THESIS

WILDFIRES AND PRECIPITATION IN THE LOWLANDS OF GUATEMALA: AN ANALYSIS OF PRECIPITATION AND VEGETATION INDICES AS POTENTIAL WILDFIRE DRIVERS

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In partial fulfillment of the requirements

For the Degree of Master of Arts

Colorado State University

Fort Collins, Colorado

Summer 2023

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ABSTRACT

WILDFIRES AND PRECIPITATION IN THE LOWLANDS OF GUATEMALA: AN ANALYSIS OF PRECIPITATION AND VEGETATION INDICES AS POTENTIAL WILDFIRE DRIVERS

Wildfire is an inevitable natural disaster that is considered exclusive to dry and temperate regions. However, the increasing wildfire occurrences in tropical and humid forest regions urge us to investigate the drivers of this natural phenomenon for a humid forest region. Although wildfire is inevitable, it can be managed with proper strategies; thus, identifying the drivers of wildfire in humid and tropical regions is imperative. This thesis focuses on identifying the role of precipitation as a driver for wildfire occurrences and fuel generation for fires in a humid forest ecological system in the lowlands of Guatemala (Petén). Using the data library and cloud computation system of the International Research Institute for Climate and Society (IRI), INAB (Instituto Nacional de Bosques/Guatemala's Forest Authority) fire records for Guatemala, and geospatial tools like GIS and Google Earth Engine, the thesis identifies the influence of precipitation on vegetation and wildfires in Petén. The findings suggest that precipitation's influence on Petén's wildfires is two-dimensional. Precipitation influences vegetation or total fuel generation and fire occurrences by influencing fuel availability by influencing green-up and the dry down of fuels in a humid forest ecosystem. This two-dimensional influence makes precipitation one of the most critical drivers of wildfire for tropical-humid forest ecology. Besides the seasonal accumulative precipitation, the precipitation pattern and amount at different times within a preceding season of the fire months

highly influence vegetation conditions and fire frequencies. The findings also suggest that seasonal precipitation forecasting could potentially be a tool for wildfire management and forecasting.

ACKNOWLEDGEMENTS

I want to thank Professor Diego Pons for helping me throughout the Journey. It is only possible due to his continuous motivation and direction. My special thanks to Professor Stephen J. Leisz for helping me with my writing; without his support, the Journey would have been impossible. I would also like to thank Professor Camille Stevens-Rumann; her classes and meetings helped me shape my thesis and conclude it meaningfully. I would also like to thank Professor Carrie Chennault for being so helpful and supportive since my first day at CSU. Finally, I want to show my deepest gratitude to the Department of Anthropology and Geography and my friends for being helpful and supportive throughout the Journey.

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1.1 Introduction

Fire has shaped the environment and the landscape globally, and it has always been essential for the development of human civilization. While fire is an integral part of the natural environment, it may also create great suffering for humankind and nature. Wildfires can cause significant loss for humans and nature. Wildfires are termed unplanned fires or unauthorized human-caused fires in forested areas. Fire has become a worldwide issue and affected worldwide forest systems irrespective of the firefighting capacity and tactics (Bowman et al., 2009). South Asian tropical forests in 1997-1998 cost around 9.3 billion USD, whereas Latin America in the same period cost around 15 billion USD and 20 million ha of burned forest (Bowman et al., 2009). This tremendous loss of doubt in the existing fire management system and limited understanding of the fire causes. Since 2000, in the US alone, about 70,072 wildfire events have occurred, resulting in about 7 million acres of land burned every year (CRS, 2022). Between 2021-2022 wildfires cost about $11.2 billion USD across the United States alone (Sleight, 2022). Although forest covers are considered carbon sinks and air purifiers worldwide, carbon is released and air polluted while forest areas burn. Besides the plant species and air pollution, biodiversity is also vulnerable to wildfires.

Forest fire predictability, and understanding of the drivers of wildfires, are becoming important due to increased wildfire activity worldwide (Pausas & Keeley, 2021). The comparatively lower cost to contain the fire incident when it is smaller (in size) demands further research to understand the driving force of wildfires. About 98 percent of total fire incidents in the USA are usually stopped before they reach 120 hectares in size, whereas the remaining 2 percent of incidents cause around 97 percent of the total loss by fire incidents (Noth et al., 2015). This highlights the importance of understanding the factors that contribute to fires (pre-conditions) that allow for Early Warning Systems (EWS) to reduce the impact of wildfires.

Climate can significantly influence initiating or increasing the possibility of wildfires. Where most of the literature suggests a negative correlation between precipitation and wildfires (Pilliod et al., 2017), a greater amount of rainfall in a unique geospatial location, like in a tropical forest ecosystem, may increase the number of wildfire incidents because of increased vegetation may contribute to fuel availability during a fire season. A body of literature argues that higher precipitation in previous seasons may positively influence vegetation growth and fuel generation for the upcoming years, thus increasing the probability of wildfire frequencies and intensities once this vegetation dries down (Turco et al., 2017). Bowman et al. (2009) explains antecedent wet periods may create substantial herbaceous fuels or dry season which dry up the fuel may influence the wildfire occurrences, where he substantially mentioned historical analysis on his argument. These apparent contradictions deserve local assessments to understand the potential associations between precipitation and wildfires.

While forest cover loss in Latin American countries has decreased in recent years, the rate of forest cover loss has been increased in Central American countries during the past two decades (Sesnie et al., 2017). Forest fire is one of the leading causes behind this forest cover loss in Central America, especially during 2019 - 2020 (Belmaker, 2021; Central America Burns, 2020). All countries except Costa Rica in Central America show an increase in forest fires in this region (Central America Burns, 2020). Guatemala and Honduras have lost more of their forests than the other Central American countries. Forest cover loss due to wildfire incidents in Guatemala during the 2018-2019 fire season was about 10,179 hectares, and the Petén department (political boundary including most of Guatemala's northern lowlands) was the most affected region. About nine out of ten active fires in Guatemala have been spotted in Petén during the fire season since 2001(CONRED, 2019). Guatemala registered about 1,398 forest fires in the 2019-2020 fire season, with an affected area of 78,129 ha (Green Climate Fund, 2022). The most critical fire seasons for Guatemala in the past couple of decades were 2003, 2005, 2007, 2019, and 2020. The most active fire months are March and April, with a temperature slightly above average (Green Climate Fund, 2022). According to INAB (Instituto Nacional de Bosques), the average number of fires per season in Guatemala is 790, with an average of 30,824 ha of burned area in each season (Green Climate Fund, 2022). The historical data (2000-2020) also indicates that about 39 ha of forest has been affected on average in each fire incident (Green Climate Fund, 2022). In comparison to the historical data, the present scenario is alarming, as Guatemala experienced about 1,398 fire events in the 2019-2020 fire season compared to the historical average, which was about half of that (790).

According to the Green Climate Fund (2022), the leading cause of such an increase in frequency is drought and climate change. The geographic location of Guatemala has made it prone to climate change, and it is one of the ten most affected countries by climate change (Zhongming, 2014). About 85.7% of Guatemala's territory is prone to drought risk, and the drought of 2014 was the worst in the last 40 years (Zhongming, 2014). Evidence suggests that an increase in drought conditions may increase the risk of wildfires in the future (Zhongming, 2014). At the same time, available projections suggest an increase in temperature (about 3.3 degrees Celsius) and a decrease in rainfall of about 28 percent for Guatemala (Zhongming, 2014). This change will create an alarming situation for Guatemala by creating an ambient environment for fire incidents (Fig. 1). Compared to all South American countries, the increase in forest fire incidents in Central American countries is alarming, especially since, during the last decade, there has been a significant increase in forest fire frequencies in Central America (Belmaker, 2021).

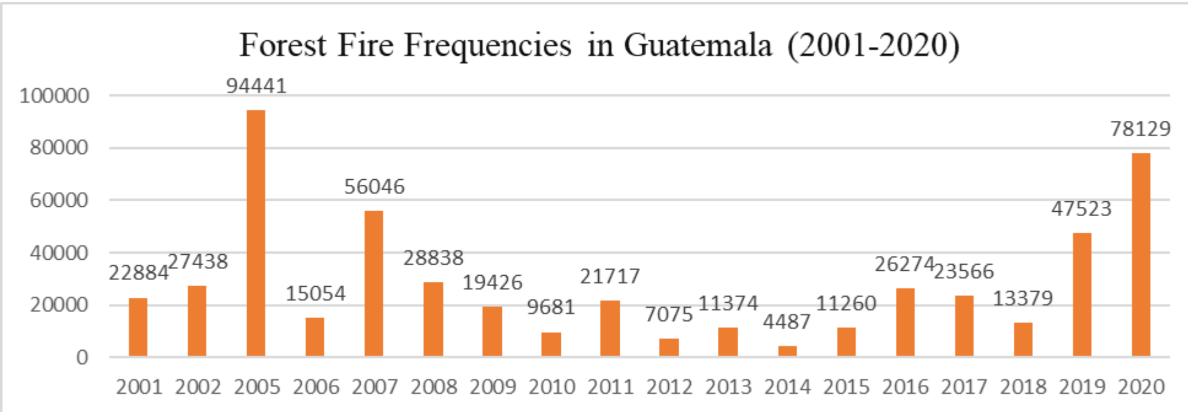


Fig. 1: Forest fire frequencies in Guatemala; 2001-2020 (Green Climate Fund, 2022).

The forest areas of Central America, especially the protected forest areas of Guatemala, are one of the most complex forest systems among the Central American countries. In the 2009-2019 period, Central America registered a total of 26.2 Mha (million ha) of burned area, with about 180,000 fire events registered, while South America (SA) reported about 340 Mha of burned area, caused by almost 1.3 million wildfire events (Belmaker, 2021). The forest ecosystem of Central America is fragile and can hardly survive the first fire incidence, let alone a second wildfire within five years of the first (Armenteras, 2021). Although Guatemala has a lower rate of forest cover loss (30.4%) compared to other Central American countries, the increased incidents could be alarming for such vulnerable forest ecosystems (Belmaker, 2021).

Because of its extensive variation in altitude and precipitation in a relatively smaller area, Guatemala is recognized as a megadiverse country (Castañeda, 2008). The country is a biological corridor between the northern and southern hemispheres with a relatively old geological origin and location between the Neotropical and Holarctic origins (Monterroso et al., 2020). Following the

Holdridge-based methodology the ecosystem of Guatemala can be divided into thirteen different life zones (Iarna-URL, 2018). Of the 13 different life zones our study area encompasses the humid tropical forest, and the tropical dry forest (Petén)

Among these thirteen zones, the humid tropical forest, and the tropical dry forest cover about 55% of the national territory of Guatemala, and both ecosystems have been significantly degraded, depleted, and polluted over time (Monterroso et al., 2020). About two-thirds of these ecosystems (by coverage) have been affected and degraded (Monterroso et al., 2020). Petén (one of 22 departments of Guatemala) represents Guatemala's humid tropical and subtropical forest biome. The moist subtropical broadleaf forest ecosystem is complex and rich in biodiversity (Gómez & Méndez, 2007). The tropical forest in Petén is the largest remaining tropical forest in Central America but increasing wildfires in Guatemala due to climate changes and erratic climate behavior along with anthropogenic activities (agricultural expansion and development) creating a threat to this unique ecosystem (Monzon-Alvarado et al., 2012). Monzon-Alvarado et al. (2012) also blamed the management practice and the changes in climatic components. Although many articles have prioritized anthropogenic activities as the leading cause of forest loss and forest fire by coverage, climate change plays the most crucial role in wildfires (not human-led fires) in the tropics (Gonzalez, 2020).

Despite their humid climate, forest fires are increasingly creating pressure on this ecosystem; however, fires in the tropics have received less importance compared to the dry and temperate regions (Juarez-Orozco et al., 2017). The importance of tropical forests in biodiversity and ecological services has been overlooked for many years regarding wildfire risks because of their lower-frequency fire regime (Juarez-Orozco et al., 2017). The existing literature on forest fires in the tropics mainly discussed the anthropogenic influence and causes of fires, but investigation for natural fires still needs to be investigated. Agricultural expansion, mining, development, and ranching are the leading cause of forest fires in the tropics, although natural wildfires are also increasing significantly. The thesis aims to contribute to the research gap by focusing on naturally ignited wildfires only and try to understand if / how climatic components (precipitation, vegetations) influence forest fire occurrences in a humid tropical region of Guatemala (Petén).

1.2 Vegetation Indices

Understanding the influence of precipitation on vegetation is essential, as vegetation is the fuel for wildfires (Michael et al., 2022). Vegetation indices help to understand vegetation growth and condition through a measurable scale which helps to quantify and compare the growth and condition of vegetation in response to precipitation. The Normalized Difference Vegetation Index (NDVI) is the most used indices for investigating vegetation status (Rousta et al., 2020; Liou & Mulualem, 2020; Dutta et al., 2015). NDVI is calculated based on near-infrared reflection and the absorption of red-visible radiation by the chlorophyll pigments in green leaves (Mushore et al., 2019). The calculation or ratio between NIR (near-infrared) and RED (red-visible) spectra is done using satellite imagery which remotely senses the reflectance from the earth's surface.

The IRI (International Research Institute for Climate and Society, Columbia University) Data Library uses the MODIS moderate resolution vegetation indices products (Rousta et al., 2020). The NDVI ranges from negative 1 to positive 1 (-1 to +1), where MODIS provides 250 m of resolution with a 16-day composite (Rousta et al., 2020). The NDVI value corresponding to areas with vegetation ranges from 0.2 and 1 (Rousta et al., 2020). A NDVI value greater than 0.5 represents a healthy to dense vegetation, whereas a range from 0.2 to 0.5 represents sparsely to very little vegetated areas (Drori et al., 2020). Rousta et al. (2020), to investigate seasonal and yearly vegetation coverage, divided the NDVI into different categories (0.2–0.3, 0.3–0.4, 0.4–0.5, 0.5–0.6, 0.6–0.7, and 0.7–0.8).

NDVI = (NIR-RED)/(NIR+RED) ---(i)

Mostly used remotely sensed database, and the formula for calculating NDVI are -

NDVI (Landsat 8/ Landsat 9): NIR = B5, Red = B4

NDVI (Landsat 5 TM): NIR = B4, Red = B3

NDVI (Sentinel 2 MSI): NIR = B8, Red = B4

NDVI (MODIS): NIR = B2, Red = B1

MODIS also has an atmospherically corrected NDVI dataset that can be accessed by Google Earth Engine API's.

SMN (Smoothed NDVI) is a widely used vegetation index used to understand the correlation or impact of precipitation on vegetation cover (Jiang et al., 2021). Even though there is a slight bias for sensor degradation and orbital drift, data availability, accessibility, and a long-term correlation analysis make the SMN very useful (Jiang et al., 2008). SMN also helps to understand the starting and senescence of the vegetation over the season (Bunrit et al., 2016). The International Research Institute for Climate and Society (IRI) Data Library provides access to SMN through expert codes.

Similar to NDVI, the **Vegetation Condition Index (VCI)** is also widely known in the field of remote sensing (Quiring & Ganesh, 2010). The VCI is widely used to identify vegetation and crop yield in relation to precipitation and agricultural drought (Quiring & Ganesh, 2010). Quiring &

Ganesh (2010) found a positive correlation between precipitation and NDVI, as well as precipitation and VCI, which helped identify crop production.

The VCI attempts to compare the current NDVI (Normalized Difference Vegetation Index) with a range of NDVI values observed in previous years. Typically, the VCI is expressed as a percentage, indicating whether the current value falls within the minimum and maximum values observed in previous years or represents an extreme value (Poupard & Castel, 2023). Lower and higher VCI values indicate poor and favorable vegetation conditions, respectively. The VCI ranges from zero (0), indicating highly abnormal conditions, to 100, representing optimal vegetation conditions. To calculate the VCI, NDVImax and NDVImin can be derived each year using Raster interpolation in ArcGIS Pro (Rousta et al., 2020). However, the expert mode in the IRI data library offers direct access to VCI through specific codes, simplifying the process and reducing the likelihood of complex calculation errors.

VCI = 100 * (NDVI - NDVI min) / (NDVI max - NDVI min) ------------(ii)

Even though VCI is a widely used index, it has about 4% error; a Thermal Condition Index or Temperature Condition Index (TCI) is sometimes more accurate in correlating precipitation with Vegetation growth (Quiring & Ganesh, 2010). TCI has a similar level of potential as VCI in identifying drought conditions or vegetation stress (Liu et al., 2020). TCI indices also help to understand the moisture content in plants, where the correlation between this index and precipitation represents the precipitation's impact on vegetation in terms of drought stress. Understanding drought stress is essential in this research as the drought situation may increase the availability of fuel for forest fires (Richardson, et al., 2022; Little et al., 2016). TCI characterizes vegetation health and stress or a combined estimation of foliage's moisture content and thermal conditions (Zou & Sanchez-Azofeifa, 2020). TCI also represents the stress of vegetation, either dryness or excessive wetness (Zou & Sanchez-Azofeifa, 2020). TCI relates the current temperature with long-term maximums and minimums. The process assumes higher temperature trends to cause a deterioration in vegetation conditions (FAO, 2014). TCI indices estimate the temperatures and then modify them to represent different vegetation responses reflecting the temperature condition. TCI varies from 0 to 100, with 0 referring to an extremely dry condition and 100 to an extremely wet vegetation condition.

TCI = LST_{max} - LST_i /LST_{max} -LST_{min} (Liu et al., 2020) -------------------------(iii)

[Where, LST_{max} = historical maximum in Land Surface Temperature; LST_{min} = Minimum values in Land Surface Temperature at each desired time step over the study period; LST_i = Land Surface Temperature in an individual month]

The TCI method has been developed by Kogan (1995), where he successfully used the thermal channels (TIR/ Thermal Infrared bands) to identify drought condition (Gaznayee & Al-Quraishi, 2019).

Classification of TCI to Identify a drought Condition (Kogan, 1995; Gaznayee & Al-Quraishi, 2019):

Drought Categories	Values
Extreme drought	≤10
Severe drought	10<& ≤20
Moderate drought	20<& ≤30
Mild drought	30<& ≤40
No drought	≥40

The TCI drought categories represent that the higher the values of TCI, the lower the drought, which means increased wetness in vegetation reflectance. The higher values also indicate a higher level of precipitation that results in higher TCI or wetness.

Vegetation Health Index (VHI) combines Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI) to create a VHI value, which was created by Kogan in 1995 (Tran et al., 2023; FAO, 2014). The VHI is derived from integrating VCI and TCI, where the integrated result of VCI and TCI expect to provide a better assessment of drought conditions or lack of precipitation rather than depending on a single indexing (Masroor et al., 2022). The TCI drought categories indicates that the higher the values of TCI, the lower the drought, which means increased wetness in vegetation reflectance. The higher values also indicate a higher level of precipitation that results in higher TCI or wetness.

VHI= $\alpha \times VCI + (1-\alpha) \times TCI$ ---(iv)

[Where, α is a coefficient determining contribution of VCI and TCI (NOAA, 2023)]

Or **VHI =** $0.5\ TCI + 0.5 VCI$ (Zuhro et al., 2020; Masroor et al., 2022) ------- (iv)

A lower VHI value indicates increased vegetation stress and poor vegetation condition due to increased temperature and dryness. Thus, a lower VHI value over a more extended period could indicate drought or loss of vegetation health (FAO, 2014), similar to TCI indices scaling when used to identify a drought situation. Zuhro et al. (2020) classified the VHI values into five categories to understand vegetation's water stress (drought).

Stress level	VHI values
Extreme Stress	0-10
Severe Stress	10-20
Moderate Stress	20-30

Mild Stress	30-40
No Stress	>40

In this research, the IRI data library has been used for accessing all the vegetation indices (NDVI, SMN, VCI, TCI, and VHI) and correlating it with the available CHIRPS precipitation data using proper codes in the expert mode of IRI data library (Pons et al., 2021). Even though the VCI and TCI indexes are highly dependent on the aridity of an area, both indexes are crucial for understanding the drought condition or relation to the precipitation of an area (Kukunuri et al., 2022).

1.3 Precipitation, Vegetation Indices, and Wildfires

The widely used remote sensing indexing to quantify and identify vegetation greenness, vegetation density, and changes in vegetation cover for a forested area is the NDVI or Normalized Difference Vegetation Index (Charizanos & Demirhan, 2023; Aybar et al., 2020). As noted above NDVI is a quantitative satellite-based indexing of vegetation cover that can be used to analyze and determine the health, coverage, and life cycles of trees or green vegetation (Charizanos & Demirhan, 2023). Vegetation indices can be used to determine climate changes, like precipitation or drought as well (Zhe & Zhang, 2021). Several scientific studies used the NDVI index to predict and determine the wildfire impacts and significantly contributed to the literature on wildfire prediction in relation to vegetation conditions (Charizanos & Demirhan, 2023).

Amiri and Pourghasemi (2022) represented NDVI values directly referencing vegetation health based on spectroscopic analysis (Charizanos & Demirhan, 2023). NDVI indices that have an average of 0.65 or lower are typically linked to vegetation that is moderately healthy or unhealthy

(Tasmanian Fire Service, 2020). During the examination of forested areas, the prevalent vegetation types that exhibit low NDVI values are commonly identified as a typical form of fuel for wildfires, as described by the Tasmanian Fire Service (TFS, 2020). The vegetation dynamics show a positive response to changes in precipitation and negative responses to drought in most cases (Zhe & Zhang, 2021). Wildfire is highly dependent on fuel availability, mainly the density and availability of different vegetation types and the growth of plants (Michael et al., 2022). Besides vegetation availability, factors like precipitation also play a significant role in a wildfire (Michael et al., 2022). Research findings indicate that a consistently hot and arid climate leads to the drying of forest vegetation, making it more susceptible to wildfires and this increased vulnerability can be assessed by utilizing vegetation indices (Charizanos & Demirhan, 2023; Royal Commission into National Natural Disaster Arrangements, 2020). The utilization of NDVI in Probabilistic Risk Assessment for wildfire events involves employing NDVI curves to represent water stress, thereby establishing a relationship with precipitation (Hernandez-Leal et al., 2006; Charizanos & Demirhan, 2023).

NDVI may also be used for the wildfire possibility or wildfire prediction for a complex tropical forest ecology (Michael et al., 2022). Zhang et al. (2013) investigated vegetation vulnerability using NDVI in relation to a forest fire in China, where they declared NDVI as the best exploratory variable for fire occurrence in the region with 84 % of accuracy (Charizanos & Demirhan, 2023). Dlamini (2011) used NDVI for a wildfire prediction approach using MODIS remote sensing data, and the result came up with 96.6% accuracy in predicting wildfires following Bayesian network modeling.

Swain (2021) discussed the relationship between precipitation and wildfire events in his study on California. His findings showed that lower precipitation, both in quantity and time, provokes drying up the vegetation and increases fuel availability. Swain (2021) identified delayed rainy season and the sharpness (a decrease in seasonal length) of the season increase the dryness of vegetation, thus accelerating wildfire occurrences. Vegetation changes could be measured by NDVI, VHI, TCI, and VCI. However, this relation or influences of climatic factors like precipitation and temperature on wildfire has changed to some extent in the post-industrial period due to increasing direct anthropogenic influence (ignition & suppression) on wildfire (Pechony & Shindell, 2010). The increasing anthropogenic influence is causing about 75 % of today's wildfire incidents regarding frequencies or ignitions. Although this study focuses only on naturally caused fires, anthropogenic activities like fire suppression, which increases fuel availability, also influence natural fire in frequencies and intensities.

Swain (2021) focused on fuel availability, taking the precipitation anomaly as a reason for vegetation dryness. While Swain (2021) argued that less rain is a reason for more wildfires, some authors stated that enough rainfall in preceding years might also be responsible for wildfires by increasing biomass (vegetation growth). Although these two statements might seem contradictory, they have a significant relationship. The increased precipitation in preceding months with decreased precipitation in fire seasons may create an ideal situation for wildfire (Swain, 2021). Where seasonal anomalies or changes like an extended dry season merging with fire seasons may worsen the condition (Swain, 2021)

Precipitation is related to vegetation growth and can be identified by vegetation indices, especially NDVI (Chen et al., 2020). Chen et al. (2020) explains that the relationship between vegetation indices and precipitation could be strong enough to justify the impact of precipitation on vegetation, thus fuel generation for wildfire. Different studies on forest fire predictions concerning vegetation conditions provide a plausible explanation for the specific fire risk using VHI and

NDVI indices, where greenness in normalized vegetation index (NDVI or SMN) was a proxy for vegetation moisture conditions (Michael, et al., 2022; Wehner, 2017).

Even though there is substantial evidence and research that vegetation always shows a linear response to precipitation, the response depends on many factors and creates the possibility of lagged responses (Wu et al., 2015). Vegetation growth (measured by different vegetation indices) has about one to two months of lagged response to precipitation and two to six months of seasonal precipitation anomalies, and the response is significant (Chen et al., 2020). Besides the lag in response to precipitation, the level of response is also strongly related to the tree species and the elevation (Chen et al., 2020). Other important factors influencing vegetation responses to precipitation are topography, slope, aspects, and elevation (Wu et al., 2015). Besides physiography, spatiality significantly influences vegetation indices worldwide (Wu et al., 2015; Chen et al., 2020). Mean annual precipitation (MAP) could play an active role in determining spatial distributions of vegetation sensitivity, thus reflecting the changes in NDVI value due to changes in precipitation regimes or seasons (Chen et al., 2020). Vegetation indices have been successfully used in much research on tropical areas (similar to the climate of Petén) to identify the response of vegetation concerning precipitation (Camberlin et al., 2007; Chen et al., 2020). Although this research only considered the amount of precipitation, the frequency and distribution of precipitation also significantly impact vegetation responses for a particular place (Chen et al., 2020). Even though it is critical, little research has been conducted on vegetation response to precipitation, especially considering precipitation frequency and distribution (Chen et al., 2020).

Although drought and dry weather are apparent contributing factors for wildfire, it is not like 'with drought comes fire' or vice versa (Littell et al., 2016). Fire-drought relation is more complex and depends on the forest system, fuel complex, moisture content, and forest environment (Littell et al., 2016). The increasing evidence of wildfires in tropical regions seeks further investigation of the drivers behind wildfires. Drought may help to increase the fuel availability over the region and help to increase the likelihood of fire ignition and affect fire behavior. However, the fire-drought relationship is also scientifically dependent on climate change, even though climate change does not directly influence creating a drought situation (Maloney et al., 2014; Littell et al., 2016). However, drought responsible for wildfires may be classified into four major types (meteorological, agricultural, hydrological, and socio-economic); they can also be classified into other categories (Ndayiragije & Li, 2022). These four types of droughts can also be further classified into two broad types: meteorological, which is dependent on precipitation, and socio-economic drought, which is dependent on demand and supplies of goods (Ndayiragije & Li, 2022). Crausbay et al. (2017) defined the ecological drought by summing up environmental, climatic, hydrological, socio-economic, and cultural aspects of drought under the same umbrella, while few others defined reduced groundwater levels and extreme discharges of surface water as groundwater drought (Ndayiragije & Li, 2022). However, mainly the meteorological drought has been studied in terms of wildfires.

Like precipitation and dryness, vegetation health's relation to wildfire is critical to understanding the possibility and reason for wildfire occurrences. Fuel loading (vegetation biomass) is considered one of the most critical drivers of wildfires (Stavi, 2019). Vegetation indices help to understand the probable fuel loadings, and thus the tendency for wildfire. Although wildfire is often considered a disaster when humans are present, ecologists believe that wildfire could be helpful for biodiversity and forest regeneration (Dupuy, 2020). Despite being beneficial to some extent, wildfires should be managed properly to save natural resources. The best way to manage is to predict, for example, in the US, where about 98% of the wildfire is controlled (Noth et al., 2015), and for that, the drivers of the wildfire must be identified.

1.4 Aim and Objectives

This research aims to identify if there is evidence of an influence of precipitation on vegetation and increasing wildfire events despite a humid tropical region (semi-tropical in the northernmost corner of Guatemala). The research will help to identify the potential drivers of wildfires in the lowland of Guatemala. It will also contribute to the research gap in predicting wildfires in a humid tropical forest area. Once the wildfire drivers are identified, the research will also try to investigate the potential of seasonal climate forecasting on precipitation in the lowlands of Guatemala. Once a significant influence of precipitation is discovered, seasonal precipitation forecasting may be used as a potential wildfire risk management tool.

Wildfire behavior is controlled by three environmental components weather, fuel, and topography (Henzi, 2021). Weather includes precipitation, temperature, and relative humidity, which may turn the vegetation into available fuel for forest fires. Lower relative humidity and higher temperatures can create an ideal situation for wildfire and fuel availability. On the other hand, Significant precipitation followed by rapid development of drought conditions or rapid vegetative growth followed by extreme drought results in a dry and available fuel in a forest ecosystem that is highly susceptible to ignition (Henzi, 2021). Wind speed and direction also has a significant influence on fire spread and changes in directions. Air in favor of wildfire may increase the spread and intensity by supplying oxygen for the fire.

Topography, on the other hand, is not as changeable as the weather variables, but aspect (direction of a slope faces), elevation, slope, and features (canyons, valleys, rivers, and other elements of a landscape) have a significant influence on wildfire (Henzi, 2021). Although the topography cannot be changed, it could also influence weather and fuel conditions. Aspect and slope significantly influence the weather by controlling the wind and light directions and amounts, where elevation influences the humidity and the dryness of the fuel. Fuel plays the most critical role in the management of wildfires. Where weather and topography cannot be changed in most cases, fuel can be removed or reduced through prescribed burning to manage wildfires (Henzi, 2021).

This research aims to understand the two critical factors of the fire triangle: climate and fuel (Fig. 2). It also tries to understand their influence on wildfire occurrences in the humid-tropical forest of Petén, Guatemala. The research provides a straightforward statistical analysis of how these factors may influence vegetation and fire occurrences based on the last 38 years of precipitation and vegetation data (1983-2021) and the 21 years of fire records of Petén (2001 to 2021).

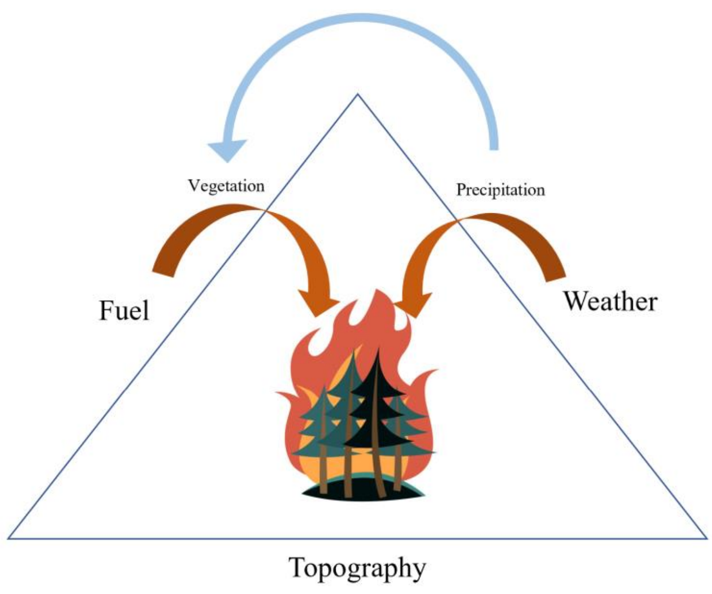


Fig 2. Research aims to analyze factors and their relationships in wildfires of Petén, Guatemala.

1.4.1 General Objective:

The General objective of the research is to investigate if there is any influence of seasonal precipitation on vegetation and wildfire occurrences. The research will also investigate how precipitation affects the fuel availability of forest fires and influences forest fire occurrences in Petén.

1.4.2 Specific Objectives:

- Identify if there is any correlation of vegetation indices (NDVI, SMN, VCI, TCI, and VHI) and precipitation.
- Identify if there is any significant correlation between those indices, precipitation and wildfire occurrences in Petén, Guatemala.

2.1 Study Area

Guatemala (Republic of Guatemala) is a country in Central America, also known as the country of eternal spring. It is famous for its numerous volcanoes and mountains. Guatemala covers an area of 108,890 square kilometers with a population of 16,581,273 and is bordered by Mexico, Honduras, El Salvador, and Belize. The Pacific Ocean borders the country to the West, while the Caribbean Sea borders to the East.

The fire season in Guatemala typically begins in mid-March and lasts about 13 weeks. Wildfire occurrence is increasing in Guatemala, where only in 2022, about 580 fire alerts were reported (Global Forest Watch, 2023). These 580 fire incidents considered in the report were high confidence alerts only, which means there may have been many more that were not recorded. Guatemala, from its 6.94Mha of natural forest (64% of the country's area coverage), has lost about 230 thousand hectares of forest cover by 2021, where it lost about 48.7 thousand hectares only in 2021 (Global Forest Watch, 2023). The main reason behind the loss is forest fires, especially those caused by human activities. According to Instituto Nacional de Bosques (INAB), human-caused forest fires are widespread in Guatemala and a concern of the management authorities. Through different management mechanisms, the fire caused by human activities, especially agricultural fires, has been reduced to 24% in 2008 from 40% in 1998 (IFFN, 2010). Although it is claimed that human-caused fires have been reduced, in 2021, about 34% (183 of 533 fires reported to INAB) of the reported forest fires were human-influenced (INAB, 2022). Although there are many other drivers of forest cover loss in Guatemala, wildfire is one of the main reasons for forest cover change in recent history. In 2016 wildfires alone caused about 30 percent of all tree cover loss of that year, recognized as one of the highest forest losses in recent history (Global Forest Watch, 2023). In 2022, about 54 thousand hectares of forest cover were burnt, while 2003 was the most devastating year for wildfires, with about 850 thousand hectares burned (Global Forest Watch, 2023). All these fire events in Guatemala caused about 15% of the country's total vegetation cover loss between 2001 and 2021(Global Forest Watch, 2023).

The study area (Petén) is the northernmost region of Guatemala (16.9120° N, 90.2996° W), consisting of an area of about 13,843 sq miles (35,853.205 sq km). The region covers about one-third of the country's entire landscape with a tropical climate and is the largest department (administrative jurisdiction) among 22 departments of Guatemala. About 545,600 people live in this area in 14 municipalities, mostly covered by forest. The area is historically significant to ancient Mayan civilization (more than 25,000 sq km of protected areas; Fig. 4) and experiencing increasing wildfire events despite a tropical climate. The annual mean temperature in Petén is about 25° C, with highly variable precipitation between 900-2500 mm per year (Schupbach, 2015). The area is susceptible to the Intertropical convergence zone (ITCZ), which controls the regional rainfall (Schupbach, 2015) and is widely known for biodiversity. Besides its geographical and ecological importance, Petén is considered the birthplace of Mayan civilization. Many archaeological sites and Mayan city remain are found here, where Tikal was one of the largest Mayan cities in Petén. Petén combines natural resources with human civilization's histories, making this area significantly important to anthropologists, social scientists, and natural scientists.

About 800 communities are living in the Petén region, but the region is accountable for about 58% of the surface area affected by fire (Berenter, et al., 2021). On average, about 3,500 sq km of land has been affected by wildfires in Petén annually since 2010, and it is not only a risk to forest cover but also a tremendous burden on the people who are living in this region (Berenter, et al., 2021).

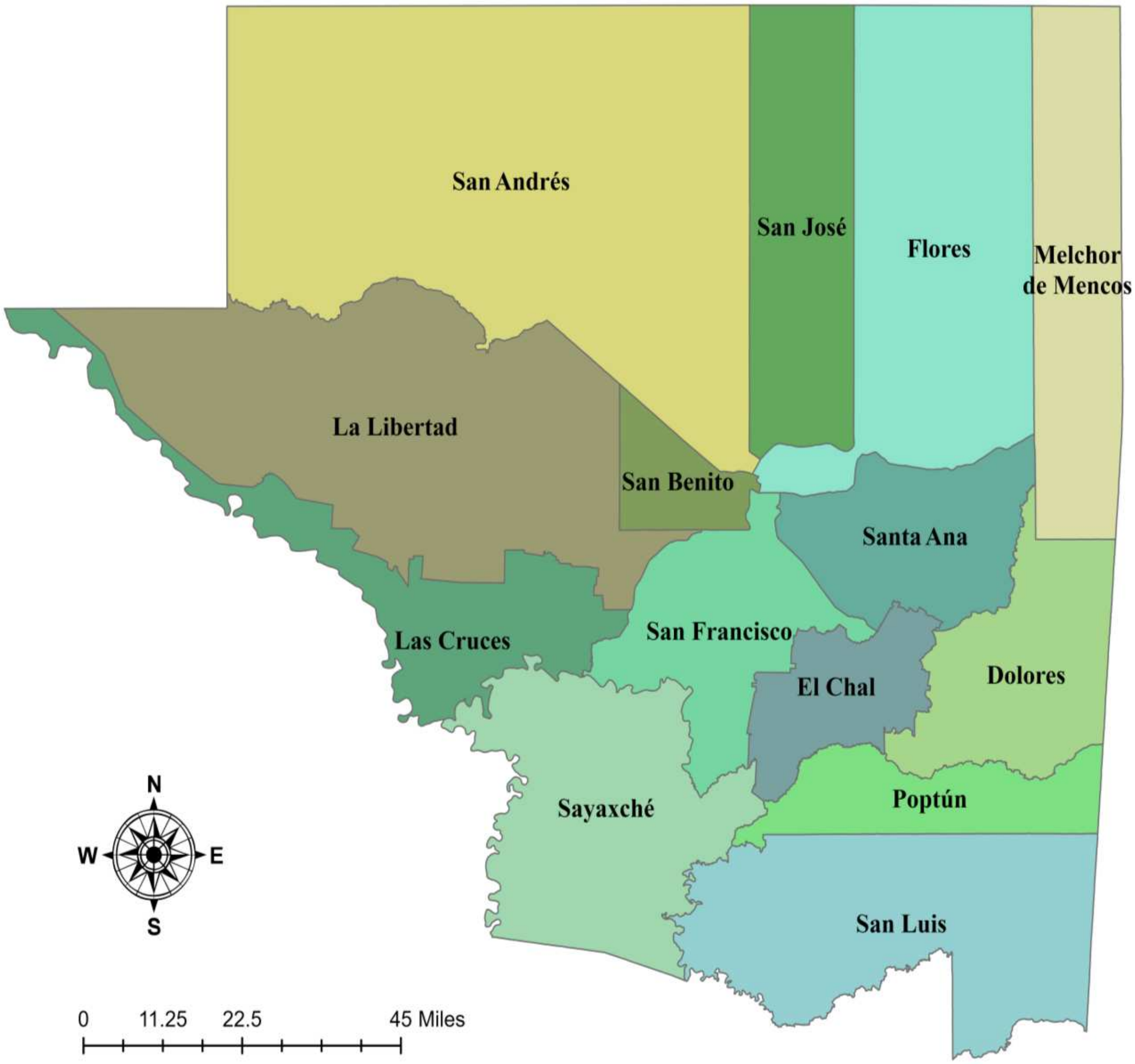


Fig. 3: Map of Petén, Guatemala. The map represents all 14 municipalities in different colors to delineate their boundaries.

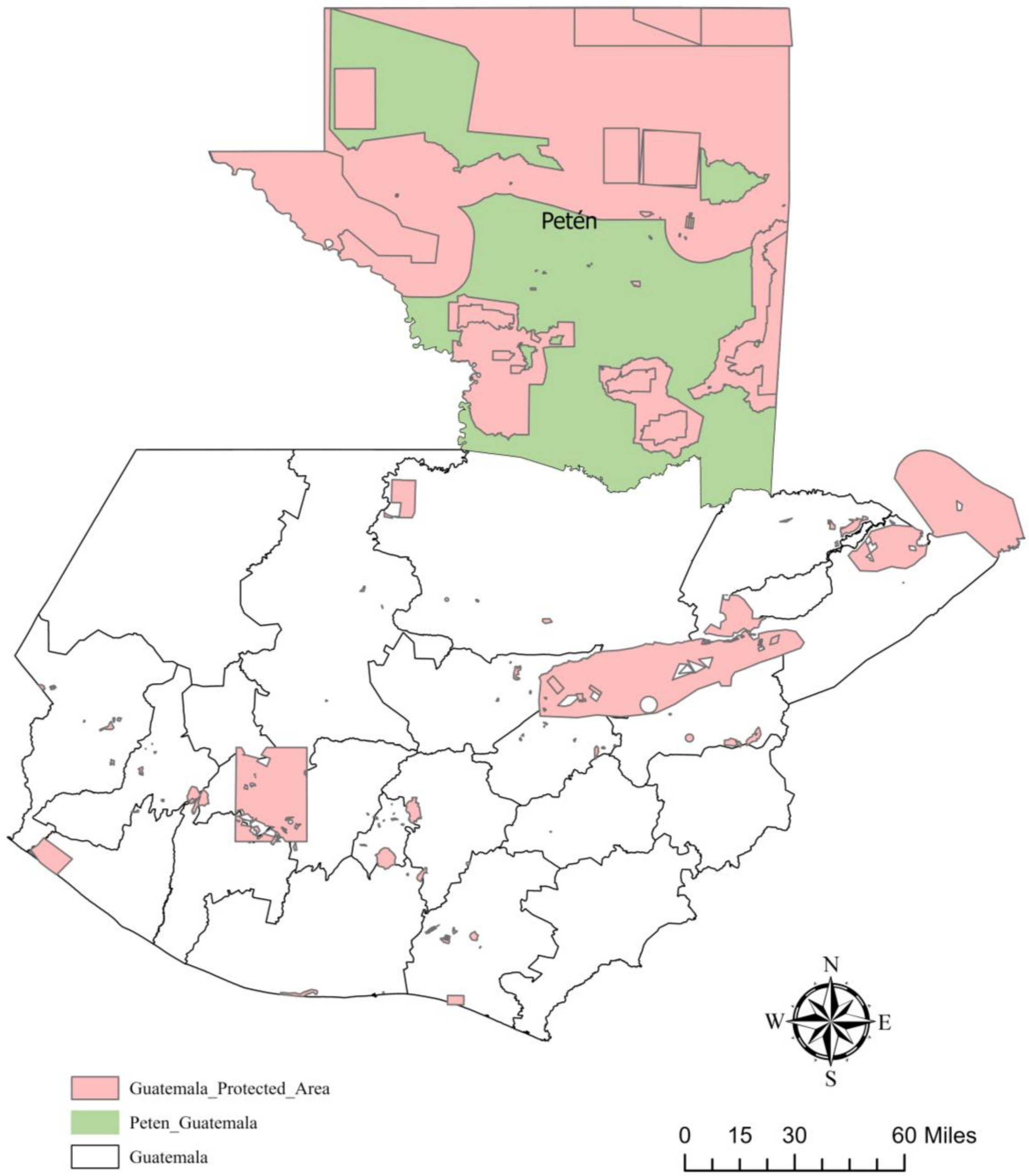


Fig. 4: Petén, Guatemala (Protected Planet, 2023). The illustration displays the study area's position relative to Guatemala. It utilizes green to depict the expanse of Petén, while pink represents the protected areas in Guatemala. Furthermore, the map emphasizes the significance of the study site by indicating that most of the areas being studied are protected areas.

Table 1: Type of fires (forest/ non- forest) in Petén from 2001 to 2021 (INAB, 2022):

Year	**Forest Fire**	**Non-Forest/ Human Caused**
2001	13	10
2002	40	32
2003	172	48
2004	3	2
2005	61	26
2006	22	8
2007	68	17
2008	26	19
2009	76	17
2010	42	6
2011	91	23
2012	62	13
2013	18	6
2014	25	11
2015	11	5
2016	156	1
2017	110	35
2018	65	27
2019	268	27
2020	203	50
2021	34	27

Among the forest fires, all of them were not caused naturally (Table 1). Many fires reported are human caused fires, mostly for agricultural expansion. However, in 2021, about 44.26 percent of the fire recorded by INAB was caused or initiated by human activities. Although the research is focused on wildfires only, the data represents a greater influence of anthropogenic activities behind the forest fires and forest cover losses in Petén.

3.1 Methods

The research followed a quantitative approach and statistical analyses. The analysis involves investigating the correlation between precipitation, vegetation indices, and fire occurrences to identify if there is any correlation between precipitation and vegetation or precipitation and fire occurrences. The precipitation and vegetation indices have been accessed from the IRI International Research Institute for Climate and Society data library). For the fire occurrences data, the database was provided by INAB (Instituto Nacional de Bosques/ Guatemala's National Forest Authority). The research also tried to understand the correlation between vegetation and fire occurrences in Petén, where the Google Earth Engine tool has been used to calculate the seasonal NDVI with the help of different geospatial tools.

3.2 Precipitation and Vegetation Indices Correlation

The IRI (International Research Institute for Climate and Society) Data Library is a powerful and easily accessible web-based data repository and analysis tool, which helps to access, analyze, and download climate-related data using a standard web browser. The data library is a powerful tool for analyzing, visualizing, and interpreting different climate data.

The IRI data library stores and uses NOAA NESDIS surface reflectance data for vegetation indices and readily produces different indices (NDVI, SMN, VCI, TCI, and VHI). On the other hand, the IRI data library also incorporates Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). CHIRPS has over 30 years rainfall dataset (from 1981). CHIRPS incorporates (0.05° resolution) satellite imagery and station data which helps to create time series for precipitation trend analysis and seasonal drought monitoring.

With proper code (Annex 1) in the IRI data library expert mode, the CHIRPS precipitation (global monthly precipitation data) can be correlated with the NOAA NESDIS vegetation indices (NDVI, SMN, VCI, TCI, and VHI) to identify if there is any correlation between them or not. The analysis here uses data from 1983 to 2021 for correlation identification. The IRI expert codes try to correlate 39 years of available data, and it is easily customizable to correlate two different datasets (Pons et al., 2021). The geospatial area coverage is also easily customizable for data access and analysis. The IRI data library has covered the study area (Petén, Guatemala), divided into 12 separate areas for precipitation and vegetation indices data (Table 2). The IRI data library assigns each area a unique code. However, the two of 12 unique areas were further divided and became 14 municipalities by the government of Guatemala. Although divided into 14 municipalities by Guatemala Government, the IRI data library still uses the older categorization of data availability to reduce the complexity of historical data acquisition and analysis.

Table 2: Municipality and their assigned codes for Petén in IRI Data Library.

No.	**Municipality Codes by IRI Data Library**	**Name of the Municipality**
1	7271	Melchor de Mencos
2	7272	Flores
3	7273	San José
4	7274	San Andrés
5	7275	La Libertad
6	7275	Las Cruces
7	7276	San Benito
8	7277	Santa Ana
9	7278	Dolores
10	7278	El Chal
11	7279	San Francisco

12	7280	Sayaxché
13	7281	Poptún
14	7282	San Luis

Using the expert mode of the IRI data library, the correlation between precipitation and vegetation growth (different Vegetation indices) can be determined and presentable in a correlation map (sample codes included in Annex 1). The correlation between precipitation and different vegetation indices available in the IRI data library can be represented in grids ranging from -1 to +1 in color grading.

3.3 Vegetation in Relation to Preceding Precipitation

Existing literature suggests that precipitation significantly influences vegetation cover, health, temperature, and other aspects. Although the influence is evident and well established by scientific research, there is a lag (Time difference) in this correlation while influencing. Many authors explained that the vegetation response lag to precipitation might be from one month to three months. Fortunately, the IRI Data Library may be used to identify the lagged correlation with proper codes. In this research, the lagged time correlation between precipitation and vegetation response (measured through different indices) describes the influence of preceding precipitation on vegetation growth, temperature, or moisture content.

The code in the IRI Data Library expert mode (Annex 01) helps to identify the response of seasonal (3 months) vegetation indices if the precipitation occurs one, two, or three months earlier. The codes also help to correlate or show if there is any correlation between the precipitation and the vegetation response (Pons et al., 2021) in a lagged time (one, two, or three months). Lagged correlation refers to the correlation between the precipitation and vegetation indices, where precipitation has occurred earlier (1, 2, or 3 months) than the acquired vegetation indices. The lagged correlation between the precipitation and fire occurrences follows the same approach to identify if there is any correlation between fire occurrences and preceding precipitation (preceding months or seasons).

3.4 Precipitation and Wildfire Occurrence

The expert codes give full access to customize and download the precipitation data by area of interest (Pons et al., 2021). The municipal codes (7271 to 7281) represent different municipalities of the study area (Petén) and are used to access the precipitation data by the municipality. Downloading and sorting the precipitation anomalies uses the same municipal codes with slightly different scripting in the expert mode. All the precipitation data (precipitation and precipitation anomalies) are in mm (millimeter) units. CHIRPS monthly precipitation data was downloaded in a columnar table format (for every individual department/ municipality), and further analyses and calculations were completed in MS Excel.

Precipitation anomalies represent the deviation from the average rainfall of each month or season. IRI data library can customize and download the precipitation anomalies in a columnar table format (both higher and lower precipitation than the average) by area of interest, like the regular precipitation data. However, the same municipal codes with different scripting in IRI expert mode help access Petén's seasonal precipitation anomalies from 1981 to 2021.

3.5 Fire Frequency and Precipitation Correlation

A 'Pearson's correlation' was drawn between precipitation and fire occurrences from 2001 to 2021 to identify the influence of precipitation on fire occurrences. The data availability has shaped the analysis time frame from 2001 to 2021. The correlation calculation between precipitation and fire occurrences has also been conducted with precipitation of lagged months and seasons to understand if the preceding precipitation influences fire occurrences of the fire months. The literature review and fire history database of INAB strongly suggested that fire occurrences are more likely to happen in March, April, and May (Green Climate Fund, 2022). For the convenience of the study, all the months have been grouped into twelve different seasons, which helps to categorize the data and compare within seasons.

Seasonal categorization is an essential concept of this study. The categorization of the data and analyses focuses on a seasonal basis because the seasonal precipitation can be predicted using appropriate modeling of seasonal precipitation forecasting. The study opens an opportunity to predict fire occurrences in advance if there is any strong correlation between seasonal precipitation and fire occurrences. As the precipitation can be forecast, the research also tries to follow the seasonal approach in analyzing the impacts of seasonal precipitation on fire occurrences and vegetation.

Table 3: Categories of season used in this research

Name of Season	Months of the Season
Season 01	Jan-Feb-Mar
Season 02	Feb-Mar-Apr
Season 03	Mar-Apr-May
Season 04	Apr-May-Jun
Season 05	May-Jun-Jul
Season 06	Jun-Jul-Aug
Season 07	Jul-Aug-Sep

Season 08	Aug-Sep-Oct
Season 09	Sep-Oct-Nov
Season 10	Oct-Nov-Dec
Season 11	Nov-Dec-Jan
Season 12	Dec-Jan-Feb

The same categorization (Table 3) has been followed for correlating the fire occurrence with precipitation and running the correlation between precipitation and vegetation indices. The calculation for Season 11 and Season 12 is complex as they contain data from two years (season 12 consists of December of a year and January and February from the following years). The database has been modified carefully for these two seasons to solve the issue. For example (Table 4), the fire occurrences of a fire season (Mar-April-May) of 2001 have been correlated to the precipitation of season 12 (Dec-Jan-Feb) while considering three months of lag. In this case, the precipitation of December is from the previous year (2000).

Table 4: Demonstration of lagged season while analyzing correlations

Year	2010	2010	2010	2011	2011	2011	2011	2011	2011	2011	2011
Months	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	July	Aug
≤ 3 Months Lag ≥											
Months	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	July	Aug
≤ 2 Months Lag ≥											
Months	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	July	Aug
≤ 1 Month Lag ≥											
Months	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	July	Aug
≤ No Lag/ Same Season≥											

The table above exemplifies the time differences while correlating two variables and how the approach incorporates precipitation data from a previous year while calculating three months of preceding precipitation concerning fire or vegetation indices of a fire season.

3.6 Seasonal Average (Mean) NDVI Calculation

Seasonal mean NDVI has been calculated from MODIS NDVI data (MODIS/061/MOD13Q1) using Google Earth Engine (GEE) and Google Colab Notebooks (Islam et al., 2023). Google Earth Engine and Google Colab Notebooks provide tremendous flexibility to conduct calculations with data availability. Considering the data availability and resolution, the MODIS NDVI data were used in this research, which was also used for the analyses while correlating the vegetation indices with the precipitation in the IRI data library. MODIS NDVI is produced in a 16-day interval and provides a consistent comparison (spatial and temporal) of different vegetation indices like NDVI and EVI (NASA, 2023). MODIS provides an atmospherically corrected Red, NIR, and Blue Bands reflectance, making the NDVI more accurate. MODIS NDVI data also have a continuity with the NOAA AVHRR NDVI time series record, which makes the historical analysis of NDVI less complex. Considering all the attributes, this research has used the MODIS NDVI for seasonal mean NDVI calculation. Using cloud masking and calculating the seasonal mean NDVI for the fire season (in GEE), further analysis in relation to INAB forest fire occurrences in Petén since 2001 has been done using MS Excel tools.

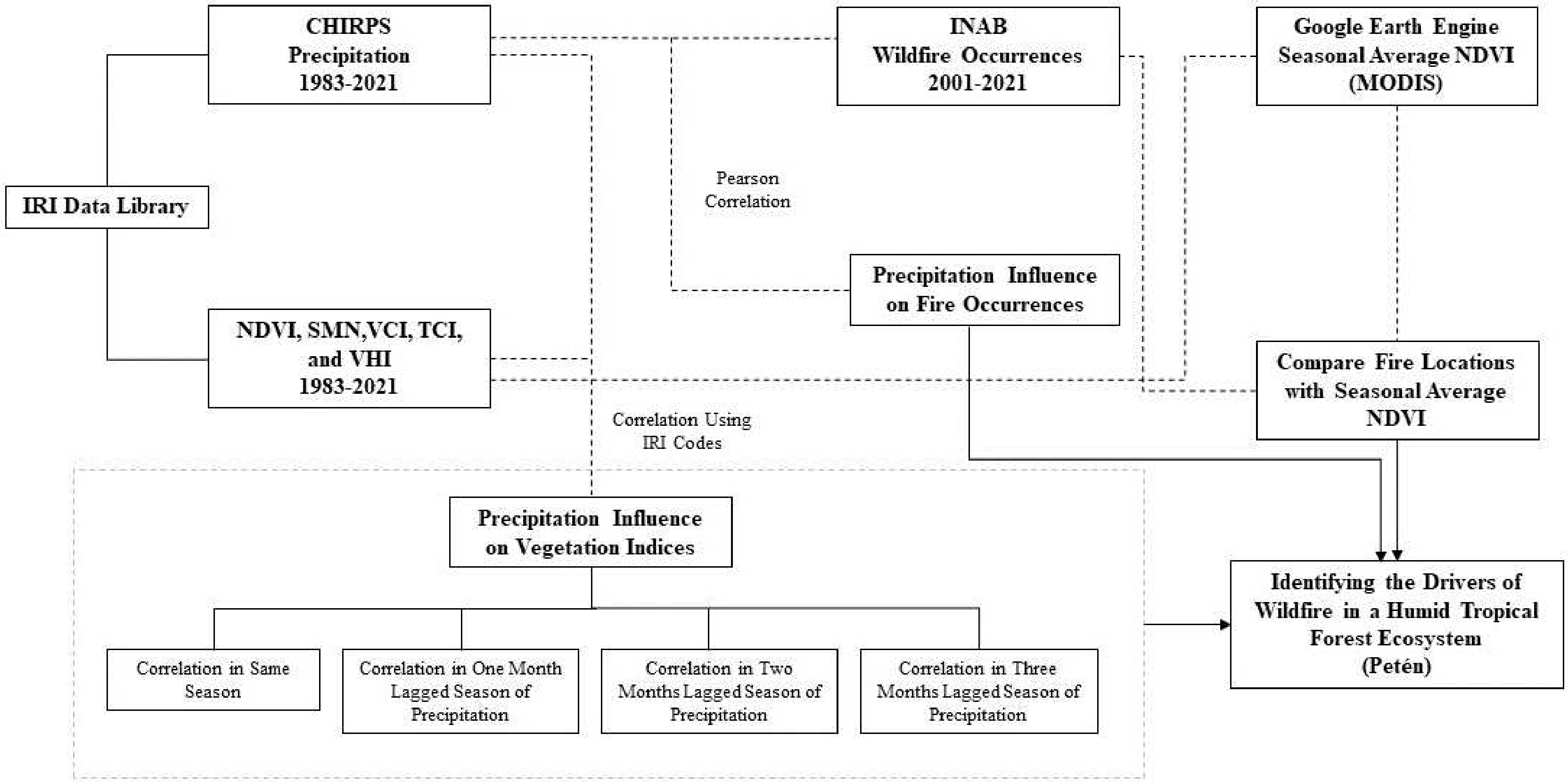


Fig. 5: The methodology flowchart involves accessing different datasets from available sources. It begins by analyzing the relationship between CHIRPS precipitation data and MODIS vegetation indices (Using IRI data library), followed by correlating precipitation with fire occurrences (INAB Fire occurrence data). Lastly, the correlation between NDVI (MODIS) values and fire occurrences is explored. These steps collectively contribute to the identification of wildfire drivers in Petén.

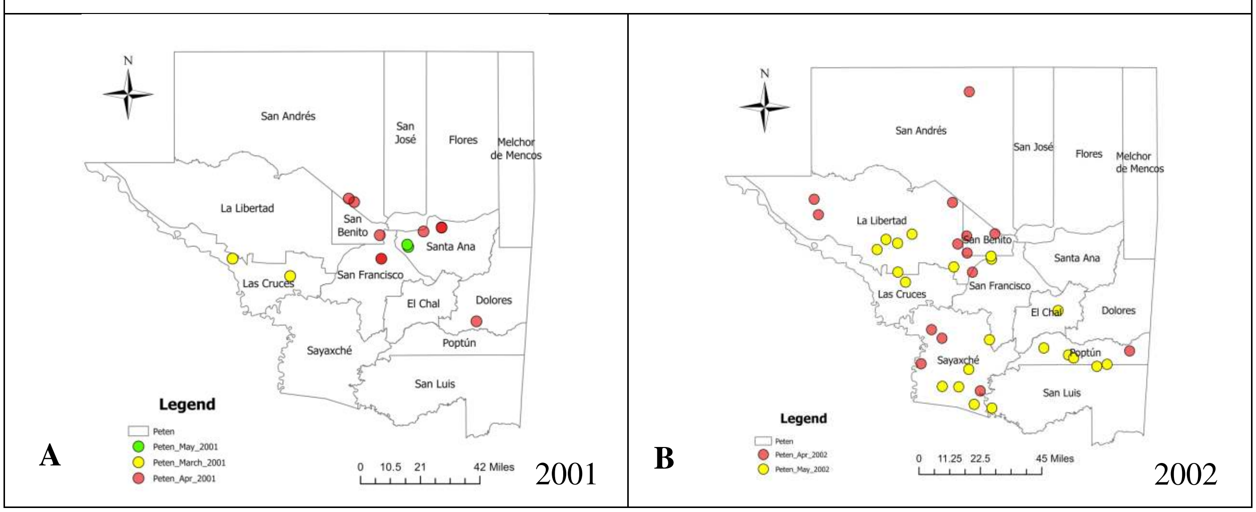
4.1 Findings and Discussion

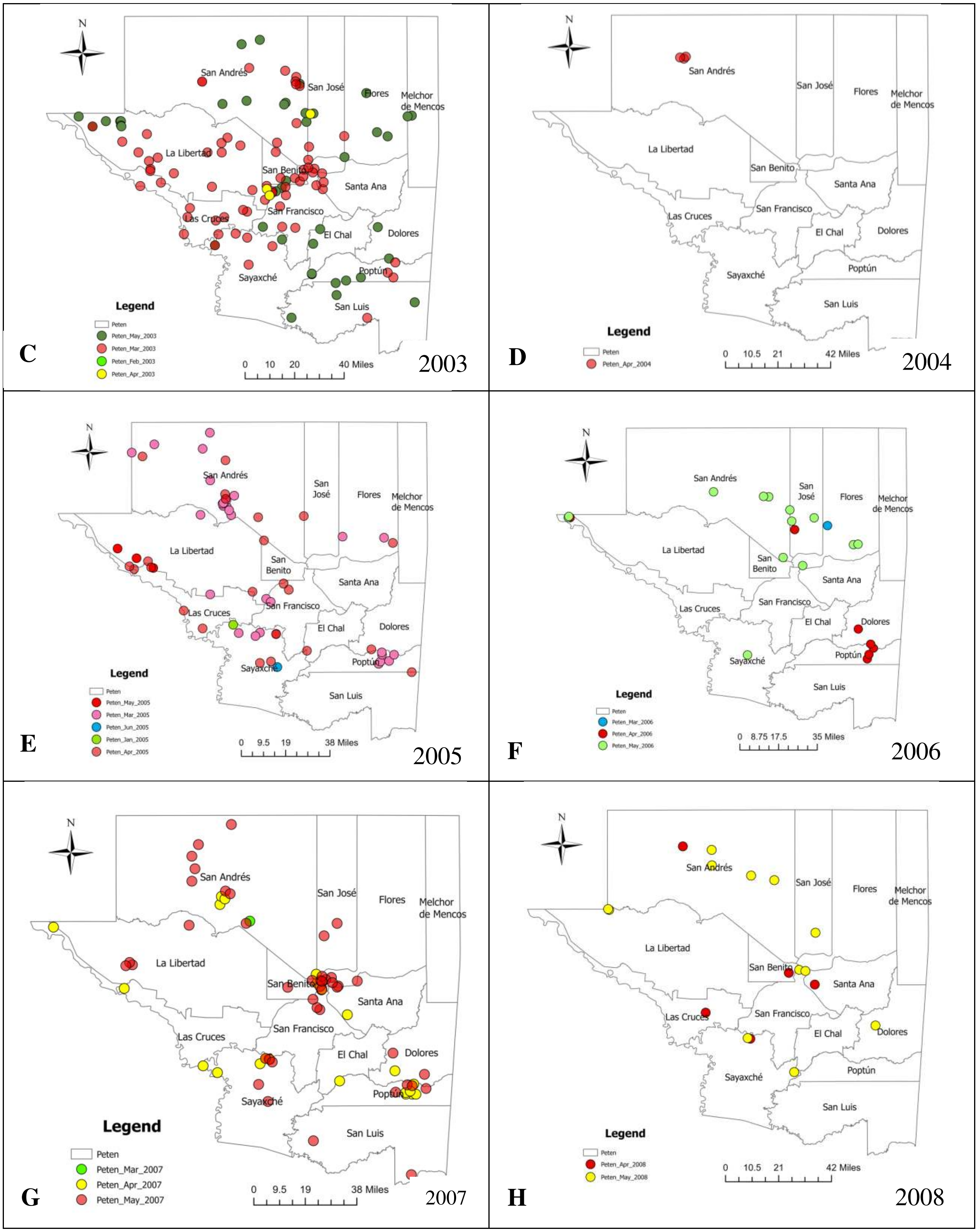
This chapter incorporates and discusses the findings of the research. The chapter starts with the visual representation of the geolocation of the wildfire occurrences in Petén, Guatemala, since 2001. The monthly fire occurrences help to illustrate the concentration of fire in different months and help to determine the fire season for further analysis of the correlation between seasonal precipitation and seasonal fire occurrences. The chapter then discusses the correlation between precipitation and vegetation indices in different seasons, as vegetation is an essential element of the fire behavior cycle. After analyzing the influence of precipitation on different vegetation indices (NDVI, VCI, VHI. TCI, and SMN), the correlation between precipitation and fire occurrences in Petén is identified. Finally, the chapter also discusses the influence of vegetation indices (NDVI) on forest fire occurrences in Petén.

4.2 Wildfires in Petén:

The forest fire events have been presented using the latitude and longitude of the recorded wildfires since 2001 by INAB.

Geolocations of wildfires in Petén since May 2001 to Dec 2021 from INAB Data





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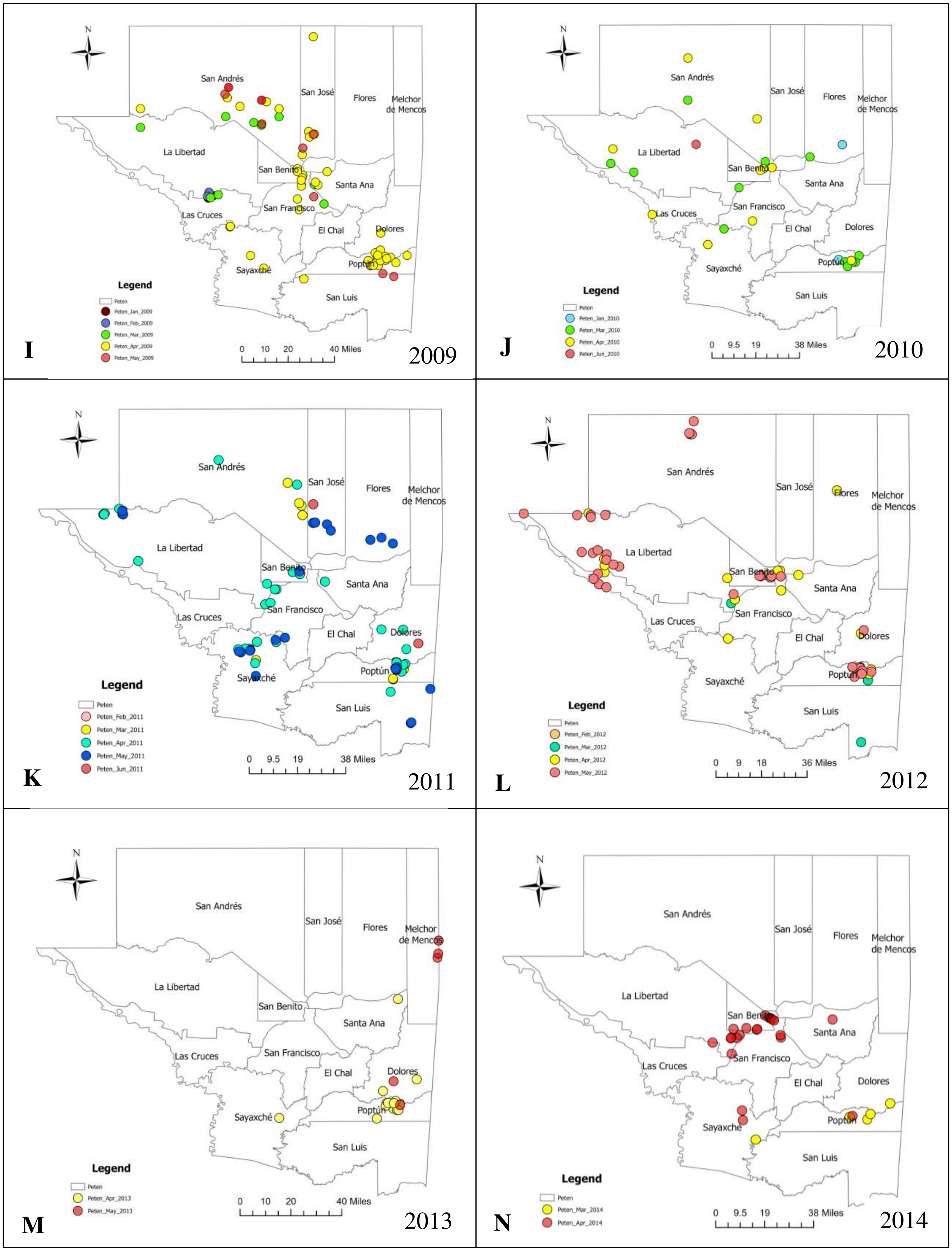
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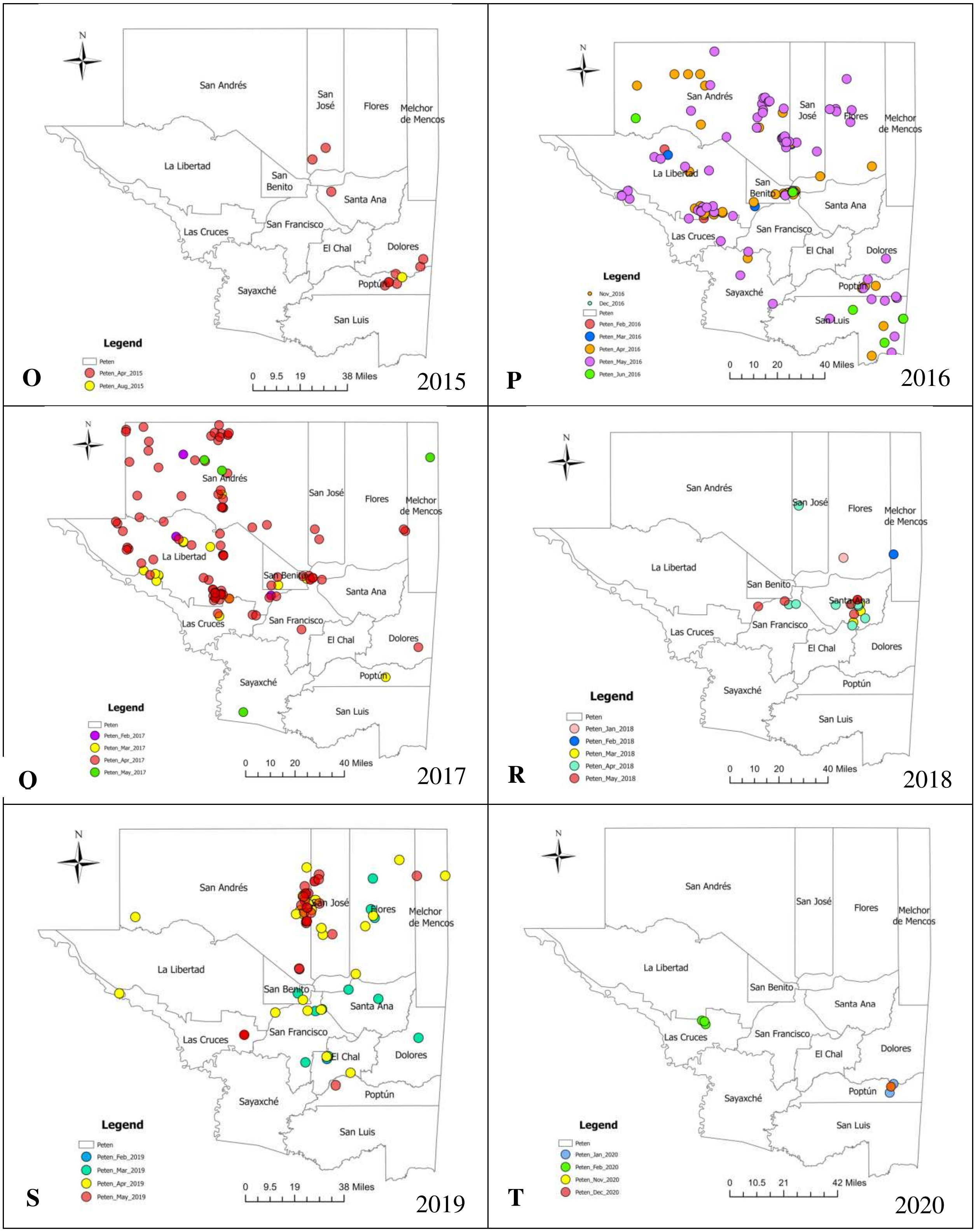
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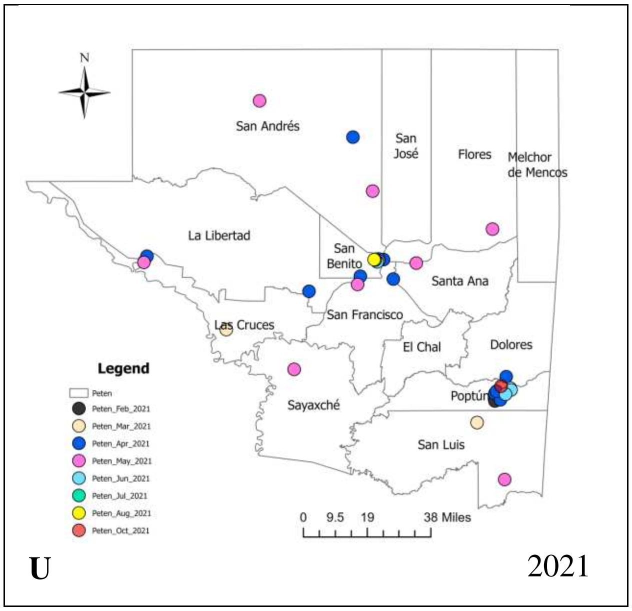


Fig. 6: Geolocations of wildfires in Guatemala, where A-U representing each year of geolocation of wildfires in Petén from 2001 to 2021.

The geolocations and wildfire occurrences by month from 2001 to 2021 provide a few characteristics of forest fires in Petén. The data suggests that the most prominent months of wildfire occurrences are March, April, and May. According to the seasonal categorization, Mar-Apr-May is named 'Fire Season' or 'Season 03' in this study. All the analyses and findings of this research are primarily focused on this Fire Season and try to understand if precipitation influences vegetation growth and the fire occurrences of these fire months (season). Seasonal categorization will help in future studies of forecasting fire, as seasonal precipitation can be forecasted.

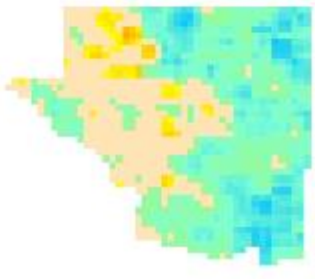
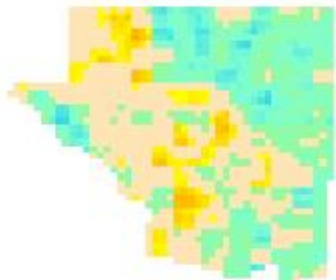
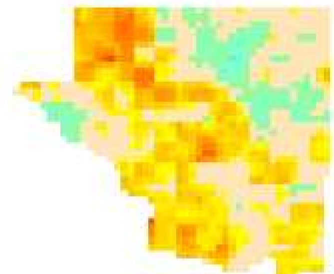
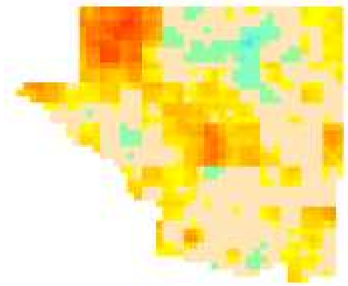
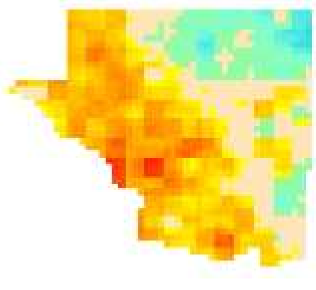
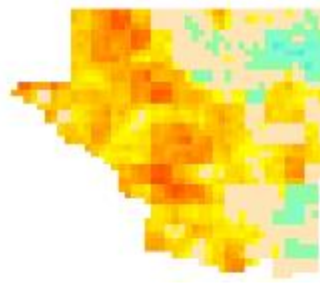
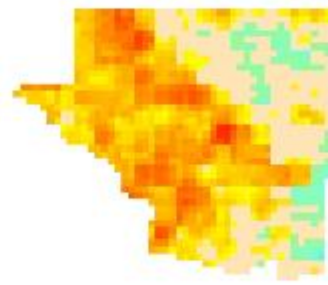
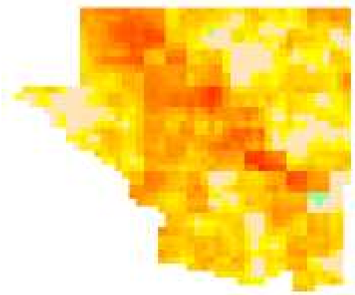
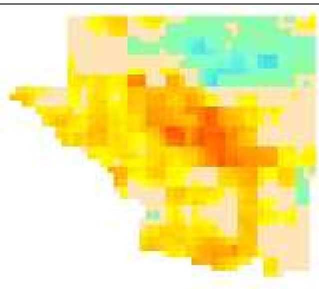
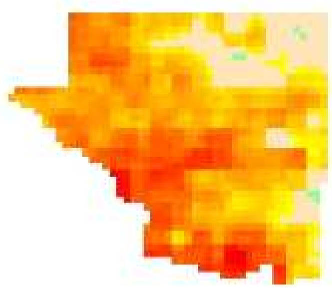
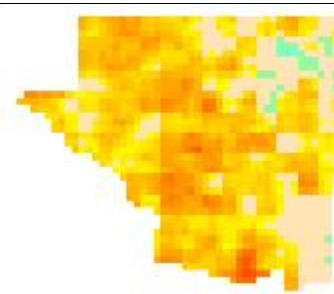
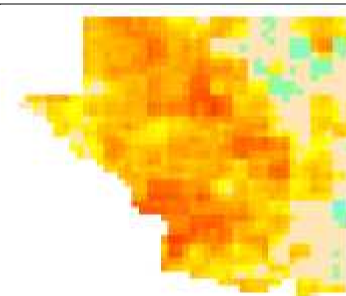
Table 5: Fire seasons or monthly wildfire occurrences in Petén since 2001 (INAB).

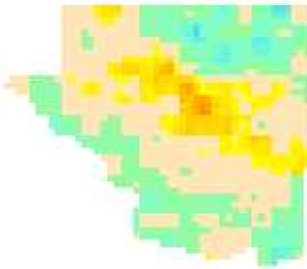
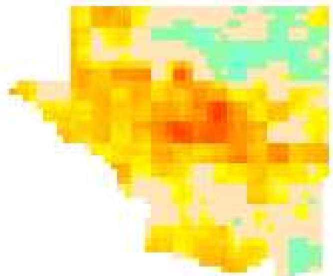
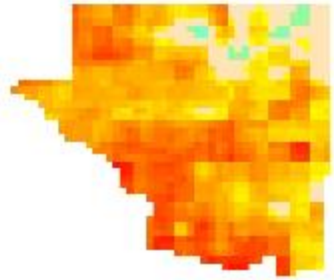
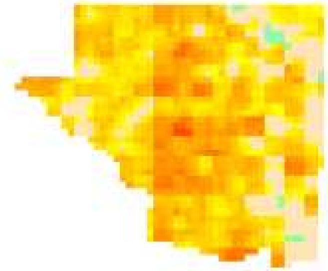
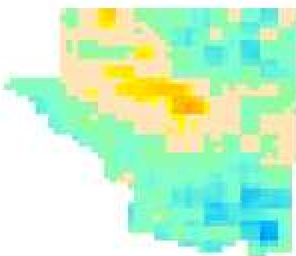
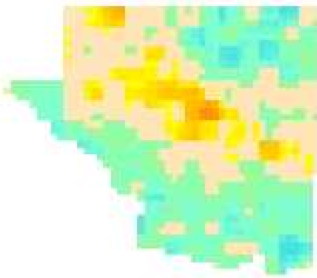
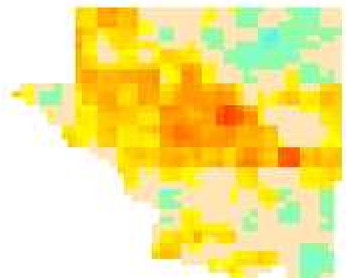
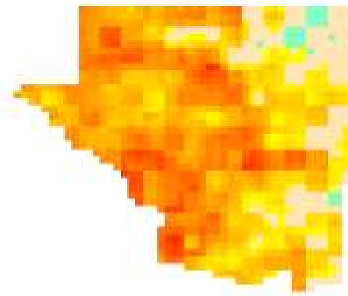
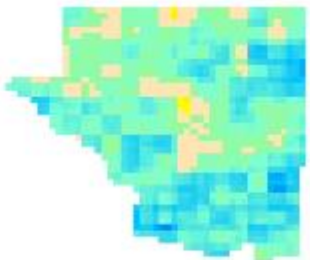
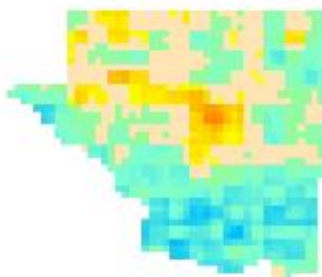
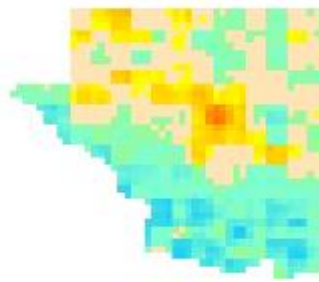
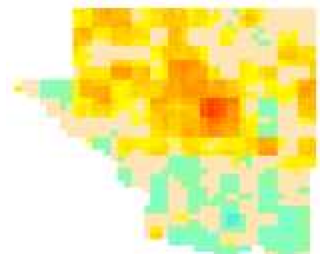
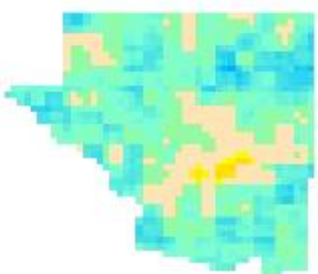
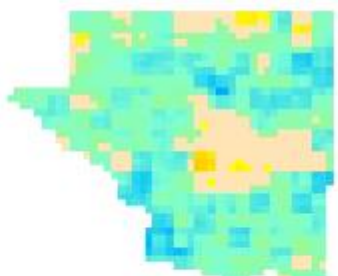
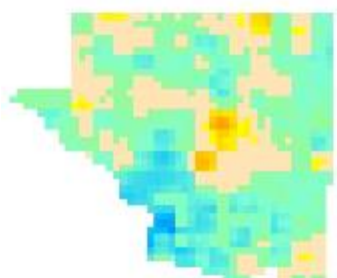
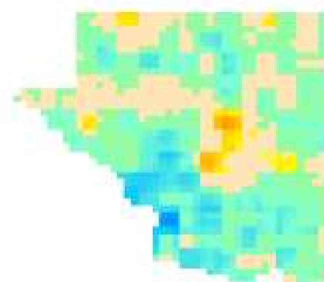
Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2001			2	9	2							
2002				14	21							
2003		5	71	5	42							
2004				3								
2005	1		29	24	3	1						
2006			1	8	13							
2007			1	25	43							
2008				5	12							
2009	3	2	11	47	11							
2010	2		15	12		1						
2011		1	9	41	26	2						
2012		1	5	22	34							
2013				14	5							
2014			5	21								
2015				10				1				
2016		2	5	52	70	5						
2017		3	16	84	4							
2018	1	2	6	9	6							
2019		1	16	30	29							
2020	2	3									1	1
2021		1	4	13	9	3	1	1		1		

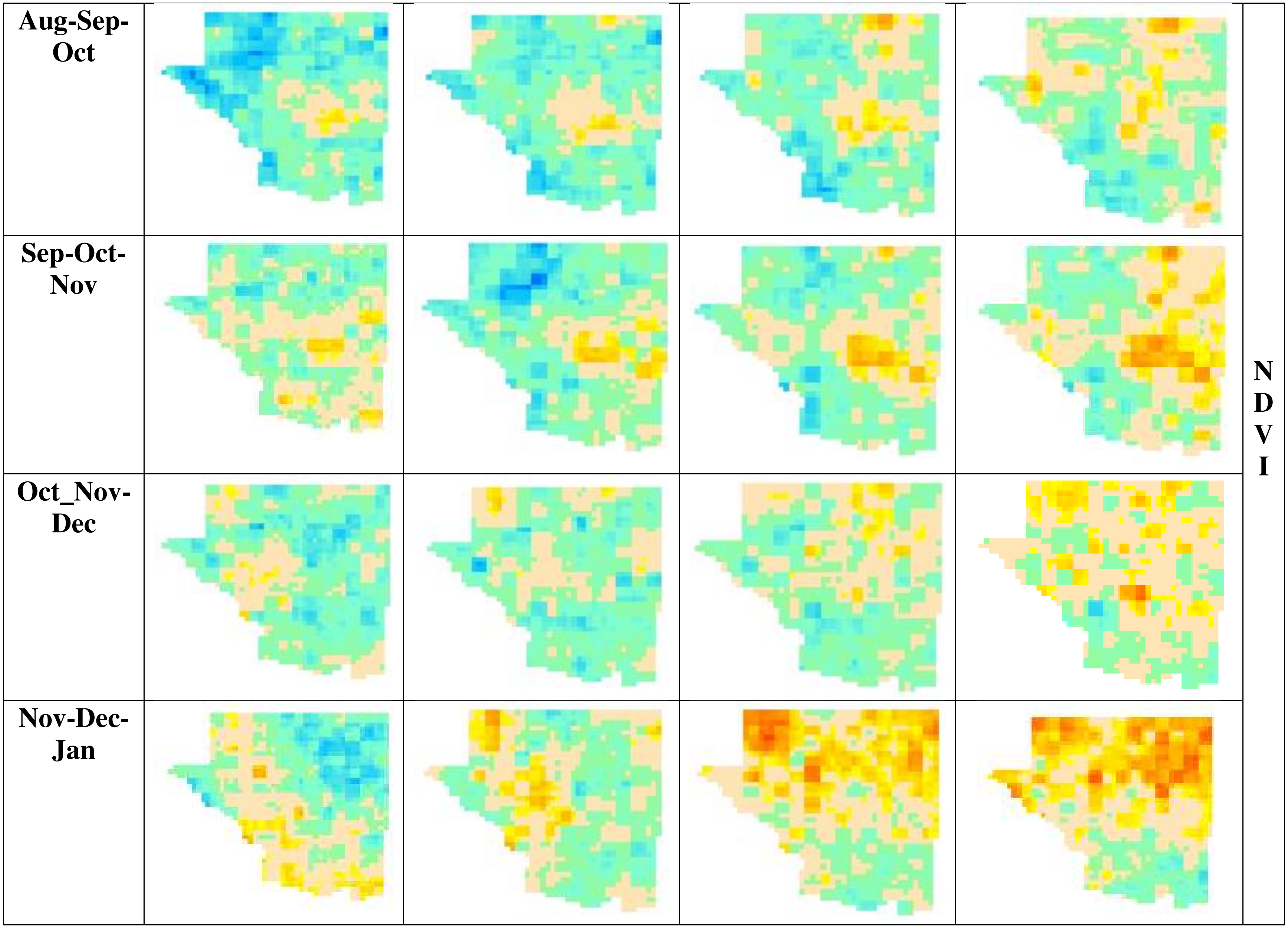
The data on fire occurrences in Petén from 2001 to 2021 (INAB, 2022) shows a significant concentration in March-April-May. About 95.30 percent of the fire occurrence (974 0f 1022) has occurred in the Fire Season (March-April-May). The table above also shows how the fire occurrence seasons have spread in recent years, where the fire incidents occur in months or seasons that have not experienced any fire in the last 15-20 years. Although the data here represents a shorter period (only 21 years), climate change and erratic precipitation may be the reason behind the recent shift in fire occurrences. These shifts are also essential to understand as the management system is mainly focused on the Fire Season. However, the observed changes in months with fire occurrences make it difficult to determine a precise fire season, thus, increasing the challenges to the existing fire management system.

4.3 Normalized Difference Vegetation Index (NDVI) and Precipitation

Table 7 visually shows the correlation between precipitation and NDVI from 1983 to 2021 in Petén. The red pixels represent the highest correlation between precipitation and NDVI indices, whereas the blue shows the opposite. The figures were produced by cloud analysis using the IRI data library expert mode (Pons et al., 2021). No lag indicates the correlation between NDVI and precipitation during the same period, whereas the 1-month, 2-month, and 3-month lag represents the correlations where the precipitation happened 1-month, 2-month, and 3-month earlier consecutively. For example, while calculating No Lag, Jan- Feb-Mar NDVI correlates to Jan- Feb-Mar precipitation. For one month of lagged correlation Jan- Feb-Mar NDVI correlates to Dec-Jan-Feb precipitation. For the columns, the NDVI remains the same for a defined season, where the precipitation shifts backward (1-month, 2-month, and 3-month) to identify how the precipitation of preceding seasons is correlated to the vegetation indices representing the vegetation growth and condition. Vegetation change is a crucial part of this research as it is tied to the total fuel condition of the study area, even though the total available fuel is difficult to determine using this method.

NDVI in Relation to Precipitation of Same Season, and Lagged Seasons					
Season	**No Lag** (Same time)	**1 Month Lag**	**2 Months Lag**	**3 Months Lag**	
Jan-Feb-Mar					
Feb-Mar-Apr					**NDVI**
Mar-Apr-May					

Apr-May-Jun					
May-Jun-Jul					**NDVI**
Jun-July-Aug					
Jul-Aug-Sep					


Aug-Sep-Oct
Sep-Oct-Nov
Oct_Nov-Dec
Nov-Dec-Jan
NDVI

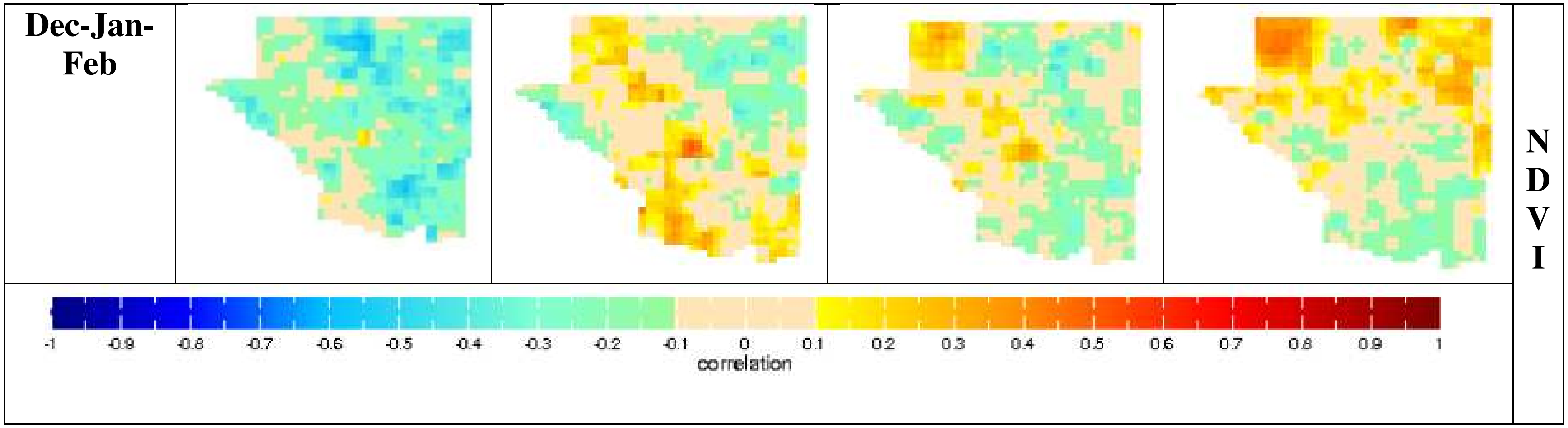
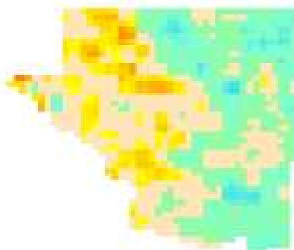
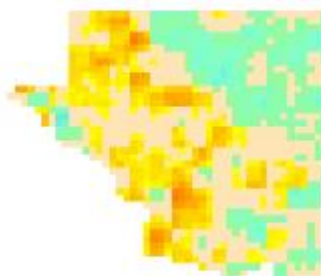
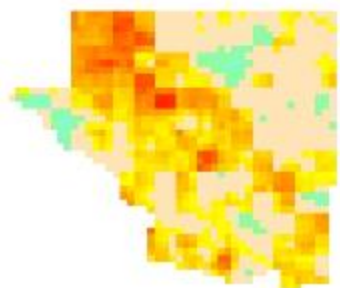
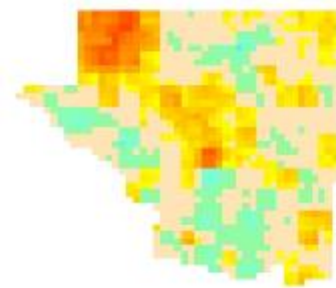
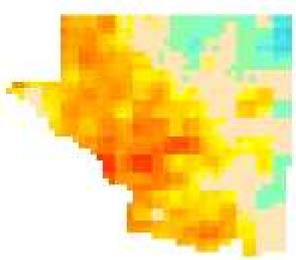
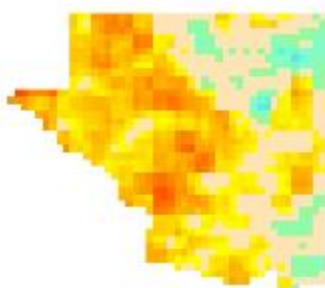
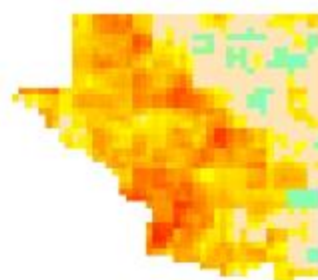
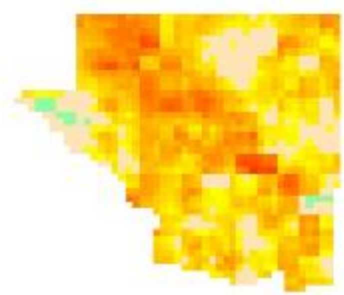


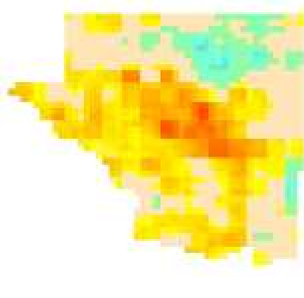
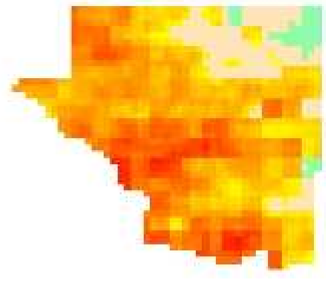
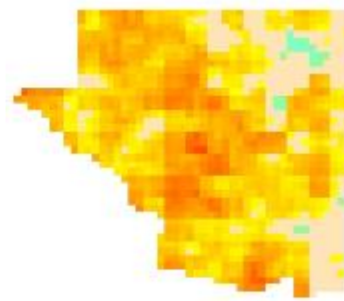
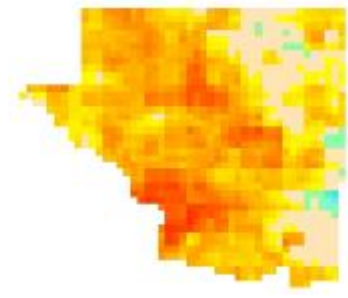
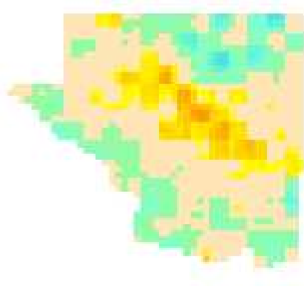
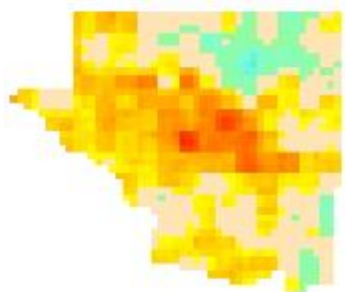
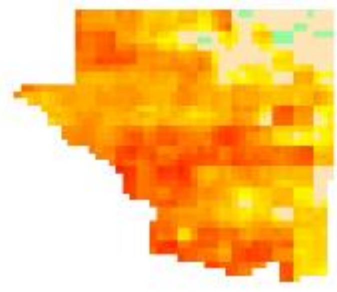
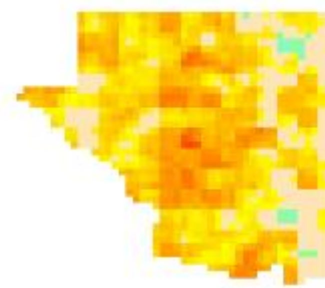
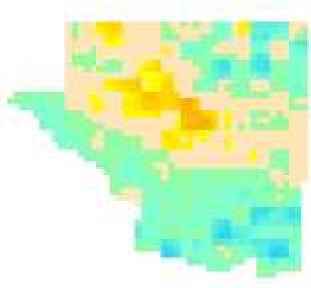
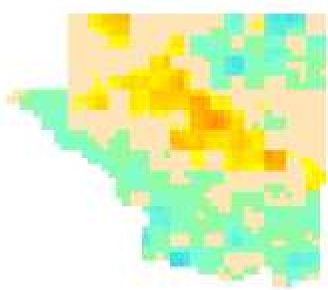
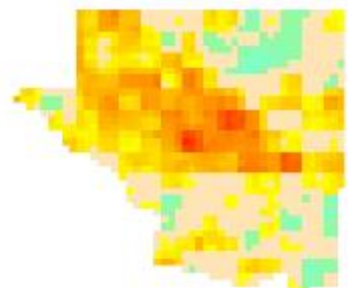
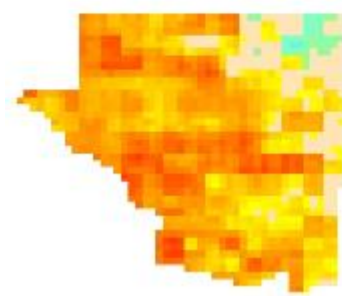
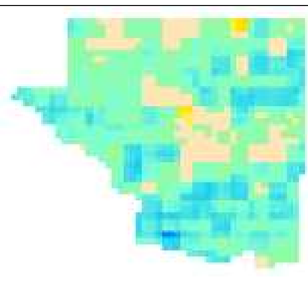
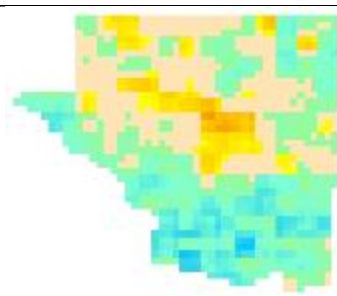
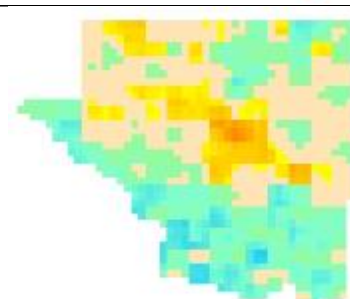
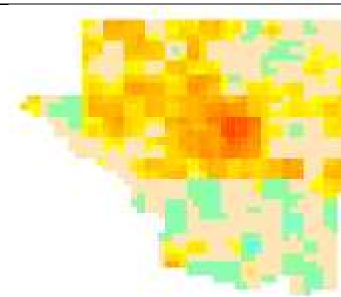
Fig. 7: NDVI in Relation to Precipitation of Same Season, and Lagged Seasons

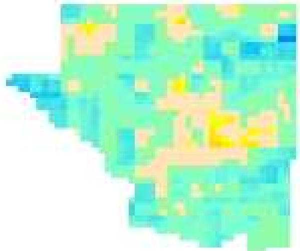
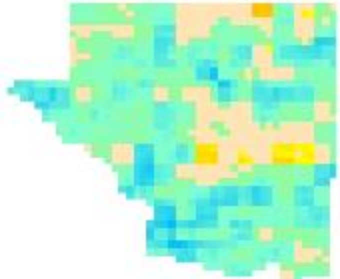
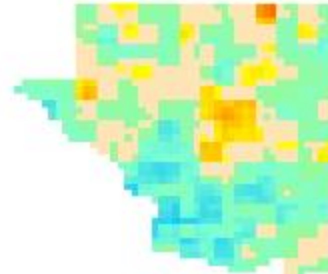
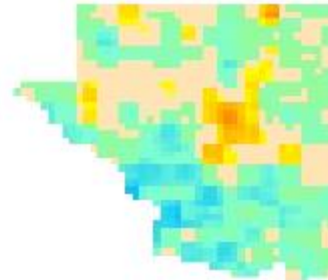
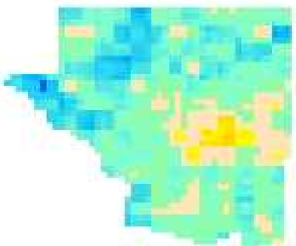
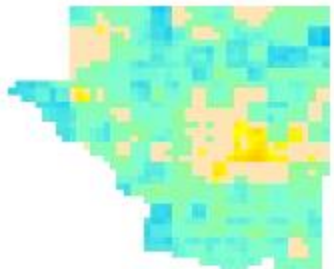
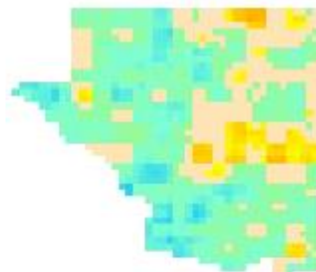
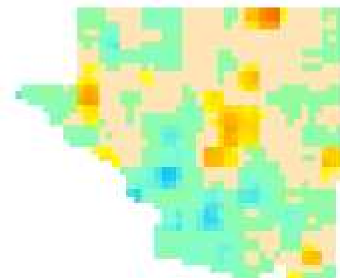
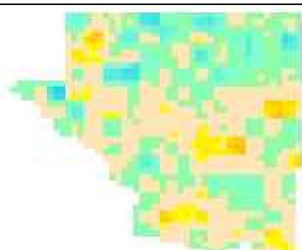
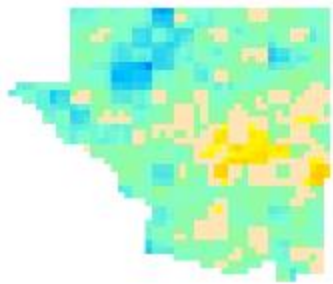
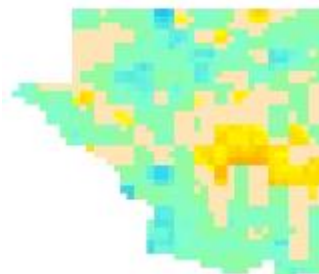
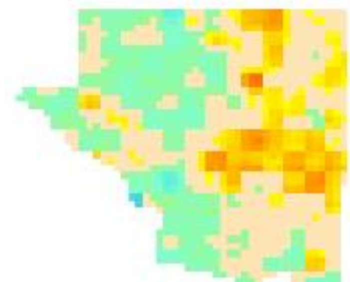
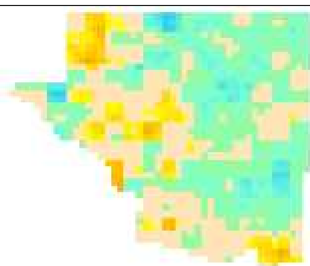
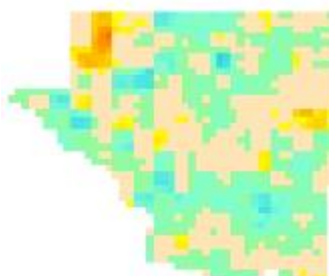
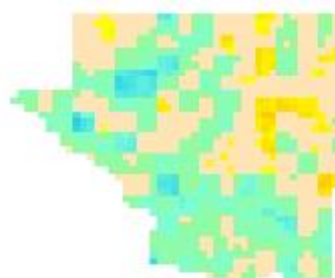
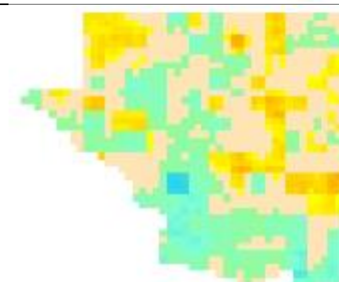
NDVI shows a moderate to negative relationship in response to precipitation in different seasons and lagged season correlation. However, in 2 and 3 months of preceding seasonal precipitation, precipitation significantly influences NDVI through the fire season (Mar- Apr-May). The positive correlation during the fire season in lagged time represents that higher precipitation in the prior season (one, two, or three months of lag) has increased the NDVI value representing vegetation growth. The results show an increase in vegetation or increased fuel during the fire season, even though the available fuel for the forest fire is hard to identify from this correlation.

4.4 Seasonal Midpoint NDVI (SMN), or Smoothed NDV and Precipitation

The analysis results in Table 8 suggest a correlation between SMN and precipitation similar to that seen in the NDVI analysis (SMN itself is an extended form of NDVI) but more concisely in seasons 2, 3, and 4. The results also show a prominent correlation between three-month lagged precipitation and 1 and 2 months of lagged precipitation, where one-month lagged rainfall has a minor influence on SMN in the Lowlands of Guatemala (Petén).

SMN in Relation to Precipitation of Same Season, and Lagged Seasons					
Season	**No Lag**	**1 Month Lag**	**2 Months Lag**	**3 Months Lag**	
Jan-Feb-Mar					**SMN**
Feb-Mar-Apr					

Mar-Apr-May					**S M N**
Apr-May-Jun					
May-Jun-Jul					
Jun-July-Aug					

Jul-Aug-Sep					
Aug-Sep-Oct					
Sep-Oct-Nov					**S M N**
Oct_Nov-Dec					

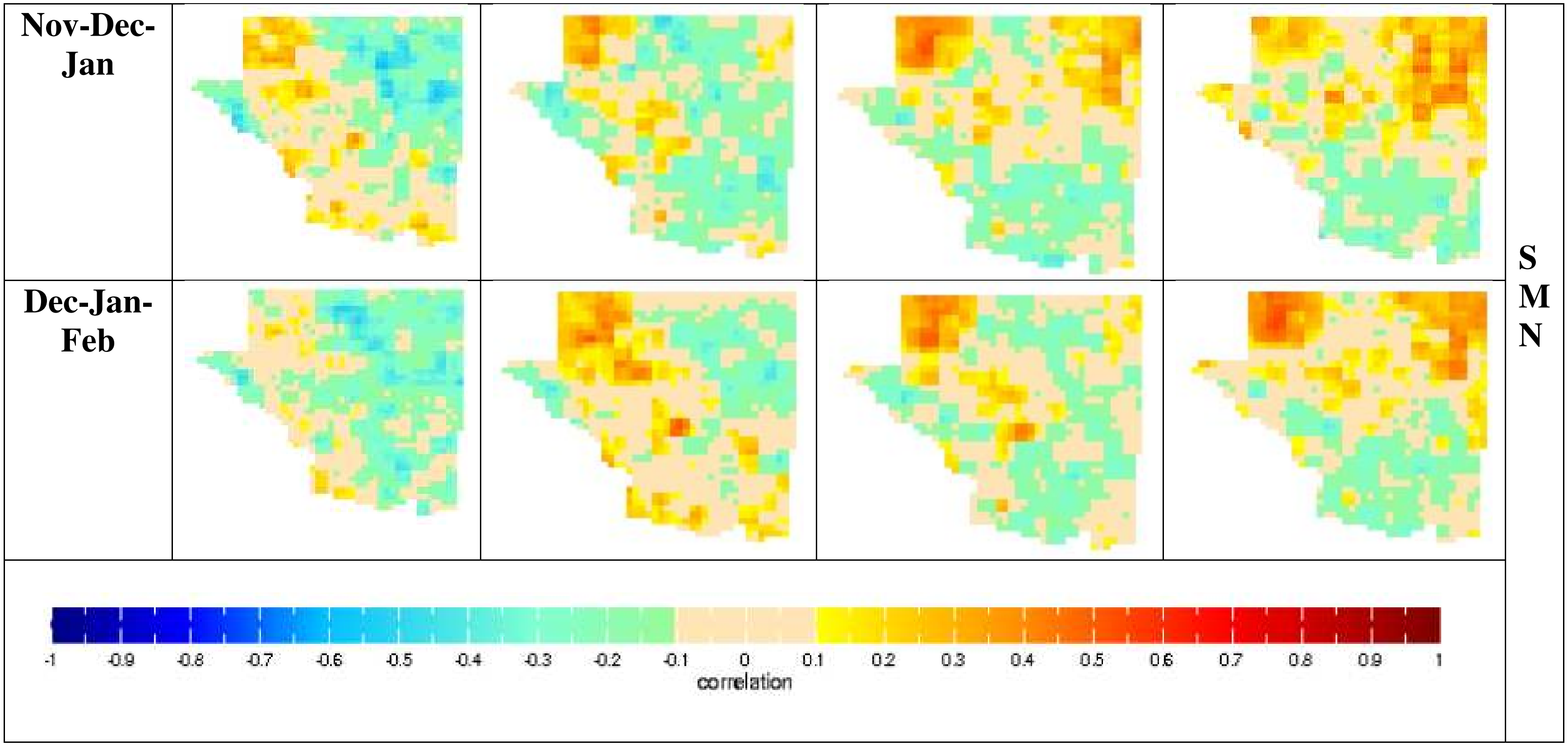
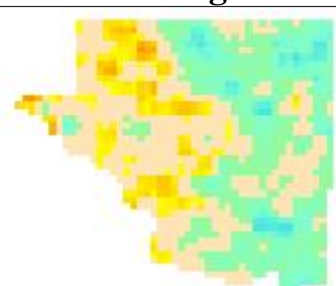
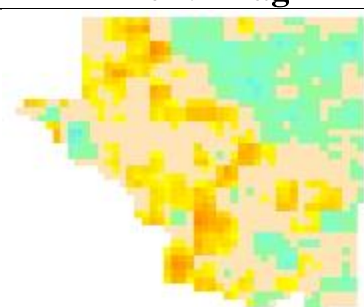
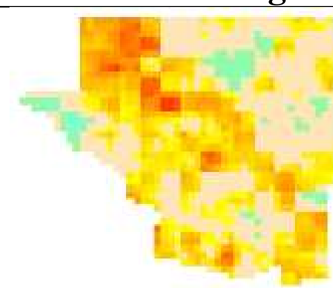
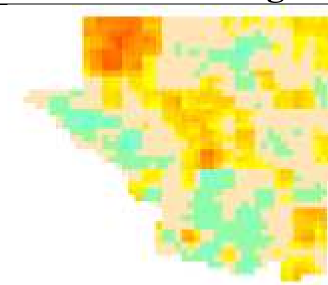
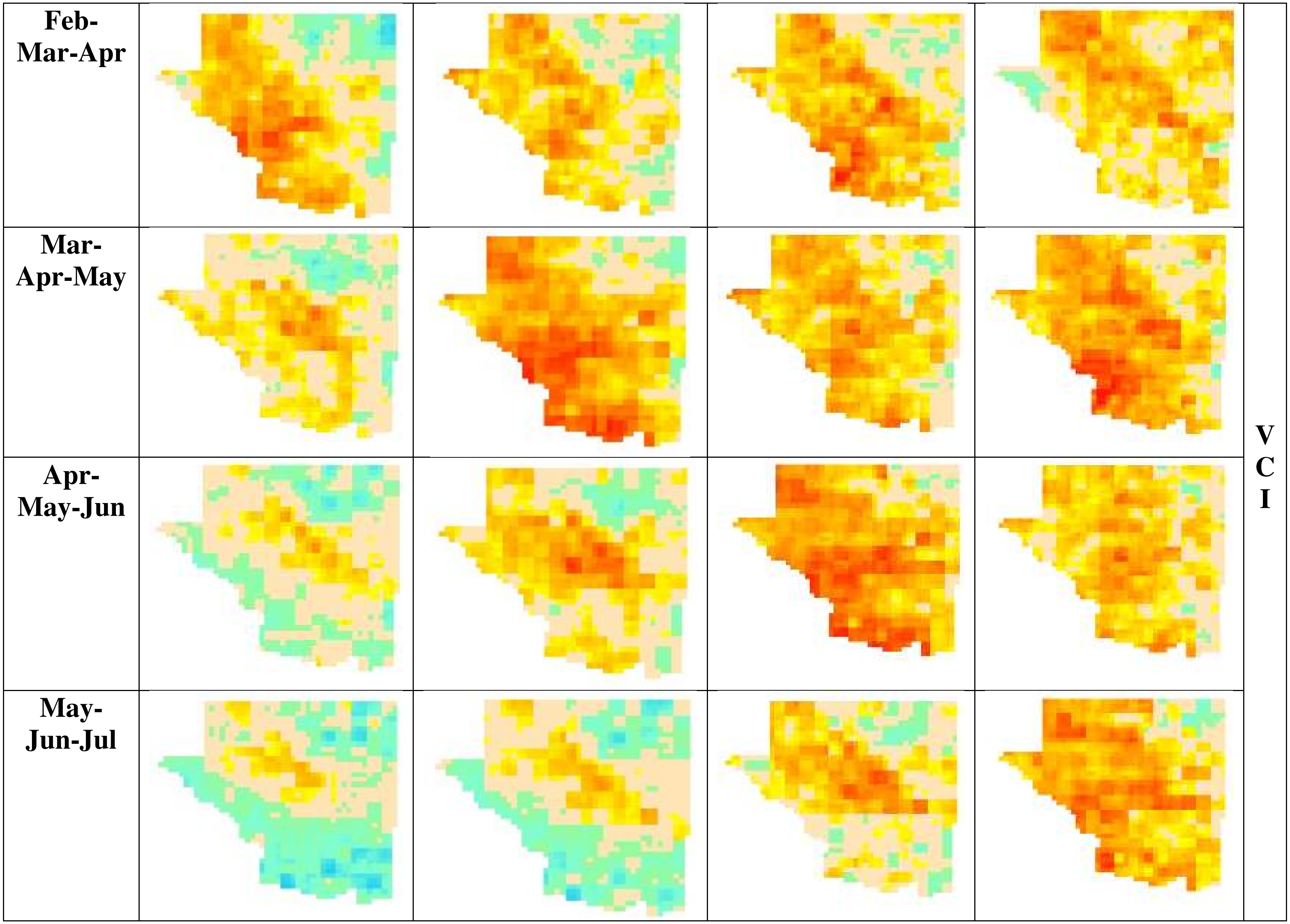


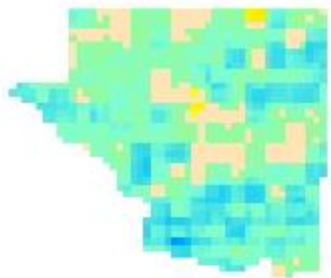
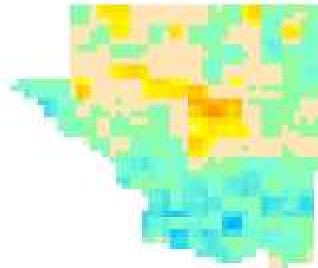
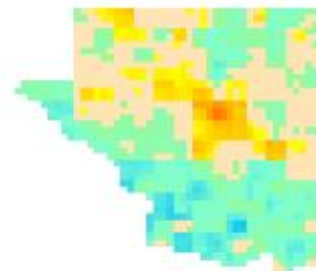
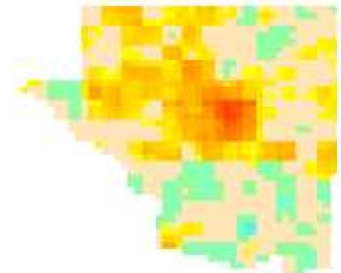
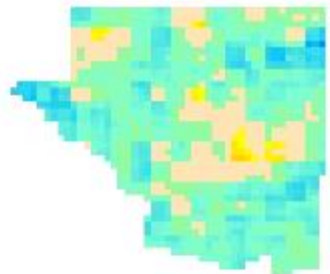
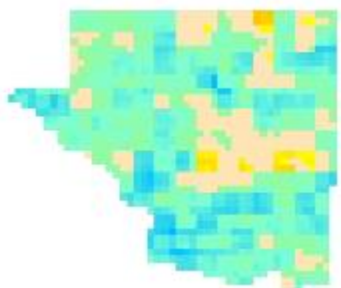
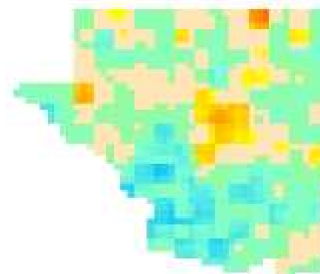
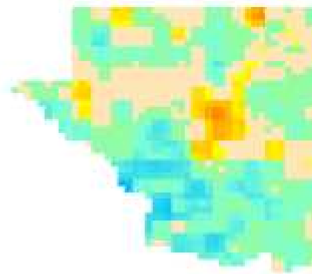
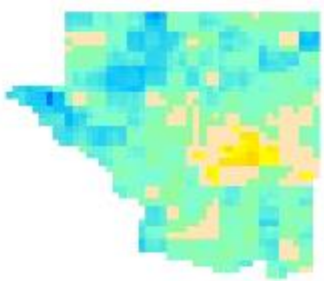
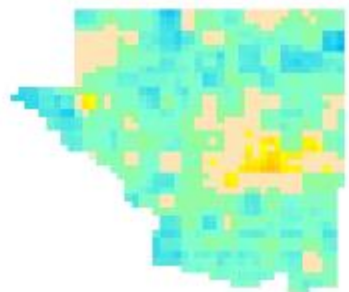
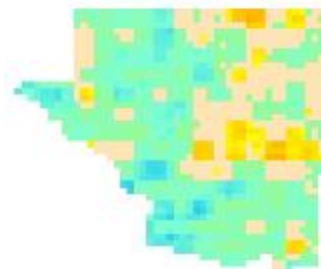
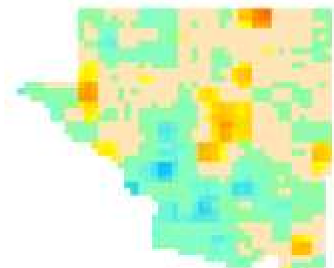
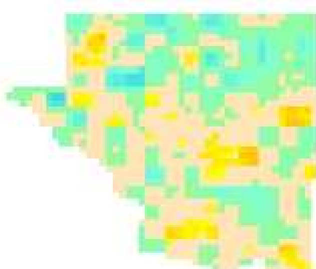
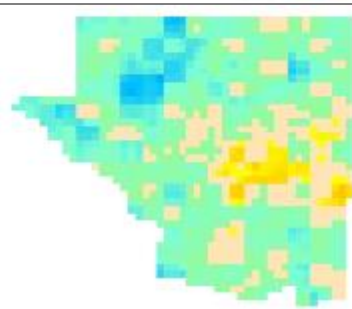
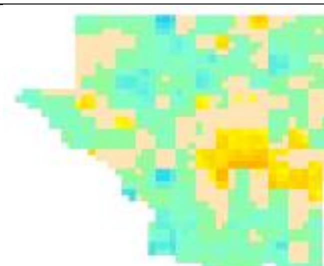
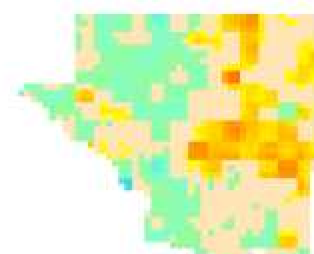
Fig. 8: SMN in relation to precipitation of same season, and lagged seasons

4.5 Vegetation Condition Index (VCI) and Precipitation

The analysis of VCI and precipitation shows a significant correlation between precipitation and vegetation conditions for seasons 2, 3, and 4 (Table 9). While calculating the correlation, precipitation of preceding seasons emphasizes VCI, but precipitation in the same season has less or no effect on VCI. The results imply that the precipitation in prior periods influences vegetation condition, while precipitation in the same season does not impact the VCI. Besides, seasons 2, 3, and 4 have zero to a slight negative correlation between precipitation and VCI.

VCI in Relation to Precipitation of Same Season, and Lagged Seasons					
Season	**No Lag**	**1 Month Lag**	**2 Months Lag**	**3 Months Lag**	
Jan-Feb-Mar					**VCI**


Feb-Mar-Apr
Mar-Apr-May
Apr-May-Jun
May-Jun-Jul
VCI

Jun-July-Aug					**V C I**
Jul-Aug-Sep					
Aug-Sep-Oct					
Sep-Oct-Nov					

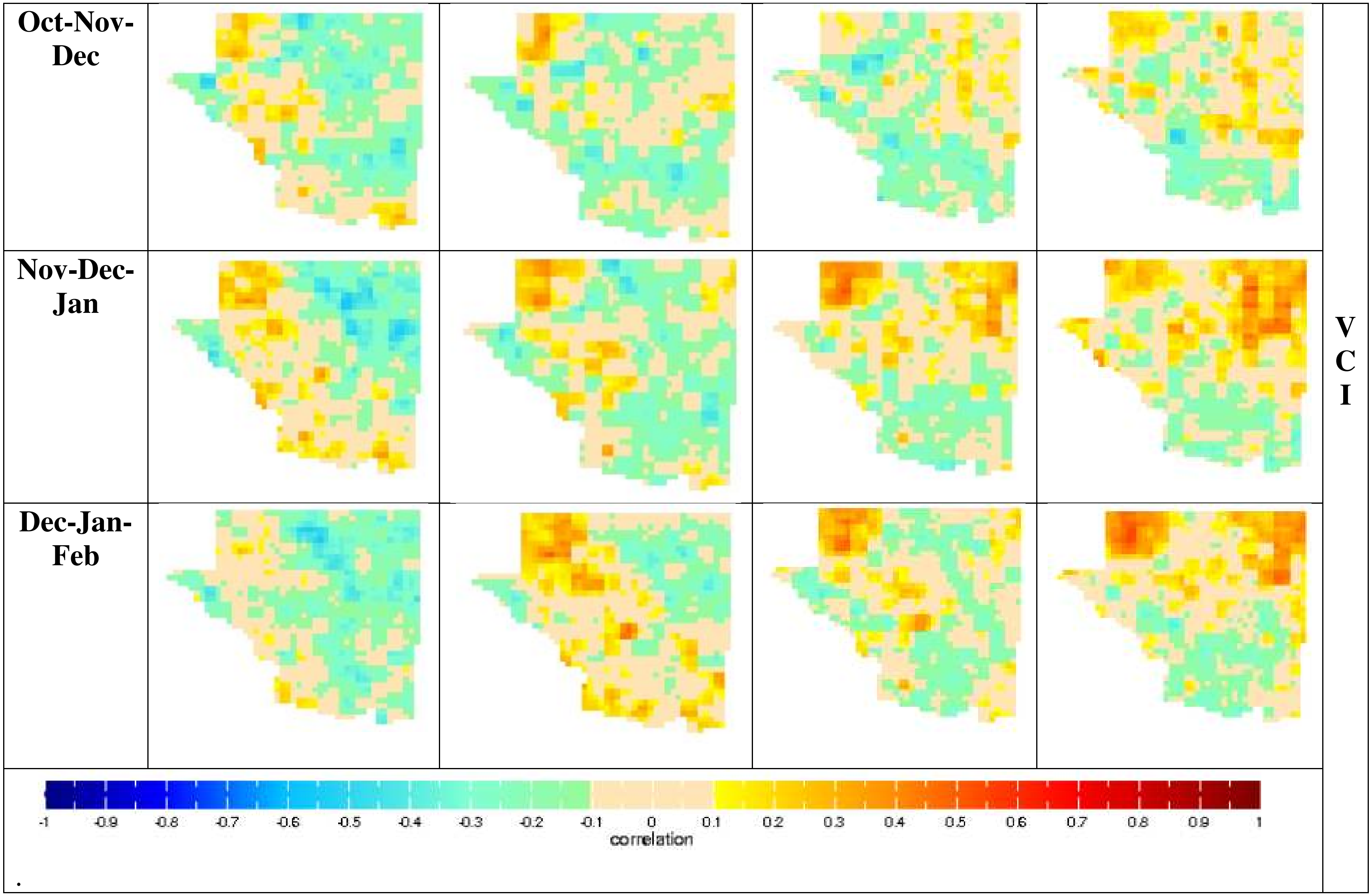
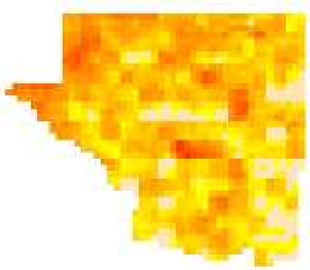
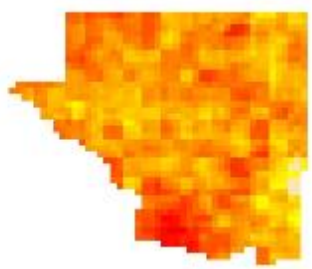
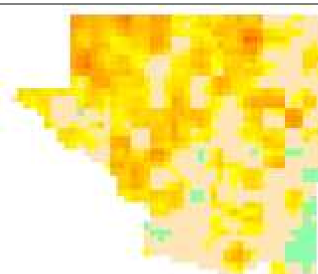
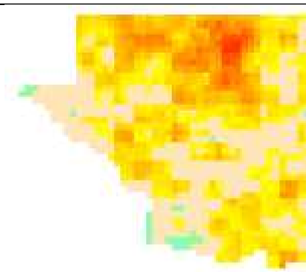
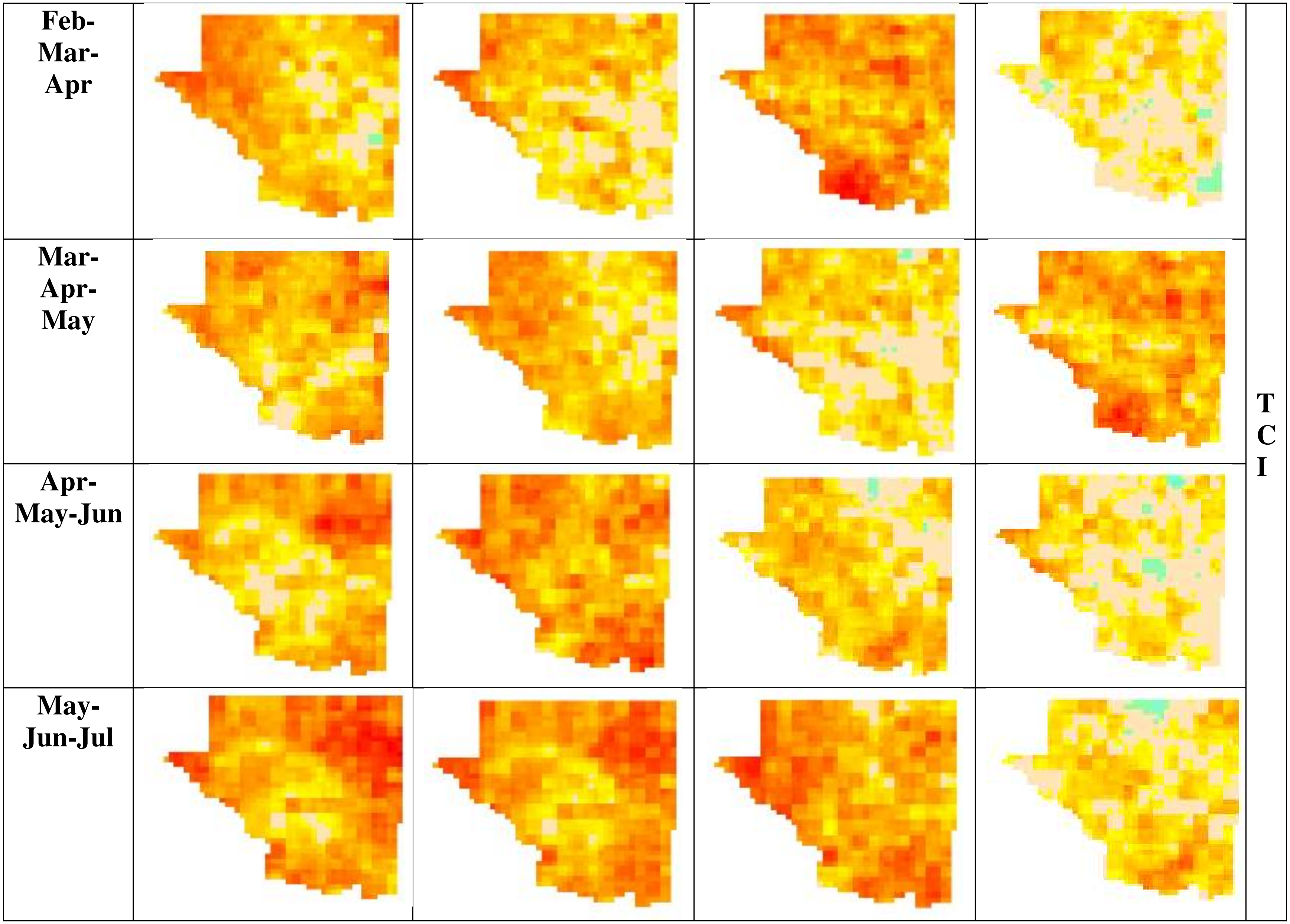


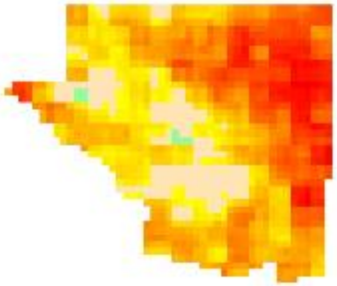
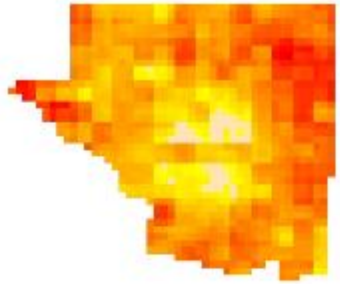
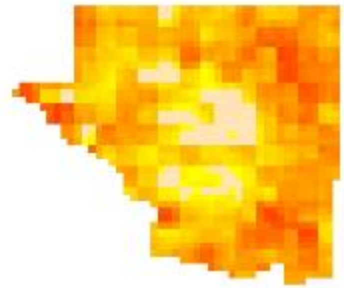
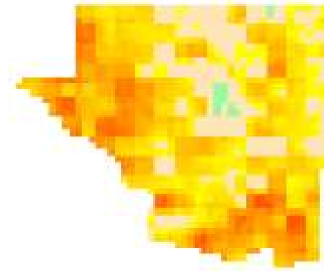
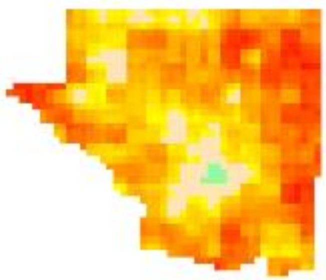
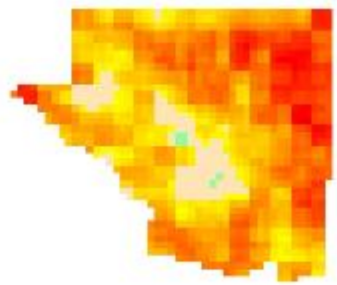
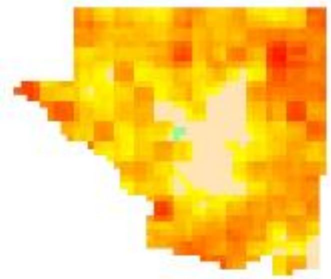
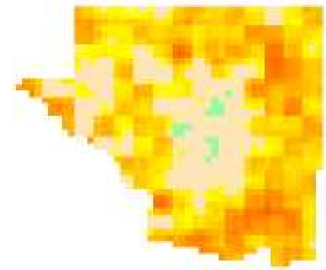
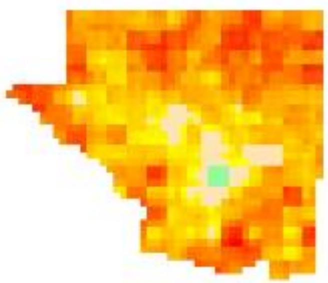
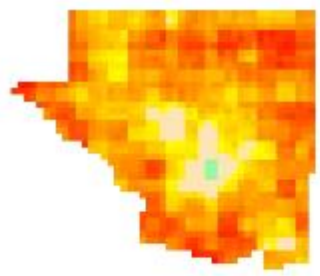
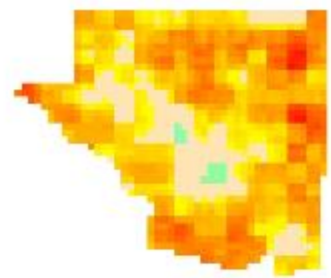
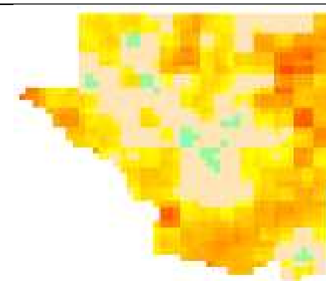
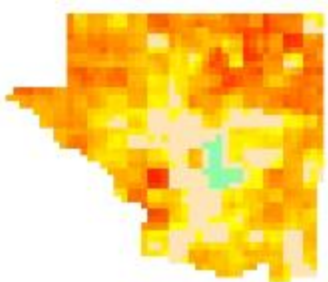
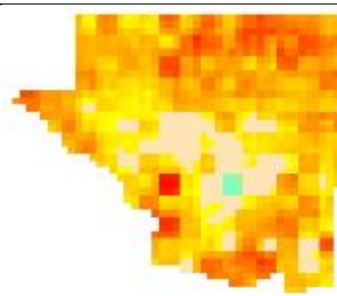
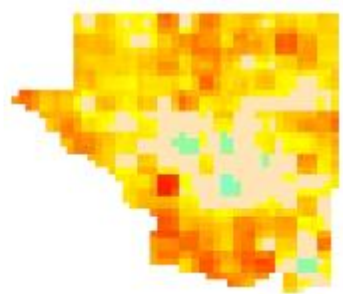
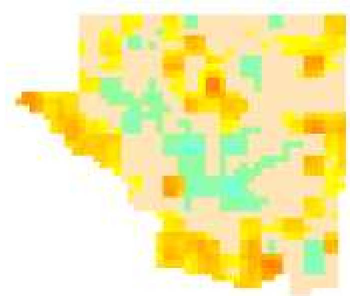
Fig. 9: VCI in relation to precipitation of same season, and lagged seasons.

4.6 Temperature Condition Index (TCI) and Precipitation

TCI shows a strong correlation with precipitation; interestingly, it has the highest correlation among all five indices. The results also show that the correlation is strong from no lag to 2 months of lagged correlation. As higher rainfall results in a higher TCI value (Kogan, 1995), precipitation and TCI of the same season and the immediate preceding season show the highest correlation. As the higher TCI values represent higher wetness or fuel moisture, the precipitation of the same season or immediate preceding season represents the wetness or moisture content of the foliage. The results validate the hypothesis and support the basic theory of TCI in relation to precipitation.

TCI in Relation to Precipitation of Same Season, and Lagged Seasons					
Season	**No Lag**	**1 Month Lag**	**2 Months Lag**	**3 Months Lag**	
Jan-Feb-Mar					**TCI**


Feb-Mar-Apr
Mar-Apr-May
Apr-May-Jun
May-Jun-Jul
TCI

Jun-July-Aug					**TCI**
Jul-Aug-Sep					
Aug-Sep-Oct					
Sep-Oct-Nov					

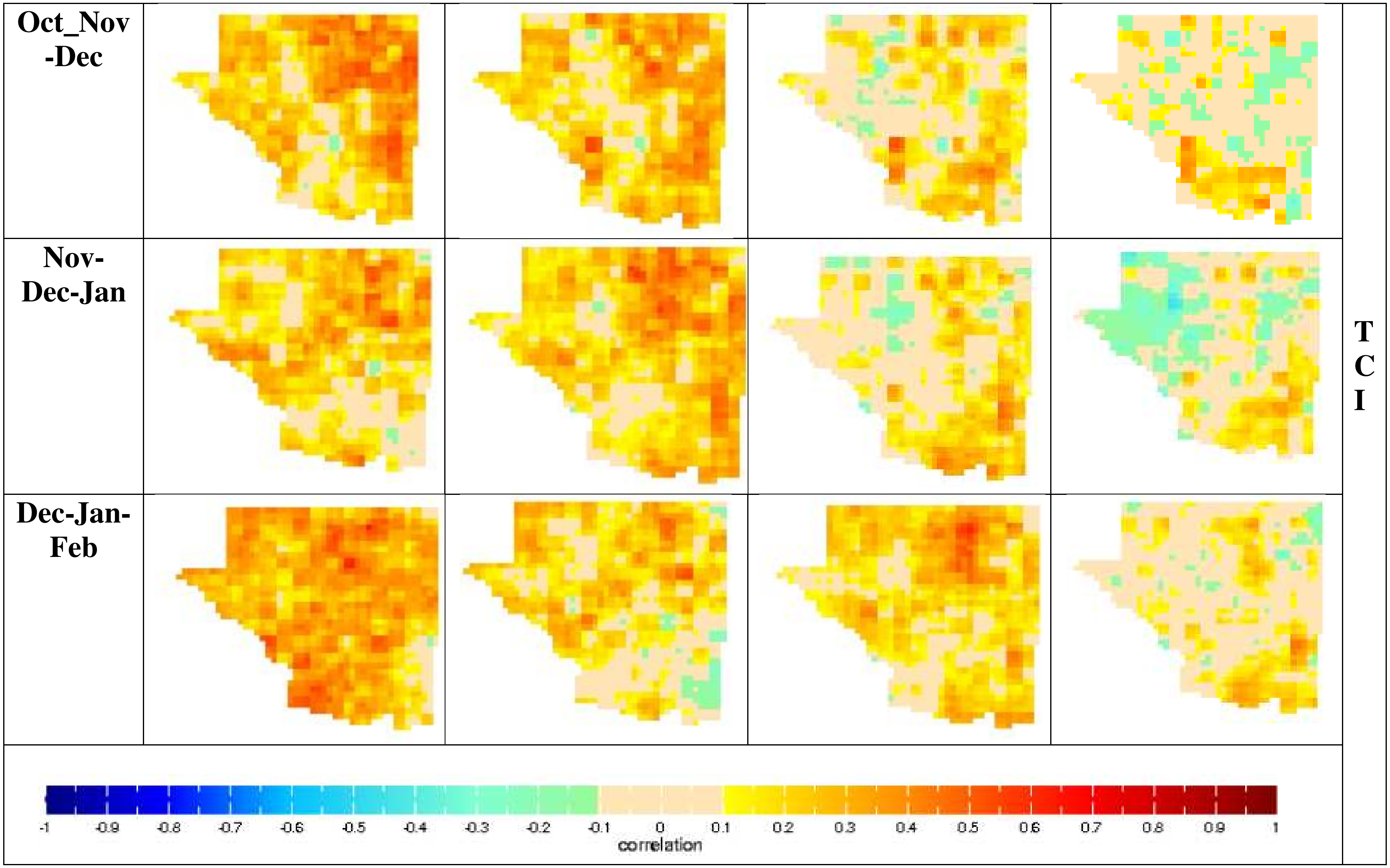
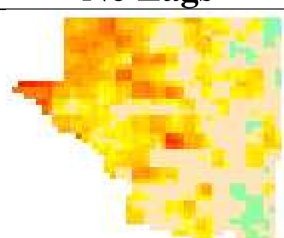
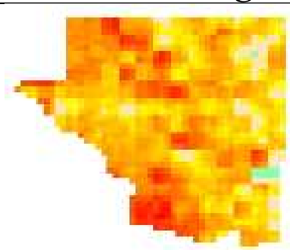
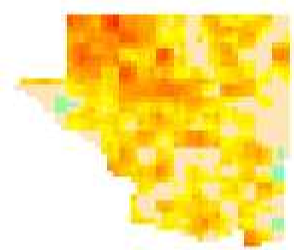
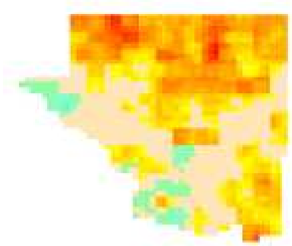


Fig. 10: TCI in relation to precipitation of same season, and lagged seasons.

TCI is one of the most important indices that help identify available fuel for wildfire. The lower the TCI is, the more available fuel there is. The results indicate that preceding seasonal precipitation has a more significant influence on fuel availability, where precipitation in the same season increases the vegetation's wetness, thus decreasing the available fuel for wildfire. The negative correlations for three months of preceding seasonal precipitation with TCI indicate the possibility of a drought situation or more available fuel for wildfire.

4.7 Vegetation Health Index (VHI) and Precipitation

This analysis used the same approach as the NDVI and precipitation analysis while analyzing the lagged precipitation impacts on VHI. However, VHI also indicates fuel availability, as stressed vegetation is more vulnerable to fire.

VHI in Relation to Precipitation of Same Season, and Lagged Seasons				
Season	**No Lags**	**1 Month Lag**	**2 Months Lag**	**3 Months Lag**
Jan-Feb-Mar				

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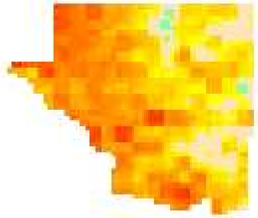
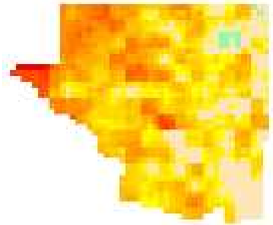
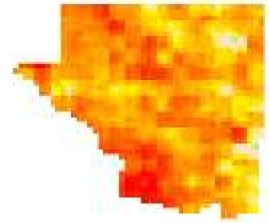
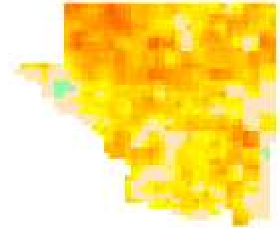
Mar-Apr</td><td></td><td></td><td></td><td></td><td rowspan="4">V
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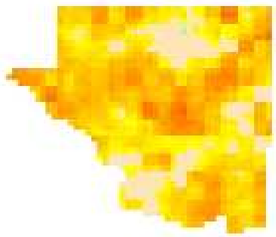
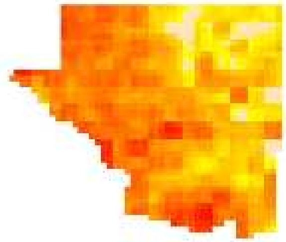
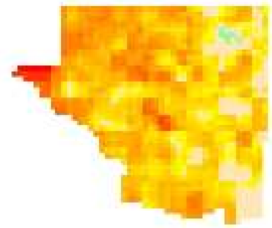
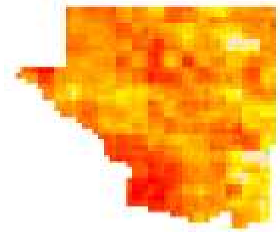
Apr-May</td><td></td><td></td><td></td><td></td></tr>
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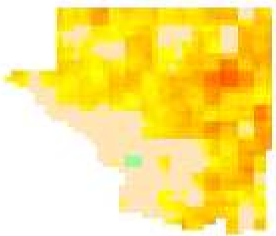
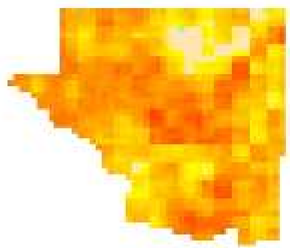
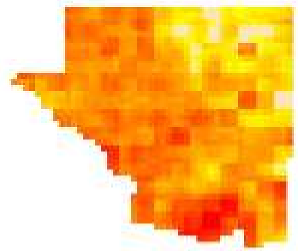
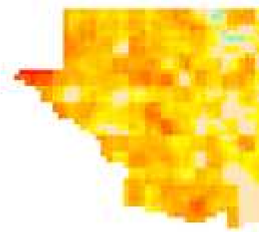
May-Jun</td><td></td><td></td><td></td><td></td></tr>
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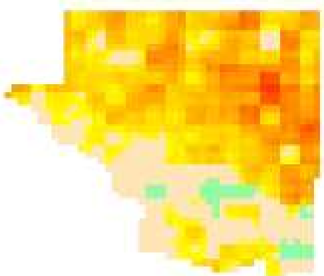
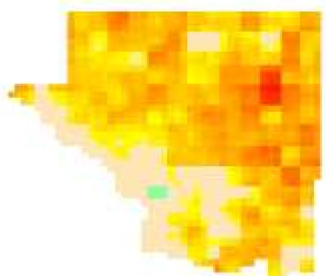
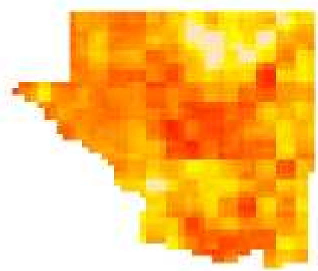
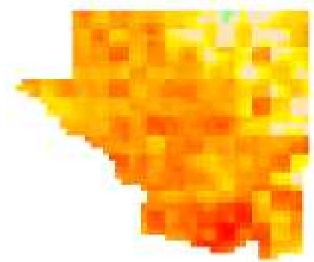
Jun-Jul</td><td></td><td></td><td></td><td></td></tr>
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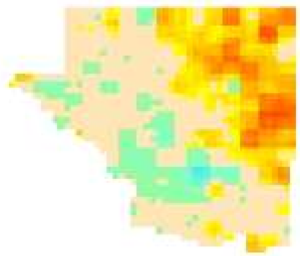
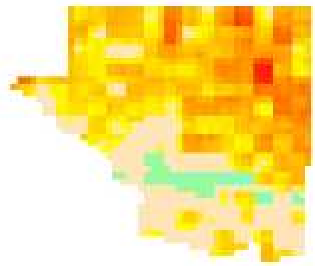
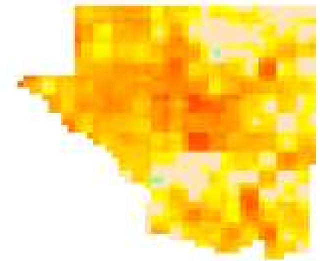
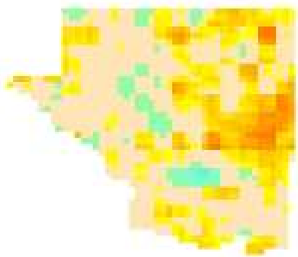
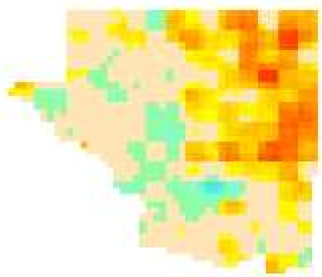
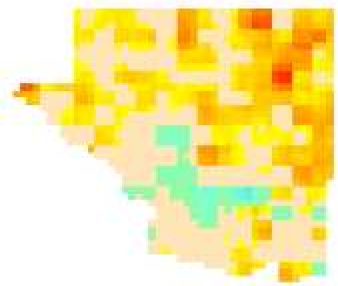
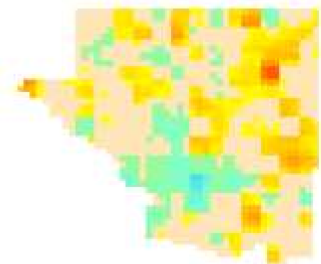
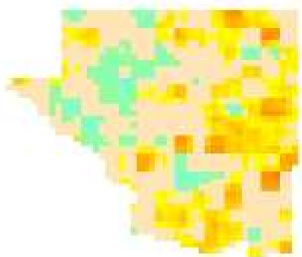
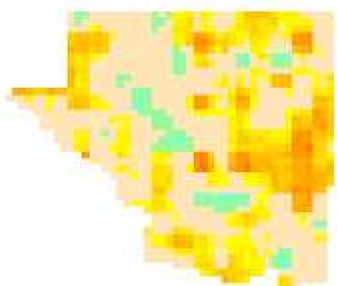
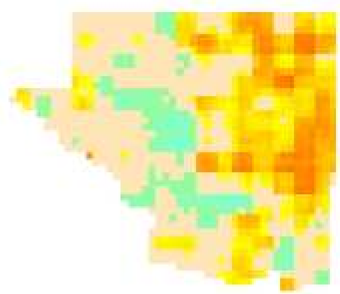
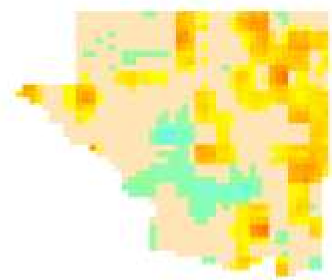
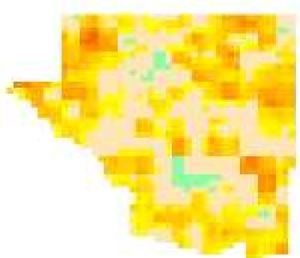
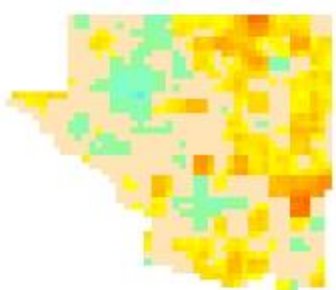
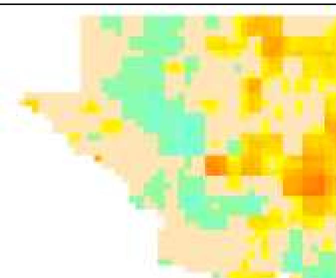
Jun-July-Aug					**VHI**
Jul-Aug-Sep					
Aug-Sep-Oct					
Sep-Oct-Nov					

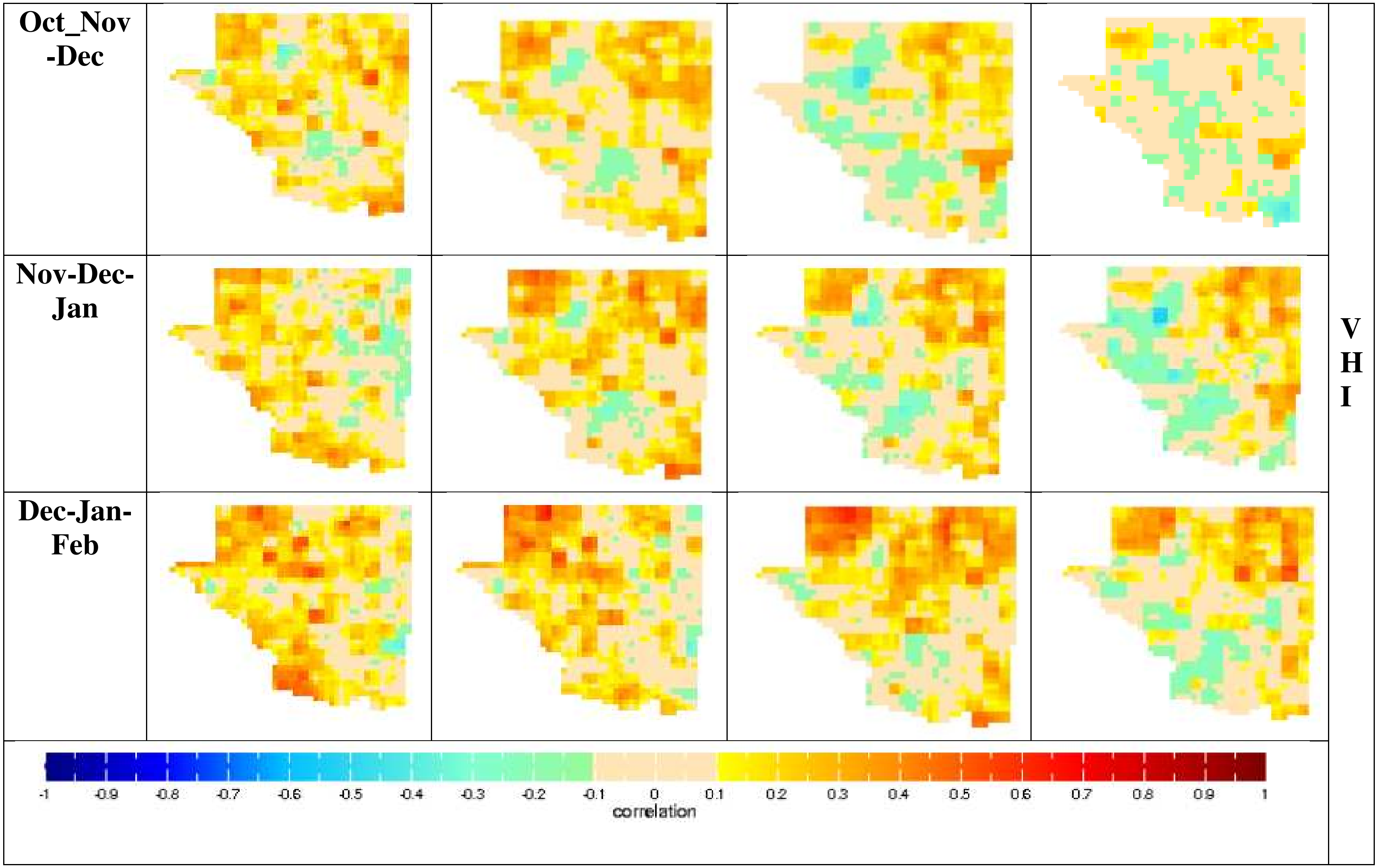


Fig. 11: VHI in relation to precipitation of same season, and preceding seasons

VHI shows a strong correlation with precipitation, significantly while correlating with a preceding season of precipitation, supporting the argument of lagged influence on vegetation health by precipitation. The findings indicate that precipitation highly influences vegetation health, while precipitation happened 1-3 months earlier. VHI shows a stronger correlation with precipitation (preceding seasons) than NDVI concerning the fire season. The correlation here is evident as precipitation directly supplies water to the plants, and the VHI is one of those indices that rely on the water content of foliage. The less prominent correlation between precipitation and VHI in later months (July to January) could be caused by changes in seasons and maturity and development of foliage that decrease the healthy chlorophyll reflectance. The result also identifies the influence of one, two, or three months of preceding precipitation in increasing the fuel, even though the fuel available for fire occurrences is hard to identify.

Finally, from all these analyses and correlations, the results may be summarized as the vegetation indices are highly influenced by 1, 2, and 3 months of preceding precipitation. In most cases, the 1-month lagged correlation is lower compared to 2 and 3 months of preceding seasonal precipitation. Only the TCI values give a different response, suggesting that precipitation of preceding seasons has decreased correlation with TCI values as the wetness dries up with time. As precipitation in the same season tends to increase the wetness, no-lagged (same seasons) precipitation, and TCI show the highest correlation, as the higher TCI value means a higher wetness condition.

If the interpretation of NDVI and TCI is combined, the results represent a growth in vegetation by preceding precipitations (one, two, and three months), whereas the TCI represents an increase in dryness of vegetation while precipitation has happened (one, two, and three months). More specifically, preceding precipitation, on the one hand, increases the growth of vegetation in the following months; on the other hand, the moisture content of the vegetation decreases in the following months. So, if the precipitation is happening three months earlier, the total fuel for fire increases during the fire season, while the fuel's dryness (availability) also increases during the fire season.

Besides the correlation of these two factors (precipitation and vegetation indices), air, aspects (direction of a slope faces), altitude, temperature, fuel composite, and the weather could also impact the fire occurrences. For example, drought before a fire season may increase the probability of fire occurrences by influencing (decreasing) the TCI value because of added dryness. The increased dryness may result in increased fuel availability during the fire season, thus increasing fire incidents.

Sharper (brief and decreased in length) or shorter Rainy seasons, above-average temperatures, and drought just before the fire season followed by an above-average rainy season may also worsen the situation and create an ideal condition for wildfire in Petén.

4.8 Precipitation and fire occurrence

Identifying the influence of precipitation on wildfire occurrence is one of the primary objectives of the research. The research started with a view to analyzing and finding if there is any impact or influence of precipitation on wildfire occurrences in a humid forest ecosystem (Petén). The

Pearson correlation between forest fire occurrences and precipitation, especially the 1-3 months preceding precipitation, shows a noticeable influence of precipitation on forest fire occurrences in Petén (Table 12).

The fire occurrences in March show a negative correlation with 1, 2, and 3 months of preceding seasonal accumulative precipitation, meaning that lower precipitation in those times may increase the forest fire occurrences in March. A similar conclusion may be drawn for April, where forest fires in May give a different result. About 54% of the time, there is a positive correlation between fire occurrences and 2 and 3 months of preceding seasonal precipitation before May. Where 71.42% times in 2 (Jan-Feb-Mar) and 3 (Dec-Jan-Feb) months of seasonal preceding precipitation gives a positive correlation with fire occurrences of May. Although precipitation of same seasons (Jan-Feb-Mar, and Dec-Jan-Feb) has a negative correlation with forest fire of March and April. The results imply that where the precipitation of season 12 (Dec-Jan-Feb) and season 1 (Jan-Feb-Mar) may positively influence the fire occurrences of May, it could negatively impact the fire occurrences of March. More specifically, the increased precipitation of season 12 and season 1 decreases the fire incidents in March but increases the fire occurrences in May.

Table 6: Seasonal accumulative rainfall in relation to fire occurrences in fire season months (March, April, And May) with lagged precipitation:

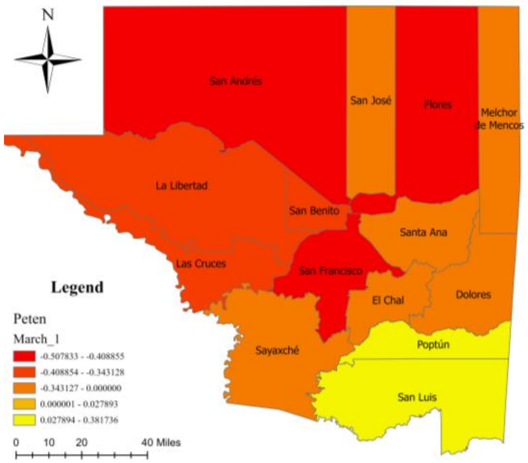
Municipality	March			April			May		
	1 Month Lag in season Dec-Jan-Feb	2 Month Lag in season Nov-Dec-Jan	3 Month Lag in season Oct-Nov-Dec	1 Month Lag in season Jan-Feb-Mar	2 Month Lag in season Dec-Jan-Feb	3 Month Lag in season Nov-Dec-Jan	1 Month Lag in season Feb-Mar-Apr	2 Month Lag in season Jan-Feb-Mar	3 Month Lag in season Dec-Jan-Feb
7271 Melchor de Mencos	No Fire since 2001	No Fire since 2001	No Fire since 2001	-0.382892995	-0.191941309	0.027461395	-0.183474166	-0.209337288	-0.230160248
7272 Flores	-0.507833376	-0.359117837	-0.288383645	-0.162845565	-0.13962197	-0.167952041	-0.21849	0.102102	0.134954
7273 San José	-0.294281852	-0.133732009	-0.159041742	-0.3032445	-0.3368061	-0.3321253	-0.346768555	-0.21921183	0.096956469
7274 San Andrés	-0.408855042	-0.380754593	-0.383735382	-0.677776353	-0.672040402	-0.515261863	-0.235549339	-0.362410189	-0.501677508
7275 La Libertad	-0.343128378	-0.07173	0.068880296	-0.518564215	-0.397384405	-0.087179214	0.294454	0.120899	0.105002
7275 Las Cruces	-0.343128378	-0.07173	0.068880296	-0.518564215	-0.397384405	-0.087179214	0.294454	0.120899	0.105002
7276 San Benito	-0.35821659	-0.185599565	-0.167502519	-0.304167334	0.094121284	0.362375904	-0.05670681	0.027527309	0.115950678
7277 Santa Ana	-0.073722723	-0.1792813	-0.141090121	0.383487863	0.259882	-0.05017	-0.02273	0.220979	0.242808
7278 Dolores	-0.312036707	-0.236527686	-0.192699715	0.202036277	0.005405293	-0.141074437	-0.04178	0.194068	0.109042
7278 El Chal	-0.312036707	-0.236527686	-0.192699715	0.202036277	0.005405293	-0.141074437	-0.04178	0.194068	0.109042
7279 San Francisco	-0.43442	-0.28174	-0.09073	-0.22014	-0.21786	-0.2349	-0.03348	0.212316	0.273451
7280 Sayaxché	-0.252539292	-0.024192067	-0.046007289	0.043216298	-0.083235736	-0.150282306	-0.004312657	0.123162939	-0.081414965
7281 Poptún	0.147803534	-0.132762745	-0.040430026	0.388108448	0.133608945	-0.128784538	0.146035886	0.369981368	0.305695312
7282 San Luis	0.381736303	0.440880445	0.499924395	-0.20287	-0.09715	0.276770877	-0.17617826	-0.057442473	-0.067448732

Melchor de Mencos municipality has no proper correlation (first 3 boxes) as it has not experienced any fire in March since 2001. Although the fire occurrence in Petén has been recorded since 2001, for the lagged correlation analysis of the precipitation data of 2000 has been included. For example, the 3-month lagged or preceding precipitation for March of 2001 is the accumulative rainfall of Oct-Nov-Dec in 2000. A similar approach is followed for all lagged seasons, e.g., the 3 -months lagged seasonal precipitation of May 2010 (which is Dec-Jan -Feb) includes Dec 2009, January 2010, and February 2010.

4.9 Fire Occurrences of Petén in Fire Months in Relation to Seasonal Accumulative Precipitation of Preceding Months :

The symbology of these maps has followed the inverted symbology using ArcGIS pro to visualize which area is more influenced (negative correlation) by precipitation on a monthly basis of the fire season (March-April-May) of Petén.

The map shows that almost all of the area of Petén is firm to moderately influenced by the seasonal precipitation in the 1, 2, and 3 preceding months. Figures 6 to 8 show fires in March in relation to preceding seasonal precipitation, where San Luis municipality is an exception. San Luis shows a positive correlation between preceding precipitation in response to fire occurrences in March (0.381736303, 0.440880445, and 0.499924395 for 1, 2, and 3 months of seasonal lagged precipitation, consecutively). The result implies that the San Luis Municipality is prone to fire occurrence in March if there is higher precipitation in preceding seasons. Although the results seem arbitrary compared to the other municipalities in Petén in considering the fire occurrences of March, the lagged seasonal precipitation probably influenced the vegetation growth, thus increasing fuel availability for wildfires. The comparatively higher altitude and dispersed vegetation may also be a reason behind its (San Luis municipality) different correlation with precipitation. The argument is also supported by the findings for other municipalities considering 2 and 3 months of preceding seasonal precipitation. As the time difference between the five-months (Mar-Apr-May) and preceding rainy season increases, the maps represent an increase in yellow areas, representing a divergence from the direct negative correlation to a more positive correlation. The divergence from negative to positive correlation coefficient represents an increase in fire occurrences along with the increase in precipitation of preceding seasons. The positive correlation may be a result of increased fuel density and fuel availability due to increased vegetation.


N
San Andrés
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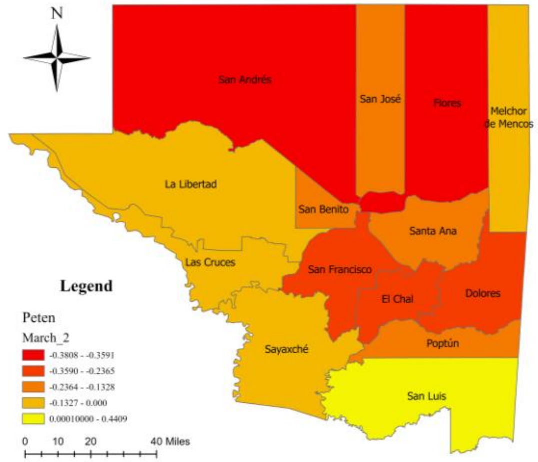
Melchor de Mencos
La Libertad
San Benito
Santa Ana
Las Cruces
San Francisco
El Chal
Dolores
Sayaxché
Poptún
San Luis
Legend
Peten
March_1
-0.507833 - -0.408855
-0.408854 - -0.343128
-0.343127 - 0.000000
0.000001 - 0.027893
0.027894 - 0.381736
0 10 20 40 Miles

A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Melchor de Mencos
La Libertad
San Benito
Santa Ana
Las Cruces
San Francisco
El Chal
Dolores
Sayaxché
Poptún
San Luis
Legend
Peten
March_2
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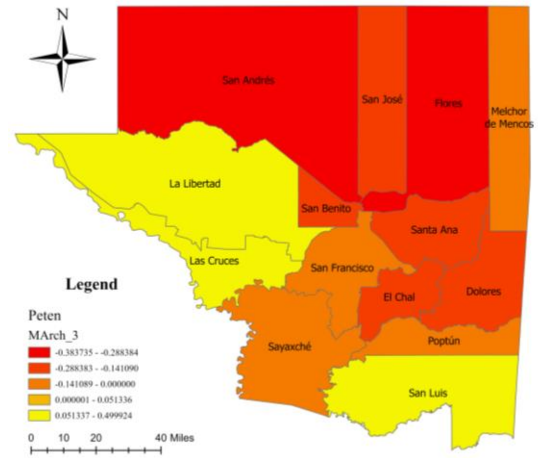
-0.3590 - -0.2365
-0.2364 - -0.1328
-0.1327 - 0.000
0.00010000 - 0.4409
0 10 20 40 Miles

B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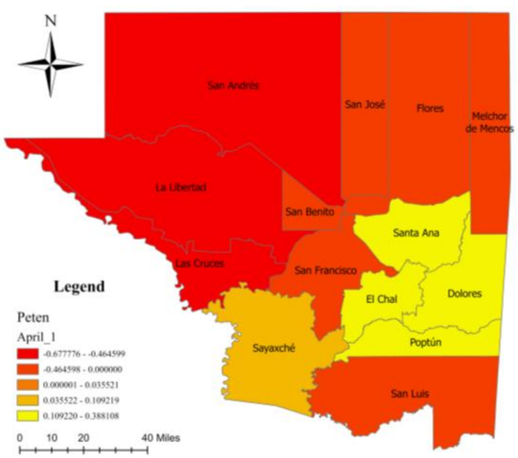
San Benito
Santa Ana
Las Cruces
San Francisco
El Chal
Dolores
Sayaxché
Poptún
San Luis
Legend
Peten
MArch_3
-0.383735 - -0.288384
-0.288383 - -0.141090
-0.141089 - 0.000000
0.000001 - 0.051336
0.051337 - 0.499924
0 10 20 40 Miles

C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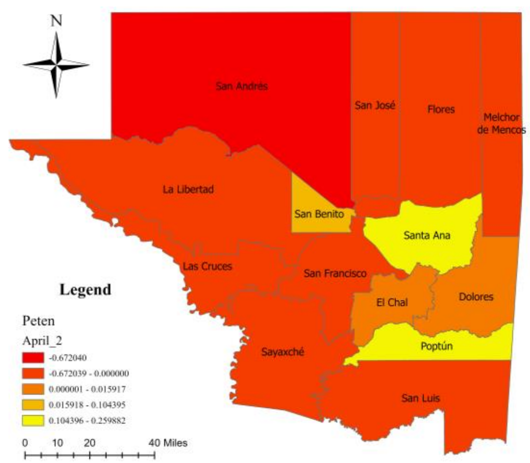
La Libertad
San Benito
Santa Ana
Las Cruces
San Francisco
El Chal
Dolores
Sayaxché
Poptún
San Luis
Legend
Peten
April_1
-0.677776 - -0.464599
-0.464598 - 0.000000
0.000001 - 0.035521
0.035522 - 0.109219
0.109220 - 0.388108
0 10 20 40 Miles

D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San Benito
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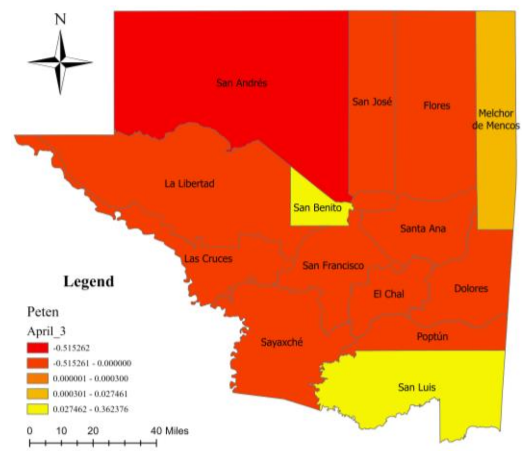
Las Cruces
San Francisco
El Chal
Dolores
Sayaxché
Poptún
San Luis
Legend
Peten
April_2
-0.672040
-0.672039 - 0.000000
0.000001 - 0.015917
0.015918 - 0.104395
0.104396 - 0.259882
0 10 20 40 Miles

E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Melchor de Mencos
La Libertad
San Benito
Santa Ana
Las Cruces
San Francisco
El Chal
Dolores
Sayaxché
Poptún
San Luis
Legend
Peten
April_3
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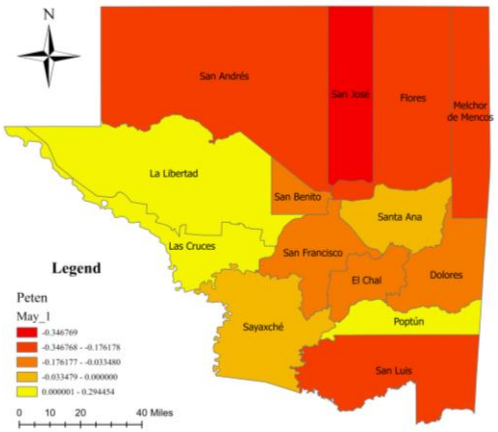
0.000001 - 0.000300
0.000301 - 0.027461
0.027462 - 0.362376
0 10 20 40 Miles

F



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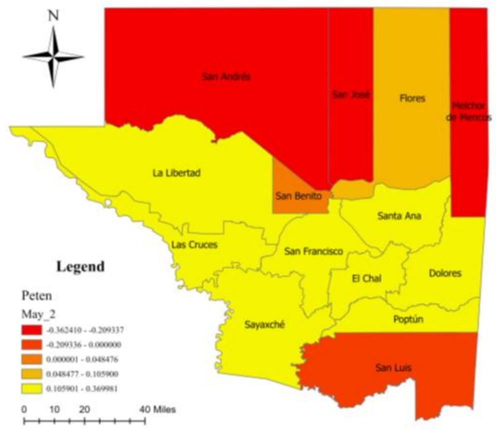

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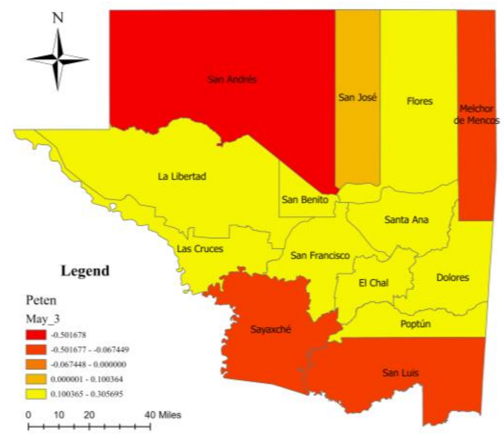


I

Fig. 12: Maps representing the correlation between seasonal precipitation and fire occurrences for each municipality for each fire month.

A -	Correlation Between Accumulative Precipitation of Season 12, and Fire Frequency of March	**F -**	Correlation Between Accumulative Precipitation of Season 11, and Fire Frequency of April
B -	Correlation Between Accumulative Precipitation of Season 11, and Fire Frequency of March	**G -**	Correlation Between Accumulative Precipitation of Season 2, ad Fire Frequency of May
C -	Correlation Between Accumulative Precipitation of Season 10, and Fire Frequency of March	**H -**	Correlation Between Accumulative Precipitation of Season 1, and Fire Frequency of May

D - Correlation Between Accumulative Precipitation of Season 1, and Fire Frequency of April

E - Correlation Between Accumulative Precipitation of Season 12, and Fire Frequency of April

I - Correlation Between Accumulative Precipitation of Season 12, and Fire Frequency of May

San Luis municipality shows a different correlation with precipitation for April and May. It shows a negative correlation for April and May, suggesting that higher precipitation decreases fire occurrences. The result is different here because of the overlapping of fire months while accumulating the precipitation for calculating correlation. The result again strongly suggests that the precipitation in fire months decreases the fire occurrences during the fire season. However, precipitation earlier than the fire season may increase fire occurrences. Results from the analysis and visualization of April and May also support the previous argument, as most municipality's fire occurrences are influenced by preceding seasonal precipitation.

The relationships differ for different months and create difficulties in generalizing the findings, suggesting that the precipitation of the same season has a different influence on fire occurrences for different months of the fire season. While looking into the seasonal influence of precipitation for a specific month of the fire season, some other months of the fire season (Mar-Apr-May) become included, which makes it difficult to determine the seasonal fire behavior of Petén. The table below (Table 13) represents how the previous seasonal precipitation includes the fire months while analyzing the monthly fire occurrences of Petén instead of seasonal fire occurrences. The findings also suggest using seasonal fire occurrences instead of monthly fire frequencies for a finer result.

Table 7: Overlapping of months while analyzing fire occurrences of a fire month (March, April, Or May) with seasonal precipitation.

Fire Occurrences of May	**Preceding Season of Precipitation**	**March**	**April**
1 Month Lag	Feb-**Mar-Apr**	Overlapping	Overlapping
2 Months Lag	Jan-Feb-**Mar**	Overlapping	1 Month Lag
3 Months Lag	Dec-Jan-Feb	1 Month Lag	2 Months Lag

The table above shows how the correlation between monthly fire occurrences and seasonal precipitation includes the precipitation of fire months as well, thus creating a convoluted outcome while identifying the influence of seasonal precipitation on monthly fire occurrences. The Fire of April results differently than the other two months (March and May). Where March and May show an increase in fire occurrences with the increased precipitation in preceding seasons, such a scenario decreases for April. This overlapping could be a reason for such incongruous results, as the analyses involve the precipitation within the fire season and, most of the time, which is considered a daunting factor for fire occurrences within the fire season.

Finally, from the correlation between forest fire occurrences and precipitation, it seems that precipitation preceding the “fire months” influences fire occurrences in those later months. The results also suggest that analyzing the fire as cumulative seasonal forest fires will be more logical than individual months to identify the influence of seasonal precipitation. The research tried to conduct further analyses considering the fire occurrences of the fire season as a seasonal accumulative fire of fire months (Mar-Apr-May) in response to seasonal precipitation.

4.10 Seasonal Precipitation and the Fire Occurances in Fire Season (March-April-May):

Every municipality of Petén, in terms of fire precipitation in the fire season, shows a negative correlation to fire occurrences. This correlation strongly suggests that less precipitation during a fire season provokes fire incidences, whereas increased precipitation has decreased the fire events during the fire season (Mar-Apr-May). The results also suggest that the municipal authorities should be prepared for increasing forest fire activity if there is a forecast of lower precipitation during fire seasons in Petén.

While precipitation and wildfire of the same season show a negative correlation, precipitation of a preceding season (2 and 3- months of seasonal lagged precipitation) positively correlates with the fire occurrences in a fire season. The increased positive correlation between wildfire occurrences and preceding precipitation reminds the influence of precipitation on vegetation growth and increasing total fuel or fuel availability for wildfire. However, the availability of fuel may also depend on the fuel composite, fuel continuity, and topography (Annex 2: DEM and Fire occurrences in Petén) and the fuel moisture content (influenced by precipitation) only. This positive correlation of fires with preceding seasonal precipitation is higher in places like Santa

Ana, Poptún, and Sayaxché. These areas are higher in altitude compared to other municipalities of Petén. Their unique geography and biomass could also be the reason behind this higher correlation coefficient (Annex DEM figure), besides the influence of precipitation on vegetation. The preceding seasonal precipitation creates a window to grow more vegetation and more available fuel for forest fires. Moreover, increased rainfall in the same season leads to fewer fires due to increased wetness.

Table 8: Correlation of seasonal precipitation with fire occurrence of the fire season of Petén; Guatemala.

Municipality	**March -April-May Seasonal Accumulative Fire Occurrence**			
	No Lag/ March April May	**1 Month Lag / Feb-March-April**	**2 Month Lag/ Jan-Feb-March**	**3 Month Lag / Dec-Jan-Feb**
7271 Melchor de Mencos	-0.066844193	-0.263714402	-0.405732858	-0.277242119
7272 Flores	-0.380681617	-0.165859722	-0.174528006	-0.156549493
7273 San José	-0.40737084	-0.360762941	-0.327788736	-0.448771389
7274 San Andrés	-0.276822501	-0.342802497	-0.649267244	-0.72432564
7275 La Libertad	-0.13440109	0.023751006	-0.40472578	-0.339802908
7275 Las Cruces	-0.13440109	0.023751006	-0.40472578	-0.339802908
7276 San Benito	-0.243643419	-0.151116331	-0.383620275	-0.058086565
7277 Santa Ana	-0.311110439	-0.02779948	0.260556607	0.132598939
7278 Dolores	-0.224926204	-0.219493683	0.086180302	-0.083254961
7278	-0.224926204	-0.219493683	0.086180302	-0.083254961

El Chal				
7279 San Francisco	-0.333878821	-0.178347447	-0.128019627	-0.206963031
7280 Sayaxché	-0.162300155	0.044103452	0.126092968	-0.156648845
7281 Poptún	-0.011518378	0.137131874	0.331497985	0.239674521
7282 San Luis	-0.503687495	-0.221575808	-0.10675358	-0.079521529

The visual representation in Figure 15-18, each municipality in terms of correlation between seasonal precipitation and seasonal fire occurrences (2001 to 2021), helps to see how Precipitation is related to forest fire occurrences. The map has been designed in an inverted symbology as the lower the correlation, the higher the negative impact of precipitation on fire and vice-versa. The darker red indicates a more negative correlation between Seasonal precipitation and the forest fire occurrence during the Fire season of Petén.

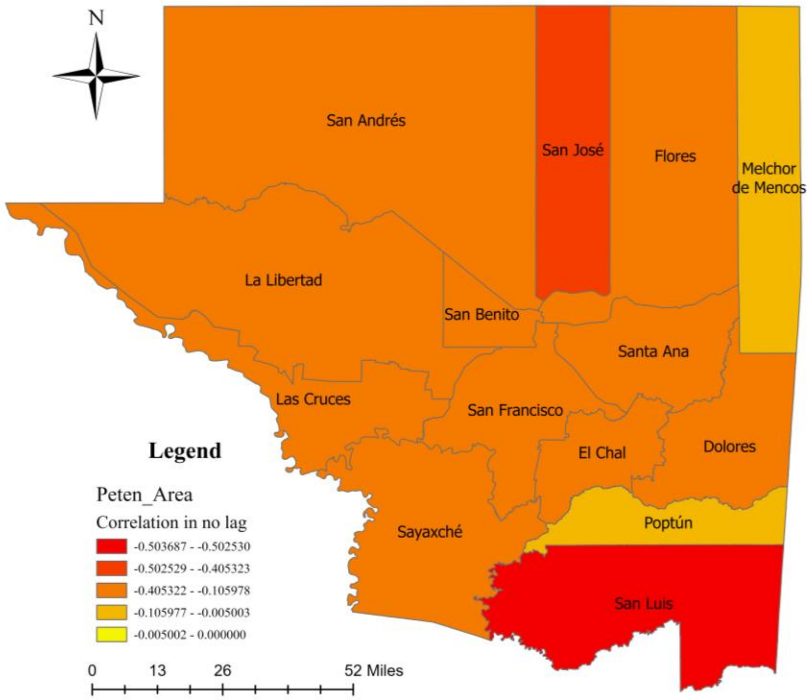


Fig. 13: Correlation between seasonal precipitation and seasonal fire of (March- April-May)

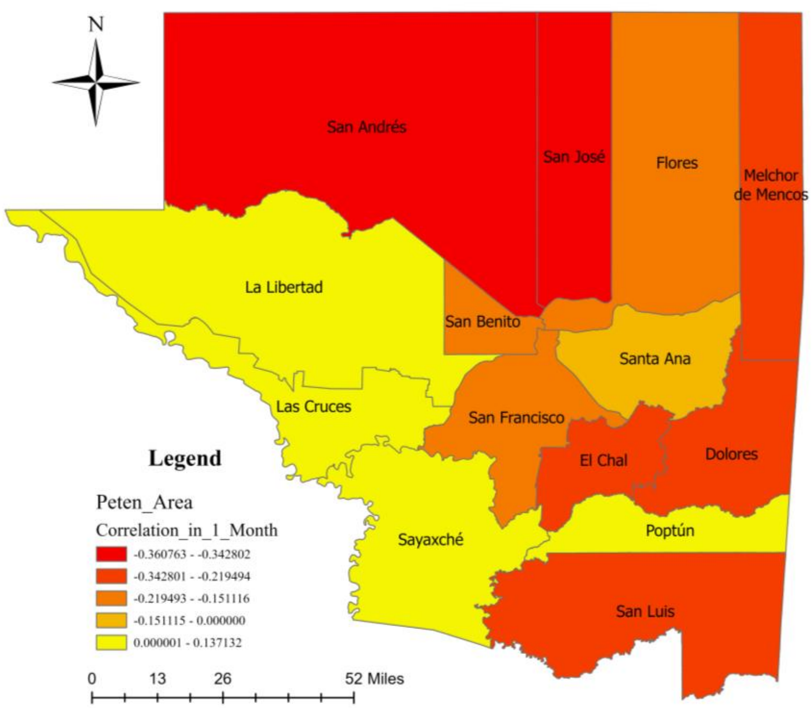


Fig. 14: Correlation between seasonal precipitation and seasonal fire (March- April-May) of 1 month of lagged precipitation

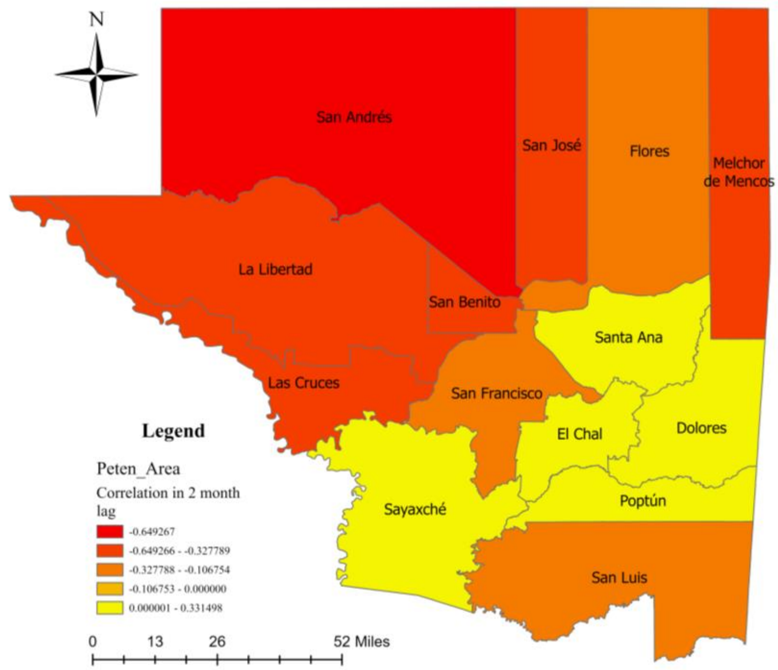


Fig. 15: Correlation between seasonal precipitation and seasonal fire (March- April-May) of 2 months of lagged precipitation

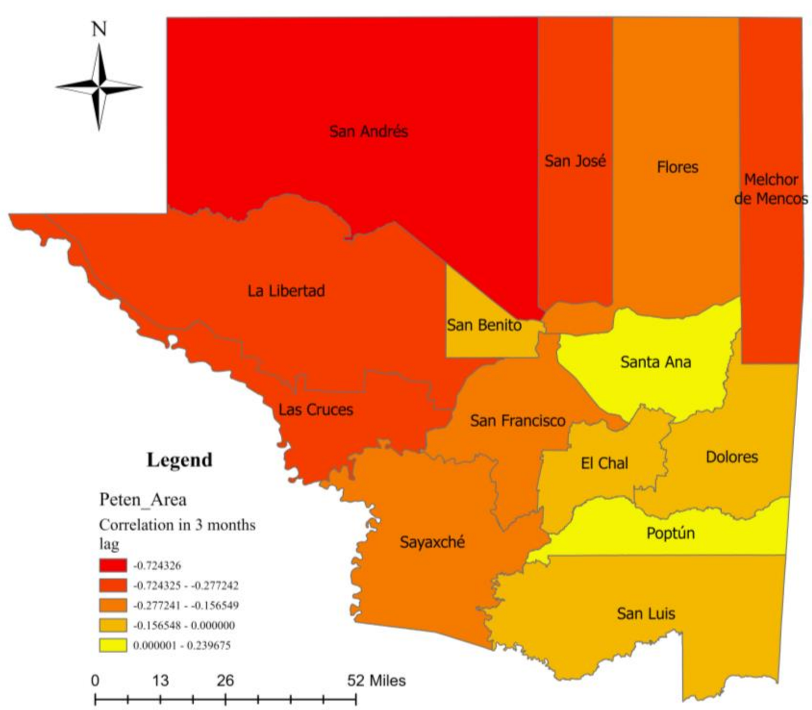


Fig.16: Correlation between seasonal precipitation and seasonal fire (March- April-May) of 3 months of lagged precipitation

Even though there is a noticeable correlation between precipitation and wildfires in different municipalities of Petén, the statistics (Table 15) show an in-depth overview and the significance of these findings. The table (Table 15) shows that only San Luis (for the same season), San Andres (for two and three months of preceding precipitation), and San Jose (for three months of preceding precipitation) are statistically significant at 95 and 99 percent levels of significance. Few municipalities (6 of 15) show a positive correlation between precipitation and fire occurrences, especially for two and three months preceding seasonal precipitation. However, no municipality shows a positive correlation between wildfire and precipitation for the same season, which strongly argues that only a dry fire season will be prone to wildfire occurrences.

Table 9: Statistics of seasonal precipitation and seasonal fire occurrence (March- April-May) in different lags.

Municipality	Statistics	March -April-May Seasonal Accumulative Fire Occurrence			
		No Lag/ March-April-May	**1 Month Lag / Feb-March-April**	**2 Month Lag/ Jan-Feb-March**	**3 Month Lag / Dec-Jan-Feb**
7271 Melchor de Mencos	Correlation Coefficient (Pearson)	-0.066844193	-0.263714402	-0.405732858	-0.277242119
	Level of Confidence (95%):	0.773436	0.248056	0.068022	0.223713
	Level of Confidence (99%):	0.773436	0.248056	0.068022	0.223713
	R^2 Value:	0.004468	0.069545	0.164619	0.076863
7272 Flores	Correlation Coefficient (Pearson)	-0.380681617	-0.165859722	-0.174528006	-0.156549493
	Level of Confidence (95%):	0.088667	0.472434	0.449259	0.497982
	Level of Confidence (99%):	0.088667	0.472434	0.449259	0.497982
	R^2 Value:	0.144918	0.027509	0.03046	0.024508
7273 San José	Correlation Coefficient (Pearson)	-0.40737084	-0.360762941	-0.327788736	-0.448771389
	Level of Confidence (95%):	0.066812	0.108134	0.146899	0.04129
	Level of Confidence (99%):	0.066812	0.108134	0.146899	0.04129
	R^2 Value:	0.165951	0.13015	0.107445	0.201396
7274 San Andrés	Correlation Coefficient (Pearson)	-0.276822501	-0.342802497	-0.649267244	-0.72432564
	Level of Confidence (95%):	0.224443	0.128196	0.001448	0.000205
	Level of Confidence (99%):	0.224443	0.128196	0.001448	0.000205
	R^2 Value:	0.076631	0.117514	0.421548	0.524648
7275 La Libertad	Correlation Coefficient (Pearson)	-0.13440109	0.023751006	-0.40472578	-0.339802908
	Level of Confidence (95%):	0.561352	0.918606	0.068775	0.131789
	Level of Confidence (99%):	0.561352	0.918606	0.068775	0.131789
	R^2 Value:	0.018064	0.000564	0.163803	0.115466
7275 Las Cruces	Correlation Coefficient (Pearson)	-0.13440109	0.023751006	-0.40472578	-0.339802908
	Level of Confidence (95%):	0.561352	0.918606	0.068775	0.131789
	Level of Confidence (99%):	0.561352	0.918606	0.068775	0.131789
	R^2 Value:	0.018064	0.000564	0.163803	0.115466
7276 San Benito	Correlation Coefficient (Pearson)	-0.243643419	-0.151116331	-0.383620275	-0.058086565
	Level of Confidence (95%):	0.287197	0.513196	0.086031	0.802512
	Level of Confidence (99%):	0.287197	0.513196	0.086031	0.802512
	R^2 Value:	0.059362	0.022836	0.147165	0.003374
7277 Santa Ana	Correlation Coefficient (Pearson)	-0.311110439	-0.02779948	0.260556607	0.132598939
	Level of Confidence (95%):	0.169833	0.904788	0.253975	0.566661
	Level of Confidence (99%):	0.169833	0.904788	0.253975	0.566661
	R^2 Value:	0.09679	0.000773	0.06789	0.017582
7278	Correlation Coefficient (Pearson)	-0.224926204	-0.219493683	0.086180302	-0.083254961

Dolores	Level of Confidence (95%): Level of Confidence (99%): R^2 Value:	0.326956 0.326956 0.050592	0.339081 0.339081 0.048177	0.710312 0.710312 0.007427	0.719757 0.719757 0.006931
7278 **El Chal**	Correlation Coefficient (Pearson) Level of Confidence (95%): Level of Confidence (99%): R^2 Value:	-0.224926204 0.326956 0.326956 0.050592	-0.219493683 0.339081 0.339081 0.048177	0.086180302 0.710312 0.710312 0.007427	-0.083254961 0.719757 0.719757 0.006931
7279 **San Francisco**	Correlation Coefficient (Pearson) Level of Confidence (95%): Level of Confidence (99%): R^2 Value:	-0.333878821 0.139095 0.139095 0.111475	-0.178347447 0.43924 0.43924 0.031808	-0.128019627 0.580249 0.580249 0.016389	-0.206963031 0.36804 0.36804 0.042834
7280 **Sayaxché**	Correlation Coefficient (Pearson) Level of Confidence (95%): Level of Confidence (99%): R^2 Value:	-0.162300155 0.482123 0.482123 0.026341	0.044103452 0.849447 0.849447 0.001945	0.126092968 0.586008 0.586008 0.015899	-0.156648845 0.497706 0.497706 0.024539
7281 **Poptún**	Correlation Coefficient (Pearson) Level of Confidence (95%): Level of Confidence (99%): R^2 Value:	-0.011518378 0.960479 0.960479 0.000133	0.137131874 0.553349 0.553349 0.018805	0.331497985 0.14211 0.14211 0.109891	0.239674521 0.295366 0.295366 0.057444
7282 **San Luis**	Correlation Coefficient (Pearson) Level of Confidence (95%): Level of Confidence (99%): R^2 Value:	-0.503687495 0.019917 0.019917 0.253701	-0.221575808 0.334403 0.334403 0.049096	-0.10675358 0.645107 0.645107 0.011396	-0.079521529 0.731867 0.731867 0.006324

Statistically Significant at 95 and 99 percent level of confidence

The positive correlation between wildfires and precipitation of some municipalities (orange colored in Table 15) indicates the influence of precipitation on increasing fuel availability and thus suggests that it is necessary to understand the biomass and fuel complexity of those regions.

4.11 Seasonal Precipitation Anomalies and Wildfires

Seasonal precipitation anomalies (both higher and lower than the long term normal seasonal average precipitation) also show a similar correlation to wildfire occurrence, like the seasonal precipitation with the forest fire occurrences during the fire season and the preceding period of precipitation in Petén. Seasonal precipitation anomalies represent the deviation of precipitation in units of mm/season for each season. While seasonal accumulative precipitation helps to identify the influence of precipitation on wildfires, seasonal anomalies represent how the erratic behavior of precipitation influences the wildfire occurrences besides the seasonal total precipitation. The IRI data library provides negative (-) and Positive (+) forms representing less and higher rainfall than the seasonal average.

The results show that dry seasons (lower precipitation than the seasonal average) significantly impact fire occurrences in the fire season. These two variables (seasonal precipitation anomaly and wildfire occurrences) are highly correlated, representing that a fire season with less precipitation than the seasonal average is more likely to increase forest fire occurrences than a wet season or more precipitation than the seasonal average. The apparent result could help the management authority as the seasonal anomaly is predictable (Badr et al., 2014; Wang and Fan,2009; Krishnamurti et al., 2002). The results also come up with few positive correlations, which means that excessive rainfall in the preceding seasons before the fire season may increase the probability of fire occurrence during the fire season. Although a few reasons have already been described in the previous section, the anomaly represents a finer output, where a few more municipalities are added to experience increased forest fire occurrences if there is excessive precipitation in preceding seasons (2-3 months earlier).

Table 10: Seasonal fires correlation with seasonal precipitation anomalies

Seasonal Fires correlation with 1-3 months of Preceding Seasonal Precipitation Anomalies					
Municipality	**Statistics**	**Seasonal Anomaly of S3 and Forest Fires of S3**	**Seasonal Anomaly of S2 and Forest Fires of S3**	**Seasonal Anomaly of S1 and Forest Fire of S3**	**Seasonal Anomaly of S12 and Forest Fire of S3**
7271 **Melchor de Mencos**	Correlation Level of Sig. R^2	-0.07975899 0.837776 0.002391	-0.29220890 0.257129 0.070713	-0.42980240 0.054084 0.190884	-0.31196105 0.172185 0.100965
7272 **Flores**	Correlation Level of Sig. R^2	-0.38068167 0.059882 0.183022	-0.16585977 0.331086 0.052521	-0.17452810 0.440129 0.033465	-0.15654959 0.497908 0.025897
7273 **San José**	Correlation Level of Sig. R^2	-0.40737083 0.098215 0.144546	-0.36076301 0.162577 0.105383	-0.32778873 0.183452 0.096108	-0.44877141 0.049233 0.198113
7274 **San Andrés**	Correlation Level of Sig. R^2	-0.29419052 0.236384 0.076947	-0.33949924 0.17907 0.097958	-0.62255530 0.003998 0.376676	0.0652106 0.591776 0.016292
7275 **La Libertad**	Correlation Level of Sig. R^2	-0.18592320 0.455279 0.031339	-0.05252690 0.967445 0.000095	-0.47138057 0.041971 0.210326	0.11846222 0.486131 0.027325
7275 **Las Cruces**	Correlation Level of Sig. R^2	-0.18592320 0.455279 0.031339	-0.05252690 0.967445 0.000095	-0.47138057 0.041971 0.210326	0.11846222 0.486131 0.027325

7276 **San Benito**	Correlation Level of Sig. R^2	-0.24364351 0.344316 0.049793	-0.15111637 0.748762 0.005842	-0.38362027 0.118354 0.130004	0.06532590 0.710352 0.007847
7277 **Santa Ana**	Correlation Level of Sig. R^2	-0.31111045 0.210947 0.085491	-0.02779945 0.809157 0.003326	0.26055672 0.236399 0.076942	-0.36338316 0.129593 0.122944
7278 **Dolores**	Correlation Level of Sig. R^2	-0.22492597 0.489177 0.026951	-0.21949350 0.712293 0.007738	0.08618038 0.642891 0.012204	0.10585010 0.527704 0.022521
7278 **El Chal**	Correlation Level of Sig. R^2	-0.22492597 0.489177 0.026951	-0.21949350 0.712293 0.007738	0.08618038 0.642891 0.012204	0.10585010 0.527704 0.022521
7279 **San Francisco**	Correlation Level of Sig. R^2	-0.33387899 0.144534 0.114473	-0.17834749 0.364368 0.045905	-0.12801968 0.596604 0.015874	-0.15076221 0.525125 0.022801
7280 **Sayaxché**	Correlation Level of Sig. R^2	-0.16230017 0.558334 0.019378	0.04410337 0.477364 0.028425	0.12609288 0.416696 0.036973	0.09618652 0.681605 0.009568
7281 **Poptún**	Correlation Level of Sig. R^2	-0.01151843 0.932413 0.000411	0.13713184 0.296846 0.060263	0.22602070 0.302989 0.058795	0.22602070 0.324545 0.051085
8282 **San Luis**	Correlation Level of Sig. R^2	-0.20472683 0.379711 0.043114	0.17556548 0.354807 0.047723	0.27604944 0.227172 0.079917	-0.0228406 0.916264 0.000631

Statistically Significant at 95 and 99 percent level of confidence | Statistically Significant at <95 percent level of confidence | Positive Correlation

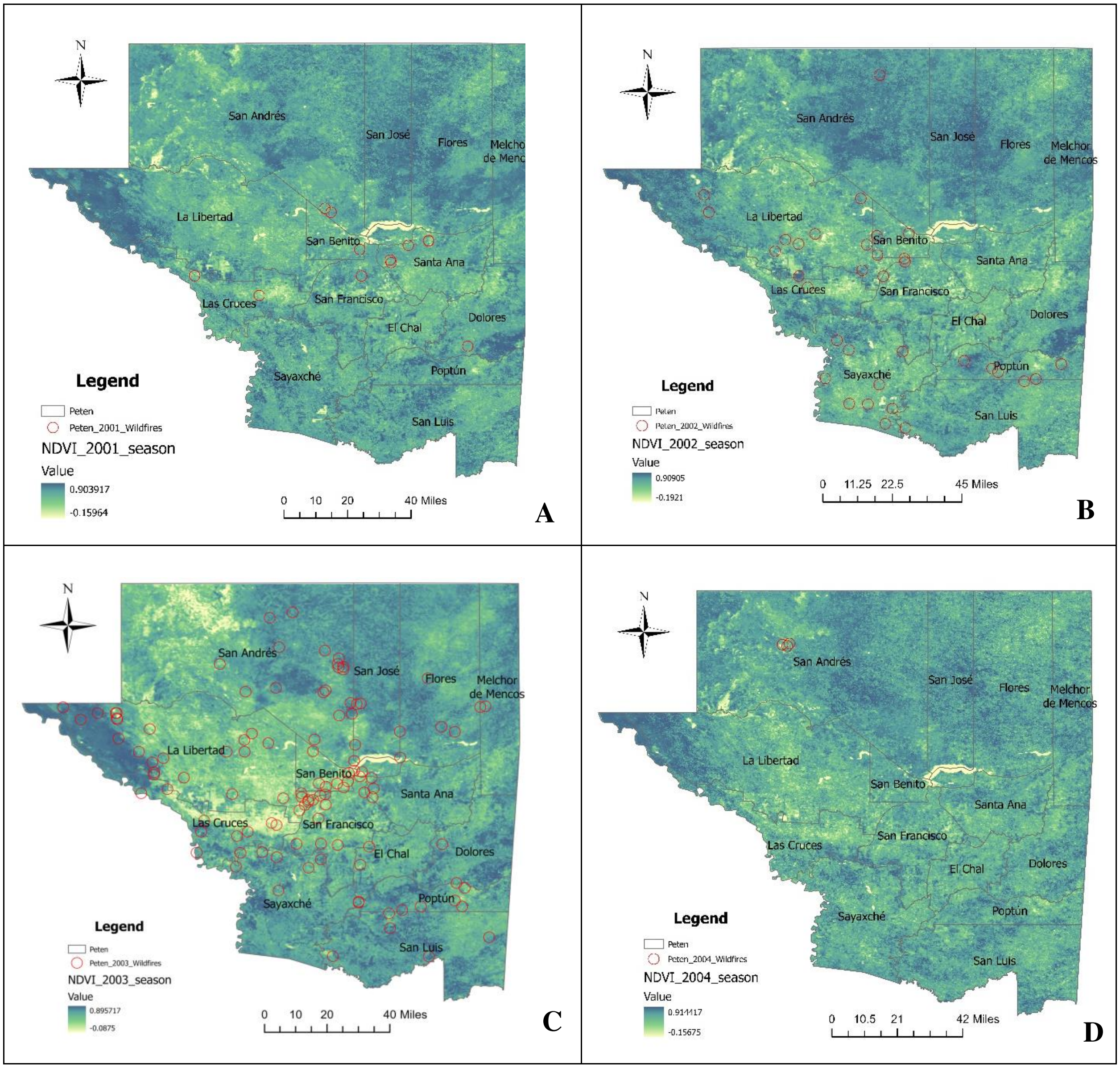
The results from the correlation between seasonal precipitation anomaly (both positive and negative) and seasonal wildfires represent a negative correlation in most cases. In other words, below-average precipitation season influences increasing wildfire occurrences in the different municipalities of Petén during the fire season. Where accumulative precipitation represents a significant correlation with wildfires for San Andrés, San José, and San Luis for 2-3 months of preceding seasonal precipitation before the fire season, seasonal precipitation anomalies come up with a better correlation coefficient supporting the findings. This result is finer because the precipitation anomaly has added a degree of weight to the earlier findings. Where the seasonal wildfire shows a positive correlation with preceding (2-3 months) accumulative seasonal precipitation in 26.19 percent of cases, the correlation rises to 40.47 percent of cases while considering the precipitation anomaly of preceding seasons of 2-3 months. The increased cases imply that the increased precipitation in the preceding season than the average precipitation increases the fire incidents during the fire seasons (Mar-Apr-May). The result indicates precipitation as a driver of wildfire but also argues for its more significant influence on vegetation growth (considering the analyses of vegetation indices) and, thus, fire occurrences. Among the municipalities, San Andrés, La Libertad, Las Cruce, and San José present a significant correlation between precipitation anomalies and forest fire occurrences. Flores and Melchor de Mencos also represent the correlation as significant, even though they are statistically not as significant as San Andrés, La Libertad, Las Cruce, and San José.

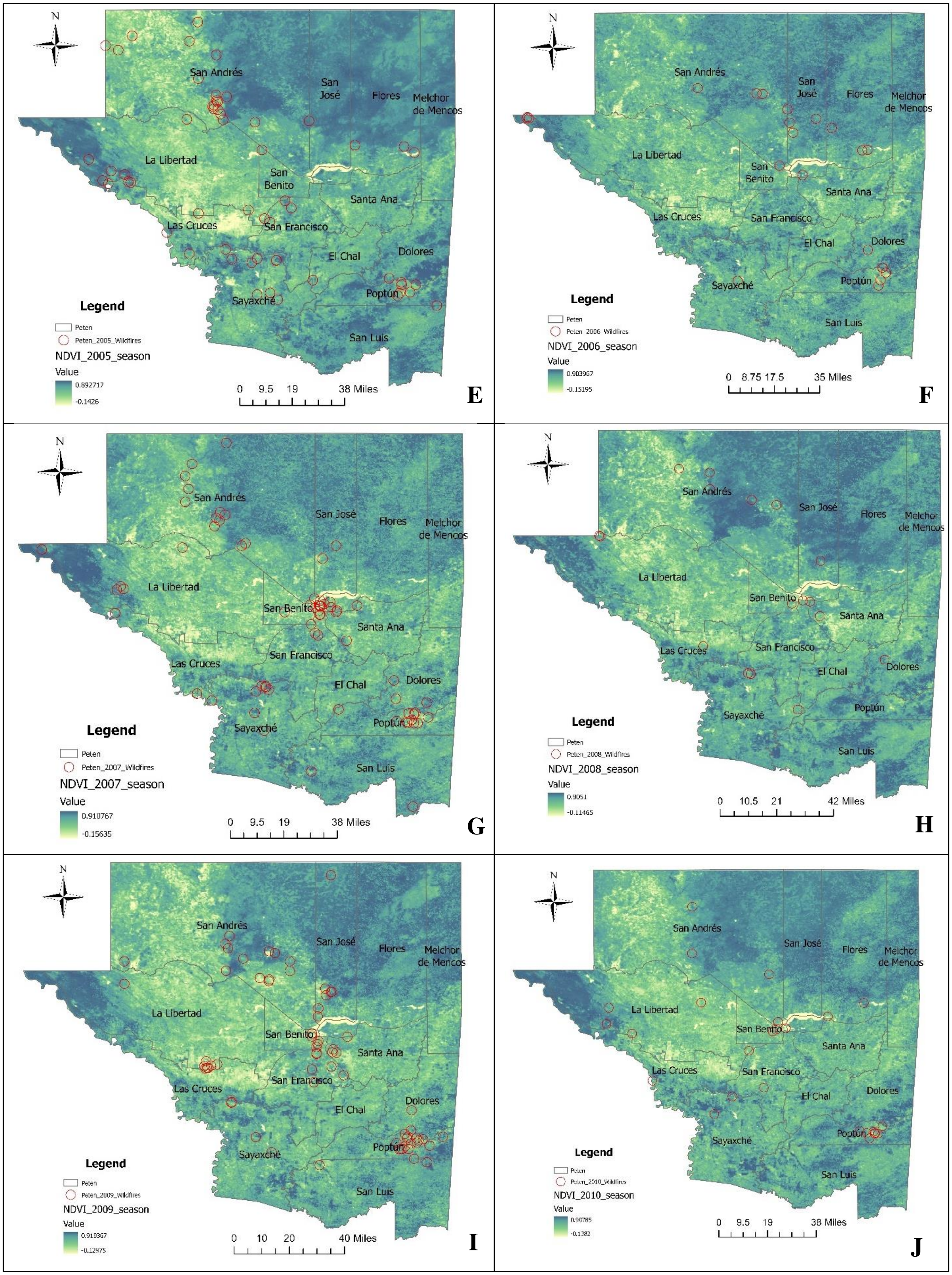
4.12 Seasonal Average NDVI and Fire Occurrences in Fire Season (March-April-May):

After Identifying the correlation between precipitation and vegetation, as well as precipitation and wildfire occurrences in Petén, the research tries to identify if there is any relation between vegetation cover and wildfire occurrences. As discussed above, NDVI is a widely used vegetation indices to understand vegetation conditions based on set criteria ranging from -1 to +1. The three months mean NDVI has been calculated using the Google Earth Engine using the MODIS dataset. The table below tries to compare the fire locations with the NDVI values. Through bilinear interpolation, the value from the NDVI raster has been extracted from each location to understand the vegetation influence on Fire occurrences. The results show that the average seasonal (Mar-Apr-May) NDVI from 2001 to 2021 for each fire occurrence location is 0.66424089, which reflects a moderate to dense forest is being affected by fire. Although the results are a little arbitrary as generally the lower value than the findings represent dry and available fuel composite.

However, the findings make sense when the ecosystem is considered a vital factor in such a result. The Petén ecosystem is a rainforest with a high density of forest area with a lot of greeneries or foliage that creates a higher value of NDVI (> 0.9) in most of the seasons, where 0.66 is much lower compared to the surroundings (Images in Table 3.3). Only the barren lands, some mountains, and the water bodies have a lower value in terms of NDVI, as the ecosystem is green for almost all seasons. The NDVI value also suggests that the fire occurrence is more likely to happen when there is available vegetation, where a preheat may increase the fuel availability compared to a lower-valued barren land or place with less fuel content. The correlation coefficient between the average mean seasonal NDVI and the fire occurrences of each year represents a negative correlation (-0.29672) with the NDVI values. The correlation explains the possibility of increased fire occurrences with the decreased value of NDVI, which is understandable considering the moisture content of the foliage. However, the result is insignificant (0.328901; $R2 = 0.052985$) with a 95% confidence level.

Geolocation of Forest fires and Seasonal (Mar-April-May) mean NDVI of Petén.

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NDVI_2007_season
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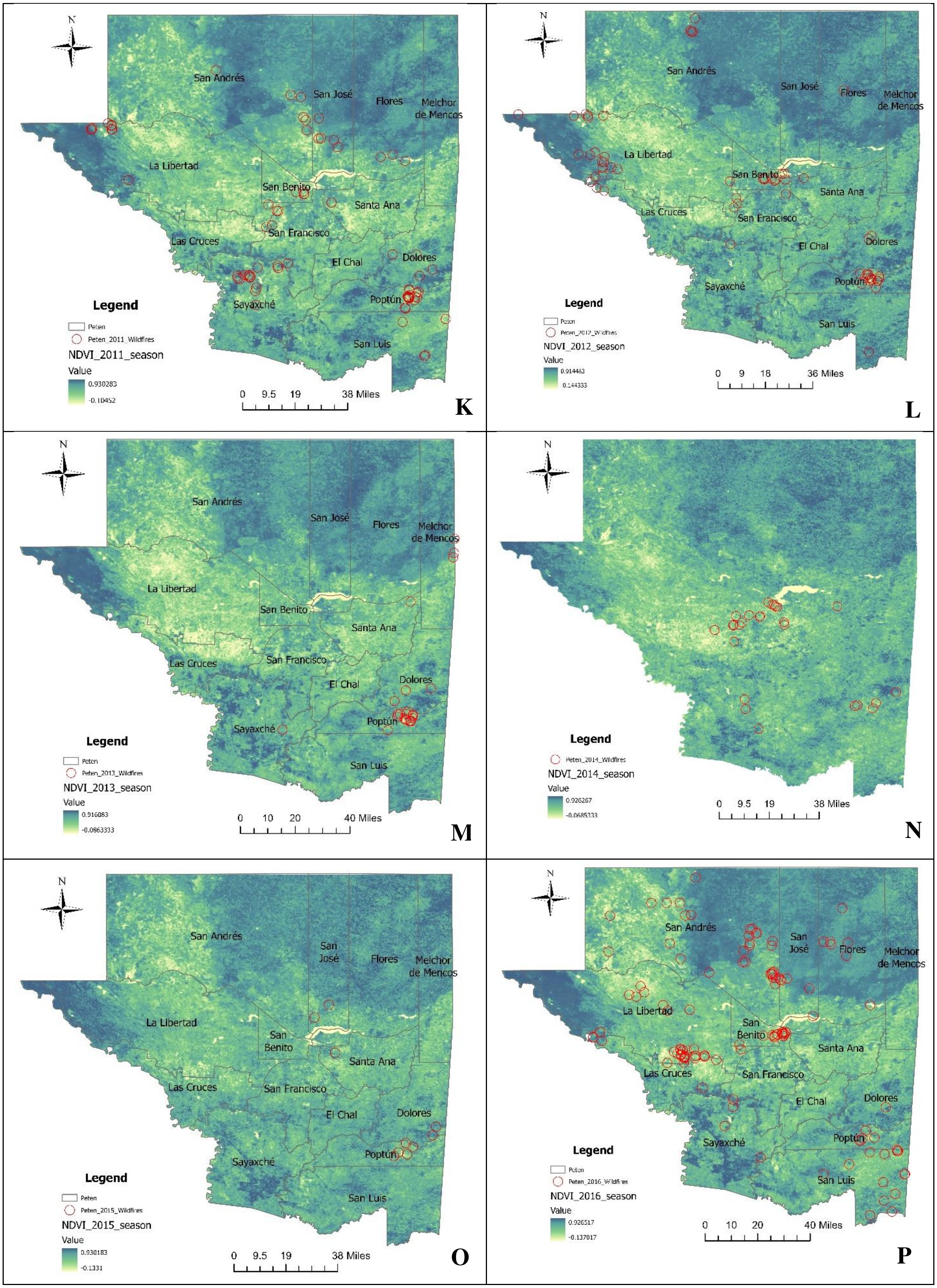
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NDVI_2016_season
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-0.137017
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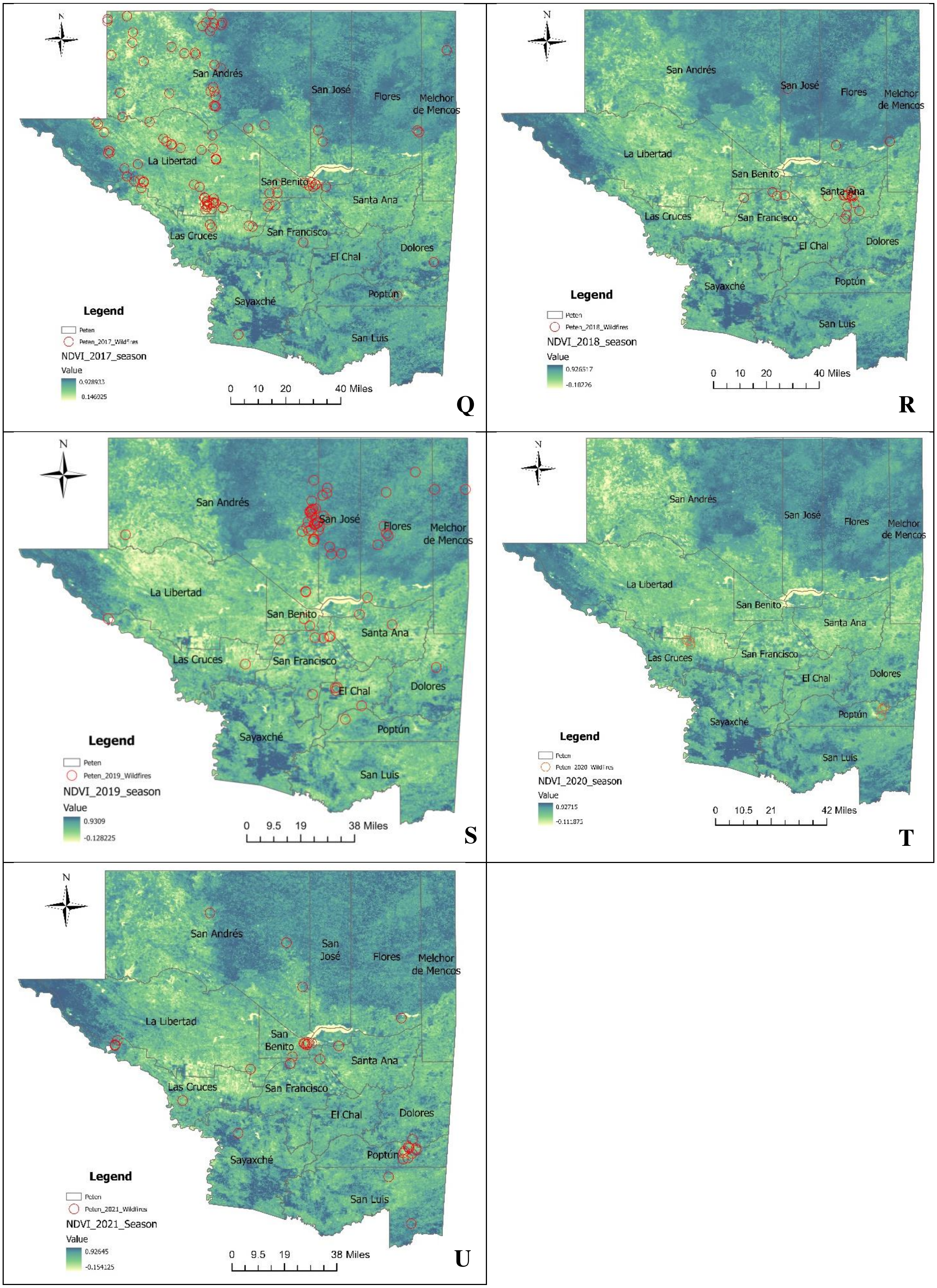

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Peten_2018_Wildfires
NDVI_2018_season
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Peten_2019_Wildfires
NDVI_2019_season
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NDVI_2020_season
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NDVI_2021_Season
Value
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-0.154125
0 9.5 19 38 Miles
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Fig. 17: Geolocation of forest fires and seasonal (Mar-April-May) mean NDVI of Petén. Figure A to U, represents each year of wildfires location from 2000 to 2021 on each year of seasonal (Mar-Apr-May) average NDVI.

Even though the correlation between the average mean seasonal NDVI and the number of wildfire occurrences is not statistically significant for each fire location, the average value of the seasonal mean NDVI from 2001 to 2021 provides a significant finding compared to the Tasmanian Fire Service standard for wildfire fuel (2020). Tasmanian Fire Service (2020) has identified that the typical type of wildfire fuel has an NDVI value of 0.65, where in this research, we found the NDVI value as 0.66 for Petén, based on the data from 2001 to 2021. This result strongly identifies vegetation cover as another driver of wildfire in a tropical forest system (Petén).

5.1 Managerial Implications

This thesis identifies precipitation and vegetation as two influential drivers of wildfires in Petén, Guatemala. The seasonal precipitation and seasonal precipitation anomalies in preceding seasons of a fire season have a greater influence on vegetation and wildfire occurrences (Fig. 18).

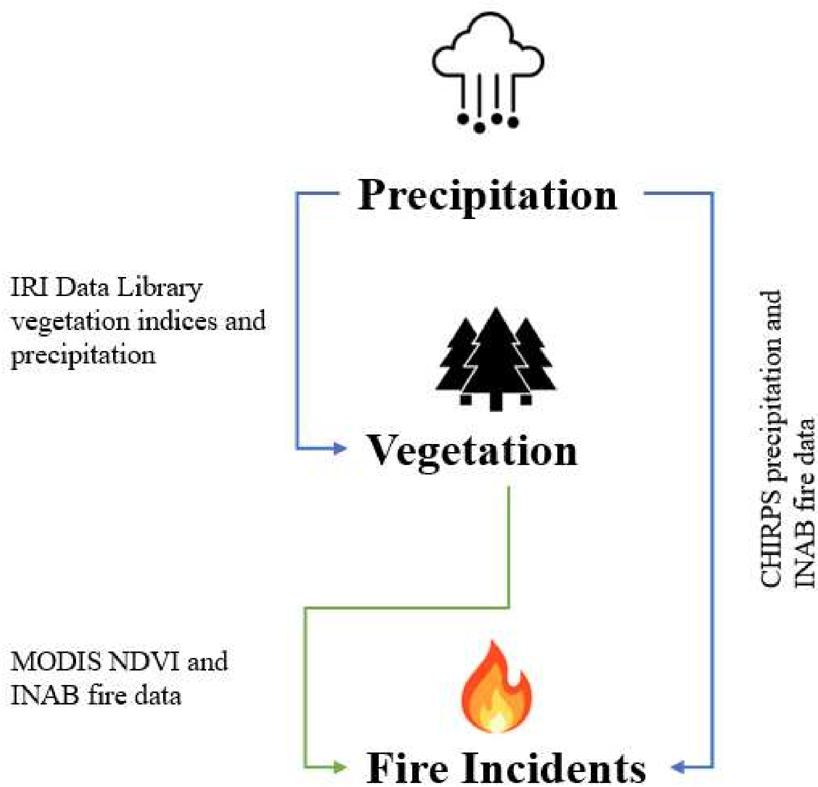

Fig. 18. Graphical presentation of the influence of precipitation and vegetation on wildfire in Petén. The figure represents how precipitation is influencing both fuel and fire occurrences, where vegetation is also influencing fire occurrences.

The results have a tremendous managerial impact on managing wildfires in Petén. The result suggests that correctly identifying precipitation patterns and amounts in the preceding months of a fire season is crucial. Besides the precipitation, vegetation condition also correlates to fire occurrences and seeks notice of changes in vegetation condition and stress. The research suggests that the fire management authority must closely monitor precipitation (pattern and amount) and vegetation to oversee and predict the upcoming fire season (fire occurrences).

The precipitation pattern is the most crucial, as it could positively and negatively affect fire occurrences. If the precipitation occurs 2-3 months earlier, there is a strong possibility of increased fuel (total fuel). However, if there is no rain in the immediately preceding months of a fire season, fuel availability will increase, thus increasing fire frequency. Besides this condition, increased precipitation in the fire season will decrease fire occurrences. In contrast, a less rainy fire season followed by prior drought conditions will make the situation highly susceptible to wildfire.

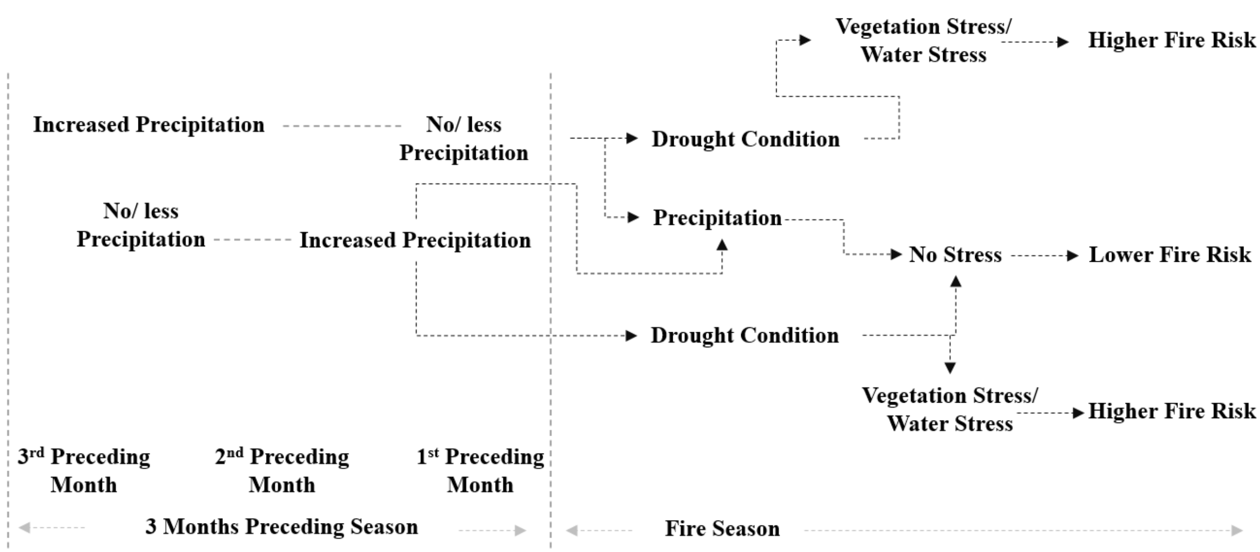

Fig. 19. The figure represents the managerial decision making while preparing for wildfire management in Petén considering the precipitation pattern and vegetation condition.

Besides the precipitation pattern, vegetation conditions (especially water stress or dryness) could be essential in understanding fuel availability. TCI and NDVI may measure vegetation stress, dryness, and greenness, giving an overall understanding of the fuel condition. The average NDVI value (0.66), which represents a less vegetative area with less greenness, is more susceptible to wildfire and hence suggests being more cautious while managing the fire of Petén.

5.2 Limitations and Future Scopes

This research is highly dependent on the NOAA NESDIS vegetation product for identifying the correlation between vegetation and precipitation, which is lower in spatial resolution producing a less accurate result. The scenario is the same for the gridded precipitation data from CHIRPS. Besides the data from IRI Data Library (Vegetation and precipitation data), the fire occurrence record provided by the INAB (Guatemala's Forest Authority) is not entirely accurate, as it consists of data that has been reported only. There is a greater possibility that many cases of wildfires remained undocumented where the fires were smaller in scale or occurred in locations that were not reported or observed by anyone. Besides the error in the numbers of fires documented, the database contains only 21 years of wildfire occurrences of Petén. Although few satellite-based sources provide more extensive temporal data (like NASA FIRMS), it is hard to distinguish between wildfires and human-led fires that are used to clean up the forest for agricultural expansion. Besides that, cloud coverage may also be an obstacle to identifying all active fires. This research only tries to incorporate wildfires that humans do not start, which justifies the reason for considering the INAB database despite some limitations.

Besides the limitations in data, the research has only tried to understand the drivers of the wildfires in Petén considering fuel (total fuel) and weather (only precipitation) only. However, considering time and data availability, another important factor (topography) of the fire behavior triangle has been avoided. Besides weather, the research only considered the seasonal accumulative precipitation, but the precipitation pattern within a season may impact the fire occurrences during the fire season (Fig. 19). Light and air also have a significant influence on fire occurrences during the fire season as well as in the preceding months. Regarding vegetation, the research has not considered the fuel complex, continuity, and fuel type, which are very important for fire spread and fire intensity.

However, despite many limitations, the research has identified the seasonal precipitation and vegetation as drivers of wildfires in a tropical-humid forest ecosystem (Petén, Guatemala). The findings open the scope for further research on predicting wildfires in Petén using seasonal precipitation as a tool. Besides precipitation, the research also seeks further investigation into whether topography could be another driver for Petén wildfires. Two-factor analysis could be the next step for identifying how both drivers (Vegetation and precipitation) are influencing the wildfires of Petén at the same time instead of only identifying their individual influence at the same time.

6. Conclusion

Whereas existing literature mostly focuses on wildfires in dry and temperate regions, this thesis investigates the drivers of wildfires (precipitation and vegetation) in a humid tropical region of Guatemala (Petén). Petén is increasingly experiencing wildfires despite having a humid tropical climate, and this research identifies two critical factors of the wildfire behavior triangle (Weather and Fuel) as the drivers of fire occurrences in tropical-humid regions (Petén, Guatemala). Although the topical-humid areas are not dry and are being ignored regarding wildfire threat, the changing climatology (precipitation pattern) and increasing fire incidents seek immediate attention. Even though humid tropical forests are not as affected as dry and temperate forests in terms of fire frequencies or fire incidents, the rich biodiversity of a tropical forest has made it more crucial to overlook.

The study investigates and explains how precipitation, a major climate element, influences fire incidents and fuel availability in a tropical humid forest ecosystem. The study found a strong correlation between precipitation and vegetation growth using different vegetation indices. The five indices used for this research (NDVI, VCI, VHI, TCI, and SMN) provide evidence that precipitation strongly influences vegetation growth, especially in the 1-3 months of preceding seasonal precipitation. Where all the indices help to identify the correlation of precipitation and vegetation growth, TCI helps to identify correlation between precipitation and fuel condition or moisture content. TCI represents a higher correlation between the seasonal precipitation and fuel moisture content while the precipitation is closer to the fire season. The higher correlation indicating that the closer the precipitation to the fire season, the wetter the fuel (less available) is during the fire season. TCI proved to be useful to identify the fuel availability for wildfire in Petén (Tropical-Humid).

In addition to the three main components of fire behavior triangle (Fig. 2), many other factors need to be considered that influence the outcome of fire. The analyses of this research reveals strong impact of vegetation and precipitation on fire events in Petén, Guatemala. Between these two components (precipitation and vegetation), precipitation influences the occurrence of fire directly and indirectly (Fig. 18). On the one hand, the higher precipitation minimizes the fire occurrence through increasing wetness and moisture content in available fuel (TCI); on the other hand, a preceding rainy season with higher precipitation helps to grow the vegetation (correlation between precipitation and vegetation indices tables), thus increasing the total fuel.

This complex relationship indicates that a preceding wet season before the fire season increases total fuel. In contrast, a dry season just before a fire season may increase that fuel's availability, thus increasing fire incidents. Although this assumption is not statistically significant as none of the correlations were found significant with the available data. Littell et al. (2016) described that even though 'with drought comes fire' is not always accurate, the drought significantly influences wildfire occurrences. This study found a strong correlation between precipitation and wildfire occurrences; even though it is not statistically significant in a 95-99% confidence level, the finding identifies precipitation as a driver for wildfires in a tropical forest system.

Many researchers have used the TCI as a tool for drought identification. This research suggests that the TCI could be a potential tool for identifying the fuel availability in Petén. Although the preceding precipitation or precipitation in the months prior to the fire season increases vegetation growth (NDVI, SMN, VCI, VHI), the time in between the precipitation and fire season also helps to increase fuel availability for the wildfires by drying up the vegetation which can be identified through TCI. The fuel availability increases when there is less to no precipitation just before or during the fire season. However, continuous precipitation with no preceding drought condition may decrease the fire occurrences, as the moisture content of the fuel will be higher and will create a lack of fuel availability, even though there could be an increased total fuel. While the continuous precipitation may decrease the fire occurrences, human interventions may increase the possibility of fire occurrences by increasing ignition along with a preceding drought condition, or even there is a continuous precipitation in preceding months of a fire season. Although there is an increase in fire occurrences by human impacts, it is hard to predict if there will be any significant increase in burned area of fire intensity.

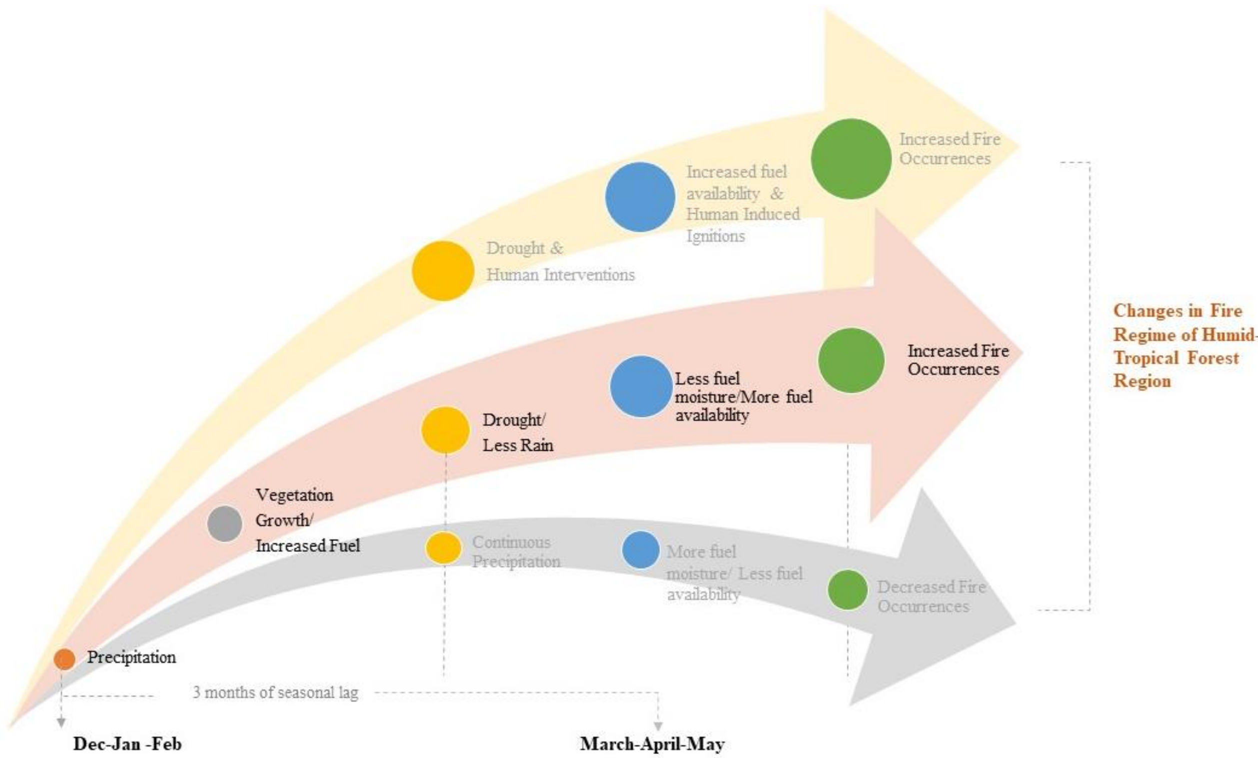

Fig 20. Preceding seasonal precipitation's influence on wildfires during fire season in a humid-tropical forest system. The figure represents how preceding seasonal precipitation influence vegetation growth, and drought conditions after the seasonal precipitation transform that vegetation into available fuel for wildfires in upcoming fire seasons; thus, increase wildfire incidents.

Seasonal precipitation anomalies are more strongly related to fire occurrences in a tropical-humid forest ecosystem than seasonal accumulative precipitation. Although the seasonal precipitation anomaly shows a similar correlation, the coefficients are more substantial and give a finer result, as the anomalies are the extended forms of precipitation or drought conditions. Besides precipitation anomalies, the averaged NDVI of the fire months (Mar-Apr-May) helps to understand vegetation's role in the wildfires of Petén. The fire occurrence geolocation suggests that a location with an NDVI value of 0.66 is more prone to fire. However, a fire occurs when the NDVI value is around 0.66, representing that a sparse to the medium-dense forest, or less green forest (stressed) is more vulnerable to wildfires in a tropical-humid forest system. Tasmanian Fire Service (2020) identified that the standard type of wildfire fuel has an average NDVI value of 0.65, where this research found the value as 0.66 for Petén. This finding strongly argues that besides precipitation the vegetation (NDVI value/ overall greenness) could be a strong indicator of forest fire prediction and management of tropical-humid forest ecosystems (Petén).

Although the research lacks statistical significance regarding precipitation and wildfire occurrences, it provides evidence supporting the argument of precipitation and vegetation as drivers for wildfires in Petén. The research also suggests that precipitation prediction could help predict fire incidents in Petén, even though precipitation prediction must incorporate the anomalies and fuel conditions, where the TCI and NDVI may be another helpful tool to understand the fuel availability.

Finally, the research contributes to the literature on understanding the drivers of wildfire in a humid-tropical forest ecosystem, which was overlooked in terms of wildfire risk zones. Even though there are a few limitations, the research findings argue that precipitation (seasonal) and vegetation are one of the most critical drivers of wildfire in Petén. The research also argues that predicting seasonal precipitation could be an essential tool in predicting wildfires for Petén.

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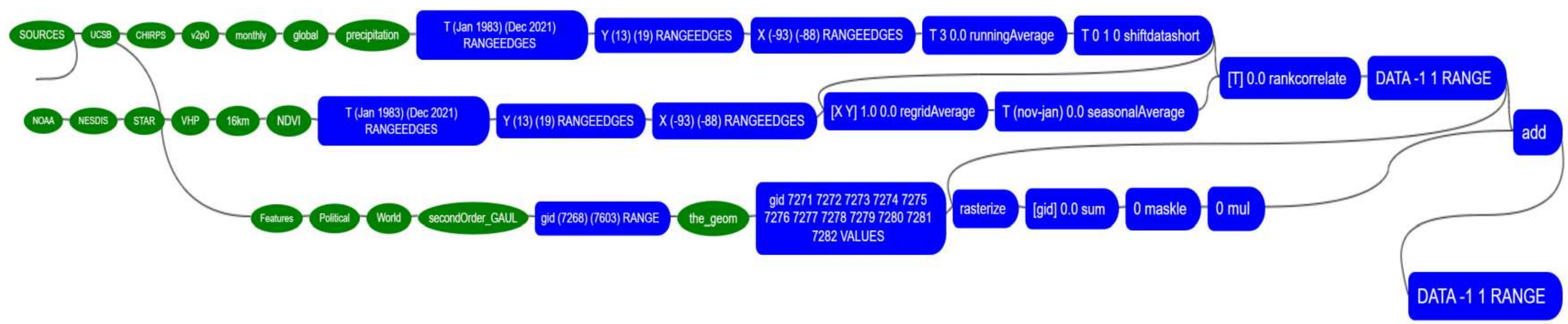
Appendix:

1.1 Methodology and codes for precipitation and vegetation indices correlation using the IRI Data Library:



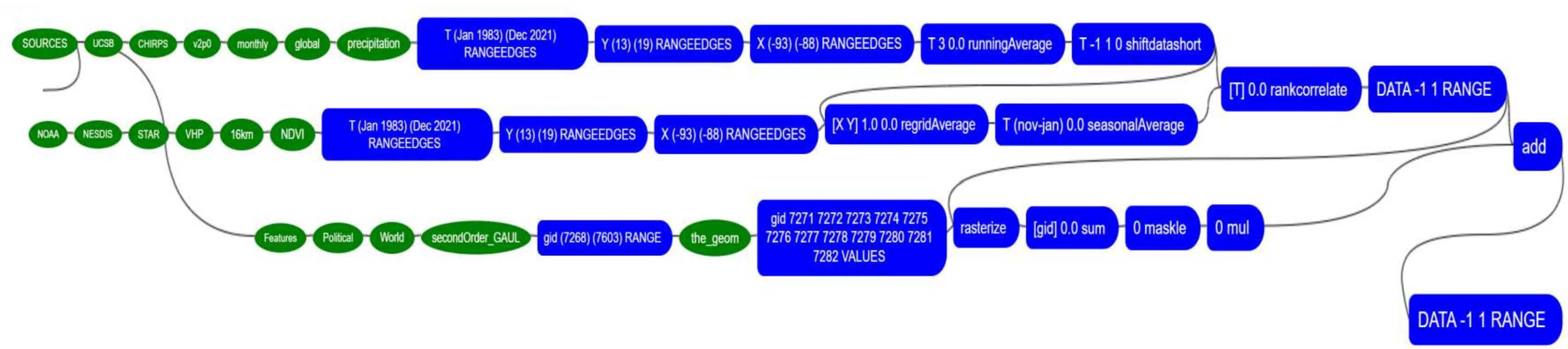
Appendix Fig 1. IRI Data Library analysis methodology for precipitation and vegetation indices correlation for same seasons.

Codes for identifying correlation between precipitation (CHIRPS) and vegetation Indices (NDVI) for same season (Pons et al., 2021):

```
[
SOURCES .UCSB .CHIRPS .v2p0 .monthly .global .precipitation
  T (Jan 1983) (Dec 2021) RANGEEDGES
  Y (13) (19) RANGEEDGES
  X (-93) (-88) RANGEEDGES
  T 3 runningAverage
  T 0 1 0 shiftdatashort
```

```
SOURCES .NOAA .NESDIS .STAR .VHP .16km .VCI
 T (Jan 1983) (Dec 2021) RANGEEDGES
 Y (13) (19) RANGEEDGES
 X (-93) (-88) RANGEEDGES
 [X Y]regridAverage
 T (nov-jan) seasonalAverage
 [T]rankcorrelate
DATA -1 1 RANGE
dup SOURCES .Features .Political .Guatemala .GAUL .Second_Order .the_geom
  gid 7271 7272 7273 7274 7275 7276 7277 7278 7279 7280 7281 7282 VALUES
  rasterize
 [gid]sum
 0 maskle
 0 mul
 add
DATA -1 1 RANGE
a- -a X Y fig- colors coasts lakes -fig
    /T_lag -3.0 plotvalue
    /plotaxislength 432 psdef
    /plotborder 72 psdef
]
```

1.2 Methodology and codes for precipitation and vegetation indices correlation using the IRI Data Library, while analyzing a lagged correlation:



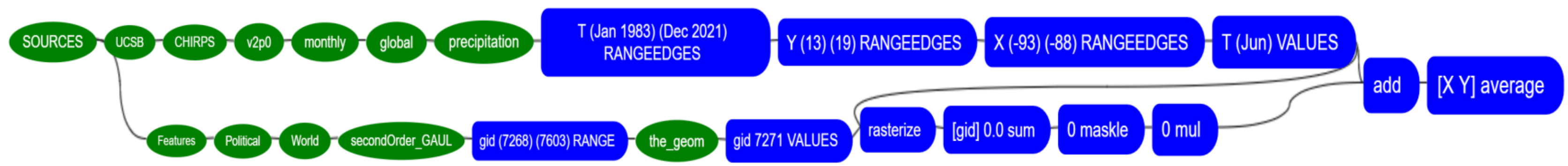
Appendix Fig 2. IRI Data Library analysis methodology for precipitation and vegetation correlation in one month lagged season.

Codes for identifying correlation between precipitation (CHIRPS data) and vegetation indices (NDVI) for a one month of preceding precipitation (Pons et al., 2021):

```
[
SOURCES .UCSB .CHIRPS .v2p0 .monthly .global .precipitation
  T (Jan 1983) (Dec 2021) RANGEEDGES
  Y (13) (19) RANGEEDGES
  X (-93) (-88) RANGEEDGES
  T 3 runningAverage
  T -2 1 0 shiftdatashort
```

```
SOURCES .NOAA .NESDIS .STAR .VHP .16km .VCI
 T (Jan 1983) (Dec 2021) RANGEEDGES
 Y (13) (19) RANGEEDGES
 X (-93) (-88) RANGEEDGES
 [X Y]regridAverage
 T (nov-jan) seasonalAverage
 [T]rankcorrelate
DATA -1 1 RANGE
dup SOURCES .Features .Political .Guatemala .GAUL .Second_Order .the_geom
  gid 7271 7272 7273 7274 7275 7276 7277 7278 7279 7280 7281 7282 VALUES
  rasterize
 [gid]sum
 0 maskle
 0 mul
 add
DATA -1 1 RANGE
a- -a X Y fig- colors coasts lakes -fig
    /T_lag -3.0 plotvalue
    /plotaxislength 432 psdef
    /plotborder 72 psdef
]
```

1.3 Methodology and codes for accessing the precipitation data using the IRI Data Library:

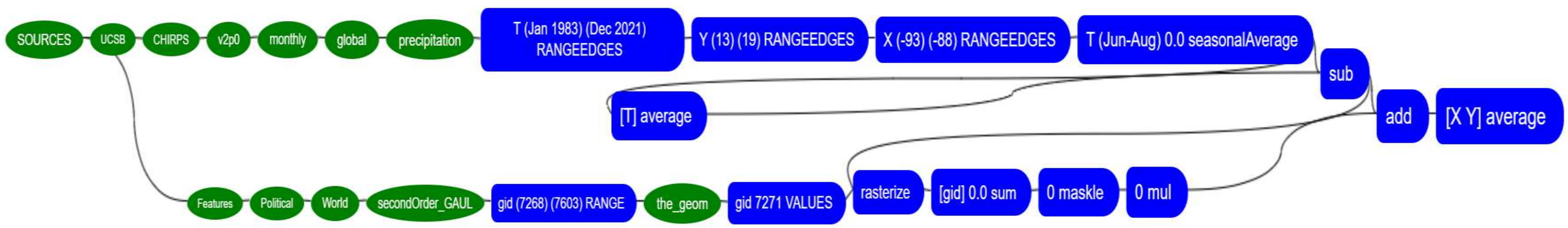


Appendix Fig 3: IRI Data Library methodology for accessing CHIRPS precipitation data for each municipality of Petén.

```
[ SOURCES .UCSB .CHIRPS .v2p0 .monthly .global .precipitation
  T (Jan 1983) (Dec 2021) RANGEEDGES
  Y (13) (19) RANGEEDGES
  X (-93) (-88) RANGEEDGES
  T (Jun) VALUES
  dup SOURCES .Features .Political .Guatemala .GAUL .Second_Order .the_geom
    gid 7271 VALUES
    rasterize
   [gid]sum
   0 maskle
   0 mul
   add
```

[X Y] average]

1.4 Methodology and codes for accessing the Precipitation anomalies data using the IRI Data Library:



Appendix Fig 4: IRI Data Library methodology for accessing CHIRPS precipitation anomalies for each municipal of Petén.

[

SOURCES .UCSB .CHIRPS .v2p0 .monthly .global .precipitation

T (Jan 1983) (Dec 2021) RANGEEDGES

Y (13) (19) RANGEEDGES

X (-93) (-88) RANGEEDGES

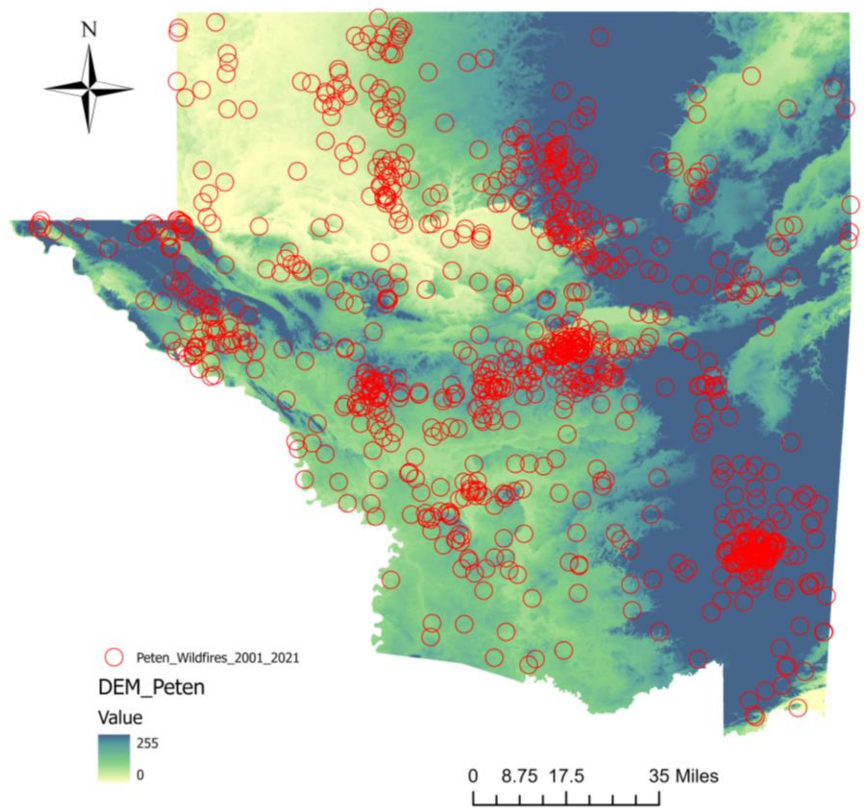
T (Jun-Aug) seasonalAverage

dup

[T]average

sub

```
  dup SOURCES .Features .Political .Guatemala .GAUL .Second_Order .the_geom
    gid 7271 VALUES
    rasterize
   [gid]sum
   0 maskle
   0 mul
   add
  [X Y] average
]
```



Appendix Fig 5. A 30m Digital Elevation Model (DEM) of Petén representing the wildfire locations from 2001 to 2021.

The Figure represents a concentration of wildfires in the higher altitude of Petén since 2001. This finding also supports the third element of the fire behavior triangle, the Topography. The finding suggests that besides the precipitation and vegetation, topography also plays a vital role in influencing the wildfire in a tropical humid forest ecosystem.