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Forecasting Indonesian National and Provincial GDP using nighttime light index

Krisna Gupta,* Timothy Kinmekita Ginting,* and Meizahra Afidatie*

National Economic Council, Republic of Indonesia

*Corresponding author: krisna@dewanekonomi.go.id; timothy.ginting@dewanekonomi.go.id; meizahra@dewanekonomi.go.id

Abstract

Economic growth is a central macroeconomic indicator that shapes the decisions of both governments and private enterprises. Therefore, tracking economic growth in higher frequency would benefit decision makers. One way to verify the official growth number is to use relevant leading indicators for economic growth that are independent from the statistical agency. In this paper, we use the Indonesian nighttime light index sourced from Blackmarble to fit historical GDP of Indonesia. Two forms of analysis are conducted: national-level using Autoregressive Distributed Lag (ARDL) and provincial level using panel data regression. The nighttime light index shows a consistent significant correlation to GDP growth across various specifications. However, the magnitude of the correlation is small, suggesting that nighttime light index alone cannot capture the full variation of GDP growth. We also find indicative evidence that the scarring effect post COVID-19 pandemic hurts long term economic growth by 2%. The ARDL specification with scarring effect show the best forecasting fit and is reasonably able to forecast GDP growth out-of-sample.

Keywords: Night Light; Growth Forecasting; BPS

1. Introduction

GDP and economic growth are arguably the most significant sources of data for the government. Economic growth rate is used as an anchor for various other indicators. It forms the foundation for critical modeling and analysis used by both governments and private investors to make economic decisions and implement policy measures. Because GDP often serves as a crucial performance indicator for the government, there is an incentive to overestimate the growth number (Martínez 2022). It is therefore essential to develop alternative methods to validate and evaluate economic growth data.

One such method lies in the use of nighttime lights as a proxy to nowcast economic growth. The use of satellite imagery, particularly in the form of nighttime lights, has increased in relevance over the last 20 years. Technology has developed to allow for the detection of signals at night coming from common artificial light sources such as streetlights, buildings, and vehicles. This data can then be used to measure human activity, a critical component of economic growth. Nighttime lights growth serves as a good predictor of economic growth at the national and sub-national levels (Henderson, Storeygard, and Weil 2012; Bickenbach et al. 2016; Martínez 2022). Henderson, Storeygard, and Weil (2012) shows how nighttime lights data are able to serve as a better predictor of economic growth than various indicators and proxies in other countries. The fact that nighttime lights data is procured from NASA as an open source ensures full transparency. The data is readily available without any preprocessing or involvement from third parties, meaning it is immune to the fluctuations in perceived credibility that are associated with statistical agencies. The independence from statistical agencies is an important condition that positions nighttime lights well as a leading indicator for GDP growth (Enders 2014).

In this paper, we utilize a raster of monthly nighttime lights data from Indonesia provided by NASA's Black Marble project (Stefanini Vicente and Marty 2023). We then average the data into quarterly, mirroring the GDP data from BPS. We then fit nighttime lights index on real GDP growth using OLS and Autoregressive Distributed Lag (ARDL) models. The ARDL model showed the most promising fit. Importantly, we find evidence of a potential structural break post COVID-19. Additionally, we provide a provincial analysis to provide cross-sectional variance. We utilise OLS, provincial fixed effect and two-way fixed effect regression.

This paper aims to test whether nighttime light can be a sole predictor of GDP without adding other variables. We find that nighttime light index provides a consistent significant correlation to GDP growth across various specifications. However, the magnitude of the correlation is small, suggesting that nighttime light index alone cannot capture the full variation of GDP growth. However, We also find indicative evidence that the scarring effect post COVID-19 pandemic (Pangestu and Armstrong 2025) hurts long term economic growth by 2%. The ARDL specification with scarring effect show the best forecasting fit and is reasonably able to forecast GDP growth out-of-sample.

The paper is organised as follows. We discuss the nighttime lights data collection process and exploratory data analysis section two. The methodology development is covered in section three. Section four discusses the model results, followed by a conclusion in section five.

2. Data Collection and Processing

NASA Black Marble (Stefanini Vicente and Marty 2023) is a a daily calibrated, corrected, and validated product suite, curated such that nighttime lights data can be used effectively for scientific observations. The product suite takes full advantage of the capabilities of the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument, which is a component of the Suomi National Polar-orbiting Partnership (NPP) satellite. The instrument consists of 22 spectral bands from the ultra-violet to the infrared, of which the day night band (DNB) in particular is used to observe nighttime lights. The DNB is ultra-sensitive, and can detect very dim light that is several times fainter than daylight. The band covers 0.5–0.9 µm wavelengths (visible green to near-infrared), which is exactly the range of light emitted by common artificial sources like streetlights, buildings, vehicles, and even fishing boats.

While the analysis of nighttime lights has become more popular over the last two decades, a surprisingly few number of studies employ the use of data from VIIRS (Gibson, Olivia, and Boe-Gibson 2020). The new nighttime lights data offers a sharper resolution and higher frequency compared to the previous generation of nighttime lights data. Black Marble's standard science removes cloud-contaminated pixels and and corrects for atmospheric, terrain, vegetation, snow, lunar, and stray light effects on the VIIRS instrument.

The data collection process was performed using the Black Marble Python package developed by the World Bank (Stefanini Vicente and Marty 2023). After mapping and defining Indonesia's coordinates as the region of interest, we were able to use the `blackmarblepy` package to access NASA Black Marble as a xarray dataset. NASA's Black Marble suite offers daily, monthly, and yearly global nighttime lights data. Rasters were able to be created at all three frequency levels. Each xarray dataset contains a nighttime lights tile that is gap-filled and corrected, with a resolution of 500m. Critically, each dataset also contains a main variable representing radiance, a numerical measure of the amount of light energy emitted or reflected from a surface per unit area in a given direction, expressed in watts per square meter per steradian $(W \cdot m^{-2} \cdot sr^{-1})$. It is this measure that allows for nighttime lights to be compared and used as a proxy for GDP growth.

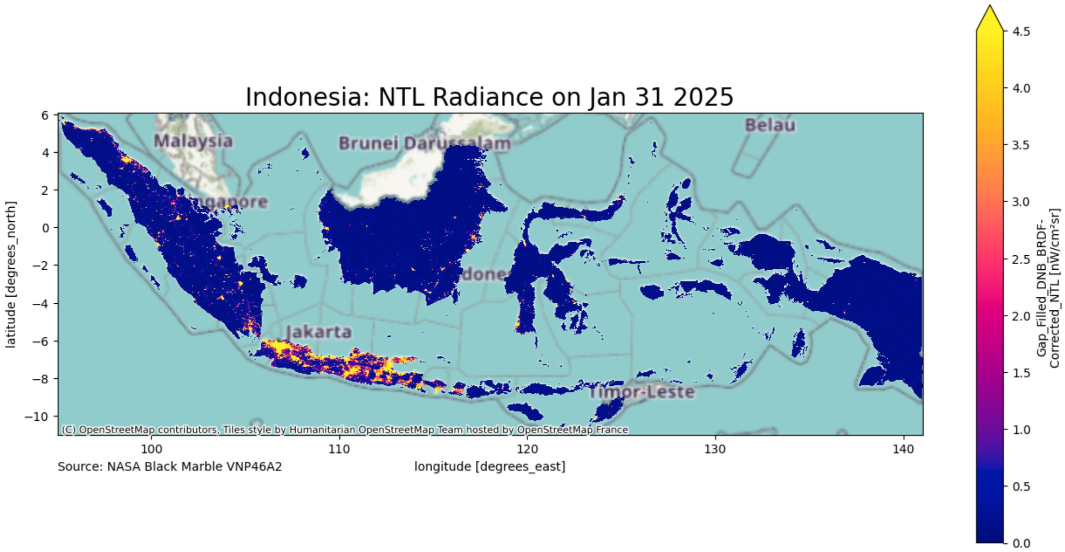

Figure 1. Annual Nighttime Lights in Indonesia, 2023

Figure 1 The figure is a visualization of the yearly raster for nighttime lights in Indonesia in 2023. There is a stark contrast between the nighttime lights activity in Java compared to other islands, which is reflective of significant gaps in various socioeconomic indicators between Java and the rest of Indonesia. The stark difference in economic activity between Java and the rest of Indonesia is well-documented in literature, and is a consequence of the landscape and soil of the island facilitating stronger agricultural yields and population growth.

Black Marble data can also be extracted for multiple time periods. The function will return a raster stack, where each raster band corresponds to a different date. The following code snippet provides examples of getting data across multiple days, for the month of May 2024 in Indonesia. We define a date range using pd.date_range.

Here we can see the fluctuations that exist within a given month, fluctuations that may be difficult to pinpoint from monthly or yearly rasters. One advantage of the flexibility of nighttime lights data is the ability to process it to suit the needs of any kind of time series analysis. In this instance, to facilitate the goal of making a proper comparison between nighttime lights and GDP, both series needed to be expressed on the same unit level. In Indonesia, GDP growth is typically reported in quarterly year-on-year terms. To align the nighttime lights data with this format, multiple steps were needed. First, monthly rasters were extracted from January 2012 to December 2024, covering the full period of available Black Marble nighttime lights data. The data was then saved as a .zip file. The radiance values were also extracted and saved as a separate .csv file.

With the radiance values extracted in a monthly form, the next steps involved transforming the data into quarterly year-on-year terms. Nighttime lights data was aggregated into quarterly terms. The data was then lagged and shifted 1 year back, from which the year-on-year change was able to be calculated.

GDP data was straightforward to collect due to the data being readily available from the BPS website (BPS 2025). Quarterly real GDP is used for the purposes of this study. The GDP series includes data from Q1-2010 to Q2-2025, but we will use Q1-2012 as our starting point in line with the availability

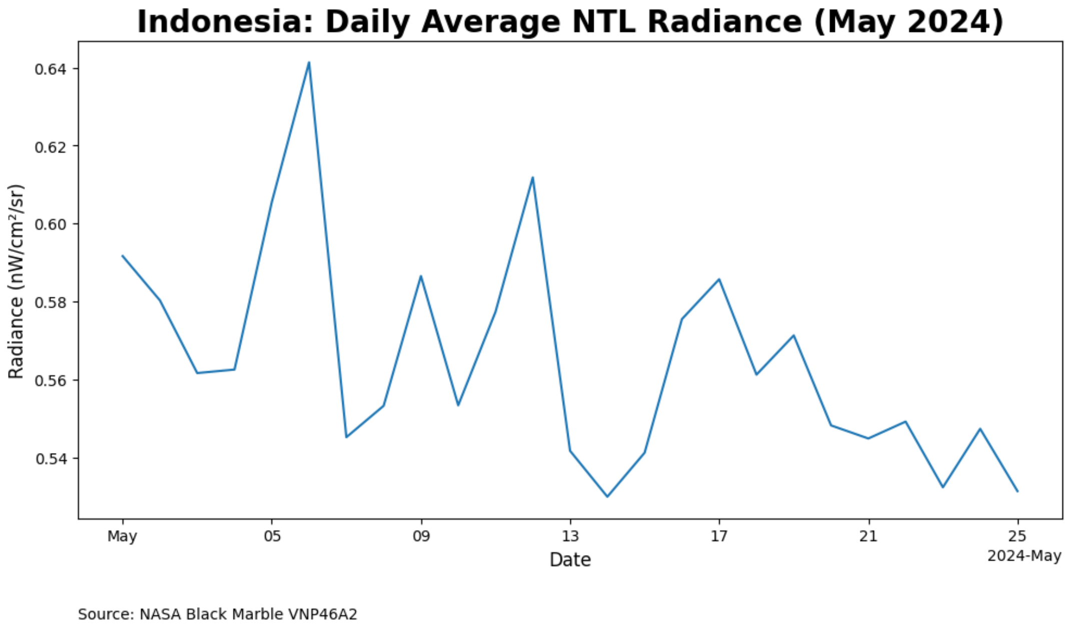

Figure 2. Daily Average Nighttime Light Radiance in Indonesia, May 2024

of nighttime lights data from NASA Black Marble. We also collets the provincial quarterly real GDP for the provincial-level regression.

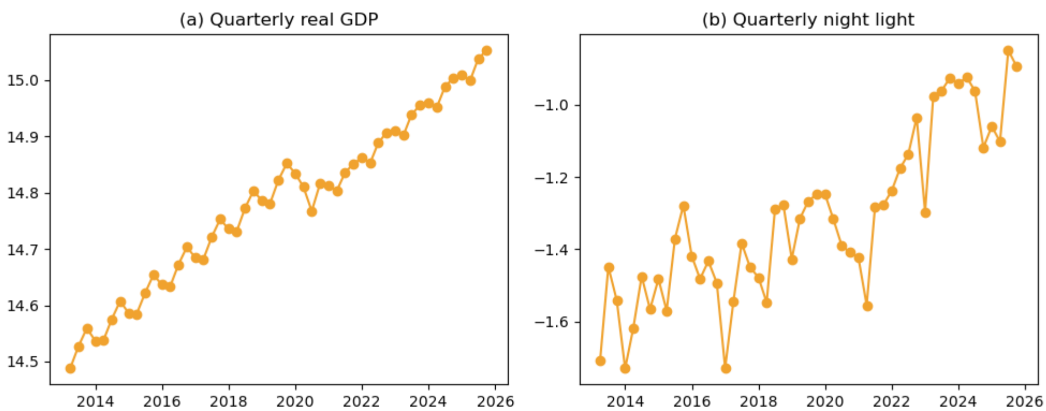

Figure 3. Indonesian economic growth and night light growth

Figure 3 shows our two main variables. The left panel is the national real GDP sourced from BPS (2025) while the right panel is the calculated night lights we gathered via Black Marble python package. Both seems to follow similar trend. However, night light index doesn't show significant drop during the COVID time, unlike GDP. Additionally, the nightlight index looks to be more stationary before 2022, and then show a positive trend. From the visual inspection, both series seems to be non-stationary.

3. Methodology

For the national level, we do not have any cross-sectional variation. Therefore, techniques that utilise cross-sectional mean cannot be exploited. Multivariate time series techniques, thus, should be the appropriate method.

First, we try a simple OLS:

$$g_t = \alpha_0 + \alpha_1 ntli_t + \epsilon_t$$

where g_t is the log of quarterly GDP at time t, $ntli_t$ is the log quarterly night light index at time t, α_0 is the constant term, α_1 is the coefficient of night light index, and ε_t is the error term. We then examine the error term and see if there is a bias in the residuals. It is reasonable to find autocorrelation in the residual with two time series data. We then use ARDL to take into account the autocorrelation (Enders 2014). We use lags determined by AIC.

$$g_t = \beta_0 + \sum_{p=1}^{P} \beta_i g_{t-i} + \sum_{q=0}^{Q} \beta_j ntli_{t-j} + \epsilon_t$$

In addtion to the above specification, we also test with quarter dummy, Covid dummy (2020-2022) and scarring dummy (2020 onwards).

For the regional level analysis allows for a cross-sectional dimension to be added to the time series data. This allows us to use panel data techniques. We can use provincial fixed effect and two-way fixed effect (TWFE) models.

In addition to the cross-sectional techniques, we employ panel distributed lag techniques to account for the dynamic nature of the relationship between nighttime lights and regional GDP as in the national level. Namely, we follow the approach of Mahraddika (2019) by using Dynamic Fixed Effects (DFE), Mean Group (MG) and Pooled Mean Group (PMG) estimators Pesaran, Shin, and Smith (1999).

4. Estimation Results

4.1 National-level analysis

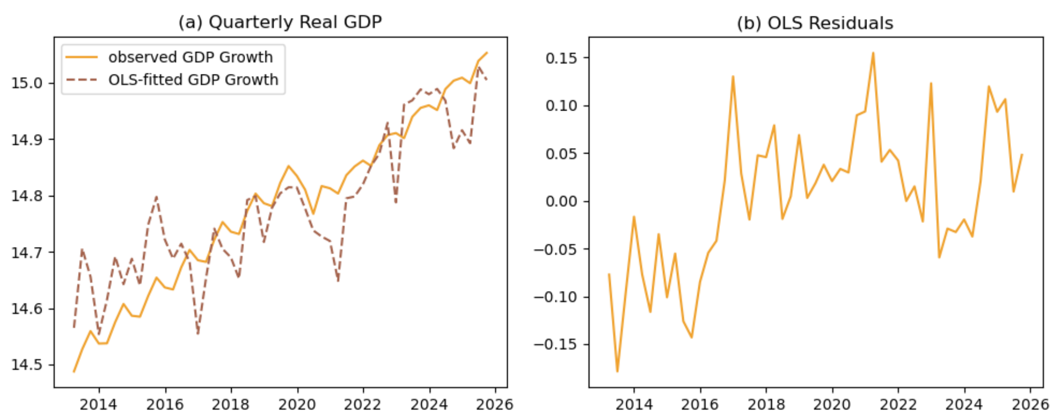

Figure 4. OLS fit and the residuals

Table 1. OLS Regression Results for log real quarterly GDP

Variable	Coefficient
const	15.4878***
	(0.0561)
ntlg	0.5401***
	(0.0407)
Observations	55
R-squared	0.7683
Adj. R-squared	0.7639
F-statistic	175.76

Figure 4 shows the OLS fit and the residuals while Table 1 show the regression result. The nighttime light show a strong correlation to the quarterly GDP. 1% increase in nighttime light index corresponds with 0.57% increase in GDP. However, Figure 4 shows a clear bias on the residuals. The model over-predicts GDP pre-2017 and underpredicts GDP post 2017. This suggest that OLS is not the proper method to model these two series.

Figure 5 shows the ARDL approach. We ran six different specifications. The panel (a) shows a baseline model with only log GDP and log nighttime light. Panel (b) adds COVID dummies, which consist of values equaling 1 for the year 2020-2022. Panel (c) adds scarring dummies, equaling 1 for all observations beginning from 2020. Panel (d) adds quarterly dummies. Panel (e) combines COVID dummies with quarterly dummies, while panel (f) use scarring dummies and quarterly dummies. The solid line represents the actual GDP data while the dashed line illustrates the predicted GDP.

We can see from the Figure 5 that all predicted values follow the actual GDP very well. However, the GDP value predicted by model with scarring, that is, both panel (c) and (f), looks to have the smallest discrepancy with the actual data.

Table 2. ARDL Regression Results

Variable	Baseline	+Covid	+Scar	+Quarterly	+Q+C	+Q+S
const	2.2942	2.9864	49.8166***	2.5612*	2.8221*	37.7501***
	(1.5716)	(1.7920)	(5.2152)	(1.3806)	(1.4232)	(4.9545)
trend	0.0008	0.0020	0.0424***	0.0013	0.0020*	0.0321***
	(0.0011)	(0.0014)	(0.0045)	(0.0010)	(0.0011)	(0.0042)
g.L1	0.5393***	0.5947***	-0.7533***	0.6644***	0.6247***	-0.6215***
	(0.1316)	(0.1331)	(0.1196)	(0.1254)	(0.1061)	(0.1025)
g.L2	-0.0804	-0.4507***	-0.9372***	0.1776	0.0812	-0.4841***
	(0.1638)	(0.1561)	(0.0865)	(0.1660)	(0.1338)	(0.1249)
g.L3	0.0036	0.2549	-0.7755***	-0.2861*	-0.1873	-0.5542***
	(0.1682)	(0.1627)	(0.1224)	(0.1691)	(0.1371)	(0.1103)
g.L4	0.3857***	0.3967***	0.0147	0.2708**	0.2861***	0.0454
	(0.1352)	(0.1234)	(0.0766)	(0.1275)	(0.1020)	(0.0631)
covid.L0		-0.0003			-0.0031	
		(0.0098)			(0.0082)	
covid.L1		-0.0482***			-0.0401***	
		(0.0129)			(0.0108)	
covid.L2		0.0370***			0.0318***	
		(0.0136)			(0.0086)	
covid.L3		-0.0272*				
		(0.0147)				
covid.L4		0.0262**				
		(0.0113)				
ntlg.L0	0.0855***	0.0350	0.0119*	0.0571**	0.0312*	0.0115**
	(0.0229)	(0.0227)	(0.0059)	(0.0212)	(0.0183)	(0.0048)
ntlg.L1	0.0033	-0.0350		-0.0275	-0.0372**	

Variable	Baseline	+Covid	+Scar	+Quarterly	+Q+C	+Q+S
	(0.0245)	(0.0209)		(0.0207)	(0.0176)	
ntlg.L2	-0.0460**					
	(0.0224)					
q1.L0						-0.0108***
						(0.0023)
q2.L0				0.0299***	0.0273***	
				(0.0077)	(0.0062)	
q3.L0				0.0293***	0.0278***	0.0079***
				(0.0078)	(0.0062)	(0.0025)
scar.L0			-0.0201***			-0.0204***
			(0.0043)			(0.0035)
scar.L1			-0.0965***			-0.0937***
			(0.0064)			(0.0053)
scar.L2			-0.0621***			-0.0400***
			(0.0127)			(0.0114)
scar.L3			-0.0679***			-0.0308**
			(0.0090)			(0.0115)
scar.L4			-0.0342***			-0.0276***
			(0.0110)			(0.0094)
Observations	51	51	51	51	51	51
AIC	-275.94	-291.52	-408.79	-287.61	-309.81	-428.67
BIC	-256.62	-264.48	-383.68	-266.36	-282.76	-399.69

Table 2 shows the estimated parameters of the 6 models. Indeed, models with scarring show the lowest AIC and BIC, which suggests these specifications are the most robust compared to the other specifications without scarring. The scarring effect leads to a 2% decrease in quarterly GDP. Importantly, the current nighttime light index is significant for all but the COVID-dummy specification. The base model shows the strongest correlation, where a 1% increase in nighttime light index correlates to a 0.0855% increase in GDP. For the scarring specification, the coefficients are 0.0119 and 0.0115 respectively. That is to say that a 1% increase in nighttime light index correlates with a 0.0119% increase in GDP.

To test whether the model can forecast GDP well, we divide the data into a training set consisting all observation prior to 2024, and testing set consists of the remaining data. The result is illustrated in Figure 6. The solid line represents the actual GDP, the dashed line represents the predicted GDP using the training set, and the dotted line represents the forecast using the testing set. We can see from the Figure 6 that the model with scarring dummies can predict with a better fit and smaller error rate.

Notably, the GDP prediction is less sensitive to nighttime lights fluctuations compared to the scarring dummy and the GDP lags. In fact, the nighttime light index becomes less useful as the training size decreases (which is reflected in the AIC and BIC). In the model with scarring dummy, the nighttime light coefficient at time 0 is only significant in 10% with or without quarterly dummies.

Indeed, the past GDP values are more important, with the AR1 coefficient is -0.7 and is significant at 0.1% level. More importantly, scarring effect shows a 0.1% level significance at all 4 lags. Scarring dummy at time 0 has a coefficient of -0.02, suggestiong about 2% lower in GDP level persistently after the pandemic.

4.2 Regional-level analysis

In parallel with the national level specification, we also extended the baseline specification by including dummy variables for the Covid-19 period (2020-2022) and the post-pandemic or the scarring effect period (2022-2025) to assess whether the relationship between provincial GDP and nighttime lights changed during and after the pandemic. We conduct the analysis using a range of econometric models. The analysis begin with pooled OLS as a baseline and further estimation using Fixed Effects (FE), Two-

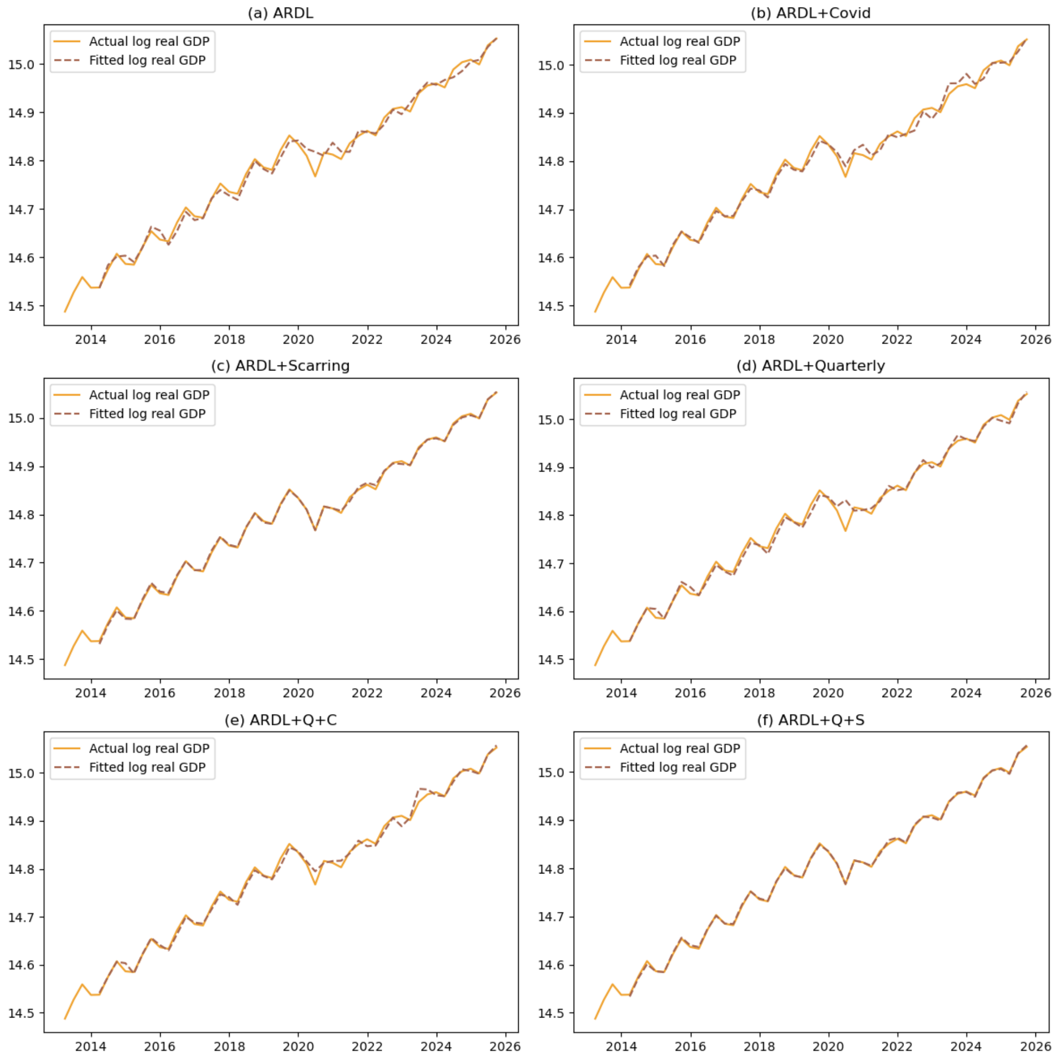

Figure 5. Quarterly real GDP, ARDL

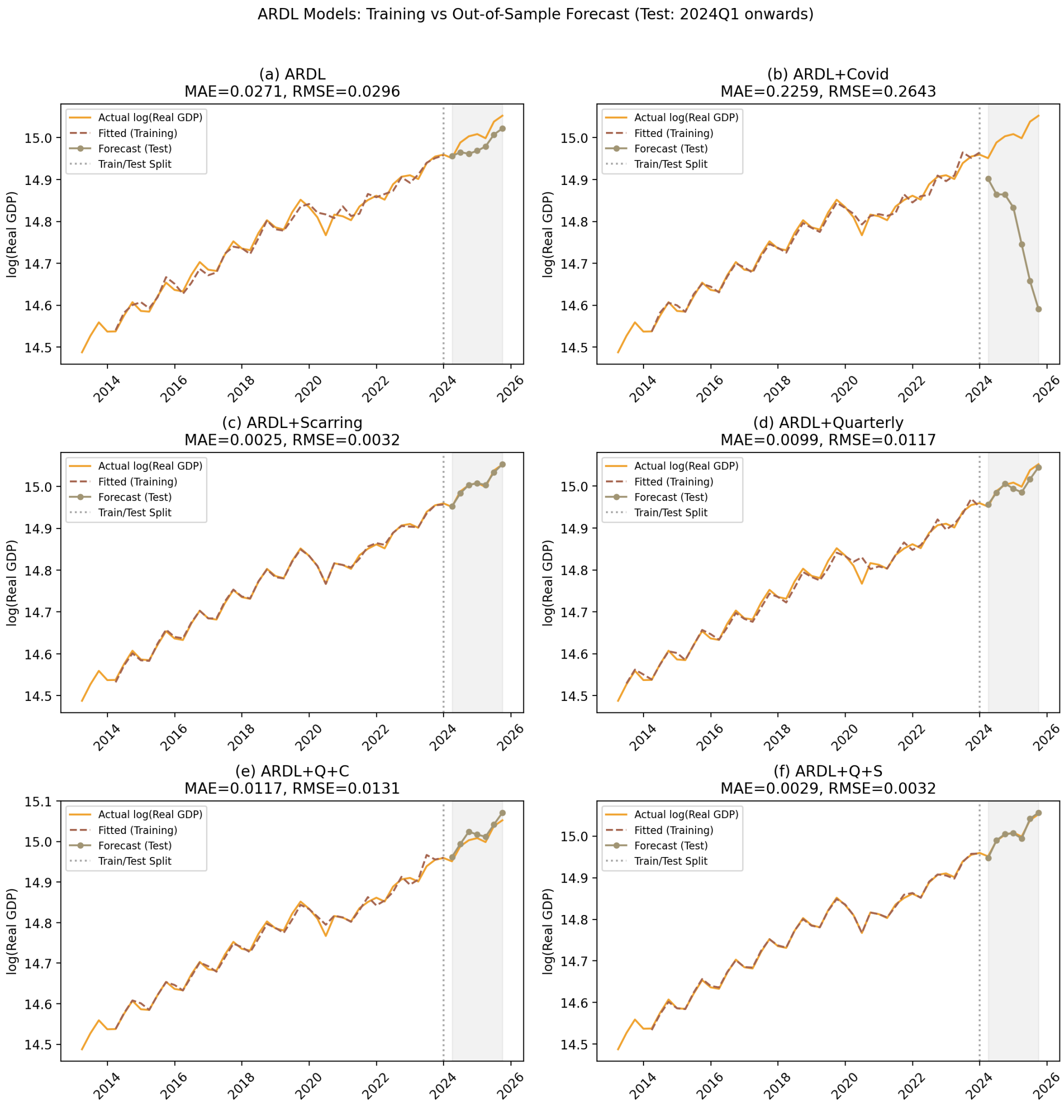

Figure 6. Economic growth prediction with ARDL

Way Fixed Effects (TWFE), and Dynamic Fixed Effects (DFE). Across all model specifications, the relationship between GDRP and nighttime lights remains consistent, indicating that nighttime light data provides a useful proxy for GDRP.

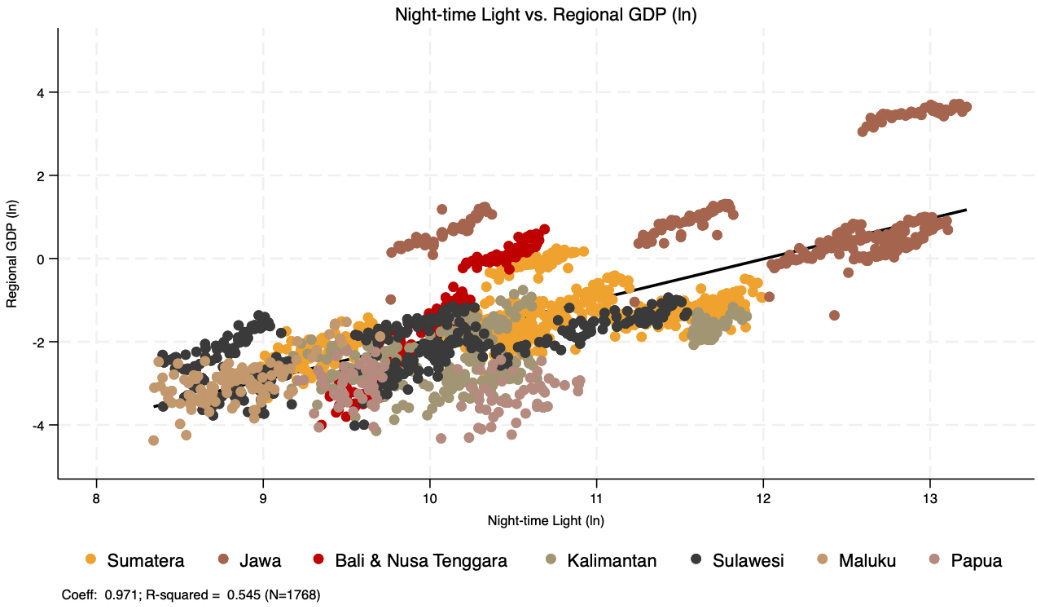

Figure 7. Nighttime-Lights vs. Regional GDP, log

Figure 7 is a scatterplot of nighttime lights against regional GDP for 34 provinces in Indonesia from 2014Q1 to 2024Q4. Java exhibits a stark contrast compared to the rest of Indonesia. NIghttime light index show a substantially higher intensity along with its RGDP (Regional GDP) compared to other island groups. The data points for Java in blue color are clustered toward the higher end of both axes, indicating higher levels of economic activity and luminosity relative to other regions. Conversely, though the linear trend between nighttime light and provincial GDP are still visible, provinces outside Java show greater dispersion. This implies more variation in the relationship between light intensity and GDP possibly due to differences in economic structure or spatial distribution of economic activities. In regions outside Java, the economic structure is dominated by agriculture, plantation activities, and mining industries. While these sectors contribute significantly to regional output, they produce comparatively low levels of nighttime lights.

Table 3. Summary statistics of nighttime lights (ln) and GDRP (ln) at quarterly frequency, 2014-2024

	Mean	Std. Dev.	Min	Max
Sumatera (10 provinces)				
Nighttime lights (ln)	-1.44	0.69	-3.35	0.23
GDRP (ln)	10.59	0.80	8.82	12.01
Java (6 provinces)				
Nighttime lights (ln)	1.03	1.17	-1.36	3.71
GDRP (ln)	12.04	1.02	9.65	13.24
Nusa Tenggara (3 provinces)				
Nighttime lights (ln)	-1.43	1.33	-4.00	0.70
GDRP (ln)	10.01	0.37	9.23	10.70
Kalimantan (5 provinces)				

	Mean	Std. Dev.	Min	Max
Nighttime lights (ln)	-2.30	0.69	-4.14	-0.75
GDRP (ln)	10.35	0.74	9.02	11.90
Sulawesi (6 provinces)				
Nighttime lights (ln)	-2.15	0.67	-4.01	-0.93
GDRP (ln)	9.77	0.87	8.22	11.55
Maluku (2 provinces)				
Nighttime lights (ln)	-2.96	0.51	-4.37	-1.52
GDRP (ln)	8.79	0.33	8.19	9.77
Papua (2 provinces)				
Nighttime lights (ln)	-3.16	0.46	-4.32	-2.22
GDRP (ln)	9.98	0.52	9.09	10.89

Table 3 shows the summary statistics of the nighttime light and regional GDP by islands. The table reinforce what is visually apparent in Figure 7: Java is the most developed island in Indonesia, with the highest average nighttime light intensity and regional GDP. It is remains to be seen if the positive relationships are different among provinces.

The varying degree of light-GDP relationship across islands (and, by extension, across provinces) suggests that using nighttime lights as a proxy for economic activity may require adjustments based on regional characteristics. For instance, provinces with economies heavily reliant on non-luminous sectors may not exhibit a strong correlation between light intensity and GDP. This highlights the importance of considering local economic structures when utilizing nighttime lights data for economic analysis. Indeed, potentially looking at national-level only might mask these regional differences.

Table 4 shows the regional panel regression. As the baseline (column OLS), we estimate the correlation between nighttime lights (NTL) and regional GDP using a pooled Ordinary Least Squares (OLS) model. the next three columns employ a fixed-effects (FE) model to control for time-invariant provincial characteristics. The last column show a two-way fixed-effects (TWFE) model that advanced the FE estimation by incorporating year fixed effects to account for common shocks affecting all provinces simultaneously. With applied time fixed-effects, the scarring and COVID dummies are no longer needed.

The regression results show a strong and statistically significant relationship at the 0.1 percent level between regional GDP and nighttime light intensity across all static model specifications. Coefficients from the OLS and fixed-effects models remain positive and stable even after controlling for COVID-19 and post-pandemic scarring effects. The overall elasticity pattern between regional GDP and nighttime light intensity remains consistent over time.

The coefficient on the OLS model corroborates that of the national level OLS. The FE model show a slightly smaller coefficient, suggesting the importance of the provincial difference. Controlling for time fixed effect, the coefficient drops to 0.0649. That is, a 1% increase in nighttime light index corresponds to a 0.0547% increase in regional GDP.

To account for the possibility that the relationship between GDP and nighttime lights evolves dynamically rather than instantaneously, we extend the analysis using a Dynamic Fixed Effects (DFE), Pooled Mean Group (PMG) and Mean Group (MG) error-correction model Pesaran, Shin, and Smith (1999). Unlike the static FE and TWFE specifications, the distributed lag framework allows for short-run fluctuations while modeling a long-run equilibrium relationship between the variables. Specifically, it incorporates lagged adjustments so that deviations from the long-run relationship can gradually converge back to equilibrium. At the same time, the model retains fixed effects (for DFE case) to control for unobserved, time-invariant provincial heterogeneity.

The DFE results provide strong evidence of a stable long-run relationship between the two variables. The error-correction term is negative and statistically significant across all specifications. Importantly,

Table 4. Panel Regression Results for log provincial GDP

	OLS			FE			TWFE		
VARIABLES	Base	+Cov	+Scar	Base	+Cov	+Scar	Base	+Cov	+Scar
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln_ntl	0.561***	0.560***	0.559***	0.284***	0.257***	0.189***	0.0547***	0.0547***	0.0547***
	(0.0124)	(0.0123)	(0.0123)	(0.0327)	(0.0279)	(0.0251)	(0.0184)	(0.0184)	(0.0184)
covid		0.110**			0.147***			0.420***	
		(0.0443)			(0.0128)			(0.0210)	
scarring			0.0814**			0.185***			0.458***
			(0.0410)			(0.0145)			(0.0220)
Constant	11.33***	11.30***	11.30***	10.92***	10.84***	10.71***	10.33***	10.33***	10.33***
	(0.0292)	(0.0314)	(0.0329)	(0.0484)	(0.0416)	(0.0380)	(0.0325)	(0.0325)	(0.0325)
Observations	1,632	1,632	1,632	1,632	1,632	1,632	1,632	1,632	1,632
R-squared	0.546	0.547	0.547	0.349	0.489	0.582	0.845	0.845	0.845
OLS	plain	Covid	Scarring						
Number of prov	34	34	34	34	34	34	34	34	34

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the magnitude and significance of the error-correction coefficient remain robust even after controlling for the post-pandemic scarring periods. This suggests that, although the pandemic caused temporary disruptions, it did not fundamentally alter the long-run linkage between economic activity and night-time light intensity.

Table 5. Panel ARDL–ECM Estimates (DFE vs MG vs PMG)

	DFE		MG		PMG	
	(1) Baseline	(2) +Scarring	(3) Baseline	(4) +Scarring	(5) Baseline	(6) +Scarring
Panel A. Long-Run Relationship						
ln_ntl	0.332***	0.589**	0.486***	-0.713	0.374	0.426
	(0.114)	(0.283)	(0.155)	(1.098)	(0.379)	(1.113)
scarring		-0.100		-0.0128		-0.0490
		(0.186)		(0.121)		(1.113)
Panel B. Short-Run Dynamics						
ECT	-0.0374***	-0.0169*	-0.0908***	-0.0395**	-0.0418	-0.0457
	(0.00851)	(0.00939)	(0.0154)	(0.0179)	(0.399)	(0.719)
Lagged Δ ln(pdrb)						
L1.	-0.602***	-0.654***	-0.620***	-1.029***	-0.578***	-0.931***
	(0.0255)	(0.0265)	(0.0349)	(0.0623)	(0.0339)	(0.0637)
L2.	-0.551***	-0.583***	-0.597***	-1.014***	-0.539***	-0.908***
	(0.0270)	(0.0277)	(0.0332)	(0.0633)	(0.0313)	(0.0644)
L3.	-0.507***	-0.544***	-0.546***	-0.963***	-0.473***	-0.860***
	(0.0265)	(0.0270)	(0.0400)	(0.0669)	(0.0363)	(0.0678)
L4.	0.264***	0.270***	0.199***	-0.103*	0.278***	-0.0135
	(0.0250)	(0.0251)	(0.0306)	(0.0527)	(0.0335)	(0.0552)
Lagged Δ ln(ntl)						

Continued on next page

Table 5. Panel ARDL–ECM Estimates (DFE vs MG vs PMG)

	DFE		MG		PMG	
	(1) Baseline	(2) +Scarring	(3) Baseline	(4) +Scarring	(5) Baseline	(6) +Scarring
D	0.0130**	0.00275	-0.00254	-0.00271	0.0229***	-0.00150
	(0.00593)	(0.00526)	(0.00841)	(0.00910)	(0.00659)	(0.00414)
L1.	0.0101*	0.000825	-0.00978	-0.00671	0.00867	-0.00830
	(0.00576)	(0.00512)	(0.00821)	(0.0101)	(0.00590)	(0.00569)
L2.	0.0170***	0.00564	0.00532	0.00270	0.0193***	0.00170
	(0.00530)	(0.00473)	(0.00768)	(0.00824)	(0.00614)	(0.00551)
L3.	0.00425	-0.00491	-0.00235	-0.00299	0.00577	-0.00602
	(0.00439)	(0.00392)	(0.00628)	(0.00794)	(0.00524)	(0.00648)
L4.	-0.00271	-0.00439	0.000898	-0.000289	0.00453	-0.00186
	(0.00327)	(0.00290)	(0.00454)	(0.00445)	(0.00427)	(0.00363)
Scarring dynamics (only for +Scarring models)						
D		-0.0563***		-0.0560***		-0.0601***
		(0.00527)		(0.00491)		(0.00484)
L1.		-0.000834		-0.0230***		-0.0187***
		(0.00544)		(0.00730)		(0.00560)
L2.		-0.0707***		-0.0748***		-0.0752***
		(0.00521)		(0.00642)		(0.00571)
L3.		-0.0407***		-0.0770***		-0.0720***
		(0.00557)		(0.00940)		(0.00799)
L4.		0.0380***		0.00610		0.0110*
		(0.00549)		(0.00607)		(0.00575)

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5 shows the dynamic fixed effects regression results. The results show a strong and statistically significant relationship at the 0.1 percent level between regional GDP and nighttime light intensity across all static model specifications. Coefficients from the OLS and fixed-effects models remain positive and stable even after controlling for COVID-19 and post-pandemic scarring effects. The overall elasticity pattern between regional GDP and nighttime light intensity remains consistent over time.

The distributed lag results corroborates the national results. That is, the short-term changes in nighttime lights have a weak implication to the GDP's convergence to its long-term equilibrium. More importantly, while the scarring is not significant in the long-term, the small error-correction term suggesting a slow adjustment to the long-term equilibrium after shocks.

With the ECT value of -0.0374 in the baseline DFE model, it would take approximately 27 quarters (or about 6.75 years) for regional GDP to fully adjust back to its long-run equilibrium after a shock. The results corroborates Reinhart and Rogoff (2014)'s findings on the slow adjustment of GDP to its long-term trend around 6-8 years.

However, when we include the scarring dummy, the ECT value decreases to -0.0169, indicating an even slower adjustment process. In this case, it would take approximately 59 quarters (or about 14.75 years) for regional GDP to fully revert to its long-run equilibrium following a shock. This suggests that the post-pandemic scarring effect has prolonged the time it takes for regional economies to recover and stabilize after disruptions.

Recent studies have highlighted the possibility of a hysteresis, or a long-lasting, potentially permanent impact of a deep crisis Reinhart and Rogoff (2014). When an economy face a deep crisis, it can have a lasting impact amid an increase of risk permia which hinders banks from lending to firms. This creates a feedback loop as firms are unable to invest and grow, corroding the economic growth potential.

Indonesia's experience from the 1998 crisis provides a historical precedent for such hysteresis effects, where growth rates never really returned to pre-Asian Financial Crisis level.

5. Conclusion

We ran national-level and regional-level regression to inspect the relationship between nighttime light index and GDP. Overall, we find that nighttime light index can be used to predict GDP growth well. However, there are some caveats that need to be highlighted. Analyzing national-level and regional-level provide us with bi-variate time series analysis coupled with insights from panel data regression. We find that the OLS results are significant, large, and provide consistent estimators when regional cross-sectional variation is added. However, OLS models provide biased estimators for both the national-level and regional-level analysis. Once we take into account autocorrelation (from the ARDL specification) and provincial bias (using fixed effects), the correlation strength of the nightlight index decreases.

There are two potential key takeaways from the national-level analysis. First, the scarring effect is critical for forecasting GDP, more than it might be for other indicators. We can see this especially when we use quarterly dummies. From Figure 5, The panel (c) and (f) show that quarterly dummies do not significantly add insight, while panel (d) and (e), panels with quarterly dummies without scarring, show a looser fit. This finding is consistent with other studies that examine the potential scarring effect from the COVID pandemic in Indonesia (Pangestu and Armstrong 2025).

Secondly, the nightlight index does not perform as well as we think. We find that that the nighttime light index fluctuates in a different way compared to GDP. This is most apparent during the COVID-19 pandemic, where GDP drops significantly, while the nighttime light index experiences only a modest drop.

Various potential reasons can explain this phenomenon. On days where the satellite view of the Earth is obstructed by clouds, nighttime lights values are often gap-filled and estimated based on the number of available clear pixels. This means that the nighttime light index might not accurately capture the actual emitted light in Indonesia amid cloud cover, atmospheric conditions, or other factors that affect the quality of satellite imagery especially during the rainy months of the tropical region.

Secondly, the Indonesian government has been increasingly implementing electricity subsidies during hard times. The nighttime lights index is unable to identify situations involving a heavy downturn where the government decided to step in to maintain electricity consumption.

The regional level analysis corroborates the national-level findings. That is, a potential existence of hysteresis, or the scarring effect of pandemic, is found in the regional-level analysis as well. The DFE base results confirms the literature speed of convergence, but the scarring effect reduces the speed of convergence even further. Additionally, the nightlight index also not as important as we think, as the short-term dynamics show weak significance.

Nevertheless, the ARDL model shows promise in forecasting national GDP. The out-of-sample forecast shows that the model can predict GDP well, especially when we use scarring dummies using a minimal number of variables. While we have demonstrate that nighttime light index cannot be used as a sole predictor of GDP, its consistent significance across various specifications suggest that nighttime light data can be considered to feed forecasting and nowcasting models.

Reproducibility Statement

The source code and data to reproduce the analysis in this paper are available at https://www.github.com/den-econ/nitelite.

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