Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Statistical Analysis for Forest Fire Factors Using Geography Information System (GIS) and Remote Sensing Imagery

Nur Farhana Abdul Aziz[1], Norsuzila Ya'acob[1,2,*], Azita Laily Yusof[1,2], Hamdan Omar[3]

[1] School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA Shah Alam, Selangor, Malaysia
[2] Wireless Communication Technology (WiCoT), School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia
[3] Forest Research Institute Malaysia (FRIM), 68100 Kuala Lumpur, Federal Territory of Kuala Lumpur, Malaysia

ARTICLE INFO

Article history:
Received 3 April 2023
Received in revised form 1 March 2024
Accepted 14 April 2024
Available online 22 May 2024

Keywords:
Forest fire; Geography Information System (GIS); Remote Sensing; Kriging; Random Tree

ABSTRACT

About 33% of the permanent forest reserve in Selangor is covered by peat swamp forests. The most important reason for peat swamp forests is to balance the ecosystem. Nevertheless, the evolution of technology and increasing population, with the need for more space for land development has put peat swamp forests in Selangor under threat particularly because of forest fire. To overcome this risk problem, it is important to identify and justify these forest fires and a further study has been carried out to understand the problem. The study is carried out to find the factors that triggered forest fires at Kuala Langat South Forest Reserve (KLSFR) from 2013 until 2020. Temperature, rainfall, relative humidity, wind speed, NDVI, and LULC are choosing as to know the most triggered factors by measuring their correlation value. The data are processed using GIS and Remote Sensing (Landsat 8). The temperature, rainfall, relative humidity, and wind speed data interpolate using the Kriging method as a statistical analysis. While LULC is classified using the Random Trees method. The value of the correlation of temperature (0.4256), rainfall (-0.7613), relative humidity (-0.2484), wind speed (-0.8615), and NDVI (0.1945) respectively. Furthermore, LULC is classified into five classes, which are high-density forest, medium-density forest, agriculture, bare soil, and waterbodies. Bare soil area shows the highest correlation compare to other classes, which is 0.6381. While rainfall and wind speed were identified as the most trigger factor to forest fires.

1. Introduction

Peat swamp forest is a remnant of lowland rainforest which becomes an important habitat for various endangered species of flora and fauna [1]. Typically, peat swamp forest grows after the mangrove forest along the coastal area, and it covers an area exceeding 3 km to 5 km from the river delta. Generally, peat swamp forest has high humus materials content and causes the color of peat swamp appear in brownish or black. Biological diversity and land covering areas of peat swamp forests are crucial for ecosystem sustainability. About 30% of the peatland areas in Malaysia are

* *Corresponding author.*
E-mail address: norsuzila@uitm.edu.my (Norsuzila Ya'acob)

https://doi.org/10.37934/araset.45.2.177190

located in a Permanent Forest Reserve or Fully Protected Area. Peat soil is a wetland ecosystem that is characterized by the accumulation of organic matter derived from decaying plant material under permanent saturated water conditions. Peatland covers about 400 million hectares, mainly in the boreal, subarctic and tropic zones as well as 3% of the global soil surface which is the largest type of wetland and covers about 2.6 million hectares or 8% of Malaysia's total land area. Peatlands in Malaysia are naturally forested or known as peat swamp forests.

Recently, the peat swamp forest area has been extensively explored, especially from the agricultural sector and some of the area has also been destroyed by fire. Indirectly, this destruction will cause the percentage of plants and wildlife to decrease. At the same time, the percentage of carbon emissions will also increase due to forest fires that often occur, especially in peat swamp forests. This is because the importance of peat swamp forests is that it serves as a better absorber and carbon storage than other types of forests. Therefore, peat swamp forest ecosystems play an important role in stabilizing the local climate and slowing down the global warming process and global climate change [2].

But forest fire or unwelcome fires blazing forests and wild land caused a serious problem. The composition of meteorological conditions factors, environment, dryness of flammable items, types and sources of flammable items are the factors that trigger the combustion and contribute to forest fire [3,4]. Forest fire is environmental disaster and cause of forest sources destruction. The accident can happen due to global temperature and human activities [5]. The consequent of forest fire will reduce carbon fixation, increase soil erosion, damages agriculture and biodiversity, and also economic and property destruction [6-8]. On the other hand, there are some benefits of forest fire, there are to eradicate the numerous insects and diseases, and overcome with soil nourishes by the nutrients and minerals from the decomposition process [9].

Lately, the agricultural sector extensively explored peat swamp forest areas and some of these areas are also experiencing destruction due to fires. Indirectly, this incident decreases the percentage of plants and wildlife, while increasing carbon emissions. This is because peat swamp forests provide important absorbers and storage of carbon better than other types of forests. Therefore, peat swamp forest ecosystems play an important role in stabilizing the local climate and slowing down the process of global warming as well as global climate change [10]. To overcome this, forest fire incident analysis and in Peninsular Malaysia should be done to maintain forest sustainability in reducing losses in terms of destruction and loss of biodiversity, destruction of property, health, and public safety. Also, as a source of reference to other agencies in overcoming the impact of forest exploration and illegal logging as well as making development plans for land use. In order to make an analysis, the causes of forest fire incidents need to be identified. This study will discuss the factors that trigger forest fire incidents that happened in Kuala Langat South Forest Reserve (KLSFR).

This paper will provide a critical analysis of the causes that lead to the most relevant recent peat swamp forest fires events in Selangor, focusing in particular on North Selangor Peat Swamp Forest (NSPSF). In particular, the study assesses to what extent forest fires have been influenced by temperature, rainfall, relative humidity, wind speed, Normalized Difference Vegetation Index (NDVI), and Landuse and land cover mapping (LULC). To do so, one case study was developed on Kuala Langat South Forest Reserve (KLSFR) from 2013 until 2020.

2. Study Area

The Peat swamp forest under Permanent Forest Reserve (PFR) in Selangor, Malaysia covers 82, 890 ha, which is approximately 10.22% of the country area. The study area includes Kuala Langat South Forest Reserve (KLSFR) (Figure 1), which approximately covers 8,339.72 ha. KLSFR is located in

Sepang Districts which is surround with rapid development such as Kuala Lumpur International Airport (KLIA) and not far from farming areas and constantly being exposed with vulnerable by illegal encroachments. Furthermore, they are located in humid tropical zone, and the climate is characterized by heavy rainfall and high humidity and temperature. These study areas are chosen because forest fire is frequently happened in these areas. The study was conducted in dry season only because the event of fire only happened during the dry season which is between April to September.

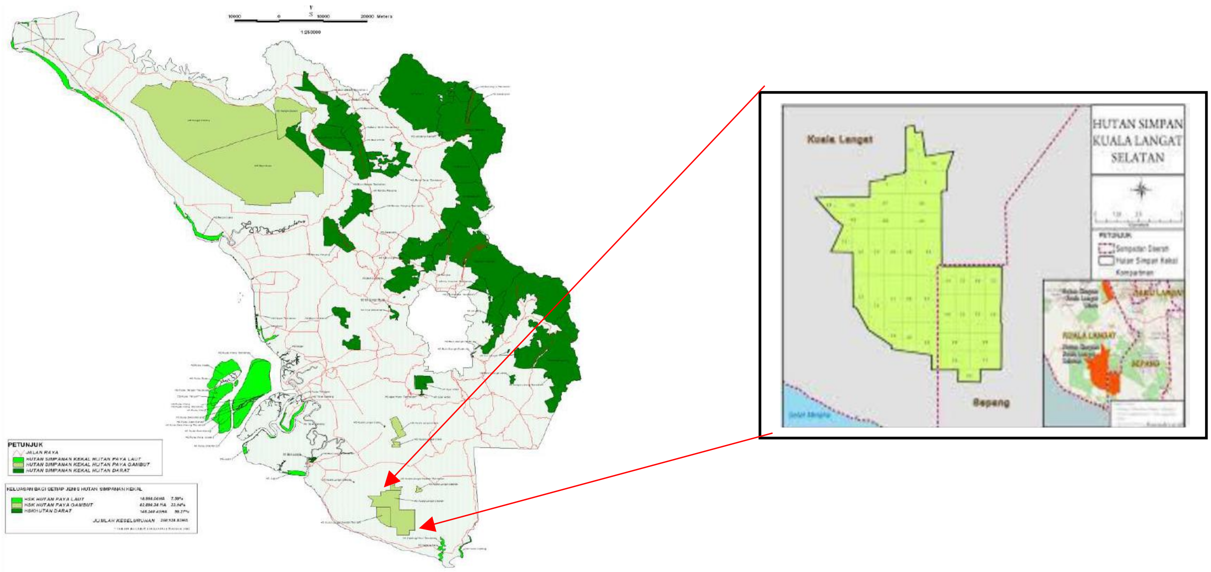


Fig. 1. Study Area

3. Forest Fire Causes

Fire has existed together with human activities for a long time, and it is an uncontrollable nature of human culture. Forest fires can be attributed to two categories: human factors and natural factors [11]. The widespread use of natural areas and forests as recreation and agriculture areas has increased the number of fire activities initiated or caused by humans. On the other hand, the accumulation of fuel that increases the potential for forest fires is due to the decline of the rural population and the neglect of agricultural areas [7].

About 90% of global biomass combustion is caused by humans and this is where most of the forest fire research emphasis is given. However, it also depends on the season and location of an area because weather and lightning can also be an important cause of forest fires. 31% of wildfires occur in the Pacific region of the United States (US), caused by lightning [12]. The total number of these fire records is approximately the same as the results of a study in Switzerland where fires recorded due to lightning were 26%. In this study, weather conditions and NDVI is taken as natural factors, while LULC is taken as human factors.

Weather condition which are temperature, rainfall, relative humidity, wind speed data were processed using GIS and interpolated using Kriging method, while NDVI, and LULC were retrieved using Landsat 8 Imagery. Furthermore, active fire data are regarded as the image pixel labelled as comprising fire and, in this study, the data collected from Visible Infrared Imaging Radiometer Suite (VIIRS) satellite. All data are processed using Arcgis Pro software.

Hotspot become the dependent variable, so every factor is undergoing the regression calculation to see the correlation each factor with hotspot in the forest. Both categories are calculate using correlation matrix.

3.1 Regression

Regression is a statistical method that researching the correlation between two quantitative variables. In this study, temperature, rainfall, relative humidity, wind speed and NDVI data were used to see they are contributing to the forest fire accident or not. While, for human factor, LULC is calculated to see how effective they are with forest fire accident.

$$Y = mX + b \tag{1}$$

Where,
Y = dependent variable,
X = independent variable,
m = estimated slope,
b = estimated intercept.

3.2 Correlation Matrix

A table displaying correlation coefficients between variables is called a correlation matrix. The correlation between two variables is displayed in each cell of the table. Data are summarised using correlation matrices, which are also used as inputs for deeper studies and as diagnostics for such analyses. In this study, natural factor and human factor are calculated to get a clear view the variables are correlated with each other or not.

$$\text{Correlation} = \frac{Cov\ (x,y)}{\sigma x \times \sigma y} \tag{2}$$

Where,
Cov (x,y) is the covariance between the two variable
σ_x = Standard deviation of x
σ_y = Standard deviation of y

4. Fire Potential Measurement Components

To calculate the possibility of fire incident, distinct methods are employed. In Europe, a fire risk index is applied, while in the United States a fire hazard rating system is applied. In Malaysia, early fire warnings are often issued during extreme droughts. Basically, scientists applied numerical systems as early warning signs of helpful situations to the beginning and progression of fires [5,13]. The idea of fire prediction comprises equally noticeable and unnoticeable factors, namely physical processes and the occurrence of hazards. fire potential defined as the appraisal of both continuous and variable fire hazard factors. These factors influence the beginning, proliferate, potential and complexity in monitoring the fire and its effects [14].

Fire potential serves as an early warning against fire threats by generating a qualitative and numerical fire hazard index with dissimilar systems and complexities have been created around the world based on the climate and environment seriousness [13]. For the example, Angstrom Index applied the plainest techniques where only temperature and relative humidity are used to measure fire potential and fire index [15]. All over Scandinavia has been utilised this system that been invented in Sweden. But fire potential cannot provide a full picture of the danger’s incidence with a single index. Therefore, the fire potential system must be changed and modified to make it as a main component to know where this singe index of warning system belongs in the potential overview.

4.1 Hotspot

Usually, forest fire event in Malaysia occurred during the dry season with hot weather and heat wave condition, which is from April to September. In Selangor, more cases of forest degradation happened nowadays due to forest fire. Peat swamp forests in the state of Selangor have been recorded to experience a series of forest fires since the 1990s. According to records obtained from Selangor Forestry Department (SFD) in 2019, the total area burned at Kuala Langat South Forest Reserve (KLSFR) from 2012 until 2018 is 1163.3 ha and the total case recorded by Fire and Rescue Department of Malaysia (JBPM) are 22 cases from 2013 until 2020 (Figure 2) [16]. The peat swamp forest area is degraded rapidly because the forest fire can spread and affect a wide area in a short time [17].

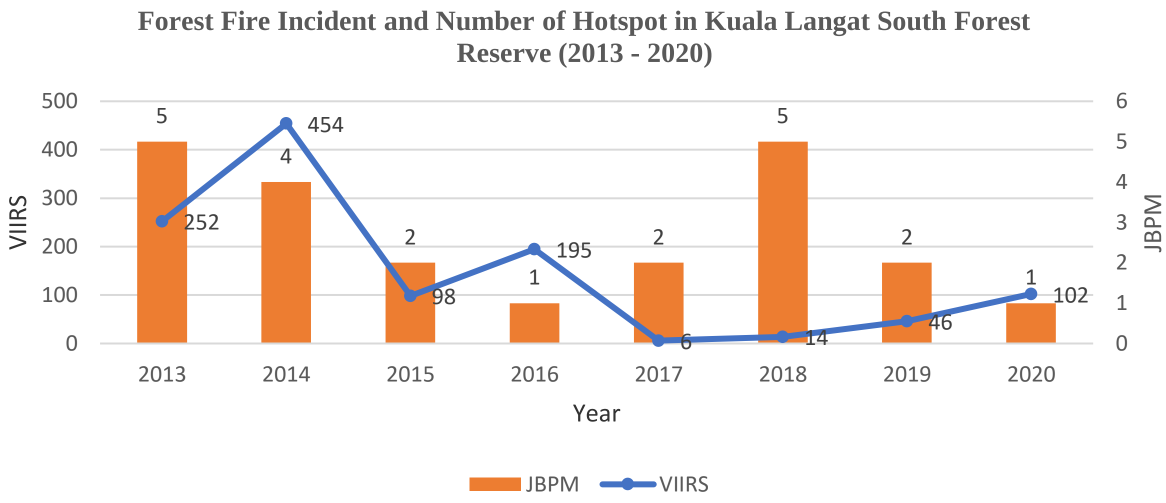


Fig. 2. Graph of Forest Fire Incident and Number of Hotspot in Kuala Langat South Forest Reserve

4.2 Weather Variables

Less rain, low humidity and high temperature are very considerable for fire event. Regular recording of accounting techniques such as the Keetch-Byram Drought Index and the Mount Soil Dryness Index are mostly beneficial in observing the total rainfall for the period of normal or dry season [18]. In some counties, there were indices which show the alterations in the global circulation designs which may alarm 6 to 9 months earlier of tremendously dry state. For example, the Southern Oscillation Index are reported the changes in atmospheric pressure of both areas in Australia can be correlated to the El Niño events [19].

4.3 Temperature

From Figure 3, the temperature at the forest was record between 30.63 ^oC until 32.83 ^oC. The value correlation of temperature and active fire data is 0.426 with R^2 value is 0.1815 and proved as positive correlation. The active fire increase as the temperature increase, and the probability of forest fire occur is increase. In addition, temperature is directly proportional with fire for ignition and prolonging the combustion activity.

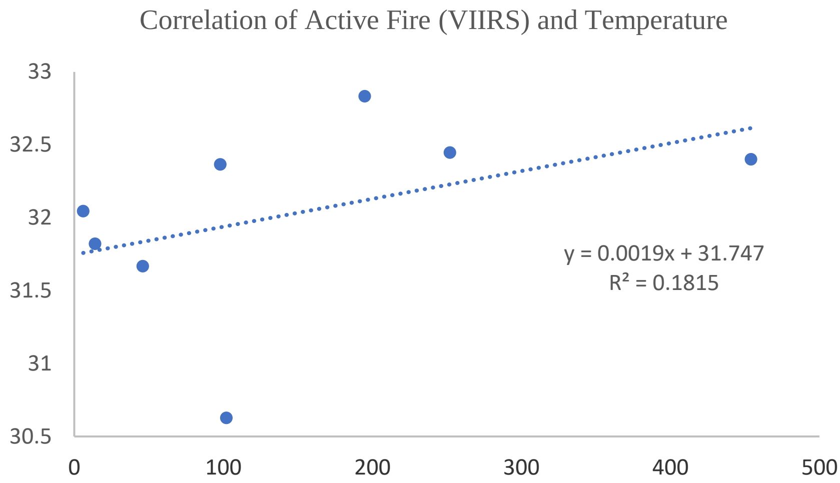


Fig. 3. Graph Correlation of Active Fire (VIIRS) and Temperature

4.4 Rainfall

The average amount of rain or rainfall in KLSFR from April to September (2013 until 2020) was 3.77m per day to 9.77mm per day. Based on Department of Irrigation and Drainage, 1mm to 10mm is categorised as light intensity. The correlation of rainfall and active fire data is -0.7613 with R^2 value is 0.5795 (Figure 4). The value indicates a strong negative correlation as the rainfall decrease, the active fire is increase.

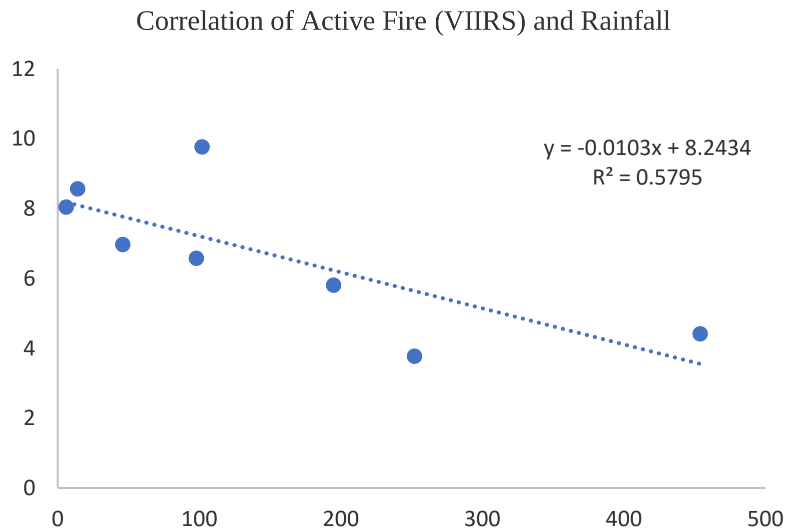


Fig. 4. Graph Correlation of Active Fire (VIIRS) and Rainfall

4.5 Relative Humidity

Based on Meteorology Department Malaysia, average humidity level in Malaysia is 80%. The relative humidity recorded in 2013 to 2019 were below than average level. The graph in Figure 5 shows a weak relationship between relative humidity and Active Fire with the correlation value is -

0.2484 with R^2 value is 0.0617. The value signifies as not corelate between the amount of water vapor in the air and active fire data.

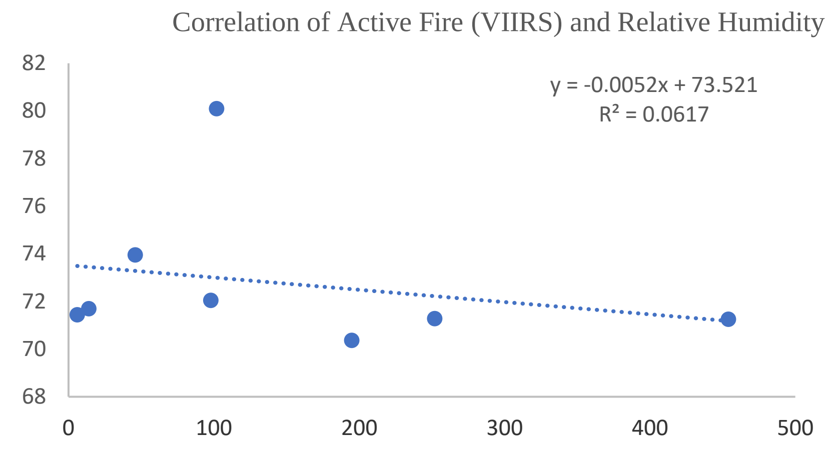


Fig. 5. Graph Correlation of Active Fire (VIIRS) and Relative Humidity

4.6 Wind Speed

Figure 6 shows a strong negative correlation between wind speed and Active Fire with -0.8615 with R^2 value is 0.7422 The wind speed during dry season not really changes from 2013 until 2020 which is between 6.8 km/h to 7.8 km/h. Besides, the wind speed at KLSFR between April to September is recorded higher than average wind speed in Selangor which is 5 km/h. Wind act as powerful effect during combustion process because of the blowing effect on the fire and can alter the direction and amount all over the day. Wind also providing oxygen during fire event, lessening fuel moisture and boosting the evaporation.

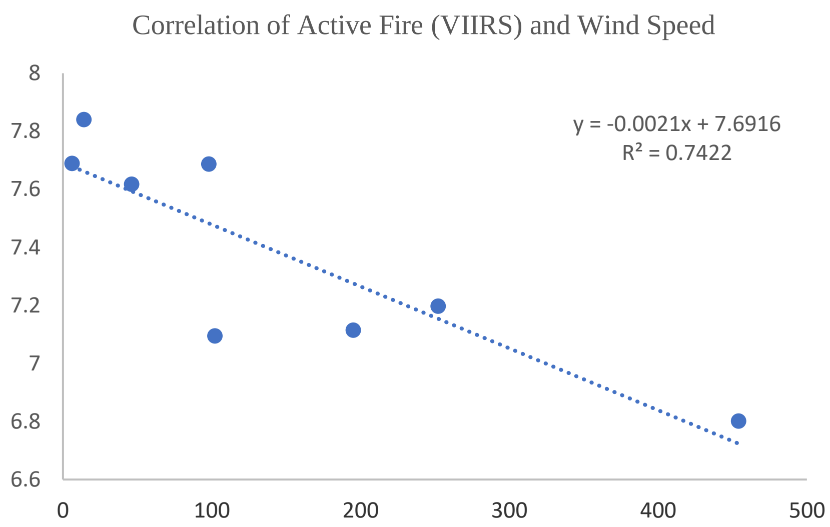


Fig. 6. Graph Correlation of Active Fire (VIIRS) and Wind Speed

4.7 Fuel Availability

Seasonal changes in fuel ease to use as fuel dries throughout the dry season will set up the earlier phase for severe fire ignition where the fuel is ready to start the fire. With the condition of organic soil that dry and flammable, excessive stress on plant will decrease the moisture content also dry plant material such as leaves, and bark can be dropped, will increase the pile up of surface fuel. Yet, most damaging fires incidence arise when terrible fire weather with excessive drought is amalgamated [5].

4.7.1 Normalized Difference Vegetation Index (NDVI)

Figure 7 shows no correlation between NDVI and Active Fire with the R^2 value is 0.0235. vegetation indices that used to measure the health of vegetation on the ground. NDVI is a surface reflectance value between two bands, visible or red and NIR bands. NDVI measure vegetation health status, it associated with tree covers that affect the fuel load, and it play as controlling the fire regime. In this study, it shows that NDVI value not really influence the forest fire incidence.

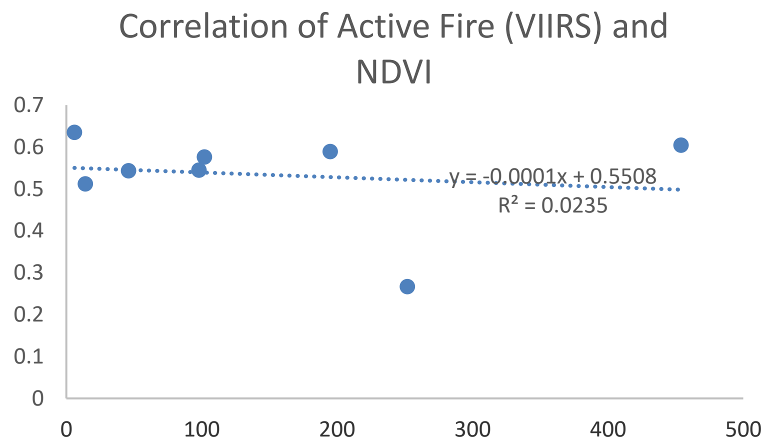


Fig. 7. Graph Correlation of Active Fire (VIIRS) and NDVI

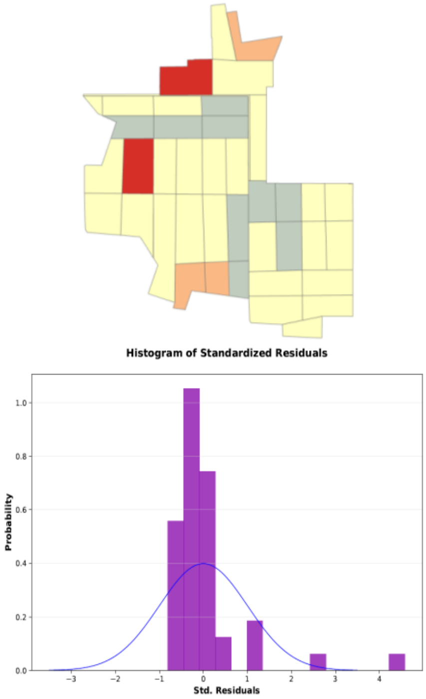
In this study, temperature, rainfall, humidity, and wind speed of study area was collected from a few stations nearby the forest. While NDVI was retrieved using Landsat 8 imagery. The data were interpolate using Geographic Information System (GIS) and opted Kriging method as a statistical analysis. Table 1 show a correlation matrix between Active fire and temperature, rainfall, humidity, wind speed and NDVI.

Table 1
Correlation Matrix

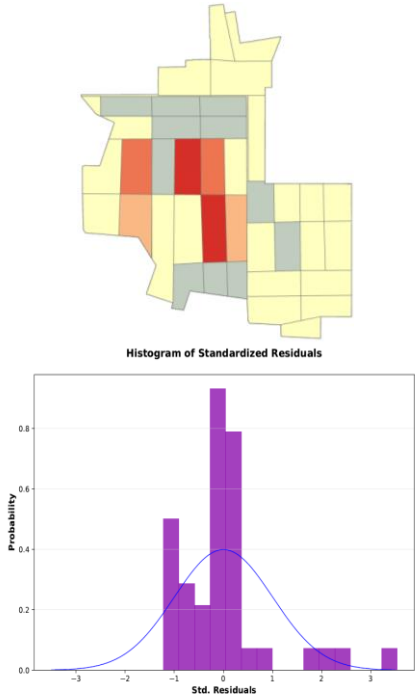
	VIIRS	Temperature	Rainfall	Relative Humidity	Wind Speed	NDVI
VIIRS	1					
Temperature	0.425992	1				
Rainfall	-0.76127	-0.78211	1			
Relative Humidity	-0.24844	-0.93242	0.647536	1		
Wind Speed	-0.86153	-0.10064	0.469935	-0.13945	1	
NDVI	-0.44107	-0.62606	0.714597	0.434519	0.406961	1

4.8 Ordinary Least Squares Regression (OLS)

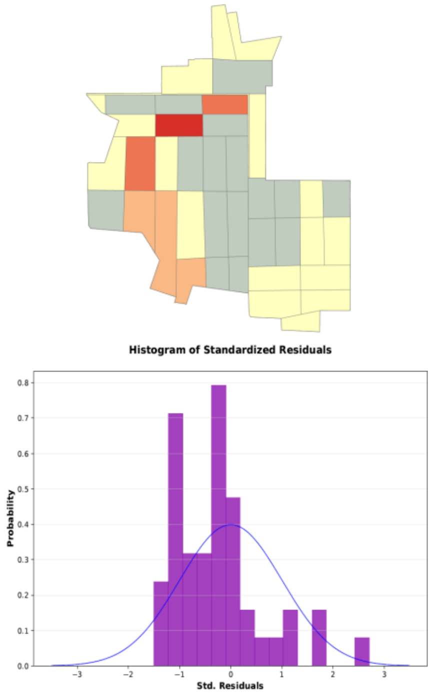
Figure 8 shows the Ordinary Least Squares regression (OLS) method. It is for calculating the coefficients of linear regression equations that represent the connection involving one or more independent quantitative variables and a dependent variable. The result come out not really good with some of them look biased model, especially 2017.



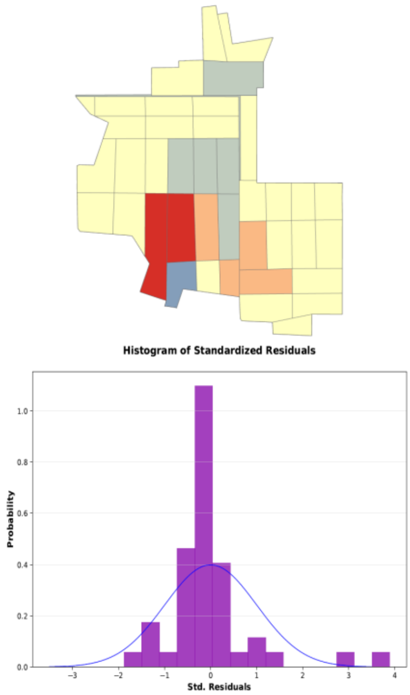
OLS 2013



OLS 2014



OLS 2015



OLS 2016

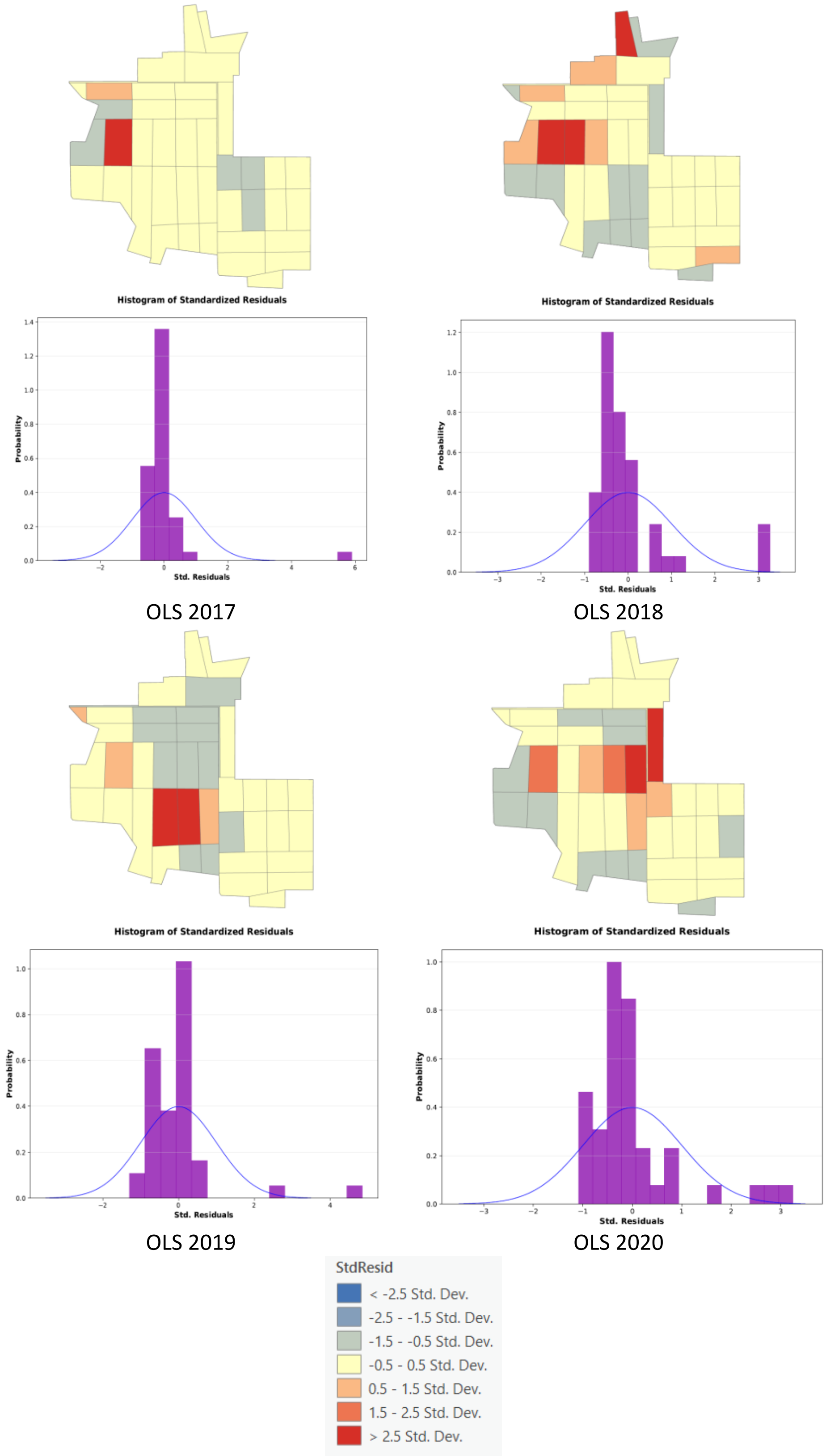


Fig. 8. OLS measurement in KLSFR from 2013-2020

5. Changes in Fuel Load

An early notice of fire risk potential will offer a big alteration in the forest fuel condition. The bustle of farmers spends peat swamp water for agricultural will cause the soil depth to reduce.

Especially when enter the dry season, the peat soil becomes dried up and the likelihood of burning is soaring thus changing the wetness of the soil natural. The moisture content for peat is around 47.65%, but it can fall to 28.15% after combustion [20]. For vegetation, persistent of dry season causes excessive stress on them. The physical state of living plants affects the fires ignitions. Figure 10 show the land use or land cover (LULC) of KLSFR. The forest area classified using Landsat 8 remote sensing imagery with 30m spatial resolutions. Besides, the image classed into 5 type of land use which are high density forest, medium density forest, agriculture, bare soil, and waterbodies using Random Tree classifier.

5.1 Land use Land Cover (LULC)

From Table 2 and Figure 9 and Figure 10, high density forest reduced about 1,708.53 ha from 2013 until 2020. While medium density forest expanded from 2013 until 2018 with 2651.155 ha. Same with agriculture, it expanded 724.25 ha from 2013 until 2020. This is due to the human doing illegal open burning activity for agriculture. In 2017, forest cover increases due to less open burning activity from the villagers. Water bodies area coverage also shrink because of combustion process. In 2018, Forest Research Institute Malaysia (FRIM) did a hydrology management as a forest management and conservation in KLSFR.

Table 2
Land use Land Cover (LULC) Area Coverage

	2013	2014	2015	2016	2017	2018	2019
High Density Forest	4177.414	3113.217	2771.654	2646.037	2673.962	2648.91	2553.014
Medium Density Forest	601.7761	2029.445	2125.342	1920.709	2928.518	3252.931	2172.212
Agriculture	1072.907	604.9188	1189.635	1079.911	699.3784	757.5627	1691.743
Waterbody	40.58532	6.105756	0	60.78819	13.82774	29.09213	8.260728
Bare Soil	2121.571	2260.566	1927.623	2306.808	1698.567	1325.757	1589.023

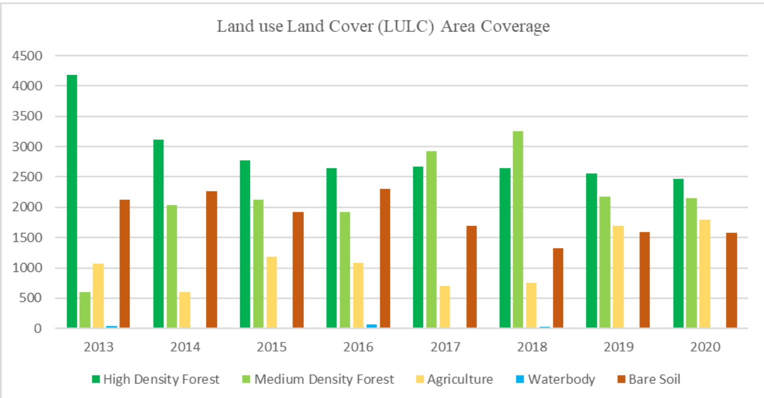


Fig. 9. Land use Land Cover (LULC) Area Coverage

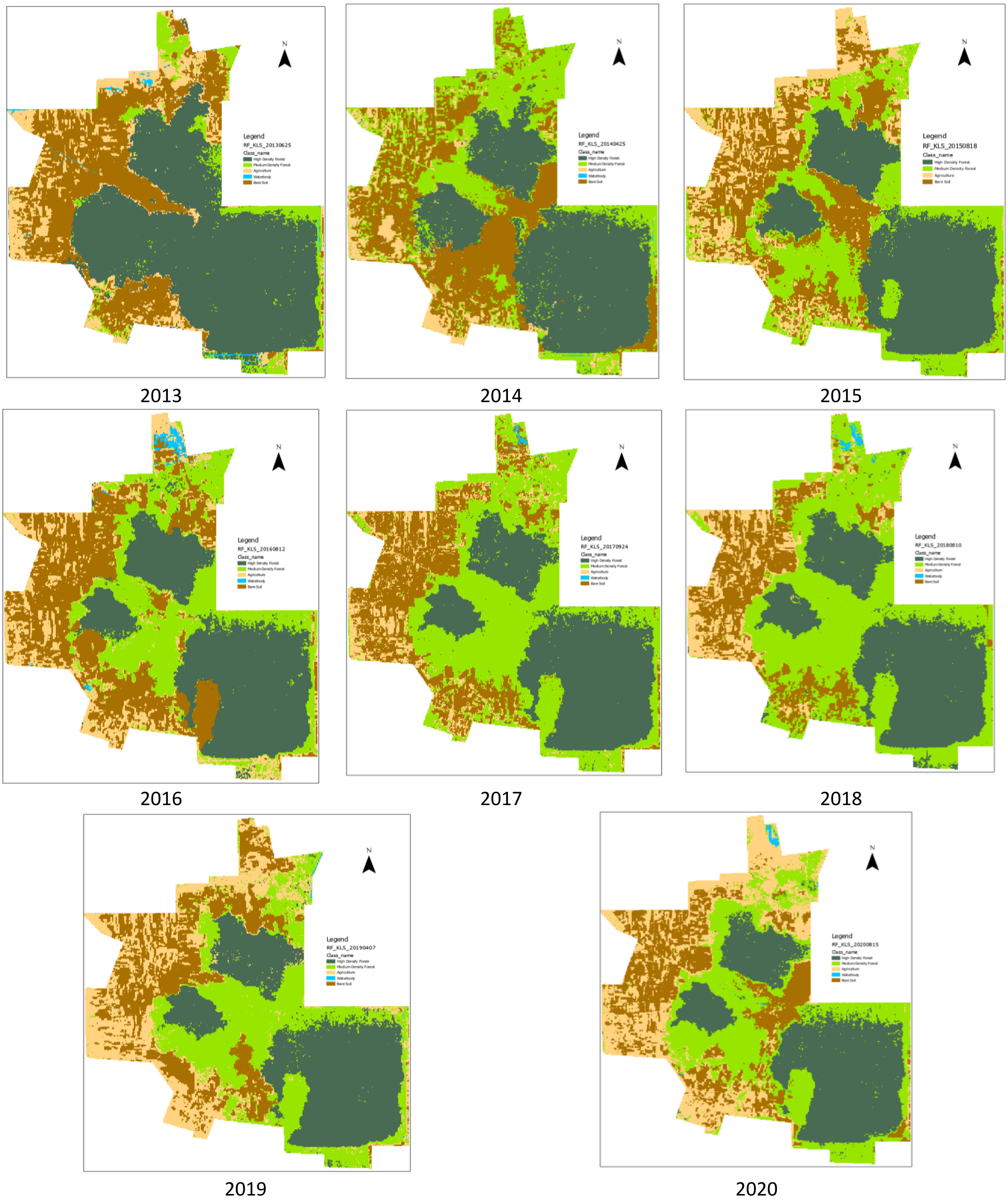


Fig. 10. Land use Land Cover Map in KLSFR from 2013 to 2020

Table 3 shows the correlation matrix between type of land use and active fire (VIIRS). Bare soil and high-density forest show a strongly positive with active fire (0.798816) (0.531256). While correlation between active fire and medium density forest (-0.5656), High Density Forest and medium density forest (-0.7868), bare soil and medium density forest (-0.65208) are strongly negative correlate. In other hand, water bodies and agriculture (-0.07165), and water bodies and active fire (0.080298) show no correlation.

Table 3
Correlation Matrix Between Type of Land Use and Active Fire

	VIIRS	High Density Forest	Medium Density Forest	Agriculture	Waterbody
VIIRS	1				
High Density Forest	0.531256	1			
Medium Density Forest	-0.5656	-0.7868	1		
Agriculture	-0.31923	-0.27494	-0.23617	1	
Waterbody	0.080298	0.243266	-0.30544	-0.07165	1
Bare Soil	0.798816	0.488381	-0.65208	-0.28597	0.320569

6. Conclusion

This study is to measure statistical analysis of forest fire factors. It divided into two types, which are natural factor and human factor. Natural factor is subdivided into 4 variables: temperature, rainfall, humidity, wind speed and NDVI. The highest positive correlation is active fire and temperature, while active fire and rainfall give the highest negative correlation. Other than regression and correlation matrix, OLS method is applied to see the relationship involving independent quantitative variables and a dependent variable from 2013 – 2020 in KLSFR. Human factor is correlation between VIIRS and LULC. LULC changes in KLSFR happened mostly due to human activities. Agriculture area and waterbodies area show no correlation with active fire. The result might be slightly different if using high spatial resolution of remote sensing imagery and use RADAR or LiDAR imagery. RADAR and LiDAR image is categorized as active remote sensing and no issues with cloud coverage.

Acknowledgment
Authors acknowledge the Ministry of Higher Education (MOHE) for funding under the Fundamental Research Grant Scheme (FRGS) (FRGS/1/2019/TK04/UITM/02/37), (600-IRMI/FRGS 5/3 (407/2019). The authors also would like to thank the School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Selangor for their valuable support.

References
[1] Global Environment Centre. "Rapid Assessment of Kuala Langat South Peat Swamp Forest in Selangor." *Global Environment Centre* (2010).
[2] Goldammer, J. G., and V. V. Furyaev. "Fire in ecosystems of boreal Eurasia: Ecological impacts and links to the global system." *Fire in Ecosystems of Boreal Eurasia* (1996): 1-20. https://doi.org/10.1007/978-94-015-8737-2_1
[3] Collins, Luke, Peter Griffioen, Graeme Newell, and Andrew Mellor. "The utility of Random Forests for wildfire severity mapping." *Remote Sensing of Environment* 216 (2018): 374-384. https://doi.org/10.1016/j.rse.2018.07.005
[4] Adab, Hamed, Kasturi Devi Kanniah, and Karim Solaimani. "Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques." *Natural Hazards* 65 (2013): 1723-1743. https://doi.org/10.1007/s11069-012-0450-8
[5] Edwards, Ryan B., Rosamond L. Naylor, Matthew M. Higgins, and Walter P. Falcon. "Causes of Indonesia's forest fires." *World Development* 127 (2020): 104717. https://doi.org/10.1016/j.worlddev.2019.104717
[6] Ilham, Zul, Nur Aida Izzaty Saad, Wan Abd Al Qadr Imad Wan-Mohtar, and Adi Ainurzaman Jamaludin. "Multi-criteria decision analysis for evaluation of potential renewable energy resources in Malaysia." *Progress in Energy and Environment* 21 (2022): 8-18. https://doi.org/10.37934/progee.21.1.818
[7] Ghorbanzadeh, Omid, Thomas Blaschke, Khalil Gholamnia, and Jagannath Aryal. "Forest fire susceptibility and risk mapping using social/infrastructural vulnerability and environmental variables." *Fire* 2, no. 3 (2019): 50. https://doi.org/10.3390/fire2030050
[8] Tan, Sie Ting, Haslenda Hashim, Poh Ying Hoo, Ahmad H. Abdul Rashid, Jeng Shiun Lim, and Wai Shin Ho. "Mitigation the transboundary haze in ASEAN country: biomass to energy GHG emission assessment." *Energy Procedia* 105

(2017): 1178-1183. https://doi.org/10.1016/j.egypro.2017.03.406

[9] Suliman, M. D. H., M. Mahmud, and M. N. M. Reba. "Mapping and analysis of forest and land fire potential using geospatial technology and mathematical modeling." In *IOP Conference Series: Earth and Environmental Science*, vol. 18, no. 1, p. 012034. IOP Publishing, 2014. https://doi.org/10.1088/1755-1315/18/1/012034

[10] Kaufman, Yoram J., Compton J. Tucker, and Inez Y. Fung. "Remote sensing of biomass burning in the tropics." *Advances in Space Research* 9, no. 7 (1989): 265-268. https://doi.org/10.1016/0273-1177(89)90173-7

[11] Anderson, I. P., and I. D. Imanda. "Vegetation fires in Indonesia: operating procedures for the NOAA-GIS stations in Palembang, Sumatra." *Forest Fire Prevention and Control Project, Palembang, European Union and Ministry of Forestry and Estate Crops, Jakarta* (1999).

[12] Peters, Matthew P., Louis R. Iverson, Stephen N. Matthews, and Anantha M. Prasad. "Wildfire hazard mapping: exploring site conditions in eastern US wildland-urban interfaces." *International Journal of Wildland Fire* 22, no. 5 (2013): 567-578. https://doi.org/10.1071/WF12177

[13] Noviarini, Diena, Mutia Delina, Ananda Mochammad Rizky, Umi Widyastuti, Osly Usman, Saparuddin Saparuddin, and Akhmad Yamani. "Early Warning System for Fire Catcher in Rain Forest of Sumatera Using Thermal Spots." *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences* 103, no. 1 (2023): 30-39. https://doi.org/10.37934/arfmts.103.1.3039

[14] Mourao, Paulo Reis, and Vítor Domingues Martinho. "Forest fire legislation: Reactive or proactive?." *Ecological Indicators* 104 (2019): 137-144. https://doi.org/10.1016/j.ecolind.2019.04.080

[15] Hamadeh, Nizar, Ali Karouni, Bassam Daya, and Pierre Chauvet. "Using correlative data analysis to develop weather index that estimates the risk of forest fires in Lebanon & Mediterranean: Assessment versus prevalent meteorological indices." *Case Studies in Fire Safety* 7 (2017): 8-22. https://doi.org/10.1016/j.csfs.2016.12.001

[16] Jabatan Perhutanan Semenanjung Malaysia (JPSM). "Laporan Kajian Pengurusan dan Pemuliharaan Hutan Simpan Paya Gambut Bagi Negeri Selangor di Bawah Peruntukan Rancangan Malaysia Ke Sebelas (RMKe-11)." *Jabatan Perhutanan Semenanjung Malaysia*, 2020.

[17] Jabatan Perhutanan Negeri Selangor. "Pelan Pengurusan Kebakaran Hutan bagi Hutan Simpan Kuala Langat Utara (HSKLU) dan Hutan Simpan Kuala Langat Selatan (HSKLS) (2017 - 2021)." *Jabatan Perhutanan Negeri Selangor*, 2016.

[18] Fraisse, Clyde W., Norman E. Breuer, and David Zierden. "Drought Decision-Support Tools: Introducing the Keetch Byram Drought Index-KBDI." *University of Florida*, 2011.

[19] Pramanik, Malay, Poonam Singh, Gaurav Kumar, Vijay Prakash Ojha, and Ramesh C. Dhiman. "El Niño Southern Oscillation as an early warning tool for dengue outbreak in India." *BMC Public Health* 20 (2020): 1-11. https://doi.org/10.1186/s12889-020-09609-1

[20] Sule, H. A., Ahmad Ismail, and M. N. A. Amal. "A Review of the Ichthyofauna of Malaysian Peat Swamp Forest." *Pertanika Journal of Tropical Agricultural Science* 39, no. 4 (2016): 421-458.