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Investigating the Relationship between the Influencing Fire Factors and Forest Fire Occurrence in the Districts of Rompin, Pekan, and Kuantan in the State of Pahang, Malaysia, Using Google Earth Engine

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***Abstract*— Forest fires pose a significant threat to ecosystems and human livelihoods. Understanding the role of climatic factors in fire occurrence is crucial for effective fire management and prevention. This study analyses the influences of temperature, precipitation, and wind speed on fire incidents in the districts of Rompin, Pekan, and Kuantan in Pahang, Malaysia. The investigation is motivated by newspaper articles dated early March 2021, which report that the fires in these districts were triggered by an extended period of hot and dry conditions, as highlighted by the Director of the Fire and Rescue Department of Pahang, Malaysia. However, no further investigation or detailed discussion has been deliberated. By examining the historical climatic data and fire incidents, this study aims to investigate the relationships between these climatic variables and fire occurrences. The results reveal that higher temperatures and lower precipitation are associated with increased fire susceptibility due to reduced soil moisture. In contrast, wind speed does not appear to impact fire spread significantly. These findings will undoubtedly provide valuable insights into the complex interactions between climatic variables and regional fire incidents, enabling policymakers and fire management authorities to develop targeted fire prevention and mitigation strategies.**

***Keywords*—Forest fire; Google Earth engine; Malaysia; factors; Pahang; temperature; precipitation.**

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I. Introduction

In recent years, the occurrence and severity of wildfires have become significant environmental concerns worldwide [1]–[6]. These devastating events threaten ecosystems, biodiversity, human lives, and property [7]. The impacts of global climate change have resulted in elevated temperatures and decreased precipitation, creating a prolonged period of dry and warm conditions conducive to the ignition and rapid spread of wildfires [8]. Understanding the underlying climatic factors contributing to fire occurrence is crucial for effective fire management and prevention strategies [9], [10]. However, the specific relationships between climatic variables and fire occurrence require further investigation, particularly in diverse geographic regions with unique climate and environmental characteristics [11]–[13].

Among the examined climatic variables, temperature [14], precipitation [15], and wind speed [16]–[18] have been widely recognized as influential factors in shaping fire regimes. Considering the importance of these three dominant factors, this study aims to comprehensively analyse their impacts on fire occurrence in the districts of Rompin, Pekan, and Kuantan in Pahang. By examining historical climatic data and fire records, we endeavor to uncover the role of these climatic variables in influencing fire patterns and their implications for fire management and prevention efforts.

To achieve this goal, Google Earth Engine (GEE) [19] is utilized to analyze the long-term temperature, precipitation, and wind speed data collected from TerraClimate [20] dataset. We can identify these climatic variables' temporal and spatial patterns by examining their relationship with fire occurrence. The findings will contribute to the scientific understanding of fire-climate relationships and provide valuable information for policymakers, land managers, and local communities in their efforts to mitigate fire risks and protect both the environment and human well-being. Overall, this study aims to enhance our understanding of the complex interactions between temperature, precipitation, and wind speed concerning fire occurrence in Rompin, Pekan, and Kuantan districts.

A. Study Area

The district of Pahang, which includes Rompin, Pekan, and Kuantan, is selected as the area of interest for this study, as shown in Fig. 1. These districts are chosen due to the occurrence of several fires reported in newspaper articles [21]–[24] during early March 2021. Specifically, the fires included Muadzam Shah, which burned over 300 ha in the Rompin district, Leban Chondong (2 ha) in Pekan, Kampung Cenderawasih & Sungai Miang (2 ha) in Pekan, and Kampung Alur Beruang (3 ha) in Kuantan. Moreover, the selection of these districts is based on the analysis of 20 years of MODIS hotspots [25], which revealed them to have the highest number of fire hotspots.

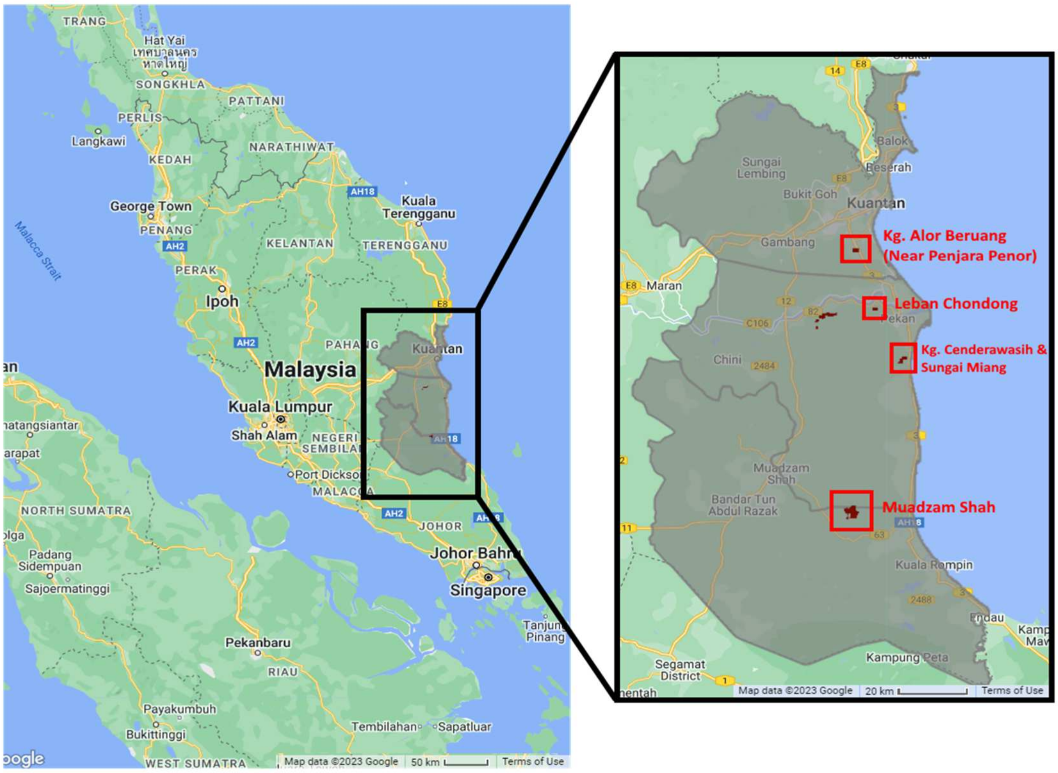

Fig. 1 Study Area - Districts of Rompin, Pekan, and Kuantan in the State of Pahang

Given the successful validation of the MCD64A1 burnt area dataset in detecting small-scale fires in the Rompin district of Pahang [26], it is deemed valuable to incorporate this dataset to enhance further the interpretation and visual representation of fire occurrences in the three districts, as illustrated in Fig. 1. The MCD64A1 dataset has been filtered to include only data from 1st March 2021 to 31st March 2021 in Rompin, Pekan, and Kuantan, allowing us to focus on the specific timeframe and region of interest. By integrating the MCD64A1 burnt area dataset into the figure, valuable insights can be gained into the extent and distribution of the detected fires during the specified period. It is worth noting that the MCD64A1 dataset shows a fire in Pulau Manis, located in the Pekan district at coordinates 3.496139ºN, 103.20257ºE. This particular fire was not mentioned in any of the newspaper articles. As a recommendation for future studies, the Sentinel and Landsat satellite data can be utilized to investigate further and verify the fire detected in Pulau Manis.

B. Background Study

Understanding the factors contributing to forest fires is crucial since it provides valuable insights into developing effective fire prevention and management strategies [10]. Generally, incorporating the most influential factors into machine learning models can significantly enhance their performance [27]. The accuracy and effectiveness of these models in predicting and forecasting forest fires heavily rely on the quality and relevance of the features used [28]. Generally, numerous factors impact forest fires [2], [29]. However, given the complex relationship between the climatic, environmental, topographic, and anthropogenic factors, it is suggested that the primary factors influencing fire may vary depending on the study region [11], [12]. In this section, the general key factors that contribute to forest fires will be explored. Previous studies performed in the Pahang region to identify the primary factors associated with the fires are also deliberated.

A. Factors Affecting Forest Fires: A General Overview

Forest fires are complex events influenced by a multitude of factors. In a recent systematic review by [2], one of their work's principal objectives was identifying the key factors utilized in models to map fire susceptibility. Through an analysis of 94 articles, a total of 144 factors were identified, representing a comprehensive set of variables employed in previous studies to create fire risk maps. The top factors were slope, elevation, aspect, distance to road, distance to residential areas, land cover, NDVI (Normalized Difference Vegetation Index), temperature, precipitation, and wind speed. It is important to note that the sequence in which these factors are listed does not indicate their rankings. The frequency of factor usage among the 94 articles has been leveraged to establish their rankings. Considering the emphasis placed by the Director of the Fire and Rescue Department of Pahang [21]–[24] on the prolonged spell of the hot and dry season, this section will primarily investigate the influence of climatic conditions, temperature, precipitation, and wind speed. By examining the role of these factors, valuable insights can be gained to enhance fire management strategies and mitigate the risks associated with forest fires. Typically, climatic variables are known to significantly influence the likelihood of fire occurrence, as they directly affect moisture levels, accumulation of fuels, rate of spread, and rate of combustion [16], [30].

Temperature increases are frequently linked to drier conditions [14], resulting in enhanced evaporation and plant transpiration [31], lowering soil moisture levels. These changes in climatic conditions significantly impact forest ecosystems, leading to the drying of vegetation and increased susceptibility to forest fires. The combination of higher temperatures and reduced soil moisture creates an environment where forests become more prone to ignition and fire spread.

Precipitation, commonly called rainfall, influences forest fire dynamics [15]. Lower precipitation (i.e., reduced rainfall) reduces soil moisture content, making forests more susceptible to fire ignition and spread. The vegetation becomes drier and more prone to ignition with lower soil moisture levels. Dry fuels, such as dead leaves, twigs, and branches, accumulate and create a highly flammable environment. The lack of moisture also affects the moisture content of live fuels, making them more susceptible to combustion (i.e., requiring less heat to be ignited). Additionally, lower precipitation can result in drought conditions, further exacerbating the risk of forest fires. The combination of dry fuels and reduced moisture content in vegetation creates an environment conducive to forest fires' rapid spread and intensification.

Wind speed significantly impacts the dynamics and spread of wildfires [16], [18]. Cruz and Alexander [17] comprehensively analyzed 118 wildfires in different ecosystems, including temperate shrublands, Australian dry eucalypt forests, and North American conifer forests. It was found that the forward rate of spread of fires in dry forest conditions is strongly influenced by wind speed. The study revealed that the forward rate of spread was approximately 10% of the wind speed. In other words, a higher wind speed corresponds to a higher rate of fire spread, leading to a more rapid and extended spread of fires.

B. *Related Studies of Forest Fires in Pahang*

This section explores relevant research on forest fires in Pahang, our area of interest. Several studies have investigated and incorporated various fire factors to develop fire risk and susceptibility maps in the different parts of Pahang. For a more in-depth analysis of Malaysia's various initiatives and strategies to combat forest fires from 1989 to 2021, we recommend referring to the comprehensive review paper [6].

Setiawan et al. [32] employed the Spatially Weighted Index Model, considering factors such as land use, slope, aspect, elevation, and road distance, to generate a fire risk map for Pekan, Pahang. Mahmud et al. [33] developed a user-friendly ArcView system that incorporated slope, road, elevation, and aspect attributes to produce a fire susceptibility map for the peat swamp area in Pahang. Razali et al. [34] integrated land cover, road distance, and canal buffers to create a fire hazard rating model and deliver a fire risk map for Pekan, Pahang. Ismail et al. [35] utilized factors such as moisture content, peat depth, dryness index, bulk density, water table, stand density, and species composition to generate a fire risk map for several forests in Peninsular Malaysia, including the Pekan forest reserve. Jamaruppin et al. [36] analyzed land surface brightness temperature data from Landsat 8 to investigate fire incidents in Pekan by comparing pre-fire and post-fire temperatures. In a recent study by [25], GEE was utilized to conduct a temporal and spatial analysis of fires in Pahang. The study focused on the period from 2001 to 2021 by utilizing the 20-year FIRMS hotspots dataset to examine the occurrence and distribution of fires over the specified timeframe.

Previous studies have focused on developing fire susceptibility maps for the state of Pahang, aiming to identify high-risk areas by integrating multiple factors. However, these studies have not examined the specific role of climatic variables in causing fires in Pahang. Understanding the influence of climatic factors on fire incidents is essential for accurate fire risk assessment and effective fire management strategies. Therefore, it is necessary to investigate the significance of climatic variables concerning fire occurrences in Pahang.

II. Materials and Method

In our research, GEE [19], a powerful cloud-based platform that provides access to satellite data for academic and non-commercial purposes at no cost, is utilized. By leveraging this platform, we aimed to examine the link between climatic variables such as temperature, precipitation, wind speed, and the occurrence of fires in the Rompin, Pekan, and Kuantan districts during early March. The platform allowed us to efficiently process and analyze large datasets [37], enabling us to investigate the relationship between these variables and fire incidents. The code used for our analysis can be downloaded at the following website link: https://github.com/chewyeejian/GEE_CITIC2023_Pahang_ClimaticVariablesAnalysis.

A. *Dataset*

This study utilizes the TerraClimate [20] comprehensive global terrestrial surfaces dataset of monthly climate and climatic water balance. TerraClimate offers a high spatial resolution of approximately 4 km. The dataset, accessible through GEE covers a temporal range from 1958 to 2022 on the date of access (June 2023). It comprises 14 bands, encompassing various variables such as actual evaporation, water deficit, Palmer Drought Severity Index, reference evapotranspiration, precipitation accumulation, runoff, soil moisture, downward surface shortwave radiation, snow water equivalent, minimum temperature, maximum temperature, vapor pressure, vapor pressure deficit, and wind speed.

To address the specific objectives of this study, our analysis focused on the maximum temperature, precipitation, and wind speed variables. These variables are chosen based on the valuable input from the Fire and Rescue Department of Pahang [21]–[24] and the significant factors highlighted by

Chicas and Østergaard Nielsen [2]. By leveraging the extensive capabilities of GEE, this study aimed to explore the potential relationship between these climatic factors extracted from TerraClimate and the occurrence of fires in the Rompin, Pekan, and Kuantan districts during the early March period.

B. *Analysis of Climatic Variables*

Several maps displaying the monthly maximum temperature, precipitation, and wind speed data for the past six months before the fire triggered in the study area are produced to determine the potential influence of prolonged hot and dry seasons. Given that the fire occurred in early March 2021, the climatic variables for October 2020, November 2020, December 2020, January 2021, February 2021, and March 2021 have been incorporated to deliver the maps.

Furthermore, taking advantage of the extensive temporal availability of the TerraClimate datasets, the 10-year climatic variables to determine whether 2021 exhibits the highest temperatures or driest conditions compared to the past decade will also be assessed. This comparative analysis will cover the period from 2011 to 2021, allowing us to evaluate if 2021 represents the hottest and driest season within this 10-year timeframe.

III. Results and Discussions

All the figures and graphs presented in this research paper are generated using the GEE Code Editor (JavaScript). While the results from these graphs can be exported to a CSV format to create customized charts that offer more detailed insights, the default graphs from GEE have been intentionally retained to facilitate reproducibility by other researchers.

A. *Temporal and Spatial Analysis of Temperature, Precipitation, and Wind Speed for 6 Months*

To investigate the potential correlation between maximum temperature, precipitation, and wind speed and the occurrence of forest fires in the study area, individual maps are generated for each month spanning from October 2020 to March 2021. Fig. 2 displays the maximum temperature, Fig. 3 showcases the precipitation, and Fig. 4 illustrates the wind speed. Referring to Fig. 2, it is evident that the maximum temperatures exhibited a decreasing trend from October 2020 to December 2020. However, starting from January 2021, the temperature gradually increased, reaching maximum temperatures of 32-34 ºC in specific locations by March.

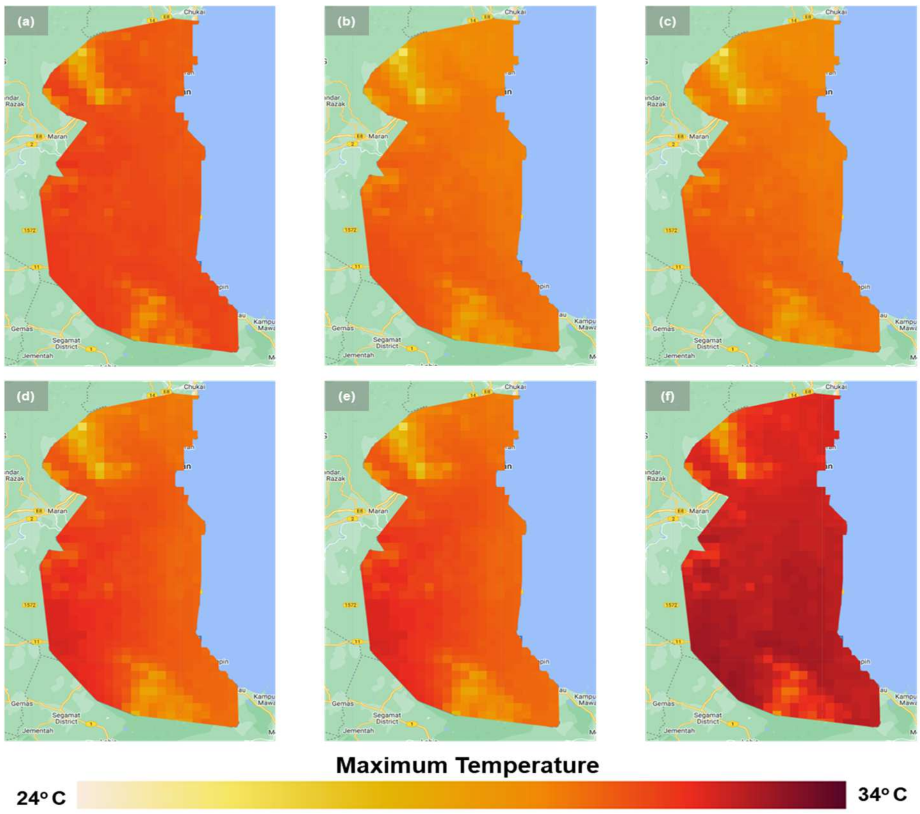

Fig. 2 Maximum Temperature for 6 months before the Fire in Rompin, Pekan, and Kuantan.
(a) October 2020, (b) November 2020, (c) December 2020, (d) January 2021, (e) February 2021, (f) March 2021

In Fig. 3, the precipitation data, representing rainfall patterns, clearly indicates the seasonal variations in Malaysia. October 2020 to December 2020 correspond to the rainy season, attributed to the Northeast Monsoon [38]. The northeasterly winds associated with the monsoon result in extreme rainfall, often leading to floods on the east coast of peninsular Malaysia, including Terengganu, Kelantan, and Pahang. It is worth noting that the January 2021 precipitation data is missing, and further investigation is required. Comparing the rainy seasons from October to December with February and March 2021, it is evident that precipitation significantly decreased during the latter months.

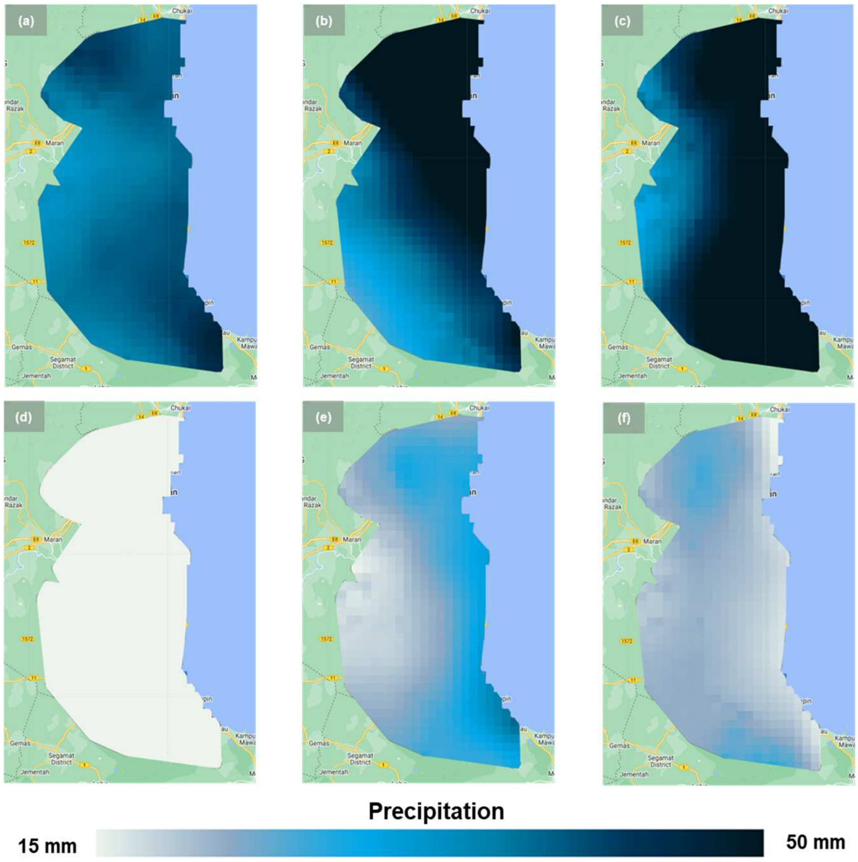

Fig. 3 Precipitation for 6 months before the Fire in Rompin, Pekan, and Kuantan.

(a) October 2020, (b) November 2020, (c) December 2020, (d) January 2021, (e) February 2021, (f) March 2021

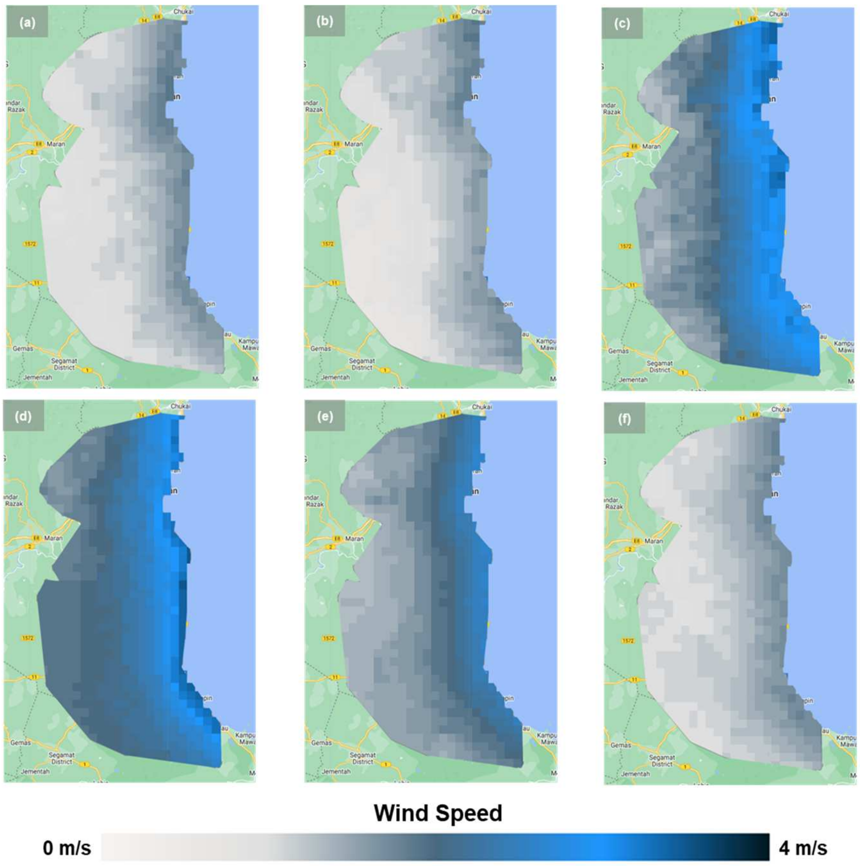

Fig. 4 Wind Speed for 6 months before the Fire in Rompin, Pekan, and Kuantan.
(a) October 2020, (b) November 2020, (c) December 2020, (d) January 2021, (e) February 2021, (f) March 2021

Fig. 4 shows that the wind speed gradually increased from October 2020 to January 2021 and decreased from February 2021 to March 2021. The higher wind speeds during the end of the year can be attributed to the influence of the Northeast Monsoon. While wind speed appeared to have some effect on the rate of fire spread in general [16]–[18], it can be deduced that it did not play a significant role in the fires in the three districts, as March recorded a shallow wind speed.

Based on the analysis, it is clear that the climatic factors of temperature and precipitation are vital in contributing to the occurrence of fires, aligning with the claims made by the chairman of the Fire and Rescue Department of Pahang. The following section will investigate the 10-year monthly maximum temperature and precipitation for the three districts to understand better the fires that occurred. Wind speed will be excluded from the discussions, as it can be assumed to have a lesser impact based on the findings in Fig. 4.

B. Temporal Analysis of the Maximum Temperature and Precipitation for 10 Years

To reveal the trend of maximum temperature and precipitation, the annual average values from 2010 to 2021, cumulative monthly values across 2010 to 2021, and the monthly values from 2010 to 2021 are plotted. Fig. 5 – 7 depict the maximum temperature trends, focusing on the annual average, cumulative monthly, and monthly values, while Fig. 8 – 10 presents the precipitation trends similar to the maximum temperature. These plots provide insights into the long-term patterns of the climatic variables over ten years.

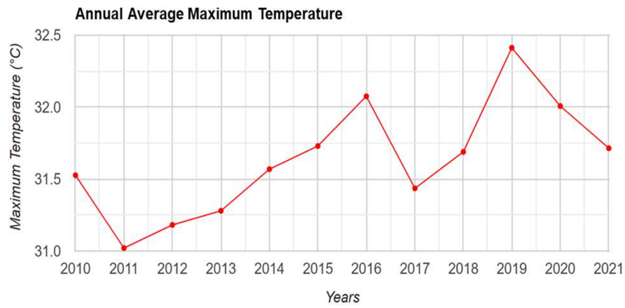

Fig. 5 Annual Average Maximum Temperature from 2010 to 2021

Fig. 5 provides an overview of the annual average maximum temperature values, enabling us to observe any noticeable changes or trends in temperature over the 10 years. The figure depicts a clear trend in the maximum temperature, showing an overall increase until 2016, followed by a decrease in 2017, and reaching its peak in 2019 at 32.412 °C. Interestingly, the decline in maximum temperature in 2017 aligns with the findings of our previous work [25], where the number of MODIS fire hotspots detected was the lowest in that year. The cumulative monthly maximum temperatures in Fig. 6 illustrate the maximum temperature data each month, offering a perspective on how the temperature fluctuates throughout the years. Fig. 7 displays the monthly maximum temperature and provides a detailed analysis of temperature variations every month, allowing us to identify any seasonal or monthly patterns. It is worth noting that Fig. 6 and Fig. 7 both further illustrate that the highest temperatures were consistently recorded between March and May in most years. This observation closely resembles the trend of the MODIS hotspots, which exhibited the highest number of detections between February to April throughout the year [25]. Given the significant occurrence of both the highest maximum temperature and MODIS fire hotspots in March and April, it is reasonable to speculate that the climatic variable of maximum temperature strongly influences the majority of forest fires in the study area.

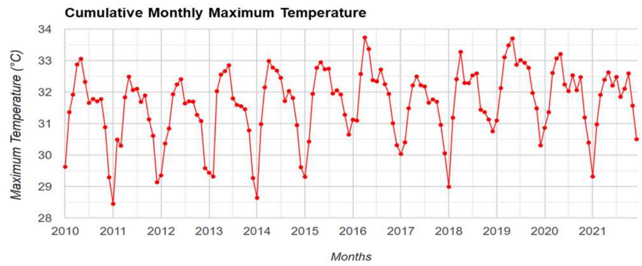

Fig. 6 Cummulative monthly maximum temperature across 2020 to 2021

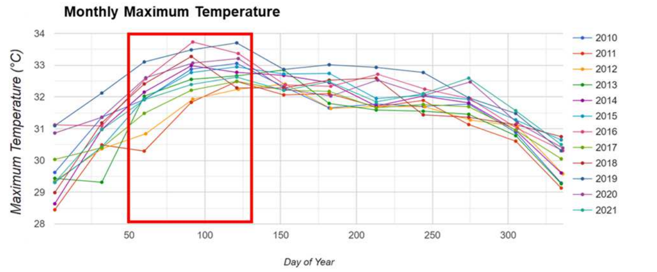

Fig. 7 Monthly Maximum Temperature from 2010 to 2021

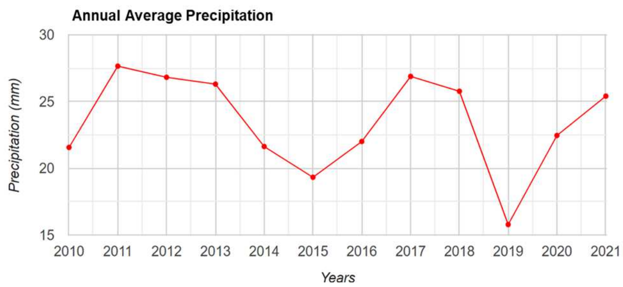

Fig. 8 Annual Average Precipitation from 2010 to 2021

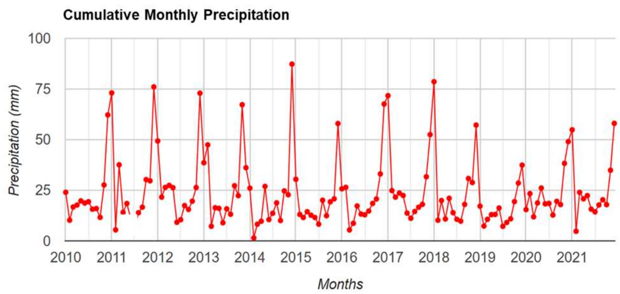

Fig. 9 Cumulative Monthly Precipitation across 2010 to 2021

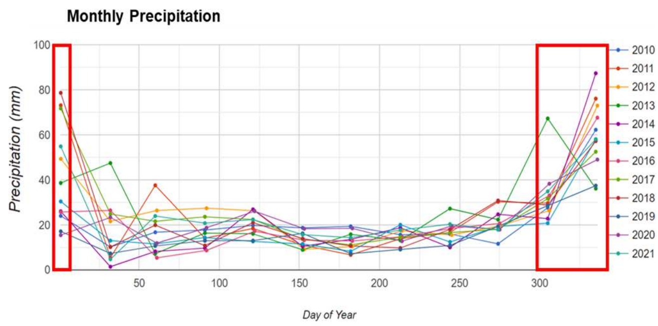

Fig. 10 Monthly Precipitation from 2010 to 2021

Similarly, Fig. 8 presents the annual average precipitation values, allowing us to identify any significant changes or trends in precipitation over the ten years. By examining Fig. 8, it becomes apparent that no noticeable trend in rainfall can be observed during the analyzed period. However, it is worth noting that the lowest recorded precipitation occurred in 2019, with a value of 15.78 mm. The cumulative monthly precipitation values in Fig. 9 showcase the precipitation data each month, offering insights into the patterns of precipitation accumulation throughout the year. Fig. 10, representing the monthly precipitation, provides a more granular view of precipitation variations every month. From Fig. 9 and Fig. 10, it can be observed that there is a consistent pattern of high precipitation from November to January across the ten years, which aligns with the findings from the precipitation map presented in Fig. 3. Similarly, in the analysis of MODIS fire hotspots conducted in our previous work [25], the lowest number of hotspots were detected from November to January across the years. It is therefore postulated that higher precipitation during this period may contribute to a lower probability of forest fire occurrence, likely due to increased soil moisture and the cooling effect of precipitation during the Northeast Monsoon season (refer to Fig. 7, where temperatures are lower from November to January). Generally, aside from November to January, the precipitation remains relatively consistent throughout the years. Overall, the analysis highlights the significance of temperature and precipitation as contributing factors to fire occurrence in the study area.

IV. Conclusion

In conclusion, this research paper investigated the factors contributing to forest fires in the Pahang region, specifically in Rompin, Pekan, and Kuantan districts. GEE is used to access the TerraClimate dataset, which provides climatic variables such as temperature, precipitation, and wind speed. These variables are then utilized to analyze the climatic conditions and the fire incidents in the area of interest. The results showed that temperature and precipitation significantly influence fire factors in the occurrence of fires in the study area.

The results presented in Section V show that March to May consistently recorded the highest temperature throughout the 10-year analysis, aligning with the distribution of MODIS hotspots identified in our previous studies [25]. These findings advocate for allocating additional firefighting resources to be readily available during this critical period. The analysis of temperatures and precipitation reinforces the findings emphasized in previous studies [14], [15], indicating that higher temperatures and lower precipitation (i.e., less rainfall) contribute to an increased likelihood of fire occurrence due to a drier condition created resulting from a decrease in soil moisture. It is worth noting, however, that windspeed does not appear to play a significant role in the spread of fire within the study area, deviating from the general factors identified [16]–[18].

Further research and integration of additional data sources, such as topographic variables (e.g., slope, elevation, and aspect), anthropogenic variables (e.g., distance to roads and distance to residential areas), environmental variables (e.g., land cover and NDVI), and other climatic variables (e.g., radiation and humidity) are recommended to enhance the understanding of fire incidents in the region. Moreover, by harnessing the capabilities of machine learning [3], [4] and advanced deep learning models [39]–[61], along with the integration of diverse data sources, it becomes feasible to enhance the prediction and forecasting of forest fire incidents.

Additionally, it is strongly encouraged to conduct similar analyses for the entire peninsular Malaysia. Expanding the study's scope to cover the whole region allows a more comprehensive understanding of the climatic variables and their impact on fire severity. This broader analysis will offer valuable insights and facilitate the formulation of effective prevention measures. Such endeavors will mitigate the severity of fires, preserve lives, and safeguard the country's precious environment.

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