DROUGHT MONITORING WITH REMOTE SENSING BASED LAND SURFACE PHENOLOGY APPLICATIONS AND VALIDATION

by

Mohamed Abd salam M El Vilaly

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Mohamed Abd salam El Vilaly entitled Drought Monitoring with Remote Sensing Based Land Surface Phenology Applications and Validation and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

____ Date: 06/27/213
Stuart E. Marsh (Co-Advisor)

____ Date: 06/27/213
Kamel Didan (Co-Advisor)

____ Date: 06/27/213
Michael A. Crimmins

____ Date: 06/27/213
Charles F. Hutchinson

____ Date: 06/27/213
David Phillip Guertin

Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copies of the dissertation to the Graduate College.

I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

____ Date: 06/27/2013
Dissertation Director: Stuart E. Marsh

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SIGNED: Mohamed Abd salam M El Vilaly

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DEDICATION

I dedicate my dissertation work to:

My lovely family, Audra El Vilaly and Emil Mohamdy Vilaly

My parents, Mohamdy and Aichetou

Grandmothers, Mariem and Minetou

My uncles, Mohamed, Mena, Filali, and Masoud

My sisters and brothers

Darryl White and Emmett White

Residents of the village of Tanout, Niger, where I met my wife

This dissertation is dedicated to the thousands of sisters and brothers who perished during the great droughts that swept the Sahel and Saharan deserts of Africa during my childhood in Mauritania.

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ABSTRACT

Droughts are a recurrent part of our climate, and are still considered to be one of the most complex and least understood of all natural hazards in terms of their impact on the environment. In recent years drought has become more common and more severe across the world. For more than a decade, the US southwest has faced extensive and persistent drought conditions that have impacted vegetation communities and local water resources. The focus of this work is achieving a better understanding of the impact of drought on the lands of the Hopi Tribe and Navajo Nation, situated in the Northeastern corner of Arizona. This research explores the application of remote sensing data and geospatial tools in two studies to monitor drought impacts on vegetation productivity. In both studies we used land surface phenometrics as the data tool. In a third related study, I have compared satellite-derived land surface phenology (LSP) to field observations of crop stages at the Maricopa Agricultural Center to achieve a better understanding of the temporal sensitivity of satellite derived phenology of vegetation and understand their accuracy as a tool for monitoring change.

The first study explores long-term vegetation productivity responses to drought. The paper develops a framework for drought monitoring and assessment by integrating land cover, climate, and topographical data with LSP. The objective of the framework is to detect long-term vegetation changes and trends in the Normalized Difference Vegetation Index (NDVI) related productivity.

The second study examines the major driving forces of vegetation dynamics in order to provide valuable spatial information related to inter-annual variability in vegetation productivity for mitigating drought impacts.

The third study tests the accuracy of remote sensing-derived LSP by comparing them to the actual seasonal phases of crop growth. This provides a way to compare and validate the various LSP algorithms, and more crucially, helps to characterize the remote sensing-based metrics that contrast with the actual biological phenophases of the crops.

These studies demonstrate how remote sensing data and simple statistical tools can be used to assess drought effects on vegetation productivity and to inform about land conditions, as well as to better understand the accuracy of satellite derived LSP.

Keywords: Drought, Land Surface Phenology, Vegetation Index, Crops, Hopi, Navajo.

CHAPTER 1: INTRODUCTION

Problem Context

Droughts are some of the most damaging natural hazards menacing the economic, social, and political elements of our society (Chen et al., 2012; Riebsame, Changnon Jr, & Karl, 1991; Wilhite & Buchanan-Smith, 2005; Woodhouse & Overpeck, 1998). They are a recurrent part of our climate and are considered one of the most complex and least understood climate-related hazards due to their tremendous influence on social-political-economic-environmental interactions (Glantz, 2003; Hagman, 1984; Mishra and Desai, 2005; Sönmez, Koemuescue, Erkan and Turgu, 2005; Wilhite, 1990; Woodhouse and Overpeck, 1998; Wu and Chen, 2013).

From 1900 to 2004, more than 807 global droughts were recorded. During this time, more than 1.8 billion people were affected; 11 million people lost their lives; and billions of dollars in economic losses were incurred as a result of droughts (Below et al., 2007; UNESCO, 2012). Due to the multi-dimensional impact of droughts on global agricultural, hydrological, eco-environmental, and social-economical systems, droughts have been categorized as the second most geographically widespread hazard after floods, according to the United Nations (UNESCO 2012). However, droughts are considered the most devastating hazard when the number of people affected by drought is taken into considerations (Hewitt, 1997; Keshavarz et al., 2013; Obasi, 1994; Wilhite, 2000). From the 1970s to the early 2000s, the percentage of the Earth's land area experiencing very severe drought doubled (NCAR, 2005).

In recent years drought has become more common and more severe across the world, and the extent of drought-affected areas has increased (Easterling et al., 2000; FAO., 2011; Hoerling, 2003; IPCC, 2007; Meehl, 2004; Mishra et al., 2010) . Furthermore, drought is now recognized as one of the principal causes of crop loss and severe food shortage, particularly in developing countries (FAO., 2011; Parida et al., 2008). For the last decades, droughts have constantly threatened the world's food security (Eriksen et al., 2012; FAO., 2011). In addition to their effect on natural resources and economies, droughts can threaten livelihoods and communities, causing displacement and migration of peoples (FAO., 2011; Parida et al., 2008).

In the Southwestern United States, droughts are relatively common phenomena due to land surface-ocean interactions (Cook et al., 2007; Seager et al., 2007). Several studies have shown that both climate and human activities are the key driving forces of landscape changes in the American Southwest (Seager et al., 2007). This finding renders it difficult to detangle the impacts of droughts and human activities on vegetation.

Intermittent droughts have been a consistent feature of the history of the southwestern United States (Cook et al., 2004; Gray, 2003; Griffin et al., 2013). However, recent drought conditions on the Colorado Plateau, where the Hopi Tribe and Navajo Nation are located, have taken a different pattern: instead of fluctuating between dry and wet conditions, this area has become increasingly dry. Across the region, a scarcity of rain gauge networks has challenged traditional drought monitoring tools. Furthermore, limited hydro-climatological and ecological monitoring in this area has created a challenging environment for resource managers trying to assess current conditions and anticipate future climatic impacts at seasonal to inter-annual time scales.

The current capacity for monitoring drought on the lands of the Hopi Tribe and Navajo Nation is limited due primarily to a lack of long-term temperature and precipitation monitoring sites in this area. Therefore, classic drought monitoring indices, such as the Palmer Drought Severity Index (PDSI) (Palmer, 1965), the crop moisture index (Byun and Wilhite, 1999; Palmer, 1968; Shafer and Dezman, 1982), the Surface Water Supply Index, and the Standardized Precipitation Index (SPI) (McKee et al., 1993), cannot adequately capture a drought of this magnitude and its impact over time. Given the scarcity of monitoring stations, these indices cannot characterize the spatial patterns of drought across the landscape. In addition, several studies have reported common weaknesses related to the use of these indices to monitor drought because they rely on monthly time scales, and are not sufficiently accurate in capturing the beginning, end, and accumulated stress of drought.(Blenkinsop et al., 2007; Byun et al., 1999; Mu et al., 2013; Sivakumar et al., 2010).

Because of these challenges, this study has investigated the use of remote sensing indices to capture and assess the spatial patterns of the impacts of the region's recent drought on vegetation productivity along vegetation community and elevation gradients. Remote sensing allows for fast and efficient monitoring and tracking of land surface processes on different scales, from the local to global (Anyamba et al., 2005; Bastiaanssen et al., 1999; Delegido et al., 2013; Lausch et al., 2013; Papes et al., 2012; Pocas et al., 2013; Schmugge et al.,2002).

In this research, I developed a remote sensing approach to monitoring drought and assessing remote sensing-derived Land Surface Phenology (LSP) as a viable remote sensing tool. This research developed a framework for drought monitoring and assessment, as well as began to establish the accuracy of the remote sensing-derived LSP algorithms when compared to actual crop growing season phases. For drought assessments, the main goals are: (1) to evaluate the magnitude of inter-annual variability in vegetation productivity, and then quantify its temporal variability relative to rainfall variation and elevation gradients, (2) to detect any long-term vegetation change and trends in the NDVI-related productivity parameters, and (3) to assess environmental drivers associated with vegetation productivity changes across time and space. For the assessment of remote sensing-derived LSP, this work addressed three fundamental challenges in remote sensing: (1) how to validate remote sensing-based land surface phenology metrics, (2) how to compare the extracted parameters with actual field observations of phenology given the heterogeneous nature of remote sensing observations, and (3) how to evaluate the overall performance of the most common land surface phenology algorithms.

Study Area

This research was conducted at two sites. The first study site covers the main land of the Hopi Tribe and Navajo Nation of Arizona. The second site is located at the University of Arizona's Maricopa Agriculture Center, located northwest of Tucson.

The Hopi Tribe and Navajo Nation of Arizona are located in the northeastern corner of the state in the lower Colorado River basin. Collectively, the Hopi Tribe and Navajo Nation cover over 77,700 square km. The area is characterized by cold winters and very hot summers. The annual rainfall of the lowland Navajo Nation averages from 100-150 mm (less than 6 inches) and the average annual temperature varies between 11^{o}C in the higher altitudes and 14ºC in the lowlands. Climatic patterns vary from south to north across the area (Redsteer et al., 2011). The seasonal rainfall varies along elevation gradients and is low and moderate in the early winter, increasing in February and March, and then decreasing quickly in April. May through June is a very dry period in the area (Grahame et al., 2002). Vegetation cover varies throughout the area as a result of differences in rainfall and average temperature, soil types, elevations, and land management.

Explanation of Dissertation Format

The main body of this dissertation consists of three appendices (A, B, and C). For all three manuscripts, the theoretical frameworks used were developed with the guidance of the dissertation committee. In applying the theoretical frameworks to reach the overall objectives of the studies, I developed a methodological approach based on the use of remote sensing data and geospatial tools. The first paper (Appendix A), entitled "Long-term vegetation productivity responses to drought on the land of the Hopi Tribe and Navajo Nation", and explored any long-term vegetation changes and trends in the NDVI related productivity parameters in the area. I was the first authors on this work and was responsible of the research design and interpretation. The second paper (Appendix B), entitled "Vegetation responses to climate variability on the lands of the Hopi Tribe and Navajo Nation", relied on the first paper framework to analyze inter-annual variability in vegetation productivity. I was the first author, and developed the methodological (theoretical and analytical) framework for this research. Dr. Kamel Didan and I established the methodological frame work for the third paper. Using this frame work I was in charge of implementing the methodology for analyzing the data and interpreting the results.

Finally, following the composition of each paper, I worked closely with my dissertation committee to incorporate its feedback into the preparation of this document.

CHAPTER 2: PRESENT STUDY

Summary

This dissertation relies on the use of remote sensing data and geospatial analysis to develop a monitoring tool aimed at assessing drought impacts on vegetation dynamics over the last 22 years on the lands of the Hopi Tribe and Navajo Nation, as well as to validate remote sensing-based land surface phenology metrics using field observations of croplands at the University of Arizona's Maricopa Agriculture Center. The methods, results, and conclusion of this research are summarized in the papers appended to this dissertation. The challenges addressed by this dissertation include the development of an approach for the use of remote sensing data and geospatial tools to monitor vegetation dynamics across different vegetation communities in arid and semiarid regions in the southwestern U.S. The following section outlines the central findings of this dissertation. Here, I proposed and presented an integrated approach for data selection, tools development, and need for validation and characterization to support the accurate monitoring of the impact of drought on vegetation.

Appendix A: Long-term vegetation productivity responses to drought on the land of the Hopi Tribe and Navajo Nation

(Note: this article will be submitted to the Journal of Arid Environments)

Periodic droughts are common in the southwest United States (Cook et al., 2004; Gray, 2003; Griffin et al., 2013). But unlike the intermittent droughts characteristic of the larger region, recent drought conditions on the Colorado Plateau, where the Hopi Tribe and

Navajo Nations are located, have emerged and persisted steadily over time. This challenges traditional drought monitoring considering the sparse network of rain gauges across the region. Limited hydro-climatological and ecological monitoring across the region has created a challenging environment for resource managers trying to assess current climatic conditions and anticipate their future impacts at seasonal to inter-annual time scales. In order to assess the impacts of both climate change and human activity on the region's ecosystem structure and function, it would be useful to develop a geospatially explicit drought monitoring system and remote sensing data was an obvious choice. This can help inform decision makers about ecosystem responses to these dynamics, while also helping to predict future climate and human impacts.

I utilized the15-day composite multi-sensor Normalized Difference Vegetation Index (NDVI) time series data from 1989 to 2010. Multi-sensor Normalized Difference Vegetation Index time series data were acquired from the vegetation index and phenology project (vip.arizona.edu). This sensor-independent and continuous NDVI time series derived from AVHRR (1981-1999), SPOT (1998-2002) and MODIS (2000-2010) is used in this study (Didan et al., 2010). More details about the datasets can be found on the Vegetation Index and Phenology Laboratory website: (http://vip.arizona.edu/viplab_data_explorer.php). We acquired and analyzed the 15-day composites, at 5.6 km, to characterize the inter-annual changes of vegetation productivity along elevation gradients. The use of the multi sensor seamless NDVI data enabled us to successfully extend our analysis back to 1989. This study is one of the first studies that have deployed this new dataset to characterize vegetation responses to drought on the lands of Hopi tribe and Navajo Nation.

This greenness Normalized Difference Vegetation Index (NDVI) has been widely used to characterize vegetation response to climate change and variability at different scales: from local, regional, to continental (Ahmad, 2013; Pocas et al., 2013; Tucker, 1979; White et al., 2009). We developed a framework relying on four different steps. The first step involves generating three annual indictors related to vegetation productivity from the 15-day composite multi-sensor NDVI time series. These annual indicators included: (1) annual cumulative NDVI (∑NDVI, a proxy of Gross/Net Primary Production, GPP/NPP) (Chen et al., 2013; Hwang et al., 2008), (2) maximum annual NDVI, and (3) annual NDVI amplitude (difference between annual maximum and minimum NDVI). These annual indicators were extracted during the snow-free period from March to November of each year to reduce snow impacts on NDVI values (Delbart et al., 2006; Shi et al., 2008; Zhang et al., 2004). The second step was to characterize vegetation productivity along both elevation gradients and within vegetation communities by analyzing the long-term averages of each NDVI-related productivity measurement. The third step involved assessing the long-term trends in vegetation productivity among each annual indicator related to NDVI productivity. In this step, the trend analysis was based on two variables: time (22 years) as the independent variable and the annual NDVI related productivity as the dependent variable. Many studies have relied on this technique to quantify vegetation response to climate change, study phenological change, and capture land cover change (Fensholt et al., 2012; Wright et al.,, 2012; Yin et al., 2012). The last step employed the

Rain-Use Efficiency (RUE) indicator to assess vegetation capacity to efficiently transform water and nutrients to biomass over the last 22 years. RUE is a key indicator of the state of vegetation cover function particularly in semiarid ecosystems (LeHouerou, 1989; LeHouerou, 1984; Yang et al., 2010).

At the Hopi and Navajo Nation, our results confirmed that over the last 22 years, the area has experienced a significant reduction in productivity, particularly in areas dominated by shrubland. As expected for such an arid area, rainfall is the most fundamental and driving factor of vegetation productivity, especially for areas dominated by grassland and shrubland (limited root depth).

Our results also found that the forested areas at higher elevations were less prone to rainfall variability. This independence can be explained by factors related to rooting depth, size, and resiliency of trees in the area. Rooting depth determines a tree’s ability to access deeper soil moisture during dry periods, and thus influences its intrinsic resiliency to precipitation reduction through its capacity to store water.

The RUE-based analysis did not show any widespread or significant changes, which support the finding that rainfall patterns only explain 21% of the observed changes in vegetation productivity.

From our results, the 15-day multi-sensor NDVI record and simple statistical tools were able to capture the spatial variation of vegetation response to drought impacts. It is expected that the resulting maps, that provide a spatial context of change, can serve as a valuable tool for adaptive range management.

Appendix B: Vegetation responses to climate variability on the lands of the Hopi Tribe and Navajo Nation

(Note: this article will be submitted to the Journal of Arid Environments)

The overall goal of this study was to look at the inter-annual variability in vegetation productivity in the study area, as well as to examine the existing relationships between vegetation variability and environmental variables. Landscape change in the southwestern United States, as in any region, is strongly linked to both climate and human activity. As such, detangling the anthropogenic from the climatic drivers of drought in terms of vegetation productivity presents a challenge (Seager et al., 2007). Although drought is a normal part of the southwestern United States' climatic chronicle (Cook et al. 2007; Seager et al., 2007), the present drought on the Colorado Plateau, where the Hopi Tribe and Navajo Nation are located, has emerged slowly challenging traditional drought monitoring metrics based on sparse rain gauge networks across the region. Assessment of the present drought and its impacts on the ecosystem of the Hopi Tribe and Navajo Nation can benefit from the use of remote sensing data to supplement the area's limited hydro-climatological data.

To reach the main objective of this study, a methodological framework was implemented using different remote sensing data and tools. The first step was to extract two key annual NDVI-related productivity measurements: (1) integrated annual NDVI (a proxy of Gross/ Net Primary Production, GPP/NPP) and (2) maximum annual NDVI, from the 15-day composite multi-sensor NDVI time series from 1989 to 2010. These two annual NDVI measurements of vegetation productivity are considered response variables. The second step was to select the appropriate explanatory variables (environmental variables: climate data, vegetation types, soil, and topographic characteristics). After selecting both response and explanatory variables, the next step was to generate the coefficient of variation (CoV = standard deviation/mean) of the response variables and examine them by vegetation type. The last step was to study vegetation-environment relationships by conducting a stepwise multiple linear regression analysis (SMLR) in order to find the key environmental variables of the inter-annual variability in vegetation productivity over the last 22 years.

The results of the spatial distribution of the inter-annual variability in vegetation productivity suggested that: (1) needleleaf forest at middle elevations showed the highest inter-annual variability in cumulative NDVI; (2) larger CoV values related to maximum NDVI were observed at low elevations where grasses are the dominant vegetation types; and (3) in terms of the key environmental variables used to explain variability in vegetation productivity, climate drivers were most strongly correlated with the inter-annual variability in vegetation productivity. Specifically, the inter-annual variability in spring precipitation and temperature seem to be the most significant drivers that correlate positively with the inter-annual variability in vegetation productivity in the study area. However, the inter-annual variability in summer precipitation and temperature showed a decreasing relationship with the inter-annual variability in vegetation productivity and they showed a strong impact of vegetation productivity. It was found that the inter-annual variability in winter, spring and summer temperature were the most powerful drivers in the inter-annual variability in maximum NDVI for shrubland areas. Those positive correlations between the inter-annual variability in vegetation productivity and spring precipitation and temperature can be explained by the change in soil moisture levels. For example, the strong correlations between spring temperature and vegetation productivity in the area may relate to the local vegetation species response to the warmer season (spring season). This variability in spring temperature can easily effect the evaporative demands which is one controlling factor of vegetation growth in the area.

Appendix C: Assessment of satellite derived land surface phenology with field observations of stages of crop development.

(To be submitted to the Journal of Applied Remote Sensing)

Phenology is an integrative tool capable of addressing key questions of the impacts of climate change on ecosystem states and functions, especially when coupled with the geospatial capabilities of remote sensing. The need to develop an accurate system for monitoring and understanding land surface phenology over space and time has become urgent due to evidence of the strong relationship between climate and vegetation dynamics (Heumann et al., 2007; Zhang et al., 2003; Zhao et al., 2013). Over the last decade, land surface phenology applications have provided valuable information for vegetation change and response to climate, for species distribution and richness, as well as for wildlife habitat suitability (Fairbanks et al., 2004; Morisette et al., 2006; Sun et al., 2008; Tuanmu et al., 2010; Viña et al., 2008).

Studying the phenology of natural or managed land in a global context requires the use of remote sensing to capture large-scale spatial and temporal dynamics. What remains unclear is the accuracy of remote sensing-based data compared to the ground-observed phenology. Specifically, three challenges remain: (1) how to validate remote sensing-based land surface phenology; (2) how to compare extracted parameters with actual phenological field observations in light of the complex and heterogeneous nature of remote sensing observations; and (3) how to evaluate the overall performance of the most common land surface phenology algorithms.

To address these fundamental challenges, this work aimed at characterizing and validating the remote sensing based phenology metrics with field observation of growing season metrics. Here we used cropland field observations of cotton and corn as sources of accurate field observations of land surface phenology. The field observations considered in this research was limited to planting and harvesting dates being the two key parameters that can relate the impact of climate to growing season (White et al. 2009, Reed et al., 1996, Myneni et al. 1997). In this study, we used MODIS 250m16-day and daily records of vegetation index (VI). The VI time series data were preprocessed to remove pixels contaminated by clouds and aerosols. The resulting gaps were replaced using simple interpolation. Four algorithms: 1) Half-Maximum Method (Coops. et al., 2012; White et al., 1997) , 2) Savitzky-Golay, 3) Asymmetric Gaussian, 3) and Double Logistic methods which are part of the TIMESAT (Jonsson and Eklundh, 2004) phenology extraction software package, were used to generate phenological information (start and end of growing season, peak date of the maximum NDVI, and the maximum NDVI) for each pixel.

We found that remote sensing based phenology metrics are indeed capable of providing information for monitoring vegetation and response to climate. The different algorithms and vegetation indices used in this study were able to consistently identify the different development stages of crops, but with varying degrees of accuracy depending on the thresholds used and data smoothing methods and parameters. The results suggested: (1) the Half-Maximum algorithm always detects the start of growing season late compared to Gaussian, Double-Logistic, and Savitzky-Golay. (2) the Savitzky-Golay estimated the start of growing season earlier than other algorithms (Gaussian and Logistic). The difference in terms of days can vary between 1 to 8 days depending on the thresholds used. (3) The Half-Maximum algorithm detects the end of growing season earlier compared to the Gaussian, Double-Logistic, and the Savitzky-Golay algorithms. However, The Savitzky-Golay usually identifies the end of growing season later compared to the Half-maximum, Logistic and Gaussian algorithms. We found that that the start and the end of growing season derived from daily VI are earlier than the 16-day composite VI.

Conclusions

The approaches used in these three research studies support key conclusions regarding vegetation response to droughts on the land of the Hopi Tribe and Navajo Nation. Moreover, these studies reveal that the use of remote sensing can play a fundamental role in monitoring drought and agricultural production particularly in remote areas where there is a lack of field based measurements. The first study reveals the importance of the multi-sensor vegetation index time series for detecting the long-term response of vegetation to drought. The second study shows how we can use remote sensing data to identify vegetation dynamics and associated environmental variables. The third study demonstrates how to validate and use satellite-derived land surface phenology to monitor the different stages of cropland development and the impact of the extraction algorithm selection on the results.

This research thus makes valuable contributions to the study of ecosystem response to drought at local, regional, and global scales. It also shows the value of remote sensing tools and data in support the characterization of complex phenomenon like drought and vegetation dynamic under changing climate.

In the context of climate change impacts on terrestrial ecosystem services at different spatial and temporal scales, it becomes urgent to have a strong understanding of how natural hazards, such as droughts, influence vegetation dynamics from local at regional to global scales. This research: (1) showed how the use of multi sensor seamless NDVI data (vip.arizona.edu) enabled us to successfully extend our analysis back to 1989, (2) proposed an integrated system of data/tools to monitor drought and their impacts on ecosystems, as well as to inform range management about land conditions and help identify areas where adaptive management actions could be applied, and (3) provided a viable approach for remote sensing land surface phenology validation, which can be applied at a global scale to monitor vegetation response to climate change.

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APPENDIX A: LONG-TERM VEGETATION PRODUCTIVITY RESPONSES TO DROUGHT ON THE LAND OF THE HOPI TRIBE AND NAVAJO NATION

Mohamed Abd salam El Vilaly[1,2] , Kamel Didan[1], Stuart E. Marsh[2,3] , Willem J.D. Van Leeuwen[2,3], and Michael A. Crimmins[4]

[1] Vegetation Index and Phenology Lab, Department of Electrical and Computer Engineering, [2]Office of Arid Lands Studies, [3] Arizona Remote Sensing Center, School of Natural Resources and the Environment,[4] Department of Soils, Water and Environmental Science. The University of Arizona, Tucson AZ, USA

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Author for correspondence:

Mohamed Abd salam El Vilaly

Phone: 520-271-8748

Email: abdsalam@email.arizona.edu

Abstract

For more than a decade, the Hopi Tribe and Navajo Nation have faced extensive and persistent drought conditions that have impacted vegetation communities and local water resources while exacerbating soil erosion. Moreover, these persistent droughts threaten ecosystem services, agriculture, and livestock production activities, and make this region sensitive to inter-annual climate variability and change. Recent analyses of climate and hydrological data have confirmed that the area has been going through a drier period which is threatening its socio -economic development. The objective of this research is to employ remote sensing data to monitor the ongoing drought and inform management and decision-making. A drought assessment framework was developed that integrates climate, and topographical data with land surface remote sensing time series data in order to examine the land condition of the region over the period 1989-2010. Multi-sensor Normalized Difference Vegetation Index time series data was acquired from the vegetation index and phenology project (vip.arizona.edu) from 1989 to 2010 at 5.6 km were analyzed to characterize the intra-annual changes of vegetation, seasonal phenology and inter-annual vegetation response to environmental factors. A multi-linear regression has been applied to several metrics related to vegetation phenology derived from the NDVI time series to detect potential vegetation changes and to examine the existing relationship between vegetation dynamics and rainfall. The results suggest that vegetation behavior is foremost governed by rainfall (R-square =0.74). Trend analyses confirmed that around 80 percent of pixels showed a general decline of greenness with confidence level of 95% ($p< 0.05$), while 4 percent showed a general green up. Vegetation in the area

showed a significant positive relationship in response to elevation and precipitation gradients. This correlation was more prominent at mid-elevation which could be explained by the snowmelt dynamic of the area. These results can be used to aid in monitoring and understanding the climate changes and variability impacts on vegetation productivity, ecosystem services, and water resources of the region, and to inform decision-makers and range managers at the Hopi Tribe and Navajo nation.

Keywords: drought, phenology, remote sensing, time series, vegetation dynamic, Hopi and Navajo Nation.

Introduction

Globally more than 807 droughts were recorded between 1900 and 2004 during which more than 11 million people lost their lives, more than1.8 billion people were affected, and (list in billions of dollars)in economic losses caused by droughts (Below et al., 2007; UNESCO, 2012). Due to their multiple impacts on global agricultural, hydrological, eco-environmental, and social-economical systems, droughts have been categorized the second most geographically widespread hazard after floods, according to United Nations (UNESCO, 2012). However, droughts are classified among all the natural hazards as the most devastating hazard when the number of people affected by drought is taken into consideration (Hewitt, 1997; Keshavarz et al., 2013; Obasi, 1994; Wilhite, 2000). From the 1970s to the early 2000s, the percentage of Earth's land area experiencing very severe droughts doubled, according to the National Center for Atmospheric Research (NCAR, 2005).

Degradation of natural resources has become one of the major dominating issues threating ecosystem functions in arid and semi-arid environments. Over 40% of the world's land surface, on which more than one billion people live, is considered arid and semi-arid (Bainbridge, 2012; Deichmann and Eklundh, 1991; Reynolds et al., 2003; UNDP/UNSO, 1997). Arid and semi-arid vegetation community structure, function, and pattern are always shaped by both climate and anthropogenic variables at different levels (Kaplan, 2012a). Rainfall input to dry lands is the main force driving both water and primary production (Fensholt et al., 2012; Kaplan, 2012a; Noy-Meir, 1973; Noy-Meir, 1973; Paruelo et al., 2000; Sala et al.,1988).

The Hopi Tribe and Navajo Nation are situated in the northeastern corner of Arizona with much of the land in the lower Colorado River basin. Collectively, the Hopi Tribe and Navajo Nation represent over 77,700 square km of land area. Hydroclimatic observations, albeit limited, demonstrate that the region has been suffering through an almost 15 year long drought (Crimmins et al. 2013).Winter rainfall has been below average for 11 of the past 15 years leading to a decline in range conditions, an increase in soil erosion and a reduction in surface water flows. The ranching industry in that region has been hard hit by this ongoing drought.

Droughts are common in the southwest United State (Cook et al., 2004; Gray, 2003; Griffin et al., 2013), but the recent drought conditions on the Colorado Plateau, where the Hopi Tribe and Navajo Nations are located, have emerged slowly challenging traditional drought monitoring metrics based on sparse rain gauge networks across the region. Limited hydro-climatological and ecological monitoring across the region has created a challenging environment for resource managers trying to assess current conditions and anticipate future climatic impacts at seasonal to inter-annual time scales.

Due to the complex climatic mechanisms and limited long-term temperature and precipitation monitoring sites critical for monitoring drought, classic drought monitoring indices, such as Palmer drought severity index (PDSI), the crop moisture index (Byun et al., 1999; Palmer, 1968; Shafer et al., 1982), the surface water supply index and the standardized precipitation index (SPI) are challenging to interpret with respect to potential drought impacts at different time-scales and might not be able to capture spatial patterns in potential drought impacts across the landscape. In addition, several studies have reported common weaknesses related to the use of these indices to monitor drought because they rely on monthly time scale and are not accurate sufficient in capturing the beginning, end, and accumulated stress of drought. (Blenkinsop et al., 2007; Byun et al., 1999; Mu et al.,2013; Sivakuma et al., 2010).

Because of these challenges we proposed using complementary remote sensing (RS) indices to capture and assess spatial patterns in the impact of the recent droughts on vegetation productivity across vegetation communities and elevation gradients within the region. Remote sensing provides for fast and efficient monitoring and tracking of land surface process on different scales from local to global using (Anyamba et al., 2005; Bastiaanssen et al., 1999; Papes et al., 2012; Pocas et al., 2013; Schmugge et al., 2002).

Various biophysical variables derived from satellite data, such as the Normalized Difference Vegetation index (NDVI) and land surface temperature (LST), Leaf Area Index (LAI) among others, have become central to environmental assessments when environmental dynamics occur at different scales from instant to long-term and from local to regional (Cai and Sharma, 2010; Justice et al., 1985; Karnieli , 2003; Li et al., 2013; Siren et al., 2013; White et al., 2006).

Productivity of natural and agricultural lands has been widely used as an indicator of vegetation status (Gamon et al., 2013; Peng et al., 2013; Wessels et al., 2007). The timing, magnitude and spatial patterns of vegetation dynamic from inter-seasonal to decadal scales are highly influenced by both short-term climate variability and long-term climate change. This vegetation dynamic at different spatial and temporal scales can be studied using various biophysical variables derived from remote sensing data which can quantify total biomass and characterize the unique seasonal and spectral reflectance of canopy structures and functions as well as to capture spatial and temporal variation (Horion et al., 2012; Mark et al., 1999; Ryu et al., 2010).

Remote sensing based phenology studies, including phenological states (Gonsamo et al., 2012; Ivits et al., 2013; van Leeuwen et al., 2010), photosynthetic, or biomass estimations provide critical information regarding ecosystem responses to climate variability (Melaas et al., 2013b) and play an important input for climate–carbon cycle modeling (Colditz et al., 2008). This entails the analysis of NDVI time series to derive various phenological metrics (e.g., timing of start, peak, length of the growing season, amounts of greenness).

In global change studies, remotely sensed phenological data have provided detailed information about the existing relationship between changes in vegetation cycles (e.g., start and end of growing season and productivity) and climate change (Brown et al., 2012; Cong N. et al., 2013; Ivits E.et al., 2013; Myneni et al., 1997; Parmesan et al., 2003) as well as disturbances and stressors like fires (Lozano F.J.et al., 2012; Tan et al., 2013; van Leeuwen, 2008) and droughts (Hwang et al., 2008; Saatchi et al., 2013; Tucker, 1979).

The Normalized vegetation index (NDVI), based on the ratio of the sum and the difference of NIR (near-infrared) and red reflectance (Tucker, 1979; Wilkie and Finn, 1996) derived from different remote sensing sensors such as the Advanced Very High

Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat. The NDVI in combination with several biophysical indicators has become a useful tool to monitor regional- or global-scale phenological cycles and changes (Dall'Olmo and Karnieli, 2002; Fisher et al., 2007; Stellmes et al., 2013). Nevertheless, the need for ground validation of such remote sensing assessments related to vegetation dynamics in responses to climate and human disturbances is still emphasized by the remote sensing community (He et al., 2012; Samalens et al., 2012).

Seasonal patterns of vegetation activity derived from long-term satellite data are widely used to understand vegetation dynamics, monitor land cover change, and track the impact of climate change and inter-annual variability on vegetation productivity (Bachoo et al., 2007; Villa et al., 2012).Vegetation is one of the most fundamental features of arid and semi-arid ecosystems (Kaplan, 2012b). Precipitation is an important factor for ecosystem processes in arid landscapes due to its major impacts on vegetation productivity (Pennington and Collins, 2007).

Change in vegetation productivity measured as the above-ground net primary production (ANPP), as result of change in precipitation patterns are an important component in the feedback between climate-ecosystem-hydrology, which strongly influence carbon, water, and energy allocation at the land surface (Troch et al., 2009). One of the most used techniques to assess changes in vegetation productivity as result of seasonal and annual climate patterns is trend analyses (Michaud et al., 2012; J. Peng et al., 2012). Rain Use Efficiency (RUE) has been widely used to measure vegetation response to climate change and variability (Huxman et al., 2004; Yang et al., 2010). RUE is one of the most used indicators to study vegetation responses to climate variability in arid and semi-arid area. Both trend and RUE were used to assess vegetation productivity changes as result to the ongoing drought in Hopi Tribe and Navajo nation.

The overall goals of this study are to develop a better understanding of the current status and response of vegetation to droughts using RS data and statistical techniques and tools to inform range management and decision-making across the area about land conditions, as well as to help identify where to apply and orient adaptive management actions. This work aims at developing a framework for drought monitoring and assessment, integrating land cover, climate, and topographical data with land surface remote sensing time series data. The main objectives of this framework are (1) to evaluate the magnitude of inter-annual variability in vegetation productivity and then quantify its temporal variability relative to rainfall variation and elevation gradients, (2) to detect any long-term vegetation changes and trends in the NDVI related productivity parameters, and (3) to investigate the relationship between these changes and trends in NDVI and rainfall. More specifically:

- How did seasonal and inter-annual vegetation productivity vary on the lands of the Hopi tribe and Navajo nation from 1989 to 2010?
- How can trend analysis of vegetation productivity derived from remote sensing data provide a common understanding of the current status of drought in this region?

- How can the derived information from trend analysis be useful to monitor droughts and inform management and decision-making?

Data and Method

2.1 Study Area

The Hopi Tribe and Navajo Nation of Arizona are situated in the northeastern corner of the state in the lower Colorado River basin. Collectively, the Hopi Tribe and Navajo Nation cover over 77,700 square kilometers (Fig. 1). The area is characterized by cold winters and very hot summers. The annual rainfall is less than 10 inches and the average annual temperature vary between 40ºF and 50ºF. Climatic patterns vary from south to north across the area. The seasonal amount of rainfall varies along elevation gradients and is low and moderate in the early winter, increases in February and March, and then decreasing quickly in April. May through June is a very dry period in the area (Grahame, John D. and Thomas D. Sisk, ed, 2002). Vegetation cover varies throughout the area as a result of differences in rainfall and average temperature, soil types, elevations, and land management.

2.2 Remote Sensing data

- **NDVI Time Series, Climate, Topographic Data, and Vegetation Types**

Multi-sensor Normalized Difference Vegetation Index time series data were acquired from the vegetation index and phenology project (vip.arizona.edu) from 1989 to 2010. This sensor independent and continuous NDVI time series derived from AVHRR (1981-1999), SPOT (1998-2002) and MODIS (2000-2010) is used in this study (Didan et al., 2010). More details about the datasets can be found on the Vegetation Index and Phenology Laboratory website: (http://vip.arizona.edu/viplab_data_explorer.php). We acquired and analyzed the 15-day composites, at 5.6 km, to characterize the intra-annual changes of vegetation productivity and inter-annual vegetation responses to rainfall along vegetation types.

Climate data came from the Oregon State University's Parameter-elevation Regressions on Independent Slopes Model (PRISM) (Di-Luzio et al., 2008) dataset, at 4 km spatial and monthly temporal resolution. Average seasonal monthly rainfall data were generated for the period 1989-2011 and the long term (inter-annual) average of rainfall was computed over the period. All PRISM data were resampled to 5.6 km to match the NDVI pixel size using Arcmap software.

Topographic and elevation data are based on the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) with a spatial resolution of 30 m (ASTER Validation Team, 2009). Elevations range between 821-3771 meters (Fig 2a) corresponding to ecological zones with low to high vegetation cover. The pixel size of the elevation data was resampled to 5.6 km to match the NDVI time series data. Arcmap software was used to resample the elevation data using majority as the resampling type.

Land cover types were extracted from the 2005 North American Land Cover at 250 m spatial resolution database produced by the North American Land Change Monitoring System (NALCMS) project (NALCMS, 2005). It is important to note that the land cover of the region is fairly stable due to f natural and anthropogenic changes. According to this classification, the area is characterized by 11 diverse land cover types (Fig 2b), including: shrubland which represents the primary land cover type in the area. The second important land cover type is needleleaf forest at higher elevation.

2.3 Methodology

The main goal of this research is to analyze and investigate vegetation responses to drought across the Hopi Tribe and Navajo Nation areas during the last 22 years, from 1989 to 2012. The length of the study period was mainly controlled by the long term Difference Vegetation Index (NDVI) at 5.6km (available from1981 to 2010). The aim of this research is to characterize the extent to which drought impacts have influenced or shaped the spatial temporal trends in land surface phenology related to productivity. We have used the 15-day composite multi-sensor Normalized Difference Vegetation Index (NDVI) time series from 1989 to 2010. This biophysical index has been widely used to characterize vegetation dynamics at different scales: from local, regional, to continental scales (Ahmad, 2013; Pocas et al., 2013; Tucker, 1979; White et al., 2009).

To understand the dynamics and the main forces driving the ecosystem process of the region, a framework consisting of four steps was developed. The first step was to derive the annual NDVI related productivity variables: (1) the annual cumulative NDVI, (2) maximum annual NDVI, (3) annual relative NDVI (difference between annual Max and Min NDVI). The second step was to quantify the vegetation productivity along elevation gradients as well as within each vegetation community by looking at the long term average of each NDVI related productivity variables and examining the relationship between the long term average NDVI and the long-term average of precipitation during the last 22 years. In the third step we investigated the spatial and temporal trends in vegetation productivity across the region. And finally, in step four trend analysis of Rain-Use Efficiency (RUE) was conducted in order to assess vegetation capacity to transfer water and nutrients to biomass during the last 22 years.

To assess rainfall effects on vegetation productivity, we computed the RUE index which is the ratio between the annual cumulative NDVI and the total annual rainfall for each year. The Rain Use Efficiency index (RUE) measures the capacity of vegetation to efficiently transform water and nutrients to biomass, has been widely used to investigate the relationship between change in vegetation productivity and rainfall (Huang L. et al., 2013; Kaplan, 2012a; LeHouerou, 1984).

- **Deriving NDVI related productivity parameters**

Phenological phases derived from remotely sensed time series vegetation indices assume that the time series signal follows seasonal and annual vegetation cycles (Huete et al., 2006; Jonsson et al., 2002; Melaas et al., 2013a; Sakamoto etal., 2013; Zhang et al., 2003), which requires spurious noise be minimized during data filtering and compositing. The simplest algorithm used for the derivation of phenological events is based on the threshold technique, which assumes that phenological events start when the vegetation index (VI) crosses a preset threshold value (Lloyd, 1990; Reed et al., 1994).

Several software tools are available to extract phenologically key events (White et al., 2010) from vegetation time series data, such as the Time Series Generator (TiSeG) (Colditz et al.,2008), the Time Series Product Tool (TSPT) (McKellip et al., 2008), TIMESAT (Jonsson et al., 2004), and the Phenological Parameter Estimation Tool (PPET) (Ross et al., 2008). In general, these tools allow for the extraction of the phenological events, but most of them suffer from limitations when there is more than one unique growing season (Arlete et al., 2011).

In order to avoid these issues, using our framework we extracted three annual NDVI related productivity parameters: the annual cumulative NDVI (∑NDVI, a proxy of Gross/Net Primary Production, GPP/NPP), maximum annual NDVI, and annual relative NDVI amplitude or annual relative (difference between Max and Min annual NDVI). These variables (Fig.2) were extracted during the snow free period from March to November of each year in order to minimize the impact of snow on NDVI values (Delbart et al., 2006; Shi et al., 2008; Zhang et al., 2004).

The annual cumulative NDVI is an effective proxy of biomass production and is integrative descriptor of ecosystem functioning that has been used extensively to characterize vegetation dynamics (An-Price et al., 2013; Boschetti et al., 2013). Empirical models and biomass harvesting studies have shown a strong correlation between the integrated NDVI and biomass productivity; (Boschetti et al., 2013; Ouyang et al., 2012; Parviainen et al., 2010; Pei et al. 2013; Prince.S.D., 1991; Sala, 2000). Many studies have used these bio-variables to capture changes in ecosystem functioning across the globe (Alcaraz et al., 2006; An-Price et al., 1997; Weiss et al., 2004) .

- **Long-term trends in vegetation productivity**

Many studies have used NDVI trends at different temporal and spatial scales using parametric and non-parametric approaches to assess ecological responses to climate change, study phenological changes, crop status, and land cover change (Fensholt et al., 2012; Wright et al., 2012; Yin et al., 2012). The most common approach to detect changes in vegetation productivity is the use of the ordinary least-squares (OLS) linear regression model (Liu et al., 2012; Turasie, 2012; Wang, 2012). This statistical technique is widely used for evaluating vegetation trends (Liang et al., 2012; Ma & Frank, 2006) . In this study, the general trend in vegetation change was determined based on the time series analysis of the different annual NDVI related productivity.

In the model time (22 years) is the independent variable; while the dependent variables were the annual NDVI related productivity parameters. The model helps detect the trends over time of each productivity parameter. Using equation 1 defined by:

$$Y = Ax + B + \varepsilon \qquad (1)$$

Where X is the independent variables (time), Y is the modeled change variables (dependent variables), A is the slope, B represents the intercept, and ε error in the model.

To assess the inter-annual trends in vegetation productivity, we analyzed the slopes and strength of the correlation coefficients of the regression model considering only significant change ($p < 0.05$).

- **Rain-Use Efficiency (RUE)**

Rain-Use efficiency (RUE) is a key indicator of the state of vegetation cover function particularly in semiarid ecosystems (LeHouerou, 1984; Yang Y. et al., 2010). RUE is the ratio of aboveground net primary production (ANPP) to annual rainfall and is often expressed as the amount of dry land plant materiel production on 1 ha in 1yr per 1 mm of rainfall. Variations in RUE can be explained by difference in annual rainfall and vegetation productivity (Huxman et al., 2004).

Spatiotemporal variations of RUE can be used to assess ecosystem dynamics and degradation (Kaplan, 2012a; Kaplan, 2012b; Troch et al., 2009; Varnamkhasti et al., 1995). In this study we calculated the RUE for each year in order to examine its spatiotemporal patterns; we also used the $\sum$NDVI as a proxy of ANPP (McBride et al., 2011). We then conducted a regression analysis of RUE to investigate the relation between inter-annual change in vegetation productivity and rainfall. This allows separating between changes related to climate variability and those related by other sources of disturbance (e.g. fire, management,).

Results

3.1 Vegetation Productivity

The vegetation dynamics were characterized by the long-term (inter-annual) average NDVI related productivity-parameters: ∑NDVI, maximum NDVI, and the relative NDVI. Figure 4 shows the spatial distribution of the long-term average of ∑NDVI, maximum, NDVI, and the relative NDVI for the period 1989-2010 across the area. These results confirm that vegetation productivity increases with elevations as expected. This can be explained by the spatial patterns of rainfall along elevation gradients which is can be related to more water balance, cooler temperature and lower evapotranspiration. Any deviations from this expected relationship would indicate unfavorable conditions, such as fires, soil degradation, land management practices and other factors. The moderating effect of rainfall along mid and high elevations (2300- 3771m) is very strong on ∑NDVI and maximum NDVI (see Fig 4a and 4b). High elevation areas are dominated by needle leaf forest (ponderosa pine), while shrubland and grassland dominate the lower elevation areas.

As expected, the vegetation productivity is highly correlated with rainfall gradients, which are in turn also highly correlated with elevation gradients (increase in rainfall with increased elevation). This is evident in the direct correspondence between the spatial distribution of annual ∑NDVI (Fig 4a), the annual maximum NDVI (Fig 4b), and annual relative NDVI (Fig 4c).

3.2 Spatial correlation between vegetation productivity and rainfall

A spatial linear regression model was developed to study the relationship between the long term average NDVI related productivity parameters and the long term average rainfall in order to characterize the productivity variation along elevation gradients. This analysis looked at the spatial inter-annual variations in the regression parameters by examining the strength (p-value < 0.05) of the correlation coefficients, (R^2), and the spatial variation of the model residuals.

This allowed evaluating the model performance and at which level vegetation productivity is controlled by rainfall distribution across the area. The residuals analysis of the observed NDVI related productivity and the modeled NDVI related productivity by regression model reveal the areas where the correlation is weak and/or where the changes in vegetation productivity are controlled by more factors than rainfall. A strong correlation was observed with R^2 values between 0.79 – 0.86 for ∑NDVI, Max-NDVI, and relative-NDVI versus rainfall. Figure 5d, 5e and 5f display the spatial distribution of residuals resulting from the regression model.

Correlation coefficient between the long term average ∑NVID and the long term average rainfall was quite high ($R^2 = 0.79$) indicating, as expected, a strong positive correlation (Fig 5a). 91.78 % of the area shows a significant relationship between the long term average ∑NVID and the long term average rainfall, while 8.22 % of the area shows no significant relationship. These results confirm the strong dependency of productivity on rainfall in the area particularly among shrublands and grassland areas.

The residuals vary between -164 and 88 (VI units) over the study area at the 95 % confidence level. The range between [-164 to -31] (VI unit) corresponds to overestimation, while [32 to 88] indicates underestimation. Values between [-31 to 31] correspond to the 95% confidence level and a strong correlation. The residuals map reveals the areas where the correlation is significant or non-significant, or where the vegetation productivity is controlled by more factors than rainfall alone. It is important to note that high residuals with no significant relationship between the long term average ∑NDVI-rainfall were found at middle and high elevations where the temperate needleleaf forest is the most dominant vegetation type. This indicates that rainfall input in vegetation productivity is not the most force driving among this vegetation types. This independence from rainfall needs to be investigated in order to know which environmental variables control vegetation productivity along this vegetation type. It is important to explore variability in snow cover in the area in order to see how that has been impacting vegetation indices over time in middle and high elevations.

The relationship between the long term average rainfall and the long term average Max-NDVI showed a strong correlation coefficient (R^2 = 0.83) at the 95 % confidence level (Fig 5b). It is important to note that 88.53 % of the entire area including Hopi Tribe and Navajo Nation area show a significant relationship with the long term average rainfall, while only 11.47 % of the area doesn't show a significant relationship with the long term average rainfall. Figure 5e displays the spatial variation in residuals resulting from the spatial relationship between the long term average Max-NDVI and rainfall. The overall residuals of the regression model range between -0.66 and 0.39 (VI units) and show that the range between [-0.66 to -0.13] indicate the overestimated relationship, while [0.13 to 0.39] corresponds to the area where the relationship is underestimated. Values range between [-0.12 to 0.12] refers to a significant relationship at the 95 % confidence level.

As expected, not all pixels showed a significant spatial relationship between these variables. The non-significant relationship between the long term average Max-NDVI and the long term average rainfall is found at middle and high elevations where the needleleaf forest is the most dominant vegetation type. The significant correlation between Max-NDVI and rainfall was observed at low elevations. This results show that rainfall has a strong affect on vegetation productivity in these areas where grasslands and shrublands are the dominant vegetation types.

The R^2 of the regression model between the long term average rainfall and the long term average relative NDVI was 0.86 with 95 % confidence level. 93.09 % of the study area show a significant relationship between the long term average relative NDVI and the long term average rainfall. Only 6.91 % in the study area indicate no significant relationship between the long term averages relative NDVI and the long term average rainfall. Figure 5f displays the spatial distribution of the residuals. Values range between [-0.194 to -0.047] cover the area in which the spatial relationship was overestimated, the range between [-0.048 to 0.458] refers to an underestimated relationship. Values between [-0.046 to 0.046] correspond to the 95 % confidence level and a significant correlation. The results indicate that rainfall is a dominant factor in relative NDVI among shrublands and grasslands and that relative NDVI among needleleaf forest is mot controlled by rainfall factor.

These results confirm that rainfall in low elevations, where shrublands and grasslands are the dominant vegetation types, play an important role in vegetation productivity, while this finding is not quite confirmed among needleleaf forest at high elevations.

3.3 Inter-annual variability by vegetation type

In order to separate the specific response of each land-cover type to the long term average rainfall we developed linear regression models for each of the three major land cover types: grassland, shrubland, and needle-leaf forest. The results show a significant positive correlation between the long term averages NDVI related productivity-parameters and the long term average rainfall across all three biome groups (table 1).

The coefficient of correlation between the long-term average rainfall and the long-term average ∑NDVI was 0.83 for grass, 0.73 for shrub, and 0.26 for forest. The coefficient of correlation between MaxNDVI and rainfall was 0.88 for grass, 0.79 for shrub, and 0.45 for forest, while the coefficient of correlation between relative NDVI and rainfall was 0.92 for grass, 0.81 for shrub, and 0.39 for forest. These results confirm that vegetation productivity is for the most part controlled by rainfall, although weaker at higher elevations (smaller R^2). The results suggest that in high elevations where needle-leaf forest is the most dominated vegetation type, a rainfall does not show a strong effect on vegetation productivity or no longer plays a major role in NDVI related vegetation productivity.

3.4 Evaluating spatiotemporal trends in vegetation productivity

To detect any trends or changes in NDVI-related productivity over the study period, a per-pixel linear regression was developed. The results of this per-pixel linear trend analyses are shown in Table 2 and Figure 6. The slope of the regression serves as an indicator of the direction and strength of change over time. Only the slope and coefficient of correlation of the significant trends with confidence 95 % ($p < 0.05$) level were considered.

In general, significant changes in vegetation productivity were observed (Table 2 and Fig.6). For instance, around 60.13 % of the area shows a significant decrease in ∑NDVI, while 36 % only shows no significant change. Most of the decrease in ∑NDVI related vegetation productivity corresponded to grassland and shrubland areas along low elevations. While, most observed increase in ∑NDVI (3.87%) corresponded to the middle-elevation areas, which dominated by needle leaf. Assuming droughts are the main driver of these reductions, the observed and opposite increase at higher elevation can be linked to snow melt dynamics, which may be providing additional soil moisture during the drier periods.

3.4.1 Spatiotemporal trends in ∑NDVI

Using these spatiotemporal linear regression models, we evaluated the trend over time and space by looking at the strength of the correlation coefficients, and the slope of the regression. These regression parameters capture the direction and strength of change in vegetation productivity. We only considered the pixels with significant changes at the

95% confidence level. The remaining pixels with insignificant change are colored gray in figure 7. The spatial distribution of the slope and the coefficient of correlation for ∑NDVI are shown in figure 7a and 7b.

64% of the pixels show significant change, compared to 36 % with insignificant changes. Only 3.87% of the area showed slight increase in ∑NDVI related productivity, mainly at higher elevations. A strong decrease in vegetation productivity (from -7 to -2 VI units) is mainly observed between 1800 and 2000 m in elevation, which corresponds to areas dominated by ponderosa pine forests with some area in low elevation dominated by grasslands. The correlation coefficient (R^2), Fig. 7b, varied between 0.18 and 0.8, with high values (from 0.5 to 0.84) mainly at low elevations where grasslands and shrublands are the main vegetation types. There are few forest pixels, at high elevations, which show fairly high correlation coefficients (0.6 to 0.8).

The results indicate that vegetation productivity(∑NDVI) among the most dominant vegetation types, grasslands, shrublands, and ponderosa pine forests, are experiencing decreases over the last 22 years as results of drought impacts in the area. It is important to note that some areas covered by ponderosa pine forests showed increases in productivity as result of the recent long-term drought. This might be linked to temperature fluctuations and snow dynamics in the area.

3.4.2 Spatiotemporal trends in maximum NDVI

The overall trend in the inter-annual maximum NDVI, indicated a significant changes (Fig. 8), approximately 50.04 % of the study area showed a significant decrease versus only 2.4 % significant increase and 47.56 % had insignificant changes in maximum NDVI related productivity (Fig. 8a). The significant decreases in the inter-annual maximum NDVI were observed across all vegetation types and elevation gradients.

The range [-327 to -100 VI units *10000] corresponds to the area that shows a significant decrease in vegetation productivity. These areas are mostly located in mid-elevations and are forested. The range between [-99 to 0] corresponding to areas covered by shrublands and grasslands. Severe decreases in the inter-annual maximum NDVI related to vegetation productivity were found at middle elevations within forested areas.

Figure 8b shows the spatial distribution of the coefficient of correlation for every pixel resulting from the regression model with the spatial patterns following the general elevation gradients. The R^2 increases from high to low elevations. The areas with a strong decrease in vegetation productivity related to maximum NDVI corresponded to areas where the regression coefficient varies between 0.40 and 0.57.

3.4.3 Spatiotemporal trends in relative NDVI

Figure 9 shows the spatial distribution of the temporal trend results in the inter-annual relative NDVI. 32.93 % of the area showed significant change in vegetation productivity related to the relative NDVI, of those only 2 % showed significant increase along mostly washes and stream areas. The remaining 30.93 % showed mostly a decrease. This further confirms that a large portion of the region is experiencing significant vegetation productivity decline, with small pockets of significant increase. It is important to note that most of the significant changes were observed over the shrubland and forested areas.

Figure 8b displays the spatial distribution of the coefficient of correlation over the areas, revealing that the coefficient of correlation increases with elevation. High R^2 was observed in middle-elevation where the inter-annual relative NDVI shows a significant decline over the last 22 years.

3.5 Factors Controlling Vegetation Changes

Figure 9 shows the spatial distribution of the results obtained from the RUE temporal trend analysis with a confidence level of 95 % ($p<0.05$). The aim here is to identify areas where RUE drops over time due to decreased soil moisture retention or increased evaporation. Attention was placed on pixels showing significant negative trends. RUE showed strong correspondence with the areas of negative regression slopes and vegetation decreases in the ∑NDVI (Fig.7a). 21% of the area showed significant changes in RUE, with 19 % negative. Only 2 % of the area exhibited a positive trend in RUE. The rest of the area, 79% exhibited insignificant changes over the considered period. The areas with an increasing RUE trend showed strong correspondence (97 %) with areas that showed declines in the inter-annual ∑NDVI. Most of the positive trends are found in the southwestern part of the area at higher elevations, which is dominated by ponderosa pine forests. This could be explained by the rooting depth of these trees and their ability to access and make efficient use of the limited soil water reserves during droughts. These negative trends are mainly located at the northern part of the area and along lower elevations. It is also important to note that these negative trends concern for the most part the grasslands and shrublands of the area. The decrease in RUE along these areas may be related to the limited rooting depth and poor soil moisture retention.

The RUE-based analysis did not show any widespread or significant changes, which seems to support the earlier finding that rainfall patterns only explained 21% of the changes in vegetation productivity.

Conclusions

The present study aimed at developing and presenting an understanding of the impact of the recent and still ongoing droughts on vegetation productivity on the lands of the Hopi Tribe and Navajo Nation. This work looked at the major factors that may be responsible for the region's ecosystems variability at inter-annual to decadal scales. Our framework illustrated how remote sensing data, especially the multi-sensor NDVI records used in this study, and simple statistical tools can be used to assess drought effects on vegetation productivity and to inform range management about land conditions, as well as to help identify where to apply and orient adaptive management actions.

The Hopi Tribe and Navajo Nation region is considered arid and semi-arid making them vulnerable to climate change and human pressure (grazing, fires, and land use change). This work looked at the inter-annual variation of vegetation productivity over the last 22 years and how this productivity changed with rainfall, elevation gradients, and cover types. The results show that the spatial distribution of the vegetation productivity roughly corresponds to the mean inter-annual rainfall at low and middle elevations, but at higher elevations productivity is not responsive to rainfall.

At the region's scale, the correlation between the long-term (inter-annual) average-NDVI related productivity-parameters, and rainfall varies between 0.79 and 0.89 (Fig.5). As expected, for arid areas, rainfall is the most fundamental factor for vegetation productivity especially for the areas dominated by grassland and shrubland (Table 1). In contrast, forested areas of higher elevation exhibited less dependency on rainfall. This lower dependency can be explained by many factors related to rooting depth of trees that enables accessing deeper soil moisture during the dry periods and the intrinsic resiliency of trees to precipitation reduction due to their ability to store water.

Over the last 22 years the region's vegetation experienced significant reduction in productivity, particularly in the Navajo nation where around 74 % of the area revealed significant decrease in ∑NDVI ($p<0.05$). The decreasing trends of all NDVI related vegetation productivity parameters were mostly observed over the shrubland dominated areas with the highest decrease in mid- elevation. Forested areas at higher elevations were less prone to rainfall and subsequently droughts, which can be explained by factors related to the rooting depth, size, and resilience of these large trees. Rooting depth determines a tree's ability to access deeper soil moisture during dry periods, and thus influences its intrinsic resiliency to precipitation reduction through its capacity to store water.

The RUE-based analysis did not show any widespread or significant changes, which support the finding that rainfall patterns only explained 21% of the observed changes in vegetation productivity.

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Tables

Table 1: Correlation coefficients for the main land cover types and different NDVI-based productivity parameters vs. rainfall.

	Grassland	**Shrubland**	**Forest**
∑NDVI	0.83	0.73	0.26
Max-NDVI	0.88	0.79	0.45
Relative-NDVI	0.92	0.81	0.39

Table2: Percent of area with significant and non-significant slopes for the annual NDVI related vegetation productivity during the last 22 years.

Vegetation productivity	Negative Change	Positive Changes	No-Significant Change
	Percent	Percent	Percent
∑NDVI	60.13	3.87	36.00
Max-NDVI	50.04	2.40	47.56
Relative-NDVI	30.93	2.00	67.07

Figures

Figure 1: Map of study area showing the distribution of weather station sites

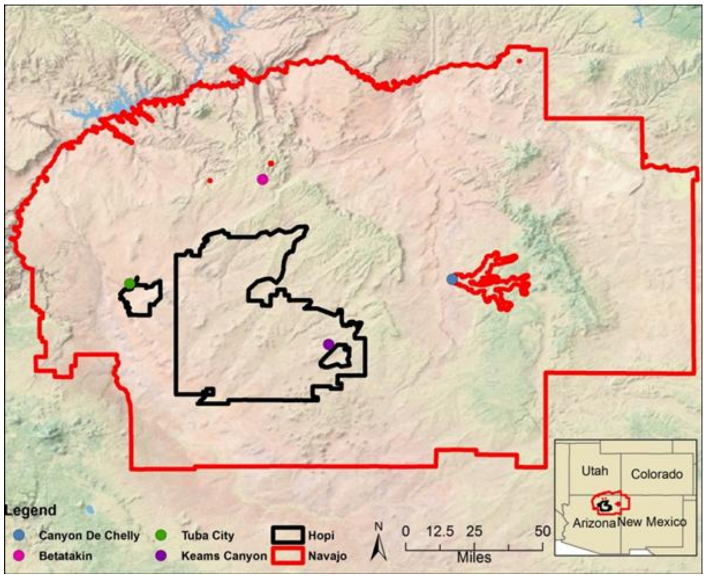


Figure 2: (a) map of elevation gradients across the area, and (b) map of the dominant vegetation types (2005 North American Land Cover at 250 m spatial resolution database).

A

B

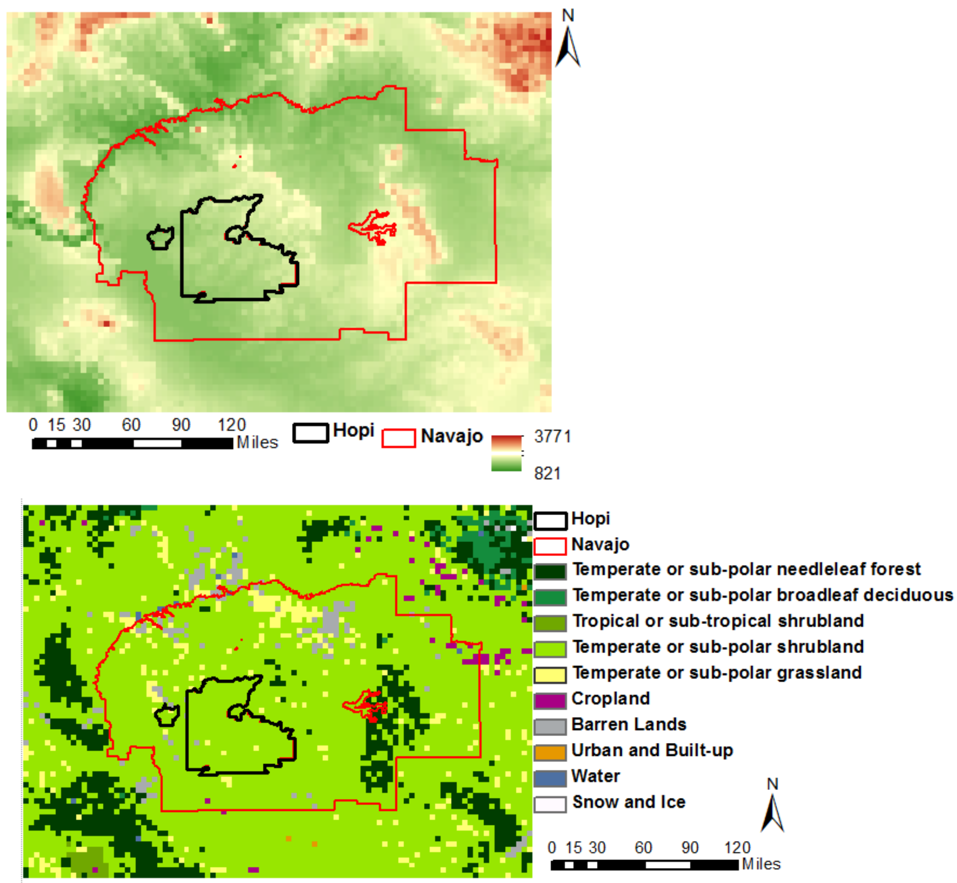


Figure 3: Conceptual model showing the NDVI based vegetation productivity parameters generated in this study. The maximum, relative NDVI, and (∑NDVI values were extracted for each pixel. The annual cumulative NDVI (∑NDVI) was computed by integrating the area under the curve for each pixel.

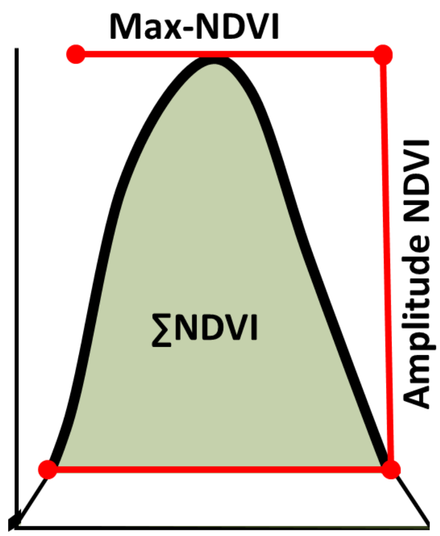


Figure 4: (a) the long term (inter-annual) average ∑NDVI (VI unit), (b) the long term (inter-annual) average Maximum NDVI, and (c) the long term (inter-annual) average NDVI amplitude (difference between Max and Min NDVI) from 1989 to 2010

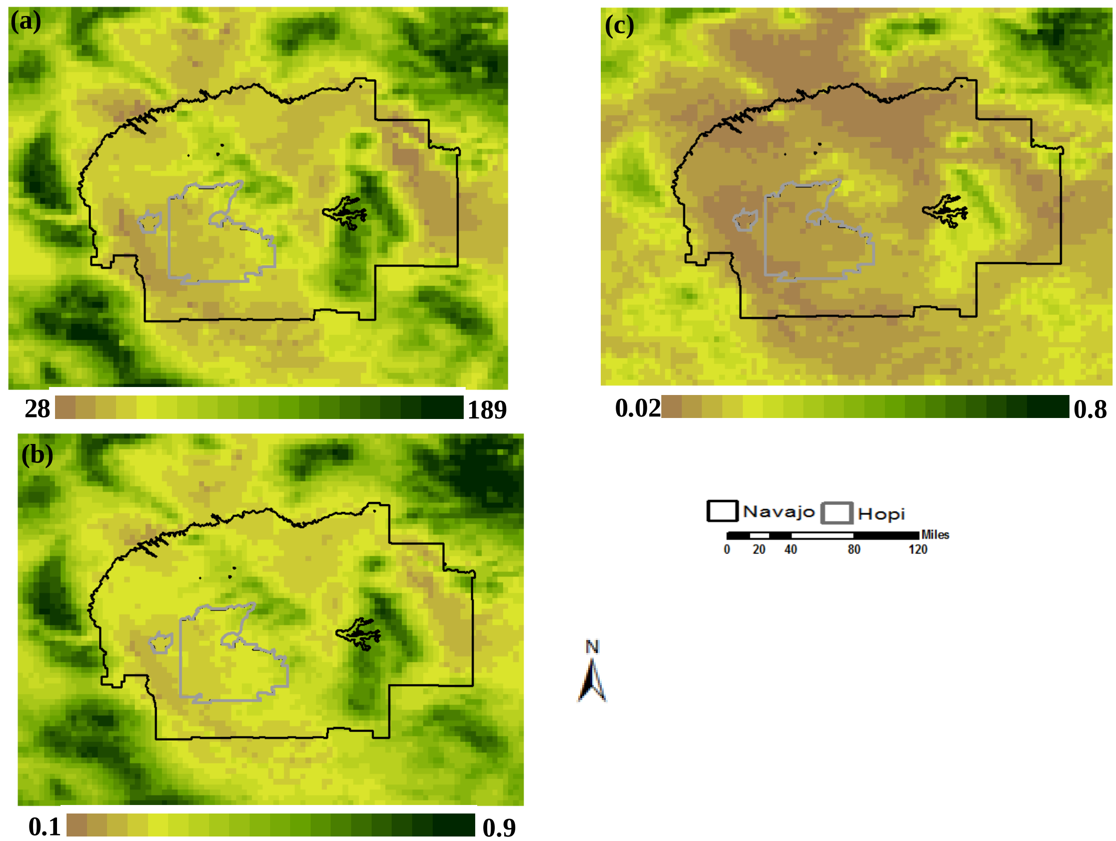


Figure 5: Relationship between the long-term average rainfall and the long-term average NDVI related productivity variables across the area for (a) ∑NDVI-Rainfall, (b) for MaxNDVI-Rainfall, (c) for NDVI amplitude -Rainfall. Residual map resulting from the regression model for (d) ∑NDVI-Rainfall, (e) for MaxNDVI-Rainfall, (f) for NDVI amplitude (relative) -Rainfall.

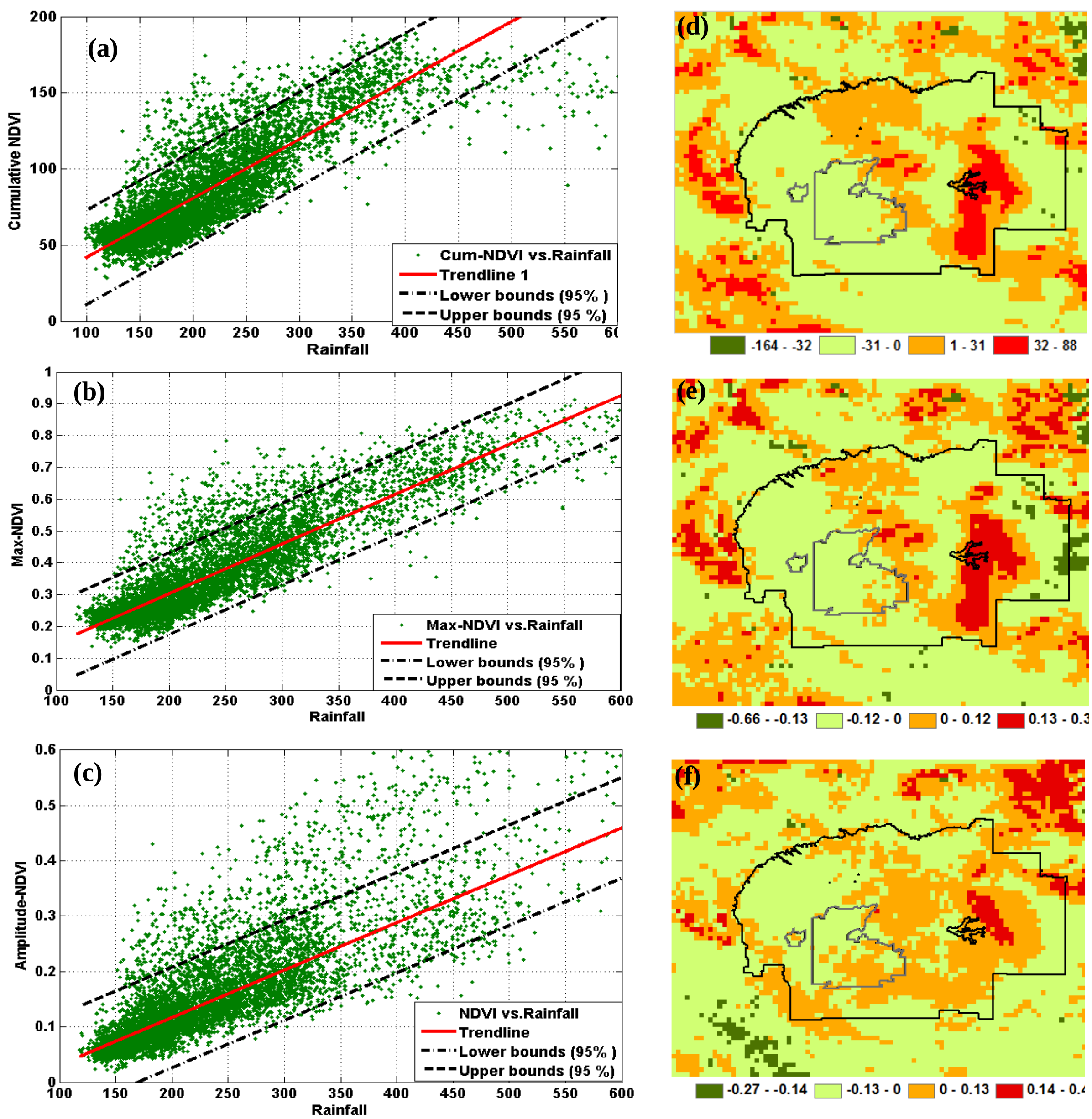


Figure 6: Percent areas with a significant positive, negative, and unchanged vegetation productivity resulting from trend analyses of the time series of NDVI related vegetation productivity over the last 22 years.

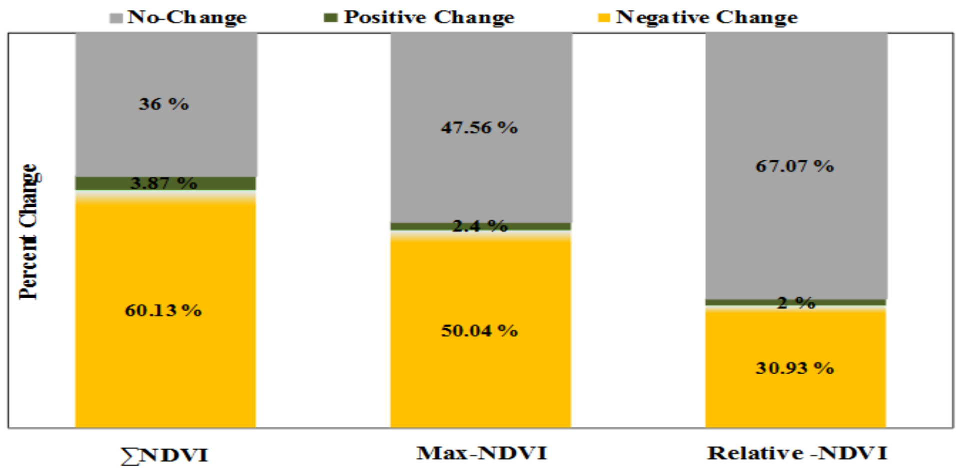


Figure 7: Spatial patterns of (a) the slope of the significant ∑NDVI temporal trends and (b) coefficient of correlation (1989-2010) at 95% confidence interval (p<0.05).

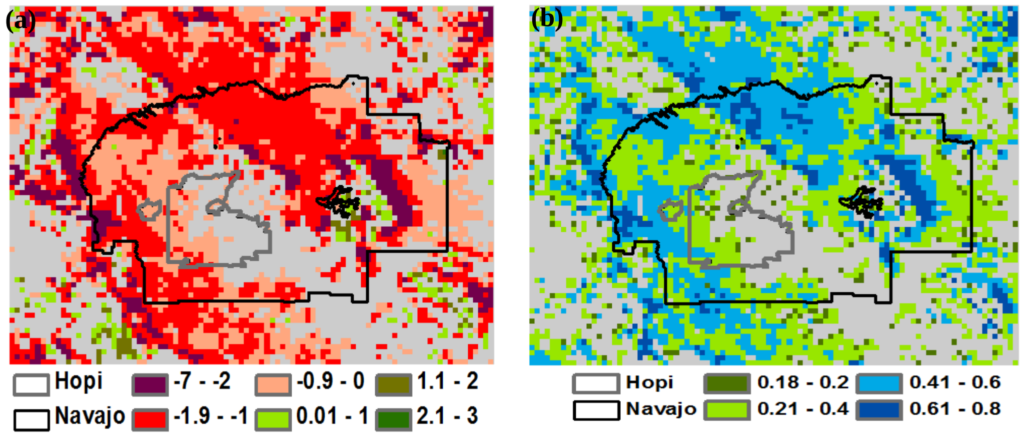


Figure 8: (a) linear slope of maximum NDVII over time (22 years) for the area and (b) the coefficient of correlation over the study period

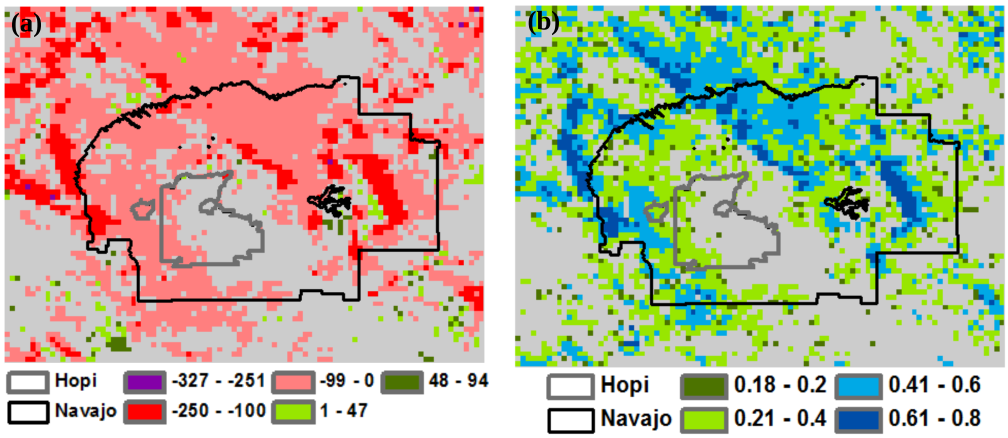


Figure 8: Spatial patterns of (a) the linear slope of temporal trends in the annual NDVI amplitude and (b) the coefficient of correlation over the same period.

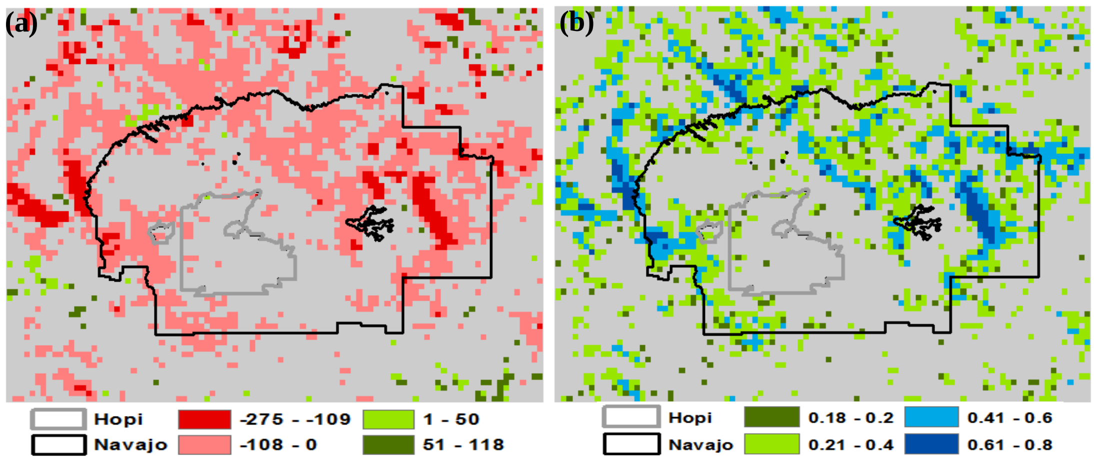
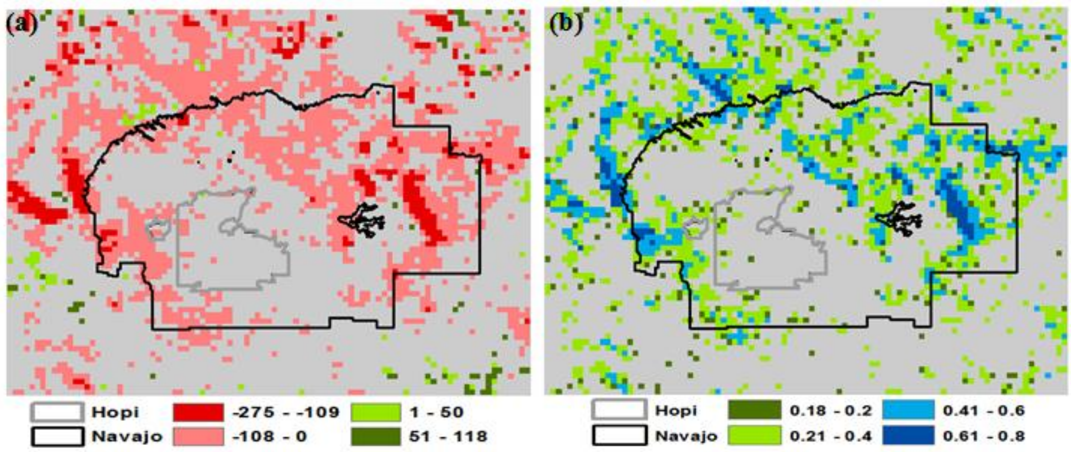


Figure 9: (a) Linear slope of RUE over the considered period 1989-2010 (b) linear slope of ∑NDVI for the same period



APPENDIX B: CHARACTERIZE THE ENVIRONMENTAL AND CLIMATIC DRIVERS OF VEGETATION PRODUCTIVITY ON THE LANDS OF THE HOPI TRIBE AND NAVAJO NATION

Mohamed Abd salam El Vilaly[1,2] , Kamel Didan[1], Stuart E. Marsh[2,3] , Willem J.D. Van Leeuwen[2,3], and Michael A. Crimmins[4]

[1] Vegetation Index and Phenology Lab, Department of Electrical and Computer Engineering, [2]Office of Arid Lands Studies, [3] Arizona Remote Sensing Center, School of Natural Resources and the Environment,[4] Department of Soils, Water and Environmental Science. The University of Arizona, Tucson AZ, USA

This article will be submitted to the Remote Sensing

Author for correspondence:

Mohamed Abd salam El Vilaly

Phone: 520-271-8748

Email: abdsalam@email.arizona.edu

Abstract

This research looks at the major driving force of vegetation dynamics in the lands of Hopi tribe and Navajo Nation during the last 22 years in order to provide valuable spatial information related to inter-annual variability in vegetation productivity for mitigating the impact of drought. The present drought impact on the Colorado Plateau, where the Hopi Tribe and Navajo Nation are located, have appeared slowly and relatively unnoticed in conventional national drought monitoring efforts like the National Drought Monitor. To address, the effect key environmental drivers of vegetation dynamics in the area, a drought assessment framework was developed integrating land cover, climate, and topographical data with land surface remote sensing time series data. Two NDVI-related productivity measurements serving as response variables, integrated annual NDVI (a proxy of Gross/ Net Primary Production, GPP/NPP) and maximum annual NDVI were derived from the 15-day composite multi-sensor Normalized Difference Vegetation Index (NDVI) time series. We also derived the phenoclimatic variables land cover thematic maps, and topographic drivers as the explanatory variables. For each NDVI-related productivity and phenoclimatic driver, we computed spatially the coefficients of variation (CoV) over the last 22 years. We then examined the inter-annual variation of each response variables in order to detect spatial differences in vegetation biomass changes among elevation gradients as well as among vegetation communities. After looking at the inter-annual variability in each response variables, we studied vegetation-environment relationships by conducting a stepwise multiple linear regression analysis in order to explain the source of the variability in vegetation productivity. Our results suggested that

the inter-annual variability of cumulative NDVI showed high variability in middle elevations where needleleaf forest is the dominant vegetation type. We also found that there was a significant change related to the inter-annual variability in maximum NDVI at low elevations. These low elevation areas are mostly dominated by shrublands and grasslands. Our analysis also showed that the spatial variation in inter-annual CoV of cumulative NDVI was better explained by climate drivers than by topographic drivers. Specifically, the inter-annual variability in spring precipitation and temperature seem to be the most significant drivers that correlate positively with the inter-annual variability in vegetation productivity in the study area. However, the inter-annual variability in summer precipitation and temperature showed a decreasing relationship with the inter-annual variability in vegetation productivity and they showed a strong impact of vegetation productivity. It was found that the inter-annual variability in winter and spring and summer temperature were the most powerful drivers in the inter-annual variability in maximum NDVI for shrubland. Finally, the inter-annual variability related to NDVI productivity among forested area was not controlled by the inter-annual variability in phenoclimatic drivers.

Keywords: drought, remote sensing, time series, vegetation response, Hopi and Navajo Nations.

Introduction

Drought is one of the natural hazards always threatening society at different economic, social, and environmental scales (Chen et al., 2012; Wilhite et al., 2005). Droughts are a recurrent part of our climate and are still considered one of the most complex phenomenon and one of the least understood among all natural hazards in terms of its impact on vegetation productivity (Glantz, 2003; Hagman, 1984; Mishra et al., 2005; Wilhite, 1990; Wu et al., 2013). In recent years drought has become more common and more severe across the world, and the extent of drought-affected areas has increased (Easterling et al., 2000; FAO., 2011; Hoerling, 2003; IPCC, 2007; Meehl, 2004). Drought has been recognized as one of the principal causes of crop loss and severe food shortages, particularly in developing countries (FAO., 2011; Parida et al., 2008). For the last decades, droughts have constantly threatened the world's food security (Eriksen etal., 2012; FAO., 2011). In addition to the economic damage and damage to natural resources, droughts can severely impact lives and communities causing displacement of people and migration (FAO., 2011; Parida et al., 2008).

Studying the spatial and temporal dimensions of drought in relation to climatological, oceanic, and atmospheric parameters is a fundamental key for developing drought monitoring systems in order to provide valuable information for better early warning and knowledge-based decision support systems that would help to mitigate impact of future droughts on society (Arshad et al., 2008; Tadesse et al., 2005). Therefore, in any given place, effective drought monitoring system would take into consideration past and present climatological conditions (Tadesse et al., 2005). Monitoring drought patterns and their impact on vegetation productivity at different spatial and temporal scales still presents some challenges due to the complex relationship between vegetation, environmental and biophysical factors (Chapin et al, 2011; Propastin et al., 2001; Vicente-Serrano et al., 2012).

Due to water limitation, several sites across the globe have shown recent declines related to forest productivity and tree survival (Allen et al., 2010; Zhao & Running, 2010). This water limitation causing declines in vegetation productivity at many places across the globe has been linked to lack of reduced precipitation or increase in evaporative demands, which is generally related to droughts (Williams et al., 2012). In the southwestern United States, the drought impacts on forests have been well documented and considered sever since 1990s as a result of the observed temperature increase recorded during this period (Breshears et al., 2005; J. L. Weiss et al., 2009a; Weiss et al., 2009b; Williams et al., 2012).

With the increase of destruction, fragmentations, and degradation of natural land cover worldwide due to human impact and to a lesser degree climate change, the need for better management is becoming urgent (Carmel et al., 2001). Deep understanding of ecosystem dynamics in space and time leading to prediction of future ecosystem statuses could assist decision makers to maintain biodiversity through good planning and management systems (Medvigy et al., 2012; Western et al., 1989; Zhao et al., 2013). One of the useful tools for decision making in ecosystem management has relied on the spatially explicit dynamic models (Boumans et al., 1990; Freeman et al., 2012; Steele et al., 2012; Turner et al., 1995) , but those spatially explicit dynamic models are still facing some issues for ecosystem management where there are more than two vegetation species (Turner et al., 1995).

In the southwestern United States, droughts are relatively a common phenomenon due to land surface-ocean interaction (Cook et al., 2007; Seager et al., 2007) .Several studies have shown that both climate and human activities are the key driving forces of changes in landscape in the American Southwest (Seager R et al., 2007). This finding makes the assessment of vegetation response to droughts in the region difficult due to the human dimensions of this problem.

Droughts in the United Sates are the most costly weather-related disaster (Mishra et al., 2010). From 1980 to 2003, the cost of drought was estimated at more than $144 billion dollars (Ross et al., 2003). The recent ongoing drought in the area will have multiple impacts, not only on economic activity but also on the ecosystem services (Cook et al., 2007; Fye et al., 2003; Swetnam et al., 2010). One concern of the ongoing drought in the region is the storage capacity of the Colorado River and taxing of the regional aquifers (Gastélum et al., 2013; Wilhite et al., 2005).

The present drought impact on the Colorado Plateau, where the Hopi Tribe and Navajo Nation are located, have appeared slowly and relatively unnoticed in conventional national drought monitoring efforts like the National Drought Monitor. Assessment of the present drought and its impacts on the Hopi and Navajo Nation area presents some difficulties due to lack of the Hydro-climatological data. This situation has created a challenging environment for resource managers to assess current conditions and anticipate future climatic impacts at seasonal to inter-annual time scales. Temporal and spatial dimensions of drought are complex and vary from one place to another (Wilhite, 2000b), making the development of one framework for drought monitoring at the global scale difficult.

The goal of this study is to examine the major driving force of vegetation dynamics in the region during the last 22 years in order to provide valuable spatial information related to inter-annual variability in vegetation productivity for mitigating the impact of drought. In any given location, vegetation dynamics is driven by multiple environmental factors including climate, topography, soil proprieties, and various human disturbances related factors (Kariyeva et al., 2011). The main objective of this work is to develop a spatial model that can be used to study the vegetation response to climate variability at different spatial and temporal scales in order to assist managers and decision makers to maintain biodiversity in Hopi and Navajo lands. These goals can be expressed as a series of questions:

- How has the vegetation productivity of the Hopi tribe and Navajo Nation responded to climate variability during the last 22 years?
- What are the environmental variables driving inter-annual vegetation dynamics in the area?
- Can these environmental drivers be used to explain the variability of the vegetation dynamic across time and space in the area?

Data and Method

1.1. Study area

The Hopi tribe and Navajo Nation of Arizona occupy the northeastern corner of the state in the lower Colorado River basin. Collectively, the Hopi tribe and Navajo Nation lands cover over 77699.643square km (Fig 1). The area is known for its cold winters and very hot summers. Average annual temperature varies between 40ºF and 50ºF. Climatic patterns vary from south to north across the area. Annual rainfall is less than 10 inches and varies along elevation gradients. Rainfall is low and moderate in the early winter, increases in February and March, and then decreases quickly in April. May through June is a very dry period (Grahame et al., 2002). Vegetation cover varies through the area as a result of climate, soil types, elevations, and land management.

1.2.Datasets

Remote Sensing data

Fifteen-day composite multi-sensor Normalized Difference Vegetation Index (NDVI) time series data were acquired from the vegetation index and phenology project (vip.arizona.edu) for the available period 1989 to 2010 at 5.6 km spatial resolution to study vegetation response to climate variability. This product represents a sensor-independent and continuous NDVI time series derived from AVHRR (1981-1999), SPOT (1998-2002) and MODIS (2000-2010) data (Didan et al, 2010). More details about the datasets can be found on the Vegetation Index and Phenology Laboratory website: http://vip.arizona.edu/viplab_data_explorer.php. These data were analyzed to characterize the intra-annual changes of vegetation, seasonal phenology, and inter-annual vegetation responses to climate variability and environmental factors.

Climate data were generated from Oregon State University's Parameter-elevation Regressions on Independent Slopes Model (PRISM) (Di-Luzio et al., 2008) dataset at 4 km spatial and monthly temporal resolution. Average seasonal monthly rainfall and temperature data were analyzed in order to characterize the climate patterns over the last 22 years in the area. The rainfall and temperature data were resampled to the NDVI spatial resolution of 5.6 km.

Topographic data are based on the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) with a spatial resolution of 30 m (ASTER, 2009) Elevations range between 821 m to 3771 m corresponding to eco-zones with low to high vegetation cover (Fig. 3). Pixel size of the elevation data was resampled to 5.6 km to match NDVI pixel size.

Land cover types were generated from the 2005 North American Land Cover product at 250 m spatial resolution produced by the North American Land Change Monitoring System (NALCMS., 2005). According to this classification, the land of the Hopi tribe and Navajo Nation is characterized by shrubland, and grassland and needleleaf forest (Fig. 4). The pixel size of the NALCMS was resampled to 5.6 km, using the dominant class approach, to match the NDVI pixel size. Overall, the land cover of the area is fairly stable because of limited natural and anthropogenic change.

1.3.Methodology

- **Response Variables: Deriving Metrics of NDVI-Based Vegetation Productivity**

Two NDVI-related productivity measurements were derived from the 15-day composite multi-sensor Normalized Difference Vegetation Index (NDVI) time series. The NDVI time series consists of 22 years of images at 24 images per year, resulting in 528 gridded images across the area. NDVI has been used in many studies to assess vegetation dynamics, monitor land cover change, and track the impact of climate change and human disturbances on vegetation productivity across the world (Ahmad, 2013; Bachoo et al., 2007; Pocas et al., 2013).

A proposed framework (Fig. 5) was developed to capture the seasonal patterns of vegetation activity. For the purpose of this study, two key NDVI-related productivity measurements related to greenness were extracted for each year using these frameworks: (1) integrated annual NDVI (a proxy of Gross/ Net Primary Production, GPP/NPP), and (2) maximum annual NDVI. We only extracted these greenness metrics during the snow-free period from March to November of each year in order to minimize snow impacts on NDVI values (Delbart et al., 2006; Shi et al., 2008; Zhang et al., 2004). Many studies have used such bio-variables, integrated annual NDVI and maximum annual NDVI, to capture changes in ecosystem function across the world (Alcaraz et al., 2006; Price et al., 2013; Weiss et al., 2004).

- **Explanatory Variables: Obtaining Key Environmental Drivers**

The potential explanatory variables hypothesized to be the key drivers of vegetation dynamics in this study are: climate data, vegetation types, and topography characteristics. Table 1 lists the different environmental variables used in this study.

2. Methodology

To understand the source of vegetation dynamics and the main environmental forces driving the ecosystem changes in the lands of the Hopi tribe and Navajo Nation, a four-step framework was developed using both response and explanatory variables. The first step consisted of selecting the appropriate set of potential explanatory variables by testing the near-linear dependencies among the variables. This test allows the determination of the multicollinearity levels between the variables and selection of the appropriate explanatory variables. The second step was to examine variations in the coefficient of variation (CoV) of the NDVI-related productivity variables (response variables) as the ratio of the standard deviation and the mean at the area level as well as among vegetation communities. The third step was to study vegetation-environment relationships by conducting a stepwise multiple linear regression analysis (SMLR) in order to explain the source of the variability in vegetation productivity. The final step was to locally evaluate the regression model performance using overall model residuals.

- **Detecting multicollinearity among the explanatory variables**

Several techniques are available in the literature to detect multicollinearity in multiple regression analyses, such as Eigen system analysis (Castillo-Santiago et al., 2012; Walker, 1989), condition number technique (Vinod et al., 1981), and the examination of the correlation matrix. For the purpose of this study, the examination of correlation matrix of explanatory variables was used in order to determine the degree of correlation between variables. This method is widely used to detect multicollinearity issues in multiple regression models (Davison et al., 2011; Kariyeva et al., 2011).

Eleven explanatory (dynamic and static) variables were selected for this test: two topography-based factors, elevation and aspect, one vegetation type's variable, eight climate-based variables (6 seasonal precipitation and temperature-based variables, one total annual precipitation, and one average annual precipitation). Climate data were divided into the standard four seasons (JFM, AMJ, JAS, and OND), but in this study we selected only three seasons (JFM, AMJ, JAS) that we hypothesized the main force driving vegetation dynamics in the area. We calculated the coefficient of variation of seasonal precipitation and temperature over the considered months over the last 22 years. As a result of this test, two variables were excluded from the potential explanatory variables list, annual cumulative and mean annual precipitation, due to their high multicollinearity ($R^2 > 0.8$) with other seasonal variables.

- **Inter-annual variability of NDVI-related productivity parameters**

Many studies have used inter-annual coefficient of variation (CoV) as a simple indicator to study spatiotemporal variation in vegetation productivity in different climates and ecosystems (Jordan et al., 2012; Kariyeva et al., 2011; Milich et al., 2000; Wan et al., 2009; Weiss et al., 2001). High variability in CoV across pixel/landscape and over any considered period can be used as an indicator of changes in vegetation biomass (Weiss et al., 2001). For this reason the use of CoV in this study can be useful to study changes in vegetation productivity.

In the study, the inter-annual CoV of NDVI-related productivity variables were spatially generated over the study area in order to detect spatial difference in vegetation biomass variability among elevation gradients as well as among vegetation communities. Two statistical analyses, the Kolmogrov-Smirnov (K-S) test (Dahlin et al., 2012; Pena-Yewtukhiw et al., 2008) and the boxplot technique (Härdle et al., 2012), were also used to analyze variations in the inter-annual CoV of the NDVI-related productivity variables over the whole area as well as among vegetation types. The K-S test is non-parametric test that shows the maximum absolute difference in the cumulative probability curves among the data (Henareh et al., 2013; Moller et al., 2012). Boxplots are widely used to visually summarize and compare groups of data. We used the K-S test because it is so sensitive to differences anywhere in the cumulative distribution functions (CDFs). Therefore, the two statistical tests were used to determine which NDVI-related productivity parameter had the largest inter annual variability as a result of droughts and precipitation events.

- **Vegetation- environment relationships**

Stepwise multiple linear regressions were used to study the relationship between inter-annual variability in vegetation productivity and inter-annual variability in environmental variables. Many studies have used these analyses to quantify variability in vegetation dynamics over time and space (Busetto et al., 2010; Chu and Guo, 2012; Fu et al., 2010; Wan H et al., 2009). To determine the long-term responses of NDVI-related productivity to environmental variables, a spatial-temporal relationship model was developed. This required bringing all variables used into one spatial model to express the variability in NDVI-related productivity as a function of environmental factors at time scales of 22 years over the whole area as well as among vegetation communities. Residuals from the model were analyzed to find some explanations related to the weakness of the model and if there were other factors that might be the source of the weakness.

COV-NDVI related productivity variables = f (CoV-dynamic climate, land cover, topography,) (1)

This study provided an idea about potential environmental drivers that have impacted the spatial temporal variability in vegetation productivity in the region during the last 22 years. This allows to spatially seeing how those environmental variables can be used to assess vegetation responses to drought in the regions by looking at the spatial distributions of the model residuals in order to provide perspective for land managers' decision making in the area.

Results

- **Spatial patterns of inter-annual CoV of the NDVI-related productivity variables**

Figure 6 shows the spatial distribution of the inter-annual CoV of cumulative NDVI over the study period. The lowest inter-annual CoV values (i.e., those less than 0.1) were concentrated along high elevations indicating that these areas had experienced the least temporal changes in vegetation productivity over the study period. These areas are mostly dominated by needleleaf forest. The inter-annual CoV generally increases with the decrease of elevations. The range from 0.21 to 0.56 corresponds to the area with the highest inter-annual CoV, sign of a greater variability in vegetation productivity. Most of the areas with the highest inter-annual CoV values are observed in low and some mid-elevation areas where shrubland is the most dominant vegetation type.

Figure 7 shows the spatial differences of the inter-annual CoV of the maximum annual NDVI for each pixel over the study area. The coefficient of variation (CoV) of the maximum annual NDVI was used as a factor to describe the change of vegetation productivity and to compare the amount of variation in different vegetation communities. The CoV varies between 0.1 and 2. The larger CoV values were observed over lower elevations and over some areas located at middle elevations. These areas are dominated by shrubland and grasslands, indicating that the areas experience the most temporal variability over the last 22 years. The entire region shows a very high degree of temporal variability in vegetation productivity as measured by Max-VI. More than 98 % of the area showed a CoV greater than 0.5 CoV. This indicates that the maximum inter- annual NDVI is very instable over time and changes frequently.

- **The amplitude of inter-annual variation in vegetation productivity**

Box plots were used to show the overall patterns of the inter-annual variability of NDVI-related productivity. To that end, pixel values of the inter-annual CoV of each NDVI-related productivity were extracted. The box plots provide a useful way to visualize the range of the variability among each COV NDVI related productivity at the whole area. Figure 9 shows box plots comparing the inter-annual variability among the inter-annual CoV of NDVI-related productivity in the area. For example, the distribution of CoV of the annual cumulative NDVI shows less inter-annual variability than the maximum NDVI CoV. The inter-annual CoV of the annual maximum NDVI has the widest distribution and most obvious range. Peak values differ among the CoV of NDVI-related productivity and vary between 0.4 and 1.7.

As figure 8 shows, the inter-annual CoV of cumulative NDVI presents less variability than the inter-annual CoV of annual maximum NDVI related productivity. This suggests that difference in variability is likely related to inter variability of climate or other variables rather than vegetation characteristics in the area.

In order to confirm the obtained results from the plot box approach, a two-sample Kolmogorov-Smirnov (K-S) test was conducted on the inter-annual CoV of NDVI-related productivity to evaluate differences across the entire frequency of the inter-variability among the CoV of each NDVI-related-productivity. The K-S test allowed us not only to see the differences in the median or extremes but also to see the level of variability among the CoV. For instance, the K-S test results obtained from the comparison between the inter-annual CoV of cumulative and maximum NDVI show a significant difference in terms of variability with maximum percent difference of 99 % (D= 0.99) and p-value less than 0.001. The cumulative distribution (Fig.9) of the inter-annual CoV of cumulative and maximum NDVI demonstrates that the maximum NDVI shows more variability. The results confirmed that the cumulative NDVI demonstrated less inter-annual variability compared to the maximum. This means that the level of sensitivity to climate variability among these variables is different and shows that vegetation productivity related to maximum NDVI has experienced more inter-annual variability.

- **Inter-annual variation in CoV of the NDVI-related productivity across vegetation communities**

To study the inter-annual variability in productivity among vegetation communities, we extracted the pixel values for three dominant vegetation communities in the area: needleleaf forest shrubland, and grassland. The Kolmogorov-Smirnov test and the box plot approach were used to quantify the difference in inter-annual variability in NDVI-related productivity among these three vegetation communities. Figure 10 is an explanatory diagram of the inter-annual CoV of cumulative and maximum NDVI among these three biomes. As figure 10 shows, needleleaf forest demonstrate less variability than grassland and shrubland in terms of productivity (Fig. 11i, ii, iii). This finding suggests that needleleaf forest productivity is less sensitive to climate variability, but shrubland and grassland productivity show higher variability. The K-S test results confirmed that the cumulative distribution of the inter-annual CoV of NDVI-related productivity among vegetation communities is different. This finding indicates that shrublands and grassland show more sensitivity to climate variability. This can be related to the level of resilience among those vegetation communities and their access to water during drought or dry season.

- **Inter-annual spatial variation in vegetation productivity as a function of environmental variables**

A multiple linear regression approach was applied in order to study the existing relationship between vegetation dynamics and environmental variables. The inter-annual spatial variation in vegetation productivity was analyzed as a function of nine environmental variables in order to explain the source of the inter-annual variation across the area. Two inter-annual CoV of NDVI-related productivity were used as response variables, CoV of cumulative and maximum NDVI. The contribution of the potential explanatory variables to the inter-annual variability in vegetation productivity differed from one response variable to another. Table 2 illustrates the number of explanatory variables included in the multiple liner regression with a confidence level of 95%. The following sections describe the modeling results for each response variable.

The results of the multiple linear regression approach used to assess the main forces driving variability in NDVI-related vegetation productivity are shown in table 3. The number of explanatory variables involved in the multiple linear regressions for the inter-annual variability of maximum NDVI was less than those for the inter-annual CoV of cumulative. The inter-annual CoV of cumulative NDVI had the largest explanatory variables.

The proportion of the inter-annual variability in cumulative NDVI explained by the potential explanatory variables was around 34% with a root mean square error (RMSE) of 0.002 (see table 2). All explanatory variables show a significant correlation at 95 % confidence level in the study area as a whole. Inter-seasonal variability of temperature seems to be the most important factor affecting the vegetation dynamics in the area during the last 22 years.

Spatial variation in inter-annual CoV of cumulative NDVI was explained better by climate drivers than by topography. Among all explanatory variables, spring precipitation and temperature, as well vegetation type showed a positive estimated coefficient (Est-Coeff). This indicated that those explanatory variables are in increasing relationship with the inter-annual variability of cumulative NDVI. The inter-seasonal of winter and summer temperature and summer precipitation as well as the topography factors (aspect and elevation) indicated a negative estimated coefficient, which meant that the inter-annual variability in vegetation productivity (cumulative NDVI) showed a decreasing relationship with those climate factors. This result suggests that there is a strong positive feedback between the inter-annual variability in vegetation productivity and the inter-seasonal spring temperature in the area. The determination coefficient of the significant relationship between the inter-annual CoV of cumulative NDVI and explanatory variables varies between – $8.5e^{--05}$ and 0.4. Furthermore, topographic and vegetation types drivers showed a weak estimated coefficient in the regression model (see table 3).

The inter-annual variability in maximum NDVI was best explained by climate drivers rather than topography drivers. The Inter-seasonality of spring precipitation and temperature showed a significant relationship ($P <0.05$) in the regression and are in increasing relationship with the inter-annual variability in maximum NDVI. The inter-seasonality of winter temperature and summer precipitation and temperature, as well as topographic variables (aspect and elevation) are in a decreasing relationship with maximum NDVI CoV. However, the inter-seasonality of spring and summer temperature presented a strong estimated coefficient compared to the rest of the explanatory variables. This suggested those drivers are in a strong relationship with the inter-annual variability of maximum NDVI. The amount of variability in maximum NDVI CoV explained by the explanatory variables was 26 % (see table 4).

In order to better understand the regressions' uncertainty resulting from the spatial regression model between the inter-annual variability in response and explanatory variables, the spatial distribution of the regression residuals was generated for each model. The residual maps (Fig.12) show the spatial distribution of residuals resulting from each model. Figure 12 shows where the model is strong, weak and/or where the changes in the inter-annual NDVI CoV related to vegetation productivity were controlled by more factors than those used in the regression model.

Spatial patterns of the residuals demonstrated that the models for the cumulative NDVI produced the lowest amount of residuals in the CoV values of the NDVI-related vegetation productivity (Fig. 12a) compared to those resulting from maximum. This referred to the number of pixel that didn't show a significant correlation with the potential explanatory variables.

The residuals of the model obtained from the cumulative NDVI vary between –0.3 and 0.27 CoV-VI unit over the study area with a standard deviation of 0.1 at the 95 % confidence level. The range between [-0.3 to -0.1] corresponds to overestimation, while [0.101 to 0.27] indicates underestimation. Values between [-0.1 to 0.1] correspond to the 95% confidence level and a strong correlation. The model performed well at low elevations where shrubland and grassland are the dominant vegetation types. In general, the relationship between the inter-annual variability of cumulative NDVI was overestimated and no significant correlation was found in high elevation areas where needleleaf forest is the dominant vegetation type. This means that the inter-annual variability in cumulative NDVI among shrubland and forest at middle and high elevations is strongly controlled by other variables rather than the explanatory variables used in this study. This might be related to the inter-annual variability in snow over these areas during the last 22 years.

The spatial pattern of residuals obtained from inter-annual variability of maximum NDVI (Fig. 112b) varies between -1.5 and 0.44 with a standard deviation of 0.06 at the 95 % confidence level. A large percent of the area seems to be overestimated by the model where the residuals range between [-1.5 and -0.12]. These areas are mostly located in low and high elevations where both shrublands and needleleaf are the major vegetation types. The range value of the residuals between [-0.119 to 0.12] correspond to the 95% confidence level and show a strong relationship between the inter-annual variability of maximum NDVI and the explanatory variables included in the model(see table 8 for the significant ones). These results show that the inter-annual variability in maximum NDVI related productivity in middle and high elevation is not controlled by climate, topographic drivers, or soil characteristics.

- **Inter-annual spatial variation in vegetation productivity among vegetation types as a Function of the Potential Environmental Variables**

To better understand the potential drivers of the inter-annual variability in vegetation productivity among vegetation types in the area, the inter-annual variability of NDVI-related productivity was modulated as a function of the same potential drivers. Table 5 illustrates the results by the stepwise multivariate regression approach used for the three dominant vegetation types in the area: grasslands, shrublands, and needleleaf forest. The amount of variability in NDVI-related productivity explained by the potential explanatory variables varies from one vegetation type to another. The percent of the explanatory variables involved in each regression model also varies from one vegetation type to another.

The inter-annual variability in cumulative NDVI among grasslands explained by the explanatory variables was around 14 %. The percent of the explanatory variables included in the regression model for grasslands was 30 % (3 out of 9 explanatory variables showed a significant relationship with cumulative NDVI at the 95% confidence level). The two topography drivers, aspect and elevation, were included in the model and showed a negative relationship with the inter-annual variability in cumulative NDVI for grasslands. The inter-seasonal of spring precipitation showed a negative estimated coefficient in the regression model. This suggests that the inter-annual variability in grassland productivity is in decreasing relationship with spring precipitation, aspect and elevation (see table 5a).

The regression model was able to explain 46 % in the inter-annual variability in maximum NDVI for grasslands. Only one explanatory (11% of the potential explanatory variables) variables showed significant correlations to the inter-annual variability in maximum for grasslands (see table 5b). The significant driver included in the regression was elevation which was in a decreasing relationship with the inter-annual maximum NDVI. This suggested that the inter-annual variability in maximum NDVI for grasslands is more controlled by elevation gradients. The dominate grasslands in the area is plains grasslands, which are commonly dominated by blue Grama.

The regression model for shrublands (see table 6) resulted in $R^2 = 0.27$ for the inter-annul variability in cumulative NDVI model and $R^2 = 0.31$ for the inter-annual variability in maximum NDVI model. Climate and topography drivers were significantly correlated to the inter-annual variability in cumulative NDVI of shrublands (see table 6a). The inter-annual variability in spring precipitation and summer precipitation and temperature seem to be the most positive contributors to the inter-annual variability in cumulative NDVI related productivity for shrubland. However, summer precipitation and temperature, as well as topographic drivers showed a significant relationship, but in negative ways.

Table 6b illustrates the resulted obtained for the maximum NDVI among shrublands. Winter temperature, spring precipitation and temperature, and summer precipitation contributed strongly to the inter-annual variability of maximum NDVI for shrublands and they are in a decreasing relationship with shrubland productivity. However, spring precipitation and summer temperature presented an increasing relationship with the inter-annual variability of the maximum NDVI for shrublands. These results suggest that the interseasonal temperature for all seasons plays an important role in the inter-annual variability in shrubland in the area.

The regression model between the inter-annual variability in NDVI-related productivity for frost area (pinon-juniper woodlands) and the potential explanatory variables showed very low correlation: R^2 =0.09 for maximum NDVI CoV, R^2 = 0.28 for cumulative NDVI CoV (see table7). Table 7a illustrates the results for the inter-annual variability of cumulative NDVI. An aspect driver seems to have strong impacts on forested areas; this can be explained by the variation in sun light in these areas covered by this vegetation type. The inter-annual variability in maximum NDVI for forest areas was not in strong relationship with the potential explanatory variables used in the study because of amount of the variability explained in the model, only 8% (see table 7b). This suggests that the variability in maximum NDVI for forested areas is not controlled by the variability in the climatic drivers that were used in this study.

Conclusion

This paper discussed the inter-annual variability of vegetation dynamics over Hopi tribe and Navajo Nation lands in the context of a changing climate and anthropogenic pressure during the last 22 years. This study provided key information related to the existing relationship between vegetation dynamics and environmental drivers in the lands of the Hopi tribe and Navajo Nation. The research framework based on the multi-sensor NDVI time series, data, and methodology adopted by this study can be useful to assess vegetation responses to climate variability across the world and particularly in arid and semi-arid areas.

Due to the relatively coarse spatial resolution of the data used in the study, our results could be improved by using finer spatial resolution. This matter is particularly related to the vegetation and climate datasets used in this study. For instance, the 2005 North American Land Cover at 250 m spatial resolution database used in this study simplified the landscape in the area. Across Hopi alone the landscape varies from pinon-juniper woodlands to barren land. Future research should rely on: (1) developing a new classification of landscape across the study area, and (2) using local weather station data to generate the different climate variables used in this study. This approach will require increasing the number of weather stations in the area.

Two annual NDVI proxy vegetation related productivity parameters were derived from the NDVI time series from 1989 to 2010. The spatial distribution of the inter-annual variability of these parameters suggested that:

1. The highest inter-annual variability of cumulative NDVI was observed at middle elevations where needleleaf forest is the dominant vegetation type,

2. For the inter-annual variability of maximum NDVI, the larger CoV values were observed over lower elevations and over some areas located at middle elevations. These areas are dominated by shrubs and grasses. This indicates that these areas have undergone more temporal variability over the last 22 years,

3. It is important to note that grassland at low elevations show the highest inter-annual variability. More variability was observed among shrublands, indicating that this vegetation type is more sensitive to climate variability across the area due to the spatial distribution of shrublands along elevation gradients.

Based on a stepwise regression model this work identified the key environmental drivers of the spatial temporal patterns in vegetation productivity in the lands of the Hopi tribe and Navajo Nation. Potential environmental drivers, based on the confidence level of 95 % ($p < 0.05$), were selected using a stepwise regression model. The results showed that the number of environmental variables contributing to the inter-annual variability in vegetation productivity varies across NDVI-related productivity measurements employed in this study. The spatial variation in inter-annual CoV of cumulative NDVI was better explained by climate drivers than by topographic drivers. Specifically, the inter-annual variability in spring precipitation and temperature seem to be the most significant drivers that correlate positively with the inter-annual variability in vegetation productivity in the study area. However, the inter-annual variability in summer precipitation and temperature showed a decreasing relationship with the inter-annual variability in vegetation productivity and they showed a strong impact of vegetation productivity. It was found that the inter-annual variability in winter, spring and summer temperature aspect were the most powerful drivers in the inter-annual variability in maximum NDVI for shrubland areas. Those positive correlations between the inter-annual variability in vegetation productivity and spring precipitation and temperature can be explained by the change in soil moisture levels. For example, the strong correlations between spring temperature and vegetation productivity in the area may relate to the local vegetation species response to the warmer season (spring season). This variability in spring temperature can easily effect the evaporative demands which basically the main key of vegetation growth in the area. In terms of the inter-annual variability in maximum NDVI, spring temperature and summer precipitation and temperature were the most forceful drivers (see table 4). This can be explained by the effect of those drivers on soil moisture levels that help the local vegetation grow. The regression model used to assess the relationship between vegetation dynamics and environmental drivers among vegetation types showed that spring precipitation was in a positive relationship with the inter-annual variability in cumulative and maximum NDVI for shrubland areas (see table 10). However, the inter-annual variability in forest didn’t show any correlation with climate drivers in the area.

This study showed a strong interaction between vegetation productivity dynamics and precipitation and temperature regimes in the area, specifically along areas dominated by shrubland.

The study also shows that information related to vegetation productivity derived from remote sensing is useful for studying inter-annual variability of vegetation productivity in arid areas. The proposed framework adopted by this study was valuable in identifying the major forces driving the region's vegetation cover variability.

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Tables

Table 1: Explanatory variables used in this study including climate drivers (dynamics variables) and topography drivers (static variables).

Variable	Derived variables	Spatial resolution	Source
Topographical characteristics	- Elevation** - Aspect ** - Slope**	30 m	ASTER
Climate data	- Seasonal precipitation* - Seasonal temperature *	4 km	PRISM
Vegetation types	- Vegetation communities **	250 m	NALCMS

*There are four seasons: winter (JFM), spring (AMJ), summer (JOS).

** Static variables.

Table 2: Number of dynamic and static variables included to model of the inter-annual variation in response variables. For instance, the inter-seasonal of w winter, spring and summer of precipitation and temperature were present in the regression mode for the inter-annual variability of cumulative NDVI.

Explanatory Variables **Response Variables**	**Dynamic Variables**	**Static Variable**	**Total Variables**
CoV of Cumulative NDVI	**8**	**2**	**10**
CoV of Maximum NDVI	**7**	**3**	**10**

Table 3: Statistical results obtained by the multiple linear regression models (stepwise regression model) for the response variable (the inter-annual variability of cumulative NDVI) showing the estimated error, standard error, and p-value for each explanatory variable as well as for the whole model results.

Variables	Estimated Coefficient	Standard errors	P-Value
Spring Precipitation	0.001	0.02	$1.003\ e^{-11}$
Spring Temperature	0.4	0.18	0.03
Summer Precipitation	-0.2	0.01	$1.7e^{-38}$
Summer Temperature	-1.25	0.01	$2.56e^{-09}$
Winter Temperature	-0.04	0.013	0.0016
Aspect	$-1.3e^{-04}$	$9.3e^{-07}$	$1.36e^{-36}$
Elevation	$-8.58e^{-05}$	$5.47e^{-06}$	$3.1\ e^{-52}$
Vegetation Types	0.001	$4.82e^{-04}$	$4.56e^{-05}$
Whole Model	Intercept = 0.48 RMSE = 0.002 R-Square = 0.34 P-value = $2.24e^{-210}$		

Table 4: Statistical results obtained by the multiple linear regression models (stepwise regression model) for the response variable (the inter-annual variability of maximum NDVI) showing the estimated error, standard error, and p-value for each explanatory variable as well as for the whole model results.

Variables	Estimated Coefficient	Standard errors	P-Value
Spring Precipitation	0.08	0.02	0.002
Spring Temperature	0.86	0.2	0.001
Summer Precipitation	-0.23	0.02	$6.17e^{-29}$
Summer Temperature	-2.45	0.3	$4.8e^{-17}$
Winter Temperature	-0.07	0.01	$1.85e^{-04}$
Aspect	$-1.35e^{-04}$	$1.2e^{-05}$	$1.8e^{-04}$
Elevation	$-9.07e^{-05}$	$7.04e^{-06}$	$7. 9e^{-37}$
Whole Model	Intercept = 0.48 RMSE = 0.06 R-Square = 0.26 P-value = $9.5e^{-521}$		

Table 5: Statistical results obtained by the multiple linear regression model (stepwise regression model) for the response variable (a: the inter-annual variability of cumulative NDVI and b: the inter-annual variability of maximum NDVI) showing the estimated error, standard error, and p-value for each explanatory variable as well as for the whole model results for grasslands.

(a)

Variables	Est-Coeff	Std.Err	P-Value
Summer Precip	-0.13	0.03	$8.3e^{-04}$
Aspect	$-9.2e^{-05}$	$2.8e^{-05}$	0.001
DEM	$-4.68e^{-05}$	$1.6e^{-05}$	0.004
Whole Model	*Intercept = 0.33* *RMSE = 0.03* *R-Square = 0.14* *P-value = $9.1e^{-05}$*		

(b)

Variables	Est-Coeff	Std.Err	P-Value
Elevation	$-4.7e^{-04}$	$4.4e^{-05}$	$5.02e^{-20}$
Whole Model	*Intercept = 2* *RMSE = 0.11* *R-Square = 0.46* *P-value = 5.02^{-20}*		

Table 10: Statistical results obtained by the multiple linear regression model (stepwise regression model) for the response variable (a: the inter-annual variability of cumulative NDVI and b: the inter-annual variability of maximum NDVI) showing the estimated error, standard error, and p-value for each explanatory variable as well as for the whole model results for shrublands.

(a)

Variables	Est-Coeff	Std.Err	P-Value
Spring Prec	0.11	0.01	$1.4e^{-09}$
Summer Prec	-0.2	0.016	$6.9e^{-35}$
Summer Tempe	-0.82	0.19	$2.9e^{-05}$
Aspect	$-1.21e^{-04}$	$1.02e^{-05}$	$3.9e^{-33}$
Elevation	$-7.78e^{-05}$	$5.28e^{-06}$	$1.4e^{-46}$
Whole Model	*Intercept = 0.37* *RMSE = 0.04* *R-Square = 0.27* *P-value = $2.35e^{-138}$*		

(b)

Spring Prec	0.24	0.07	$8e^{-04}$
Spring Temp	-2.9	0.96	0.002
Summer Prec	-0.16	0.05	0.005
Summer Temp	2.96	0.88	7.99^{e-04}
Winter Temp	-0.98	0.29	7.3^{e-04}
Elevation	-3.9^{e-04}	2.06^{e-05}	$6.8e^{-77}$
Whole Model	*Intercept = 0.94* *RMSE = 0.17* *R-Square = 0.31* *P-value = $9.13e^{-162}$*		

Table 6: Statistical Results obtained by stepwise regression results from the multiple linear regression for the response variable (a: cumulative NDVI and b: maximum NDVI) showing the estimated error, standard error, and p-value for each explanatory variable as well as for the whole model results for shrublands

(a)

Variables	Est-Coeff	Std.Err	P-Value
Summer Temp	-0.6	0.26	0.02
Aspect	-1.32^{e-04}	$3e^{-05}$	3.04^{e-05}
Elevation	$7.6e^{-05}$	$1.7e^{-05}$	$3.1e^{-05}$
Whole Model	*Intercept = 0.32* *RMSE = 0.036* *R-Square = 0.27* *P-value = 2.691e^{-09}*		

(b)

Variables	Est-Coeff	Std.Err	P-Value
Elevation	$-2.2e^{-04}$	$6.31e^{-05}$	$4.14e^{-4}$
Whole Model	*Intercept = 1.54* *RMSE = 0.13* *R-Square = 0.09* *P-value = 4.14e^{-04}*		

Figures

Figure 1: Map of study area showing the distribution of weather station sites

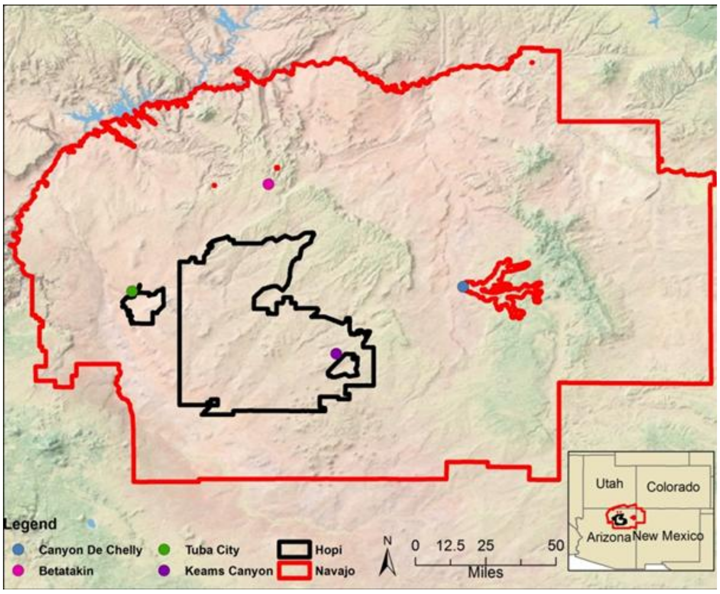


Figure 3: Map of elevation gradients across the area at 5.6 km.

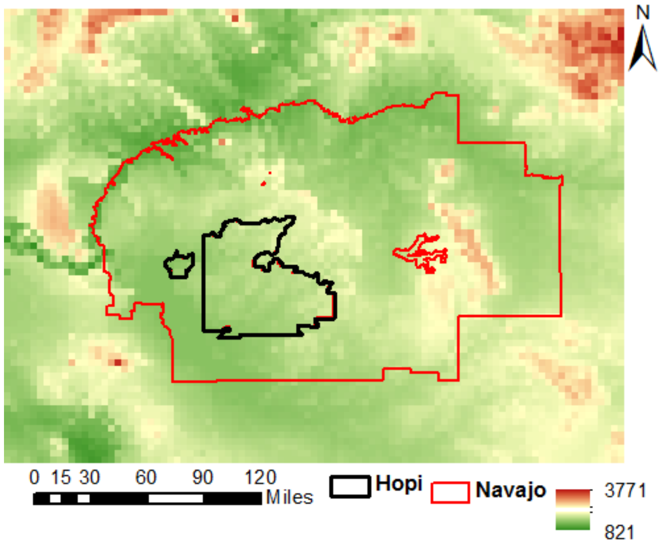


Figure 4: Map of the dominant vegetation types (2005 North American Land Cover at 250 m spatial resolution database).

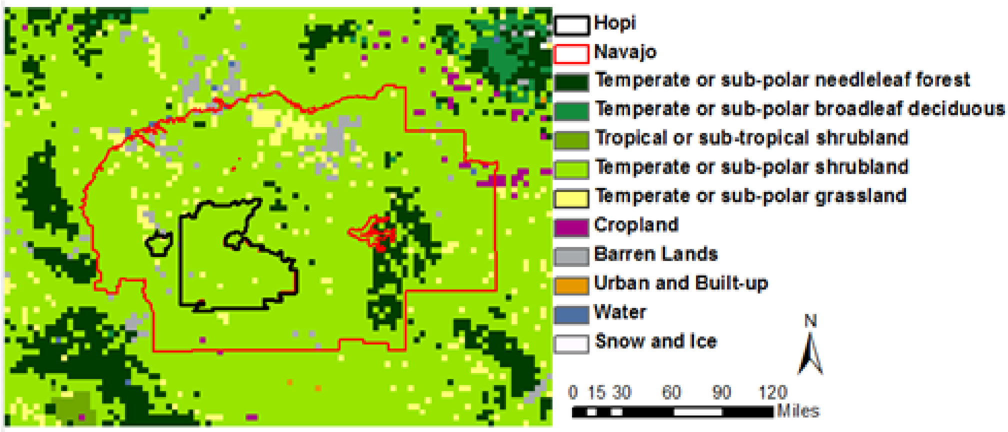


Figure 5: Conceptual model showing different components of vegetation productivity used in this study. Two vegetation productivity metrics are computed from March to October for each year. The maximum annual and the annual cumulative were extracted for each pixel. The annual cumulative NDVI (∑NDVI) was computed by integrating the area under the curve for each pixel

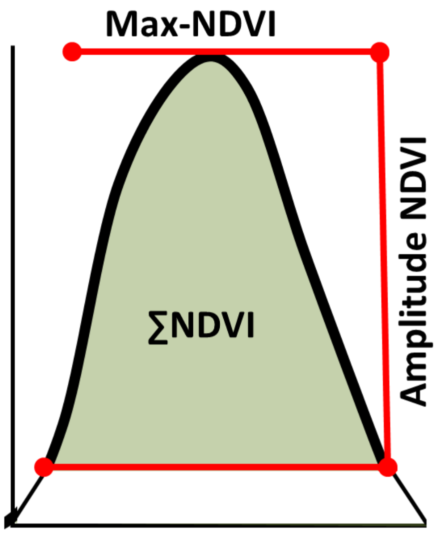


Figure 6: The spatial distribution of the inter-annual CoV cumulative NDVI

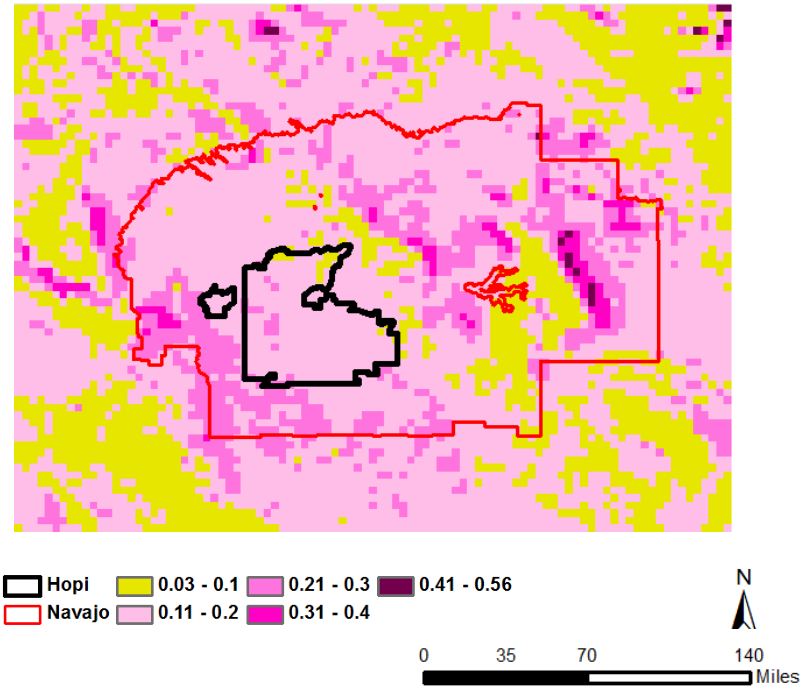


Figure 7: The spatial distribution of inter-annual CoV of maximum annual NDVI

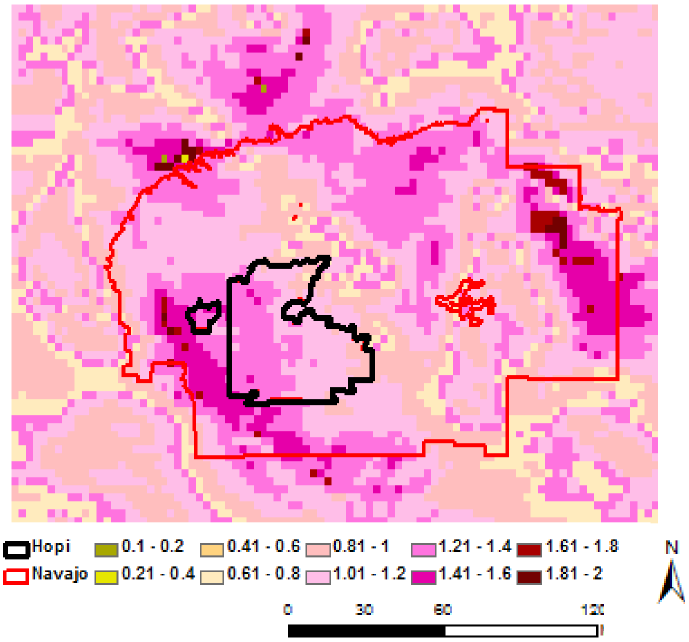


Figure 8: Box plot illustrating the variation of COV of NDVI-related productivity in the study area. Each box shows upper and lower quartiles along with 75th and 25th percentiles, median. The inter-annual coefficients of variation are shown on the y-axis. The different NDVI-related productivity is shown on the x-axis:

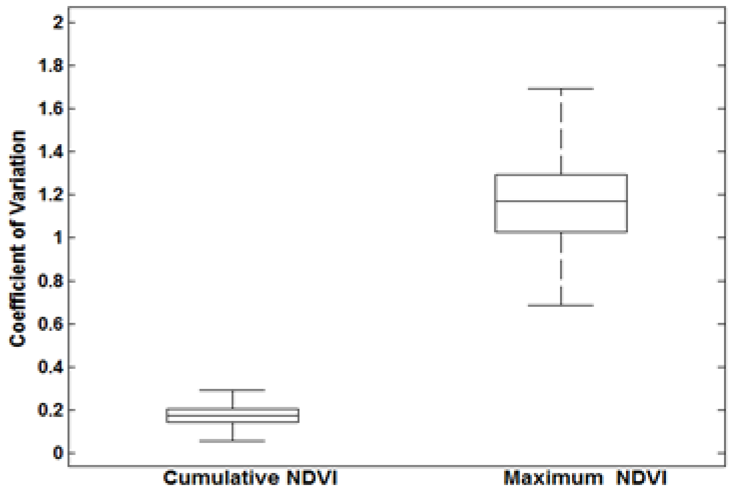


Figure 11: Box plot illustrating the variation of CoV of cumulative NDVI, (i) CoV of maximum NDVI, and (ii) relative NDVI among shrubland (A), grassland (B), and needleleaf forest (C). Each box shows upper and lower quartiles along with 75th and 25th percentiles, and median. The inter-annual coefficients of variation are shown on the y-axis. Cumulative distribution (i_1 through i_3) and maximum NDVI(ii_1 through ii_3) of CoV of each vegetation type resulting from Kolmogorov–Smirnov test showing the maximum absolute difference in the cumulative probability curves which are scaled to be between 0 and 1.

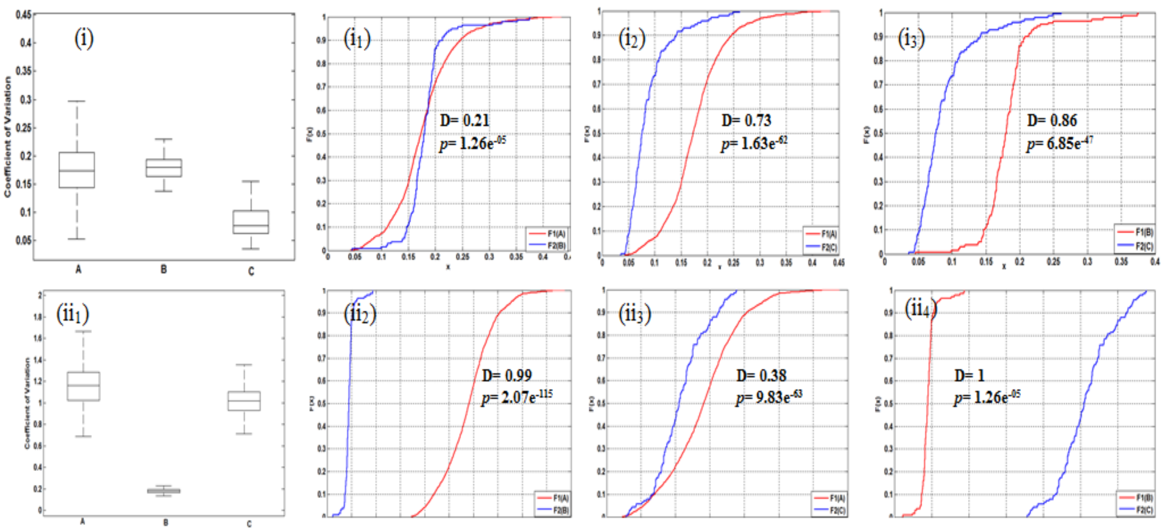
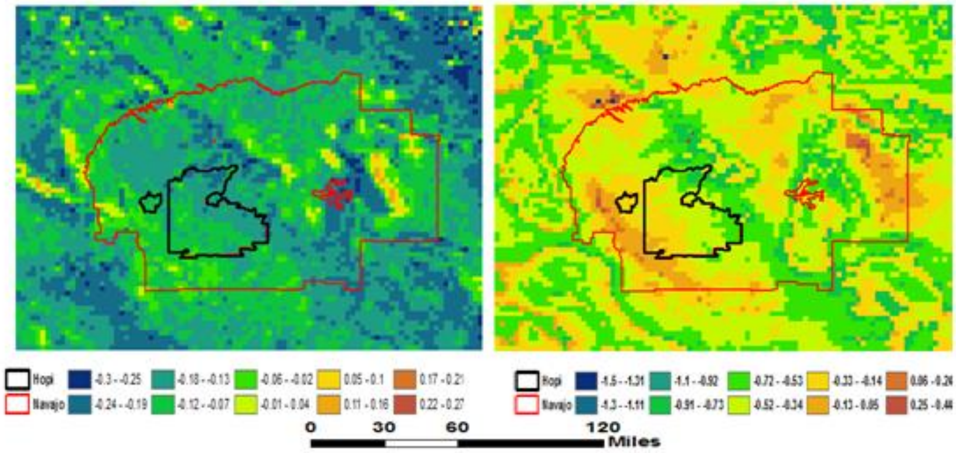


Figure 15: spatial distribution of residuals resulting from the multiple regression models: (a) for inter-annual CoV of cumulative NDVI, (b) for inter-annual CoV of maximum NDVI.



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APPENDIX C: ASSESSMENT OF SATELLITE DERIVED LAND SURFACE PHENOLOGY WITH FIELD OBSERVATIONS OF STAGES OF CROP DEVELOPMENT.

Mohamed Abd salam El Vilaly[1, 2,] Kamel Didan[1, 3], and Stuart E. Marsh[2] , an Armando Barreto [1, 3]

[1] Vegetation Index and Phenology Lab, Department of Electrical and Computer Engineering, [2]Office of Arid Lands Studies, School of Natural Resources and the Environment, [3] Agricultural and Biosystems Engineering Department.

The University of Arizona, Tucson AZ, USA

This Paper was prepared to submit to the Journal of Applied Remote Sensing

Author for correspondence:

Mohamed Abd salam El Vilaly

Phone: 520-271-8748

Email: abdsalam@email.arizona.edu

Abstract

Land surface phenology is an integrative science capable of addressing key questions about the impacts of climate change on ecosystems states and functions. Studying the phenology of natural or managed land in a global context requires the use of remote sensing to address the scale and coverage. What remains unclear is how accurate remote sensing based data are from the observable phenology of crops on the ground. Specifically, three challenges remain: (1) how to validate remote sensing-based land surface phenology; (2) how to compare extracted parameters with actual phenological field observations in light of the complex and heterogeneous nature of remote sensing observations; and (3) how to evaluate the overall performance of the most common land surface phenology algorithms. To address these questions, we propose an assessment of the capability of four land surface phenology algorithms, the Half - Maximum method, Savitzky-Golay, Asymmetric Gaussian, and Double Logistic methods; to accurately characterize the phenology of irrigated crops at the University Arizona Maricopa Agriculture Center (MAC). These crops allow for adequate remote sensing analysis due to their spatial extent and the dynamics of their green cover (0-100% during the growing season). For the remote sensing component, we used the MODIS 250m daily and16-day record of vegetation index (VI). For the validation we used phenological data observed in the field at MAC. Four key phenology metrics were compared across these data sets, Start, End, Peak date of the growing season, and the peak of VI value of the growing season. The aim was to characterize the extracted metrics and assess the performance of these algorithms. Our results suggest that the start and the end of the growing season derived from daily VI are earlier than the 16-day composite VI. We found that the Half-Maximum algorithm always detects the start of growing season late compared to Gaussian, Double-Logistic, and Savitzky-Golay. The Savitzky-Golay estimated the start of growing season earlier than other algorithms (Gaussian and Logistic). The difference in terms of days can vary between 1 to 8 days depending on the thresholds. The results suggested that the Half-Maximum algorithm detects the end of growing season earlier than the Gaussian, Double-Logistic, and Savitzky-Golay algorithms. The Savitzky-Golay usually identifies the end of growing season later than any algorithms for all vegetation indices. The study demonstrates the fundamental role that remote sensing can play globally within the agriculture sector.

Keywords: Land Surface Phenology, Vegetation Index, Crops.

Introduction

Monitoring and understanding land surface phenology over space and time has become a key indicator of the complex relationship between climate factors and vegetation dynamics (Heumann et al., 2007; Zhang et al., 2003; Zhao et al., 2013). Since 1950, the global mean temperature has been rising due to increasing greenhouse gases, such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), in the atmosphere (IPCC, 2007). This increase in greenhouse gas concentrations is contributing to a change in the earth's climate, and altering regional and local climatic and weather patterns (IPCC, 2007). The consequences of climate change are observed through many events, such as melting glaciers, more extreme weather events, and shifting seasons and biomes (IPCC, 2001). The combination of climate change and global population growth threatens agricultural production, processing, and related services, as well as global food security (Atzberger, 2013; Colditz et al., 2008; Dixon, 2012).

The current debate on global and climate change is for the most part dominated by the fate of natural systems due to their spatial extent, momentum, and complexity (Rohr et al., 2013; Tompkins et al., 2004). Although they play a major role, cropped and managed lands figure very little into this debate, perhaps due to the fact that their managed state makes it difficult to tease out any natural from unnatural changes. However, the sensitivity of crop production to variability in climate is important due to the high percentage of cropped lands (Osborne et al., 2013; Traore et al., 2013). To this end, a key aspect of crop production that is expected to show immediate response to climate change is the crop growing season, or phenology. Crop phenology defines the nature and progress of the growing season and is an integrator of all environmental factors controlling crop production (Peña-Barragán et al., 2011; Shaykewich, 1995).

Remote sensing has long played an important role in monitoring and studying agricultural activities due to its ability to provide necessary and reliable data on a timely basis (Atzberger, 2013; Espindola et al., 2013; Lloyd, 1990). Vegetation development stages, or phenology, depend on climate and environmental variables, such as soil moisture and condition, and air temperature, among others. These factors play an important role in plant productivity and condition, particularly in agricultural production (Atzberger, 2013; Iler et al., 2013; Lloyd, 1990). Understanding and predicting crop phenology based on crop development stages could improve crop management practices, crop growth models, and decision support systems (Atzberger, 2013; Boote et al., 2013; Palacios-Orueta et al., 2012).

Studying the phenology of natural or managed land in a global context requires the use of remote sensing data (Atzberger, 2013; Kerr et al., 2003). Land surface phenology is presented as an integrative science capable of addressing key questions of the impacts of climate change on ecosystems states and functions, especially when coupled with remote sensing-based growing season extraction algorithms. Three fundamental challenges need addressing in the context of estimating land surface phenology with remote sensing observations: 1) how to validate remote sensing-based land surface phenology metrics; 2) how to compare the extracted parameters with actual field observations of phenology given the heterogeneous nature of remote sensing observations; and 3) how to evaluate the overall performance of the most common land surface phenology algorithms.

To address these questions, and circumvent the limitations of field-based observation of species phenology (plants, buds, flowers, etc.) we proposed to use cropped land to help characterize the performance of remote sensing-based land surface phenology algorithms. Cropped land provides key traits that are fundamental to this work: (1) homogeneous and well defined land cover with sufficient spatial coverage; (2) detailed record keeping by farmers and managers of the crop growing season; and (3) abundant quantitative information about the crop productivity, biomass, yield, water use and carbon storage. These characteristics may help address the earlier questions.

The field site for this work is the University of Arizona's Maricopa Agriculture Center, located northwest of Tucson, Arizona. This center grows a wide range of irrigated crops like alfalfa, corn, sorghum, and cotton. These crops are typical of the area, and will change from 0% to 100% green cover during the growing season. For the remote sensing component, we used the MODIS Terra daily and 16-day record of vegetation Index (NDVI, EVI, and EVI2). Following White et al.'s (2010) intercomparison of land surface phenology algorithms, we extracted four growing season metrics (Start and End of Season, Date of growing season peak, and the growing season maximum VIs). Most of these metrics are simple time-related phenometrics (phenophases) that are fairly easy to validate and compare. We compared these metrics with the farmers' record of plantings, emergence, flowering, fruiting, and harvest dates.

The aim of this study was therefore to understand and characterize the accuracy of the remote sensing derived land surface phenology parameters and assess the performance of the various extraction algorithms using farm crops growing season phases.

Data and Methods

a) Study Area, Remote Sensing Data, and Analysis

The study area is the University of Arizona's Maricopa Agriculture Center, located northwest of Tucson, Arizona. This center grows irrigated crops such as alfalfa, corn, and cotton. This center corresponds to the MODIS tile h08v05, covering the US southwestern region. The field observation of crop development stages were extracted from the Center's crop records. For this study, two fields were selected - F-6 and F-38 (see Fig 1). The records kept track of the grown crops, the planting, and the harvesting dates. Table 1 illustrates the selected fields with the planted crops and planting and harvesting dates. The selected fields were large enough to cover at least one homogenous pixel of 250m. This was one of the main criteria for selecting the fields.

b) Background: Growth and Development Stages of Cotton and Corn

- Cotton Physiology

After introducing cotton seeds to moist soil, the cotton plant follows a general time frame during which the plant crosses different development stages. Under favorable conditions, the planted cotton seed enters the germinating or emergence phase in about four to nine days. After the first stage, the second stage in the cotton life cycle is the seeding stage during which leaves appear in about two to four weeks from planting. Table 2 shows the average number days needed for each stage of the cotton plant.

- **Corn plant cycle**

The corn plant cycle varies by geographic location depending on planting dates, environmental factors, and locations. Many development stages occur between the emergence stage and the stage of physiological maturity. The length of time between each growth phase is strongly dependent on factors such as soil moisture, planting date, as well as environmental factors. The corn growth stage is divided between vegetative and reproductive stages. The complete vegetative phase consists of many sub-stages starting form emergency (VE), to nth leaf (Vn), with n referring to the number of leaves on the plant. Table 3 illustrates the six stages of the vegetative phase of the corn plant cycle. Figure 2 outlines some of the stages of the corn plant.

c) Remote sensing data

Spectral vegetation indices (VIs), defined as the arithmetic ratio of two or more bands associated with the spectral characteristics of vegetation, are widely used to monitor spatial and temporal vegetation activity and structural variations in the canopy (Gitelson et al., 2002; Tirelli, 2013; Tucker et al., 1980; Tucker, 1979). Because they are closely linked to the chlorophyll content and structural characteristics of green vegetation VIs derived from satellite image data have become the primary source for numerous remote sensing applications related to vegetation dynamics, phenology monitoring, and mapping land use/land cover change at different spatial and temporal scales (Atzberger, 2013;

Baret et al., 1991; Begue et al., 2011; Grahame et al., 2002; Li et al., 2013; Prince, 1991; van Leeuwen et al., 2010).

- Vegetation indices, such as the Normalized Difference vegetation index (NDVI) and Enhanced Vegetation Index (EVI, Huete et al., 2002) and (EVI2, Jiang et al., 2006), have found wide application in monitoring the earth's vegetation cover (Jiang et al., 2008; Saleska et al., 2007). NDVI is the most used index due to its simplicity and rationing properties that reduces noise caused by changes in sun angles, topography, cloud shadow, as well as atmospheric conditions (Justice et al., 1998). The Enhanced Vegetation Index (EVI) (Huete et al. 2002) has been proposed to reduce the influence of atmospheric and canopy background on the vegetation signal (Luzio et al., 2008; Garbulsky et al., 2013; Jiang et al., 2008). In this study, the primary VI data sources are the 16-day NDVI and EVI and daily NDVI from the NASA Terra Satellite's Moderate Resolution Imaging Spectroradiometer (MODIS) sensor. The reason we selected those VI's is to see how the difference in phenological metrics derived from the VIs by the different proposed algorithms. **Pre-processing remotely sensed data**

Cloud cover, aerosols, shadows, and viewing geometry (Bidirectional Reflectance Distribution Function, BRDF) have major effects on vegetation indices (Atzberger et al., 2011; Paudel et al., 2013). In order to minimize the impact of cloud cover, atmospheric contaminants, and shadows on the vegetation index quality, both daily and 16-day composites of the MODIS vegetation index were filtered using the MODIS vegetation index pixel level quality assurance (QA) information. Only pixels with MODLAND_QA of 00 (observation with no cloud and no other contaminant) or 01 (observation may have aerosol or other issues) (Roy et al. 2002) were considered for this analysis. To further eliminate poor quality data we looked at the aerosol load. Although MODIS data is corrected for aerosols (Justice et al., 2002), the performance of the atmosphere correction algorithm depends on the aerosol quantity. Low to average aerosol loads are corrected fairly easily and accurately, but at high aerosol loads or in case the algorithm cannot estimate the aerosol load and uses standard profiles the correction is no longer efficient (Vermote et al., 1997) and the data may be inaccurate. In this study only pixels with no to average aerosol loads are retained, all other observation are discarded to minimize errors in the time series profiles. The resulting profile with missing dates was gap filled using a simple linear regression approach (Figure 3a and 3b).

Extraction of Phenological Information

The annual phenological metrics, or phenometrics, were derived from the NDVI and EVI time series for both daily and 16-day composites for the selected fields and years based on the assumption that the seasonal vegetation cycles can be defined through a regular pattern. The seasonal vegetation cycle can be represented by two stages: (1) the first stage represents the permanent background level, and (2) the second one describes the seasonal changes which are known as seasonal dynamics (Clerici et al., 2012; Lambin et al., 2001; Li et al., 2013; Mas, 1999) . This seasonal dynamics of vegetation are characterizing the vegetation growth, such as start and end growing season.

Four phenological algorithms were used in this study to assess and understand their differences. This includes the Half-Maximum Method (Coops N.C. et al., 2012; White et al., 1997), Savitzky-Golay, Asymmetric Gaussian, and Double logistic methods using the TIMESAT software (Jonsson & Eklundh, 2004) were used in this study to derive four phenometrics (figure 4). For the three algorithms used by the TIMESAT time-series analysis software, consistent NDVI thresholds for start of growing season, 20% , 30% , and 40%, were used to control the phenological retrieval. Lower thresholds did not work well and failed to indicate the start of growing season. It should be noted that the use of these user defined thresholds introduce a bias in the different developmental stages of the crops. For example, a lower threshold may show an earlier start of growing season, while a higher threshold may indicate a later start of the growing season. Using these thresholds, three timing and greenness metrics were extracted: (1) start of growing season - the time for which the left edge of the curve, or VI value, has increased by 20% , 30% or 40% of the distance between the pre–season minimum and the seasonal maximum; (2) the end of growing season wherein the right edge of the curve has decreased to the same threshold levels; (3) the date of the season's maximum VI signal; and (4) the season's maximum VI value. These phenometrics are strong and valuable indicators for understanding vegetation growth trends and changes in seasonality for different vegetation types (Baeza et al., 2010; Sala, 2000; van Leeuwen et al., 2013). Furthermore, timing of these phenol-metrics is an indicator of the carbon cycle strength and timing (Di-Bella et al., 2004; Prince.S.D., 1991). Metrics related to greenness, such as the maximum seasonal NDVI, are widely used to capture seasonal vegetation productivity (Jonsson & Eklundh, 2002; Sala, 2000).

Results and Discussion

- **Extraction phenological information of Corn F6-2012**

Since the overall objective of the study is to validate satellite derived land surface phenology related to crop development stages, four different algorithms were tested to derive four phenological phases. The 2012 corn field was planted on April 18th (DOY=109 DOY) and harvested on December 13th (DOY=347). The time from planting to emergence usually takes between 4 and 5 days. Table 4 shows the start of growing season derived from the different remotely sensed data using the proposed algorithms. The Half-Maximum algorithm indicates a start of growing season of July 1st for the daily NDVI, July 2nd for the 16-day composite EVI, and July 3rd for the 16-day composite EVI. This suggests that the Half-Maximum algorithm detected the start of growing season at the16-leaf fully emerged stage. The three thresholds algorithms Gaussian, Logistic, and Savitzky-Golay were used with three thresholds 20%, 30%, and 40%. With the 20% threshold, the daily NDVI indicates a start of growing season of June 12th for Savitzky-Golay, June 13th for Gaussian, and June 15th for Double-Logistic. These dates correspond to the 12 leaf fully emerged stage. The 16-day NDVI and EVI fell at the 12-leaf fully emerged stage. Figure 5 shows the start of growing season for each vegetation index with the thresholds used for each algorithm. It is important to note that the start of growing season derived using the Savitzky-Golay algorithm showed an early start of growing season.

The corn field was harvested on December 13th (DOY=347). The end of growing season derived by each algorithm for all vegetation indices are shown in table 5. The Half-Maximum algorithm showed an early end of growing season compared to the threshold algorithms. However, the Savitzky-Golay with all thresholds shows a later end of growing season compared to Gaussian and Logistic methods. Figure 6 shows the differences between the start of growing season derived from daily NDVI and the 16-Day composite. The difference in days varies from one algorithm to another, from 1 to 4 days between Savitzky-Golay and Gaussian, and Logistic. However, the different between Half maximum and others can reach 20 days depending on the thresholds (see table 5)

Table 6 shows the maximum vegetation index for corn, as well as the day of the year corresponding to the maximum VIs. It appears as though the Half-Max algorithm derived an early maximum NDVI (i.e. DOY 229 for the daily NDVI), while Gaussian shows a late maximum NDVI. In terms of maximum NDVI, the Savitzky-Golay algorithm derived larger NDVI values during the annual corn cycle. The Savitzky-Golay, Gaussian, and Logistic algorithms captured the day of year of the maximum VIs at the maturity stage across the daily and 16-day composite VI. However, the Half maximum algorithms captured the day of the year of the maximum VI at the dent stage. Figure 7 shows the different stages captured by each vegetation index, according to the threshold percentage used by the various algorithms.

- **Extraction of phenological information for cotton field F38**

Temperature and moisture play an important role in the growth of cotton plants. The developmental phases of cotton plants follow five main stages: (1) germination and emergence, (2) seedling establishment, (3) leaf area and canopy development, (4) flowering and boll development, and (5) maturation. Field 38 was planted with cotton on April 26th, 2012. Under favorable conditions, cotton plants take 4 to 9 days to emerge after planting. This means that the emergence stage took place around May 4th (DOY=125). Table 7 illustrates the start of growing season derived from each algorithm for the vegetation indices. The start of growing season derived from daily NDVI and 16day-NDVI and EVI using the Half-Max algorithms was detected around July 27th and 28th. These dates corresponded to the flower to open-boll growth stage of the cotton plant.

The Savitzky-Golay extracted an earlier start of growing season across the vegetation indices compared to the Gaussian and Double-Logistic methods, as well as the Half-Max method. For instance, the start of growing season derived from the VI time series using Savitzky-Golay with the threshold of 20 % was detected on June 16th for daily NDVI, on June 18th for daily EVI2, on June 17th for 16-day composite NDVI, and on June 24th for 16-day composite EVI. This indicates that the start of growing season derived from remotely sensed data can vary from one index to another. It’s important to note that the 20% threshold captured both square stage for daily NDVI and flower stage for 16-day composite NDVI and EVI. However, the 30 and 40% thresholds across all VIs and algorithms were able to capture the first flower stage.

On November 28th, the field was treated with Ethephon, a growth regulator for cotton plants. The use of Ethephon usually accelerates the opening of mature unopened cotton bolls and enhances defoliation which readies the plant for harvest. Table 8 illustrates the end of growing season extracted by the various methods considered in this work. The Half-Max algorithm detected the end of growing season on November 19th for daily NDVI, on November 17th for 16-day composite NDVI, and on November 16th for 16-day composite EVI. The Savitzky-Golay detected the end of growing season late compared to all other methods. Figure 8 shows the comparison of the end of growing season for cotton.

The Half-Max algorithm detected an early day of maximum vegetation index, which was September 17th for daily NDVI and September 12th for both 16-day composite NDVI and EVI2. However, among all algorithms, the Savitzky-Golay algorithm showed an early day of maximum VI across all vegetation indices. The Half-Max provided the larger maximum vegetation indices during the seasonal development of cotton. Table 10 illustrates the day of the year with the maximum vegetation indices generated by the algorithms.

Conclusions

This work compared and validated a series of land surface phenology (LSP) extraction algorithms. Our results indicate that these remote sensing based metrics, derived from the different vegetation indices and algorithms, produce results that are quite different from the actual biological phenophases for the two crops used in this study. The algorithms evaluated here are widely used across different vegetation types from the local to global scale, yet the observed differences point to some serious issues that must be considered before data derived from these algorithms are used.

Validation of remote sensing land surface phenology is fundamental to research and proper applications, particularly for global scale biosphere atmosphere interaction studies. Incorporating field observations of crop development stages with satellite-derived land surface phenology allowed us to understand and characterize the performance of the considered algorithms.

Using the MODIS 16-day and daily NDVI and EVI data records we compared land surface phenology metrics extracted by four different algorithms using two crops. The results suggest:

- The Half-Maximum algorithm always detects the start of growing season late compared to Gaussian, Double-Logistic, and Savitzky-Golay, especially when using a threshold of 20 %;

- The Savitzky-Golay estimated the start of growing season earlier than other algorithms (Gaussian and Logistic). The difference in terms of days can vary between 1 to 8 days depending on the thresholds This is valid across all vegetation indices;

- The Half-Maximum algorithm detects the end of growing season earlier than the Gaussian, Double-Logistic, and Savitzky-Golay algorithms. The Savitzky-Golay usually identifies the end of growing season later than the other algorithms for all vegetation indices;

- The day of year which corresponds to the maximum seasonal VI was detected by Half maximum algorithms earlier than the other algorithms;

- The Gaussian and logistic algorithms seem to underestimate the maximum VI across both crops used in this study. This can be related to noise in the VI time series. However, The Half-Maximum and Savitzky-Golay are less sensitive to noise in the VI time series and provide a reasonable VI maximum values;

- Results suggest that the start and the end of growing season derived from daily VI are earlier than the 16-day composite VI.

The results also showed that the proposed thresholds used by the algorithms to detect the start of growing season were not able to detect the emergence stage of corn and cotton (see Fig 5). However, the 20 % threshold was able to detect the 12-leaf fully emerged phase of corn, the 30 % threshold captured the 14-leaf fully emerged stage, the half maximum and the 40 % threshold detected the 16-leaf fully emerged phases of corn e (see Fig 5).

With potential to aid decision-making in agriculture, satellite-derived land surface phenology can provide key information about crop sensitivity (growing season temporality and productivity) to ongoing global climate change.

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Tables

Table 1: Crop types and Date of planting and harvesting for each selected field.

Field-6			
Year	Crops	Planting	Harvesting
2012	Corn	April 18th	December 13th
Field-38			
Year	Crops	Planting	Harvesting
2012	Cotton	April 26th	October 15th

Table 2: Average number of days needed for each growth stage of the cotton plant cycle. The Cotton Foundation: http://www.cotton.org/tech/ace/growth-and-development.cfm.)

Growth Stage	Days
Planting to Emergence	4 to 9
Emergence to First Square	27 to38
Square to Flower	20 to 25
Planting to First flower	60 to 70
Flower to Open Boll	45 to 65
Planting to Harvesting	130 to 160

Table 3: Average number of days considered for each phase of the corn plant. Source: How a Corn Plant Develops. Special Report No. 48. Iowa State University of Science and Technology, Cooperative Extension Service, Ames, Iowa. Reprinted 2/1996.

Vegetative Stages		Reproductive Stages	
Stages	Approximate days after planting	Stages	Approximate days after planting
VE Emergence	6-10	R1 Silking	60-65
V1 First leaf	11-17	R2 Blister	66 – 74
V2 Second leaf	18-21	R3 Milk	76 – 86
V3 Third leaf	21-25	R4 Dough	84– 88
V4 fourth leaf	25-29	R5 Dent	90 – 100
V5 fifth leaf	29-33	R6 Maturity	105 – 120
V12-V17	46-60		

Table 4: Day of year corresponding to planting and start of growing season dates, defined by algorithm for corn field F6 in 2012

Vegetation indices	Planting	Threshold	Gaussian	Logistic	Savitzky-Golay	H-Max
Daily NDVI	109	20%	165	167	164	183
	109	30%	173	179	173	183
	109	40%	180	184	179	183
16-Day NDVI	109	20%	168	178	166	185
	109	30%	178	183	175	185
	109	40%	184	188	183	185
16-Day EVI	109	20%	164	166	162	184
	109	30%	177	177	168	184
	109	40%	183	184	180	184

Table 5: Day of year corresponding to the date of harvesting and the date of start of growing season, defined by each algorithm for corn field F6 in 2012

Vegetation indices	Harvesting	Threshold	Gaussian	Logistic	Savitzky-Golay	H-Max
Daily NDVI	347	20%	337	338	339	310
	347	30%	325	323	326	310
	347	40%	315	311	316	310
16-Day NDVI	347	20%	351	352	355	326
	347	30%	337	337	339	326
	347	40%	326	326	327	326
16-Day EVI	347	20%	349	348	351	325
	347	30%	336	336	340	325
	347	40%	325	326	328	325

Table 6: Day of year corresponding to the date of maximum productivity and the maximum value of VI (seasonal cumulative of VI) for corn field F6 in 2012

	Daily NDVI		**16-Day NDVI**		**16-Day EVI2**	
	DOP	MAX	DOP	MAX	DOP	MAX
Gaussian	243	3555	245	3537	250	2667
Logistic	239	3562	245	3553	249	2687
Savitzky-Golay	230	3764	243	3684	248	2726
Hmax	229	3797	208	3545	208	2674

Table 7: Day of year corresponding to the date of planting and start of growing season defined by each algorithm for cotton field in 2012

Vegetation indices	Planting	Threshold	Gaussian	Logistic	Savitzky-Golay	H-Max
Daily NDVI	117	20%	164	170	168	210
	117	30%	182	183	175	210
	117	40%	194	194	210	210
Daily EVI2	117	20%	166	167	170	210
	117	30%	180	180	182	210
	117	40%	191	193	212	210
16-Day EVI	117	20%	186	196	176	211
	117	30%	199	207	188	211
	117	40%	210	215	198	2011

Table 8: Day of year corresponding to the date of harvest and the end of growing season, defined by each algorithm for cotton field F38 in 2012

Vegetation indices	Ethephon	Threshold	Gaussian	Logistic	Savitzky -Golay	H-Max
Daily NDVI	333	20%	347	342	348	324
	333	30%	338	334	336	234
	333	40%	330	327	335	324
16-Day NDVI	333	20%	348	346	358	322
	333	30%	341	339	349	322
	333	40%	335	333	341	322
16-Day EVI	333	20%	342	344	347	321
	333	30%	333	334	339	321
	333	40%	327	328	330	321

Table 9: Day of year corresponding to the date of planting and start of growing season defined by each algorithm for cotton field F38 in 2012.

	Daily NDVI		**16-Day NDVI**		**16-Day EVI**	
	DOP	MAX	DOP	MAX	DOP	MAX
Gaussian	266	6265	281	6759	275	6613
Logistic	270	6347	284	7098	276	6643
Savitzky-Golay	265	7219	277	6904	275	6674
Hmax	261	7030	256	7230	256	6845

Figures

Figure 1: Study area with selected fields at Maricopa Agricultural Center

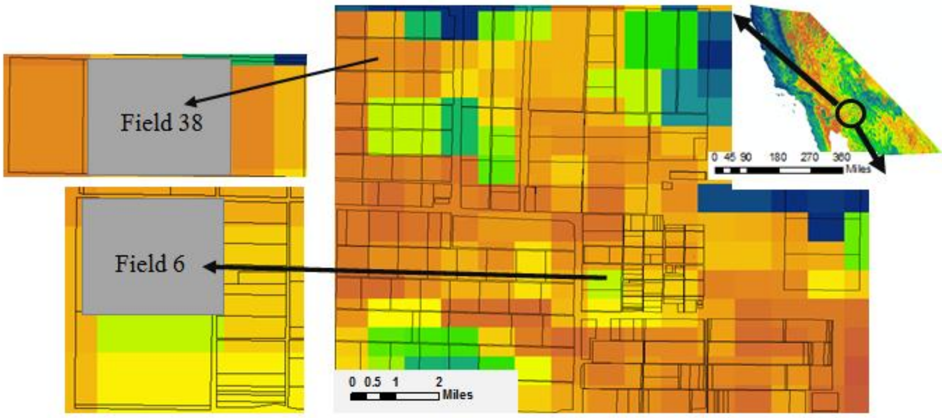


Figure 2: Corn Growth Stage Development. Source: University of Illinois Extension: http://weedsoft.unl.edu/documents/growthstagesmodule/corn/corn.htm#

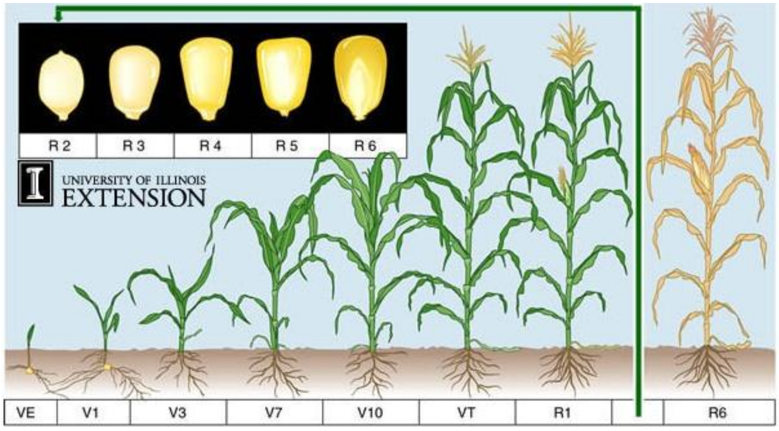


Figure 3: Daily NDVI and EVI2 extract for a single pixel in the study area. (b) 16-day composite NDVI and EVI.

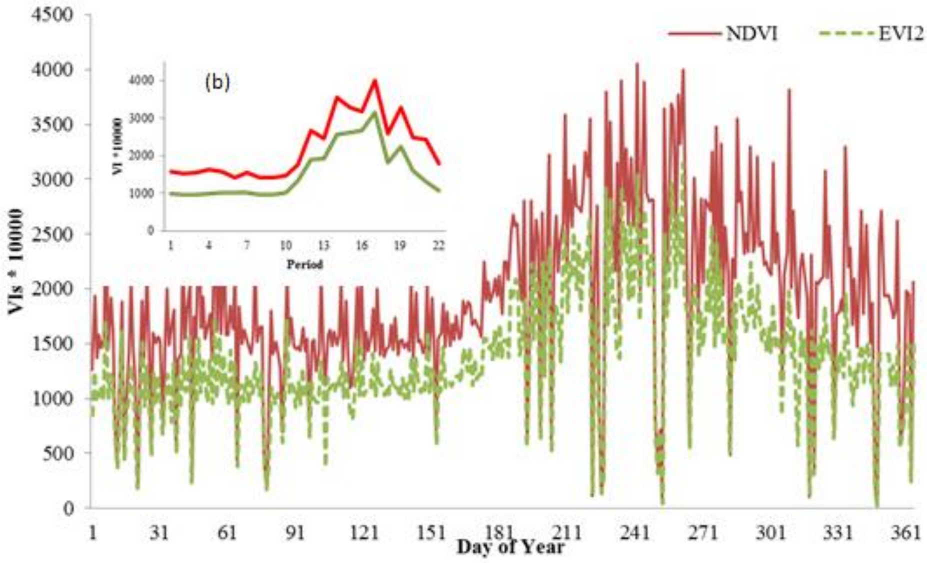


Figure 4: Conceptual model showing seasonal curve of crops outlining the phenological phases generated by Half-Maximum and by multiple thresholds, 20%, 30%, and 40%.

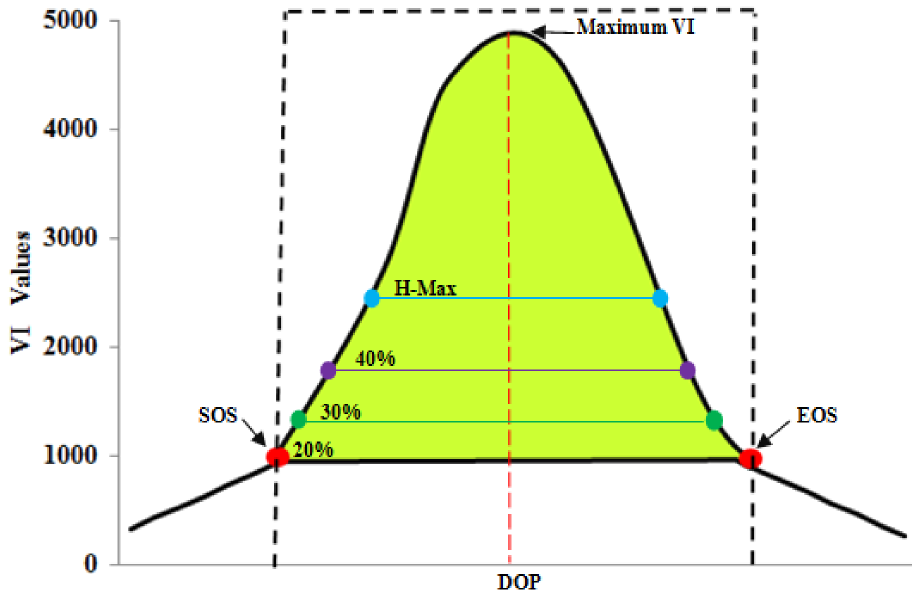


Figure 5: Corn development stages captured by each vegetation index using the Savitzky-Golay algorithm under multiple thresholds.

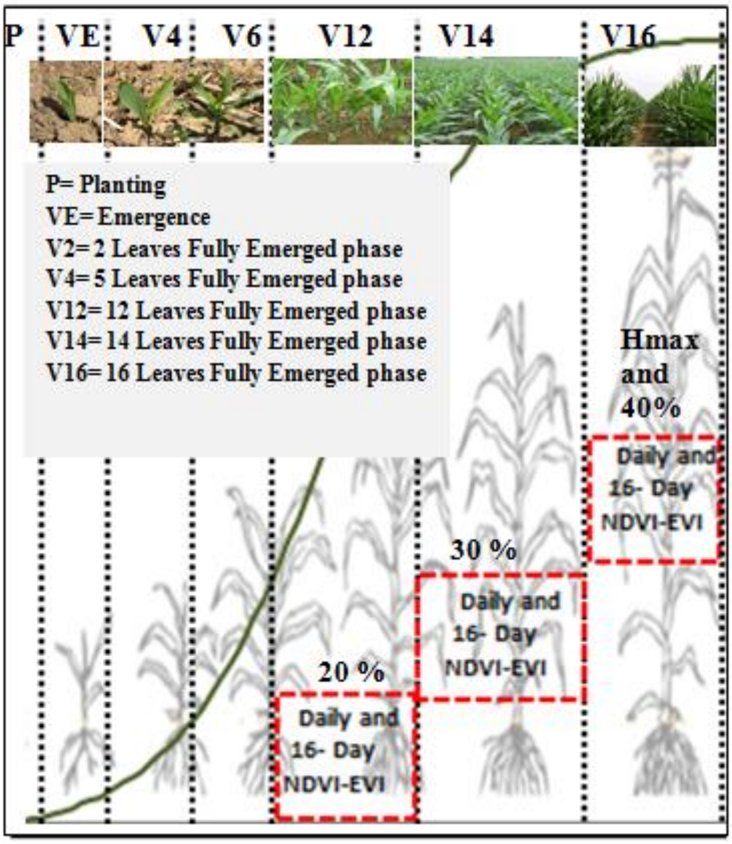


Figure 6: End of growing season by vegetation index, according to threshold percentage for corn field F6 in 2012. (A) for threshold of 20%, (B) for threshold of 30%, (C) for threshold of 40%.

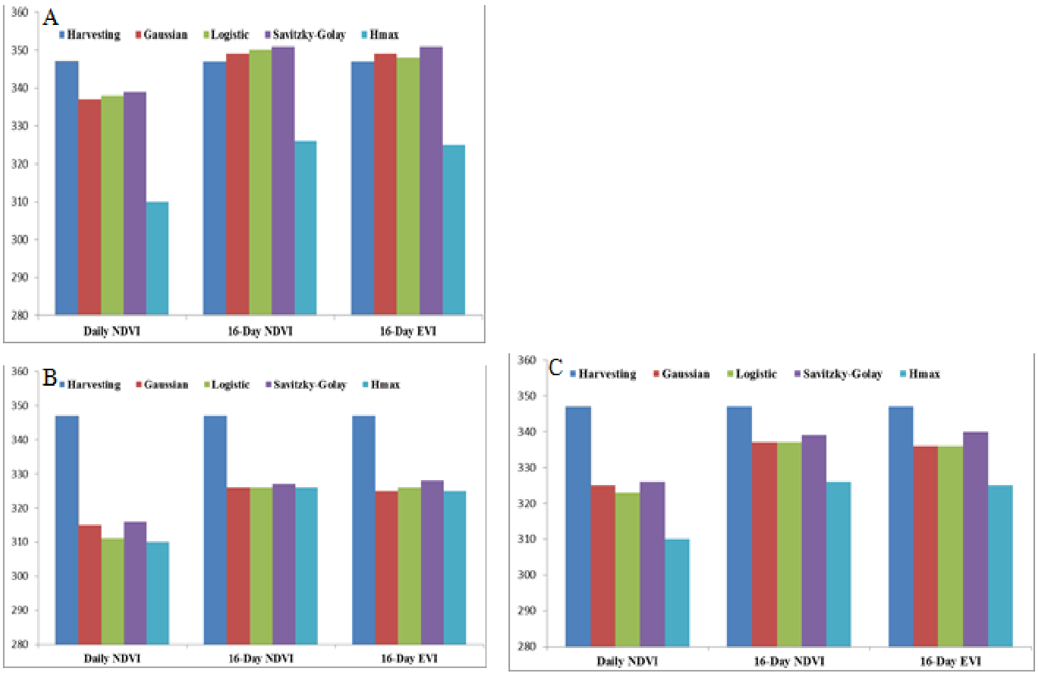
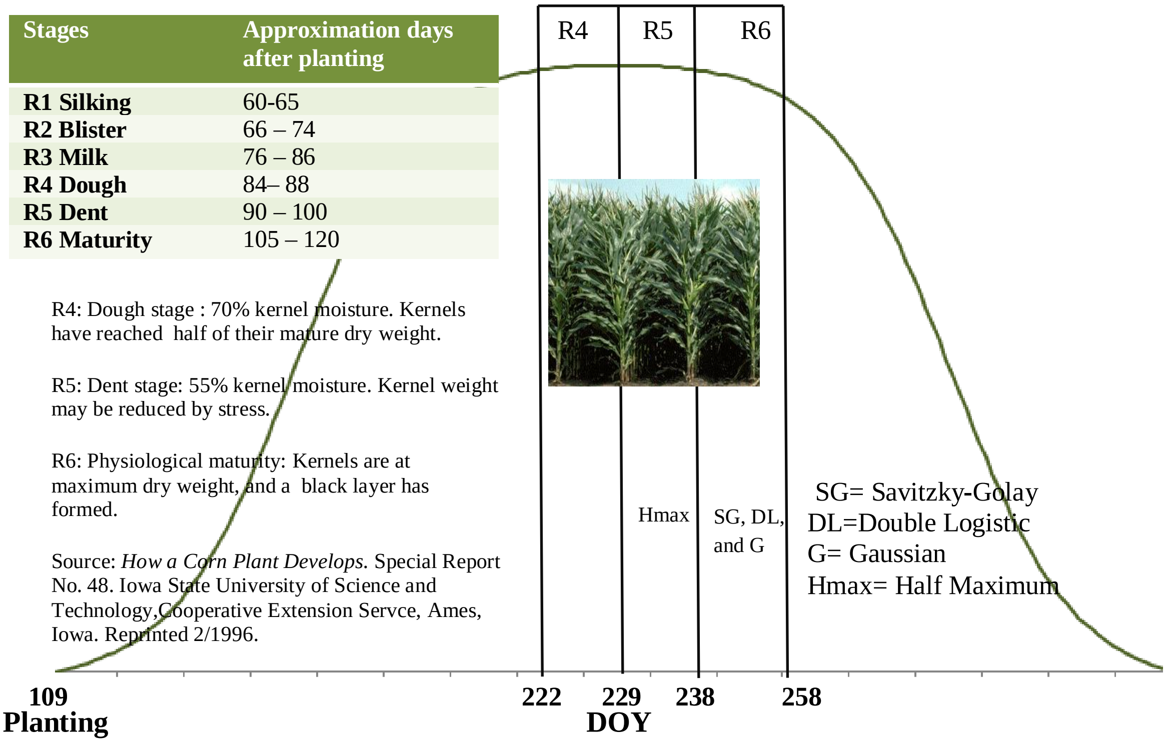


Figure 7: Day of year for maximum VI and corresponding growth stages for corn field in 2012.



Stages	Approximation days after planting
R1 Silking	60-65
R2 Blister	66 – 74
R3 Milk	76 – 86
R4 Dough	84– 88
R5 Dent	90 – 100
R6 Maturity	105 – 120

Figure 8: End of growing season by VI, according to threshold percentage for cotton field F38 in 2012.