EVALUATING THE USABILITY OF NIGHTTIME LIGHT DATA FROM VIIRS SATELLITE IMAGES FOR MODELING SOCIO-ECONOMIC PARAMETERS

VIIRS UYDU GÖRÜNTÜLERİNDEN TESPİT EDİLEN GECE IŞIKLARININ SOSYOEKONOMİK PARAMETRELERİN MODELLENMESİNDE KULLANIMININ DEĞERLENDİRİLMESİ

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Submitted to

Graduate School of Science and Engineering of Hacettepe University

as a Partial Fulfillment to the Requirements

for the Award of the Degree of Master of Science

in Geomatics Engineering

2025

To my family

For their endless support and love

ABSTRACT

EVALUATING THE USABILITY OF NIGHTTIME LIGHT DATA FROM VIIRS SATELLITE IMAGES FOR MODELING SOCIO-ECONOMIC PARAMETERS

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February 2025, 63 Pages

The availability of night light maps through remote sensing technologies provides a unique opportunity to directly observe human activities from space. Nighttime lights (NTL) have enabled several applications, such as mapping urban areas, estimating population and gross domestic product (GDP), and monitoring disaster and conflict zones. It is also known that satellite-sensed night light images are correlated with socioeconomic parameters such as urbanisation, economic activity, and population. On the other hand, they have been used to understand the environmental impacts of light emissions (light pollution), including their effects on human health. NTL detected from satellite data are increasingly used by economists to detect economic activity. The increasing prevalence of their application may reflect either the absence or assumed inaccuracy of more traditional economic indicators such as national or regional GDP.

This thesis aimed to analyse the NTL from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor aboard the Suomi National Polar-orbiting Partnership (Suomi NPP) satellite and to analyze the relationship between these data and economic indicators at state and nation levels in the U.S.A. In addition, shadow economy indices for six different states are also computed to reveal the usability. Studies in the literature have generally been conducted with the Defense Meteorological Satellite Programme (DMSP) sensor, and this satellite no longer provides data. Here, the VIIRS is preferred because it provides up-to-date data, higher radiometric and geometric resolution, and, therefore, more accurate night light analysis. According to the results, night lights analysed with VIIRS satellite data strongly correlate with state-level economic indicators. This finding suggests that NTL data obtained from the VIIRS can be an effective tool for assessing the spatial and temporal distribution of economic activities.

Keywords: Remote Sensing, Night Lights, Visible Infrared Imaging Radiometer Suite, Defense Meteorological Satellite Program, Gross Domestic Product

ÖZET

VIIRS UYDU GÖRÜNTÜLERİNDEN TESPİT EDİLEN GECE IŞIKLARININ SOSYOEKONOMİK PARAMETRELERİN MODELLENMESİNDE KULLANIMININ DEĞERLENDİRİLMESİ

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Şubat 2025, 63 Sayfa

Gece ışıkları haritalarının uzaktan algılama yöntemleri ile elde edilebilmesi, beşeri faaliyetlerin uzaydan doğrudan gözlemlemek için önemli bir imkan sunmaktadır. Gece ışıklarının uydu algılayıcıları ile tespiti, kentsel alanların haritalanması, nüfus ve gayri safi yurt içi hasıla (GSYİH) tahmini, afetlerin ve çatışma yaşanan bölgelerin izlenmesi gibi bir dizi uygulamaya olanak sağlamıştır. Ayrıca, uydulardan algılanan gece ışıkları görüntülerinin; kentleşme, ekonomik faaliyet ve nüfus gibi sosyoekonomik parametrelerle ilişkili olduğu bilinmektedir. Diğer yandan, ışık emisyonlarının (ışık kirliliği) insan sağlığı üzerindeki etkileri de dahil olmak üzere çevresel etkilerini anlama konusunda kullanım alanı bulmuştur. Uydu verilerinden tespit edilen gece ışıkları, ekonomi uzmanları tarafından ekonomik faaliyet tespiti amaçlı giderek daha fazla kullanılmaktadır. Bu verilerin artan uygulama yaygınlığı, ulusal veya bölgesel GSYİH gibi daha geleneksel ekonomik istatistiklerin ya yokluğunu ya da varsayılan yanlışlığını yansıtabilmektedir.

Bu tez çalışması, Suomi National Polar-orbiting Partnership (Suomi NPP) uydusunda bulunan Visible Infrared Imaging Radiometer Suite (VIIRS) algılayıcısından elde edilen verileri kullanarak gece ışıklarının analizini ve bu verilerin Amerika Birleşik Devletleri'nde eyalet ve ülke seviyesindeki ekonomik göstergelerle ilişkisini incelemeyi amaçlamıştır. Ayrıca, altı farklı eyalette gölge ekonomi indeksleri analiz edilmiştir. Literatürdeki çalışmalar genellikle Defense Meteorological Satellite Program (DMSP) verileri ile yapılmış olup, bu uydu artık veri sağlamamaktadır. VIIRS ise güncel veri sağlaması, daha yüksek radyometrik ve geometrik çözünürlük sağlaması ve dolayısıyla daha yüksek doğrulukta gece ışığı analizi yapabilmesi nedeniyle tercih edilmiştir. Elde edilen sonuçlara göre, VIIRS uydu verileri ile analiz edilen gece ışıkları, eyalet düzeyindeki ekonomik göstergelerle güçlü bir korelasyon sergilemiştir. Bu bulgu, VIIRS uydu verileri ile elde edilen gece ışıklarının ekonomik faaliyetlerin mekânsal ve zamansal dağılımını değerlendirmek için etkin bir araç olabileceğini ortaya koymaktadır.

Anahtar Kelimeler: Uzaktan algılama, Gece Işıkları, Visible Infrared Imaging Radiometer Suite, Defense Meteorological Satellite Program, Gayri Safi Yurt İçi Hasıla

ACKNOWLEDGMENTS

The completion of this Master thesis, I feel deep satisfaction and appreciate the learning opportunities I have gained regarding the thesis subject. I would like to thank many people who have been with me throughout this academic journey and supported me continuously.

First and foremost, I would like to express my deepest gratitude to my supervisor, Prof. Dr. Sultan Kocaman Gökceoğlu, for her continuous support, expertise, and invaluable guidance throughout this research. Her insights have been a cornerstone of my academic and personal progress. It has been a privilege to work under her supervision.

I am also deeply thankful to my thesis committee members, Prof. Dr. Özgür Teoman, Prof. Dr. Saygın Abdikan, Assist Prof. Dr. Murat Durmaz, and Assoc. Prof. Dr. Nusret Demir, for their constructive feedback and valuable suggestions that significantly enhanced the quality of my work.

I would especially like to thank Prof. Dr Oğuzhan Dinçer, who always helped and guided my work by sharing his expertise and ideas. I am grateful for his contributions to my thesis and his valuable time.

I am also profoundly grateful to my family, especially my mother and father for their unconditional love and encouragement. Also, I would like to thank my friends. Their unwavering support has always been my source of strength.

CONTENTS

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ABBREVIATIONS

Abbreviations

DMSP	Defense Meteorological Satellite Program
EDR	Environmental Data Records
GDP	Gross Domestic Product
GEE	Google Earth Engine
GRETL	Gnu Regression, Econometrics and Time-series Library
NTL	Night Time Lights
OLS	Ordinary Least Squares
SEI	Shadow Economy Index
U.S.A.	United States of America
VIIRS	Visible Infrared Imaging Radiometer Suite

1. INTRODUCTION

This section provides an overview of the problem addressed in the thesis, emphasizing the limitations of traditional nighttime lights (NTL) data sources like the Defense Meteorological Satellite Program (DMSP) and the advantages of Visible Infrared Imaging Radiometer Suite (VIIRS) data for economic analyses. It outlines the study's objectives, which include examining the relationship between VIIRS-derived night lights and various economic indicators, as well as assessing their impact on socioeconomic structures. Additionally, the contribution of this thesis to the literature is highlighted, particularly in using high-resolution and up-to-date VIIRS data to explore the determinability of the shadow economy and its potential for broader socioeconomic analyses. Lastly, the structure of the thesis is presented.

1.1 Problem Definition

As detected by satellites, the NTL is increasingly used in economic research, especially as a proxy for local economic activity [1]. Several studies have used NTL data in the field of economics and validated national or regional gross domestic product (GDP) using traditional statistics on economic activity as a benchmark for assessing the usefulness of NTL data [2]. Most of these studies utilize data from the DMSP, which is characterized by its low spatial resolution but has provided a long and consistent time series of data. However, other disciplines are rapidly moving to use newer and better data from the VIIRS [3].

EROS-B was the first commercial satellite to provide high spatial resolution NTL images. It started NTL observations in 2013 with a resolution of 0.7 meters. However, these panchromatic images do not provide enough spectral information to determine lighting types [4].

The Operational Land Imager (OLI) sensor on the Landsat 8 satellite launched in 2013 [5] has high spatial resolution compared to VIIRS and DNB (Day/Night Band) sensors. Still, it has a limited ability to detect night lights. The results of the studies show that the Landsat 8 OLI sensor can only detect high-intensity light sources in urban areas or gas flares in sensor-level measurements. However, since the OLI sensor was not designed for low-light night imaging, it is less sensitive to low-light emissions than the VIIRS DNB sensor. The detection limits of Landsat 8 cannot provide the sensitivity required for detailed mapping or monitoring of urban lighting [5,6].

With multi-spectral NTL imagery in the red, green, and blue bands and the ability to detect low light levels, the JL1-3B satellite launched in 2017 provided a significant step forward in night landscape analysis and the identification of lighting types [7]. Subsequently, the JL1-07/08 satellites launched in 2018 were equipped with panchromatic and advanced multi-spectral bands, allowing for a better understanding of environmental impacts, such as the effects of intense lights on nocturnal bird migration [8,9]. However, the costs are high and data access is limited as these satellites are generally designed for commercial use. Furthermore, imagery from these systems is limited in terms of the long time series and consistency needed for economic analysis, especially over large geographic areas.

Launched on 2 June 2018, the Luojia 1-01 satellite has been providing a new source of NTL data at a resolution of 130 m showing a potential for mapping urban extent [10,11]. The data of this satellite correlates well with the VIIRS data, providing more spatial detail and change detection capabilities. Although this satellite offers innovative technologies, it does not yet have an extensive time series for analyses. In addition, the lack of multi-temporal data and the influence of clouds and moonlight limit the widespread use of these data [8].

Table 1.1 provides a comparative overview of recent spaceborne sensors used for NTL mapping. It is organised according to their spatial resolution. The table highlights the key technical specifications of these sensors, including spatial resolution, years of operation, temporal resolution, radiometric range, and spectral band. The table covers sensors from widely used platforms such as DMSP/OLS and VIIRS/DNB to high-resolution commercial satellites such as Jilin and EROS-B [12].

Table 1. 1 Comparison of recent space-borne sensors for night-lights mapping, sorted by their spatial resolution.

Sensor	Spatial resolution (m)	Operational years	Temporal resolution	Radiometric range	Spectral bands
DMSP/OLS [13]	3000	Digital archive available for 1992–2013	Global coverage can be obtained every 24 h	10^{-6} to 10^{-9} W/cm^2/sr/μm 6 bit Min detectable signal 4 10-5 W/m/sr	Panchromatic 400–1100 nm
VIIRS/DNB [14]	740	Launched in Oct 2011	Daily images can be downloaded.	14 bit Min detectable signal 3 10-5 W/m/sr	Panchromatic 505–890 nm
Landsat 8 [6]	15–30	Launched in 2013	Night-time images acquired irregularly	14 bit Only very bright objects are detected.	Seven bands
Jilin-1 (JL1-3B) [7]	0.9	Launched January 2017	Commercial satellite acquires images on demand	8 bit	430–512 nm (blue), 489–585 nm (green), and 580–720 nm (red)
JL1-07/08 [8]	<1	Launched January 2018	Commercial satellite acquires images on demand	N\A	Panchromatic and multi-spectral (blue, green, red, red edge, and near-infrared bands)
EROS-B [4]	0.7	Night lights images offered since mid-2013	Commercial satellite acquires images on demand	16 bit	Panchromatic

The DMSP NTL data, which are more popular than the VIIRS data, suffer from various artefacts such as blurring, top-coding, and lack of precise calibration. However, the newer VIIRS data with higher quality have been rarely used in the field of economics due to the availability of relatively short-term data. However, the DMSP does not continue to provide data as of today. On the other hand, the VIIRS has been providing high-resolution data since 2011. In rural (non-urban) areas, DMSP data serve as a weak GDP indicator. The relationship between city lights and GDP is known to be twice as noisy for DMSP data as for VIIRS data [1].

Despite the up-to-date and high-resolution data provided by the VIIRS, few studies have attempted to analyse the relationship between NTL data from VIIRS and economic indicators. This gap highlights the need for an in-depth investigation into how VIIRS NTL data can be effectively utilized to model and predict economic activity, particularly in regions where traditional economic data may be scarce or unreliable.

1.2 Thesis Objectives

The VIIRS provides up-to-date, high-resolution data for cities, districts, and smaller regions. This thesis investigated the usability of VIIRS data for analyzing the relationship between economic data and NTL data [1]. To achieve this purpose, the objectives of this thesis were defined as follows:

- To determine the levels of NTL across different U.S.A. states using the VIIRS data.
- To analyze the relationship between VIIRS-derived NTL data and economic indicators such as GDP and the shadow economy.
- Assess the impact of NTL data on economic development and social structure.

1.3 Thesis Contribution

A literature review reveals that most studies on NTL have been conducted using the DMSP data, primarily because it has been available for an extended period (e.g., see [15–17]). However, the DMSP sensor was not specifically designed for NTL analysis and has not provided data since 2013. In contrast, VIIRS data was specifically developed to capture NTL information, offering a more suitable alternative for such analyses. Launched in 2011, the VIIRS continues to provide data at the time of this writing. This thesis investigated the NTL using VIIRS data in the U.S.A., conducted socioeconomic analyses using NTL data, and, in particular, investigated the detectability of the shadow economy. The main findings show that the VIIRS-based NTL data correlates strongly with the official GDP figures at the state level, demonstrating its reliability for socioeconomic analysis. Additionally, the results indicate that the VIIRS data can effectively capture patterns related to the shadow economy, offering valuable insights into economic activities not reflected in official statistics.

1.4 Thesis Outline

The following section discusses the scientific and theoretical background of this study in detail. It systematically reviews significant studies in the literature, summarizing the key findings. Additionally, it highlights the sources and characteristics of the data used in this research, detailing how the data were collected, the conditions under which they were obtained, and their limitations.

The Materials and Methods section describes the data sets used in this research and the methods used to analyse these data in detail. This chapter outlines the statistical techniques, software, and modeling tools used in the analysis, detailing the processes followed and the rationale behind their selection. It aims to provide a clear and transparent explanation of the methodology employed, ensuring the scientific validity and reliability of the study.

In the Results section, the thesis findings are presented in detail. This section supports the results obtained by graphs, tables, and statistical analyses.

The Discussion section provides the implications of the results, how they relate to other studies in the literature and the findings' limitations. In addition, the contribution of these findings to the field and the research limitations are also discussed, and how they can guide future studies are evaluated.

Finally, under the Conclusion and Future Work section, the main findings of the thesis are summarised, and the contributions of these findings to the literature are emphasized. In addition, considering the potential limitations of the research, suggestions for future research in this field are presented. Thus, the findings of the thesis study and how these findings can form a basis for future research are evaluated within a general framework.

2. BACKGROUND

This section provides a comprehensive review of the literature and the methods relevant to this thesis. A broad definition and importance of GDP, which form the foundation for assessing economic activity using alternative data sources, is followed by the review of studies using remote sensing for economic analyses and highlighting the integration of satellite data in this field. The section also investigates the use of NTL data in economic research, comparing studies that rely on DMSP data with those employing the VIIRS data.

2.1 Gross Domestic Product (GDP) and Shadow Economy

The Gross Domestic Product (GDP) represents the total market or monetary value of all final goods and services produced within the borders of a country over a specific period. As a key metric, the GDP serves as an overarching indicator of goods and services production and a tool for evaluating an economy's performance. It is a fundamental variable in understanding economic growth, acting as a comprehensive measure to track a nation's economic health and productive capabilities. By quantifying economic activity and newly generated value in monetary terms, GDP facilitates analysis and enables comparisons across different regions [18].

GDP is an essential indicator in several fields of social studies. It also plays an important role in political decision-making processes. However, its measurement remains inadequate on a global scale [19]. In underdeveloped countries, such as those in Africa, reliable national GDP data are often unavailable. In non-democratic regimes, statistical data may be unreliable due to potential misreporting by local governments. Even in developed economies, measurement errors are unavoidable if the shadow economy is not accounted for. The shadow economy refers to economic activities that are not officially registered, taxed, or regulated. Activities often undertaken to evade taxation, regulation, or legal restrictions are included in the scope of the shadow economy. For example, the use of illegal labor, tax evasion, illicit trade, and unauthorised small business activities are among the most prominent elements of the shadow economy [20,21]. Furthermore, GDP figures become even more uncertain when converted into international dollars compared to figures from other countries [22].

The comparison of NTL imagery between North Korea and South Korea is a striking visual representation of the utility of remotely sensed data in economic analyses (Figure 2.1). While South Korea's illuminated landscape reflects its vibrant and formalized economic activities, North Korea's comparative darkness highlights the absence of reliable economic indicators and the limitations of state-reported data. This stark contrast showed the potential of NTL data as an alternative proxy for measuring economic activity, particularly in regions where official GDP estimates are unavailable, unreliable, or subject to political manipulation [23]. Following this visual revelation, economists began integrating satellite-derived NTL intensity values into their analyses to estimate GDP and uncover hidden aspects of economic performance. The North and South Korea example thus marks a pivotal moment in adopting remote sensing techniques, driving forward the use of NTL data as a valuable tool for monitoring regional and global economic disparities.

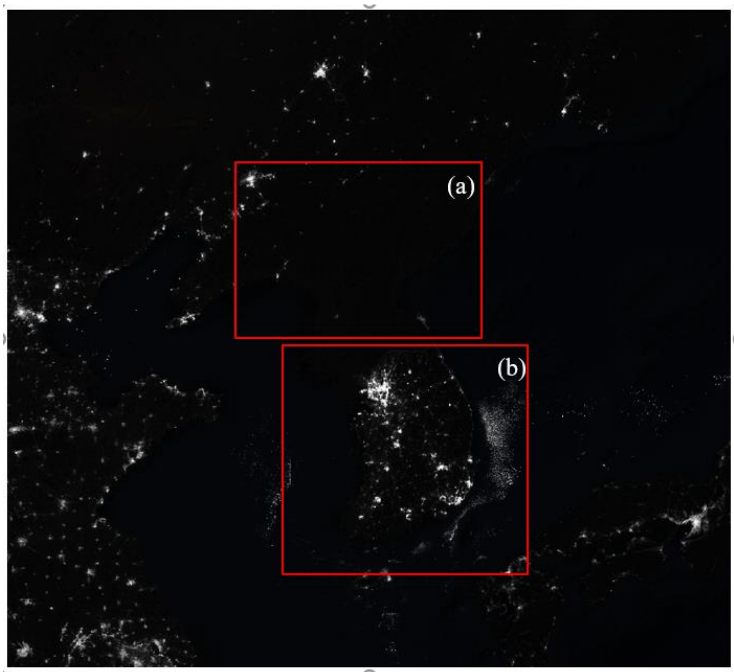

Figure 2. 1 (a) Night Light for North Korea, (b) Night Light for South Korea.

Governments in developed countries directly measure variables used to estimate GDP. However, these measurements are rarely conducted with high spatial and temporal resolution, and data collection methods lack standardization across countries. In underdeveloped or conflict-ridden regions, such data is often not collected at all [24].

GDP calculations are usually the result of a systematic analysis of raw data, which is collected from a variety of sectors. This process involves the collection of national income and product statistics, processing survey data, and integrating data by different methods such as expenditure, production, and income. In processing the data, nominal and real GDP are calculated and adjusted to account for changing prices. In the U.S.A., the Bureau of Economic Analysis (BEA) is responsible for calculating and publishing GDP. The BEA is part of the Department of Commerce and produces the national income and product accounts [25].

The GDP serves a fundamental role in countries by acting as a broad measure of economic performance and a cornerstone for strategic planning [26]. Governments extensively utilize GDP trends to craft fiscal and monetary policies to foster economic growth. Similarly, businesses rely on GDP data to evaluate market potential and identify risks tied to economic slowdowns, informing their investment strategies. Additionally, GDP serves as a vital benchmark for international comparisons, enabling the assessment of one country's economy against others and providing a basis for macroeconomic analysis through its correlation with variables like inflation, unemployment, and overall economic stability [27].

The application of GDP yields notable results, such as evaluating the impact of policy decisions by determining the success of fiscal and monetary measures. It also aids in economic forecasting, where institutions such as the Federal Reserve analyze GDP data to anticipate growth trends and set interest rate policies. Moreover, GDP per capita offers a valuable metric for assessing living standards and understanding national welfare levels.

The advantages of GDP include its role as a holistic indicator of an economy's scale and productivity, helping policymakers to establish economic goals and develop effective stimulus strategies. It also facilitates international comparisons while enabling long-term planning by offering a reliable framework for analyzing economic patterns, investment prospects, and developmental goals [28]. These characteristics make GDP an essential tool for comprehending and addressing the complexities of national economies.

2.2 Remote Sensing Studies with Nighttime Light Data

Studies using NTL are increasing in their popularity and number. Numerous studies have been conducted to explore its potential applications. The two main sources of NTL data are the DMSP which operated by Department of Defense and provides data from 1992 onwards, and the Day-Night Band (DNB) of the VIIRS, onboard the Suomi satellite that was launched in 2011 by NASA and the National Oceanic and Atmospheric Administration (NOAA) [3]. Therefore, the literature review given in the following is based on the data of these two sensors [1].

Considering the main technical specifications, the wavelength range for DMSP-OLS spans 0.4–1.1 μm, while VIIRS DNB covers a more refined range of 505–890 nm. Spatial resolution is a significant differentiator, with DMSP-OLS offering a 2.7 km resolution compared to the much finer 742 m provided by VIIRS DNB. Both systems share a temporal resolution of 12 hours and a geographic extent of 75°N/65°S/180°E/180°W. The specified overpass times differ slightly, with DMSP-OLS capturing data between 8:30–9:30 and 20:30–21:30, whereas VIIRS DNB records at 13:30 and 1:30. DMSP-OLS operates at 6-bit resolution, while VIIRS DNB achieves 12- or 14-bit, enabling greater sensitivity to light variations. Regarding the measurement units, the DMSP-OLS provides relative values on a 0–63 scale, while VIIRS DNB measures radiance in nanoWatts/cm²/sr. Finally, VIIRS DNB includes onboard calibration for enhanced accuracy, which is absent in DMSP-OLS. These differences highlight the superior capabilities of VIIRS DNB for detailed and accurate nighttime light analysis [29].

2.2.1 Studies with the DMSP data

The DMSP was launched in the mid-1960s as a meteorological program of the US Department of Defence and either aimed to collect meteorological data or for military reconnaissance [12]. Although not specifically designed for NTL data, researchers have used DMSP data in their studies for over 40 years.

Since the DMSP was not designed for NTL determination, it suffers from significant blurring, dubbed 'blooming' or 'overglow'. Especially blurring yields to problems for scientific research in urban areas. However, DMSP data are highly popular among social scientists due to their usefulness as a neighborhood-level proxy for indicators such as electrification, GDP, and population. Researchers can easily access DMSP data, which offers a globally standardized long-term dataset and is available annually between 1992 and 2012. Despite its inherent errors, these advantages have made DMSP data a preferred choice for many researchers over the years [24].

Researchers have used DMSP data in various areas, including analyzing how changes in electricity policies affect community electrification rates, assessing the impact of new projects (such as infrastructure and superstructure) on population growth, analyzing how government investments (e.g., building roads, extending railways) predict economic development, and estimating the extent of damaged areas [15], GDP estimation at sun-national scales [16], research a global fingerprint of macro-scale changes in urban structure [17], mapping urbanization dynamics at regional and global scales [30], shedding light on the shadow economy [31] etc. In all these studies, however, blurring in DMSP data has been a confounding factor for neighborhood-level analyses, forcing researchers to be more careful with their results or to test their hypotheses at lower resolutions. As researchers aware of the blurring problem are discouraged from conducting neighborhood-level analyses or choose not to pursue such analyses, the sample size of the studies in question is consequently reduced [24].

2.2.2 Studies with the VIIRS Data

In contrast to the DMSP, the VIIRS, which was launched in October 2011, was designed to measure NTL. For this purpose, it is equipped with a special panchromatic sensor – the Day and Night Band (DNB)[32]. It collects global low-light imaging data which is a significant improvement on the comparable data that has been collected by the DMSP Operational Linescan System over the last 40 years [33].

Compared to the DMSP, the VIIRS/DNB is significantly improved in the following aspects:

- data availability (daily images are provided for free),
- higher spatial resolution (740 m compared to approximately 3 km for the DMSP),
- radiometrically calibrated data (its radiometric resolution is 256 times finer and its sensitivity to radiance 10 times higher [32]) that are sensitive to low light levels and non-saturated in urban environments, and reduced overglow.

Consequently, the production of nighttime lighting products used in the studies was switched from the DMSP to the VIIRS data in 2012, with the last annual DMSP products produced in 2013 [33].

The first products made available based on VIIRS/DNB data began providing global monthly composites of night lights in April 2012, which has allowed us to improve our understanding of several topics. For example, modeling the regional economy of a country [34], socioeconomic activity in cities [35], evaluation of the VIIRS land and cryosphere Environmental Data Records (EDR), specifically Surface Reflectance, Land Surface Temperature, Surface Albedo, Vegetation Indices, Surface Type, Active Fires, Snow Cover, Ice Surface Temperature, and Sea Ice Characterization [36]; analyzing vegetation health to assess 500 California drought [37]; tracking cultural patterns in demand for energy services [38]; and detecting insurgency in a country[39], etc.

As shown in Figure 2.2 and Figure 2.3, there is a bluring effect in the DMSP data, which can lead to errors, particularly in smaller regions [40]. Figure 2.2 compares VIIRS and DMSP NTL data for the state of Wisconsin, illustrating the differences in resolution and light intensity detection between the two datasets. The VIIRS data provide a clearer and more detailed representation of light patterns, while the DMSP data exhibit significant blurring and over-saturation in brightly lit areas. Figure 2.3 shows a similar comparison for Illinois state, emphasizing the same trends. The VIIRS data demonstrate superior spatial resolution and accuracy in capturing variations in light intensity, particularly in urban areas, compared to the DMSP data, which suffer from lower resolution and data saturation. The VIIRS data preferred in this study because they provide up-to-date monthly and annual data, offer better resolution than DMSP, are specifically designed to detect night lights, and are easily accessible.

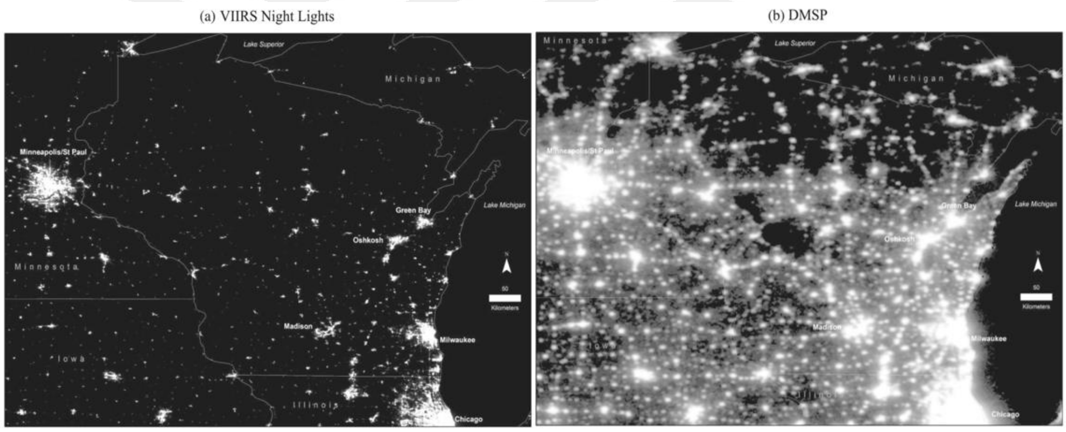

Figure 2.2 Nightlight image for Wisconsin (annual composites for 2013).

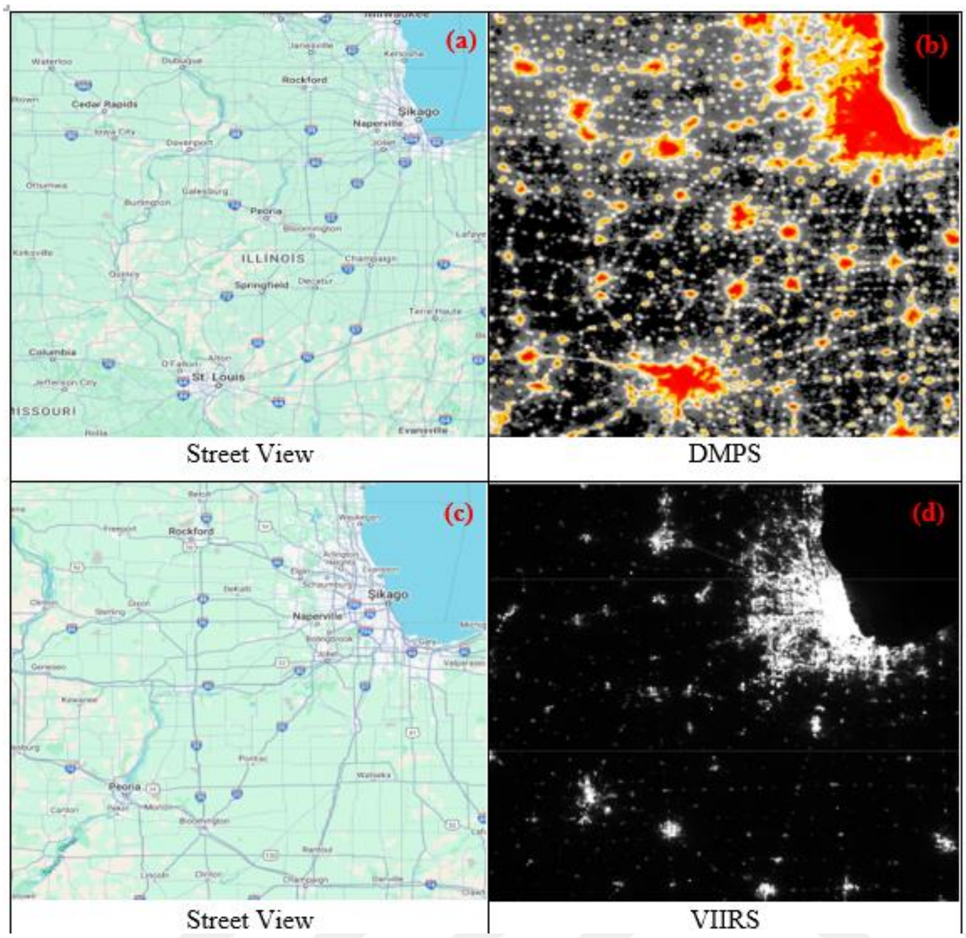

Figure 2.3 of VIIRS and DMSP data for Illinois state using annual composites for 2013. (a) Street view map of Illinois, providing geographical context; (b) NTL data from the DMSP sensor, illustrates lower spatial resolution and data saturation in highly illuminated areas; (c) Street view map highlighting the same region for comparison purposes; (d) NTL data from the VIIRS sensor, showcasing higher spatial resolution and improved accuracy in detecting variations in light intensity (Source of street view map is GEE [41]).

3. MATERIALS AND METHODS

This section explains the datasets, tools, and techniques employed in this study to ensure a comprehensive and reproducible analysis. The section begins with an overview of the methodological workflow, outlining the sequential steps to address the research objectives. The study area is then described, providing context for the geographical focus and its relevance to the research. The specifications and characteristics of the VIIRS dataset, including its resolution, temporal coverage, and suitability for NTL analysis, are elaborated upon. The proposed methodology is then discussed, detailing the analytical framework and its implementation. This includes the use of Google Earth Engine (GEE) as the primary platform, which was released in 2010 as a cloud computing platform with substantial computational capabilities [42] and designed to store and process big data sets for analysis [43]. The preprocessing steps applied to the VIIRS data to ensure accuracy and consistency and the validation techniques employed to assess the reliability of the results are also discussed. Together, this section provides a clear and systematic presentation of the methods, ensuring the scientific rigor and reproducibility of the study.

3.1 Overall Methodological Workflow

This thesis aimed to evaluate the socioeconomic consistency of NTL and GDP data by comparing them and investigating the detectability of the shadow economy through these data. The methodological workflow of this study is illustrated in Figure 3.1. The first step of the study was to determine representative regions to ensure the reliability of the analyses. Then, VIIRS satellite data were processed using a large-scale geographic data analysis platform, i.e., the GEE. In the final stage, the relationship between the NTL and GDP was assessed, and analyses were carried out on the usability of these data as shadow economy indicators. This methodological approach aimed to demonstrate the potential of satellite-based data in economic analysis.

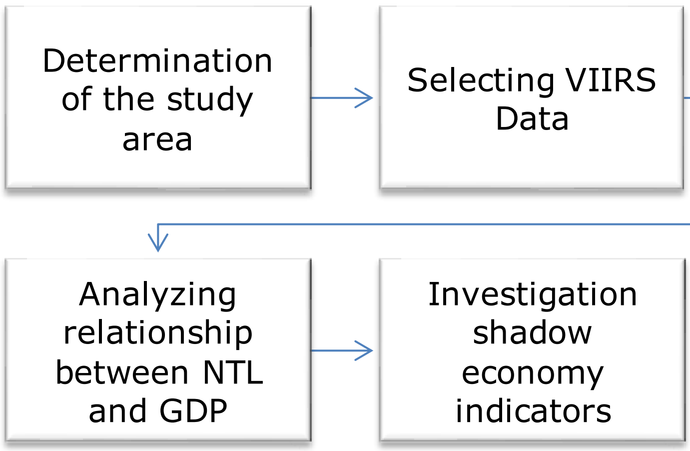

Figure 3.1 The methodological workflow chart.

3.2 Study Area

In this thesis, the study was conducted in an area covering the entire U.S.A. (except for the states of Alaska and Hawaii) (Figure 3.2). The U.S.A. consists of 50 states and one federal district and spreads over a large geographical area in the middle of the North American continent. This area includes every state and the islands of the U.S.A. The study area has a large and diverse topography with a total surface area of 9.8 million km^2.

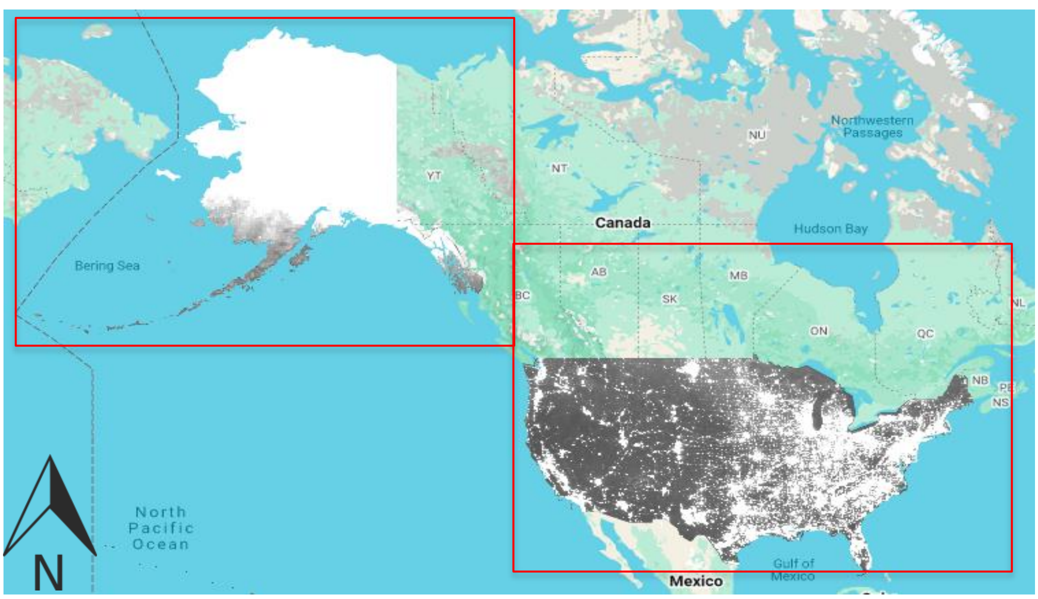

Figure 3.2 The U.S.A. map with NTL (the source of the base map is GEE [41]).

The geographical structure of the U.S.A. is characterized by the Appalachian Mountains in the east, the Rocky Mountains in the west, and a vast mountain range along the Great Basin and the Pacific coast. The Mississippi River and vast plains are located in the country's central regions where agricultural activities are concentrated. Desert areas and mountainous regions characterize the western states. In addition, the coastal regions of the U.S.A. are home to densely populated cities and industrial centers. The population of the U.S.A. is approximately 337 million according to the 2024 census [44], and population density varies significantly among the states. There are densely populated states such as California, Texas, and Florida, as well as more sparsely populated regions such as Alaska and Wyoming. This diversity provides a meaningful framework for analyzing the study area with NTL data. These different physical characteristics, which are shown in Figure 3.3 [45], create significant differences in the regional distribution of NTL data, and this is taken into account in the analysis process of this study. In particular, high population density and highly industrialized areas have high levels of NTL data, while rural and sparsely populated areas have very low levels.

Figure 3.3 Physical map of the U.S.A. [45].

The demographic structure in the U.S.A. varies across states. In the study area, the differences between large cities (such as New York, Los Angeles, and Chicago) and rural areas in terms of density and socioeconomic characteristics have effectively analyzed the NTL data. The distribution of NTL data directly reflects the population's socio-economic status, settlement density, and industrialization rate. This provides an appropriate basis for examining the relationship between NTL data and social and economic indicators. The population density of the U.S.A. is illustrated in Figure 3.4 [46].

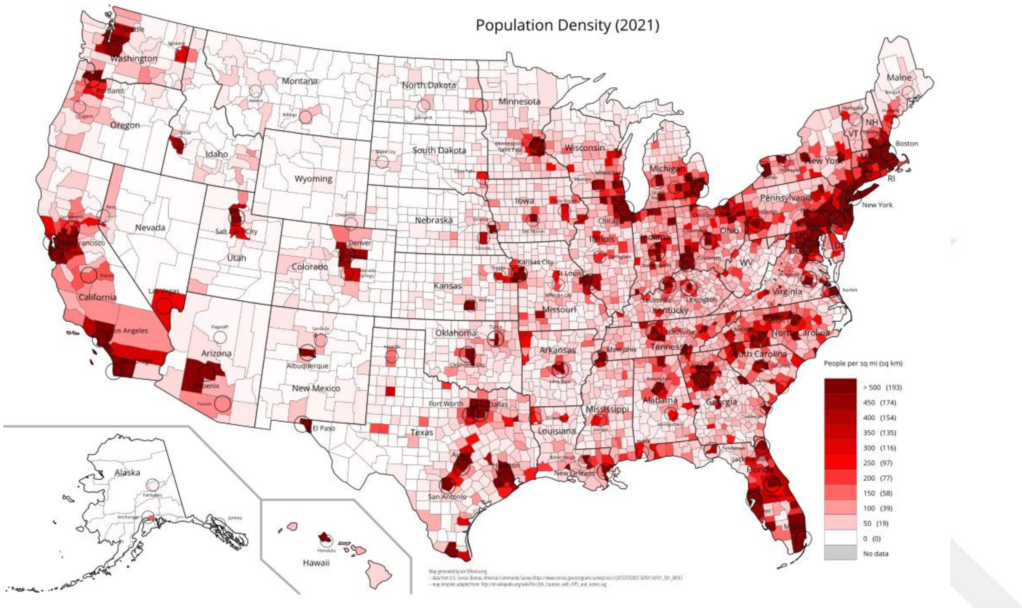

Figure 3. 4 Population density map of U.S.A. (2021) [46].

This large study area covers all states of the USA and provides an ideal data source for NTL data to reflect and analyze regional differences. The USA is an appropriate sample area for this research as it is a diverse country with different levels of socio-economic urbanization, industrialization, and population density. Understanding the relationship between NTL data, population density, and economic activities provides meaningful results regarding sustainable urbanization, energy consumption, and socio-economic indicators. In line with this information, analyzing all states of the USA increases the diversity of data in line with the purpose of the research. It enables the results to be interpreted with a broader perspective.

3.3 VIIRS Specifications and Study Dataset

In this research, the “VIIRS Nighttime Day/Night Annual Band Composites V2.1” dataset was used. The annual global VIIRS NTL dataset is a time series produced from yearly and monthly cloud-free average radiance grids spanning 2013 to 2021 [47]. This data has been provided by the Earth Observation Group, the Payne Institute for Public Policy, and the Colorado School of Mines. The main data specifications are given in Table 3.1 [47,48]. The dataset covers April 1, 2012, to January 1, 2021, with a spatial resolution of 463.83 meters [49]. The Delivery File Type indicates that the data is compressed in .gz format to optimize storage and transfer efficiency. The Delivery File Content specifies various statistical metrics, such as average, median, and maximum radiance values, as well as their masked counterparts, which exclude data influenced by light contamination or outliers. The dataset is provided in the GeoTIFF format, which ensures compatibility with geospatial software for analysis. The dataset uses the EPSG:4326 coordinate reference system (CRS) based on geographic latitude and longitude, ensuring global coverage. The 15 arc-second resolution (~500 meters at the Equator) allows for high spatial detail. The Coverage defines the geographic extent, ranging from 180°W to 180°E and 75°N to 65°S, ensuring nearly global availability [47].

Table 3. 1 The main specifications of VIIRS Annual Band Composites V2.1 data [47].

Delivery File Tyle	**gz (gzipped)**
Delivery File Content	average, average-masked, cf_cvg, cvg, max, median, median-masked, min
Image File Type	GeoTIFF
Unit	(average, average-masked, max, median, median-masked, min) $nW/cm^2/sr$
CRS	EPSG:4326 (Geographic Latitude/Longitude)

Resolution	15 arc-second (~500m at the Equator) (463.83 meters)
Coverage	180W, 75N, 180E, 65S
Availability	2012-04-01T00:00:00Z–2021-01-01T00:00:00Z

Table 3.2 outlines the key bands provided in the VIIRS/DNB dataset. The average and average_masked bands represent the average radiance values, with the latter excluding data affected by noise. The cf_cvg band provides cloud-free coverage information, indicating the number of valid observations per pixel, which helps assess data quality in regions with fewer observations. The cvg band records the total number of observations free from sunlight and moonlight interference. Maximum, median, median_masked, and minimum bands provide statistical radiance values, with masked versions filtering out unreliable data [50].

Table 3. 2 The main specifications of the VIIRS/DNB bands [50].

Name	**Description**
avarage	Average DNB radiance values.
average_masked	Average Masked DNB radiance values
cf_cvg	Cloud-free coverages: the total number of observations that went into each pixel. This band can be used to identify areas with low numbers of observations where the quality is reduced.
cvg	Total number of observations free of sunlight and moonlight.
maximum	Maximum DNB radiance values.
median	Median DNB radiance values

median_masked	Median masked DNB radiance values.
minimum	Minimum DNB radiance values

The GDP data used in this research was also obtained from the World Bank's World Development Indicators (WDI) database [51], which provides reliable and widely recognized economic indicators. The dataset includes annual GDP values in constant US dollars, adjusted for inflation, ensuring comparability across years. It is organized at the national level and covers a broad temporal span, allowing for consistent analysis over time.

3.4 Methodology

This section outlines the comprehensive approach adopted in this thesis for acquiring, processing, and analyzing the NTL data. The GEE platform was preferred as the primary tool due to its capabilities, including access to an extensive geospatial data catalog, cloud-based processing power, and an integrated development environment for algorithm implementation. The preprocessing steps involved leveraging custom code on GEE to extract and process NOAA VIIRS NTL data, focusing on annual averages for 2014–2021. The workflow included loading geographic boundaries, specifying the study area, extracting NTL data, and calculating regional averages. These averages were visualized in a time-series format and exported for further analysis. The final stage of the methodology includes validation steps to assess the reliability of the results. The detailed workflow is shown in Figure 3.5.

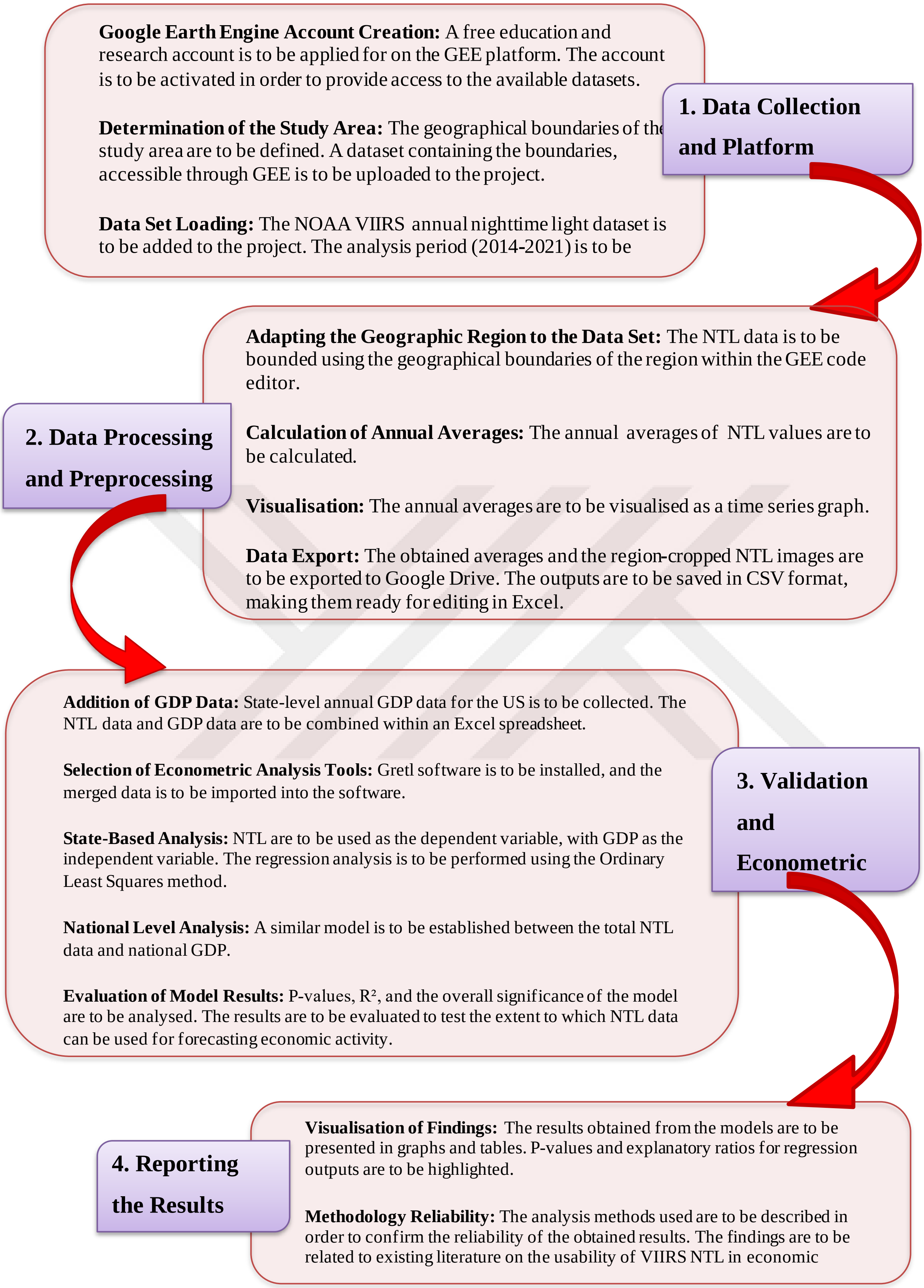

Figure 3.5 Detailed methodological workflow.

3.4.1 The GEE Platform

The GEE platform was utilized in this thesis to access and process the NTL data. The platform offers several utilities. First, the GEE is a cloud-based computing platform that uses Google's infrastructure, a multinational technology company known for its search engine and cloud computing services [52], to make it easier to access and process geospatial data [53]. This platform requires an account to access and is free for educational and research purposes. Secondly, it has a dynamic platform that facilitates large-scale algorithm development and promotes high-impact research through free and open access [43]. In addition, the GEE has a huge petabyte-scale catalog. It collects information from many satellites, such as the Landsat series (e.g., Landsat 8, Landsat 9) [54], the Sentinel constellation of European Space Agency (e.g., Sentinel-1 and Sentinel-2) [55], and the Moderate Resolution Imaging Spectroradiometer (MODIS) [56], [57]. Finally, its intuitive interface has a code editor and an integrated development environment (IDE) for elaborating algorithms using JavaScript. It also has a graphical window allowing the user to see the processes. For these practical reasons, the GEE platform was chosen to be used in this research for data acquisition and processing.

3.4.2 Preprocessing

For the processing and utilizing the data, a code developed on the GEE platform was used. This code provides a workflow that analyses annual NTL averages for a region using NOAA VIIRS NTL data. Firstly, satellite image datasets which contain NTL data were loaded from GEE. With the help of a dataset containing first-level administrative boundaries, the boundaries of the desired region were imported into the project. This dataset contains the borders of countries or states and was provided by the GEE. In the next step, a dataset containing NOAA VIIRS annual NTL data was added. This dataset shows the NTL data distribution around the world for specific years. By entering the state's name to be handled, the NTL data of that region is taken, and the map center is set (see Figure 3.6).

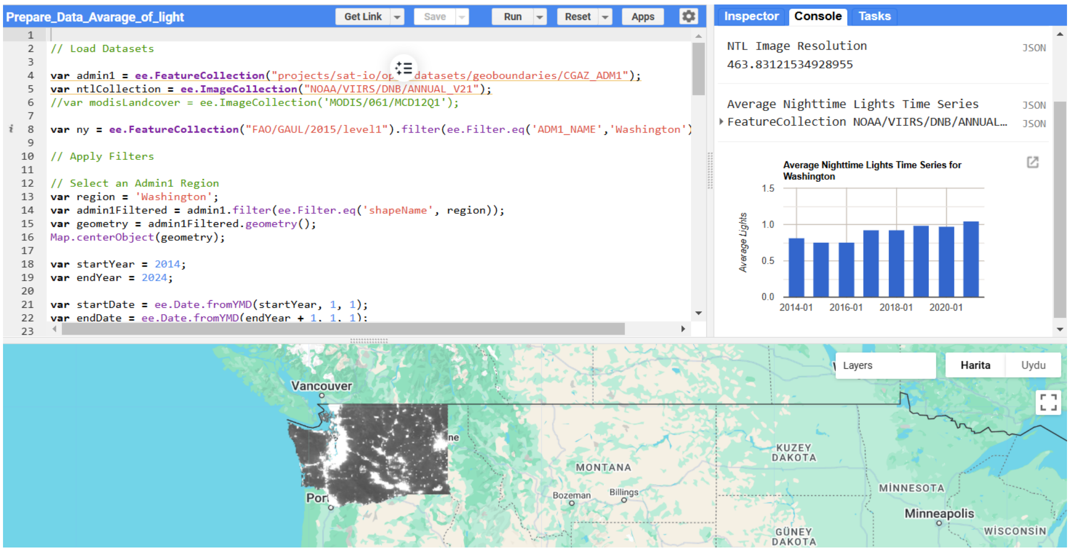

Figure 3.6 Map visualisation of NOAA VIIRS annual NTL data for the selected region (Washington state).

In the next step, the time interval (2014-2021) and the avarage band preference to be used added to the code. The projection of the first image is obtained, and its nominal resolution is defined as the default resolution. This resolution information is used as a scale parameter to calculate average NTL values. As the next step, the average NTL time series is obtained by applying the function written to calculate the average NTL for a specific region in each image. With the help of the *reduceRegion* function, the data is reduced within a certain geometry, and the average value is found using *ee.Reducer.mean()*. A feature is returned containing the average NTL value and the time information of the image (see Appendix -1). Finally, the average NTL time series is visualised as a bar chart, and the cropped NTL images are exported to Google Drive, which is a cloud-based storage service that enables users to store and access files online [58].

3.4.3 Validation

The study used different validation methods to determine whether there is a statistically significant relationship between the VIIRS NTL data and the GDP. Within the scope of the study, state-level GDP data for the U.S.A. between 2014-2021 and VIIRS NTL data for the same period are used. These data sets were combined in an Excel spreadsheet, a versatile software tool widely used for data management and analysis. It enables users to perform complex calculations, organize large datasets, and generate meaningful insights through various functions [59] and loaded into the Gnu Regression, Econometrics, and Time-series Library (Gretl) program. Gretl is an open-source software for statistical analysis and econometric modeling. Gretl, which offers a wide range of functions, especially in economic data analysis and modeling, supports many statistical techniques such as regression, time series, and panel data analysis [60]. The analyses performed based on the Ordinary Least Squares (OLS) method.

Firstly, the analyses were conducted at the state level. In this analysis, the NTL data was used as the dependent variable, and the GDP data was used as the independent variable. The model can be expressed as in equation (1).

$$NightLightsi = \beta 0 + \beta 1 \cdot GDPi + \epsilon i \qquad (1)$$

GDPi is the annual GDP of the *i*-th state and *NightLightsi* is the average annual night lights of the same state. *β0* and *β1* are the model coefficients and ϵi is the error term. As a result of the analysis, the significance level of the model, the p-values of the coefficients, and the explanatory ratio (R^2) evaluated.

Secondly, an analysis covering the U.S.A. as a whole is conducted. In this analysis, similarly, the national GDP is used as the dependent variable and the total NTL data representing the whole country is used as the independent variable. The model is structured in the same way and evaluated with similar metrics.

Both analyses provide essential clues to understanding the usability of VIIRS NTL data for GDP forecasting. The model results revealed a statistically significant relationship between night lights and economic activity, thus supporting the accuracy and reliability of the methodology used.

3.4.4 Relationship between NTL-GDP

Economic activity measured by the intensity of night lights, Y, in state s at time t is a function of official GDP, as shown in equation (2). This formula states that economic activity (measured by light intensity) in a given region can be estimated in terms of GDP.

$$Y_t^s = U_t^s \cdot GDP_t^s \tag{2}$$

where U is a coefficient indicating the size of the shadow economy and its discrepancy with official GDP. A higher U value can suggest that a significant portion of economic activity occurs outside official records, implying a large shadow economy. Conversely, a lower U value can indicate that most economic activities are captured within the formal economy. Y is the NTL data representing economic activity in a given state or region in a given year t.

Since NTL data (Y) serves as a proxy for economic activity, this relationship allows for an alternative estimation of regional economic output. If a region exhibits high light intensity despite a relatively low reported GDP, this discrepancy can signal substantial informal or unregistered economic activities. This approach is particularly useful in developing regions or economies with high levels of informality, where official statistics may not fully capture economic performance.

Expressing the economic activity in state s relative to the USA gives us an index of the size of the shadow economy relative to the USA. The formula is shown in equation 3.

$$\frac{U_t^S}{U_t^{USA}} = \frac{\frac{Y_t^S}{GDP_t^S}}{\frac{Y_t^{USA}}{GDP_t^{USA}}} \tag{3}$$

This formula is used to compare the size of the shadow economy in a given region to the average economic activity across the U.S.A. In the formula, the proportional difference between the NTL data and GDP in the region is compared to the proportional value for the U.S.A. as a whole. A ratio greater than 1 suggests that informal economic activity in the region is more intense than the national average. On the other hand, a ratio less than 1 indicates that the region has a lower level of shadow economy activity than the national average. This formula allows conclusions to be drawn about where regional economic activity is located relative to the national average, and about the existence and potential size of shadow economy.

The analysis highlights the potential of using NTL data not only for the GDP estimation but also as a proxy to gauge the extent of informal or shadow economic activities within regions. This approach underscores the versatility of remote sensing data in capturing dimensions of economic activity that remain obscured in official records.

4. RESULTS

This section presents the findings of the analyses to investigate the relationship between VIIRS NTL data and GDP. The results are based on the application of OLS models, both at the state level and for the U.S.A. as a whole, for 2014–2021. Key metrics such as model coefficients, R-squared values, and significance levels were provided to evaluate the explanatory power of NTL data in capturing economic activity. Additionally, this section provides the results for the shadow economy. By calculating a shadow economy index (SEI) for the selected states (six in total), insights provided into the potential role of informal economic activities in regions with varying demographic and economic structures. This index derived using NTL intensity as a proxy for economic activity and complements the traditional GDP analysis with remote sensing data.

The findings are organized into three parts. The first part focuses on state-level analyses, exploring variations in the relationship between night lights and GDP across different states. The second part investigates the aggregated national-level analysis. The third part discusses the implications of shadow economy measurements derived from NTL data.

4.1 State-Level Analyses

The state-level analysis aimed to investigate the relationship between economic activity, measured by state-level GDP, and VIIRS night lights data, which serves as a proxy for economic activity. The analysis conducted using the OLS method, with NTL as the dependent variable and GDP as the independent variable. The results are presented in Table 4.1. From the results in Table 4.1, the analysis yielded the following key results:

- The constant term is estimated as 535,738 with a highly significant p-value (<0.0001). This suggests that even in the absence of GDP, a baseline level of night lights activity exists, likely reflecting non-economic sources of light emissions.

- The coefficient for GDP is 1.56605, with a highly significant t-ratio of 23.56 and a p-value (<0.0001). This indicates a strong positive relationship between GDP and night lights intensity, suggesting that higher economic activity correlates with greater night lights emissions.

- The R-squared value is 0.592, indicating that approximately 59.2% of the variation in night lights intensity can be explained by variations in GDP at the state level. The adjusted R-squared value of 0.591 further supports the model's robustness by accounting for the degrees of freedom.

The model's high F-statistic (555.0261) and its corresponding p-value (1.96e-76) provide strong evidence against the null hypothesis, confirming that GDP significantly explains the variations in night lights. However, it is important to note that approximately 40.8% of the variation remains unexplained, which may be attributed to other factors, such as demographic characteristics, infrastructure development, or shadow economic activities.

Table 4.1 Results of the state-level analyses from OLSs using observations 1-400 (n = 384).

	Coefficient	*Std. error*	*t-ratio*	*p-value*	
const	535738	43684.7	12.26	<0.0001	***
gdp	1.56605	0.0664735	23.56	<0.0001	***

Mean dependent var	1181714		S.D. dependent var	1042364
Sum squared resid	1.70e+14		S.E. of regression	666412.5
R-squared	0.592327		Adjusted R-squared	0.591260
F(1, 382)	555.0261		P-value(F)	1.96e-76

4.2 National-Level Analyses

The national-level analysis focused on evaluating the relationship between GDP at the national scale (USAgdp) and the total night lights intensity for the entire U.S.A. (USAlite). This analysis utilized the OLS method, with USA lite as the dependent variable and USAgdp as the independent variable. The results are given in Table 4.2. The key findings of this analysis are as follows:

- The constant term is estimated as 3.95179e+07, with a highly significant t-ratio of 25.65 (p-value < 0.0001). This indicates a baseline level of night lights intensity at the national level, independent of GDP variations, potentially reflecting non-economic light sources.

- The coefficient for USAgdp is 1.79142, with a highly significant t-ratio of 23.58 and a p-value < 0.0001. This demonstrates a strong positive correlation between national GDP and total night lights intensity, affirming the hypothesis that economic activity is a primary driver of night lights emissions.

- The R-squared value is 0.593, indicating that 59.3% of the variation in USAlite is explained by changes in USAgdp. The adjusted R-squared value of 0.592 further confirms the model's robustness while accounting for the number of observations and predictors.

- The F-statistic of 555.9238 and its associated p-value (<1.64e-76) reject the null hypothesis, reinforcing the significance of USAgdp in explaining variations in NTL intensity.

Table 4.2 Results of the national-level analyses from the OLS using observations 1-400 (n = 384).

	Coefficient	*Std. error*	*t-ratio*	*p-value*	
const	3.95179e+07	1.54090e+06	25.65	<0.0001	***
USAgdp	1.79142	0.0759783	23.58	<0.0001	***

Mean dependent var	75693832		S.D. dependent var	4366084
Sum squared resid	2.97e+15		S.E. of regression	2790022
R-squared	0.592717		Adjusted R-squared	0.591651
F(1, 382)	555.9238		P-value(F)	1.64e-76

These findings further validate the use of VIIRS night lights data as a robust and scalable proxy for economic activity at a state and national scale. The analysis revealed that VIIRS night lights data could explain approximately 60% of the variation in GDP, leaving 40% unexplained. This unexplained proportion likely corresponds to other influencing factors not captured by the model, one of which is the shadow economy. To investigate this further, shadow economy indices calculated for a selection of rural and densely populated states in the U.S.A. However, the remaining unexplained variance indicates the need for additional research to incorporate complementary indicators or advanced modeling techniques for a more comprehensive understanding of economic dynamics.

4.3 Shadow Economy Index

Following the significant results obtained from the national-level and state-level analyses, the SEI calculated to provide further insights into the informal economic activities across different regions. As previously described, this index is derived by taking the ratio of the GDP-to-night lights intensity (GDP/Lite) for a given state and comparing it to the national GDP-to-night lights ratio (USAGDP/USALite). A ratio lower than 1 suggests that the economic activity in the state is largely consistent with formal economic indicators, with little or no signs of informality. However, significant deviations from 1 may indicate the possible presence of shadow economic activities, where the intensity of night lights does not align with the reported formal GDP. This approach allows for the identification of states where the intensity of night lights deviates from formal economic indicators, signaling the potential presence of a shadow economy.

The results summarized in Table 4.3, Table 4.4, and Table 4.5 indicate that certain states exhibit a relatively high SEI. Rural landscapes, low population density, or proximity to international borders predominantly characterize these states. Such factors contribute to more extensive informal economic activities due to reduced regulatory oversight, increased cash-based transactions, and limited access to formal markets. High SEI values in these states suggest a significant share of economic activities outside the formal economy. Figures 4.1, 4.2, and 4.3 show a map of total NTL data between 2014 and 2021 for these states.

Table 4.3 Shadow Economy Index Calculations for Alabama (2014–2021).

year	GDP	lite	USAlite	USAgdp	SEI
2014	197064	1046039	72202184	17608138	1.294
2015	203113	1016215	73908648	18295020	1.238
2016	208824	1019524	67576616	18804912	1.358
2017	216616	1143955	79192736	19612102	1.307
2018	226264	1090918	76388488	20656516	1.303
2019	234798	1073675	77149024	21539982	1.276
2020	235325	1093774	75960968	21354104	1.306
2021	260018	1114896	83171992	23681172	1.220

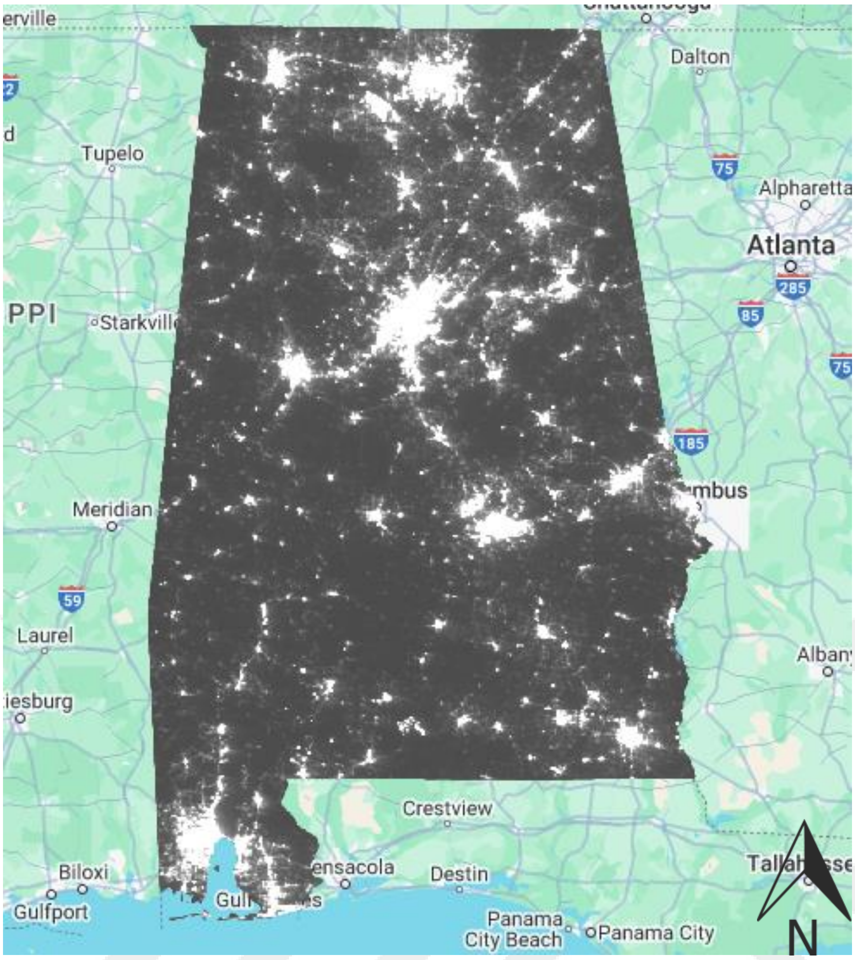

Figure 4.1 Map of total NTL data for Alabama state (from 2014 to 2021) (Central latitude and longitude coordinates are 32.318230, -86.902298).

Table 4.4 Shadow Economy Index Calculations for North Dakota (2014–2021).

year	GDP	lite	USAlite	USAgdp	SEI
2014	61108.3	1404927	72202184	17608138	5.606
2015	56952.2	1295049	73908648	18295020	5.628
2016	52666.3	962045	67576616	18804912	5.083
2017	56530.2	1457438	79192736	19612102	6.384

2018	60377.1	2051313	76388488	20656516	9.187
2019	60892.5	2336169	77149024	21539982	10.711
2020	55568.5	1557017	75960968	21354104	7.876
2021	63838.5	1405494	83171992	23681172	6.268

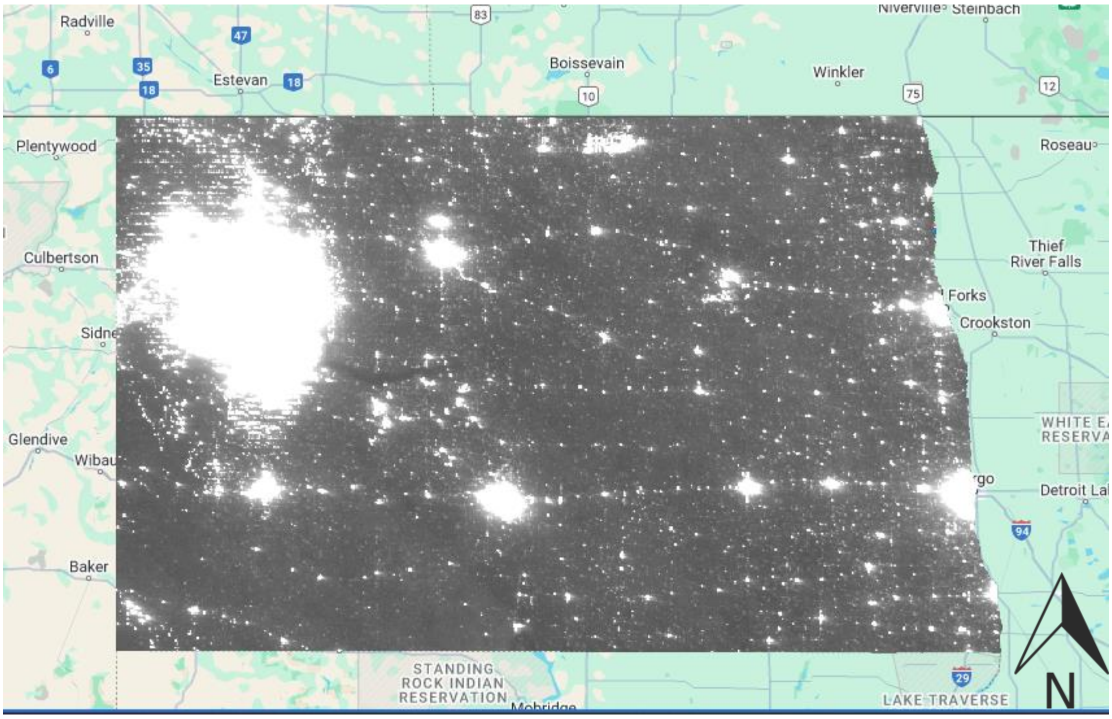

Figure 4.2 Map of total NTL data for North Dakota state (from 2014 to 2021) (Central latitude and longitude coordinates are 47.650589, -100.437012).

Table 4.5 Shadow Economy Index Calculations for Montana (2014–2021).

year	GDP	lite	USAlite	USAgdp	SEI
2014	45203.8	645011	72202184	17608138	3.479

2015	46542.4	514300	73908648	18295020	2.735
2016	45859.4	439764	67576616	18804912	2.668
2017	48470.5	989960	79192736	19612102	5.058
2018	51152.1	1066506	76388488	20656516	5.638
2019	52715.6	1015761	77149024	21539982	5.379
2020	52958.8	1115845	75960968	21354104	5.923
2021	60399.7	1216380	83171992	23681172	5.734

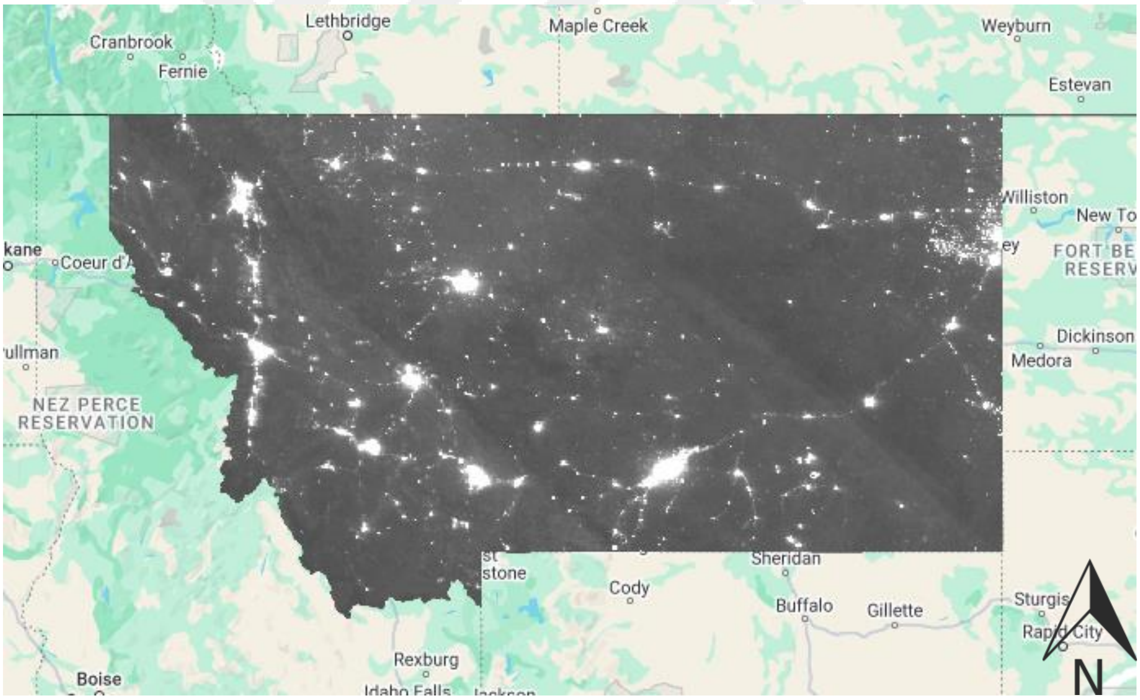

Figure 4.3 Map of total NTL data for Montana state (from 2014 to 2021) (Central latitude and longitude coordinates are 46.965260, -109.533691).

Conversely, the states shown in Table 4.6, Table 4.7, and Table 4.8 demonstrate lower SEI values. These states typically have higher levels of urbanization, better-developed infrastructure, and stronger institutional frameworks, all of which contribute to reducing the scope of shadow economic activities. The formal economy accounts for a more significant proportion of economic transactions in these regions, which is reflected in the lower index values. Figures 4.4, 4.5, and 4.6 show a map of total NTL data between 2014 and 2021 for these states.

Table 4.6 SEI calculations for California (2014–2021).

year	**GDP**	**lite**	**USAlite**	**USAgdp**	**SEI**
2014	2.30E+06	3457099	72202184	17608138	0.366
2015	2.50E+06	3364456	73908648	18295020	0.333
2016	2.60E+06	3308806	67576616	18804912	0.354
2017	2.70E+06	3858190	79192736	19612102	0.353
2018	2.90E+06	3856772	76388488	20656516	0.359
2019	3.10E+06	3839901	77149024	21539982	0.345
2020	3.10E+06	3992789	75960968	21354104	0.362
2021	3.40E+06	4044212	83171992	23681172	0.338

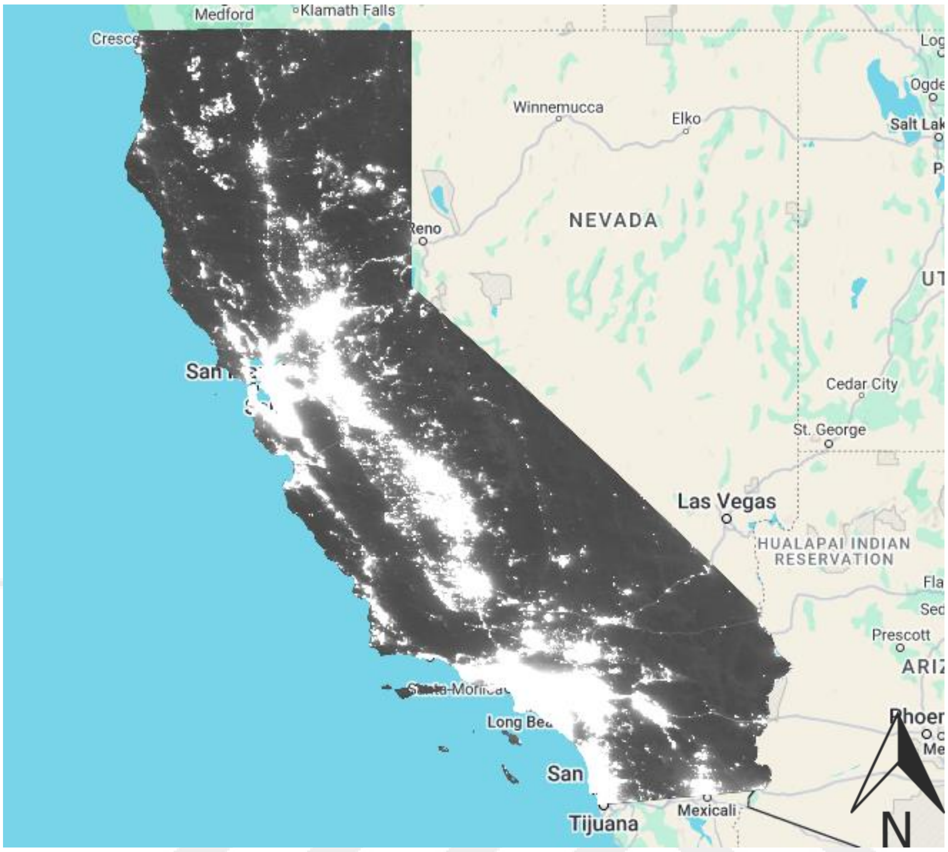

Figure 4.4 Map of total NTL data for California state (from 2014 to 2021) (Central latitude and longitude coordinates are 36.778259, -119.417931).

Table 4.7 Shadow Economy Index Calculations for New Jersey (2014–2021).

year	GDP	lite	USAlite	USAgdp	SEI
2014	543824	918097	72202184	17608138	0.411
2015	565808	922443	73908648	18295020	0.403
2016	578651	826898	67576616	18804912	0.397
2017	590087	885612	79192736	19612102	0.371
2018	619340	838451	76388488	20656516	0.366

2019	643318	872316	77149024	21539982	0.378
2020	631552	862065	75960968	21354104	0.383
2021	695443	921288	83171992	23681172	0.377

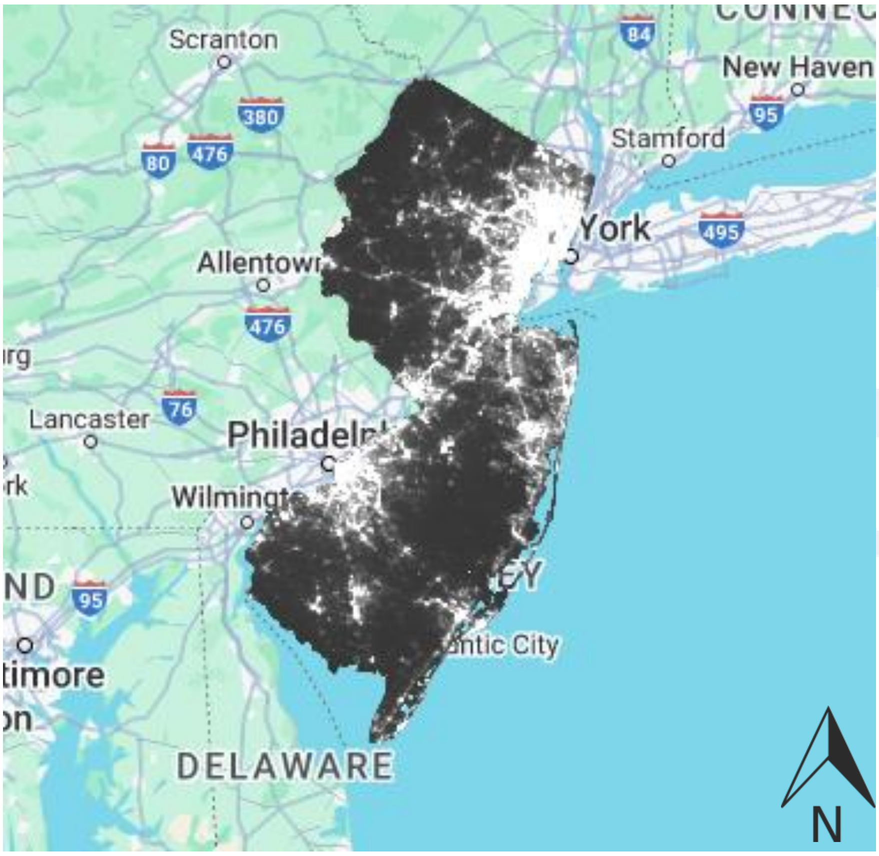

Figure 4.5 Map of total NTL data for New Jersey state (from 2014 to 2021) (Central latitude and longitude coordinates are 39.833851, -74.871826).

Table 4.8 Shadow Economy Index Calculations for New York (2014–2021).

year	GDP	lite	USAlite	USAgdp	SEI
2014	1.40E+06	1582962	72202184	17608138	0.275

2015	1.50E+06	1554035	73908648	18295020	0.256
2016	1.60E+06	1390655	67576616	18804912	0.241
2017	1.60E+06	1577428	79192736	19612102	0.244
2018	1.70E+06	1520774	76388488	20656516	0.241
2019	1.80E+06	1566498	77149024	21539982	0.242
2020	1.80E+06	1543089	75960968	21354104	0.240
2021	1.90E+06	1625110	83171992	23681172	0.243

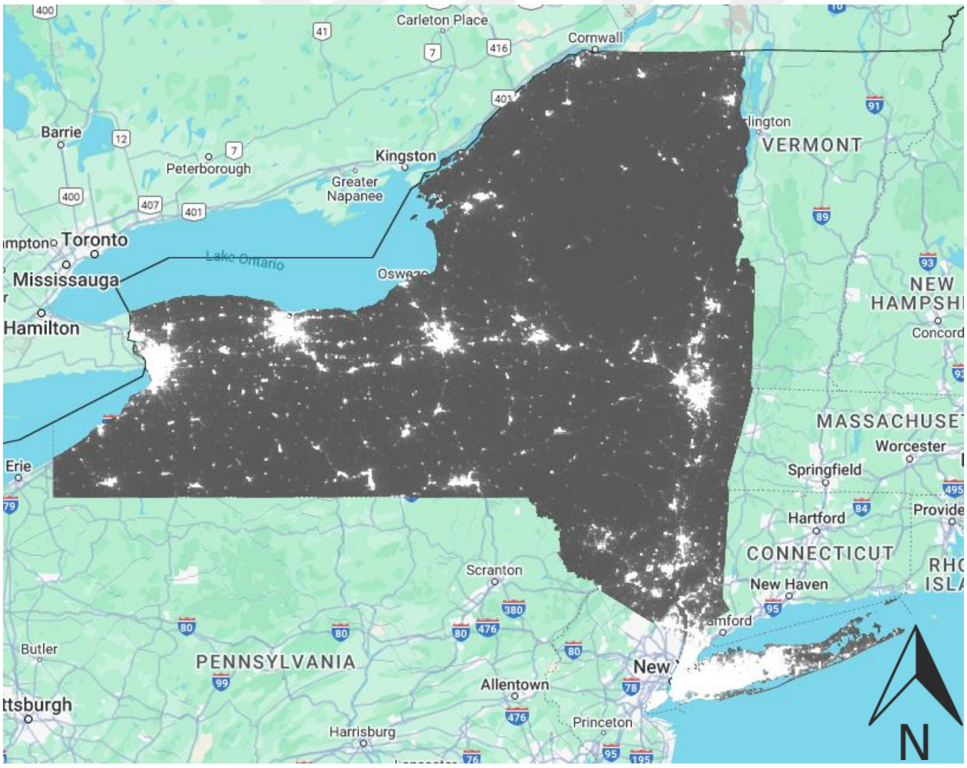

Figure 4.6 Map of total NTL data for the state of New York (from 2014 to 2021) (Central latitude and longitude coordinates are 43.000000, -75.000000).

These findings highlight the utility of the SEI as a tool for understanding spatial variations in informal economic activity. Overall, the SEI provides a nuanced perspective on the relationship between formal economic indicators and informal activity, demonstrating its potential as a proxy for understanding economic disparities across regions.

5. DISCUSSION

The study demonstrates the utility of VIIRS NTL data as a proxy for regional economic activity and the informal economy, showcasing its robustness in analyzing GDP-NTL relationships. Integrating the SEI offers a novel approach to identifying and quantifying informal economies across regions.

5.1 NTL and GDP: Insights from State and National Levels

The analyses reveal a significant and positive relationship between VIIRS NTL and GDP at both state and national scales. At the national level, NTL data demonstrated a strong ability to explain variations in GDP, underscoring its potential as a comprehensive indicator of aggregate economic activity. This finding aligns with previous studies while extending the literature by confirming the applicability of NTL data even in a highly developed country like the U.S.A.

The relationship between nighttime lights and GDP is also statistically significant at the state level. However, the model's explanatory power at this scale is more limited. This indicates that a broader range of factors beyond NTL intensity alone influences economic activities at the state level. Several factors beyond NTL intensity likely contribute to economic variations among states, including the extent of the shadow economy, sectoral composition, industrial diversification, urbanization patterns, and demographic heterogeneity. These structural differences introduce additional sources of variation that may not be adequately reflected through light intensity alone. Future research should explore these dimensions in greater depth to refine the accuracy of NTL-based economic estimations and improve model precision at the regional level.

Moreover, it is crucial to acknowledge that economic activity is shaped not only by quantifiable indicators such as GDP and NTL intensity but also by qualitative socioeconomic and cultural dynamics. Variations in consumption behavior, social structures, institutional frameworks, and regional policy environments can significantly influence economic output. Additionally, cultural norms, labor market characteristics, and infrastructure disparities may mediate the observed relationship between nighttime luminosity and economic performance. To develop a more holistic and nuanced understanding of the interplay between NTL data and economic activity, future studies should integrate multidisciplinary approaches that account for both quantitative and qualitative determinants of economic performance.

5.2 Shadow Economy Index: Measuring Informal Activities

A significant contribution of this study is the application of the SEI to analyze the extent of informal economic activity across states. The SEI is calculated as the GDP ratio per unit of light for a given state to the corresponding ratio for the entire U.S.A. States with higher SEI values, such as those in rural or border regions, indicate a more significant proportion of informal economic activities. For instance, states with high SEI values often exhibit lower levels of urbanization and higher reliance on informal labor markets. This finding is consistent with the literature, which associates higher shadow economy levels with limited formal economic integration and weaker regulatory oversight.

Conversely, states with lower SEI values, typically those with higher urbanization levels, such as metropolitan areas, show a smaller informal economy. This suggests that formal economic activities dominate these regions, reducing the relative contribution of unregistered or hidden economic transactions. Including the SEI in this analysis provides critical insights into the spatial distribution of the informal economy and highlights its correlation with socio-economic and geographic characteristics.

While the SEI offers valuable insights, its interpretation is subject to certain limitations. The threshold assumption, where an SEI value of 1 implies no shadow economy, and values greater or less than 1 indicate varying degrees of informality, should be treated cautiously. Given the complexity of informal economies, rigid thresholds may oversimplify the phenomenon. Future research should explore more flexible threshold settings or probabilistic approaches to capture the nuances of the shadow economy.

Furthermore, the precise quantification of the shadow economy remains a challenging endeavor due to its concealed nature. Informal activities, by definition, evade official statistical reporting, making their direct measurement difficult. Several contextual factors—including migrant labor dynamics, rural and urban development disparities, the prevalence of cash-based transactions, sector-specific informality, and the presence of economic clusters such as industrial zones or free trade areas—significantly shape the magnitude and distribution of informal economic activities. Ignoring these spatial and sectoral heterogeneities may lead to aggregation bias and misinterpretation of the actual scale of informal economies. As such, future studies should consider localized or industry-specific analyses rather than relying solely on state- or national-level aggregates. A more granular approach, focusing on specific industrial sectors or geographic regions with known informality patterns, could yield more accurate and policy-relevant estimates of shadow economic contributions.

Additionally, it is important to recognize that the SEI functions as an index rather than a direct measurement tool, meaning that its values should be interpreted as approximations rather than definitive estimates. The reliability of the SEI depends on its underlying assumptions, model specification, and data sources, all of which introduce inherent uncertainties and potential biases. Consequently, researchers and policymakers should exercise caution when drawing absolute conclusions from SEI values and instead use the index as a comparative and trend-based analytical instrument rather than an exact quantification of the shadow economy.

5.3 Digital Economy and the Role of Nighttime Lights

The integration of NTL data into economic analyses has traditionally centered on capturing tangible, physically observable economic activities, such as industrial production, infrastructure expansion, and urbanization. The underlying assumption in these studies is that increased economic activity correlates with higher levels of artificial illumination, making NTL data a useful proxy for regional economic performance. However, as the global economy undergoes a structural transformation, with a growing emphasis on digital and knowledge-based industries, the applicability of NTL data as a universal economic indicator warrants reconsideration.

In highly developed economies, particularly those with a strong digital services sector, economic growth may not necessarily be accompanied by a proportional increase in light emissions. Digital industries—such as e-commerce, cloud computing, fintech, remote work, and software development—generate significant economic value with minimal physical infrastructure and relatively low energy consumption, thereby reducing their visibility in satellite-derived light intensity data. This discrepancy introduces potential measurement biases, as traditional NTL-based economic models may systematically underestimate economic output in regions where digital industries constitute a substantial share of GDP.

To mitigate these limitations and enhance the robustness of NTL-based economic models, future research should incorporate complementary proxies for digital economic activity.

5.4 Linear vs. Non-linear Relationships in GDP-NTL Analysis

This study employed a linear approach to examine the relationship between GDP and NTL intensity, revealing significant positive associations at both state and national levels. However, it is acknowledged that this relationship may exhibit non-linear characteristics in certain contexts, particularly in highly urbanized regions where saturation effects may diminish the marginal impact of increased light intensity. Non-linear models, such as quadratic or logarithmic specifications, could better capture these dynamics. Future research should explore non-linear methods to improve the precision of GDP estimates, especially in regions where economic activities are spatially concentrated or where high levels of light saturation are observed.

5.5 Selection of Observation Date

The observation date for this study is selected as January 1, primarily due to data availability and its positioning at the beginning of the calendar year. This choice facilitates direct comparisons with annual economic indicators such as GDP and other macroeconomic measures. However, the selection of a single reference date introduces certain methodological limitations that warrant careful consideration.

One primary concern is the potential impact of seasonal and meteorological variations on NTL intensity measurements. January coincides with winter conditions in many regions, which can influence satellite-derived luminosity in several ways. For example, snow cover in higher latitudes and temperate zones can enhance reflectivity, leading to overestimations of light intensity in affected areas. This phenomenon can distort economic activity estimations, particularly in northern regions. Additionally, seasonal reductions in outdoor activities due to colder temperatures may cause variations in nighttime illumination patterns, particularly in sectors reliant on tourism, retail, or entertainment. Additionally, January coincides with a period of significant seasonal population movements, particularly due to holiday travel, temporary workforce migrations, and post-holiday economic slowdowns. These transient shifts can introduce noise into the data, making it more challenging to derive stable economic indicators based solely on a single-date observation.

Future studies could benefit from considering alternative dates or averaging observations across multiple time points to mitigate seasonal biases and improve the stability of the estimates.

5.6 Spatial Distributions of Nighttime Lights within States

The spatial distribution of NTL exhibits substantial variation across different states, particularly in those with large geographical areas and diverse economic structures. While urban centers tend to generate high-intensity light emissions, rural and less densely populated regions often appear relatively dark, despite hosting significant economic activities such as agriculture, resource extraction, and decentralized manufacturing. This uneven distribution of luminosity introduces potential biases in state-level analyses, as traditional NTL-based models may disproportionately capture urban economic activity while underrepresenting the economic contributions of rural and peri-urban areas.

The limitations stemming from spatial aggregation can reduce the explanatory power of NTL-based economic assessments at the state level. For example, a state with a few highly illuminated metropolitan areas but extensive low-emission rural zones may exhibit misleadingly low average light intensity, despite having a strong agricultural or resource-based economy. Conversely, small states with compact urban centers may appear overrepresented in light-based economic analyses, even if their actual economic output is comparable to larger, more spatially dispersed states.

To enhance model precision and better account for within-state heterogeneity, future research should consider methodological refinements. For example, employing geospatial clustering techniques, such as k-means clustering, density-based spatial clustering, or hierarchical spatial segmentation, to identify economically significant zones within states. These techniques can help differentiate high-intensity commercial and industrial hubs from low-intensity residential or undeveloped areas, improving the accuracy of NTL-based economic models.

5.7 Potential Data and Sensor Limitations

In this study, approximately 40% of the variation in the model remains unexplained, prompting a need to investigate potential data and sensor-related limitations. Sensor sensitivity, calibration errors, and temporal inconsistencies in data collection could contribute to this unexplained variance. Furthermore, certain economic activities, particularly those occurring indoors or in low-light conditions, may not be adequately captured by NTL data.

Future research should address these limitations by integrating additional datasets, such as socioeconomic surveys, industrial output statistics, or alternative satellite imagery sources. Conducting sensitivity analyses to identify the extent of sensor-induced biases and employing correction methods could significantly improve the explanatory power of NTL-based economic models.

5.8 Contributions to the Literature

The study contributes to the existing literature by evaluating the utility of VIIRS NTL data in economic analyses. It demonstrates that NTL data serve as a forecasting tool and a valuable indicator for examining broader issues such as economic development and regional disparities. Through its findings, this research provides several key contributions to the field:

- By establishing the statistical significance of nighttime lights as an economic proxy in a developed country context, this research broadens the applicability of remote sensing data, which has traditionally been utilized in studies focusing on underdeveloped or developing regions. Previous studies (e.g., see [61][62]) have primarily focused on using NTL data to monitor economic activity in emerging economies. This study, by validating the effectiveness of this approach in a developed country context, expands on the work of these scholars and confirms the broader relevance of this data source. Previous studies have investigated either at the country level (e.g., see [63]) or city level (e.g., see [64]). Using both country and city-level analyses, this thesis has obtained results by evaluating the night light analysis from both perspectives. The dual-scale analysis demonstrates that NTL can serve as an effective tool for macroeconomic assessments at the national level while also highlighting regional disparities and informal economic activity at the micro (state) level.

- The introduction of the SEI bridges a critical gap in the literature by offering a quantifiable approach to assess the informal economy using remotely sensed data. This methodological advancement enhances the capacity to analyze economic disparities across regions. Previous work (e.g., see [65] [66]), attempted to measure informal economic activities through survey-based methods, which often suffer from underreporting and data reliability issues. The SEI method, which leverages VIIRS NTL, presents a more objective and scalable way to study the informal sector, providing a fresh perspective on measuring unrecorded economic activities. This innovation also complements earlier studies (e.g., see [67]) that used economic surveys but lacked a robust spatial tool to measure informal economies at regional levels.

The study's findings show that NTL data is useful for monitoring economic development, assessing regional inequalities, and supporting policy planning. Particularly in regions with scarce traditional economic data, nighttime lights data can provide crucial insights. This aligns with previous research (e.g., see [68][69]), which illustrated the potential of NTL for regional economic monitoring in countries with limited official data. However, unlike some of these studies that primarily focus on broader economic metrics, this study highlights the additional value of NTL in understanding informal sector activity and regional economic disparities.

In conclusion, this study has demonstrated the usability of NTL data in economic analyses and contributed to the literature in methodological and applied terms. The integration of the SEI in this analysis also lays the groundwork for future studies aiming to refine informal economy measurements and explore economic inequality across regions.

6. CONCLUSION AND FUTURE WORK

This study aimed to explore the relationship between VIIRS NTL data and GDP, focusing on understanding its potential as an economic indicator and its implications for shadow economy measurements. By leveraging both state- and national-level analyses, the findings provide significant insights into the usability of remote sensing data in economic studies and highlight important methodological and practical considerations. The VIIRS satellite system stands out among remote sensing technologies with its ability to detect low light intensities and provide comprehensive data.

The results demonstrated that VIIRS nighttime lights data are a strong predictor of GDP, particularly at the national level, where they explained a substantial portion of GDP variation. For example, the regression analysis indicated that nighttime lights explained approximately 59.3% of the variance in GDP at the national level ($R^2 = 0.592$). This finding reinforces the role of NTL data as a comprehensive indicator of macroeconomic activity, consistent with prior research. At the state level, however, the explanatory power was lower, with the model accounting for 59.2% of GDP variation ($R^2=0.591$), suggesting that regional factors such as industrial composition and urbanization have a more significant influence at finer spatial scales. These results emphasize the need for a multifaceted approach when analyzing economic activity at finer spatial scales.

One of the novel aspects of this study was the integration of NTL data to measure the shadow economy. The calculation of the SEI revealed that states with higher SEI values, such as North Dakota and Montana, exhibited significant informal economic activity, with SEI values ranging from 2 to 10, suggesting a larger share of unreported economic activities. These states, often rural or border regions, showed lower levels of formal economic activity and higher levels of informal sector engagement. Conversely, states such as New York and California, which are more urbanized, showed lower SEI values, indicating a higher degree of formalization. These findings underscore the potential of using VIIRS NTL as a tool to identify and quantify informal economic activities, providing policymakers with actionable insights into regional economic inequalities and the size of the shadow economy.

The study also has certain limitations. At the state level, the relatively lower explanatory power of NTL data points to the need for incorporating additional variables, such as energy consumption, industrial composition, and demographic characteristics, into future models. Moreover, the analyses relied on a linear relationship between GDP and nighttime lights; exploring non-linear models or machine-learning approaches could enhance the robustness of the findings. Another limitation is the exclusive focus on the U.S.A. While this provided a robust case study, extending the analysis to other countries with varying levels of economic development could offer a broader understanding of the applicability of NTL data.

Future research could expand on this work in several directions.

- To increase the explanatory power of state-based models, future studies could include variables such as population density, energy consumption, industrial structure, and geographic factors. By combining these with VIIRS data, models could provide a more comprehensive view of economic activity and better explain regional disparities.

- Conducting a temporal analysis of changes in the shadow economy could offer insights into the dynamics of informal economic activities. Monitoring how the size of the shadow economy changes over time in response to economic policy, external shocks, or regional development efforts would provide valuable information for policymakers.

- Extending this methodology to other countries with varying levels of economic development would further validate the usefulness of NTL data as an economic indicator. Comparative studies could explore how different social, economic, and geographic conditions influence the relationship between NTL and economic performance.

- Future work could combine VIIRS nighttime lights data with other remote sensing datasets, such as air pollution levels, infrastructure development, and land use data, to create a more holistic framework for analyzing economic development and regional disparities. This multi-dimensional approach could help policymakers better understand the interactions between different economic and environmental factors.

- Finally, the application of NTL data to social policy could be explored further. For instance, analyzing economic development trends, regional inequalities, and post-disaster recovery patterns using nighttime lights could inform policy decisions related to resource allocation, regional development strategies, and economic resilience.

Such analyses can help policy makers to better plan resource allocation and monitor economic growth.

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APPENDIX: CODE FOR COMPUTING ANNUAL TOTAL NTL BY STATE

```
// Load Datasets
var admin1 = ee.FeatureCollection("projects/sat-io/open-datasets/geoboundaries/CGAZ_ADM1");
var ntlCollection = ee.ImageCollection("NOAA/VIIRS/DNB/ANNUAL_V21");

// Select Region (Wyoming)
var region = 'Wyoming';  // Change the region name as needed
var admin1Filtered = admin1.filter(ee.Filter.eq('shapeName', region));  // Filter by region
var geometry = admin1Filtered.geometry();  // Get the geometry of the selected region

// Define the Time Range for the Analysis (2014-2024)
var startYear = 2014;
var endYear = 2024;
var startDate = ee.Date.fromYMD(startYear, 1, 1);  // Start date (January 1st, 2014)
var endDate = ee.Date.fromYMD(endYear + 1, 1, 1);  // End date (January 1st, 2025)

// Filter NTL Data by Time Range and Region
var ntlFiltered = ntlCollection
  .filter(ee.Filter.date(startDate, endDate))  // Filter by date range
  .filter(ee.Filter.bounds(geometry));  // Filter by the selected region's boundaries

// Function to Calculate the Total Nighttime Lights for Each Image
```

```
var calculateNightLights = function(image) {
  var stats = image.reduceRegion({
    reducer: ee.Reducer.sum(),  // Sum of the 'average' nighttime lights
    geometry: geometry,  // Region geometry
    scale: 500,  // Resolution (500m for VIIRS data)
    maxPixels: 1e10  // Maximum number of pixels for the operation
  });
  var totalLights = stats.getNumber('average');  // Get the total sum of lights
  var feature = ee.Feature(null, {
    'totalLights': totalLights,  // Store the total lights value
    'system:time_start': image.get('system:time_start')  // Store the image date
  });
  return feature;
};

// Apply the Nighttime Lights Calculation to the Image Collection
var nightLightsTimeSeries = ntlFiltered.map(calculateNightLights);

// Create a Chart to Visualize the Nighttime Lights Time Series
var chart = ui.Chart.feature.byFeature(nightLightsTimeSeries, 'system:time_start', 'totalLights')
  .setChartType('ColumnChart')  // Set chart type to column chart
  .setOptions({
    title: 'Sum of Nighttime Lights (2014-2024) for ' + region,  // Chart title
    vAxis: { title: 'Total Lights' },  // Y-axis title
    hAxis: { title: 'Year' },  // X-axis title
```

```
  legend: { position: 'none' }  // Hide legend
 });
print(chart);  // Print the chart in the console

// Select the First Image from the Filtered NTL Collection
var imageToExport = ntlFiltered.first();  // Get the first image in the filtered collection

// Export the Image to Google Drive
Export.image.toDrive({
 image: imageToExport,  // The image to export
 description: 'VIIRS_Wyoming_Annual_Lights',  // File name for the exported image
 folder: 'GEE_exports',  // Optional: Folder in Google Drive to save the image
 region: geometry,  // Define the region for export
 scale: 500,  // Image resolution (500m)
 maxPixels: 1e10  // Maximum number of pixels for export
});
```