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Money Laundering Observation from Outer Space

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Abstract

This paper examines the potential of nighttime light (NTL) data as an alternative data source to predict the number of money laundering events. The study is based on the assumption that money laundering as one of financial crime categories is linked to economic development, and previous research has explored the relationship between NTL and both economic data and crime. Panel regression analysis with random effects was used to investigate the potential of NTL data to estimate money laundering activity, which was measured using Suspicious Transaction Reports (STRs) data as a proxy variable. The results suggest that NTL data can be a promising tool for estimating money laundering activity, providing new insights into the use of alternative data sources in predicting this illegal activity. The findings of this research could also contribute to the development of more effective anti-money laundering strategies by law enforcement and policymakers.

Keywords: *Nighttime-light Data; Suspicious Transaction Reports (STRs); Money Laundering; Google Earth Engine; Alternative Data Sources.*
JEL Classification: R12, E59, K14, C88, C82

INTRODUCTION

The development of high-resolution satellite imagery has provided an invaluable alternative dataset for researchers studying socio-economic activity (Doll et al., 2006; Steele et al., 2017). One of the most important data that are sourced from satellite imagery is nighttime light (NTL), which becomes reliable and consistent data utilized in many studies to measure the level of socio economic activity (Andiojaya et al., 2022; Chotia & Rao, 2017; Gibson et al., 2021; Roberts, 2021). These researchers are trying to examine and identify the prospect of NTL data to be a promising new alternative variable to estimate socio-economic situations between different regions and countries.

The potential of NTL data as an alternative data source has become increasingly apparent in recent years, especially in the wake of the COVID-19 pandemic (Small and Sousa 2021). Traditional survey methods have been impacted by restrictions on activities, making it difficult to collect accurate and reliable data on economic activity. Moreover, the data collection and processing complexity are the main reason for the traditional methods drawbacks in producing near real time data. However, the demand for near real time data is high especially for governments who need the data to support decision making in the battle to reduce the COVID-19 impact (OECD, 2020).

NTL data presents a more advantageous alternative to conventional data collection methods due to its remote accessibility and consistency in measuring economic activity over time (Mncube and Xulu 2022; Zhang and Gibson 2022). Moreover, advancements in technology have enabled the dissemination of satellite imagery on an hourly basis, which enhances the potential of NTL as a near real-time estimator. As a result, it has become an attractive option for researchers interested in monitoring socioeconomic development across regions and over time. Several studies, such as Doll et al. (2006) and Henderson et al. (2012) explored the use of NTL to estimate a country's economy, and have reported a statistically significant correlation between NTL intensity and real Gross Domestic Product (GDP). Roberts (2021) highlights the promising utilization of NTL in predicting the economic situation during pandemic.

The utilization of NTL data as a proxy estimator is increasingly prevalent across various domains, including the field of criminality in which NTL becomes a new data source for environmental variables. Peng et al. (2022) employed NTL in an urban area to detect the social impacts of human activities at night. The results of the study indicated that changes in NTL brightness levels were capable of explaining the alterations in crime management within the research region. Furthermore, the constructed model suggested that the use of NTL as an estimator would be more effective in urban areas with higher levels of illumination. Yang et al. (2020) utilizing NTL sourced from VIIRS as the secondary co-variable to enhance the model to foretell weekly-based street crime and hotspots in Cincinnati, Ohio. The result shows the promising contribution of NTL in increasing the quality of the model.

To the best of author knowledge, given the established utility of NTL as an estimator variable in both economic and criminal contexts, limited research has explored the potential of NTL as a predictor for money laundering activities. This paper seeks to address this gap by investigating the possibility of using NTL to estimate money laundering events and examining the relationship between nighttime light and money laundering. Moreover, this study also aims to explore how this relationship may differ across various geographic areas. The findings of this research could offer new insights into the use of alternative data sources for forecasting money laundering activities and help in developing more effective anti-money laundering strategies for law enforcement and policymakers.

RESEARCH METHODS

Data Sources

To indicate the potential of money laundering activities in a certain region, this paper uses Suspicious Transaction Reports (STRs) as a proxy variable. STRs contain information on transactions that have been identified as suspicious or potentially indicative of money laundering that can be used to estimate the likelihood of money laundering activity occurring in a particular region (Dalla Pellegrina et al. 2020; Gara and Pauselli 2020). STRs data used in this paper obtained from the Indonesia Financial Transaction Report and Analysis Center (INTRAC or known as Pusat Pelaporan dan Analisis Transaksi Keuangan - PPATK in Indonesia) accessed from Anti Money Laundering and Counter of Fund Terrorism (AML-CFT) Statistics Bulletin which published monthly (PPATK, 2021).

Despite the limitations of using Suspicious Transaction Reports (STRs) data as a proxy variable for money laundering activities, it remains the most reliable source available to estimate the potential of these events in a region. Money laundering activities are often kept hidden and are challenging to detect, making it difficult to obtain comprehensive data on the overall extent of these activities (Canhoto, 2021; Domashova & Mikhailina, 2021; Rocha-Salazar et al., 2021). However, STRs data can provide valuable insights as it contains information on transactions that are suspected or potentially linked to money laundering. While it may not provide a complete picture, it is still a useful tool for law enforcement agencies and policymakers to identify areas where further investigations or interventions may be necessary to combat money laundering (Reznik et al., 2023; Viritha et al., 2015). Therefore, despite its limitations, STRs data is still the best available proxy to describe the potential of money laundering events in a particular region.

The NTL data used is obtained from Google Earth Engine (GEE). GEE is a cloud-based platform that provides access to a vast collection of satellite imagery and geospatial data, including nighttime light data from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. The VIIRS sensor captures images of Earth at night and produces a composite image of nighttime light intensity, which can be used as a proxy for economic activity in a particular area (Andiojaya et al., 2022; Mncube & Xulu, 2022). The use of GEE provides researchers with a powerful tool to access and analyze large amounts of geospatial data, including nighttime light data, at a high resolution and over long periods of time (Mills et al., 2013; Mncube & Xulu, 2022; Skoufias et al., 2019). This enables researchers to identify patterns and relationships between nighttime light and various socioeconomic variables, such as economic activity, population density, and income levels, over time and across different geographic areas.

For the purpose of this study, both sets of data were aggregated at the provincial and monthly levels (from January 2018 to December 2021). For indicating the data before and during the pandemic, this paper adds a dummy variable which 0 (zero) applied to the data before the pandemic (January 2018 to February 2020) and 1 (one) applied to the data in the period of pandemic (March 2020 to December 2021).

Panel Regression Model

In order to examine the potential of NTL data to estimate the money laundering activities over Indonesia provinces, this paper will utilize a panel regression model. Panel regression models are suitable for analyzing panel data, which includes information on various cross-sectional units (such as countries, regions, or cities) over multiple time periods (Ekananda, 2018; Greene, 2012; Gujarati & Porter, 2009). This study will specifically employ a panel regression model to investigate the connection between STRs data and nighttime light data in different provinces from January 2018 to December 2021. Generally, the panel data analysis model is expressed by equation (1).

$$STR_{it} = \alpha + \beta NTL_{it} + \varepsilon_{it} \quad (1)$$

Note:

STR_{it} = STR of i^{th} province, t^{th} quarter
α = join intercept
β = Coefficient of regression or slope
NTL_{it} = Nighttime-light Data of i^{th} province, t^{th} quarter
ε_{it} = error term of i^{th} province, t^{th} quarter
i = 1 to N
t = 1 to T

As an extra analysis, this study incorporated a binary dummy variable in the model to indicate the quarter before and during the COVID-19 pandemic. This was done to gain better insight into the effectiveness of using nighttime light data to forecast money laundering activity before and during the pandemic. The timeframe from January 2018 to February 2020 was designated as the baseline period, representing the time before the pandemic (set value to 0) and for data starting from March 2020 to December 2021 flagged as during pandemic period (set value to 1). Consequently, the model formulated in this study can be expressed as:

$$STR_{it} = \alpha + \beta NTL_{it} + DummyPandemic_t + DummyPandemic_t * NTL_{it} + \varepsilon_{it} \quad (2)$$

After conducting the Breusch-Pagan Lagrange and Haussman tests, the random effect method was selected. This outcome confirms the initial hypothesis that there is an unobservable variable that is not correlated with the independent variable, allowing the analysis to concentrate on the influence of the independent variable on the dependent variable while considering individual features such as a province's value (Gujarati & Porter, 2009).

RESULTS AND DISCUSSION

Descriptive Statistics

From figure 1, in the overall pattern, it can be divided into two main patterns. The NTL patterns for provinces in Java Island and some big Provinces which are steadier. The second pattern is the NTL pattern for provinces outside Java Island that commonly medium into small Provinces due to population and economic situation which are showing seasonality trends.

A little bit interesting for Provinces in Java Island, for example NTL in Jakarta and East Java which is the line chart of monthly nighttime-light data from January 2018 to December 2021 shows a relatively stable trend until late 2019, followed by a slight downturn for Jakarta but steadily increasing for East Java. This downturn trend may be attributed to the COVID-19 pandemic and related restrictions on social and economic activities and in those periods people in Jakarta tend to go outside Jakarta since they lost their job regarding the restriction. So that we could see the mobility outside Jakarta can be captured in the increasing NTL in the Province outside Jakarta especially in the Java Island.

The trend line for Provinces outside Java Island like Aceh and Papua, the trend showed the seasonality form, by which the magnitude of the trend variation during pandemic is wider compared to before pandemic. From the trend line, there also could be some drop points, it is possible that they exist due to disturbances in

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the observation caused by cloud coverage. In this study, these outliers are omitted from the calculation.

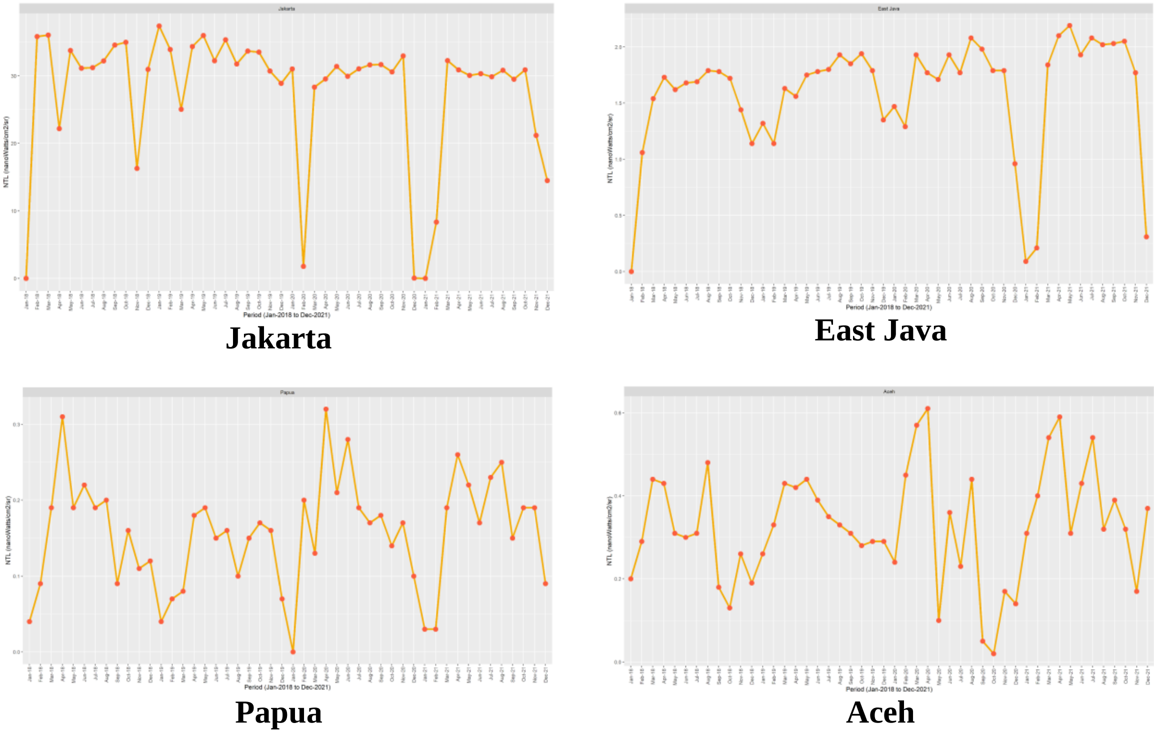

Figure 1. The example of nighttime-light trend in some Indonesia's provinces

Figure 2 describes the visual relation between nighttime-light and money laundering activities. As the visualization preview, it can be said that the connection between those variables vary. Some provinces have slight positive relations and the others have the opposite. But, if they are connected to the size of population and the GDP, especially for provinces in Java Island, they are prone to have positive relations between NTL and STRs. Whilst the other provinces have negative connections.

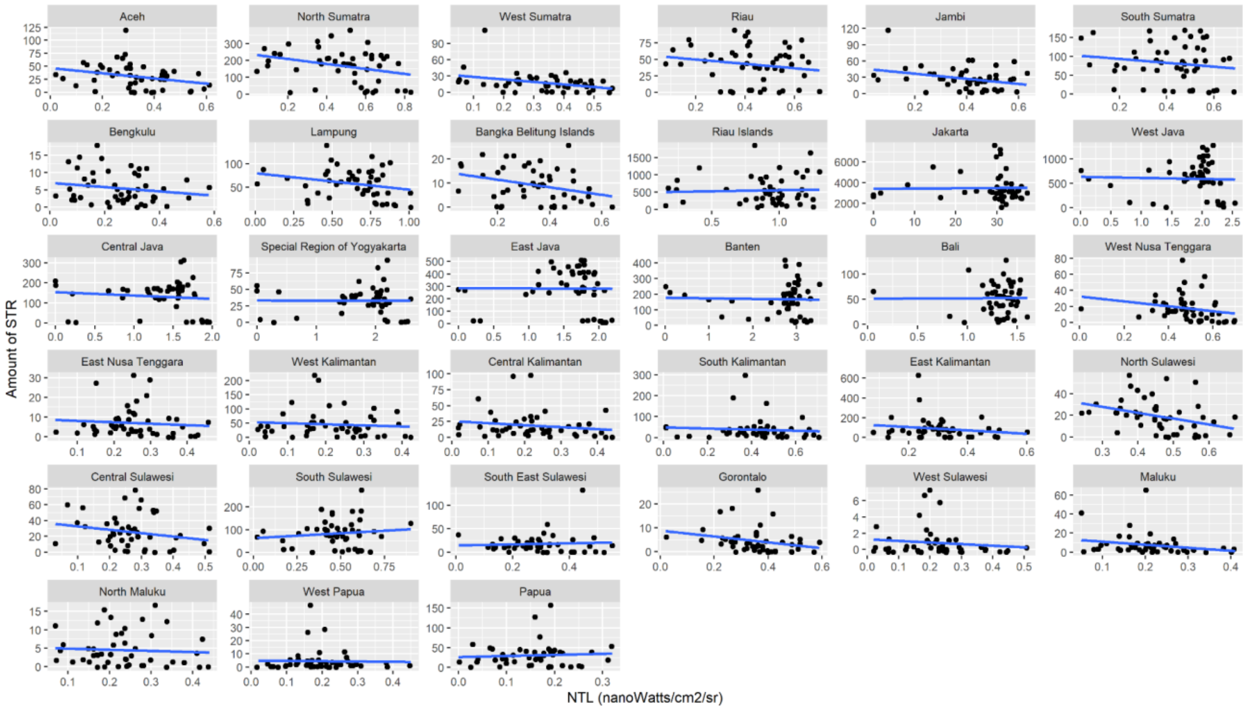

Figure 2. Scatter plot between NTL and STRs by province

Panel Data Effect Test

To begin the investigation of the potential of NTL in estimating the STRs, this paper begins with constructing three panel regression model variants. As can be seen in table 1, Pooling and Random Effect are statistically significant. To choose the best model, this study utilizes Breusch-Pagan Lagrange Multiplier tests.

Table 1. The comparison of model significance and Adjusted R^2 for Pooling Model, Fixed Effect Model and Random Effect Model.

Model	Model Significant (P-Value)	R^2 Adj
Pooling Model	<2.22e-16	0.71864
Fixed Effect Model	0.52714	- 0.21027
Random Effect Model	<2.22e-16	0.15108

The Breusch-Pagan Lagrange Multiplier tests' findings, which are presented in Table 2, show that the random effect outperforms the common effect. The Breusch-Pagan Lagrange Multiplier demonstrates that the test exhibits sufficient statistical evidence to reject the null hypothesis, leading to the selection of random effects as the panel data analysis technique.

Table 2. Hypothesis and significance result of panel data effect test

Test	Hypothesis	P-value
Breusch-Pagan Lagrange Multiplier	H0: using Common Effect Ha: using Random Effect	2.20E-16

Panel Regression Model with Random Effect

Generally, according to the panel regression model result shown in table 3 can be concluded that night light has potentiality to be an alternative data source to predict the event of money laundering in which it is represented by STRs number.

The positive value of the NTL parameter tells the higher the luminosity in a certain area is prone to be followed by STRs increasing. This finding confirms the previous research about the positive relation between economic and nighttime-light.

Tabel 3. The panel regression with random effect on STRs and NTL

	Estimate	**Std. Error**	**Pr (>|z|)**
Intercept	107.2757	23.6160	5.559e-06***
NTL	54.0836	3.2166	<2.2e-16 ***
R^2			0.15161
Adjusted R^2			0.15108
Chi Square on 3 DoF			282.714
p-value			< 2.22e-16
Note on Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1			

Table 4 shows the probability for the three variables NTL, DummyPandemic, and the interaction of NTL and DummyPandemic are significant, according to the findings of the random effect model testing. Adjusted R Squared shows 0.23943 which means that this model can explain the variation of the dependent variable around 24 percent.

Table 4. Result of Random Effect Model including Dummy Variable for Pandemic

	Estimate	**Std. Error**	**Pr (>|z|)**
Intercept	131.1774	24.5583	9.22e-08 ***
NTL	35.0408	3.2006	<2.2e-16 ***
DummyPandemic	-51.6664	14.1120	0.0002511 ***
NTL*DummyPandemic	42.7145	2.7549	<2.2e-16 ***
R^2			0.24087
Adjusted R^2			0.23943
Chi Square on 3 DoF			501.343
p-value			< 2.22e-16
Note on Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1			

Interesting conclusions were found when the model generated data during the pandemic (Q1-2020 to Q4-2021). Table 5 demonstrates that the model as a whole is significant and that the modified R2 value, which is relatively moderate at 0.32123, can account for almost 32 percent of the fluctuations in the dependent variable. According to the model, NTL is suitable for use as a stand-in for testing STR during a pandemic.

Table 5. Result of Random Effect Model of STR and NTL during pandemic (Q1-2020 to Q4-2021)

	Estimate	**Std. Error**	**Pr (>|z|)**
Intercept	61.1268	29.0633	0.03545
NTL	91.1332	4.7132	<2e-16 ***
R^2			0.32123
Adjusted R^2			0.32037
Chi Square on 3 DoF			373.872
p-value			< 2.22e-16
Note on Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1			

Evaluation of Model's Performance

The model results showed three crucial facts. First, a positive NTL estimator and statistical significance for the model. This result implies that NTL can be used to statistically estimate STR changes. As the estimator value is positive, it means that the STR will increase while light intensity increases and vice versa. This interesting finding is in line with the result of Peng et al., (2022) in which the study showed that there is a positive correlation between nighttime-light with night crime. Although their study employs NTL for different crime categories, our paper confirms the promising utilization of NTL to estimate money laundering as a financial crime.

Second, the DummyPandemic variable has a negative estimator value and is statistically significant. This demonstrates that the STRs value tends to be lower during a pandemic than it was prior to it. This circumstance demonstrates that a decline in reports of suspicious transactions has occurred as a result of the Covid-19 pandemic, which struck Indonesia between 2020 and 2021. According to the AML-CFT Statistics Bulletin published by Indonesia Financial Transaction Report and Analysis Center (INTRAC - PPATK), there is a slight decline for the number of STRs during the pandemic compared to the number of STRs before pandemic. Based on this evidence, the addition of a pandemic dummy variable refined the model accuracy.

Third, the estimated value generated by the interaction of the NTL and DummyPandemic variables (table 4) is 42.71. This value indicates that during the pandemic, the connection between nightlight shifting and STR growth was 42 points stronger than it was before the pandemic. Based on this result, it can be implied that the NTL performance in predicting the variation of STR is better in the pandemic period. This discovery strengthened the previous findings about the prospect of NTL to be used as an alternative data source to foretell the money laundering.

The Potentiality of NTL as an alternative data source for predicting Money Laundering

By utilizing the model generated above, this study builds the STRs estimation from NTL that shown in figure 4. Compared to the real STRs number displayed in figure 3, the model estimation works well for Provinces in Java Island and some Big Provinces outside Java such as North Sumatera, Riau and Bangka Belitung.

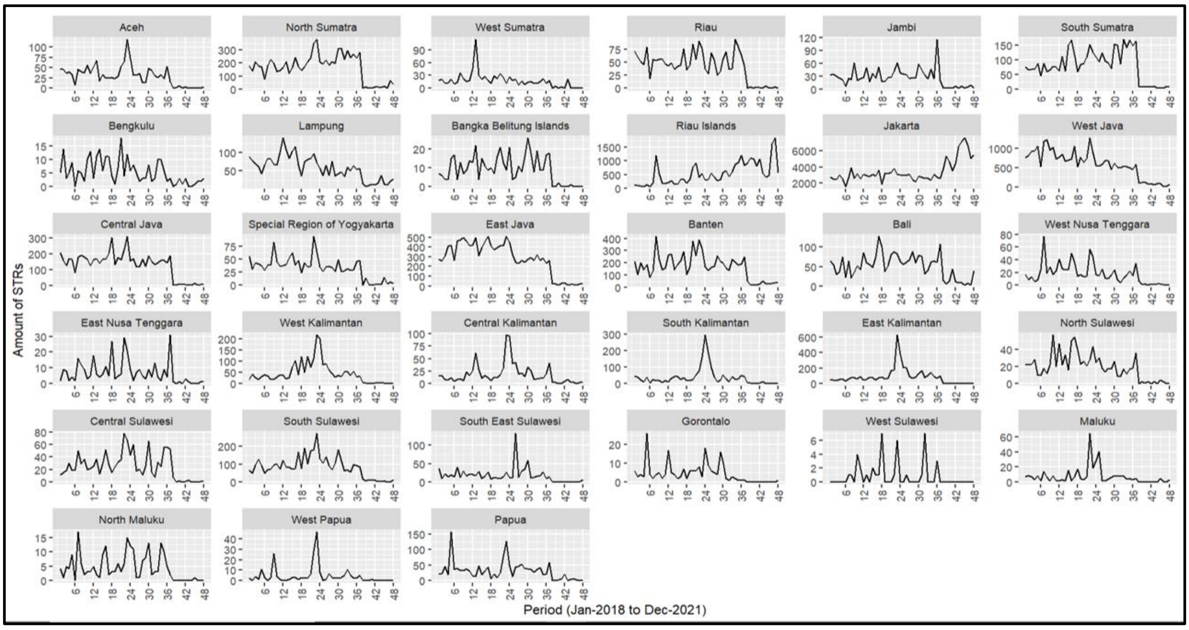

Figure 3. The trend line of real STRs number by Provinces from Jan-2018 to Dec-2021

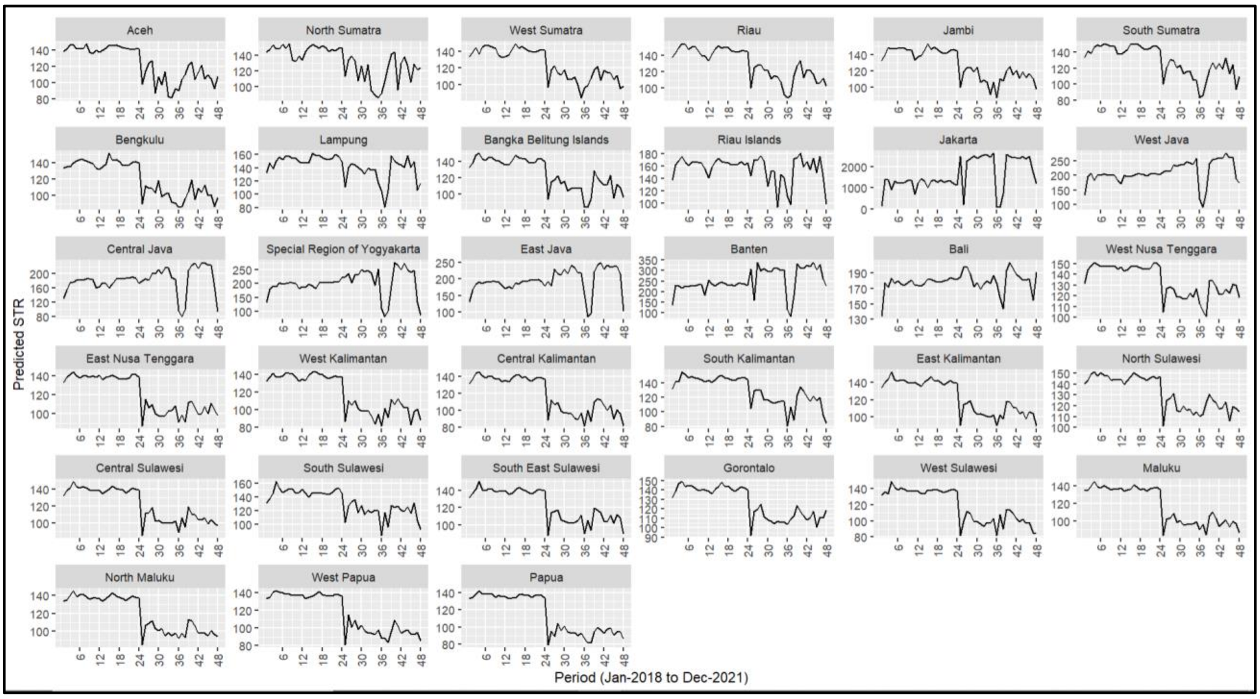

Figure 4. The trend line of predicted STR by Provinces from Jan-2018 to Dec-2021

CONCLUSION

The aim of this study is to explore the possibility of using nighttime light data as an alternative source to predict money laundering. The findings of the study suggest that there is a statistically significant relationship between nighttime light data and the number of suspicious transactions reported. In addition, there is significant proof that NTL works better in the pandemic situation. These discoveries provide strong evidence that nighttime light data can be a useful alternative data in predicting money laundering and identifying areas of high risk. Especially, this data sourced from Google Earth Engine that are open source and relatively update monthly. This situation improves the real time estimation to the money laundering combating efforts that needs immediate effort both in prevention and eradication. The study also highlights the potential of NTL as an alternative data source in anti-money laundering efforts. Nighttime light data, which is freely available and updated on a regular basis, can provide valuable information on economic activity and growth, which are closely linked to money laundering. Policymakers and law enforcement agencies can leverage this data to better understand money laundering trends and develop more effective measures to combat it.

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Competing Interests

The authors declare that there is no conflict or competing interests regarding the publication of this manuscript.

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