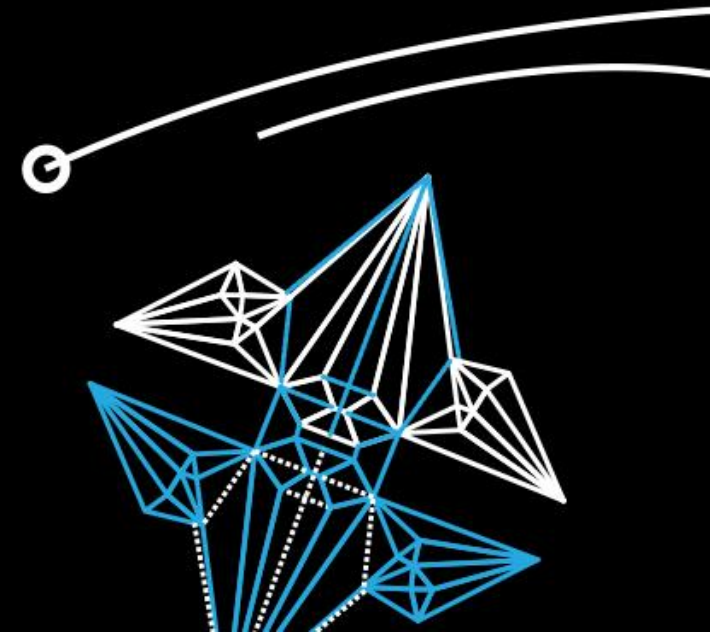
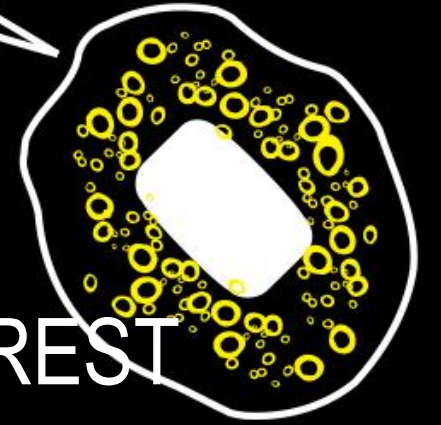


UNIVERSITY OF TWENTE.

# SEARCHING FOR SATELLITE SIGNALS OF FOREST STABILITY

THOMAS A. GROEN WITH CONTRIBUTIONS FROM INKA DIATMIKO, GOHAR SHAHINYAN, DAN KANMEGNE, KRISHNA LAMSAL,  
NIINA RAUTIAINEN, BABAK NAIMI, KOEN DE KONING, SARA ALIBAKSI, FATEMEH MAHMOUDI AND ANTON VRIELING





# WHY LOOK AT FOREST STABILITY?



## LETTER

doi:10.1038/nature13265

### Widespread decline of Congo rainforest greenness in the past decade

Liming Zhou<sup>1</sup>, Yuhong Tian<sup>2</sup>, Ranga B. Myneni<sup>3</sup>, Philippe Chais<sup>4</sup>, Sasan Saatchi<sup>5</sup>, Yi Y. Liu<sup>6</sup>, Shilong Piao<sup>7</sup>, Haishan Chen<sup>8</sup>, Eric F. Vermorel<sup>9</sup>, Conghe Song<sup>10,11</sup> & Taehee Hwang<sup>3</sup>

Tropical forests are global epicentres of biodiversity and important modulators of climate change<sup>1</sup>, and are mainly constrained by rainfall patterns<sup>2-4</sup>. The severe short-term droughts that occurred recently in Amazonia have drawn attention to the vulnerability of tropical forests to climatic disturbances<sup>5,6</sup>. The central African rainforests, the second-largest on Earth, have experienced a long-term drying trend<sup>6,11</sup> whose impacts on vegetation dynamics remain mostly unknown because *in situ* observations are very limited. The Congolese forest, with its drier conditions and higher percentage of semi-evergreen trees<sup>12,13</sup>, may be more tolerant to short-term rainfall reduction than are wetter tropical forests<sup>14</sup>, but for a long-term drought there may be critical thresholds of water availability below which higher-biomass, closed-canopy forests transition to more open, lower-biomass forests<sup>15,16</sup>. Here we present observational evidence for a widespread decline in forest greenness over the past decade based on analyses of satellite data (optical, thermal, microwave and gravity) from several independent sensors over the Congo basin. This decline in vegetation greenness, particularly in the northern Congolese forest, is generally consistent with decreases in rainfall, terrestrial water storage, water content in aboveground woody and leaf biomass, and the canopy backscatter anomaly caused by changes in structure and moisture in upper forest layers. It is also consistent with increases in photosynthetically active radiation and land surface temperature. These multiple lines of evidence indicate that this large-scale vegetation browning, or loss of photosynthetic capacity, may be partially attributable to the long-term drying trend. Our results suggest that a continued gradual decline of photosynthetic capacity and moisture content driven by the persistent drying trend could alter the composition and structure of the Congolese forest to favour the spread of drought-tolerant species<sup>2,14</sup>.

The impact of changes in precipitation patterns, such as short-term and long-term droughts, on tropical rainforests is poorly understood and currently under debate<sup>17,18</sup>. Systematic monitoring of the forests is essential to understanding their response to climate change, and remote sensing remains the only viable way of systematically and repeatedly monitoring vast remote regions such as the Congo basin<sup>19,20</sup>. This study uses Enhanced Vegetation Index (EVI)<sup>21</sup> data derived from a satellite-borne sensor, MODerate resolution Imaging Spectroradiometer (MODIS), for the period 2000–2012. EVI correlates well with leaf area index, canopy photosynthetic activity and primary productivity<sup>22–24</sup>. We focus our study on intact forested regions in the Congo basin (5°N–6°S, 14°E–31°E)

seasonal variation than rainfall, consistent with observed phenological (leaf area index) responses of tropical trees to increasing soil moisture<sup>25</sup>. We also use three gauge-measured and satellite-derived rainfall data sets<sup>26–28</sup> and other satellite products: terrestrial water storage (TWS)<sup>29,30</sup>, aerosol optical thickness (AOT), cloud optical thickness (COI), photosynthetically active radiation (PAR) and land surface temperature (LST) as climate drivers, and vegetation optical depth (VOD)<sup>31</sup> and canopy backscatter anomaly (CBA)<sup>32</sup> (together with EVI) as vegetation variables (see Methods). VOD represents water content in aboveground woody and leaf biomass and is sensitive to long-term climate change<sup>33</sup>. CBA reflects the changes in structure and moisture in upper forest layers and thus can help identify large-scale tree mortality<sup>34</sup>. TWS quantifies large-scale and low-frequency total ground, surface and vegetation water storage anomalies<sup>35,36</sup>. Unlike EVI, the microwave products CBA and VOD are least affected by atmospheric and weather conditions<sup>37,38</sup>. Most of the data are independent and thus allow a multi-factor analysis.

Although differing in data source, duration, spatial resolution and processing, the three rainfall data sets show strong and similar interannual variations during April–May–June over the study region, with the strongest negative anomalies falling in the last decade of the long-term 1950 to 2012 mean (Fig. 1a). The regional-mean rainfall declined significantly by  $-0.32 \pm 0.10$  mm per day per decade ( $7.2 \pm 2.2\%$ ,  $P = 0.002$ ) or by  $-0.56$  mm per day (12.6%) between the last and first decades for the period 1985–2012. The drying trend (Fig. 1b and c) is widespread across the study region, with 25%–62% of forested area showing a significant negative trend ( $P < 0.05$ ).

The spatial patterns of EVI trends are shown in Fig. 2, together with the corresponding trends in rainfall, TWS and CBA for the period 2000–2012. Because most of the satellite data sets are only 10–13 years long, linear regressions are used to quantify simply whether there is a trend within each data record; such a trend, however, cannot be extrapolated linearly over longer periods. Although the time series is short, EVI declined over 92% of the study area from 2000 to 2012 and in 97% of the area from 2003 to 2012, with 39% and 54% of the area showing a significant negative trend ( $P < 0.1$ ), respectively, indicating that the EVI decrease became broader in space and stronger over time. The two rainfall data sets show similar large-scale declines from 2000 to 2012. TWS declined over most of the study area, particularly over the northern Congo. CBA also declined over 85% of the area from 2001 to 2009. Overall about 12%–28% of the forested area exhibited a significant negative trend ( $P < 0.1$ ) for rainfall, TWS and CBA.

GEOPHYSICAL RESEARCH LETTERS, VOL. 38, L07402, doi:10.1029/2011GL046824, 2011

### Widespread decline in greenness of Amazonian vegetation due to the 2010 drought

Liang Xu,<sup>1</sup> Arindam Samanta,<sup>1,2</sup> Marcos H. Costa,<sup>3</sup> Sangram Ganguly,<sup>4</sup> Ramakrishna R. Nemani,<sup>5</sup> and Ranga B. Myneni<sup>1</sup>

Received 19 January 2011; revised 3 March 2011; accepted 8 March 2011; published 8 April 2011.

[1] During this decade, the Amazon region has suffered two severe droughts in the short span of five years – 2005 and 2010. Studies on the 2005 drought present a complex, and sometimes contradictory, picture of how these forests have responded to the drought. Now, on the heels of the 2005 drought, comes an even stronger drought in 2010, as indicated by record low river levels in the 109 years of bookkeeping. How has the vegetation in this region responded to this record-breaking drought? Here we report widespread, severe and persistent declines in vegetation greenness, a proxy for photosynthetic carbon fixation, in the Amazon region during the 2010 drought based on analysis of satellite measurements. The 2010 drought, as measured by rainfall deficit, affected an area 1.65 times larger than the 2005 drought – nearly 5 million km<sup>2</sup> of vegetated area in Amazonia. The decline in greenness during the 2010 drought spanned an area that was four times greater (2.4 million km<sup>2</sup>) and more severe than in 2005. Notably, 51% of all drought-stricken forests showed greenness declines in 2010 (1.68 million km<sup>2</sup>) compared to only 14% in 2005 (0.32 million km<sup>2</sup>). These declines in 2010 persisted following the end of the dry season drought and return of rainfall to normal levels, unlike in 2005. Overall, the widespread loss of photosynthetic capacity of Amazonian vegetation due to the 2010 drought may represent a significant perturbation to the global carbon cycle. **Citation:** Xu, L., A. Samanta, M. H. Costa, S. Ganguly, R. R. Nemani, and R. B. Myneni (2011), Widespread decline in

atmosphere, which in turn would accelerate global warming significantly [Cox *et al.*, 2000]. Hence, the drought sensitivity of these forests is a subject of intense study – recent articles on the response and vulnerability of these forests to droughts illustrate the various complexities [Phillips *et al.*, 2009; Saleska *et al.*, 2007; Samanta *et al.*, 2010a, 2010b; Malhi *et al.*, 2008; Brando *et al.*, 2010; Anderson *et al.*, 2010; Meir and Woodward, 2010]. Severe droughts such as those associated with the El Niño Southern Oscillation (ENSO), when the plant-available soil moisture stays below a critical threshold level for a prolonged period, are known to result in higher rates of tree mortality and increased forest flammability [Nepstad *et al.*, 2004, 2007; da Costa *et al.*, 2010]. The drought of 2005, however, was unlike the ENSO-related droughts of 1983 and 1998 – it was especially severe during the dry season in southwestern Amazon but did not impact the central and eastern regions [Marengo *et al.*, 2008]. Of particular interest are reports of loss of biomass [Phillips *et al.*, 2009], decreased vegetation moisture content [Anderson *et al.*, 2010] and higher fire counts [Aragao *et al.*, 2007] during the 2005 drought, and contradictory reports of vegetation greenness changes inferred from satellite observations [Saleska *et al.*, 2007; Samanta *et al.*, 2010a, 2010b]. This lively state of current affairs is documented in two news items [Tollefson, 2010a, 2010b].

[2] On the heels of the once-in-a-century [Marengo *et al.*, 2008] drought in 2005, comes an even more severe drought in the Amazon region [Lewis *et al.*, 2011]. The causes of the



# WHY LOOK AT FOREST STABILITY?

*Global Ecology & Biogeography* (2001) 10, 369–378

## RESEARCH LETTER



### Savanna–forest hysteresis in the tropics

LEONEL DA SILVEIRA LOBO STERNBERG *Department of Biology, University of Miami, Coral Gables, FL 33124, U.S.A. E-mail: lsternberg@umiami.ir.miami.edu*

#### ABSTRACT

A simple dynamic model relating forest area in a region, its contribution to dry season precipitation and the effect on its own establishment was developed. The model equation shows hysteresis between forest and savannas as a function of imported dry season precipitation. Regions are either dominated by forests or savannas, with each ecosystem showing stability despite changes in imported dry season precipitation. Deforestation

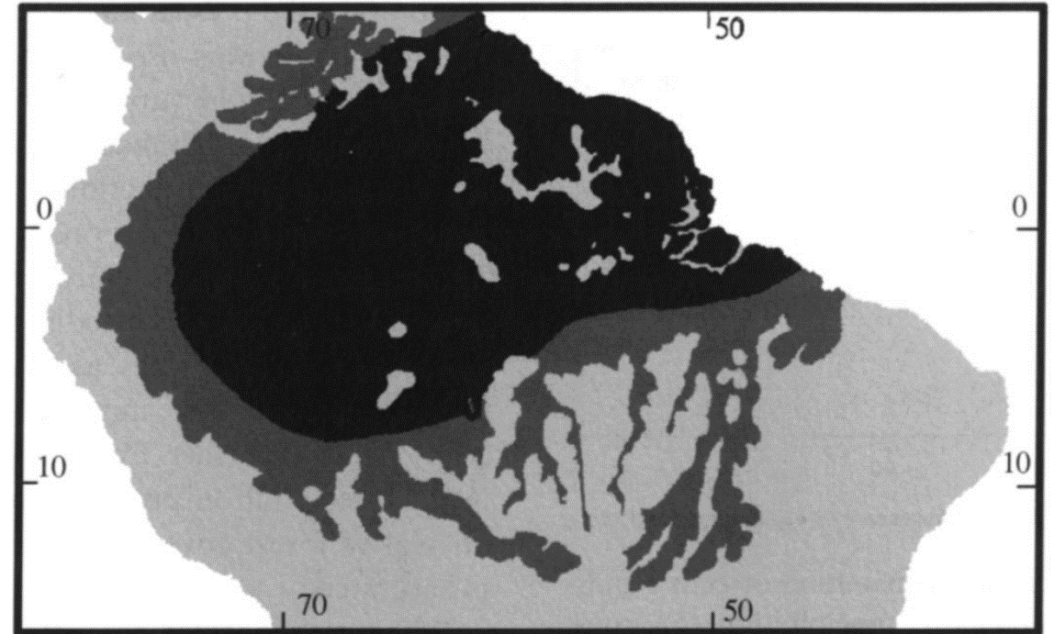
beyond a certain threshold value, however, could cause a collapse of forest ecosystems and replacement by savannas in marginal areas. The predictions of this model corroborate pollen core analysis in the Amazon basin, where historical stability of tropical forest cover has been shown despite global climate change.

**Key words** Conservation, hysteresis, palaeoclimate, palynology, refuge hypothesis, saddle node bifurcation, savanna, tropical forest.

#### INTRODUCTION

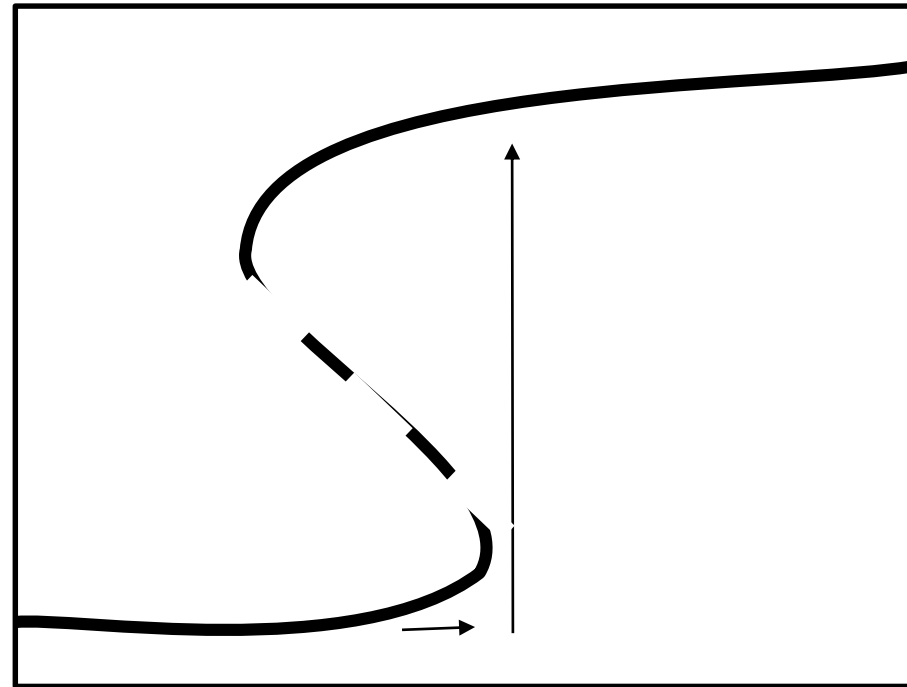
In the beautiful story *L'Homme qui plantait des arbres* [*The man who planted trees*] by Jean Giono (1982), a single man was able to change the cli-

Therefore, tropical forests modify regional climate by increasing precipitation. Interestingly, tropical forests modify climate so that it becomes more favourable for their own establishment and maintenance. In addition to modifying climate



# WHAT IS HYSTERESIS?

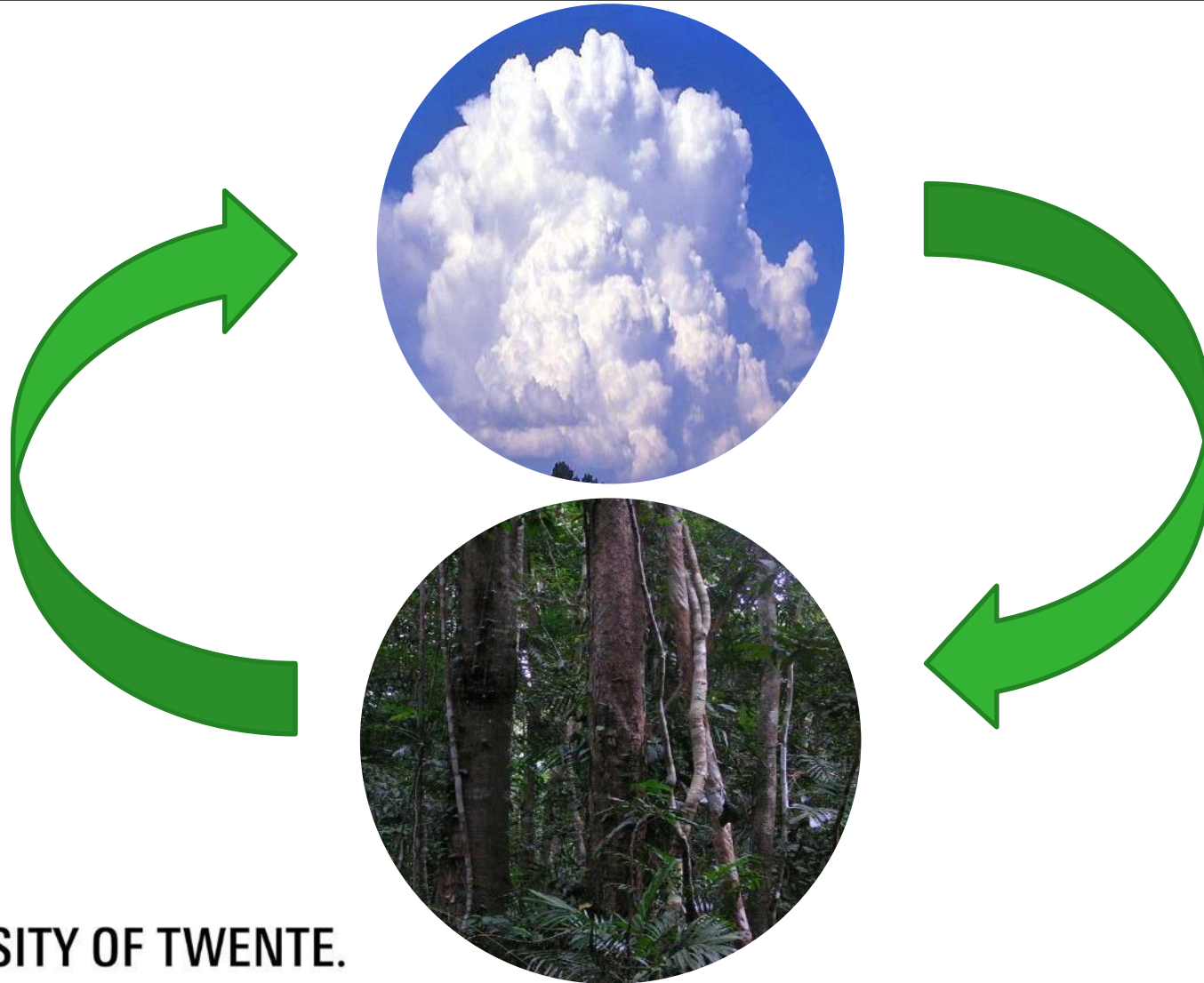
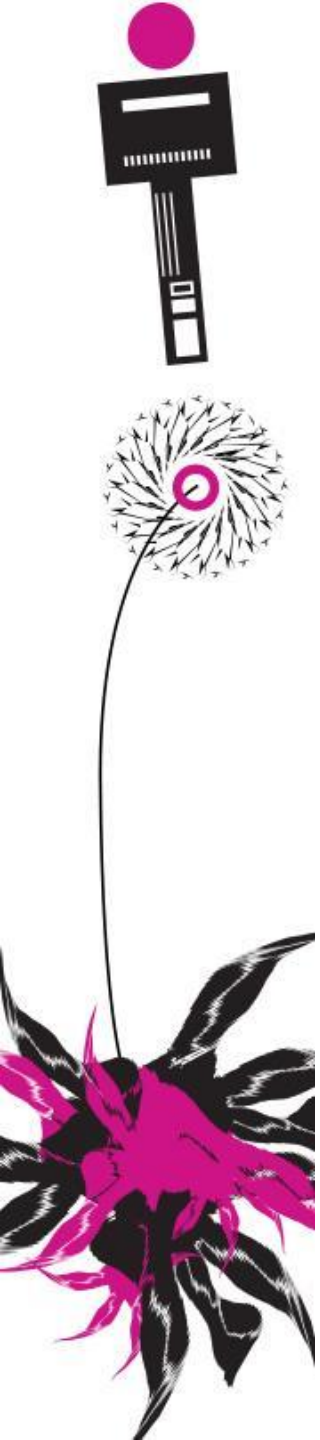
System state  
(Tree cover)



Driver  
(rainfall)

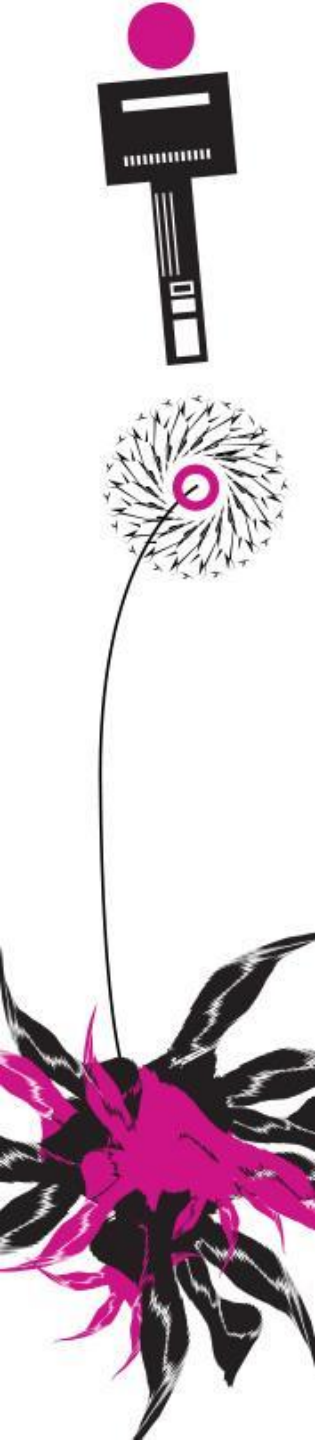
# A POSITIVE FEEDBACK LOOP EXISTS IN THIS SYSTEM...

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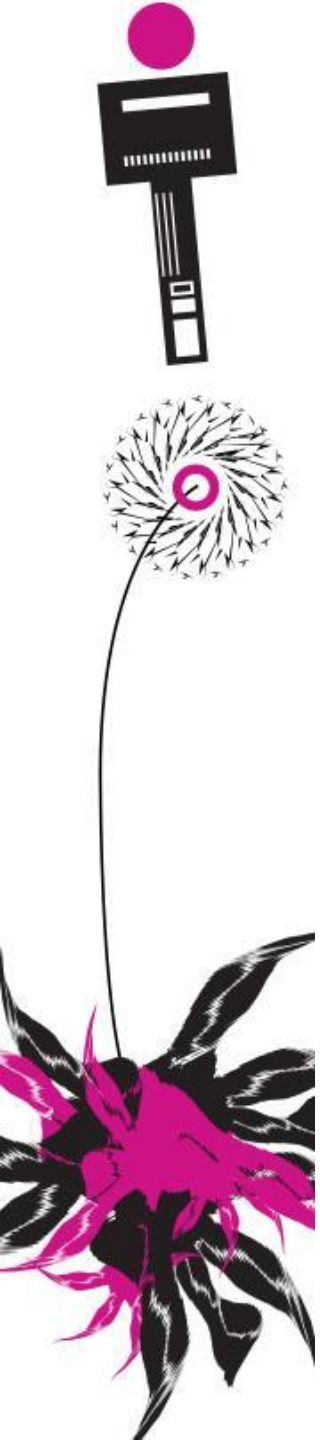




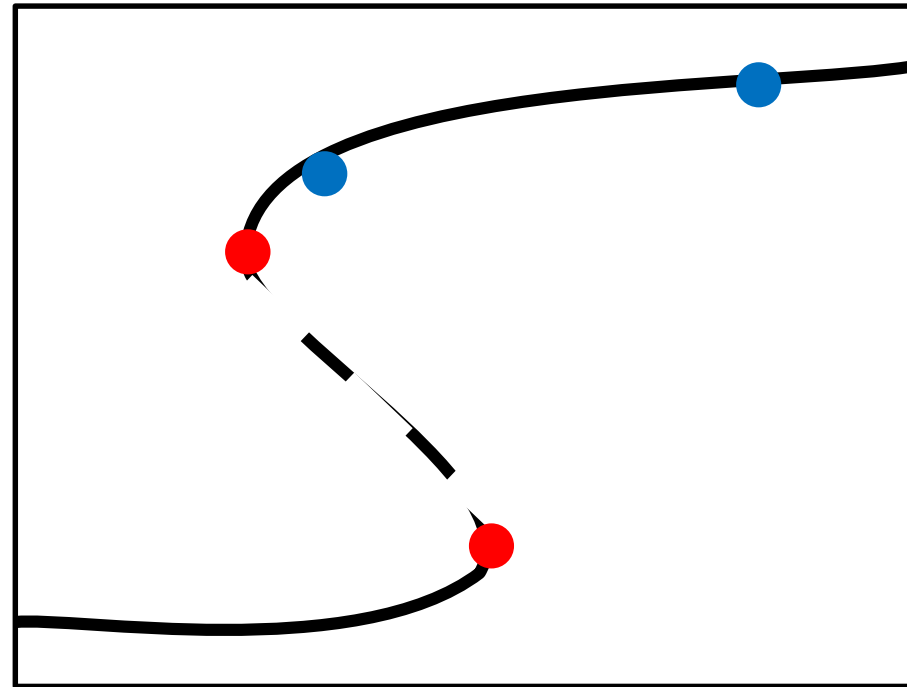
# ...AND ANOTHER ONE



# HOW TO DETECT PROXIMITY TO TIPPING POINTS

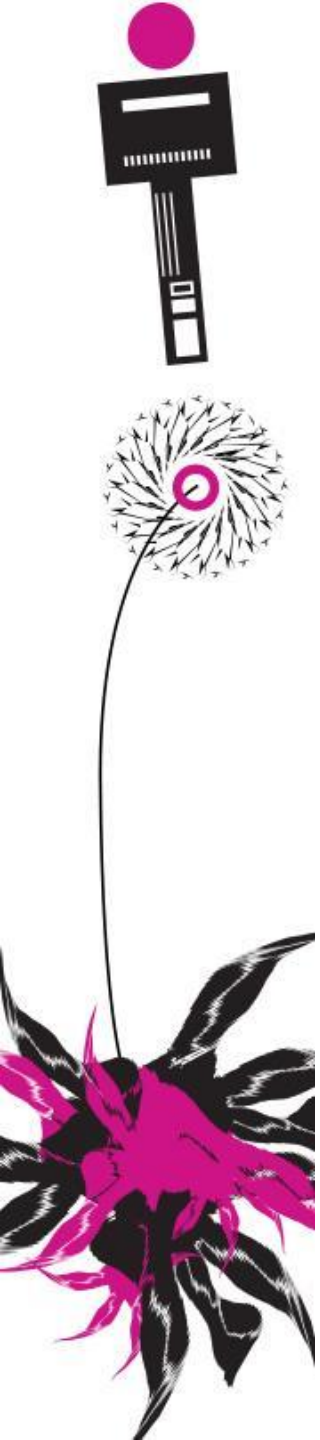


System state  
(Tree cover)

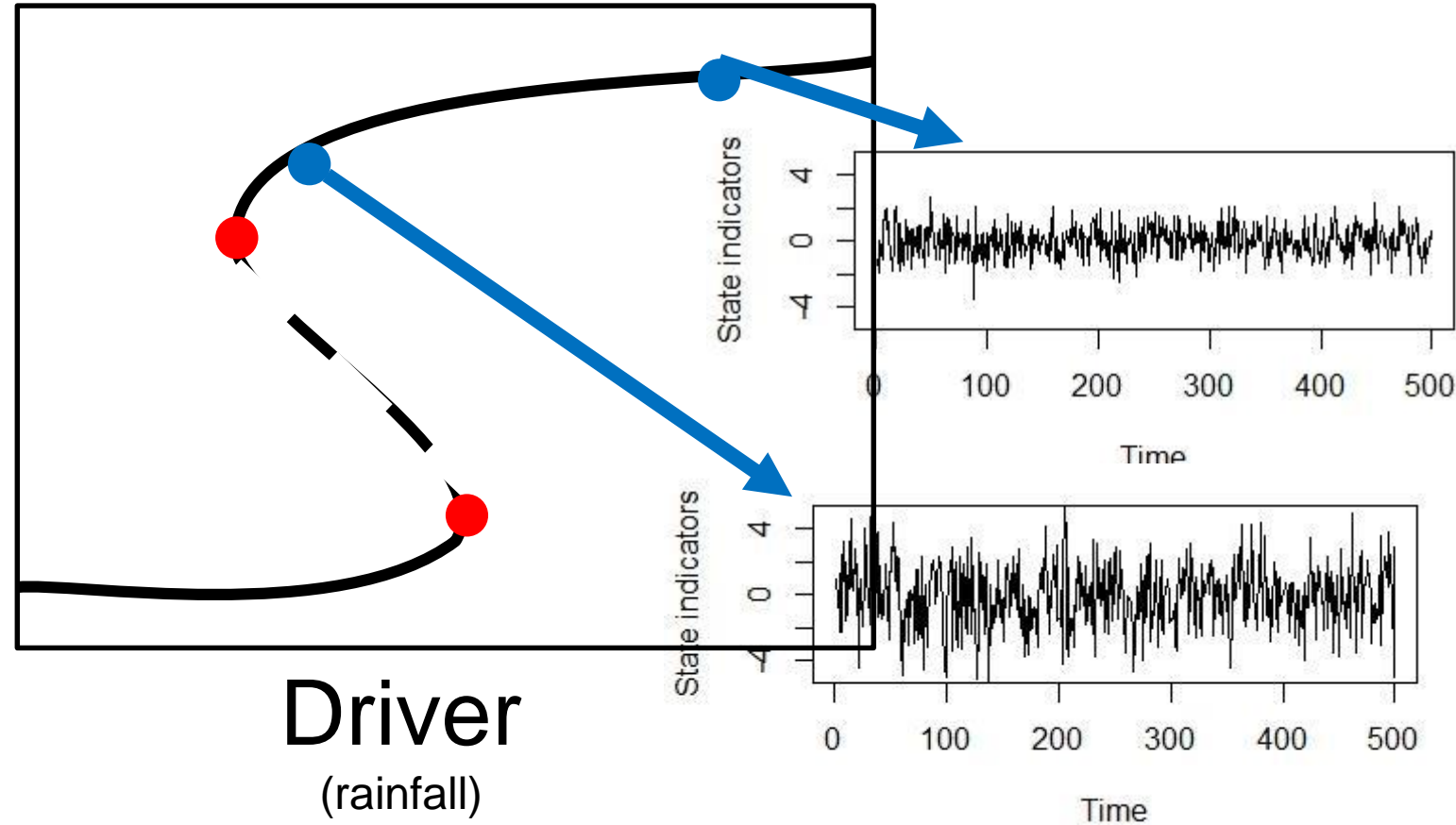


Driver  
(rainfall)

# HOW TO DETECT PROXIMITY TO TIPPING POINTS

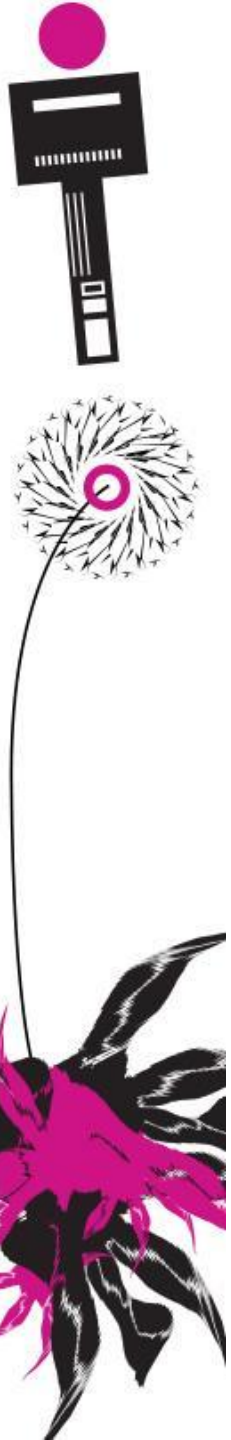


System state  
(Tree cover)





# EARLY WARNING INDICATORS FOR TIPPING POINTS



OPEN ACCESS Freely available online



## Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data

Vasilis Dakos<sup>1,2\*</sup>, Stephen R. Carpenter<sup>3</sup>, William A. Brock<sup>4</sup>, Aaron M. Ellison<sup>5</sup>, Vishwesh Guttal<sup>6</sup>, Anthony R. Ives<sup>7</sup>, Sonia Kéfi<sup>8</sup>, Valerie Livina<sup>9</sup>, David A. Seekell<sup>10</sup>, Egbert H. van Nes<sup>1</sup>, Marten Scheffer<sup>1</sup>

**1** Department of Aquatic Ecology and Water Quality Management, Wageningen University, Wageningen, The Netherlands, **2** Integrative Ecology Group, Estación Biológica de Doñana, Sevilla, Spain, **3** Center for Limnology, University of Wisconsin, Madison, Wisconsin, United States of America, **4** Department of Economics, University of Wisconsin, Madison, Wisconsin, United States of America, **5** Harvard Forest, Harvard University, Petersham, Massachusetts, United States of America, **6** Centre for Ecological Sciences, Indian Institute of Science, Bangalore, India, **7** Department of Zoology, University of Wisconsin, Madison, Wisconsin, United States of America, **8** Institut des Sciences de l'Evolution, CNRS, Université de Montpellier II, Montpellier, France, **9** School of Environmental Sciences, University of East Anglia, Norwich, United Kingdom, **10** Department of Environmental Sciences, University of Virginia, Charlottesville, Virginia, United States of America

### Abstract

Many dynamical systems, including lakes, organisms, ocean circulation patterns, or financial markets, are now thought to have tipping points where critical transitions to a contrasting state can happen. Because critical transitions can occur unexpectedly and are difficult to manage, there is a need for methods that can be used to identify when a critical transition is approaching. Recent theory shows that we can identify the proximity of a system to a critical transition using a variety of so-called 'early warning signals', and successful empirical examples suggest a potential for practical applicability. However, while the range of proposed methods for predicting critical transitions is rapidly expanding, opinions on their practical use differ widely, and there is no comparative study that tests the limitations of the different methods to identify approaching critical transitions using time-series data. Here, we summarize a range of currently available early warning methods and apply them to two simulated time series that are typical of systems undergoing a critical transition. In addition to a methodological guide, our work offers a practical toolbox that may be used in a wide range of fields to help detect early warning signals of critical transitions in time series data.

**Citation:** Dakos V, Carpenter SR, Brock WA, Ellison AM, Guttal V, et al. (2012) Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data. PLoS ONE 7(7): e41010. doi:10.1371/journal.pone.0041010

**Editor:** Bülent Yener, Rensselaer Polytechnic Institute, United States of America

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**Competing Interests:** The authors have declared that no competing interests exist.

\* E-mail: vasilisdakos@gmail.com

### Introduction

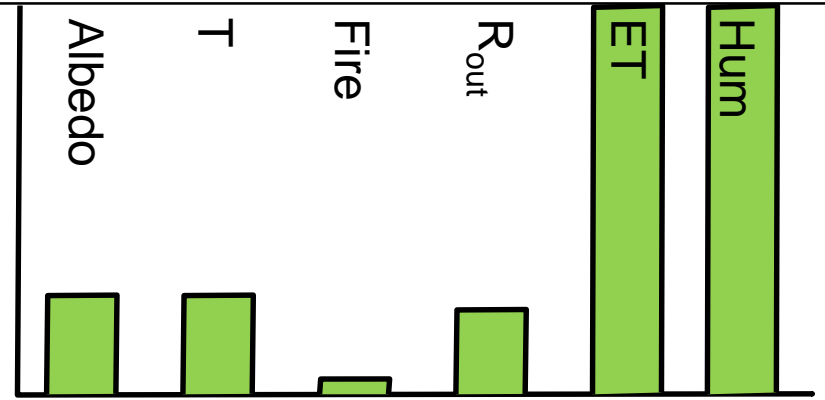
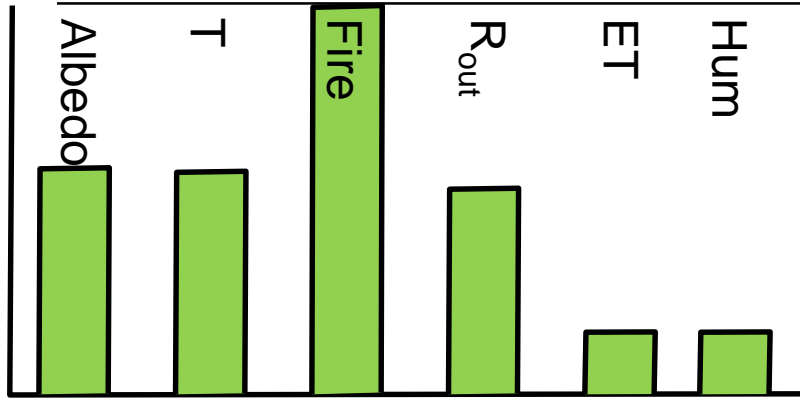
The Earth's past has been characterized by rapid and often unexpected punctuated shifts in temperature and climatic conditions [1]. Lakes and coral reefs have shifted among alternative

To overcome these challenges, numerous studies have suggested the use of generic early warning signals (or *leading indicators*) that can detect the proximity of a system to a tipping point [6]. Such indicators are based on common mathematical properties of

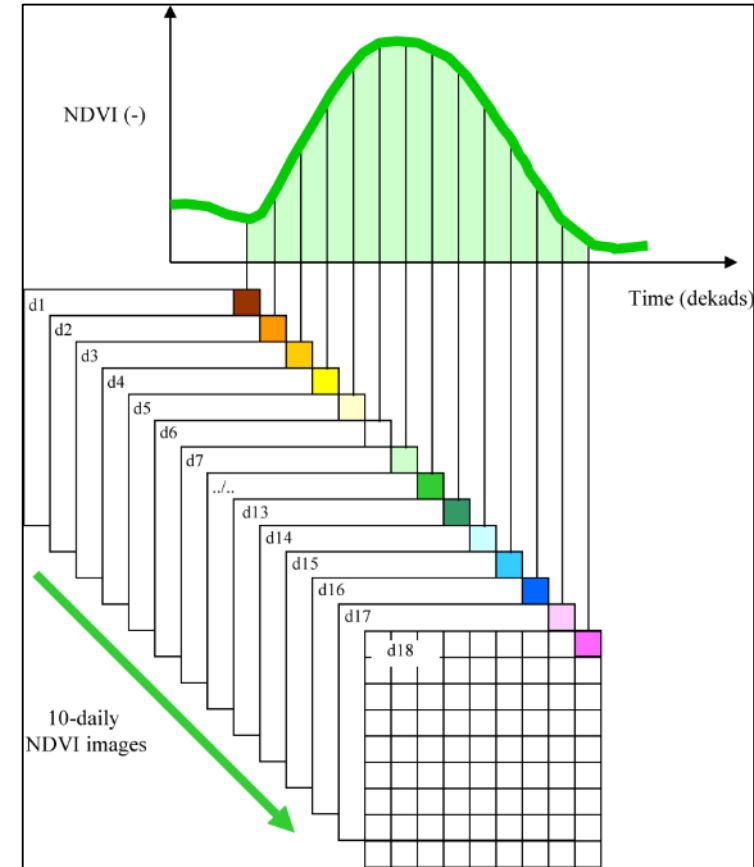
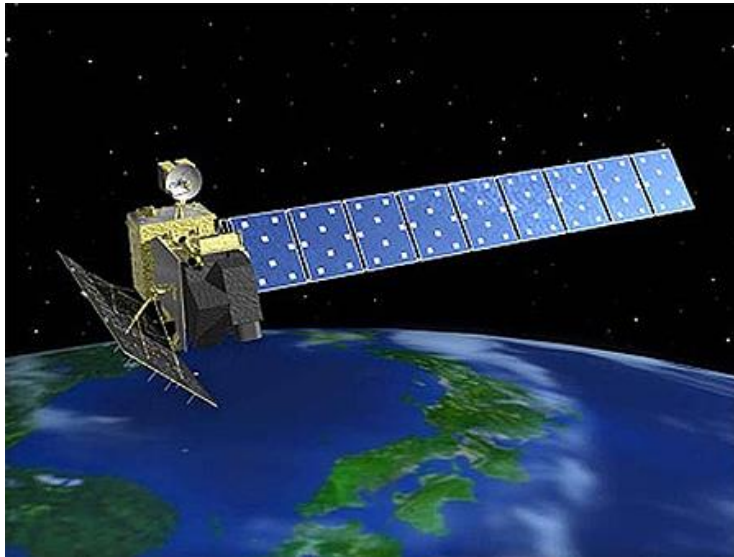
**Table 1.** Early warning signals for critical transitions.

		Phenomenon		
Method/Indicator		Rising memory	Rising variability	Flickering
metrics	Autocorrelation at-lag-1	x		
	Autoregressive coefficient of AR(1) model	x		
	Return rate (inverse of AR(1) coefficient)	x		
	Detrended fluctuation analysis indicator	x		
	Spectral density	x		
	Spectral ratio (of low to high frequencies)	x		
	Spectral exponent	x		
	Standard deviation		x	x
	Coefficient of variation		x	x
	Skewness		x	x
models	Kurtosis	x		x
	Conditional heteroskedasticity	x		x
	BDS test		x	x
	Time-varying AR(p) models	x	x	
	Nonparametric drift-diffusion-jump models	x	x	x
	Threshold AR(p) models			x
Potential analysis (potential wells estimator)			x	

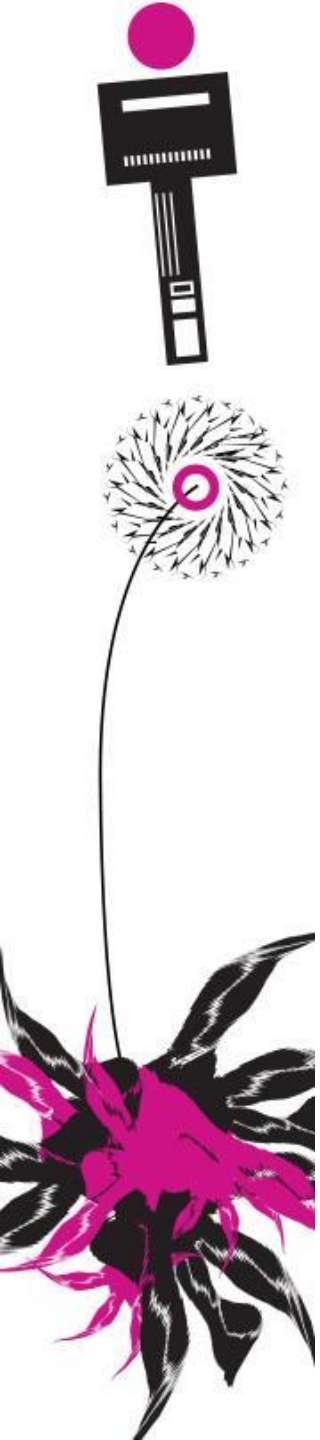
# FOREST AND SAVANNAS: HOW TO ASSESS THEIR STATE



# THIS IS WHERE EO ENTERS...







# WHAT DO WE NEED FOR THIS DETECTION METHOD

## THINKING OF REMOTE SENSING

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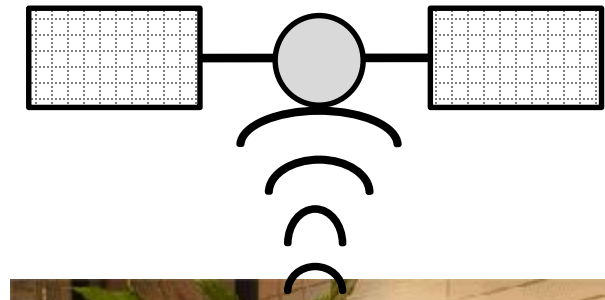
- Continuous time series of observations
- Of sufficient duration
- High frequency
- Measuring a relevant quantity
- At the right spatial scale

# TWO POSSIBLE APPROACHES

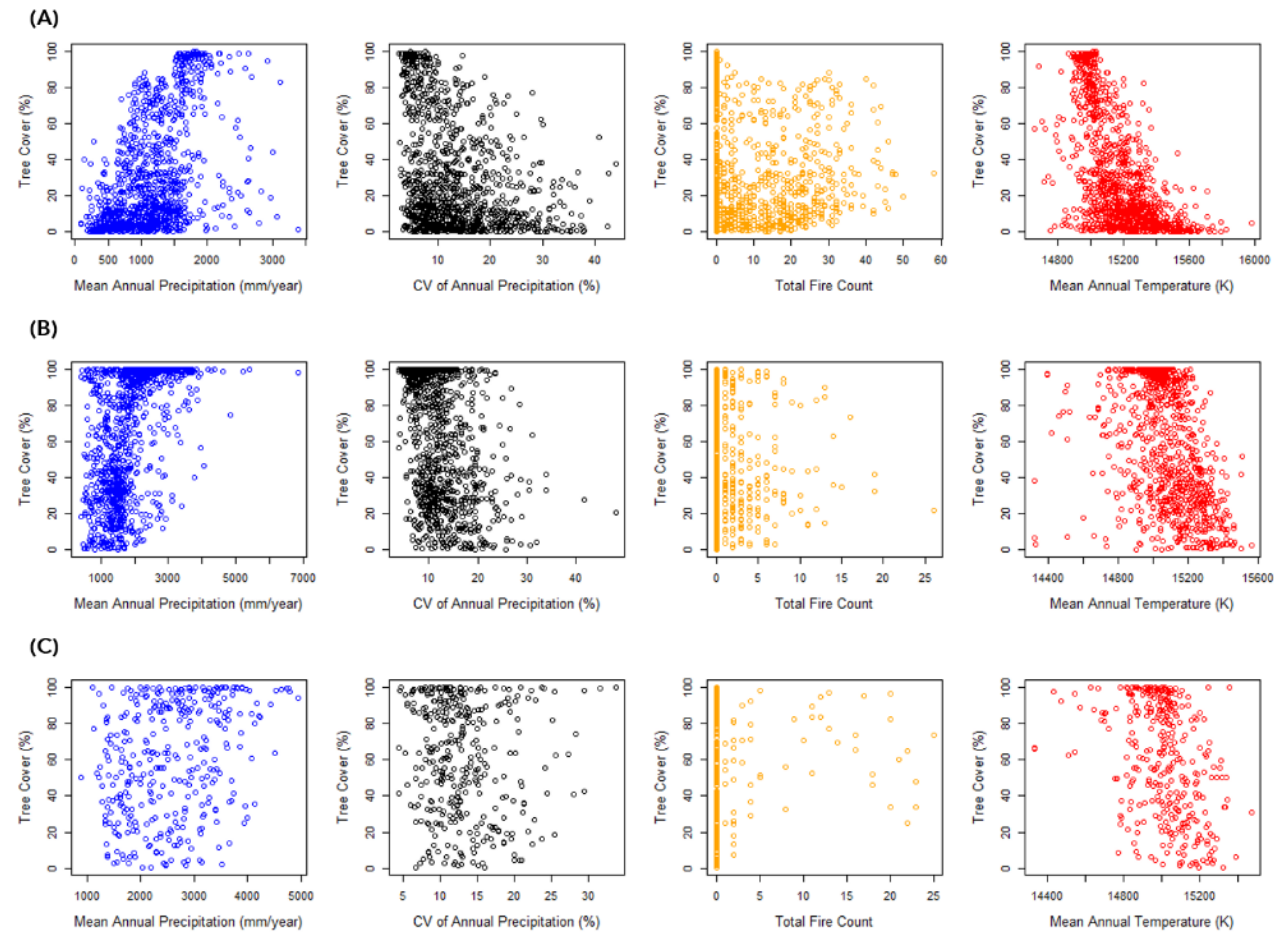
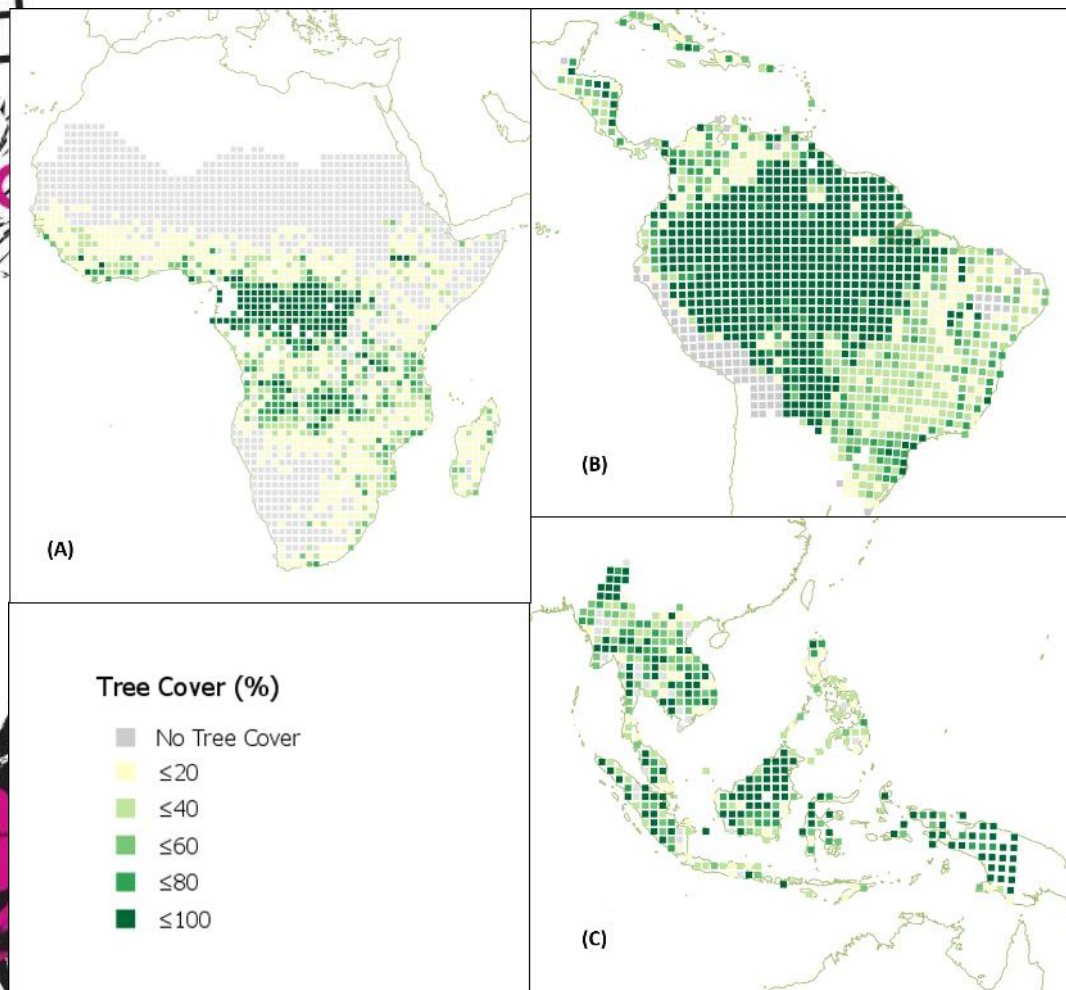
- Top Down



- Bottom Up

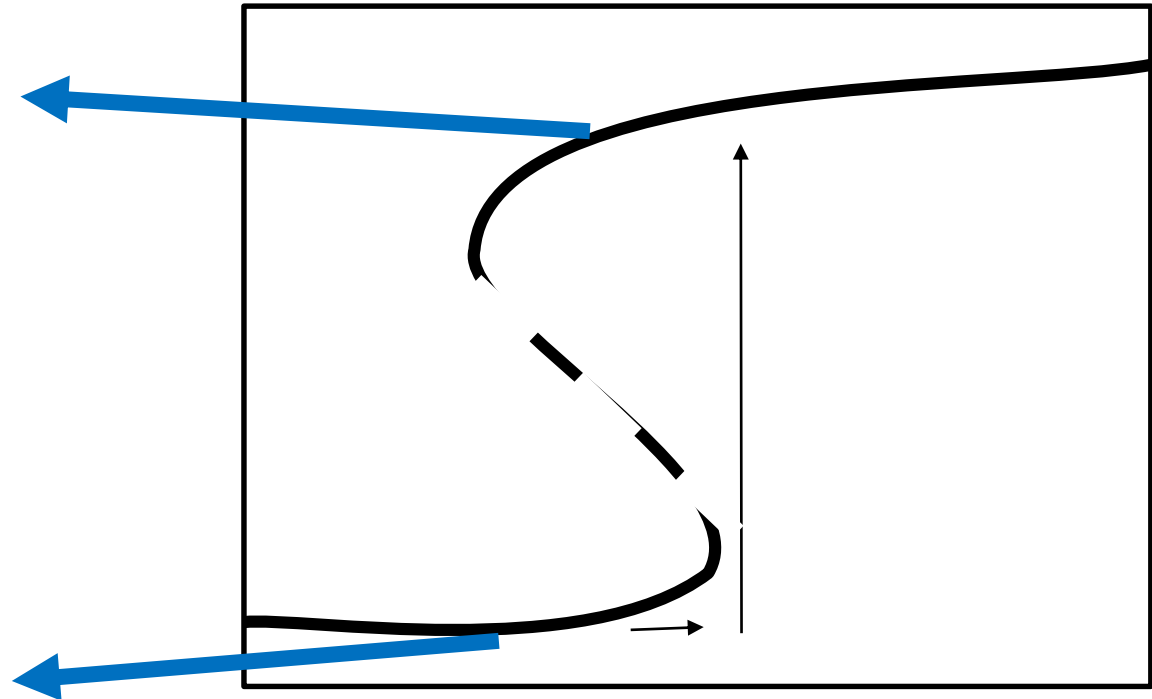
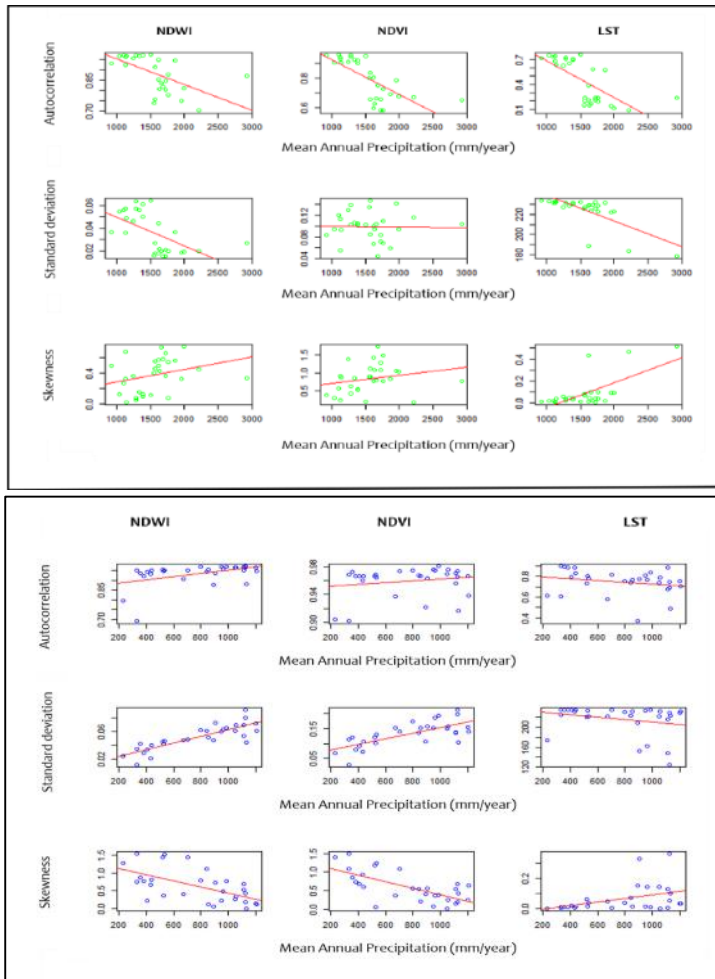


# ARE THERE SIGNS OF BISTABILITY?





# DO TIME SERIES BEHAVE AS WOULD BE EXPECTED?



# STABILITY DETECTION WITH RS



Article

## Remotely-Sensed Early Warning Signals of a Critical Transition in a Wetland Ecosystem

Sara Alibakhshi <sup>1,\*</sup>, Thomas A. Groen <sup>2</sup>, Miina Rautiainen <sup>1,3</sup> and Babak Naimi <sup>4,5</sup>

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<sup>2</sup> Faculty of Geo-Information Science and Earth Observations, University of Twente, Enschede, The Netherlands; t.a.groen@utwente.nl

<sup>3</sup> Department of Electronics and Nanoengineering, School of Engineering, Aalto University, P.O. Box 14100, 00076 Espoo, Finland

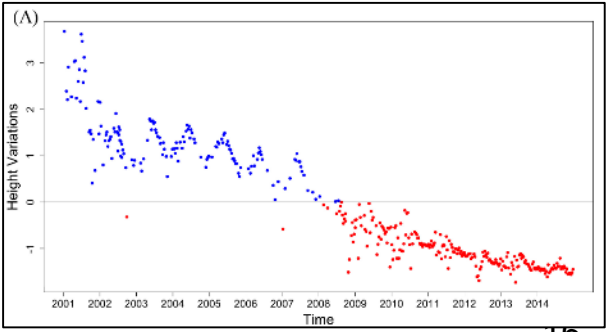
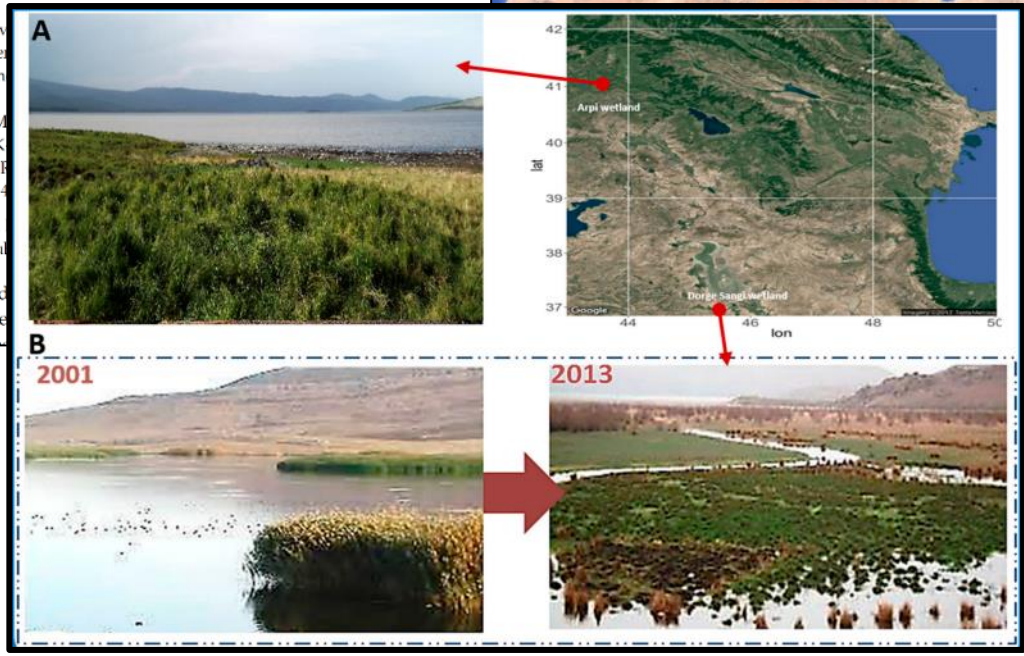
<sup>4</sup> Center for Macroecology, Evolution and Climate (CM), University of Copenhagen, Universitetsparken 15, DK-2100 Copenhagen, Denmark

<sup>5</sup> Department of Environment and Energy, Science and Technology, University of Twente, Enschede, The Netherlands

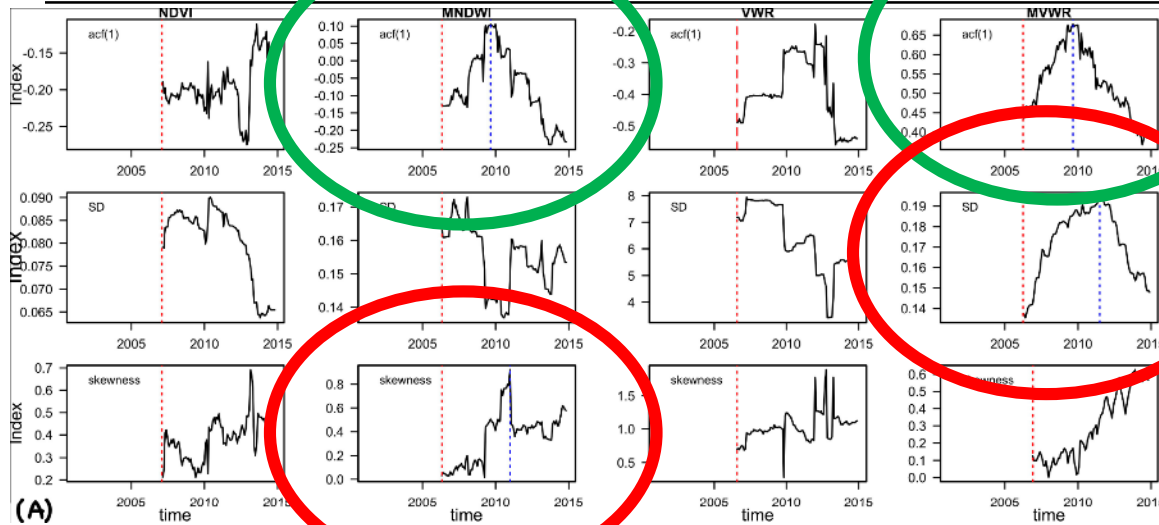
\* Correspondence: sara.alibakhshi@aalto.fi; Tel.: +358-40-4505000

Academic Editors: Qiusheng Wu, Deepak R. Mishra and ...  
Received: 30 September 2016; Accepted: 1 April 2017; Published: ...

**Abstract:** The response of an ecosystem to external changes is often nonlinear and sometimes irreversible and can occur ... The likelihood of such shifts is expected to increase ...

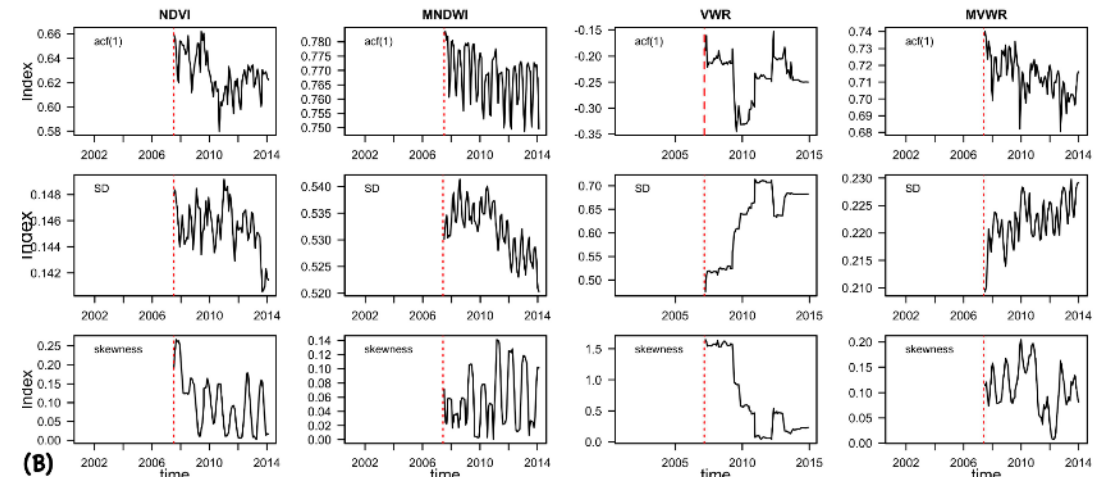


# STABILITY DETECTION WITH RS



Dorge Sangi Wetland (Iran)  
Converted into a vegetated state

Arpi Wetland (Armenia)  
Remained a wetland



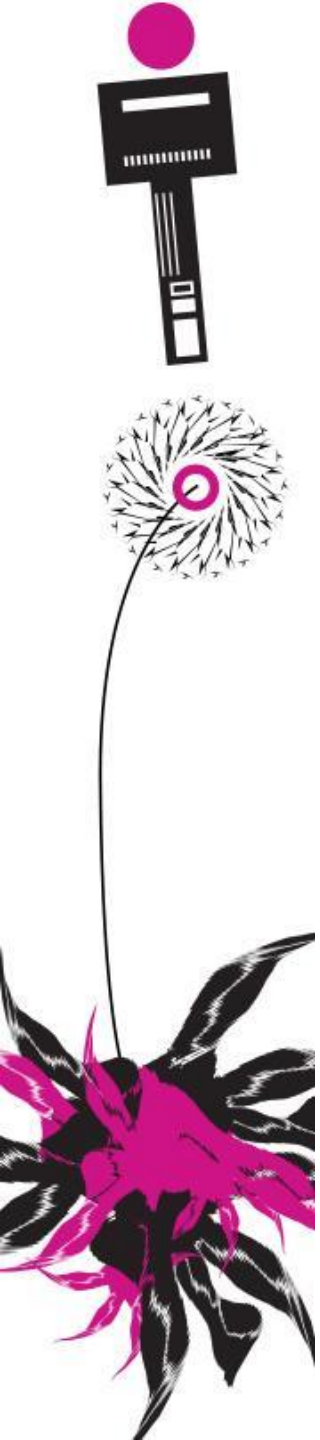


# MEDITERRANEAN SYSTEMS?



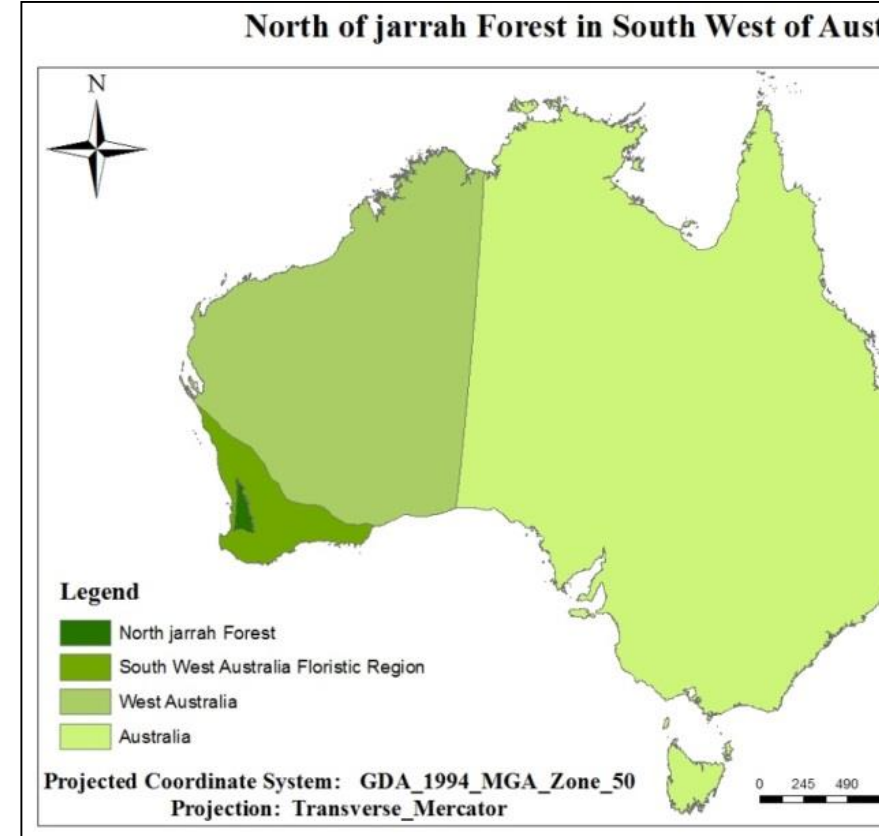
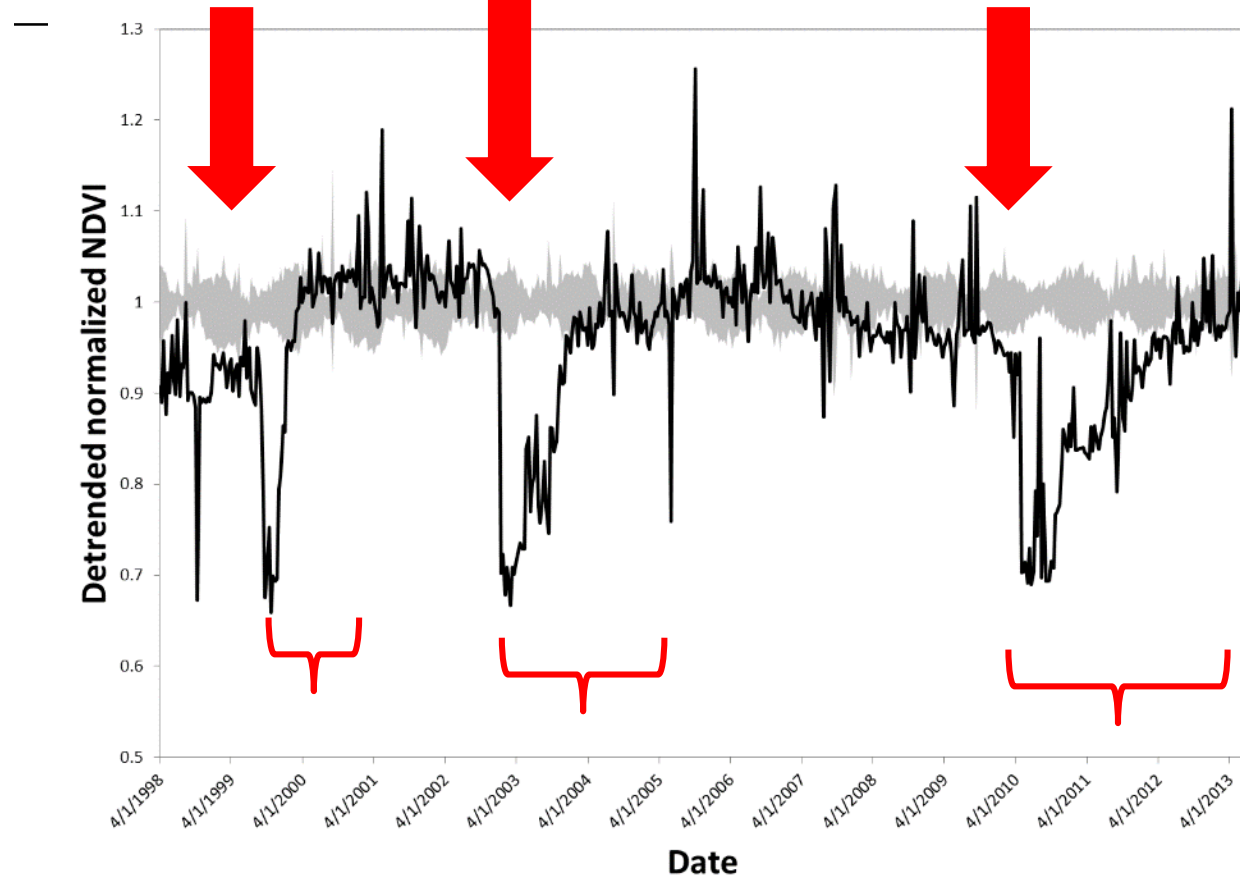
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Matusick et al.  
(2013)

UNIVERSITY OF TWENTE.





# RECOVERY AFTER FIRES

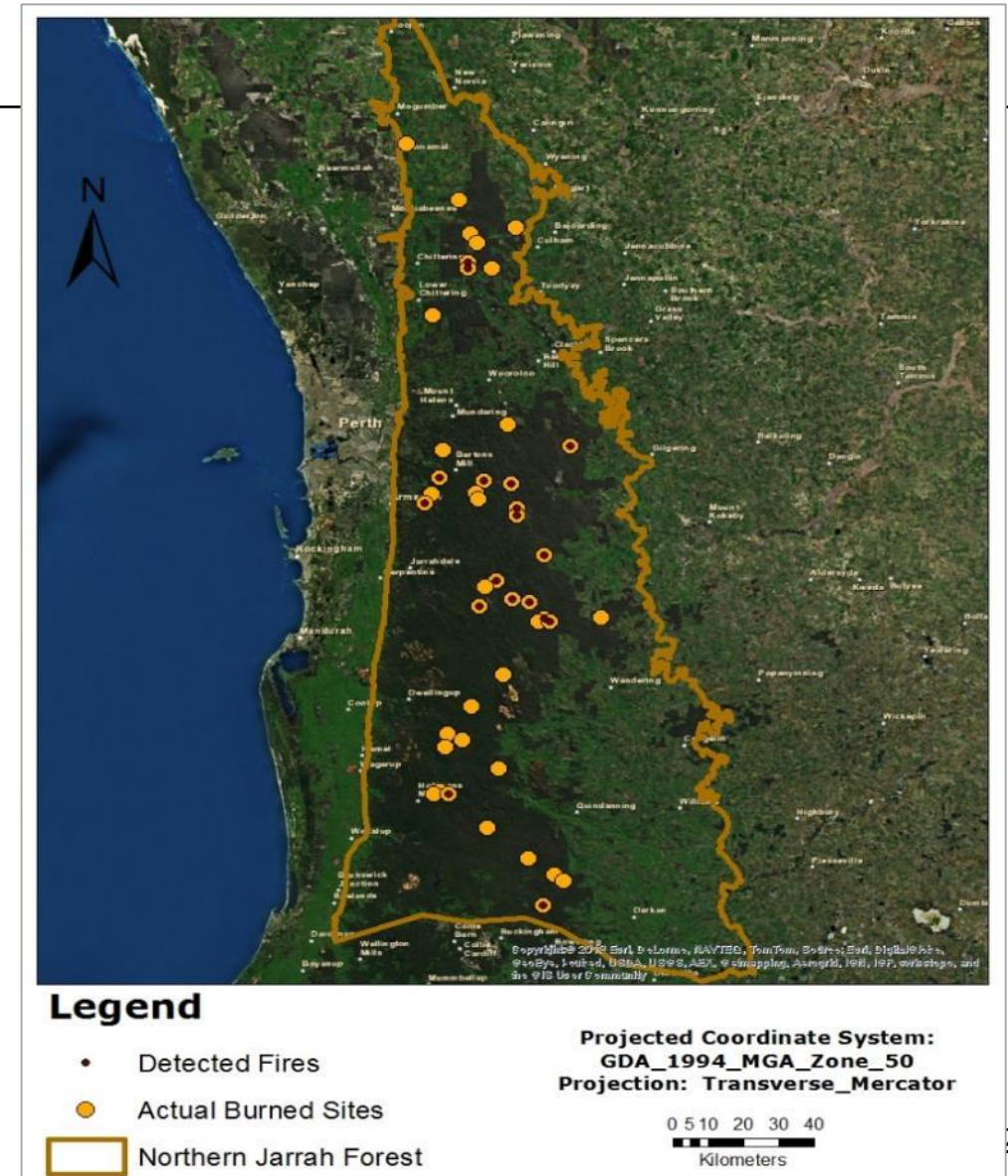


# RECOVERY AFTER FIRES

## Summary

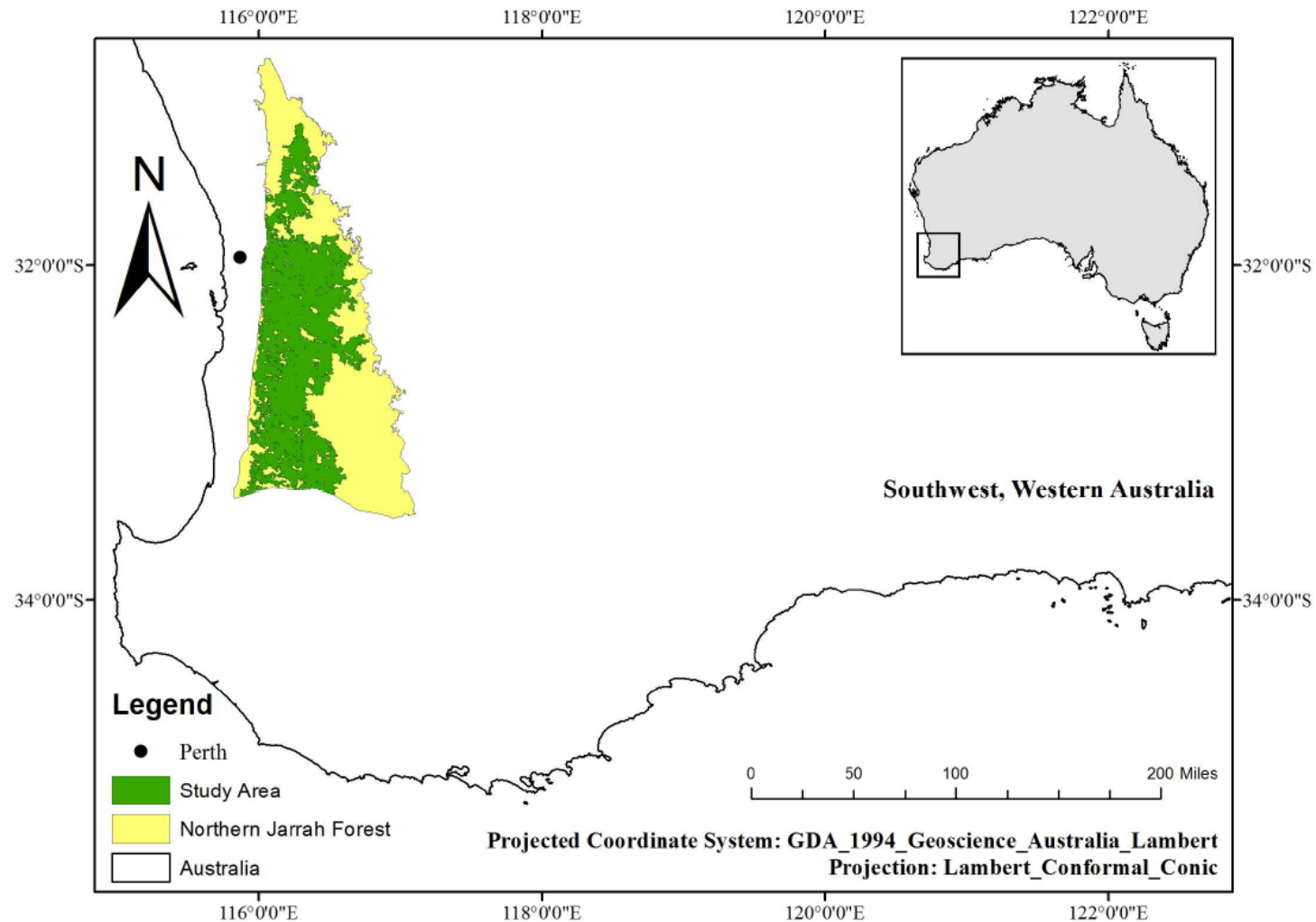
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P_value	0.0002118

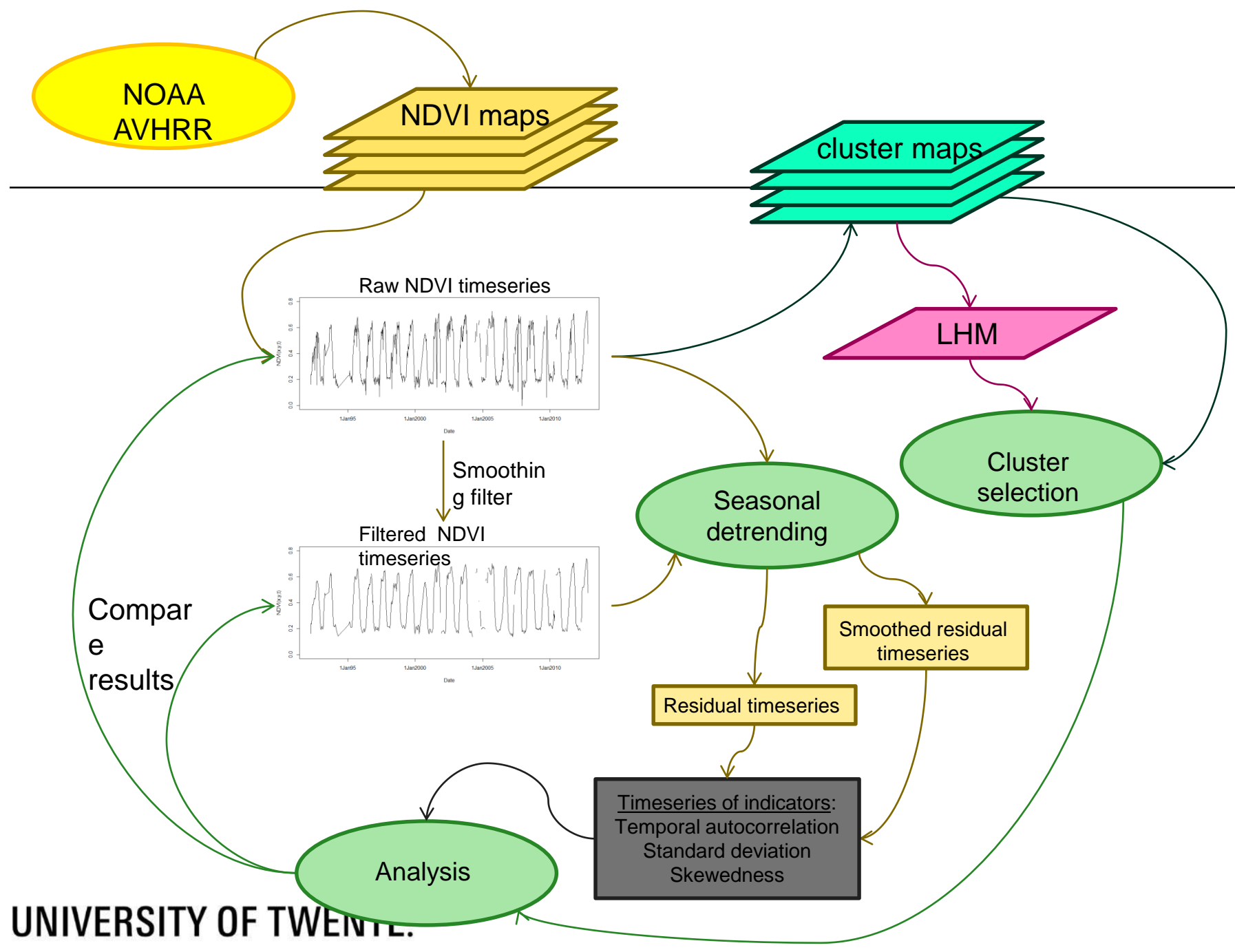
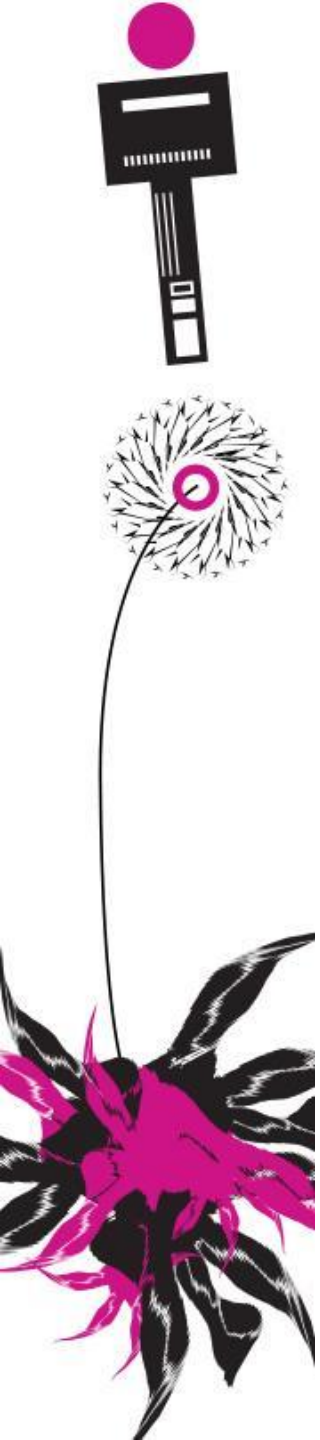
$$RT \sim \text{Fire Interval} - P_{\text{grow seas.}} + P_{\text{fire month}} + P_{\text{recov period}}$$

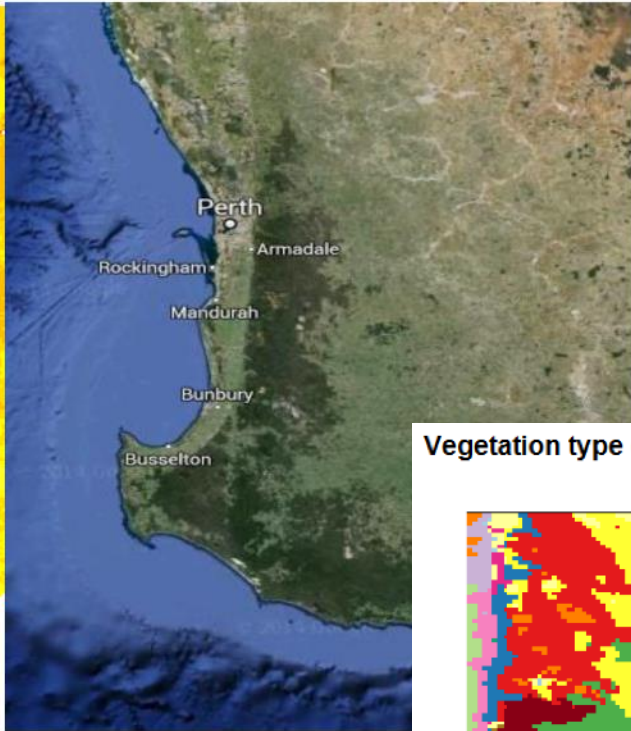
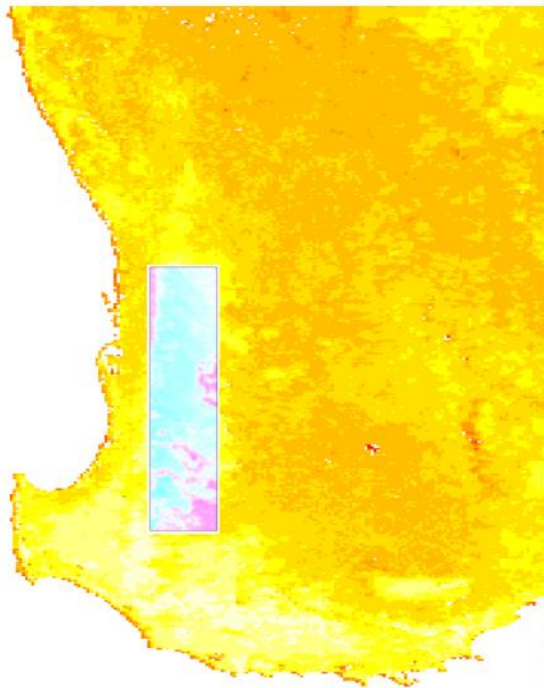
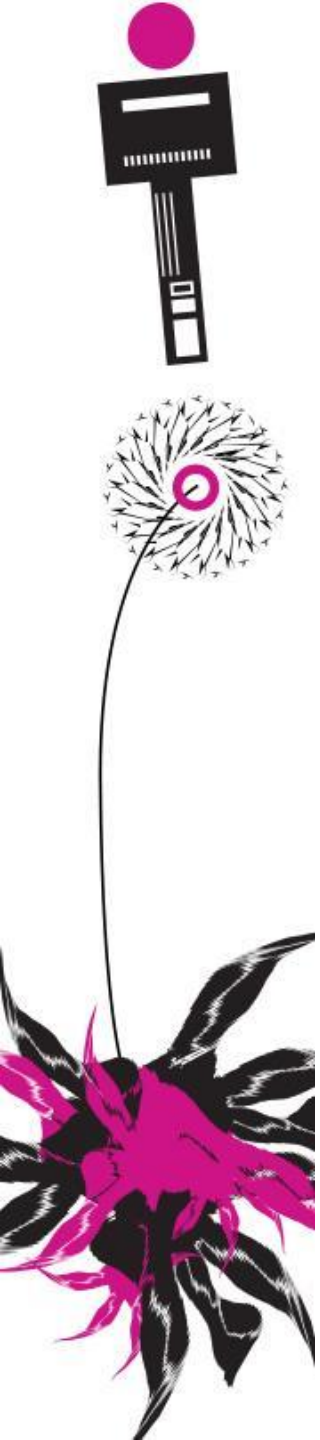




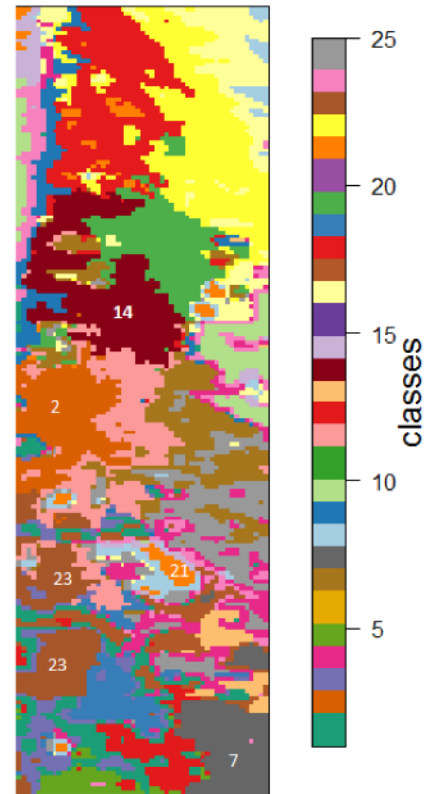
# STABILITY INDICATORS FROM CONTINUOUS TS?



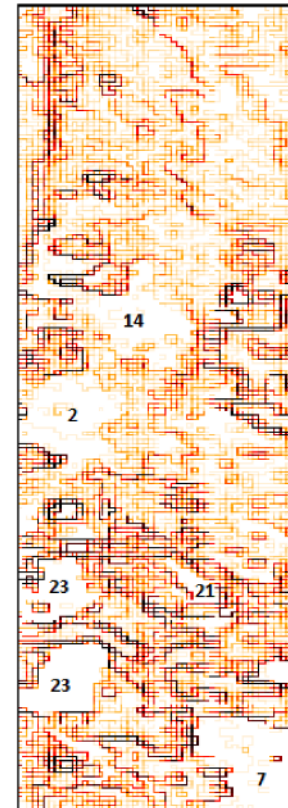




Vegetation type classes, 25 classes



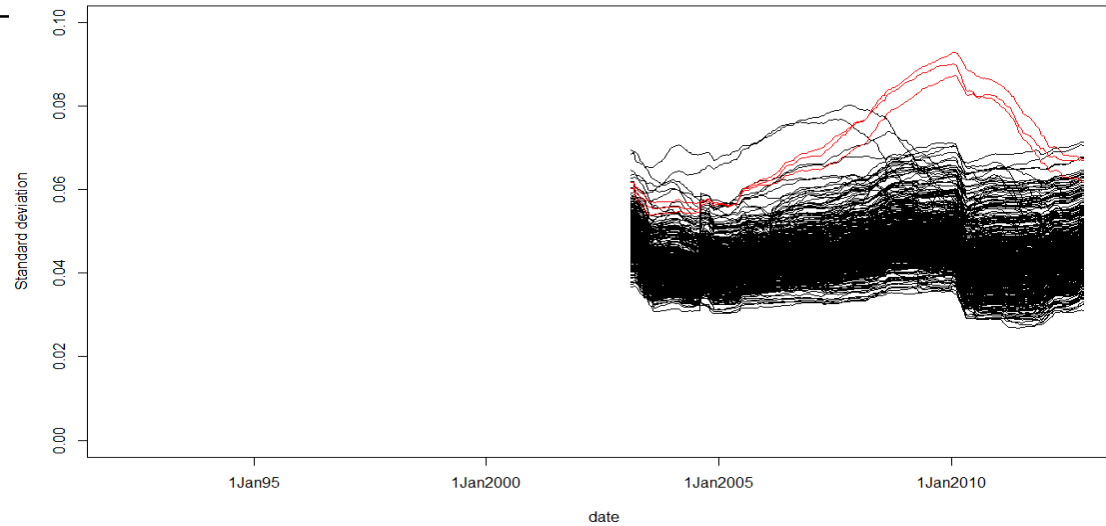
Landscape Heterogeneity Map



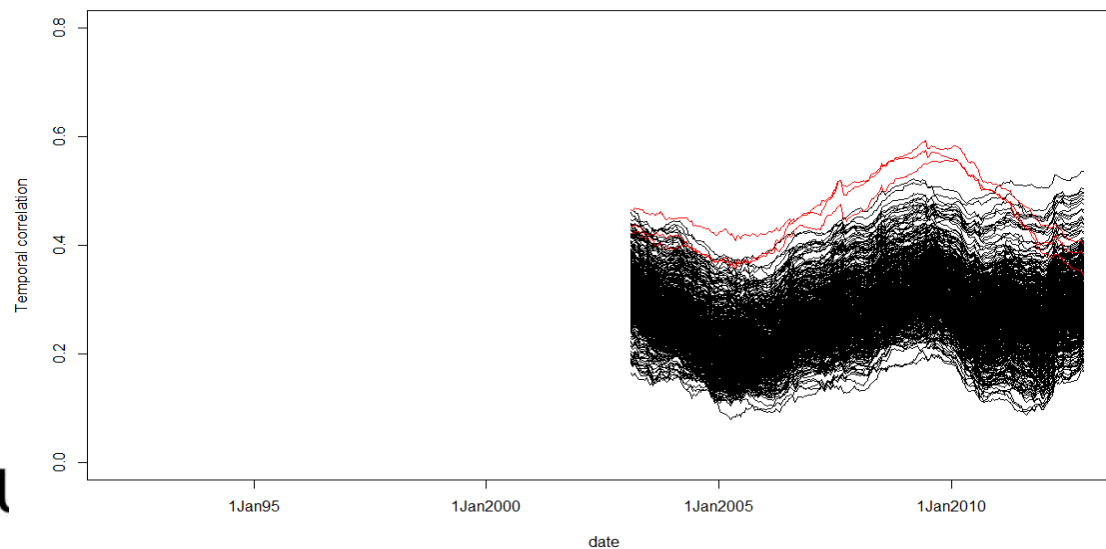


# TS ANALYSIS WITHIN HOMOGENEOUS CLUSTERS

Standard deviation, cluster 2, 6th degree filter

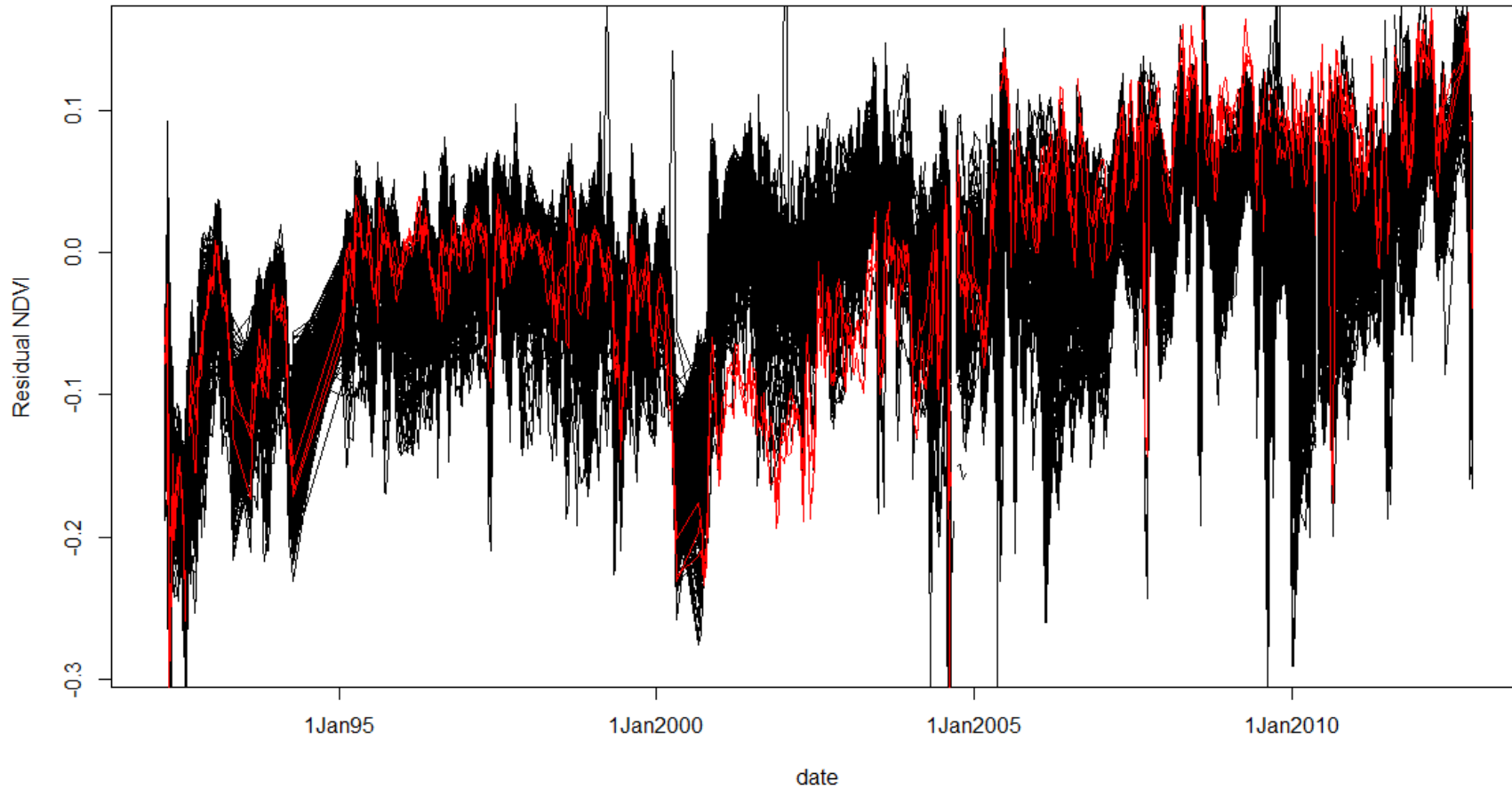


Temporal correlation, cluster 2, unfiltered

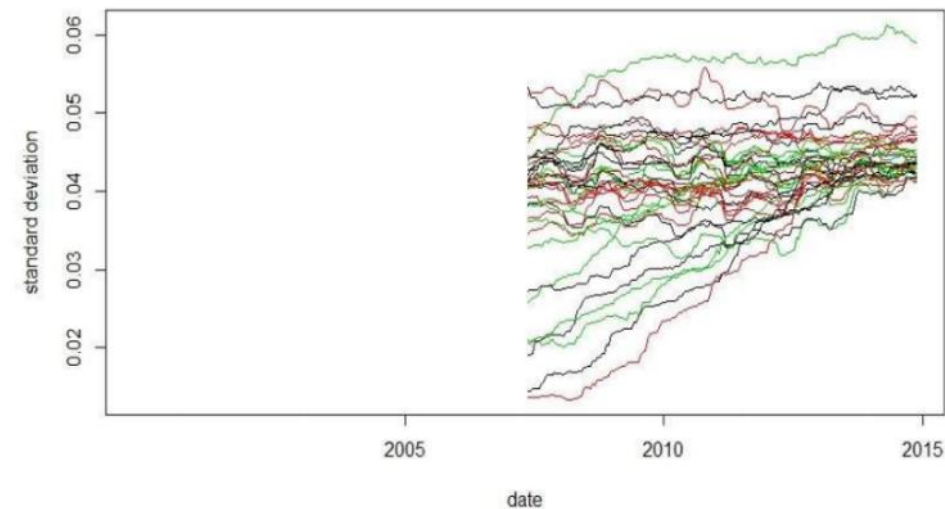
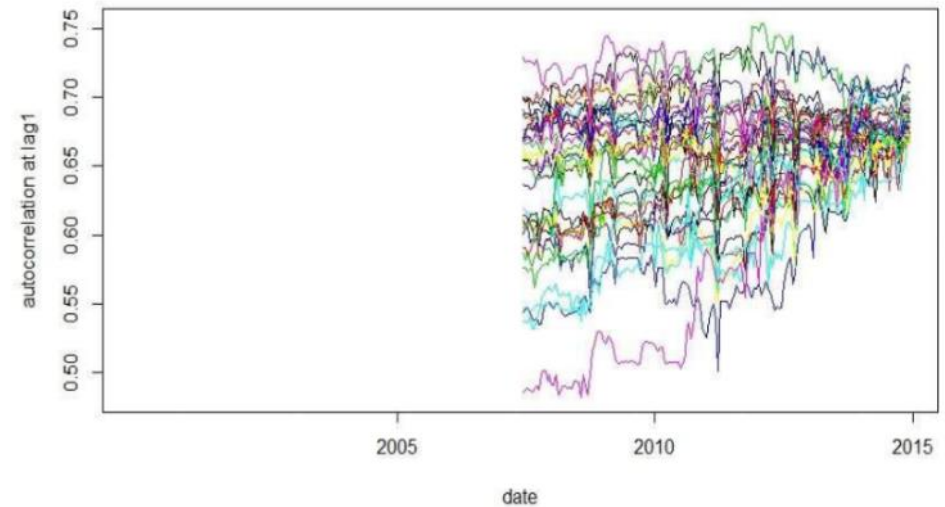
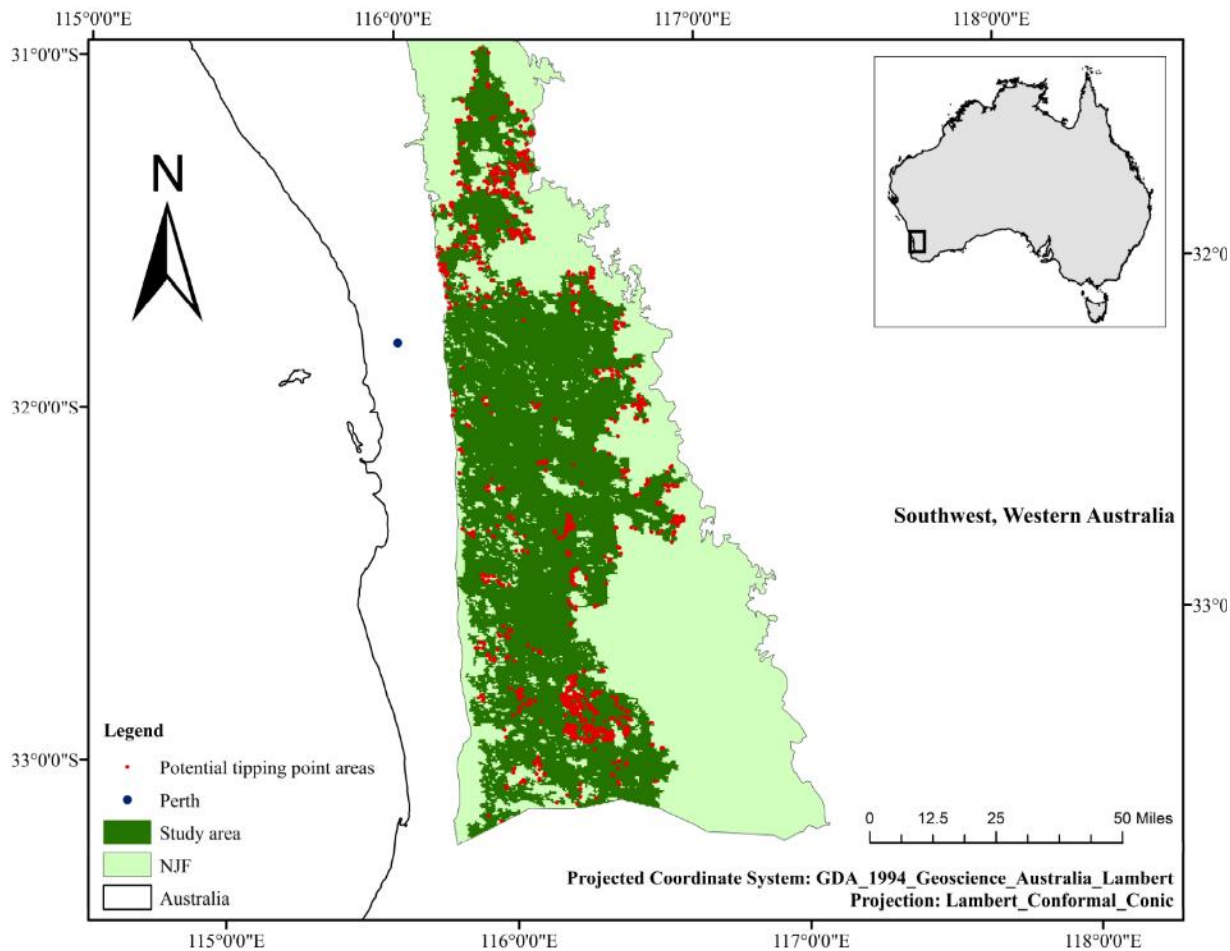


- Standard deviation and temporal autocorrelation robust against filtering
- Skewedness very sensitive to filtering and extreme values → omitted

# TS ANALYSIS WITHIN HOMOGENEOUS CLUSTERS



# TS ANALYSIS ACROSS ENTIRE SYSTEM





# FIRE AS THE TIPPING EVENT

Sufficiently moist Ecosystems unlike

Ecosystems that experience  
to burn

- mainly grasses and herbaceous plants
- high humidity

Sections



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What ignited many of California's worst wildfires a mystery



← If c  
beco  
Or b

WEATHER ALERT Freeze Warning  
abc 7 NEWS WATCH LIVE  
San Francisco East Bay South Bay Peninsula North Bay  
San Francisco, CA 57°  
Log In

abc #ChooseKindness  
GLEN glenn PACER  
www.abc.com/choosekindness

COMPLEX FIRE  
Biggest wildfire in California history fully contained

San Francisco Chronicle  
Meer informatie >

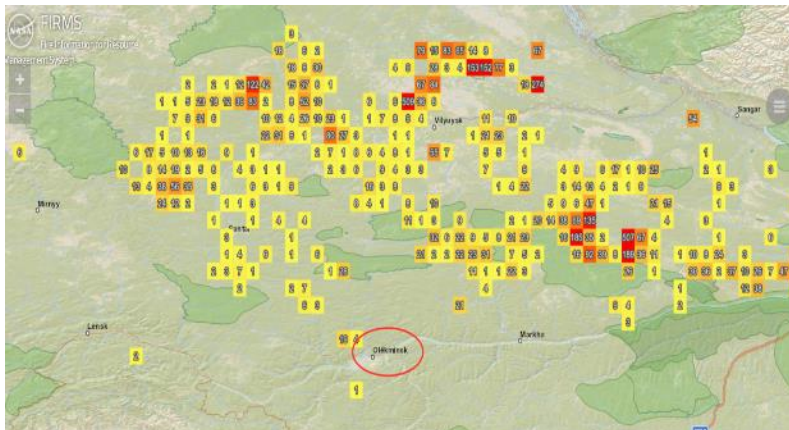
CALIFORNIA WILDFIRES  
California wildfires remain major threat despite new rainfall year  
Gwenolyn Wu | Oct. 1, 2018 | Updated: Oct. 1, 2018 4:59 a.m.

The Press Democrat



# FIRE AS THE TIPPING EVENT

- See fire as the manifestation of a “tipping event”
- Cluster based on detrended EWS signals
- Test how fire events associate with these types of clusters





# WRAP UP

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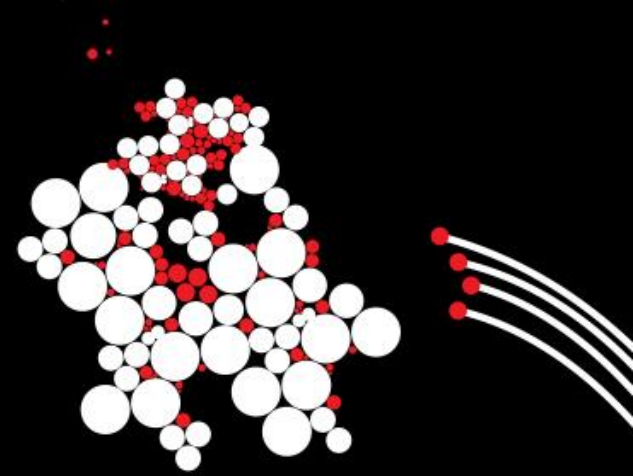
- RS based EWS indicators work (sometimes)
- Top down approach gives supporting evidence (but is circumstantial)
- Need Bottom up cases (When you know about collapsed (or collapsing) ecosystems -> **let me know!**)
  - Which RS product to use
  - Determine at which threshold EWS indicate tipping point





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THANK YOU FOR LISTENING

