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# VALIDATION OF FOREST FIRE HOTSPOT ANALYSIS IN GIS USING FOREST FIRE CONTRIBUTORY FACTORS

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**ABSTRACT**

Forest fires have been showing an increasing trend in the past few years. Hundreds of hectares of forests are damaged every year. Thus, it is crucial to identify and implement appropriate forest fire management measures. GIS hotspot analysis has become an advantageous technique for the analysis of spatial clustering of forest fires. However, inadequate research has been undertaken on the validation of forest fire hotspot analysis in GIS. The objective of this paper is to validate forest fire hotspots identified by two statistical-based and one non-statistical-based GIS hotspot analysis methods, namely Getis-Ord Gi*, Anselin Local Moran's I and Kernel Density Estimation (KDE), in a study area. The three hotspot analyses were validated by evaluating the spatial interference between the identified forest fire hotspots by each method and existing forest fire contributory factors. The study found that KDE resulted in better spatial matching of forest fire hotspots and forest fire contributory factors, compared to Getis-Ord Gi*. However, Anselin Local Moran's I did not identify any statistically significant forest fire hotspots in the study area.

Keywords: GIS; Hotspot; Forest; Fire; Brunei Darussalam; Getis-Ord Gi*; KDE; Local Moran's I

## INTRODUCTION

Forest fires have become a seasonal phenomenon in the Southeast Asian region. The region was hit by significant forest fires in the years 1982-1983, 1987, 1991, 1994, 1997-1998 [1], and more recently, in 2013 and 2015. Climate change and adverse health, economy and biodiversity are among the negative impacts of widespread forest fires that affect spacious areas of forest in Indonesia and result in significant smoke haze and carbon emissions [2]. Forest fire activities particularly in Brunei Darussalam also show an increasing trend in the past few years (Fig. 1), where forest fire occurrences in the country has increased by 80 percent between 2007 and 2016.

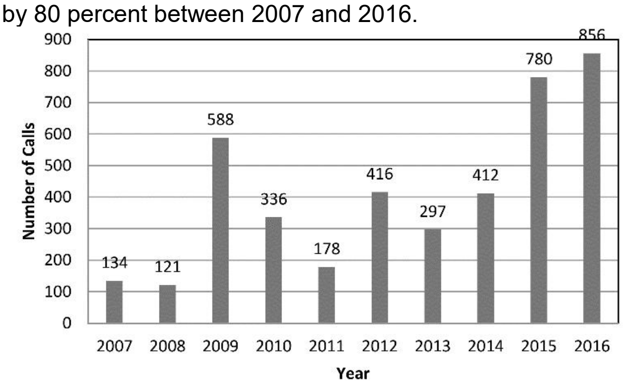


Fig. 1. Number of Forest Fire Calls in Brunei (2007-2016).

The Belait district has been one of the most impacted districts by forest fire in Brunei Darussalam. Belait has the biggest impacted area by forest fire in Brunei due to the extensive presence of peatland. Fires in peatland usually take a significantly long time to be extinguished, because they can survive with low temperatures and limited oxygen availability. In 2016, fires in Belait's peatlands took more than two months to extinguish and approximately 274 hectares of peatland were affected by fire [3]. Hence, this research selected Belait as a study area, in order to evaluate the accuracy of three different GIS hotspot analysis methods in the identification of forest fire hotspots.

Hotspot analysis has become an advantageous technique for analysing and visualising geographically-distributed events, and therefore enabling their management. This involves the visualisation of geographic data, which then enables the identification of 'hotspots', which are areas with higher density or where events or activities are clustered. Hotspot analysis has been extensively utilised on variety of cases such as public health research [4-6] traffic accidents [7-10] and crime prediction [11].

Hotspot analysis is usually conducted with the help of Geographic Information System (GIS) [12-14]. GIS provides tools that can help to identify and prioritize the geographical location of events and hotspots. It enables the development of maps and the visualisation of scenario's outcomes [15]. Hotspot analysis can also assist in decision-making, management and prevention of incidence. The identification of hotspots can help to suggest suitable remedial and mitigation measures. For instance, Truong and Somenahalli [16] generated a pedestrian-vehicle crash hotspot map using GIS, this then enabled the identification of causal factors, determination of appropriate mitigation measures and the planning of a safer transit system. Mekonnen and Melesse [14] identified soil erosion hotspots using GIS and remote sensing for Northwest Ethiopian Highlands; the resulting hotspot map enabled them to determine soil-erosion susceptible areas and prioritise areas for planning and implementation of watershed management programmes.

There are numerous geostatistical methods for hotspot analysis in GIS, each with its own advantages and disadvantages. Some of the common hotspot analysis methods include Kernel Density Estimation (KDE), Gi*, thematic mapping of geographic areas, and grid thematic mapping [17]. These tools have been useful in determining hotspots of events and subsequently their management. Choudhary, Ohri [18] used KDE to identify road accident hotspots. Based on the identified hotspots, they were able to determine high-density areas of accidents, and hence determine effective strategies for road safety management. Additionally, Rosenshein and Scott [19] used another hotspot analysis method known as Getis-Ord Gi* to identify hotspots of 911 calls in Portland. Determination of crime hotspots can be useful for crime reduction through planning and allocation of law enforcement and crime reduction resources [17].

hotspot mapping has been found to be increasingly popular in wildfire management studies. Widfire hotspot maps can help to evaluate fire risk and determine appropriate measures for its management. For instance, Feltman, Straka [20] determined wildfire hotspots in South Carolina, and the results were crucial for understanding forest wildfire occurrence patterns. Additionally, Caceres [21] generated fire risk maps with the help of Getis-Ord Gi* hotspot analysis in GIS. Kuter, Yenilmez [22] generated fire density map with the help of KDE for forest fire risk analysis.

Getis-Ord Gi* analysis identifies the clusters of high or low values in a study area [23]. It computes z-score and p-values for georefrenced data, which indicate the statistical significance of clustering of high-value data into hotspots and low-value data into coldspots. Anselin Local Moran's I is a GIS hotspot analysis method for identification of local clusters and spatial outliers [24]. For each statistically significant feature in the dataset, it computes a Local Moran's I value, a z-score, a pseudo p-value, and a code that describes the type of cluster [25]. A high positive local Moran's I value means that the corresponding feature has similarly high or low values as its neighbours. In this case, the locations of similar features are statistically significant spatial clusters that are either high-high clusters or low-low clusters. In contrast, a high negative Local Moran's I value shows that the location of investigated feature is a spatial outlier, which has high or low value that is surrounded by other low or high values respectively [26]. The main difference between Getis-Ord Gi* and Anselin Local Moran's I is the method by which they analyse the features, where Local Moran's I only consider neighbouring values without including the value of the feature being analysed. In contrast, Getis-Ord Gi* considers all features including the feature in question [27]. This enables Local Moran's I to identify outliers within the hotspots. The choice of which analysis is more accurate thus depends on the questions that need to be answered [28]. KDE does not perform statistical significance testing of identified hotspots. KDE works by generalising or smoothing discrete point data, and thus producing a continuous density surface out of discrete points.

Prior to using local measures, global measures of spatial autocorrelation can be used to indicate the spatial pattern of geographic data, whether it is clustered, dispersed or randomly distributed. Some examples of global measures are Global Moran's I and Getis-Ord General G statistics. If global measures indicate a clustered pattern of geographic data, local measures of spatial autocorrelation, such as Getis-Ord Gi* and Anselin Local Moran's I, can then be used to identify the spatial location and extent of these clusters [29].

Recent research compared different methods of hotspot analysis to evaluate their performance at the identification of hotspots. Manepalli, Bham [30] compared road traffic accident hotspots identified by KDE and Getis-Ord Gi* methods. The outputs of both methods resulted in similar hotspots. Flahaut, Mouchart [31] compared Anselin Local Moran's I and KDE methods for the identification of road traffic crash hotspots, and found that the outcomes of both methods were nearly identical. Wubuli, Xue [28] compared the outputs of Anselin Local Moran's I and Getis-Ord Gi* to detect spatial clusters of Pulmonary Tuberculosis (TB) in China. They found that Getis-Ord Gi* identified nearly identical 'hotspot' locations to those identified by Anselin Local Moran's I. However, Getis-Ord Gi* showed wider spatial extent of the hotspots and coldspots with different intensities to those identified by Anselin Local Moran's I.

Despite the wide-range applications of GIS hotspot analysis methods for the identification of forest fire hotspots, there has been little research to verify the accuracy of predicted forest fire hotspots from these GIS analysis methods. This paper thus contributes to knowledge by creating and demonstrating a novel method of validation, wherein three GIS hotspot analysis methods, namely Anselin Local Moran's I [24], Getis-Ord Gi* [23] and KDE, will have their predicted forest fire hotspots compared against spatial distribution maps of forest fire contributory factors in Belait. The proposed validation method in this paper also will identify the most accurate method, among these three GIS hotspot analysis methods, whose predicted forest fire hotspots interfere the most with forest fire contributory factors.

## MATERIALS AND METHODS
### STUDY AREA

The area of interest in this study is the Belait district in Brunei Darussalam (Fig. 2). It is the largest district in the country with the area of 2,727 km². More than 80 percent of the area is covered with forests such as peat swamp forest, heath forest, mixed dipterocarp forest, fresh swamp forest and secondary forest.

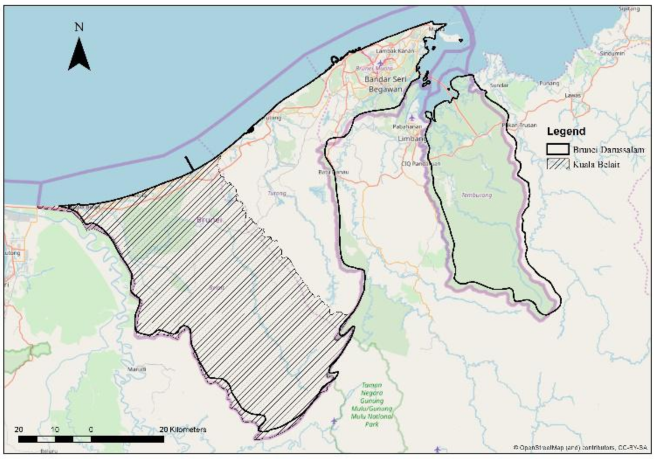


Fig. 2. Kuala Belait District.

Belait is the second most populated district in Brunei Darussalam with population about 69,600 inhabitants [32]. Most of its population are concentrated at the Northern part of the district towards the shore, while the majority of the Southern part of the district is still forested with dispersed settlements. The oil and gas industry located along the coastal area contributes significantly to Brunei Darussalam's economic development; any interruptions to its operation from forest fire could result in immense loss to the country's growth and development.

### FOREST FIRE CALLS

Most of forest fire calls in Belait are concentrated at the Northern part of the district and are close to settlements and roads. Figure 3 shows the spatial distribution of forest fire calls in Belait.

Belait district is vulnerable to forest fire due to the presence of peatland [33]. Forest fires in the district are often regarded as large scale and are usually laborious to extinguish. An average of 1.2 ha of forested areas in the district were damaged by fires in 2016, this is more than a size of a field. Additionally, the majority of forest fire incidents are due to human activity particularly during dry period. In 2018, it was reported that in the first two months (January-February), the district recorded the highest number of forest fire calls with a total of 25 calls. This was because Brunei was experiencing hot and dry weather in early 2018 [34]. Brunei usually faces an increased number of forest fire incidents during dry seasons [35]. Figure 4 shows the number of calls among the four districts in the first two months of 2018.

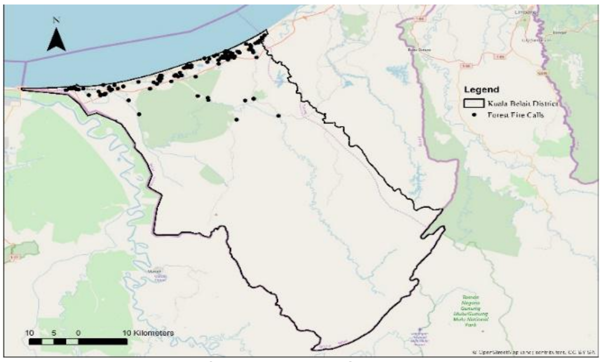


Fig. 3. Distribution of Forest Fire Calls in the Belait District, January - August 2016.

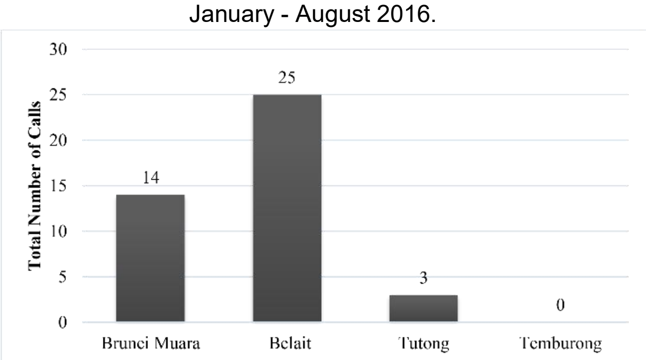


Fig. 4. Number of Forest and Bush Fire Calls in the first two months of 2018 [3].

## METHODS

This study was conducted to compare two statistical-based and one non-statistical-based GIS hotspot mapping techniques namely, Getis-Ord Gi*, Anselin Local Moran's I and Kernel Density Estimation (KDE), and evaluate their accuracy at identifying forest fire hotspots in Belait using GIS maps of Belait's forest fire contributory factors.

Necessary data was collected from various sources. Forest fire calls data for January to August 2016 was collected from Brunei Fire and Rescue Department. The locations of the fire calls were imported into ArcGIS software and displayed as XY data. Getis-Ord Gi*, Anselin Local Moran's I and KDE hotspot analysis methods were then applied to the forest fire calls to identify forest fire hotspots within the study area. The output from each hotspot analysis method was then validated by evaluating the interference between identified hotspots by the three hotspot analysis methods and forest fire contributory factors. The higher the interference of hotspots identified by a particular method, the more accurate the method is. Four forest fire contributory factors namely, population density, elevation, forest cover and annual precipitation, were considered to evaluate the accuracy of predicted hotspots from each method. Figure 5 shows an overview of the hotspot identification and validation methods.

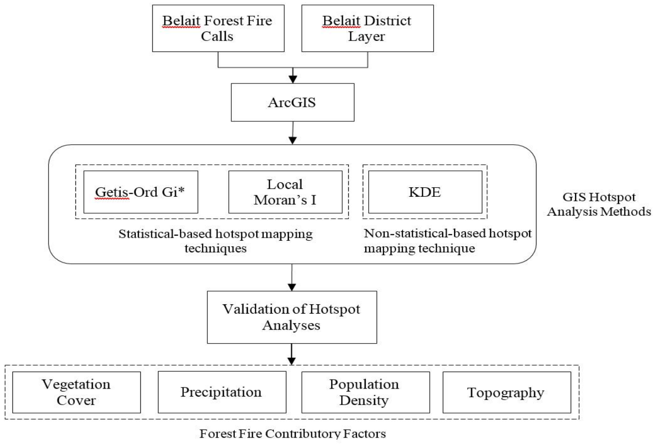


Fig. 5. Overview of Forest Fire Hotspot Identification and Validation Methods

Some items of the spatial data in this study were obtained from Google Earth and OpenStreetMap. Layers produced using Google Earth included study area, residentail areas, vegetation covers, polygons of annual precipitation, topography and population density. Population census data was obtained from the Department of Statistics and the Department of Economic Planning and Development. The population data was then imported into ArcGIS desktop 10.2 and was combined with the layer of residential areas to create the population density GIS layer.

## RESULTS AND DISCUSSION
## FOREST FIRE HOTSPOTS
## GLOBAL SPATIAL AUTOCORRELATION MEASURES

Global spatial autocorrelation measures, namely General G statistic and Global Moran's I, were applied to the forest fire call dataset in ArcGIS to test the spatial pattern of the dataset over the whole study area. The global autocorrelation measures resulted in different spatial patterns (Fig. 6).

General G analysis indicated that the forest fire calls in Belait are arranged in statistically significant clusters of highly frequent forest fire incidents. On the other hand, Global Moran's I indicated that the forest fire calls were randomly distributed in Belait rather than being arranged in clusters. In order to identify the spatial location and extent of the statistically significant clusters indicated by General G statistic, and confirm the output from Global Moran's I, local measures namely Getis-Ord Gi* and Anselin Local Moran's I were conducted to test for local statistically-significant clusters in the forest fire dataset.

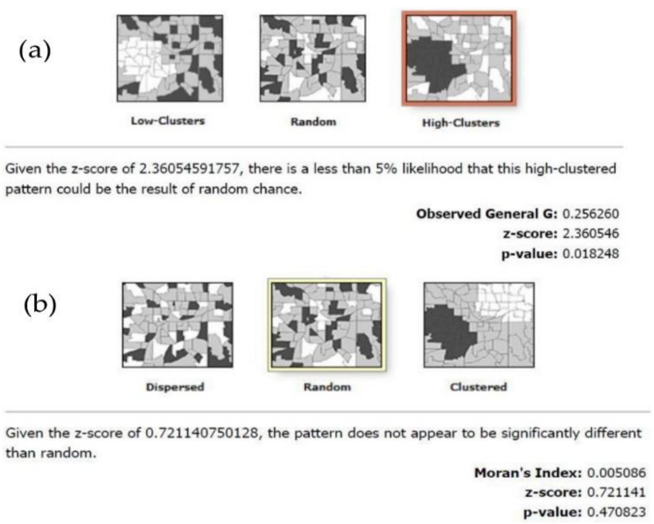


Fig. 6. (a) General G Statistics and Z value (b) Global Moran's I and Z value; indicating clustering/random pattern of forest fire calls in Belait.

1.1.1. Local Spatial Autocorrelation Measures

Three different GIS hotspot analysis methods were applied in this study for forest fire hotspot mapping. The results of Getis-Ord Gi* and Anselin Local Moran's I analyses are shown in Figure 7.

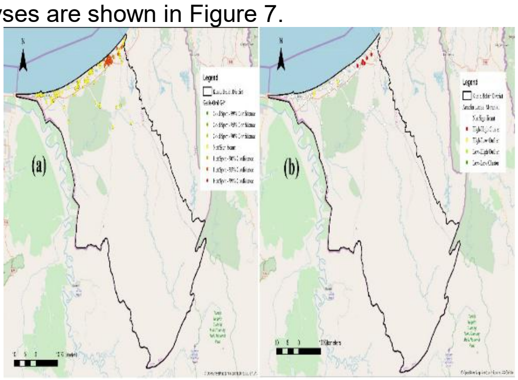


Fig. 7. (a) Output of Getis-Ord Gi* Local Statistics (b) Output of Cluster and Outlier Analysis of Anselin Local Moran's I.

Based on the output of Getis-Ord Gi* statistics in Fig. 7a, Getis-Ord Gi* identified one statistically significant cluster of forest fire calls (hotspot) in Belait. In contrast, Anselin Local Moran's I (Fig. 7b) showed no apparent clusters of forest fire calls, which agreed with the output from Global Moran's I and z value in Figure 6b.

Although both analyses adopt similar approach, the outputs differed. Getis-Ord Gi* was able to identify a single forest fire hotspot while Anselin Local Moran's I did not identify any hotspots in Belait. Further confirmation was required to ascertain whether or not the hotspot area identified by Getis-Ord Gi* is a valid forest fire hotspot. This necessitated the application of a non-statistical-based hotspot analysis method, such as KDE, to the forest fire calls in Belait.

1.1.2. Kernel Density Estimation (KDE)

KDE converted the forest fire point shape file into a continuous surface map of many different forest fire intensities (Fig. 8). In addition to the hotspot area identified by Getis-Ord Gi* in Figure 7a, KDE resulted in three additional hotspot areas of moderate forest fire intensity, as shown in Green in Fig. 8. Although these additional hotspots determined by KDE were not statistically significant by Getis-Ord Gi*, Figure 8 showed that there were other potential forest fire hotspots in Belait. This discrepancy between the results from the three hotspot analysis methods necessitated the validation of the forest fire hotspots predicted by the three methods.

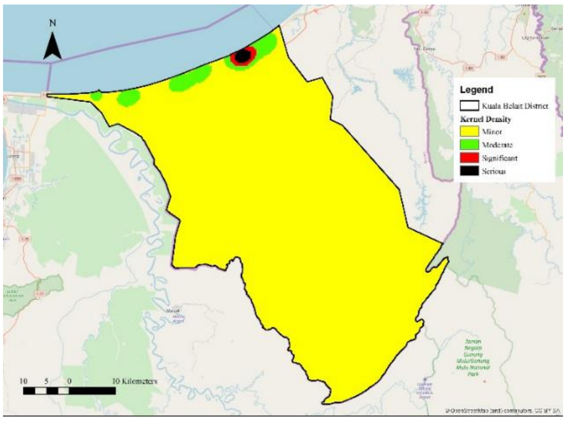


Fig. 8. Forest Fire Hotspots Predicted by KDE.

## VALIDATION OF HOTSPOT ANALYSES

Due to the discrepancy between the results from Getis-Ord Gi*, Anselin Local Moran's I and KDE hotspot analysis methods, validation was undertaken for these results against GIS maps of forest fire ignition contributory factors in Belait. Validation can help to examine which of the methods have the most spatial interference between its predicted forest fire hotspots and various forest fire contributory factors. Weather and forest microclimate, forest types, fire fuels and aspect or topography of forest areas are variables that influence the spread and development of fires particularly during extended dry period [36]. Erden and Coskun [37] reported that population density, human accessibility, land-use and elevation are major indicators of spatial distribution of fire ignitions. Additionally, Catry, Rego [38] demonstrated that population density, elevation and land-use showed strong correlation with forest fire ignition.

This research paper considered four forest fire contributory factors, namely population density, elevation, forest cover and annual precipitation of Belait, to validate the outputs from Getis-Ord Gi*, Anselin Local Moran's I and KDE. These contributory factors were used to map the spatial distribution of forest susceptibility to fire ignition in Belait.

## VEGETATION COVER

Vegetation cover is one of many factors that contribute to forest fire ignition. This is because each forest type has its own characteristics, which affect susceptibility to catch a fire. Forests such as mixed dipterocarp and freshwater forests are the least susceptible to fire since they are usually wet throughout the year. Hence, the occurrence of fire in these forests is minimal. However, during a prolonged dry period, there is a tendency for forest fuel to build up as the rate of dying undergrowth vegetation increases during the dry period due to shortage of water. This increase in forest fuel can facilitate the spread of fires.

Beach and heath forests are reported to be the most vulnerable types to catch a fire during a normal dry period compared to other forest types [36]. These forests become bushy and derelict after being frequently burnt. These conditions can promote the cycle of annual fire occurrence [36]. Additionally, during a prolonged dry period and El Nino dry spells, peat swamp forest can become vulnerable and susceptible to catch a fire. Fire in peat swamp forest is usually laborious and difficult to extinguish due to its smouldering behaviour.

Figure 9 displays the interference between the forest fire hotspots predicted by Getis-Ord Gi* and KDE, and forest types in Belait. There are three main forest types that interfered with these hotspot areas, namely secondary/beach forest, peat swamp forest and a small part of heath forest. Secondary forest is a forest regenerating after significant disturbance and has dense ground growth. It tends to catch fire easily because the forest canopy is open and large trees are scarred, enabling sunlight to reach and dry out ground vegetation [39]. Moreover, secondary forests in Belait are found in heavily populated areas which make them vulnerable to catch fire.

Given the different characteristics of forest types in Belait and their susceptibility to catch fire during dry periods, it can be seen that the hotspots determined by both KDE and Getis-Ord Gi* are mainly within fire-susceptible vegetation types. This also indicates that secondary/beach and heath forest vegetation covers in Belait may have been disturbed at the locations interfering with forest fire hotspots, and thus they become more susceptible to catch fire. Forest preservation and the reduction of forest-clearing activities may help to maintain the nature of these vegetation covers and reduce their susceptibility to catch fire.

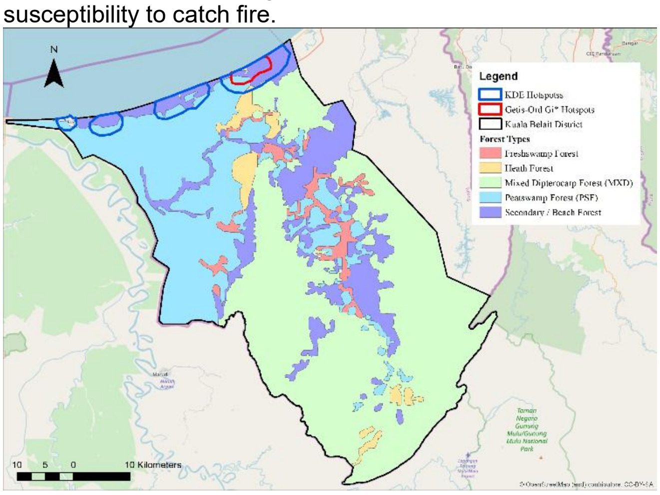


Fig. 9. Getis-Ord Gi* and KDE Hotspots versus Forest Vegetation Covers in Belait.

## PRECIPITATION

Weather variables, such as precipitation, wind speed, relative humidity and air temperature, have a major contribution to forest fire ignition and spread. They influence the moisture content of vegetation (forest fire fuel), and therefore the ease of fire ignition [40]. The likelihood of an area catching fire can be determined based on prevailing weather conditions. In Brunei, forest fires are observed to intensify during dry periods. This confirms that weather variables affecting fuel moisture content can control the ignition of forest fire.

Figure 10 shows the annual rainfall distribution in Belait. The northern region of the district is shown to record the lowest annual rainfall (<2500mm). It is thus the driest and most susceptible region to fire ignition, particularly during prolonged dry periods, which is consistent with the forest fire hotspot areas identified by Getis-Ord Gi* and KDE. This can support Brunei Fire and Rescue Department at the allocation of its resources to these hotspot areas, in order to prevent and combat forest fire particularly when dry periods approach.

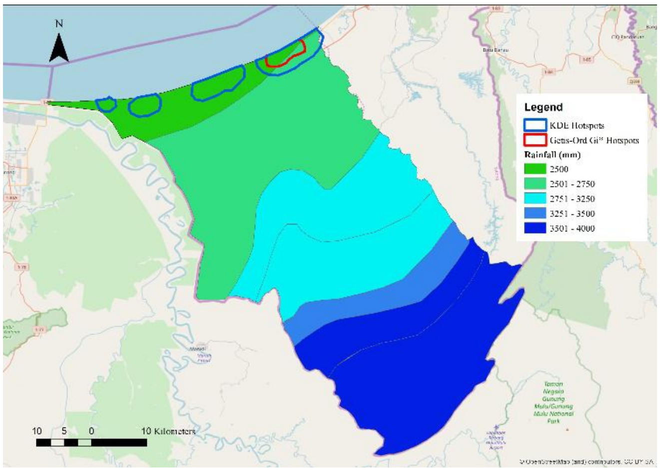


Fig. 10. Getis-Ord Gi* and KDE Hotspots versus Annual Precipitation Distribution in Belait.

## TOPOGRAPHY

Elevation influences the amount and timing of precipitation as well as exposure to prevailing winds. It also affects the seasonal drying of forest fuel. In lower elevations, fuels tend to dry out earlier in the year because of higher temperature and lower precipitation. In addition, fire behaviour tends to be less severe at higher elevation due to high rainfall and moisture [41]. It is observed that the hotspot regions determined by Getis-Ord Gi* and KDE are located at the region of the lowest elevation as shown in Fig. 11, so this further validates the hotspot locations determined by these two methods.

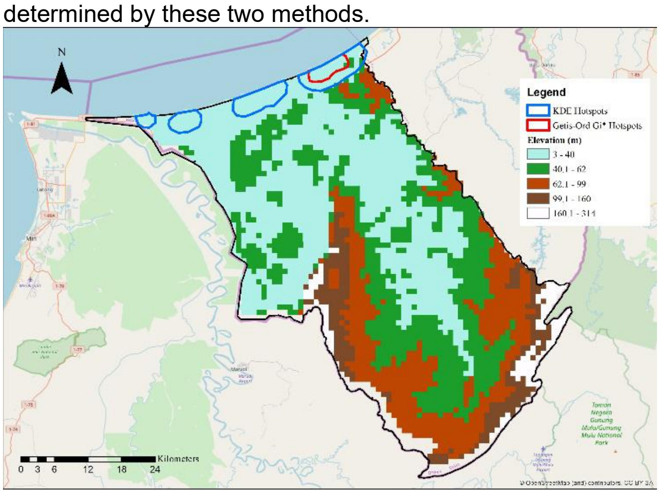


Fig. 11. Getis-Ord Gi* and KDE Hotspots versus Elevations in Belait.

## POPULATION DENSITY

Studies confirmed that there is a positive correlation between population density and forest fire occurrence [38, 42]. This indicates a higher probability of fire occurrences in densely populated areas. Additionally, forest fire occurrences in Brunei are reported to be commonly triggered by dry and hot weather aggravated by irresponsible acts of open burning by humans [43]. Therefore, the presence of human settlements within the northern region of Belait further promote conditions for forest fire to take place in that region.

Figure 12 shows the population density per km² for villages and areas in Belait. Most of population in Belait is located at the northern part of the district. Based on Figure 12, it can be seen that the hotspot area identified by Getis-

Ord Gi*, and 3 of KDE's hotspots, interfere with densely populated villages and areas.

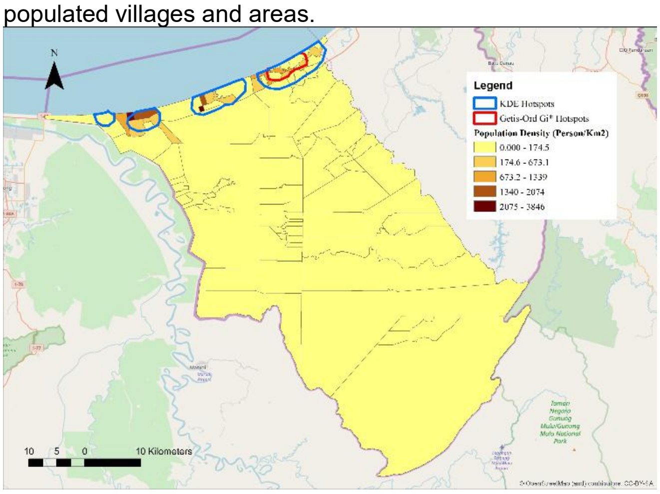


Fig. 12. Getis-Ord Gi* and KDE Hotspots versus Population Density in Belait.

Forest fire in Brunei is reported to be commonly caused by human activities, which explains the high fire occurrence close to the densely populated regions. From this, further preventative and control measures can be drawn or suggested in order to minimise forest fire occurrence in the hotspot areas. Brunei introduced a Zero Burning Policy in 2001 to prohibit and prevent activities that release smoke emission to the atmosphere [44], however there have been difficulties enforcing it in practice. By determining the forest fire hotspot regions, regular monitoring of these regions, to reduce and control open burning activities in densely populated areas, may support the implementation of the policy.

## CONCLUSIONS AND RECOMMENDATIONS

Three different widely used GIS hotspot analysis methods were compared and validated to evaluate their accuracy at the identification of forest fire hotspots in Belait. Anselin Local Moran's I, Getis-Ord Gi* and KDE analyses determined no hotspot, one hotspot and four forest fire hotspots respectively. Fire ignition contributory factors such as population density, elevation, vegetation cover and precipitation were then considered in order to validate the hotspots detected by Getis-Ord Gi* and KDE. These hotspots were found within zones with fire-susceptible vegetation, least rainfall, lowest elevation and high population densities, all of which were significant forest fire contributory factors. This validated the forest fire hotspots identified by Getis-Ord Gi* and KDE, and implied the inability of Anselin Local Moran's I to identify forest fire hotspots in Belait. The KDE's forest fire hotspots, which were additional to Getis-Ord Gi*'s hotspot, interfered with the forest fire contributory factors that were used for the hotspot validation. Therefore, KDE's forest fire hotspots had more interference with forest fire contributory factors that those of Getis-Ord Gi*. Even though KDE is a non-statistical-based hotspot analysis method, this indicated that KDE was more accurate and reliable than Getis-Ord Gi* at the identification of forest fire hotspots in Belait.

With the determination of the most appropriate analysis methods for forest fire hotspot identification, further potential follow-up work includes using overlay GIS analysis to combine further fire ignition contributory factors to those considered in this paper, such as relative humidity, air temperature and fuel map. The study can also be extended by considering fire calls over a period exceeding 10 years to identify and prioritise forest fire hotspots, considering changes in land use.

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