Using Artificial Intelligence Technique in Estimating Fire Hotspots of Forest Fires

*Agustiyara*¹, Eko Priyo Purnomo², Rijal Ramdani³

¹²³Department of Government Affairs and Administration, Jusuf Kalla School of Government (JKSG), Universitas Muhammadiyah Yogyakarta
*Corresponding e-mail: agustiyara@umy.ac.id

Abstract

This paper aims to assess the fire detection systems in estimating hotspots in forest fires, in other words, a way of considering the possible scale of fires. Since it needs to have precise and fast mechanisms to make the right decision in case of a forest fire. In this paper, the hotspot resulted from potential forest fires was estimated using the Artificial Intelligence (AI) technique, which contained certain parameters, such as time, when the fire broke out, and unit area of the existing environment. Fire estimation can be built as a large-scale framework that gathers hotspot data from multiple regions. The current estimation systems, such as sipongi.menlhk.go.id and geospasial.bnpb.go.id as forest fire databases, are used to identify forest fire possibility and risk at any given time. The data was from the SiPongi and BNPB in Indonesia and contained forest fire hotspot records from 2010 and 2020. The output from the estimation methods applied in this paper predicted the scale of the hotspot i.e., large, medium, or small fire. Furthermore, the Geographical Information System (GIS) based model was used to calculate the forest fire hotspot, landscape, and topographic data in the selected provinces. In this case, AI is used to classify the regions at risk of forest fires and estimate the burned area for recent forest fires. The results of these estimates are presented and compared to similar studies in the literature.

Keywords: Forest Fires, AI, Estimation, Hotspot

1. Introduction

Forest fires and land use require a great deal of local and central government concern [1]. These problems have affected 1,753 peoples with ISPA due to the fire and haze, moreover, a lot of places have been impacted [2]. Aside from that, the land fires caused environmental, economic, and social impacts that were severely affected Riau Province, as well as Jambi, South Sumatra, South Kalimantan, West, and East Kalimantan [3]. It was estimated to be as much as USD16 billion in the financial loss within the sectors of health, education, germplasm, carbon emissions, and others [1]. Which is higher than land fires in 1997 [3]. However, the lack of management on the peat swamp ecosystem and the long dry season due to El Nino caused much more haze compared to the mineral soil [4]. It was estimated to be 2.61 million hectares of land burned, 33% is peatland covering 869,754 hectares [4]. While fires in mineral soil covering 1,741,657 hectares or 67% [5]. The impact of this disturbance damaged a lot of aspects, from water resources, carbon emissions, destruction of vegetation, loss of biodiversity, health costs, disruption of business trips, and costs of restoring ecosystems [6]. The global effects of fires include global warming, a decrease in temperature, light intensity, and a potential effect on El Nino [3], [7].

For the case of land fires, forest fires require estimation systems using databases based on computational intelligence models [8]. Several studies analyzed forest fire estimation such as [5] artificial
intelligence explanation on social science perspectives. It generated forest fires hotspots, in which the areas are taken into account, on how well a human could understand the information in the forest fire estimation systems [9]. Performed on the estimation of the burned area in forest fires, it created a model-based Geographic Information System (GIS) in estimating forest fire impact using climate, landscape, and geographic data [10]. In one map application, related agencies used a web-based information system to identify potential risks for forest fires and to estimate the area burned for existing forest fires. Early forest-fire estimation studies indicate crucial problems, to restrict database costs in particular [9]. However, applications are likely in many sub-fields of artificial intelligence, such as forest haze, input validation machine learning techniques [15], and explaining classification model predictions [1].

We then concentrate on Riau-Indonesia as a regional case study, because Indonesian emissions from there make a significant contribution to the global annual fire [3]. According to some reports, fires in Equatorial Asia, mostly in Indonesia, constitute an average 8 percent of global fire emissions, but more than a third over potential fire intenseness years [2]. Three main factors exacerbate haze over the Riau-Indonesia region: (1) forest fire estimation systems, (2) agricultural degradation and management by fire, and (3) Indonesia’s carbon-rich peatlands [3], [4]. Although fires occur every year in Indonesia, these three natural and human factors lead to especially extreme haze in 1997, 2006, 2016, and 2018. Each of the years differs we explored the forest fire estimation systems on estimates of weighted smoke in Riau-Indonesia.

Concerning the forest fires hotspots in Riau-Indonesia, it is important to understand the underlying forest fire estimation systems “web-based information” that shows fires hotspot in each province in Indonesia. Various technologies are used to strengthen government capacity to control forest fires [16], including disaster risk management and haze disasters. BPBD (Indonesian National Board for Disaster Management) has been established to use different tools and a range of other NGOs and BPBD’s stakeholder partners to expand their capabilities in developing forest fires sensing using computational intelligence techniques. The current estimation systems such as sipongi.menlhk.go.id and geospasial.bnpb.go.id as forest fire databases are used to identify forest fire possibility and risk at any given time.

This paper aims to promote the existing research into the field of social science in AI. The artificial intelligence of social science publications is still small in number. Including the fires hotspot estimation system presented in this paper, based on relevant theories on explanation. Also, GIS-based models were used in calculating the forest fire hotspot, landscape, and topographic data in the selected provinces. In this case, AI is used to classify the regions at risk for forest fires and estimate the burned area for recent forest fires.

2. Related Works
   a. Fires Hotspot Estimation System

   There have been several studies in which fires hotspot estimation system with application or software were combined to analyze a web-based information system and sensor data to obtain accurate results. The key dimensions of the estimation system refer to [1], [8] proposed a study of estimation using the GIS analysis. In this study, estimation methods investigated were Multilayer Perceptron (MLP), Radial Basis Function Networks (RBFN), Support Vector Machines (SVM). The best model proved to be MLP models with an accuracy rate of more than 65 percent with three clusters (small, medium, and large). However, there might not be enough fire visuals to train the model effectively. It is expected to be applicable in providing an overly generalized understanding of deforestation linked to forest fires as in burned areas. Since smoke can only be recognized by the system [17]. Fires hotspot estimation system performed by real-time fire estimation. Moreover, considering the forest fire hotspot, it is suitable for real forest-fire-rescue needs. Nonetheless, limited work exists on spreading and saving forest fires as an AI technique [18].
Forest fire estimation systems have formed a forest fire database that can be counted. It has increased the importance of building alertness to natural disasters [1]. The estimation systems are useful for landscape information, topography, real-time weather data, etc. It uses subsystems such as Fire Weather Index (FWI) and Fire Behaviour Prediction (FBP) [2]. Forest fire detection is very essential for successful prevention since if a forest fire exceeds a certain scale, it will be difficult to manage [16]. If the estimation systems managed to be developed, it can quickly detect a forest fire, compared to satellite monitoring. The institution may manage information on the scale of fires to control forest fire risks [8]. It can automatically send warnings to administrators and disaster management about the scale of fires and risk burns areas [18]. Hence, fire detection systems by estimating the hotspots in forest fires and estimating a way of considering the possible scale of fires in burned areas.

b. Artificial Intelligence

Drawing from broad literature, a comprehensive view of artificial intelligence that there is substantial progress in applications requiring detailed understanding, such as information collection [19], and question-answering engines. Artificial Intelligence (AI) emphasized knowledge acquisition through developing methods either manually or automatically [18]. Thus, the information-based solutions are well-known for the cost and manageability issues, but the growing availability of shared online information is a recent development. It provides a comprehensive picture of research for AI, for example, artificial intelligence in medical & education [25], risks disaster management of general artificial intelligence [23], [27]. Artificial intelligence (AI) has recently gained particular significance in society and is an interdisciplinary research area. AI development is rising exponentially through technology companies such as Google, Facebook, IBM, and Microsoft that begin innovations such as Google's AlphaGo, IBM's Watson, Apple's Siri, and Amazon's Echo have been launched, bringing great attention to the community [24]. While AI has been explored over decades, the term is not yet broadly acknowledged. However, in term of public sector, public organization level such agencies, institutional and key actors who has power and influence on social networks. Besides, the ability to engage the stakeholder’s participation in any level of government organization (vertical and horizontal links) [16]. Administration based on the capacity of institutional structures and innovation which effect to integrated technological development [16].

To construct a substantial framework for AI research into governmental context with an emphasis on information and challenges. The terms “artificial intelligence” and “public AI,” and “governing AI”, accordingly provides AI resources in particular that concentrate on analytics techniques and issues in the public sector [16]. From the fundamental understanding, it seems advisable to develop in the public organization context [23]. AI-based systems support e-government and help reduce workload and enhance workflows, it reduces processing times [25]. Governing AI represents governance of autonomous intelligent systems, especially in the long-term AI challenges, for example; as inaccurate or poor data may lead to failures. AI technology and a lack of funding are some of the main challenges faced by organizations when AI programs begin [24]. In this regard, the government plays a significant role, in concentrating on creating and encouraging a well-educated community from the diverse workforce to create sustainable knowledge and expertise [16].

Most importantly, the approach of [16] who represents artificial intelligence and the government sector, highlighting the AI technology into database or application with human-computer interaction and base-data system [18] are crucial to study. Within the scope of the analysis, we indicate that public organizations and government offices are already using AI in
mapping hotspot areas from fires hotspot, but there is a need for the respective know-how to be transferred to government works.

3. Using Artificial Intelligence in Estimating Fire Hotspots of Forest Fires

The current estimation systems such as sipongi.menlhk.go.id and geospasial.bnpb.go.id as forest fire databases uses to identify forest fire possibility and risk at any given time. The data was from the SiPongi and BNPB in Indonesia and contained forest fire hotspot records from 2010 and 2020. The output from the estimation methods applied in this paper predicted the scale of the fire’s hotspot i.e., large, medium, or small fire [11]. For example, if the burned area of a particular forest fire was 150 hectares, then that fire would be represented as a small fire with a degree of \(\frac{150 - 63.86}{273.05 - 63.86} = 0.41\), and as a medium fire with a membership degree of \(\frac{273.05 - 150}{273.05 - 63.86} = 0.59\) [16].

Multilayer Perceptron (MLP) was implemented in this research, to find the estimation systems of fires hotspot in burned areas [26]. The forest fires hotspots in the burned area were clustered into five categories [very small fire, small fire, medium fire, big fire, very big fire] see Fig.1.

![Figure 1. The forest fires hotspots categories](image)

Using GIS analysis data with considerable numbers of study areas, a respiratory disorder caused by forest fires was analyzed [11]. The result of mapping models based on the GIS-based measures the potential and dominant districts that coverage respiratory disorders [11]. The data site is mainly using geo-referenced from shape file features that were extracted and interpreted as the major district in the form of a thematic layer [18]. The statistical data was generated varying years from low to very high. Furthermore, the data were calculated as the major areas both of forest fires hotspot and respiratory disorder and it was found varying between low, moderate, and high.

AI elements used in this study were adapted from broad literature and adjusted to fit the objective and context of our study [1]; [27]; [23]; that indicates a significant impact on the AI into governmental context with an emphasis on information and challenges. For example, several factors are responsible for forest fires; temperature, relative humidity, and wind are key aspects in the spreading of the forest fire. When conditions are extremely dry, fire and smoke are more extreme and far-reaching during the prominent El Niño – Southern Oscillation (ENSO) years. In 1972, 1982–1983, 1987, 1991, 1994, 1997–1998, and then again in 2015 large-scale haze events were observed (see Fig.2).
Details and forecasts on the extent of forest fires and land fires using the method can be used as a guide for the restoration and reduction of fires. The use of satellite imagery, which is built into an information-based method, is an innovative technology used to estimate the level of forest hotspots and land fires. The identification model used in this study shows that the fire severity level in 2015 was categorized as high with an area of 45,000 hectares, while in 2019 the fire severity was categorized as medium or low fire hotspots, with most of the islands of Sumatra and Kalimantan being more or less high [27].

Based on the collection of hotspot data in 2015 and 2019, it was obtained from the LAPAN website (http://modis-catalog.lapan.go.id/monitoring) combined with sipongi.menlhk.go.id and geospasial.bnpb.go.id as forest fire databases which are processed data from Terra/Aqua MODIS imagery. Hotspot data collected are daily, weekly, monthly, and annually. Estimation of the fire area with point density analysis can determine hotspots easily and quickly to determine the area indication of the area of fire which has clustered hotspots to produce an area sufficient to describe how wide the burned area is [11], including if an information-based system is not used in estimating the magnitude of these hotspots are very high.

In 2015, fires hotspot on the latest Landsat view data was able to be shown clearly. Delineation takes place manually to prevent atmospheric mistakes, for example in Landsat imagery, where burned areas frequently have a thin smog and cloud cover that makes automatic delineation difficult [27]. This approach or device is designed to identify areas where hotspots occur. Knowing hotspots where land and forest fires are found, this may occur in protected areas with or without permits. Also, using information technology to view hotspots that cause forest and land fires can be done quickly, precisely, easily, and cheaply with the help of geographic information systems [3]. The use of artificial intelligence to monitor forest and land fires through fire hotspots estimation can provide accurate information over a wide area without taking a long time to obtain. In 2019, the information system created involves several related agencies, such as BMKG (Meteorology, Climatology and Geophysics Agency), BAKOSURTANAL (National Survey and Mapping Coordination Agency), Ministry of Forestry, and BPBD. BMKG is a part that interacts directly with the information system created. BMKG provides input in the form of daily weather data as a basis for calculating fire spots. Meanwhile, other agencies, like the BPBD, Ministry of Forestry, Local Government, and the community getting information on the level of forest and land fire hazards (in the form of hotspots) based on daily weather data.

The estimation system used is based on the consideration of the level of fires that have occurred in Indonesia, including in several areas such as Sumatra, Sulawesi, Papua, Kalimantan where fires may occur in land clearing areas [27]. Forest fire prevention and control as well as Hotspot analysis are conducted to determine the trends of fires, both temporal and spatial. In general, this information is useful for the authorities to carry out planning, combined with artificial intelligence with hotspot information, early warning, and determining the alert status can be done. Information dissemination is very important to prevent and control forest and land fires effectively and efficiently [11]. The use of various information media is used to disseminate fire information, either through software or an artificial intelligence-based system that contains information on monitoring hotspots and monitoring the impact of fires. Besides, GIS

![Figure 2. Estimation of the Hotspot in Forest Fires Using AI](image-url)
web development also makes it easier for stakeholders who have access to information on hotspots in various regions [18]. Fire monitoring is an important aspect that needs to be developed in an effective and efficient fire management system. There are several function-based systems; fire impact assessment and fire management procedures for the environment and social, fires estimation is functioning information to all stakeholders in an actual and free manner and increased accountability in decision making that increases community capacity in social control, supports various parties in interpreting fire information [11].

Apart from providing real-time information about hotspot locations, analysis is also carried out on hotspot historical data. This provides an overview of the level or condition of fires that occurred based on time and other spatial thematic data. Dissemination of information is one of the main things to ensure the success of point fire control efforts. Besides being useful for planning hotspot monitoring activities, it is also very useful for fire prevention. The estimation of land and forest fire hotspots includes the collection of processing and provision of information related to hotspot information, fire monitoring, and fire impact assessments aimed at supporting efforts to prevent, suppress, and handle post-fires to make them more effective and efficient. In line with [1]; [8] that disaster rescues have to face up to the particular challenges presented by each form of environmental catastrophe.

On the other hand, capacity building is carried out using various approaches, both in collaboration with stakeholders to ensure the sustainability of the implementation and development of information-based systems. However, in its implementation, the development of this information-based system requires more specialized expertise, as it cannot be fully implemented or optimized by local governments. This is due to the inadequate roles and responsibilities of government agencies and stakeholders related to efforts to control forest and land fires as a whole through estimating fire spots.

For the most part, the application of technology-based information is often hampered by the problem of the absence of policy support, this explains that the problem of forest and land fires is still not a priority in the activities of government agencies both at the provincial district and central government levels as seen from the lack of budgets issued by points including proper institutional development is essential.

Additionally, fires in Indonesia mostly occur on degraded peatlands and peat swamp forests. Therefore, all efforts to control, rehabilitate and justify fire need to be focused on degraded areas of peatland and forest. This is very important given the limited resources and capabilities possessed by most local governments in Indonesia. Including in the field of law or justice, the controversy over arson by the community is often a persistent problem. The burning of land for fields by the community often does not have a big impact, considering that it is relatively small and controlled. However, this is not the case with burning land in peat areas, even by the community. The culture of clearing land using fire is seen as local wisdom which only occurs in dryland areas, not on peatlands.

4. Conclusion

The Indonesian government should not ignore the destruction of forest fires. Given the size and scale of the losses caused by forest disasters and land fires, it is important to estimate the level of forest fires and land fires, each of which is based on a system estimation of the hotspot in forest fires using an artificial intelligence technique based on regular weather elements. Also, a GIS that has such capacity that allows pattern recognition of information that is more functional and geographical. Performance from the estimating methods used in this paper calculates the size of the fire hotspot, i.e. big in 2015 and medium fire in 2019. In this case, AI was used to identify regions at risk of forest fires and to estimate the area burned for recent forest fires.

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