of greenness, and is calculated as the ratio of difference between near-infrared radiation and visible red radiation divided by the sum of near-infrared radiation and visible (red) radiation. NDVI is widely applied in vegetation mapping and monitoring including e.g. phenological change detection (Verbesselt et al. 2010), land-use classification (de Bie et al. 2012), forest classification (DeFries et al. 1995), drought mapping and monitoring (Peters et al. 2002; Sruthi and Aslam 2015), assess productivity changes (Tucker et al. 2001), as well as mapping and monitoring net primary productivity (Ricotta et al. 1999). The challenge with NDVI is that it gets saturated at high biomass levels (Gitelson 2004; Mutanga and Skidmore 2004; Unsalam et al. 2004) and hence may not be suitable to map and monitor dense vegetation.

To overcome the saturation effect and improve sensitivity at high biomass and correct atmospheric distortions, an optimized vegetation index called enhanced vegetation index (EVI) has been developed as a standard vegetation product for Terra and Aqua Moderate Resolution Imaging Spectroradiometers (MODIS) (Jiang et al. 2008). Like NDVI, EVI also provides a degree of greenness of the vegetation and is applied on mapping and monitoring phenology (Zheng et al. 2016), crop mapping studies (Wardlow et al. 2007), estimating gross primary productivity (Wu et al. 2011), etc. EVI as explained in Jiang et al. (2008) is calculated as

$$EVI = G \frac{N - R}{N + C1R - C2B + L}$$

where,

N, R, and B are surface reflectance for near-infrared, red, and blue bands respectively

G is a gain factor

C1, C2 are the coefficients of aerosol resistance term

L functions as the soil-adjustment factor

Changing trends in ecosystem variables can be detected and estimated using satellite observations (Andrew et al. 2014). For forest ecosystems, satellite derived estimates of vegetation indices (eg. EVI) may help to assess ecosystem states. Changes and oscillations in the ecosystem variables like e.g. GPP indicate the health of an ecosystem (Brouwers and Coops 2016), and could help to identify a point where external disturbances might lead to change in ecosystem state. This can be explained by the argument that a regime shift from one ecosystem state to another, for example forest to non-forest state would lead to the long-term increase in the statistical properties (autocorrelation at lag-1, standard deviation, and skewness) of the time series of the ecosystem variable (Dai et al. 2012; Dakos et al. 2012). There is a need for a time series of data from the study area to verify whether the ecosystem is indeed changing. The satellite time series analysis provides an opportunity to identify those changes and quantify the changes from where ecosystem might go into alternate states.

1.6 Research Gap

Many forest ecosystems are prone to sudden, widespread and long lasting change in their state, which puts the forest ecosystem at the risk of collapse (Lindenmayer et al. 2016). Forest crown dieback and collapse due to various environmental conditions like drought, fire, and heat stress, etc. have been recorded around the globe (Ganey

and Vojta 2011; Granzow-de la Cerda et al. 2012; Matusick et al. 2013; Steinkamp and Hickler 2015). One prominent example of severe forest die back and unprecedented forest collapse due to extreme heat and drought conditions is the Mediterranean type forest ecosystem in southwestern Australia (Matusick et al. 2013). Such evidence of forest collapse resulting from environmental and climatic disturbances might prove crucial in testing whether these collapses could be identified by precursor signals from remote sensing. One of the ways to assess whether the system is approaching a state shift phase is to derive the signals from satellite time series based on the theory of tipping point to detect the collapses prior to when they occurred.

There have been studies done to understand the changes and sensitivity of various systems to external environmental conditions. Various methods are being developed to detect early warning signals of tipping points. However, the proposed methods largely emphasize the use of simulated ecological data (Dakos et al. 2012) or spatial patterns (Kéfi et al. 2014) rather than time series. Examples of model based studies are climate systems (Lenton et al. 2008), vegetation – climate equilibrium using dynamic models (Hickler et al. 2005; Hirota et al. 2011; Barbosa et al. 2015) and lakes and ocean studies (Scheffer et al. 1993; Longworth et al. 2005; Scott et al. 2008; Gruber 2011). Although some researchers (Dakos et al. 2009; Scheffer et al. 2009) studied early warning signals of critical transitions and tipping points in ecosystems with natural disturbances, evidences to support the theory of CSD and tipping points in real ecosystems are largely insufficient. Carpenter et al. (2011) studied early warning of regime shifts in a lake ecosystem, but this is on a relatively small scale. The application of this rapidly expanding knowledge and theory in tipping points and critical transition in studying a large-scale ecosystem is still a pending question and is yet to be tested and applied in real world and complex ecosystems like forest ecosystems.

This study is an attempt to apply the emerging theory of tipping points to the North Jarrah Forest (NJF) forest ecosystem in south western Australia, which is being increasingly affected by alternate drying and warming climatic conditions (Abbott and Le Maitre 2010; CSIRO and Bureau of Meteorology 2015). Matusick et al. (2013) reported a severe forest die back and unprecedented forest collapse due to extreme heat and drought conditions in Western Australia. The fact that canopy collapse and forest diebacks occurred in the NJF forest ecosystem makes it an appropriate ecosystem to test whether we can detect these collapse in retrospect, applying the early warning indicators of tipping points and critical transitions.

While acknowledging the theoretical and methodological advancements in early warning signals and tipping points, there is a lack of evidence of early warning signs and tipping points in forest ecosystem that are derived using Earth observation data. There might be a huge potential in the applicability of those methods and indicators on detecting early warning signals of tipping points as it can meaningfully contribute in planning and management of forests ecosystem, reduce the risk of ecosystem collapse, and maintain the ecosystem services forest ecosystems provide. Therefore, the current research is designed to apply the theories of early warning signals and tipping point transitions in forest ecosystems using satellite derived EVI.

1.7 Research Objectives

The aim of this research is to analyze time series of remotely sensed satellite data to identify potential critical transition in a forest ecosystem. The specific objectives are:

- a. To identify whether the areas with high levels of early warning indicators are undergoing critical transitions.
- b. To analyze if generic early warning indicators of tipping points - autocorrelation-at-lag-1, variance, and skewness increase before a critical transition in a forest ecosystem.

1.8 Research Questions

This research tries to find answers to the following research questions:

- a. Do high values of early warning indicators based on satellite remote sensing time series correctly identify areas that have undergone transitions?
- b. Does the increase in long term trend in autocorrelation-at-lag-1, skewness and variance indicate areas that underwent a sudden transition between alternative states?

1.9 Hypothesis

- a. Hypothesis 1: The high values of early warning indicators based on satellite remote sensing time series correctly identify areas that have undergone transitions.
- b. Hypothesis 2: Increased autocorrelation-at-lag-1, variance, and skewness of EVI indicate areas that underwent critical transition.

Chapter 2. Data and Methods

2.1 Study Area

2.1.1 General

The Northern Jarrah Forest (NJF) is located in the Southwestern Botanical Province or bioregion of Western Australia, directly east of Perth (Figure 1) and covers an area of 1,127,600 ha (Havel 1975). The NJF stands atop the Darling Plateau with an average elevation of 300 m above mean sea level (Williams and Mitchell 2002). The NJF lies in the Mediterranean ecosystem of south western Australia which is recognized as one of the 10 Australian ecosystems most vulnerable to tipping points (Laurance et al. 2011).

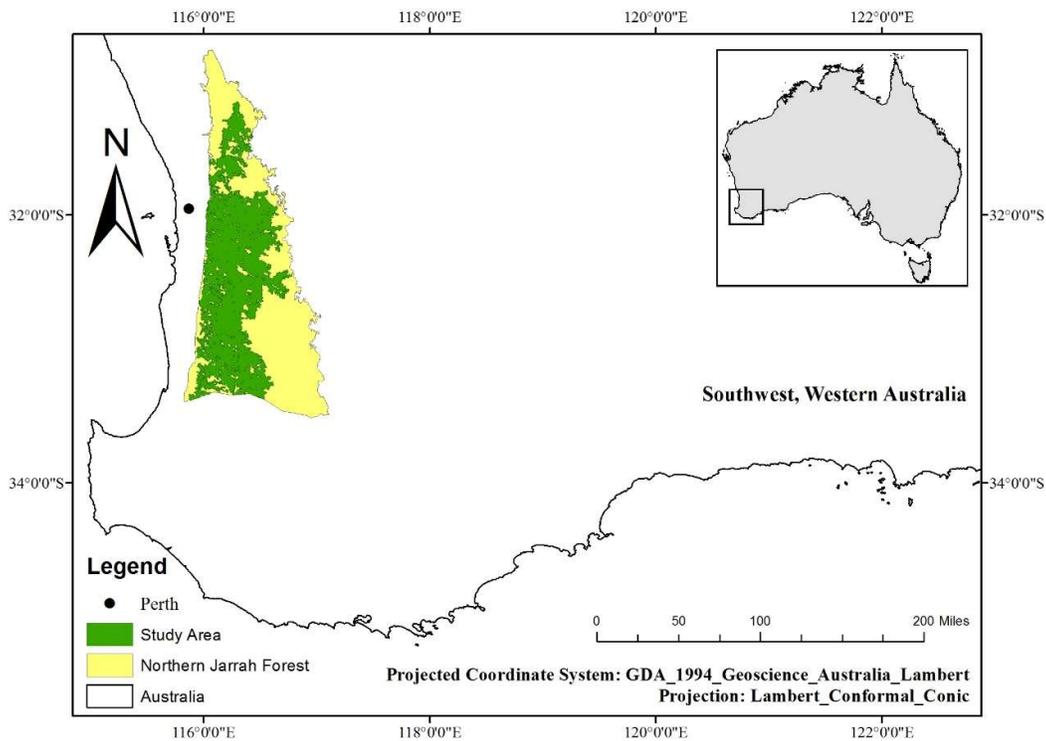


Figure 2. Map featuring the study area and the North Jarrah Forest.
Map prepared by: Author

2.1.2 Vegetation and Biodiversity

The Mediterranean ecosystem of the southwestern bioregion of Australia is a global biodiversity hotspots and contains a highly diverse endemic plant diversity (Myers et al. 2000). The NJF is a habitat for over 850 vascular plant species, contributing to Southwestern Botanical Province being one of the global biodiversity hotspots (Mittermeier et al. 2011).

The NJF is classified as medium-open forest with average canopy height of 10-30m and canopy cover between 30-70% (Williams and Mitchell 2002). The NJF is an evergreen dry sclerophyll forests dominated by Jarrah plant (*Euclayptus marginata*

Donn ex Smith) (Dell and Havel 1989). The NJF has a 4 to 7-meter understory of small trees, mainly *Alocasuarina fraseriana* Miq., *Banksia grandis* Willd. *Persoonia* spp., and ground cover of woody shrubs and grass-trees *Xanthorrhoea perissii* Endll., *Kingia australis* R. Br. and the cycad *Macrozamia riedlei* (Dell and Havel 1989). The dominant land uses in the NJF include forest, mining, plantation forestry, water production and recreation (Dell and Havel 1989).

2.1.3 Hydroclimatic Characteristics

The NJF experiences a Mediterranean type of climate characterized by hot and dry summers and cool and wet winters (Peel et al. 2007), which has been rapidly changing since the 1970s (Suppiah et al. 2007). The precipitation ranges from 700 mm to 1100 mm (Gentilli 1989). The winter rain, the characteristic of Mediterranean ecosystems, occurs from mid-April to late October (mid-autumn to mid-spring) and is usually characterized by sudden and heavy showers (Gentilli 1989; Bates et al. 2008). Southwestern Australia suffers a seasonal drought that may last from 4 to 7 months (Gentilli 1989). The summer droughts are the most intense droughts and they frequently occur between January and February although they can affect any months from November to April (Gentilli 1989). The region has experienced a pronounced precipitation shifts since 1970s (Bates et al. 2008). The mean annual precipitation was around 14% lower during 1975 to 2004 compared to mean annual precipitation before 1975 in contrast to the average temperature that has increased at the rate of 0.15°C per decade (Bates et al. 2008). A study done by CSIRO and Bureau of Meteorology have indicated that this area is expected to experience even more climatic variability and drought than already observed (CSIRO and Bureau of Meteorology 2015), and thus that the area will most probably be prone to sudden shifts even more in the future (Abbott and Le Maitre 2010).

2.2 Methods

To answer the research questions, the method as presented in Figure 3 is followed. The research is divided into three steps a) data collection and preparation (section 2.2.1) – involving satellite data download, extracting science dataset (SDS) layers, projection and preparing AOI vector file b) data processing (section 2.2.2) - including data filtering and smoothing and preparation of time series and c) data analysis (section 2.2.3) - about testing metric-based generic early warning indicators of critical transition and tipping points. The R scripts used to download, process and analyze MODIS data are presented in Appendix I.

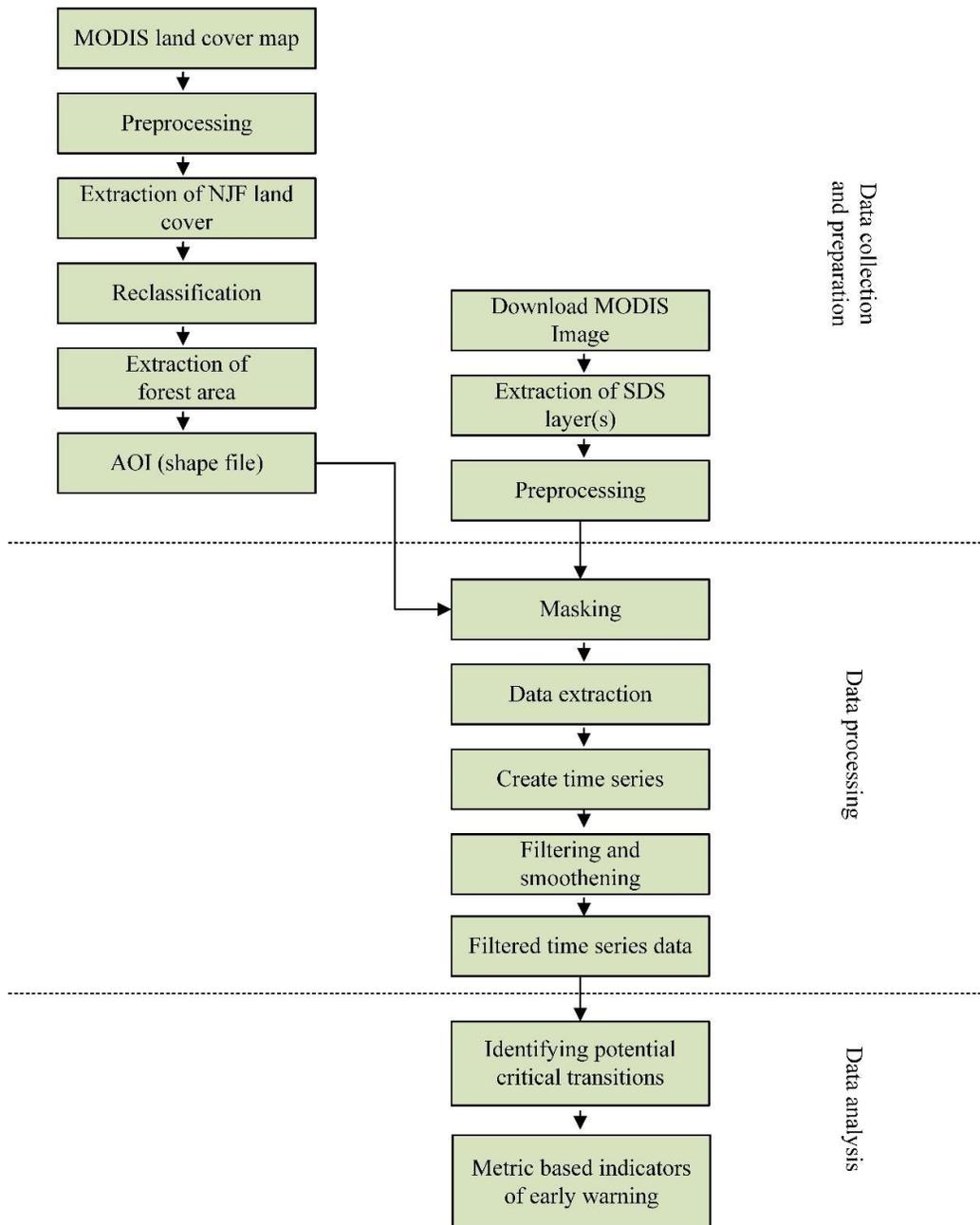


Figure 3. Methodological flow chart explaining research steps.

2.2.1 Data Collection and Preparation

2.2.1.1 MODIS Data

In this study, data from the MODIS are used to detect tipping point transitions in forest ecosystem. The MOD13A1 Version 6 product for vegetation index from 2001 to 2015 was retrieved from online Reverb ECHO- the next generation Earth science discovery tool, courtesy of the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, <https://reverb.echo.nasa.gov/reverb/>.

MOD13A1 is a 16-day composite vegetation index generated using two 8-day composite surface reflectance granules (MxD09A1) in the 16-day period and has 500 meter spatial resolution (LP DAAC 2017). The granule has 12 science dataset (SDS) layers. The second SDS layer, i.e. the EVI dataset layer, is used in this study. The EVI layers was extracted from 2001 to 2015, generating a time series of 15 years. MODISTsp package in R environment (Busetto and Ranghetti 2016) is used for SDS extraction.

2.2.1.2 Creating the Mask

A mask of the NJF area was created based on existing land cover data. The MODIS land cover type product MCD12Q1 (LP DAAC 2012) of 500 meter spatial resolution retrieved from online Reverb ECHO- the next generation Earth science discovery tool from LP DAAC website, <https://reverb.echo.nasa.gov/reverb/> was used to create the mask. The MCD12Q1 land cover type has 16 HDF Science Data Set Layers, each layer characterizing a global land cover classification system. For this study, the International Geosphere-Biosphere Programme (IGBP) land cover type classification was used for classifying land cover into forest and non-forest categories. First, the reclassified land cover map with forest and non-forest areas for NJF was masked out. From the masked image, only forest area is extracted and converted into vector – which is the area of interest (AOI).

An exploratory analysis was done to identify pixels that are not forest area. A relative measure of dispersion based on the 1% and 99% of quantile deviation of EVI values are calculated and plotted to identify pixels with too high or too low values (hereafter denoted as outlier pixels). The outlier pixels were selected and overlay operation was done in ArcGIS to see whether the land cover represented by the pixels are consistent or different over time. Once the overlay operation is completed, the output was opened in Google Earth to see the type of land cover category the pixel represents. Based on higher resolution information from Google Earth, the pixels which are found not to be forest (e.g. mining areas, agriculture land, water bodies and small forest patches in the agriculture land) were excluded and the AOI is then refined and updated.

2.2.2 Data Processing

Using AOI vector file, each of the MODIS images are masked. The masked EVI layers (images) are stacked and a satellite image time series is prepared, so that each pixel in the dataset (540 rows*175 columns) contains time series of EVI values. Filtered time series is prepared applying Savitzky-Golay filter method (Savitzky and Golay 1964). The second-degree polynomial and moving window of five is used to filter the time series. The filtering technique is applied to reduce impact of any noise resulting from atmospheric distortions or cloud contaminations and to smooth out the irregular roughness to see a clearer signal. When applying the Savitzky-Golay filter method, considerations are made so that the time series is not over-fitted because it is expected that the Savitzky-Golay filter would influence some of the statistics that are part of the time series analysis, for example the algorithm does not distinguish between natural variations in EVI and atmospheric distortions. It is assumed that the pixels affected by atmospheric distortions and cloud contaminations are lifted according to the Savitzky-Golay filter method. The Savitzky-Golay filter is based on

smoothing of the time series by re-estimating points in a moving window with a least-squares polynomial fitting procedure (Savitzky and Golay 1964).

All the analyses are implemented in the R software environment v. 3.4.0 (R Development Core Team 2013) using functionalities of the raster package for reading, writing and manipulating satellite images (Hijmans et al. 2016) and rts package for manipulating time series of satellite images (Naimi 2016).

2.2.3 Data Analysis

The extracted time series of EVI are then used to calculate the early warning indicators of tipping points and identify the pixels where early warning indicators are flagging a possible signals of tipping points.

2.2.3.1 Leading Indicators of Tipping Points

In this study, the approach as suggested in Carpenter and Brock (2006), Dakos et al. (2009), Kuehn (2011) and Dakos et al. (2015) is used to generate early warning indicators of tipping points or critical transitions using the statistics that measure critical slowing down in relevant system variables. Metric-based indicators (Dai et al. 2012; Dakos et al. 2012) are used to quantify the changes in the statistical properties of the EVI time series including temporal autocorrelation at lag-1, standard deviation, and skewness.

2.2.3.2 Metric-based Early Warning Indicators

Metric-based indicators of critical transition and tipping points are used to analyze the changes in the statistical properties of the observed time series – autocorrelation (Dakos et al. 2009), variance (Carpenter and Brock 2006; Guttal and Jayaprakash 2009), and skewness (Guttal and Jayaprakash 2009; Scheffer et al. 2009). Here, we analyze the changes in the statistical properties of the observed EVI time series.

The temporal autocorrelation-at-lag-1 is defined as the correlation between EVI values at time (t) and (t-1). The autocorrelation can be calculated (Dakos et al. 2008) as:

$$\rho_1 = \frac{E[(z_t - \mu)(z_{t+1} - \mu)]}{\delta_z^2}$$

where μ is the mean and δ is the variance of variable z_t .

Variance is the second moment around the mean of a distribution and can be measured as standard deviation:

$$SD = \sqrt{\frac{1}{n-1} \sum_{t=1}^n (z_t - \mu)^2}$$

or alternatively as the coefficient of variation $CV = SD/\mu$ (Carpenter and Brock 2006).

Skewness is the standardized third moment around the mean of a distribution and can be calculated as (Scheffer et al. 2009):

$$SK = \frac{\frac{1}{n} \sum_{t=1}^n (z_t - \mu)^3}{\sqrt{\frac{1}{n} \sum_{t=1}^n (z_t - \mu)^2}}$$

Before the metric based early warning indicators are applied and tested, the data is detrended and smoothed. Detrending is done to eliminate the effects of non-stationary conditions on the leading indicators. Gaussian, linear and loess filters, and first-differencing are the most commonly detrending approaches (Lenton et al. 2012). In this research, the first-differencing detrending approach is used. The first difference of the EVI time series is the series of changes from one period to the next i.e. the difference of EVI values of one moment and the preceding moment along the time series is the first difference. If e_t denotes the value of the time series EVI at period t , then the first difference of EVI at period t is equal to $e_t - e_{t-1}$. The detrending of the time series is done to reduce the longer-term dynamics, so that any anomalies are better captured by the analysis.

The size of the moving window might influence the long-term trend in the indicators of tipping points. A small moving window can lead to a more noisy time series while a large moving window can smoothen the fluctuations that may be indicative of a critical transition (Alibakhshi et al. 2017). A moving window of half the size of the time series is used to identify critical transitions. Examples include identifying a critical transition in a wetland ecosystem (Alibakhshi et al. 2017) and climate change (Dakos et al. 2008). Also in this study, the early warning indicators of critical transition and tipping points are calculated in a moving window of half of the length of the time series and are assessed for any unusual increase over time with the first-differencing detrending approach.

The top 1% quantile of all three leading indicators at a given moment (the last year we have data) are identified. The pixels that show long term increasing trend in the statistical properties (autocorrelation-at-lag-1, standard deviation and hence variance, skewness) are identified as potential tipping points. The identified pixels are further analyzed on the behavior of the EVI time series. It is expected that the statistical properties of the observed time series show the evidences of critical transitions and tipping point, i.e. a long term increasing trend in the statistical properties.

All the analyses are implemented in the R software environment v. 3.4.0 (R Development Core Team 2013) using functionalities of the early warnings package for calculating generic early warning indicators and identifying potential tipping points and critical transitions (Dakos 2014).

Chapter 3. Results

3.1 Potential Critical Transitions

The analysis started examining the statistical changes in time series of EVI. The time series of a subset of the top 1% quantile of all three leading indicators - autocorrelation-at-lag-1, standard deviation and skewness are plotted. Plotting time series of all pixels would produce overlapping lines, which makes it difficult to see trends in the time series. A subset is plotted to see the visible trends in the time series.

The long-term trends in time series for autocorrelation-at-lag-1 (Figure 4), standard deviation (Figure 5) and skewness (Figure 6) are shown below. Long term increasing trends are clearly visible in autocorrelation-at-lag-1 and standard deviation, but not in skewness where different behavior is observed (Figure 6). In skewness, some pixels show a gradual increase whereas some pixels show an abrupt increase in 2009, 2013 and 2014.

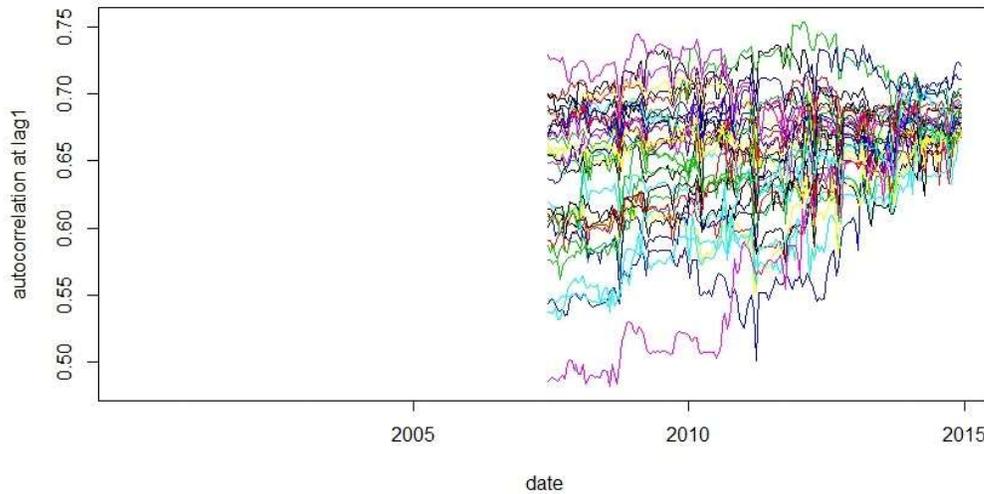


Figure 4. Long term trends of autocorrelation-at-lag-1 of the Savitzky-Golay filtered EVI time series.

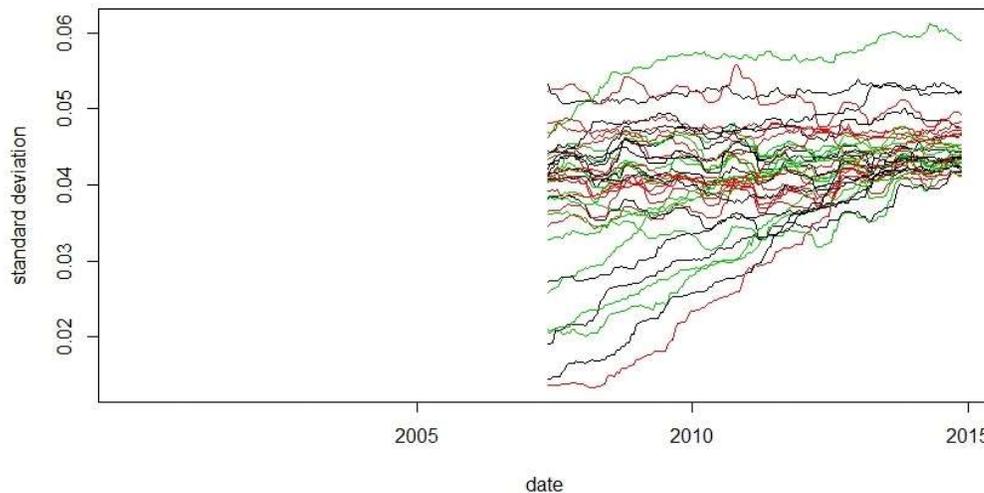


Figure 5. Long term trends of standard deviation of the Savitzky-Golay filtered EVI time series.

It is found that the overall behavior of the autocorrelation-at-lag-1 and the standard deviation time series was robust against first-difference detrending and moving window of half of the length of the time series. However, skewness is found to be very sensitive to noise (Figure 6) and shows large jumps in the time series, which might be the time when a sudden shift might have occurred.

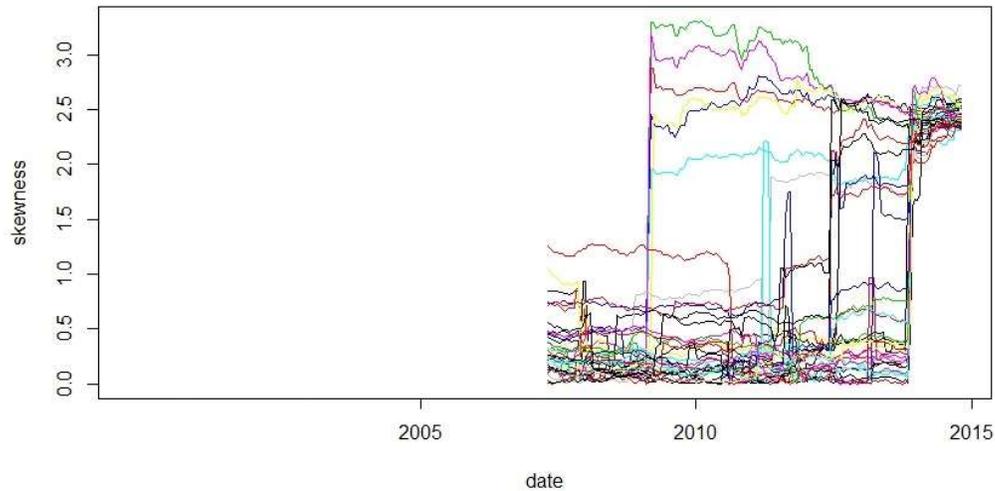


Figure 6. Long term trends of skewness of the Savitzky-Golay filtered EVI time series.

Further analysis is based on the long-term trends in time series of autocorrelation-at-lag-1, standard deviation and skewness. The pixels with long term increasing trend in autocorrelation-at-lag-1, standard deviation and skewness are considered as outliers (Figure 7) which might be the ‘potential tipping point’ areas. The identified potential tipping point areas are shown in Figure 7.

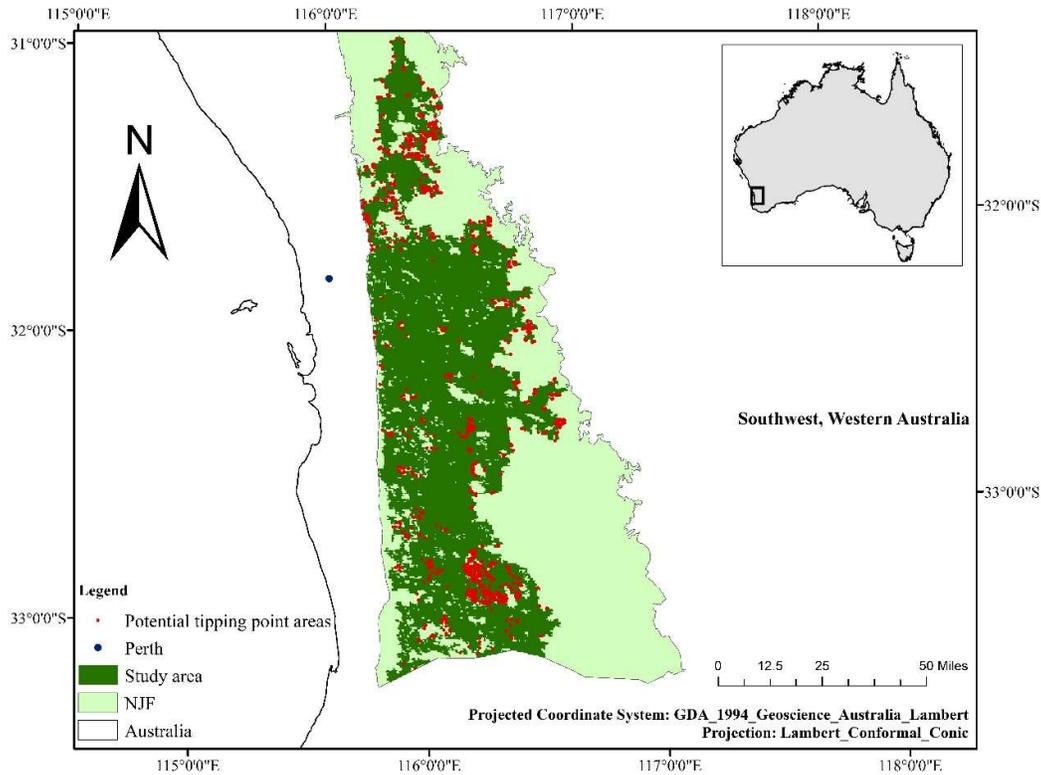


Figure 7. Potential tipping point areas in the NJF forest ecosystem as indicated by all three metric-based early warning indicators.

The pixels with a long term increasing trend in early warning indicators are expected to be less resilient and more sensitive to disturbances. So, a less resilient pixel would be more likely to collapse when a disturbance occurs than a resilient pixel (without a trend in early warning indicators). Figure 8 shows all the identified potential tipping point areas in Google Earth.

For the pixels with strong trends in autocorrelation-at-lag-1 or standard deviation or skewness, changes in land cover (and possible collapse of forest) were monitored using imagery from Google Earth at different time. The pixels with the strongest trends in the leading indicators did not corresponded to collapsing forests, or forests suffering from dieback. Instead, many of the identified pixels (around 83% of the total identified pixels) are mining areas or the areas close to mining areas or on the edge of forest-agricultural areas, which might have been largely influenced by human activities (Figure 8).

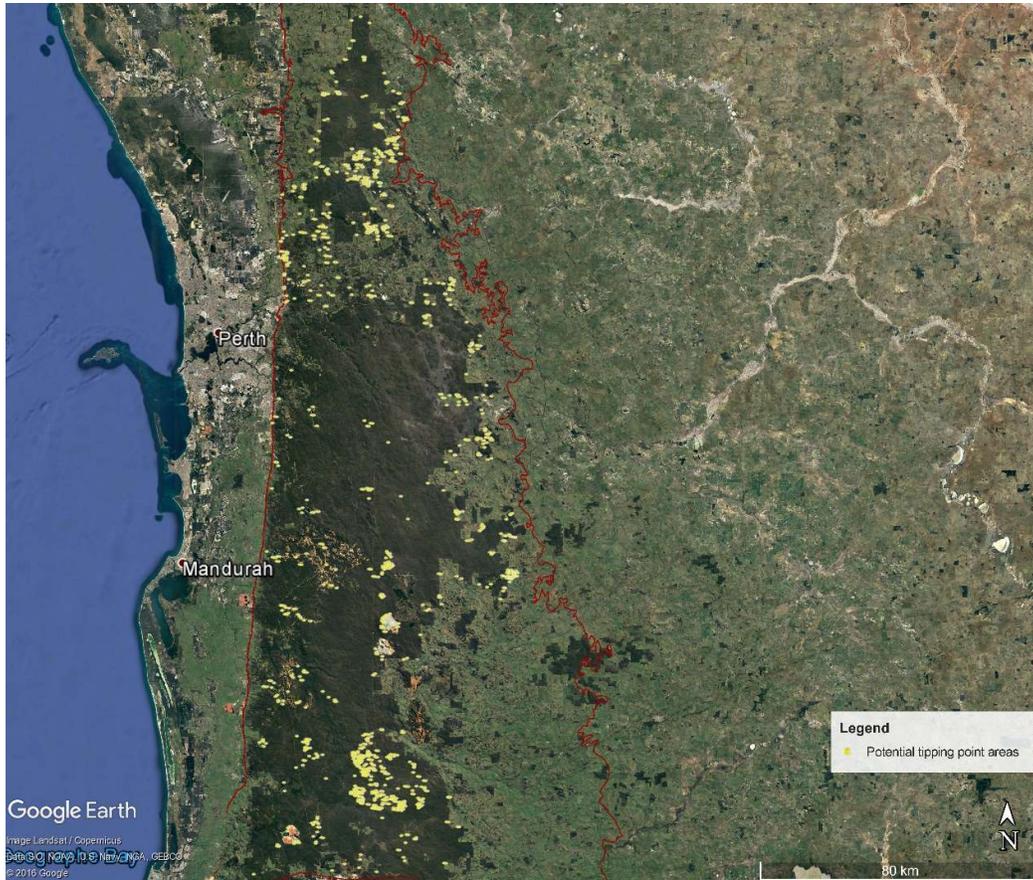


Figure 8. Location of potential tipping points as observed in Google Earth.

From the Figure 8, we can see that many of the identified potential tipping point areas are on the edges between forest and agricultural land and susceptible to human interferences.

Figure 9, Figure 10 and Figure 11 show the expansion of mining activities and subsequent changes in the forest. If we compare the Google Earth images for 2001, 2010 and 2015, we can see a large increase in the mining areas, and subsequent forest loss. In Figure 11 (2015), we can observe that the lost forest areas due to mining in 2001 (Figure 9) are recovered. We can also see the increased forest loss due to mining in 2015 compared to 2001 and 2010. The continuous expansion of mining areas has lead the change in forest area. This might be one reason why we see long term increasing trends of early warning indicators.

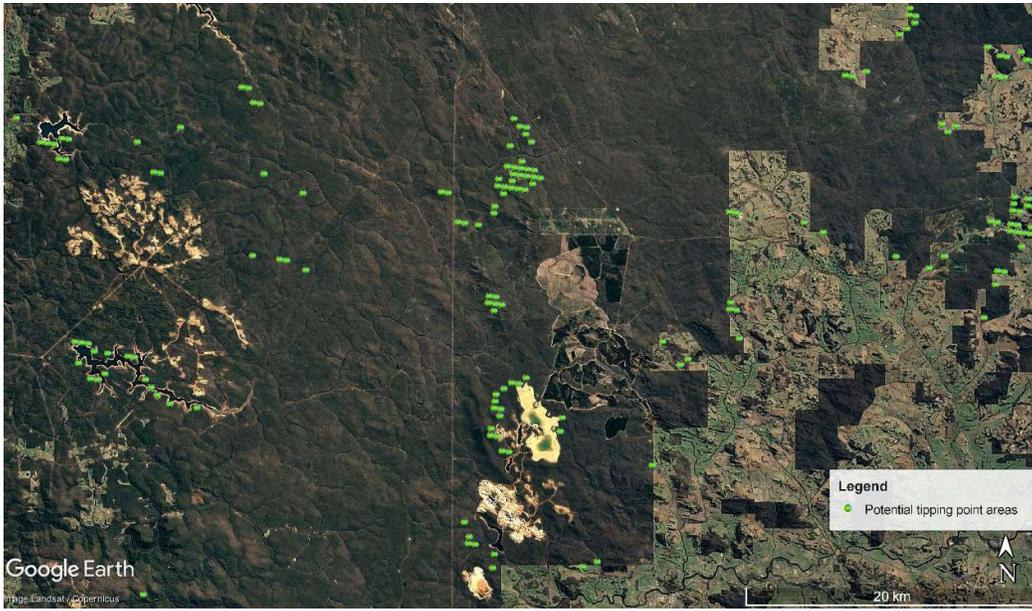


Figure 9. Potential tipping points and mining areas in the NJF in 2001 as seen in Google Earth.

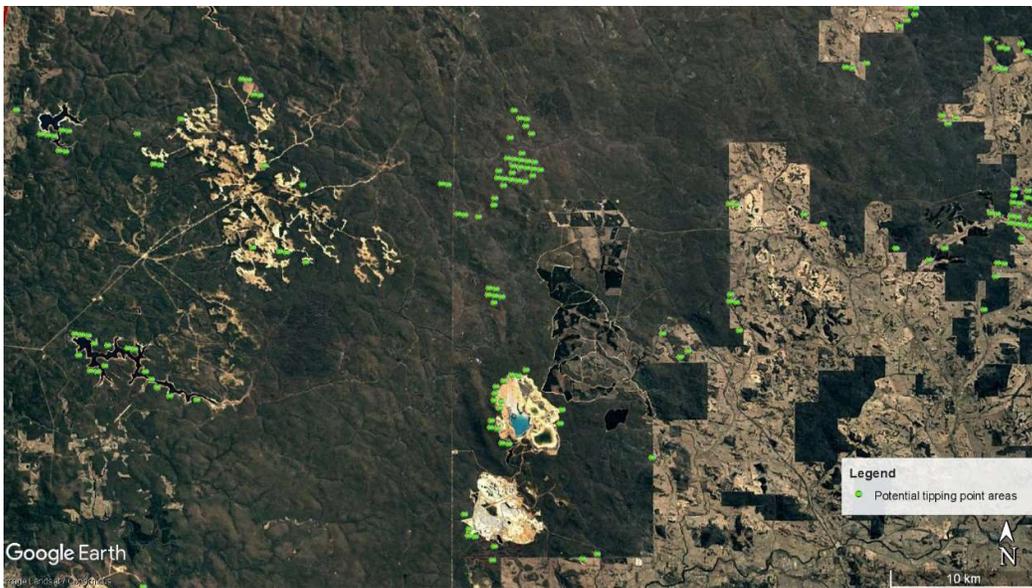


Figure 10. Potential tipping points and mining areas in the NJF in 2010 as seen in Google Earth.

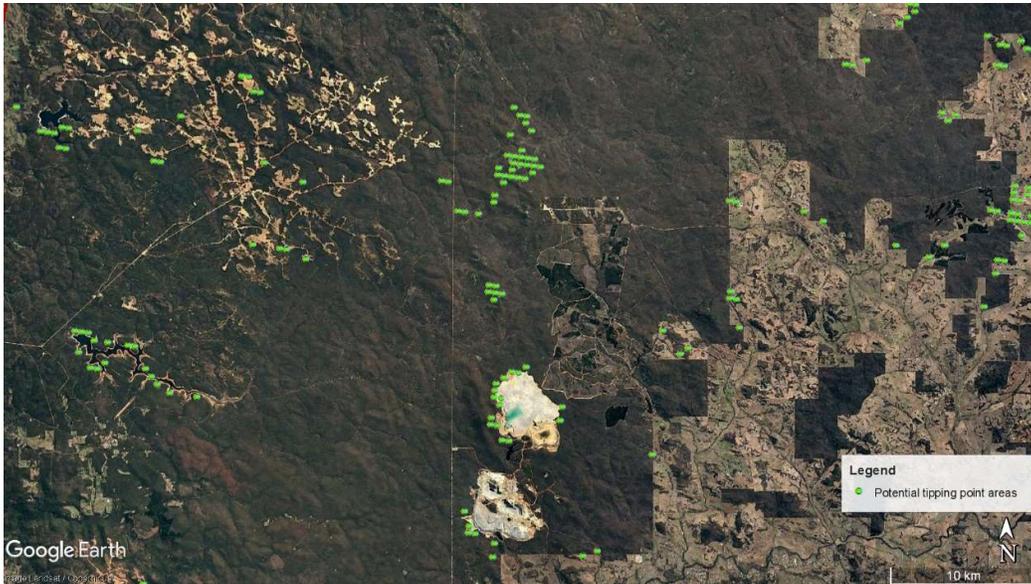


Figure 11. Potential tipping points and mining areas in the NJF in 2015 as seen in Google Earth.

Around 17% of the pixels that are identified as potential tipping points are in the middle of the forest. It is expected that those pixels (Figure 12) were not biased by mining or other land use interferences. Those pixels are monitored using imagery from Google Earth from 2001 to 2015. The imagery did not show any change in forest cover, i.e. no collapse is recorded on those pixels. Google Earth view for the year 2001, 2005, 2010 and 2015 are shown in the Figure 12, Figure 13, Figure 14 and Figure 15.



Figure 12. Overlay of identified potential tipping point in the middle of forest with Google Earth image from 2001.

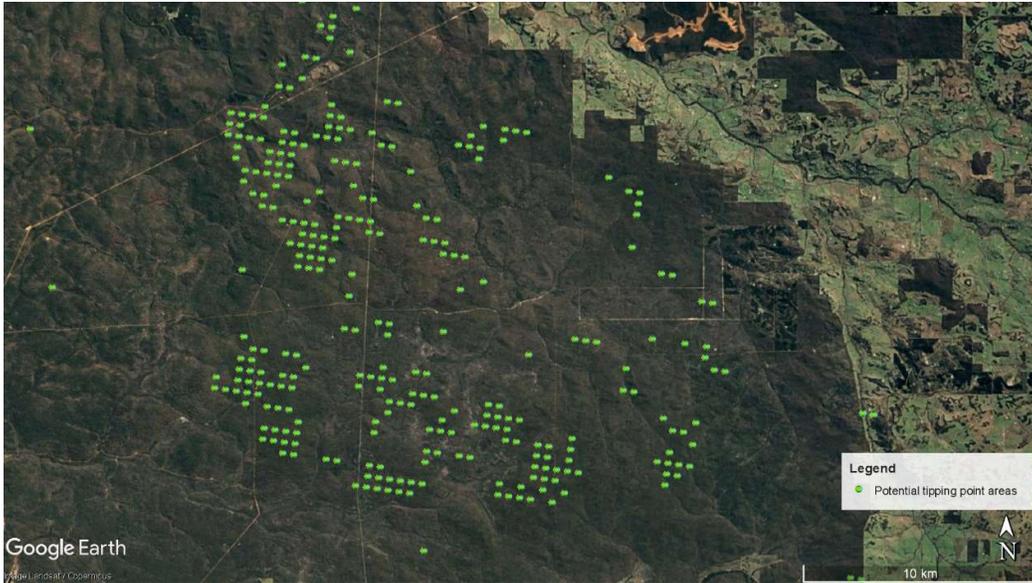


Figure 13. Overlay of potential tipping point areas in the middle of forest with Google Earth image from 2005.



Figure 14. Overlay of potential tipping points in the middle of forest with Google Earth image from 2010.



Figure 15. Overlay of potential tipping points in the middle of forest with Google Earth image from 2015.

Chapter 4. Discussion

This research assessed the use of remote sensing derived ecosystem variables to measure the state of the ecosystem and identify potential critical transitions and tipping points in the NJF forest ecosystem. Due to high climatic variability and drought occurrences in the region, the NJF ecosystem is getting increasingly dry, and reports of forest canopy collapse in the region have been recorded in the past (Matusick et al. 2013). Similarly, the NJF forest ecosystem was identified as one of the most vulnerable Australian ecosystem approaching tipping point (Laurance et al. 2011). This finding encouraged this study to attempt to identify potential critical transitions and tipping points and test whether the recorded forest collapses could be identified using remote sensing data. Considering that the indicator's behavior before a critical transition is straightforward and promising to assess in real situations (Scheffer et al. 2009; Dakos et al. 2012), it was expected that generic early warning indicators of tipping points and critical transitions would be detected in the NJF ecosystem. The study identified potential critical transitions and tipping point areas, and quantified early warning indicators for the NJF forest ecosystem but the strongest signals did not flag any forest that showed any signs of collapse or an impending shift. Rather, it largely identified the areas that were mined in the past and are susceptible to human interference and land use change. These detected signals are likely to be false alarms, given that most the identified pixels cover mining and agricultural areas. Also, the identified pixels in the middle of the forest did not show evidence of forest collapse when monitored using Google Earth images from different years.

Although Scheffer et al. (2009) and Dakos et al. (2012) mentioned detecting early warning signals of critical transitions in time series data is straightforward and promising to assess in real situations, the current study identified potential tipping point areas but failed to detect changes and true instabilities in the NJF forest ecosystem. There might be several possible reasons why the results indicated a non-tipping forest ecosystem.

CSD indicators are sensitive to false alarms

CSD based early warning indicators are promising tools for detecting critical transitions due to their generic nature (Scheffer et al. 2009). Therefore, it is tempting to think that before impending transitions in an ecosystem, there happens sudden rise in statistical characteristics like temporal autocorrelation, variance and skewness that indicate an approaching transition (Dakos et al. 2015). However, not all critical transitions are expected to exhibit such changes in the statistical pattern of the time series of their measured variables (Scheffer et al. 2001; DeYoung et al. 2008; Boettiger et al. 2013). They can also reflect environmental stochasticity and give false alarms that the ecosystem is approaching a tipping point (Dakos et al. 2015).

Our result found long-term increasing trends in the statistical properties (autocorrelation-at-lag-1, standard deviation and skewness) in EVI time series. There might be several reasons for this. According to Dakos et al. (2015), the increasing trends in autocorrelation-at-lag-1, variance and skewness can be also observed in ecosystems with high magnitude of environmental stochasticity or chaotic dynamics. Since the NJF forest ecosystem is suffering extreme and persistent reductions in precipitation, increase in temperature, heat waves (CSIRO and Bureau of

Meteorology 2015) and fire events (Evans and Lyons 2013) frequently in the past decade, this might have led the increasing positive trends in autocorrelation-at-lag-1, standard deviation and skewness. This trend might have reflected the changes in the patterns of the environmental stochasticity rather than a truly approaching critical transition. Therefore, it can be said that environmental and climatic variability might have triggered the rise in indicators to act as a source of false alarm of impending critical transition or tipping point. This might be the reason why the long-term trends are observed in the early warning indicators, and why they are not yet able to be interpreted as early warning indicator of tipping point.

The forest is resilient and not yet close to tipping point

Forests in MTF ecosystems have evolved with extreme variabilities, disturbances and fluctuations in temperature and precipitation (Roberts et al. 2001). This resulted in the forests developing an unique adaptation and survival capacities (James 1984). Matusick et al. (2013) reported severe crown die back and canopy collapse in the NJF corresponding with record dry and heat conditions in 2010/11 and Coleoptera infestations. Regardless of the collapse, the forest went through a period of regrowth and recovery, and it was found that 52% ($\pm 3.6\%$) of the trees that showed sudden and unprecedented collapse during June and July 2010/2011 had re-sprouted in October and November 2011 (Matusick et al. 2013). From this, we can understand the ability of the NJF to bounce back and recover from disturbances. In other terms, the NJF forests resisted the changes and persists with minimal transformation induced by climatic variabilities and fire. The dominant vegetation in the NJF – the eucalypts, are not only fire resistant, but are also self-sustaining and have the capacity to regenerate abundantly after fire (Mount 2013). Ruthrof et al. (2015) also found that Northern Jarrah Forest of southwestern Australia has resistance and resilience mechanisms to cope with drought and external environmental variabilities. The ability of trees to bounce back from disturbances by substantial regrowth and re-sprouting of the vegetation indicate that the NJF ecosystem is still resilient. The regrowth and re-sprouting also suggests that the system was recovering from the collapse. However, the question here is how long the resilience can be maintained by the forest when extreme climatic variabilities and environmental conditions continue exerting pressure for a longer time. There might be a point where the forests tip. A longer monitoring of external environmental conditions (e.g. drought, rainfall and fire) and forest regeneration might prove useful to know the ability of forest to resist the changes.

When a system is closer to a tipping point, it results in a loss of resilience and even small perturbations can invoke a shift to an alternative, undesirable and contrasting state (Scheffer et al. 2001; Scheffer 2009). In contrast, the NJF forest is resilient to droughts, climatic variability and external environmental conditions. Due to this, we cannot yet expect the NJF ecosystem to shift abruptly from one state to another unforeseen, undesirable and contrasting states with a relatively small change in external condition. This does not correspond with the theoretical definitions of critical transition and tipping points – which is defined as the ecological threshold beyond which a relatively small change in external condition may cause the system to shift abruptly from one state to another unforeseen, undesirable and contrasting states, which may be largely irreversible (Scheffer et al. 2009; Bestelmeyer et al. 2011; Laurance et al. 2011). So, the possible reason for not being able to detect critical transitions and tipping points is that the forest is still resilient, and the environmental variabilities and external conditions are not strong enough to easily trigger the system

to shift to another state. This explains why the result showed signals of critical slowing down (increases in autocorrelation-at-lag-1, standard deviation and skewness) at some locations, but these were not corresponding to the forest areas.

Inclusion of ecosystem variables that represent ecosystem more closely

The generic early warning indicators of critical transition and tipping point may fail to announce a true transition if a wrong variable is measured (Dakos et al. 2015). It is expected that CSD affects a system as a whole but all ecosystem variables are not equally sensitive to approaching critical transitions, and hence all ecosystem variables may not exhibit the generic early warning indicators of impending critical transitions (Carpenter et al. 2008; Batt et al. 2013). In this study, we used EVI as an ecosystem variable to identify critical transition and tipping points. Time series of vegetation indices are mostly used to quantify map and monitor vegetation dynamics, drought, phenology, change detection and biophysical interpretations. We assumed that EVI time series would effectively characterize the process and dynamics that NJF is undergoing. The analysis of EVI time series quantified early warning indicators for the NJF forest ecosystem but the strongest signals did not flag any forest that showed any signs of collapse or an impending shift while monitored using Google Earth images from different years. Analysis of ecosystem variables that represent NJF ecosystem more closely might be required to measure the variabilities and changes the forest is undergoing. For forest ecosystems, analysis of direct ecosystem variables like biomass, NPP in addition to vegetation indices (which are used as proxy for biomass or greenness) might prove useful, because changes and oscillations in these ecosystem variables for e.g. GPP indicate the health of an ecosystem (Brouwers and Coops 2016), and could help to identify the true changes in the ecosystem state.

One limitation in this study might be the resolution and frequency of the data. For example, satellite data with high spatial and temporal resolution are recommended as the challenges in statistical detection of leading indicators can be improved with high resolution and high frequency data (Scheffer et al. 2009; Carpenter et al. 2011). One promising option would be an airborne light detection and ranging (LIDAR) dataset that may provide a high resolution and high frequency data of the desired ecosystem variables, for example biomass. LIDAR can be used to assess forest biomass. Biomass is a more direct ecosystem state variable than the enhanced vegetation index, which is a measure of greenness. Modelling individual trees, crown structure and area using LIDAR could yield more accurate results in terms of trend in biomass and spatial indication where the biomass has declined, increased or remained stable. A data fusion approach can be used for estimating biomass using space borne LIDAR with synthetic aperture radar (SAR) and passive optical image combinations for calculating more accurate estimation of biomass (Montesano et al. 2013). Considering this superiority, time series of LIDAR data could provide an opportunity to detect spatial and temporal indicators, and increased accuracy in detecting critical transitions and tipping points. However, it requires expensive tools and high data storage capacity. Another option would be using very high spatial and temporal resolution satellite imagery.

Understanding thresholds and baseline values

Most of the indicators to detect critical transitions and tipping points have been derived from simulated data, simple models and tested through controlled experiments (Scheffer et al. 2009). Although empirical evidence support the

recognition of the science and theory of tipping point, demonstration of these approaches in real ecosystems has been very limited (Scheffer et al. 2009; Dai et al. 2012; Seekell et al. 2012). Due to this challenge, it is argued that detecting critical transitions and tipping points in complex real ecosystems is very difficult and not straight forward, and may not work in complex real ecosystems (Eslami-Andergoli et al. 2014).

The recent empirical methodological developments and metric based indicators lacked explanation on the baseline values that could indicate whether a transition is approaching. Though the baseline measurement and threshold values depend on the nature of the system and the variables that are measured, there is no absolute value or threshold defined for ecosystems which if crossed signify a tipping ecosystem. This limits the understanding on how far the system has transformed compared to its initial state. The results from this study highlights the limitations in the application and interpretation of the early warning indicators to understand regime shifts in complex and dynamic ecosystems like forest. This is a huge challenge to test and apply the generic early warning signals of impending critical transitions and tipping points indicators in real-world time series. With regard to the challenges, the studies could be done in explaining the thresholds in baseline values for tipping points. The thresholds and baseline values might be determined in retrospect by looking at the signals for areas that have tipped in the past.

Despite the strong theoretical underpinning and increasing number of empirical studies and demonstrations, this research in contrast has shown that metric based early warning indicators are not a panacea for anticipating critical transitions and tipping points in forest ecosystem. There are evidences that generic early warning indicators of CSD have largely failed to detect the known transitions (Lindgren et al. 2012) though positive results have been derived from testing early warning indicators (Beaugrand et al. 2008; Litzow et al. 2008; Hewitt and Thrush 2010). The current study also shows some positive indicators, possibly as false alarms. The theory on tipping points in ecosystems has attracted quite a lot of attentions and the knowledge and evidences on understanding the dynamics and complexities in tipping points detection are gradually increasing. However, the understanding and quantification of critical transitions and tipping points in real-world ecosystems remains challenging. One of the possible approach to fill the gap would be integrating observation based approaches (earth observation and remote sensing) with a process based approach (dynamic vegetation models) and validate the results with ground observation data. Using this integrated approach will allow to understand the complex interplay of drivers, triggers, or other processes of critical transition and tipping points and provide insights in the observed forest dynamics and patterns.

Chapter 5. Conclusion

The study attempted to increase the empirical base of the early warning indicators of critical transition and tipping points by using time series of EVI derived from MODIS satellite images. The time series of EVI are used to generate early warning indicators of critical transitions. Metric-based indicators of critical transition and tipping points (autocorrelation-at-lag-1, standard deviation and skewness) are used to quantify the changes in the statistical properties of the observed time series. The study identified potential critical transition and tipping point areas, and quantified early warning indicators for the NJF forest ecosystem but the high values of early warning indicators did not flag forest that showed any signs of an impending shift. In contrast, it largely identified areas that were mined in the past and are susceptible to human interferences and land use change. Some forest pixels were also identified but it did not show any collapse while monitored using imagery from Google Earth at different times. There might be several possible reasons why the results indicated a non-tipping forest. The possible false indication of tipping points was found possibly due to the environmental and climatic variability that might have triggered the rise in indicators to act as a source of false alarm of impending critical transition or tipping point, but alternatively, it could also be that NJF forest ecosystem is not yet close to tipping points i.e. forest is still resilient. The results show that detecting critical transitions and tipping points in real-world ecosystems may not be as promising and straightforward as suggested by model simulations.

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Appendices

Appendix I. R script

```
#####
# Date created: 02 February 2017
# Date modified: 10 May 2017
# NAME OF SCRIPT: Thesis_R_Scripts
# AUTHOR: KRISHNA LAMSAL
#####

# DATA COLLECTION AND PREPARATION
#####
#1. MODIS Data download, projection & extraction of scientific data (hdf) layers
#####

##### for MODISstp #####
# Source - Github MODISstp package

install.packages("gWidgetsRGtk2")
library(gWidgetsRGtk2)
install.packages("devtools")
library(devtools)
install.packages("xml2")
install.packages("RGtk2")
install.packages("rgdal")
install_github("lbusett/MODISstp")
library(MODISstp)
MODISstp()

#####
#2. Processing the downloaded MODIS images and
# PROJECT, CROP AND MASK THE MODIS IMAGE TO GET AOI
#####

#### Reading a single raster
r_ref <- raster('MOD13A1_EVI_2001_001.tif')
plot(r_ref)
crs(r_ref)
projection(r_ref)
res(r_ref)
dim(r_ref)

#### Reading the shape file of the study area
shape <- readOGR(dsn='C:/Users/Krishna/Desktop/EVI_Analysis/studyarea',
                layer='studyarea')

# Checking the desired projection (GDA 1994 Geoscience Australia Lambert)
# GDA94 <- "+proj=lcc +lat_1=-18 +lat_2=-36 +lat_0=0 +lon_0=134 +x_0=0 +y_0=0
#           +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_defs "

# the original MODIS tiles are stored in "EVI_tiff_Orig" folder and
# they are projected, cropped and masked using the following script
```

```

rm(list = ls())
setwd("C:/Users/Krishna/Desktop/EVI_Analysis/EVI_tiff_Orig")
library(raster)
library(rgdal)
library(gdalUtils)
library(MODIS)

filelist <- Sys.glob('MOD*')
filelist

for(i in 1:length(filelist)){
  print(paste(Sys.time(), '-----', i))
  file <- filelist[i]
  filename_out <- paste('reproj_out/', substr(file, 1, 20), '_reproj.tif', sep='')
  if(!file.exists(filename_out)){
    gdalwarp(file, 'test.tif', proj4string(r_ref), proj4string(shape), tr = c(463.3127165, 463.3127165),
            r = "near", overwrite=T)
    tmp <- raster('test.tif')*0.0001
    tmp[tmp<=0] <- NA
    tmp <- mask(crop(tmp, shape), shape)
    writeRaster(tmp, filename_out, NAflag=-99)
  }
}

# Here the gdalwarp function transforms the coordinate system (from and to), output resolution,
# resampling (nearest neighbour) and rescaling EVI values
# The output files are stored in folder names "reproj_out", which is used for further analysis

# EXTRACTING THE COORDINATES OF THE AREA
r_ref <- raster ('MOD13A1_EVI_2001_001_reproj.tif')
sp <- rasterToPolygons(r_ref)
points <- SpatialPoints(sp)
coords <- coordinates(points)

# Extraction the EVI values for RAW stack based on coordinates
data.raw <- extract(MODIS.raw, points)
write.table(data.raw, "rawEVI.txt")

```

```

#####
#3. PRELIMINARY ANALYSIS
#####
library(reshape)
library(reshape2)
library(zoo)
library(ggplot2)

### READING AND PLOTTING RAW DATA (to identify non-forest pixels)
melt.unfilt <- read.table("rawEVI.txt", header = T, sep = ' ' )
unfiltdata <- melt(melt.unfilt)
head(unfiltdata)

quants.unfilt <- boxplot(unfiltdata$value~unfiltdata$variable, xlab = "Year",
                        ylab = "EVI", ylim = c(0.0, 0.8), xlim = c(1, 345))

names(quants.unfilt)
head(quants.unfilt)
quants.unfilt$stats

ggplot(unfiltdata, aes(factor(variable), value)) +
  geom_boxplot(outlier.colour=NULL, linetype=1) +
  labs(ylim=c(0, 0.7), x = 'Year', y = 'EVI') +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 7))

# Here, the outliers are identified and opened in google earth to see
# if they are forest or non-forest pixels, and the later are moved
# and AOI is refined/updated based on operations in ArcGIS

```

```

# DATA PROCESSING
#####
#4. DATA EXTRACTION (Based on refined/updated AOI from preliminary analysis)
#####
# Reading the shape file - refined/updated( AOI)
aoi <- readOGR(dsn= 'C:/Users/Krishna/Desktop/studyarea_29042017',
              layer = 'studyarea')

# Reading an output raster
r_ref <- raster('MOD13A1_EVI_2001_001_reproj.tif')
r_ref
dim(r_ref)

# load the required libraries and list the files
filelist <- list.files('C:/Users/Krishna/Desktop/EVIdata', pattern='MOD.*')
filelist

outpath <- "C:/Users/Krishna/Desktop/MOD_Final/"
dir.create(outpath)
# add output directory
outfiles <- paste0(outpath, filelist)
outfiles

for(i in 1:length(filelist)) {
  print(paste(Sys.time(), '-----', i))
  r <- raster(filelist[i])
  rc <- mask(crop(r, aoi), aoi)
  rc <- writeRaster(rc, outfiles[i])
}

# files masked with updated AOI

```

```

#####
#5. DATA FILTERING AND SMOOTHENING
#####

## For this, specify working directory for the AOI extracted MODIS files (rasters)
# and run the following scripts
rm(list = ls())
setwd("C:/Users/Krishna/Desktop/MOD_Final")
## load the required libraries

# Stacking and Preparing TS
evi.files <- list.files(path = "C:/Users/Krishna/Desktop/MOD_Final", pattern = '.tif$')
evi.stack <- stack(evi.files)
MODIS.raw <- evi.stack
MODIS.raw

# SAVITZKY GOLAY FILTERING FOR THE STACK
filter_data <- function(x) {
  v <- as.vector(x)
  z <- substituteNA(v, type = "zeros")
  evi.ts <- ts(z, start=c(2001,1), end=c(2015,23), frequency=23)
  x <- sgolayfilt(z, p = 2, n = 5) ## polynomial degree 2 and moving window 5
  return(x)
}

MODIS.filtered <- calc(MODIS.raw, filter_data)

# EXTRACTING THE COORDINATES OF THE AREA
r_ref <- raster('MOD13A1_EVI_2001_001_reproj.tif')
sp <- rasterToPolygons(r_ref)
points <- SpatialPoints(sp)
coords <- coordinates(points)

# Extraction the EVI values for RAW and FILTERED MODIS stack based on coordinates
data.raw <- extract(MODIS.raw, points)
write.table(data.raw, "rawEVI.txt")

# For p = 2, n = 5 filtering
data.filt2 <- extract(MODIS.filtered2, points)
write.table(data.filt2, "filteredEVIp2n5.txt")

# Combine EVI values with coordinates
combine2 <- cbind(coords,data.filt2)
write.table(combine,"xy_EVI_filtp2n5.txt")

#####
#6. TIME SERIES EXTRACTION
#####

# Extract dates
dates_evi <- extractDate(evi.stack, pos1 = 1, pos2 = 345, asDate = FALSE, format= "%Y/%m/%d")
dates_evi$inputLayerDates
# only extracting required vector

year <- substr(dates_evi$inputLayerDates, 13, 16)
doy <- substr(dates_evi$inputLayerDates, 18, 20)
dates1 <- strptime(paste(year, doy), format="%Y %j")
dates <- as.Date(dates1)

```

```

# Creating a RasterStackTS object:
# For p = 2, n = 5
evi_filt_ts2 <- rts(MODIS.filtered2, dates)
write.rts(evi_filt_ts2, "filtTS2")

# Write RAW Timeseries
evi_raw_ts <- rts(evi.stack, dates)
write.rts(evi_raw_ts,"rawTS")

# EXTRACTING THE TIME SERIES DATA
data.raw.ts <- extract(evi_raw_ts, points)
raw.ts.df <- data.frame(data.raw.ts)
write.table(raw.ts.df, "dataRawTS.txt")

data.filt.ts2 <- extract(evi_filt_ts2, points)
filt.ts.df2 <- data.frame(data.filt.ts2)
write.table(filt.ts.df2, "filtered_p2n5TS.txt")

# EXTRACTION AND ANALYSIS OF EARLY WARNING INDICATORS (VALUES)
#####
#7. Plotting statistical parameters and identifying outliers
#####
## STANDARD DEVIATION, MOVING WINDOW 50 AND FIRST DIFFERENCE DETRENDING
df.sd<-NULL
for(i in 1:ncol(d))
{
  temp <- generic_ews(d[,i],, winsize = 50, detrending = "first-diff")
  df.sd <- cbind(df.sd,temp$sd)
}
write.table(df.sd, "standarddeviation.txt")
#####

## SKEWNESS, MOVING WINDOW 50 AND FIRST DIFFERENCE DETRENDING
df.sk<-NULL
for(i in 1:ncol(d))
{
  temp <- generic_ews(d[,i],, winsize = 50, detrending = "first-diff")
  df.sk <- cbind(df.sk,temp$sk)
}
write.table(df.sk, "skewness.txt")
#####

## AUTOCORRELATION AT LAG 1, MOVING WINDOW 50 AND FIRST DIFFERENCE DETRENDING
df.acf1 <- NULL
for(i in 1:ncol(s))
{
  temp<-generic_ews(s[,i],, winsize = 50, detrending = "first-diff")
  df.acf1<-cbind(df.acf1,temp$acf1)
}
write.table(df.acf1, "autocorrelation_lag1.txt")
#####

```

```

# QUANTILES and PLOTS for AUTOCORRELATION AT LAG 1
quantile(autocor[173,], probs = c(0.05, 0.95)) # for top and bottom 5 percent
quantile(autocor[173,], probs = c(0.1, 0.99)) # for top and bottom 1 percent
quantile(autocor[173,], probs = c(0.01, 0.999)) # for top and bottom 0.1 percent
autocor_top_5 <- autocor[which(autocor[173,] >=0.380)] # 2033 pixels
autocor_top_1 <- autocor[which(autocor[173,] >=0.5481055)] # 405 pixels
autocor_top_0.1 <- autocor[which(autocor[173,] >=0.6674007)] # 41 pixels
matplot(autocor_top_5, type = 'l', lwd = 1, col = 1:50, lty = 1, xlab = "date",
        ylab = "autocorrelation at lag1", xlim = c(-172, 172))
matplot(autocor_top_1, type = 'l', lwd = 1, col = 1:50, lty = 1, xlab = "date",
        ylab = "autocorrelation at lag1", xlim = c(-172, 172))
matplot(autocor_top_0.1, type = 'l', lwd = 1, col = 1:50, lty = 1, xlab = "date",
        ylab = "autocorrelation at lag1", xlim = c(-172, 172))

#####

# QUANTILES and PLOTS for SKEWNESS
quantile(sk[173,], probs = c(0.5, 0.95))
quantile(sk[173,], probs = c(0.1, 0.99))
quantile(sk[173,], probs = c(0.01, 0.999))
sk_top_5 <- sk[which(sk[173,] >=1.111536)] # 2024 pixels
sk_top_1 <- sk[which(sk[173,] >=1.765774)] # 405 pixels
sk_top_0.1 <- sk[which(sk[173,] >=2.317011)] # 41 pixels
matplot(sk_top_5, type = 'l', lwd = 1, col = 1:50, lty = 1, xlab = "date",
        ylab = "skewness", xlim = c(-172, 172))
matplot(sk_top_1, type = 'l', lwd = 1, col = 1:50, lty = 1, xlab = "date",
        ylab = "skewness", xlim = c(-172, 172))
matplot(sk_top_0.1, type = 'l', lwd = 1, col = 1:50, lty = 1, xlab = "date",
        ylab = "skewness", xlim = c(-172, 172))

#####

# QUANTILES and PLOTS for STANDARD DEVIATION
quantile(sdev[173,], probs = c(0.05, 0.95))
quantile(sdev[173,], probs = c(0.1, 0.99))
quantile(sdev[173,], probs = c(0.01, 0.999))
sdev_top_5 <- sdev[which(sdev[173,] >=0.02434907)] # 2024 pixels
sdev_top_1 <- sdev[which(sdev[173,] >=0.03219518)] # 405 pixels
sdev_top_0.1 <- sdev[which(sdev[173,] >=0.041122)] # 41 pixels
matplot(sdev_top_5, type = 'l', lwd = 1, col = 1:50, lty = 1, xlab = "date",
        ylab = "standard deviation", xlim = c(-172, 172))
matplot(sdev_top_1, type = 'l', lwd = 1, col = 1:50, lty = 1, xlab = "date",
        ylab = "standard deviation", xlim = c(-172, 172))
matplot(sdev_top_0.1, type = 'l', lwd = 1, col = 1:50, lty = 1, xlab = "date",
        ylab = "standard deviation", xlim = c(-172, 172))

#####
#####

```

Department of Physical Geography and Ecosystem Science, Lund University

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