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Geospatial Artificial Intelligence for Early Detection of Forest and Land Fires

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Abstract.
Over the years, early detection of forest and land fires has been conducted using hotspot data provided by the National Institute of Aeronautics and Space (LAPAN), based on its interpretation of satellite images. The hotspot data have tremendously helped firefighting efforts and further enforcement. However, the system has several shortcomings, especially due to its inability to distinguish forest and land fires from other hot surfaces or fires caused by common human activities. Furthermore, this method also requires labor-intensive verification, and heavily relies on human factors for advanced analysis and validation. Recently, the DG of Law Enforcement of the Ministry of Environment and Forestry (DGLE MoEF) has been piloting a new approach through advancement in artificial intelligence, called Geospatial Artificial Intelligence (GeoAI). By utilizing recorded satellite image data from 2017 - 2019, the machine has been trained to recognize the pattern and tone of the image in burnt areas so that it can validate the presence of the burnt area based on the history of Sentinel-2 imagery for the past week at each cluster. DGLE MoEF found that the burnt area data processed by GeoAI has better accuracy than the hotspot count for forest and land fire identification. Moreover, GeoAI may ease forest and land fire analysis and verification by automatically overlaying forest area and company concessions at the burnt area. GeoAI's innovation in forest and land fire monitoring can produce more accurate and complete early detection data of forest and land fires than currently available hotspot data. The results of hotspot clustering that detect fires may assist firefighters in rapidly extinguishing the fire, and support law enforcement officers in determining the appropriate target location. Therefore, GeoAI technology may increase the effectiveness and efficiency of resources allocated by law enforcement officers in providing better and more responsive public services.

Keywords: GeoAI, geospatial technology, artificial intelligence, forest fire, hotspot

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1. Introduction

Indonesia forest fires in 2015 were burned massively in forest areas and land across the country. Total economic damage and losses predicted at the time is around 221 trillion Rupiah[1]. Forest fires harmed public health, hampered economic activity, harmed the transportation industry, and caused losses to neighboring countries such as Malaysia, Singapore and Philippines from trans-boundary haze pollution. Forest fires have also caused damage to forest ecosystems. The loss of potential biodiversity and the destruction of habitats for wild plants and animals due to forest fires also increases the threat to the preservation of Indonesia's wild flora and fauna. Furthermore, forest and land fires caused a significant increase in greenhouse gas emissions in 2013-2016[2], thereby contributing to global climate change. In the last decade, fire disasters have occurred almost every year in Indonesia. Tan et al.[3] suggesting that anthropogenic activities were strong determinants of burning. The last massive Indonesia forest fire occurred in 2019. Gaveau et al.[4]show that more than 3.11 million hectares area burned in 2019, 31 % of which on peatlands.

The large area of forest in Indonesia is one of the challenges in detecting the exact location of forest fires. Satellite imagery data is mostly utilized to locate forest fires because it offers broad range data and is frequently updated. The need for spatial information of forest and land fires has developed for a rapid response to firefighting activities and crime investigations. Indonesia governments are increasingly concerned about high accuracy and frequent availability of forest and land fires early detection. Over the years, forest and land fire early detection were conducted over hotspot data utilization and analysis provided by National Institute of Aeronautics and Space (LAPAN) based on its interpretation of satellite images[5].

The Directorate General of Law Enforcement Ministry of Environment and Forestry (DGLE MoEF) as the working unit in charge in enforcing law on responsible parties in which causing forest fires has utilized satellite imagery and geospatial processing tools to monitor forest fire and its pattern. Currently, DGLE MoEF has built a forest fire monitoring system using hotspots data provided by LAPAN to identify near-real time hotspots overlaid with forest area, peatland indication area, and concession information. Daily a specialized team under DGLE MoEF called Center of Intelligence team collected, analyzed, and reported hotspot monitoring on forest and non-forest area, including concessions, peatlands area, palm oil plantation. The hotspot report was followed up by the law enforcement officers, e.g., inspectors, investigators, and forest rangers for the enforcement. The law enforcement officers proceed with ground checking and further inspection and/or investigation, that may result in sanctions: administrative sanction, criminal sanction and/or civil lawsuit. As an immediate prevention of further human-factors burning, DGLE MoEF sealed the burnt area while the law enforcement process took place. Since May 2019 to July 2020 there have been 101 burnt areas owned by corporations sealed by DGLE MoEF. Some of those sealed areas will be followed up with law enforcement by imposing administrative sanction, civil lawsuit and criminal investigation. As an example, a company in West Kalimantan, after being sealed, then sued by DGLE MoEF for civil lawsuit. On 29 July 2020, the court granted the civil lawsuit and decided that the company was proven to have caused a fire in areas of 600 hectares and caused peatlands damage in Ketapang Regency, West Kalimantan.

Hotspot analysis has become an advantageous technique for analyzing and visualizing geographically distributed

events. This involves the visualization of geographic data, which then enables the identification of hotspots, which are areas with higher density or where events or activities are clustered. Forest and Land Fires Hotspot indicates forest and land fire events where the relative temperature is higher than temperature nearby. Temperature data can be obtained from brightness temperature recorded by satellite's sensors. Satellites will identify a pixel as a hotspot if it has a temperature over 330 Kelvin[6].

However, the system has several shortcomings, especially due to its inability to distinguish forest and land fires with other hot surfaces or fires caused by common human activities. Additionally, this method also required labor-intensive verification, and heavily relied on human factors for advanced analysis and validation. Indradjad et al.[7] shows that the hotspot detection capability from satellite data still has weaknesses in detecting fire events and in detecting fire areas. Hotspot data currently available often shows the location of fires in factory areas, settlements and rice fields. Therefore, improvements are needed in determining fire location. Artificial Intelligence (AI) is an emerging technology which applies learning techniques from statistics to find patterns in large sets of data and make predictions based on those patterns[8]. AI is used in a wide variety of applications, from critical aspects like urban infrastructure, environmental health[9], law enforcement[10] and forestry[11], to mundane aspects like virtual assistant and chat bot[12].

As an avid user of hotspots for further analysis and enforcement, the DGLE MoEF realized the need for improvement in terms of forest and land fires early detection and advance analysis. The forest and land fires monitoring system using hotspots data was labor intensive since it needs further expertise on location analysis and verification. Consequently, the process became time-consuming, contrary to public expectation of responsive law enforcement. To answer these constraints, the DGLE MoEF has been piloting a new approach through advancement in artificial intelligence, called Geospatial Artificial Intelligence (GeoAI) to detect forest and land fires. GeoAI is a scientific discipline that combines innovations in spatial science, artificial intelligence methods in machine learning (e.g., deep learning), data mining, and high-performance computing to extract knowledge from spatial big data[9]. GeoAI technology offers more advantages in environmental modeling, including the ability to manage large amounts of spatial and temporal data in multiple formats, high efficiency, flexibility in managing algorithms and workflows, and ease of duplication in different areas. This method is expected to increase effectiveness on the decision-making process, especially when the forest fires create a surging number of areas in Indonesian forest where the manual method is no longer effective. By combining AI and GIS, it can quickly visualize and predict forest fire events, and with the help of spatial analysis it can identify when, where and how a fire occurred and the impacted areas, also to identify responsible parties by designating land concessions or the companies.

2. Method

In our study, we conducted secondary research by documenting the development of GeoAI Forest and Land Fires in the DGLE MoEF and its potential to improve forest and land fires early detection and law enforcement. As preliminary needs assessment, we dissected existing forest and land fires monitoring practices by DGLE MoEF to discover challenges and constraints for effective enforcement using current practices. Afterwards we test the GeoAI which has been developed by DGLE MoEF using hotspot data and satellite images from April to June 2021 to detect forest and land fire events. GeoAI for Forest and Land Fires workflow process consisted of four major steps (see Fig. 1). Firstly, hotspot data were extracted from LAPAN WebGIS Platform (http://modis-catalog.lapan.go.id/) sourced from satellite image processing of Terra MODIS, Aqua MODIS, S-NPP VIIRS, NOAA-20 VIIRS and Landsat-8 OLI. Thereafter, occurrences of forest and land fires are identified by observing the spatial and temporal patterns of the hotspots using ST-DBSCAN clustering algorithm. The multispectral imagery in each cluster was collected to detect fire and smoke using a deep learning model Convolutional Neural Networks (CNN). The fire detection model has trained on thousands Sentinel-2 satellite images of historical fires which occurred in 2017-2019. The final step is delineation of the active fire area on the satellite image using the SentinelHub script and measuring its area.

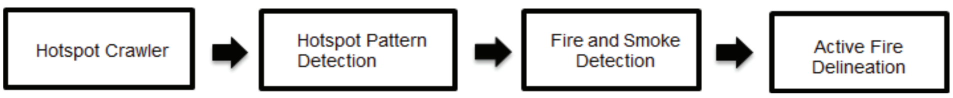

Figure 1: Workflow Process.

As the GeoAI model was destined as decision making tools, the model developed was presented in an interactive dashboard using ArcGIS Dashboard. As a ready-to-use dashboard, the user may customize the dashboard appearance based on information to be highlighted as requested by the decision makers or other related parties.

3. Result and Discussion

3.1. Existing Forest and Land Fires Monitoring by DGLE MoEF

To minimize the impact of forest and land fires in Indonesia, continuous monitoring is carried out so that fire occurrences can be detected early. For law enforcement purposes, it is important to detect forest and land fires quickly so that the field officer can initiate inspections and carry out further investigations. LAPAN has developed a WebGIS-based information system that provides monitoring of daily hotspots[5]. The use of hotspot data sourced from LAPAN is in accordance with the Letter of the Minister of Environment and Forestry No. 208/MENLHK/PPI/PPI.4/4/2016 dated 20 April 2016 regarding Hotspot Data Synergy. Since LAPAN hotspot data can be displayed near real-time compared to data obtained from NASA considering the location of the LAPAN earth station is in Indonesia, LAPAN also ensures network availability and stability as well as data continuity. Hotspot data currently provided by LAPAN is sourced from satellite image processing of Terra MODIS, Aqua MODIS, S-NPP VIIRS, NOAA-20 VIIRS and Landsat-8 OLI.

Location verification and investigation of suspected arson requires a huge amount of time, effort and money. For this reason, information on fire indications is needed as a basis for determining the right target location and allocating resources efficiently. LAPAN has classified hotspot data based on confidence level, however the currently available high confidence level hotspot data from LAPAN often shows the location of fires in factory areas, settlements, and community rice fields. The research carried by Indradjat et al.[7] shows that the hotspot detection accuracy rate from the MODIS sensor is 45% and for the VIIRS sensor is 23%, the low accuracy rate indicates the need to improve the hotspot information system, especially those derived from VIIRS data.

Since 2017, the process to monitor hotspots in DGLE MoEF has been conducted manually by utilizing GIS and remote sensing methods. After obtaining hotspot data, further spatial analysis is carried out by overlaying hotspot to forest areas and production forest concession areas. Thereafter, the latest satellite imagery will be observed to find signs of fire such as smoke and burned areas. Some of the challenges faced in the current hotspot monitoring process are as follows:

1. Hotspot data retrieval consistency is hard to achieve

Information on the existence of hotspots is obtained by downloading data from LAPAN's WebGIS manually. The process is carried out every day at around 6 pm (GMT+7) then followed by further spatial analysis. The accuracy and speed of the spatial analysis process will greatly depend on the discipline and ability of human resources who carry out the work, thus exact data retrieval consistency is hard to achieve manually.

2. Difficulty in recognizing patterns from hotspots to indicate fires

   Not all hotspots are forest and land fires, so knowledge of hotspot distribution and patterns is needed. GIS Analysts need to have advanced knowledge of fire and smoke signs, in order to avoid human error when conducting visual hotspot interpretation.

3. Reporting takes a lot of times when hotspots occur massively

   Hotspot data obtained is analyzed every day to support team operations in the field. Fire analysis reports need to be written in a short time so that information can be quickly disseminated for rapid follow-up investigations. Currently, verification of hotspot location, accessibility and identification of protection area status is still conducted manually. With limited GIS Analyst personnel, the process will be a challenge when fires occur on a massive scale.

4. The need for a system that helps speed up the dissemination process

   Currently, the hotspot analysis reports are disseminated to the supervisors every day around 9 PM followed by sending the report to the nearest regional head office and further instructing the nearest field officers from the hotspot location to conduct ground check. It would be better if the dissemination process was carried out automatically so that the information was delivered efficiently without delay.

3.2. Optimization of Forest and Land Fires Early Detection Using GeoAI

Developments in the field of remote sensing, internet and communication technology have encouraged the geospatial field to provide data with a detailed scale, covering a large area and available from time to time, making it possible to conduct near real time studies. New breakthroughs in the field of AI have also opened up opportunities for processing complex geospatial data that are difficult to process using traditional spatial analysis methods to be easy to collect, analyze and present results. The combination of developments in the geospatial and AI fields is increasingly supported by the development of computers, including the Graphics Processing Unit (GPU) which offers support for more efficient data processing and cloud computing which allows virtual data storage[9].

To accelerate the DGLE MoEF forest and land fires investigation process, an automation system has been developed that includes the following capabilities:

1. Automatic hotspot data crawling

   Automatic hotspot data retrieval helps to increase efficiency because it obtains data at the same time every day, thus reducing the delay which often occurred because of human error. The Geo-AI Forest and land fire system starts with automating the retrieval of hotspot data for the last 24 hours from WebGIS LAPAN every day at 6 pm.

2. Hotspot Clustering based on Spatial Temporal pattern using ST-DBSCAN Algorithm

   The occurrence of forest and land fires can be predicted from concentrated hotspots which form clusters based on proximity of distance and time (Fig. 2). Therefore, to increase efficiency in detecting fires, a system that can automatically classify spatially and temporally scattered hotspots is needed. Spatial Temporal Density-based Spatial Clustering of Applications with Noise (ST-DBSCAN) has the power to find clusters according to spatial, temporal, and non-spatial values of the object[13]. This algorithm is widely used as density-based clustering in spatial data mining and has also been used to obtain interesting patterns for analysis on the occurrence of fire hotspots[14]. The Geo-AI forest and land fires clustering system uses parameter 1 km proximity, 24 hours' time period and minimum five hotspots gathered to determine hotspot clusters.

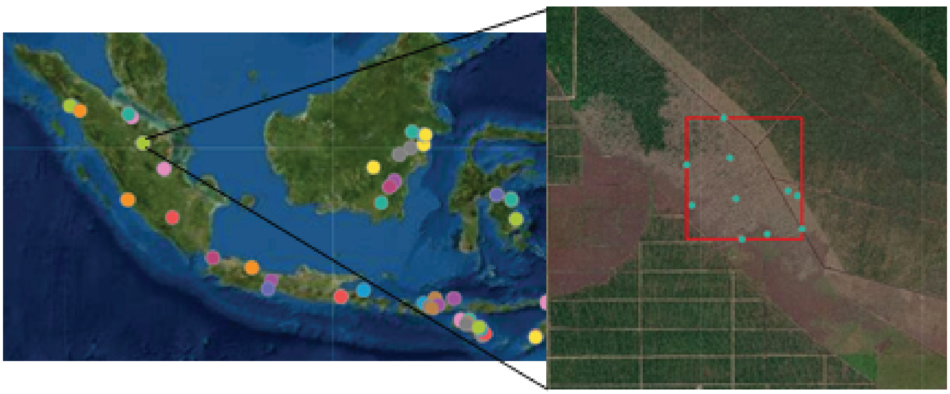

Figure 2: Hotspot clustering result using ST-DBSCAN.

3. Fire and Smoke Detection Using Deep Learning

The appearance of fire and smoke in satellite imagery at hotspot locations reinforces the signs of forest and land fires occurring in one location. Recognition of fire signs in satellite imagery conducted using deep learning methods. Deep learning models were trained to detect the appearance of burnt areas using sample images. Convolutional Neural Networks (CNN) are used to classify images and discover if fire and smoke have appeared on the satellite images in the last five days (Fig. 3). Data requirements for this model to work is Sentinel 2 imagery with short wave infrared (SWIR) color composite. The newly burnt land reflects shortwave infrared that appears strongly in SWIR bands; thus, it makes SWIR band valuable in mapping fire damage[15].

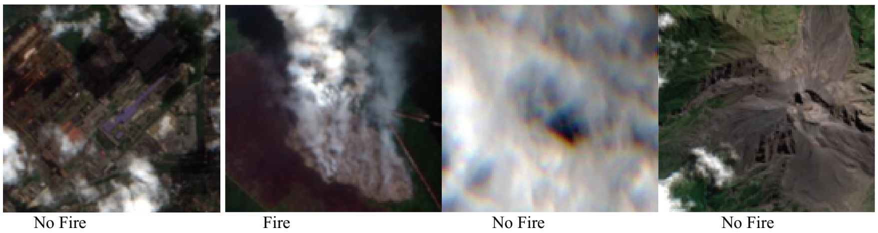

Figure 3: Result of fire detection and classification.

4. Active fire delineation

Sentinelhub script has been used to detect active fire areas on Sentinel-2 images in the selected cluster location. Afterward, the machine automatically performs delineation and calculation of burnt areas as illustrated in Fig. 4. Optical satellite data from MultiSpectral Instrument (MSI) on Sentinel-2, starting from 2015, have a potential five-day temporal resolution and have a spatial resolution of 10-20 m thus it is suitable for detecting active fires especially when there is a need to obtain images with high spatial resolution and temporal frequency[15].

Figure 4: Active fire delineation.

3.3. Findings on GeoAI Ability for Advanced Analysis of Forest and Land Fires

After the model training and development of GeoAI finished, we compared hotspots data from April to June 2021 with GeoAI in the same period. The result shows that verified clusters with burnt area indication have much smaller in number compared to hotspot count provided by LAPAN (see Fig. 5). The result also presents more focused fire spots location findings which can narrow down fire location. Nevertheless, in terms of accuracy, the GeoAI result is required to be verified through ground check.

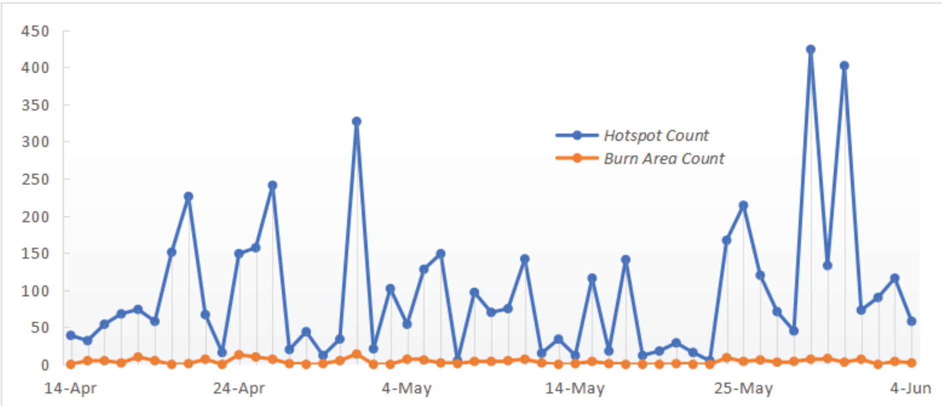

Figure 5: Comparison of the Number of LAPAN Hotspot and Cluster with Burnt Area Indication by GeoAI.

For common users, the analysis result was presented by interactive dashboard (see Fig. 6). The dashboard shown was customized based on user necessity. For the illustration, the dashboard displays cluster analysis results embedded in the Indonesia map, where the orange dots show cluster locations which indicate the burnt area. The dashboard also may inform the number of hotspot clusters in forest and non-forest area (or even other specified area determined), number of fire spots, amount of burnt area, or rank the location with most burnt area indication.

It was found out that the entire GeoAI of Forest and Land Fires Early Detection process from hotspot data collection to active fire delineation only takes 7.5 minutes and the data processing schedule can be adjusted as needed. The GeoAI still needs to be improved to be able to completely replace human work in forest and land fire analysis. To maximize its function, improvements of GeoAI on Forest and Land Fires are needed, including development of the following capabilities:

1. Automatic spatial analysis and reporting

   Further analysis is carried out on indications of forest and land fires. The analysis includes identification of company information where the fire occurred, area

Figure 6: GeoAI on Forest and Land Fires Dashboard.

protection status, location address and accessibility. Automation of the analysis can increase work productivity, especially when the number of hotspots appears massively.

2. Automatic result dissemination

Lastly, rapid dissemination of daily hotspot information to the nearest field officer is required. Optimization of the workflow can be done using the messaging API which allows reporting results to be sent regularly and automatically. With this capability, delays in sending results and human error caused by heavy work overload that occur in manual processes can be avoided.

After comparing both manual hotspot analysis and advanced analysis on forest and land fires by GeoAI, it was concluded that the latter method may ease the labor work fires analysis (see Table 1). Table 1 highlighted GeoAI advancement in forest and land fires analysis that can be easily assisted by machines so that it shortens processing time and does not require extensive human labor. This can close the gap in knowledge and the availability of spatial experts, considering that not all agencies have adequate human resources in geospatial expertise.

3.4. Enabling Environment for GeoAI of Forest and Land Fires Early Detection

The implemented platforms should ideally conform to the standard ArcGIS Platform architecture, including ArcGIS Server Enterprise (with extensions capabilities), ArcGIS Desktop (with extensions), ArcGIS online, and Mobile as illustrated in Fig. 7.

Table 1: Efficiency comparison on manual analysis and GeoAI Analysis

Comparison	Manual Hotspot Analysis	GeoAI Forest and Land Fires
Process time	1-5 hours, depend on operator's ability	average processing time 7,5 minutes
Update	Manual, depend on necessity and workforce	Automatically conducted in a defined schedule
Hotspot clustering	None	Perform spatial and temporal clustering using ST-DBSCAN algorithm. Cluster parameters on 1 km radius, time span 24 hours and minimum consisted of five hotspots.
Forest and land fires validation	Conducted by overlaying hotspots data with satellite images and observing fire signs manually on GIS application. Usually, field officers conduct ground checks based on this information.	Automatically detect fire signs using deep learning methods CNN from satellite images on the last five days.
Burnt area calculation	Manually search for the latest satellite images, observe burnt areas, delineate and calculate the area. It can also be done using the land classification method but requires advanced skills. Generally, this step takes a long time so it is not used as a basis for determining the target location for ground checks.	Automatically detect active fire using Sentinelhub script and calculate its area. This process does not require a lot of time.
Checking fire locations and its status	Conducted by overlaying hotspots data with the latest forest area maps on GIS application, followed by documenting findings in the report.	Automatically conducted overlay analysis using script. The system is currently under development for automatic reporting.
Gathered company information where the fire occurred	Conducted by overlaying hotspots data with company concession maps manually on GIS application.	Conducted by overlaying hotspots data with company concession maps automatically

The architecture is designed to facilitate the use of ArcGIS Enterprise and Geo-AI to determine areas where forest and land fires occur quickly and comprehensively in Indonesia, thereby simplifying the process of prevention, supervision, protection, and law enforcement in the environmental and forestry domains. Furthermore, it supports law enforcement operations as the basic platform on which real-time image monitoring and analysis databases and integration will take place. ArcGIS Enterprise consists of two main components, the first is a Portal for ArcGIS as a home for managing content, creating applications, user management, and a central access point, the second is ArcGIS Server as a GIS service provider, which is a component that provides data services in map format. Both are the basis for the development of the ArcGIS Platform so that it can produce output in a short time that can be disseminated to various applications and channels. To support forest and land fire monitoring, ArcGIS Image Server extension from ArcGIS Enterprise is needed which provides distributed computing facilities and imagery or image data storage systems that also support the analysis and presentation

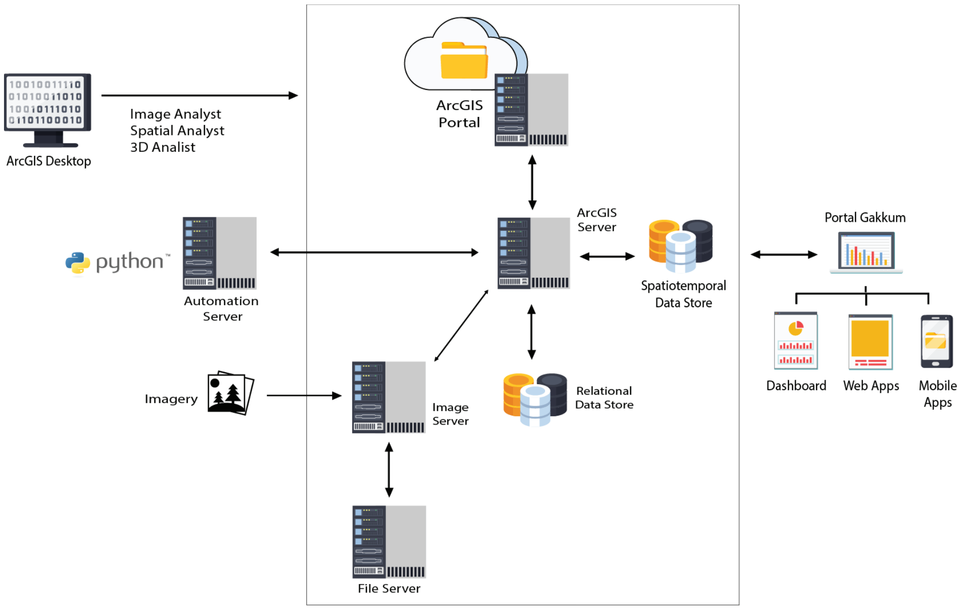

Figure 7: System Design ArcGIS Platform for Geo-AI.

of large collections of image data, elevation data, raster, and other remote sensing data. The ArcGIS platform can access data from various sources such as spatial data formats, text, CSV tables, APIs (json, xml, etc.), images, and access to database server tables.

In addition, Automation Server plays the role as a server to deploy scripts that have been made. Automation Server will fetch data or feed data to GIS Server. Basically, it has capabilities as automation and machine learning so that it can be used in determining areas where the forest and land fires occur in Indonesia quickly and comprehensively. Meanwhile, ArcGIS Desktop is used to build database schemes, data management, archiving, and a center for creating analysis workflows. To support analysis and tools production, there are several extensions used, namely: Spatial Analyst to analyze starting from queries, spatial modeling, and cell-based raster data; Image Analyst provides the ability to analyze images or images and then extract data and information using manual methods or computer assistance; and 3D analyst which can be used to create, visualize, and analyze geospatial information data in a three-dimensional context. Lastly, Data Store is a database component that supports spatial data storage that is integrated with Portal for ArcGIS and ArcGIS Server. This makes it easier for users to publish their data on-the-fly. The data store supports storage including relational data storage as spatial data storage from raw data and stores the results of spatial data analysis, and spatial temporal big data storage as streamlined storage of observation data and ArcGIS Server.

4. Conclusions and Recommendation

GeoAI on Forest and Land Fires piloted by DGLE MoEF shows exceptional potential to accelerate forest and land fire analysis, obviate human error and improve efficiency in early detection and law enforcement implementation. Regardless, the GeoAI needs to develop more capabilities required for fires early detection and law enforcement, including automatic spatial analysis, reporting and dissemination.

The GeoAI model on detecting Forest and Land Fires was still in development and needs further enrichment in terms of dataset, variables, features, and so on. As GeoAI is a machine learning model, to improve its accuracy some measures may be undertaken, that is:

1. Increase the number of training datasets. The satellite imagery year range utilized might be broadened upon its availability, thus the machine might get better predictions and delineation.

2. Add more variables and better feature processing. The model was developed solely based on geospatial expertise, yet it does not rule out needs of other expertise. As the GeoAI was developed for forest and land fires, relevant expert input on new variables will be very valuable.

3. Employment of higher resolution satellite imagery and/or more frequent satellite imagery available. On the side notes, for delineation purposes, the designated satellite imagery must have SWIR bands.

4. Adding data verification and validation results as model input. The verification and validation might be conducted through ground check.

As for future enactment of GeoAI in forest and land fires early detection and law enforcement, there are some challenges to be addressed:

1. GeoAI model development and implementation demanded substantial resources and cost for the system infrastructure and expert services. For cost effectiveness, the GeoAI model ownership may be scaled up to ministry level so that other related working units in the Ministry of Environment and Forestry might benefit from GeoAI advancement as well.

2. It needs further review on policy and legal basis on GeoAI application for government. The regulations to be concerned of are Law No 4 year 2011 on Geospatial Information as revised by Law No 11 year 2020 on Job Creation including its

derivative Government Regulation No 45 year 2021 and Law No 21 year 2013 on Aerospace.

3. As the GeoAI model was developed to support law enforcement on forest and land fires crime, it must be considered whether the result from GeoAI is sufficient to be used as evidence in court.

Despite those considerations, the GeoAI model shows encouraging results in accelerating the effectiveness and efficiency of resources allocated by the law enforcement officers in providing better and responsive public services.

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