FIRE-CLIMATE RELATIONSHIPS IN CONTINENTAL SOUTHEAST ASIA

by

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Abstract

Despite the prevalence of fire in continental Southeast Asia (SEA) and its important ecological role, little is known about the drivers of geographical variation of fire activity in the region. My research investigated 1) how the geographic variation in fire activity is associated with climate, landcover, and human influence, and 2) what and where are distinct fire regimes located in continental SEA. I quantified the response of fire activity to climate, landcover, and anthropogenic metrics and defined spatially constrained clusters with similar fire patterns. We used satellite remote-sensing data from 2001 to 2021 at 0.25° spatial resolutions. Climatic variables that decrease vegetation moisture and the presence of human establishments were important predictors of fire activity. We identified fire regimes that were associated with deforestation in Cambodia and Laos, agricultural activity in Vietnam, and ecological fires in the forest-savanna mosaics in Cambodia. Exploring the spatial distribution of fire patterns and its' anthropogenic or climatological drivers of fire is key to understanding Southeast Asian ecosystems. Implications of these results could further encourage ecologically appropriate fire management strategies.

Lay Summary

Fire is a common occurrence in continental Southeast Asia that has widespread effects on the ecosystem. The long-term impact of fire depends on the frequency, intensity, and extent of the fires, while also considering the type of vegetation and climate the ecosystem experiences. Using satellite observations from 2001 to 2021, I researched 1) how fire patterns are influenced by climate, humans, and vegetation types, and 2) where similar fire patterns occur and how they compare. Climatic conditions, such as hot temperatures and severe dry seasons, were linked to greater fire activity. The presence of human establishments was also important in distinguishing the prominence of fire activity. We identified fire patterns associated with deforestation in Cambodia and Laos, agricultural activity in Vietnam, and naturally occurring fires in the forest-savanna mosaics in Cambodia. Investigating how, where, and why these fires occur will promote our understanding of Southeast Asian ecosystems and encourages appropriate fire management strategies.

Preface

Naomi Schwartz provided major contributions to the conceptualization and design of my research. This work was conducted as part of a collaboration with Dr. Miriam Marlier and Claire Bekker at the University of California Los Angeles. My committee members, Dr. Simon Donner and Dr. Miriam Marlier, provided feedback during the statistical analysis and thesis development process. Tony Zhang provided feedback during the writing and editing process.

Portions of the fire and rainfall variable calculations were modified from code provided by Naomi Schwartz, Claire Bekker, and Elise Pletcher. I formulated and developed the rest of the code for data collection, wrangling, and analysis. I was responsible for manuscript composition and preparation, and a version of this thesis is intended for peer-review publication.

The remainder of this thesis is my own independent, original, and unpublished, work reviewed by Naomi Schwartz.

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List of Abbreviations

		Unit
BA	Burned area	Km^2/year
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station	
FF	Fire Frequency	Years
FRP	Fire Radiative Power	Megawatts (MW)
FS	Fire Size	Km^2/fire
HII	Human Influence Index	
%IncMSE	Percent increase in mean squared error	
MAP	Mean Annual Precipitation	mm
MAT	Mean Annual Temperature	Celsius
MCWD	Mean Climatological Water Deficit	
MODIS	Moderate Resolution Imaging Spectroradiometer	
NF	Number of Fires	Fires/year
pctnatveg	Percent Natural Vegetation	%
RF	Random forest	
SEA	Southeast Asia	
SI	Seasonality index	
SKATER	Spatial "K"luster Analysis Tree Edge Removal	
VPD	Vapor Pressure Deficit	Kilopascals (kPa)

Acknowledgements

I would like to acknowledge that this research was conducted on the traditional, ancestral, and unceded territory of the xwməθkwəy̓əm (Musqueam) People.

My sincere gratitude to my supervisor, Naomi Schwartz, for granting me this opportunity and sharing her time, support, dedication, and patience throughout my project. Learning and growing in this program would not be possible without you! I thank my supervisory committee, Dr. Simon Donner and Dr. Miriam Marlier, for sharing your expertise and feedback throughout my project.

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I'm also endlessly grateful for Jacko, Lilo, Kea, Vero, and Clinton for your unconditional support, encouragement, and solidarity.

Chapter 1: Introduction

Fire is a significant source of ecosystem disturbance, helping to modify or maintain several global biomes (Bond and Keeley 2005). Within each biome, fire activity outside the historical range of variability can have negative ecological impacts. Investigating fire patterns in recent history (past 20 years) is necessary to benchmark any changes in regional fire regimes.

Fire regimes in continental Southeast Asia (SEA) contain different fire patterns that have varying influence on the ecosystem. Different fire patterns include agricultural fires (Jones 1998), forest-savanna mosaic fires (Pletcher, Staver, and Schwartz 2022), and deforestation fires (Min-Sung et al. 2023). However, few studies have distinguished the geographical distribution and drivers of the fire patterns observed in Southeast Asian ecosystems. This research investigates the relationship between fire and the climatic, anthropogenic, and landcover drivers in continental Southeast Asia, followed by a description of the spatial pattern of observed fire regimes.

1.1 Ecological Role of Fire

Fire can alter ecosystem structure, species composition, and function by acting as an environmental constraint (Bond and Keeley 2005; Abreu et al. 2017). In regions with a history of natural fire disturbance, local plant species have adaptations that allow the plant to persist within the fire regime. Ecosystems with fire-adapted vegetation are more resilient and recover quickly after burning (Bond and Keeley 2005). For example, many grasses have deep underground roots that allow grass to survive through fires that occur above ground. Grasses can quickly regenerate after being burned using the nutrients stored in the root system (Bond and Keeley 2005). On the other hand, fire can be disastrous to plants that are not fire-adapted. Ecosystems that rarely experience burning may struggle to regrow after a fire event (Cochrane 2003). Fire has critical and sweeping impacts on various ecosystems, substantiating the need to understand the drivers of fire activity.

1.2 Fire regimes

Fire regimes describe the temporal and spatial fire patterns in a given location (Bond and Keeley 2005; McLauchlan et al. 2020). How, where, and why fires occur varies across landscapes and environmental conditions. Thus, studying regional fire regimes is necessary to improve our understanding of how fires impact local ecosystems. Metrics that describe the fire regime include fire frequency, intensity, size, burned area, and seasonality. Together, these metrics provide insight into the unique characteristics of observed fire patterns.

1.2.1 Fire Frequency

Fire frequency describes the time interval between successive burns and is measured as the number of fires that occur per year (Cwynar 1978; Forman and Boerner 1981). Frequency is determined by how often conditions for fire exist, the availability of ignitions, paired with the amount and condition of vegetative fuel (Steel, Safford, and Viers 2015). The frequency of fire events influences the plant species that are able to establish and modify how ecosystems respond after burning (Bond and Keeley 2005). Therefore, recurring fire impacts the composition of vegetative communities and helps determine the spatial distribution of certain ecosystems.

1.2.2 Fire Intensity

Fire intensity describes the total amount of energy released during the active combustion of a fire. During a fire event, energy is released through convection, radiation, and conduction (Johnston et al. 2014). Within remote sensing, fire intensity is often represented as fire radiative power (FRP), which is a term that specifically describes the amount of energy released through radiation (in megawatts) during the fire (Johnston et al. 2014). FRP is linked to the amount of burned biomass (Wooster, Zhukov, and Oertel 2003). Thus, identifying the FRP grants us insight into the type and quantity of vegetation burned (Steel, Safford, and Viers 2015).

1.2.3 Fire Size

Fire size describes the spatial extent of the burned region and is calculated by measuring the area covered by each individual fire event in square kilometers. The size of each fire can be determined by climatic, topographic, and vegetative conditions that promote or constrain the spread of fire (Graham, McCaffrey, and Jain 2004). Larger fire sizes can decrease the diversity in landscape patches (Chuvieco 1999), which changes the structure and complexity of the ecosystem.

1.2.4 Burned Area

Burned area is the total area burned by a collective of fires within a region, measured in square kilometers. The same burned area may represent a few large fires or many smaller fires, thereby summarizing total area burned (Hantson, Pueyo, and Chuvieco 2015). Large burned areas would indicate that fires affected a large area in the ecosystem, thus impacting a greater amount of the vegetative community (Hantson, Pueyo, and Chuvieco 2015).

1.2.5 Fire Seasonality

Fire seasonality represents the time of year that fires occur throughout the year (Mackenzie et al. 2021). Fires could occur seasonally or year-round; thus, fire seasonality highlights whether fire activity follows seasonal trends. Fire seasonality considers the length and timing of the fire season, which is determined by landcover type coupled with climatic and anthropogenic activity (Mackenzie et al. 2021; Magi et al. 2012). Altered fire seasons influence post-fire plant recovery (Mackenzie et al. 2021). Thus, variations in fire seasonality will impact plant populations and community compositions (Miller et al. 2019).

1.3 Drivers of fire

Anthropogenic activity and climatic patterns vary geographically and exert different degrees of influence on regional fire regimes. Humans change or control fire regimes through igniting, encouraging, or suppressing fires over long periods of time (T. V. Nguyen et al. 2023; Jones 1998). Humans can also alter land cover, which affects the availability and spatial arrangement of fuels. Climate can influence fire by creating atmospheric or vegetative conditions that change the likelihood of fires to ignite and persist (Corona-Núñez and Campo 2022; Fuller and Murphy 2006; Hantson, Pueyo, and Chuvieco 2015). In the following section, I elaborate on each of these drivers in greater detail.

1.3.1 Climatic Drivers of Fire

Climate describes prevailing weather conditions over time, which influence long-term patterns of fire activity (i.e.: fire regime). Climatic factors that impact fire include precipitation, vapor pressure deficit, temperature, and seasonality (Alvarado et al. 2017; Aldersley, Murray, and Cornell 2011; Grünig, Seidl, and Senf 2022). Each climactic factor affects atmospheric or vegetative fuel conditions, thus influencing the probability and behavior of fire (McLauchlan et al. 2020; Archibald et al. 2010; Zubkova et al. 2019). The geographic variation of these climatic effects facilitates differences in fire activity across global landscapes.

1.3.1.1 Precipitation

Precipitation patterns have important impacts on fire activity (Alvarado et al. 2017; Aldersley, Murray, and Cornell 2011). Investigating where, how, and when precipitation occurs is critically important to understanding how each aspect of the rainfall pattern interacts with the fire regime. Metrics such as mean annual precipitation (MAP; measured in millimeters), rainfall seasonality, and dry season severity are used to assess precipitation (Schwartz et al. 2020). For example, rainfall seasonality describes how rainfall is distributed throughout the year, which dictates the seasons that climatically suppress fire and stimulate vegetation growth. Likewise, severe dry seasons result in dry vegetative and atmospheric conditions, increasing the likelihood for more extreme fires (Russell-Smith and Edwards 2006). Evaluating the variability in precipitation is critical to understanding fire-rainfall interactions.

1.3.1.2 Vapor Pressure Deficit

VPD describes the difference between the amount of water vapor contained in the air and the potential vapor storage capacity, measured in kilopascals (kPa) or pounds per square inch (psi). Vegetation moisture conditions are linked to VPD (Wollaeger and Runkle 2015), which have important implications for vegetation fires. High VPD indicates dry and flammable vegetative fuel loads that contribute to large burned areas (Sedano and Randerson 2014). Quantifying VPD will enhance our understanding of the climatic and vegetative influences on the fire regime.

1.3.1.3 Temperature

Globally, high temperatures create environmental conditions that promote increased fire activity (Aldersley, Murray, and Cornell 2011; Jain et al. 2022; Thirumalai et al. 2017). Warm temperatures can dry out vegetation, thus increasing the susceptibility of fuel to ignite.

Specifically, temperatures greater than 28°C is associated with larger burned areas (Aldersley, Murray, and Cornell 2011). Researching the contributions of temperature to fire occurrence is a necessary component to understanding how climate influences the fire regime.

1.3.2 Human Influence on Fire Activity

Humans have major and long-lasting influence on patterns of fire activity (Bowman et al. 2011). Humans have exerted diverging controls on fire activity through promoting or suppressing fires. Anthropogenic activities that promote fires include using fire as a tool to clear land (Dhandapani and Evers 2020). Fire activity has also been suppressed or controlled to protect human populations and infrastructure (Bowman et al. 2011; Pechony and Shindell 2009). Human interventions that modify fire regimes create changes in the vegetation structure and communities of existing environments (Ratnam et al. 2011; McLauchlan et al. 2020; Hoffmann et al. 2012; T. V. Nguyen et al. 2023). Thus, assessing how humans affect the fire regime will further inform our understanding of the anthropogenic influence on ecological changes.

To quantify human influence, previous studies have used metrics such as population density, socioeconomic factors, road density, livestock density, and land management (Corona-Núñez and Campo 2022; Alvarado et al. 2017; Zubkova et al. 2019). Investigating these anthropogenic factors could help identify how and why fire patterns are modified. For example, humans sometimes promote fire activity in agricultural cropland (Bowman et al. 2011). Fire is an inexpensive and effective practice used to clear agricultural waste before sowing new crops and is often associated with increased burned area and burn frequency (Andela et al. 2017). Humans substantially influence existing fire regimes, thus investigating human factors will enhance our understanding of anthropogenic drivers of fire.

1.4 Geographic bias against continental SEA

Challenges with investigating the ecology in continental SEA could be associated with constraints in resources and data availability (Reid et al. 2013), coupled with a political framework that priorities economic growth over ecological sustainability (Sasmi and Shi 2023). Major geographic bias in ecological research exists, where most studies are focused on Europe and North America (Wilson et al. 2007; Pyšek et al. 2008; Trimble and van Aarde 2012). Research priorities are often determined by market forces that direct funding to specific economic agendas, such as research for agricultural production (Wilson et al. 2007). Furthermore, economic status also dictates whether individuals have educational access to become scientists, which creates bias in the language, cultural background, and geographic interests of the scientists themselves (Wilson et al. 2007; Trimble and van Aarde 2012). Thus, economically disadvantaged regions, such as continental SEA, are understudied and often overlooked in ecological research.

Furthermore, the fires that are investigated in SEA are primarily focused on insular SEA. For example, research attention is drawn towards the peatland fires in Malaysia and Indonesia due to the severe human health impacts from air pollution (Page et al. 2009; Gaveau et al. 2014; Hein et al. 2022). However, differentiating between the fire patterns of continental and insular SEA is necessary because of the climatic and terrain differences between each landscape (Miettinen, Stibig, and Achard 2014). Recent evidence also shows increases in fire activity in continental SEA (Vadrevu et al. 2019), but there is a critical gap in the research for where and why these fires are occurring on a landscape-wide scale. Taking a comprehensive view of the large-scale fire patterns helps to benchmark the current fire regimes, which will benefit efforts to monitor future changes in fire activity.

1.5 Fire Relationships in Continental SEA

Different types of fire occur in continental SEA, but the relationships between the drivers of fire and the subsequent ecological impacts are particularly understudied (Dupuis et al. 2020; Sunderland et al. 2015). Southeast Asian ecosystems were previously highlighted as biodiversity hotspots (Myers et al. 2000), thus research about ecological disturbances in this region are important to conservation and management efforts. Despite the minimal research in this region, investigating the geographic distribution of fire and its' drivers is critical to understanding the ecosystems in continental SEA. Here, I discuss the different roles and drivers of fire in continental SEA.

In continental SEA, humans impact fire patterns by affecting fire ignition, frequency, occurrence, and spread (Jones 1998; Stolle et al. 2003; Dennis et al. 2005; T. V. Nguyen et al. 2023). Fires from human activity involve agricultural clearing, urban development, and land conversion (Koh and Sodhi 2010; Sodhi et al. 2004; Biswas et al. 2015). For example, fires are ignited to burn natural landscapes for conversion to rubber and oil plantations (Dhandapani and Evers 2020). Likewise, fire clears cultivated land between crop generations in swidden (i.e.: slash-and-burn) agricultural practices (Biswas et al. 2015; Inoue 2018; Nelson and Noweg 2021). How humans use fire influences the fire regime and imparts different ecological impacts.

Fire plays essential ecological roles in continental SEA (Pletcher, Staver, and Schwartz 2022). SEA is home to deciduous dipterocarp formations that are unique forest-savanna mosaics (Ratnam et al. 2011). There, fire acts as an environmental filter to limit woody encroachment into savannas by reducing seedling and sapling growth (T. T. Nguyen, Murphy, and Baker 2019). The low-intensity and high-frequency surface fires help maintain the open, savanna-like structure (Ratnam et al. 2011). These fire patterns play an essential ecological role in the forest-savanna ecosystems, yet much is unknown about the geographic distribution and drivers of these types of fires in continental SEA.

1.6 Remote Sensing

Efforts to quantify large-scale fire regime patterns have increasingly incorporated remote sensing techniques, which have emerged as a prominent method to evaluate landscape change and disturbance. Current methods often incorporate publicly accessible satellite-based datasets with products that have been available for several decades. With the progressing advancement in imaging technology, the potential for remote sensing products to capture and monitor ecosystem disturbance has increased (Curnick et al. 2021; Frazier and Hemingway 2021). The widespread application of remote sensing methods is useful for large-scale assessments that would otherwise be difficult to achieve without these technologies.

Specifically, satellite remote sensing provides a comprehensive view of fire and climate patterns at varying temporal and spatial resolutions. Within the realm of fire detection and monitoring, several studies have established the benefits of incorporating satellite imagery to analyze landscape disturbance and change (Hawbaker et al. 2020; Jones 1998; Balch et al. 2020). Satellite remote sensing products such as Moderate Resolution Imaging Spectroradiometer (MODIS) are commonly used for fire research. MODIS instruments are located on NASA's Earth Observation Aqua and Terra satellites and have detected active fires and thermal anomalies globally since 2000. The MODIS fire algorithm primarily captures large fires and struggles to capture small, low-intensity fires (Giglio, Schroeder, and Justice 2016). Therefore, research using MODIS products is most appropriate when investigating large fires at landscape-wide scales.

1.7 Research Questions

My research presents an ecologically focused perspective on drivers of spatial fire patterns in continental SEA. Understanding the spatial distribution of fire patterns and their anthropogenic or climatological drivers is critical to understanding Southeast Asian ecosystems. My study is the first to describe where and how fire regimes differ across continental SEA and pinpoint the relationship between fire and its' important drivers in this region. With this, my specific research questions include the following:

1) How is the geographic variation in fire activity associated with climate, landcover, and human influence in continental SEA?
2) What and where are the distinct fire regimes in continental SEA?

I analyzed fire regime characteristics in continental SEA to establish connections between climatic, landcover, and anthropogenic influences. I further distinguished where fires in forested landcover are associated with forest loss. We expect the important climactic variables to affect atmospheric conditions and vegetation moisture. We also expect variation in fire regime based on landcover and land use. My research will be the first to explore a greater dimensionality of fire regime characteristics and drivers of fire within continental SEA.

Chapter 2: Materials and Methods

2.1 Study Site

Continental SEA is defined as Thailand, Laos, Myanmar (Burma), Cambodia, and Vietnam (4.85-29.55° Latitude and 90.95-110° Longitude). Continental SEA typically has a dry season between November and April (Corlett 2014), with the peak fire season from February until April (Vadrevu, Ohara, and Justice 2021; Corlett 2014). The summer monsoon season is typically from May to September, often bringing tropical typhoons with heavy rainfall (Gupta 2005). The annual average rainfall is 1940mm with an average annual temperature of 23°C. Mean annual precipitation (MAP) is highest along the western coast of continental SEA, at around 4000mm per year. Precipitation gradually decreases inland with MAP near 1000mm in the driest portions of central Myanmar, then increases with moderately heavy precipitation on the southeastern coastline ranging around 2000-3000mm of rainfall. According to the Köppen-Geiger climate classification, continental SEA has a mix of temperate and tropical climatic conditions (Beck et al. 2018). Temperate conditions with dry winters and hot summers are prevalent in latitudes north of 20°. Tropical rainforest occurs along the coast of continental SEA, while tropical savanna climates dominate the remainder of the mainland. The biomes within continental SEA consist primarily of tropical and subtropical moist and dry broadleaf forests (Olson et al. 2001).

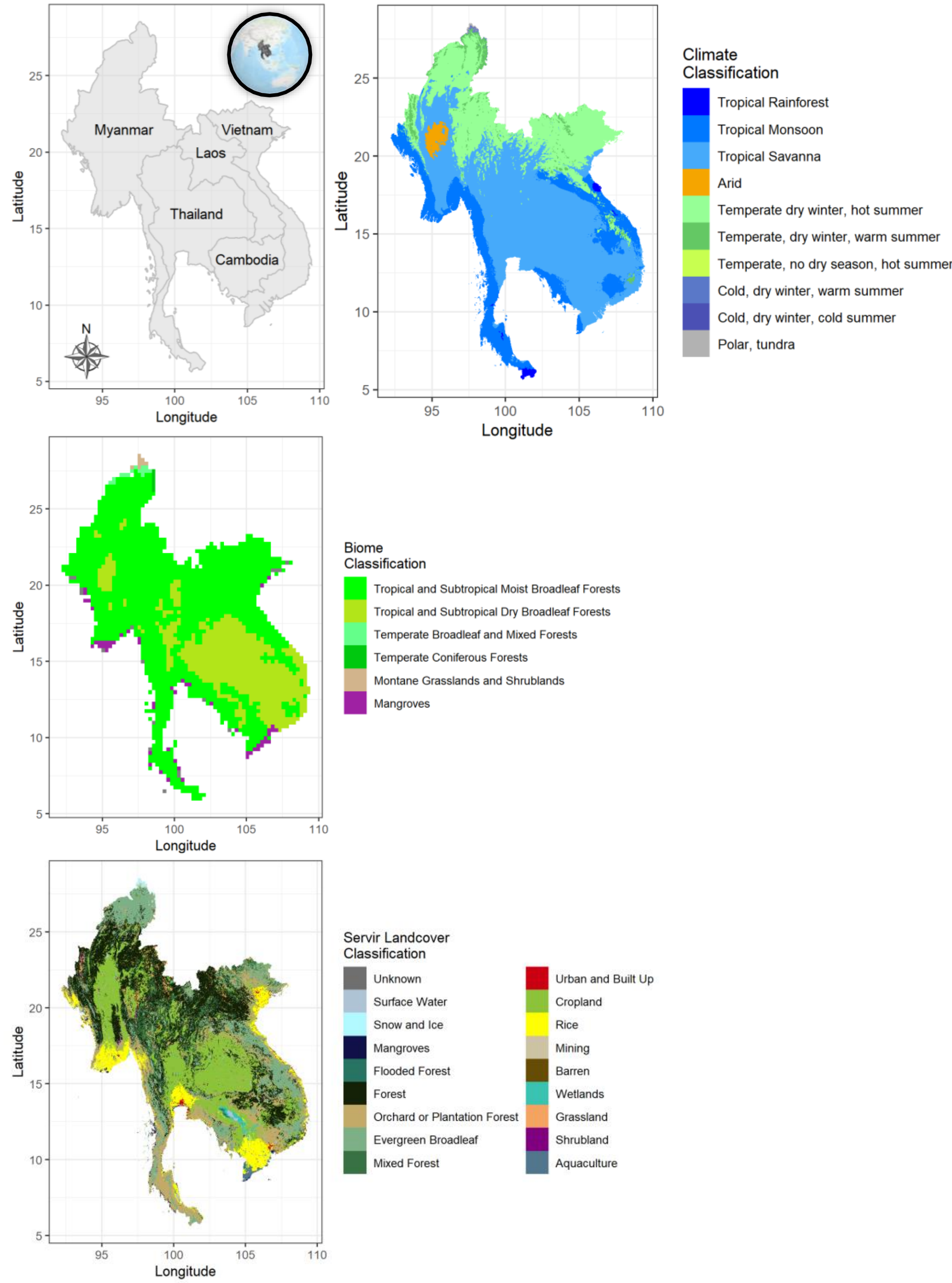

Figure 1. Study Area.

Top row depicts the geographic location of continental Southeast Asia (left) and the Köppen climate classification (right) provided by Beck et al. 2018. Middle row depicts the World Wildlife Fund Terrestrial Ecoregions of the

World Biome classification map, provided by Olson et al. 2001. Bottom row displays landcover classifications based on SERVIR landcover mapping dataset.

2.2 Data Processing

My study used satellite remote-sensing data products from June 2001- May 2021. All raster datasets were aggregated to 20-year averages at 0.25° spatial resolutions. Since I wanted to test for fires in different types of landcover, I chose a spatial resolution of 0.25° to ensure that we captured variability within the vegetated landcover. I tested 0.1°, 0.25°, and 0.5° grid cells, and found that 0.25° resolution showed a reasonable range of grid cells with high and low natural vegetation, indicating that we captured variability in naturally vegetated landcover. Coarser resolutions resulted in grid cells with similar average values for the naturally vegetated landcover and would thus be unsuitable for distinguishing the differences between fires in varying landcover types. I calculated five variables describing fire activity and seven variables describing the climatic, anthropogenic, and landcover drivers (Table 1).

Trends in fire activity occur seasonally, where rainfall in the previous months contributes to vegetation growth which fuels the following fire season. Then, the dry severity of the dry season influences whether the vegetation is dry enough to burn. To capture the natural cycle of fire seasonality, I characterized a 12-month period where peak fire activity occurs in consecutive months. Similar to water years in hydrologic studies, fire also occurs in patterns where partitioning by a standard calendar year may result in error or misinterpretations (Boschetti and Roy 2008). In my research, I define the fire year from starting from June and ending in May. The fire year aligns with each calendar month such that the months during the high fire periods highlight the fire season in continental SEA. I calculated the optimal fire year to start in June, because June was the first month with below median and average fire activity, which indicated the end of the fire season and the beginning of the following fire year. Starting the fire year in June also captures a few months of precipitation prior to the fire season.

2.2.1 Quantifying Fire Regime

In this section, I describe how I quantified each fire regime variable: frequency, intensity, burned area, number of fires, and fire size. All fire variables were derived from different MODIS products.

2.2.1.1 Quantifying Fire Frequency

Fire frequency (FF) describes the total number of years a fire occurred in each grid cell for the study period (Figure 2; map A). Grid cells were reclassified as 1 if a burned pixel was present, and 0 if no pixels were burned. Here, I refer to ‘pixel’ as the original resolution of the gridded product, and ‘grid cell’ for the resampled data at 0.25° spatial resolutions. I derived FF from MODIS Burned Area Monthly Global 500m (MCD64A1) by summing the total number of years that each grid cell burned to display the how many years a fire burned within the grid cell. FF calculations were performed in Google Earth Engine.

2.2.1.2 Quantifying Fire Radiative Power (Fire Intensity)

Fire Radiative Power (FRP) represents fire intensity, defined as the mean annual total FRP for each pixel in the 20-year study period (Figure 2; map B). FRP was derived from MODIS Terra Thermal Anomalies & Fire Daily Global 1km (MOD14A1.061). MODIS Terra Thermal Anomalies and Fire Daily Global dataset are produced every eight days, with a daily temporal resolution and 1km spatial resolution. I compiled the daily images by summing FRP values to produce annual images based on the previously described fire year. Then, I calculated the mean FRP per pixel over the study period to output the mean annual FRP across the study region. The mean annual FRP explains the yearly average fire intensity per grid cell, which represents how much radiative energy was released from biomass burning each year. Calculations for the average radiative energy released from biomass burned were also calculated but omitted from this study due to the high correlation between total and average FRP values. FRP calculations were performed in Google Earth Engine.

2.2.1.3 Quantifying Burned Area, Number of Fires, Fire Size

Burned area, number of fires, and fire size were calculated using fire perimeter data from the University of Colorado's Earth Labs FiredPy initiative (Balch et al. 2020). The FiredPy collection includes global fire event shapefiles delineated from MODIS Burned Area Product Collection 6 with the purpose of increasing public access to fire history data (Balch et al. 2020). The delineation process involves aggregating burned pixels based on a spatial and temporal input to identify pixels that belong to each unique fire event. In the dataset, each fire event is represented by a single polygon that contains information such as the start and end date of the fire event, fire spread, and total burned area. I downloaded fire perimeters for each country in my study area from the pre-generated Earth Lab data collection repository (https://github.com/earthlab/firedpy). Downloaded fire perimeters contained polygons of delineated fires from November 2000 to July 2021. Fire polygons were reduced to points representing the cell center, then calculations were performed for the polygons using the overlapping grid cell. These calculations were processed in ArcGIS Pro Version 2.8.1.

The number of fires (NF) describes the average number of fires that occurred within each grid cell over the 20-year study period (Figure 2.2; map D). To calculate this, I found the total number of fires per grid cell, then divided that by the 20-year study period to receive the average number of fires per year (fires/year).

Using the total number of fires from the previous calculation, I disaggregated the fires into each landcover type to further calculate the percentage of fires within different landcover classes. The percent of fires in each landcover type was calculated using the SERVIR-Mekong Landcover dataset at 30m resolutions (SERVIR; http://servir-rlcms.appspot.com/static/html/map.html). SERVIR landcover types were classified into four classes: saturated vegetation, forests, agriculture, and low-lying vegetation. Saturated vegetation contained flooded forests, wetlands, and mangroves. The forest class consisted of forests, evergreen broadleaf, and mixed forests. Agriculture landcover included cropland, rice, and orchard or plantation forest. Finally, low-lying vegetation included grassland and shrublands. Calculations were conducted in ArcGIS Pro Version 2.8.1.

Burned area (BA) describes the average area burned for each grid cell aggregated over the study period (Figure 2.2; map C). I calculated the total burned area in square kilometers for all fire events per year for each grid cell. Then, I averaged the total burned area across the past 20 fire years. With this calculation, "burned area" represents the average of the annual total burned area (km^2/year) within a grid cell.

Fire size (FS) is a measure of the area covered by each individual fire event and is related to how fragmented burned areas are within a given grid cell (Figure 2.2; map E). I calculated the average burned area per grid cell for each fire year; then, I calculated the average across the years to determine "fire size." With this calculation, "fire size" represents the average burned area for each individual fire in kilometers squared per fire (km^2/fire). Thus, areas that experience smaller, more fragmented fires would have a small fire size, and areas with large continuous fires would have a large fire size.

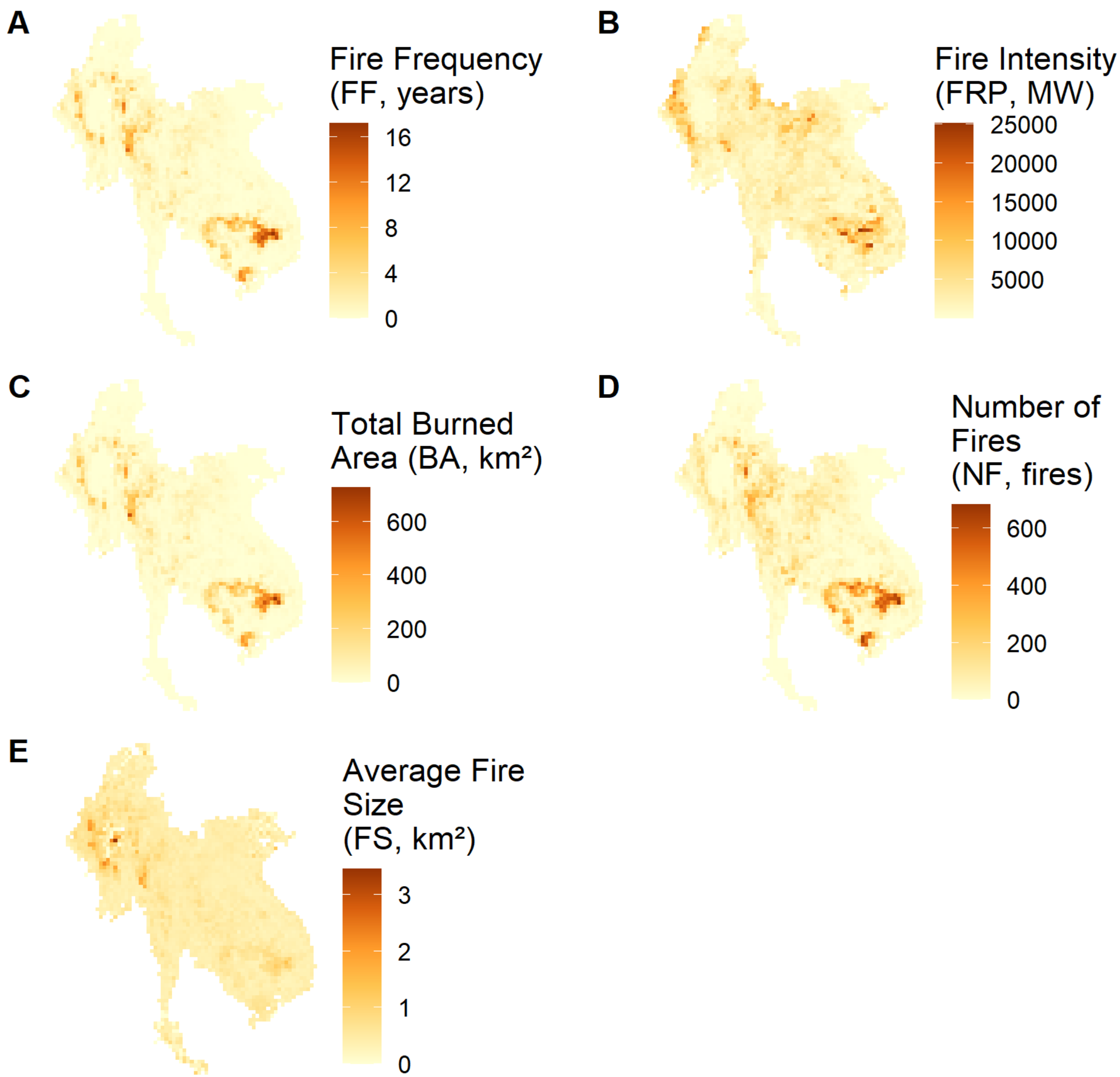

Figure 2. Geographic Variation of Fire Activity.

Maps for the geographic distribution for each fire activity metric is shown. Each map is accompanied by the abbreviation and units (i.e., Fire frequency (FF, years)). Five fire activity metrics were calculated: fire frequency, fire radiative power (aka fire intensity), burned area, number of fires, and fire size.

2.2.2 Quantifying Climate variables

To characterize climate, I used rainfall, temperature, and VPD data. I used rainfall data from Climate Hazards Group InfraRed Precipitation with Station Pentad Version 2.0 data (CHIRPS), which is a gridded precipitation dataset that was developed for drought monitoring. CHIRPS is a 0.05° spatial resolution, quasi-global (50° S - 50° N) dataset with product availability since 1981. The CHIRPS dataset combines precipitation measurements from thermal infrared satellite products and station gauge data (Funk et al. 2015). CHIRPS precipitation estimates are reliable in the Lower Mekong River Basin (Dandridge et al. 2019).

I selected rainfall metrics to capture seasonal precipitation patterns. The rainfall variables derived from CHRIPS included mean annual precipitation (MAP), seasonality index (SI), and Maximum Climatological Water Deficit (MCWD). MAP is a simple metric that describes the overall quantity of yearly rainfall in millimeters. I calculated MAP as the annual average over the 20-year study period (Figure 3; map A).

MCWD describes the severity of accumulated water stress experienced in the dry season from low precipitation levels (Figure 3; map B). MCWD was calculated as described by Aragao et al. 2007, where the most negative values indicate the most severe dry seasons, and is calculated as such:

$$If\ WD_{n-1}(i,j) - E(i,j) + P_n(i,j) < 0;$$

$$then\ WD_n(i,j) = \ WD_{n-1}(i,j) - E(i,j) + P_n(i,j);$$

$$else\ WD_n(i,j) = \ 0$$

MCWD is the most negative value of the monthly water deficits (WD) among the months in each hydrological year. In the equation, each month is represented by n, monthly potential evapotranspiration is represented by E, monthly precipitation is represented by P, and the coordinates for each pixel are represented by (i, j). The WD was calculated cumulatively for each month. Monthly precipitation was set to 100mm per month, where monthly rainfall less than 100mm would indicate that WD was present; this threshold was applied based on prior forest micrometeorology research (Shuttleworth et al. 1989).

SI describes the relative seasonality of precipitation patterns, highlighting how precipitation is distributed throughout the year (Figure 3; map C). I derived SI according to calculations described by Feng et al. (2013).

$$seasonality = \left(\sum_{m=1}^{12} \overline{p}_m \, log_2\left(\frac{\overline{p}_m}{q_m}\right)\right) \times \overline{R}/\overline{R}_{max}$$

First, we compute the long term mean monthly precipitation ($\overline{p}_m$) that is normalized by the mean annual precipitation ($\overline{R}$) per month (m). This is measured against a uniform rainfall distribution for all months ($q_m = \frac{1}{12}$) and the observed maximum annual rainfall ($\overline{R}_{max}$). High seasonality is indicated by larger index values representing regions that experience more precipitation concentrated in distinct seasons (i.e., rainy season vs. dry seasons), whereas smaller index values experience uniform precipitation throughout the year without defined rainfall seasons.

Mean Annual Temperature (MAT) was derived from MODIS Terra Land Surface Temperature and Emissivity Daily Global 1km (MOD11A1.061) and aggregated over the 20-year study period (Figure 3; map D). This dataset provides daily temperature values in Celsius since February 2000 at 1km resolutions. MAT below 12°C was masked to focus on regions that experience regular fire activity.

Vapor Pressure Deficit (VPD) describes the difference between the amount of water vapor in the air and the potential vapor pressure at saturation, which has an effect on vegetation moisture (Wollaeger and Runkle 2015). Here, VPD is calculated in kilopascals (kPa) and represents the mean VPD per grid cell calculated over the 20-year study period. VPD was derived from the University of Idaho's TerraClimate Monthly Climate and Climatic Water Balance for Global Terrestrial Surfaces dataset (Figure 3; map E). This dataset integrates climatological normals from WorldClim (https://www.worldclim.org/data/index.html) , Climate Research Unit Ts4.0, and the Japanese 55-year Reanalysis. TerraClimate has provided monthly climatic water balance data since 1958, covering 1/24th degree spatial resolutions.

Climate datasets were accessed in Google Earth Engine and imported into R version 4.1.1 for further processing.

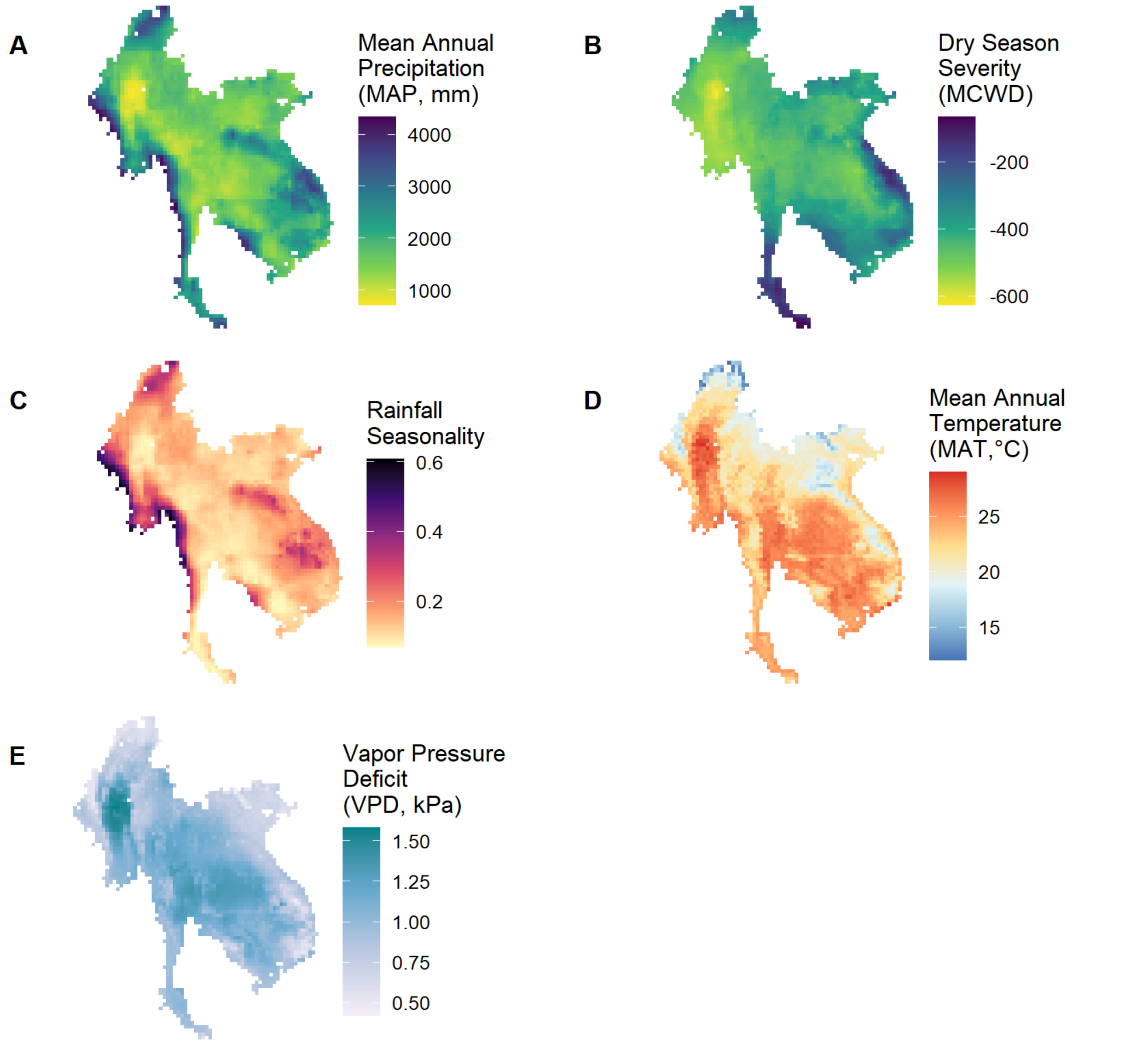

Figure 3. Geographic Variation of Climate Variables.

Maps for the geographic distribution for climate variables are shown. Each map is accompanied by the abbreviation and units, if relevant (i.e., mean annual precipitation (MAP, mm)). Five climate metrics were calculated: mean annual precipitation, dry season severity (aka maximum climatological water deficit), seasonality index (aka rainfall seasonality), mean annual temperature, and vapor pressure deficit.

2.2.3 Anthropogenic influence

The percentage of natural vegetation and the human influence index were calculated to account for anthropogenic effects (Figure 4). The percentage of natural vegetation raster was important for disaggregating the fires that occurred primarily in natural landcover, as compared to fires that occurred in agricultural vegetation (i.e.: cropland and plantations). The human influence index raster helped distinguish how human presence and infrastructure influenced fire.

The percentage of natural vegetation (pctnatveg) raster was derived by reclassifying the SERVIR dataset (Figure 4; map A). Here, SERVIR land cover types were divided into anthropogenic or natural vegetation. The anthropogenic class included urban and built-up, cropland, aquaculture, barren, rice, orchard or plantation forest, and mining. The natural vegetation class included wetlands, forest, flooded forest, mixed forest, shrubland, mangroves, grassland, and evergreen broadleaf. Percent urban and natural landcover calculated at 0.25° resolutions to distinguish the amount of natural or urban landcover present. Regions with greater than 15% urban landcover were masked out to focus on the ecological impacts of fire in vegetated landscapes.

I also measured anthropogenic effects using the Human Influence Index (HII) from the Wildlife Conservation Society (Wildlife Conservation Society - WCS and Center for International Earth Science Information Network - CIESIN - Columbia University 2005). This dataset accounts for infrastructure, land use, population density, night-time lights, roads, and railways at 1km spatial resolutions and was resampled into 0.25° grid cells (Figure 4; map B). Here, human influence refers to human presence, infrastructure, and establishments, where HII values increase with greater impacts to the land through human occupation and development.

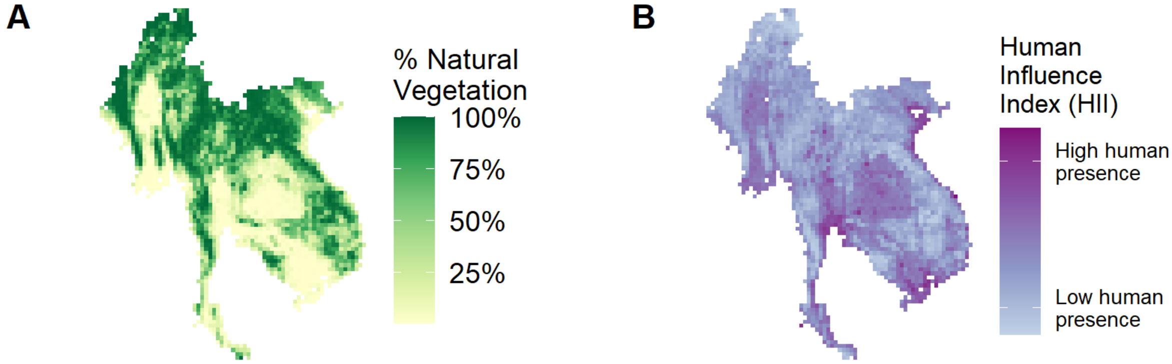

Figure 4. Geographic Variation of Human Influence Variables.

Maps for the geographic distribution of the percent natural vegetation and the human influence index are shown. Percent natural vegetation accounts for wetlands, forest, flooded forest, mixed forest, shrubland, mangroves, grassland, and evergreen broadleaf landcover classes based on SERVIR Landcover dataset. Human Influence Index dataset accounts for infrastructure, land use, population density, night-time lights, roads, and railways from the Wildlife Conservation Society.

Category	Variable	Abbr.	Units	Description	Data Product
Fire regime	Fire Radiative Power	FRP	megawatts	Fire intensity - Release of radiant energy from biomass burning	MODIS Thermal Anomalies & Fire[1]
	Fire Size	FS	km^2	Mean size of burned area, indicating how far fire events spread	FiredPy[2]
	Number of Fires	NF		Mean number of fire events	FiredPy[2]
	Fire Frequency	FF	years	Total number of years fire occurred	MODIS Burned Area Monthly[3]
	Burned Area	BA	km^2	Mean total burned area	FiredPy[2]
Climate	Mean Annual Precipitation	MAP	mm	Mean annual rainfall	CHIRPS[4]
	Maximum Climatological Water Deficit	MCWD		Relative severity of the dry season	CHIRPS[4]
	Seasonality Index	SI		Relative rainfall seasonality, describes annual distribution of rainfall	CHIRPS[4]
	Mean Annual Temperature	MAT	°C	Mean Annual Temperature	MODIS LST and Emissivity[5]
	Vapor Pressure Deficit	VPD	kPa	Vapor Pressure Deficit, indicator of biomass growth potential	TerraClimate[6]
Anthropogenic	Human Influence Index	HII		Weighted sum of anthropogenic influence	Wildlife Conservation Society[7]
	Percent Natural Vegetation	pctnatveg	%	Percentage of area covered by wetlands, forests, shrublands, mangroves, and grasslands	SERVIR-Mekong Landcover[8]

Table 1. Variable Summary.

The climatic, anthropogenic, and landcover explanatory and fire regime response variables are described with the associated data products that were used to derive the variables. Variables were calculated as 20-year means per grid cell, for fire years 2001-2021 (June 2001- May 2021). Superscript numbers under Data Product refer to the datasets listed in the "Datasets Used" section below.

2.2.4 Random Forest Regression Modelling

I used Random Forest (RF) regression models to determine how each driver related to fire activity. RF is an ensemble learning algorithm for regression and classification analysis in ecological contexts (Oliveira et al. 2012; Cutler et al. 2007). Previous studies have used RF regression to determine important variables influencing fire activity (Jiang, Zhou, and Raghavendra 2020; Archibald et al. 2010). RF performs accurately with highly correlated variables and does not make assumptions about the variable distribution (Cutler et al. 2007). The RF consists of many decision trees created by bootstrapped samples of the original data. This bootstrapping technique makes the results less sensitive to the original dataset. A random subset of the predictor variables determines splits in each decision tree. The outcome for the combination of decision trees is then averaged to determine the regression output. RF requires two user-defined model parameters: the number of trees (ntree) and the number of variables at each split (mtry).

Individual RF regression models were run for each of my response variables: fire radiative power, burned area, fire frequency, fire size, and the number of fires. My predictor variables included precipitation (MAP, MCWD, SI), climate (MAT, VPD), and anthropogenic influence (pctnatveg, HII). The ntree was set to 500 to obtain stable outcomes, and mtry was equal to 2, which is the default value calculated by the number of predictor variables divided by 3. Important predictor variables were identified using the percent increase in mean squared error (%IncMSE), which describes the percent decrease in model accuracy if that variable was left out of the model (Genuer, Poggi, and Tuleau-Malot 2010). The percent variance explained (pseudo-R^2) was calculated via the internal RF package. The RF regression was run in R using the randomForest version 4.7-1.1 package (Liaw and Wiener 2002).

2.2.5 Spatially Constrained Clustering

To identify clusters of homogenous fire regime, I implemented a spatially constrained clustering algorithm. Incorporating spatial constraints in the clustering algorithm was critical to maintaining regional climatic and landcover similarity within clusters when identifying the fire regimes. This clustering algorithm follows the Spatial "K"luster Analysis Tree Edge Removal (SKATER) method, which uses a divisive hierarchical approach to prune the minimum spanning tree based on dissimilarity between clusters while maintaining spatial contiguity (AssunÇão et al. 2006). Variables in the clustering analysis included the fire variables (i.e., fire radiative power, burned area, fire frequency, fire size, and the number of fires) normalized with a z-score transformation and the number of fires in forest and agriculture. Clusters were generated using the "spatially constrained multivariate clustering" tool in ArcGIS Pro Version 2.8.1.

I ran Kruskal-Wallis rank sum tests and Pairwise comparisons using Wilcoxon rank sum test with continuity correction test for each fire and driver variable to evaluate statistical differences between clusters. These tests were performed as opposed to an ANOVA because assumptions of normality were not met. Each region was subsequently numbered and then named after its qualitative features. The spatial clustering of similar fire activity regions led to the delineation of eight unique fire regime clusters and was qualitatively compared using boxplots to distinguish whether fires were associated with human or climatic drivers.

2.2.6 Disaggregating Forest Fires Associated with Forest Loss

To distinguish between forest fires, I disaggregated the forest fires to consider the proportion of fires that are associated with forest loss according to the Hansen Global Forest Change dataset (Hansen et al. 2013). Here, I identified regions where fire is associated with forest loss between the years 2001 and 2022 using, 1) fire activity data from MODIS Terra Thermal Anomalies Daily (MOD14A1 V6.1), 2) forested landcover data identified using the SERVIR Landcover dataset, and 3) forest loss using Hansen Global Forest Change v1.10 dataset. Burned grid cells were reclassified as 1 if forest loss occurred in at least one pixel during the study period and 0 if none of the pixels experienced forest loss. The proportion of pixels associated with forest loss was calculated when reducing the resolution to 0.25° grid cells. All calculations were conducted in Google Earth Engine.

Chapter 3: Results

3.1 Drivers in geographic variation of fire activity

3.1.1 Fire activity associations with landcover

The majority of fires in continental SEA occurred in forested and agricultural landcover, with a greater proportion of fires occurring in agriculture. I compared the proportion of fires by landcover within each country because fire policy, management, and practices vary across country borders. Forest fires were the most common in Myanmar and Thailand, while agricultural fires were the most common in Vietnam. Proportions of agricultural and forest fires were similar in Cambodia and Laos. The percentage of fires that occur in grass, shrubland, and saturated vegetation is collectively less than 5% of fires for the entire region. In comparison to the other countries, grassland and shrubland fires were most prominent in Thailand and Myanmar, while Laos had the highest percentage of fires in saturated vegetation (Figure 5).

3.1.2 Country-level variations in fire activity

Each country displayed different geographical variations of fire activity. Cambodia experienced the highest fire frequency, intensity, number of fires, and total burned area, where high values of these fire activity metrics occurred along the northern and western borders (Figure 2). Central Myanmar also experienced substantial fire activity with the greatest average fire size. The least fire activity was observed in Vietnam, where fire frequency, number of fires, and total burned area were lowest along the eastern Vietnamese coast.

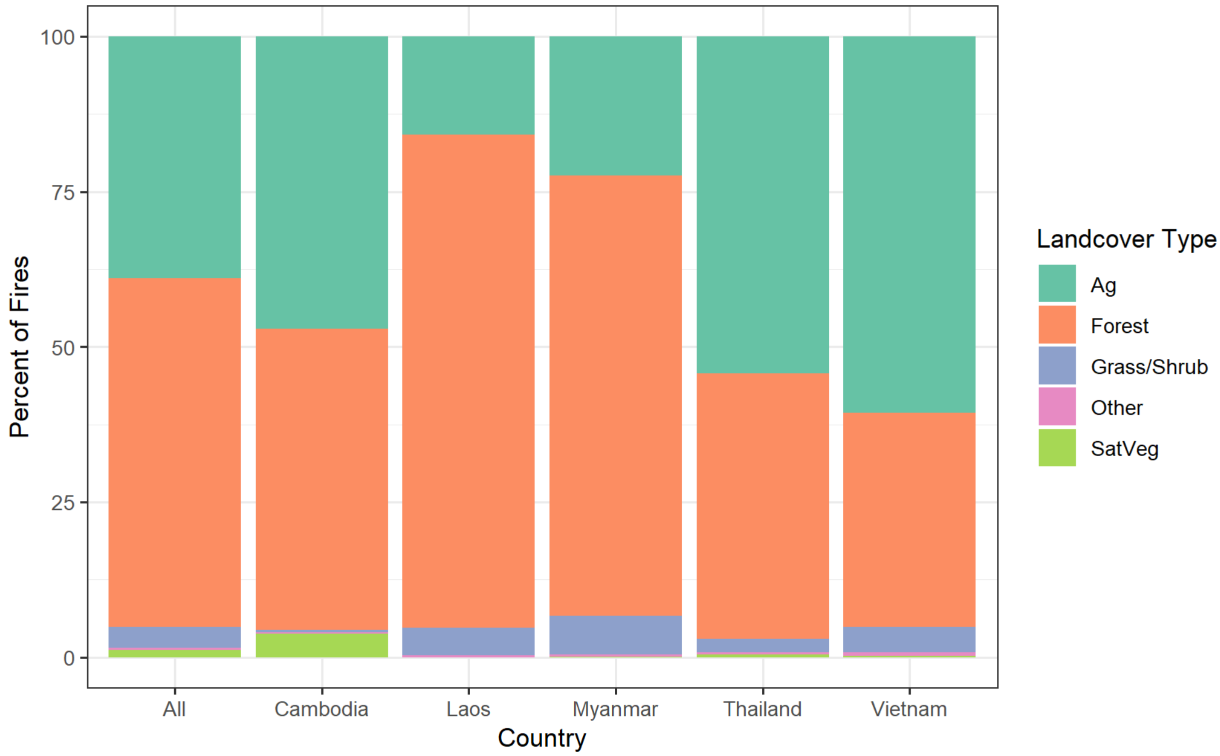

Figure 5. Percent of Fires by Landcover Type.

Proportions of fire occurrence are shown by landcover type for each country (i.e., Cambodia, Laos, Myanmar, Thailand, and Vietnam) and for all countries (i.e., All). Most fires occur in forest and agricultural (ag) landcover, with few fires occurring in grasslands and shrublands (grass/shrub), saturated vegetation (SatVeg), and other.

	Cambodia	Vietnam	Thailand	Laos	Myanmar
Forests	31.47	43.76	30.92	77.04	56.63
Agriculture	57.52	46.09	63.38	19.31	35.38
Low-lying vegetatior	0.55	1.75	0.93	2.39	4.29
Saturated vegetation	7.69	1.10	1.40	0.06	1.34

Table 2. Percent of Landcover Type by Country.

This table shows the percentage of landcover type in each country. The percentage of landcover type was calculated using the area of each landcover type divided by the total area of the country.

	FRP	BA	FS	NF	FF	MAP	MCWD	SI	pctnatveg	MAT	VPD	HII
Min.	23	0	0	0	0	718.2	-626.03	0.06881	0	12.05	42.02	26.4
1st Qu.	992.4	2.973	0.3629	7.1	0.08124	1465.2	-471.38	0.11369	0.1076	21.13	82.97	781
Median	2049.3	13.277	0.4327	29.65	0.36239	1753.2	-433.09	0.14405	0.5617	23.25	100.67	1134
Mean	2751.5	37.279	0.4777	58.57	0.999	1937.3	-415.48	0.17103	0.5095	23.02	99.42	1223
3rd Qu.	3444.1	37.195	0.5345	69.83	1.00886	2249	-376.3	0.19344	0.88	25.3	115.28	1652.6
Max.	25148	725.82	3.4569	681.85	17.1946	4341.2	-65.47	0.60856	1	29.04	158.33	3557.5

Table 3. Variable Summary Statistics.

Minimum, 1st Quartile, Median, Mean, 3rd Quartile, and Maximum values are shown for each variable. Variables are as follows: Fire Radiative Power (FRP), Burned Area (BA), Fire Size (FS), Number of Fires (NF), Fire Frequency (FF), Mean Annual Precipitation (MAP), Seasonality Index (SI), Mean Annual Temperature (MAT), percent natural vegetation (pctnatveg), Vapor Pressure Deficit (VPD), and Human Influence Index (HII).

3.1.3 Fire activity associations with climate and human influence

The random forest models explained 34-56% of the variance across the fire activity variables (Table 4). Climatic drivers were found to be consistently important for fire activity along with the presence of human influence. We found that fire intensity was most influenced by dry season severity, temperature, human influence, and seasonality (Figure 6). Similarly, for burned area, fire frequency, and the number of fires, we found that dry season severity, temperature, human influence, and vapor pressure deficit were the most influential predictors (Figures 7-9). Finally, the most important predictors for fire size were dry season severity, temperature, human influence index, and percent natural vegetation (Figure 10). These important drivers capture the climatic and anthropogenic factors that impact long-term fire activity.

Partial dependence plots derived from RF models indicated the general shape of the relationship between each fire activity metric and driver (Figures 6-10; plots A-D). My findings show that mean annual temperatures above 25°C coupled with severe dry seasons and low human influence led to a substantial increase in fire activity (Figures 6-10; plots A-D). Here, the plots indicate that hotter temperatures were associated with higher fire activity. High fire activity was associated with more severe dry seasons (more negative MCWD). Finally, low-to-moderate human influence index values were associated with higher fire activity, where fire activity drops substantially with high human presence and establishments (Figures 6-10; plots A-D). Next, VPD was a significant predictor for burned area, number of fires, and fire frequency (Figure 7-9, respectively). This relationship indicated that fire activity increased with VPD, where high VPD values correspond with drier vegetation. Furthermore, seasonality was an important predictor for fire intensity, where more seasonal regions experienced higher fire intensities (Figure 6; plot D). Finally, the percentage of natural vegetation is an important driver for fire size. As the percentage of natural vegetation increases, the fire size also increases (Figure 10; plot C).

Variable	# of trees (nTrees)	# of variables tried at each split (mtry)	% Var explained
Fire Radiative Power	500	2	48.79
Burned Area	500	2	54.77
Number of Fires	500	2	54.31
Fire Size	500	2	34.82
Fire Frequency	500	2	56.06

Table 4. Random Forest Parameters.

Random forest regression models for each fire activity metric were run with the given parameters. Percent variation explained (pseudo-R^2; % Var explained) describes the goodness of fit for each model.

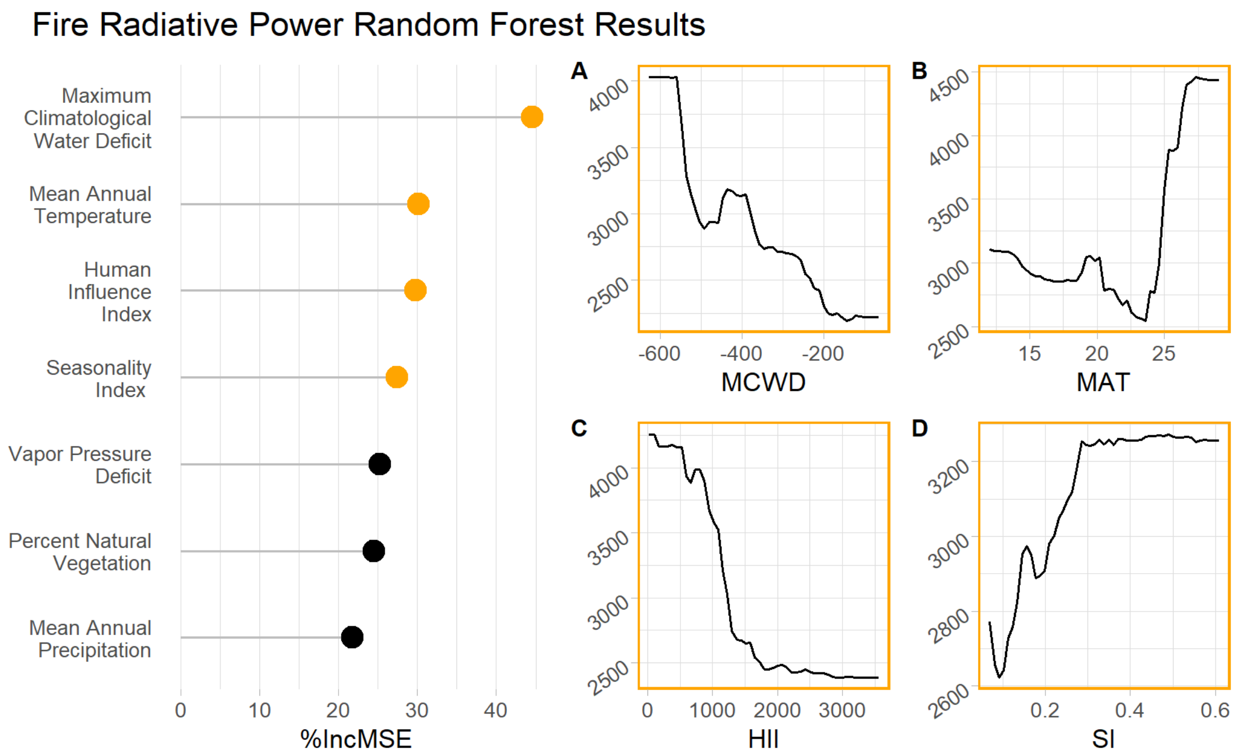

Figure 6. Random Forest Results for Fire Radiative Power.

Random forest identified the most important drivers for fire intensity (FRP) that occur in continental SEA. The variable importance plot (left) ranked the importance of each driver using the mean decrease in accuracy. The top four most important drivers are in orange, where the corresponding partial dependence plots are shown to the right (plots A-D).

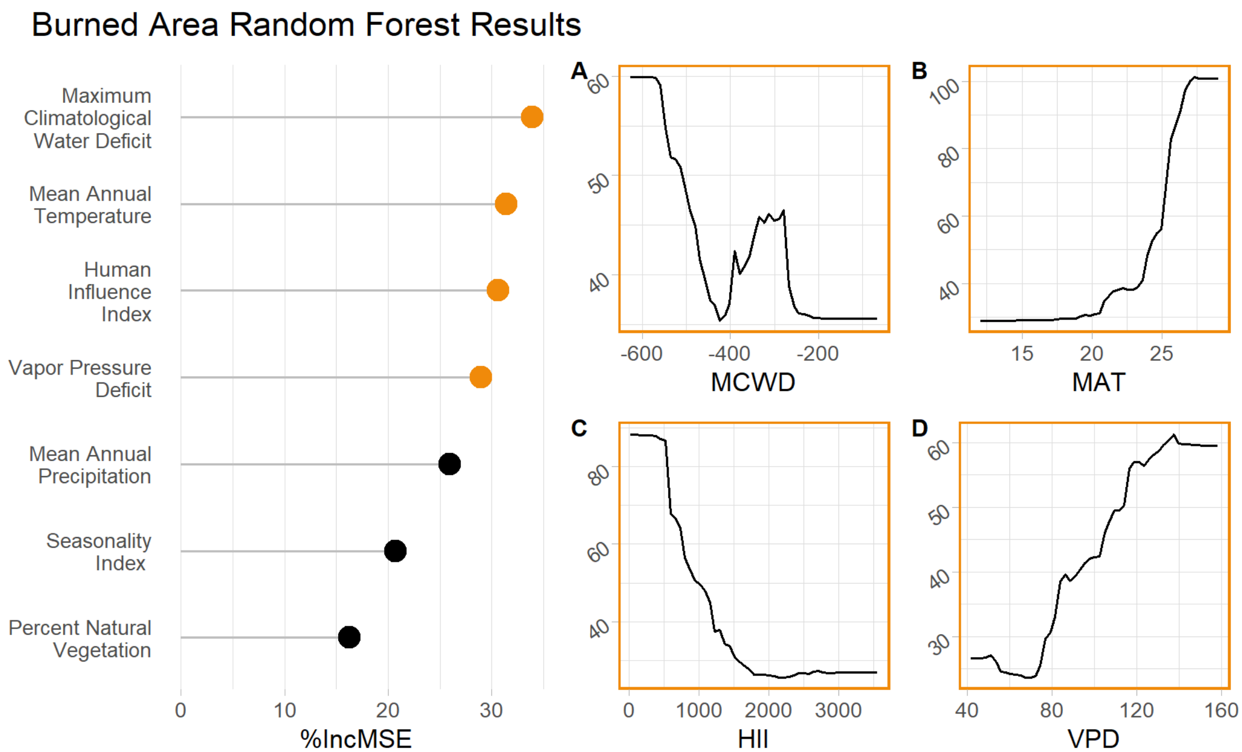

Figure 7. Random Forest Results for Burned Area.

Random forest identified the most important drivers for burned area that occur in continental SEA. The variable importance plot (left) ranked the importance of each driver using the mean decrease in accuracy. The top four most important drivers are in orange, where the corresponding partial dependence plots are shown to the right (plots A-D).

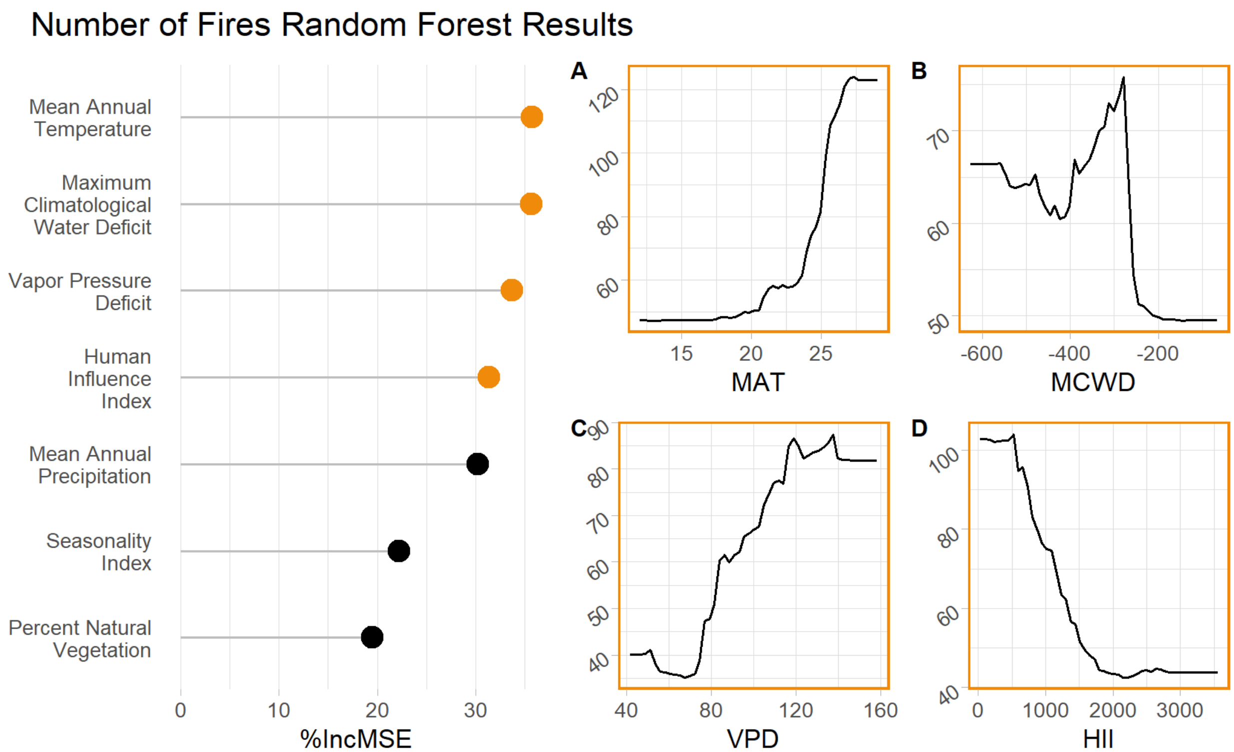

Figure 8. Random Forest Results for Number of Fires.

Random forest identified the most important drivers for the number of fires that occur in continental SEA. The variable importance plot (left) ranked the importance of each driver using the mean decrease in accuracy. The top four most important drivers are in orange, where the corresponding partial dependence plots are shown to the right (plots A-D).

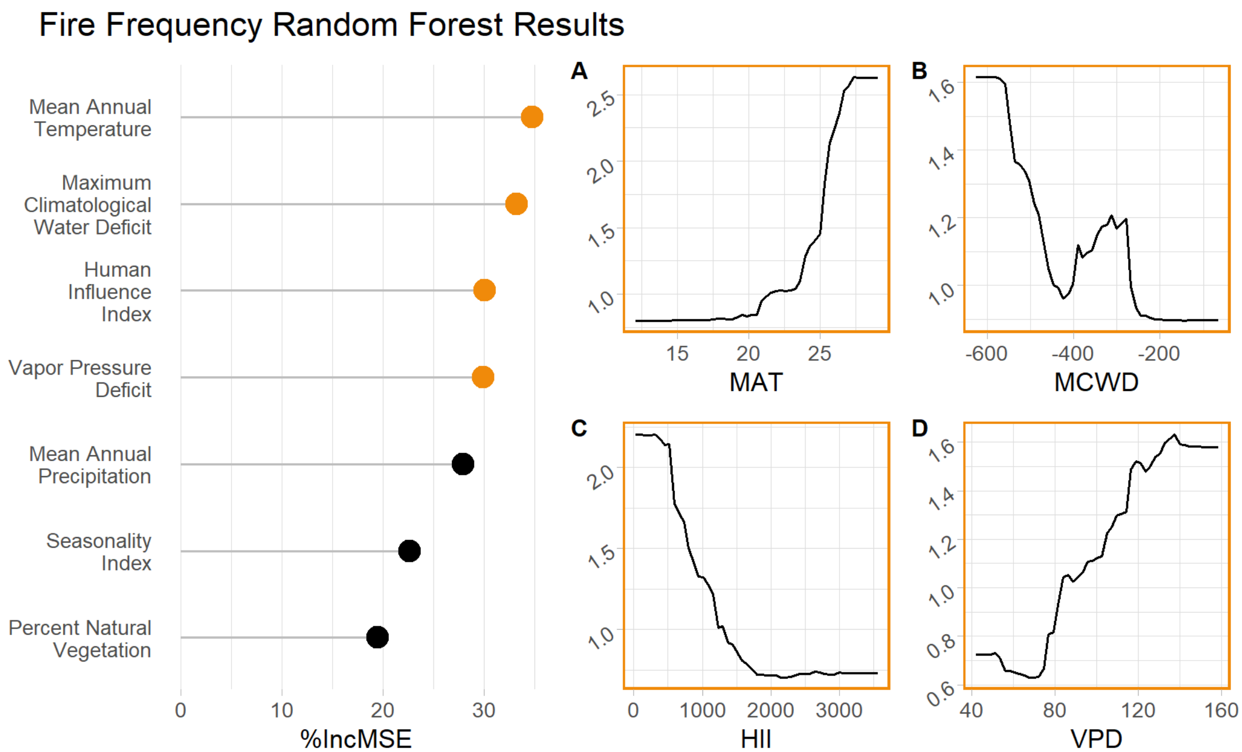

Figure 9. Random Forest Results for Fire Frequency.

Random forest identified the most important drivers for fire frequency that occur in continental SEA. The variable importance plot (left) ranked the importance of each driver using the mean decrease in accuracy. The top four most important drivers are in orange, where the corresponding partial dependence plots are shown to the right (plots A-D).

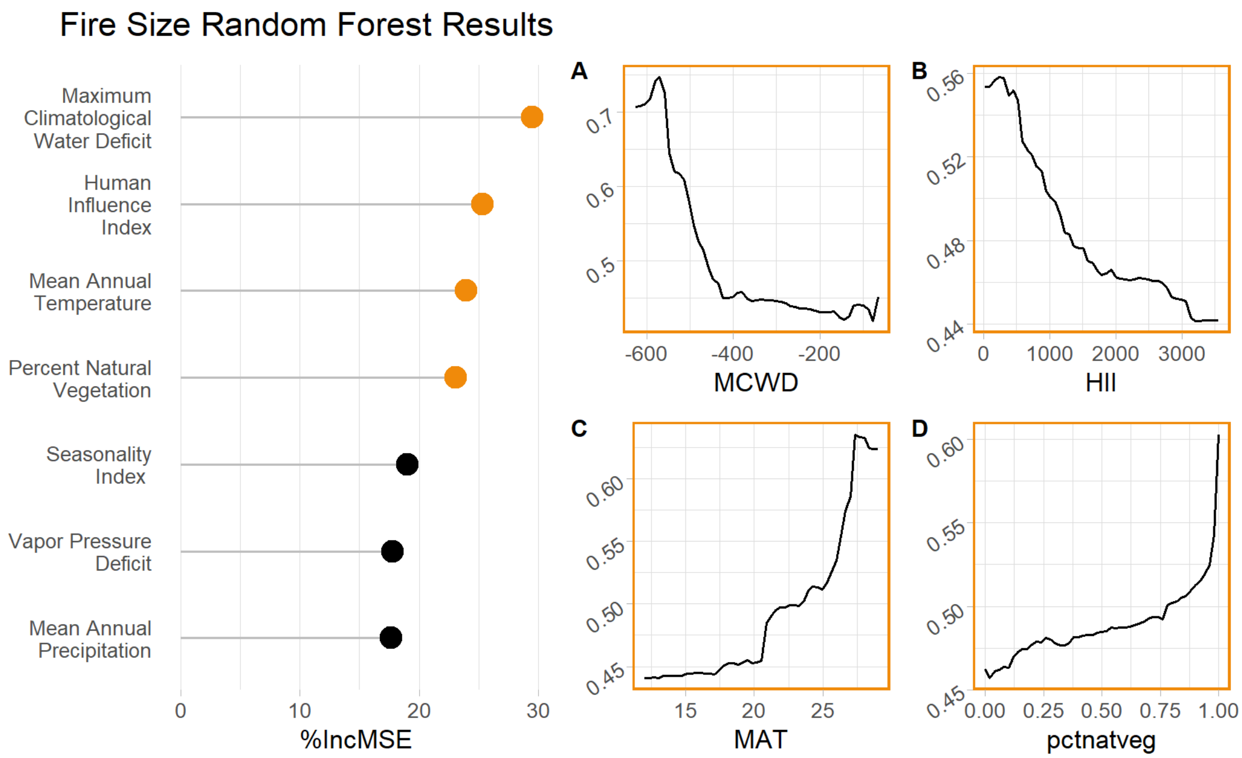

Figure 10. Random Forest Results for Fire Size.

Random forest identified the most important drivers for fire size that occur in continental SEA. The variable importance plot (left) ranked the importance of each driver using the mean decrease in accuracy. The top four most important drivers are in orange, where the corresponding partial dependence plots are shown to the right (plots A-D).

3.2 Identifying distinct fire regimes in continental SEA

3.2.1 Cluster Descriptions

I delineated and described eight unique and spatially contiguous fire regime clusters in continental SEA (Figure 11). Cluster 0 is comprised of grid cells with minimal fire activity without any distinct fire regime patterns and is therefore omitted from further analysis.

Cluster 1 presented frequent, large, and intense fires in the forests and agricultural lands of Cambodia. In regard to the associated drivers of fire, cluster 1 reported seasonal rainfall patterns with high annual precipitation and severe dry seasons. These climactic factors are also coupled with high temperatures and high VPD. Furthermore, cluster 1 shows low human influence index values and a high percentage of natural vegetation in comparison to the other clusters.

The fire activity in cluster 2 showed frequent, large, moderate intensity fires in Cambodia's agricultural and forested regions. The climatic drivers associated with cluster 2 include high temperatures, moderate precipitation, and moderate VPD. This cluster has low seasonality, therefore experiencing evenly distributed annual rainfall. Consequently, the dry seasons are comparably mild. Moderate human influence index values are shown in this cluster with low percentages of natural vegetation.

Clusters 3 and 5 contain similar fire patterns and are geographically adjacent, where cluster 3 is located in Myanmar and cluster 5 is predominately in Thailand. Clusters 3 and 5 clusters have fires patterns that are infrequent, small, fragmented, and low intensity. Fires primarily occur in forests and agricultural land. Climatic associations include moderate-low temperatures, moderate-low precipitation, moderate VPD, and severe dry seasons. Cluster 3 and 5 differ in regard to rainfall seasonality; cluster 3 has moderately low seasonality and cluster 5 experiences a variable range of seasonal rainfall. Both clusters contain moderate human influence index values and moderate-to-high percent natural vegetation.

Cluster 4 is displays frequent, large, and low intensity fires in Southern Vietnam's agricultural land. Compared to the other clusters, cluster 4 has the lowest median annual precipitation, the least severe dry seasons, and least seasonal rainfall patterns, coupled with high temperatures and moderate VPD. Furthermore, this cluster is also distinguished by the highest median human influence index values and the lowest percentages of natural vegetation.

Cluster 6 was composed of occasional, moderately sized, high intensity fires in the forests and agricultural regions of south-central Myanmar. Climatically, this cluster experiences moderately high temperatures, high precipitation, severe dry seasons, relatively high rainfall seasonality, and moderate VPD. Human influence index values in cluster 6 are moderate, paired with moderate percent natural vegetation.

Cluster 7 contains occasional, fragmented, and moderate intensity fires in the agricultural regions of Thailand. The cluster is associated with the highest temperature and VPD, paired with moderate precipitation, moderately severe dry seasons, and moderate seasonality. This cluster has high human influence index values and low proportions of natural vegetation.

Finally, cluster 8 depicts infrequent, small, fragmented, and high intensity fires in the forests of northern Laos and along the border of Myanmar. In comparison to the other clusters, cluster 8 demonstrates the lowest temperatures and lowest VPD, coupled with moderate dry seasons, relatively high precipitation, and high rainfall seasonality. The median human influence index is the lowest in this cluster, with the highest percentage of natural vegetation.

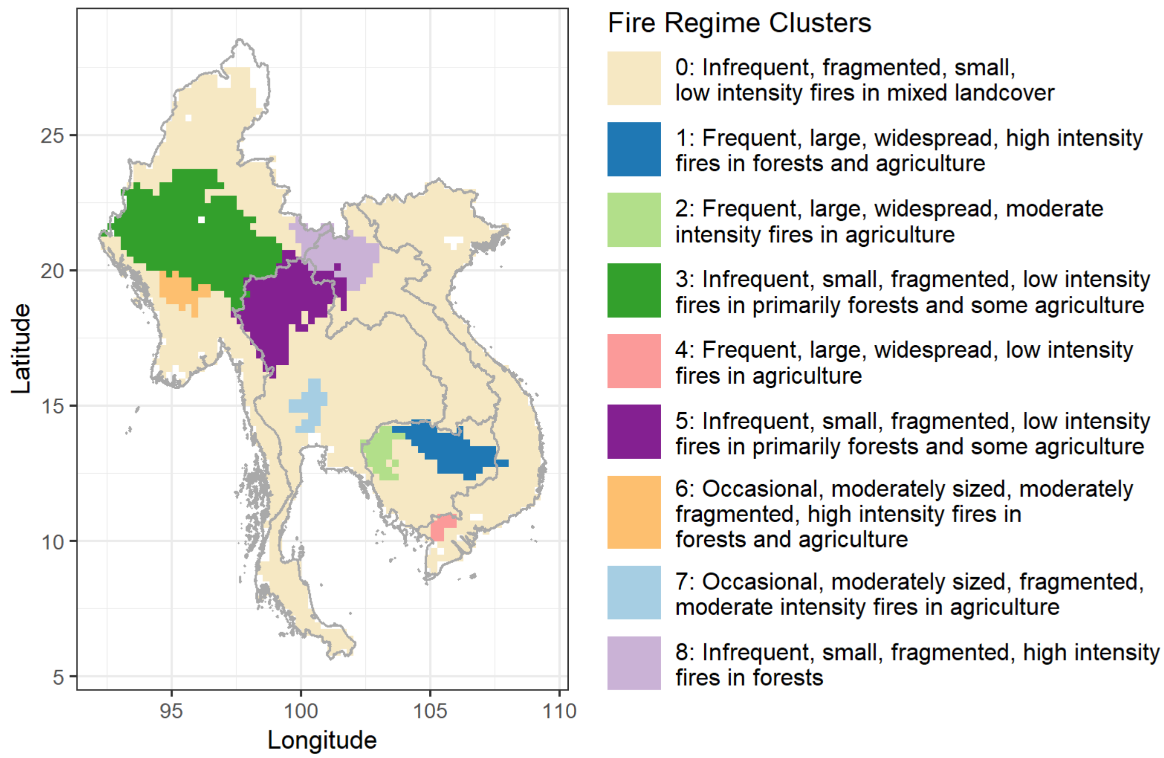

Figure 11. Fire Regime Clusters.

Spatial distribution of fire regime clusters is displayed and labeled with a description of the distinct features identified by: 1) fire radiative power (intensity: high, moderate, low), 2) burned area (large, medium, small), 3) number of fires and frequency (frequent, occasional, infrequent), 4) fire size (extent: widespread, moderately sized, fragmented), and the 5) landcover type (forest or agriculture). Grey lines distinguish country boundaries.

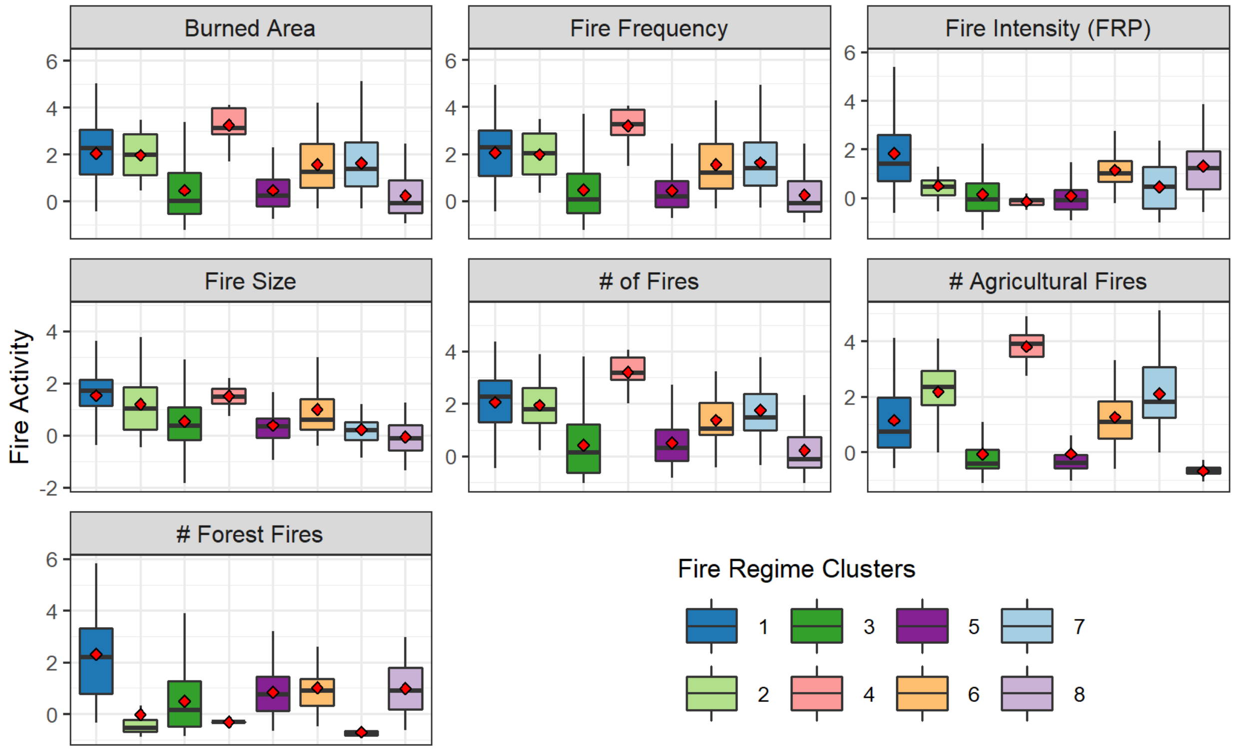

Figure 12. Distribution of Fire Activity per Cluster.

Boxplots display the distribution of each z-score transformed fire activity metric and number of fires in agriculture or forested landcover (y-axis) between each distinct cluster (x-axis) distinguished by color. Boxplots show the mean (red diamonds) and the 25th, 50th, and 75th percentile for fire activity metric. The range of the data is shown with outliers removed.

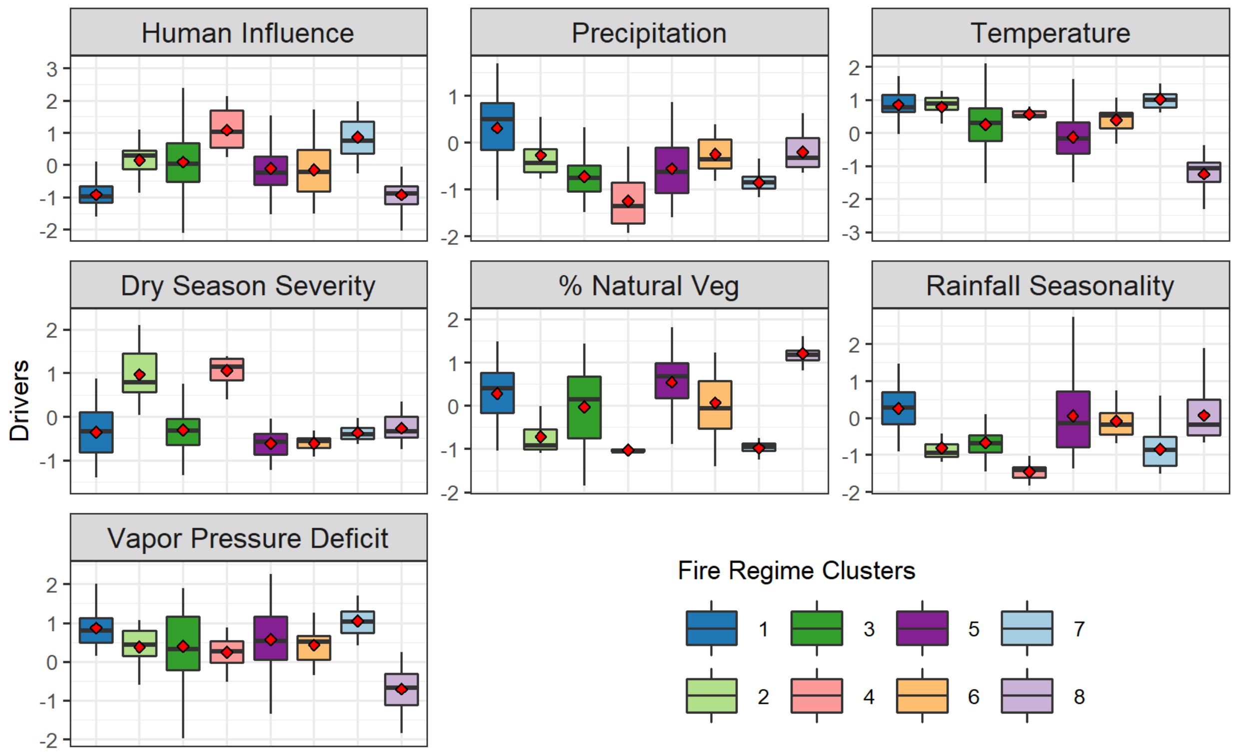

Figure 13. Distribution of Drivers per Cluster.

Boxplots display the distribution of each z-score transformed driver of fire (y-axis) by each distinct cluster (x-axis) distinguished by color. Boxplots show the mean (red diamonds) and the 25th, 50th, and 75th percentile for fire activity metric. The range of the data is shown with outliers removed.

Clusters	n	FRP			BA			FS			NF			FF		
		mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd
0	1810	2243.52	1729.27	2152.48	16.94	8.06	29.52	0.42	0.40	0.13	33.36	18.57	46.26	0.45	0.22	0.77
1	72	9080.60	7299.88	5371.24	262.18	253.23	173.99	0.70	0.70	0.22	345.40	374.53	171.24	7.00	6.81	4.59
2	31	3887.61	3688.70	1441.60	138.96	141.54	62.15	0.59	0.57	0.15	224.34	221.40	91.63	3.67	3.74	1.65
3	309	3245.34	2446.65	3019.34	70.63	39.06	87.82	0.72	0.66	0.37	84.16	58.15	89.59	1.94	1.11	2.36
4	11	1646.16	1580.81	592.15	330.22	335.36	85.53	0.66	0.65	0.05	485.82	510.70	112.26	8.54	8.88	2.31
5	159	2601.95	2195.31	1683.32	50.04	38.61	43.68	0.52	0.48	0.18	83.07	75.75	50.88	1.27	1.04	1.03
6	30	4249.09	4122.03	2562.76	90.42	55.12	82.62	0.98	0.84	0.50	83.45	74.58	43.31	2.48	1.53	2.25
7	27	3632.25	2647.47	1853.16	70.37	61.59	33.86	0.46	0.44	0.06	147.14	137.15	62.91	1.93	1.65	0.97
8	80	5818.23	5281.03	2860.81	30.53	24.87	19.55	0.43	0.42	0.07	61.90	55.00	36.27	0.83	0.73	0.52

Table 5. Cluster Summary Statistics.

Mean, median, number of grid cells (n), and standard deviation (sd) are shown for each cluster between each fire variable. Fire variables are as follows: Fire Radiative Power (FRP), Burned Area (BA), Fire Size (FS), Number of Fires (NF), Fire Frequency (FF).

Kruskal-Wallis Rank Sum Test				
	Variable	Chi-squared	df	p-value
Fire	FRP	389.24	8	< 2.2e-16
	BA	667.45	8	< 2.2e-16
	FS	639.29	8	< 2.2e-16
	NF	620.99	8	< 2.2e-16
	FF	670.18	8	< 2.2e-16
Drivers	MAP	486.32	8	< 2.2e-16
	MCWD	615.95	8	< 2.2e-16
	SI	315.87	8	< 2.2e-16
	MAT	281.83	8	< 2.2e-16
	VPD	300.64	8	< 2.2e-16
	pctnatveg	275.05	8	< 2.2e-16
	HII	189.42	8	< 2.2e-16

Table 6. Kruskal-Wallis Rank Sum Test.

Medians between clusters were tested using a Kruskal-Wallis test to determine if clusters were statistically different for each fire and driver variable. Fire variables are as follows: Fire Radiative Power (FRP), Burned Area (BA), Fire Size (FS), Number of Fires (NF), Fire Frequency (FF). Driver variables are as follows: Mean Annual Precipitation (MAP), Maximum Climatological Water Deficit (MCWD), Seasonality Index (SI), Mean Annual Temperature (MAT), Vapor Pressure Deficit (VPD), Percent Natural Vegetation (pctnatveg), Human Impact Index (HII).

Differences in Fire Activity Per Cluster (Pairwise comparisons test)									
Clusters		0	1	2	3	4	5	6	7
FRP	1	*							
	2	*	*						
	3	*	*	*					
	4	X	*	*	X				
	5	*	*	*	X	*			
	6	*	*	X	*	*	*		
	7	*	*	X	X	*	*	X	
	8	*	*	*	*	*	*	*	*
BA	1	*							
	2	*	*						
	3	*	*	*					
	4	*	X	*	*				
	5	*	*	*	X	*			
	6	*	*	*	*	*	*		
	7	*	*	*	*	*	*	X	
	8	*	*	*	*	*	*	*	*
FS	1	*							
	2	*	*						
	3	*	X	*					
	4	*	X	X	X				
	5	*	*	*	*	*			
	6	*	*	*	*	*	*		
	7	*	*	*	*	*	*	*	
	8	X	*	*	*	*	*	*	*
NF	1	*							
	2	*	*						
	3	*	*	*					
	4	*	*	*	*				
	5	*	*	*	*	*			
	6	*	*	*	X	*			
	7	*	*	*	*	*	*	*	
	8	*	*	*	X	*	*	*	*
FF	1	*							
	2	*	*						
	3	*	*	*					
	4	*	X	*	*				
	5	*	*	*	X	*			
	6	*	*	*	*	*	*		
	7	*	*	*	*	*	*	X	
	8	*	*	*	*	*	*	*	*

Table 7. Differences in Fire Activity Per Cluster.

Fire clusters were compared with pairwise comparisons using Wilcoxon rank sum test to determine which of the clusters were statistically different from the others per fire variable. Asterisk (*) denotes significant differences at p-value = 0.05 and (X) denotes not statistically different.

Differences in Drivers of Fire Per Cluster (Pairwise comparisons test)									
Clusters		0	1	2	3	4	5	6	7
MAP	1	*							
	2	*	*						
	3	*	*						
	4	*	*	X	X				
	5	*	*	X	X	X			
	6	*	*	X	X	X	*		
	7	*	*	*	*	*	*	*	
	8	*	*	X	X	X	*	X	*
MCWD	1	X							
	2	*	*						
	3	*	*	*					
	4	*	*	X	*				
	5	*	*	*	*	*			
	6	*	*	*	*	*	*		
	7	*	*	*	*	*	*	*	
	8	X	X	*	*	*	*	*	*
SI	1	*							
	2	*	*						
	3	*	*	*					
	4	*	*	X	*				
	5	*	*	*	*	*			
	6	*	X	*	*	*	*		
	7	*	*	*	*	*	*	*	
	8	*	*	*	*	*	X	*	*
MAT	1	*							
	2	*	X						
	3	*	*	*					
	4	*	*	*	*				
	5	*	*	*	*	*			
	6	*	X	X	*	X	*		
	7	*	*	*	*	*	*	X	
	8	*	*	*	*	*	*	*	*
VPD	1	*							
	2	*	*						
	3	*	*	*					
	4	X	*	*	X				
	5	*	*	X	*	*			
	6	*	*	*	*	*	*		
	7	*	*	*	*	*	*	*	
	8	*	*	*	X	X	*	*	*
pctnatveg	1	X							
	2	*	*						
	3	*	*	*					
	4	*	*	*	*				
	5	*	*	*	*	*			
	6	X	X	*	X	*	*		
	7	*	*	*	*	X	*	*	
	8	*	*	*	*	*	*	*	*
HII	1	*							
	2	X	*						
	3	*	*	*					
	4	*	*	*	*				
	5	*	*	*	X	*			
	6	X	*	X	X	*	X		
	7	*	*	*	*	X	*	*	
	8	*	*	*	*	*	*	*	*

Table 8. Differences in Drivers of Fire Per Cluster.

Fire clusters were compared with pairwise comparisons using Wilcoxon rank sum test to determine which of the clusters were statistically different from the others per driver. Asterisk (*) denotes significant differences at p-value = 0.05 and (X) denotes not statistically different.

3.2.1.1 Fire activity associations with forest loss

Within forested landcover, I quantified the proportion of fire activity co-occurring in the same grid cells as forest loss. In the entire region, 28.8% of the forested grid cells that burned were associated with forest loss. Regions where forest loss intersected with fire activity were heavily prevalent in Cambodia, south-central Vietnam, and along the northwestern portion of Laos (Figure 14). The greatest percentages of forest fires that are associated with forest loss occur in Cambodia, followed by Laos and Vietnam (Table 9). Quantifying where burned grid cells are associated with forest loss allows us to determine where the fires could be contributing to deforestation or helping maintain forest-savanna mosaics.

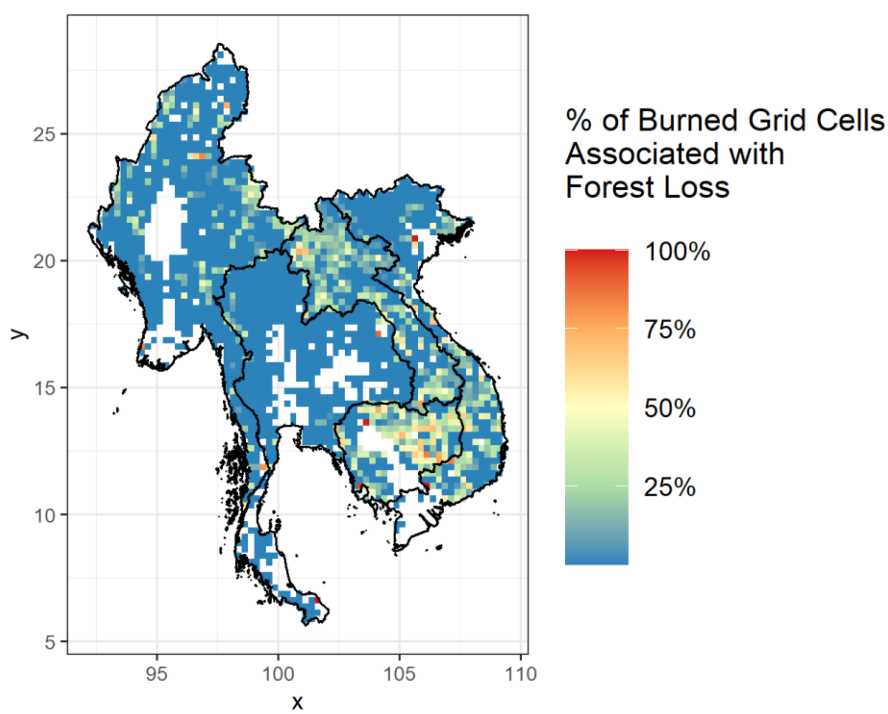

Figure 14. Percent of Burned Grid Cells associated with Forest Loss.

Proportions of burned forested grid cells that overlap with forest loss for the Hansen Global Forest Change dataset are shown for continental Southeast Asia.

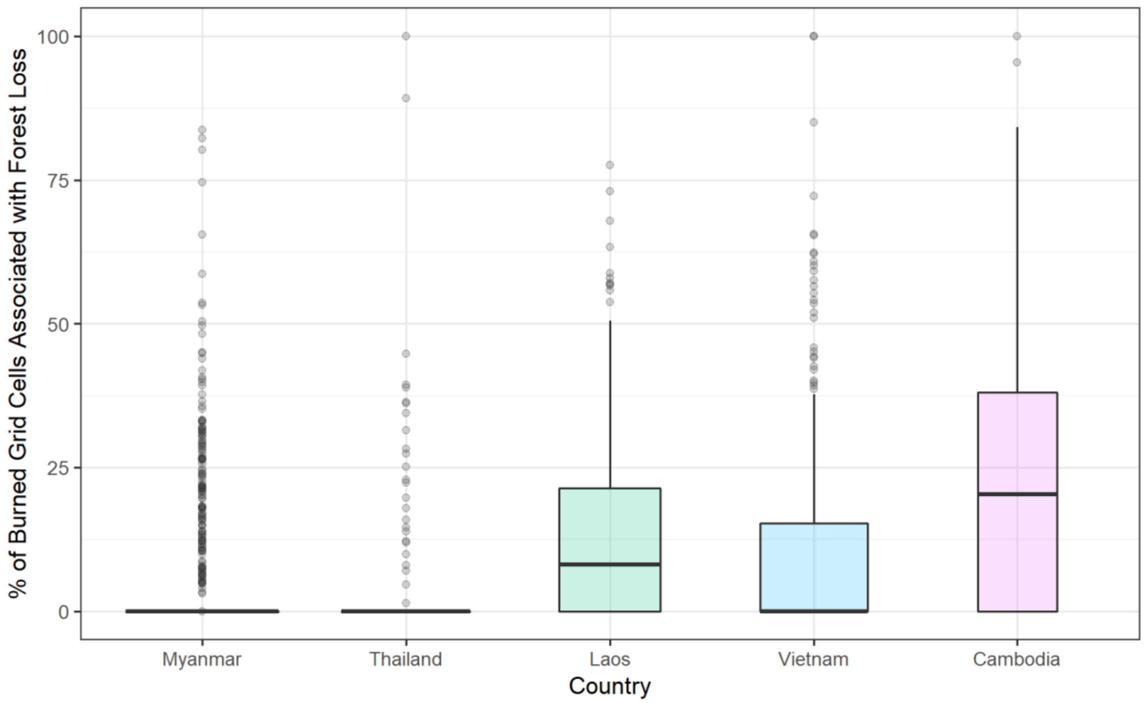

Figure 15. Boxplots for Forest Loss per Country.

The distribution of the percentage of burned forested grid cells that overlap with forest loss are shown for each country in continental Southeast Asia.

% Forest Fires associated with Forest Loss	
Cambodia	64.97%
Laos	57.45%
Vietnam	36.29%
Myanmar	19.80%
Thailand	5%

Table 9. Forest Fires associated with Forest Loss.

The percentage of forest fires associated with forest loss are shown for each country in continental Southeast Asia.

Chapter 4: Discussion

My research assessed the anthropogenic, climatic, and landcover drivers that influence fire activity and defined the geographic variation of existing fire regimes. Specifically, I found that the important climatic predictors of fire activity are strongly associated with decreased vegetation moisture. Furthermore, I found that human presence and establishments also help define the fire regimes that occur in continental SEA. Finally, I found variations in fire activity depending on land use and landcover. Put together, my research broadly describes how the key drivers of fire relate to observed fire patterns in continental SEA.

4.1 Forested ecosystems have greatest fire activity

I found fire activity to be greatest in forested landcover, with 56% of the fires occurring in mixed forest types. My conclusions are consistent with earlier research that suggested the greatest fire activity in Cambodia is within forested landcover (Jones 1998). Laos and Myanmar are predominately covered in forested landcover (Table 2), and the majority of fires are within forested regions (Figure 5). Cambodia and Thailand have more agricultural land than forests (Table 2) yet displayed similar proportions of fires in agriculture and forest (Figure 5). Forested and agricultural landcover are similarly proportioned in Vietnam (Table 2), but the fires primarily occur in agricultural land (Figure 5). Examining the landcover where fires occur can provide valuable insights into the variation of fire patterns influenced by vegetation types.

Within the fire activity in forested landscapes, the most substantial connections between fire activity and forest loss occurred in Cambodia and Laos. Here, 65% of the burned forested grid cells in Cambodia and 57% in Laos overlapped with forest loss, indicating that fire might contribute to changes in the forested landscapes within these regions (Table 7). Previous research has found that Cambodia has the highest rates of deforestation within continental SEA in recent decades, while Laos displays high proportions of forests that experience disturbance (Potapov et al. 2019). With this, few papers have tied the changing forested landscapes directly to fire activity in this region.

My results suggest that fire may contribute to the deforestation in Cambodia and Laos. For Cambodian fires specifically, my finding is corroborated with results from Min-Sung et al., who found that deforestation in Cambodia was linked to high fire activity (Min-Sung et al. 2023). However, Tyukavina et al. 2022 found contrasting outcomes demonstrating that forest loss in Cambodia and Laos resulted from non-fire deforestation practices. Possible explanations for this discrepancy could be due to the type of deforestation practiced in SEA, where common deforestation practices in Indonesia begin by felling trees prior to burning (Gaveau et al. 2014). Further research could disaggregate the causes of forest loss in SEA and determine whether fire is a driving force for deforestation.

I acknowledge that my forested land classification combines multiple forest types (e.g., seasonally dry evergreen forests and deciduous dipterocarp formations), where forests have varying flammability and fire adaptations (Jones 1998; Bond and Keeley 2005). With the resolution of my study, I am limited in differentiating the variations in forest types. Therefore, my results are generalizations about forest fires, as I cannot distinguish fire activity between different types of woody vegetation.

4.2 Climactic influence on vegetation moisture impacts fire activity

Climatic conditions affecting vegetation moisture, such as temperature and vapor pressure deficit, are key components to fire activity in continental SEA. My results are consistent with existing literature demonstrating the influence of climate on dry vegetation and fire activity (van der Werf et al. 2008; Jiang, Zhou, and Raghavendra 2020; Archibald et al. 2010; Alvarado et al. 2017). Future climate projection models have demonstrated that SEA is expected to experience overall drier conditions (Supari et al. 2020; Tangang et al. 2019; Supharatid, Aribarg, and Nafung 2022), coupled with steadily increasing surface temperatures (Suzuki, Takeda, and Thein 2009; Li et al. 2019). Thus, the projected climatic shifts will likely impact future fire activity.

4.2.1 Evidence for ecological fires

Cluster 1 is a distinct fire regime that is located among the deciduous dipterocarp formations in northeastern Cambodia. Here, frequent fire disturbance contributes to maintaining the distribution between forest and savanna (Pletcher, Staver, and Schwartz 2022). The fire regime identified in cluster 1 shows large, frequent, and intense fires. Large and frequent fires are consistent with fire patterns observed in tropical mesic savannas (Ratnam et al. 2011), however the intensity and overlap with forest loss suggests that fires also contribute to deforestation in this region. Disaggregating the role that fire plays in this ecosystem will require further research into how the landscape is changing and how to define the present ecosystem. Currently, the classification of these forest-savanna mosaics is under debate, where emerging evidence shows that the mosaic structure is misclassified as a forest and should instead be classified as a savanna (Ratnam et al. 2016; 2011). The ecological relationship with fire differs between forests and savannas. Thus, defining the correct ecosystem type affects how fire management policies could change existing ecosystems. My results show the potential for naturally occurring frequent fires to exist in this region in conjunction with deforestation fires, which encourages further research to define and enforce ecosystem-appropriate fire management adaptations.

4.3 Human relationships with fire activity

4.3.1 Human establishments generally result in decreased fire activity

Human presence and infrastructure were inversely related to fire activity, where fires were more frequent in regions with minimal human establishments. Previous studies have shown that urban or developed areas correspond with reduced fire activity due to land management or fire suppression practices aimed at protecting human establishments (Alvarado et al. 2017; Andela et al. 2017; Boulanger et al. 2013). Further, road density and other anthropogenic infrastructure may act as fire breaks or help facilitate fire monitoring and suppression, which results in decreased or minimized fire activity (Oliveira et al. 2012). With the destructive potential of fire near human populations and infrastructure, decreased fire activity with greater human establishments is expected.

4.3.2 Evidence for human-driven fires

4.3.2.1 Human-driven agricultural fires

The fire patterns observed within cluster 4 suggest a fire regime that has been influenced by agricultural activity. Cluster 4 presents large, frequent, and low intensity fires that align with the characteristics of fires commonly used for shifting cultivation in agricultural areas (Devineau, Fournier, and Nignan 2010; T. V. Nguyen et al. 2023; Andela et al. 2017). In the context of the Central Highlands of Vietnam, an shift in the fire regime was associated with widespread agricultural fire practices that increased ignition potential and allowed fires to occur annually (T. V. Nguyen et al. 2023). The high fire activity observed in the Central Highlands of Vietnam resembles the fire regime described for cluster 4, where both regions show increased fire frequency linked to agricultural activity. The fire patterns identified in cluster 4 present strong indications of a fire regime shaped by humans through agricultural land management.

4.3.2.2 Human-driven fires in forests

The fire regime identified in cluster 8 is associated with deforestation fires. Previous research has found that fire patterns tied to deforestation tend to exhibit higher intensity because the fires are used to remove natural vegetation from the area (Cano-Crespo et al. 2022). Accordingly, cluster 8 displayed small, high intensity fires with high associations of burned and lost forest. Further research has demonstrated that frequent forest disturbance occurred in this region due to the high presence of young forests (Potapov et al. 2019). Our results suggest that the fire activity might contribute to the observed forest disturbances within this portion of northern Laos.

4.4 Limitations

My research used remotely sensed satellite data to broadly describe fire-driver relationships. In particular, I used MODIS fire products to quantify fire activity in this study. MODIS products primarily capture large thermal anomalies, and does not capture small, low-intensity fires (Boschetti and Roy 2008; Maier et al. 2013). Therefore, my research is biased towards emphasizing fire regimes with larger and more intense fire events, such as deforestation fires. As a result, my research struggles to capture the surface fires that occur in forest-savanna landscapes, where fires are low-intensity and obscured by intact canopy cover. Future work could supplement my research with ground-verified fire data or higher-resolution imagery to incorporate finer-scale fire activity.

Furthermore, my variables were selected by conducting a broad literature review identifying primary drivers of fire activity globally, and considered when remotely sensed datasets were available for SEA. I did not include all the variables that impact fire activity, such as soil moisture, wind, and topography (Bond and Keeley 2005; Boulanger et al. 2013). Local weather stations and field data were also absent from this study. Additional research could include supplementary information or data sources to enhance and validate how the variables drive fire activity.

Previous studies have investigated drivers of fire activity with finer temporal resolutions, resulting in a greater understanding of annual and interannual effects on fire (Corona-Núñez and Campo 2022; Zubkova et al. 2019). Interannual analysis allows for investigation into the effects of climatic anomalies, which has helped identify drivers of extreme events (Jain et al. 2022; Vadrevu et al. 2019). My study aimed to describe an overview of the long-term fire regime trends. Therefore, investigating fire-driver relationships at shorter time scales still remains necessary for future consideration.

4.5 Key Takeaways and Significance

Continental SEA encompasses different fire regimes driven by variations in human activity, climatic factors, and landcover types. Climatic factors that affected vegetation moisture (i.e.: temperature, dry season severity, and vapor pressure deficit) and human establishments were important predictors of fire activity. We identified fire regimes that were associated with human drivers, such as deforestation in Cambodia and Laos and agricultural activity in Vietnam. We also distinguished ecological fires in the forest-savanna mosaics in Cambodia. Identifying the geographic distribution of fire patterns and their underlying drivers is essential for understanding Southeast Asian ecosystems, which could further inform ecologically appropriate fire management solutions.

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