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Pacific Islands

Pacific Observatory

MONITORING ECONOMIC ACTIVITY BY NIGHTTIME LIGHT DATA

19 April 2023

Nighttime Lights – Application for the Pacific

Nighttime Lights- Applications for the Pacific

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Executive Summary

This note provides a deep dive into the quality of nighttime lights (NTL) data for Pacific Island Countries (PICs). It explores their potential to generate and complement regional socio-economic statistics. NTL data has been widely used as a proxy of economic activity. It has been used to both disaggregate estimates of national economic output and predict economic growth. Although applying the first use case in PICs is technically feasible, validation is difficult given the lack of sub-national economic indicators.

Previous studies show that the correlation between NTL and Gross Domestic Product (GDP) in the PICs is not strong enough to reliably predict national growth. Studies that have attempted to predict GDP based solely on regressions with NTL data have underestimated the economic output from small island states. Important industries such as agriculture, fishing, and tourism are not well captured by lighting intensity.

Despite these limitations, we find other applications where NTL provides complementary value to official statistics. Overall, this study finds most promise in the use of NTL to:

- Monitor the gas industry in Papua New Guinea
- Support poverty mapping exercises, and
- Generate detailed electrification statistics.

For example, the data can be used to monitor the extractives sector in Papua New Guinea. At the aggregate level, the production output for gas/petroleum is strongly correlated with sum of lights (SoL), with an elasticity of 0.98. Monthly NTL data can also be a useful indicator to examine whether a given mine operation is activate, expanding, or causing spillover settlement growth.

Although NTL analysis tends to miss rural populations in most islands, the distribution of lights nonetheless holds valuable information to support poverty mapping exercises. A new methodology leveraging daily NTL data is able to generate disaggregated electrification rates across Pacific areas, with reasonable correlation to survey-derived electrification rates.

Daily lights provide limited value to examine the spatio-temporal impacts and recovery from the volcanic eruption in Tonga. Most satellite observations from Visible Infrared Imaging Radiometer Suite (VIIRS) for the relevant period were affected by data quality issues. As this archive is relatively new, more case studies with different types of natural disasters need to be examined to provide a conclusive assessment of this novel application.

Introduction

Measurements of light captured at night have become an increasingly popular data source for economists and social scientists. Nighttime lights (NTL) statistics have been used extensively to measure the extent of urban areas and to proxy economic activity. Given its ubiquity and ease of access, NTL data has become a popular choice as an economic variable, particularly in countries where economic statistics are lacking.

Combined, two public satellites – Defense Meteorological Satellite Program (DMSP) and Visible Infrared Imaging Radiometer Suite (VIIRS) – provide data with global coverage and monthly cadence since 1992. A new partnership between the World Bank and United States National Oceanic and Atmospheric Administration (NOAA) has unlocked access to daily scenes from both archives.

Researchers have used NTL to study economic dynamics at various scales, whether to estimate growth in GDP, or map the distribution of economic activity at local levels.[1] The main assumption behind the use of lights as an economic proxy is that consumption and production activities during the evening require some form of lighting. However, there are several reasons why this relationship might not be as strong in Pacific Island Countries (PICs).

1. The overpass time of the more accurate VIIRS satellite is after-midnight when centers of production may not be emitting light. [2]
2. Satellite data for the Pacific territories is also highly susceptible to clouds, causing frequent interruptions in data coverage.
3. Populations in the Pacific Island states are predominately rural and produce too little light to be captured by these satellites.[3]
4. Perhaps most importantly, there is a risk that important economic activities from the islands such as fishing, agriculture and tourism are not captured well by luminosity signals.

The objective of this feasibility note is to test these limitations and assess the usability of NTL to generate statistics for the PICs.

The note is divided into four sections. To begin with, an overview of the relevant literature and main approaches to generating economic statistics from NTL data is provided, with a review of the previous efforts to apply them in the Pacific context. In the second section, a quality assessment of NTL data for PICs is presented, that explores the distribution of values and issues with cloud coverage. The third section provides a case study to investigate whether NTL data can be used to predict output from the extractives industry in Papua New Guinea, and test the correlation of results with sub-national poverty levels. The last section explores two other use cases for NTL in PICs: tracking recovery from natural disasters and estimating electrification rates.

[1] Zhao et al. (2019)

[2] VIIRS data has a higher spatial resolution, is better suited to detect light at lower intensities, and greatly reduced blooming effects. A detailed overview of these improvements was covered in Gibson et al. (2020), and is also described in the OpenNightLights tutorials.

[3] Gibson, Susan, and Boe-Gibson (2020)

Section 1 - Literature Review

1.1. Socio-Economic Applications of NTL

Although DMSP and VIIRS were originally designed for meteorological purposes, a growing literature has documented their capacity to detect human activity and proxy economic variables. The following review highlights general findings and notable applications which could be tested in the Pacific context, categorized into three main groups.

- Cross-section: Disaggregating economic measures to finer spatial scales
- Time-series: Predicting growth in GDP
- Proxying electricity consumption

1.1.1. Cross-section: Disaggregating economic measures to finer spatial scales

A recurring objective has been to disaggregate socioeconomic indicators from the national level into sub-national units, or into a spatial grid.[4] These studies typically use a cross-section of GDP, nighttime lights, and gridded population to "spread" GDP data into smaller units. To give a simplified example, national-level GDP can be weighted by the proportion of night lights reflectance per pixel to construct pixel-level GDP. Additional information about the composition of labor per district can be used to create weights to differentiate agricultural vs. non-agricultural GDP.

This approach is often combined with regression analysis to calibrate NTL statistics to official GDP measures. The coefficients found are multiplied with sub-national sum of lights to estimate corresponding GDP. This method has yielded disaggregated results that are well correlated with official statistics where available. However, studies have flagged small islands as outliers because they are dimmer than what would be expected given the observed relationship between GDP and lights.[5] This poses the risk that gridded products based solely on regression coefficients might underestimate the economic output of small islands.

1.1.2. Time-series: Predicting growth in GDP

A second and more challenging use case associates the increase in lights to economic growth. Economists have investigated how to weigh NTL and national accounts to construct "true" GDP measures by examining the distribution of error on both ends.[6] These investigations have produced contrasting views on how useful lights are to proxy economic growth. Some are more cautious and note that lights add limited value in the measurement of growth and development. However, other research concludes that lights could augment GDP measurements and play a significant role in improving GDP measures, particularly in low-income countries with underdeveloped statistical capacity.

While some studies have concluded that the growth elasticities of the two time series are too small or unstable,[7] similar studies based on data from South Asia have found that the elasticities hold true, particularly for the manufacturing and services sectors in the region.[8]

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[4] Sutton, Elvidge, and Ghosh (2007); Ghosh et al. (2010); Doll, Muller, and Morley (2006)
[5] Ghosh et al. (2010)
[6] Henderson, Storeygard, and Weil (2012); Hu and Yao (2019); Chen and Nordhaus (2011)
[7] Addison and Stewart (2015)
[8] Beyer (2018). Maldives is noted as an exceptional country in the region where the elasticity does not hold.

More contemporary research has shifted to use of the improved VIIRS data, which provides the added benefit of tracking quarterly GDP.[9] Across all the reviewed literature, a general finding has been that lights are more useful for cross-sectional work than for time series analysis.[10] Click or tap here to enter text.

1.1.3. Proxying electricity consumption

Another economic variable that has been strongly linked to NTL data is energy use.[11] In one particular study, out of all the economic variables considered , only nightlights provided a strong fit to proxy growth rates in electricity consumption.[12]

Building upon this established correlation, researchers have developed a new method that leverages daily NTL scenes and high-resolution settlement maps to generate new electrification statistics. This method separates anthropogenic lights from background brightness, and then calculates the probability that a settlement pixel is electrified, as well as the proportion of nights that it was lit throughout a given year. Aggregating these results to the district-level showed strong correlations with electrification rates reported in Demographic Health Survey (DHS).

1.2. Previous Use of NTL in the Pacific

Despite the vast economic literature, the application of NTL data to research in the Pacific has been limited. Selected research has focused on the observance of correlations between lights and population density in Papua New Guinea. These correlations were used to calculate a measure of economic intensity based on one million Kina per light unit.[13] However, even within this research niche, NTL does not provide any additional value in the analysis conducted of household welfare.

More attention has been given to the use of lights to analyze economic recovery from natural disasters. In this branch of work, damage modeling is used to identify affected vs. non-affected pixels. A comparison is set up to monitor the change in lights before and after a disaster occurs. Such analyses are novel, but depend on monthly or daily lights data which has limitations. It can be subject to noise from measurement errors, interruptions due to cloud coverage, and seasonal trends. Despite efforts to remove noise, a study of natural disasters in five South East Asian countries reported inconsistent results and warned researchers of the limitations of VIIRS data.[14]

A similar methodology was applied to a study of the 2015 cyclone Pam in the South Pacific islands.[15] Click or tap here to enter text.The authors calculated damage indices for wind speed and storm surge and disentangled the effects of these indices on NTL intensity. The findings suggest that the data is good enough to assess short-term shocks to the economy and differentiate recovery patterns by geographic area.

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[9] Beyer et al. (2022)
[10] Gibson, Susan, and Boe-Gibson (2020)
[11] Min and Gaba 2014; Doll and Pachauri 2010; Falchetta et al. 2019; Mensan Gaba et al., n.d.
[12] Addison and Stewart (2015)
[13] Edmonds et al. (2018)
[14] Skoufias, Strobl, and Tveit (2021)
[15] Mohan and Strobl (2017)

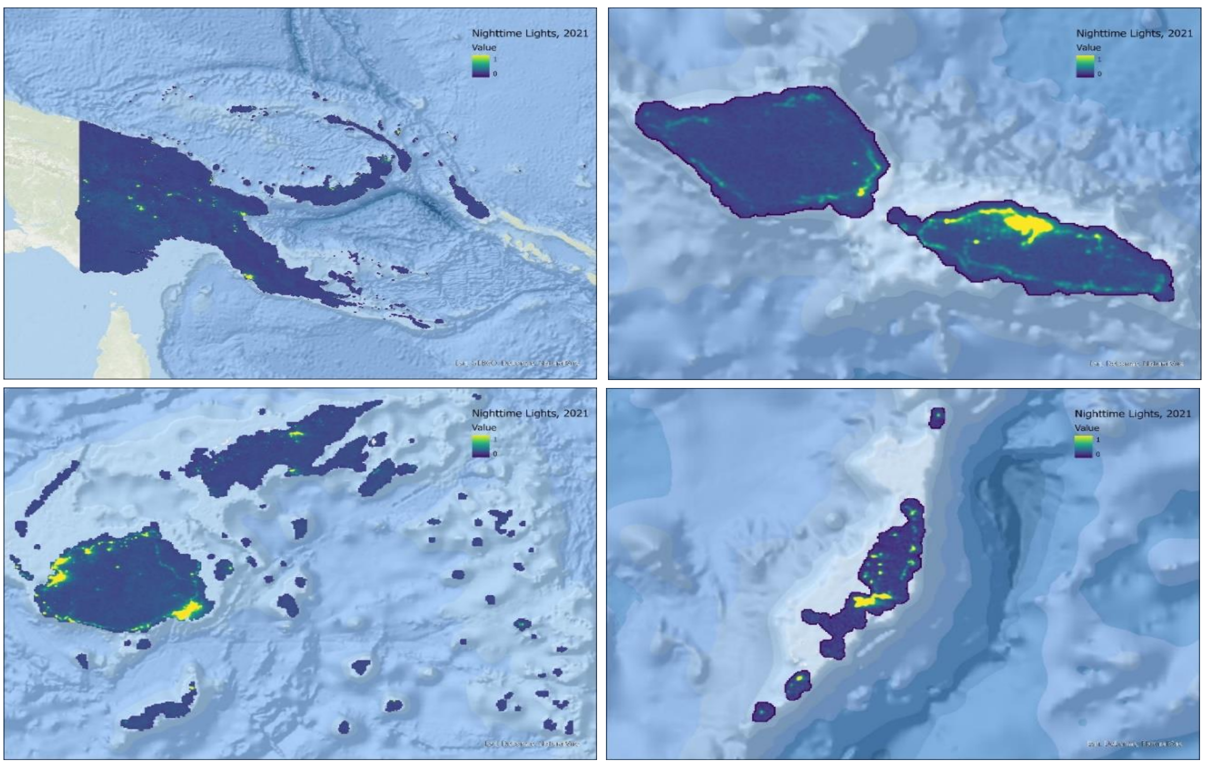
Section 2 - Data Quality Assessment

This section examines the distribution and temporal quality of NTL data from the VIIRS satellite for selected Pacific Islands. All analytical steps were implemented in python leveraging the Google Earth Engine API. Annotated notebooks to replicate the analysis can be found in the Pacific Observatory github repository.[16] Additionally, maps and graphs for all islands are available on the online version of this technical note.[17]

2.1. Annual Maps of Lights

Maps to track NTL coverage in the PICs can be generated from raw annual composites for each island. The radiance value from monthly values is averaged in each region, after non-cloudy observations are removed. Lights are then visualized on a scale from dark purple – a radiance value of 0, to bright yellow – a radiance value greater than or equal to 1.[18] This exercise was conducted to track NTL values in four PICs in 2021 (**Error! Reference source not found.**). NTL coverage in Fiji, Palau, Papua New Guinea and Samoa was drawn from VIIRS data.

Figure 1 | NTL Maps, 2021 (VIIRS). Top left: Papua New Guinea, top right: Samoa, bottom left: Fiji, bottom right: Palau



The maps above show that NTL values for most areas are low, with higher values clustered around human settlements. Beyond cities and towns, in some islands it is possible to identify infrastructure features, such as roads along coastal areas. Low radiance values are hard to interpret as the satellite is very sensitive to

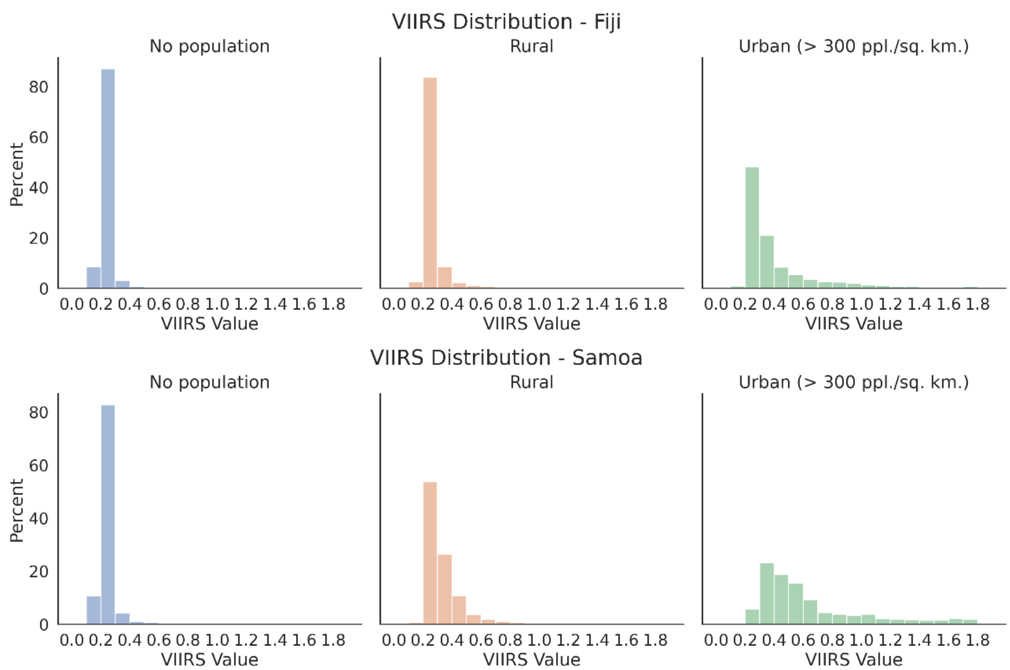
[16] https://github.com/worldbank/pacific-observatory
[17] https://worldbank.github.io/pacific-observatory/ch1_intro.html
[18] Measured in nanoWatts/cm2/sr.

various sources of light. For reference, previous studies have noted radiance values for specific features: 3.28 for a bridge, and 3.65 for a vessel.[19]

It is to be expected that radiance values for populated areas are high, although previous studies have warned that rural areas may not be detected. This assumption was investigated by matching the NTL composite with a population grid. Facebook's High Resolution Settlement Layer was used to map the distribution of human population at a resolution of 30m. This population layer was generated by combining census data with computer vision techniques and is available for all islands.[20]

After matching the population data to the VIIRS annual composites, VIIRS values for different population density thresholds in Fiji and Samoa were plotted into histograms (**Error! Reference source not found.**).

Figure 2 | Distribution of VIIRS values (top: Fiji, bottom: Samoa)



The left panel shows the distribution of light values for unpopulated areas, the center is for rural areas, and the right is for urban areas, defined as cells with population density higher than 300 people per square kilometer. Although the distribution for all graphs is heavily skewed towards 0, populated areas show a longer tail of pixels with slightly higher luminosity values.

A similar test was then performed, that draws from a methodology developed by Elvidge et al. in 2021. The annual composite was refined to remove background noise, solar and lunar contamination, as well as features unrelated to electric lighting such as aurora, fires, flares and volcanoes.[21] Click or tap here to

[19] Cao and Bai (2014)

[20] High Resolution Population Density Maps + Demographic Estimates by CIESIN and Meta was accessed on May 2022 from https://registry.opendata.aws/dataforgood-fb-hrsl. Meta and Center for International Earth Science Information Network - CIESIN - Columbia University. 2022. High Resolution Settlement Layer (HRSL). Source imagery for HRSL © 2016 Maxar.

[21] Elvidge et al. (2021)

enter text.This latest “clean” annual composite was retrieved from the Earth Observation Group at the Payne Institute for Public Policy.

With this cleaned data, a value of 0 is defined as non-lit background, and any value above 0 is attributed to anthropogenic lights. The share of pixels with lights was then categorized into unsettled, rural, and urban areas (Table 1).

Table 1: % Pixels with lights in the cleaned VIIRS 2021

Country	No population	Rural	Urban (> 300 ppl. /sq. km.)
Federated States of Micronesia	6.2%	31.0%	53.1%
Fiji	1.6%	22.0%	69.6%
Kiribati	1.5%	9.8%	30.6%
Marshall Islands	5.1%	24.8%	73.6%
Nauru	88.2%	100.0%	100.0%
Palau	8.3%	59.4%	100.0%
Papua New Guinea	0.2%	3.4%	15.1%
Samoa	3.5%	26.8%	78.7%
Solomon Islands	0.1%	2.0%	12.5%
Tonga	18.5%	72.6%	96.9%
Tuvalu	5.5%	4.9%	NA
Vanuatu	0.4%	5.3%	31.3%

Urban areas are relatively well captured in NTL, compared to a very small share of rural pixels that seem to be emitting light. Tonga and Nauru have high shares for rural pixels, but they are also locations with high mining and volcanic activity.

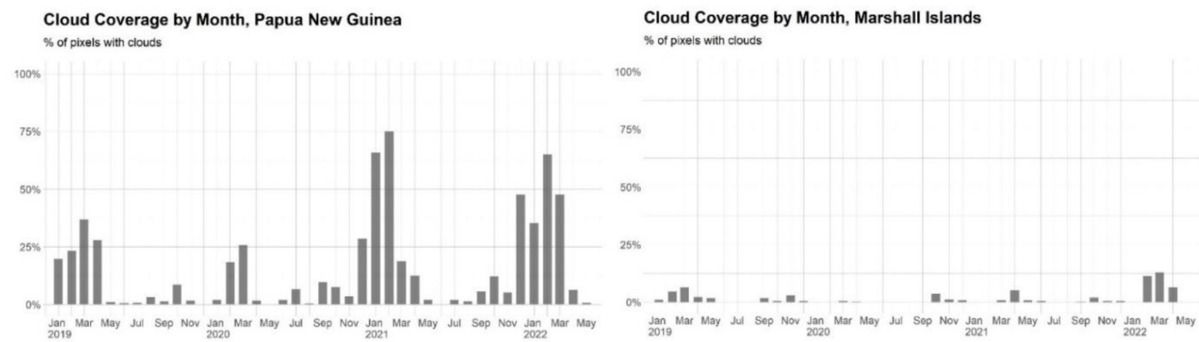
2.2. Cloud Coverage

While many of the applications discussed in section one take advantage of the temporal cadence of nighttime lights to derive trends, it is equally important for researchers to pay attention to the consistency of time-series observations before drawing economic interpretations from the trends.

The following analysis examines the percentage of area for each island that was affected by clouds. The monthly VIIRS composites are based on the average value from daily scenes. The authors of the dataset provide a quality-control dataset to specify how many valid observations were available to calculate the monthly value. In some areas, there was not one day from the entire month with a cloud-free observation available.

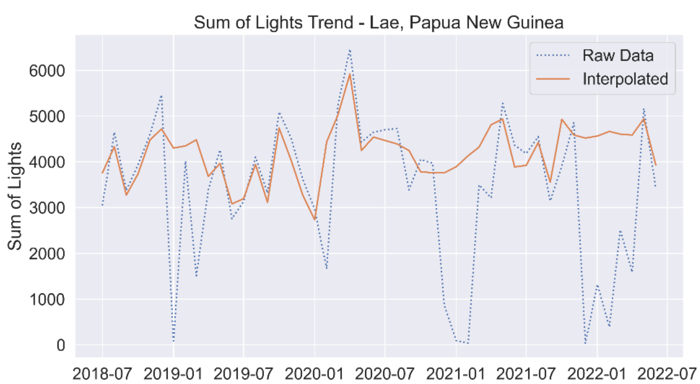
A review was conducted of the percentage of pixels without any valid data for each month from 2019 to 2022 in Papua New Guinea and Marshall Islands (Figure 3). Clouds were found to be particularly disruptive in December to March, the wet season. No coverage was available for more than half of Papua New Guinea’s area in 2021 and 2022. The disruption is less drastic in smaller islands but can still affect average values.

Figure 3 | Cloud Coverage by Month



To mitigate issues with cloud coverage, a light weight approach was applied. Missing values were interpolated with valid observations from nearby months. A pixel-level moving window linear regression was then implemented to substitute values from the 3 months before and after each missing observation. In the Lae region of Papua New Guinea, the raw data shows drastic drops in NTL – attributed to months with high cloud coverage – while the interpolated trend is more stable (Figure 4).

Figure 4 | Interpolation of NTL time-series in Lae, Papua New Guinea



This interpolation technique is used further in the applications outlined in section 3.

Section 3 - Economic Applications

This section investigates whether signals from NTL can be used to proxy economic statistics in Papua New Guinea. Papua New Guinea was chosen because a significant proportion of its national economic activity is composed of industrial production and extractives. These industries are more likely to be captured by NTL data. There is also significant variance of poverty levels, which adds a further dimension to test whether NTL data accurately captures these trends. While Papua New Guinea is exceptional in the region due to its size, section 4 examines other applications that extend better to smaller islands.

3.1. Extractives

Sites of extractive industries in Papua New Guinea were used to test the hypothesis that detected changes in radiance levels are related to changes in mining production or economic output. Mining sites produce the highest levels of lights the country. Despite being a predominantly rural country, sites of extractive operations such as Ok Tedi, Porgera, Hides, Agogo, and Lagifu all produce radiance measures higher than what is captured in major cities. Some of these sites have mining operations where the infrastructure contains lights that are left on overnight. Other sites contain processing facilities connected to the Liquified Natural Gas pipeline, where NTL may be able to detect episodes of flaring.

Methodology

To explore the connection between NTL at extractive industry sites and economic output, a database of mining sites and gas facilities was compiled. Official maps were reviewed, and their geolocation was confirmed through crowd-sourced data.[22] 4-kilometer buffers were drawn around each site and the sum of lights (SoL) for each site at monthly and annual frequencies was calculated. For the monthly time series, the VIIRS monthly images (2014-2022) were used to follow the moving-window linear interpolation described in section 2.2.

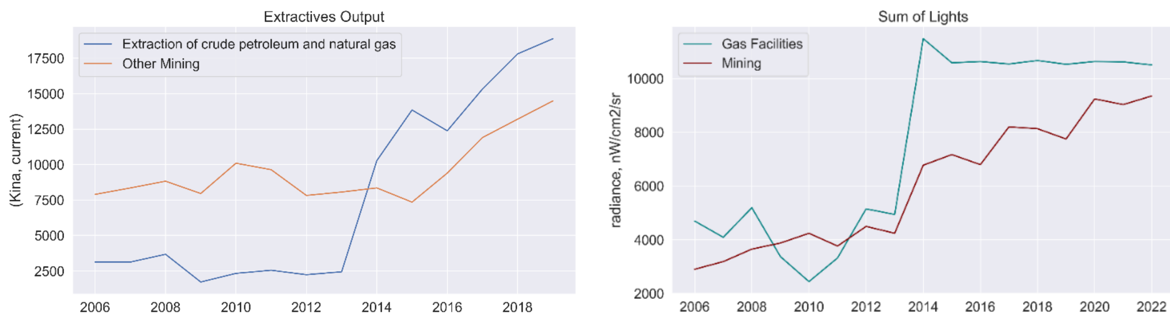
The annual time series was based upon two sets of NTL data: the VIIRS annual composites generated by the Earth Observation Group (2013-2021), and the DMPS-OLS annual composites provided by NOAA (1992-2013). Multiple differences between satellites made it challenging to combine statistics from both datasets. To address these challenges, the harmonizing technique developed by Daynan Crull was followed. This technique uses the overlap between both platforms to define a local region of interest. It then applies various transformations to fit the DMSP composites to VIIRS using a Gradient Boosting decision-tree based algorithm.[23] As a final step, the harmonized annual images are used to calculate the SoL and summarize the national aggregates of lights into two types of operation – mining or gas.

To compare these results with economic measures, national sector-level GDP statistics were curated. Latest published national accounts spanning 2006 to 2019 were obtained from the PNG National Statistics Office, and were supplemented by facility-level production reported through the Extractives Industry Transparency Initiative (EITI) 2019 Report. In some facilities, the amount of gold and copper mines were reported, typically from 2014 to 2019. The degree of correlation between extractive industry national account output and SoL from all locations was then investigated (**Error! Reference source not found.**).

[22] Mindat Database (Hudson Institute of Mineralogy), retrieved from https://www.mindat.org/loc-2438.html, MiningInfo (Google Sites), retrieved from https://sites.google.com/site/mininginfosite/

[23] Implementation available via https://github.com/worldbank/NTL_Harmonizer/tree/main/harmonizer

Figure 5 | National Aggregates. Left: output (PNG NSO), right: sum of lights (DMSP/VIIRS)



To run the test, a natural logarithmic transformation was applied to both series, and the difference in year-to-year logged values was compared. A linear regression was then specified to test their degree of correlation (Equation 1). The coefficient c1 can be interpreted as a growth elasticity index.

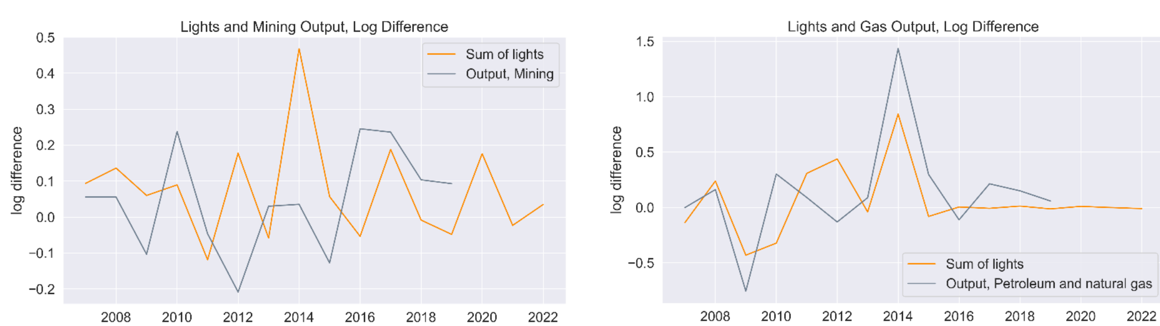
Equation 1 – Linear regression to test the degree of correlation between extractive industry output and sum of lights in PNG

$$\Delta \ln(output) = c0 + \ c1 * \Delta \ln(sum\ of\ lights)$$

Results

Although both time series show an upward trend, alignment of the data by type of industry with log differences highlights varying levels of agreement for mining and gas (**Error! Reference source not found.**). Changes in lights and output do not appear to correlate with mining activity. However, results show that lights have a stronger correlation with gas – NTL data captured the strong increase in gas production in 2014, as well as changes that occurred in the years prior, from 2007 to 2010. These findings were further confirmed by regression results. The elasticity found between lights and output for gas was significant at 0.98, while the coefficient for mining was -0.07 and therefore not significant. The static trend in lights for recent years (2019 to 2021) signals that gas production has remained constant.

Figure 6 | Log Difference Lights and Output. Left: mining, right: gas



Despite the strong correlation found for gas, the possibility to extend this use case to a predictive framework is limited. There are not enough observations to properly test a predictive model, with no gas production values available at the site-level.

Monthly lights can be a useful indicator to examine whether a given mine is active or inactive. An increase in NTL for mining locations can be a signal of exploration activities, expansion of an operation, or spillover settlement growth. On the other hand, NTL trends for gas facilities are much more volatile, as they also capture gas flare episodes. An interactive map to explore these trends was developed with Google Earth Engine and is publicly available.[24]

Testing the correlation between changes in NTL to changes in the amount of copper or gold that is mined at the site level proved to be challenging. As an example, in Porgera a slight increase in annual lights was not reflected in any change in local production levels. High-frequency production data might illuminate a stronger correlation.

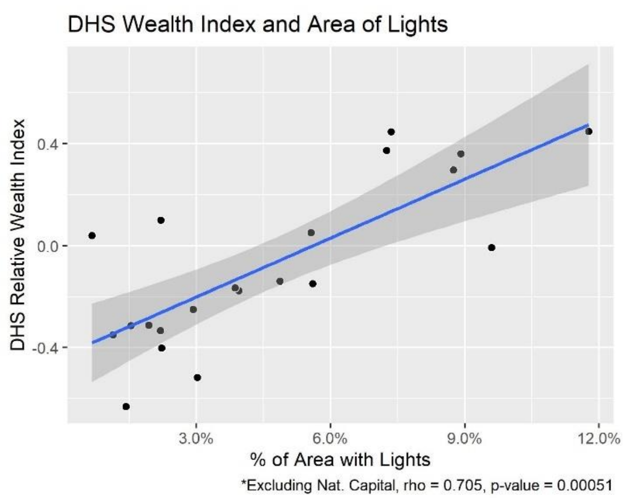
3.2. Poverty Mapping

Even though light output is low in rural areas in Papua New Guinea (Table 1), the correlation between NTL metrics and province-level poverty rates was tested.

Methodology

In order to test this relationship, a relative wealth index was constructed from the latest survey available.[25] the index used is based on household assets and amenities, whereas the more established methods to measure poverty are based on consumption or income.

Figure 7 | Correlation between relative wealth and area of lights



Results

The clean NTL annual composite for 2019 contains valuable information about the distribution of asset wealth across provinces. The statistic with the highest correlation to relative wealth is the share of settled area with lights, with a correlation coefficient of 0.705. SoL was also correlated, but with a lower coefficient of 0.58. This suggests that the extent of areas electrified, rather than the intensity of lights, is more indicative of poverty.

[24] https://afche18.users.earthengine.app/view/png-mining.
[25] DHS, 2016 to 2018.

The correlations identified hint that NTL statistics can be used as supplementary features in small area poverty estimation exercises. It is recommended that future exercises test whether this relationship holds true at the district-level. NTL data could be used alongside a suite of satellite-derived indicators and combined with survey data to aid poverty mapping in the region.

Section 4 - Other Use Cases

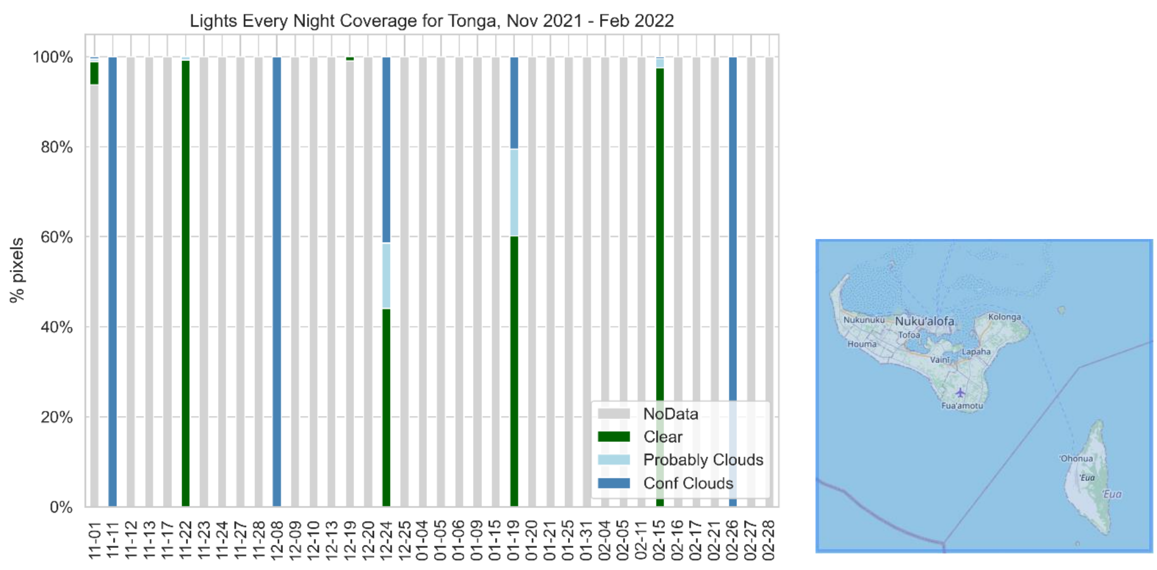
4.1. Recovery in Tonga

On January 15th, 2022, the Hunga-Tonga-Hunga-Ha'apai volcano in Tonga erupted. The eruption was so extreme that it was categorized as a once-in-1000-years event. It dispersed clouds of ash and set off several tsunami waves, which together cost an estimated US$90.4M in damages.[26]

This analysis examines whether scenes from the newly released Light Every Night dataset can be used to assess the disruption to electricity use in buildings and consequent recovery of economic activities.[27]

Few studies have examined the availability of satellite data for the Pacific islands. Public satellites, such as Sentinel-1, do not cover some of the smaller islands in the Pacific.[28] Although VIIRS has a daily revisit rate for most areas in the world, analysis shows that the coverage is much scarcer for Tonga. The availability and quality of data for the two biggest islands, Tongatapu and 'Eua, was assessed from November 2021 through February 2022 (**Error! Reference source not found.**).

Figure 8 | Data quality in Tonga by day, Nov 2021 - Feb 2022



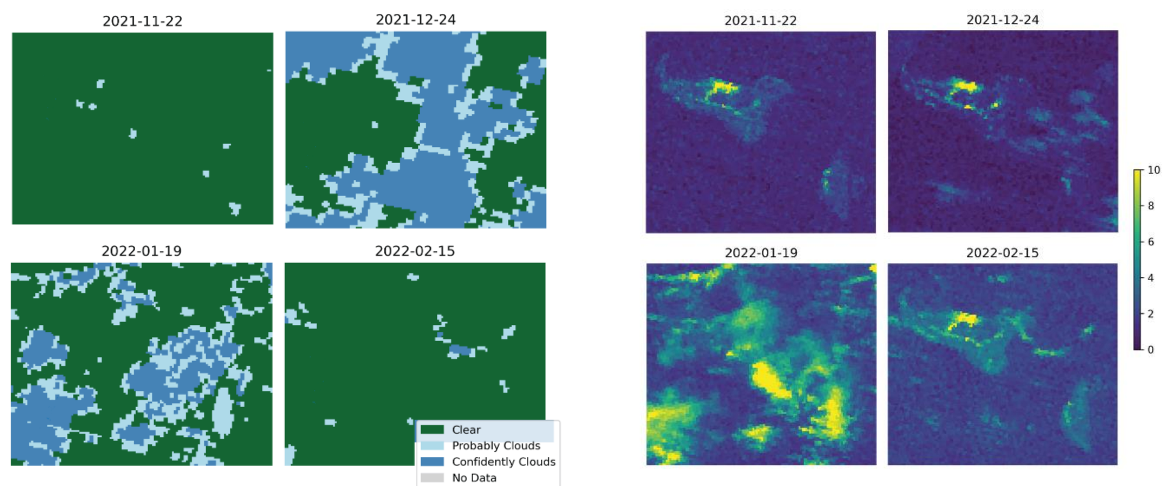
Each radiance image has a corresponding data quality image, which flags various issues with the data. The Suomi satellite only overpasses 8 to 10 days per month, but most of the images captured do not

[26] GRADE, World Bank (2022)
[27] https://blogs.worldbank.org/opendata/light-every-night-new-nighttime-light-data-set-and-tools-development
[28] Digital Earth Pacific (2022)

contain any valid observations.[29] Only 7 images were available over the four months considered, and 3 of those were heavily impacted by clouds. The study therefore drew on data from the remaining 4 images that had substantial clear observations – the green bars in Figure 8 above.

Error! Reference source not found. below presents maps of data quality and NTL radiance for the 4 days available. The image closest to the largest eruption, January 19th, shows high radiance, possibly from consecutive volcanic activity or residual ash. Lights in February seem comparable to the levels captured in November, prior to the first eruption that occurred on December 20th. To get a wider view of the changes, the monthly SoL by region or group of islands was charted.

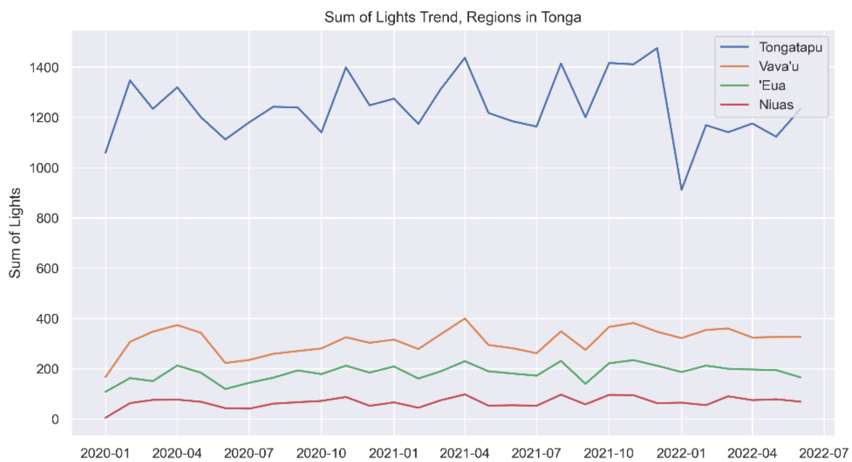
Figure 9 | Daily maps of data quality (left) and VIIRS radiance (right) for Tonga



An important decrease in lights on the main island, Tongatapu, was observed in January 2022. However, monthly lights recovered quite rapidly to a level comparable to historical averages. A possible interpretation of this could be that power was restored by the time the satellite captured NTL data for February. Unfortunately, daily cadence is not available to conduct a detailed assessment of when lights recovered. Future analysis could therefore examine pixel-level changes with detailed settlement maps.

[29] The exact cause for this is unknown. The description of the quality flag is as follows: "This bit is set to 1 if no data is available for that scanline/section of orbit, or the grid cell is outside the bounds of the swath."

Figure 10 | Monthly sum of lights for regions in Tonga



This assessment highlights a key trade-off in pursuing higher temporal resolutions for analysis. Although daily images can provide temporal precision to investigate specific events, the images are typically much noisier, can be affected by clouds, and may not be available in remote areas. Monthly composites are more stable, though they may only be based on a few cloud-free observations. Annual composites are generated with a more intense cleaning and noise-removal procedure, making them more optimal for economic analysis. However, they cannot be used to assess short-term dynamics.

4.2. Electrification

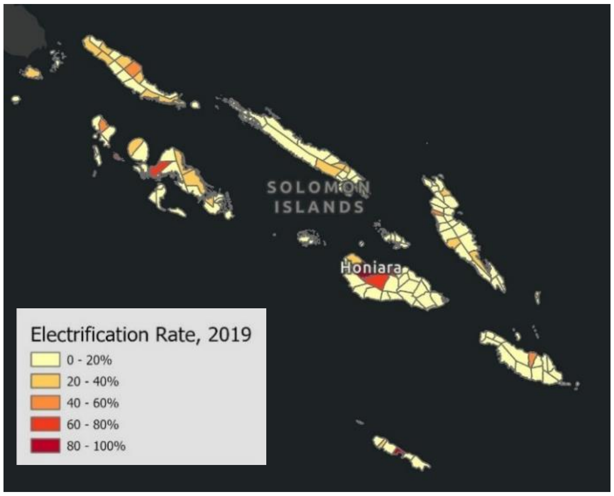
This section introduces electrification statistics derived from the High-Resolution Electricity Access project.[30] The model developed also relies on the Light Every Night dataset, in combination with High-Resolution Settlement Maps. These sources were used to generate electrification statistics at a high spatial resolution. The methodology is described in depth on the project website and can be summarized with the following steps:

1. Match daily NTL scenes with high resolution settlement maps
2. Remove observations with poor data quality and outliers
3. Sample lights from uninhabited locations to measure background noise
4. Estimate if a settlement is brighter than background noise through a linear mixed effects model.

The output of this model are pixel-level probabilities that each settlement was electrified on a given year. These outputs were downloaded and summarized to calculate ward-level electrification rates. We define electricity rates as the share of settlement with a lit probability score higher than or equal to 0.5. Results were summarized for the Solomon Islands and Vanuatu (**Error! Reference source not found.**).

[30] Min, Brian and O'Keeffe, Zachary (2021). High Resolution Electricity Access Indicators Dataset. Center for Political Studies, University of Michigan. http://www-personal.umich.edu/~brianmin/HREA/methods.html

Figure 11 | Electrification Rates, Solomon Island and Vanuatu



Most wards in these regions are classified with low electrification rates (0 to 20), except for the main cities and more populated areas. A summary of these outputs to the national level results in rates much lower than what is reported in the World Development Indicators – 30% in Solomon Islands and 36% in Vanuatu. In Papua New Guinea, electrification rates derived from the HREA dataset are generally higher than those observed in the latest electrification survey, but the correlation coefficient of 0.84 is still high.[31]

The spatial disaggregation provided by this method is invaluable. If used correctly, it could allow for targeted development operations in island states. To optimize this approach, more effort is needed to validate these statistics with household surveys.

[31] 2021 Phone survey implemented by the World Bank Energy and Poverty teams.

Conclusion

This study has assessed the statistical applications of NTL data in the Pacific subregion. This concluding section summarizes lessons learned and key opportunities and limitations from each application explored.

Data Quality

NTL data is often matched with economic data by aggregating gridded radiance levels to the country or sub-national level. This assessment stresses the importance of examining the quality and distribution of NTL data before conducting any aggregation. Temporal aggregations of NTL data for PICs need to account for missing observations due to cloud coverage. Future researchers should also take the heavy data bias towards urban populations into consideration. While satellites are sensitive enough to capture limited shares of rural population, the primary sources of light are urban centers and locations with high mining or volcanic activity.

VIIRS data represents a significant improvement over the older DMSP data. However, the raw data is noisy and sensitive to non-anthropogenic sources of light. Researchers are encouraged to utilize processed versions of the data, which can account for straylight and solar/lunar contamination. While this study focused on composites generated by the Earth Observation Group, the database can be expanded by incorporating the new suite of Black Marble data produced by NASA.

Summary of Statistical Applications

Table 2 | Summary of opportunities / limitations for each statistical application

Application	Opportunities	Limitations
1. GDP Cross-Section	• Vast literature available on constructing gridded or sub-national GDP based on NTL and labor composition.	• Hard to validate given the lack of sub-national GDP statistics in Papua New Guinea and other PICs.
2. GDP Growth	• NTL can augment GDP statistics in some settings, including in countries with low statistical capacity.	• Previous literature suggests weak elasticity between GDP and NTL in small island states. • A combination of NTL and supplementary datasets on agriculture, fishing, and tourism are likely to provide a better fit.
3. Extractives Gas	• This study found strong correlation between lights emitted by gas facilities and the output reported on national accounts. • Provides opportunity to monitor a critical sector through NTL measures.	• Limited number of observations from national accounts. • Site-level output data could help build a more sophisticated nowcasting model.
4. Extractives Mining	• The use of high-frequency NTL data to monitor mining activity and settlement growth around mines can be explored.	• This study found no correlation between changes in light intensity and mining output at the annual level.

5. Poverty	• The extensive margin of NTL correlates strongly with asset-based poverty in Papua New Guinea at the province level. • NTL statistics could be used as supplementary features in poverty mapping exercises. • High-frequency observations of NTL are a public and timely resource to assess the impact and recovery from natural disasters	• Despite the correlation found, NTL alone is not sufficient to create poverty maps. • Further investments in surveys are needed to leverage the use of NTL and geospatial data for poverty mapping.
6. Natural Disasters	• High-frequency observations of NTL are a public and timely resource to assess the impact and recovery from natural disasters	• Due to issues with data quality, the daily Light Every Night datasets had limited use in the Tonga tsunami case study. • Data needs to be assessed with further case studies.
7. Electrification	• NTL can provide a cost-effective method to produce electrification statistics with more spatial disaggregation and nuance (energy reliability vs. access).	• Validation needs to be scaled to more island states by integrating electrification rates derived from recent surveys.

Future Research

Overall, this study finds most promise in the use of NTL to:

1. Monitor the gas industry in Papua New Guinea
2. Support poverty mapping exercises, and
3. Generate detailed electrification statistics.

Monitor the gas industry in Papua New Guinea

This first use case will benefit from more detailed data on gas production at the site-level. The annual NTL data captures a significant spike in production in 2014, when the Papua New Guinea LNG production started. A dataset with higher cadence for gas output will enable a more sophisticated modelling approach to understand whether subtle changes in production are also captured. This new research should consider not just NTL, but other variables which have been used in oil estimation studies, such as temperature recordings from flaring events.

Support poverty mapping exercises

This second area will require a thorough curation of recent household income and expenditure surveys in the region. NTL statistics should be used in combination with other satellite-derived indicators and household surveys to generate small area estimates of poverty. Surveys still represent the most critical input, and NTL will potentially add value based on what level of disaggregation is possible.

Generate detailed electrification statistics

Lastly, the findings on electrification are encouraging, as the method is easily reproducible with new NTL data. This ease of production calls for a broader scale up of validation tests with recent surveys from other islands beyond Papua New Guinea.

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