Observed Data of Forest Fire Hotspots effects on Respiratory Disorder by Arc-GIS in Riau Province, Indonesia

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Abstract. The paper shows that air quality aspects rise from forest fires in Indonesia and they have associations with a wide range of adverse health outcomes, including respiratory health problems. Due to the unpredictable nature of forest fires, it is challenging for public health authorities to evaluate the potential exposures before they occur reliably. Using GIS software, zoning was made on Riau Province, Indonesia. The data shows that the highest fire hotspot was in 2015 by 12,854 and the lowest was 527 in 2017 as well as the lowest Respiratory Disorder Cases in 2017 was 371,044. The Finding proves that smoke has a significant negative effect on increasing respiratory problems Therefore, it also indicates that smoke and haze forecastings are effective tools and challenging to be developed that can be used as public health predictions and establish a suitable policy on forest fires. However, their inherent uncertainties limit their widespread adoption. Observed measurements from air quality monitoring networks and remote sensing platforms are more reliable, but they are inherently retrospective.

Keywords: Forest fire, air quality, respiratory disorder, GIS, Indonesia

1. Introduction

Riau Province is the major province in Indonesia that always faces the haze and smoke problem every year. The data can be used for researchers, government officers, and scholars who want to do understand, develop, and analyze the significant correlation between haze, forest fire, and issues [1]. Furthermore, Vegetation fires are common in Southeast Asia, particularly Indonesia [2]. Fires are used by people to clear and convert land for agricultural purposes, mainly for palm oil plantation [3]. It is often used for land clearing because of its effectiveness and cheapness [4].

In another research [5][6], forest fire based on artificial intelligence (AI), they established a prediction of risk for forest fire based on a smart forest Predict the threat of forest fire against preceding climates. In Indonesian forests, AI built a predictive model for detecting fire hotspots [6]. On the other hand, however, this activity produces a sickening and deadly cloud of smoky pollution caused by the widespread burning of land and forests in Indonesia [3]. While 60 percent of the fires in Sumatra originate in the province of Riau. Riau has the highest incidence of vegetation fires in Indonesia compared to any province in terms of the number of fires per square kilometer [3]. The province continues to rapidly and rampantly log the remaining forests, making the dryland forests almost exhausted [7]. Thus, the swamp forest or the peatland becomes a new goal for land conversion [8]. Conversion is a key and planned component of Riau's development strategy.

The peak in the province of Riau occurred in June when the lowest rainfall recorded during the year was 56.08 mm in 2013 [3]. This amount of rainfall was far below normal (average of 30
years), which was 145.06 mm, while in April and May (the period before the fire) there was also a lack of rainfall which allowed the hotspot to accumulate in June.

Exposure to forest fire smoke (FFS) is associated with multiple adverse health effects, mostly respiratory ones. Forest fires are increasing in frequency and intensity as global climate changes occur and can be responsible for periods of extremely poor air quality. Exposure to fine particulate matter (PM2.5) from forest fire smoke (FFS) has been associated with a range of adverse health effects, from reduced birth weight to mature mortality. However, the clearest evidence is from acute respiratory effects studies, with inconsistent and inconclusive results for cardiovascular effects and cause-specific mortality [9].

Therefore, the research took place in the province of Riau. Data from this research were collected through secondary data from BMKG, the Health Office, and the Primary Health Services. The spreadsheet of Microsoft Excel was used to organize, enter, and infer the data collected. GIS data were used to describe each hotspot as well as respiratory disorders in each territory for the longitudinal effect of smoke fire during 2015-2018.

2. Methodology

The data sets analyzed the observed data of forest fire hotspots' effects on the respiratory disorder in Riau Province and conducted its zoning via GIS software. Microsoft Excel spreadsheet was used to organize the data as well [10]–[13]. Artificial intelligence has been used to determine the risk of fire. In addition, logistic regression is used in more sophisticated approaches to include fire hazard modeling. Multi-criteria analysis is a focus that has been proposed in recent research and analysis of metrics in the form of a model of GIS-based spatial data [14], [15].

Twelve regencies were selected based on the existence of an oil palm plantation area to determine the fire hotspots in Riau Province. Data of fire hotspots came from the Meteorology, Climatology, and Geophysical Agency in each selected regency. The location of the stations is in Fig. 1. To obtain the data of respiratory disorder cases, the researchers collected data from the Community Health Centre in twelve districts and took the whole sample of the patients. All collected data were analyzed, and zoning via GIS software and Microsoft Excel spreadsheet was used to organize the data as well [10]–[12], [16]–[32]. The zoning areas via GIS software aims to build a thematic layer were generated as a classification map of the research data areas. The data were uses coded numbers can be classified into 12 areas, from 2014 to 2018, the parameters such as <42 middle, moderate are 43-137, high >137. The data remains different thematic layers such as Fig. 2 forest fires hotspot, Fig.3 respiratory disorder.
3. Finding and Discussion

The research data was conducted based on combined spatial data collecting from 12 districts. The forest fire hotspot was approximately covering Riau province. Additional information such as the number of hotspots during the last five years are provided. The statistical data was found varying fires hotspot year from low to very high. In 2014-2015 as major forest fires hotspot according to data of study areas. Being estimated by drawing each district on GIS data, zoning area is also measuring the level of the hotspot in different parameters. The mapping areas represent that coverage forest fires hotspot from 2014 to 2018 as the highest areas.

**Figure 2. Forest Fire Hotspots – The trends and accumulative data on the first figure.** (A) forest fires hotspot distribution in 2014-2018 which can be generated that fires hotspots are in 12 districts, (B) forest fires hotspot in 2015 almost holding ninth districts, (C) forest fires hotspot in 2016 was decreasing and located in the same area as 2014 out of six districts, (D) the fewer fires hotspot distribution is in 2017, only one district as major fires hotspot distribution, (E) forest fires hotspot in 2018 shows the potential fire hotspot in the three same districts such in 2014 – 2018. Mapping of each year is listed.
Using GIS analysis data with considerable numbers of study areas, a respiratory disorder caused by forest fires was analyzed. The result of mapping models based on the GIS-based measures the potential and dominant districts that coverage respiratory disorder. The data site mainly using georeferenced from shapefile features were extracted and interpreted as the major district inform the thematic layer. The statistical data was generated varying years from low to very high. Further, the data was calculated as the major areas both of forest fires hotspot and respiratory disorder and it was found varying between low, moderate, and high.

There are twelve districts/areas on the map, nine of which are in the high category of hotspots in Fig 3. High incidence of acute respiratory disease occurs in Indragiri Hilir, Siak, Kampar, Rokan Hulu, and Dumai. Mostly locations with high hotspot categories have a high incidence of acute respiratory disease. This result is similar to what happened in North Thailand, where the concentration of PM10 was the highest. It indicates a noticeable impact of PM10 on the increasing number of respiratory patients in the area [27]. In North Carolina, there have been increased visits to the emergency department with a respiratory diagnosis due to high smoke density [28]. Researchers identified 32 days of extreme PM10 concentrations due to bush fire or vegetation-reduction burns. Research conducted in Australia between 1994 and 2002 identified 32 days with extreme PM10 concentrations due to bushfires or vegetation-reduction burns and found an increase in hospital admissions.
Figure 3. The map of forest fire distribution and its association with a respiratory illness on the first figure. (A) hotspot and respiratory disorder distribution from 2015 to 2018 in 12 districts, (B) hotspot and respiratory disorder in 2015 which can be generated high distribution are in ninth districts, (C) hotspot and respiratory disorder in 2016 holding six districts, (D) hotspot and respiratory disorder in 2017 was decreasing and located only one district as a hotspot and respiratory disorder, (E) forest fires hotspot in 2018 shows the potential hotspot and respiratory disorder in the four same districts such in 2015 – 2018. Mapping of each year is listed.

In 2015-2018, as the intensity and size of wildfires increase, so do the associated costs and vulnerable and at-risk populations adversely affected by wildfire smoke. Consequently, the public
health impacts of wilderness fire smoke are of greater importance and merit the attention of all those responsible for land and air quality management decisions and wilderness fire policies that protect the health of the public and at-risk populations and those affected by the wilderness fire policy. As a result, the government needs a wide range of decision-makers and stakeholders to address this issue, including local, state, federal, and tribal governments and agencies/offices responsible for land and forest use and fire management, environmental quality, and public health.

Most of the health effects of understanding wildfire smoke originate from studies of urban particulate matter, specifically fine particulate matter. These studies have shown that short-term exposures (i.e. days to weeks) to fine particulate matter, a major component of smoke, are associated with increased premature mortality and worsening of pre-existing respiratory and cardiovascular disease. Children, pregnant women, and elderly people are also particularly vulnerable to exposure to smoke. Also, fine particles are respiratory irritants, and exposure to high concentrations can cause persistent cough, phlegm, wheezing, and difficulty breathing. Exposures to fine particles can also affect healthy people, causing respiratory symptoms, temporary reductions in lung function, and pulmonary inflammation. Particulate matter may also affect the physiological mechanisms of the body that remove inhaled foreign material from the lungs, such as pollen and bacteria [33].

4. Conclusion
The increasing frequency of large wildfires, the expansion of the wilderness-urban interface, the area between uninhabited land and human development, and the growing and the aging population are increasing the number of people at risk from wildfire smoke, thus highlighting the need for broader stakeholder cooperation to address the health effects of wildfire. The map model was achieved by means of an artificial intelligent fire hotspot detection system. Therefore, AI can be used to refine fire susceptibility maps for fire suppression resource planning, development function, and early warning programs. While much is known, many issues remain and require further population-based, clinical, and occupational health research. Health effects measured over much wider geographic areas and for longer periods will better define the risk of adverse health outcomes, identify sensitive populations and assess the impact of social factors on the relationship between exposure and health outcomes. Improving exposure models and access to large clinical databases foreshadow improved risk analysis to facilitate more effective risk management. Fuel and smoke management remain important components for the protection of the population.

5. Competing Interests
The authors declare that they have no known competing personal interests that could have appeared to influence the work reported in this paper.

6. References

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