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Artificial Intelligence Remote Sensing for Open-pit Mining Detection in the Tropical Environment of Indonesia

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Abstract

The purpose of this study is to build an Artificial Intelligence Remote Sensing model for Open-pit Mining Detection in the Tropical Environment of Indonesia. This is done based on the characteristics of the climate and environmental conditions in Indonesia which are humid or tropical and have vegetation. There are various challenges and variations of surface objects in the field that are similar to mining objects, as well as following the development of satellite image classification methods that are currently being developed. In this study, the classification process for Open-pit Mining Detection is carried out by applying the Random Forest (RF) algorithm. The result of accuracy assessment based on the reference availability of SPOT 6/7 data which consists of Procedure Accuracy (PA), User Accuracy (UA), and Overall Accuracy (OA) are 90.41%; 84.21%, and 72.03% respectively.

Index Terms : Artificial Intelligence, Remote Sensing, Mining, Tropocal Environment, Indonesia

I. INTRODUCTION

Remote sensing has an important role for the mining sector that has spectral, spatial and temporal capabilities. This can be used to monitor mining activities and changes periodically in large areas, and areas that are difficult to access, so that their utilization can be controlled and measured. Research for detection of mining areas using remote sensing data has been carried out using optical satellite data of medium spatial resolution, especially from hyperspectral sensors such as hyperion and multispectral, namely Landsat-8, ASTER and Sentinel-2 [1,2]. The presence of silicates, carbonates, clay, hydroroxyl and iron oxides minerals can be detected from Visible-Near Infrared (VNIR), Shortwave Infrared (SWIR) and Themal Infrared (TIR) spectral which are the key spectrals for mineral identification from remote sensing satellites [3–6]. Spectrally, VNIR (0.4-1.0 μm) was used to sharpen the presence of iron oxide minerals [5]. Meanwhile, SWIR (1-3 μm) is intended for the detection of AL-OH, Mg-OH, CO3, NH4 and SO4 minerals [5,7], and TIR (7-14 μm) can be used to detect silicates and carbonates [3,5]. The mining area detection method developed from analysis with visual interpretation techniques, namely using the Red Green Blue (RGB) composite satellite imagery with an understanding of the geological structure [8]. The visual interpretation method provides good accuracy, but this method is very subjective depending on the level of interpreter expertise, difficult to standardize, and is not effective for rapid mapping on a large scale. Digital techniques have also been implemented for mining mapping, including the band ratio technique to separate exposed rocks [2,9]. Mixture Tuned Matched Filtering (MTMF) for sub-pixel classification and analysis focus on target objects [2], Independent Component Analysis (ICA) for transformation separates objects [2,5], and Principal Component Analysis (PCA) to minimize and sharpen target information, especially for the case of mixed pixels, covered with vegetation and there is noise/interference [6,10]. Digital techniques generally require a threshold value for mapping which is a weakness due to differences in location and environment, which will have different threshold values. These weaknesses can be overcome by the Artificial Intelligence method which can integrate several parameters from multi data, multi sensors from satellite imagery quickly and efficiently without complicated formulations. Satellite data can provide good mapping for mining and geological exploration in arid or semi-arid climates where exposed rocks are visible on the surface, but it is still a challenge for humid or tropical climates where mineral deposits are covered by thick vegetation and soil [2]. An alternative way to detect mines in a tropical environment is to pay attention to areas with sparse vegetation with the assumption that if there is a high concentration of metal in the area, vegetation growth will be disrupted. This is the beginning of the key to separating locations that have the potential to contain mining and non-mining minerals. The purpose of this study is to build an Artificial Intelligence Remote Sensing model for Open-pit Mining Detection in the Tropical Environment of Indonesia. This is done based on the characteristics of the climate and environmental conditions in Indonesia which are humid or tropical and have vegetation. There are various challenges and variations of surface objects in the field that are similar to mining objects, as well as following the development of satellite image classification methods that are currently being developed. This method has never been carried out in previous studies and is an attempt to address the challenges and difficulties in detecting mining areas in tropical humid and vegetated areas. This is a new breakthrough in the remote sensing application community for mining.

II. RESEARCH METHODOLOGY

A. Study area

Study areas for the development of the Artificial Intelligence Remote Sensing model for Open-pit Mining Detection are throughout the Tropical Environment of Indonesia (Fig 1). The development is carried out by creating a learning model for sample set training that can provide machine learning in recognizing patterns, as well as input parameters in detecting various variations of the characteristics of open-pit mining objects in the study area. Furthermore, a running model was conducted for several test case locations that could represent conditions in Sumatra, Kalimantan, Sulawesi, Java, Bali, NTB and NTT. This area is very suitable for mine mapping case studies, so this location was chosen as a test case location for the implementation of the model.

The annual Sentinel-2 mosaic data in 2021 has been used as the main data in this study by considering its spatial characteristics to be able to detect community mining areas which are generally carried out in small areas (Artisanal and Small-Scale Mining). Several things that can be taken into consideration using Sentinel-2 data are that it has spectral characteristics capable of detecting gold, tin, iron, copper, manganese and nickel in bands 3, 4, 6, 8 and 11, and also 4/8 band ratio for malachite detection [2]. Meanwhile, SPOT 6/7 high resolution data has been used as reference data for visual interpretation in determining learning for sample set training and also for reference in determining accuracy assessment in this study. The data that has been used in this study can be seen in Table 1.

Fig 1. *Study area in the tropical environment of Indonesia*

B. Data availability

Table 1. *The data that have been used in this study*

No	Data Type	Description	Data source
1	Multispectral Annual Sentinel-2 optical data in 2021	Multitemporal Free-cloud Level-2 SR	ESA
2	SPOT-6/7 high resolution satellite image data in 2020 - 2021	Reference data for visual interpretation in determining learning for sample set training and reference in determining accuracy assessment	LAPAN

C. Research stages

There are 5 stages of the method in this study (Fig 2) which will be carried out to achieve the research objectives. These stages are used to build an Artificial Intelligence Remote Sensing model for Open-pit Mining Detection in the Tropical Environment of Indonesia.

Stage-1 teacher learning for sample set training

In the first stage, teacher learning is determined for the sample set of training data. This determination is carried out thoroughly for the Indonesian tropic environment, which can provide machine learning in recognizing patterns, as well as input parameters in detecting various variations of the characteristics of open-pit mining objects. The training set sample for the open-pit mining class was determined randomly, according to the availability of various mining objects in the tropical environment of Indonesia. Meanwhile, the training sample set for the non-open-pit mining class is determined based on the Grid Feature Index (GIF). The GIF with a size of 20 km x 20 km was used to systematically frame samples.

Stage-2 process machine learning classification

In the second stage, a machine learning classification process is carried out based on the input data that was created in the first stage (input layer stacking parameter bands on the Sentinel-2 satellite image and the results of teacher learning sample set training). At this stage, the classification process is carried out by applying the Random Forest (RF) algorithm. It is a digitally supervised classification approach, consisting of a combination of tree classifiers. Each classifier is created using a random vector sampled independently of the input vector. Furthermore, each tree cast will provide calculations on the most dominant class unit to classify certain classes corresponding to the input vector. In detail, the RF classifier formulation is presented in Equation (1).

$\{h(x, \theta k), k = 1, 2, \ldots\}$,
(1)

where h is the result of the random forest classification; x is the input sample; and θk is the random vector sample as a class in the random forest classification [11-13].

Stage-3 post classification
In the third stage, a post classification process is carried out using a Majority Segment-based Filtering (MaSegFil) approach [14]. The process at this stage is carried out to eliminate pixel noise (paper and salt effect) resulting from the classification in the second stage. Thus, the processing results from the post-classification stage that have been carried out can be obtained post-land use land cover classification data.

Stage-4 Re-classification attribute
In the fourth stage, the attribute reclassification process as a result of post land use land cover classification processing is carried out in the third stage. This process is carried out to obtain open-pit mining and non-open-pit mining classes.

Stage-5 Accuracy assessment
The fifth stage is the last stage in determining the results of the open-pit mining classification based on the results of the re-classification in the previous stage. Accuracy assessment is carried out based on available reference data. The available SPOT 6/7 high resolution data having the same recording year were used as reference data. Furthermore, calculations are carried out to get the percentage value of Procedure Accuracy (PA), User Accuracy (UA), and Overall Accuracy (OA).

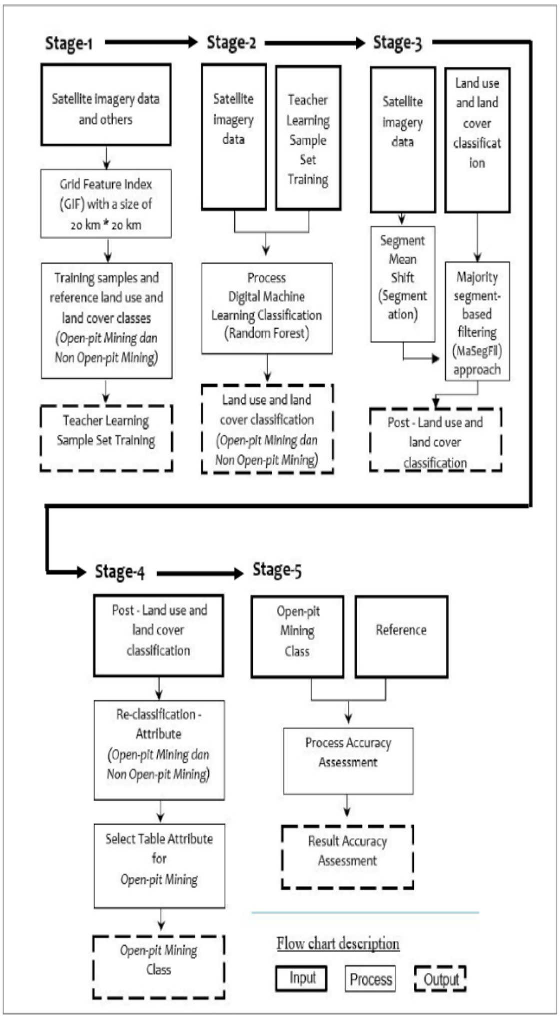

Fig 2. *The stages of the method in this study*

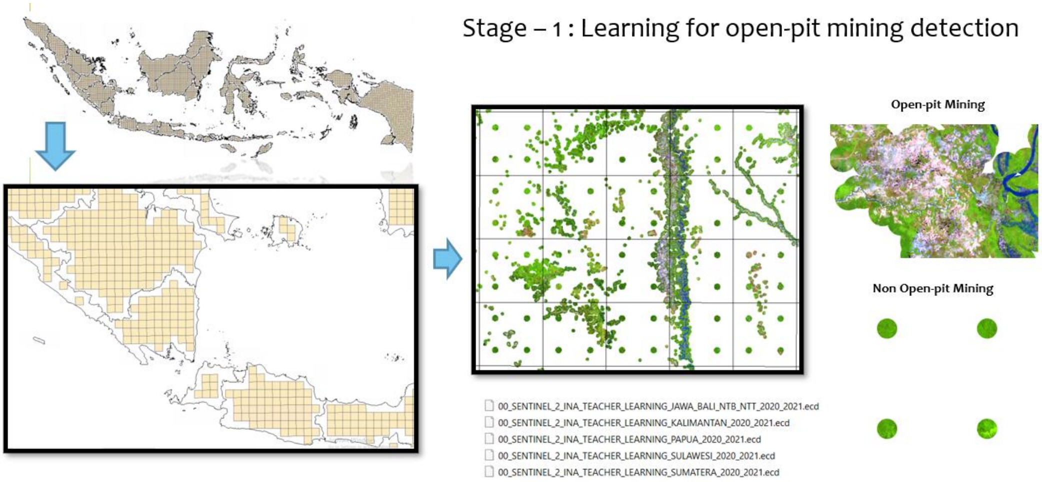

Fig 3. *The result of stage-1 teacher learning for sample set training open-pit mining in the tropical environment of Indonesia*

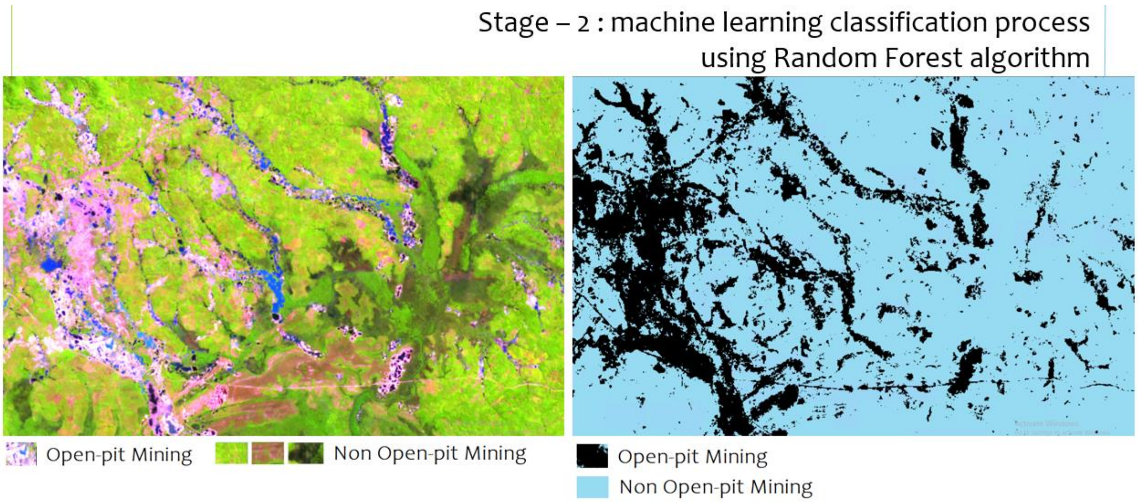

Fig 4. *The result of stage-2 machine learning classification process using Random Forest algorithm for detection of open-pit mining and non open-pit mining*

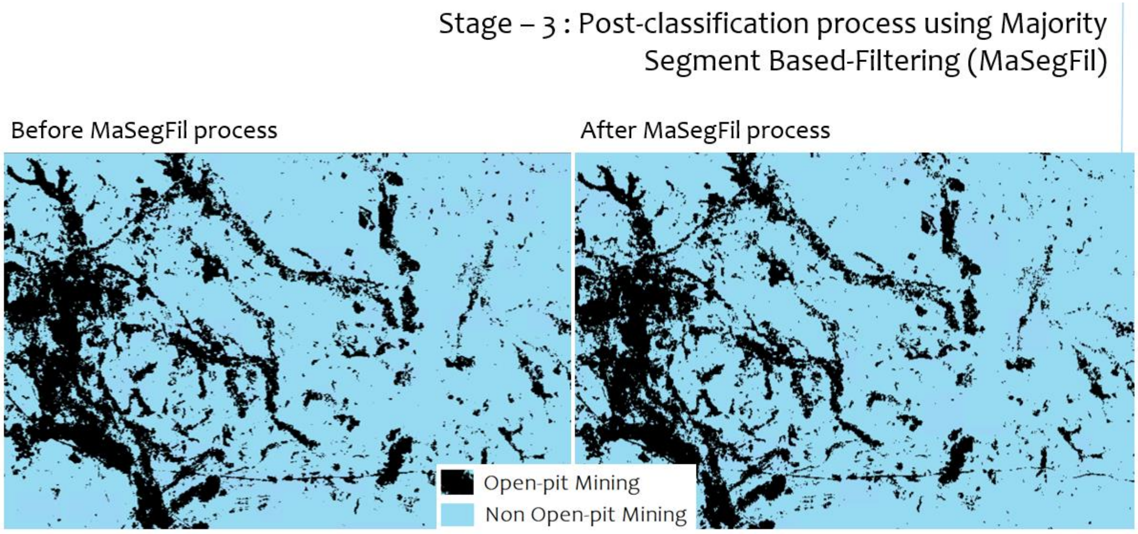

Fig 5 *The result of stage 3 post-classification using Majority Segment Based-Filtering (MaSegFil)*

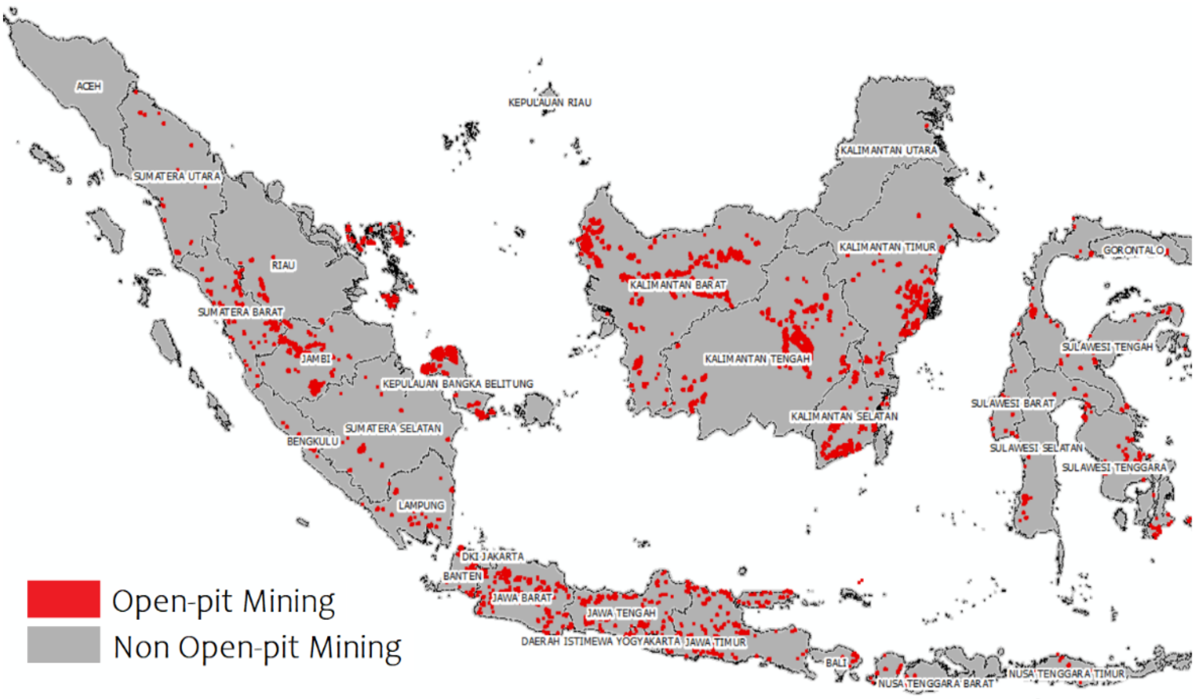

Fig 6 *The results of running model was conducted for several test case locations that could represent conditions in Sumatra, Kalimantan, Sulawesi, Java, Bali, NTB and NTT*

III. RESULT AND DISCUSSION

The result of training set sample for the open-pit mining class was determined randomly, and the training sample set for the non-open-pit mining class is determined based on the Grid Feature Index (GIF) to systematically frame samples can be presented in Fig 3. The result of machine learning classification process using Random Forest algorithm for detection of open-pit mining and non open-pit mining can be presented in Fig 4. The result of post-classification using Majority Segment Based-Filtering process to eliminate pixel noise resulting from the classification can be presented in Fig 5. The result of running model was conducted for several test case locations that could represent conditions in Sumatra, Kalimantan, Sulawesi, Java, Bali, NTB and NTT can be presented in Fig 6.

The result of accuracy assessment based on the reference availability of SPOT 6/7 data which consists of Procedure Accuracy (PA), User Accuracy (UA), and Overall Accuracy (OA) are 90.41%; 84.21%, and 72.03% respectively. There are limitations to the model in this study, which is used to detect open-pit mining areas based on Sentinel-2 optical remote sensing satellite imagery data. The smallest size of an open-pit mining object that can be detected is 0.1 Ha. This is because the image data used as input is a pixel size of 10 m x 10 m. The use of optical data also has the limitation of not being able to penetrate the cloud. In the condition of an area that is always covered by clouds when recording by satellite, of course it affects the results of the information being non-existent or incomplete.

IV. CONCLUSION

In this research, the Artificial Intelligence Remote Sensing model for Open-pit Mining Detection in the Tropical Environment of Indonesia has been developed. This is done based on the characteristics of the climate and environmental conditions in Indonesia which are humid or tropical and have vegetation. Based on the model created using the Random Forest algorithm, a test case study location has been carried out for the regions of Sumatra, Kalimantan, Java, Bali, NTB and NTT. The results showed that accuracy assessment based on the reference availability of SPOT 6/7 data which consists of Procedure Accuracy (PA), User Accuracy (UA), and Overall Accuracy

(OA) are 90.41%; 84.21%, and 72.03% respectively. In future research, it can be done by combining multi-sensors from various optical satellite images, such as Landsat-8, ASTER which can be used as input for the Artificial Intelligence Remote Sensing model for open-pit mining detection. So that the limitations of the research carried out can be resolved, with better assessment accuracy.

REFERENCES

1. Z. Adiri et al., "Recent advances in the use of public domain satellite imagery for mineral exploration: A review of Landsat-8 and Sentinel-2 applications," Ore Geol. Rev. 117, 103332 (2020) [doi:https://doi.org/10.1016/j.oregeorev.2020.103332].
2. Z. Adiri et al., "Mineralogical mapping using Landsat-8 OLI, Terra ASTER and Sentinel-2A multispectral data in Sidi Flah-Bouskour inlier, Moroccan Anti-Atlas," J. Spat. Sci. 65(1), 147–171, Taylor & Francis (2020) [doi:10.1080/14498596.2018.1490213].
3. F. D. van der Meer et al., "Multi- and hyperspectral geologic remote sensing: A review," Int. J. Appl. Earth Obs. Geoinf. 14(1), 112–128 (2012) [doi:https://doi.org/10.1016/j.jag.2011.08.002].
4. E. Bedini, "Mineral mapping in the Kap Simpson complex, central East Greenland, using HyMap and ASTER remote sensing data," Adv. Sp. Res. 47(1), 60–73 (2011) [doi:https://doi.org/10.1016/j.asr.2010.08.021].
5. A. B. Pour and M. Hashim, "Identification of hydrothermal alteration minerals for exploring of porphyry copper deposit using ASTER data, SE Iran," J. Asian Earth Sci. 42(6), 1309–1323 (2011) [doi:https://doi.org/10.1016/j.jseaes.2011.07.017].
6. R. Rajan Girija and S. Mayappan, "Mapping of mineral resources and lithological units: a review of remote sensing techniques," Int. J. Image Data Fusion 10(2), 79–106, Taylor & Francis (2019) [doi:10.1080/19479832.2019.1589585].
7. S. Grebby et al., "The Impact of Vegetation on Lithological Mapping Using Airborne Multispectral Data: A Case Study for the North Troodos Region, Cyprus," in Remote Sensing 6(11) (2014) [doi:10.3390/rs61110860].
8. C. Nyamekye et al., "Examining the performances of true color RGB bands from Landsat-8, Sentinel-2 and UAV as stand-alone data for mapping artisanal and Small-Scale Mining (ASM)," Remote Sens. Appl. Soc. Environ. 24, 100655 (2021) [doi:https://doi.org/10.1016/j.rsase.2021.100655].
9. M. Safari, A. Maghsoudi, and A. B. Pour, "Application of Landsat-8 and ASTER satellite remote sensing data for porphyry copper exploration: a case study from Shahr-e-Babak, Kerman, south of Iran," Geocarto Int. 33(11), 1186–1201, Taylor & Francis (2018) [doi:10.1080/10106049.2017.1334834].
10. B. Zoheir et al., "Multispectral and Radar Data for the Setting of Gold Mineralization in the South Eastern Desert, Egypt," in Remote Sensing 11(12) (2019) [doi:10.3390/rs11121450].
11. M. Pal, "Random forest classifier for remote sensing classification,"International Journal of Remote Sensing, vol. 26, no. 1, pp. 217–222, 2005.
12. A. D. Kulkarni and B. Lowe, "Random forest algorithm for land cover classification," International Journal on Recent and Innovation Trends in Computing and Communication, vol. 4, no. 3, pp. 58–63, 2016.

13. S. Tian, X. Zhang, J. Tian, and Q. Sun, "Random forest classification of wetland landcovers from multi-sensor data in the arid region of Xinjiang, China," Remote Sensing, vol. 8, no. 11, pp. 954–1014, 2016.
14. F. Yulianto, G. Nugroho, G. Aruba Chulafak, and S. Suwarsono, "Improvement in the Accuracy of the Postclassification of Land Use and Land Cover Using Landsat 8 Data Based on the Majority of Segment-Based Filtering Approach," Sci. World J., vol. 2021, 2021, doi: 10.1155/2021/6658818