2018

Vulnerability of Protected Areas to Human Encroachment, Climate Change and Fire in the Fragmented Tropical Forests of West Africa

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VULNERABILITY OF PROTECTED AREAS TO HUMAN ENCROACHMENT, CLIMATE CHANGE AND FIRE IN THE FRAGMENTED TROPICAL FORESTS OF WEST AFRICA

BY

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A dissertation submitted in partial fulfillment of the requirements for the

Doctor of Philosophy

Major in Geospatial Science and Engineering

Specialization in Remote Sensing Geography

South Dakota State University

2018

VULNERABILITY OF PROTECTED AREAS TO HUMAN ENCROACHMENT, CLIMATE CHANGE AND FIRE IN THE FRAGMENTED TROPICAL FORESTS OF WEST AFRICA

This dissertation is approved as a creditable and independent investigation by a candidate for the Doctor of Philosophy degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidates are necessarily the conclusions of the major department.

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I happily dedicate this dissertation to my dear wife, Eunice.

ACKNOWLEDGEMENTS

I earnestly express my greatest gratitude to the Almighty God for the gift of life, the strength, and the power of endurance during this academic journey. Lord you are worthy of it all!

I wish to express my sincerest and deepest appreciation to my PhD advisor Dr. Michael C. Wimberly for his excellent guidance, devotion, and tolerance. I am particularly grateful to my PhD advisory committee members: Dr. Mark Cochrane, Dr. Tom Loveland (USGS - EROS), Dr. Niall Hanan and Dr. Alexander Smart (graduate faculty representative) for their assistance in diverse ways.

I extend a special appreciation to Dr. John Stanturf, former Project Leader, US Forest Service Center for Forest Disturbance Science (CFDS) in Athens, Georgia. Dr. Stanturf helped me nurture the idea for embarking on a PhD studies when he first visited Ghana in 2010. He subsequently hosted me as a visiting scientist at CFDS, during which he recommended and facilitated my entry into this very exciting PhD program at GSCE. Dr. Stanturf remained extremely supportive throughout my PhD study. My story is never complete without thanking my former supervisor, Dr. Dominic Blay, who inspired and supported me to take up this challenge. So sad, Dominic bowed out of this life before this mission could be accomplished. I am always grateful to you Dominic.

I thank Mr. Gray Tappan, USGS Earth Resources Observation and Science (EROS) Center, for all his assistance. My sincere thanks to Dr. Zhihua Liu and Dr. Izaya Numata for supporting me in various ways, and in particular for their technical assistance. I appreciate past and present members in Dr. Wimberly's research group for their support in diverse ways. I thank my colleague PhD students, especially Fangjun Li for his friendliness and peer advice.

I thank the Forestry Research Institute of Ghana (FORIG) for their support. I sincerely appreciate the following district managers of the Ghana Forest Service Division for their support during my field work in Ghana: Mr. Kwaku Ntiamoah (Sunyani District), Mr. Rex Twum-Damoah (Dormaa Ahenkro District), and Mr. Awuku (Bechem District). My appreciation to colleague members of staff, friends, family and all loved ones who supported me during my studies.

I thank the Ghanaian and the African community in Brookings for the memorable bond of friendship. It has been a wonderful experience! I thank my brother-in-law, George Opoku-Kusi, for supporting me in diverse situations.

There is no better way to express my profound gratitude to my dear wife, Eunice, and my lovely kids, NanaYaa, Awurama, Nana Kusi, Stanturf and Eunibel, for their sincere sacrifice, patience, prayers, and encouragement. Truly, you are my world!

This work was supported by NASA Earth and Space Science Fellowship (grant NNX14AL23H) awarded to Francis Dwomoh; USDA Forest Service, Southern Research Station through cooperative agreements 11-CA-11330136-098 and 14-CA-11330136-015; and the NASA SERVIR Applied Sciences Team through grant NNX16AN22G.

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ABSTRACT

VULNERABILITY OF PROTECTED AREAS TO HUMAN ENCROACHMENT, CLIMATE CHANGE AND FIRE IN THE FRAGMENTED TROPICAL FORESTS OF WEST AFRICA

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2018

The Upper Guinean region of West Africa is home to some of the most globally significant tropical biodiversity hotspots, providing ecosystem services that are crucial for the region's socio-economic and environmental wellbeing. Nonetheless, following decades of human-caused destruction of natural habitats, protected areas currently remain the only significant refugia of original vegetation relics in landscapes that are highly fragmented. Aside from having strong geographic variation in land use, climate, vegetation, and human population, the region has also experienced remarkable biophysical and socio-economic changes in recent decades. All these factors influence the fire regime and the vulnerability of forests within protected areas to fire-mediated changes and forest loss, yet little is known about fire regimes and fire-vegetation interactions within the region. Therefore, the overarching goal of this dissertation was to improve our understanding of the interactions of climate, land use, and fire regimes, as well as effects of fire on forest resilience in the Upper Guinean region of West Africa.

I conducted the first comprehensive regional analysis of the fire regime across the gradient from humid tropical forests to drier woodlands and woody savanna. This analysis revealed that different components of the fire regime were influenced by different environmental drivers. As a result, the various combinations of these environmental factors create distinctive fire regimes throughout the region. The results

further showed increasing active fire trends in parts of the forested areas, and decreasing trend in fire activity across much of the savannas that were likely linked with land cover changes. An analysis of fire-vegetation interactions in the forest zone of Ghana provided evidence of alternative stable states involving tropical forest and a novel non-forest vegetation community maintained by fire-vegetation feedbacks. Furthermore, an analysis exploring recent drought-associated wildfires in the forest zone of Ghana revealed widespread fire encroachment into hitherto fire-resistant moist tropical forests, which were associated with forest degradation.

These findings suggest that ongoing regional landscape and socio-economic changes along with climate change will lead to further changes in the fire regimes and forest vegetation of West Africa. Hence, efforts to project future fire regimes and develop regional strategies for adaptation will require an integrated approach, which encompasses multiple components of the fire regime and consider multiple drivers, including land use and climate. Furthermore, projections of future vegetation dynamics in the region will need to consider land use, vegetation, fires, and their dynamic landscape-scale interactions in the context of broader responses to climate change and human population growth. Overall, this dissertation produced novel results about the pathways and drivers of disturbance land cover change that are necessary for improving our understanding of ongoing changes in a lesser-known part of the tropics. These findings are also relevant for predicting and mitigating similar fire impacts in tropical forests worldwide.

CHAPTER 1

Introduction

1. Introduction and Background

Tropical forest ecosystems are critical component of the Earth system providing vital ecosystem functions. Of all terrestrial ecosystems, tropical forests are known to house the highest biodiversity of both flora and fauna. They are the largest reservoir of terrestrial carbon in living biomass and thus a critical component of the global climate system (Chambers et al., 2007). Tropical forests are important for climate regulation and play a key role in the global water and energy balance. Forests influence climate through chemical and biophysical processes that control fluxes of water, energy, and atmospheric constituents including CO_2 concentrations. Climate in turn affects forest ecosystems through shifting species distributions, tree growth and mortality, seasonality of ecosystem processes, and disturbances including fire (Seppälä et al., 2009). Among these influences, change in wildfire events is expected to be the major means through which climate change will impact tropical forest patterns and ecosystem functions (Cochrane & Barber, 2009).

Wildfire is a formidable ecological process shaping patterns and processes across diverse terrestrial ecosystems. The complex interactions of ignition sources with vegetation, climate, and topography give rise to fire regimes, an ecological concept describing the range of fire characteristics occurring at a given geographic location and period (Archibald, 2016; Whitman et al., 2015). In this era of rapid global change, understanding fire regimes in the tropics requires consideration not only of the changing climatic patterns, but also their interaction with land use factors, infrastructure, and demographic processes (Uriarte et al., 2012). More importantly, in environments such as West Africa, where wildfires are human-caused, consideration of human land use and land cover changes is critical because the interplay of climate change and land use determine the future fire regimes (Cochrane & Barber, 2009).

In tropical forests, human impacts such as deforestation, forest fragmentation and degradation greatly increase fire risk (Cochrane et al., 1999; Cochrane & Barber, 2009). Enhanced fire risk promotes recurrent fires, further altering vegetation composition and structure and maintaining fire-dependent vegetation in a self-reinforcing positive feedback loop (Cochrane et al., 1999). Climatic extremes can enhance such positive fire-vegetation feedbacks. In tropical forests, extreme drought events have led to sharp increases in tree mortality and decreases in tree growth, potentially due to water stress and hydraulic failure (Corlett, 2016; Nobre et al., 2016). In particular large trees suffer the most drought-induced mortality; leading to reduced shading over lower canopy, and the forest floor including litterfall and soil. The resulting increases in incident radiation in these areas increases temperature and dryness, further increasing vulnerability to later droughts as well as fire (Nobre et al., 2016). As a result, fires during subsequent droughts have been associated with abrupt increases in fire-induced tree mortality, monumental canopy damage, and rapid invasion of flammable grasses into the forest (Brando et al., 2014; Le Page et al., 2017).Thus, frequent forest fires facilitated by droughts can lead to rapid forest cover loss and create conditions likely to push these forest ecosystems to tipping points, beyond which forest resilience is lost and system feedbacks lead to regime shifts (Reyer et al., 2015b) .

Knowledge of fire regimes and their drivers, as well as fire-mediated regimes shifts is essential for projecting how fire regimes will respond to future change in climate and land use, and for developing strategies to adapt to these changes. In particular, the Upper

Guinean region of West Africa has strong geographic variation in landuse, climate, vegetation, and human population and has experienced remarkable biophysical and socio-economic changes in recent decades (Boone et al., 2009; CILSS, 2016; DeSA, 2015; Malhi & Wright, 2004). Following decades of human-caused destruction of natural habitats, protected areas currently remain the only significant refugia of original vegetation relics in landscapes characterized by high fragmentation. As a result, the protected areas are highly endangered by immense land use and climate-related pressures. Especially within forest reserves, fire is likely to be an important agent of forest degradation and loss due to the increasing human footprint in the landscape through forest fragmentation, degradation, and fire spread from agricultural areas. Additional stress from climate perturbations, such as droughts, may amplify forest fires and render forest reserves more vulnerable to further degradation.

To date, there has been no comprehensive analysis of fire regimes and the potential threat posed to forests within protected areas of the region. Therefore, this dissertation focusses on understanding the interactions of climate, land use, and fire regimes, as well as effects of fire on forest resilience in the Upper Guinean region of West Africa, an important but lesser studied part of the tropics.

2. The Study Area: Upper Guinean Region of West Africa

The study area encompasses a portion of the Upper Guinean forest region and consisted of five West African countries distributed along the Atlantic coast between Senegal and Togo. This area covers approximately 985,480 km^2 and includes Ghana, Côte d'Ivoire, Liberia, Sierra Leone, and Guinea. The climate is characterized by a strong rainfall gradient with peak rainfall (≈4000 mm/year) near the coasts of Guinea, Sierra Leone and Liberia. Rainfall decreases rapidly in a north-easterly direction to only ≈1200 mm/year at the forest savannah-boundary (Poorter et al., 2004) and less than 1200 mm/year in the driest portions of the study area. Generally, decreasing rainfall is associated with a longer dry season and higher inter-annual variability of rainfall (Barbé et al., 2002). The rainfall regimes are modulated by the Intertropical Convergence Zone (ITCZ) and the West Africa Monsoon (WAM) and are influenced by teleconnections with climate modes, such as the El Niño-Southern Oscillation (ENSO) and Atlantic Multidecadal Oscillation (AMO) (Barbé et al., 2002; Liebmann et al., 2012).

Along this rainfall gradient, natural vegetation varies from dense evergreen rainforests, to moist and dry closed-canopy semi-deciduous forests, to woodlands and savannas (Poorter et al., 2004).The area is mainly covered by four of the World Wide Fund (WWF) terrestrial ecoregions of the world (Olson et al., 2001). These are the Eastern Guinean Forests (EGF, 18.7%) and Western Guinean Lowland Forests (WGLF, 21.0%), together comprising the Upper Guinean Forests (UGF); and the Guinean Forest-Savanna Mosaic (GFSM, 31.7%) and West Sudanian Savanna (WSS, 24.1%) ecoregions (Figure 1). The Guinean Montane Forests and Mangroves ecoregions were not included in the analysis due to their small area (4.5%). The UGF block covers some of the wettest parts of the region and it is characterized by dense evergreen rainforests, as well as moist to dry closed-canopy semi-deciduous forests. The Guinean Forest-Savanna Mosaic is influenced by complex interactions between soil conditions, climate, and anthropogenic activities including cultivation and fires. The West Sudanian Savanna is in the zone of disturbance-determined (unstable) savannas, where disturbances such as herbivory and fire are important to maintain tree-grass coexistence (Sankaran et al., 2005).

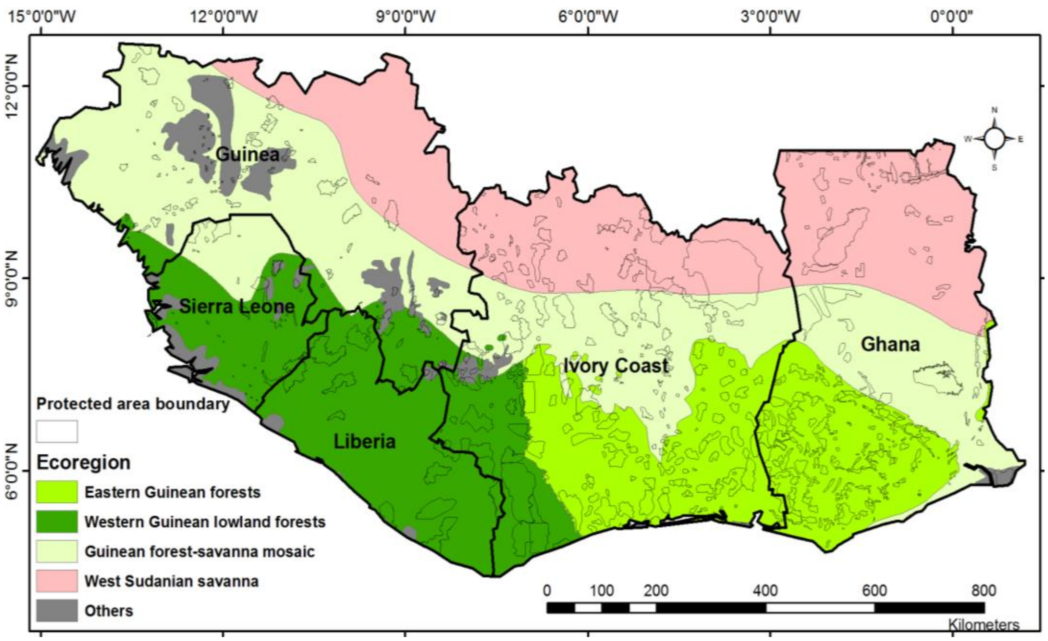

Figure 1. Map indicating area of the Upper Guinean region covered in the regional fire regime analyses. In this map, the study region is overlaid with terrestrial ecoregions of the world (Olson, et al., 2001)

Over the past four decades West Africa has lost a staggering portion of its natural vegetation, including savannas, woodlands, and forests, to expanding croplands and human settlements. As a result, the remaining natural vegetation is highly fragmented (CILSS, 2016; Ichoku et al., 2016). The principal land use is agriculture based on food and cash crops, chiefly cereals, cocoa, tubers, rubber, and fruit trees (CILSS, 2016). Other important land use practices include agro-pastoralism and tree harvesting for fuelwood, especially charcoal, in the drier savanna-dominated regions; mining and timber exploitation in the forested regions (CILSS, 2016). West Africa's population almost doubled between 1990 and 2015 (180 – 353 million), and it is projected to nearly double again by 2050, from 353 million to 797 million, (DeSA, 2015). Likewise, the region has been experiencing climate change in recent decades. Temperatures have become warmer, and precipitation has either not changed or declined for many locations below the Sahel, especially along the Guinea Coast (Sylla et al., 2016).

A vital component of West African ecosystems is the tropical humid forest referred to as the Upper Guinean forest, UGF. The UGF is a global biodiversity hotspot (Myers et al., 2000) providing ecosystem services crucial for the socio-economic and environmental wellbeing of the region. However, the UGF has become one of the most human-modified forest ecosystems in the tropics (Norris et al., 2010; Poorter et al., 2004), having lost over 80% of its original forest cover, with the remainder distributed in a fragmented agriculture-forest mosaic (Norris et al., 2010). Nonetheless, among countries in the UGF, Ghana has a long history of forest reservation beginning around the 1910s. The aim for forest reservation was to create "permanent forest estates" in the country's tropical high forest zone for sustainable benefits to society. As a result, Ghana has uniquely maintained a substantial area of closed-canopy forests in a protected network of reserves. Majority of these forest reserves are actively managed for sustainable timber production. Timber harvesting is done through selective logging, in which selected commercial timber species of merchantable size and typically scattered over the forest area, are felled during cutting cycles. The tropical high forest zone of Ghana, covering approximately 8.1 million hectares, occupies the southern third of the country (Hall & Swaine, 1981) (Figure 2). At the beginning of the 20th century about a third of the country was estimated to have been forested. However, substantial portions of the forest cover was lost during the 20th century, and by the late 1980s only about 25% of the original forest (2.1 million ha) remained (Adam et al., 2006). Currently, the only significant natural forests left in the high forest zone are those contained in the reserves, which are distributed within a matrix of agriculture and human settlements.

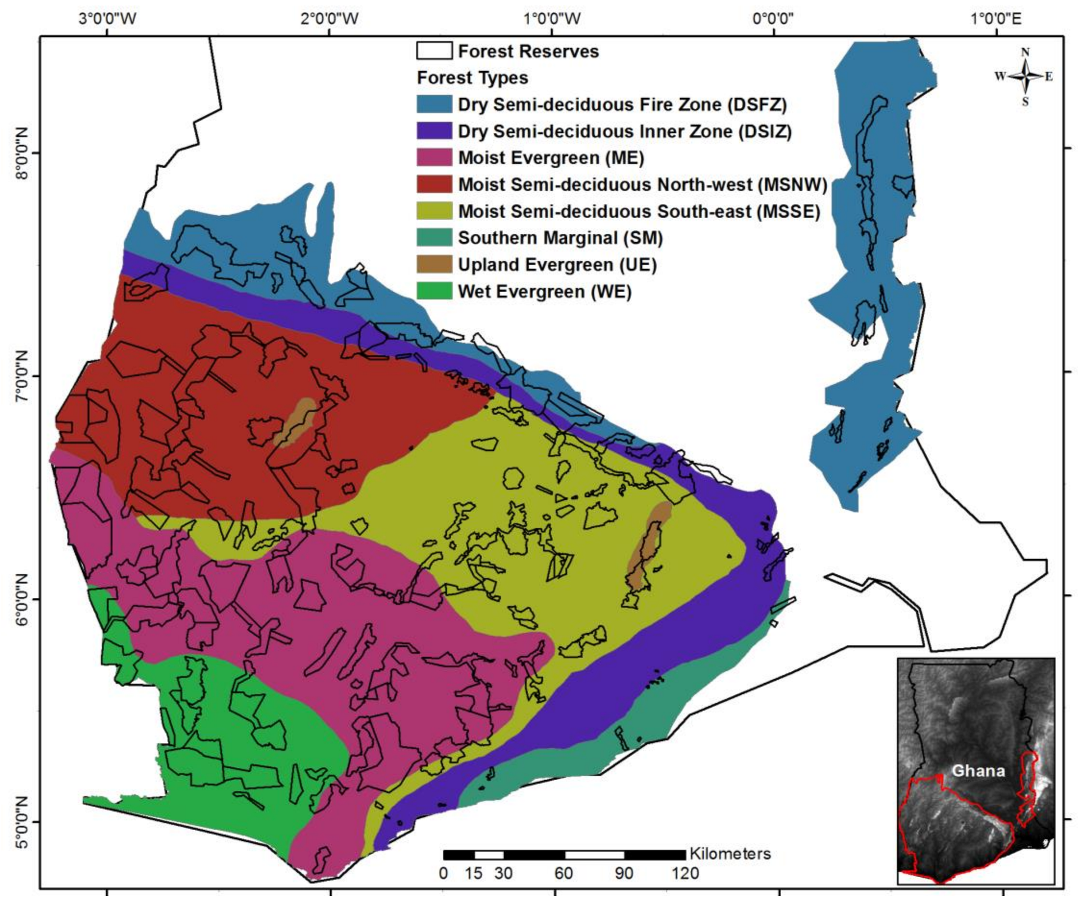

Figure 2. Ghana map (inset) highlighting the forest zone in southern Ghana and the distribution of forest types and forest reserves within the forest zone. In the inset map, the background is a digital elevation model indicating low (dark gray) to high elevation (bright gray). The high forest zone is outlined in red. Note: Area of the South-east outlier forest type is very small and not mapped, but it is dispersed to the south and east of the SM forests (Hawthorne, 1995).

The high forest zone of Ghana has been classified into seven main forest types based on floristic composition and rainfall regime (Hall & Swaine, 1981) (Figure 2). Ranging from wettest to driest, these types include Wet Evergreen (EW), Moist

Evergreen (ME), Upland Evergreen (UE), Moist Semi-deciduous (MS, with two subtypes: North-west and South-east), Dry Semi-deciduous (DS, with two subtypes: Fire Zone and Inner Zone), Southern Marginal (SM), and South-east Outlier (SO). The Wet Evergreen (1750 – 2250 mm annual rainfall) has the highest diversity of plant species. However, many of the most important commercial timber species are contained in the moist (1500-1750 mm annual rainfall), and dry (<1500 mm annual rainfall) forest types (Adam et al., 2006). In recent years, these reserves have come under immense pressure due to over-harvesting and agricultural encroachment, raising concerns about their sustainability.

3. Research Goal and Research Objectives

The overarching goal of this dissertation was to improve our understanding of the interactions of climate, land use, and fire regimes, as well as effects of fire on forest resilience in the Upper Guinean region of West Africa. This overarching research goal was pursued through three main research objectives, each of which was further elaborated with specific research questions.

Research objective #1 (Dissertation Chapter #2): To understand fire regimes and their drivers in the Upper Guinean region of West Africa.

i. What are the spatial patterns and interrelationships of multiple fire regime components in the Upper Guinean region?
ii. What are the overall trends in fire activity and how do they differ amongst the humid forest and the savanna-dominated ecoregions?

iii. How do the relative influences of climatic, topography, vegetation type, and human activity vary across different fire regime components?

Research objective #2 (Dissertation Chapter #3): To explore the overarching hypothesis that fire-mediated alternative stable states exist in the semi-deciduous tropical forest zone of Ghana, and that increased fire activity has pushed some forests to a new state in which a novel ecosystem with low tree density is maintained by fire.

i. Is there evidence of persistent forest loss?
ii. Is there evidence of fire-vegetation feedbacks?
iii. Is there evidence of hysteresis (the difficulty of ecosystem recovery once a catastrophic transition is reached)?

Research objective #3 (Dissertation Chapter #4): To explore the susceptibility of forest reserves in the moist forest zone of Ghana to fire during a regional drought and fire event in 2016.

i. Was the extent of forest fire in 2016 higher than expected compared with the entire 15-year study period?
ii. Were the 2016 fires associated with unusually severe drought conditions?
iii. Were spatial patterns of forest canopy condition and drought severity related to the pattern of burning inside forest reserves during the 2016 fires?

4. Research Relevance

Within the tropics, the Upper Guinean region of West Africa has distinctive bio-physical and socio-economic environments, which strongly suggest that knowledge from studies of fire in other tropical regions is not directly transferable. This region has a strong geographic variation in land use, climate, vegetation, and human population and has experienced phenomenal biophysical and socio-economic changes in recent decades. The West African region has lost a disproportionate amount of its natural vegetation, and currently the landscape is highly heterogeneous with fine-scale land use patterns (CILSS, 2016; Malhi et al., 2013). The region has a marginal tropical climate (Malhi & Wright, 2004) and experienced rapid and significant climatic change in recent decades (Boone et al., 2009). In addition, the region has been characterized as having disproportionate dependence on forest resources, high levels of poverty, high population growth, and recent history of wars and political instability. All these factors influence the fire regime and the vulnerability of protected areas to fire-mediated changes and forest loss, yet little is known about fire regimes and fire-vegetation interactions within the region.

Much of our knowledge of fire regimes in West Africa has been gleaned from studies conducted at broader continental to global extents (Archibald et al., 2013; Hantson et al., 2015a; Hantson et al., 2015b), and most of these regional to continental scale fire studies have not explicitly addressed the tropical regions of West Africa (Andela & van der Werf, 2014), where fire is relatively rare but a potential catastrophic force for ecosystem regime shifts (Dwomoh & Wimberly, 2017). Thus, a comprehensive regional analysis addressing multiple components of the fire regime across the gradient from humid tropical forests to drier woodlands and woody savanna is a research priority, hence this research. The results of this dissertation provide critical baseline knowledge to support projections of future fire regime changes and aid in the development of regional adaptation strategies.

Although climate change is expected to cause vegetation shifts, changes in the fire regime is expected to be the primary means by which such vegetation shifts will occur (Cochrane & Barber, 2009) as the synergy between climate change and land cover change can exacerbate the impact of fire in tropical forest ecosystems (Silvestrini et al., 2010). For instance, positive feedbacks in the forest fire regime due to deforestation, logging, and climate change will likely accelerate forest degradation and cause radical loss of tropical forests (Nepstad et al., 2008; Silvestrini et al., 2010). The ecological basis for such disturbance-driven vegetation shifts have been underpinned by the concept of alternative stable states (Scheffer et al., 2001b). This concept suggests that terrestrial ecosystems, such as tropical forests, have tipping points beyond which environmental change triggers rapid and radical shifts to novel alternative states (Higgins & Scheiter, 2012; Johnstone et al., 2016; Nobre et al., 2016; Reyer et al., 2015a; Scheffer et al., 2001a). The concept of alternative stable states has become the centerpiece of contemporary ecological discourse (Scheffer, 2009) because the threats to ecosystem resilience have been heightened by the complexities of current global change.

However, support for the existence of alternative stable states in terrestrial vegetation remain controversial, due to the predominant use of theoretical models, and the dearth of empirical evidence backed by time-series data (Bestelmeyer et al., 2013). Such studies are even rarer in tropical forests. Moreover, due to lack of long-term data, most previous analyses on alternative stable states neglected the temporal component by substituting time for space (Hirota et al., 2011; Staver et al., 2011). Thus, there is an outstanding need for ecological studies underpinned by long-term data to test whether regime shifts exist in tropical forests and the tipping points at which feedbacks cause alternative stable states (Reyer et al., 2015a). This dissertation research which uses long-term satellite observations does not only help to address this ecological knowledge gap, but also provide valuable information on a data-poor region of the tropics largely understudied. This work is therefore a unique research contribution to tropical forest and disturbance ecology.

Whilst forest degradation processes, such as selective logging, may not directly cause regime shifts they compromise resilience thereby rendering forest ecosystems more fragile to regime shifts by stochastic events, such as fire (Scheffer, 2009; Scheffer et al., 2001b). In the Amazon, fragmented forests are found to be more vulnerable to droughts and fire due to increased edge effects that foster rapid forest degradation (Numata & Cochrane, 2012). However, in Ghana Fauset et al., (2012) found drought-tolerance of semi-deciduous forest, suggesting that these forests may be more resilient to longer term drought. There is a knowledge gap on how these highly fragmented forests of Ghana will respond to fire during periods of severe water stress. By relating forest degradation and drought stress to fires in Ghana forest zone, this dissertation provides additional details about the specific factors that increase the risk of fire encroachment into moist tropical forests. These findings are relevant for predicting and mitigating similar fire impacts in tropical forests worldwide.

5. Summary of Chapters

This dissertation has been organized into five chapters, including this introduction chapter. The second chapter addresses research objective #1. This chapter explored the influences of climate, land use, vegetation, and human land use on multiple fire regime components across the entire gradient of ecoregions in the region. The analyses utilized the MODIS fire products and a variety of geospatial and remotely sensed datasets to characterize the spatial patterns and interrelationships of multiple fire regime components, characterize recent trends in fire activity, and used booted regression trees to explore the relative influences of climate, topography, vegetation type, and human activity on fire regimes. This chapter was published in 2017 in *Remote Sensing*.

The third chapter addresses research objective #2. This chapter used remotely-sensed Earth observations combined with field measurements to address hypotheses about forest resilience and disturbance-mediated tipping points in tropical forest ecosystems. This objective was achieved by addressing three research questions, each focused on a specific characteristic of systems with alternative stable states: persistent change, feedbacks, and hysteresis (Bestelmeyer et al., 2011; Petraitis, 2013; Scheffer, 2009). This chapter was published in 2017 in *Landscape Ecology*.

The fourth chapter addresses research objective #3. This chapter used remotely-sensed Earth datasets to explore recent drought-associated wildfires in the forest zone of Ghana, to better understand the linkages between forest degradation, drought stress, and the response of fire in forest reserves. The manuscript will be submitted to *Environmental Research Letters*.

Finally, the fifth chapter summarizes the major research findings of all the three research objectives and presents a synthesis of the dissertation. The chapter ends by highlighting recommendations for future research.

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CHAPTER 2

Fire Regimes and Their Drivers in the Upper Guinean Region of West Africa

Dwomoh, F. K., & Wimberly, M. C. (2017). Fire Regimes and Their Drivers in the Upper Guinean Region of West Africa. *Remote Sensing*, *9*(11), 1117.

Journal Impact Factor: 3.244

Abstract

The Upper Guinean region of West Africa exhibits strong geographic variation in land use, climate, vegetation, and human population and has experienced phenomenal biophysical and socio-economic changes in recent decades. All of these factors influence spatial heterogeneity and temporal trends in fires, but their combined effects on fire regimes are not well understood. The main objectives of this study were to characterize the spatial patterns and interrelationships of multiple fire regime components, identify recent trends in fire activity, and explore the relative influences of climate, topography, vegetation type, and human activity on fire regimes. Fire regime components, including active fire density, burned area, fire season length, and fire radiative power, were characterized using MODIS fire products from 2003 to 2015. Both active fire and burned area were most strongly associated with vegetation type, whereas fire season length was most strongly influenced by climate and topography variables, and fire radiative power was most strongly influenced by climate. These associations resulted in a gradient of increasing fire activity from forested coastal regions to the savanna-dominated interior, as well as large variations in burned area and fire season length within the savanna regions and high fire radiative power in the westernmost coastal regions. There were increasing trends in active fire detections in parts of the Western Guinean Lowland Forests ecoregion and decreasing trends in both active fire detections and burned area in savanna-dominated ecoregions. These results portend that ongoing regional landscape and socio-economic changes along with climate change will lead to further changes in the fire regimes in West Africa. Efforts to project future fire regimes and develop regional

strategies for adaptation will need to encompass multiple components of the fire regime and consider multiple drivers, including land use as well as climate.

1. Introduction

Wildfires are a principal force shaping ecological patterns and processes across diverse terrestrial ecosystems. The complex interactions of ignition sources with vegetation, climate, and topography give rise to fire regimes, an ecological concept describing the range of fire characteristics occurring at a given geographic location and time period (Archibald, 2016; Whitman et al., 2015). Fire regimes can be characterized by various metrics, including fire size, seasonality, frequency, intensity, and severity. Examining multiple components of the fire regime is therefore necessary for understanding the geographic patterns, drivers, and ecological effects of fire (Liu & Wimberly, 2015). This knowledge is essential for projecting how fire regimes will respond to future changes in climate and land use, and for developing strategies to adapt to these changes. West Africa, in particular, is a region where fire has a significant impact on terrestrial ecosystems (Dwomoh & Wimberly, 2017; Ichoku et al., 2016). The region also exhibits strong geographic variation in land use, climate, vegetation types, and human population, all of which influence spatial heterogeneity of fire regimes. The main goal of this study was to explore the influences of climate, vegetation, and land use on multiple fire regime components across the forest and woody savanna zones of West Africa.

Over the past four decades West Africa has lost a substantial portion of its natural vegetation, including savannas, woodlands, and forests, to expanding croplands and human settlements. As a result, the remaining natural vegetation is highly fragmented (CILSS, 2016; Ichoku et al., 2016). A recent analysis of satellite remote sensing data indicated a decreasing trend of woody vegetation cover across the savanna ecoregions along with widespread degradation of the humid forests (Liu et al., 2017). The tropical humid forest (also known as the Upper Guinean forest, UGF), a globally significant biodiversity hotspot (Myers et al., 2000), is estimated to have lost over 80% of its original forest cover, with the remainder distributed in a fragmented agriculture-forest mosaic (Norris et al., 2010; Poorter et al., 2004). Moreover, West Africa’s population almost doubled between 1990 and 2015 (180 to 353 million), and it is projected to nearly double again by 2050, from 353 million to 797 million (DeSA, 2015). The region has also been experiencing climate change in recent decades. Temperatures have become warmer, and precipitation has either not changed or declined for many locations below the Sahel, especially along the Guinea Coast (Sylla et al., 2016).

In the rapidly changing environment of West Africa, fire regimes are affected by changes that alter fuel conditions and ignitions, but fire also serves as a driver of vegetation and land use change. As a result, fire and vegetation change are linked via strong positive and negative feedbacks (Dwomoh & Wimberly, 2017). Yet, studies of fire regimes in this region are rare. Quite recently, Prichard et al. (Prichard et al., 2017) reviewed fire regimes across the world’s major bioregions and pointed out the relative scarcity of literature on African savannas. Surprisingly this review did not include any examples of research on tropical forest fires in Africa.

Much of our knowledge of fire regimes in West Africa has been gleaned from studies conducted at broader continental to global extents. In a global characterization of fire regimes, Archibald et al. (Archibald et al., 2013) found that most of the region was dominated by relatively frequent, small-sized fires with low intensity. Additionally, the West African fire regime was largely controlled by human impacts (Archibald, 2016). Another global analysis of burned areas also indicated that human activities strongly influence fire size distribution in West Africa through land cover changes, fire ignitions, landscape fragmentation, and fire management (Hantson et al., 2015a; Hantson et al., 2015b). Multiple studies have found evidence of decreasing fire activity in the dry, savanna-dominated regions across Africa (Andela & van der Werf, 2014; Grégoire et al., 2013; Grégoire & Simonetti, 2010). Most regional to continental scale fire studies have not explicitly addressed the tropical forest regions of West Africa, where fire is relatively rare. However, there is evidence that fires have encroached into the northern portions of the dry tropical forest zone in recent decades, leading to degradation and eventual loss of forest vegetation (Dwomoh & Wimberly, 2017).

Although studies of fire have been conducted in other tropical regions, the distinctive physical and social environments of West Africa suggest that knowledge from such studies is not directly transferable. For example, land use pressure in the forested zone is dominated by selective logging, small-scale slash-and-burn farming and bush meat hunting, in contrast to the agro-industrial pressures that are prevalent in the tropical Americas (Malhi et al., 2013). Disproportionate dependence on forest resources, high levels of poverty, and recent history of wars and political instability are all important socio-economic characteristics of the Upper Guinean region. Given these unique features, better regional information about the patterns and drivers of fire regime is needed to support projections of future fire regime changes and aid in the development of adaptation strategies. To help meet these needs, we conducted a regional study of fire regimes in the forest and woody savanna dominated portions of West Africa and addressed the following research questions:

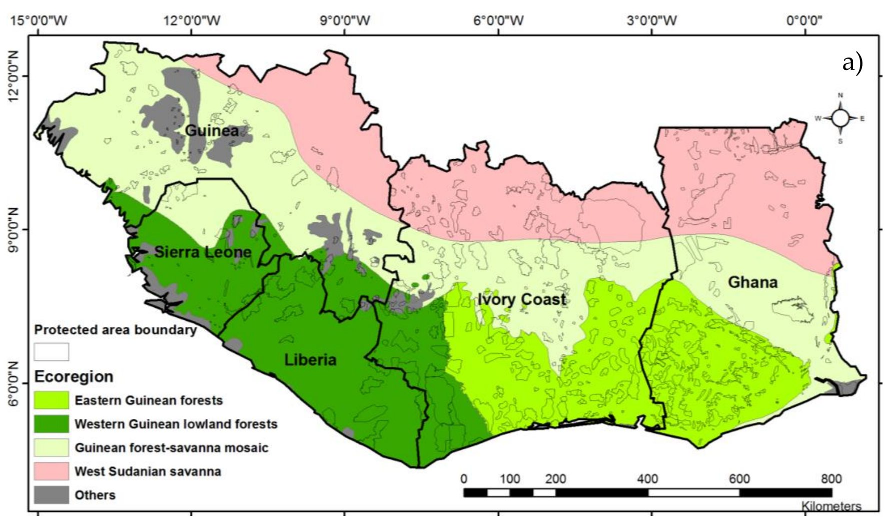
1. What are the spatial patterns and interrelationships of multiple fire regime components in the Upper Guinean region?
2. What are the overall trends in fire activity and how do they differ amongst the humid forest and the savanna-dominated ecoregions?
3. How do the relative influences of climate, topography, vegetation type, and human activity vary across different fire regime components?

2. Materials and Methods

2.1 Study Area

Our study area encompassed a portion of the UGF region and consisted of five West African countries distributed along the Atlantic coast between Senegal and Togo. This area covered 985,480 km^2 and included Ghana, Côte d'Ivoire, Liberia, Sierra Leone, and Guinea (Figure 1). The climate is characterized by a strong rainfall gradient with peak rainfall (≈4000 mm/year) near the coasts of Guinea, Sierra Leone and Liberia. Rainfall decreases rapidly in a north-easterly direction to only ≈1200 mm/year at the forest savannah-boundary (Poorter et al., 2004) and less than 1200 mm/year in the driest portions of the study area. Generally, decreasing rainfall is associated with a longer dry season and higher inter-annual variability of rainfall (Barbé et al., 2002). The rainfall regimes are modulated by the Intertropical Convergence Zone (ITCZ) and the West Africa Monsoon (WAM) and are influenced by teleconnections with climate modes, such as the El Niño-Southern Oscillation (ENSO) and Atlantic Multidecadal Oscillation (AMO) (Barbé et al., 2002; Liebmann et al., 2012).

Along this rainfall gradient, natural vegetation varies from dense evergreen rainforests, to moist and dry closed-canopy semi-deciduous forests, to woodlands and savannas (Poorter et al., 2004). The area is mainly covered by four of the World Wide Fund (WWF) terrestrial ecoregions of the world (Olson et al., 2001). These are the Eastern Guinean Forests (EGF) and Western Guinean Lowland Forests (WGLF), together comprising the Upper Guinean Forests; and the Guinean Forest–Savanna Mosaic (GFSM) and West Sudanian Savanna (WSS) ecoregions (Figure 1a). The principal land use is agriculture based on food and cash crops, chiefly cereals, cocoa, tubers, rubber, and fruit trees (CILSS, 2016). Other important land use practices include mining and timber exploitation in the forested regions, agro-pastoralism, and tree harvesting for fuel-wood, especially charcoal, in the drier savanna-dominated regions (CILSS, 2016).



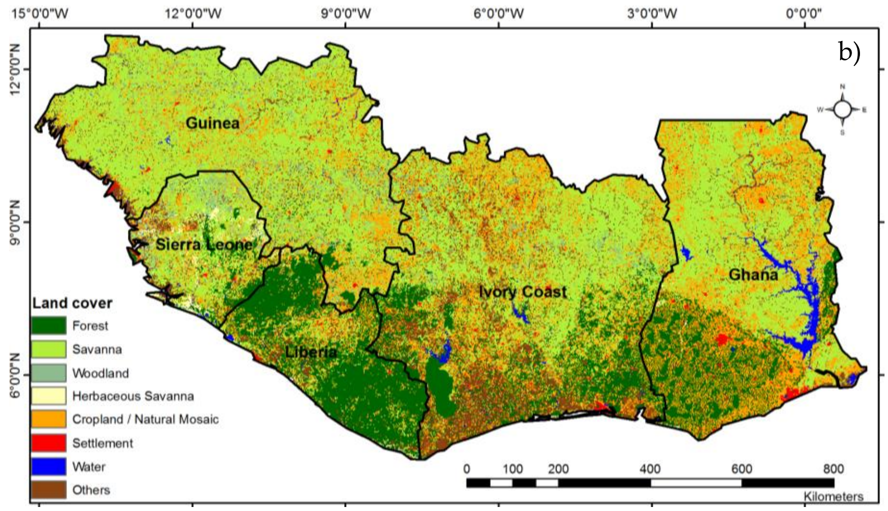


Figure 1. Map of study the area overlaid with: (a) terrestrial ecoregions of the world (Olson, et al., 2001); and (b) a 2 km spatial resolution West African land cover/land use map for 2013 developed by the USGS. We aggregated the original cover types into eight general classes.

2.2 Remotely-Sensed Fire Data

Active Fires

We obtained active fire detections at 1-km resolution from the combined MODIS Terra (10:30 am/pm equatorial nominal overpass time) and Aqua (1:30 pm/am equatorial nominal overpass time) active fire product MCD14ML, level 3 Collection 6 (Giglio, 2013; Giglio et al., 2016b). We used the detection confidence and hot-spot type fields in the MCD14ML data to respectively remove low confidence fires (<30%) and non-vegetation fires. We used the fire radiative power (FRP) measurement associated with each MODIS active fire detection as a measure of fire intensity (Giglio, 2013). FRP is the rate of fire energy released per unit time, and this information is retrieved using MODIS mid-infrared wavelengths (Wooster et al., 2003). In Collection 6 of the MCD14ML product, FRP retrieval uses a radiance-based approach in which the 4-µm radiance of individual fire pixels and surrounding background pixels are compared (Giglio et al., 2016b; Wooster et al., 2003). FRP can be interpreted as a measure of biomass combustion rate, and is increasingly used by the atmospheric emissions modeling community to estimate vegetation burning emissions (Freeborn et al., 2008; Tang & Arellano, 2017).

Burned Area

We used the MODIS burned area product, MCD64A1 Collection 6, to measure burned area. This product uses an improved algorithm that incorporates both surface reflectance and active fire input data (Giglio et al., 2009). Consequently, this product has generally improved burned area detection than the previous product MCD45A1, with higher accuracy and significantly better detection of small burns (Giglio et al., 2016a). The MCD64A1 product has a spatial resolution of 500 m at a daily time step.

2.3 Derived Fire Regime Variables

We summarized the active fire and burned area data from 2003 to 2015, covering the period within which data were simultaneously collected by both MODIS Terra and Aqua satellites. Four main grid-based fire regime metrics were calculated: mean annual active fire density, percent mean annual burned area, fire season length, and mean fire radiative power (Table 1). We also generated other indicators of fire seasonality, including peak fire month, the percentage of active fire detections occurring in the peak month, and the percent monthly distributions of active fires and area burned by ecoregion. Variables were summarized for a grid of 0.25° raster cells and for the four major ecoregions described previously.

Active Fire Density

We summarized the active fire data into time series of monthly and annual active fire counts for each grid cell and ecoregion. We used the annual active fire densities to compute the mean annual active fire density (fires km^{-2} year^{-1}) for each grid cell and ecoregion.

Annual Burned Area

Monthly and annual burned areas were calculated for each grid cell and ecoregion and summarized as a percent of the total land area. We used the annual burned area data to compute the mean annual burned area (% year^{-1}) for each grid cell and ecoregion.

Fire Season Characteristics

We used the grid-based monthly time series data to compute a monthly climatology of active fire density for each grid cell using methods developed by Chuvieco et al. (2008) and Moreno and Chuvieco (2013). Following these same authors, we computed fire season length as the number of calendar months within a year in which the monthly fire climatology was greater than the long-term average annual fire density per each grid (Moreno & Chuvieco, 2013). We further identified the peak fire month for each grid cell as the calendar month in which the maximum climatological fire density was recorded (Giglio et al., 2006). We also calculated the percentage of active fire detections recorded in the peak fire month as a proportion of the total annual active fire detections for each grid cell. To examine the intra-annual variability of fire activity by ecoregion, we used the ecoregion-based monthly fire data to calculate the percent of total active fire counts and the percent of total burned area that occurred during each month.

Mean Fire Radiative Power

We calculated the mean fire radiative power (MW km^{-2}) for each climate grid by averaging fire radiative power values of all fire pixels over all years in each grid cell. The distribution of mean fire radiative power was heavily right-skewed. Therefore, we carried out a logarithmic (base 10) transformation to make the distribution more symmetric and reduce the influence of outlying values.

2.4 Predictor Variables for Analyses of Fire Drivers

Predictor variables were selected to characterize the major climatic, land cover/land use, and human factors that we expected to be associated with the geographic pattern of fire regimes (Argañaraz et al., 2015; Hawbaker et al., 2013) (Table 1). We used the Tropical Rainfall Measuring Mission (TRMM) monthly product 3B43-v7 at 0.25° spatial resolution to generate mean annual rainfall and annual maximum cumulative water deficit (MCWD). MCWD estimates accumulated water deficit within a particular year and is an indicator of the intensity and length of the dry season (Aragão et al., 2007). More negative values of MCWD indicate higher levels of moisture stress. We computed MCWD using methods described by Aragão et al. (2007). We also included annual potential evapotranspiration estimates from the CGIAR-CSI Global-Aridity and Global-PET Geospatial Database (Trabucco & Zomer, 2009). Higher values of potential evapotranspiration indicate greater moisture stress. All predictor variables were aggregated to match the 0.25° spatial resolution of the TRMM data.

We generated vegetation cover and vegetation change maps from 2-km spatial resolution USGS region-specific land cover/use maps for West Africa for 2000 and 2013, which were created through visual interpretation of Landsat images (CILSS, 2016). Some of the detailed USGS cover types were aggregated into broader classes. The "forest" class included forest, degraded forest, woodland, and swamp forest. The "savanna" class included savanna, bowe, and herbaceous savanna. The "cropland" class included agriculture, irrigated agriculture, agriculture in shallows and recession, and cropland and fallow with oil palms. We expressed these classes as percent cover at the 0.25° grid cell resolution.

We obtained a protected area (PA) boundaries polygon layer from the World Database on Protected Areas (accessed in November 2016). We reclassified PAs into two classes (production reserve and eco-reserve) based on their level of protection as defined by the Protected Categories System of the International Union for Conservation of Nature (IUCN). Production reserve (PR) encompassed PAs of IUCN category VI, which are designated for natural ecosystems' protection and sustainable use. Eco-reserves (ER) encompassed PAs of IUCN category I to V, which are designated to maintain and protect biodiversity and ecosystem integrity with minimal human influence. We assigned all areas outside PAs to non-protected (NP) status. We rasterized the PA polygons by resampling to the TRMM grid, and retaining PA status as the raster values.

The new Gridded Population of the World (GPWv4) dataset, at 1 km grid resolution (CIESIN, 2015) was used to obtain 2010 population density estimates. We extracted the major roads (functional class 0-3) GIS layer from the Global Roads Open Access Data Set (gROADSv1, (Center for International Earth Science Information Network - CIESIN - Columbia University & Information Technology Outreach Services - ITOS - University of Georgia, 2013)). We ran the Euclidean distance function in ArcGIS 10.2 to generate a

Table 1. Data layers used in the analyses. All variables were re-scaled to the TRMM spatial resolution of 0.25°.

Data Layer	Sources and Description	Variable Name (Units)
Fire variables		
Active Fire Density	Mean annual fire density for 2003–2015 derived from 1 km monthly MODIS active fire product MCD14ML collection 6 (Giglio et al., 2016b)	AfDens (fires 10^{-3} km^{-2} $year^{-1}$)
Fire Radiative Power	Mean fire radiative power per pixel of active fire detections for 2003–2015 derived from MCD14ML collection 6	mFRP (MW km^{-2})
Fire Season Length	Length of the active fire period for 2003–2015 generated from MCD14ML collection 6	FSL (months/year)
Burned Area	Mean annual burned area for 2003–2015, as a percent of grid cell area, generated from 500 m monthly Burned Area product MCD64A1 Collection 6 (Giglio et al., 2016a)	BurnedArea (% $year^{-1}$)
Predictor variables		
Vegetation		
Forest cover 2000	Proportion of grid cell covered by forest in 2000, derived from 2 km resolution USGS land cover map (CILSS, 2016)	Forest2000 (%)
Forest Change	Change in proportion of forest between 2000 and 2013 (generated from (CILSS, 2016))	ForestChng (%)
Savanna cover 2000	Proportion of grid cell covered by savanna in 2000, derived from USGS land cover map (CILSS, 2016)	Savanna2000 (%)
Savanna Change	Change in proportion of savanna between 2000 and 2013 (generated from (CILSS, 2016))	SavannaChng (%)
Protected Area Status	IUCN Protected Categories System(IUCN & UNEP-WCMC, 2016)	PaStatus: 1: Production-Reserve (PR), 2: Eco-Reserve (ER), 3: Non-protected (NP)
Climate		
Mean Annual Precipitation	Mean annual precipitation for 2003–2015, derived from Tropical Rainfall Measuring Mission (TRMM) monthly product 3B43-v7 (Huffman et al., 2007)	Precipitation (mm/year)
Mean Annual Cumulative Water Deficit	Mean annual maximum cumulative water deficit for 2003–2015, calculated from TRMM product 3B43-v7	MCWD (mm/year)
Potential Evapotranspiration	Global Aridity Index & Potential Evapo-Transpiration Climate Database, ≈1 km resolution(Trabucco & Zomer, 2009)	PotentialEvapo (mm/year)
Human		
Population Density	Population density in 2010 generated from Gridded Population of the World (GPWv4), ≈1 km resolution from CIESIN (Center for International Earth Science Information Network—Columbia University, 2015)	PopDens (persons/km^2 log10 scale)
Distance to Road	Euclidean distance to major roads (functional class 0–3), derived from Global Roads Open Access Data Set (Center for International Earth Science Information Network - CIESIN - Columbia University & Information Technology Outreach Services - ITOS - University of Georgia, 2013)	Dist2Road (km log10 scale)
Cropland 2000	Proportion of grid cell covered by cropland/agriculture in 2000, generated from USGS land cover map (CILSS, 2016)	Crplnd2000 (%)
Cropland Change	Change in proportion of cropland between 2000 and 2013, generated from USGS land cover map (CILSS, 2016)	CrplndChng (%)
Distance to Cropland	Euclidean distance to cropland in 2000, generated from USGS land cover map (CILSS, 2016)	Dist2Crplnd (km)
Topography		
Slope	Slope from ≈90 m resolution SRTM DEM (Jarvis et al., 2008)	Slope (degrees)

raster grid of distances to the nearest major road. We calculated slope from a 90 m spatial resolution digital elevation model using ArcGIS 10.2.

To check for excessive data redundancy, we screened the intercorrelations among the predictors and found that nearly all had Pearson correlations <0.65 and >−0.65 (Table 1). An exception was MCWD which had stronger correlations with the savanna and forest variables.

2.5 Analysis Methods

Question 1: What Are the Spatial Patterns and Interrelationships of Multiple Fire Regime Components in the Upper Guinean Region?

To characterize the spatial patterns of fire activity in the Upper Guinean region, we mapped the four main fire regime components: mean annual active fire density, percent mean annual burned area, fire season length, and mean fire radiative power. We graphed the bivariate relationships amongst these fire regime components, and used the Kendall non-parametric rank correlation coefficient test to determine the direction and the strength of correlations among their spatial patterns. We also mapped peak fire month and the corresponding percent of fire detections and graphed the seasonal cycle of fire distribution and tabulated summaries of fire regime characteristics by ecoregion.

Question 2: What Are the Overall Trends in Fire Activity and How Do They Differ Amongst the Humid Forest and the Savanna-Dominated Ecoregions?

We used the non-parametric Mann–Kendall test to test for increasing monotonic upward or downward trends in annual time series active fire density and burned area for each grid cell and ecoregion. The Mann–Kendall test was used for trend detection in previous fire regime analysis (Rodrigues et al., 2013). We followed criteria outlined in Liu et al. (2017) for the grid-based trend test and set a significance level of 0.1. Trends were calculated only for grid cells with at least six data points, and at most eight consecutive missing data points.

Question 3: How Do the Relative Influences of Climate, Topography, Vegetation Type, and Human Activity Vary across Different Fire Regime Components?

We used Boosted Regression Trees (BRT) to determine the most important environmental drivers of each of the four main fire regime components: active fire density, burned area, fire season length, and fire radiative power. BRT is a nonparametric machine-learning approach combining the advantages of regression trees, which relate a response to their predictors by recursive binary splits, and boosting algorithms, which combine many simple models to give improved predictive performance (Elith et al., 2008). It is relatively insensitive to outliers and is able to handle various data types, accommodate missing data in predictor variables, automatically model interactions among explanatory variables, and produce easily interpretable results (Elith et al., 2008). We implemented BRT analyses using the *gbm* functions in the *dismo* package in R 3.4.1 (Elith & Leathwick, 2016).

In order to avoid overfitting, we used cross-validation procedure to identify optimal model parameters (tree complexity-*tc*, learning rate-*lr*, and number of trees-*nt*), and the best combination of these parameters was selected by maximizing the variance explained by the model. Model fitting were evaluated using 10-fold cross-validation correlation between observed and model fitted datasets (Elith & Leathwick, 2016). We used a Gaussian error model and a bag fraction of 0.75, and obtained the best *tc* = 3 for all BRT models of the four fire regime components. In the active fire density model, *lr* of 0.075, and *nt* of 2400 were selected. In the burned area model, *lr* of 0.05, and *nt* of 2160 were selected. In the fire season length model, *lr* of 0.025, and *nt* of 2100 were selected. In the fire radiative power model, *lr* of 0.075, and *nt* of 1800 were selected.

BRT measured the relative influence of each predictor variable based on the number of times that variable was selected for splitting, weighted by the squared improvement to the model resulting from these splits, and averaged over all trees (Elith et al., 2008). The relative influence of each variable was scaled to a total of 100%, with higher values indicating stronger influence on the fire regime component. The marginal effect of each variable was visualized using partial dependence graphs, which showed the effect of that variable on a fire regime component after accounting for the average effects of all other variables (Elith et al., 2008).

3. Results

Question 1: What Are the Spatial Patterns and Interrelationships of Multiple Fire Regime Components in the Upper Guinean Region?

Figure 2 depicts geographic distributions of the four main fire regime components. An overarching gradient of fire activity were evident in relation to patterns of precipitation and vegetation, with the highest values of active fire density, burned area, and fire radiative power clustered in the Guinean Forest–Savanna Mosaic (GFSM) and Western Sudanian Savanna (WSS) ecoregions in the North. In contrast, there was much lower fire activity in the Western Guinean Lowland Forest (WGLF) and Eastern Guinean Forest (EGF) ecoregions located in the South. However, the different fire regime components also exhibited distinctive patterns. Unusually high active fire density and relatively long fire seasons ranging from 4 to 6 months were observed in the western portion of the study area at the boundary between the WGLF and the GFSM (Figure 2). The highest fire radiative power was concentrated near the coast in the westernmost portion of the study area. In contrast, burned area was highest in the WSS and GFSM ecoregions in the northeastern portion of the study area. This area also had slightly lower active fire density than the northwestern region, along with a relatively short fire season length of 2–3 months.

Among the fire regime components, the strongest relationship was between active fire density and burned area ($\tau = 0.61$, $p < 0.0001$, Figure 3). Active fire density had a moderate relationship with fire radiative power ($\tau = 0.48$, $p < 0.0001$). All other relationships were weak and mostly nonlinear (Figure 3).

At the ecoregion scale, active fire density was highest in the GFSM, followed by WSS and then WGLF; and burned area was highest in the WSS, followed by GFSM, and then WGLF (Table 2). Among all ecoregions, the forested EGF recorded the lowest active fire density, burned area, and fire radiative power (Table 2). Fire season averaged about 3-months in all ecoregions (Table 2). Within ecoregions fire season length was spatially heterogeneous, with fire seasons longer than three months localized in the north-western part of the study area and in portions of the EGF.

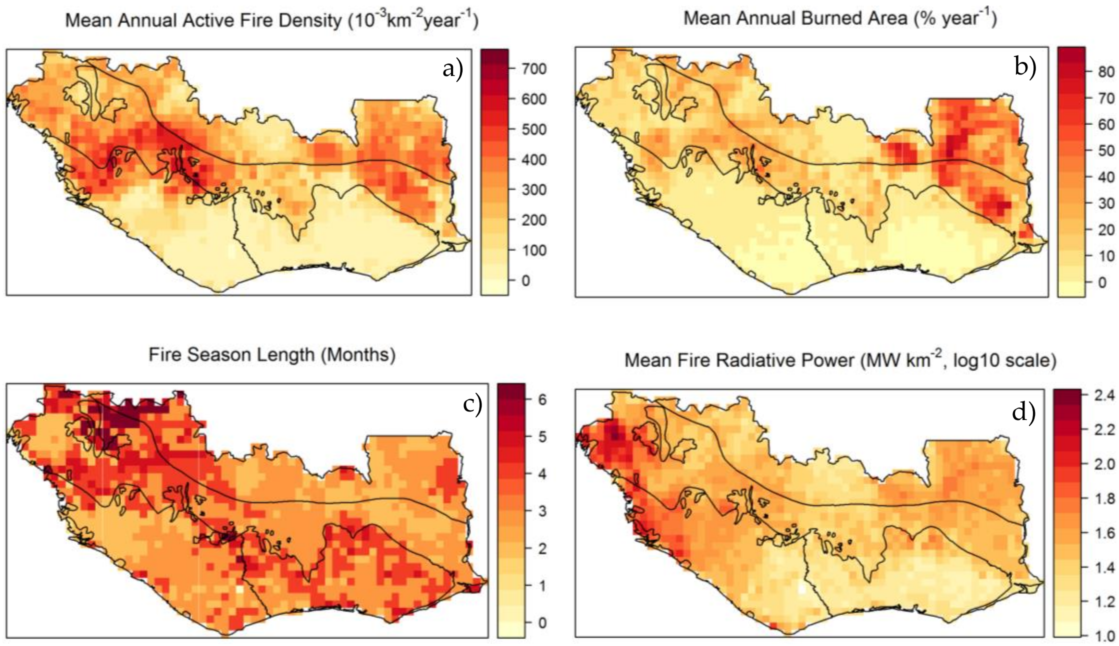


Figure 2. Maps of four major fire regime components, which were the response variables in the BRT models: (a) active fire density; (b) percent burned area; (c) fire season length; (d) fire radiative power.

Table 2. Summary of fire regime characteristics (mean ± standard deviation) across ecoregions for the period 2003–2015.

Fire Regime Metric	**Western Guinean Lowland Forests (WGLF)**	**Eastern Guinean Forests (EGF)**	**Guinean Forest Savanna Mosaic (GFSM)**	**West Sudanian Savanna (WSS)**
Annual Active Fire Density (fires 10^{-3} km^{-2} year^{-1})	162 ± 51	54 ± 11	297 ± 24	267 ± 31
Percent Annual Burned Area (% year^{-1})	3.8 ± 1.6	1.8 ± 0.7	21.2 ± 3.8	27.2 ± 4.5
Fire Season Length (months)	2.9 ± 0.8	3.4 ± 0.7	3.3 ± 1.0	3.2 ± 0.9
Fire Radiative Power (MW km^{-2})	47 ± 79	23 ± 34	42 ± 86	34 ± 44

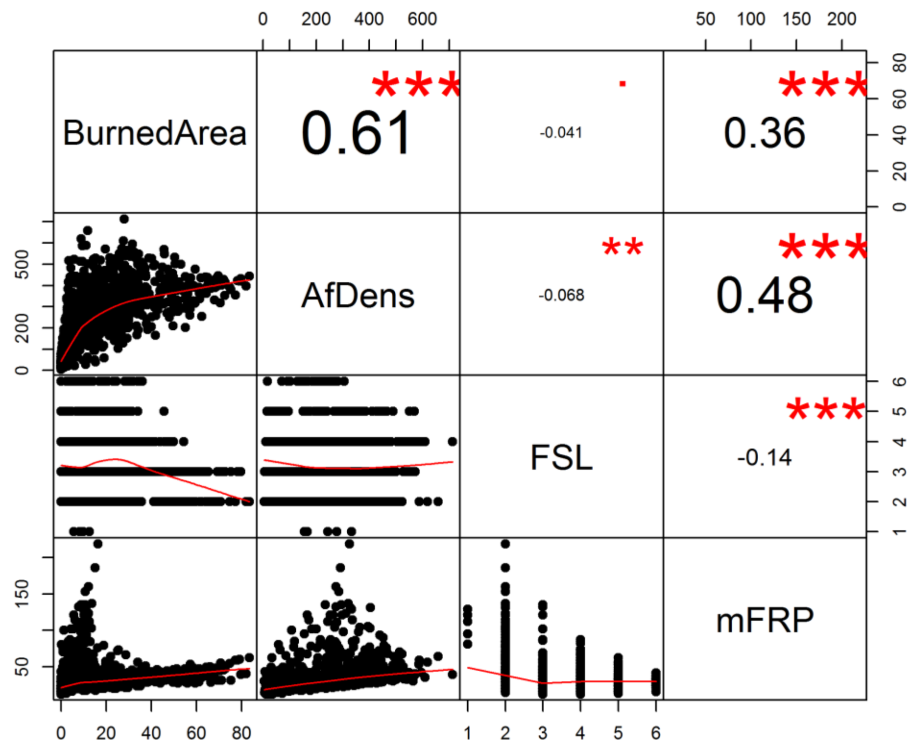


Figure 3. Bivariate relationships amongst the four fire-regime components, with Kendall non-parametric rank correlation coefficients indicating the direction and strength of correlations among each component pairs. Each variable's name (Table 1) is shown on the diagonal. The lower triangle shows the bivariate scatter plots with a fitted smoothed line. The upper triangle shows the correlations and associated p-values: *** p <0.001, ** p < 0.05, ▪ p >= 0.05. Larger font sizes indicate stronger correlations.

The fire season generally occurred between November and May, with variation in seasonal patterns across ecoregions (Figure 4). In the savanna ecoregions, most fires occurred between November and February, while in the forested ecoregions most fires occurred between January and May. The savanna-dominated ecoregions had earlier peak fire months, mainly December and January (Figure 5a). On the contrary, in the forested ecoregions fire activity peaked later in the fire season, mainly in March and April. The percentage of active fire detections during the peak fire month was highly spatially varied (Figure 5b).

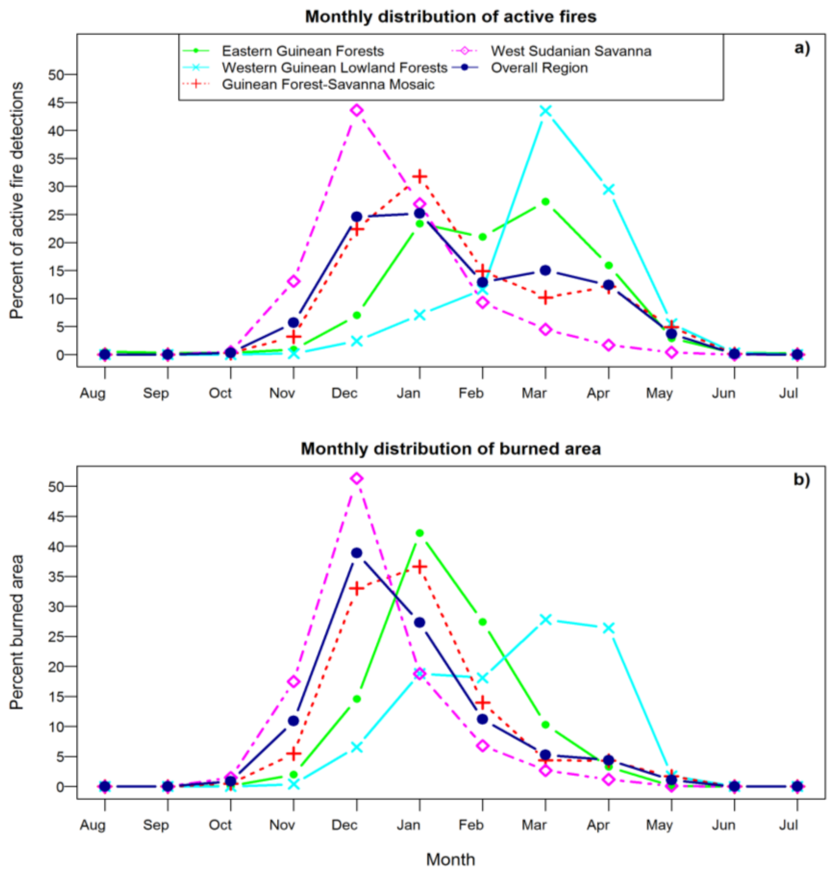


Figure 4. Seasonal cycle of fire activity represented by the monthly percent distribution of: (a) MODIS active fire detections; (b) burned area, across ecoregions and the entire study area.

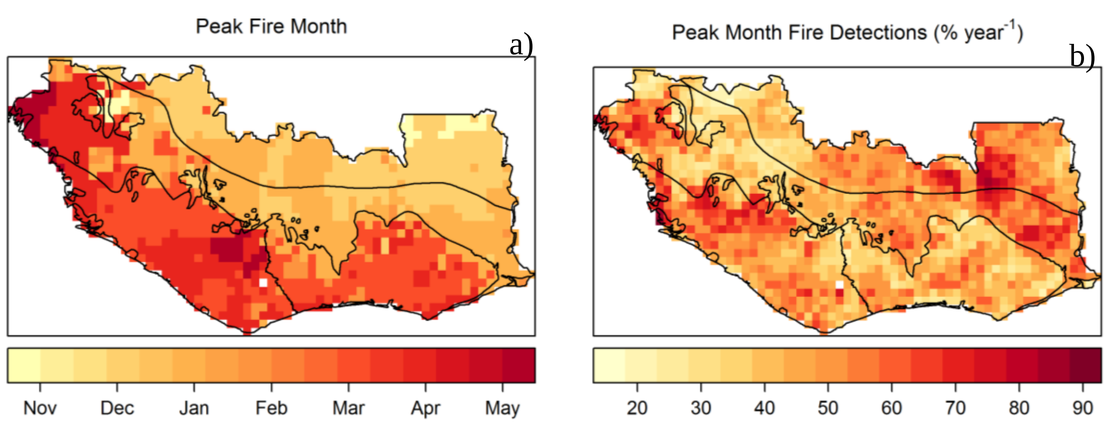


Figure 5. Maps indicating: (a) calendar month with the maximum active fire detections; (b) the percentage of the total annual active fire detections recorded in the peak fire month.

Question 2: What Are the Overall Trends in Fire Activity and How Do They Differ Amongst the Humid Forest and the Savanna-Dominated Ecoregions?

At the ecoregion level, the trend in active fire density was weakly positive in the WGLF ecoregion and weakly negative in the EGF and WSS ecoregions (Figure 6a, Table 3). There were also weak decreasing trends in burned area in the EGF, GFSM, and WSS ecoregions (Figure 6b, Table 3). However, the temporal trends in fire activity also varied geographically within ecoregions (Figure 7). We found clusters of increasing active fire detections in parts of the WGLF, particularly in Sierra Leone and western Liberia (Figure 7a). There were also clusters of decreasing active fire and burned area in the central portions of the WSS and the GFSM, particularly in Côte d'Ivoire (Figure 7).

Table 3. Nonparametric Mann–Kendall tests to detect trends in fire activity at ecoregion scale from 2003–2015. Positive Kandall's tau statistic values indicate increasing trends, whilst negative values indicate decreasing trends

Fire Regime Metric	Statistic	Western Guinean Lowland Forests	Eastern Guinean Forests	Guinean Forest Savanna Mosaic	West Sudanian Savanna
Annual Active Fire Density	Tau	0.359	−0.333	−0.103	−0.385
	p-value	0.1 *	0.127	0.669	0.077 *
Annual Burned Area	Tau	0.077	−0.333	−0.359	−0.308
	p-value	0.76	0.127	0.1 *	0.161

* Significant at $\alpha = 0.1$

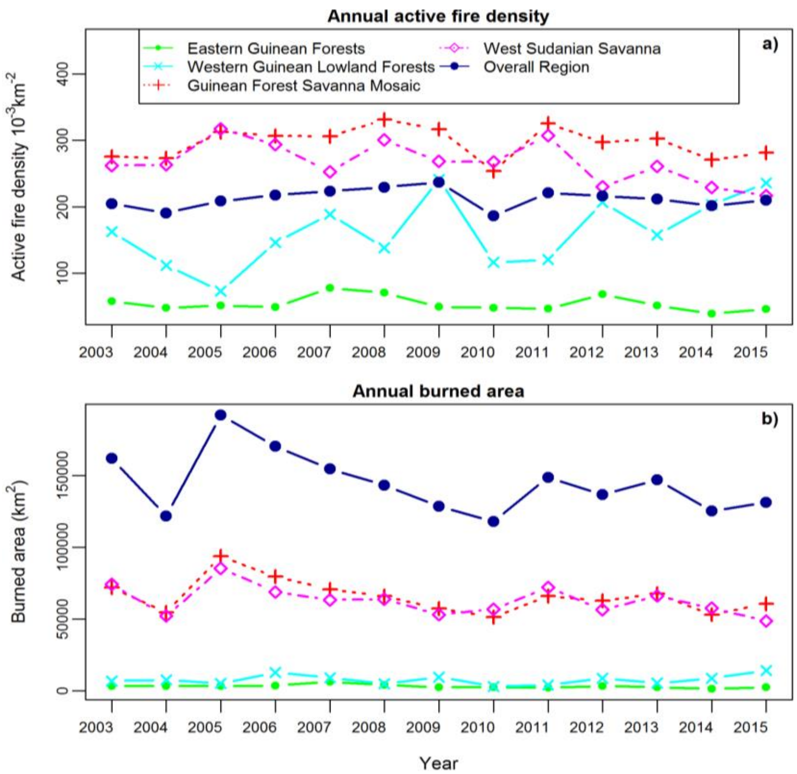


Figure 6. Time series of: (a) annual MODIS active fire density; (b) total burned area across ecoregions and the entire study area for the period 2003–2015.

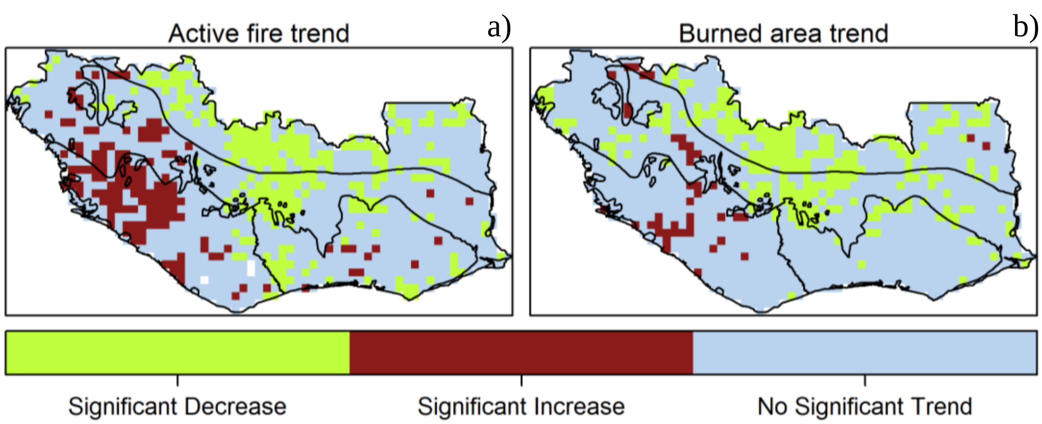


Figure 7. Results of Mann–Kendall trend test of annual: (a) MODIS active fire density; (b) percent burned area for each grid cell for the period 2003–2015. Cells with p-values less than or equal to 0.1 are highlighted in the maps. Grid cells without enough data points to calculate trends are shown in white.

Question 3: How Do the Relative Influences of Climate, Topography, Vegetation Type, and Human Activity Vary across Different Fire Regime Components?

Cross-validated correlations between the BRT predictions and observed values were 0.91 for active fire density, 0.88 for burned area, 0.64 for fire season length, and 0.89 for fire radiative power. The most important predictor variables identified by the BRT algorithm varied among the four fire regime components (Figure 8).

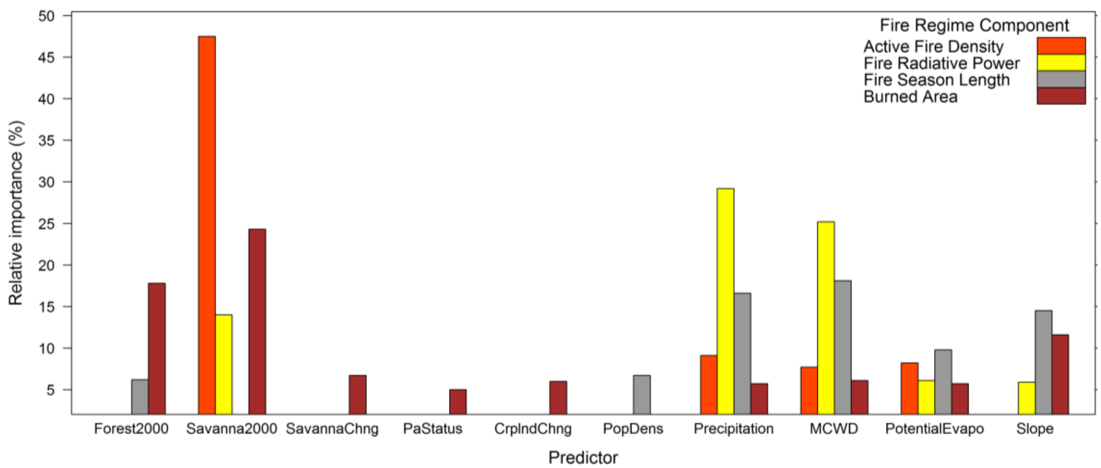


Figure 8. Relative influences of the top 10 predictors from the BRT models of fire regime components. Only variables with relative importance values ≥5% of the variation are plotted here. Abbreviations of predictor variables and their descriptions are provided in Table 1.

For active fire density, savanna cover was the most influential variable followed by precipitation, potential evapotranspiration, and maximum cumulative water deficit (MCWD). All these variables were positively associated with active fire density, except MCWD (Figure 9a). MCWD had a nonlinear relationship, in which active fire density was highest at intermediate water deficits (MCWD ≈ −150, Figure 9a) which may provide dry conditions favorable for fire activity. In contrast, high moisture stress (low MCWD values) may suppress fire activity due to low primary productivity and fuel availability, and low moisture stress (high MCWD values) may limit fire activity because of high fuel moisture. Forest cover and distance to roads had weaker influences on active fire density (4.8%, and 4.2% relative importance, respectively; Appendix Figure S2 - 1).

For burned area, the most important predictor variables were savanna cover, forest cover, slope, savanna cover change, MCWD, cropland change, potential evapotranspiration, precipitation, and protected area status in order of decreasing importance. Burned area was positively associated with savanna cover, but negatively associated with forest cover and slope. Loss of savanna cover during the study period was associated with lower burned area, whereas gain in savanna cover was associated with higher burned area (Figure 9b). A higher gain in cropland was generally associated with higher burned area (Appendix Figure S2 - 2). Burned area was lowest at the highest water stress (low MCWD values) and increased with decreasing water stress (increasing MCWD values).

For fire season length, the three climatic indices, slope, population density, and forest cover were the most important predictor variables (Figure 9c and Appendix Figure S2 - 3). The fire season was longest when water deficit was high (lowest MCWD values). Fire season length decreased with decreasing water stress up to an MCWD value of −200 mm/year, and then increased slightly at the lowest levels of water stress (highest MCWD values). Annual precipitation was negatively associated with fire season length except at the lowest precipitation levels (≤1200 mm/year). Potential evapotranspiration was positively associated with fire season length. Thus, for all three climatic variables, longer fire seasons were generally associated with drier conditions. Slope had a nonlinear relationship with fire season length, with a positive association at low slope values and a negative association at higher slope values. Population density was positively associated

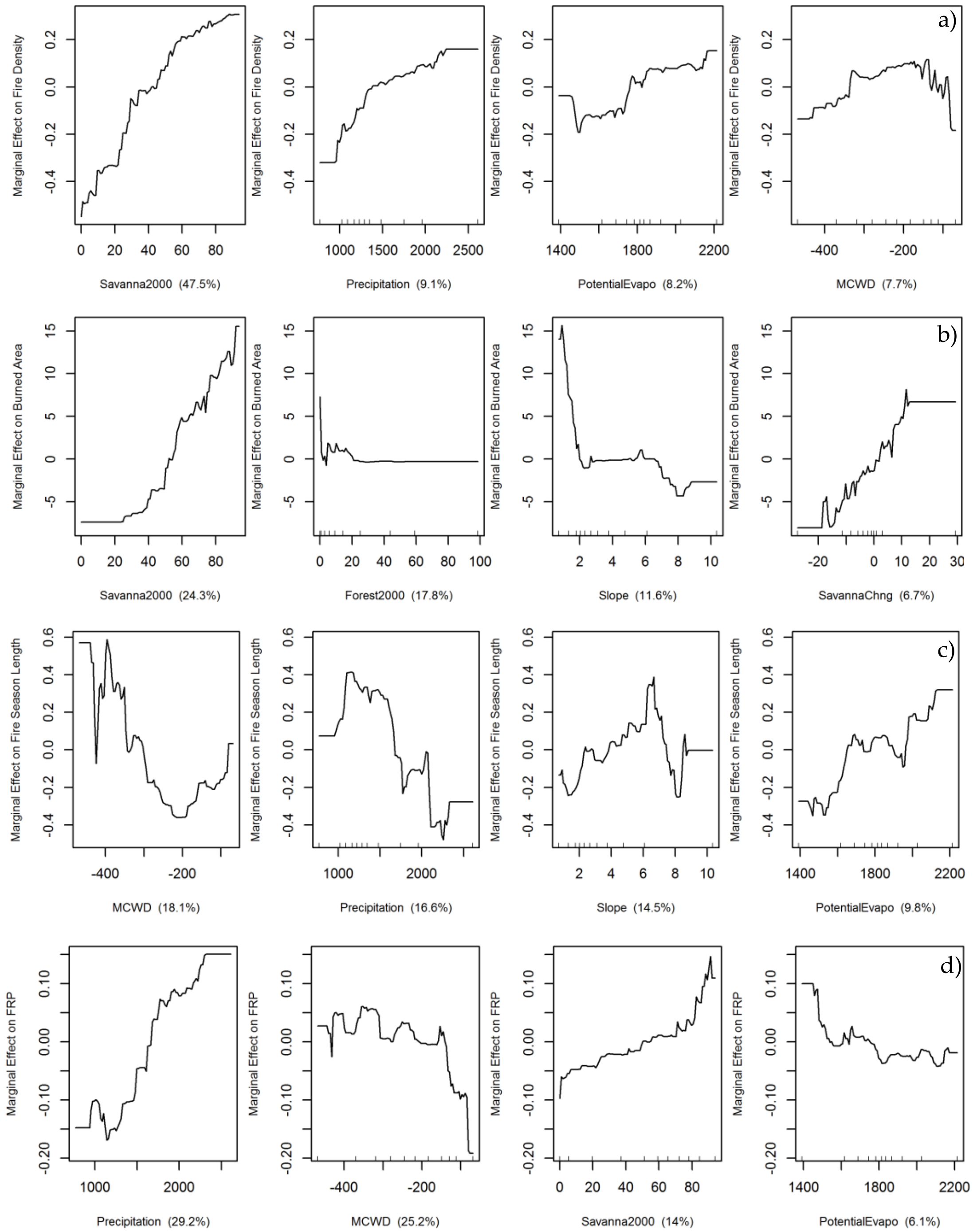


Figure 9. Partial dependence plots of the top four (4) predictors from the BRT model for each fire regime component: (a) active fire density; (b) percent burned area; (c) fire season length; (d) fire radiative power. The plots represent the effect of each predictor on fire activity after considering the average effect of all predictors in the model. Abbreviations of predictor variables and their corresponding full names are described in Table 1.

fire season length. Forest cover also had a unimodal relationship with fire season length, where the longest fire seasons were associated with 20–40% forested land cover (Appendix Figure S2 - 3).

For fire radiative power, the three climatic indices had the strongest influences followed by savanna cover and slope (Figure 9d and Appendix Figure S2 - 4). Thus, the four most influential drivers were the same for fire radiative power and active fire density, although their levels of influence varied and the relationships with MCWD and potential evapotranspiration were different. Fire radiative power was positively associated with higher annual precipitation and negatively associated with evapotranspiration, suggesting that fire intensity was highest in wetter and more productive environments. In contrast, fire radiative power was highest when water deficit was high (lowest MCWD values) and decreased with decreasing water stress (highest MCWD values), suggesting that greater moisture stress during the dry season was also associated with more intense burning (Figure 9d).

4. Discussion

4.1. Vegetation Constraints on Regional Patterns of Fire Activity

There was strong variability in the spatial and temporal patterns of fires across the Upper Guinean region. As expected, the savanna-dominated ecoregions were the epicenters of fire activity, with the highest density of active fires, burned area, and to large extent fire intensity. Savannas are fire-adapted ecosystems, with abundant fine fuels and low fuel moisture during the dry season (Murphy & Bowman, 2012; Pausas, 2015; Ratnam et al., 2011). Savanna also constitutes the most widespread vegetation type in the study area (Figure 1 and Appendix Figure S2 - 5) and thus provides the majority of fuels that support ignition and fire spread. Therefore, concentration of fire activity in the savanna and mixed forest–savanna ecoregions was not surprising. Less fire activity was observed in the humid forest ecoregions because these forests tend to offer some buffering against fire encroachment. Tropical forests are usually fire resistant because they have relatively low amounts of herbaceous fuels and relatively high fuel moisture in their shaded understories (Cochrane, 2003).

In the BRT analyses, active fires and burned area both had the strongest associations with savanna vegetation type. The geographic distribution of savanna was in turn related to the overarching regional gradients of precipitation and moisture stress, but the BRT results emphasized that vegetation, rather than climate per se, had the strongest proximal influence on fire activity. Recent vegetation change was also identified as an important driver of fire. Our finding that savanna loss was associated with lower burned area is consistent with previous studies which found reductions in burned area due to conversion of savannas to agriculture (Andela et al., 2017; Andela & van der Werf, 2014; Grégoire et al., 2013). However, cropland gain during the study period was also associated with higher burned area, and this relationship may reflect the use of fire to clear forested areas for agriculture. In contrast to savanna, forest areas with lower cover were associated with more burned area. These results emphasize that whereas human disturbances through forest fragmentation and degradation tend to enhance fire activity in forested areas, such disturbances tend to diminish fire activity in savanna-dominated landscapes.

We also observed trends in fire activity that are likely associated with regional changes in land use and vegetation patterns. Increasing trends in active fire detections were identified in the Western Guinean Lowland Forest (WGLF) ecoregion. This result affirms recent findings by Ichoku et al. (2016) who reported increasing active fire detections in parts of forested West Africa. Recently, Liu et al. (2017) observed decreasing trends of woody vegetation in the WGLF, an indication of forest loss and degradation in that area. Thus, increasing active fire detections here may be connected with a generally decreasing tree cover and increasing amounts of herbaceous/shrub vegetation and fine fuels, as has been documented in other forested regions of West Africa (Dwomoh & Wimberly, 2017). Furthermore, our observation of a generally decreasing trend in fire activity in savanna-dominated ecoregions is consistent with previous studies which reported declining fire activity in African savannas (Andela & van der Werf, 2014; Grégoire et al., 2013; Ichoku et al., 2016). Liu et al. (2017) reported decreasing trends in woody cover and increasing enhanced vegetation index (EVI) across much of the woody savanna and forest–savanna mosaic ecoregions, suggesting that decreasing fire activity is indeed linked with increasing agriculture and declining tree cover in these areas.

4.2. Distinctive Fire Regimes in the Transition and Savanna Zones

Differences in multiple fire regime components between the northeastern and the northwestern parts of the study area underscored the complexity of factors controlling fire regimes. When the fire season is long with a late peak, as in the northwestern subregion, the fires that start early in the season are usually smaller in size (Archibald et al., 2013) and thus have the potential to break up fuel continuity and reduce total burned area later in the season. It has been shown in a variety of ecosystems that fires reduce fuel loads and thereby inhibit spread of subsequent fires and reduce burned area (Parks et al., 2016;

Price et al., 2015). Moreover, many parts of the northwestern landscape have rugged topography (Appendix Figure S2 - 5), which may have inhibited fire spread leading to lower area burned in the northwestern subregion. These relationships were reflected in the BRT analyses, which found that rugged landscapes with steeper slopes had generally lower burned area and longer fire seasons than landscapes with lower slopes and more gentle terrain.

In contrast, the shorter fire season and earlier peak fire month in the northeastern subregion suggest that flammable and contiguous fuels allowed large areas to burn within a shorter period. These findings are consistent with experimental results from the Kruger National Park in South Africa which found that total burned area was mainly controlled by fuel availability rather than the number of fire events (Archibald, 2016). The northeastern landscape was generally flat and encompassed the largest protected areas of savanna in the study area, located in central and northern Ghana and north-eastern Côte d’Ivoire (Figure 1 and Appendix Figure S2 - 5), thereby providing the most contiguous savanna cover with continuous fuel beds that are conducive to ignition and rapid fire spread. The BRT results showed that protected eco-reserves, which are mostly savannas, had more burned area than other protection categories (Appendix Figure S2 - 2), meaning that fires were more likely to burn in continuous savanna landscapes where human interference is minimal.

Notwithstanding these explanations, we acknowledge that this observed dichotomy between active fire and burned area may also reflect the geographic variability in the probability of ignitions growing into fires large enough to be detectable by the MODIS burned area algorithm. Although the current burned area product, MCD64A1, has improved detection of small burned areas (Giglio et al., 2016a), its performance in highly heterogeneous landscapes such as this study area has not been quantified. Thus, burned area may be underestimated in the northwestern portion of our study area if the fire regime there is comprised of many small fires. However, we believe that relative geographic differences in fire regimes that we have observed are valid: many smaller fires occurring over a longer fire season in the northwest versus fewer, larger fires burning more area over a shorter fire season in the northeast.

Archibald et al. (2013) reported that small-sized and low intensity fires dominate the West African fire regime. However, we found particularly high fire intensity values in western part of the study area. This distinct pattern of fire intensity could be partly explained by the climatic conditions in the far western portion of the study area. This area is unique in that it has high annual precipitation combined with high moisture stress during the dry season as reflected in high maximum cumulative water deficits (Appendix Figure S2 - 5), as well as the latest peak fire months within the study area. The BRT results confirmed that precipitation and maximum cumulative water deficit were the two most important drivers of fire radiative power. Thus, the high fire radiative power in this region may reflect a combination of high fuel loads generated during the growing season followed by low fuel moisture during the fire season, leading to relatively high fire intensity compared to other portions of the study area with either lower fuel loads or higher fuel moisture during the fire season. Furthermore, the late peak fire month in this area likely increased the potential for high intensity fires because fuels later in the fire season are exposed to prolonged dry and warm conditions and therefore have lower fuel moisture than in the early season (Barrett & Kasischke, 2013).

4.3. Climatic Influences on Fire Regime Components

Our findings that more severe moisture deficits were associated with fewer active fires and less burned area, but were also associated with longer fire season lengths and higher fire radiative power (FRP), emphasize the heterogeneous impacts of moisture stress on the fire regime. The general association between drier conditions and lower fire activity indicates that after accounting for differences between major vegetation types, fuel loads rather than fuel moisture are the primary factor limiting fire initiation and spread. High levels of moisture stress lead to reduced primary productivity and consequently result in reduced fuel loads that limit fire activity, whereas more rainfall and lower moisture stress lead to increased fuel loads and fuel continuity.

The overriding influence of the three moisture variables on FRP (Figure 9d and Appendix Figure S2 - 4) emphasize that climatic variables, rather than vegetation type, were the main determinants of fire intensity (Archibald, 2016; Barrett & Kasischke, 2013). As discussed in the previous section, the BRT results indicate that FRP is constrained by a combination of productivity and fuel moisture effects. The highest FRP levels occurred where annual precipitation was high and evapotranspiration was low, indicating the potential for high productivity throughout the growing season, but cumulative moisture stress was high, indicating severe moisture stress and low fuel moisture during the dry season.

Fire season length was most strongly influenced by climate, topography, and population density. Although vegetation types and their associated fuels primarily control the spatial variability in ignition and fire spread, they have less influence on the timing of fire activity during the year. The association of longer fire season length with higher cumulative moisture deficit supports earlier observation by Giglio, et al. (2006) that fire season length in the tropics is largely controlled by duration of the dry season. This relationship was further supported by the positive associations of fire season length with potential evapotranspiration and negative association with precipitation. Nonetheless, our analyses also showed that human population density was an important modifier of fire season length but not active fire density nor burned area. The association of population density with longer fire seasons suggests that anthropogenic activities have more control on the timing of fires than the amount of fire events in these highly-human modified landscapes. Thus, the longer fire seasons in the Eastern Guinean Forest ecoregion may reflect the constraints of climate as well as land use practices, which tend to make fires more persistent even though they are less widespread (Chuvieco et al., 2008).

5. Conclusions

In the Upper Guinean Region of West Africa, different components of the fire regime were influenced by different environmental drivers. As a result, the various combinations of these environmental factors create distinctive fire regimes throughout the region. The strong gradient of increasing fire activity from the wetter coastal regions to the drier regions in the north was related primarily to the shift from forest to savanna vegetation types rather than direct climatic effects. Within the savanna zone, there was a distinction between fire regimes with high active fire density, low burned area, long fire seasons, and late peak fire months compared to fire regimes with fewer active fires, higher burned area, shorter fire seasons, and earlier peak fire months. There was also an area of particularly high fire intensity located in the westernmost coastal regions of the study area. These differences were attributable to the combined effects of vegetation cover, recent land use changes, topography, and climate. Increasing trends in active fire detections in parts of the forested zone and decreasing trends in both active fire detections and burned area in the savanna zone were likely associated with differential impacts of land use change in these distinctive ecoregions. We conclude that while ongoing climate change will continue to influence fire regimes throughout the region, land use change and the resulting feedbacks between fire and vegetation will have a major impact as well. Efforts to project future fire regimes and develop regional strategies for adaptation will therefore need to encompass multiple components of the fire regime and consider multiple drivers, including land use as well as climate. It will also be essential to develop a stronger understanding of how these drivers affect the timing and spatial pattern of ignitions, the abundance and spatial connectivity of available fuels, and the amount of biomass consumed by fire.

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CHAPTER 3

Fire Regimes and Forest Resilience: Alternative Vegetation States in the West African Tropics

Dwomoh, F. K., & Wimberly, M. C. (2017). Fire regimes and forest resilience: alternative vegetation states in the West African tropics. *Landscape Ecology*, *32*(9), 1849-1865.

Journal Impact Factor: 3.615

Abstract

Context Terrestrial ecosystems, including tropical forests, are hypothesized to have tipping points beyond which environmental change triggers rapid and radical shifts to novel alternative states.

Objective We explored the overarching hypothesis that fire-mediated alternative stable states exist in the semi-deciduous tropical forest zone of Ghana, and that increased fire activity has pushed some forests to a new state in which a novel ecosystem with low tree density is maintained by fire.

Methods We combined a 30-year time series of remotely-sensed data with field measurements to assess land cover trends, the effects of fire on forest vegetation, and the reciprocal effects of vegetation change on fire regimes, in four forest reserves. We analyzed precipitation trends to determine if shifts in vegetation and fire regime reflected a shift to a drier climate.

Results Two of the reserves experienced forest loss, were impacted by frequent fires, and transitioned to a vegetation community dominated by shrubs and grasses, which was maintained by fire-vegetation feedbacks. The other two reserves experienced less fire, retained higher levels of forest cover, and resisted fire encroachment from surrounding agricultural areas. Precipitation remained relatively stable, suggesting a hysteresis effect in which different vegetation states and fire regimes coexist within a similar climate.

Conclusion There is potential for human land use and fire to create novel and persistent non-forest vegetation communities in areas that are climatically suitable for tropical forests. These disturbance-mediated regime shifts should be taken into account when assessing future trajectories of forest landscape change in West Africa.

1. Introduction

There are increasing concerns that human-induced global changes, including climate change, land use change, and habitat loss (Brook et al., 2013), could plunge the Earth system into a divergent regime with severe ecological consequences, including major extinctions and substantial losses of ecosystem function (Barnosky et al., 2012). Connected with these concerns is the idea that the Earth's subsystems, including ecosystems, have tipping points beyond which environmental change triggers rapid and radical shifts to novel alternative states (Higgins & Scheiter, 2012). Tropical forest ecosystems are major components of the terrestrial biosphere that provide vital ecosystem services, including protection of biodiversity and large carbon reserviors (Cramer et al., 2004). Tropical forests are also important for climate regulation and play a key role in the global water and energy balance. If these forests are susceptible to rapid state shifts occurring at critical thresholds of environmental change, the resulting changes could have severe local, regional, and global implications including threats to ecosystem resilience, ecosystem services and human wellbeing. In this study, we used a long-term dataset of remotely-sensed Earth observations to provide insights into tropical forest resilience and disturbance-mediated tipping points in the West African tropics.

The term "tipping point" describes the critical threshold beyond which changes exceed ecological resilience and the ecosystem shifts radically and nonlinearly into a different state that is potentially irreversible (Scheffer et al., 2009). An important property of systems exhibiting alternative stable states is hysteresis, a term used to describe the difficulty of system recovery once a catastrophic transition is reached (Scheffer, 2009). Hysteresis is the net result of both positive and negative feedbacks between the ecosystem state and its rate of change (Scheffer & Carpenter, 2003). Positive feedbacks drive rapid state shifts by magnifying small deviations and destabilizing the system, and then negative feedbacks maintain the system once it is shifted into a new state by countering deviations from that state (Boulton et al., 2013). Environmental drivers, including climate variations, nutrient inputs, and land use typically change slowly compared to ecosystem responses (Bestelmeyer et al., 2011; Scheffer et al., 2001). However, these environmental changes can trigger disturbances such as large fires, severe droughts, disease and pest outbreaks, and species invasions that result in rapid transitions to other ecosystem states. When there are strong negative system feedbacks, the ecosystem may not return to the pre-disturbance state even when environmental conditions are similar to those that supported the initial ecosystem condition prior to the disturbance.

Alternative stable states are hypothesized to occur in tropical forests as a result of vegetation interactions with fuels, microclimate, and fire regimes (Brando et al., 2014; Silvério et al., 2013). Although closed-canopy tropical forests seldom burn because their shaded understories support few herbaceous fuels and maintain high fuel moisture, they become more fire prone once fire or logging opens the canopy, resulting in more fine fuels and drier conditions in the understory (Cochrane et al., 1999; Hoffmann et al., 2012). Frequent, severe, or combined fires limit the establishment of fire-sensitive forest tree species and favor pyrophilic grass and shrub establishment by increasing mortality of seed trees, reducing density and diversity of seedlings, and inhibiting tree seed germination (Paritsis et al., 2015; Silvério et al., 2013). As a result of these positive feedbacks, forest disturbance can lead to rapid overstory canopy loss, resulting in a switch from a fire-resistant forest to fire-dependent vegetation maintained by a self-reinforcing negative fire feedback (Devisscher et al., 2016).

It is extremely difficult, if not impossible, to rigorously test for the existence of multiple stable states using observational data (Petraitis, 2013). However, evidence for alternative stable states can be inferred from observations in time and space by detecting characteristic patterns, including surges in time series; multimodal frequency distributions of ecosystem state variables; dual biological response to drivers; and sharp spatial boundaries between contrasting communities (Scheffer & Carpenter, 2003). Using these approaches, alternative stable states have been documented in a variety of terrestrial ecosystems. Odion et al. (2010) affirmed the presence of alternative community states of sclerophyll and forest vegetation states that are maintained by different self-reinforcing fire feedbacks in northwestern California. Wood & Bowman (2012) similarly concluded that vegetation communities in temperate southwest Tasmania may exist as alternative stable states maintained by fire-vegetation-soil feedbacks. In tropical regions, intense fires associated with droughts can facilitate large-scale grass invasion in tropical forests, prompting the suggestion that such triggers could cause significant portions of the Amazon forest to be displaced by grass-dominated vegetation (Silvério et al., 2013).

Despite widespread interest in the topic, there is still a dearth of long-term empirical studies focused on fire-driven alternative stable states in tropical forests. Here we utilize a 30-year time series of satellite remote sensing data to explore fire-mediated alternative stable states in the West African tropical forest (referred to as the Upper Guinean forest). The Upper Guinean forest is a global biodiversity hotspot and has become one of the most human-modified forest ecosystems in the tropics (Norris et al., 2010; Poorter et al., 2004), having lost over 80% of its original forest cover, with the remainder distributed in a fragmented agriculture-forest mosaic (Norris et al., 2010). The Upper Guinean forest is also considered climatically marginal, having the highest temperatures and longest dry seasons of all tropical forest systems worldwide (Malhi & Wright, 2004). Moreover, a number of protected areas in this region were impacted by large fire events during the 1980s El Niño–driven droughts (Hawthorne, 1994). Thus, the remnant Upper Guinean forests are highly vulnerable to fire and fire-mediated forest loss, and the region provides a suitable testbed for studying alternative stable states established and maintained by fire in tropical forest ecosystems.

This paper addresses the overarching hypothesis that fire-driven alternative stable states exist in the semi-deciduous tropical forest zones of Ghana, and that increased fire activity has compromised forest resilience by pushing the system past a tipping point to an alternative stable state in which a novel ecosystem with low tree density is maintained by fire. We used an exploratory approach in which we quantified patterns of landscape change and fire activity in space and time and then qualitatively assessed whether the observations were consistent with expectations for a system with alternative stable states. We addressed three research questions, each focused on a specific characteristic of systems with alternative stable states: persistent change, feedbacks, and hysteresis (Bestelmeyer et al., 2011; Petraitis, 2013; Scheffer, 2009).

(i) Is there evidence of persistent forest loss? If the system has shifted to an alternative stable state, then we expect to see a major shift in vegetation structure and composition with no trends of recovery to a forested condition.

(ii) Is there evidence of fire-vegetation feedbacks? We interpret spatial and temporal associations of high fire activity with low forest canopy cover as evidence of a positive feedback between fire and forest loss. We also contrast fire activity between reserved areas and the surrounding agricultural matrix to determine whether forests resist the spread of agricultural fires (negative feedback) and whether deforested areas facilitate the spread of agricultural fires (positive feedback).

(iii) Is there evidence of hysteresis? If persistent shifts to non-forest vegetation and increases in fire activity have occurred over periods when precipitation has remained stable or increased rather than decreasing, then we can infer a hysteresis effects in which the different states can exist under similar climatic conditions.

2. Methods

2.1 Study Area

The study area is located between latitudes 7°00’ - 7°40' north and longitudes 2°20' - 3°00' west in the Brong Ahafo region of western Ghana (Figure 1). A forest landscape including four forest reserves was selected for this study. *Pamu Berekum* and *Tain Tributaries Block II* (hereafter called *Tain II*) measure 189 km^2 and 509 km^2 respectively. *Pamu Berekum* is located at the northern edge of the dry semi-deciduous forest type. *Tain II* is located at the southern edge the fire-zone subtype of the dry demi-deciduous forest type. *Asukese* and *Mpameso* measure 265 km^2 and 323 km^2 , respectively and are located approximately 60 km to the south near the northern boundary of the moist semi-deciduous northwest forest type (Figure 1). These sites were chosen because they allow us to compare two sets of reserves in a relatively similar climatic setting but with very distinctive change trajectories following a period of high fire activity associated with the exceptional pan-tropical El Niño-induced droughts in the 1980s (Swaine, 1992). In this cloudy and data-poor region, the selected reserves are among the few for which relatively long time series of Earth observation data are available.

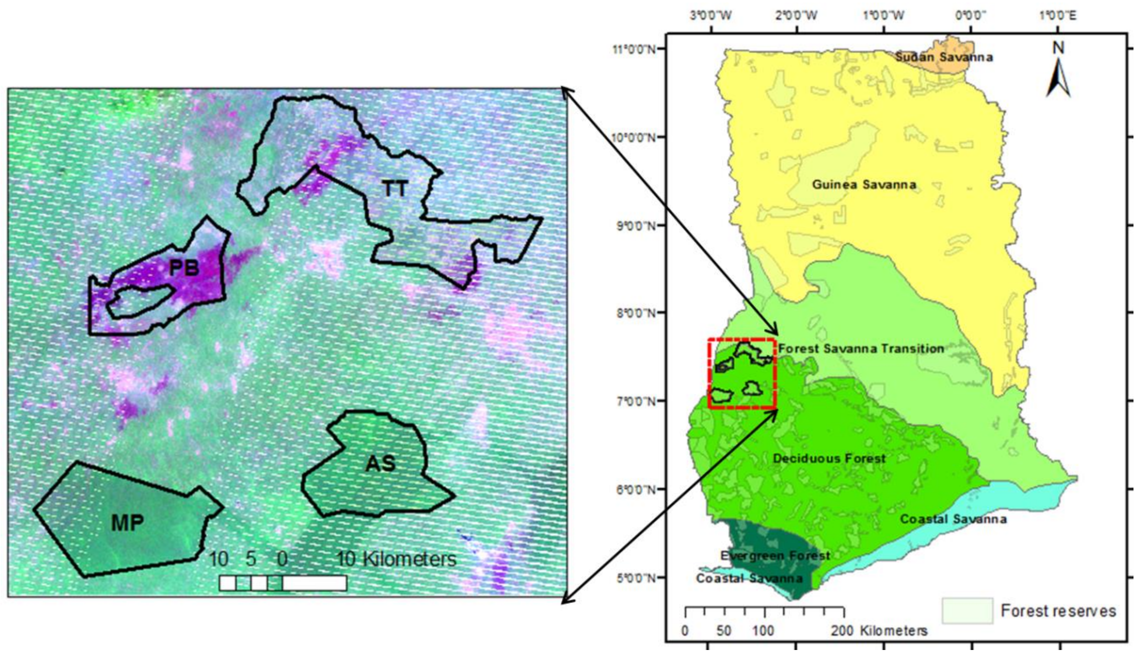

Figure 1. Vegetation map of Ghana (*right*) with the study area (*left*) on a background Landsat ETM+ image from 5 February 2013 in 743 false color composite. On the left, dark green represents forest cover, dark purple represents recently burned vegetation, and white spaces indicate no data due to Landsat 7 SLC-off data gaps. *AS* Asukese Forest Reserve, *MP* Mpameso Forest Reserve, *PB* Pamu Berekum Forest Reserve, *TT* TainTributaries Block II Forest Reserve.

Based on data collected from 1976 to 2013 from three meteorological stations located within the study area, mean annual rainfall ranges from 1194 to 1292 mm, and mean daily temperature is about 25° C in the wet season (April-October) and 27°C during the dry season (November-March). The study area is among the most floristically diverse and economically important forest areas in Ghana. Historically, forests in this region were densely stocked and characterized by multi-layered and continuous canopies with abundant lianas and many large, buttressed trees (Hall & Swaine, 1981). The most common valuable timber species in the area include *Antiaria toxicaria*, *Triplochiton scleroxylon*, *Khaya* spp., *Entandrophragma* spp. and *Milicia excelsa*.

Currently, the most significant original tropical forests left in the region are those contained in protected forest reserves (Alo & Pontius, 2008). Outside of the protected areas, farming represents their primary source of food, income, and security (Blay et al., 2008). The high human population density outside protected areas makes them susceptible to fires because of forest fragmentation and fire spread from agricultural areas. There is also considerable pressure from both legal and illegal logging inside the protected areas to meet high wood demands (Hawthorne, 1994; Marfo, 2010).

2.2 Remote Sensing Data

We used Landsat TM/ETM+ images acquired during the dry season (November-March) to maximize cloud-free acquisitions and minimize false change detection due to seasonality and phenological differences. A total of 26 images from 1984 to 2015, with cloud cover 25% or lower, were selected from Landsat path/row 195/055. Whenever more than one image was available for a particular dry season, the image with the most conspicuous burn scars and the least cloud contamination was selected. The periods 1984-1995, 1996-2005, and 2006-2015 had nine, seven, and 10 images, respectively. All the images were Level 1 terrain corrected (LT1), atmospherically corrected, and converted to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) tool (Masek et al., 2006). With the exception of a few images from the European Space Agency, most images were downloaded from the USGS EROS archive (Table S3 - 1 in Appendix).

Cloud and cloud shadow masks were obtained through an automated cloud and cloud shadow detection algorithm, Fmask (Zhu & Woodcock, 2012). A separate Random Forest classification approach, using both the reflective and thermal bands, was used to mask clouds from the 1984 image due to poor performance of the Fmask algorithm. The Carlotto technique for de-hazing implemented in the ImgTools software was used to correct for atmospheric contamination of images affected by haze and smoke (Souza et al., 2013).

2.3 Mapping Fires

The normalized burn ratio (NBR) was used to map burned area in each image. After fire, the reflectance of burned areas typically increases in the middle infrared (MIR) because of soil exposure and decreases in the near infrared (NIR) due to leaf tissue damage. The NBR thus uses MIR and NIR reflectance to map burned areas (Key & Benson, 2006). We used NBR thresholds, guided by manual interpretation of the Landsat imagery and field observations, to map fire perimeters in all years with available Landsat imagery with threshold values ranging from 0.06 – 0.18.

The differenced NBR (dNBR) calculates the change between pre- and post-fire NBR estimates as a measure of severity and has been shown to be effective in broadleaf as well as coniferous forest types (Wimberly & Reilly, 2007). We mapped fire severity within burned perimeters using the dNBR in 1989 because suitable images for both pre- and post-fire were available only for that year. Because there is no systematic way of generating fire severity classes from continuous values of dNBR, we adopted the approach employed by Numata et al. (2011) using a mean cluster analysis to classify the dNBR values of burned pixels into three classes of fire severity (low, medium and high).

We also obtained MODIS active fire detections at 1-km resolution at the time of Terra (10:30 am/pm Equatorial nominal overpass time) and Aqua (1:30 pm/am Equatorial nominal overpass time) satellite overpass from the monthly product MCD14ML, level 3 Collection 6 (Giglio et al., 2016). We characterized the spatial distribution and frequency of active fires for the period 2001-2015. We summarized the active fire detections into an annual active fire density time series (number of active fires per 100 km^2) for each forest reserve, as well as the 5-km buffer zone surrounding each reserve.

2.4 Mapping Forest Vegetation Change

We used the disturbance index (DI), which is based on the tasseled cap (TC) transformation, to map changes in forest conditions over time (Healey et al., 2005) The TC transformation compresses the data in the six optical-infrared bands of Landsat TM/ETM+ images to three orthogonal indices called brightness, greenness and wetness (Baig et al., 2014). Brightness is a weighted sum of all the bands, and is often used as a measure of soil exposure. Greenness is a measure of the contrast between the NIR band and the visible bands and is sensitive to the amount of photosynthetically active vegetation (Baig et al., 2014). Greenness is thus analogous to Red/NIR-based greenness indices such as NDVI and EVI. Wetness is a measure of contrast between the NIR and MIR bands and is sensitive to the moisture content of soil and vegetation. In vegetated areas, wetness can be interpreted as an indicator of canopy structure, soil or surface moisture, or the amount of dead or dried vegetation (Cohen & Goward, 2004). Tasseled Cap transformation coefficients were obtained from Crist (1985).

We rescaled the TC indices into normalized brightness (Br), normalized greenness (Gr) and normalized wetness (Wr) by normalizing the respective TC index by the mean and standard deviation of representative forested pixels in each image scene. The reference forest pixels were selected from local image windows containing a mask of stable forest reserves across the entire image scene. This forest mask comprised 14 forest reserves, including national parks that were identified as relatively stable through time in the Landsat images time series. Compared to other vegetated surfaces, dense forest pixels are generally darker in the visible and middle infrared bands. Therefore, these pixels formed a peak at the lower end of the histograms for these bands (Huang et al., 2008). Our reference forest pixels were selected by identifying the first peak in the histogram of the Landsat red band from our stable forest mask. Even though reflectance values of the reference pixels might change between images due to scene-to-scene variability, the selection approach has been shown to be insensitive to these inter-image variations as long as the histogram peaks can be identified (Huang et al., 2008).

The DI is a linear transformation of the three normalized TC indices derived from Landsat TM/ETM+ images.

$$\mathrm{DI} = \mathrm{Br} - (\mathrm{Gr} + \mathrm{Wr}) \qquad \textbf{Equation 1}$$

The DI works on the assumption that disturbed forest exhibits high brightness, low greenness and low wetness. Thus, disturbed areas are spectrally dissimilar to forests and therefore have high DI values. Undisturbed forest has spectral characteristics close to the reference forest pixels and therefore has low DI values (Healey et al., 2005). This approach has been shown to be effective at detecting changes in forested land cover (Hilker et al., 2009; Sieber et al., 2013). Validation of the 2015 DI index with the available Google Earth high-resolution imagery indicated a good separation of forest canopy cover classes by the DI, with a multi-class AUC value of 0.98 (see Appendix S3 - 1).

2.5 Field Inventory

In March 2014 we conducted forest inventory in 11 representative sample plots distributed across the four forest reserves to characterize the conditions shown by the vegetation indices. The numbers of plots sampled in each reserve were two (AS), four (MP), two (PB), and three (TT). In each plot we established belt transects of 100 m x 10 m (0.1 ha). Within these transects, we measured and recorded the diameter at breast height (DBH in cm) of all trees with DBH ≥10 cm. Also, we estimated canopy cover (%) at 1 m intervals along each transect. We established three circular subplots of radius 5.65 m (area 100 m^2) at every 50 m along the belt transect to measure all small trees of DBH ≥2 cm and <10 cm. (>2 m tall). Within each subplot, we took ocular estimates of litter and combined grass/shrub cover. The tree counts were summarized to provide tree density and basal area estimates.

2.6 Meteorological Data

We analyzed precipitation data from three meteorological stations located in the towns of Bechem, Sunyani, and Wenchi, spanning the latitudinal gradient of the study area (Appendix, Figure S3 - 1). We considered two rainfall metrics: the total annual precipitation (TAP) and the maximum climatological water deficit (MCWD). MCWD estimates accumulated water deficit within a particular year, and this rainfall metric is a useful indicator of the intensity and length of the dry season (Aragão et al., 2007). We computed MCWD using methods described by Aragão et al. (2007). TAP is a major determinant in the distribution of tropical tree cover and vegetation types, whereas rainfall seasonality (here represented by MCWD) affects fuel moisture and fire regimes in the tropics (Hirota et al., 2011; Staver et al., 2011).

2.7 Analysis methods

Question 1: Is there evidence of persistent forest loss?

We graphed time series of mean DI, brightness, greenness and wetness indices for each reserve and conducted trend analysis to quantify trajectories of vegetation change. We used the non-parametric Mann-Kendall test to test for increasing monotonic upward or downward trend in forest canopy disturbance after 1989 (Gocic & Trajkovic, 2013). We also used the field inventory data collected in March 2014 to provide a more detailed characterization of current vegetation structure and composition in representative plots distributed across the reserves.

Question 2: Is there evidence of fire-vegetation feedbacks?

To determine whether fire regimes were different in reserves that experienced forest loss compared to the intact reserves, we also graphed the annual time series of MODIS active fire density and Landsat percent area burned for each reserve. We used Welch's one way ANOVA test and the Games-Howell post-hoc test, from the *userfriendlyscience* package in R, to compare mean differences in active fire density and burned area among the four reserves for the entire time series. We used these tests because the data were heteroscedastic and also violated the normality assumption, and therefore did not meet the assumptions for one-way ANOVA or its non-parametric equivalent, the Kruskal-Wallis test. We also compared fire severity in the four reserves in 1989 using the Landsat-derived dNBR measurements.

To assess the interactions between vegetation in the reserves and fire ignited in the surrounding agricultural matrix, we used paired t-tests to evaluate differences in fire activity between the interior and the 5-km buffer surrounding each reserve. This analysis tested whether the vegetation in the reserves generated negative fire feedbacks by resisting the spread of fires ignited in the surrounding agricultural matrix, or generated positive feedbacks by facilitating fire spread from the matrix.

Question 3: Is there evidence of hysteresis?

We analyzed TAP and MCWD from 1990-2013 using the non-parametric Mann-Kendall test and breakpoint analysis to determine whether or not the changes in vegetation and fire regime after 1990 could be explained by a shift to a drier climate. Breakpoints in time series are points at which the mean changes, and such analyses are useful for determining when abrupt transitions occur and thus identifying potential regime shifts (Bestelmeyer et al., 2011). Cumulative sum (CUSUM) plots, residual sums of squares (RSS), Bayesian Information Criterion (BIC) and F-statistic analyses were used for abrupt change point detection in the precipitation time series (Bestelmeyer et al., 2011).

3. Results

Question 1: Is there evidence of persistent forest loss?

The time series of DI, brightness, greenness, and wetness showed varied responses across the study sites (Figures 2 & 3). From 1990 onward, DI was higher and exhibited a significant increasing trend in PB (0.1 significance level) and TT (0.05 significance level), but remained low with no significant trend in AS and MP (Table 1). No significant increasing or decreasing trend in greenness was detected in any of the reserves. There were significant decreasing trends in wetness in the northern reserves (PB and TT), but no significant trends in the southern reserves (AS and MP). There was a significant increasing trend in the brightness index in TT, but no significant trends in PB and the southern reserves. Based on these results and visual inspections of the trends, there was no evidence of recovery of forest conditions in PB and TT, and no evidence of increasing forest disturbance in AS and MP.

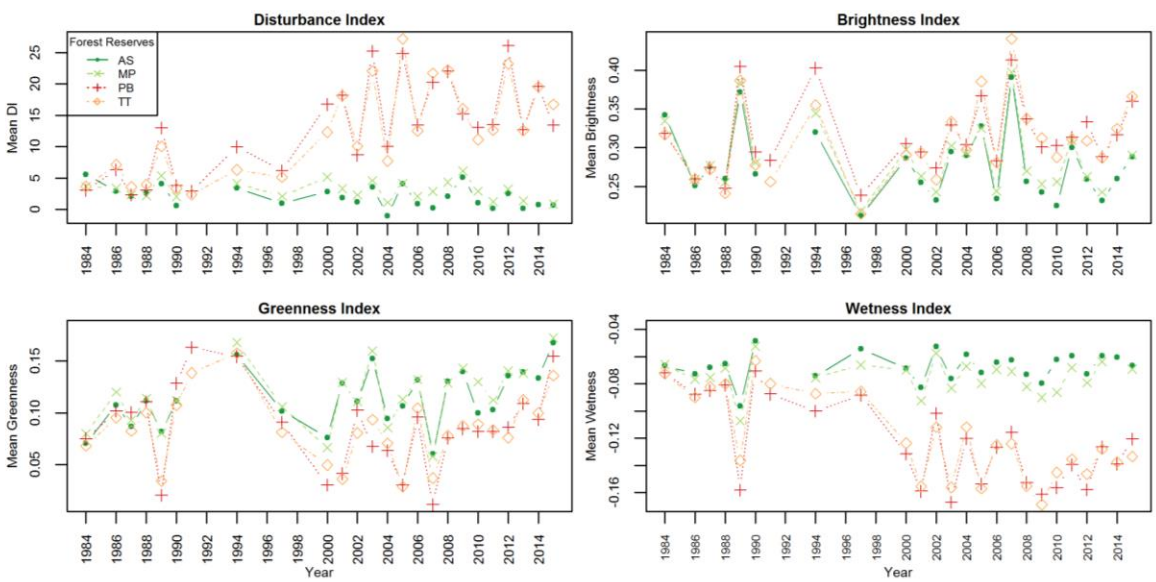

Figure 2. Time series of disturbance index and tasseled cap brightness, greenness and wetness indices across the four reserves.

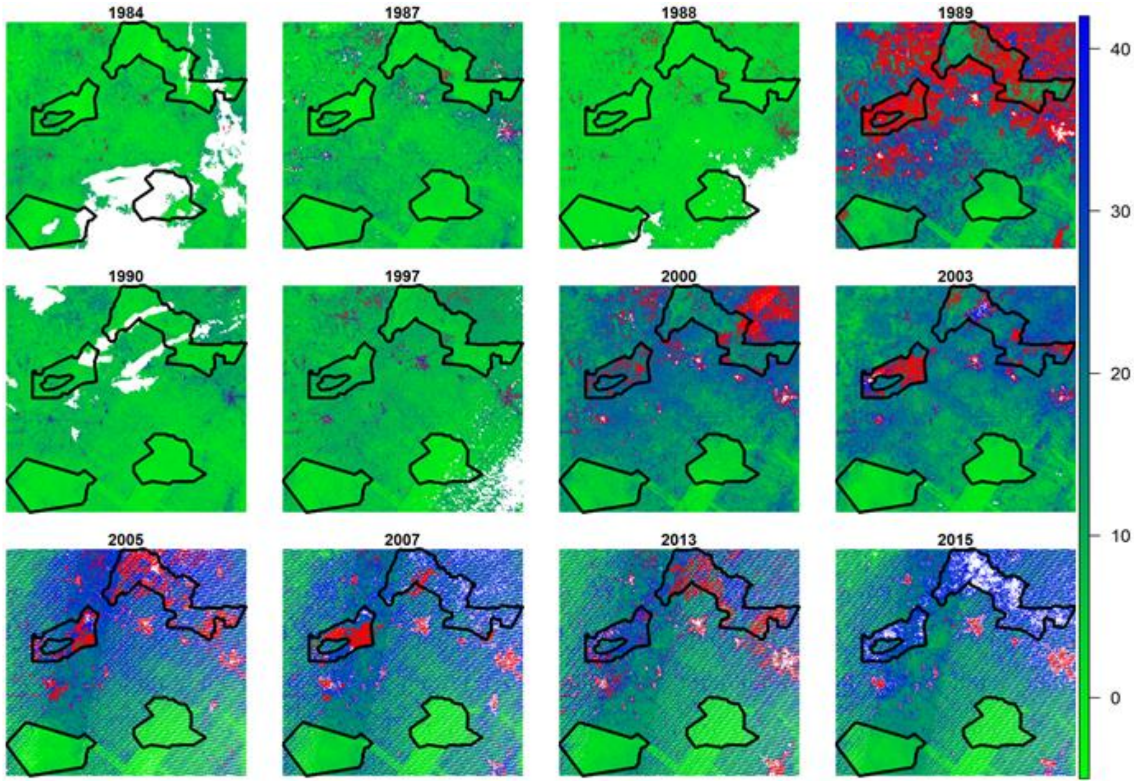

Figure 3. Disturbance index time series maps showing vegetation cover changes within the forest reserves. Colors represent a gradient from closed forest (green) to degraded forests or low vegetation cover (blue). Red represents recently burned sites; white spaces indicate non-vegetated surfaces or no data.

Table 1. Nonparametric Mann-Kendall test to detect trends in DI, brightness, greenness, and wetness indices from 1990 to 2015

Vegetation Index	Statistic	AS	MP	PB	TT
Disturbance index	tau	-0.158	-0.15	0.316	0.432
	p-value	0.363	0.405	0.056*	0.009**
Brightness index	tau	-0.018	-0.072	0.221	0.284
	p-value	0.944	0.705	0.183	0.086*
Greenness index	tau	0.205	0.268	0.032	0.053
	p-value	0.234	0.13	0.871	0.77
Wetness index	tau	-0.018	-0.111	-0.326	-0.4
	p-value	0.944	0.544	0.048**	0.015**

Positive Kandall's tau statistic values indicate increasing trends, whilst negative values indicate decreasing trends. ** Significant at 0.05 significance level, * significant at 0.1 significance level

The forest inventory data from 2014 indicated that most of PB and TT lacked a forest canopy (Table 2). We also sampled one small remnant forest patch in TT, which had a relatively high basal area but also had lower tree density and canopy cover than the other plots located in unlogged forests. In contrast, the representative plots in AS and MP had higher tree densities, basal areas and canopy cover, although canopy cover tended to be lower in plots with evidence of recent logging.

Table 2. Summary of vegetation characteristics of representative field plots sampled in March 2014

Reserve	Logging status	Tree density (stems ha^{-1})		Basal area (m^2 ha^{-1})		Canopy cover (%)	Shrub cover (%)	Litter cover (%)
		Trees 5-10cm dbh	All tree ≥5 cm dbh	Trees 5-10cm dbh	All tree ≥5 cm dbh			
AS	Recent logging*	67	137	0.28	4.7	27	100	100
AS	No recent logging	500	900	2.18	30.99	64	0	53
MP	Recent logging	767	1067	3.07	34.87	45	47	50
MP	No recent logging	533	953	2.01	22.39	73	5	72
MP	Recent logging	200	470	0.74	8.38	27	53	45
MP	Recent logging	433	863	1.68	27.75	70	5	90
PB	No forest	0	0	0	0	0	100	85
PB	No forest	167	207	0.47	1.71	1	100	85
TT	No forest	67	67	0.15	0.15	0	98	100
TT	No recent logging	0	230	0	27.15	40	68	85
TT	No forest	0	10	0	4.36	5	100	100

* Recent logging indicates field evidence of logging activity at least in the recent two decades.

The inventory data showed that shrub/grass cover was generally lower in the AS and MP plots than in the PB and TT plots (Table 2). In AS and MP the shrub and herbaceous layers were dominated by species typical in forest gaps and the forest understory, including herbs in the genus *Afromomum* and the family *Marantaceae*. However, in PB and TT the shrub and herbaceous layers were dominated by heavy thickets formed by a mixture of *Pennisetum purpureum* (elephant grass), the shrubs

Chromolaena odorata and *Solanum erianthum*, and copious regeneration of *Ficus spp.* The percentage of the forest floor covered by litter varied widely among all the sampled locations, but was generally higher in PB and TT and in plots with recent logging.

Question 2: Is there evidence of fire-vegetation feedbacks?

The time series of Landsat burned area showed that the largest annual burned area was recorded in 1989 and that this fire in this year was more widespread in the two northern reserves, PB and TT, than the southern reserves, AS and MP (Figure 4). During that year, 66.0% of PB and 39.0% of TT were burned at moderate to high severity (Figure 5). In contrast, only 2% of MP and less than 0.10% of AS were burned at moderate to high severities.

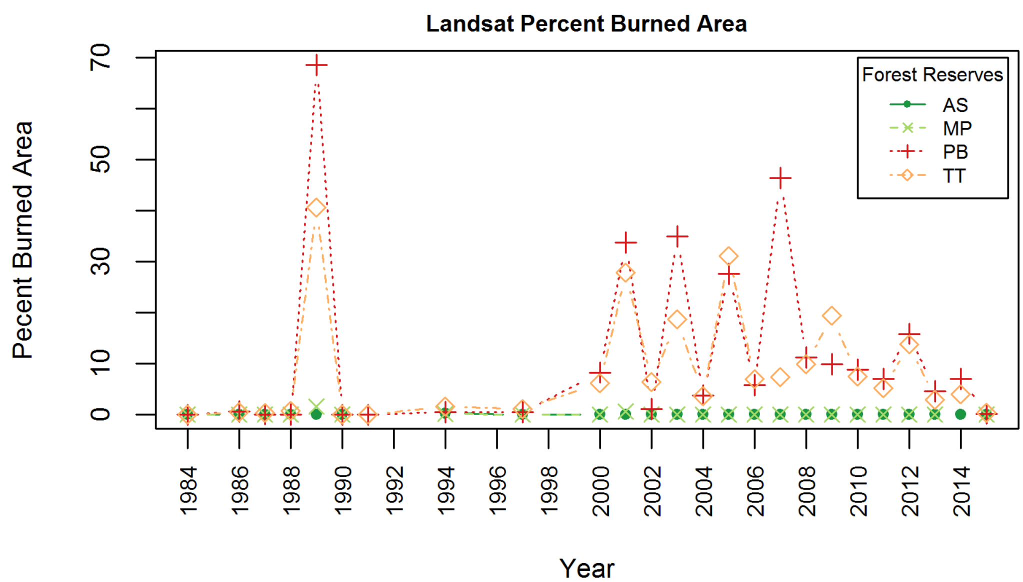

Figure 4. Time series of burned area mapped from Landsat TM/ETM+ imagery.

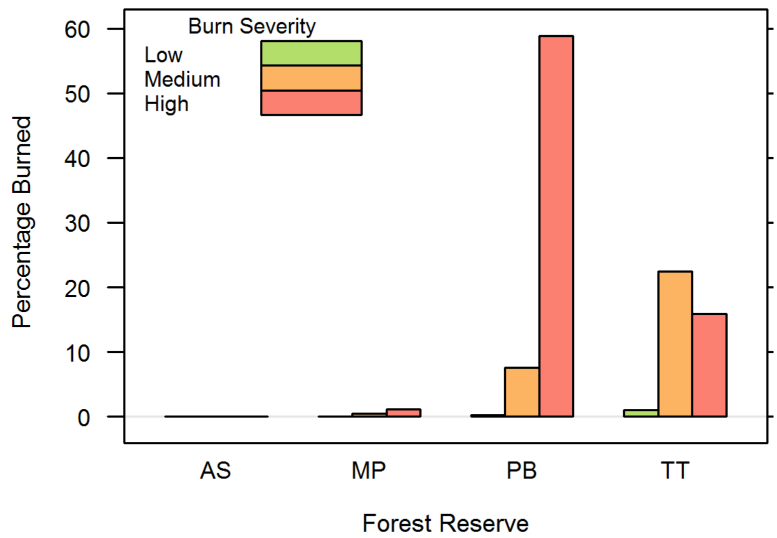

Figure 5. Immediate (7-weeks) post-fire burn severity measured by the differenced normalized burn ratio (dNBR) summarized across four forest reserves in 1989.

There were significant differences in Landsat burned area (F= 8.67, p < 0.001, Welch's one-way ANOVA; Figure 4) and MODIS active fire density (F= 21.92, p < 0.001, Welch's one-way ANOVA; Figure 6 and Figure 7) across all the reserves. For both the Landsat burned area and the MODIS active fire annual time series, there was more fire activity in the two northern reserves that had minimal forest cover (PB and TT) than in the two southern reserves that retained a mostly intact forest canopy (AS and MP, Figure 4 and Figure 6). The Games-Howell post hoc tests confirmed that for both fire variables, there were no significant differences (0.05 significance level) between TT and PB, or between AS and MP (Appendix, Figure S3 - 4). However, mean values in TT and PB were significantly higher than in AS and MP.

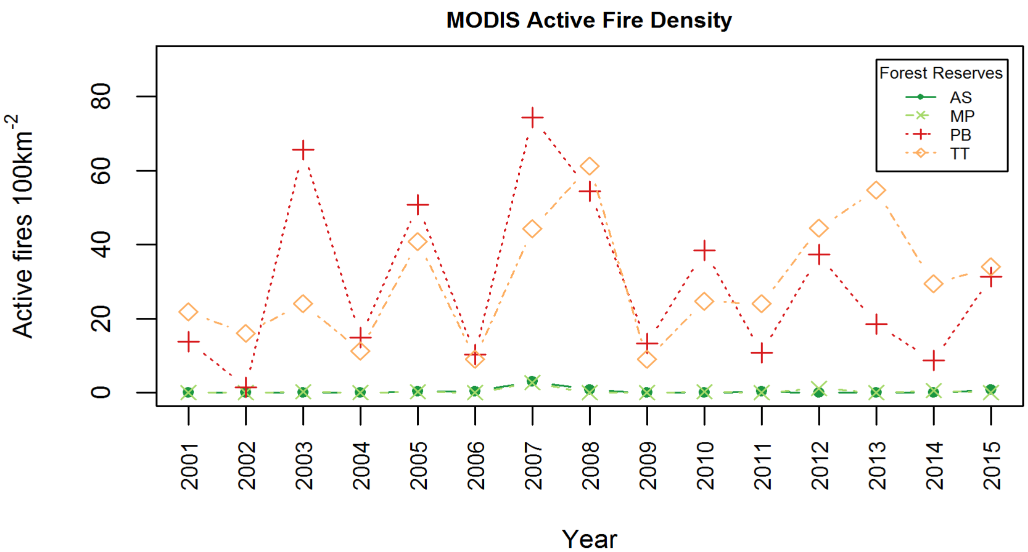

Figure 6. MODIS active fire density time series

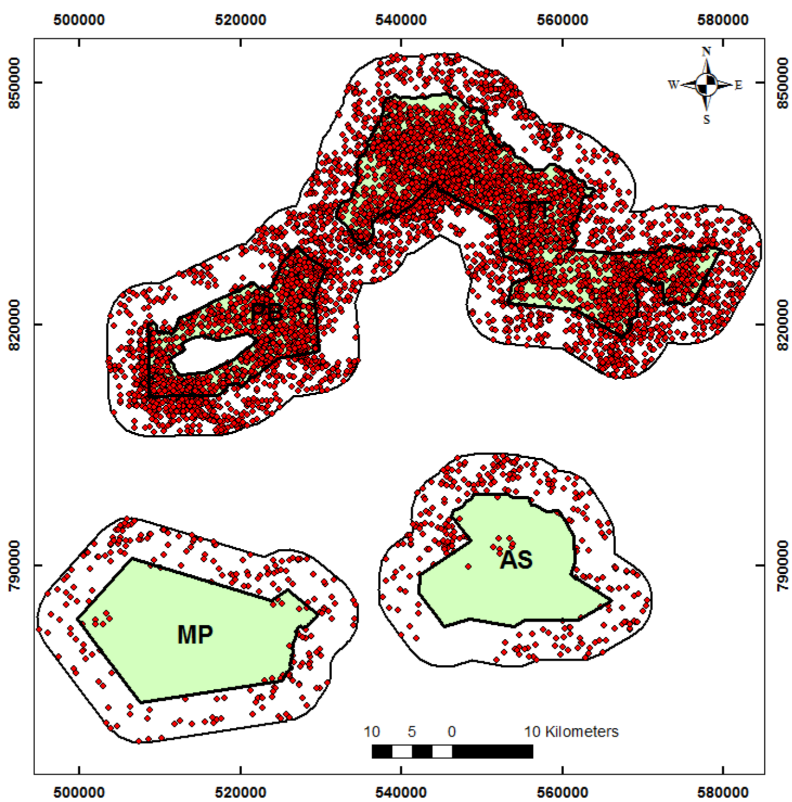

Figure 7. Spatial distribution of MODIS active fires, 2001 - 2015, within forest reserves and 5 km buffer zones around the reserves.

There were more active fires in the reserve interiors than in their corresponding buffers in the highly disturbed northern reserves (Figures 7, 8; paired t-test, $p= 0.002$ and $p<0.001$ in PB and TT, respectively). In contrast to the northern reserves, there were more active fires in the buffer zones of each reserve than within reserve boundary in the less disturbed southern reserves (Figures 7, 8; paired t-test, $p< 0.0001$ in both AS and MP). Overall active fire densities were lower both in the reserves and buffer of AS and MP compared to PB and TT. We inferred that the non-forest vegetation in PB and TT exhibited positive feedbacks that facilitated the growth and spread of agricultural fires ignited in the surrounding matrix, whereas the forest vegetation in AS and MP exhibited negative feedbacks and resisted spread of fires from the surrounding matrix. This inference is supported by the fire patterns shown in Figure 3, in which fire scars in PB and TT after 2000 tend to be adjacent to the edge of the reserve and extend into and sometimes through the entire reserve, whereas no substantial fire scars are seen in AS and MP.

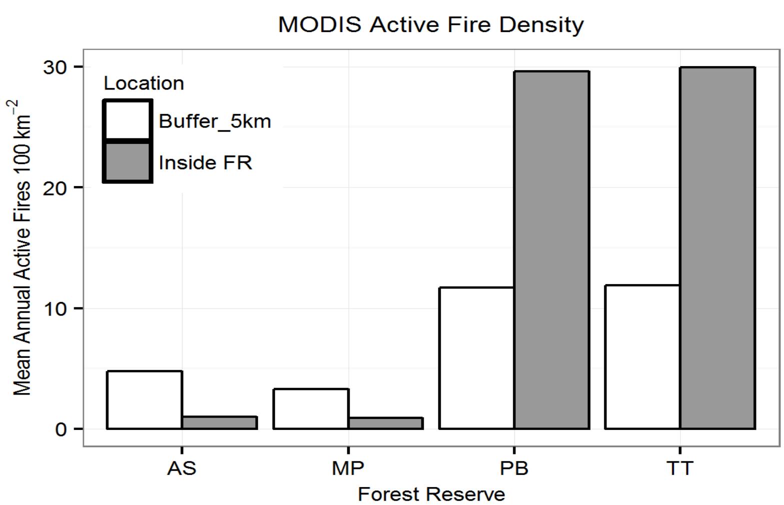

Figure 8. Mean annual MODIS active fire density within reserves and 5-km buffers around each reserve.

Question 3: Is there evidence of hysteresis?

Precipitation was similar along a north-south gradient throughout the study area. Mean annual precipitation (± standard deviation) from 1976 to 2013 ranged from 1244 ± 171 at Wenchi in the north to 1194 ± 171 at Sunyani between the northern and southern reserves to 1282 ± 228 at Bechem in the south.

Precipitation trends indicated a gradual increase in TAP in all the weather stations punctuated by some dry years in 1990s and the 2000s (Figure 9). These increases were statistically significant in all the weather stations (p-value <0.01), except at Wenchi. The MCWD trend did not show evidence of worsening drought stress during the dry season (Appendix, Figure S3 - 3). Instead there was a statistically significant improvement in moisture conditions in Bechem (p-value <0.05), and no statistically significant change in Sunyani and Wenchi. No abrupt changes in precipitation were detected in any of the time series. Thus, the non-forested conditions in PB and TT have been maintained throughout a time period during which precipitation has generally been stable or increasing, and thus climatic suitability for forests has also been stable or increasing.

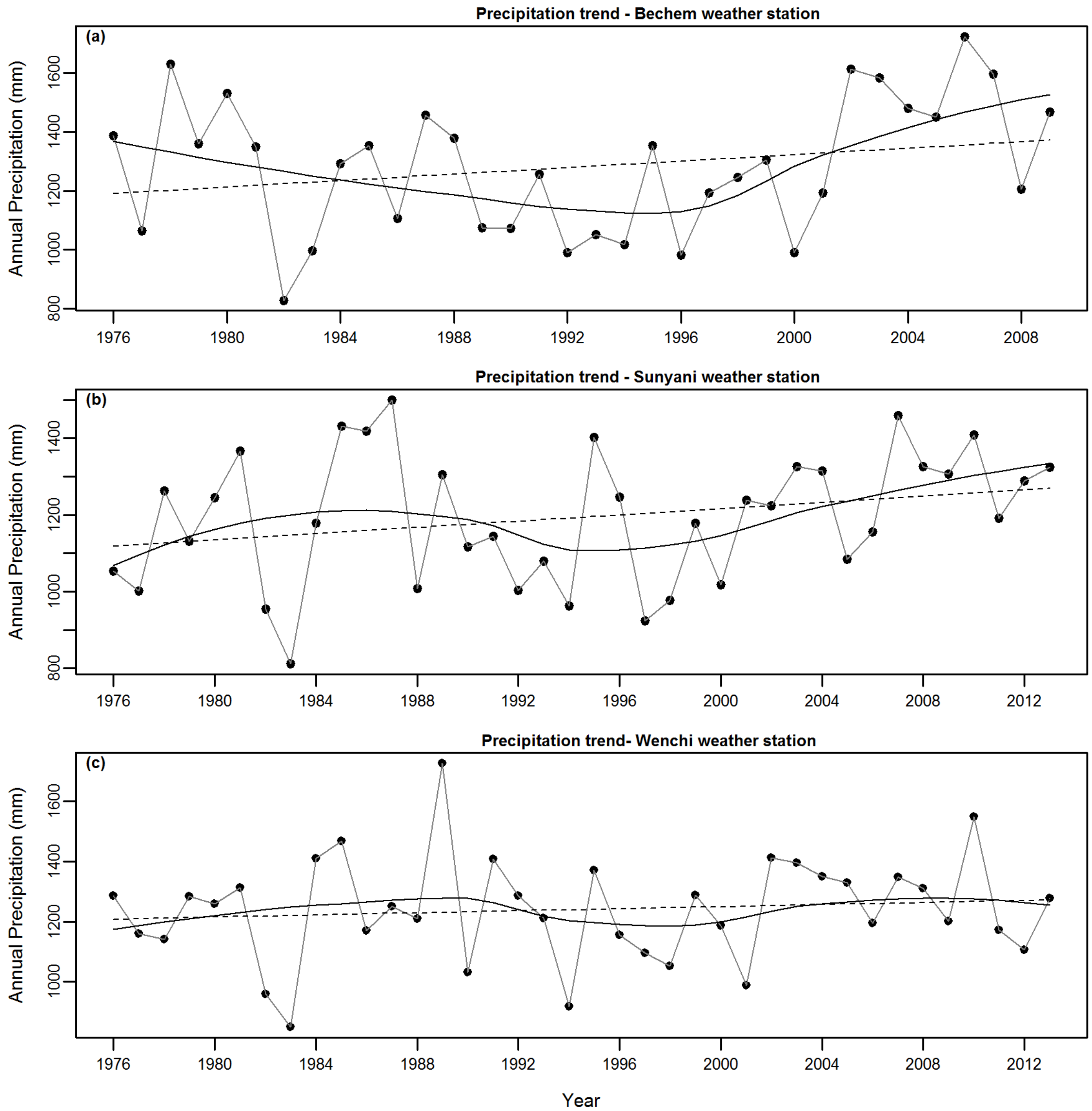

Figure 9. Time series of annual precipitation from three meteorological stations spanning the latitudinal gradient of the study area. Data cover the periods (a) 1976-2009, (b) & (c) 1976-2013. Dashed lines represent linear trends; solid lines represent locally smoothed trends.

4. Discussion

Although our time series of Landsat observations encompassed more than 30 years from 1984 through 2015, the results need to be interpreted in the context of longer-term trends. Mentions were made of historical fires in the reserves in our study area for several decades before the 1980s, noting that they were mainly occasional forest-floor fires which did not cause severe damage to the forest (Hall & Swaine, 1981). A study of historical fire records in Ghana's forest zone from 1910 to 1993 showed that periods of widespread fires coincided with droughts, but also found a sharp rise in fire frequency beginning in the early 1980s (Orgle, 1994). Swaine (1992) also observed this trend of increasing fire incidence in the 1980s and argued that a coupled interaction between human land use changes and climatic changes were responsible. Forest assessments conducted between 1986 and 1988 indicated that widespread burning had occurred in numerous reserves in the semi-deciduous forest zone, and that large portions of the reserves that we studied burned in the early 1980s (Hawthorne, 1994), although we did not detect these fires in the Landsat record. However, only PB and TT were reburned by the extensive and severe fires that we observed in 1989.

These repeated fires in the 1980s played a key role in a shift from forest to grass and shrub-dominated vegetation in the two northern reserves. Even though the spectral indices showed rapid recovery in 1990, these reserves likely became more susceptible to subsequent fires because of reduced canopy cover, increased fuel loads, and decreased fuel moisture following multiple disturbances (Brando et al., 2014; Cochrane et al., 1999). Therefore, we strongly suspect that PB and TT experienced additional fires that were not detected in the sparse Landsat record of the 1990s. Generally, large canopy trees have thicker bark and are able to survive fires than smaller trees, but they succumb to fire upon repeated burns (Balch et al., 2015). It is also possible that fire damage to canopy trees during the 1980s could have led to delayed mortality of the injured trees over the subsequent decade. Based on our satellite observations combined with information from the historical record and knowledge of tropical forest fire ecology, we suggest that the most likely scenario is that repeated fires gradually eroded the resilience of the two northern reserves.

From 2000 onward, the deforested northern reserves burned more frequently than the forested southern reserves, and these frequent fires have maintained grass and shrub-dominated vegetation in the northern reserves by limiting the establishment of fire-sensitive forest tree seedlings. Results from experimental and field-based studies in the Amazon affirm that repeated fires significantly impede successful regeneration of woody forest species, but foster the spread of invasive grasses (Balch et al., 2015; Silvério et al., 2013). In the northern reserves, the fire-maintained vegetation is mainly a mosaic of the invasive and fire-prone shrub, *Chromolaena odorata* and tall grasses such as *Pennisetum purpureum* (elephant grass), and *Panicum maximum* (Amissah et al., 2011; Swaine, 1992) with low densities of forest tree species (Figure 10). The grasses and shrubs tend to be very aggressive competitors, curtailing seedling establishment and growth of forest tree species. In an experimental study in Ghana, Honu & Dang (2000) recorded that decreased seedling growth and survival was associated with *Chromolaena odorata* infestation, and that tree regeneration was significantly enhanced following removal of this invasive shrub. Loss of overstory trees due to fire also reduces seed sources and limits seedling establishment due to the absence of nurse trees, reduced competitive advantage, and harsh environmental conditions (Paritsis et al., 2015).

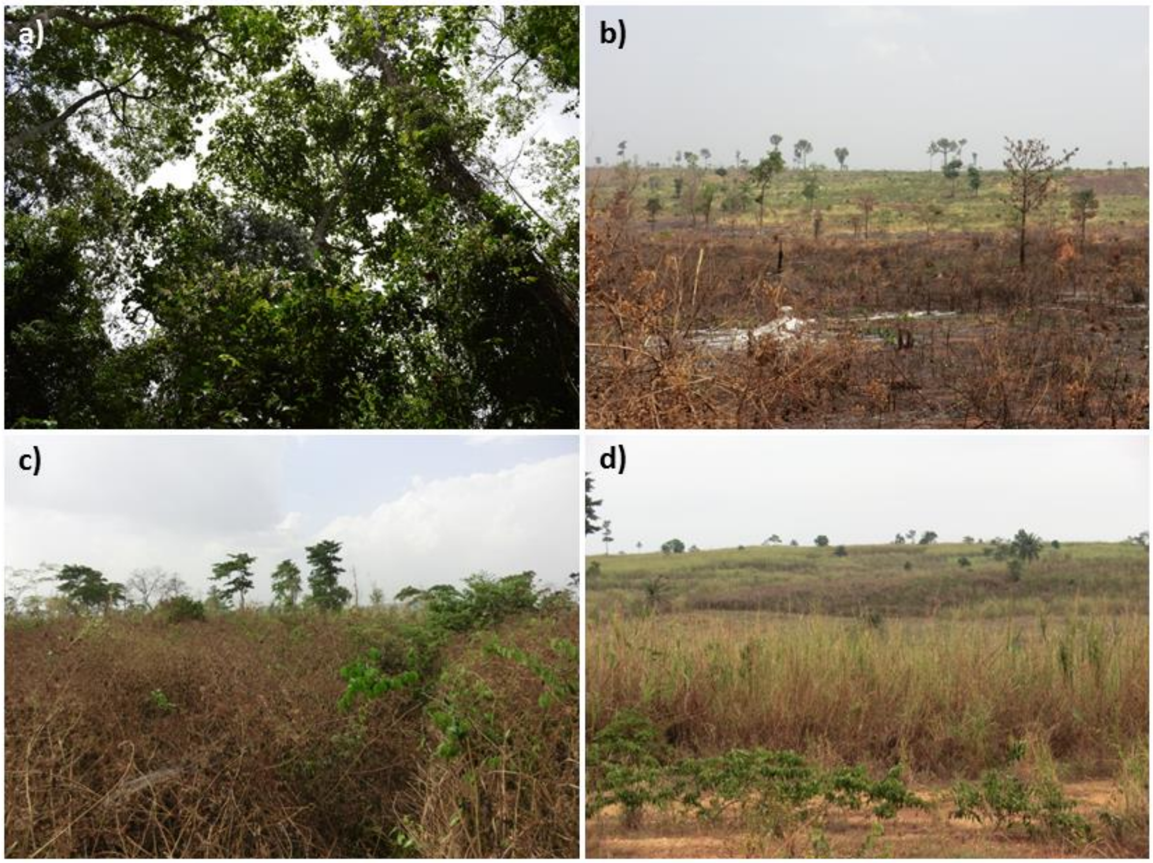

Figure 10. Pictures showing conditions of: a) canopy cover in unburned forest in AS, b) a degraded and recently burned area in PB with few isolated trees, c) frequently burned vegetation in TT dominated by *Chromolaena odorata*, and d) frequently burned vegetation in PB dominated by *Pennisetum purpureum* (elephant grass).

Our results showing more fires in the interiors than outside the northern reserves suggest that fires ignited in the surrounding landscape matrix and subsequently burned into these reserves, where the pyrophilic grasses and shrubs facilitated their spread. Fire is the main land preparation tool for agriculture in the area, and fire spread from agricultural areas is one of the main sources of fire ignition in the forest reserves (Appiah et al., 2010). We infer a positive feedback whereby the vegetation in these reserves amplified the effect of these ignitions through rapid spread rates and propagated fires through the reserve and back into the surrounding landscape. Contrasting results showed fewer fires in the interiors than in the buffers of the relatively intact southern forest reserves, suggesting a negative feedback, whereby the closed canopy forests inside the reserves prevented fire spread from the adjacent agricultural matrix because of less live fuels and higher fuel moisture in the shaded understory.

These interactions between the reserves and the surrounding landscapes emphasize the important effects of human land use on fire regimes. Forest reserves in Ghana have mostly been protected against conversion to cropland and other agricultural land uses. However, forest rehabilitation and plantation activities, such as the *Taungya* agroforestry system, do occur inside some reserves and have been cited as sources of forest fires in Ghana (Orgle, 1994). Most forest reserves in Ghana are logged, primarily through selective logging of individual trees (Adam et al., 2006) , and illegal logging is also widespread (Marfo, 2010). Logging disturbs the forest canopy and result in fragmented forests that are more vulnerable to fire (Hawthorne et al., 2012). Many forests in Ghana were subjected to heavy timber exploitation beginning in the early 1960s and continued into the early 1980s (Adam et al., 2006; Treue, 2001). All the reserves in our study area are known to have experienced heavy logging prior to the 1980s, and this logging is believed to have led to increased fire susceptibility following the severe drought of 1982 - 1983 (Hawthorne, 1994; Hawthorne & Abu-Juam, 1995; Orgle, 1994). Thus, human activities such as agriculture and timber extraction helped to create the conditions that resulted in increased fire susceptibility and led to the observed regime shifts in the northern reserves.

Our finding of divergent fire regimes associated with contrasting vegetation types in areas with similar rainfall suggests that fire-vegetation feedbacks can maintain distinctive vegetation and fire regimes in areas with similar climate, a finding also confirmed by Dantas et al. (2013). This result also fits the conceptual model of Staver et al. (2011), who concluded that in climates with intermediate annual rainfall (1000 – 2500 mm) and a dry season shorter than seven months, fire is a major determinant of alternative vegetation states. Another recent assessment of Afrotropical vegetation similarly concluded that fire has the potential to maintain tropical forests and savannas as alternative biome states under a broad range of environmental conditions (Dantas et al., 2016). Our results thus suggest a hysteresis effect, in which a disturbance-driven state change was followed by maintenance of a new, non-forested vegetation community under levels of precipitation that continued to support forests at nearby locations. Even though the variability in soils, topography, and other climatic conditions across our study area is not large, there is also the potential for fire-vegetation feedbacks and the resulting hysteresis to magnify relatively small environmental differences into much larger disparities in disturbance regimes and vegetation characteristics (Beisner et al., 2003).

It is important to note several challenges associated with the present study. Like most tropical regions, there are few historical data documenting changes in the landscape, so we gleaned pieces of evidence from multiple sources to arrive at our conclusions. We acknowledge that persistent cloud cover and missing image data constrained our remote sensing analyses to years when cloud-free Landsat images were available. In particular, Landsat acquisitions in our study area were rare in the 1990s due to downlinking problems as well as the commercialization of the Landsat program during that era (Goward et al., 2006). Our Landsat record did not go far back enough to capture earlier fires associated with the 1982-1983 severe droughts. There are also areas of missing data in images acquired after May 2003 due to failure of the Landsat 7 ETM+ Scan Line Corrector (SLC-Off). It is also recognized that MODIS hotspot detections may be limited by unfavorable observing conditions and the timing of the satellite overpass (Giglio et al., 2016). The coarse spatial resolution of MODIS also means that we may have missed lower intensity and smaller fires, especially understory fires. Hence, total numbers of fires are likely underestimated, although spatial and temporal comparisons of relative numbers of hot spots are still valid.

Whilst there are few empirical studies on alternative stable states in terrestrial ecosystems, such studies on tropical forests are even rarer. Although the use of remotely sensed data in the study of alternative stable states is not new, previous studies have often neglected the temporal component by substituting time for space in their analyses (Hirota et al., 2011; Staver et al., 2011). Our approach combining field measurements and multiple spectral vegetation indices from long-term time series Landsat imagery is thus a unique contribution. This study demonstrates the potential for land use change and fire to create novel and persistent non-forested vegetation communities in regions that are climatically suitable for forests. These changes were not immediate, but occurred slowly because of delayed tree mortality, continued impacts of human disturbances such as logging, and gradual erosion of forest resilience due to repeated fires. A critical implication is that assessments of future vegetation dynamics in the region will need to consider land use, fires, and their dynamic landscape-scale interactions in the context of broader drivers related to climate change and human population growth. In particular, further research focused on elucidating the drivers and mechanisms of forest degradation and fire encroachment may allow for the detection of early warning signals and the development of strategies to prevent further forest loss in tropical West Africa.

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CHAPTER 4

Forest Degradation Promotes Fire during Drought in West African Tropical Forests

Abstract

Forest reserves in Ghana are the only significant refugia of natural tropical forest relics, but they are threatened by significant land use pressures leading to widespread forest degradation. Additional stress from climate perturbations, such as droughts, can reduce fuel moisture and lead to fires that render the reserves more vulnerable to further degradation. Here we explore recent drought-associated wildfires in the forest zone of Ghana to better understand the combined effects of forest degradation and drought stress on fire in the forest reserves. We used remotely sensed Earth observations from MODIS and Landsat 8 along with precipitation data from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS). In 2016, Ghana's forest reserves experienced an uncharacteristic surge in active fire detections that was associated with intense drought during that year. Approximately 2,137 km^2 of forest reserve area were burned. We further found that reserves in the moist semi-deciduous forests, the largest and most economically valuable forest type, were the most affected by fire, accounting for more than 50% of all active fires and burned area in 2016. There was a higher percentage of burned area in degraded forest reserves than in more intact reserves. These results suggest that although drought predisposes tropical forests to fire, forest degradation also critically influences the spatial pattern and extent of burned forests. These results underscore the vulnerability of Ghana's forest reserves, particularly in the moist semi-deciduous type, to fires during severe droughts.Thus, it will be essential to reduce forest degradation and implement effective fire management to maintain forest resilience under changing future climates.

1. Introduction

Climate change can lead to extreme droughts that facilitate large tropical forest fires, and such disturbances are currently among the most formidable threats to tropical forest ecosystems worldwide (Brando et al., 2014; Silvestrini et al., 2010). Several studies have examined the impact of recent droughts on tropical forests, especially in the Amazon (Alencar et al., 2011; Alencar et al., 2015; Brando et al., 2014), but the effects of drought on the highly fragmented tropical forests of West Africa has received less attention. However, fragmented forests are known to be particularly vulnerable to drought and fire due to increased edge effects that alter forest microclimates and foster rapid forest degradation (Numata & Cochrane, 2012). As a result, warmer and drier climates could lead to more frequent fires that compromise forest resilience and ultimately lead to loss of tropical forest (Brando et al., 2014). Moreover, positive feedbacks in the forest fire regime involving land use change, logging and climate change will likely accelerate forest degradation and forest loss (Nepstad et al., 2008; Silvério et al., 2013; Silvestrini et al., 2010).

Within the West African humid tropics, Ghana has maintained a substantial area of closed-canopy forests in a protected network of reserves, which are currently the only significant refugia of the original tropical forest relics. However, these reserves are under immense pressure due to timber harvesting and agricultural encroachment, raising concerns about their sustainability (Damnyag et al., 2013; Hawthorne et al., 2012; Vaglio Laurin et al., 2016). These concerns have been exacerbated by additional stresses caused by ongoing climate change. In particular, in 2016 the forest zone of Ghana experienced an upsurge in fire activity, further heightening concerns among forest stakeholders. The forest zone is largely assumed to be fire-resistant due to high canopy cover that retains high humidity and limits growth of herbaceous fuels. Consequently, fire spread is inhibited by forests, and fire frequency is therefore much lower than in the drier woodland and savanna regions to the north (Dwomoh & Wimberly, 2017b). However, a recent study has shown that fires encroached into the northern portions of the forest zone during the 1980’s and 1990’s, leading to degradation and eventual loss of forests (Dwomoh & Wimberly, 2017a).

Tropical forest degradation and deforestation ultimately result in substantial carbon emissions, with global impacts on the balance and stability of the climate system (Gibbs et al., 2007; Mollicone et al., 2007; Skutsch et al., 2007). This concern prompted the United Nations Framework Convention on Climate Change (UNFCCC) initiative called Reducing Emissions from Deforestation and Degradation (REDD+) as a global strategy to curb tropical deforestation and forest degradation (Pistorius, 2012). Essentially, REDD+ is a climate change mitigation mechanism that aims to curb emissions from deforestation and forest degradation by enhancing forest carbon stocks in developing countries. In return, developing countries are expected to be compensated by wealthy nations for achieving REDD+ goals.

In the framework of REDD+, conservation of protected areas, especially forested ones, is critically important (Melillo et al., 2016; Nogueira et al., 2018). Protected areas cover about 12.2% of Earth’s land area and store approximately 15% of the terrestrial carbon stocks (Campbell et al., 2008). Ghana, having already lost over 75% of its original forest cover, has turned to REDD+ as an opportunity to better manage its remaining forest fragments and to restore degraded ones. As a result, Ghana has since 2008 been at the forefront of REDD+ processes within the West African sub-region, and the country's high forest zone remain the focus of REDD+ activities (Stanturf et al., 2011). Large amounts of carbon held in the forest biomass are released into the atmosphere when trees burn, and fire-induced forest loss is a major hindrance to achieving REDD+ because fire not only leads to loss of carbon in trees, but also limits the future potential of forests to sequester more carbon. Drought increases the risk of forest fires, leading to further forest degradation, and as a consequence can deter the achievement of forest conservation goals.

Our overarching objective was to assess the influences of drought conditions and forest degradation on temporal and spatial patterns of fire occurrence in tropical West Africa. We used satellite-based earth observations of fire, precipitation, and forest condition to study forest fires in the forest zone of Ghana to answer the following research questions:

1. Was the extent of forest fire in 2016 higher than expected compared with the entire 15-year study period?
2. Were the 2016 fires associated with unusually severe drought conditions?
3. Were spatial patterns of forest canopy condition and drought severity related to the pattern of burning inside forest reserves during the 2016 fires?

By examining the combined influences of forest degradation and drought stress on fires in forest reserves, this study provides insights into the specific environmental factors that increase the risk of fire encroachment into moist tropical forests. This new knowledge can help to inform management efforts in protected areas and support ongoing climate change adaptation and mitigation processes (including REDD+) in the region.

The findings are also relevant for predicting and mitigating similar fire impacts in tropical forests worldwide.

2. Materials and Methods

2.1 Study area

Ghana is located in West Africa along the Atlantic coast between latitudes 4.5-11.5°N, and longitudes 3.50W - 1.30E. It has a total area of 238,500 km^2 and a population of over 25 million. Ghana's climate is largely modulated by the movement of the Inter-Tropical Convergence Zone (ITCZ) and the West African Monsoon, leading to distinctive wet and dry seasons. These seasons vary from north to south along a series of eco-climatic zones (Stanturf et al., 2011). Vegetation distribution is associated with a precipitation gradient, where precipitation is highest in the south-western corner of Ghana and lowest in the northern and eastern parts of the country. There are two major vegetation types: the tropical high forest zone (hereafter referred to as the forest zone) made up of closed forest of tall trees, and savanna vegetation characterized by more or less open canopy trees and shrubs scattered among a distinct ground layer of grass. Our analysis focused on the forest zone, which covers approximately 8.1 million hectares and occupies the southern third of the country with an arm stretching into the northern part of the Volta Region (Hall & Swaine, 1981) (Figure 1 a).

At the beginning of the 20th century about a third of the country was estimated to have been forested (Hall & Swaine, 1981). However, substantial portions of the forest cover were lost during the 20th century, and by the late 1980s only about 25% of the original forest (2.1 million ha) remained (Adam et al., 2006). Currently, the only large areas of natural forest left in the forest zone are contained in a protected network of reserves, which are embedded with an agriculture-dominated landscape matrix. Majority of these forest reserves are actively managed for sustainable timber production. Timber harvesting is done through selective logging, in which selected commercial timber species of merchantable size and typically scattered over the forest area, are felled during cutting cycles. Mean annual rainfall ranges from less than 750 to over 2,000 mm. Mean annual maximum and minimum temperatures within the forest zone range 29.3 – 32.0 °C and 21.8 – 23.6°C respectively (Amissah et al., 2014). February and March are typically the hottest and driest months, whereas August is typically the coldest and wettest month (Hall & Swaine, 1981).

The forest zone has been classified into seven main forest types based on floristic composition and rainfall regime (Hall & Swaine, 1981) (Figure 1 a). Ranging from wettest to driest, these zones include Wet Evergreen (EW), Moist Evergreen (ME), Upland Evergreen (UE), Moist Semi-deciduous (MS, with two subtypes: North-west and South-east), Dry Semi-deciduous (DS, with two subtypes: Fire Zone and Inner Zone), Southern Marginal (SM), and South-east Outlier (SO). The Wet Evergreen (1750 – 2250 mm annual rainfall) zone has the highest diversity of plant species. However, many important commercial timber species are contained in the moist (1500-1750 mm annual rainfall), and dry (<1500 mm annual rainfall) forest types (Adam et al., 2006).

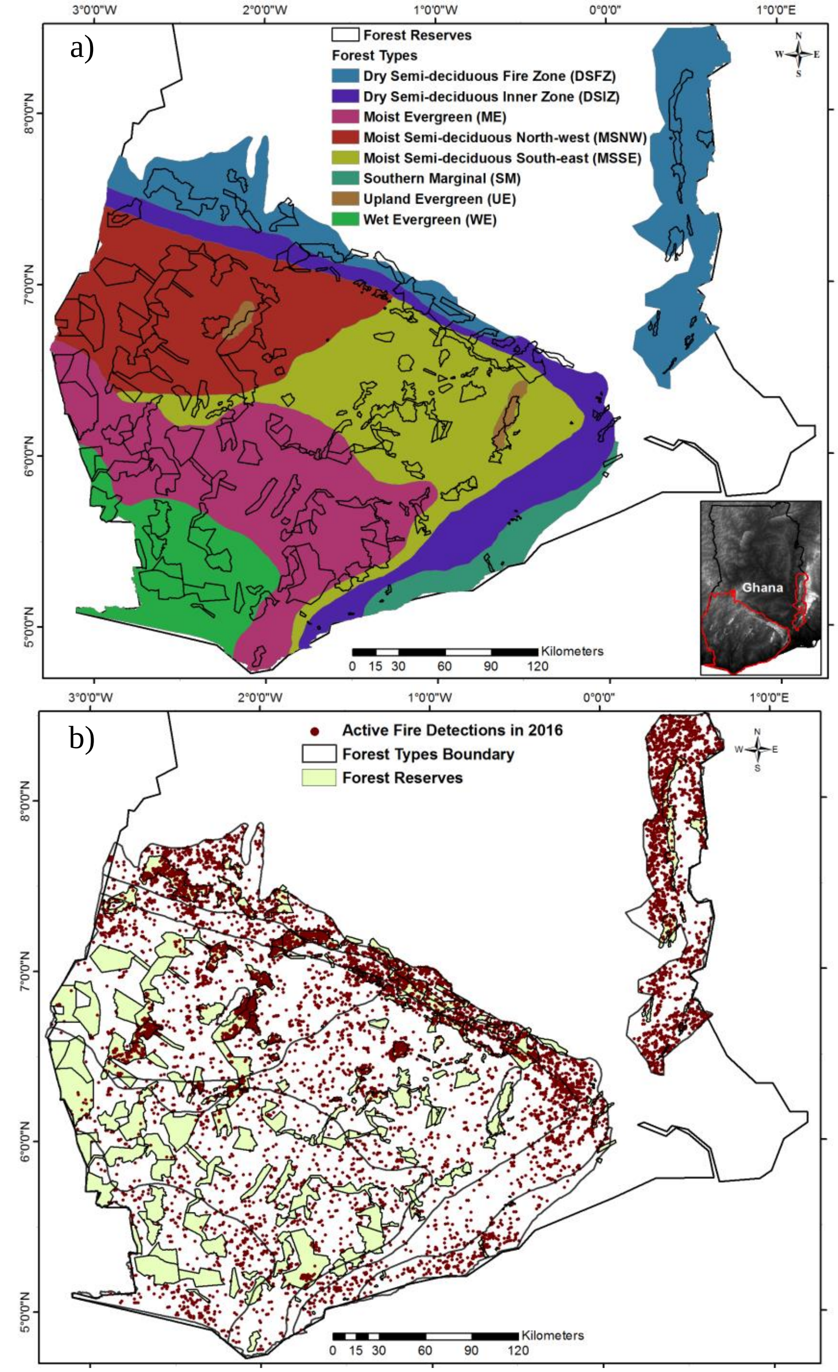

Figure 1. Study area map showing: a) The southern portion of Ghana (inset) highlighting the forest zone and the distribution of forest types and forest reserves; b) Active fire detections within the forest zone in 2016. Note: The area of the South-east outlier forest type is very small and not mapped, but it is dispersed to the south and east of the Southern Marginal forests (Hawthorne, 1995). In the inset map, the background is a digital elevation model indicating low (dark gray) to high elevation (bright gray). The high forest zone is outlined in red.

2.2 Data

2.2.1 Active fire dataset

We obtained active fire detections at 1-km resolution from the combined MODIS Terra (10:30 am/pm equatorial nominal overpass time) and Aqua (1:30 pm/am equatorial nominal overpass time) active fire product MCD14ML, level 3 Collection 6 (Giglio, 2013; Giglio et al., 2016). After removing low confidence (<30% confidence) and non-vegetation fires, we summarized the fire points as annual active fire density time series (fires km^{-2} $year^{-1}$) for each forest type and the entire study area. We also partitioned the the time series into fires falling either inside or outside forest reserves. These data were summarised for the 2003 to 2017 hydrological years. The hydrological year was defined as the 12-month period beginning May 1st, which approximates the start of the rainy season, through April 30th of the following year. Thus, the period May 1st, 2002 to April 30th, 2003 belongs to the 2003 hydrological year.

2.2.2 Precipitation dataset and precipitation indices

We used the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) monthly precipitation dataset at 0.05° spatial resolution (Funk et al., 2015) to generate seasonal and annual rainfall anomalies, including the annual maximum cumulative water deficit (MCWD). MCWD estimates accumulated water deficit within a particular year and is a useful indicator of the intensity and length of the dry season (Aragão et al., 2007). Low, negative values of MCWD indicate greater moisture stress. We calculated MCWD using methods described by Aragão et al. (2007) and also generated time series of total annual precipitation and dry season (November to March) water deficit. These indices were based on the same hydrological years as the active fire data. All precipitation indices were calculated for each CHIRPS grid cell and then summarized for each forest type and for the entire high forest zone.

2.2.3 Landsat data and Landsat-derived datasets

We mapped forest degradation and burned area using the Landsat-8 Operational Land Imager (OLI) Level-2 surface reflectance product generated from the Landsat Surface Reflectance Code (LaSRC). We used only the subset of Landsat TM/ETM+ equivalent bands (OLI bands 2-7) for further processing. Our study area was covered by six Land path/rows (paths 193 to195, and rows 055 to 056, appendix Figure S4 -1, appendix Table S4 - 1). We compiled all relatively cloud-free (≤ 30% cloud cover) images within the period 6th December 2015 - 3rd April 2016, although one January 2015 image was used to fill minor data gaps on path/row 195/055. We did not obtain satisfactory results from the Fmask cloud screening product (Zhu & Woodcock, 2012) delivered with the images. Hence, we masked out clouds, cloud shadow and water pixels using Tasseled Cap (TC) vegetation index thresholds as follows:

a. cloud = *TC wetness* ≤ -0.13 and *TC brightness* >0.44
b. cloud shadow and water = *TC wetness* ≥ -0.05 and *NIR* ≤0.2 and *TC brightness* ≤0.31

In each path/row, the earliest available images without conspicuous evidence of fire scars were used as the pre-fire image (mainly December and early January images) against which all subsequent images within the period were paired to assess immediate post-fire effects.

Landsat burned area mapping

We used the relative delta normalized burn ratio (RdNBR) to map burned area in forest reserves during the 2016 fire season. The RdNBR relies on changes in the short-wave infrared (SWIR, wavelength 1.547 – 1.749µm) and near infrared (NIR, wavelength 0.772 – 0.898µm) reflectance values between pre- and post-fire to detect burned vegetation, and it has been shown to be advantageous over similar indices in eliminating biases due to pre-fire vegetation conditions (Miller et al., 2009; Miller & Thode, 2007). We employed an RdNBR threshold approach in which a manually selected RdNBR thresholds greater than 200 was used to identify burned pixels. However, due to the highly heterogeneous vegetation cover in the study area we found that the RdNBR threshold alone tended to overestimate fire scars in highly degraded forests. We thus used change between pre- and post-fire normalized difference moisture index (dNDMI > 0.16) to further constrain burn scar detection by RdNBR. The normalized difference moisture index, which is based on Landsat NIR and SWIR bands, is sensitive to canopy water content and has been used as an input for mapping burned vegetation in other studies (Meddens et al., 2016).

Using these vegetation indices thresholds, we identified all burned pixels during the main 2016 fire season, which encompassed the period December 2015 to March 2016. We composited all the burned pixels to derive the burned area map and applied a majority filter within a seven-pixel circular radius moving window to the burned area map to minimize image noise.

Landsat-derived forest disturbance mapping

We mapped pre-fire forest canopy disturbance using the tasseled cap (TC) transformation-based forest disturbance index (DI), developed by Healey et al. (2005). Three TC indices derived from six optical-infrared bands of Landsat imagery were required for computing the DI: brightness, greenness, and wetness. Brightness is a weighted sum of all the bands and is used an indicator of soil exposure. Greenness is a measure of the contrast between the NIR band and the visible bands and is sensitive to the amount of photosynthetically active vegetation (Baig et al., 2014). Wetness is a measure of the contrast between the NIR and SWIR bands and is sensitive to the moisture content of soil and vegetation. In vegetated landscapes, wetness can be interpreted as an indicator of canopy structure, soil or surface moisture, or the amount of vegetation biomass (Cohen & Goward, 2004). We applied TC transformation coefficients based on surface reflectance from Crist (1985).

The DI is a straightforward index that has been widely used for mapping forest disturbances in a variety of ecosystems (de Beurs et al., 2016; Dwomoh & Wimberly, 2017a; Sieber et al., 2013). Essentially, the DI is a linear transformation of standardized values of the three TC indices (normalized brightness - *Bn*, normalized greenness - *Gn* and normalized wetness - *Wn*) as follows:

$$\mathrm{DI} = \mathrm{Bn} - (\mathrm{Gn} + \mathrm{Wn}) \qquad \textbf{Equation 1}$$

Disturbance events disrupt the forest canopy, thereby exposing more background soil, and reducing both vegetation greenness and wetness simultaneously. Consequently, disturbed forests have higher DI values than intact or less disturbed forests.

We obtained *Bn*, *Gn*, and *Wn* by standardizing the respective TC indices by the mean and standard deviation of representative forested pixels within each Landsat path/row of the available pre-fire images. We manually selected representative forested pixels using Brightness and Wetness thresholds. Definition of these thresholds was guided by visual interpretation of the Landsat imagery, high-resolution imagery from Google Earth, and field observations. Brightness thresholds were less than or equal to the range 0.27 to 0.32, whereas TC Wetness thresholds were greater than the range - 0.070 to - 0.075. To be selected as a reference forest pixel, a pixel had to meet both criteria.

2.3 Analysis methods

Research question 1: Was the extent of forest fire in 2016 higher than expected compared with the entire 15-year study period?

We computed time series standardized anomalies of active fire density for each forest type and the entire high forest zone. Similarly, we computed time series standardized anomalies of active fire density inside and outside forest reserves for each forest type and the entire high forest zone. We calculated the anomalies for each year as departures from the 2003 – 2017 mean, normalized by the standard deviation (σ). We graphed these time series anomalies by forest type and location inside or outside forest reserves.

Research question 2: Were the 2016 fires associated with unusually severe drought conditions?

We calculated time series of standardized anomalies of precipitation indices for each forest type and the entire high forest zone following the same procedure used for active fire density. To evaluate the relationship between fire detections inside reserves and drought intensity, we used Spearman rank correlation tests between standardized anomalies of active fire density and the maximum cumulative water deficit (MCWD). We carried out these tests for the entire high forest zone and for the moist semi-deciduous forest types where most fires were concentrated. We also mapped the pixel-level MCWD standardized anomaly to examine the spatial extent of drought in 2016. We followed same procedure used by Saatchi et al. (2013), in which the anomaly for each pixel in a particular year was calculated as a departure from the 2003 – 2017 mean, excluding the measurement from that year and normalized by the standard deviation (σ).

Research question 3: Were spatial patterns of forest canopy condition and drought severity related to the pattern of burning inside forest reserves during the 2016 fires?

To focus this analysis on the forest reserves, we masked the Landsat-derived burned area and DI data to the forest reserve boundaries. From the burned area map, we calculated the percent burned area of each reserve and summarized area burned and percent reserve area burned by forest zone. We also calculated the mean drought anomaly (MCWD anomaly) for each forest reserve.

We used DI thresholds to categorize the DI map into degraded and intact forest. Based on visual interpretation of the Landsat imagery, high-resolution imagery from Google Earth, supplemented by field observations and our knowledge from previous field work (Dwomoh & Wimberly, 2017a), we set a DI value of two (2) as the threshold beyond which a pixel was considered disturbed or degraded. Similar DI threshold values have been used in previous studies (de Beurs et al., 2016; Healey et al., 2005; Hilker et al., 2009). We calculated the percentage of each reserve classified as disturbed (hereafter called *percent degraded forest*) or relatively intact (hereafter called *percent intact forest*).

We also estimated mean DI for each reserve. Based on the mean DI values we further classified each reserve into one of two disturbance status, “degraded reserve” or “intact reserve” using the same DI threshold of two (2) defined above.

To infer the relationships between pre-fire forest canopy condition and area burned, we used Spearman rank correlation test between *percent reserve area burned* and *percent degraded forest* for all reserves in the forest zone. We also run the same correlation test between *percent reserve area burned* and drought anomalies (MCWD anomalies) for all reserves. The same correlation tests were also performed using only burned reserves in the semi-deciduous forest type where fire was widespread in 2016. In addition, we used one-tailed Wilcoxon rank test to compare differences in percent reserve area burned between degraded and intact reserves for all burned reserves in the semi-deciduous forest type.

3. Results

Research question 1: Was the extent of forest fire in 2016 higher than expected compared with the entire 15-year study period?

For the study period 2003 – 2017 there were 87,169 active fires in the entire forest zone, of which 15,987 were located inside forest reserves. The year 2016 had the most active fire detections in the entire forest zone (Figure 1b), with fire anomaly 2.1 times higher than the long-term average fire detections for the overall forest zone (Figure 2a). The 2016 fire season was uncharacteristic because it recorded not only the highest number of active fire detections (9,123), but also the highest proportion of active fire detections inside forest reserves (2,819 fires). The standardized fire anomaly for fires occurring inside forest reserves was three times higher than the long-term average (Figure 2a). Overall, 30.9% of all active fires in 2016 (2,819 fires) were located inside forest reserves, versus an annual average of 18.3% (1,066 fires) over the 15 years study period. The year 2007 was also identified as a high fire year over the entire study area (Figure 2a). However, in 2007 only 17.5% of all active fires were located inside forest reserves, and fire anomalies were higher outside than inside forest reserves.

The distribution of 2016 fire detections inside forest reserves by forest type indicated high active fire densities in the two moist semi-deciduous forest types (Figure 2 b & Appendix Figure S4 - 2 a), which together accounted for 52.3% (1,475 fires) of all active fires detected inside forest reserves in the entire forest zone that year. In 2016, the Moist Semi-deciduous North-West sub-type (MSNW) and the Moist Semi-deciduous South-East sub-type (MSSE) both recorded standardized fire anomalies that were three times larger than the long-term average (2016 anomalies: 3.5 σ in MSNW and 3.1 σ in MSSE). However, the difference in fire anomalies inside and outside forest reserves was much higher in the MSNW than the MSSE. It was only in the 2016 fire year that exceptionally high fire detections were found inside forest reserves in the entire forest zone, and that forest reserves within the two moist semi-deciduous forest types had the largest fire anomalies.

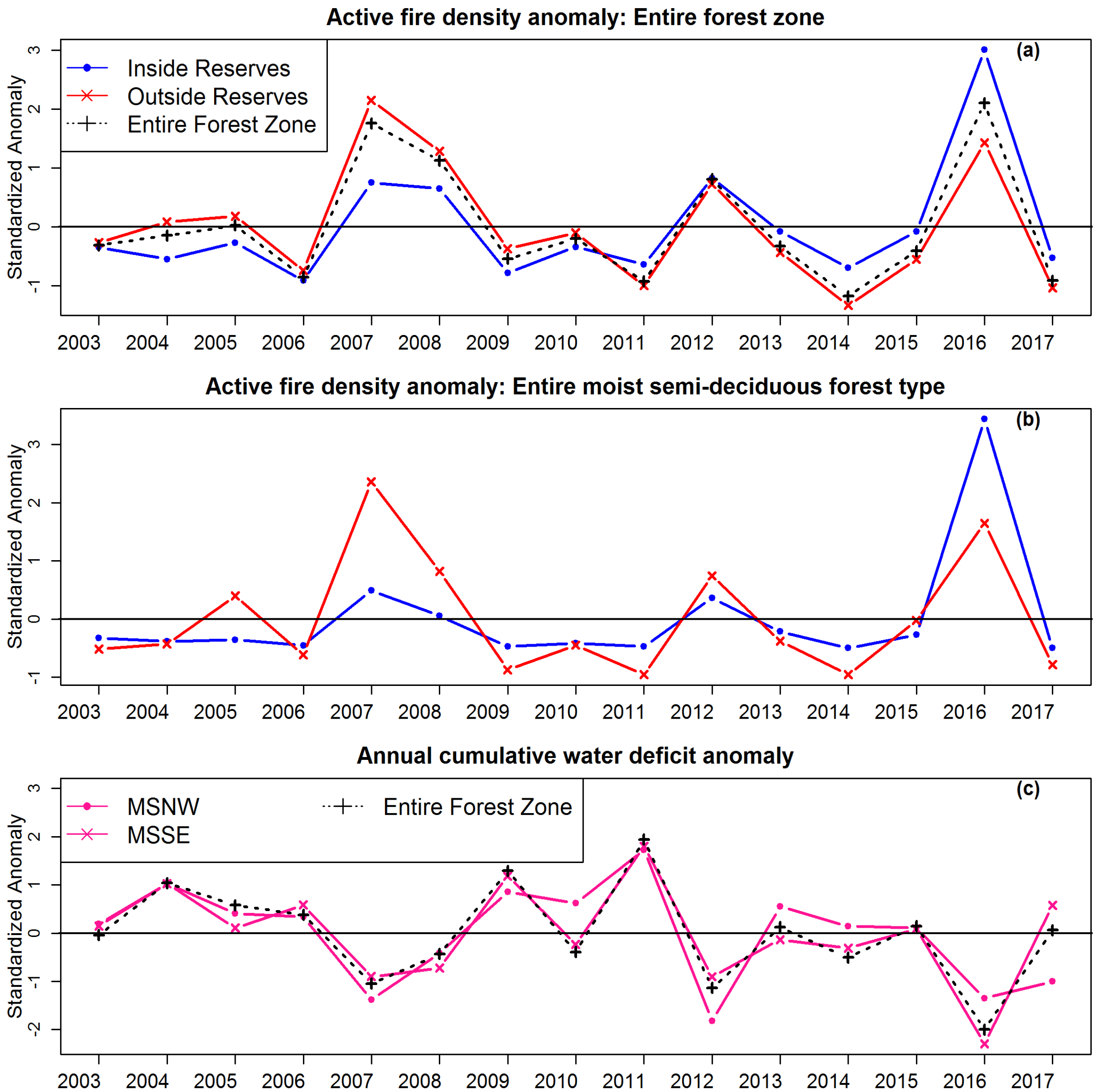

Figure 2. Standardized anomalies of: a) active fire density over the entire forest zone of Ghana; b) active fire density in the moist semi-deciduous forest types; and c) maximum cumulative water deficit (MCWD) for the two moist semi-deciduous forest types and the entire forest zone: MSNW = Moist Semi-deciduous North-West sub-type, MSSE = Moist Semi-deciduous South-East sub-type.

Research question 2: Were the 2016 fires associated with unusually severe drought conditions?

The year 2016 was the driest during the 15-year study period, showing the largest negative precipitation anomalies with a cumulative water deficit anomaly twice as low as the long-term average for the overall forest zone (Figure 2c & 3). Similar trends were observed with other precipitation metrics, including total annual precipitation and dry season water deficit anomalies (Appendix Figure S4 - 2a & S 3). Partitioning of 2016 precipitation anomaly by forest type indicated large negative water deficits in the two moist semi-deciduous forest types (Figure 2 c & 3; Appendix Figure S4 – 2b), the Moist Semi-deciduous North-West sub-type (-1.4 σ) and the Moist Semi-deciduous South-East sub-type (-2.3 σ). All the other forest types were similarly dry (Appendix Figure S4 – 2b & S 3). The years 2007 and 2012 were also identified as potential drought years over the entire study area (Figure 2c), albeit with lower drought intensity than 2016.

We found a significant negative association between active fire density inside reserves and cumulative water deficit for the entire forest zone (Figure 2 c, ρ = -0.68, p = 0.0069). Similarly, we found a significant negative association between active fire density inside reserves and cumulative water deficit for each of the semi-deciduous forest types (MSNW: $\rho = -0.72$, $p < 0.005$; MSSE: $\rho = -0.58$, $p < 0.05$). Thus, lower precipitation in 2016 was associated with higher fire detections in the forest zone during the study period.

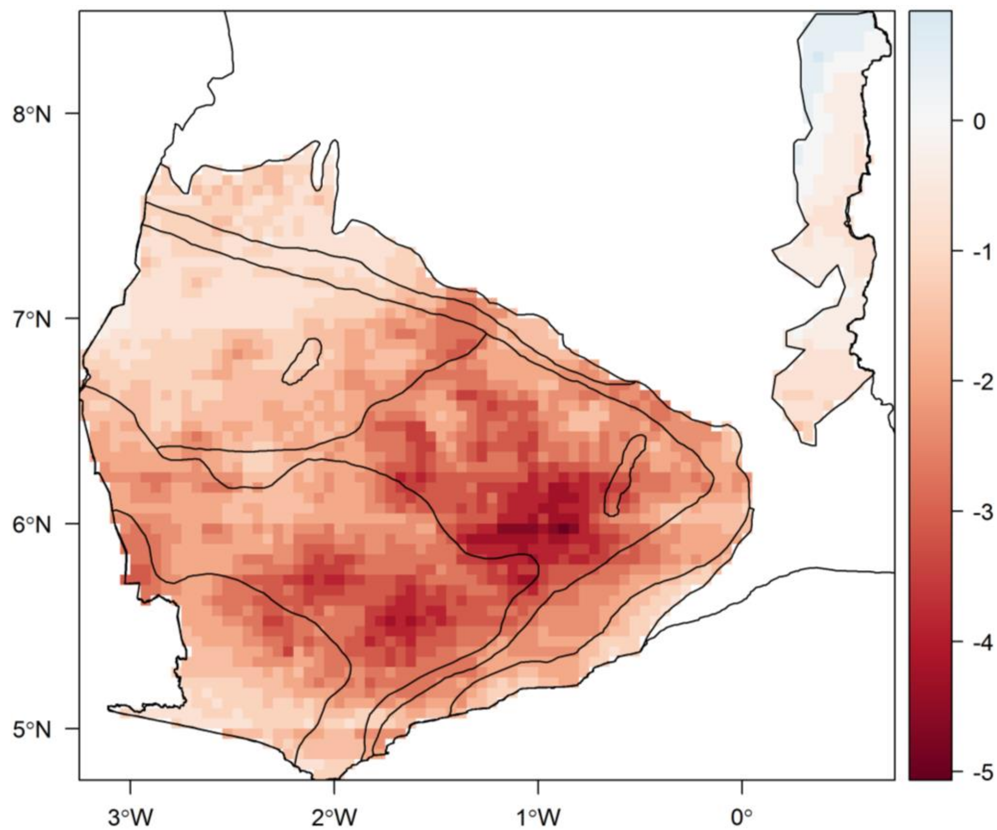

Figure 3. Standardized anomalies of maximum cumulative water deficit (MCWD) showing the spatial pattern of drought in the forest zone of Ghana in 2016. Blue indicates positive anomalies and red indicates negative anomalies.

Research question 3: Were spatial patterns of forest canopy condition and drought severity related to the pattern of burning inside forest reserves during the 2016 fires?

We estimate that 2,137 km^2 burned inside forest reserves during the 2016 fire season, representing approximately 12.5% of the forest reserve area in the entire forest zone (Figure 4a). Out of the total area burned, the majority (58%) occurred in the North-west (MSNW) and South-east (MSSE) moist semi-deciduous forest types subtypes, which accounted for 42.5% and 15.5% (Figure 5a) respectively. Approximately 38% of the total burned area occurred in the fire zone (DSFZ) and inner zone (DSIZ) dry semi-deciduous forest types subtypes, which accounted for 21.8% and 16.2% (Figure 5a) respectively. Approximately 1.5% and 0.5% of the total burned area occurred in the moist evergreen (ME) and wet evergreen (WE) forest types respectively. The remaining minor forest types collectively accounted for 2.4% the total burned area.

We estimate that 7,016 km^2 was degraded immediately prior to the fires in 2016, representing approximately 41% of the forest reserve area in the entire forest zone, (Figure 4b). Approximately 40% of the reserved area of the Moist Semi- deciduous type was degraded, and together this forest type accounted for 14% (9% of the MSNW and 5% of the MSSE) of total degraded forest area in the forest zone (Figure 4b & Figure 5b). Almost the entire reserved area of Dry Semi-deciduous forest was degraded, and together this forest type accounted for 15.7% (11% of the DSFZ and 4.6% of the DSIZ) of total degraded forest area in the forest zone. Approximately a third of the reserved area of the Moist Evergreen forest type was degraded, and accounting for 9.8% of total degraded forest area in the forest zone. Approximately 10% of the reserved area of the Wet Evergreen forest type was degraded, accounting for 1.2% of total degraded forest area in the forest zone. The remaining minor forest types collectively accounted for less than 0.5% of the total degraded forest area. Our binary classification of reserves into degraded or intact indicated that 109 out of the total 197 reserves covered in this study were degraded.

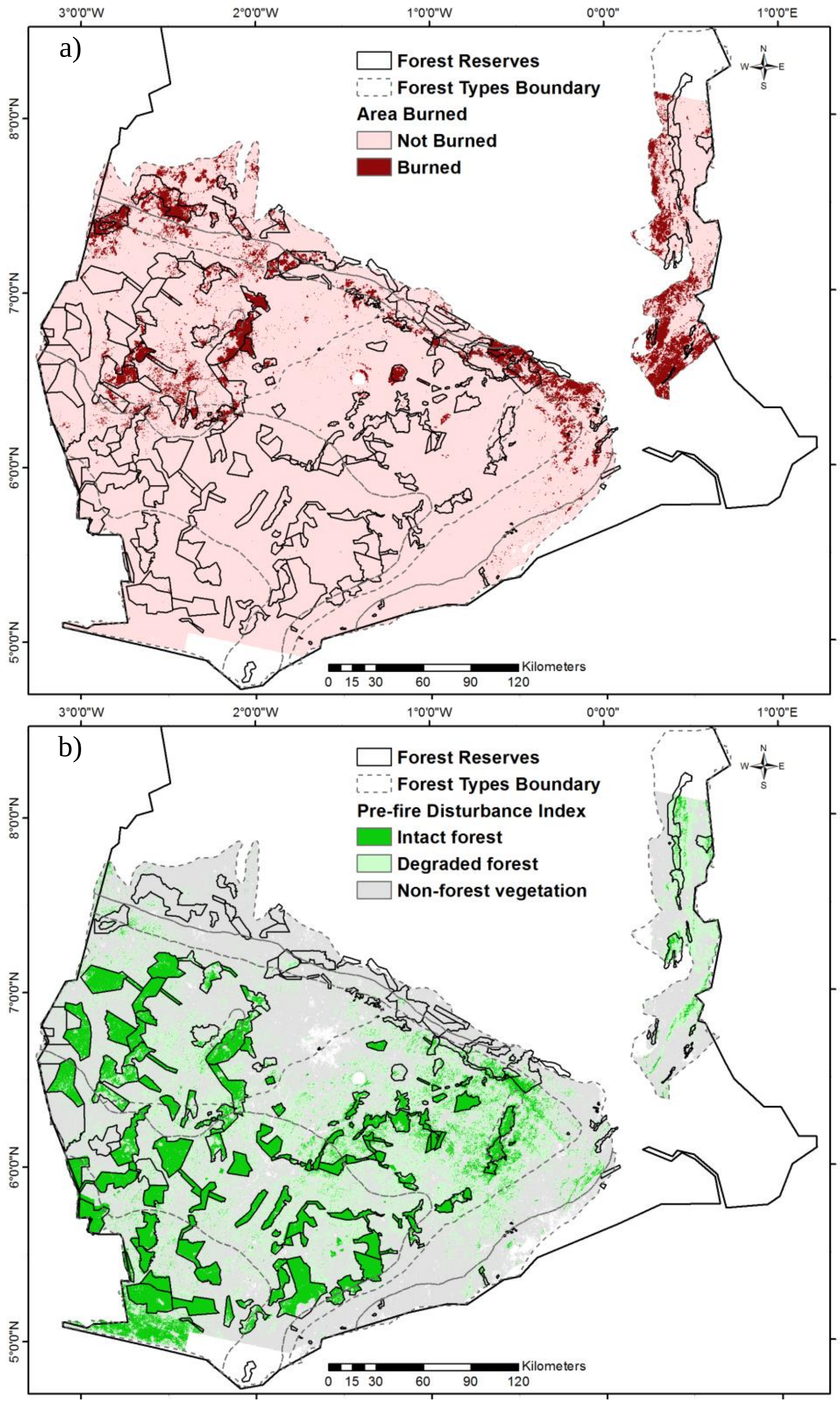

Figure 4. Maps of Landsat-derived: a) burned scars indicating forest reserves burned in 2016; b) disturbance index indicating 2016 pre-fire forest canopy conditions in forest reserves. White color represents non-vegetated areas and missing data due to clouds.

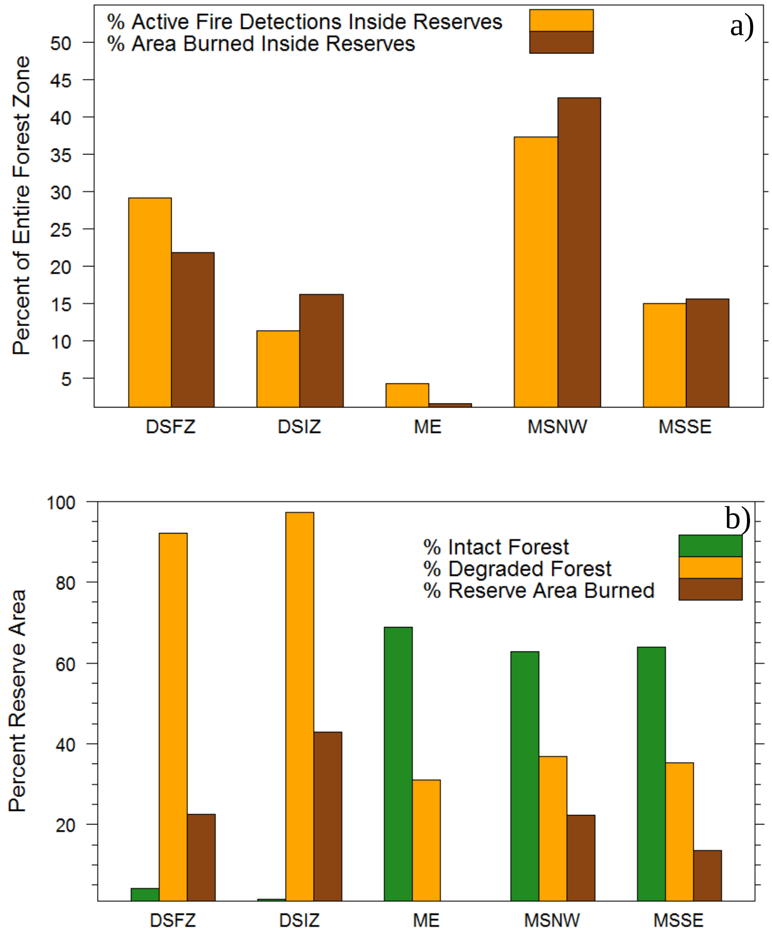

Figure 5.: a) Percent distribution of total area burned and active fire detections inside forest reserves in the entire high forest zone in 2016; b) Summary, per forest zone, of immediate pre-fire forest canopy condition and area burned inside forest reserves. Note: DSFZ = Dry Semi-deciduous Fire Zone sub-type, DSIZ = Dry Semi-deciduous Inner Zone sub-type, ME = Moist Evergreen Forest Zone, MSNW = Moist Semi-deciduous North-West sub-type, MSSE = Moist Semi-deciduous South-East sub-type.

There was a positive correlation between percent degraded forest and percent reserve area burned for all reserves in the entire forest zone ($r = 0.56$, $p < 0.001$). Similarly, there was a positive correlation between percent degraded forest and percent reserve area burned involving burned reserves in the semi-deciduous forest types alone ($r = 0.45$, $p < 0.001$) (Appendix Figure S4 - 6). Median percent reserve area burned was higher in degraded forest reserves than intact forest reserves (Figure 6, W = 492, p-value

= 0.01363). There was a positive correlation between drought anomalies and percent reserve area burned for all reserves in the entire forest zone ($r = 0.52$, $p < 0.001$). However, there was no significant correlation between drought anomalies and percent reserve area burned involving burned reserves in the semi-deciduous forest types alone ($r = 0.05$, $p = 0.71$).

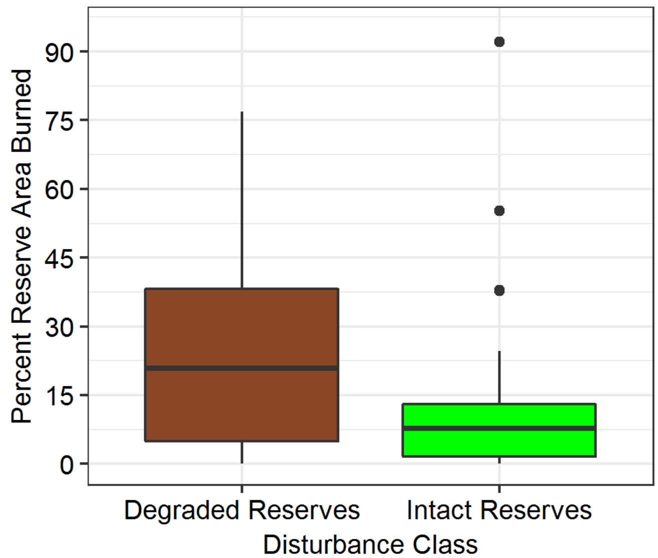

Figure 6. Percent forest reserve area burned in 2016 by disturbance class as a proxy for pre-fire forest canopy condition of burned forest reserves in the moist semi-deciduous forest type (number of reserves burned = 55).

4. Discussion

This study documented a surge in fire activity inside forest reserves in Ghana during the 2016 fire season. Burned area was particularly high in the moist semi-deciduous forest type, which is the most extensive and economically important forest type in Ghana. The widespread occurrence of fire in the moist semi-deciduous forests reflected the relatively high levels of degradation and extremely dry conditions in this forest type. Within the moist semi-deciduous forest type, burned area was more strongly associated with the spatial pattern of forest degradation than with precipitation anomalies. In particular, we observed more severe drought in the South-east subtype (MSSE) than the North-west subtype (MSNW). However, both active fires and burned area were much higher and more widespread in the North-west subtype than the South-east subtype, suggesting that extensive forest degradation in this subtype was the main factor promoting more spread of fire into the forest reserves.

Forest degradation has become a widespread phenomenon in tropical countries, impacting large forest areas annually and sometimes even more area than forest loss (Baccini et al., 2017; Nophea & Francis, 2009; Souza et al., 2013; Zhuravleva et al., 2013). Our finding of positive associations between forest degradation and burned area concurs with previous studies in the Amazon that found higher fire activity in degraded forest than relatively intact forest (Balch et al., 2015; Brando et al., 2014; Brando et al., 2016). Similarly, in a broader-scale analysis of fire regimes in the Upper Guinean subregion of West Africa, Dwomoh and Wimberly (2017b) found that forested regions with less forest cover, which is likely the result of forest degradation, were associated with more burned area. Closed-canopy tropical forests are usually fire-resistant because they have insufficient fine fuel loads and maintain high fuel moisture in their shaded understories (Cochrane, 2003). However, forest degradation breaks down the canopy and renders forests more flammable and fire-prone, because the understory becomes drier and fine fuels build up quickly (Cochrane et al., 1999; Hoffmann et al., 2012).

Degradation makes forests more susceptible to fire, but fire is also an agent of forest degradation that leads to further reductions in tree density and canopy cover. Thus, the extensive fires in 2016 have the potential to lead to more fires and forest loss in the future, as observed in a long-term study of four reserves in the northwestern part of the current study area (Dwomoh & Wimberly, 2017a). Time-series analysis of vegetation and fire indicated that widespread fires during the 1980s precipitated positive fire-vegetation feedbacks that led to eventual loss of forest cover in two of the reserves studied (Dwomoh & Wimberly, 2017a). We postulate that if forests burned in 2016 experience fires again sooner than they can recover, the future fires may be more severe and widespread due in part to greater fuel loads from vegetation killed by earlier fires and lower humidity due to reduced canopy cover (Cochrane et al., 1999). Damage from such repeated fires is expected to be substantial even in fire years without severe drought.

In the forested zone of Ghana, there are multiple, interacting drivers of forest degradation. Previous increases in fire detections were associated with earlier droughts in 2007 and 2012. Here, we speculate that fire-vegetation feedbacks from these previous drought-associated fires may have contributed to forest degradation in some reserves and helped to facilitate the widespread fires of 2016. Other drivers of forest degradation, including legal and illegal logging as well as agriculture encroachment in the reserves (Hawthorne et al., 2012; Marfo, 2010; Vaglio Laurin et al., 2016) have also likely enhanced these fire – vegetation feedbacks. It is important to note that timber harvesting in the reserves is by selective logging, which typically involves the removal of individual matured commercial trees at the rate of 2-3 trees/ha (Duah-Gyamfi et al., 2014). As a result, timber logging does not directly cause forest loss, but reduces canopy cover thereby increasing fire risk. Agriculture encroachment occur at very fine spatial scales and are mostly based on food and cash crops including cocoa, cereals, tubers and fruit trees. The use of fire for agricultural land preparation may provide ignition sources because slash-and-burn is the main method for clearing the land for cultivation. Occasionally, ignitions may emanate from within the reserves, when fires used in land preparation at the initiation of forest restoration and rehabilitation operations, such as the *Taungya* agroforestry system, get out of control. Therefore, careful fire protection, combined with efforts to reduce degradation, will be required to ensure resilience of these moist forests in this era of climate change characterized by frequent climatic extremes.

Satellite remote sensing is the only source of data that is suitable for this kind of broad-scale study, but we acknowledge that understory forest attributes and processes are often not adequately captured. Optical-infrared sensors such as the Landsat Operational Land Imager and MODIS only observe the top of the canopy and not condition of the understory. Although they can reliably detect variability in canopy cover, they cannot estimate fuel loads or other understory characteristics that may also influence fire susceptibility. We also believe that our estimates of burned area are conservative, particularly in the moister forest zones where the canopy obscures evidence of low-severity understory fires. Moreover, active fires in tropical forest understories are difficult to detect, especially those with very low intensity. Cloud cover also obscures satellite observations and may also result in underestimation of active fire detections.

Based on results of this and previous studies (Dwomoh & Wimberly, 2017a), we argue that fire has become a key driver of forest degradation and loss in the moist forest areas of Ghana, and that ongoing climate change and climate variability will intensify fire risk and ultimately compromise forest resilience. Tropical forests become more susceptible to fire during severe drought, when high moisture stress desiccates the otherwise moist fuels making them more flammable (Cochrane, 2003). Future research priorities should include predictive models for forecasting potentially high-risk fire seasons and locations ahead of time, as well as longer-term projections of fire regime shifts as a function of climate and land use change. Such research outcomes may allow for the detection of early warning signals and the development of strategies to prevent further forest loss in tropical West Africa. Furthermore, in prospective studies, it will be necessary to examine the impact of droughts and fires on tree mortality, timber stocks, watersheds, biodiversity, carbon emissions, and the livelihoods of forest-dependent local communities.

5. Conclusion

The occurrence of extensive fires inside forest reserves in 2016 underscores the vulnerability of Ghana's forest reserves to fires during severe droughts. Fire activity was concentrated in degraded reserves, emphasizing that degradation predisposes forests to the impacts of drought and fire. This study provides the first quantitative assessment of a widespread fire event covering the entire forest zone of Ghana. Results indicate that forest degradation metrics derived from satellite imagery are useful for identifying critical areas in the forest zone where extensive forest degradation renders reserves highly susceptible to fire in drought years. The concentration of fire in the moist semi-deciduous forest type has serious implications for the forestry sector in Ghana because this forest type is the most economically valuable in terms of commercial timber species. Considering that majority of forest reserves are located in this forest type, it is imperative that forest managers integrate fire risk as a core component of current forest management. There is a need for urgent action because these extensive fires may initiate positive fire-vegetation feedbacks in some reserves and have the potential to lead to more widespread forest loss. The consequences can be catastrophic because fire – vegetation feedbacks may be strengthened by frequent droughts, which are projected to become more common with climate change (Sylla et al., 2016a; Sylla et al., 2016b). In the future, operational systems for monitoring forest degradation and fires will be useful for prioritizing management efforts in protected areas and support ongoing climate change adaptation and mitigation processes (including REDD+) in the region.

6. References

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CHAPTER 5

Research Summary and Recommendations

5.1 Summary of Research Results

The overarching of goal of this dissertation was to improve our understanding of the interactions of climate, land use, and fire regimes, as well as effects of fire on forest resilience in the Upper Guinean region of West Africa. My dissertation research broadened our understanding of fire regimes and fire-vegetation interations in the West African tropics, a region where logistical limitations, including scarcity of data, have mostly contrained this kind of sub-regional study.

This dissertation is a very unique contribution to forest and fire ecology in that it addresses critical gaps in baseline knowledge of fire regimes in the study area; pathways and drivers of disturbance land cover change; as well as forest resilience in an understudied part of the tropics with distinctive biophysical and socio-economic environments. More specifically, my research provided the first comprehensive assessment of fire regimes across the forest and forest-savanna transition zones, including maps and assessments of major drivers of fires in the Upper Guinean region (Dwomoh & Wimberly, 2017b). Furthermore, I have presented strong evidence that fire-vegetation feedbacks have the potential to drive forest degradation and ultimately forest loss in reserves in the forest zone of Ghana (Dwomoh & Wimberly, 2017a). I have also shown that these linkages between degradation and fire are facilitating more encroachment of fire into the reserves, as occurred in the widespread fires in 2016. A summary of results of the three main research objectives are presented in the sections below.

Research Objective #1: To understand fire regimes and their drivers in the Upper Guinean region of West Africa.

To address this research objective, we conducted a regional study to characterize the spatial patterns and interrelationships of multiple fire regime components, identify recent trends in fire activity, and explore the relative influences of climate, topography, vegetation type, and human activity on fire regimes.

We found strong variability in the spatial and temporal patterns of fire activity, as well as the drivers of multiple fire regime components, including active fire density, burned area, fire season length, and fire radiative power. Both active fire and burned area were most strongly associated with vegetation type, whereas fire season length was most strongly influenced by climate and topography variables, and fire radiative power was most strongly influenced by climate. These associations resulted in a gradient of increasing fire activity from forested coastal regions to the savanna-dominated interior, as well as large variations in burned area and fire season length within the savanna regions and high fire radiative power in the westernmost coastal regions. There were increasing trends in active fire detections in parts of the Western Guinean Lowland Forests ecoregion and decreasing trends in both active fire detections and burned area in savanna-dominated ecoregions (Dwomoh & Wimberly, 2017b).

Research Objective #2: To explore the overarching hypothesis that fire-mediated alternative stable states exist in the semi-deciduous tropical forest zone of Ghana, and that increased fire activity has pushed some forests to a new state in which a novel ecosystem with low tree density is maintained by fire.

To address this objective, we conducted analyses on forest resilience and disturbance-mediated tipping points in tropical forest ecosystems. By using time series of remotely-sensed Earth observations and field measurements covering four forest reserves in the semi-deciduous forest zone of Ghana, we addressed three specific characteristics of systems with alternative stable states: persistent change, feedbacks, and hysteresis.

Results of this study showed that two of the reserves in the north of the study area experienced forest loss, were impacted by frequent fires, and transitioned to a vegetation community dominated by shrubs and grasses, which was maintained by fire-vegetation feedbacks. The other two reserves experienced less fire, retained higher levels of forest cover, and resisted fire encroachment from surrounding agricultural areas. Over the study period, precipitation remained relatively stable, suggesting a hysteresis effect in which different vegetation states and fire regimes coexist within a similar climate (Dwomoh & Wimberly, 2017a). Consistent with earlier studies, this result showing divergent fire regimes in association with contrasting vegetation types within similar rainfall regimes suggests that fire–vegetation feedbacks can maintain distinctive vegetation and fire regimes in areas with similar climate (Dantas et al., 2013; Dantas et al., 2016).

Research Objective #3: To explore the susceptibility of forest reserves in the moist forest zone of Ghana to fire during a regional drought and fire event in 2016

To meet this objective, we conducted analyses relating pre-fire forest degradation and drought stress to fires in forest reserves in the entire high forest zone of Ghana. The results showed that in 2016, Ghana’s forest reserves experienced a surge in active fire detections that was associated with severe drought during that year. This fire burned approximately 12.4% (2,137 km^2) of the total forest reserve area of the forest zone.

Although, the severe drought was widespread throughout the forest zone, fire response was particularly high in the moist semi-deciduous forest type, which is the most extensive and most economically important forest type in Ghana. While reserves in this forest type represents approximately 38% of total reserve area of the forest zone, it accounted for approximately 52.3% (1,475 fires) of all active fire detections and 58% (1,239 km^2) of area burned in 2016 in the entire forest zone. In these fire-impacted moist forests, there was higher burned area in degraded reserves than relatively intact reserves. Within the two sub-divisions of the moist semi-deciduous forest type, we observed more severe drought in the South-east subtype (MSSE) than the North-west subtype (MSNW). However, fire was more widespread in the North-west subtype than the South-east subtype, suggesting that extensive forest degradation in the North-west subtype may have promoted more fires in that subtype.

5.2 Synthesis of Research Results

Our comprehensive regional analyses of the fire regime revealed that different components of the fire regime were influenced by different environmental drivers (Dwomoh & Wimberly, 2017b). As a result, the various combinations of these environmental factors create distinctive fire regimes throughout the Upper Guinean region of West Africa. The regional fire regime analyses revealed decreasing trends in fire activity across much of the savannas that were likely linked with increasing agriculture and declining woody cover. The same analyses further revealed increasing active fire trends in parts of the forested areas that were likely associated with decreasing tree cover and increasing amounts of herbaceous/shrub vegetation and fine fuels. Furthermore, extensive fires in the forest zone of Ghana during a recent regional drought in 2016 corroborate the increasing importance of fires in the humid forest regions. These results suggest that ongoing regional landscape and socio-economic changes along with climate change will lead to further changes in the fire regimes in West Africa. Hence, efforts to project future fire regimes and develop regional strategies for adaptation will require an integrated approach, which encompasses multiple components of the fire regime and consider multiple drivers, including land use and climate.

Moreover, in the rapidly changing environment of West Africa, fire regimes are affected by changes that alter fuel conditions and ignitions, but fire also serves as a driver of vegetation and land use change. As a result, fire and vegetation change are linked via strong positive and negative feedbacks (Dwomoh & Wimberly, 2017a). We found evidence for the existence of alternative stable states involving tropical forest and a novel non-forest vegetation community maintained by fire-vegetation feedbacks (Dwomoh & Wimberly, 2017a). This result highlights the potential for land use change and fire to create novel and persistent non-forested vegetation communities in regions that are climatically suitable for forests. Findings from the regional fire regime analyses indicating increasing fire trends in the Western Guinean Lowland Forests ecoregion (Dwomoh & Wimberly, 2017b), further suggest that these fire-vegetation feedbacks may be operating in those areas as well.

The results on forest resilience and fire-mediated regime shifts further revealed that the landscape changes were not immediate, but occurred slowly because of delayed tree mortality, continued impacts of human disturbances such as logging, and gradual erosion of forest resilience due to repeated fires (Balch et al., 2015; Cochrane, 2003; Silvério et al., 2013). An important lesson from these results is that assessments of future vegetation dynamics in the region will need to consider land use, fires, and their dynamic landscape-scale interactions in the context of broader drivers related to climate change and human population growth. Likewise, projections of future fire regime shifts will need to consider land cover and land use change because the fire regime study found that land use and vegetation were important constraints on fire. In future research, detailed assessment of the drivers and mechanisms of forest degradation and fire encroachment may allow for the detection of early warning signals and the development of strategies to prevent further forest loss in tropical West Africa.

Strong drought in 2016 was associated with an upsurge of fire in hitherto fire–resistant forest reserves in Ghana. This result provides insights into susceptibility of moist tropical forest to fire in the face of disturbances and changing climate (Alencar et al., 2015; Aragão et al., 2007; Brando et al., 2014). The finding of more fires in degraded reserves with relatively less severe drought and fewer fires in relatively intact reserves with more severe drought suggests that though drought predisposes moist tropical forests to fires, the extent of forest degradation prior to fire critically influences the spatial variability and the extent of forest burned.

The 2016 widespread fires in the moist semi-deciduous forests, which were previously assumed to be largely fire–resistant, underscore vulnerability of Ghana's forest reserves to fires in a changing climate. With this finding, it is reasonable to argue that the 2016 widespread fires may be initiating positive fire-vegetation feedbacks in some reserves and have the potential to lead to more widespread forest loss as observed in the long-term study of the four reserves (Dwomoh & Wimberly, 2017a). Historical analysis of fires in the four reserves indicated that large fires in the 1980s potentially precipitated the positive fire-vegetation feedbacks that lead to eventual loss of forest in the two northern reserves in the study area. Thus, if forests burned in 2016 experience fires again sooner than they can recover, these future fires will potentially be more severe and widespread due in part to greater fuel loads from earlier fires and lower humidity due to reduced canopy cover (Cochrane et al., 1999). Damage from such repeated fires is expected to be substantial even in fire years without severe drought.

Our results further suggest that previous increases in active fire detections in the forest zone were associated with earlier droughts in 2007 and 2012. We thus speculate that fire-vegetation feedbacks from these previous drought-associated fires may have supported the widespread fires of 2016. This fire – vegetation feedbacks may have been strengthened by ongoing forest degradation resulting from legal and illegal logging as well as agriculture encroachment in the reserves (Hawthorne et al., 2012; Marfo, 2010; Vaglio Laurin et al., 2016). With ongoing climate change, most parts of West Africa is projected to become warmer and drier, with frequent climatic extremes (Sylla et al., 2016a; Sylla et al., 2016b). These conditions will further enhance fire-risk, and pose severe threat to resilience of the already stressed fragmented forests. There is thus the urgent need to carefully incorporate fire risk into management of these otherwise fire-resistant forests to avert a looming catastrophic forest loss due to the interactions of forest degradation, climate variability, and fire.

5.3 Recommendations for Future Research

By examining multiple components of the fire regime and their drivers in the regional analyses of fire regimes, this study provides critical baselines for the projection of future fire regimes in the region. The West African region is undergoing substantial socio-economic and environmental changes that are modifying its socio-ecological systems. Therefore, future research to project fire regimes and develop adaptation strategies should consider multiple components of the fire regime and their linkages with future climate, socio-economic projections, and land use change in the region. Future research priorities should include predictive models for forecasting short-term high-risk fire seasons and locations ahead of time, as well as longer-term projections of fire regime shifts as a function of climate and land use change. Such research outcomes may allow for the detection of early warning signals and the development of strategies to prevent further forest loss in tropical West Africa.

As pointed out already, empirical studies of alternative stable states in tropical forest ecosystems remain scanty, despite the critical need for better understanding of the phenomena in real systems. Thus, results from the analyses of fire regimes and forest resilience documenting empirical observations of potential regime shift in a tropical forest landscape could inform model frameworks on alternative stable states in tropical forest ecosystems. In prospective studies, research elucidating the drivers and mechanisms of forest degradation and fire encroachment in the humid forest areas should have attention.

Results from the analyses of fire regimes and forest resilience as well as the 2016 fires in forest reserves of Ghana indicated forest vulnerability, particularly of dry and moist tropical forests, to fire encroachment and forest loss. There is the urgent need to carefully integrate fire risk in the management of these forests to prevent further fire-mediated loss of these important ecosystems. It is reasonable to advocate that fire-risk management should be a key component of ongoing REDD+ strategies in these forest areas. Furthermore, time-series analysis on the spatial patterns of burned area and fire effects in the fire-sensitive forested areas is recommended. Such a study could combine Landsat data with newer sensors like Sentinel to get more repeat measurements over persistent cloudy areas. In this regard, inclusion of detailed socio-economic data on forest-dependent livelihoods, land tenure rights and fire protection, detailed demographic and migration data, along with historical logging and forest inventory records may provide additional perspectives to complement findings in this research. Field work to characterize fuels and micro environments in degraded forest will be helpful to enhance our understanding of fire behavior. This knowledge is imperative to enhance sustainability of the regions remaining protected areas in this era of rapid global change.

In tropical forest monitoring, satellite optical remote sensing has largely been successful at revealing canopy-level disturbances. Notwithstanding this success, other important understory processes are not readily trackable on optical remote sensing imagery. For instance, optical remote sensing alone cannot reliably estimate fuel loads or other understory characteristics that may also influence fire susceptibility. Likewise, tracking and quantifying forest recovery rates for various types of disturbances require an integrated approach involving several kinds of remotely-sensed data coupled with detailed plot data. Such studies largely remain unexplored in this study area, where both data sources remain scarce. In prospective studies, integrated approach involving multispectral data from VIIRS, Landsat, and Sentinel and along with lidar and plot data will be necessary. It may be helpful to monitor persistent cloudy areas with sensors onboard unmanned aircrafts, as these technologies become readily affordable. Moreover, establishing operational systems for monitoring forest degradation will be useful for prioritizing management efforts in protected areas and support ongoing climate change adaptation and mitigation processes (including REDD+) in the region.

Whilst we could detect and map the widespread fire scars of 2016 in forest reserves on Landsat 8 images, these fire scars were not readily detectable on MODIS burned area product MCD64A1. Here, we argue that despite recent improvements in the MCD64A1 for the detection of small burned areas (Giglio et al., 2016), its performance in highly heterogeneous and forested landscapes such as this study area needs more improvement. Current efforts on burned area mapping from VIIRS should consider addressing such deficiencies, including accuracy assessment of the product in these environments. Furthermore, development of alternative regional or globally available burned area data from moderate resolution sensors such as Landsat and Sentinel will be helpful to the research community.

Overall, this dissertation produced novel results about the pathways and drivers of disturbance land cover change that are necessary for improving our understanding of ongoing changes in a lesser-known part of the tropics. This research has provided the first comprehensive analyses of the fire regime in the Upper Guinean region, showing heterogeneity in multiple components of the fire regime as a consequence of inherent heterogeneity in the underlying drivers of fire. These results thus expand our understanding of the spatio-temporal dynamics of tropical forest fires in response to human and climatic pressures. By providing stronger evidence that tropical forest landscapes can exist as alternative stable states, the study provides valuable knowledge on fire-mediated tropical forest ecosystem regime shifts, as well as the vulnerability of forested protected areas in the region to fire. Furthermore, this dissertation research documented fire-vegetation feedbacks using multiple data sources in four forest reserves, and more widespread vegetation impacts on fire in the study of 2016 fires. The study indicates that more forests are losing resilience and becoming vulnerable to degradation and change to non-forested state than may have been previously thought. These findings offer improved insights into the effects of strong positive and negative feedbacks between land cover and fire that have pushed some West African forest landscapes past a tipping point and culminated in widespread landscape change. These findings are relevant for predicting and mitigating similar fire impacts in tropical forests worldwide. This new knowledge will also help prioritize management efforts in protected areas and support ongoing climate change adaptation and mitigation processes (including REDD+) in the region.

5.4 References

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APPENDIX

Chapter 2 Supporting Information

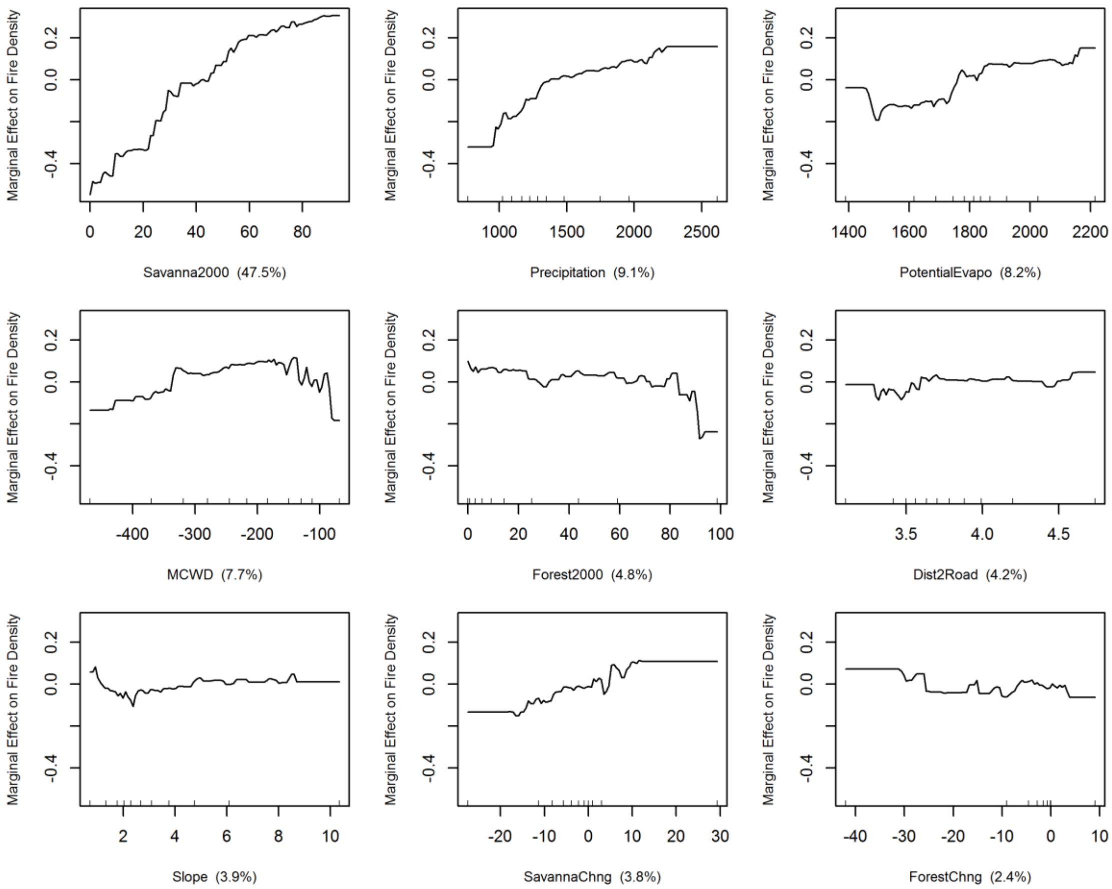

Figure S2 - 1: Partial dependence plots of the nine most important variables influencing the spatial pattern of active fire density.

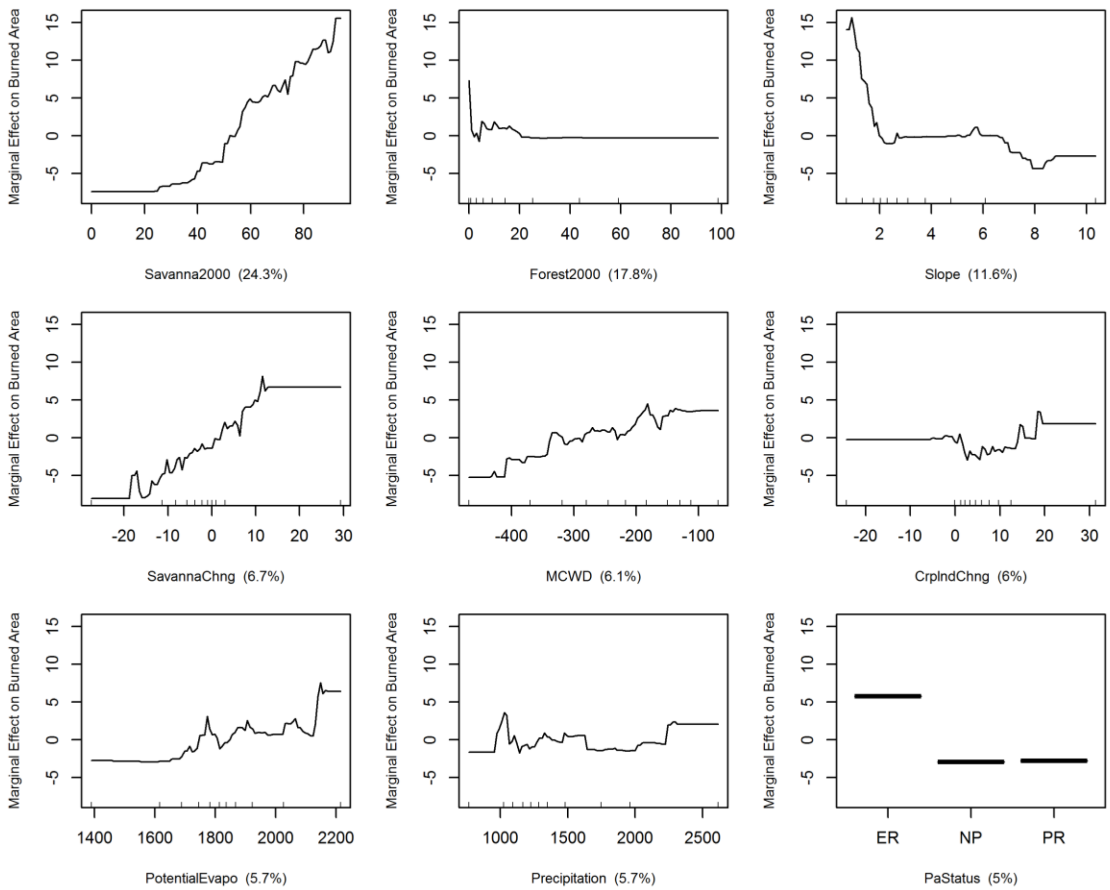

Figure S2 - 2: Partial dependence plots of the nine most important variables influencing the spatial pattern of burned area.

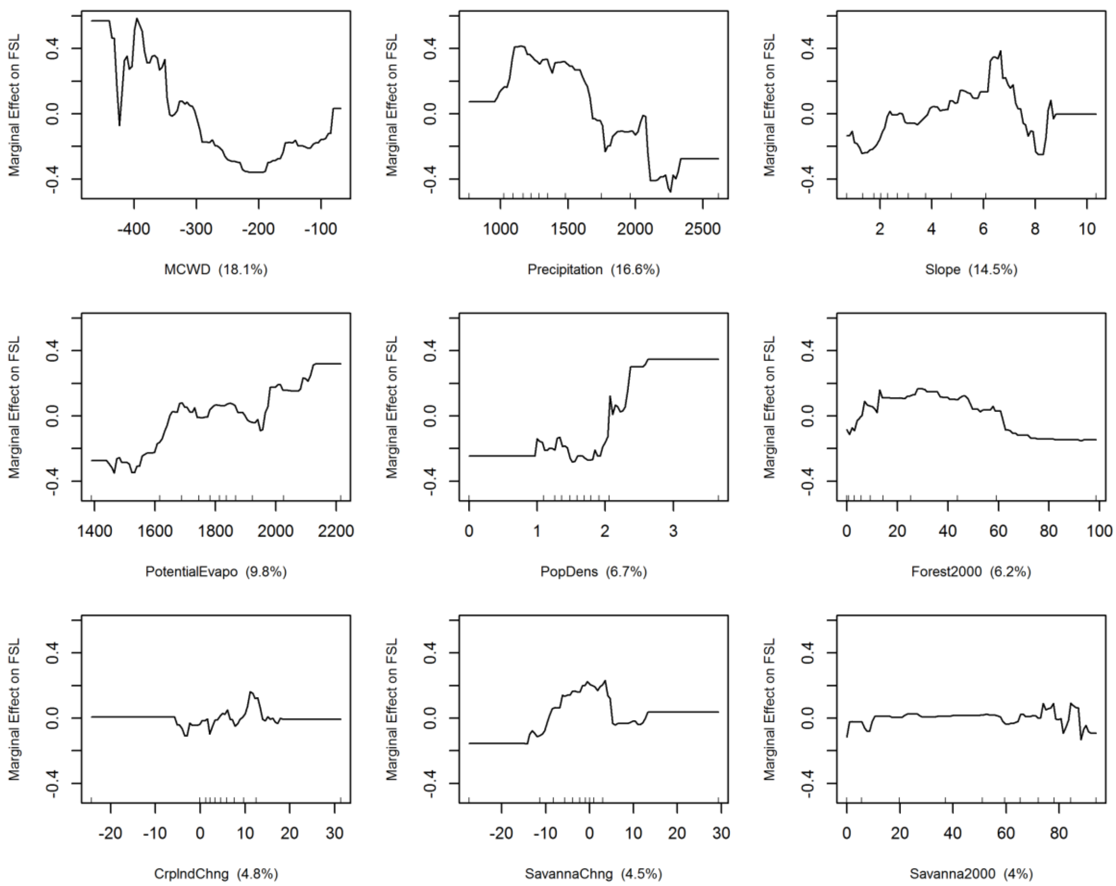

Figure S2 - 3: Partial dependence plots of the nine most important variables influencing the spatial pattern of fire season length.

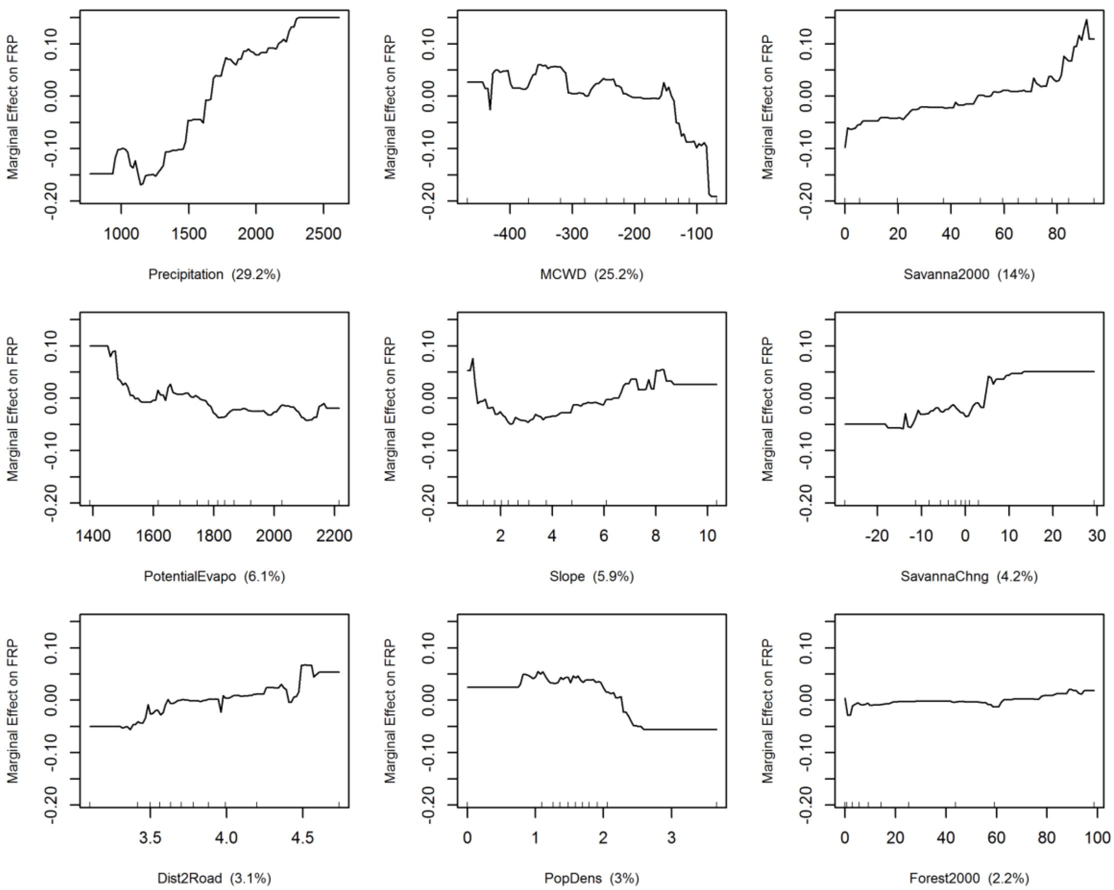

Figure S2 - 4: Partial dependence plots of the nine most important variables influencing the spatial pattern of fire radiative power.

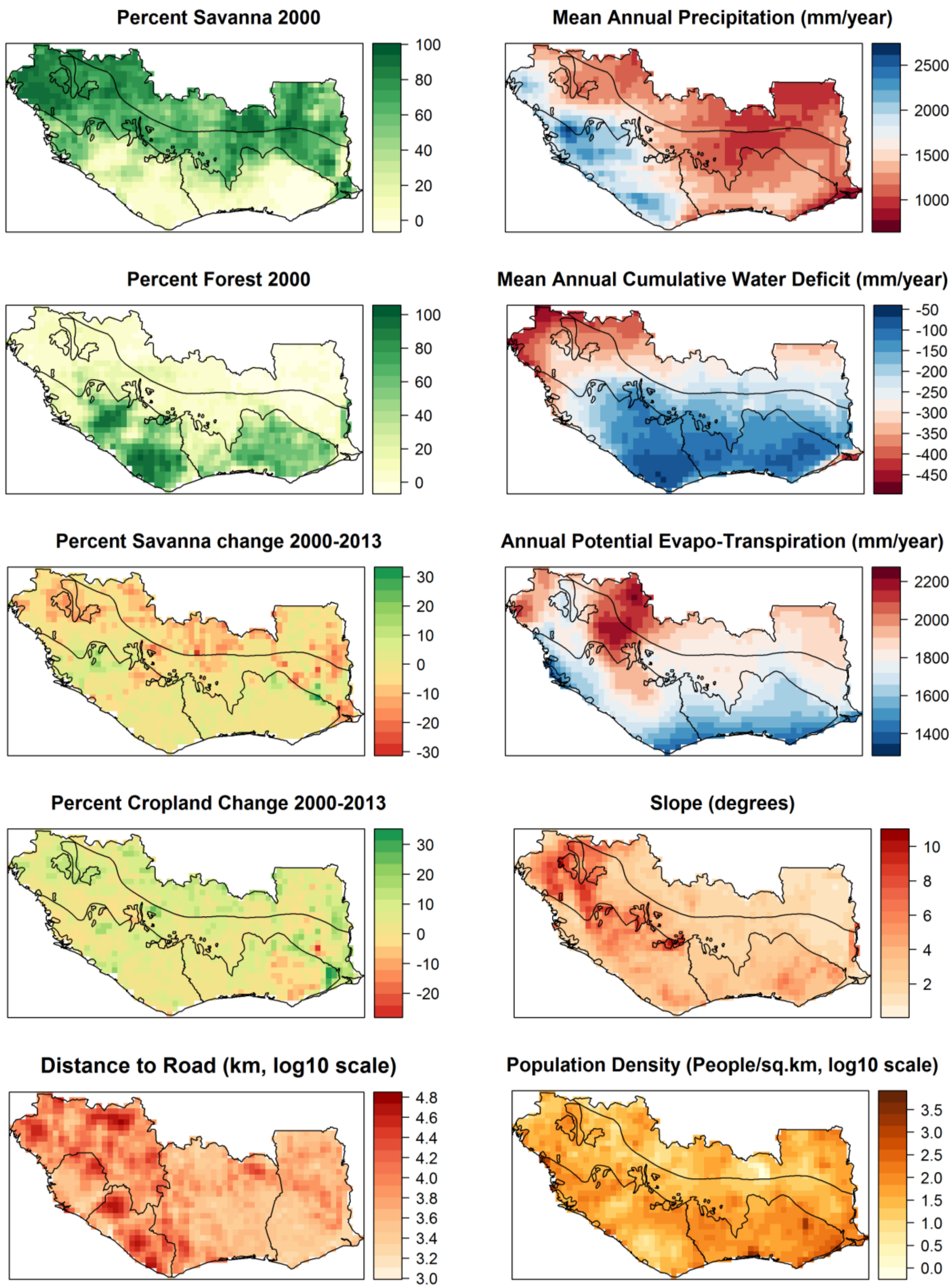

Figure S2 - 5: Maps of the 10 most important independent variables in the BRT models.

Chapter 3 Supporting Information

Table S3 - 1: List of Landsat TM/ETM+ data used in this study (path/ row 195/055)

Landsat Scene Identifier	Sensor	Date Acquired	Cloud Cover %	Note
LT51950551984349XXX04	TM 5	14-Dec-84	20	
LT51950551986018XXX07	TM 5	18-Jan-86	0	
LT41950551987365XXX01	TM 4	31-Dec-87	0	
LT41950551988352XXX01	TM 4	17-Dec-88	10	
LT41950551989002XXX02	TM 4	2-Jan-89	0	
LT41950551989050XXX01	TM 4	19-Feb-89	20	
LT51950551990365ESA00	TM 5	31-Dec-90	0	Source: ESA
LT41950551991008XXX03	TM 4	8-Jan-91	20	
LT51950551994104ESA00	TM 5	14-Apr-94	12	Source: ESA
LT51950551997016ESA	TM 5	16-Jan-97	5	Source: ESA
LE71950552000033EDC00	ETM+	2-Feb-00	0	
LE71950552001051EDC00	ETM+	20-Feb-01	12	
LE71950552002358EDC00	ETM+	24-Dec-02	0	
LE71950552003073EDC01	ETM+	14-Mar-03	6	
LE71950552004012EDC01	ETM+	12-Jan-04	4	SLC-Off
LE71950552005046ASN00	ETM+	15-Feb-05	9	SLC-Off
LE71950552006001ASN00	ETM+	1-Jan-06	0	SLC-Off
LE71950552007020ASN00	ETM+	20-Jan-07	0	SLC-Off
LE71950552008023ASN00	ETM+	23-Jan-08	0	SLC-Off
LE71950552009041ASN00	ETM+	10-Feb-09	8	SLC-Off
LE71950552010028EDC00	ETM+	28-Jan-10	20	SLC-Off
LE71950552011015ASN00	ETM+	15-Jan-11	0	SLC-Off
LE71950552012018ASN00	ETM+	18-Jan-12	19	SLC-Off
LE71950552013004ASN00	ETM+	4-Jan-13	0	SLC-Off
LE71950552014007ASN00	ETM+	7-Jan-14	25	SLC-Off
LE71950552015346ASN00	ETM+	12-Dec-15	5	SLC-Off

* ESA = European Space Agency

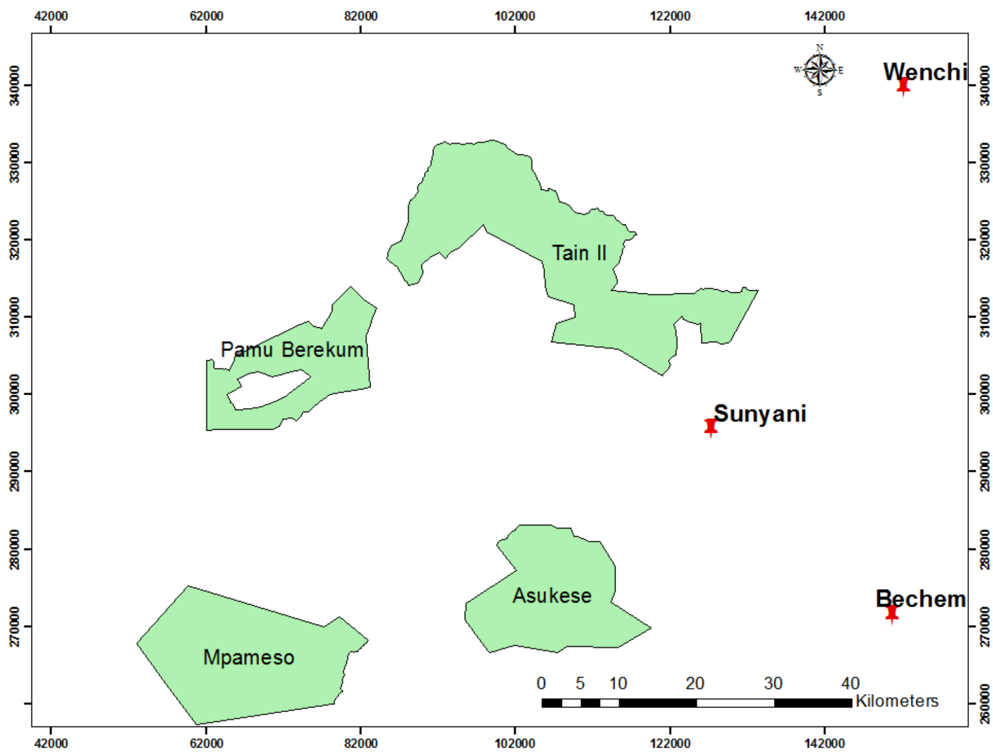

Figure S3 - 1: Map showing location of weather stations used in this study

Appendix S3 - 1: Validation of the Landsat-based disturbance index

The disturbance index (DI) maps, reflecting the level of tree canopy cover, were assessed using Google Earth high-resolution imagery from 2014 and 2015. 100 validation points were randomly sampled from the most recent Landsat image taken in 2015. 30 x 30m Landsat pixels corresponding to each point was converted into a polygon overlaid on the Google Earth imagery, and visually interpreted. The proportion of tree cover within the polygon was used as the criteria for categorizing each pixel into three classes as high, medium or low tree cover. These classes were defined as follows:

- High canopy cover: >70% tree canopy cover
- Medium canopy cover: 30-70% tree canopy cover

- Low canopy cover < 30% tree cover

The area under the Receiver Operating Characteristic (AUC) curve showed a good separation between the different classes of tree canopy cover by the DI. A multi-class AUC value of 0.98 was obtained by averaging AUC for all pairwise comparisons (Hand & Till, 2001). A graph of the DI validation is shown in Figure S3- 2 below.

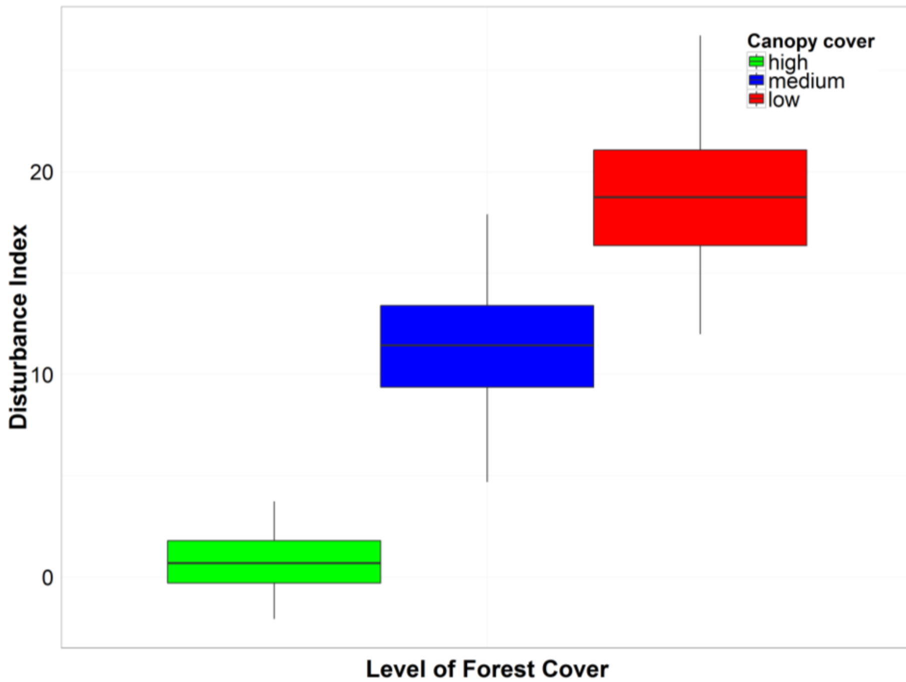

Figure S3 - 2: Validation of the disturbance index for 2015 by comparison with tree cover classes measured from high resolution imagery in Google Earth.

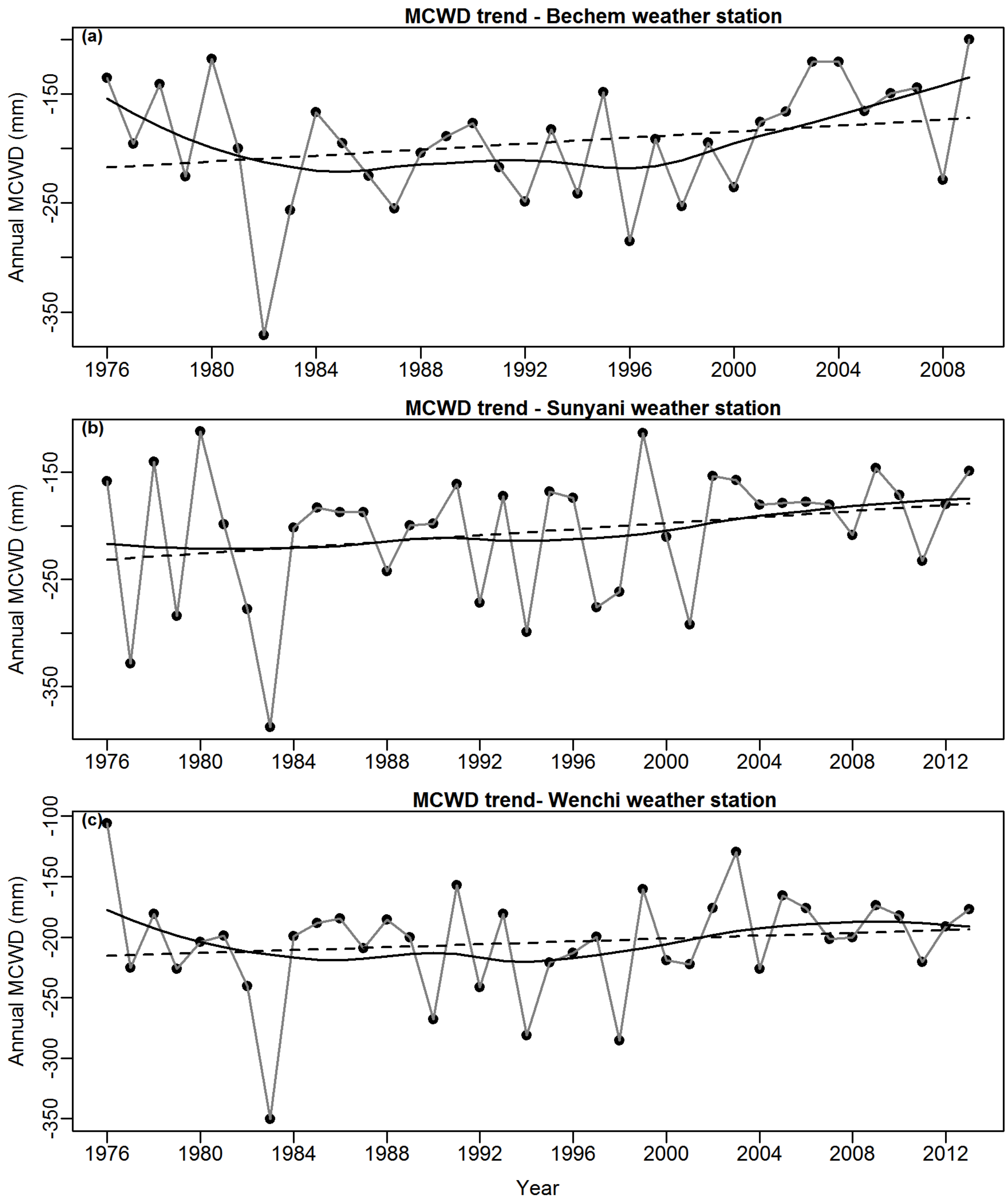

Figure S3 - 3: Trends in maximum climatological water deficit (MCWD) generated from precipitation data from three meteorological stations spanning the latitudinal gradient of the study area. Data covers the period (a) 1976-2009, (b) & (c) 1976-2013. Dashed lines represent linear trends; solid lines represent locally smoothed trends.

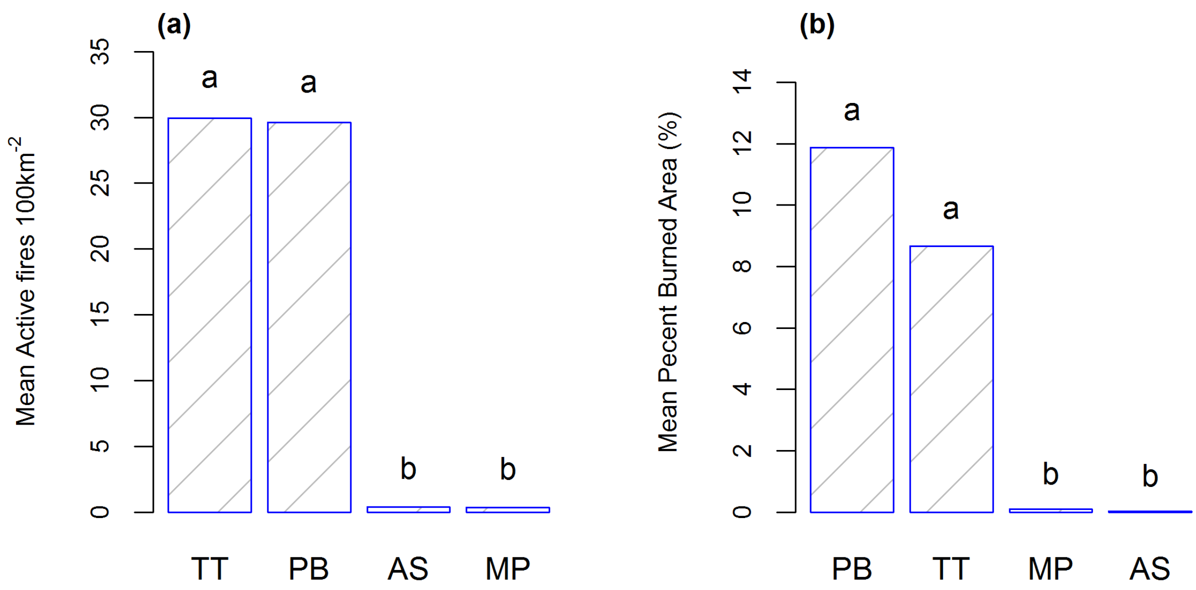

Figure S3 - 4: Multiple comparisons of least significant differences of a) mean active fire density, and b) mean percent burned area across forest reserves. Significance level is 0.05. Mean values with the same letter are not significantly different.

SI Reference

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Chapter 4 Supporting Information

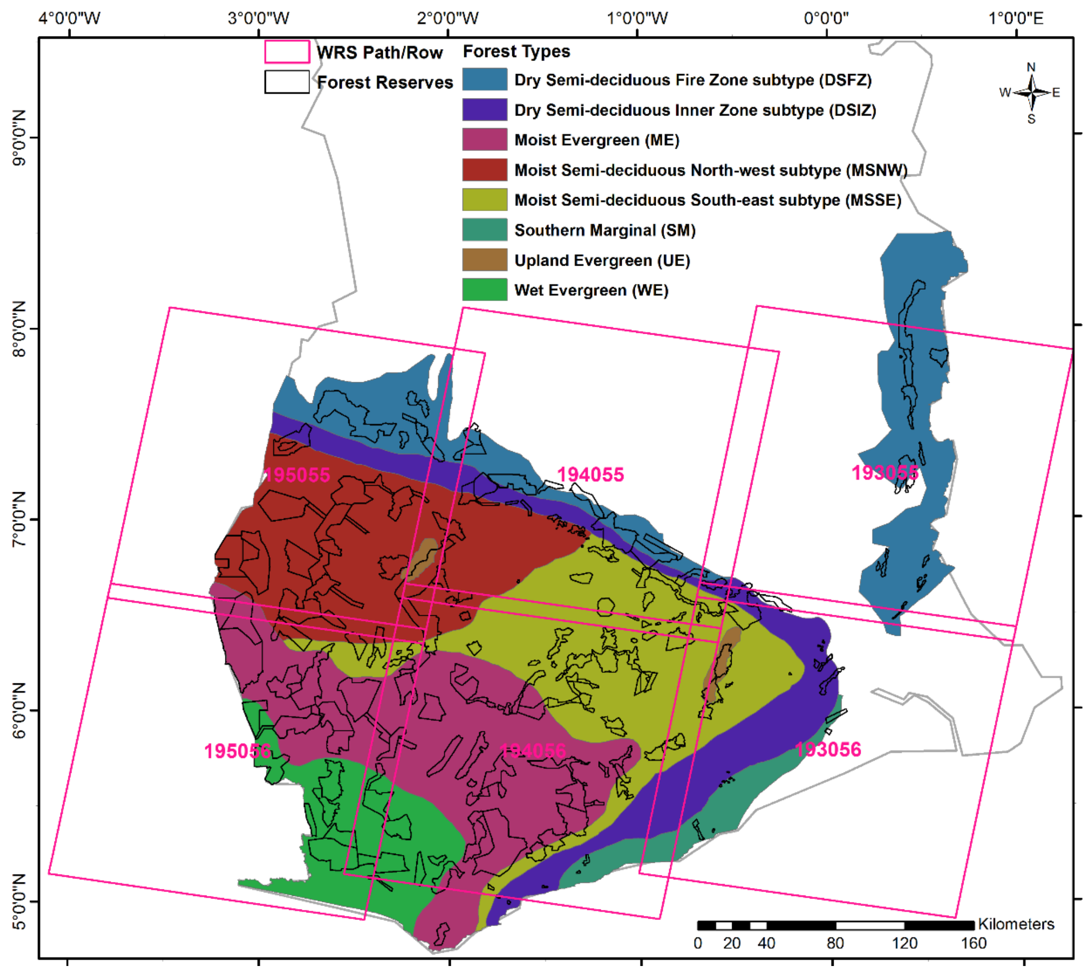


Figure S4 - 1: Study area map showing forest types in the forest zone, as well as the six Landsat path/rows covering the area.

Table S4 - 1: List of Landsat-8 Operational Land Imager images used for mapping disturbance index and burned area

Path/Row	Scene Identifier	Acquisition Date	Remarks
193055	LC08193055201512060 1T1	06-Dec-2015	Pre-fire image
	LC081930552015122201T1	22-Dec-2015	Post-fire image
	LC081930552016012301T1	23-Jan-2016	Post-fire image
	LC081930552016031101T1	11-Mar-2016	Post-fire image
193056	LC081930562015122201T1	22-Dec-2015	Pre-fire image: No conspicuous fire scars
	LC081930562016020801T1	08-Feb-2016	Post-fire image
	LC081930562016031101T1	11-Mar-2016	Post-fire image
194055	LC081940552015122901T1	29-Dec-2015	Pre-fire image
	LC081940552016013001T1	30-Jan-2016	Post-fire image
	LC081940552016021501T1	15-Feb-2016	Post-fire image
	LC081940552016031801T1	18-Mar-2016	Post-fire image
194056	LC081940562015122901T1	29-Dec-2015	Pre-fire image
	LC081940562016013001T1	30-Jan-2016	Post-fire image
	LC081940562016040301T1	03-Apr-2016	Post-fire image
195056	LC081950562015122001T1	20-Dec-2015	Pre-fire image 1
	LC081950562016010501T1	05-Jan-2016	Pre-fire image 2: Fill minor data gaps in pre-fire image 1
	LC081950562016020601T1	06-Feb-2016	Post-fire image
	LC081950562016030901T1	09-Mar-2016	Post-fire image
	LC081950562016032501T1	25-Mar-2016	Post-fire image
195055	LC081950552015122001T1	20-Dec-2015	Pre-fire image 1
	LC081950552015011801T1	18-Jan-2015	Pre-fire image 2: Fill minor data gaps in pre-fire image 1
	LC081950552016020601T1	06-Feb-2016	Post-fire image
	LC081950552016030901T1	09-Mar-2016	Post-fire image

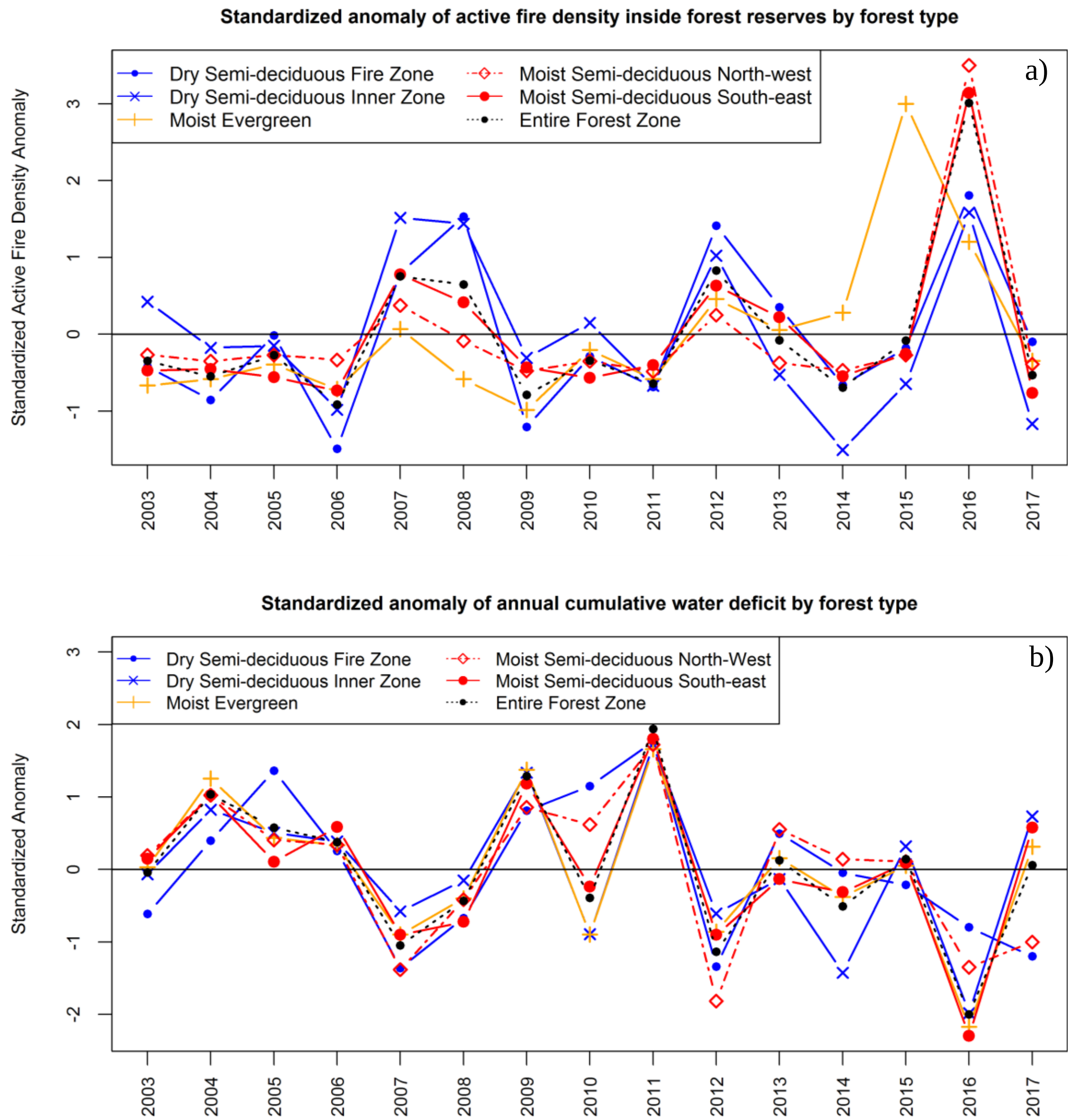
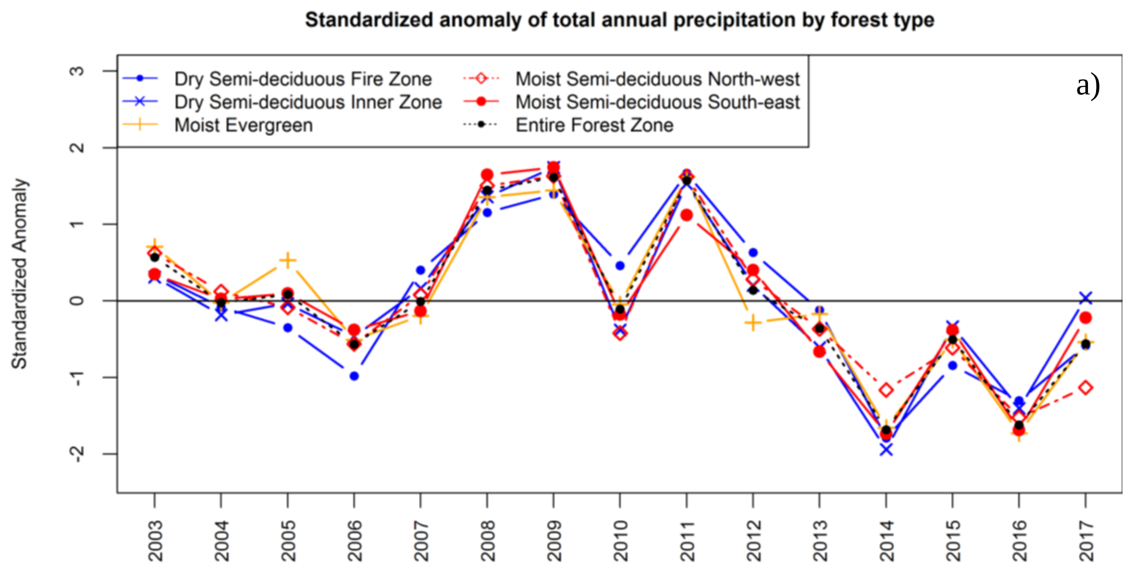


Figure S4 - 2: Time series standardized anomaly of: a) active fire density & b) maximum cumulative water deficit by forest type.



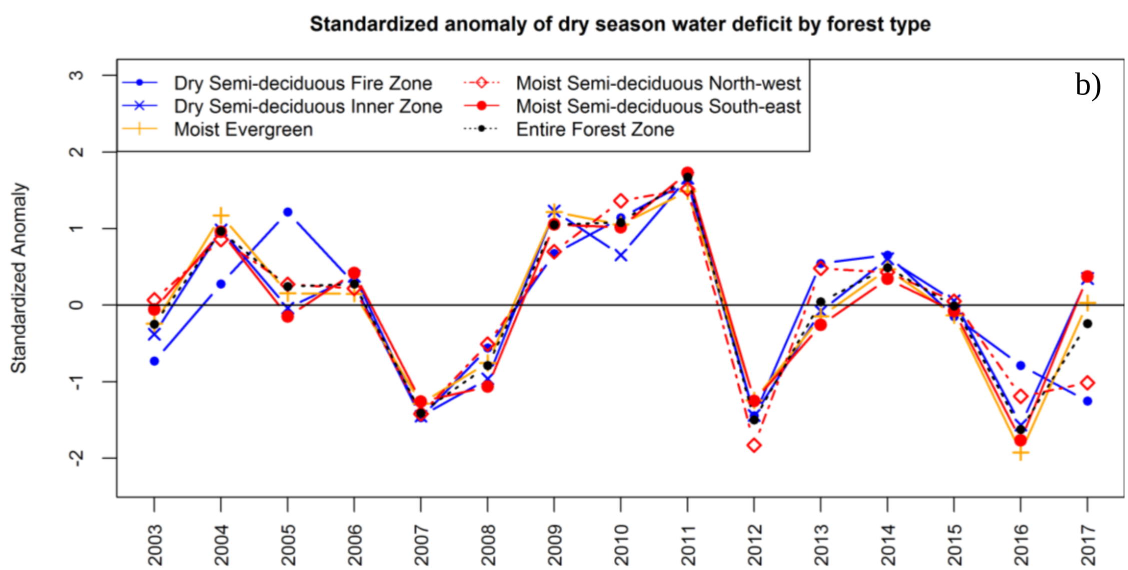


Figure S4 - 3: Time series standardized anomaly of: a) total annual precipiation & b) dry season (November to March) water deficit by forest type.

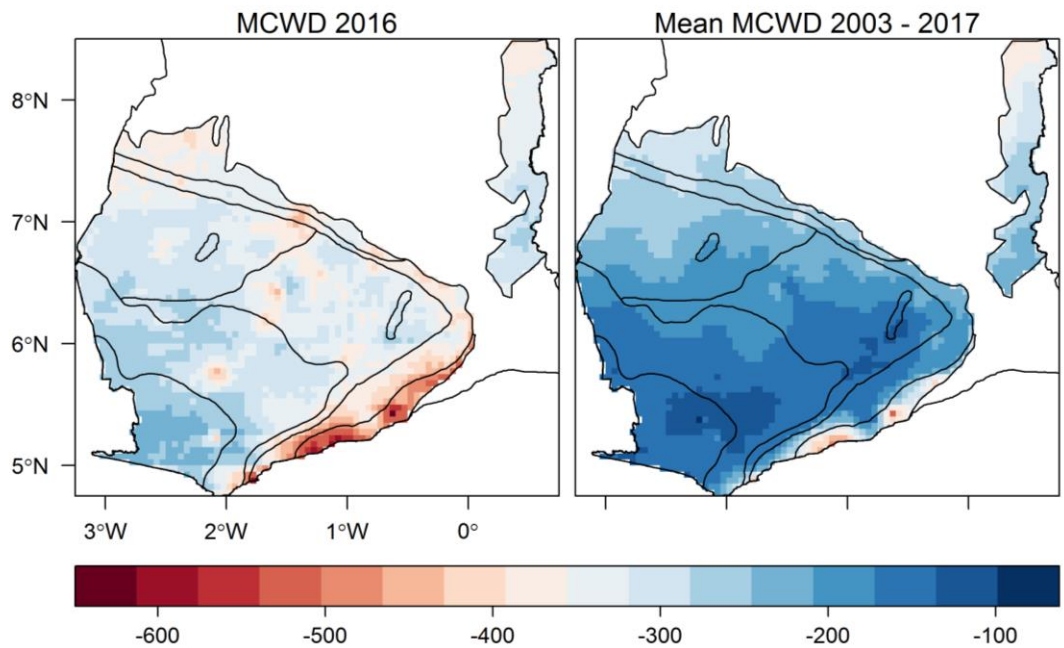


Figure S4 - 4: Maps of maximum cumulative water deficit (MCWD, mm/year) showing the spatial extent of drought in the forest zone in 2016 compared to the average MWCD the period 2003 to 2017 hydrological years.

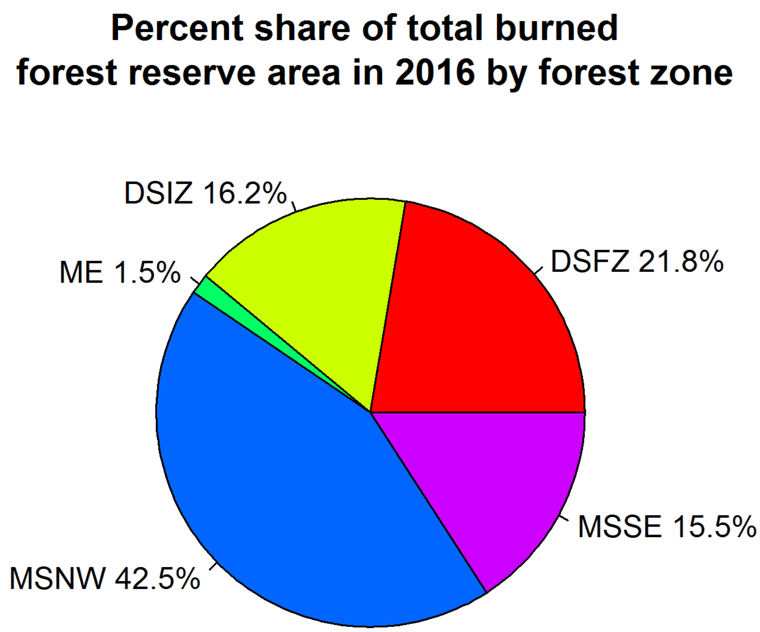


Figure S4 - 5: Distribution of area burned inside forest reserves in each forest zone. A total of 2,137 km^2 was burned in 2016. Note: DSFZ = Dry Semi-deciduous Fire Zone sub-type, DSIZ = Dry Semi-deciduous Inner Zone sub-type, ME = Moist Evergreen Forest Zone, MSNW = Moist Semi-deciduous North-West sub-type, MSSE = Moist Semi-deciduous South-East sub-type.

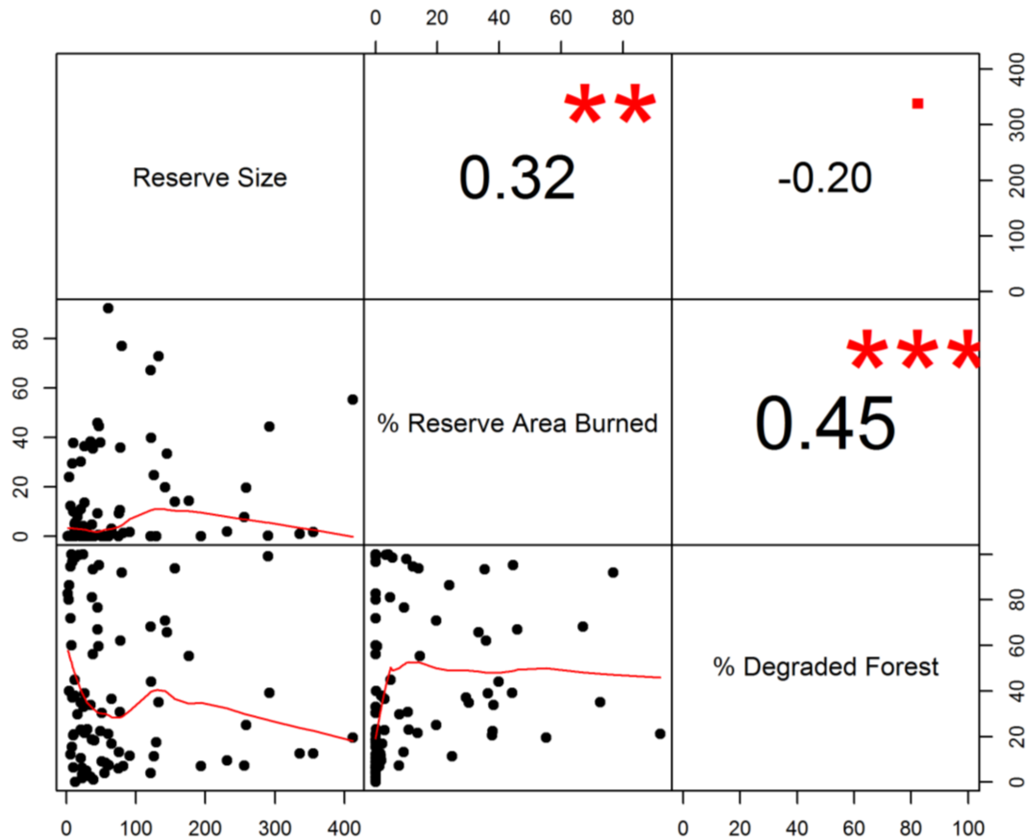


Figure S4 - 6: Spearman correlation for moist semi-deciduous forest zones only. The upper triangle shows the correlations and associated *p-values*: *** $p < 0$, ** $p < 0.001$, ▪ $p < 0.05$. Larger font sizes indicate stronger correlations.