FINE: An R Shiny web application for analysing spatial and spatiotemporal patterns of forest fire incidents in Sumatra, Indonesia

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ABSTRACT

This project involves conducting Spatial Point Pattern Analysis on forest fires in Indonesia. Specifically, we will analyse Indonesian forest fire hotspot data using this method. A hotspot is defined as a location with a higher temperature than its surroundings as defined by the Indonesian Meteorology, Climatology, and Geophysical Agency.

The goal of the project is to create a web application that aims to aid users in performing exploratory data analysis, kernel density estimation, first-order spatial point pattern analysis, second-order spatial point pattern analysis, and spatiotemporal area analysis.

The user will be able to make use of the data from all these analyses without needing to write a single line of code or in-depth knowledge about the dataset in the first place, allowing usage of the analysis data for studies and other purposes.

KEYWORDS

Geospatial analytics, R Shiny, spatial point patterns analysis, spatiotemporal analysis, forest fire incidents

1 Introduction

Between 2015 and 2019, Singapore experienced severe haze due to forest fires in Indonesia, particularly in the Sumatra and Kalimantan regions. However, there has been little to no haze in the region in recent years. This sparked our interest in investigating the occurrences of forest fires in Indonesia.

Using geospatial analytics, we can easily download, manipulate, and analyse data with the R programming language. Geospatial analysis is incredibly useful in extracting insights and patterns from spatial data that may otherwise go unnoticed. However, this method is not easily accessible to individuals with little to no coding experience. Additionally, although there is a lot of data available on the internet, it can be tedious to obtain and consolidate, with some websites requiring users to log in to view the data.

To address these issues, we created an interactive web application named FINE: Fire Incidents Explorer. This application is aimed to allow users to carry out analysis simply through interacting with a graphical user interface. By providing an interactive consolidated platform for users to view data and perform corresponding analyses, we make the data easily accessible while still allowing for flexibility through the user interface.

2 Literature Review

To select relevant features to be included in FINE, we refer to existing research done on analysing geospatial point events, particularly in the domain of forest fire incidents, and make comparisons to existing applications.

2.1 Existing Analytical Methods on Point Patterns

The scope of the problem that FINE wishes to address bears similarity to the research conducted by Arisanty et al. (2021) on spatiotemporal patterns of burned areas in South Kalimantan throughout the years 2016-2019. Their data was sourced from SiPongi+, the official forest fire data portal of the Indonesian Ministry of Environment and Forestry. Spatiotemporal hot spot analysis was performed using Getis-Ord Gi* statistic and Moran's index on aggregated data of the burned areas, while density of land fires was analysed using kernel density.

Kwak et al. (2009) examined the spatiotemporal patterns of human-caused forest fires in Korea. To do so, they leveraged kernel intensity estimation to analyse the spatial intensity of the events, Ripley's K function to detect second-order spatial patterns on the point events, and Poisson regression to estimate the distribution of event occurrences using various independent factors.

As the data used in FINE is primarily in the form of point patterns, we also investigated existing analytical methods on spatiotemporal point patterns analysis. Soale (2016) made use of the space-time inhomogeneous K-function to examine the second order properties of earthquake point patterns distributed throughout space and time. It is an extension of the conventional Ripley's K-function, which adds a time dimension to the calculation.

Referring to these existing literatures, we decided that first-order and second-order spatial pattern analysis tools would be of interest to the users. We added kernel density estimation feature for first-order spatial pattern analysis. However, we expand the second-order spatial pattern analysis to include four conventionally-used functions: K, L, F, and G. Additionally, we will also use Getis-Ord Gi* statistics and space-time K-function for spatiotemporal analysis to identify the changes in forest fire incident patterns over time.

2.2 Existing Geo-visualisation Applications

2.2.1 Sipongi+

SiPongi+ is the official forest fire data portal of the Indonesian Ministry of Environment and Forestry. This web application features an interactive map displaying daily forest fire hotspot data as point events. Users can download historical hotspot data filtered by region, time range, satellite type, and confidence level. Additionally, the portal provides annual data on carbon dioxide emissions and burnt area by province/city.

2.2.2 LAPAN's BRIN Fire Hotspot

BRIN Fire Hotspot is the official forest fire data portal of the Indonesian National Institute of Aeronautics and Space (LAPAN). According to the usage guide, the web application displays hotspots collected from satellites above Indonesia and enables users to filter by region, time, and confidence level. Users can view a summary of the total hotspots from all satellites and their confidence levels.
Compared to SiPongi+, the main difference is that BRIN Fire Hotspot allows users to select between two view modes: pixel or cluster. In pixel mode, every individual hotspot point is shown, whereas cluster mode aggregates them into a single centroid based on the clusters to which the hotspots belong. Additionally, users can see a radius of the heat intensity. Users can also download the hotspot point data in CSV format.

2.2.3 FIRMS

Fire Information for Resource Management System is an application created by NASA. Records active fires as well as any fire related data throughout Earth. Allows users to even observe time since detection of fire incidents by hotspots, in hours (from 1 hour since detection to >24 hours). Users can switch between data obtained from different satellites. Furthermore, they can also view the orbiting paths of the satellites. The website shows data of gridded fire hotspots which have varying colours to show the frequency of fire incidents in those grids. This provides a count of fire hotspots within 0.25 x 0.25 degree grid size for the MODIS (Moderate Resolution Imaging Spectroradiometer) and VIIRS (Visible Infrared Imaging Radiometer Suite) devices mounted on the satellites. Users can observe historical data as well as current real time data of hotspots. Historical data allows the user to view hotspot data as per selected date, while current shows hotspot data up to a week.

3 Data Acquisition and Preparation

Like Arisanty et al. (2021)'s research, we acquired the raw data for forest fire hotspots from SiPongi+ (https://sipongi.menlhk.go.id/). It is a web application that features an interactive map displaying daily forest fire hotspot data as point events. The website collects hotspot point data from five types of satellite images: TERRA/AQUA, SNPP, NOAA20, NASA-MODIS, NASA-SNPP, and NASA-NOAA20. Users can download historical hotspot data filtered by region, time range, satellite type, and confidence level. Additionally, the portal provides annual data on carbon dioxide emissions and burnt area by province/city. FINE focuses on forest fire data from the island of Sumatra in the years 2015-2019. The geospatial boundary data of Indonesian sub-districts are retrieved from Indonesia Geospasial (https://www.indonesia-geospasial.com/) portal in the form of shapefiles. As our area of study is confined to Sumatra, we only retrieve data for the following provinces: Aceh, North Sumatra, West Sumatra, Riau, Riau Islands, Jambi, South Sumatra, Bengkulu, Lampung, and Bangka Belitung.

Before being used in the application, the data is pre-processed separately using R. The packages used for data pre-processing are tidyverse and sf. To improve accessibility, the columns written in Bahasa Indonesia are translated into English. The administrative divisions are translated as such:

Bahasa Indonesia	**English**
Provinsi	Province
Kota / Kabupaten	City / Regency
Kecamatan	District
Desa / Kelurahan	Sub-district

Table 1. English translation of Indonesian administrative divisions

The geospatial data is projected to EPSG 23845, which is the Indonesian coordinate reference system (CRS). The pre-processed data are then saved into RDS format to be used by the main Shiny application.

4 Application Features

Building upon the insights gained from literature review, FINE's features were curated to allow users to conduct analysis on forest fire incidents with ease.

4.1 Exploratory Data Analysis

Before conducting any statistical analysis on the data, users will be able to look at an overview of the data. FINE allows the users to view an interactive point map that shows the locations of all the fire hotspots. The map is implemented using R's tmap package, which is built on top of leaflet. To further sieve out information, users are given the options to filter by location, satellite type, and date range. The map's functionality is partially inspired by R stpp's plot function, which allows users to see a 3-dimensional scatterplot that changes according to a date range. When selecting a date range, users will be able to see the latest hotspots within that date range highlighted in red. This aims to allow users to see the appearance of individual hotspots over time.

Figure 1. Default point map

Additionally, users can opt to color code the points based on the confidence levels at which they are detected.

Figure 2. Point map color-coded by confidence levels

To examine the temporal data, users can see static time-series plots generated by R's ggplot package. It displays the change in aggregated count of forest fire hotspots by month over a year for an area of interest that the user can specify.

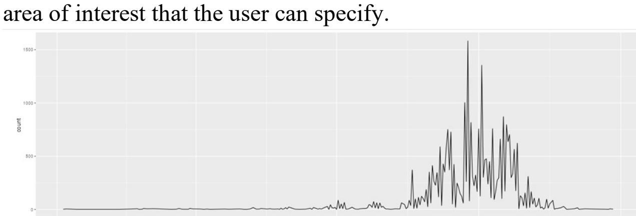

Figure 3. Time series plot

This section is aimed at allowing users to select a specific area of interest and time range of interest to conduct further analyses using the other functions of the application.

4.2 Kernel Density Estimation Map

Users can perform kernel density estimation on hotspots on different cities in Indonesia. The user could pick which province they want to observe, and from the province which city they want to observe. Kernel density estimation map will plot out the density of point features on the map, in this case, being the forest fire hotspots. FINE lets the user pick between adaptive bandwidth and fixed. They are also able to select a kernel method from Epanechikov, Gaussian, Quartic, and Disc. The user also gets to pick the year they want to view the kernel density of hotspots for, from 2015 to 2019. The user is then shown the kernel density estimation map for all the hotspots from low to high confidence.

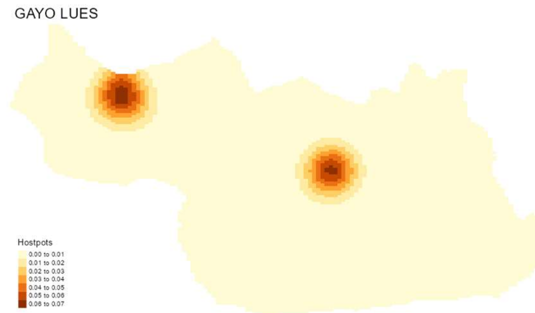

Figure 3. Kernel Density Estimation Map

4.2.1 General Formula

$$\lambda_z(s) = \frac{1}{\sigma_z(s)} \sum_{i=1}^{n} \frac{1}{\tau^2} k\left(\frac{s - s_i}{\tau}\right)$$

4.2.2 Kernel Functions

Different kernel functions can be used to plot the map, and the formulas used for the functions are given below.

4.2.2.1 Epanechikov

$$K(u) = \frac{3}{4}(1 - u^2),\ |u| \leq 1$$

4.2.2.2 Quartic

$$K(u) = \frac{15}{16}(1 - u^2)^2,\ |u| \leq 1$$

4.2.2.3 Gaussian

$$K(u) = \frac{1}{2\pi} e^{-\frac{1}{2}u^2}$$

4.2.2.4 Disc

$$D(u) = \frac{k(u)}{\pi}$$

4.3 Spatial Cluster Analysis

After performing First-Order spatial point pattern analysis in the form of Kernel Density Estimation to identify areas of interest, users can use this feature to conduct Second-Order spatial point pattern analysis to examine the interactions between events.

FINE hence supports a number of statistical tests for Complete Spatial Randomness that can be used to test for and identify different spatial clustering patterns that may be present at the specified time period and location. In particular, we will be looking out for random, clustered or dispersed spatial point patterns using these tests.

4.3.1 Statistical Test Set-Up

Our testing Hypotheses are as follows:

Null Hypothesis, $\boldsymbol{H_0}$: The distribution of forest fires in the selected region and time period is random.

Alternative Hypothesis, $\boldsymbol{H_1}$: The distribution of forest fires in the selected region and time period is not random.

The selected function will then be used to obtain our estimate from our observed data, which will be plotted as solid black line in the resulting plot.

In order to determine if this observed value is statistically significant, we will make use of the Monte Carlo simulation test. This function will perform the selected number of independent simulations of the selected data, and the maximum and minimum values from this simulation will then be used as the confidence interval for the selected significance level. This is represented on our plot by the grey envelope, as can be seen in the following sections. We will therefore consider all values that fall outside of this grey envelope to be statistically significant, in which case we can reject the Null Hypothesis and conclude that the observed spatial point pattern is not random.

4.3.2 F Function

The F Function, alternatively known as the Empty Space function, measures the distribution of distances from an arbitrary location to its nearest observed point. It does this by randomly sampling point locations within the study region before calculating the minimum distance from said locations to a point event, or r_{min}. The formula for the F Function can hence be summarized as:

$$F(r) = \frac{num\ points\ where\ r_{min}\ \leq r}{num\ of\ sample\ points}$$

The output of this F Function estimate can be observed as the solid black line below.

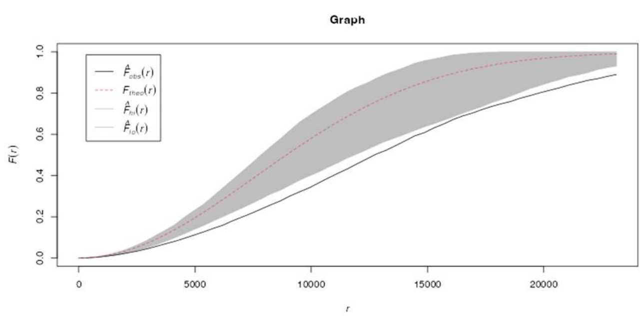

Figure 4. Example output of F Function on a Clustered Pattern

When interpreting this statistical test, we must pay attention to where the estimate falls in relation to the grey envelope. If lies within the envelope, the spatial clustering pattern is said to be random as the pattern observed is not statistically significant at the specified significance level. However, if the estimate lies above or below the envelope at any interval of r, we can say that that the hotspot events follow a dispersed or clustered pattern respectively for that interval.

4.3.3 G Function

The G Function works similarly to the F Function, measuring the distributions of distances from an arbitrary *point* to its nearest neighbour rather than from an arbitrary location. Similarly, the function randomly samples events before calculating the minimum distance from it to another point event to give r_{min}. The formula for calculating the G Function is hence as follows:

$$G(r) = \frac{num\ points\ where\ r_{min}\ \leq r}{num\ of\ sample\ points}$$

The output of the G Function estimate can be seen as the solid black line in the plot below.

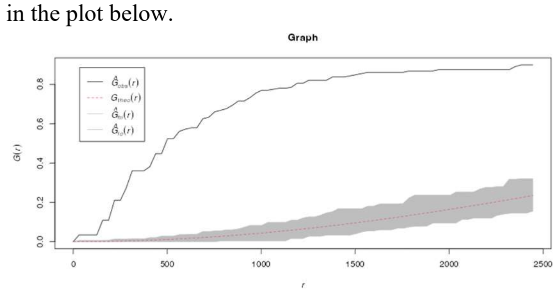

Figure 5. Example output of G Function on a Clustered Pattern

Once again, the interpretation of this statistical test is dependent on where the estimate falls in relation to the grey envelope. If the observed value lies within the envelope, the spatial clustering pattern is classified as random and not statistically significant at the specified significance level. When the estimate lies above or below the envelope at any interval of r, we can say that that the hotspot events follow a clustered or dispersed pattern respectively for that interval.

4.3.4 K Function

Ripley's K Function attempts to combat the limitation of the nearest neighbours approach of the previous two mentioned functions by using an estimate of spatial dependence. This is calculated by aggregating the distance between points at regular intervals. This can be summarized in the following equation:

$$K(r) = \frac{R}{n^2}\sum\sum_{i\neq j}\frac{I_r(d_{ij})}{w_{ij}}$$

Where R is the area bounded by the radius r, n is the number of points, $I_r(d_{ij})$ is a dummy variable which returns I if d_{ij} is less than r and 0 otherwise, and w_{ij} is the edge correction.

The output of the K Function estimate is as shown below on the plot:

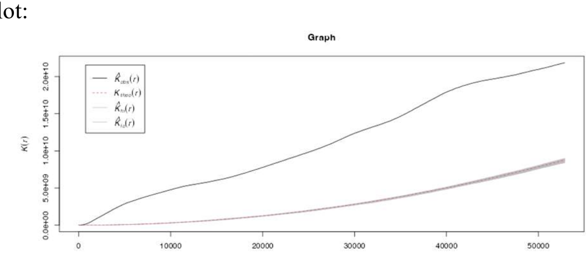

Figure 6. Example output of K Function on a Clustered Pattern

Values falling within the envelope are classified as having a random spatial point pattern as values lying in this region are not statistically significant at the specified significance level. On the other hand, when the K estimate lies above or below the envelope at any interval of r, we can say that that the clustering pattern is statistically significant and hotspot events follow a clustered or dispersed pattern respectively for that interval.

4.3.5 L Function

Last of all, we have the Besag's L Function. In short, the L function is a normalized version of the K Function, allowing easier comparison between theoretical and actual values when the radius value is small. The equation for the L function is therefore simply:

$$L(r) = \sqrt{\frac{K(r)}{\pi}}$$

And the output for this function is as shown in the plot below.

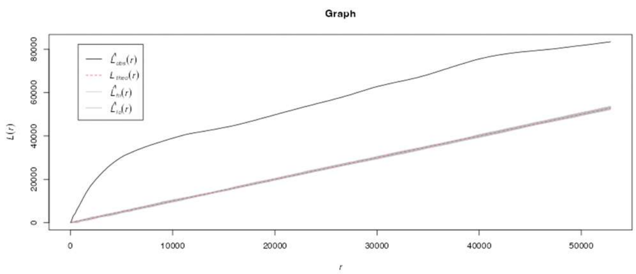

Figure 7. Example output of F Function on a Clustered Pattern

The interpretation of this plot remains the same as for K Function. Within the grey envelope signifies a random spatial point pattern that is not statistically significant in any way, while observed values outside the envelope show a statistically significant spatial point pattern at the relevant significance level the test is carried out at. If the estimate lies above the envelope at any interval of r, the hotspot events follow a clustered pattern whereas if the estimate lies below the hotspot events are said to be dispersed.

4.4 Spatiotemporal Analysis

Users can conduct spatiotemporal analysis on how forest fire incidents change over time and space. FINE supports analysis both at point level and at area level.

4.4.1 Space-time K Function

The space-time K Function is an extension of the regular Ripley's K Function. It is a statistical tool that allows for the analysis of clustering and dispersion of point events both in space and time. In the inhomogeneous case, it considers the spatial and temporal variation in the intensity of the point process under study. Meanwhile, the homogenous case assumes that the underlying process generating the point pattern is constant in space and time. FINE allows the users to analyse point events occurring in a specific sub-district over the time frame of a specific year, both of which the users can select. It leverages the STIKhat function of R stpp package created by Gabriel et al. (2013) to compute a non-parametric estimate of the space-time K Function defined as:

$$\widehat{K}_{ST} = \frac{1}{|S \times T|}\frac{n}{n_v}\sum_{i=1}^{n_v}\sum_{j=1;j>i}^{n_v}\frac{1}{w_{ij}}\frac{1}{\lambda(s_i,t_i)\lambda(s_j,t_k)}1_{\{\|s_i-s_j\|\le u;t_j-t_i\le v\}}$$

Where λ denotes the first-order intensity of the process, which is:

$$\lambda(s,t) = \lim_{|ds|\to 0,|dt|\to 0}\frac{E[Y(ds,dt)]}{|ds||dt|}$$

Values of $K_{ST} > \pi u^2 v$ indicates clustering, whereas $K_{ST} < \pi u^2 v$ indicates dispersion. The range for these values can be visualised through FINE using 3 different types of plots: contour, image, and perspective, adapted from stpp's plotK function.

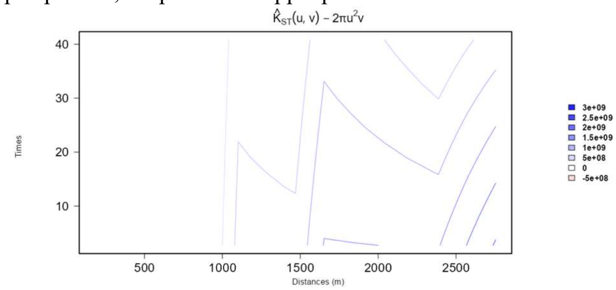

Figure 8. Contour plot of space-time K-function

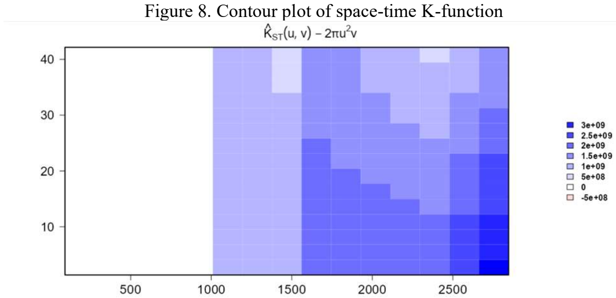

Figure 9. Image plot of space-time K-function

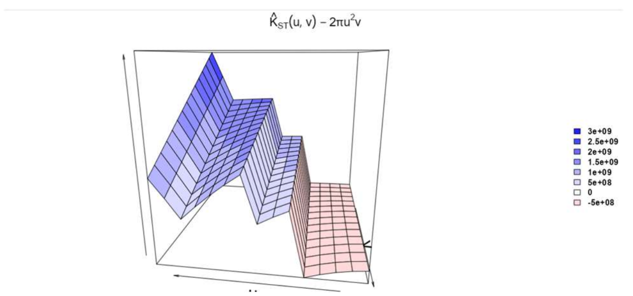

Figure 10. Perspective plot of space-time K-function

4.4.2 Emerging hot spots analysis (by area)

Emerging Hot Spot Analysis (EHSA) is a spatiotemporal analysis technique used to identify locations where the density of a specific event is increasing or decreasing rapidly over time. In the event of a decrease, it is instead referred to as a "cold spot". Note that a distinction has to be made in this case between the fire hotspots (i.e. the point events where temperature is higher than its surrounding areas) and the spatial "hot spots", which refers to spatial clusters of significantly high number of fire hotspots. FINE allows users to conduct EHSA on the aggregated count of fire hotspots at the sub-district level of a certain city or province. FINE utilises the emerging_hotspots_analysis function of R's sfdep package created by Josiah Parry. It combines the Getis-Ord Gi* statistic to calculate local spatial autocorrelation, as well as Mann-Kendall trend test to identify trends. FINE allows users to adjust the number of time lags, number of simulations for Gi* calculation, and significance threshold in addition to selecting a specific place and year to look at. The output of the function is in the form of a choropleth map of the user-selected region, showing the sub-district boundaries. The colours indicate the kind of patterns detected with statistical significance, in accordance with the ESRI classification criteria.

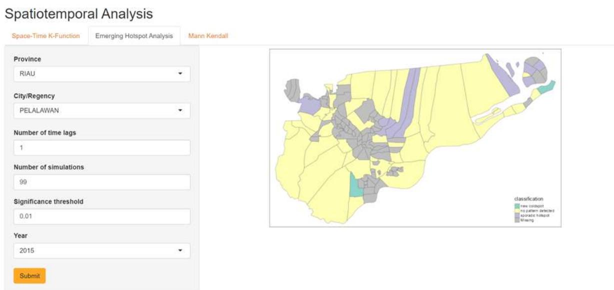

Figure 11. Example output of emerging hotspots analysis

Type of pattern	Description
No pattern detected	No statistically significant pattern detected across multiple time-step intervals
New Hot Spot / Cold Spot	A location that is a statistically significant hot spot (or cold spot) at the final time step without having been significant prior.
Consecutive Hot Spot / Cold Spot	A location with a single uninterrupted run of at least 2 statistically significant hot spot (or cold spot) bins in the final time-step intervals.
Intensifying Hot Spot / Cold Spot	A location that has been a statistically significant hot spot (or cold spot) for 90% of the time and the intensity of clustering increases.
Persistent Hot Spot / Cold Spot	A location that has been a statistically significant hot spot (or cold spot) for 90% of the time-step intervals with no trend in the clustering intensity.
Diminishing Hot Spot / Cold Spot	A location that has been a statistically significant hot spot (or cold spot) for 90% of the time-step intervals and the intensity of clustering decreases.
Sporadic Hot Spot / Cold Spot	A statistically significant hot spot (or cold spot) for the final time step interval with a history of being an on-off hot spot (or cold spot). No history of being a statistically significant cold spot (or hot spot).
Oscillating Hot Spot / Cold Spot	A statistically significant hot spot (or cold spot) for the final time step interval with a history of being an on-off hot spot (or cold spot). Has a history of being a statistically significant cold spot (or hot spot).
Historical Hot Spot / Cold Spot	The most recent time period is not hot (or cold), but at least 90% of time step intervals have been statistically significant hot spots (or cold spots).

Table 2. Types of patterns that can be observed (ESRI)

4.4.3 Mann-Kendall trend test

The Mann-Kendall test is a non-parametric statistical test used to detect whether a set of data values is monotonically increasing or decreasing, as well as the statistical significance of the trend. It is particularly useful when the data is not normally distributed or when the data has a significant amount of noise, as it requires no assumptions about the distribution of the data. FINE allows the users to perform Mann-Kendall tests on computed Getis-Ord Gi* statistics of aggregated count of fire hotspots within a sub-district in a specific year. This allows users to drill deeper into the insights that they have obtained from the Emerging Hotspots Analysis section. FINE utilises the MannKendall function of R's Kendall package to perform the test. The output of the analysis is a time series plot showing the values of the Gi* statistics by time and a table showing the results of the Mann-Kendall test.

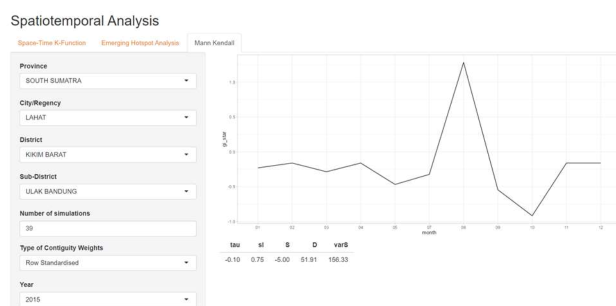

Figure 12. Example output of Mann-Kendall trend test

5 Findings

In order to test our application, we decided to use our application to investigate when and where the highest density of hotspots occurred during our chosen study period.

To do this, we first started by first doing some exploration with our EDA tool. Starting with our Point Map visualisation, we quickly realised that South Sumatra had by far the largest amount of points. We then moved to our Time Series to pinpoint the time period with the highest number of occurrences of hotspots.

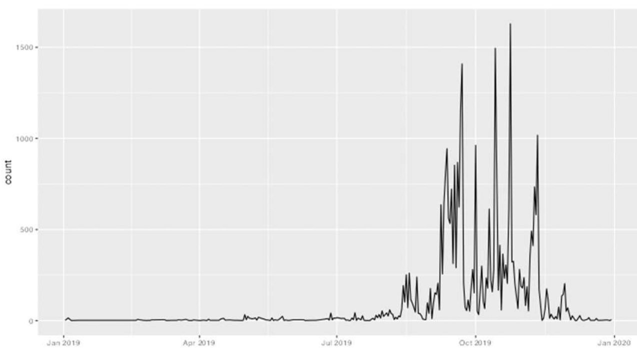

Figure 13. Time Series of Hotspot Events in South Sumatra 2019

From the time series, we determined that hotspot activity peaked around October and was especially high in the years of 2015 and 2019.

With these findings, we decided to narrow down our investigation area and time period to South Sumatra in 2019. For the sake of computation time in our further analysis, we decided to further reduce our study domain to the city of Ogan Komering Ilir, and to the month of October where appropriate, as this selected location and time period had the highest density of hotspot events.

In order to get more insight into the distribution of these hotspot events throughout South Sumatra, we can use our Kernel Density Estimation tool to generate a kernel density map. This will give us a better idea of the intensity of point distribution throughout South Sumatra.

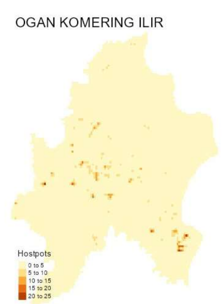

Figure 14. Kernel Density Estimation Map of Hotspot Events in Ogan Komering Ilir, South Sumatra 2019

As we can see from our Kernel Density Estimation, high intensities of hotspot events seem to be dotted around the Districts of Pampang and Cengal.

Moving on to Spatial Clustering Analysis, we can carry out the Complete Spatial Randomness test using our Spatial Cluster tool to determine the observed spatial point pattern in this region.

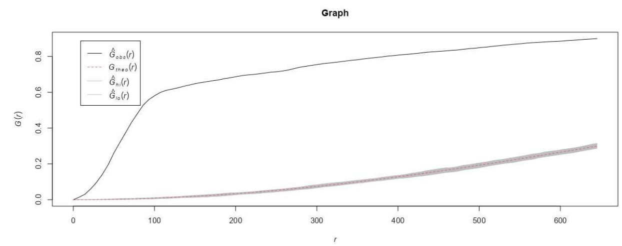

Figure 15. Complete Spatial Randomness Test with G Function of Hotspot Events in Ogan Komering Ilir, South Sumatra, October 2019

From this output, we can clearly see that the hotspot events classify as clustered and are statistically significant for all plotted distances, as indicated by the observed value lying high above the grey confidence interval envelope.

And last of all, we can go further to do some Spatiotemporal Analysis of the region to see the hotspot patterns over time across the region.

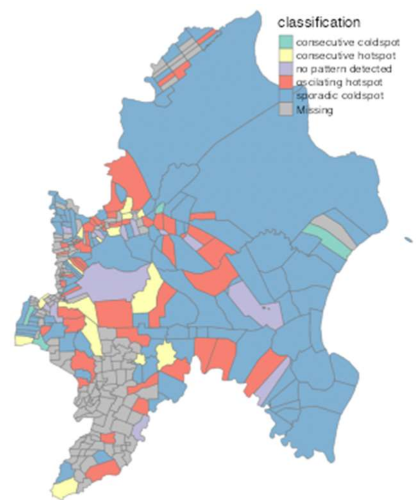

Figure 16. Emerging Hotspot Analysis of Hotspot Events in Ogan Komering Ilir, South Sumatra 2019

We can see that a large number of regions are classified as Sporadic Coldspots. This is likely as, recalling the Time Series, hotspot activity peaks only in the later months of the year. As such, the vast majority of the time the region would be classified as a cold spot, only occasionally classifying as a hotspot during the months of August to November.

As we can see from this comprehensive analysis, our interactive web application tool for exploring spatial and spatiotemporal patterns in data can effectively allow users to interpret and extract relevant information from geospatial data.

To evaluate the depth of this analysis, we compared our findings to a similar study on the Spatial analysis of Wildfire in the South Sumatra Peat area during 2019 Drought Season (Putra et al., 2021). In this journal, very similar findings were reported during this 1-

year period of study, with increasing hotspot activity from June to October of 2019 followed by a decrease in November 2019. It also similarly notes that the district of Ogan Komering Ilir had the highest number of hostpots due to having the largest area of peatland in the area under study. As we can see, our tool is sufficient for extracting a similar level of descriptive analysis as a research journal with a similar topic. On top of this, our web application has the added benefit of being interactive, and with a wider variety of tests so users may explore on their own.

6 Future Work

To further improve upon our application's functionality, we would like to add more tools and features that would allow users to better investigate the spatial and spatiotemporal distribution of forest fire hotspots. Below is a list of possible additions that our team believes would positively benefit users in their geospatial analyses.

Firstly, we could expand upon the Complete Spatial Randomness tests provided to include more options, as we have only included a small subset of the available tests. Implementing a wider range of tests would give users additional autonomy and customizability to perform whatever specific analysis they fancy.

While implementing the Mann-Kendall trend test, we also came across a variation of the test known as the Seasonal Mann-Kendall test. Given more time, we think this would be an apt test to add as the occurrences of forest fires in Sumatra do indeed follow a seasonal pattern.

Another extension would be to explore the Space-Time inhomogeneous K function. As explained in section 4.4.1, this variation of the Space-Time K function would allow users to evaluate if there is clustering of points both across space and time.

Lastly, we for further exploration we feel that we could also train and add in a Geographically Weighted Regression model to predict the probability of forest fire incidents happening at any point of time in a year based on the hotspot data currently available. This would greatly help relevant agencies predict and be more prepared in combating forest fires.

7 Conclusion

FINE makes the process of performing geospatial analytics on the forest fire hotspots of Indonesia more convenient, especially for users who are not as knowledgeable in coding. Our findings showed similar readings to that found in similar literature texts, and further, allows users to select which data they want to observe, presenting them with an interactive map. Reading multiple journals would be very time consuming and would require a lot of manual filtrations of data to get relevant information. FINE instead provides a platform for custom analysis that is easily operatable by users.

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