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SPATIOTEMPORAL ANALYSIS OF WILDFIRE OCCURRENCE IN PERLIS FROM YEAR 2014 TO 2024

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Abstract:

Wildfires adversely impact the economy and the environment globally. A varied combination of natural, anthropogenic, and climatic factors influences the frequency, intensity, and location of occurrences. Thus, this study aims to examine the decadal pattern of wildfires in Perlis. This study analyses the frequency and density of wildfire incidents from year 2014 to 2024, utilizing fire incident statistical data acquired from Perlis State Fire and Rescue Department. Spatial mapping and statistical analysis were employed to demonstrate the spatiotemporal patterns of fire incidents. Kernel Density Estimation (KDE) was carried out to highlight the hotspot region across Perlis state. The analysis of fire case distribution and density was segregated into three political boundaries. The results demonstrate that the patterns of fire outbreaks fluctuated between years. However, there is a significant increase in the number of fire outbreaks from year 2022 to 2024. The temporal analysis illustrates that most of the stipulated years recorded the highest number of fire cases in March. While the spatial analysis revealed that Kangar and Padang Besar experienced a moderate to very high density of cases, this study provides policymakers, land managers, and researchers with essential knowledge regarding the mechanisms of long-term wildfires, grounded in robust evidence. This understanding can assist in reducing the likelihood of wildfires and safeguarding ecosystems and populations in a changing climate.

Keywords:

Spatiotemporal Analysis, Kernel Density Estimation (KDE), GIS, Fire Hazard

Introduction

Wildfires are a prevalent natural hazard that significantly affects the economy, society, and environment globally. In recent decades, wildfires have become increasingly frequent and intense in numerous regions globally. It is estimated that about 200 million km² of forest area have been degraded in under 200 years owing to wildfires (Asori & Appiah, 2021). The elevated occurrence of wildfires can be ascribed to climatic reasons, as climate change has elevated temperatures and diminished relative humidity (Marey-Perez et al., 2023). As fire patterns are unpredictable, it is essential to understand the dynamics of wildfire propagation to develop effective strategies for preparedness, management, and prevention.

Several studies in different parts of the world revealed an increasing pattern in wildfire occurrence. A district in Ghana recorded an increasing number of cases of wildfire occurrence from year 2017 to 2020 (Asori & Appiah, 2021). Moreover, during the year 2010 to 2020 period, the Golestan National Park, in Iran, underwent a nearly twofold increase in fire ignition and burned areas (Jahdi et al., 2023). Another study conducted for the whole geographic area of Iran also reveals the northwest, northeast, and central regions of Iran showing an increasing fire density during the summer season (Karami & Tavakoli, 2025). In the past few years, the world has been jolted by a series of wildfire outbreaks, beginning with Australia's "Black Summer" in year 2019, followed by the Lahaina fire in year 2023, and the most recent Los Angeles wildfire in January 2025. Likewise, a number of forest fires that have burned hundreds of acres have also occurred in Malaysia.

Forest fires occur in Malaysia on an annual basis, regardless of their severity. In recent years, the magnitude of forest fires has significantly increased, often requiring several days to suppress. According to local newspapers, the forest fire in Kedah in year 2020 required more than 72 hours, while the fire in Pahang in year 2024 required 10 days, and the most recent fire in Sarawak required nearly five days to be extinguished (Kawi, 2025; Yusof, 2024). Despite the variability in frequency and severity of fires, these occurrences continue to pose substantial threats to the ecosystem, particularly during arid conditions. Hence, understanding wildfire patterns is crucial for both scientific study and practical decision-making. Long-term analysis can help experts determine how wildfires affect the global greenhouse gas balance and other environmental components. Therefore, assessment of the past and present fire regimes using Geographic Information System (GIS) is convenient to evaluate the temporal and spatial patterns of fires.

GIS is invaluable for analysing wildfire patterns as it facilitates the collection, aggregation, and visualization of wildfire data across temporal and spatial dimensions. Spatial analysis examines the locations of wildfires, while temporal analysis examines patterns over time. The pattern and density of forest and land fires are crucial in identifying priority regions for managing these, as the frequency of such fires has escalated annually (Arisanty et al., 2021). Wildfire hazard zones can be established by analysing the time and frequency of historical fire events in conjunction with pertinent climatic conditions (Karami & Tavakoli, 2025). Comprehending wildfire analysis is crucial for evaluating the possible impacts of wildfires on both human populations and the environment.

The study on wildfire spatiotemporal analysis has improved due to advancements in technology and data collection methods. These improvements facilitate the prediction, monitoring, and mitigation of the impact of wildfire. The incidence of fires increases during periods of drought

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and insufficient rainfall; therefore, early-warning systems that integrate seasonal climate predictions, facilitated by surveillance technologies such as satellites and drones, can assist agencies in preparing for high-risk periods and optimizing resource allocation. These strategies enable local authorities to respond prior to situations attaining the highest risk level, such as deploying firefighting teams in advance, conducting targeted patrols, and issuing public alerts. Post-fire initiatives like as damage control, reforestation, and community support programs can mitigate the enduring impacts on the environment and society.

Hence, this study aims to analyse the temporal and spatial patterns of fire incidents from the year 2014 to 2024 in Perlis. Through the analysis of fire occurrences' temporal and spatial distribution, the study seeks to identify trends, hotspots, and patterns that could improve the state's fire management and mitigation strategies. The study is limited in describing the locations and time frames of fires due to constraints in data availability. This analysis does not examine the variables or causal factors that initiate fires. Despite this constraint, the study is expected to provide valuable insights into the occurrence of fires and identify areas that are particularly vulnerable or prone to increased fire incidents. These insights can assist legislators, local governments, and fire control groups in determining priorities for monitoring, preparedness, and resource allocation. This will ultimately result in enhanced tactics for fire prevention and risk reduction in Perlis.

Literature Review

Definition of Wildfire

Wildfire, as defined by the National Fire Protection Association (NFPA), is a fire arising from an unintentional ignition source that propagates within wild land areas. Wild lands may encompass forests, grasslands, bush lands, and various habitats, including agricultural lands. In recent years, wildfires have attracted considerable attention due to their substantial impacts on ecological, economic, and diplomatic sectors (Ya'acob et al., 2022). Wildfires can have significant adverse impacts on the environment, public health, the financial sector, and communities. Along with the loss of life and property, this catastrophe also contributes to the degradation of forest ecosystems and their biological resources (Talukdar et al., 2024). Wildfires additionally eliminate rangeland species and forest trees, harm wildlife habitats and soil, degrade natural landscapes, decrease soil acidity, diminish nitrogen reserves, and promote the proliferation of inferior plant species (Velayati et al., 2024). Due to climate change and increased human development, wildfires are expected to wreak more significant destruction on a global scale in the future.

Theoretical Framework of Wildfire Ignition

Global ecosystem patterns and processes, such as the structure of vegetation, the carbon cycle, and climate, are influenced by fire. The ignition and distribution of fire can be illustrated using the fire behaviour triangle, as it models how weather, fuels, and topography have an impact on fire ignition, spread, and behaviour on the landscape. The weather comprises wind, temperature, drought severity, relative humidity, and precipitation. This component is frequently the most unpredictable and can rapidly influence the intensity of a fire, either increasing or decreasing its activity (Bowman et al., 2009). Fuels encompass the type of vegetation, amount, soil structure, and moisture content of combustible materials, such as plants or other substances. Grasses, shrubs, and other fine fuels ignite and propagate rapidly in low-intensity fire, while dense forest fuels can result in high-intensity and high-severity flames during dry weather conditions (Dillon et al., 2015). The fuel's moisture content is significantly

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crucial since drier fuels ignite more readily and facilitate the rapid propagation of fires. The topography of the terrain and land use also influences fire behaviour by altering air circulation, heat transfer, and moisture evaporation. Land use such as agriculture, forestry, and livestock grazing alters the continuity of fuel and the quantity of fuel required to ignite a fire. Commonly, vegetation fields facilitate the rapid spread of wildfires throughout the area due to the dense growth and continuous spatial structure, hence elevating the likelihood of neighbouring natural ecosystems igniting (Braun et al., 2021). The incidence of fire was also influenced by topographic diversity and altitude, indicating that regions at elevations of 50–200 m with lightly sloped terrain are likely to emerge as hotspots for fire activity (Masrur et al., 2022). These three factors collaboratively determine the rate of fire propagation, the duration of the flames, and the overall behaviour of the fire. The fire behavior triangle conceptual diagram was illustrated in Figure 1.

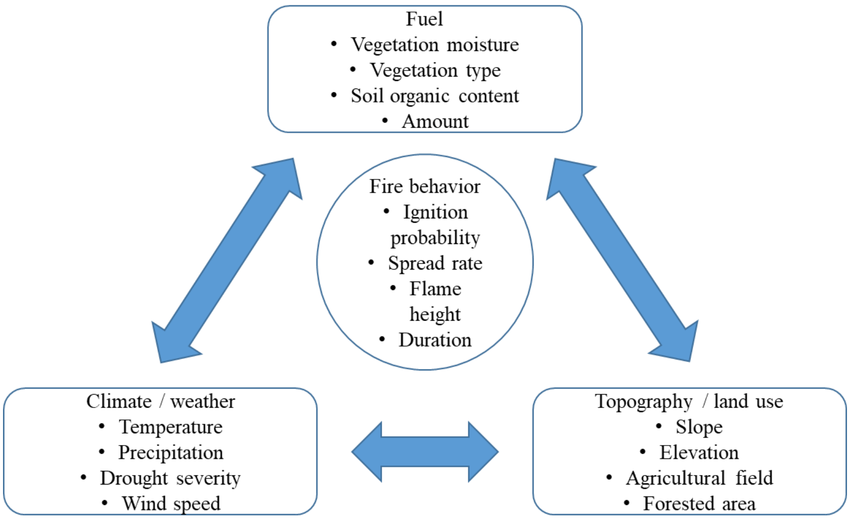

Figure 1: Fire Behaviour Triangle Model

Source: Countryman et al. (1968)

The Relation between Wildfire Occurrence and Climatic Conditions in Southeast Asia

Global climate condition, El Niño, is an inter-annual phenomenon that induces arid conditions and precipitates drought in numerous areas throughout the region (Khan et al., 2020). The occurrence of El Niño results in a delayed onset of the rainy season and extends the duration of the arid season (Nurdiati, Bukhari, et al., 2022). This phenomenon has the potential to exacerbate the severity of wildfires within the region. During El Niño events, extensive areas of the region experience prolonged drought, reduced precipitation, and elevated surface temperatures. All of these factors facilitate the ignition and persistence of fires in vegetation and peatlands. Numerous studies have shown an alarming statistical association between the intensity of El Niño and heightened fire activity. A study by Nurdiati et al. (2022), certain regions of Indonesia experience a surge in fire activity exceeding 70% during El Niño events due to exacerbated droughts throughout Southeast Asia. Besides, Cambodia, Myanmar, and Thailand also exhibited comparable outcomes, with an increase in severity of 25% in the hotspots during El Niño (Nurdiati et al., 2022).

Furthermore, investigations on the calculation of the fire weather index (FWI) under various optimal conditions in SEA reveal that reduced relative humidity results in an approximate 25% rise in FWI during El Niño years (Zheng et al., 2023). Another study conducted by Yulianti & Hayasaka (2023) reported that in 2015, a notably active fire season transpired, characterized

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by a fire rate around four times the average, coinciding with an extended drought attributed to El Niño. The impact of El Niño on fires significantly influences air quality and public health. In intense El Niño years, fires in Southeast Asia have been shown to elevate fine particulate matter ($PM_{2.5}$) and ozone concentrations to detrimental levels for public health (Hu et al., 2025). Studies on climate consistently indicate that El Niño significantly contributes to fire danger in Southeast Asia as it reduces precipitation and exacerbates droughts, hence creating favourable circumstances for wildfires.

Methods for Spatiotemporal Analysis for Wildfire Mapping

The analysis of spatial patterns of wildfire incidents utilizes GIS methods, such as Kernel Density Estimation (KDE), spatial autocorrelation, and local cluster detection. Spatial autocorrelation is characterized as the relationship between variable properties within geographic space and serves as a fundamental method for assessing whether occurrences of wildfires, extent of burnt regions, or fire severity metrics exhibit statistically significant clustering across a landscape (Xiong et al., 2019). Although this method has been extensively employed in wildfire spatial analysis, there appear to be relatively few concerns associated with it. Spatial autocorrelation, such as Moran's I, can complicate linear models by distorting parameter estimations in the presence of geographically contiguous sampling structures or observations (Schag et al., 2022). Not only that, the Moran's I approach yielded more interpretable results for larger countries, but it is not appropriate for smaller countries (Baykal, 2025). Thus, this approach is not employed in this study.

The local cluster detection, such as Getis-Ord GI*, is an analysis that calculates z-scores and p-values to determine whether to reject the null hypothesis of total spatial variation among the features (Rossi & Becker, 2019). Similar to the spatial autocorrelation method, local cluster detection also exhibits a few issues. Getis-Ord Gi*'s hotspot analysis is usually affected by the forest fire contributing factors employed in the validation of the hotspot (Zahran et al., 2020). Moreover, Getis-Ord Gi* exhibited a high incidence of identifying risky locations; yet, its positive accuracy index (PAI) was poorer than other alternative methodologies, indicating that it may detect hotspots more effectively but with lower precision. Hence, this method is excluded from this study.

Although KDE is a non-statistical hotspot analysis method, it demonstrated greater accuracy and reliability than Getis-Ord Gi* in identifying forest fire hotspots (Zahran et al., 2020). The KDE method has increased the precision and dependability of fire ignition mapping by using a symmetric probability density function for every point location, producing a smooth cumulative density function (Liu et al., 2024). This approach is also suitable to be applied for a smaller region compared to spatial autocorrelation and local cluster detection methods (Baykal, 2025). Therefore, this study utilized KDE on fire occurrence points within ArcMap 10.3 software to identify wildfire hotspots, thereby delineating areas characterized by elevated wildfire occurrence density.

Spatial Analysis Method

The KDE is a non-statistical method utilized to estimate probability densities of points and polylines for hotspot studies (Asori & Appiah, 2021). The KDE approach employs kernel density interpolation to explain the distribution of event spots inside the study area (Ma et al., 2022). This method functions by generalizing or smoothing discrete point data, thereby generating a continuous density surface from discrete points. The generated continuous surface

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has the potential to reduce the impact of uncertainty regarding fire location. A density surface is created by adding the values at every location, even for locations where no observations were made, and spreading them out based on a predetermined function, and the generated density map is influenced by the search radius (Baykal, 2025). The KDE was projected using the expression:

Equation 1: KDE Expression Used in ArcMap 10.3 Software

$$KDE = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{X - X_i}{h}\right)$$

Source: Ma et al., (2022)

Where K denotes the kernel function, and h > 0 represents a blurring parameter, commonly referred to as the bandwidth. x represents the dataset of wildfire incidents, denoted as (X1, X2, ... Xn), and Xi signifies the distance from the estimated point to sample point i. It has been effectively employed to estimate probability densities across a broad spectrum of applications, including crime mapping, population mapping, and disease outbreaks. This function operates efficiently across multiple data distribution types.

Temporal Analysis Method

Temporal analysis broadly examines changes across time by identifying patterns, trends, and shifts over various time periods. Cross-period comparison, either daily, weekly, monthly, or annually, constitutes a core methodological approach in temporal analysis, involving the examination of data or phenomena across multiple time intervals to elucidate patterns of continuity and change. The cross-period comparison is predominantly employed to track progressive changes across several applications, including deforestation and afforestation rates, crime rates, and alterations in land use.

The Mann-Kendall test is a widely utilized non-parametric statistical method for identifying trends in time series data, such as patterns of wildfires over time (Salguero et al., 2020). It assesses whether a continuous positive or negative trend exists throughout time, regardless of the data's normal distribution or linearity. The test can determine whether there is a statistically significant increase or decrease in the frequency of wildfires, the extent of area burned, or the intensity of the fires throughout the research period (Shikwambana & Kganyago, 2023). The test determines a statistic by analysing the sequence of data points and employs the sign of the differences between all pairs of observations to identify consistent patterns (Liu et al., 2024). A positive Mann-Kendall statistic indicates an upward trend, while a negative value signifies a downward trend. Subsequently, standard tables or p-values are employed to ascertain the significance of the trend. This made it an excellent option for wildfire statistics, which typically exhibit unusual trends and outliers.

Methodology

Study Area

Perlis is the northernmost state in Malaysia that lies between latitude 6°30' N and longitude 100°15’ E. The majority of the landscape was covered by semi-deciduous forest and agricultural land. The study area was divided into three political boundaries: Padang Besar, Kangar, and Arau. Despite being the smallest state in Malaysia, Perlis is a state that is generally

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hotter than other states, with the highest temperature recorded being 40°C. Perlis serves as an excellent location to investigate the wildfire patterns, since the vulnerability to seasonal monsoon variations enables experts to see distinct alterations in the timing of fire occurrences. Additionally, fire data that is readily accessible is typically maintained by local authorities, which facilitates the development of precise time-series analyses. The accessibility of reliable, localized data enhances the feasibility of conducting a comprehensive wildfire analysis study. Figure 1 shows the selected area for this study.

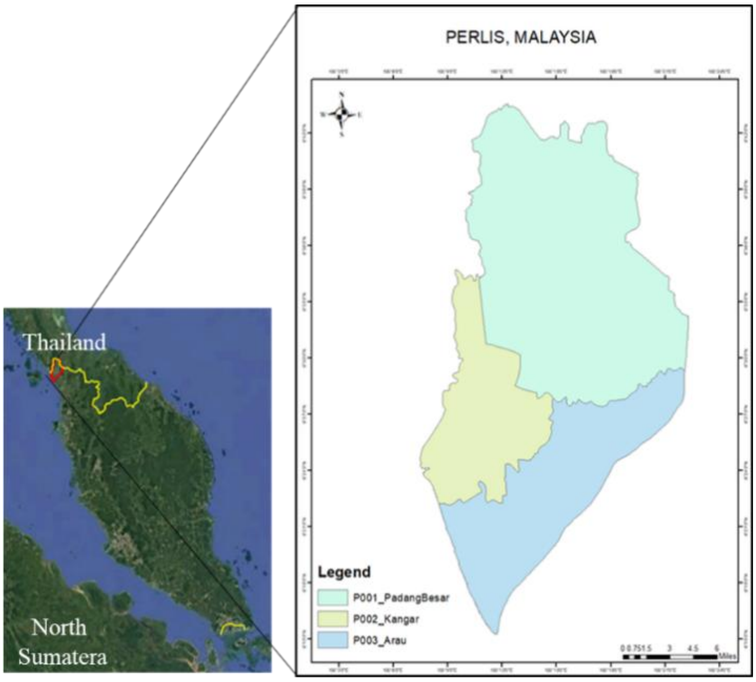

Figure 2: Study Area Map

Source: author

Data Acquisition and Extraction of Fire Incidents

The data processing was classified into several phases, which are data acquisition, data filtering, geolocation, data overlaying, and visualization. There are two datasets used in this study, which are fire cases statistical data and Malaysia's administration boundary shape file. To identify relevant cases, the statistical data on fire incidents were initially analysed. The emphasis was on the record of fire cases involving shrub lands, vegetation, and forested areas that occurred throughout the study period. Insignificant fires, such as those involving buildings or vehicles, were excluded. Data cleansing was performed to eliminate duplicate entries and rectify issues with coordinates, dates, and location names.

Spatial Analysis of Fire Incidents

The filtered data of fire cases were georeferenced using the descriptive locational information. The Perlis boundary was delineated using the Malaysian administrative shape file obtained from open open-source website. This step ensures that all spatial analyses are conducted within the studied region. After that, the georeferenced fire cases were imported into the spatial processing software and overlaid with the Perlis administrative shape file, permitting the correlation of each fire incident to its political boundary. KDE is employed on the geolocated data to identify and illustrate areas of high concentration of forest fire occurrences in Perlis. This analysis facilitates the identification of fire incidence patterns and clustering tendencies.

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Temporal Analysis of Fire Incidents

A temporal statistical graph was created in MS Excel, utilizing the filtered dataset to illustrate the temporal variations of wildfires. This graph depicts the annual and monthly variations in the incidence of wildfires and can assist in identifying seasonal patterns or long-term analysis of the frequency of fire occurrences. A spatial distribution map was produced showing reported cases segmented by political boundaries for each studied period. This enables the identification of regions with a high frequency of fires or recurrent fire incidents. Figure 2 illustrates the overall methodology of this study. Then, the Mann-Kendall Test was carried out using the MS Excel plug-in, and the results were analysed. To perform the Mann-Kendall test for temporal analysis of wildfires, it is necessary to first construct a time series dataset indicating the occurrence of wildfires over consistent time intervals. Once the time series is prepared, the Mann-Kendall test is employed to determine the presence of a statistically significant monotonic trend in the incidence of wildfires over time. The test functions by analysing all pairs of data points to determine their directional changes, as shown in Eq. 2, where n represents the quantity of data points, x_i and x_j denote the observed values at time indices i and j, respectively.

Equation 2: S Statistics of Mann Mann-Kendall Test

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i)$$

Source: Nunes (2025)

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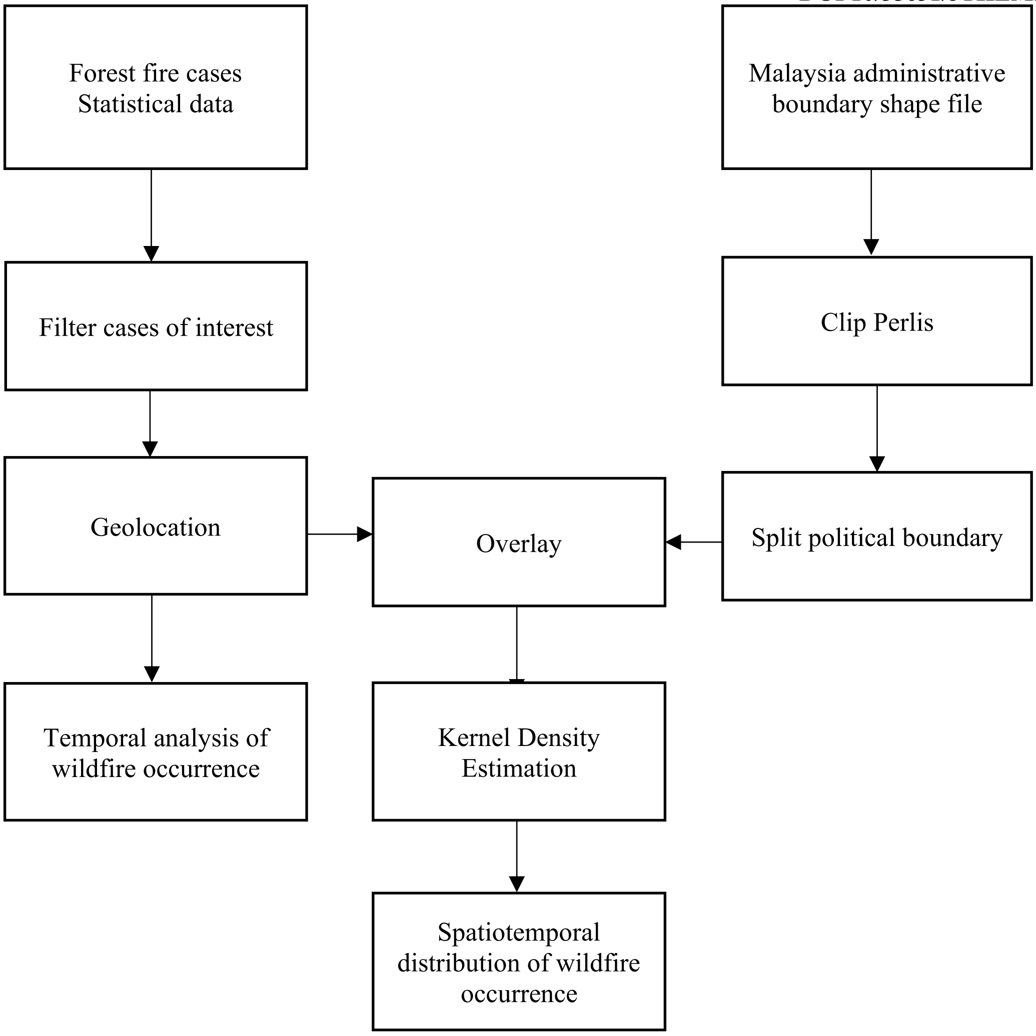

Figure 3: Overall Workflow of the Proposed Study

Source: author

Result and Analysis

Spatial Distribution of Fire Occurrences

The spatial analysis of wildfire occurrence was conducted using the KDE method on number of wildfire cases in Perlis. The map illustrates the spatial distribution of wildfire occurrence in Perlis from year 2014 to 2024. KDE integrates individual points into a continuous surface and employs colour gradients to depict areas with varying data concentration. The fire cases distribution map for each political boundary is presented in Figure 4. The colour gradients used are white for “very low density”, light blue for “low density”, pale yellow for “moderate density, orange for “high density, and red for “very high density”. The spatial analysis demonstrated that wildfires occur in various regions of Perlis, with clear clusters in specific administrative regions. The KDE analysis ranged from 0.012 to 0.254 fire/km^2 in year 2014, while in year 2024, the KDE ranged from 0.014 to 0.338 fire/km^2.

Figure 4 indicates that the majority of wildfires occur in the central and southern parts of Perlis. From the figure, the Kangar area has the majority of fire occurrence densities classified as "moderate to very high density". The pattern is consistent for each studied period. Meanwhile,

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the Arau region demonstrates "moderate to very low density" for each year, and Padang Besar exhibits "moderate to very low density" from year 2014 to 2017, but in the subsequent years, Padang Besar has experienced the majority of fire occurrence densities classified as "moderate to very high density". From year 2014, the high-density fire outbreaks clustered mainly in one region, which is in central Kangar. However, the changes in fire patterns started in year 2019, when the "moderate to very high density" was evenly scattered across the state.

The spatial analysis of wildfire occurrences from year 2014 to 2024 across LULC categories in Perlis displays distinctive patterns that illustrate the impact of land characteristics on fire distribution. Figure 5 demonstrates the wildfire distribution overlaid with the Land Use/Land Cover (LULC) map. The LULC categories were symbolized by colors, where peach for barren land, red for built-up area, dark green for forested region, yellow for paddy fields, light green for vegetation and shrub lands, and blue for water bodies. From the figure, it can be seen that wildfires predominantly occur in the built-up area, followed by paddy fields with 42% and 37% respectively. The forested regions, conversely, experience significantly fewer fire incidents; similarly, the vegetation and shrub land areas experience a moderate frequency of fire occurrences. The barren land and water bodies' exhibit minimal to no fire activity, as anticipated, since desolate areas lack burning substances, and water bodies generally inhibit the propagation of fires.

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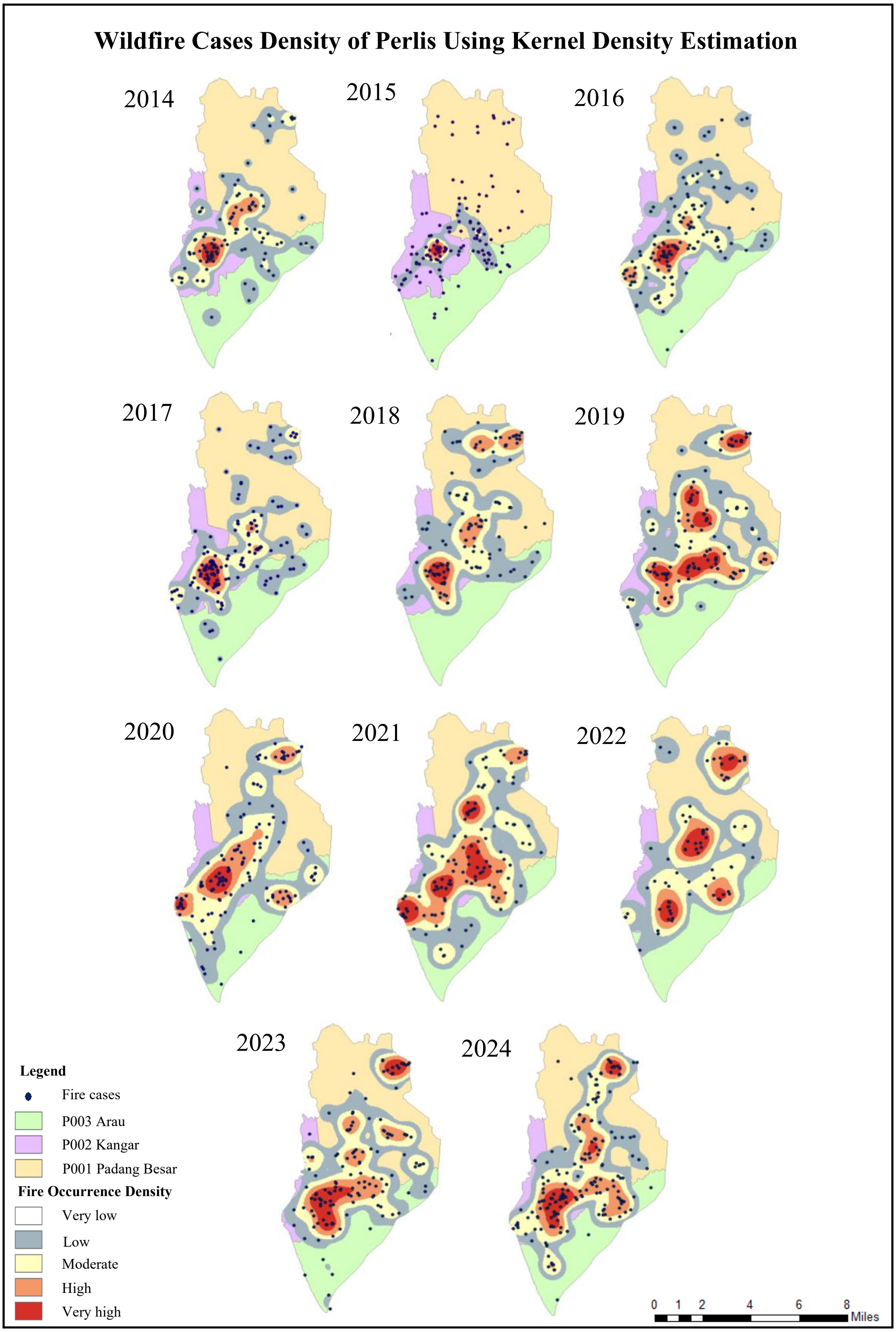

Figure 4: Distribution and Density of Wildfire Occurrences from Year 2014 to 2024 in Perlis

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Source: author

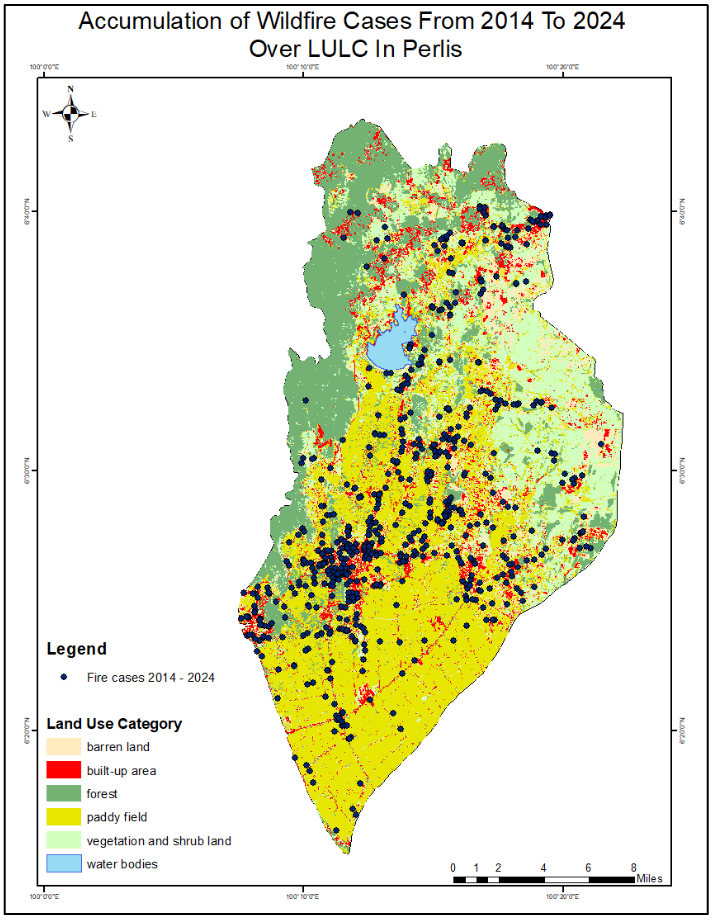

Figure 5: Distribution of Wildfire from Year 2014 to 2024 over LULC in Perlis
Source: author

Temporal Analysis of Fire Occurrence

The result revealed fluctuations in the temporal trend of fire occurrence in Perlis. The statistics revealed that a total of 1,600 cases were reported involving shrub and forest fires from year 2014 to 2024. Figure 6 outlines the total monthly fire cases reported over 10 years to identify the months with the highest incidence of fire events. From the figure, there is a distinct pattern indicating that the fire incidents are increasing annually from February to April, reaching a peak in March. Then the numbers experience a significant decline after April and remain consistently low from May to November. It can be seen that a similar pattern recurs each year. This can be inferred that the hot and arid conditions observed throughout February to April are followed by the rainy season in September to November.

The trend of fire cases reported each year is presented in Figure 7. It was found that 63.11% of wildfire occurrences has been recorded from year 2014 to 2024 showing an increasing trend. In addition, there is an increasing trend line during the observed period with sharp rises from year 2022 to 2024. The highest number of cases was noted in year 2024 with 199 cases, while the lowest was in year 2014 with 122 cases. The frequency steadily increased from year 2014 to 2017, and started to slowly decline until the year 2019. A significant drop was noted in year 2022. Notably, there has been a significant increase in the frequency of wildfires from year 2022 to 2024. From the graph, it can be seen that over the last 10 years, more than 100 cases

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were reported each year. The figures may be attributed to the predominance of shrub lands, agricultural lands, and forests in Perlis.

A Mann-Kendall trend analysis was employed to assess the presence of a statistically significant temporal trend in the annual wildfire count. Table 1 shows the summarisation of the Mann-Kendall test for wildfire occurrence from year 2014 to 2024. From the figure, it can be seen that the z-statistic was 3.317, and the p-value was 0.005. The observed rise in wildfire incidents over the study period indicates statistical significance since the p-value is 0.005 lower than the conventional significance threshold of 0.05. The results suggest that, although annual variations, an efficient long-term trend in wildfire occurrence can be established from this dataset and analysis.

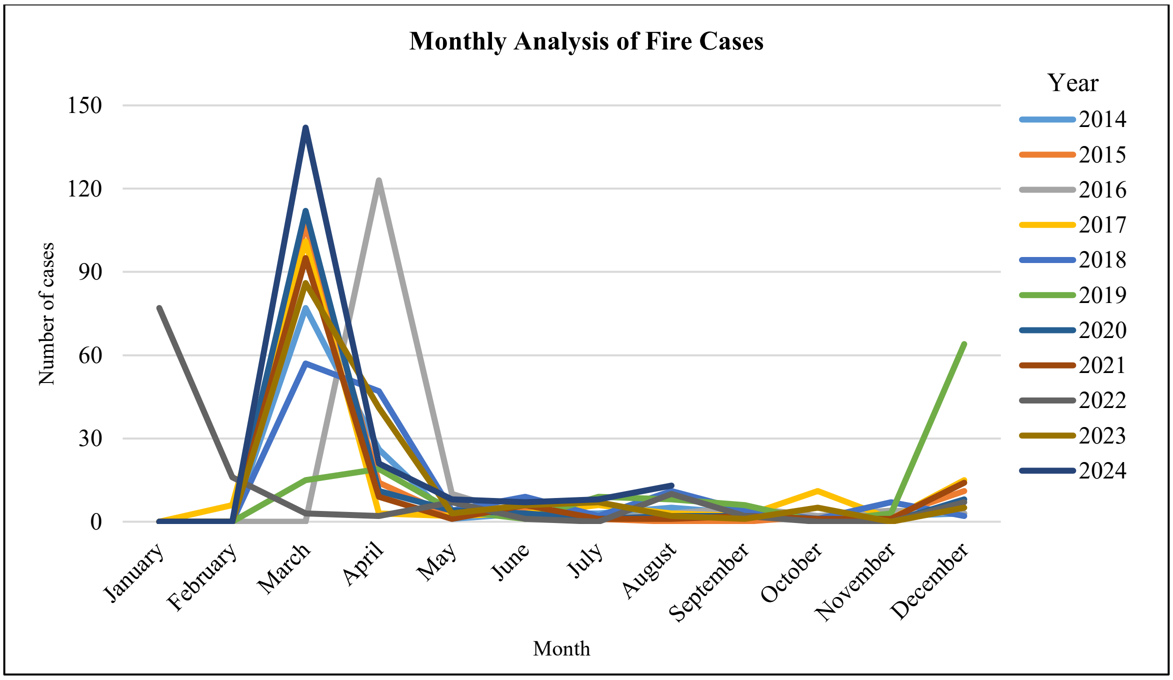

Figure 6: Monthly Analysis of Fire Cases from Year 2014 to 2024 in Perlis
Source: author

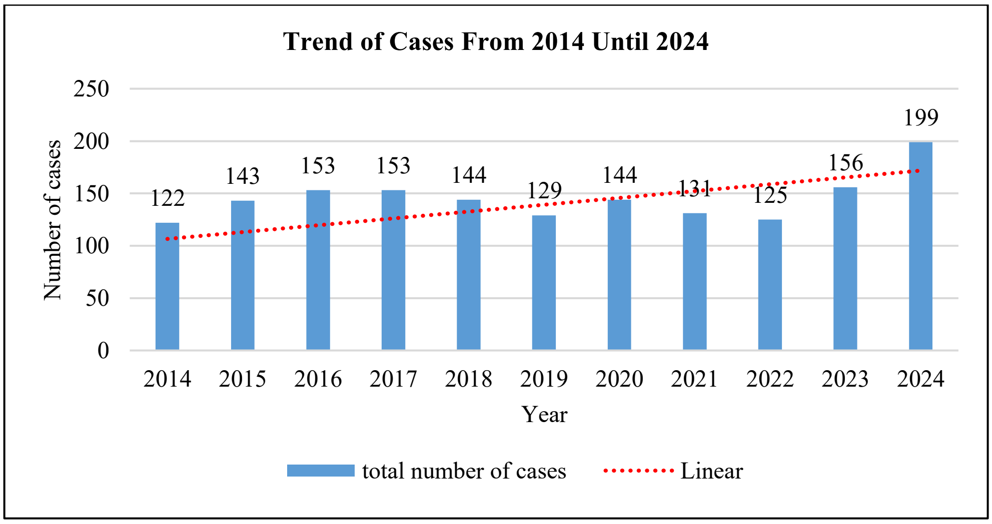

Figure 7: Trend of Annual Cases of Wildfire in Perlis from Year 2014 To 2024
Source: author

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Table 1: Mann-Kendall Trend Analysis

Variable	Mann-Kendall S	z-statistics	p-value	Confidence interval	Trend direction
Number of cases	13	3.317	0.005	95%	Increasing

Source: author

Discussion

The spatial analysis of wildfire occurrence revealed that the majority of wildfires occur in the central and northern regions of the state, particularly in areas characterized by agriculture, open grasslands, and secondary forests. These results match those observed in earlier studies, where the data indicate that the majority of hotspot occurrences are predominantly found in regions characterized by forest and oil palm plantations (Thoha et al., 2020). A similar study by Talukdar et al. (2024) also revealed that the highest forest fire density was experienced by the natural vegetation area and shrub lands, similar to the findings of this study. Apart from land cover factors, anthropogenic factors can also lead to fire outbreaks. The high-density clusters in the central region are also in proximity to residential and industrial areas, indicating that human activity significantly contributes to the causes of fire. This study supports evidence from previous observations that outlined a great population density resulting in many forest fires, and human activities exhibited moderate to high influence on the fire risk model (Wu, 2021; Horn et al., 2025).

The distribution of wildfire across different LULC categories has revealed that most of the cases occur near built-up areas and paddy fields. The dense pattern likely indicates fires initiated by humans, such as refuse incineration, roadside sparks, or accidental ignitions. The concentrated clustering indicates that seasonal agricultural practices, residual dried crop residue, and open burning approaches are presumed to contribute to elevated ignition frequencies within these regions. This coincides with the findings by Guo et al. (2024), where the incidence of minor fires in urban areas has significantly risen since year 2010. The historical severity and frequency of wildfires are rising due to the complex relationship between climatic changes and human activities (Naser & Kodur, 2025). Similar to the findings of this study, Zhang et al. (2025) revealed that the frequency and intensity of wildfires were markedly elevated in agricultural regions due to slash-and-burn activities.

Meanwhile, the temporal analysis of wildfire incidents in Perlis during the studied period reveals considerable inter-annual and seasonal variations, underscoring the significant influence of climatic factors, human activities, and land-use practices on fire patterns. The findings indicate that wildfires predominantly occur between February to April, which coincides with the arid phase of the northeast monsoon. The frequency of the events is reduced between May to October, when the season is humid. The increasing patterns are most likely associated with an extended drought period and elevated temperature during the El Niño phase that accelerates the dehydration of vegetation. In accordance with the presented results, a previous study conducted by Salsabila et al. (2020) has demonstrated that incidents of fire were recorded between July and December, coinciding with relatively low average precipitation levels. These results are also in agreement with those obtained by Chew et al. (2022), where the finding clearly demonstrates that the months of February, March, and April have the maximum number of fire incidents due to hot and dry weather within these months.

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The declining patterns from May to October are probably related to consistent rainfall, which elevated humidity and reduced the surrounding temperature. Fire incidents decreased during the wet season due to precipitation's substantial impact on soil moisture and vegetation rehydration levels. There is a low possibility of fire outbreaks when the vegetation and soil are sufficiently rehydrated. There are similarities between the findings in this study with those described by Chew et al. (2023), where a comparison of the rainy and dry seasons reveals that precipitation had a substantial effect on the frequency of fire occurrences and the temperature of the surrounding area. Besides, a study by Velayati et al. (2024) also demonstrates that a gradual decrease in the frequency of fires was observed as precipitation increased. These results are also supported by the evidence from previous observations, where forest fires are reduced when precipitation increases, and the soil moisture level has a substantial influence on forest fires, with fires decreasing as humidity levels rise (Karurung et al., 2025). Apart from climatic factors, the reduction in the number of cases between year 2018 to 2019 and year 2021 to 2022 was because to the campaign and mitigation action taken by Perlis state‘s Department of Environment (DOE). As reported by DOE Malaysia (2022), the substantial decrease in the number of cases in year 2022 was due to Perlis's DOE implementing measures to prevent open burning, along with campaigns conducted in Perlis to raise awareness about open burning.

Conclusion

Wildfires were observed to occur most frequently between February and April, which coincides with the northeast monsoon's driest period. During this period, the moisture content of vegetation significantly decreases, facilitating the ignition of fires. The yearly variations in period correspond with the persistent high-density regions on the KDE map. This indicates that fire-prone regions remain consistent over time; however, their intensity fluctuates annually. The long-term trend visualization indicated a gradual increase in the number of fires during the extremely dry season associated with the El Niño phenomenon, particularly between year 2022 and 2024, mainly clustered in the Kangar and Padang Besar region. The spatiotemporal study of fire provides critical insights into the patterns, causes, and impacts of fire occurrences across spatial and temporal dimensions. These studies demonstrate how climate change, land use alterations, and human activities influence the frequency, intensity, and propagation of fires through the integration of geographical data, GIS, and temporal modelling. Understanding the interaction of these factors facilitates the prediction of fire occurrences, aids in the strategic allocation of resources for fire suppression and response, and informs land management and policy decisions aimed at mitigating fire risks. Future spatiotemporal wildfire studies need to emphasize the integration of high-resolution, multi-source datasets to improve the accuracy and predictive capability of fire regime models. Modern satellite innovations such as VIIRS, Landsat Collection 2, and hyperspectral missions enable enhanced observation of fire ignition and propagation. Additionally, studies should evaluate the impacts of governmental initiatives and land-management strategies on long-term wildfire patterns. Further study may assess the influence of zoning regulations, prescribed burning programs, wildfire-resistant construction codes, and community preparedness initiatives on ignition patterns and fire intensity across temporal and spatial dimensions. Ultimately, spatiotemporal wildfire analysis serves as a crucial tool for enhancing environmental resilience, safeguarding ecosystems, and ensuring community safety in the context of climate change.

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