

Multi-scale Economic Impact Estimation of Disasters Based on Electricity Consumption and Nighttime Light Data

by

Ma. Flordeliza Pajarillo Del Castillo

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Chairperson of the Supervisory Committee:

Professor Toshio Fujimi

Graduate School of Informatics, Department of Social Informatics

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Abstract

As a basis for aid acquisition and allocation during disasters, economic impact estimates must possess spatial and temporal dimensions. However, disaster economic impact estimates are often spatiotemporally blind. To address this problem, this thesis proposed the use of alternative economic indicators, electricity consumption (EC) and nighttime light (NTL) datasets, to analyze the multi-scale spatiotemporal dimensions of COVID-19 and Taal Volcano eruption impacts. This research aimed to develop a method to estimate economic impacts using EC and NTL which can be adapted to various analysis scales.

This thesis developed a counterfactual-based economic impact estimation method. This method generates pre-disaster models estimating EC and NTL as economic activity indicators. Using real-world explanatory variables, this model captures the behavior of EC and NTL before a disaster, representing normal situation. The explanatory variables must be unaffected by the disaster so that their relationship with EC and NTL remains the same. Representing the normal situation, the parameters can then be used to generate a counterfactual model. By plugging in post-disaster explanatory variable values into this counterfactual model, the dynamic post-disaster situations based on real-world data can be captured and the counterfactual EC and NTL can be obtained. Then, the economic impacts can be computed either in terms of GDP or as indices. This method was used to estimate the economic impacts of COVID-19 and Taal Volcano eruption.

Although numerous studies have estimated the impacts of COVID-19, most studies failed to capture the effect of subsequent changes making it difficult for governments to dynamically adapt across time. This thesis estimated the national quarterly economic losses due to the COVID-19 pandemic from 2020 to 2021. EC and NTL were estimated using models based on statistics and weather data explaining more than 81% of the pre-pandemic values. This thesis estimated total loss amounting to 2.9 trillion PhP in 2020 and 3.2 trillion PhP in 2021. More than two-thirds of the losses were in the commercial sector as it responded to both policies and the COVID-19 case surge whereas the industrial sector was mostly affected by the lockdown implementation. This method allowed the monitoring of economic losses resulting from dynamic long-term and large-scale hazards such as the COVID-19 pandemic.

Beyond the country-level impact, it is also important to understand the spatiotemporal dimensions of economic impacts for proportionate resource distribution, timely policy implementation, and region-specific recovery strategy formulation. This

thesis examined the spatiotemporal distribution of COVID-19 economic impacts in the Philippines through the computation of the economic activity reduction (EAR) index covering three years. To estimate the EAR, the ratio of the loss over the counterfactual was computed. The counterfactual NTL was estimated by inputting the post-pandemic datasets into the pre-pandemic NTL model explaining over 81.6% of the pre-pandemic NTL. The results revealed that EAR was higher in urban regions than in rural ones. Specifically, the study found that while highly urbanized regions experienced a substantial initial economic impact following the Luzon lockdowns, the overall impact was higher in the urbanizing regions.

The economic impacts of Taal Volcano eruption in the Philippines were also analyzed. Assessment of volcanic eruption impacts, however prompt, often lacks spatiotemporal dimensions. EC and NTL were used as alternative economic indicators to estimate the economic impacts of the eruption and analyze their spatiotemporal distribution. The high-frequency EC was used to analyze the temporal distribution while high-resolution NTL was used to analyze the spatial distribution of impacts. Temporal analysis showed that ECL had two loss peaks and two recovery valleys, congruent with power outages and restoration, road closures, earthquake occurrences, the number of affected populations, evacuees, and assistance distribution. This study showed that economic impacts have a temporal dimension shaped by dynamic factors that are often neglected due to data limitations that EC data can fill. The spatial analysis showed significant NTL reductions at the intersection of ashfall extent and built-up areas. This analysis detected the municipalities with the most NTL reduction and mapped the most affected areas within the municipalities. This study highlights the uneven impact distribution within a municipality, suggesting that the NTLC map can help direct aid to the most affected citizens.

Overall, this thesis demonstrated that EC and NTL can be used complementarily to estimate pandemic and volcanic eruption economic losses and determine their spatiotemporal distribution addressing spatiotemporal blindness. These datasets and methods used in this thesis paved a way to expand the scope of economic impact estimation and a more detailed spatiotemporal distribution analysis for measuring, mapping, and monitoring the impacts. This information aids in addressing the blind spots in economic impact estimation.

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Chapter 1

Introduction

1.1. Background

In recent years, the world witnessed more frequent and intense natural hazards resulting in greater disaster economic losses in recent decades (World Meteorological Organization, 2023). Damaging disasters disrupt the normal flow of economic activities resulting in economic impacts. These impacts not only burdened the affected units but also challenged the authorities in managing these emergencies. To manage the impacts, governments must gather funds and allocate resources to the affected units. Aid acquisition and allocation to be sufficient and proportionate must be informed based on economic impact estimates (Rabarison, et al., 2015).

Economic impact estimation plays a crucial role in managing disaster situations. After the disaster, the cost of relief, restoration, reconstruction, and rehabilitation must be quantified. This cost serves as a basis for funding acquisition from private, public, or international sources. Then, these funds must be allocated proportionately and promptly to the affected units. The success of support allocation is then anchored on these economic impact estimates. Further, these estimates can inform policy formulation and emergency planning to mitigate the impacts. This information can also be used for raising disaster risk awareness.

Due to its importance in disaster management, various economic impact estimation methods have been developed. Traditionally, economic impact datasets can be obtained through sales reports, survey questionnaires, and interviews. Then, unit losses may be added up to calculate the overall cost. Although this method can provide a detailed picture of the losses, these often cover a limited scope and can be a time-consuming process due to the resource-intensive nature of this data collection process (Qiang, et al., 2020). Another way to calculate disaster economic impacts is through economic activity indicators such as GDP, IPI, or PCI. These datasets can cover a larger area but tend to be aggregated and delayed. Some of these datasets are often released with significant delays while others are available in coarse resolutions and long intervals leading to a loss of spatial and temporal dimensions (Rosvold & Buhaug, 2021).

As a basis for resource allocation, economic impact estimates must possess spatial and temporal dimensions (Shen, et al., 2018; Shen & Hwang, 2019). Authorities must know where the most affected areas are to proportionately distribute funds. Further, these impacts must be monitored for timely policy implementation (Fezzi & Fanghella, 2020). Estimates lacking in spatiotemporal dimensions or having insufficient coverage could result in mismatched, disproportionate, and delayed support, especially for large countries with high spatial variability (Shen & Hwang, 2019). Such mismatch was reported in the Philippines where aid provided did not match the impact level (Brucal, et al., 2020), and in Chile where “spatially blind policies” were implemented during the COVID-19 Pandemic (Lopez Ochoa, et al., 2021).

Unfortunately, determining the spatial and temporal distribution of these impacts can be challenging. For relief operations, the costs must be estimated hours after the event to facilitate logistical mobilization. Further, emergency aid costs are often difficult to estimate because they depend on specific situations greatly varying across regions, time, and hazard types (Ghesquiere & Mahul, 2007) that are often unpredictable. The cost of reconstruction can be estimated using pre-disaster models but the actual implementation of these efforts can take years implying changes that these models could not capture.

1.2 The problem of spatiotemporal blindness in disaster economic impact estimation

Although economic impact estimation methods have been developed, they often lack the necessary spatiotemporal dimensions for effective disaster management. Figure 1 illustrates the spatial and temporal scales that currently available datasets cover. In this graph, the horizontal axis depicts the spatial scales from micro to global scale while the vertical axis marks the temporal scales from seconds to millennia. As shown, interviews and survey questionnaires tend to cover a smaller area and shorter analysis. Statistical economic indicators like GDP are often available at the regional or national scale and have been available from quarter up to decades. As can be seen, these datasets cover limited spatiotemporal scales leading to what can be called *spatiotemporal blind spots*.

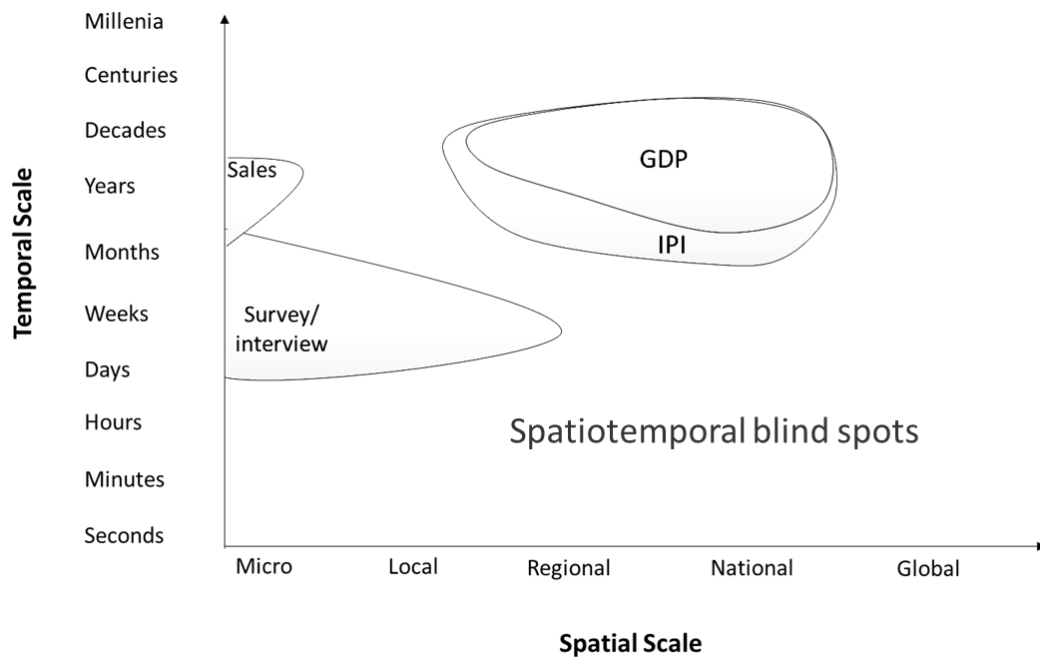


Figure 1. Spatiotemporal scales of economic impact datasets

The problem of spatiotemporal blind spots can be better understood by merging the scale of data with that of the hazard. Figure 2 illustrates the intersection between the spatiotemporal scales of hazards and data. In this graph, orange areas delineate the spatiotemporal scales of various hazards. As shown, hazards may cover a range of scales from small-scale short-term scales like snow avalanches to large-scale long-term scales like climate change or the COVID-19 pandemic.

The problem occurs when the spatiotemporal scale of the data does not match that of the hazard. For example, using national annual GDP data could dilute the impacts of a small-scale short-term hazard. Further, the spatiotemporal scale of GDP is too coarse for estimating the distribution of local and short-term hazard impacts (Roberts, 2021). Contrarily, using surveys or interviews covering a small area may neglect some of the effects of a large-scale hazard leading to a partial estimate. Such a mismatch between data and hazard scale leads to what can be called spatiotemporally blind economic impact estimates.

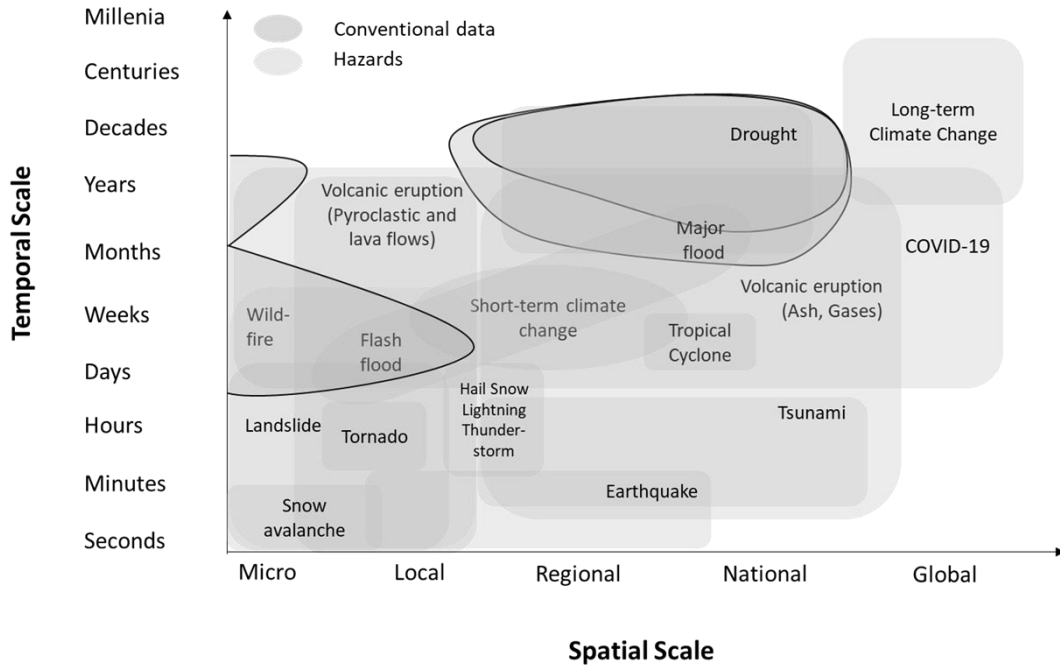


Figure 2. Hazard scales (adapted from Gill & Malamud (2014))

1.3 Solving spatiotemporal blindness in economic impact estimates using EC and NTL datasets

Impact estimates suffering from spatiotemporal blindness are often due to data limitations, especially for developing countries that have insufficient data and capacities to estimate disaster impacts (Mazhin, et al., 2021). Introducing more data options can expand the scope of current datasets resolving spatiotemporal blindness. High-frequency and high-resolution economic activity indicators can be used as alternative datasets to fill in the blind spots in economic impact estimates Figure 3.

High-resolution data for economic activity indicators can be found among the remotely sensed datasets. One data that holds a unique capacity for detecting the level of human activities is the nighttime light data or NTL (Levin & Phinn, 2016; Jia, et al., 2023; Qiang, et al., 2020). NTL is a satellite data that records nocturnal light brightness across the earth's surface. The primary strength of this data is the combination of fine spatial detail and global coverage that most statistical datasets cannot provide. The long temporal coverage (Jia, et al., 2023) and frequent data acquisition are another set of advantages. The fine spatial detail is advantageous for local impact assessment whereas the global coverage entails that the data can be used practically for observing any point in the world.

However, NTL data has several shortcomings regarding detection and consistency. NTL data can only capture nighttime economic activities. Researchers also report partial coverage of impacts due to measurement-related factors like cloud contamination and atmospheric particles such as water vapor, aerosol gases, and others (Cao, et al., 2013). These factors could cause noise, seasonal variation, and unstable measurement across time resulting in temporal inconsistency (Skoufias, et al., 2021). The other problem is the difference in economic activities, specifically those that emit light and those that do not (Strobl, 2019). For example, agricultural activities do not emit light but services and industries do. Hence, the economic activity of regions that depend on agricultural production, especially in rural areas could not be represented in full by NTL data (Sarkar, 2021; Keola, et al., 2015).

Complementing the weaknesses of NTL data would be electricity consumption data or EC. Unlike NTL, EC covers daytime and rural economic activities. EC also exhibited a strong relationship with economic activity measured through GDP or income (Yu & Choi, 1985; Lee, 2006; Topolewski, 2021; Fatai, et al., 2004). Further, EC data has high frequency. Some agencies hold daily EC records (Beyer, et al., 2021; Fezzi & Fanghella, 2020). However, EC data often comes in coarse spatial resolution and can be difficult to obtain.

High-frequency data like EC and spatially-granulated datasets like NTL are necessary to analyze the economic impact of hazards more closely. Separately, EC can enhance the temporal detail and coverage of impact estimates while NTL can reveal the spatial dimension and expand the coverage of estimates. This thesis posits that combining EC and NTL enhances the spatial and temporal details and expands the coverage of economic impact estimates resolving aggregation and coverage issues of conventional datasets. In effect, these datasets can be used to expand the spatiotemporal scales of economic impact estimation, addressing the problem of spatiotemporal blindness.

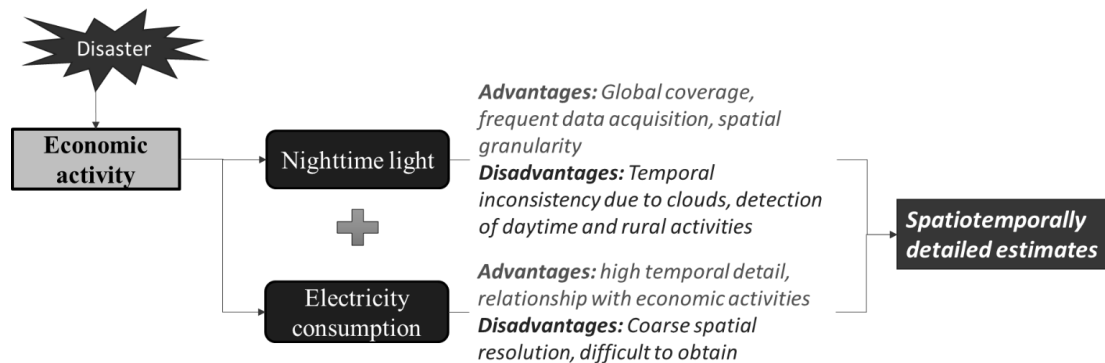


Figure 3. Research framework

1.4 Aims and scope

This research aims to develop a method for estimating the economic impacts of disasters using EC and NTL. This alternative method will enable a more detailed spatiotemporal analysis of economic impacts.

This thesis aims to use EC and NTL to estimate the impacts of two hazards in the Philippines and analyze the spatial and temporal distribution of these impacts across multiple scales. With these datasets, this thesis proposes a counterfactual-based economic impact estimation method enabling longer-term impact assessment across multiple scales.

Coronavirus Disease 2019 or COVID-19 and the Taal Volcano eruption were selected as the two hazards. COVID-19 was selected as a representative of a long-term large-scale hazard. COVID-19 resulted in significant global losses that are expected to last beyond this generation (Jorda, et al., 2020). For COVID-19, the study site will cover the Philippines which registered the highest economic losses among Southeast Asian countries in 2020 (Zhang, et al., 2022; World Bank Group, 2021). The analysis period will cover 2 years for the national quarterly scale and 3 years for the regional monthly scale (Table 1).

Table 1. Summary of analysis scales

Hazard	Site	Period	Scale
COVID-19	Philippines	2 years	National quarterly
	Philippines	3 years	Regional monthly
Taal Volcano Eruption	Luzon	18 days	Grid daily
	17-km danger zone	1 month	Municipal monthly

The Taal Volcano eruption was selected to represent a small-scale short-term hazard. The Taal Volcano erupted on January 12, 2020. This volcano is located in the Southern Luzon Region of the Philippines as shown in Figure 4. Location of Taal Volcano and the municipalities within the 17-km danger zone. This eruption covered an estimated 8,600 km² area in ashfall (Balangue-Tarriela, et al. 2022), affecting more than 700,000 people mostly living within the 17-km danger zone (NDRRMC, 2020). Weaker explosions continued for 10 days (Balangue-Tarriela, et al. 2022). For the Taal Volcano eruption, two analyses will be performed. The first analysis will cover Luzon Island for 18 days using the grid daily data. The second analysis will cover the 17-km danger zone for 1 month using the monthly municipal data.

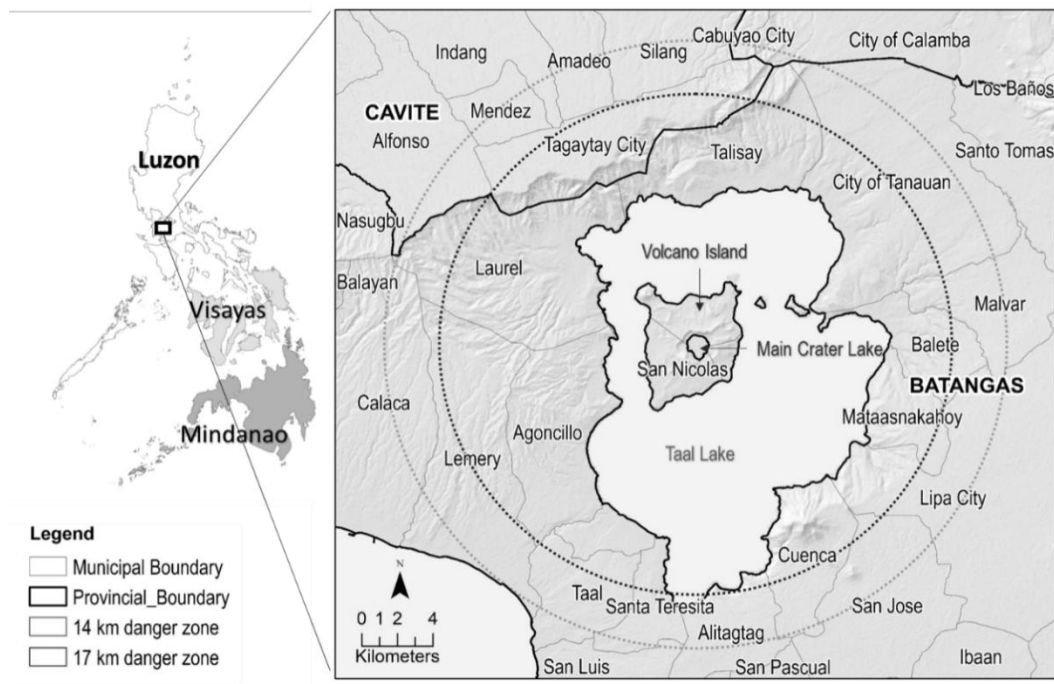


Figure 4. Location of Taal Volcano and the municipalities within the 17-km danger zone

1.5 Thesis structure

This thesis comprises seven chapters structured as shown in Figure 5.

Chapter 1 describes the current situation to explain the importance of economic impact estimates for disaster management. In this context, it identifies the problem of spatiotemporal blindness in economic impact estimates by examining the spatiotemporal scales of data and hazards. Addressing this problem of spatiotemporal blindness, it presents a research framework proposing the use of EC and NTL to refine the spatiotemporal details of disaster economic impact estimates. Based on this framework, the aims and scope of this research were stated and the thesis structure was presented.

Chapter 2 will summarize the current state of literature focusing on the use of NTL and EC as alternative measures of economic activities and disaster impact estimators. The discussion will focus on the application of these datasets and the methods performed. From this, it will identify the application and methodological gaps from which the research question was formulated.

Chapter 3 will address the research question by developing a method to estimate disaster economic impacts using EC and NTL across multiple scales. This chapter will explain the idea of the counterfactual-based economic impact estimation. Using this idea,

the process of estimating the impacts based on EC and NTL datasets will be expounded. Two ways of estimating economic impacts will be discussed. The first way is by computing the GDP loss through the GDP model. Then, several economic impact indices will be introduced to maximize the frequency and resolution of the EC and NTL datasets.

This method will be employed in three case studies to determine how it will perform for real-world data of actual disaster events occurring at various scales. The results of these case studies are discussed in Chapters 4, 5, and 6. These chapters cover the contents of three published papers (Del Castillo, et al., 2024; Del Castillo, et al., 2024a; Del Castillo, et al., 2025).

Chapter 4 will estimate the COVID-19 impacts, testing the feasibility of the method in estimating impacts in terms of GDP at the national quarterly scale. It will explain the data used for the regression models. Then, it will report the results of these models and the economic losses in terms of GDP. The quarterly impacts will be evaluated whether it was able to capture ground conditions. Other than analyzing the quarterly impacts, this chapter establishes EC and NTL as suitable proxies for GDP.

Chapter 5 will analyze the spatiotemporal distribution of COVID-19 impacts at the regional monthly scale using NTL data. It will generate NTL models based on the proposed method. A model will be used to estimate the baseline from which the impact will be estimated. Based on the results of this index, the spatial and temporal distribution of the impacts will be analyzed.

Chapter 6 will analyze the economic impacts of the Taal Volcano eruption to test how this method will perform for a local hazard. In this chapter, EC will be used to estimate the economic impact and NTL will be used to determine the spatial distribution of these impacts.

Chapter 7 will discuss the findings of this research together with the implications, limitations, and recommendations. It will also conclude the thesis.

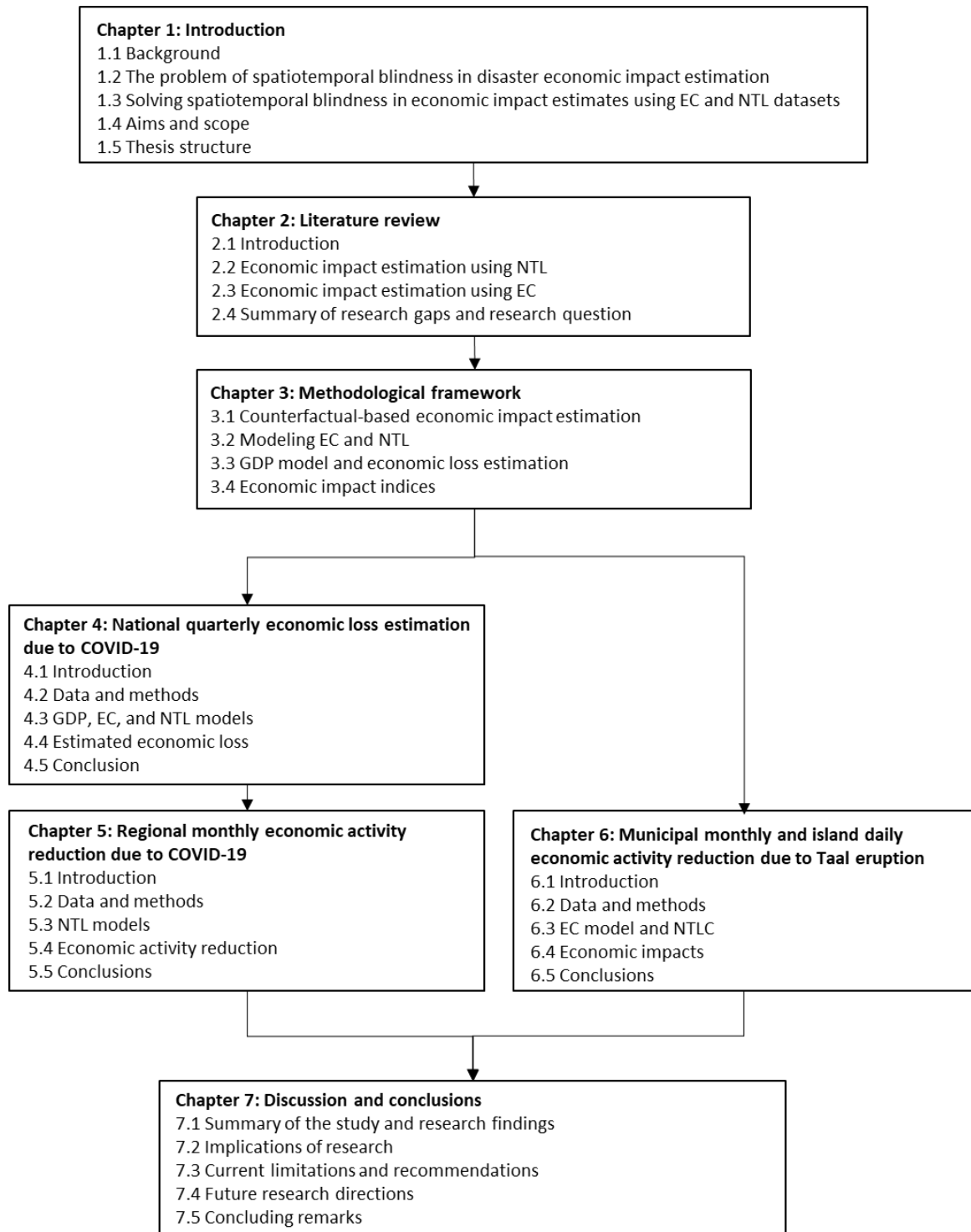


Figure 5. Thesis structure

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Chapter 2

Literature Review

2.1 Introduction

Literature offers a rich collection of studies using NTL and EC datasets separately to estimate economic activities and disaster impacts. This literature review chapter summarizes the current state of research focusing on the use of EC and NTL as alternative economic impact indicators and disaster impact estimators. The second section discusses literature on NTL while the third section focuses on EC. Over the years, numerous studies leveraged the capacity of NTL to spatialize economic data while EC data has also exhibited a strong potential as an economic activity indicator. In each section, the research gaps are identified. The application and methodological gaps are summarized in the fourth section. Based on the methodological gap, the research question is formulated. Addressing this gap opens doors towards expanding the application of EC and NTL for disaster impact estimation.

2.2 Economic impact estimation using NTL

The choice of NTL for disaster economic impact estimation draws from its ability to capture the location of economic activities and the changes in these activities after triggers like disasters. The first half of this section takes note of studies investigating the use of NTL as an economic activity indicator. The second half reviews literature discussing the application of NTL to detect disaster impacts.

2.2.1 NTL and economy

NTL data has been used in a broad range of applications ranging from socioeconomic applications to meteorological and environmental applications (Li, et al., 2017; Miller, et al., 2013). Among its applications, a critical niche is the use of NTL in studying urbanization patterns (Luqman, et al., 2019; Wang, et al., 2017) and mapping economic variables such as GDP (Chen & Nordhaus, 2019; Suarez, 2016; Sutton, et al., 2007; Zhao, et al., 2017), population (Ma, et al., 2022), and energy consumption (Falchetta & Noussan, 2019; Gao, et al., 2022; Letu, et al., 2010; Li, et al., 2019; Shi, et al., 2014; Zhu, et al., 2019).

The earlier papers correlating and regressing NTL with economic variables (Doll, et al., 2000; Henderson, et al., 2012) paved the way for its wider acceptance as a tool for mapping economic activities. Numerous papers supported these earlier findings using

NTL data as a tool for mapping spatial patterns of economic variables (Sutton & Costanza, 2022; Wu, et al., 2013; Addison & Stewart, 2015; Mellander, et al., 2015; Suarez, 2016; Prakash, et al., 2019; Agnihotri & Mishra, 2021; Chen, et al., 2021; Perez-Sindin, et al., 2021).

The number of published articles using NTL for urban studies has grown exponentially in the past decade (Zheng, et al., 2023). Up to 2017, DMSP-OLS dominated the NTL literature but after, Suomi-NPP data took over with the release of VIIRS nighttime light products (Elvidge, et al., 2017) and the generation of annual time series global VIIRS NTL data (Elvidge, et al., 2021). Table 2 lists the datasets used in the papers. The most common economic variables in the papers were GDP, population, and income.

These studies may cover global, multiple countries, a specific country, and parts of a country. Most studies cover the globe (Chen, et al., 2022; Ebener, et al., 2005; Wu, et al., 2013; Henderson, et al., 2012; Suarez, 2016; Gibson & Boe-Gibson, 2021) and multiple countries (Doll, et al., 2000; Ghosh, et al., 2010; Sutton, et al., 2007; Keola, et al., 2015; Addison & Stewart, 2015; Han, et al., 2022). The use of NTL for economic mapping has been frequently done by researchers focusing on the United States (Chen & Nordhaus, 2011; Chen & Nordhaus, 2019) and China (Liu, et al., 2020; Chen, et al., 2021; Wu, et al., 2022; Zhao, et al., 2017). A research gap exists in NTL studies in the Global South which has limited economic data and could benefit from remotely sensed data as was found in an earlier paper (Zheng, et al., 2023).

Most studies were done at the national annual level (Addison & Stewart, 2015; Agnihotri & Mishra, 2021; Chen & Nordhaus, 2011; Ebener, et al., 2005; Henderson, et al., 2012; Keola, et al., 2015; Wu, et al., 2013) and limited papers were done analyzing the sub-annual economic activities at the national scale. A growing number of studies are being done at the sub-national and sub-annual levels (Chen & Nordhaus, 2019; Gibson & Boe-Gibson, 2021; Ivan, et al., 2020; Liu, et al., 2020; Prakash, et al., 2019; Suarez, 2016; Zhao, et al., 2017; Mellander, et al., 2015). Also, there are limited studies conducted at the pixel annual (Chen, et al., 2022; Chen, et al., 2021) and sub-annual (Mellander, et al., 2013). Despite these limitations, NTL can estimate GDP across different coverages and units of analysis.

Table 2. Papers using NTL data to estimate economic variables

Paper	Data
(Doll, et al., 2000)	DMSP, GDP, CO2
(Sutton & Costanza, 2022)	DMSP, GDP
(Ebener, et al., 2005)	DMSP, population,
(Sutton, et al., 2007)	DMSP, GDP, Landsat
(Ghosh, et al., 2010)	DMSP, Landsat population, GDP
(Chen & Nordhaus, 2011)	DMSP
(Henderson, et al., 2012)	DMSP, GDP
(Ghosh, et al., 2013)	DMSP, GDP, population, income
(Wu, et al., 2013)	DMSP
(Addison & Stewart, 2015)	DMSP
(Keola, et al., 2015)	DMSP, GDP, DMSP, Population, income, establishments, employees, wage sum
(Mellander, et al., 2015)	VIIRS, GDP
(Suarez, 2016)	DMSP
(Proville, et al., 2017)	VIIRS, GDP
(Zhao, et al., 2017)	VIIRS, GDP
(Chen & Nordhaus, 2019)	VIIRS
(Falchetta & Noussan, 2019)	DMSP, VIIRS
(Prakash, et al., 2019)	VIIRS, income
(Ivan, et al., 2020)	LJ1-01, VIIRS
(Liu, et al., 2020)	DMSP and VIIRS
(Agnihotri & Mishra, 2021)	VIIRS, GDP, VI, LC, NPP, DEM, Temperature
(Chen, et al., 2021)	VIIRS, GDP, DMSP
(Gibson & Boe-Gibson, 2021)	DMSP, VIIRS, harmonized DMSP/VIIRS, global urban footprint
(Perez-Sindin, et al., 2021)	DMSP and VIIRS
(Chen, et al., 2022)	VIIRS, GDP, road networks, carbon emission
(Han, et al., 2022)	VIIRS, NPP, land cover, subnational GDP
(Pagaduan, 2022)	VIIRS
(Wu, et al., 2022)	

2.2.2 NTL and disasters

A growing body of research has used NTL to document the impacts of natural disasters on detected nighttime light emissions, interpreted as impacts (Schippers & Botzen, 2023). NTL data has become a popular tool for mapping disaster impacts and monitoring recovery due to the difficulty of obtaining socioeconomic data of high spatial resolution capable of reflecting local impacts (Schippers & Botzen, 2023), especially during emergencies when systems cannot operate normally (Qiang, et al., 2020).

Socioeconomic disruption during disasters is often reflected in NTL data as a decline in brightness (Jia, et al., 2023; Qiang, et al., 2020).

This nighttime dimming can be a result of power outages, population movement due to evacuation, reduction in road traffic due to class and work suspension and business closures, change in energy usage patterns, structural damage, and the presence of atmospheric particles or clouds. Cao, et al., (2013) observed nightlight reduction associated with power outages after the Derecho storm in Washington DC and Hurricane Sandy in the United States with the VIIRS DNB data. Their observation agreed with the survey data from power companies showing that NTL can detect power outages due to storms. Power outages are common during disasters due to physical damage to infrastructures such as toppled posts, broken powerlines, and power shutdowns.

Anthropogenic activities have also been found to influence NTL brightness. Hence, a reduction in activities after a disaster event could be reflected as NTL dimming. This was shown in several papers. Zheng, et al., (2019) showed using VIIRS DNB data that NTL is strongly correlated with human population, population density, and GDP and estimated the affected population by Typhoon Maria along the Western Taiwan Straits and the rate of recovery. Another study (Schippers & Botzen, 2023) showed that NTL change is congruent with population and employment change in a disaster-affected area and has a positive relationship with total income and real GDP. During a disaster event, class or work suspensions and business closures are common. This could lead to reduced road traffic at night. Evacuation of the population could also result in a reduction in NTL emissions.

For the above-mentioned reasons, numerous studies have used NTL to measure the immediate impacts of disaster response and monitor recovery after typhoons (Qiang, et al., 2020; Sarkar, 2021; Zheng, et al., 2019), earthquakes (Tveit, et al., 2022), and floods (Skoufias, et al., 2021). Sarkar, (2021) has shown that NTL was able to provide a quick macro-level damage estimate and indicate the location of the heavily affected areas by the Cyclone Amphan in India. In another study, Wang, et al., (2018) showed that NTL can be used to map the extent of impact and monitor recovery by computing the percent NTL change using Hurricane Sandy VIIRS NTL imageries taken before and after and plotting daily NTL. Research (Qiang, et al., 2020; Tveit, et al., 2022) has shown that NTL serves as an important tool for monitoring community resilience after disasters such as hurricanes and earthquakes. Qiang, et al., (2020) used DMSP-OLS NTL data and developed a quantitative framework to monitor the recovery of regions affected by Hurricane Katrina and estimated the disturbance, recovery, and loss as a rate of change before and after the hurricane. Although numerous studies have used NTL for impact

assessment, it has not yet been used to estimate volcanic eruption impacts. Despite its great potential, its application for estimating disaster impacts in developing countries such as the Philippines remains sparse.

Aside from the natural hazards mentioned above, biological hazards such as pandemics caused an exponential rise in NTL use in the past four years. NTL has been used to determine COVID-19 impacts in Canada (Wang, et al., 2022), China (Ghosh, et al., 2020; Lan, et al., 2021; Liu, et al., 2020; Tian, et al., 2021; Yin, et al., 2021; Wu, et al., 2021), Czech Republic (Pavlacka, et al., 2023); Germany (Jechow & Holker, 2020), Greece (Stathakis, et al., 2021), India (Beyer, et al., 2021; Dasgupta, 2022), Malaysia (Anshah, et al., 2022), Morocco (Roberts, 2021), Philippines (Guido, 2022), Saudi Arabia (Alahmadi, et al., 2021; Alahmadi, et al., 2023), Spain (Bustamante-Calabria, et al., 2021), USA (Straka, et al., 2021; Zhang, et al., 2021; Lin & Rybnikova, 2023), Sino-Burma border (Zhao, et al., 2022), and the globe (Rowe, et al., 2022; Xu, et al., 2021).

These studies typically perform pixel-based differencing approach where the changes in the images taken before and after the event were computed (Yin, et al., 2021; Xu, et al., 2021; Tian, et al., 2021; Stathakis, et al., 2021; Sarkar, 2021; Lan, et al., 2021; Jiang, et al., 2023; Beyer, et al., 2021; Alahmadi, et al., 2023), time-series analysis of regional NTL (Skoufias, et al., 2021; Ghosh, et al., 2020), and regression models (Tveit, et al., 2022; Strobl, 2019; Straka, et al., 2021; Roberts, 2020). Due to the prevalent use of change detection technique which used a static pre-disaster value as a baseline, most of the studies are limited to immediate impact assessment leaving a gap for longer-term impact analysis using NTL data.

Some papers commented on the factors affecting the accuracy of this data such as the country's development level (Chen & Nordhaus, 2011; Han, et al., 2022), urban-rural regions (Chen & Nordhaus, 2019), and agricultural components or the economy (Gibson & Boe-Gibson, 2021). While NTL can shed light on the wide-scale local-level distribution of economic impacts from disasters over a long duration, out of the numerous papers, researchers report partial coverage of impacts due to measurement-related factors and source variations. Measurement-related factors include contamination due to clouds and atmospheric particles such as water vapor, aerosol gases, and others (Cao et al., 2013). Cloud cover, in particular, could limit NTL detection, especially for weather-related disasters that are correlated with thick cloud cover (Sarkar, 2021). Monsoon seasons, when cloud-free days tend to be few, could cause a non-disaster-related drop in NTL data (Tveit, et al., 2022). Lunar radiance estimation uncertainty is another measurement-related factor (Cao et al., 2013). These factors could cause noise, seasonal variation, and unstable measurement across time resulting in

temporal inconsistency (Skoufias, et al., 2021). The other problem is the difference in economic activities, specifically those that emit light and those that do not (Strobl, 2019). For example, agricultural activities do not emit light but services and industries do. Hence, the economic activity of regions that depend on agricultural production could not be represented in full by NTL data (Keola et al. 2015; Strobl, 2019). Further, rural areas tend to be undetected in NTL data (Sarkar, 2021). Another factor is the timing of image capture. As NTL data is captured at 1:30 am, only those activities that occur at that time are captured. Hence, daytime economic activity cannot be captured. This could be a limiting factor, especially in capturing the dynamics of human response that may change far quicker than the monthly NTL data could record (Jia, et al., 2023).

These factors lead to specific limitations such as inconsistency in impact measurement as reported by several researchers. NTL captures the overall effect of responses such as population displacement and cannot provide detailed and in-depth interpretations of sectoral distribution of economic impacts (Schippers & Botzen, 2023). Overall, these the limitations point to NTL data being an impure measure of economic activities. Hence, the NTL change detected during a disaster is a result of the combined effect of the disaster and fluctuations due to impurities and time-related factors associated with the data collection (Jia, et al., 2023) indicating the need for pre-processing steps to correct for the impurities and care in interpretation.

2.3 Economic impact estimation using EC

Similar to NTL, EC datasets have shown a strong potential to capture economic activities. The first half of this section discusses studies investigating the relationship between EC and the economy. The second half notes the studies showing the changes in EC after disasters indicating that EC can also be used for disaster impact estimation which has yet to be developed.

2.3.1 EC and economy

Numerous authors have investigated the relationship between EC and the economy. Kraft & Kraft (1978) first explored the relationship between EC and the economy in the United States using data covering 1947-1974. This started a still ongoing debate on whether EC can be an indicator of a nation's economy. On the one hand, researchers contend on the usefulness of EC as an indicator of the US economy based on correlation results, energy-dependent production, and high-frequency and comprehensive data (Arora & Lieskovsky, 2014). On the other hand, other researchers argue that such links may no longer be applicable due to seasonal variation in quarterly

or monthly data, energy conservation efforts, industrial shift to information technology, and energy price fluctuation (Hirsh & Koomey, 2015).

While this contention is held in the case of the United States, numerous studies have also shown a relationship between EC and economic datasets across the world (Table 3). The Kyoto Protocol of 1992 which urged countries to reduce greenhouse gas emissions and conserve energy prompted studies focusing on the impact of energy conservation on economic growth. Hence, the directionality of causation became an important question for researchers. For over four decades, several studies comparing the EC-GDP link across selected countries (Yu & Choi, 1985; Lee, 2006; Topolewski, 2021; Fatai, et al., 2004) or for one country (Arora & Lieskovsky, 2014) with differing results. Most of these studies looked at EC and economic indicators such as GDP, GNP, or income at the national annual scale. The analyses were often performed using the Granger Causality method. The table showed that for most countries, a relationship, implied by causality, between EC and an economic indicator exists. However, the contention remains within the direction of causality.

As can be seen in the table, a country may experience different types of causality across different periods. Previous research showed that a relationship between EC and GDP exists. However, this relationship was established using a dataset from 1950 to 1999. This relationship may have changed and so there is a need to reinvestigate using recent datasets. This table shows that the direction of causality is not static. It would be important to always check the relationship of the two variables and how they are moving as this varies across countries and could influence the transferability of the method.

2.3.2 EC and natural disasters

While the link between EC and GDP has been well studied, the influence of natural disasters on EC has been less tackled in current literature. Literature shows that natural disasters affect EC (Lee, et al., 2021). Lee, et al., (2021) performed empirical analysis on data from 123 countries from 1990-2015 and showed that the effect of natural disasters on EC varies according to country, energy source type, and disaster type. Their research showed that disasters reduce EC, especially in countries with low income, those that use oil, renewable, and nuclear energy, and those that are affected by floods, wildfires, and pandemics. Another research (Doytch & Klein, 2018) studied the short-term and long-term impact of natural disasters on EC and showed that negative impact in the short run and recovery in the long run. Specifically, for developed countries, renewable energy use increased 5 years after the disaster. However, the trend varies across development stages and energy consumers. Another study (Rakshit, 2021) examined the relationship within India and found that the impact varies depending on

flood level emphasizing the lack of impact of low flood magnitude and the significant impact of high flood magnitude.

Table 3. EC and economic indicator causality direction per country across varying study periods

Country	Causality direction	Period	Source
Argentina	EC $\Leftrightarrow$ GDP	1950-1992	(Soytas & Sari, 2003)
Australia	EC $\Leftarrow$ GDP	1960-1999	(Fatai, et al., 2004)
Belgium	EC $\Rightarrow$ GDP	1960-2001	(Lee, 2006)
Canada	$\neq$	1950-1992	(Soytas & Sari, 2003)
	EC $\Rightarrow$ GDP	1965-2001	(Lee, 2006)
France	EC $\Rightarrow$ Income	1950-1992	(Soytas & Sari, 2003)
	EC $\Leftarrow$ GDP	1960-2001	(Lee, 2006)
Germany	EC $\Rightarrow$ Income	1950-1992	(Soytas & Sari, 2003)
	$\neq$	1971-2001	(Lee, 2006)
India	EC $\Leftrightarrow$ GDP	1950-1996	(Paul & Bhattacharya, 2004)
	EC $\Rightarrow$ Income	1960-1999	(Fatai, et al., 2004)
Indonesia	EC $\Rightarrow$ Income	1960-1999	(Fatai, et al., 2004)
Italy	EC $\Leftarrow$ Income	1950-1992	(Soytas & Sari, 2003)
	EC $\Leftarrow$ Income	1960-2001	(Lee, 2006)
Japan	EC $\Rightarrow$ Income	1950-1982	(Erol & Yu, 1987)
	EC $\Rightarrow$ Income	1950-1992	(Soytas & Sari, 2003)
	EC $\Leftarrow$ GDP	1960-2001	(Lee, 2006)
Malawi	EC $\Leftarrow$ Income	1970-1999	(Jumbe, 2004)
Netherlands	EC $\Rightarrow$ GDP	1960-2001	(Lee, 2006)
New Zealand	EC $\Leftarrow$ GDP	1960-1999	(Fatai, et al., 2004)
Philippines	EC $\Rightarrow$ GDP	1950-1976	(Yu & Choi, 1985)
	EC $\Leftrightarrow$ GDP	1960-1999	(Fatai, et al., 2004)
Poland	$\neq$	1950-1976	(Yu & Choi, 1985)
South Korea	EC $\Leftarrow$ GDP	1950-1976	(Yu & Choi, 1985)
	EC $\Leftarrow$ Income	1950-1992	(Soytas & Sari, 2003)
	EC $\Leftrightarrow$ GDP	1970-1999	(Oh & Lee, 2004)
Sweden	$\neq$	1960-2001	(Lee, 2006)
Switzerland	EC $\Rightarrow$ GDP	1960-2001	(Lee, 2006)
Taiwan	EC $\Leftrightarrow$ GDP	1954-1997	(Yang, 2000)
	EC $\Leftarrow$ Income	1955-1993	(Cheng & Lai, 1997)
Thailand	EC $\Leftrightarrow$ GDP	1960-1999	(Fatai, et al., 2004)
Turkey	EC $\Rightarrow$ Income	1950-1992	(Soytas & Sari, 2003)
United Kingdom	$\neq$	1950-1976	(Yu & Choi, 1985)
	$\neq$	1950-1992	(Soytas & Sari, 2003)
United States	EC $\Leftarrow$ Income	1947-1974	(Kraft & Kraft, 1978)
	EC $\Rightarrow$ Income	1948-1994	(Stern, 2000)
	$\neq$	1950-1992	(Soytas & Sari, 2003)
	EC $\Rightarrow$ Income	1973-2000	(Thoma, 2004)
	$\neq$	1950-1976	(Yu & Choi, 1985)
	EC $\Leftrightarrow$ GDP	1960-2001	(Lee, 2006)

The emergence of COVID-19 brought rise to studies investigating the impact of lockdowns on EC in Ontario, Canada (Abu-Rayash & Dincer, 2020), Hunan, China (Ai, et al., 2022), United States (Lou, et al., 2021). Other researchers developed models to estimate COVID-19 impacts across states of India (Beyer, et al., 2021), the entire

country of Italy (Fezzi & Fanghella, 2020), and counties in Eastern China (Wang & Lu, 2021). Contrarily, a dearth of literature (Lee, et al., 2021; Doytch & Klein, 2018; Rakshit, 2021) has been published on the relationship between EC and natural disasters and its use for economic impact estimation.

2.4 Research gaps and questions

Based on this literature review, numerous studies have used NTL and EC to estimate economic activities and disaster impacts. Despite the extensive literature consulted, gaps persist in the areas of the use of these datasets for developing countries. For NTL, no study has been found estimating the impacts of volcanic disasters, especially in the Philippines. For EC, its use for economic impact estimation is still limited to COVID-19. Aside from Beyer, et al., (2021), no other studies have used both EC and NTL together to estimate economic impacts. Moreover, their use for longer-term impact assessments has not been done as most studies focus on immediate impacts. This could be due to a lack of developed methodology for conducting assessments over longer analysis periods.

Overall, the gaps can be summarized into the application and methodological gaps. The literature review revealed the gap in applying EC and NTL to estimate longer-term disaster impacts, especially in the Global South. This gap could be due to the lack of methods. This literature review highlights the need for a method to determine a baseline based on dynamic real-world data for disaster economic impact assessment applicable across multiple scales. This baseline must capture real-world post-disaster dynamic situations to assess long-term impacts. This method must also be flexible across analysis scales for it to be applicable to various types of hazards, considering spatiotemporal blindness.

This thesis then asks the question of how to estimate the economic impacts of disasters based on EC and NTL. The development of this method could open doors toward expanding the application of EC and NTL for disaster impact estimation. Further, the high-frequency and high-resolution of these datasets can be maximized to address the problem of spatiotemporal blindness.

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Methodology Development

3.1 Introduction

This chapter discusses the methodological backbone of this thesis. This method addresses the methodological gap in Chapter 2. Here, a method to estimate economic impacts based on EC and NTL for multi-scale longer-term impact assessment will be proposed. The first section explains the idea of the counterfactual-based economic impact estimation method. The second section explains how this idea operates using EC and NTL datasets. The third section explains economic impact estimation in terms of GDP and using economic impact indices based on EC and NTL.

3.2 Counterfactual-based economic impact estimation

This thesis proposes using the counterfactual to estimate economic impacts of disasters. This section explains the idea of the counterfactual-based economic impact estimation method. Figure 6 illustrates the idea behind this method. In this graph, economic activity (EA) is plotted across time. Economic activity describes the overall transactions contributing to the economy of a region or country. In this thesis, economic activity represents income-generating operations whose behavior can be captured through common indicators such as GDP or alternative indicators like EC or NTL. As depicted, EA follows a predictable pattern across time until a disaster occurs which disrupts this normal pattern often resulting in EA reduction and eventual recovery.

Estimating the effect of the disaster on EA requires a baseline from which the actual EA can be compared. The baseline can be a pre-disaster value as in the case of change detection methods. Using the pre-disaster value assigns a static baseline which may lead to underestimation of the impacts in the long run. The baseline can also be a predicted value or the counterfactual. In this case, the counterfactual value is the EA had there been no disaster. This research opted to predict the counterfactual to account for the real-world post-disaster dynamic situations which is more appropriate for longer-term impact estimation.

Various counterfactual estimation methods have been developed including Time Series Analysis, Difference in Difference (DiD), Synthetic Control Method (SCM), and Regression models. This research chose to use regression models not only to capture

real-world situations but also to avoid the need for a control group that is needed for other methods such as DiD or SCM. For large-scale hazards like COVID-19, the control group can be difficult to find as almost all parts of the world are affected. Instead of a control group, regression models require explanatory variables. These variables can be selected based on real-world data to capture actual situations. However, these variables must be unaffected by the disaster to estimate the counterfactual.

In this thesis, counterfactual estimation requires a set of pre-disaster data. This pre-disaster data establishes the relationship of the explanatory variable with EA_t . Using a regression model, the pre-disaster EA can be represented through Equation 1. In this equation, EA at time t , EA_t is estimated based on an explanatory variable x_t . The coefficient β measures the relationship of x_t with EA_t , β_0 represents the intercept, and ϵ refers to the error term. β_0 and β are estimated parameters. This equation represents the behavior of EA without a disaster through the estimated parameters β_0 and β .

$$EA_t = \beta_0 + \beta x_t + \epsilon$$

Equation 1

Without a disaster, EA would continue its normal pre-disaster EA path. Hence, the counterfactual can be represented by a line extending out from the pre-disaster EA (Figure 6). This line would have the same values for the slope and intercept as the pre-disaster EA model but possessing post-disaster explanatory variable values. In other words, the counterfactual EA cEA_t can be estimated by multiplying the post-disaster explanatory variable x_t by the estimator $\hat{\beta}$ and adding the intercept $\hat{\beta}_0$, as shown in Equation 2. As cEA_t estimates the EA without a disaster, the value of the parameters $\hat{\beta}_0$ and $\hat{\beta}$ are computed using data representing a situation without the disaster which is the state before the disaster estimated in Equation 1. The values of $\hat{\beta}_0$ and $\hat{\beta}$ are similar to the intercept and coefficient estimated using the pre-disaster EA. The addition of the hat in $\hat{\beta}_0$ and $\hat{\beta}$ indicates that these parameters are previously-estimated. Having the $\hat{\beta}_0$, $\hat{\beta}$, and x_t identified, the value of cEA_t can then be estimated.

$$cEA_t = \hat{\beta}_0 + \hat{\beta} x_t$$

Equation 2

Once the cEA_t is known, the economic impact in terms of EA EA_{loss_t} can be estimated by subtracting the actual post-disaster EA aEA_t from the cEA_t (Equation 3).

$$EA\ loss_t = cEA_t - aEA_t$$

Equation 3

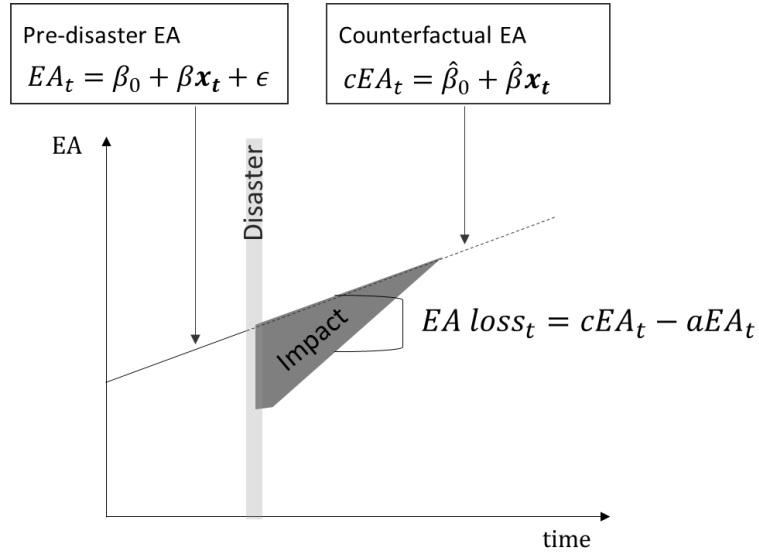


Figure 6. Counterfactual-based economic impact estimation.

3.3 EC and NTL modeling for counterfactual estimation

Following the idea explained in the previous section, this section discusses the modeling and counterfactual estimation process using national quarterly EC and NTL datasets. These datasets went through the pre-processing steps discussed in Section 3.3.6. Literature has established EC and NTL as suitable economic activity indicators. Actual data used in this thesis corroborate the findings of previous literature.

3.3.1 EC and NTL as economic activity indicators

The national quarterly NTL and GDP datasets were correlated to test their relationship in the Philippines. A strong relationship ($R^2 = 0.72$) was observed in the national quarterly GDP and NTL data (Figure 7). The time series plot of NTL and GDP shows that while the two moves closely and that NTL captures GDP peaks during the second quarter (Figure 8), there are points when NTL behaved disproportionately with GDP as in the third quarter of 2012 and 2013. Another irregularity in the data was also observed in the second quarter of 2020 when the GDP plunged but the NTL data showed some delay.

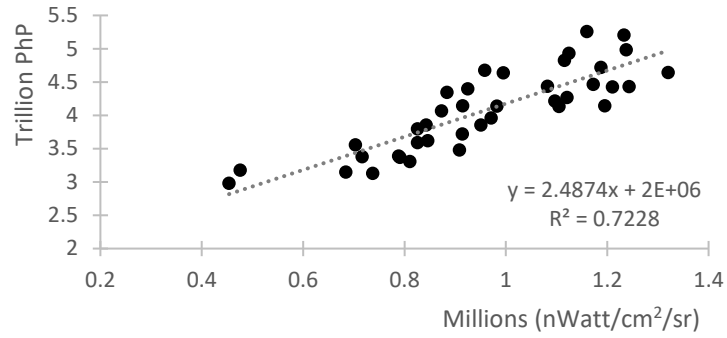


Figure 7. Relationship of GDP vs. NTL

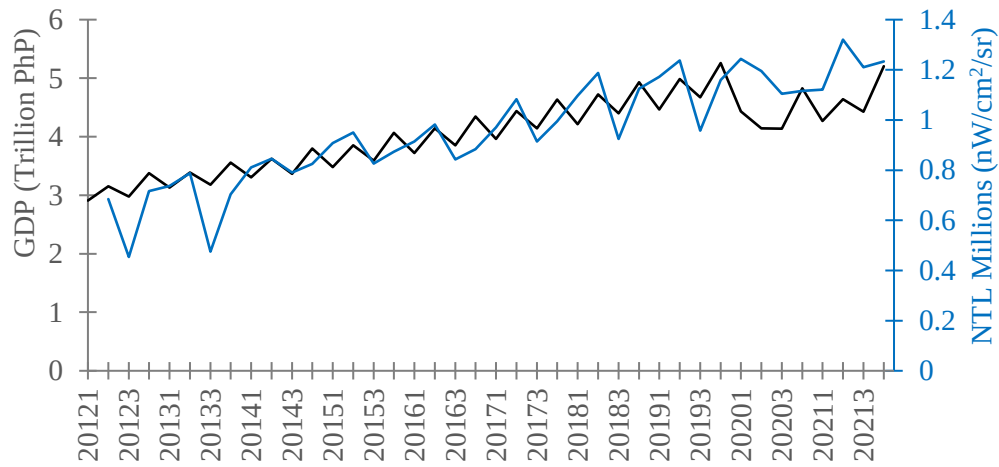


Figure 8. Time series data of GDP and NTL

Based on the national quarterly data, EC also has a strong relationship with GDP ($R^2=0.84$) (Figure 9). EC exhibited a closer relationship with GDP than NTL. The time series plot (Figure 10) showed a difference in temporal peaks between EC and GDP.

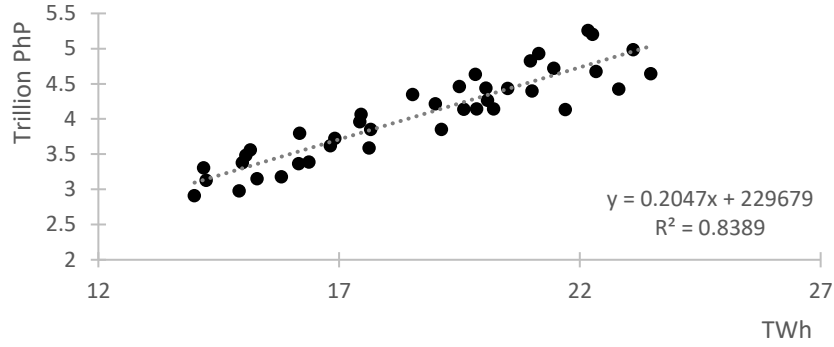


Figure 9. Correlation of EC and GDP

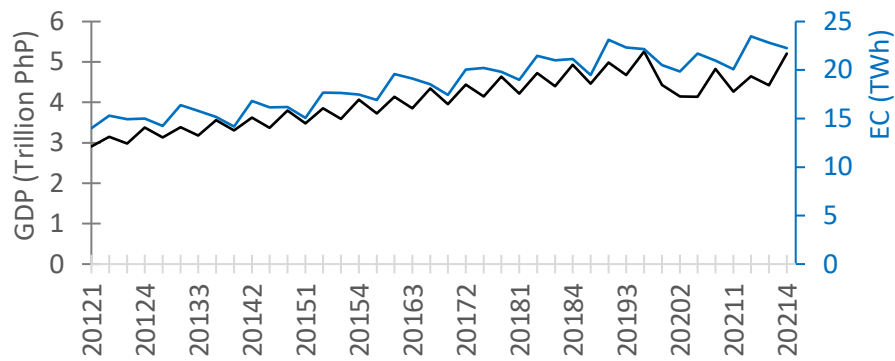


Figure 10. Time series data of GDP and EC

The regression analysis using actual data which will be reported in Chapter 4 further confirmed that EC and NTL are suitable proxies of GDP. On this basis, EC and NTL can be used as economic activity indicators. Thus, economic impacts can be estimated by substituting EA with EC and NTL datasets.

3.3.2 EC and NTL modeling

As indicators of economic activity, models representing EC and NTL before the disaster must be generated. The first step is to divide the data into the pre- and post-disaster data subsets (Figure 11). Using the pre-disaster data subset, generate the pre-disaster EC model.

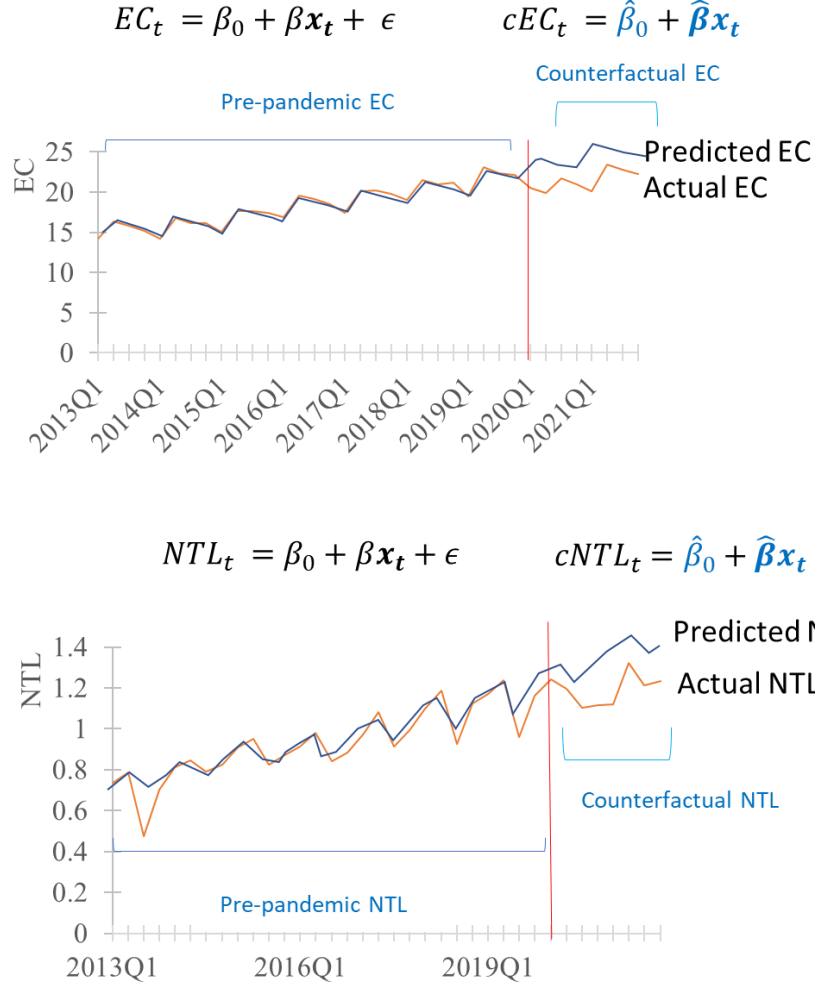


Figure 11. National quarterly EC and NTL

The pre-disaster model (Equation 4) estimates EC based on a set of explanatory variables x_t (Section 3.3.4). The natural logarithm of EC ($\ln EC_t$) to normalize the data distribution and for ease of interpretation. To this model, the $trend_t$ component was added to capture the increase in EC across years. Further, q_t or the quarter dummy variables were added to adjust for the seasonality. β_0 , β , γ , and δ are estimated parameters and ϵ represents the error.

$$\ln EC_t = \beta_0 + \beta x_t + \gamma trend_t + \delta q_t + \epsilon_t$$

Equation 4

Similarly, a pre-disaster NTL model was generated as shown in Equation 5

$$\ln NTL_t = \beta_0 + \beta x_t + \gamma trend_t + \delta q_t + \epsilon_t$$

Equation 5

Other dummy variables may be added to the models to adjust for the analysis scales. For example, using the method for regional monthly scale may use the regional dummy variables as in Chapter 5. Other categorical variables can be represented by dummy variables to improve the models. For example, the day-of-the-week dummy variables or holiday dummy variables may be included to better capture the behavior of EC as shown in Chapter 6. Week of the year fixed effects can also be added to reflect the effect of seasonal occasions on EC as in Chapter 6.

3.3.3 Estimating the counterfactual

Equation 6 represents the counterfactual EC model. In this model, the values of $\hat{\beta}_0$, $\hat{\beta}$, $\hat{\gamma}$, and $\hat{\delta}$ no longer need to be computed as they are the previously estimated values of β_0 , β , γ , and δ in Equation 4. These parameters measure the relationship of the explanatory variable with EC before the disaster. Their values would be the same for the counterfactual which represents the EC had there been no disaster. Having known the values of the estimators $\hat{\beta}_0$, $\hat{\beta}$, $\hat{\gamma}$, and $\hat{\delta}$, the counterfactual EC cEC can be computed by plugging in the post-disaster values of the independent variables.

$$\ln cEC_t = \hat{\beta}_0 + \hat{\beta} x_t + \hat{\gamma} trend_t + \hat{\delta} q_t$$

Equation 6

The same process applies for NTL. The counterfactual NTL $cNTL$ can then be computed using Equation 7. The values of $\hat{\beta}_0$, $\hat{\beta}$, $\hat{\gamma}$, and $\hat{\delta}$ were obtained in Equation 5.

$$\ln cNTL_t = \hat{\beta}_0 + \hat{\beta} x_t + \hat{\gamma} trend_t + \hat{\delta} q_t$$

Equation 7

3.3.4 Explanatory variables

This subsection explains the conditions for choosing the explanatory variables. Further, this identifies which variables are suitable for the EC and NTL models.

There are two conditions in choosing appropriate explanatory variables for EC and NTL in this counterfactual-based approach. The first condition is that they should show evidence of a relationship with EC and NTL before the disaster. They must capture the behavior of EC and NTL in some way. The second condition is that they should not be significantly affected by the disaster. If not, the variable would cause the

counterfactual to behave unpredictably which may lead to over or underestimation of the impact.

The selection of x_t was based on literature and experimentation. Bueno, et al., (2020) examined the explanatory variables that could influence the electricity demand. These variables include price, income, hours of sun, temperature, age, employment rate, foreigners, single-parent households, and trends. Another study conducted in India estimated EC based on maximum and minimum temperature (Beyer, et al., 2021). In their model, they added Day of the Week fixed effects and Week of the Year Fixed effects, trend, and Holiday dummy variables. Their model can explain 89.7 % of the pre-pandemic energy consumption in India.

In the Philippines, studies have shown that temperature is a major factor influencing residential energy consumption (Dacuycuy, 2019; Santos, 2020; Bayudan-Dacuycuy, 2017). According to HECS 2004, 56% of household consumption in the country was spent on space cooling and refrigeration which are related to temperature. In the case of NTL, land surface temperature was found to have a strong relationship with NTL (Li, et al., 2019; Li, et al., 2022).

This thesis investigated several explanatory variables including weather-related to capture the dynamic fluctuations in EC and NTL. Additionally, socioeconomic variables were also used to capture the less dynamic but operation-related factors influencing energy use and NTL emission.

3.3.5 Data inputs

The final choice of explanatory variables then depends on the analysis scale and data availability. Table 4 lists the set of explanatory variables used in this research. For the national quarterly scale, maximum temperature, average temperature, humidity and heat index can capture the changes in energy use for temperature regulation. The working age population, population, urban population, and working days were included to capture the operation and socioeconomic condition. Not all of these datasets were available for the regional monthly so satellite datasets related to weather and land cover were used. For the regional monthly analysis, mean temperature, maximum rainfall, and built-up area were used. For the grid daily, mean temperature was used.

For the national quarterly scale, Chapter 4 used the number of working days per quarter, working age population, population, urban population, average temperature, maximum temperature, heat index, and humidity. For the regional monthly scale,

Chapter 5 used mean temperature, maximum rainfall, and built-up area. For the daily grid scale, Chapter 6 used daily mean temperature.

Analysis scale	Data	Data scale	Source
National quarterly	GDP	National quarterly	PSA
	EC	National monthly	DOE
	NTL	~500 m monthly	SNPP VIIRS DNB
	Maximum temperature	Daily average per monitoring station	PAGASA
	Average temperature		
	Humidity	Computed	PSA
	Heat index		
	Working age population	National annual	Macrotrends
	Population		
	Urban population	National monthly	Official Gazette
	Working days		
Regional monthly	NTL	~500 m monthly	SNPP VIIRS DNB
	Mean temp	~1000 m daily	MOD11A1 V6.1
	Max rainfall	5566 m daily	Climate Hazard Center
	Built-up area	500 m annual	MODIS
Daily grid	EC	Hourly grid	NGCP
	Mean temp	Daily monitoring station	PAGASA

a. GDP

GDP data is available at various scales but is most commonly available at the national quarterly scale. In the Philippines, GDP data is available for provincial up to national level with quarterly and annual intervals (Table 5). GDP data is available from the Philippine Statistics Authority (Philippine Statistics Authority, 2024; PSA, 2024).

Table 5. Spatiotemporal scale covered by the GDP data

Spatial scale	Annual	Quarterly
National	2000-2024s	2000-2024s
Regional	2000-2023s	
Provincial	2018-2022s	

Note: s refers to the data with sectoral categories. In the case of GDP data, the sectoral GVAs are available.

b. EC

In the Philippines, EC data is available from three different sources: The Department of Energy (DOE), the Energy Regulatory Commission (ERC), and the National Grid Corporation of the Philippines (NGCP). Each source covers different spatial and temporal scales and coverages (Table 6). Each of the datasets covers a different period. Data from DOE and ERC has sectoral components whereas NGCP data is all-inclusive. Compared with GDP data, EC data has shorter temporal intervals and in the case of ERC data, has finer administrative scale. However, the distribution utility (DU) boundary does not necessarily correspond to any administrative boundary making it difficult to use for administrative purposes. Even though the ERC data has a finer administrative level, this data has a lot of missing data presenting challenges in analysis. Hence, it was decided not to use this data. Hence, DOE was the more comprehensive data. Among the three sources, DOE covered the longest period. Among the three sources, NGCP has the finest temporal interval covering the hourly level.

Table 6. Spatiotemporal scale covered by the EC data

	Hourly	Daily	Monthly	Yearly
DOE				
National			2008-2021s	2003-2022s
Island			2008-2021s	2003-2022s
Regional				2010-2020
DU				
ERC				
National			2013-2021s	2013-2021s
Island			2013-2021s	2013-2021s
Regional			2013-2021s	2013-2021s
DU			2013-2021s	2013-2021s
NGCP				
National	2013-2023	2013-2023	2013-2023	2013-2023
Island	2013-2023	2013-2023	2013-2023	2013-2023
Regional			2013-2023	
DU				

Note: s indicates the data with sectoral categories

c. NTL

For this thesis, the Suomi NPP VIIRS's monthly and annual nighttime light data from the Day and Night Band sensor was obtained from the Earth Observation Group of Payne Institute for Public Policy, Colorado School of Mines (Earth Observation Group, 2021; Elvidge, et al., 2013). This was preprocessed to remove extraneous luminosity (Elvidge, et al., 2017) and composited into monthly and annual data (Elvidge, et al., 2021). While the daily data is available, cloud cover could be rampant in this data. Using the monthly composites could address the fluctuations due to cloud cover.

One issue of NTL data is the noise and cloud. The data is useless for cloudy nights as the cloud covers the ground and the nighttime light emissions cannot be observed from the satellite. Hence, NTL was further pre-processed to correct noise and clouds (see Section 3.3.6). After such corrections, the nighttime light can be better observed (Figure 12).

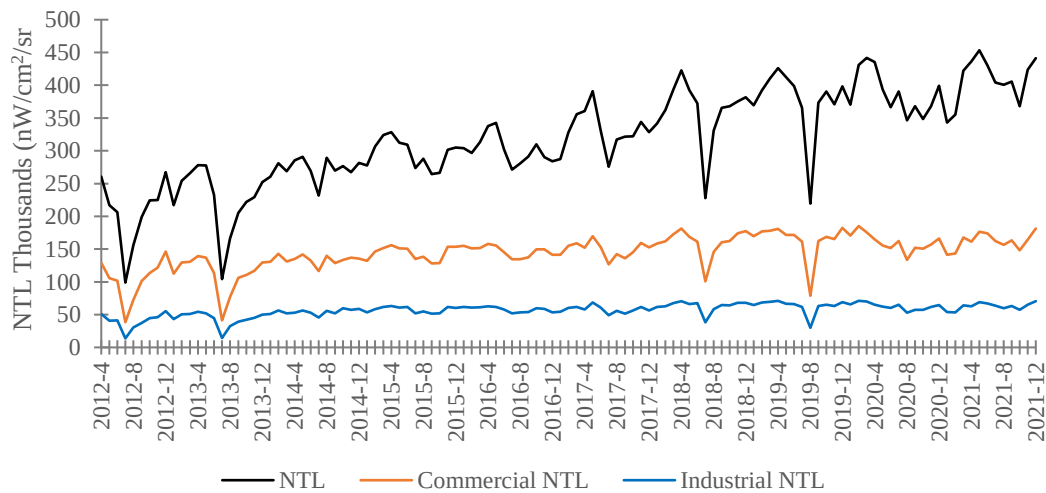


Figure 12. Pre-processed national monthly NTL (Earth Observation Group, 2021)

Figure 13 shows a typical NTL emission in the Philippines. This NTL map was from the November 2019 data. The map shows that the brightest NTL was detected in

NCR and its surrounding regions of CALABARZON and Central Luzon, similar to GDP. Aside from these regions, NTL tends to be brighter in urban centers.

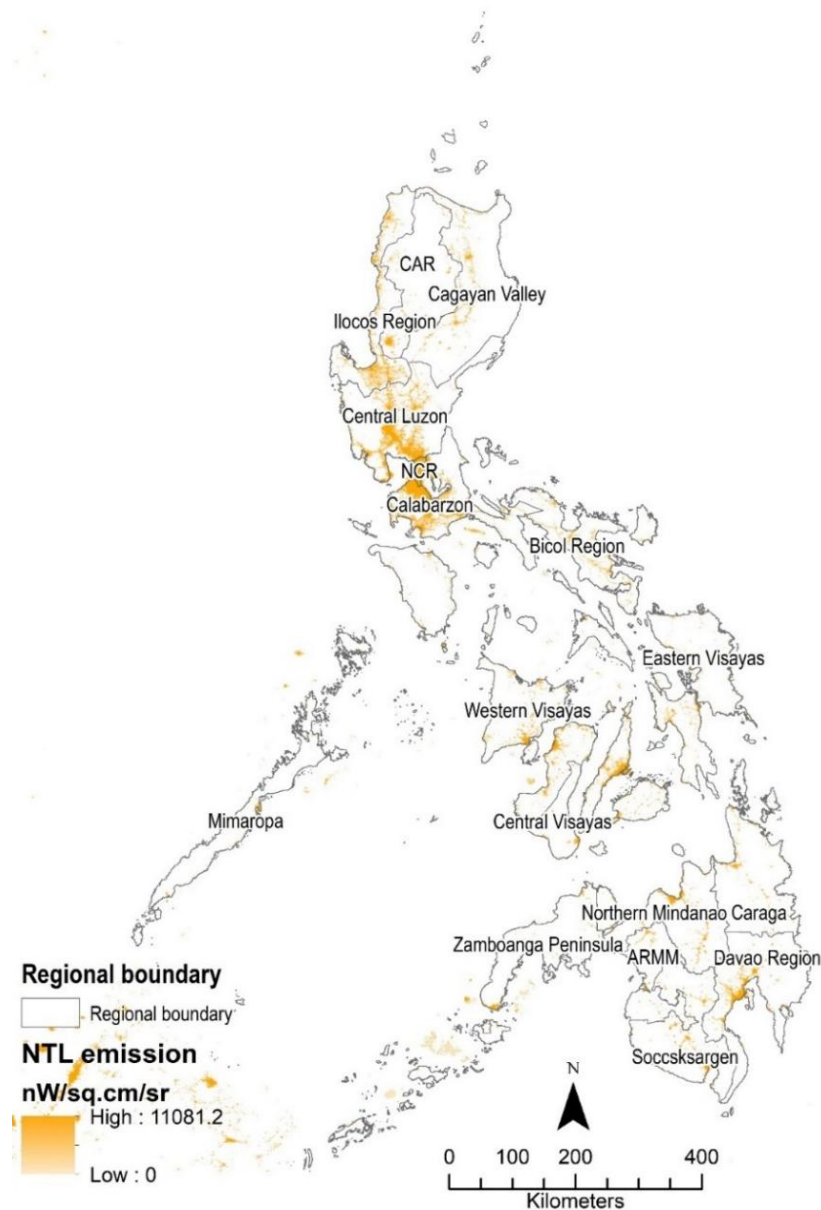


Figure 13. NTL emissions from VIIRS-DNB band (Sample from November 2019).

3.3.6 Data pre-processing

a. NTL

The monthly and annual NTL composites from Earth Observation Group have already been pre-processed. However, upon examination, it was observed that some

pixel values or Digital Numbers DN were negative. In theory, NTL's DN values should start from zero, signifying the absence of light. However, negative values could be due to background noise (Liu, et al., 2020). These negative values had to be removed as these could falsely reduce the sum of lights. The negative values were eliminated by replacing the negative monthly radiance values with the DN from the previous year DN_{t-12} , as in (Equation 8) (Del Castillo, et al., 2024).

$$DN_t = \begin{cases} < 0, & DN_{t-12} \\ \geq 0, & DN_t \end{cases}$$

Equation 8

Extraneous light was eliminated because the main aim was to measure anthropogenic light related to economic activities. To do this, the stable light mask lit_mask was used to mask the background noise from the monthly radiance band. The stable light mask is a binary data where areas with stable light have a DN value of 1 and the areas with unstable light have a DN value of 0. Unstable light was removed by multiplying the stable light mask with the positive DN values pDN , leaving only areas with stable light sDN , as in Equation 9 (Del Castillo, et al., 2024).

$$sDN_t = dn_t * lit_mask_t$$

Equation 9

As the study site is a tropical country where cloud cover can often contaminate nighttime light images, the effect of clouds had to be minimized to avoid errors resulting from undetected nighttime light emission due to clouds. Hence, cloud-contaminated pixels were identified using the cloud-free coverage band cf_cvg band which contains the number of cloud-free data collected within the month. Then, the cloud-covered pixels (pixels with 0 cf_cvg values) were replaced with the pixel value of the previous year sDN_{t-12} , as shown in Equation 10. Although complete cloud removal is impossible, especially during rainy months, this step minimizes the undetected light due to cloud cover (Del Castillo, et al., 2024).

$$cf_cvg = \begin{cases} 0, & sDN_{t-12} \\ > 0, & sDN \end{cases}$$

Equation 10

b. Scaling

The datasets need to be aggregated to the desired spatiotemporal scale to be consistent with other datasets. Table 7 summarizes the data aggregation across spatial

and temporal scales. E stands for the economic activity indicator value. The aggregation can be done by summing up the data of the smaller scales.

Table 7. Data scale aggregation

	Hourly (h)	Daily (d)	Monthly (m)	Quarterly (q)	Annually (y)
Regional (r)			$E_{rm} = \sum E_{rd}$	$E_{rq} = \sum E_{rm}$	$E_{ry} = \sum E_{rq}$
Grid (g)		$E_{gd} = \sum E_{gh}$	$E_{gm} = \sum E_{gd}$	$E_{gq} = \sum E_{gm}$	$E_{gy} = \sum E_{gq}$
National (n)	$E_{nh} = \sum E_{gh}$	$E_{nd} = \sum E_{nh}$	$E_{nm} = \sum E_{nd}$	$E_{nq} = \sum E_{nm}$	$E_{ny} = \sum E_{nq}$

3.4 Economic impact estimation

In this thesis, economic impacts were estimated as losses and as indices. The losses were estimated based on GDP data as GDP loss (GDPL). Due to the limited spatial and temporal resolution of GDP data, the spatiotemporal distribution of impacts could not be estimated in great detail. GDP data are usually available only at the national quarterly and regional annual scales. In the absence of high-resolution high-frequency GDP data, alternative datasets have to be used to determine the spatiotemporal distribution of impacts. As shown in the literature review and experimental results, indicators of economic activity such as higher spatial resolution NTL and high-frequency EC data make good indicators of economic activity. To estimate the economic impacts based on these indicators, economic impact indices were estimated based on EC as EC loss (ECL) and NTL as Economic Activity Reduction (EAR), and NTL change (NTLC) was computed.

3.4.1 GDP loss

One way of estimating the impacts using the counterfactual approach is by computing the GDP loss. Following the same idea of the counterfactual-based economic impact estimation (Figure 14), pre- and post-disaster datasets are separated. Using the pre-disaster data subset, a pre-disaster GDP model is generated. In this model, GDP is estimated based on EC and NTL which were established as economic activity indicators (Equation 11). The $trend_t$ was added to capture the increase in GDP across time and the q_t quarter dummy variables to adjust for the seasonality.

$$\ln GDP = \beta_0 + \beta_1 \ln EC + \beta_2 \ln NTL + \gamma trend_t + \delta q_t + \epsilon$$

Equation 11

In this equation, the natural logarithm of GDP $\ln GDP$ was regressed on the natural logarithm of EC $\ln EC$ and NTL $\ln NTL$. This model estimates the parameters β_0 , β_1 ,

β_2 , γ , and δ , and reports the error ϵ . Using the estimated parameters from Equation 11 and the computed natural logarithm of counterfactual EC $\ln cEC$ and $\ln cNTL$ from Equation 6 and Equation 7, the natural logarithm of the counterfactual GDP $\ln cGDP$ can be estimated (Equation 12).

$$\ln cGDP = \hat{\beta}_0 + \hat{\beta}_1 \ln cEC + \hat{\beta}_2 \ln cNTL + \hat{\gamma} trend_t + \hat{\delta} q_t$$

Equation 12

where $\ln cGDP$ is the natural logarithm of the counterfactual GDP, $\ln cEC$ is the natural logarithm of counterfactual EC and $\ln cNTL$ is the natural logarithm of counterfactual NTL. $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\gamma}$, and $\hat{\delta}$ were estimated using the pre-disaster data in Equation 11.

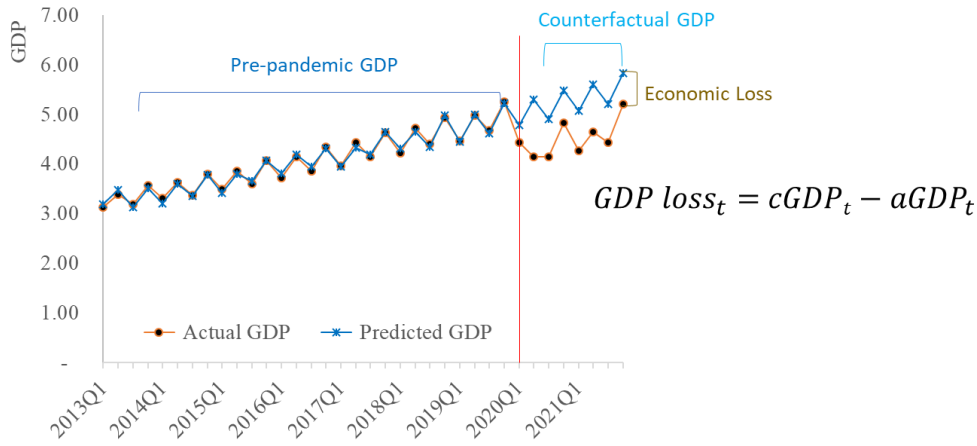


Figure 14. GDP loss estimation

The economic loss in terms of GDP is computed as the difference between the counterfactual and actual GDP (Equation 13) where $cGDP_t$ is the counterfactual GDP and $aGDP_t$ is the actual GDP. This allows the computation of losses at any point in time.

$$GDPL_t = cGDP_t - aGDP_t$$

Equation 13

3.4.2 Economic impact indices

As GDP data is limited to national or regional scales and annual or quarterly intervals, its proxies, EC and NTL can be used to refine the analysis scales taking advantage of their frequency and resolution. This sub-section introduces three indices used in this research to estimate the economic impacts and to reveal how those impacts are distributed across space and time.

a. Economic Activity Reduction (EAR)

EAR is a unitless index indicating a ratio of the difference between the actual and counterfactual over the counterfactual. EAR was estimated based on the counterfactual and actual NTL values (Equation 14). This index measures the proportion of the change over the supposed level of NTL. This index would yield a value ranging from -1 to 1 with -1 indicating a hundred percent of economic activity gain and 1 indicating the opposite. Negative values represent an increase in economic activity and positive values, a decrease in economic activity. This index was used to analyze the spatiotemporal distribution of COVID-19 impacts in Chapter 5.

$$EAR_r = \left(\frac{\ln cNTL_r - \ln NTL_r}{\ln cNTL_r} \right) \quad \text{Equation 14}$$

Here, $\ln NTL_r$ refers to the natural logarithm of NTL in region r and $\ln cNTL_r$ refers to the natural logarithm of the counterfactual NTL in region r . EAR_r computes the ratio of the loss over the counterfactual.

b. Electricity Consumption Loss (ECL)

Electricity consumption loss measures the loss in economic activity as measured through EC. ECL is the difference between the actual EC aEC_d and the counterfactual EC cEC_d . Equation 15 provides the economic impact in terms of ECL per day d .

$$ECL_d = cEC_d - aEC_d \quad \text{Equation 15}$$

A positive ECL_d indicates economic activity loss, measured using EC as an indicator of GDP. Negative EC indicates otherwise. This index was used to analyze the daily grid impacts of the Taal Volcano eruption in Chapter 6.

c. Nighttime light change (NTLC)

NTLC is a measure of economic activity change based on NTL as an indicator of NTL. In NTLC, the baseline is a pre-disaster value $averageNTL_{pre}$ (Equation 16). NTLC yields positive and negative values. Positive values indicate economic activity gain while negative values indicate economic activity reduction. This index was used to map out the pixel-level impacts of the Taal Volcano eruption in Chapter 6.

$$NTLC = NTL_{post} - averageNTL_{pre} \quad \text{Equation 16}$$

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National Quarterly COVID-19 Economic Loss Estimation

4.1 Introduction

Numerous studies have estimated the economic impacts of COVID-19 in the Philippines. One study applied the persistent inoperability input-output method and identified the worst-hit sectors (Yu, et al. 2020). Others developed compartmentalized dynamic transmission models to estimate the economic and health trade-offs under various scenarios in selected regions (de Lara-Tuprio, et al., 2022). However, most of these studies focused only on the immediate impacts and did not show the progression of the impacts across time. Hence, impact progression as a result of case surges and policy adjustments remains unknown.

To show the progression of impacts across time, other researchers used high-frequency datasets for near-real-time impact estimation. Carvalho, et al., (2021) analyzed COVID-19's regional economic impacts in Portugal using electronic payment data. Fezzi and Fanghella (2020) estimated Italy's immediate daily economic impacts with electricity consumption data. Yang, et al., (2022) assessed losses and recovery rates during China's initial lockdown using daily mobility data. However, most of these studies focused only on the lockdown duration even though the pandemic persisted together with the impacts.

High-frequency economic impacts could guide decision-makers to dynamically adapt to the rapid evolution of the disease. Researchers stated that governments should have a capacity to dynamically adapt to a variety of events for prolonged periods (Mazzucato, et al., 2021). With the economic impacts predicted to last beyond this current generation (Jorda, et al., 2020), continued monitoring of these impacts would be crucial to facilitating the recovery of the most affected sectors (McKibbin & Fernando, 2023). Continued monitoring ensures that governments can dynamically adjust measures and that this capacity can be sustained through the duration of the pandemic.

EC and NTL would be appropriate datasets for this task because they have high frequency and cover long periods. If NTL and EC can explain GDP, then, these datasets can be used to estimate the counterfactual GDP dynamically. Deducting the actual GDP from this counterfactual GDP can then give the economic loss estimate. Given that the

highest-frequency GDP data available is at the national quarterly, economic losses were estimated at this scale.

Hence, this chapter estimated the national quarterly economic losses due to the COVID-19 pandemic from 2020 to 2021. This chapter estimated the long-term distribution of the economic losses due to the pandemic across time and sectors in the Philippines using EC and NTL. Employing this approach, this study aims to address the following research questions: how much was the total, commercial, and industrial economic loss due to COVID-19 in the Philippines and how were these losses distributed across time?

4.2 Data inputs

The economic losses due to COVID-19 in the Philippines were assessed using GDP, EC, and NTL data (Figure 15). Aside from these three datasets, statistical and weather datasets were also employed in model development. The datasets were divided into pre-pandemic (2013-2019) and pandemic (2020-2021) period subsets. The pre-pandemic subset was used to establish the relationship between GDP, EC, and NTL. Further, this subset was also used to develop EC and NTL models that estimate the pre-pandemic values based on statistical and weather datasets. The pandemic period subset was used to estimate the counterfactual EC, NTL, and GDP.

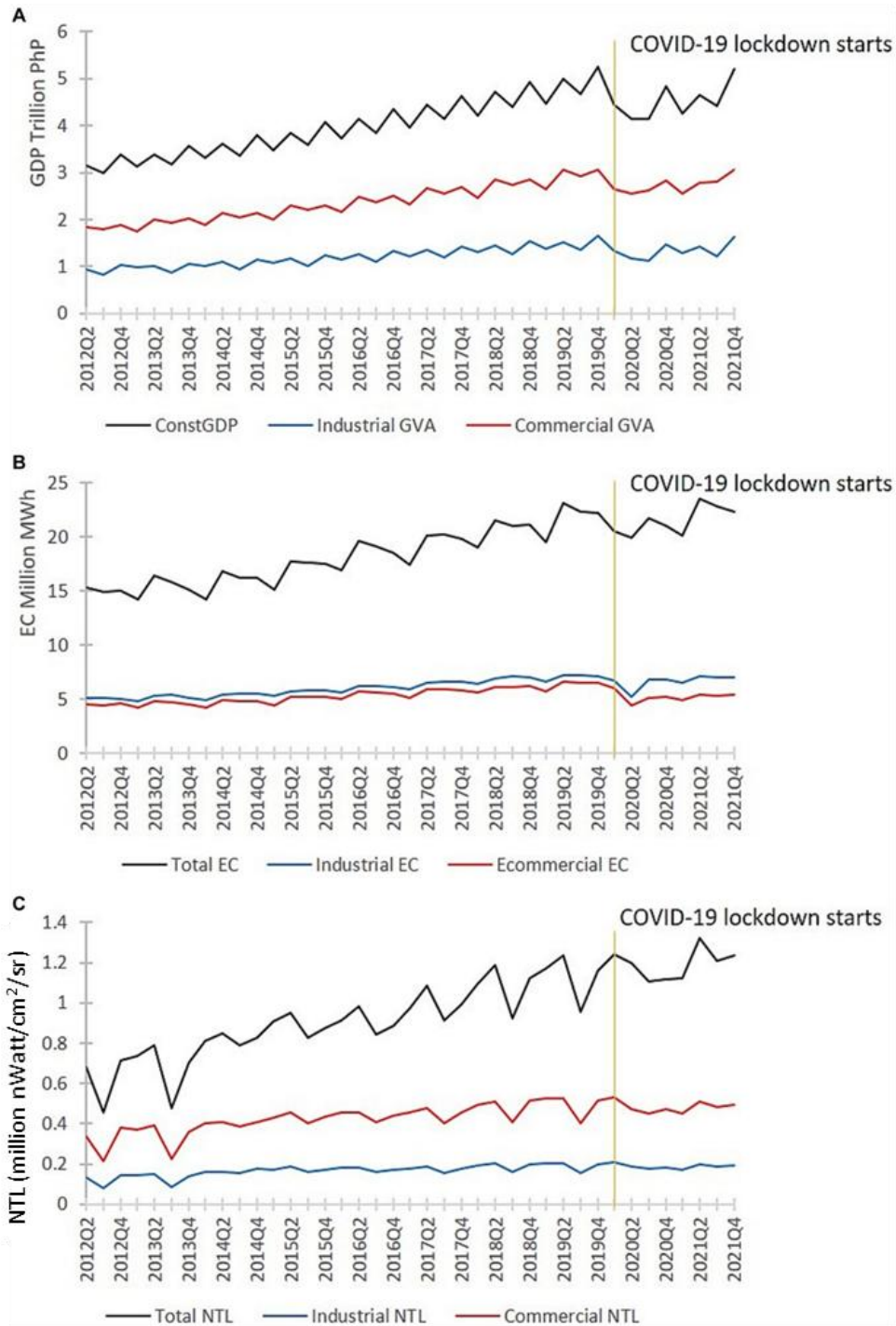


Figure 15. National quarterly GDP, EC, and NTL data (Del Castillo, et al., 2024)

4.2.1 GDP

National quarterly constant GDP based on 2018 prices sourced from the Philippine Statistics Authority (PSA) was used for modeling. Additionally, commercial and industrial gross value-added (GVA) datasets were used to assess sectoral impacts. The commercial sector, encompassing businesses involved in the transportation and

distribution of goods and services as per PSA's classification, contributes roughly 60% to the country's economy. Meanwhile, industries encompassing resource extraction, manufacturing, construction, energy, water, and waste management constitute approximately 30% of the country's GDP. Commercial and Industrial GVAs also follow this increasing trend, with the highest GVAs during the second and fourth quarters annually.

4.2.2 EC

The national monthly EC (EC_m) data were sourced from the Department of Energy and downloaded through the Freedom of Information website. These data are categorized into commercial, industrial, residential, and other sectors (Figure 15). For this analysis, the total EC data including all categories mentioned above were used. This study also used commercial and industrial EC data. These EC data generally exhibit an ascending trend, with annual peaks in the second quarter, corresponding to the year's hottest months (Figure 15). To match the scale of GDP and GVAs, EC_m was aggregated to EC_q (Equation 17, Equation 18, Equation 19).

$$ECt_q = \sum_{m=1}^3 ECt_m \quad \text{Equation 17}$$

$$ECc_q = \sum_{m=1}^3 ECc_m \quad \text{Equation 18}$$

$$ECi_q = \sum_{m=1}^3 ECi_m \quad \text{Equation 19}$$

4.2.3 NTL

This section explains the process of NTL source attribution performed in the study of Del Castillo, et al., (2024). This study attributed the NTL source to commercial and industrial sectors for analysis using OpenStreetMap data which can provide a nationwide land use map with industrial and commercial classifications (Del Castillo, et al., 2024). This dataset is a product of voluntary contributions and has been used for various applications (Herfort, et al. 2023). In the Philippines, OSM data's completeness ranges from 20% to over 80%, exceeding 80% for major cities (Herfort, et al. 2023). This study considered this OSM data the best alternative as it adequately indicates the general location of commercial and industrial sources of NTL.

The downloaded OSM shapefiles were visually examined. This visual examination determined that the data were reasonably complete and accurate. Since the data would be used to specify commercial and industrial NTL emissions in the country, its quality was satisfactory. NTL data has a ~500-meter resolution, so each cell may include mixed land uses (Del Castillo, et al., 2024). Determining the exact light source within a 500×500 -meter area is impossible, so an indicative presence of commercial or industrial establishments suffices (Del Castillo, et al., 2024).

All commercial and industrial points and polygons were extracted, with polygons converted to points for consistency. A 500-meter grid, aligned with NTL resolution, was created separately for commercial and industrial sectors. Using spatial join, commercial points were merged with commercial grids, and cells containing at least one commercial point were classified as commercial. These were then dissolved into a polygon file to outline commercial areas, which was used to extract commercial NTL sources. The same process was applied to industrial NTL. Since NTL radiance comes from mixed sources, distinguishing pure sources was not possible, so results should be considered reasonable estimates (Del Castillo, et al., 2024). Pre-processing steps were executed using RStudio and ArcGIS Desktop 10.8.2. Figure 16 illustrates the pre-processing steps.

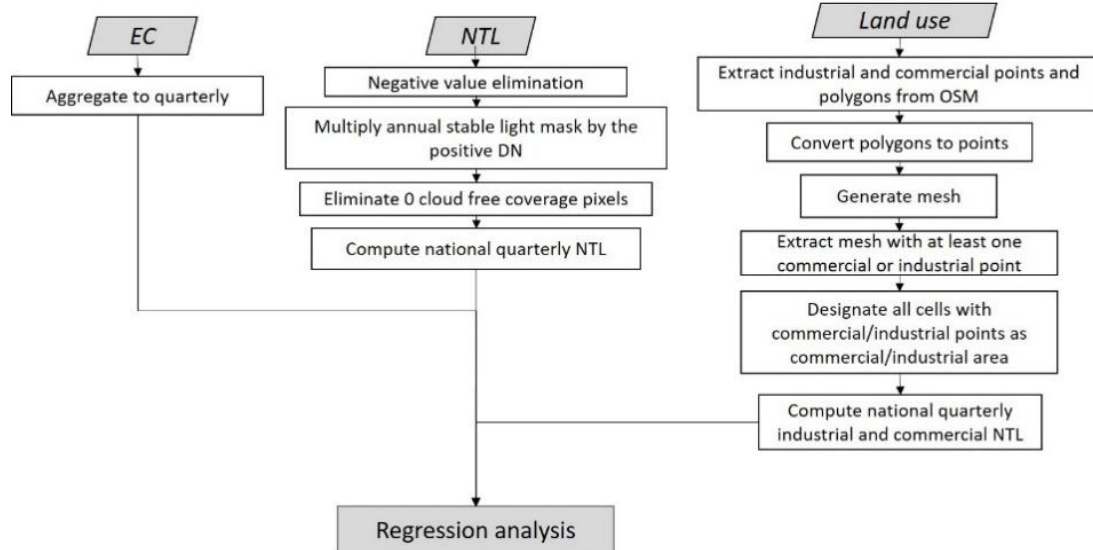


Figure 16. Pre-processing steps of EC, NTL, and land use (Del Castillo, et al., 2024)

4.2.4 Other data

Table 8 presents the independent variables used in the regression models. Daily average temperature, maximum temperature, and humidity data were obtained from PAGASA (Del Castillo, et al., 2024). The heat index was computed using temperature

and humidity data. Additionally, daily weather data from daily were aggregated into quarterly intervals (Figure 17 a and b). Data on the working-age population, representing individuals aged 15–65 years, were obtained from PSA. Annual estimates for the overall population and urban population were collected from Macrotrends (Figure 17 c).

Table 8. Variables used in the regression models. To align with the GDP data, the variables were aggregated into quarterly intervals. The datasets cover the time span from Quarter 2 of 2012 to Quarter 4 of 2021.

Variables (x)	Definitions
$\ln GDP_t$	Natural logarithm value of GDP at time t
$\ln EC_t$	Natural logarithm value of EC sum at time t
$\ln NTL_t$	Natural logarithm value of NTL sum at time t
$\ln WorkDays_t$	Natural logarithm value of number of working days per quarter
$\ln WorkAgePop_t$	Natural logarithm of working age population at time t
$\ln Pop_t$	Natural logarithm of total population at time t
$\ln UrbPop_t$	Natural logarithm of urban population at time t
$\ln AveTemp_t$	Natural logarithm of mean temperature at time t
$\ln MaxTemp_t$	Natural logarithm of maximum temperature at time t
$\ln HI_t$	Natural logarithm of heat index at time t
$\ln Humidity_t$	Natural logarithm of humidity at time t

Notes: To align with the GDP data, the variables were aggregated into quarterly intervals. The datasets cover the period from Quarter 2 of 2012 to Quarter 4 of 2021 (Del Castillo, et al., 2024)

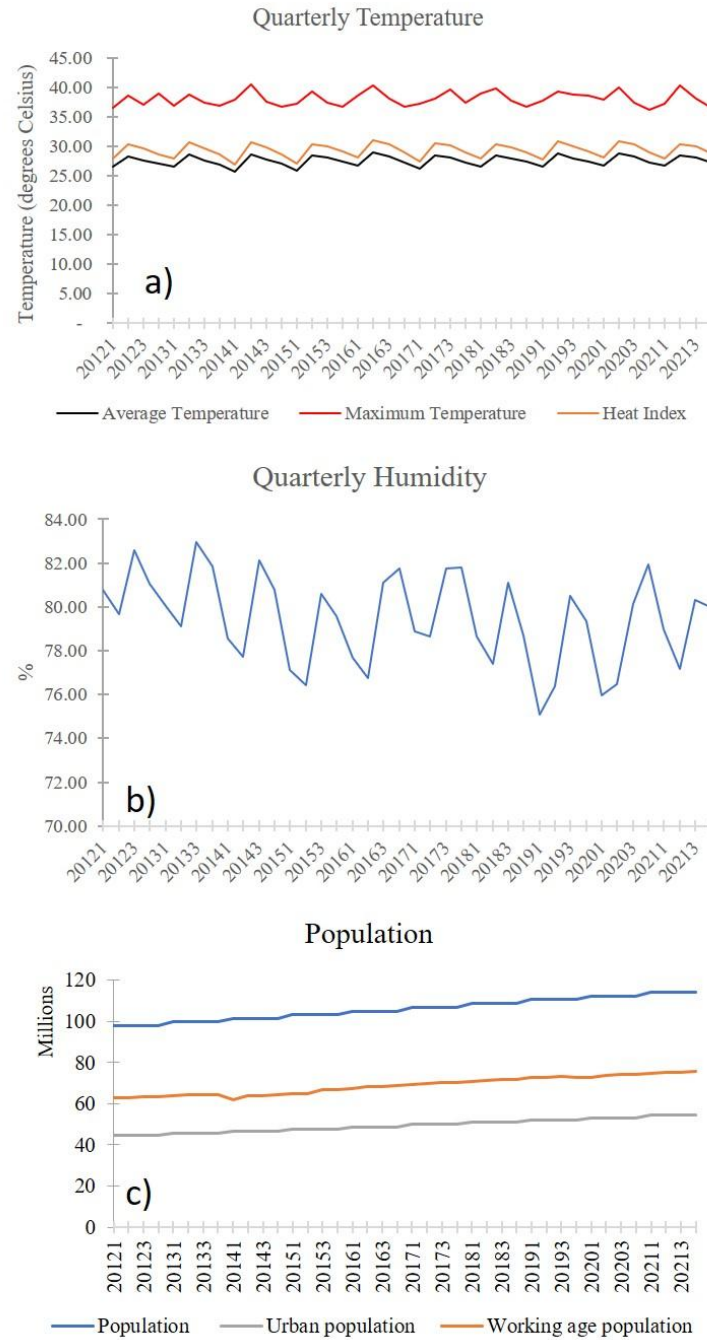


Figure 17. Other data a) quarterly temperature, b) quarterly humidity, c) annual population estimate

4.3 Models

Figure 18 depicts the economic loss estimation process. The statistical relationship between GDP, EC, and NTL was first analyzed to assess their potential as GDP substitutes (Del Castillo, et al., 2024). Statistical models were then developed to forecast

EC and NTL under a counterfactual scenario, using weather and statistical data. The next step was to project counterfactual GDP using forecasted EC and NTL in the model (Del Castillo, et al., 2024). Finally, COVID-19 economic losses were estimated by calculating the difference between actual and predicted GDP. The same method was used to assess commercial and industrial economic losses from the pandemic (Del Castillo, et al., 2024).

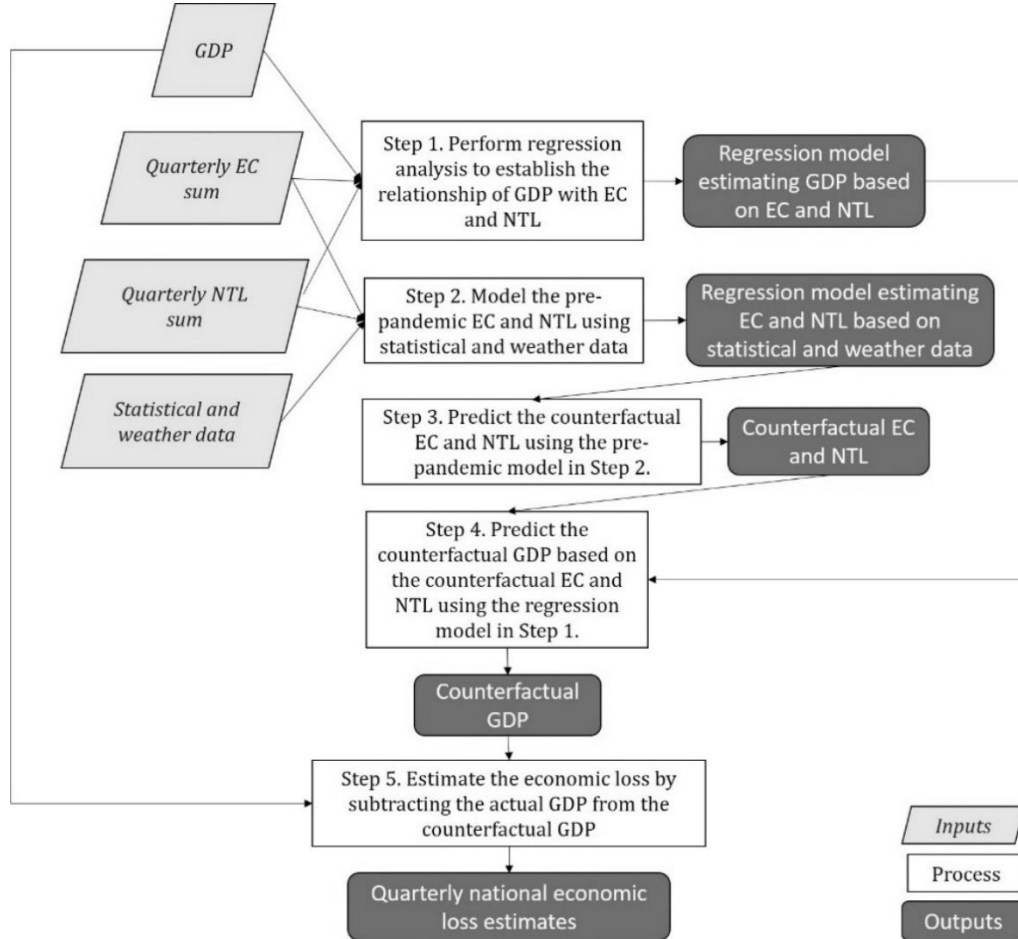


Figure 18. Economic loss estimation process flow (Del Castillo, et al., 2024)

4.3.1 Establishing the relationship of GDP with EC and NTL

Pre-pandemic data were analyzed to determine whether EC and NTL could serve as strong substitutes for GDP (Del Castillo, et al., 2024). Equation 11 represents the regression of GDP on EC and NTL, this time, aiming to determine the relationship among the variables. The results demonstrate that EC and NTL can be strong proxies for GDP (Table 9). Specifically, GDP has a stronger relationship with EC than NTL. Models based on EC (GDPt1, GDPc1, GDPi1) have a higher coefficient of determination or R^2 values compared to models based on NTL (GDPt2, GDPc2, GDPi2).

Models using both EC and NTL (GDPt3, GDPc3, and GDPi3) had lower AIC and higher R^2 values than single-predictor models suggesting that combining both data slightly improved the model's predicting capacity (Del Castillo, et al., 2024). In GDPc3, NTL was statistically insignificant but for consistency, GDPt3, GDPc3, and GDPi3 were used to forecast counterfactual GDP for 2020 and 2021, covering the COVID-19 period (Del Castillo, et al., 2024).

Table 9. Regression model results for total, commercial, and industrial GDP using 2012 Q2 to 2019 Q4 data

Coefficient (Standard error)	GDPt1	GDPt2	GDPt3	GDPc1	GDPc2	GDPc3	GDPi1	GDPi2	GDPi3
Intercept	-2.545*** (0.448)	6.331*** (0.717)	-1.623** (0.541)	-4.752*** (0.549)	4.588** (1.305)	-4.473*** (0.569)	-5.632*** (0.593)	5.463** (1.241)	-5.340*** (0.528)
ln EC	1.064*** (0.027)		0.928*** (0.058)	1.255*** (0.036)		1.182*** (0.060)	1.260*** (0.038)		1.199*** (0.043)
ln NTL		0.640*** (0.052)	0.097* (0.037)		0.768*** (0.100)	0.065 (0.044)		0.704*** (0.103)	0.061** (0.0253)
Quarter 2	-0.061*** (0.011)	0.056 (0.031)	-0.046*** (0.011)	-0.033* (0.013)	0.113* (0.050)	-0.025 (0.014)	-0.029* (0.013)	0.053 (0.052)	-0.021 (0.012)
Quarter 3	-0.105*** (0.011)	0.144*** (0.033)	-0.070*** (0.017)	-0.058*** (0.013)	0.262*** (0.056)	-0.034 (0.021)	-0.177*** (0.014)	0.103 (0.059)	-0.139*** (0.017)
Quarter 4	0.026* (0.011)	0.146*** (0.031)	0.042** (0.011)	-0.008 (0.013)	0.129** (0.050)	0.001 (0.014)	0.030* (0.013)	0.128* (0.052)	0.041** (0.012)
N	31	31	31	31	31	31	31	31	31
Fes	Qtr	Qtr	Qtr	Qtr	Qtr	Qtr	Qtr	Qtr	Qtr
R^2	0.985	0.869	0.988	0.981	0.714	0.982	0.981	0.708	0.986
Adj- R^2	0.983	0.849	0.986	0.978	0.670	0.979	0.978	0.663	0.983

Significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The standard errors were reported inside the parentheses (). (Del Castillo, et al., 2024)

The trend component was excluded from these models to prevent multicollinearity with EC and NTL, as its variance inflation factor (VIF) exceeded 10. After removal, NTL had the highest VIF: 6.8 in GDPt3, 3.3 in GDPi3, and 4.2 in GDPc3. The VIF for GDPt3 indicates slight multicollinearity between EC and NTL, but it was considered acceptable since their seasonal patterns differ, each contributing uniquely to GDP estimation (Del Castillo, et al., 2024).

4.3.2 Pre-pandemic EC and NTL models

Regression models (Equations 4 and 5) were used to estimate counterfactual total, industrial, and commercial EC and NTL (Table 10). Base models, including all variables were developed, for Total EC (ECt1) and NTL (NTL1), Industrial EC (ECi1) and NTL (NTLi1), and Commercial EC (ECc1) and NTL (NTLc1) and the final models, denoted as ECt2, ECi2, ECc2, NTLt2, NTLi2, and NTLc2, retaining the significant ones, were used for the counterfactual estimation (Del Castillo, et al., 2024). The models explain at least 99.1% of the typical pre-COVID-19 total, industrial, and commercial EC (Del Castillo, et al., 2024). Conversely, the final NTL models explain 89.1%, 81.1%, and

81.6% of the typical pre-COVID-19 total, industrial, and commercial NTL, respectively. These models were employed to forecast the counterfactual EC and NTL values during the COVID-19 period.

4.3.3 EC and NTL estimation

Counterfactual EC and NTL without COVID-19 were estimated using Equations 6 and 7, based on independent variable estimates from Equations 4 and 5 (Del Castillo, et al., 2024). Figure 19 plots the estimated and actual NTL and EC. As shown, the NTL and EC estimates captured the actual values before the pandemic. Post-pandemic estimates were higher than the actual, indicating economic activity reduction.

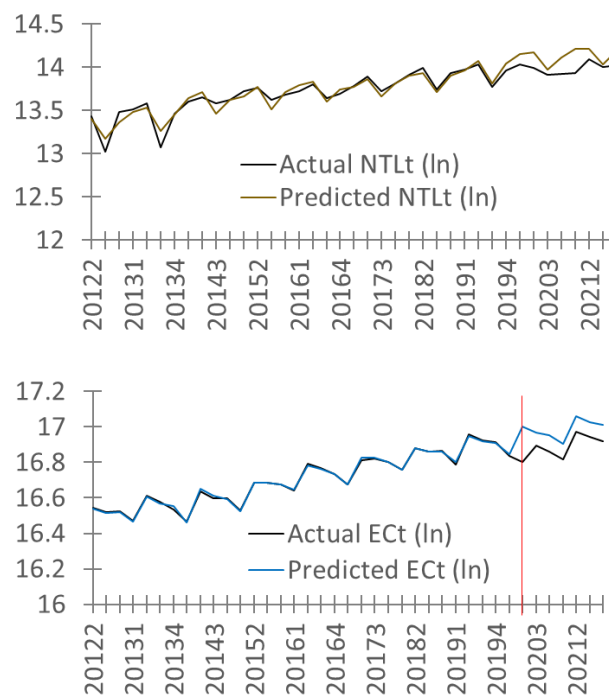


Figure 19. Estimated vs actual NTL and EC

Table 10. Counterfactual EC and NTL regression models from 2012 Quarter 2 to 2019 Quarter 4

Coefficient (Standard error)	ECt1	ECt2	ECi1	ECi2	ECc1	ECc2	NTLt1	NTLt2	NTLi1	NTLi2	NTLc1	NTLc2
<i>Intercept</i>	79.146 (140.064)	-66.007*** (6.366)	325.644 (191.813)	319.739*** (73.589)	4.741 (158.779)	-58.314*** (6.609)	-755.150 (1257.702)	-282.2*** (44.57)	-1498.535 (1489.404)	-2639.291*** (620.029)	-1215.826 (1414.958)	-271.951*** (51.383)
<i>ln WorkDays</i>	-0.138 (0.111)		-0.147 (0.152)		-0.189 (0.126)		-0.142 (0.995)		-0.210 (1.178)		-0.265 (1.119)	
<i>ln WorkAgePop</i>	0.447 (0.329)	1.058*** (0.175)	0.188 (0.451)		0.711 (0.373)	1.085*** (0.182)	-2.304 (2.958)	-3.564** (1.239)	-3.094 (3.502)		-2.233 (3.327)	-4.494** (1.429)
<i>ln Pop</i>	14.858 (10.767)		32.869* (14.745)	25.957*** (4.630)	3.207 (12.205)		29.937 (96.679)		48.671 (114.490)		36.140 (108.767)	
<i>ln UrbPop</i>	-2.773 (4.918)		-4.477 (6.735)		0.989 (5.575)		-39.656 (44.163)		-81.262 (52.299)	-99.077*** (24.323)	-63.489 (49.684)	
<i>ln AveTemp</i>	-0.134 (1.655)		0.080 (2.267)		-0.351 (1.876)		-10.267 (14.862)		-4.659 (17.600)		-9.963 (16.721)	
<i>ln MaxTemp</i>	0.183 (0.108)	0.309** (0.106)	-0.010 (0.149)		0.280* (0.123)	0.359** (0.110)	0.317 (0.975)		0.275 (1.154)		0.497 (1.097)	
<i>ln Humidity</i>	-0.075 (0.286)		-0.266 (0.392)		0.013 (0.325)		-1.814 (2.572)		-1.729 (3.045)		-2.014 (2.893)	
<i>ln IH</i>	1.212 (1.410)		0.017 (1.931)		1.250 (1.599)		10.710 (12.664)	3.197 (1.720)	7.216 (14.997)		11.570 (14.247)	5.088* (1.983)
<i>trend</i>	-0.147 (0.149)	0.035*** (0.004)	-0.416 (0.205)	-0.389*** (0.079)	-0.039 (0.169)	0.030*** (0.004)	0.470 (1.341)	0.161*** (0.028)	1.033 (1.588)	2.185*** (0.521)	0.849 (1.509)	0.158*** (0.032)
Quarter 2	0.019 (0.028)	0.127*** (0.008)	0.074 (0.038)	0.0883*** (0.006)	0.013 (0.031)	0.111*** (0.008)	-0.189 (0.249)	-0.236 (0.180)	-0.319 (0.295)	0.041 (0.048)	-0.355 (0.280)	-0.466* (0.208)
Quarter 3	0.031 (0.023)	0.108*** (0.007)	0.101** (0.031)	0.099*** (0.006)	0.028 (0.026)	0.103*** (0.007)	-0.322 (0.202)	-0.375* (0.139)	-0.405 (0.240)	-0.209*** (0.048)	-0.446 (0.228)	-0.557** (0.160)
Quarter 4	0.056*** (0.014)	0.099*** (0.007)	0.084*** (0.019)	0.089*** (0.006)	0.058 (0.016)	0.104*** (0.008)	-0.021 (0.124)	-0.071 (0.082)	-0.038 (0.147)	0.021 (0.048)	-0.059 (0.140)	-0.132 (0.095)
N	31	31	31	31	31	31	31	31	31	31	31	31
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R ²	0.997	0.994	0.994	0.993	0.996	0.993	0.920	0.913	0.865	0.849	0.872	0.853
Adjusted R ²	0.996	0.993	0.990	0.991	0.994	0.991	0.867	0.891	0.775	0.811	0.787	0.816

Notes: Significance levels are $\cdot p < 0.1$ * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The standard errors were reported inside the parentheses (.). (Del Castillo, et al., 2024)

4.3.4 Counterfactual GDP estimation

The counterfactual GDP was estimated using Equation 12. The modeled GVAs and GDP closely followed the actual values leading up to 2019Q4 indicating a strong model fit (Figure 20). Without COVID-19, Total GDP, Industrial GVA, and Commercial GVA followed positive trends, peaking in the second and fourth quarters of each year. However, with lockdowns beginning in 2020 Q1, actual values fell below projections. The gaps between counterfactual and actual values indicate economic losses, peaking in Q2 2020, highlighting the severe impact of lockdowns. (Del Castillo, et al., 2024). Both Total GDP and sectoral GVAs have yet to fully recover to the counterfactual values, signifying ongoing losses through the end of 2021.

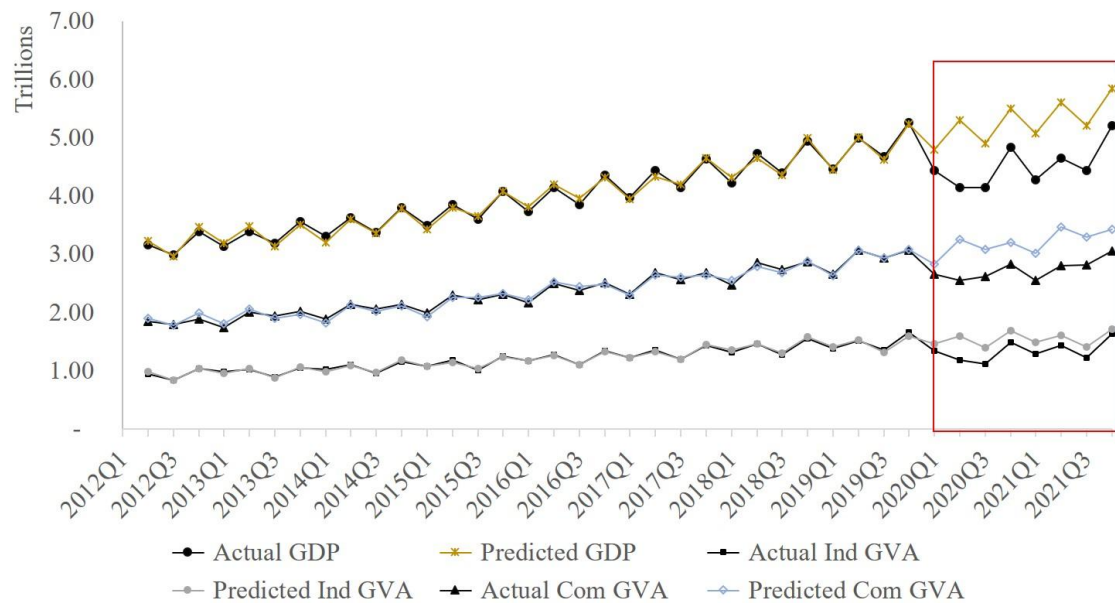


Figure 20. Actual and predicted GDP, industrial, and commercial GVAs (Del Castillo, et al., 2024).

4.4 Estimated economic loss

4.4.1 National quarterly economic loss

The economic loss per quarter was estimated using Equation 13. Across time, the highest total and sectoral losses occurred during 2020Q2, during the period of the strictest lockdown in the country (Table 11 and Figure 21). Specifically, 2020Q2 witnessed the most considerable Total GDP losses, amounting to approximately 1.15 trillion PhP (20.03 billion USD). Similarly, the industrial sector incurred substantial losses of 419.01 billion

PhP (7.66 billion USD), while the commercial sector faced significant losses of 731.38 billion PhP (13.37 billion USD) during the same quarter. Both national GDP and commercial sector losses had two peaks, while the industrial sector showed only one (Del Castillo, et al., 2024).

Across sectors, the commercial sector experienced more substantial overall losses, totaling 1.84 trillion PhP (33.66 billion USD) in 2020 and 2.39 trillion PhP (43.63 billion USD) in 2021, compared to the industrial sector's losses of 1.09 and 0.79 billion PhP (19.87 and 14.39 billion USD) during the same respective years. Consequently, 69% of the total losses were attributed to the commercial sector, while the industrial sector accounted for the remaining 31% (Del Castillo, et al., 2024).

Distinct loss patterns were reported emerging between the sectors, where the industrial sector showed no clear second peak, suggesting it was less impacted by rising COVID-19 cases and primarily affected by lockdowns (Del Castillo et al., 2024). In contrast, the commercial sector's loss paralleled the total GDP loss, indicating that both lockdowns and viral transmission affected it.

It follows that commercial losses surpassed industrial losses. Business interruptions affected more establishments and employees in the commercial sector, representing over 60% of the GDP, over 85% of operating establishments, and 75% of employment. Mobility data also supports this finding through the evidence of lowered human presence in the commercial sector, recreational places, transit stations, and workplaces (Figure 22). Furthermore, unlike industrial operations, commercial productivity was influenced by consumer behavior (Tao, et al., 2022), for example, buyers prioritized essential expenditures and preferred online purchases. Moreover, households, facing unemployment and income reduction, tended to reduce spending on non-essential items (Ajmal & Khan, 2021).

Table 11. Estimated Economic Losses and Loss Rates per quarter from 2020 to 2021

	GDP Loss (billion PhP)	GDP Loss Rate	Adjusted Industrial Loss (billion PhP)	Industrial Loss Rate	Adjusted Commercial Loss (billion PhP)	Commercial Loss Rate
2020Q1 ^a	350.79	0.07	147.82	0.10	202.96	0.07
2020Q2	1,150.46	0.22	419.08	0.26	731.38	0.22
2020Q3	764.92	0.16	285.48	0.21	479.44	0.16
2020Q4 ^b	661.67	0.12	234.27	0.14	427.40	0.13
2021Q1	807.18	0.16	242.51	0.16	564.67	0.19
2021Q2	955.98	0.17	199.53	0.12	756.46	0.22
2021Q3	779.19	0.15	229.03	0.16	550.16	0.17
2021Q4	631.34	0.11	116.16	0.07	515.19	0.15
2020	2,927.84	0.14	1,086.65	0.16	1,841.19	0.14
2021	3,173.69	0.15	787.23	0.11	2,386.46	0.15

Notes:

^a includes damage and loss from Taal Volcano Eruption amounting to 8.4 billion PhP (Laforga, 2021).

^b covers the damage and loss from Typhoon Goni and Vamco estimated to be 105 billion PhP (Laforga, 2021)

source: (Del Castillo, et al., 2024)

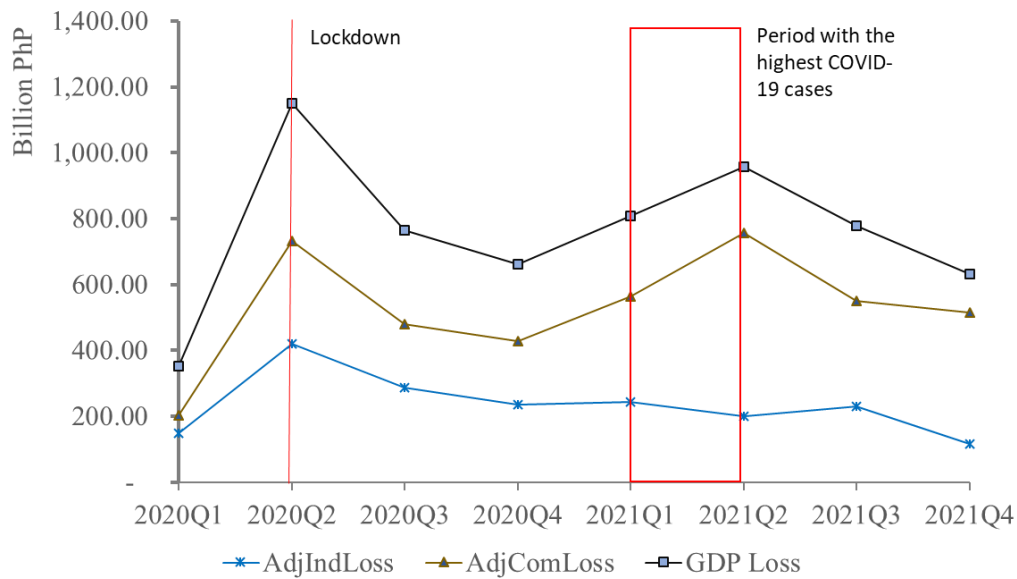


Figure 21. National Quarterly Loss (Del Castillo, et al., 2024)

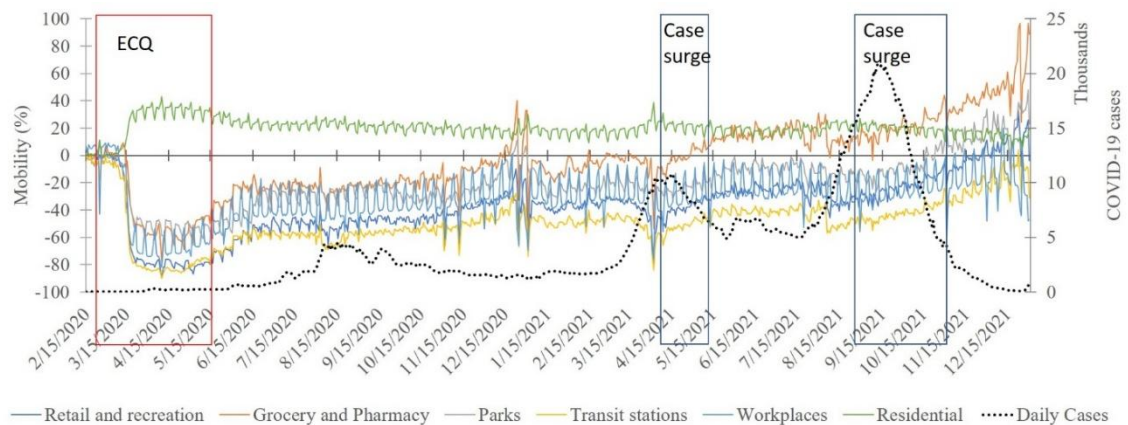


Figure 22. Daily Mobility (Del Castillo, et al., 2024)

4.4.2 Limitations

The estimated losses in this chapter excluded agriculture, as agricultural activities continued during the lockdown, leading to sectoral growth (Del Castillo, et al., 2024). Additionally, this method is unsuitable for estimating agricultural losses since EC does not distinguish agricultural energy use, and agricultural areas emit less light (Del Castillo, et al., 2024). Also, this study did not include residential losses because residential EC

increased during the lockdown evidenced through the increased mobility in residential areas (Figure 22).

The economic losses peaked during the lockdown, as expected. The national GDP's initial and more pronounced loss peak occurred during the second quarter of 2020 (Figure 21), coinciding with the stringent ECQ measures. The second peak materialized during the second quarter of 2021, aligning with an upsurge in COVID-19 cases despite the quarantine stringency remaining relatively constant.

The paper modeled (Del Castillo, et al., 2024) the total, industrial, and commercial EC, NTL, and GDP separately. Commercial and industrial losses were adjusted based on their share of the total to ensure accuracy (Del Castillo, et al., 2024). Future research can improve models by integrating all sectors into a single framework.

Note that the economic impacts from other hazards within the study period, including the Taal Volcano eruption on January 12, 2020, amounting to 8.4 billion PhP (Laforga, 2021) loss, and Typhoons Goni and Vamco in November 2020 costing 105 billion PhP (Laforga, 2021) were included in the estimated economic losses.

Further, NTL image resolution and lack of comprehensive land use data limited NTL attribution accuracy. If used on a provincial or municipal scale, existing land use maps could be used to improve the industrial and commercial NTL accuracy. Future research may also use NTL and EC data to look at the spatial distribution of economic losses.

4.5 Conclusion

This chapter provided evidence that EC and NTL are strong proxies for GDP in measuring economic activities in the Philippines based on the paper of Del Castillo, et al., 2024. According to this paper, the regression results showed that EC-based explained GDP better than NTL-based models, consistent with Beyer, et al. (2021) but combining both EC and NTL slightly enhanced the model. Second, counterfactual EC and NTL were estimated using statistical and weather-based models, explaining over 81% of pre-pandemic values. Lastly, total estimated losses were 2.9 trillion PhP in 2020 and 3.2 trillion PhP in 2021 (Del Castillo, et al., 2024). The 2020 estimate aligned with the 3.5 trillion PhP estimate of Yu, et al., (2020) and the 4.3 trillion PhP estimate of NEDA (2021) indicating that this method can generate comparable results. More than two-thirds of the losses were in the commercial sector as it responded to both policies and the COVID-19

case surge whereas the industrial sector was mostly affected by the lockdown implementation. This method enabled the monitoring of economic losses from long-term, large-scale hazards like COVID-19. The findings provide empirical evidence to support targeted strategies that balance public health and economic stability during pandemics (Del Castillo, et al., 2024).

This chapter analyzed the actual losses and their temporal and sectoral distribution. Understanding this temporal dimension is crucial for formulating policies that balance health and the economy during pandemics. Economic impacts are often reported without a temporal dimension due to data limitations. EC and NTL data addressed this gap, enabling temporal analysis and sectoral loss comparison, which can guide financial support allocation (Del Castillo, et al., 2024).

The results of this chapter demonstrated that EC and NTL are strong proxies for GDP. Future studies may use higher-resolution data to analyze spatiotemporal distribution of losses in greater detail (Del Castillo, et al., 2024). Additionally, pandemic-related policies should account for the timing of economic losses to better balance economic and health priorities.

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Chapter 5

Regional annual medium-term COVID-19 economic activity reduction estimation using NTL

5.1 Introduction

As shown in Chapter 4, COVID-19 inflicted a significant impact on the Philippines (~15% of the predicted GDP). Beyond this country-level impact, it is important to understand the spatiotemporal dimensions of economic impacts for several reasons. Primarily, researchers pointed out the importance of subnational impact estimates for a proportionate resource distribution (Lopez Ochoa, et al., 2021) and high-frequency data to monitor effects for timely policy implementation (Fezzi and Fanghella, 2020). Secondly, understanding the spatiotemporal distribution of impacts in the context of regional characteristics is essential for developing region-specific recovery strategies.

During the COVID-19 pandemic, the Philippine National Government initially enforced lockdowns, followed by additional measures from local administrative units. These units differ in demographic, socioeconomic, and geopolitical factors, influencing how economic impacts spread (Del Castillo, et al., 2024a). This chapter examines the medium-term regional spatiotemporal distribution of COVID-19's economic impacts using NTL data.

This chapter highlights the importance of prolonged impact monitoring, extending the analysis to three years—beyond most existing studies. Continuous tracking of regional economic impacts is essential for guiding recovery, as COVID-19 case surges led to dynamic responses with effects lasting beyond initial lockdowns (Del Castillo, et al., 2024a). With economic impacts expected to persist for generations (Jorda, et al., 2020), region-specific recovery measures are crucial. However, medium-term local impacts and the regional factors shaping them remain underexplored, as most studies focus on immediate consequences (Del Castillo, et al., 2024a).

Building on the results of Chapter 4, this chapter focuses on using NTL data. NTL data has finer spatial details, global coverage, extensive temporal record (Jia, et al. 2023), free access, minimum release delay, objective physical measurement (Schippers & Botzen, 2023), and frequent and regular data acquisition. Although Chapter 4 showed that

EC data better capture GDP trends, NTL has less delay and finer spatial granularity, making it ideal for continuous regional monitoring.

Most NTL-based studies used a before-and-after comparison method (Ghosh, et al., 2020; Beyer, et al., 2021; Alahmadi, et al., 2021, 2023; Xu, et al., 2021). For example, Alahmadi, et al. (2021) observed a pandemic-related NTL decline in Saudi Arabia by comparing 2019 and 2020 images. Beyer, et al. (2021) mapped COVID-19 lockdown impacts in Indian districts from April to August 2020 using VIIRS data. Xu, et al. (2021) analyzed spatial and temporal NTL changes in 20 megacities using NASA's Black Marble NTL, identifying Mumbai, Dhaka, and Manila as having the highest nighttime brightness reductions. Other studies applied regression models (Roberts, 2021; Lin & Rybnikova, 2023) or machine learning (Dasgupta, 2022). Lin and Rybnikova (2023) demonstrated that NTL can estimate GDP under COVID-19's impact and revealed varying recovery rates across U.S. states. While many studies have proven NTL's usefulness, most focused on short-term effects in the first months of lockdown (Del Castillo et al., 2024a).

This chapter used NTL to estimate the medium-term spatiotemporal distribution of economic activity reduction (EAR) during the COVID-19 pandemic in the Philippines using regional monthly NTL. This chapter then investigates how the impacts were distributed across regions and time.

5.2 Data and Inputs

The approach of this study involved developing a model estimating the pre-pandemic NTL which was used to estimate the counterfactual from which the EAR was computed (Figure 23). First, the distribution of the dataset values was analyzed. The histograms revealed a skewed data distribution. To address this, the natural logarithm was applied to the input datasets to normalize the distribution. Subsequently, the data was separated into the pre-pandemic and pandemic subsets, with March 2020 marking the start of the pandemic.

This chapter generated the model using provincial-level datasets to meet the minimum data point requirements for the spatial regression method. Then, the estimated provincial impacts were aggregated at the regional level for interpretability. The regions were ranked and labeled according to their urbanization level, with R1 representing the most urbanized and R17 the least urbanized (Figure 24). This ranking helps highlight differences in regional impacts and simplifies interpretation.

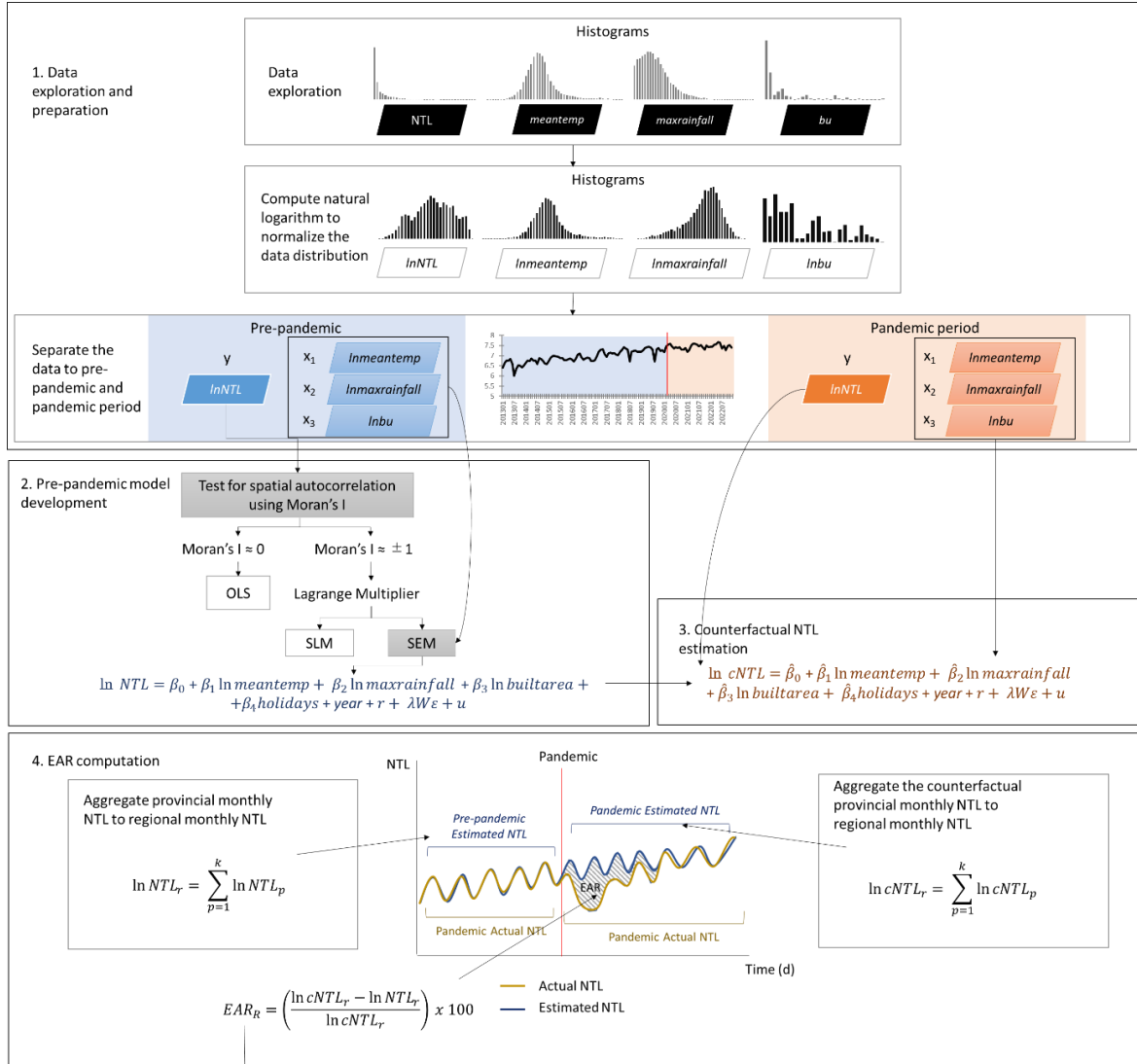


Figure 23. Overall process flow (Del Castillo, et al., 2024a).

- R1 – National Capital Region (NCR)
- R2 – CALABARZON (CALA)
- R3 – Davao Region (DAVR)
- R4 – Central Luzon (CENL)
- R5 – Soccsksargen (SOCC)
- R6 – Central Visayas (CENV)
- R7 – Northern Mindanao (NORM)
- R8 – Western Visayas (WESV)
- R9 – Zamboanga Peninsula (ZAMB)
- R10 – Caraga (CARA)
- R11 – MIMAROPA (MIMA)
- R12 – CAR (CAR)
- R13 – Autonomous Region of Muslim Mindanao (ARMM)
- R14 – Ilocos Region (ILOC)
- R15 – Bicol Region (BICL)
- R16 – Cagayan Valley (CAGV)
- R17 – Eastern Visayas (EASV)

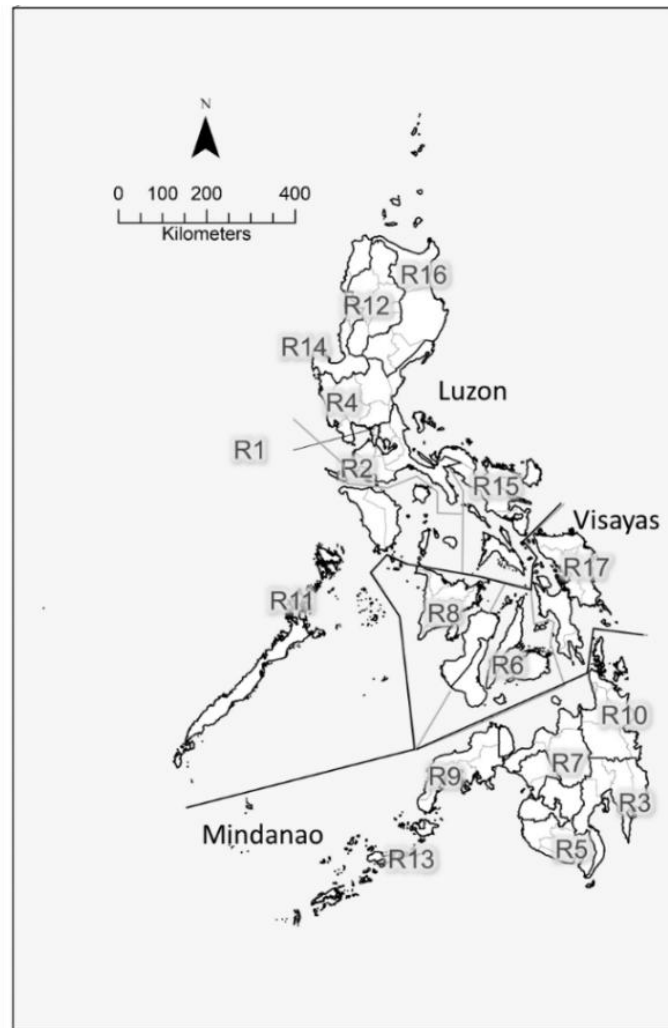


Figure 24. Location of the Philippines and its regions ranked according to urbanization level. Note: Regional names are also provided together with abbreviations (Del Castillo, et al., 2024a).

5.2.1 NTL data

The same pre-processed NTL data described in Chapter 3 and in Del Castillo, et al., (2024) was used in this analysis. After these pre-processing steps, the provincial sum of lights was computed by adding all cloud-corrected pixel values. Figure 25 shows the provinces with high and low average NTL from January 2013 to December 2022.

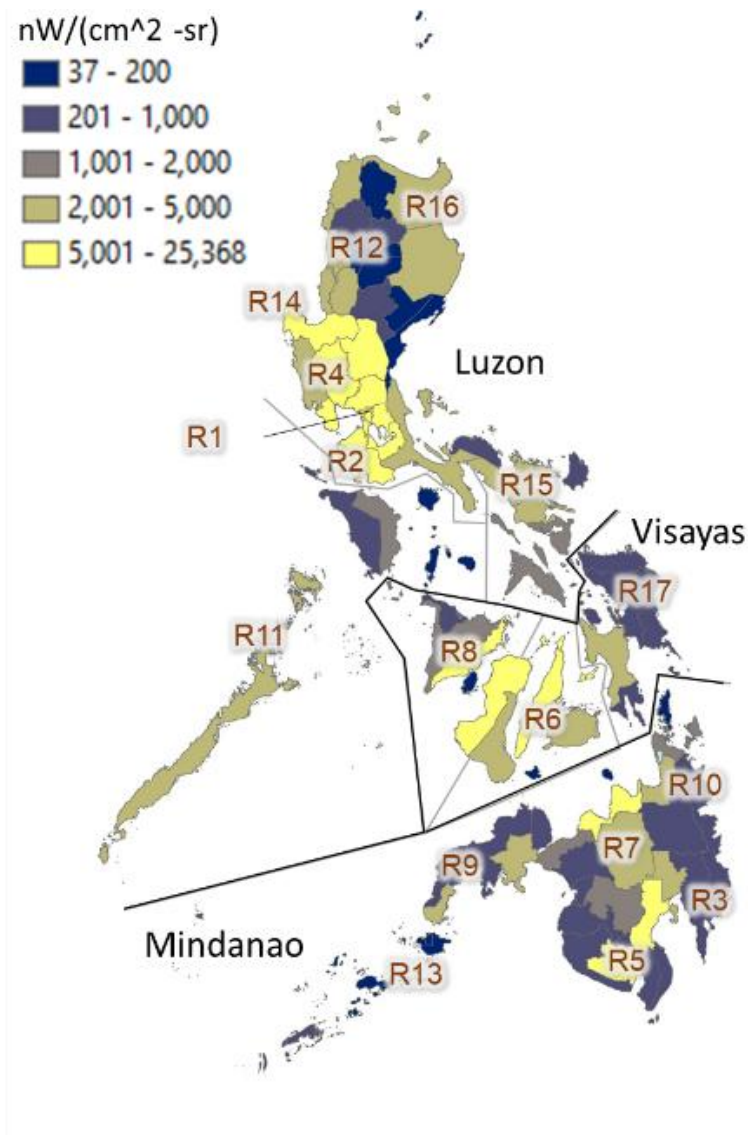


Figure 25. Provincial average NTL from 2013 to 2022 (Del Castillo, et al., 2024a)

5.2.2 Built-up areas

Built-up areas, which represent impervious surfaces and NTL emission sources, were obtained from the MCD12Q1.061 MODIS Land Cover Type dataset (NASA LP DAAC, USGS EROS Center) (Friedl & Sulla-Menashe, 2022). This dataset includes 17 land cover classes, with built-up areas defined as those having over 30% impervious surface. The built-up class was extracted, converted into polygons, and used to calculate the built-up area per province (Figure 26). Data were accessed via Google Earth Engine: MODIS Land Cover Dataset (Del Castillo, et al., 2024a).

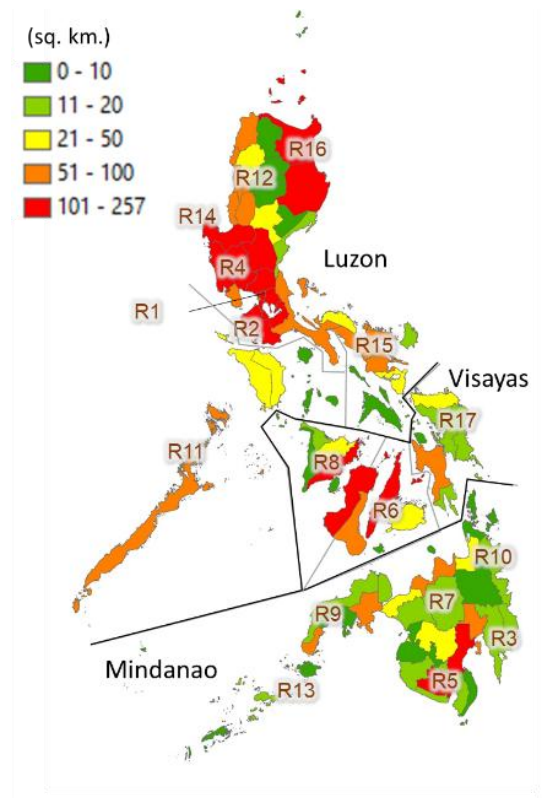


Figure 26. Average built-up area per province from 2013 to 2022 (Del Castillo, et al., 2024a).

5.2.3 Weather

Studies have shown a strong positive correlation between NTL and land surface temperature due to thermal and brightness effects in urban areas (Li et al., 2019, 2022). This study used mean temperature data from the MOD11A1.061 Terra Land Surface Temperature and Emissivity dataset (1-km resolution) to estimate NTL (Del Castillo, et al., 2024a). Data were obtained from NASA LP DAAC at the USGS EROS Center (Wan, et al., 2021). The study specifically used the daytime land surface temperature band (LST_Day_1km) with a 1,200 km grid size, averaging daily values into monthly datasets for each province (Del Castillo et al., 2024a).

Rainfall, which indicates cloud cover, reduces NTL, creating a negative relationship. Including maximum rainfall in the model indirectly accounts for cloud effects (Del Castillo, et al., 2024a). Daily rainfall data were collected from the Climate Hazards Group Infrared Precipitation with Station Data Version 2.0 (Funk et al., 2015), measured in millimeters per day with a 5,566-meter resolution. These were aggregated into monthly datasets for each province. Both temperature and rainfall data were sourced from Google

Earth Engine (Del Castillo, et al., 2024a).

5.3 NTL model and counterfactual estimate

For model development, this section first tested the NTL data for spatial autocorrelation using Moran's I to avoid biased estimates. The computed Moran's I was 0.928 (p-value < 0.01), indicating significant positive spatial autocorrelation. Therefore, spatial regression models were used instead of OLS to ensure unbiased results (Del Castillo, et al., 2024a). Then the Lagrange multiplier (LM) test was performed to determine which spatial regression model to use. The results showed significant spatial dependence in both the error and the dependent variable so the robust LM was performed. Both had significant p-values but the spatial error model (SEM) had a higher test statistic (Rao score = 25,888; p-value = <0.000) than the spatial lag model (Rao score = 8.36; p-value <0.004). This means that the residual has greater spatial dependence than the dependent variable.

Based on this, this chapter developed the SEM model where the error term ε of the OLS model was multiplied by the spatial weight matrix W and an autoregressive coefficient λ , isolating an independent error term u (Del Castillo, et al., 2024a). Then, the pre-pandemic NTL $\ln NTL$ was modeled based on the average temperature $\ln meantmp$, maximum rainfall $\ln maxrainfall$, and built-up area $\ln builtarea$. Additionally, the count of holidays $holidays$ were added to capture the impact of seasonal festivities on NTL. Finally, regional dummy variables R and year component to control for the regional variations and capture the effect of passing years on NTL were also integrated, respectively, as shown in Equation 20:

$$\ln NTL = \beta_0 + \beta_1 \ln meantemp + \beta_2 \ln maxrainfall + \beta_3 \ln builtarea + \\ + \beta_4 holidays + \gamma year + \delta R + \lambda W\varepsilon + u$$

Equation 20

where, $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \gamma, \delta$, and λ are the parameters estimated in the model. To determine whether multicollinearity among the explanatory variables exists, the variance inflation factor was computed. VIF falls within an acceptable value (VIF < 3.54).

5.2.4 Pre-pandemic NTL model

Table 12 presents the results of spatial regression models generated to estimate the pre-pandemic provincial monthly NTL. Three models with varying sets of explanatory variables were generated. Model 1, based on mean temperature, maximum rainfall, built-up areas, and holidays, all variables significant at 1%, explains 72% of the pre-pandemic NTL. The year was added in Model 2, effectively increasing the R^2 value to 0.816. Adding the regional dummy variables in Model 3 did not improve the R^2 but slightly lowered the Akaike Information Criterion (AIC), which measures the model quality based on its fit and complexity. Having the lowest AIC, model 3 estimated the counterfactual NTL.

Table 12. SEM results

	SEM		
	1	2	3
<i>lnmeantemp</i>	1.185*** (0.076)	1.179*** (0.063)	1.177*** (0.063)
<i>lnmaxrf</i>	-0.089*** (0.005)	-0.065*** (0.004)	-0.065*** (0.004)
<i>lnbu</i>	1.747*** (0.091)	1.484*** (0.091)	1.589*** (0.108)
<i>holidays</i>	0.028*** (0.003)	0.005* (0.003)	0.005* (0.003)
<i>R1</i>			0.049 (0.451)
<i>R2</i>			0.388 (0.427)
<i>R3</i>			0.657 (0.429)
<i>R4</i>			-0.328 (0.396)
<i>R5</i>			0.244 (0.427)
<i>R6</i>			0.382 (0.446)
<i>R7</i>			0.608 (0.434)
<i>R8</i>			0.505 (0.413)
<i>R9</i>			0.293 (0.459)
<i>R10</i>			1.012** (0.447)
<i>R11</i>			-0.213 (0.436)
<i>R12</i>			-0.416 (0.429)
<i>R13</i>			-0.091 (0.447)
<i>R15</i>			0.258 (0.414)
<i>R16</i>			-0.764* (0.426)
<i>R17</i>			0.381

			(0.421)
<i>year</i>		0.114***	0.114***
		(0.002)	(0.002)
Constant	-2.550***	-230.881***	-231.114***
	(0.407)	(3.861)	(3.876)
Observations	7,482	7,482	7,482
Log Likelihood	-4,166.71	-2,725.27	-2,708.75
sigma2	0.171	0.116	0.116
R ²	0.7186	0.81599	0.81599
adj-R ²	0.71841	0.81586	0.81586
Akaike Inf. Crit.	8,347.42	5,466.53	5,465.50
Wald Test (df = 1)	46,725.720***	69,313.320***	44,724.040***
LR Test (df = 1)	10,659.810***	12,936.490***	10,506.580***

Note: Standard errors are shown between parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01. Data coverage: 2013-2019 regional monthly. Source: (Del Castillo, et al., 2024a)

5.2.5 Counterfactual NTL

This section estimated the provincial monthly counterfactual NTL *cNTL* using the pre-pandemic SEM and post-pandemic explanatory variable values following the process described in a previous study (Del Castillo, et al., 2024a). The counterfactual was then estimated using Equation 21.

$$\ln cNTL = \hat{\beta}_0 + \hat{\beta}_1 \ln meantemp + \hat{\beta}_2 \ln maxrainfall + \hat{\beta}_3 \ln builtarea + \hat{\beta}_4 holidays + \hat{\gamma} year + \delta R + \lambda W\varepsilon$$

Equation 21

where $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$, $\hat{\beta}_4$, $\hat{\gamma}$, and δ are the coefficients obtained from Equation 20.

This study estimated provincial NTL using Model 3 and aggregated the actual and estimated values at the regional level for easier interpretation. Figure 27 plots the estimated monthly regional NTL (blue) and actual NTL (black). The estimated NTL shows an upward trend over the years and fluctuates seasonally, influenced by temperature and rainfall.

Before the pandemic, the estimated NTL closely followed actual values, indicating the model's accuracy. However, it did not capture sudden drops likely caused by disasters or power outages, nor temporary peaks seen in regions near Marawi City during the Marawi Siege (Del Castillo et al., 2024a).

During the pandemic, gaps between actual and counterfactual NTL indicate economic impacts. Two patterns emerged: In R1–R10, counterfactual NTL was higher, reflecting economic decline, while in R11–R17, actual NTL exceeded counterfactual values, suggesting economic gains (Del Castillo et al., 2024a).

5.3 EAR computation and Spatiotemporal analysis

For the EAR, the provincial monthly NTL NTL_p was aggregated into regional monthly NTL NTL_r (Equation 22):

$$\ln NTL_r = \sum_{p=1}^k \ln NTL_p$$

Equation 22

Here, k represents the total number of province p in region r (Del Castillo, et al., 2024).

Similarly, the counterfactual NTL $cNTL_p$ was aggregated into the regional level as represented by Equation 23:

$$\ln cNTL_r = \sum_{p=1}^k \ln cNTL_p$$

Equation 23

To compute the EAR per region r , the actual NTL was subtracted from the counterfactual NTL and divided the difference by the counterfactual NTL (Equation 24).

$$EAR_r = \left(\frac{\ln cNTL_r - \ln NTL_r}{\ln cNTL_r} \right)$$

Equation 24

Here, EAR is the ratio of economic activity reduction considered as an index of economic impact.

5.3.1 Regional monthly EAR

This chapter calculated regional monthly EAR, which measures economic impact based on NTL data (Del Castillo et al., 2024a). EAR values range from -1 to 1 but were scaled by 100 for readability. Positive EAR indicates reduced economic activity, while negative EAR reflects an increase, with values spanning from -8.65 to 25.13.

Figure 28 presents EAR by region and month, with columns representing regions ranked by urbanization and rows showing years and months. Color-coded values—yellow for negative and blue for positive—illustrate monthly changes within regions and highlight the highest EARs each month (Del Castillo et al., 2024a).

5.3.2 Spatial distribution of EAR

This study analyzed the spatial distribution of EARs and identified two key patterns. First, monthly regional EARs revealed an urban-rural divide. As shown in Figure 28, urban regions (R1–R10) generally had positive EARs, while rural regions (R11–R17) mostly had negative EARs. This suggests that economic impacts varied, with urban areas experiencing losses and rural areas seeing gains (Del Castillo et al., 2024a). Second, southern regions had higher EARs. Figure 29d, which maps the three-year average EAR per region, shows that nearly 80% of Mindanao had positive EARs, compared to only about a third of Luzon and Visayas. This suggests Mindanao was more severely affected over the three years (Del Castillo et al., 2024a).

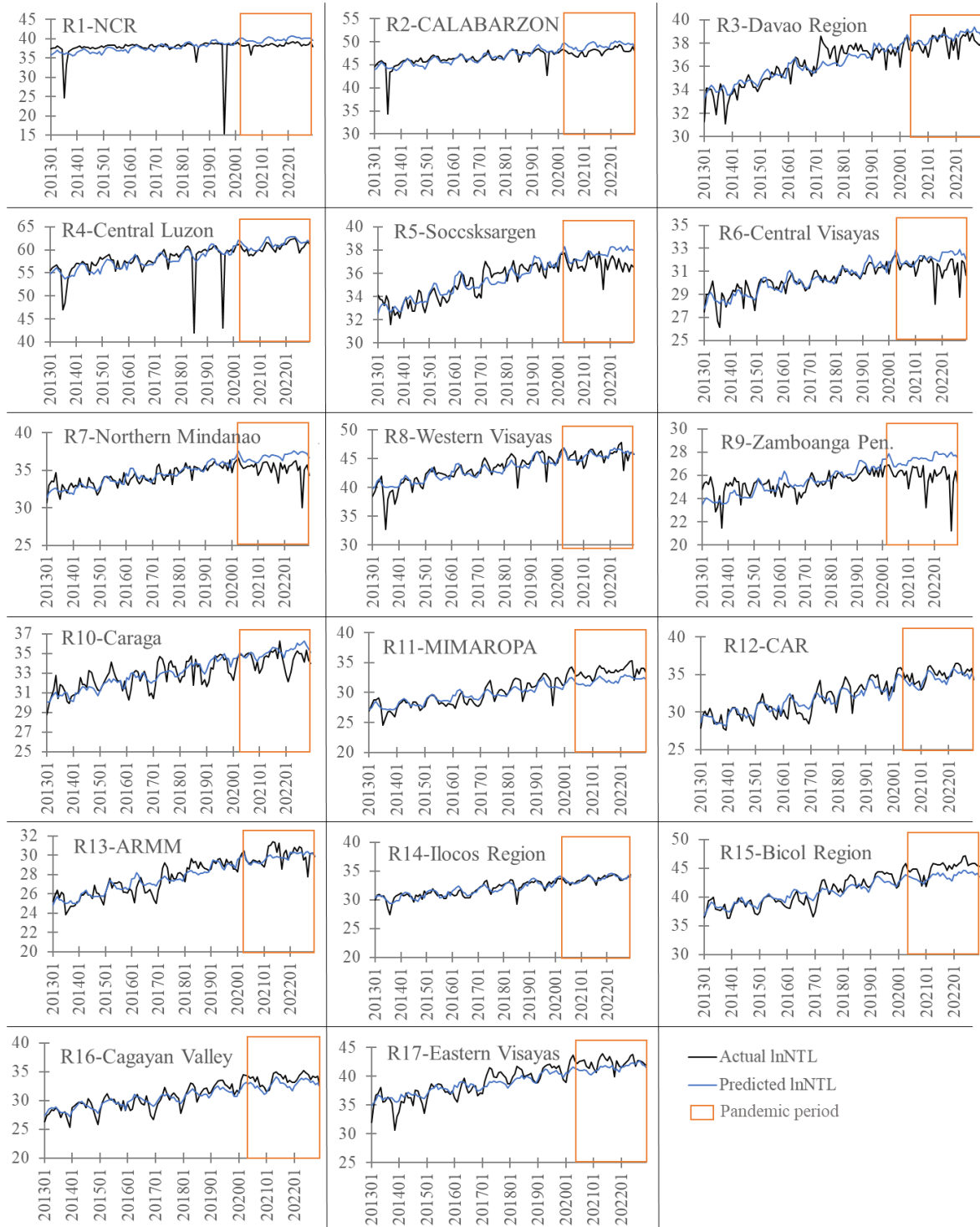


Figure 27. Monthly actual and estimated NTL values per region (Del Castillo, et al., 2024a).

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	
	NCR	CALB	DAVR	CENL	SOCC	CENV	NORM	WESV	ZAMB	CARA	MIMA	CAR	ARMM	ILOC	BICL	CAGV	EASV	
yyymm	L	L	M	V	M	V	M	V	M	M	L	L	M	L	L	L	V	Ave
202003	3.59	2.23	- 0.20	0.87	0.12	- 0.42	2.46	- 1.48	2.14	0.33	- 4.99	- 2.02	- 0.71	0.84	- 4.17	- 3.99	- 4.21	-0.57
202004	4.86	2.75	0.82	1.18	1.36	1.71	3.62	- 0.47	3.91	0.87	- 5.68	- 2.32	0.03	0.42	- 4.21	- 2.49	- 4.58	0.10
202005	3.44	2.99	2.54	1.62	1.34	2.37	4.07	- 0.92	3.81	0.43	- 4.32	- 2.19	0.70	0.78	- 2.45	- 3.00	- 3.06	0.48
202006	2.52	2.98	1.35	1.77	0.80	1.99	3.63	- 0.05	3.44	0.04	- 3.88	0.11	- 0.24	0.84	- 2.22	- 1.04	- 2.49	0.56
202007	2.18	2.20	- 0.39	0.19	1.59	- 0.18	3.13	- 2.28	3.53	- 0.76	- 5.49	- 2.50	- 0.62	- 0.87	- 3.87	- 3.11	- 3.85	-0.65
202008	9.03	2.57	0.49	1.51	- 0.57	0.29	3.24	- 2.48	3.20	- 0.17	- 6.48	- 1.09	- 0.26	0.52	- 4.08	- 2.02	- 3.91	-0.01
202009	3.13	3.88	0.83	1.89	- 0.31	0.87	3.23	- 4.38	2.33	0.81	- 4.49	- 3.25	- 0.23	- 0.50	- 4.26	- 3.92	- 3.94	-0.49
202010	1.74	2.66	2.19	1.51	1.90	0.64	2.24	1.31	1.84	2.30	- 3.87	0.02	- 0.21	- 0.54	- 2.46	- 0.57	- 1.58	0.54
202011	1.26	1.19	2.34	0.20	1.40	0.77	3.41	- 0.06	3.75	3.92	- 4.61	- 1.78	- 0.53	- 1.72	1.33	- 2.46	- 2.13	0.37
202012	1.19	0.04	0.35	- 0.30	1.41	- 1.36	1.01	- 2.50	2.46	0.36	- 4.85	- 2.56	0.80	- 1.44	- 3.22	- 2.01	- 5.19	-0.93
202101	2.21	3.15	3.44	0.46	2.93	4.10	5.82	3.95	9.61	4.89	- 0.29	2.12	2.38	0.25	2.51	0.66	- 2.13	2.71
202102	3.52	4.39	2.37	2.20	2.22	2.97	4.82	3.47	5.34	3.57	- 1.47	3.38	0.47	1.03	- 0.90	2.75	0.96	2.42
202103	3.53	2.98	- 0.80	1.67	- 0.56	1.21	3.44	- 1.42	2.95	1.00	- 4.59	1.43	- 3.18	0.77	- 3.56	- 0.34	- 3.64	0.05
202104	5.14	3.24	0.23	1.39	1.72	1.76	3.75	- 0.48	3.66	1.32	- 5.14	- 0.91	- 2.85	0.64	- 4.04	- 2.82	- 3.96	0.16
202105	3.58	3.06	0.52	1.71	0.33	- 0.32	3.13	- 1.91	3.23	1.61	- 4.84	- 1.46	- 5.19	0.06	- 4.29	- 1.40	- 5.55	-0.45
202106	3.33	2.47	- 0.58	0.93	- 0.19	- 0.16	4.41	- 1.30	5.76	0.30	- 5.58	- 1.23	- 5.05	- 0.65	- 3.05	- 1.76	- 2.92	-0.31
202107	2.13	1.17	0.69	0.25	3.07	1.70	7.36	- 0.49	6.43	1.56	- 4.68	- 1.43	- 1.35	- 0.53	- 4.64	- 3.21	- 2.42	0.33
202108	4.16	2.51	- 1.90	2.54	- 1.08	0.80	3.66	- 1.42	2.70	0.58	- 4.99	- 0.88	- 4.73	1.70	- 4.52	- 1.38	- 4.53	-0.40
202109	2.01	3.74	1.54	- 0.47	2.13	1.63	6.26	- 2.70	15.85	3.15	- 5.03	- 2.67	4.43	- 1.87	- 4.13	- 3.87	- 1.23	1.11
202110	3.09	1.75	4.59	0.62	7.87	13.86	11.34	1.86	7.23	- 3.25	- 5.52	- 2.33	- 1.32	- 1.47	- 3.68	- 1.17	2.80	2.13
202111	3.90	1.48	0.52	0.37	0.92	1.14	2.76	0.05	4.59	1.18	- 5.72	- 2.37	- 2.40	- 0.79	- 5.00	- 2.09	- 3.24	-0.28
202112	0.48	- 0.04	2.59	- 1.07	3.14	1.57	4.38	- 1.09	7.69	2.45	- 5.50	- 1.32	0.27	- 2.41	- 4.67	- 3.63	- 2.26	0.03
202201	3.29	2.24	0.98	1.73	2.66	7.16	4.72	0.52	5.97	7.59	- 3.59	- 0.27	1.11	0.31	- 4.18	- 0.54	0.59	1.78
202202	3.79	2.37	5.54	1.07	1.81	5.41	7.90	0.82	8.08	9.34	- 3.31	2.21	0.41	0.98	- 3.65	- 0.42	- 0.82	2.44
202203	3.33	1.76	1.70	0.42	2.49	4.71	5.52	0.83	6.53	7.05	- 4.19	0.37	- 1.38	0.64	- 3.54	- 1.58	- 1.06	1.39
202204	3.61	2.20	0.72	0.45	4.16	3.03	5.20	0.18	6.17	3.50	- 5.69	- 2.27	- 0.30	- 0.68	- 4.47	- 1.43	- 1.98	0.73
202205	2.13	1.40	0.76	0.10	2.08	2.48	4.81	- 1.83	4.78	2.24	- 7.46	- 3.34	- 1.82	- 1.20	- 5.75	- 3.78	- 3.04	-0.44
202206	2.77	1.44	0.50	0.76	4.04	2.44	3.71	- 3.75	4.41	2.52	- 8.65	- 2.38	- 1.25	- 0.64	- 6.11	- 1.94	- 3.32	-0.32
202207	4.13	3.01	2.00	3.58	4.42	5.90	6.82	6.38	7.72	2.53	1.21	1.48	1.89	1.30	- 3.19	- 1.55	1.29	2.88
202208	3.63	2.87	0.45	1.48	2.93	2.69	5.71	- 1.02	6.86	2.95	- 4.98	- 0.74	1.91	- 0.02	- 3.48	- 0.10	- 0.45	1.22
202209	4.25	3.14	2.79	1.26	3.98	13.85	20.80	3.25	25.13	6.27	- 2.63	- 1.53	9.00	- 0.79	- 3.39	- 1.45	0.08	4.94
202210	3.43	2.34	2.55	- 0.02	4.60	1.54	7.38	- 0.72	8.77	1.62	- 5.32	- 2.64	0.13	- 0.99	- 4.46	- 2.73	- 0.94	0.86
202211	1.76	0.85	3.08	0.19	3.24	2.64	5.04	- 0.37	5.58	3.69	- 4.57	- 1.50	0.32	0.26	- 3.30	- 2.19	- 0.65	0.83
202212	3.58	2.04	1.85	0.23	3.54	4.64	7.55	- 0.20	9.20	3.80	- 3.07	1.74	0.65	- 1.47	- 4.25	0.94	- 1.05	1.75
2020Av	3.29	2.35	1.03	1.04	0.90	0.67	3.00	-1.33	3.04	0.81	-4.87	-1.76	-0.13	-0.17	-2.96	-2.46	-3.49	-0.06
2021Av	3.09	2.49	1.10	0.88	1.88	2.52	5.09	-0.12	6.25	1.53	-4.45	-0.64	-1.54	-0.27	-3.33	-1.52	-2.34	0.62
2022Av	3.31	2.14	1.91	0.94	3.33	4.71	7.10	0.34	8.27	4.42	-4.35	-0.74	0.89	-0.19	-4.15	-1.40	-0.95	1.50
Average	3.23	2.33	1.37	0.95	2.10	2.75	5.19	-0.31	6.02	2.34	-4.54	-1.00	-0.27	-0.21	-3.51	-1.75	-2.19	0.73

Figure 28. Regional monthly EAR. Luzon (L), Visayas (V), and Mindanao (M). The regions were ranked according to urbanization levels, (R1 having the highest and R17, the lowest). Note: The reported values were multiplied by 100 to improve readability.

Red box marks the EAR peaks (Del Castillo, et al., 2024a).

5.3.3 Temporal distribution of EAR

The three-year temporal analysis of EAR revealed monthly fluctuations within each region, with regional peaks highlighted in red (Figure 28). The first peak occurred in R1 in August 2020, followed by R2 and then less urbanized regions. Over time, EAR intensified and shifted from highly urbanized areas to less urbanized ones like R9, R7, and R6 (Del Castillo et al., 2024a).

Two key patterns emerged from the timing of regional EAR peaks. First, peaks moved from highly urbanized regions to those with lower urbanization. Second, peaks gradually shifted southward, starting in Luzon in the first year and spreading to Visayas and Mindanao in the second and third years (Del Castillo et al., 2024a).

Figures 29a–c show the average annual regional EAR from 2020 to 2022. In 2020 (Figure 29a), regions with positive EAR (+EAR, shown in blue) were mainly in Luzon and Mindanao. By 2021, +EAR areas decreased in Luzon but expanded and intensified in Mindanao. In 2022, they further increased in both Mindanao and Visayas (Del Castillo et al., 2024a). In addition to monthly fluctuations, EAR values also indicated recovery trends. Figures 29e and 29f show the annual average EAR for regions with positive and negative EAR, respectively, helping identify areas showing recovery (Del Castillo et al., 2024a). In regions with positive EAR (Figure 29e), R2 and R4 exhibited a decline, indicating gradual recovery, though none reached their counterfactual values. Conversely, regions with negative EAR (Figure 29f), such as R11, R13, R16, and R17, saw increasing EAR, signaling economic decline despite earlier gains.

This study introduced a counterfactual-based approach to estimating economic impacts, enabling the calculation of medium-term EAR. This method complements the widely used change detection technique, which compares pre- and post-event NTL images (Ghosh et al., 2020; Beyer et al., 2021; Alahmadi et al., 2021, 2023) and is effective for assessing immediate impacts. However, change detection may underestimate long-term effects since it does not account for trends.

In contrast, the counterfactual approach allows for long-term impact estimation and recovery tracking. While some studies (Lin & Rybnikova, 2023) use pre-pandemic levels as the recovery point, the counterfactual value can provide a more accurate benchmark by measuring recovery as EAR returning to zero. Results show that while some regions are progressing toward recovery, many still experience positive EAR, and those with negative EAR face worsening conditions. Continuous monitoring is essential for

authorities to identify struggling regions and allocate resources effectively (Del Castillo et al., 2024a).

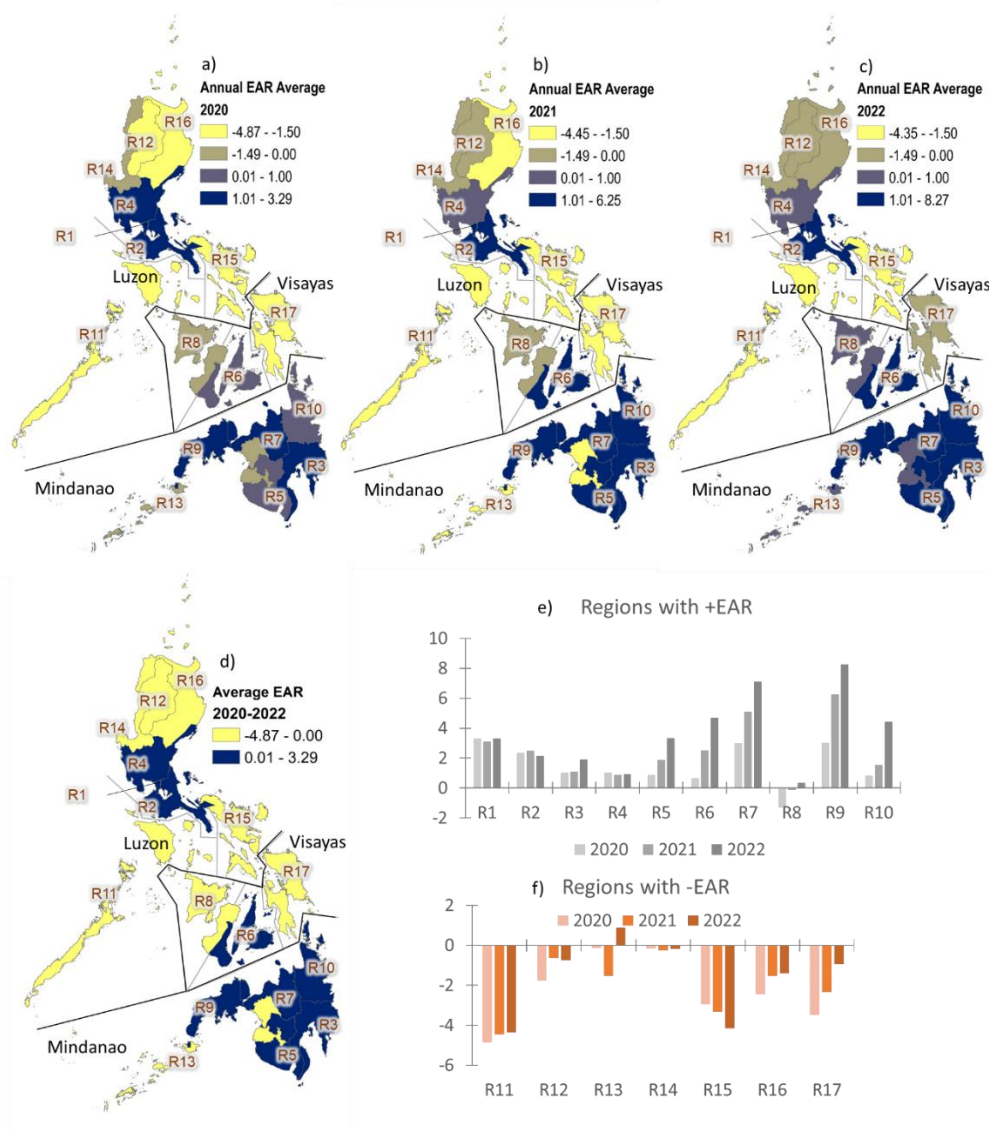


Figure 29. EAR annual average maps for 2020 (a), 2021 (b), 2022 (c), and from 2020 to 2022 (d). Annual EAR per regions with positive EAR € and regions with -EAR (f) (Del Castillo, et al., 2024a).

5.4 Conclusion

This chapter provided evidence for the use of NTL in estimating medium-term regional economic impacts due to the COVID-19 pandemic based on the paper of Del Castillo, et al., (2024a). A model was developed to estimate pre-pandemic NTL using explanatory variables such as mean temperature, maximum rainfall, built-up area,

holidays, trends, and regional dummy variables. The model explained 81.6% of pre-pandemic NTL. Using the regression results, counterfactual NTL was estimated, closely matching actual pre-pandemic regional NTL. Regional monthly EARs were then calculated, and factors influencing them were identified through regression analysis (Del Castillo et al., 2024a).

The study found that while Luzon faced a sharp initial economic impact from lockdowns, Mindanao had a higher overall medium-term EAR. Over time, EAR peaks shifted from highly urbanized regions in the first year to less urbanized areas in the second and third years, eventually migrating from Luzon to Mindanao. The three-year analysis also highlighted regional recovery trends. Key factors influencing EAR included urbanization level, poverty incidence, and hospital case numbers.

This study acknowledges several limitations. First, the method requires more data and computation, making it more time-consuming than simpler change detection approaches. Second, it only reflects economic impacts from NTL-emitting sectors, excluding agriculture. Third, smaller, unrelated events may influence EAR, such as sudden NTL drops due to weather disturbances, reduced activity, or power outages. Similarly, NTL peaks in Mindanao in 2017 may be linked to population displacement during the Marawi Siege, which was not accounted for in the pre-pandemic model.

Additionally, the method assumes no other hazards occurred during the pandemic, though some short-lived natural disasters affected specific regions. As a result, EARs may not solely reflect COVID-19 impacts but also minor events. Future research could improve accuracy by incorporating multiple hazards and using multispectral imagery to capture agricultural losses (Del Castillo et al., 2024a).

This study contributes by estimating medium-term EAR from COVID-19 using NTL data. Findings showed higher EAR in urban areas, with impacts shifting to less urban and southern regions in the second and third years. Understanding these spatiotemporal patterns and monitoring long-term effects is crucial. NTL offers valuable insights beyond immediate impacts (Del Castillo, et al., 2024a).

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Chapter 6

Multi-scale economic impact estimation of Taal Volcano eruption using EC and NTL

6.1 Introduction

Assessments of volcanic eruption impacts, however prompt, often lack spatiotemporal dimensions. Spatiotemporal dimensions are critical for proportionate and timely distribution of resources in disaster-affected areas. Sometimes, on-site data collection cannot be conducted immediately for safety reasons. Consequently, temporally blind assessments could delay response and conceal recovery trends, while spatially blind estimates lead to possible mismatched and biased resource allocation (Brucal, et al. 2020; Malik 2022).

This gap can be addressed using high-frequency EC and high-resolution NTL data (Del Castillo, et al., 2025). Both datasets exhibit a strong relationship with GDP, as shown in the regression model results (Chapter 4) and previous studies (Al-mulali & Mohammed 2015; Khan & Kong 2020; Chen, et al. 2022; Faisal, et al., 2017; Doll, et al., 2000a; Henderson, et al., 2012; Ghosh, et al., 2010).

EC data also tend to decrease during volcanic eruption (Wilson, et al., 2012) but research has not yet applied the data to estimate the impacts of local disasters. This chapter used EC and NTL data to analyze the spatiotemporal distributions of the economic impacts of the Taal Volcano eruption on January 12, 2020. It adopted the following research questions: 1) How were the economic impacts based on EC data distributed across time, and 2) which municipalities were worst affected, based on NTL data? To answer the first research question, the daily EC data was used to estimate the daily economic impacts. A regression model of pre-eruption daily EC was generated to estimate a counterfactual EC, then subtracted the actual EC from it to compute the daily EC loss (ECL). Assuming actual EC data were only affected by the eruption, the analysis covered 18 days until the first detection of COVID-19 in the Philippines on January 30, 2020. Extending the period could introduce pandemic-related influences beyond the study's scope. For the second question, NTL was used to identify the most affected municipalities by calculating NTLC, the difference between the average NTL of previous years and that of the eruption month (Del Castillo, et al., 2025).

This chapter presents an alternative means of estimating the immediate impacts of volcanic eruptions. Based on the literature review, EC data have not been utilized to examine the economic impacts of natural disasters, making this research the first to employ such data for short-term impact analysis following a local disaster. The results help identify the most affected municipalities using NTL data. Although EC and NTL data were used separately due to data resolution differences, this chapter demonstrates a method for remotely assessing the daily municipal distribution of economic impacts. This method can be applied even if significant hazards are still present onsite.

6.2 Data inputs

6.2.1 EC data

For this chapter, EC was computed from the hourly electric load data of the National Grid Corporation of the Philippines (NGCP, 2023), which tracks the country's electricity load divided into three grids, Luzon, Visayas, and Mindanao (Figure 30). Hourly energy loads were aggregated to daily. Specifically, the hourly electric grid loads $EL_{g,h}$ were aggregated to the daily electricity consumption $EC_{g,d}$ (Equation 25).

$$EC_{g,d} = \sum_{h=1}^{24} EL_{g,h}$$

Equation 25

As the Taal Volcano is located on Luzon Island, this chapter focused on the Luzon grid (Figure 30). This grid encompasses both the affected and unaffected regions. Resulting from the lack of daily EC data of finer spatial resolution, this study assumed that the unaffected regions maintained normal electricity consumption. Any reduction in electricity consumption was attributed solely to the eruption as it was the only triggering event in that month on the island throughout the study period.

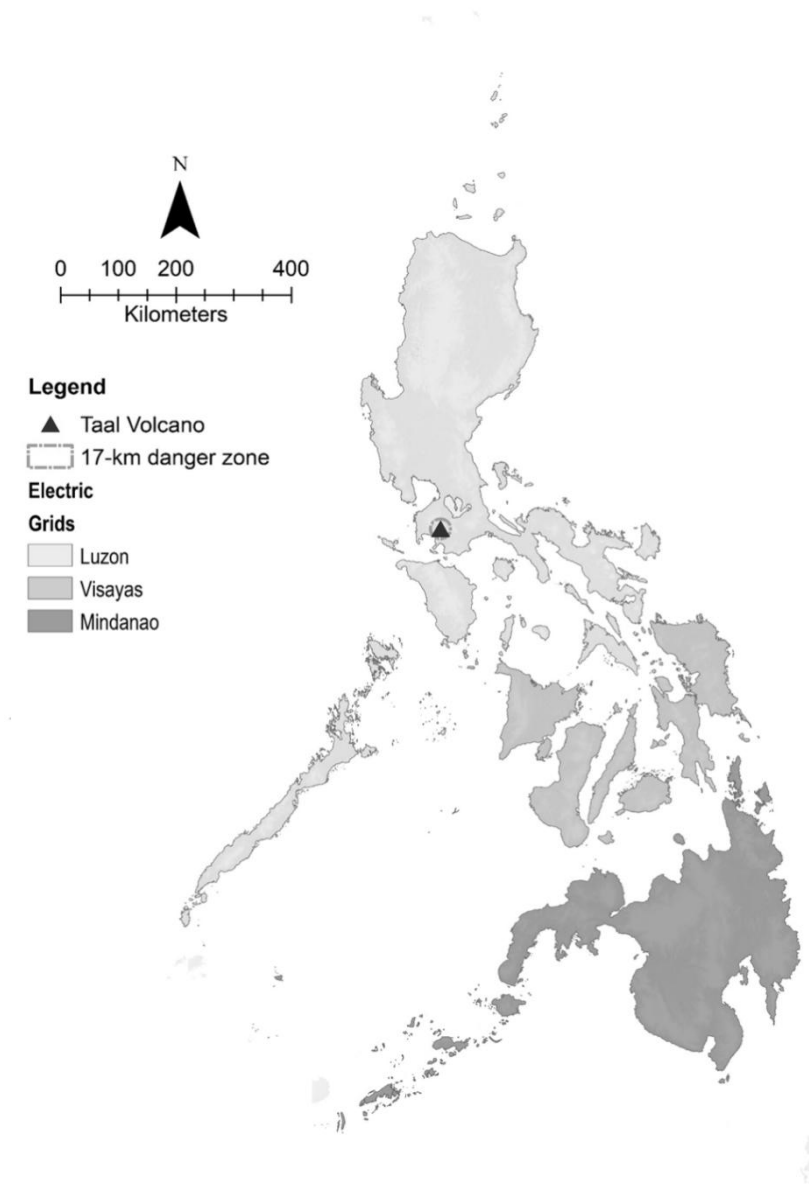


Figure 30. Electricity grids in the Philippines and the location of Taal Volcano (Del Castillo, et al., 2025)

Following Equation 25, daily Luzon EC was computed from January 1, 2013 through January 30, 2020. Figure 31 shows an ascending daily EC trend and noticeable irregularities that could indicate power interruptions, disaster events, or holiday periods such as Christmas, New Year, and other annual religious and cultural occasions.

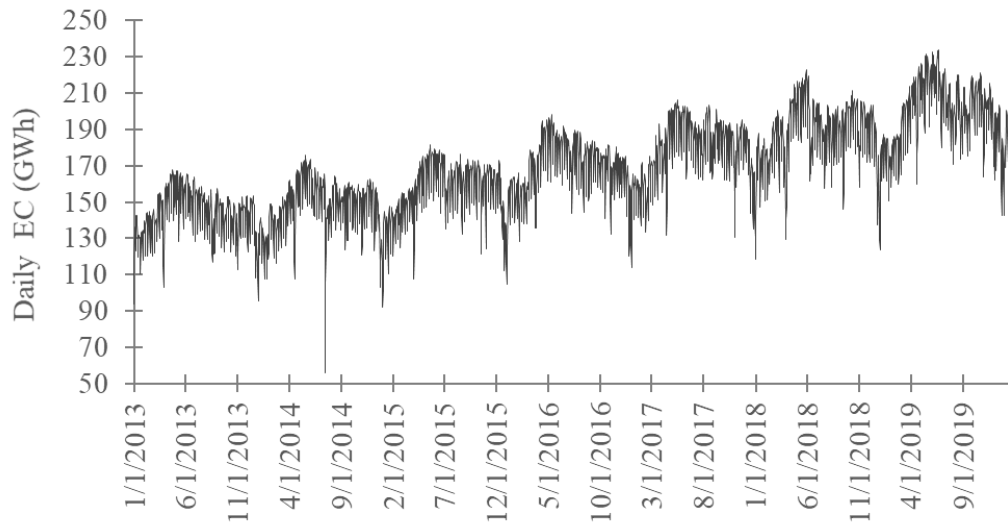


Figure 31. Daily electricity consumption in Luzon from January 1, 2013 to January 30, 2020. Data source: (NGCP, 2023) (Del Castillo, et al., 2025)

Figure 32 plots the average daily EC in Luzon across months in 2019. Generally, it fluctuates across months and weeks (i.e., Sundays) (Del Castillo, et al., 2025).

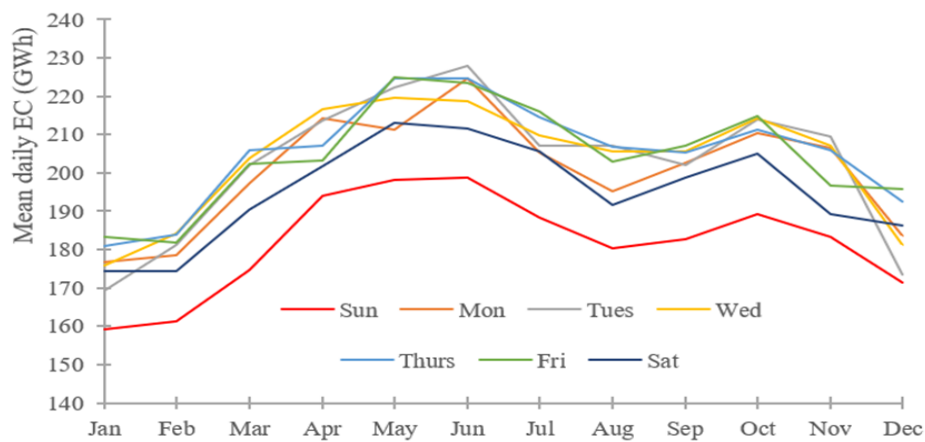


Figure 32. Daily average EC in Luzon across months from January 1, 2019 to December 31, 2019. Data Source: (NGCP, 2023) Image source: (Del Castillo, et al., 2025)

6.2.2 Temperature data

Temperature is a significant variable in residential energy consumption in the Philippines (Dacuycuy, 2019; Santos, 2020; Bayudan-Dacuycuy, 2017). Up to 56% of

household energy consumption in the country comes from space cooling and refrigeration (Department of Energy, 2018), both are related to temperature.

Daily mean temperature data per monitoring station was collected from the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA, 2023). The average of the daily mean temperature of all the monitoring stations in Luzon $meantemp_{L,d}$ was computed (Equation 26) to match the scale of EC data.

$$meantemp_{L,d} = \frac{\sum_{s=1}^n temp_{s,d}}{n}$$

Equation 26

where, $temp_{s,d}$ is the mean temperature of monitoring station s on day d over the total number of monitoring stations in Luzon n .

Figure 33 presents the $meantemp_{L,d}$ data from January 1, 2013, to January 30, 2020, showing how the mean temperature peaks from April to June and drops in January and February, coinciding with the daily EC patterns.

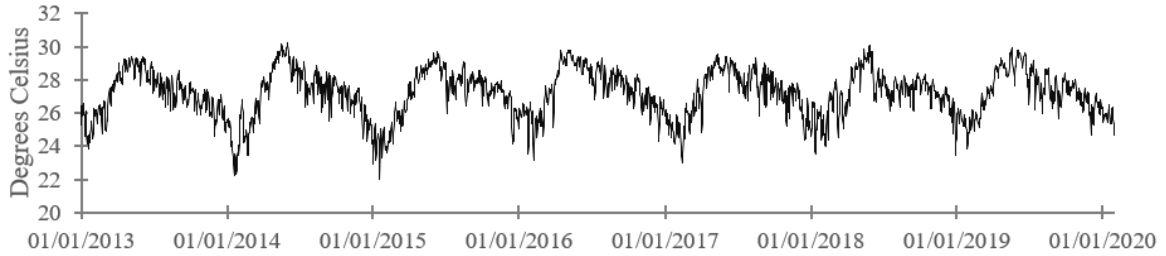


Figure 33. Daily mean temperature in Luzon. Data coverage: January 1, 2013 to January 30, 2020. Data Source: (PAGASA 2023) (Del Castillo, et al., 2025)

6.3 ECL computation

Based on the established relationship of EC with GDP (see Chapter 4), this chapter analyzed the temporal distribution of Taal Volcano's economic impacts using the daily EC data. The temporal distribution of impacts was assessed by computing the daily electricity consumption loss (ECL) estimation which involved three steps: pre-eruption EC modeling, counterfactual EC estimation, and ECL computation.

This study estimated the daily economic activity loss by subtracting the actual EC from the counterfactual EC. To obtain the counterfactual EC, a model based on the pre-eruption EC data was generated. This model established the relationship between the explanatory variables and the pre-eruption EC under normal conditions. This relationship would persist had there been no eruption. Under this condition, the pre-eruption model to estimate the counterfactual EC can be used. Then, the ECL was computed by subtracting the actual from the counterfactual (Figure 34).

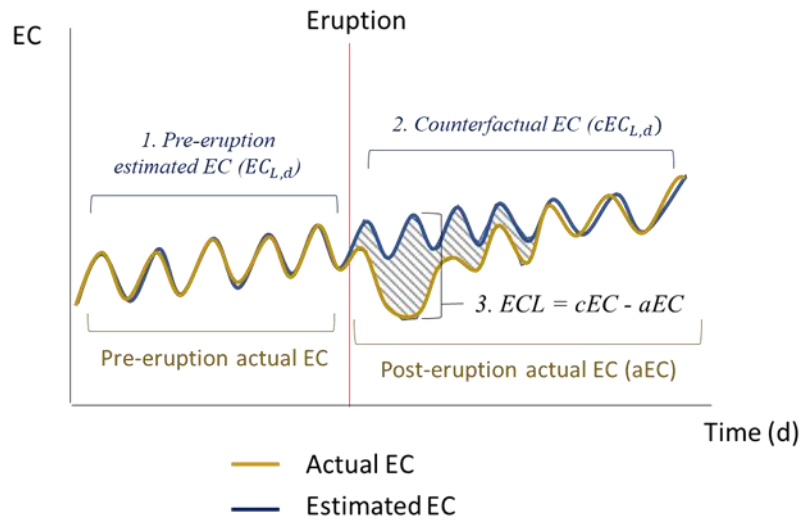


Figure 34. Illustration of ECL estimation process (Del Castillo, et al., 2025).

The process resembled the method of Beyer, et al., (2021) to determine the impact of COVID-19 lockdowns in India. They showed that national quarterly EC and NTL can substitute for GDP. They generated the daily pre-pandemic EC model per district based on the maximum temperature for cooling and heating and added the quarter-fixed effects and trend components to adjust for the seasonal variations and the effect of time in terms of years, respectively. Using the model, they predicted the daily EC per district during the pandemic period and compared it with the actual EC to measure the impacts.

6.3.1 Pre-eruption EC model

The first step in the ECL estimation process is to generate the pre-eruption EC model that captures the relationship between the dependent variable EC with the independent variables before the eruption. For this, the dataset was divided into pre- and post-eruption subsets.

Using pre-eruption data, the natural logarithm of the pre-eruption EC $\ln EC_{L,d}$ was regressed on the natural logarithm of mean temperature $\ln \text{meantemp}_{L,d}$. Mean temperature was selected as a suitable explanatory variable because it influenced energy use. Further, the mean temperature was unaffected by the eruption (Ramirez, 2020), which allowed counterfactual or “business-as-usual” estimation. Additionally, the EC patterns varied by day (Figure 32), with higher consumption on weekdays and lower on weekends. To account for this effect, the day-of-the-week dummy variable DW was added. Similarly, national holidays, which have decreased EC usage (Figure 31), were represented by the *Holiday* dummy variable, coding holidays as 1 and non-holidays as 0. Certain holidays and seasons, such as the Holy Week and Christmas, have prolonged effects, which were accounted for by adding a week of the year fixed effects $WYfe$. The trend variable was also added to capture the effect of time on EC in terms of a year—this captures the annual ascending trend of EC as shown in Figure 31. The pre-eruption model was represented in Equation 27, where the parameters to be estimated are denoted by β_0 , β_2 , and β_2 , and ε is the error term.

$$\ln EC_{L,d} = \beta_0 + \beta_1 \ln \text{meantemp}_{L,d} + \text{Holiday} + DW + WYfe + \text{trend} + \varepsilon$$

Equation 27

Four pre-eruption EC regression models were generated to compare variable explanatory power (Del Castillo, et al., 2025). The $\ln EC1$ model showed that the trend can explain 69.7% of the pre-eruption EC (Table 13). Adding the DW dummy variables in $\ln EC2$ improved the R^2 to 0.808. Including the holiday dummy variable in $\ln EC3$ further increased the R^2 to 0.859. The inclusion of the $\ln \text{meantemp}$ variable in $\ln EC4$ increased the explanatory power of the model being able to explain 90.5% of the pre-eruption EC. Among the four models, $\ln EC4$ had the highest R^2 value and was used to estimate the counterfactual EC.

6.3.2 Counterfactual EC Estimation

Using model $\ln EC4$, the counterfactual EC, or cEC , was estimated. Without the eruption, the relationship between EC and its explanatory variables in Equation 27 remains the same. Thus, the cEC can be estimated by plugging in the post-eruption data into the model represented by Equation 28.

$$\ln cEC_{L,d} = \hat{\beta}_0 + \hat{\beta}_1 \ln meantemp_{L,d} + Holiday + DW + WYfe + trend$$

Equation 28

The natural logarithm of counterfactual EC $\ln cEC_{L,d}$ was regressed on the natural logarithm of the post-eruption's mean temperature. $\hat{\beta}_0$ and $\hat{\beta}_1$ are the coefficients estimated using Equation 27.

Post-eruption data were input into the $\ln EC4$ model to estimate cEC for the entire Luzon Island (Del Castillo et al., 2025). Daily cEC estimates are shown in Table 14.

Table 13. Regression models for pre-eruption EC estimation

	$\ln EC1$	$\ln EC2$	$\ln EC3$	$\ln EC4$
trend	0.057*** (0.001)	0.057*** (0.001)	0.058*** (0.001)	0.057*** (0.0004)
MON		0.112*** (0.005)	0.117*** (0.004)	0.116*** (0.003)
TUE		0.133*** (0.005)	0.133*** (0.004)	0.133*** (0.003)
WED		0.134*** (0.005)	0.134*** (0.004)	0.133*** (0.003)
THURS		0.135*** (0.005)	0.136*** (0.004)	0.135*** (0.003)
FRI		0.128*** (0.005)	0.130*** (0.004)	0.130*** (0.003)
SAT		0.077*** (0.005)	0.079*** (0.004)	0.080*** (0.003)
HOLIDAY			-0.146*** (0.005)	-0.140*** (0.004)
$\ln meantemp$				0.043*** (0.001)
WY fe	YES	YES	YES	YES
Observations	2,567	2,567	2,567	2,567
R ²	0.697	0.808	0.859	0.905
Adjusted R ²	0.691	0.803	0.855	0.903

Data coverage: January 1, 2013 to January 11, 2020 Source: (NGCP 2023; PAGASA 2023) (Del Castillo, et al., 2025)

Table 14. Computed Counterfactual daily EC and EC Loss (Del Castillo, et al., 2025)

Date	Days from eruption	Day of The week	cEC	aEC	ECL MWh	%ECL ECL/cEC	Cumulative ECL MWh
1/12/2020	0	Sun	173,312	172,606	706	0.00	706
1/13/2020	1	Mon	191,241	177,517	13,724	0.07	14,431
1/14/2020	2	Tue	198,935	187,122	11,813	0.06	26,244
1/15/2020	3	Wed	200,305	192,796	7,509	0.04	33,753
1/16/2020	4	Thurs	204,412	197,928	6,484	0.03	40,237
1/17/2020	5	Fri	204,258	200,594	3,664	0.02	43,901
1/18/2020	6	Sat	190,530	191,766	(1,236)	(0.01)	42,665
1/19/2020	7	Sun	173,917	174,723	(806)	(0.00)	41,859
1/20/2020	8	Mon	195,260	189,502	5,758	0.03	47,616
1/21/2020	9	Tues	197,074	191,250	5,824	0.03	53,440
1/22/2020	10	Wed	201,833	191,473	10,360	0.05	63,800
1/23/2020	11	Thurs	205,055	194,000	11,055	0.05	74,854
1/24/2020	12	Fri	197,619	190,571	7,048	0.04	81,903
1/25/2020	13	Sat	164,323	172,847	(8,524)	(0.05)	73,379
1/26/2020	14	Sun	178,724	173,878	4,846	0.03	78,225
1/27/2020	15	Mon	197,918	198,460	(542)	(0.00)	77,683
1/28/2020	16	Tues	197,165	200,771	(3,606)	(0.02)	74,076
1/29/2020	17	Wed	195,036	198,899	(3,863)	(0.02)	70,213
1/30/2020	18	Thurs	187,482	195,495	(8,013)	(0.04)	62,201

The computed cEC was plotted against aEC for comparison (Del Castillo, et al., 2025). As shown in Figure 35, cEC was higher than aEC in the first two weeks after the eruption, indicating a loss. However, in the third week, aEC surpassed cEC, suggesting recovery.

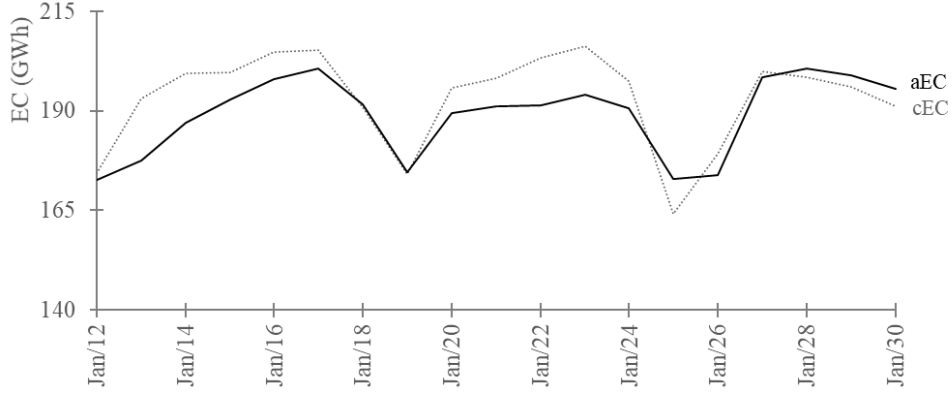


Figure 35. Predicted vs. actual EC per day (Del Castillo, et al., 2025).

6.4 Spatiotemporal impact analysis

6.4.1 EC loss

The difference between the actual EC $aEC_{L,d}$ and the counterfactual EC $cEC_{L,d}$, computed from $lncEC_{L,d}$ gives the EC loss $ECL_{L,d}$. Equation 29 gives the economic impact in terms of EC per day d .

$$ECL_{L,d} = cEC_{L,d} - aEC_{L,d}$$

Equation 29

ECL peaked the day after the eruption (Figure 36), briefly recovered on Days 6–7, rose again on Day 8, and reached a second peak on Day 11. It then dropped on Day 12, turned negative on Day 13, and rose again the next day (Del Castillo, et al., 2025). Afterward, ECL steadily declined until the end of the observation period.

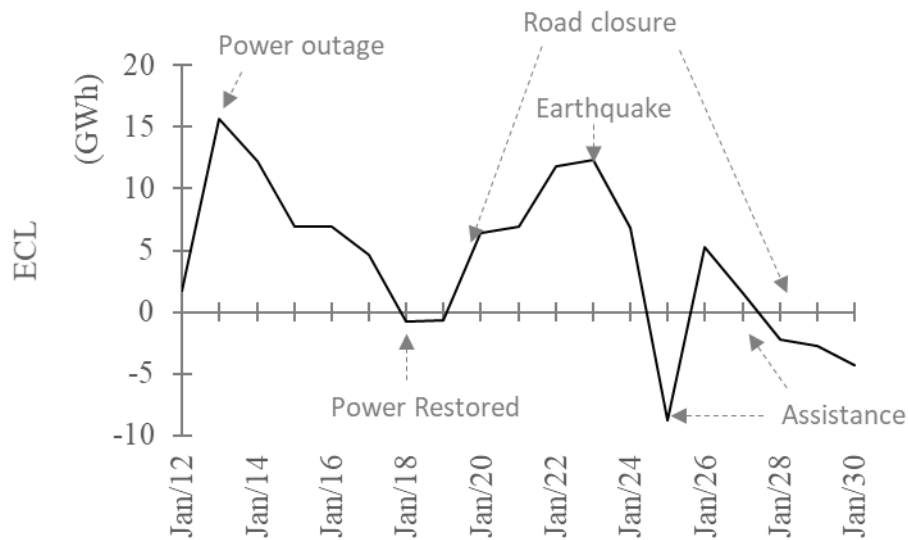


Figure 36. Daily ECL (Del Castillo, et al., 2025).

The daily temporal pattern showed two loss peaks and two recovery valleys. Two main factors likely contributed to the first peak (Del Castillo et al., 2025). The first was power disruption caused by ashfall, which led to outages in 24 municipalities across Cavite, Laguna, and Batangas (NDRRMC, 2020). Such outages are common after eruptions, as wet ashfall can cause substation insulation flashovers (Nagai & Nakada, 2022). The second factor was decreased electricity demand. During the eruption, Batangas I and II Electric Cooperatives reported lower demand due to evacuations and business closures (Del Castillo, et al., 2025; Rivera, 2020).

Power was restored in the affected municipalities after about six days (Santos et al., 2023), leading to a brief recovery (Del Castillo, et al., 2025). However, ECL rose again, reaching a second peak, likely due to the growing number of affected residents and evacuees (Del Castillo et al., 2025; NDRRMC, 2020) (Figure 37). Although the eruption lasted only 10 days, earthquakes continued, with up to 841 recorded on Day 11 (PHIVOLCS, 2024). Additionally, more roads were closed from Day 8 due to earthquake damage.

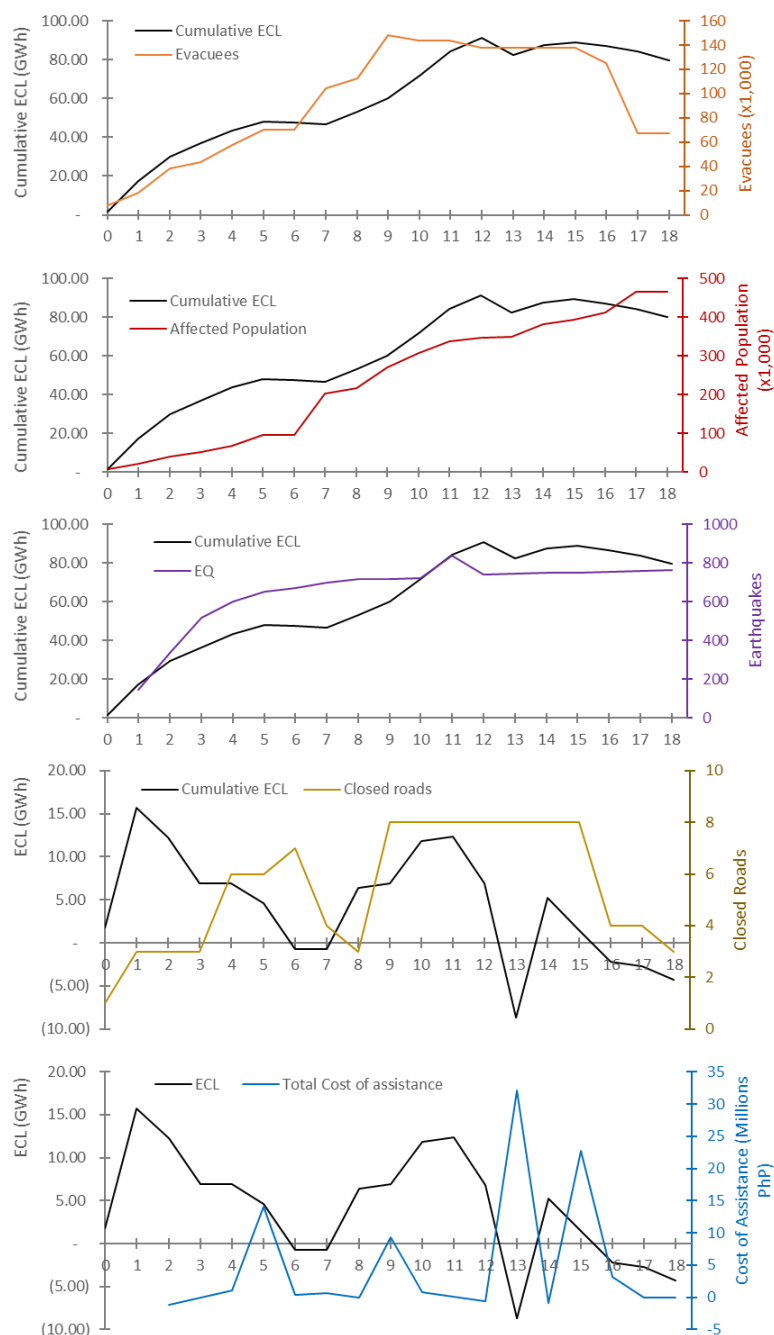


Figure 37. ECL against other reported impacts on population, evacuees, earthquakes, closed roads, assistance cost. Data source: NDRRMC situation reports (Del Castillo, et al., 2025).

ECL reached its lowest level on Day 13, likely due to increased consumption following the distribution of 32 million PhP in financial aid (Del Castillo et al., 2025; NDRRMC, 2020). The next day, ECL rose as aid dropped to less than a million. On Day

15, ECL declined again, suggesting recovery, while aid increased by 22 million PhP. From then on, ECL steadily declined for the remainder of the study period (Del Castillo et al., 2025).

Across the study period, the average %ECL (1.6%). If the GDP loss for Q1 is 350.8 billion PhP, based on the results of Chapter 4, then multiplying this by the average %ECL and the proportion of Luzon's GDP to the national GDP which constitutes 0.7, the economic loss would amount to 3.99 billion PhP. This overall estimate was comparable with other methods. Santos et al. (Santos, et al., 2023) estimated through the Input-Output method for a pessimistic scenario, covering 10 days of total losses amounting to 3.5 billion PhP, making up 1.4% of the region's annual gross regional product (GRP). A government report (NEDA IVA, 2020) estimated the losses at a total of 8.4 billion PhP or 3.3% of the annual regional GRP. Note that these results do not cover agricultural losses, as this activity does not have a substantial energy requirement.

These results supplement the government report by including household loss. Monthly EC data for the Luzon grid (DOE, 2020) disaggregates the residential (35.4%), commercial (34.7%), and industrial (28.0%) sectors. Based on this, 0.57% of the computed ECL would be from household loss. Despite the lack of sectoral disaggregation, the results revealed daily impact fluctuations. Unlike previous estimates (Santos, et al., 2023) presenting a smooth descent of economic loss, the results revealed dynamically fluctuating impacts that responded to hazard progression, population response, and support distribution. Beyond the economic value and the sectoral impacts, the temporal analysis sheds light on the population's reaction to the hazard and assistance. This information could guide responders and authorities in monitoring the impacts for prompt action. Further, this analysis confirms that EC data can capture the immediate economic impacts of an eruption extending previous research (Beyer, et al., 2021, Fezzi & Fanghella, 2020).

6.4.2 NTL change computation

This chapter uses the same pre-processed Suomi NPP VIIRS data as Chapters 4 and 5. Figure 38 displays NTL data from January 2017 to January 2020, with blue areas indicating low NTL values and yellow areas indicating high values. Comparing these images shows changes in nighttime brightness. Post-eruption dimming was observed within the 14-km danger zone, especially in Talisay, Laurel, Agoncillo, Taal, and San

Nicolas (Del Castillo, et al., 2025). Meanwhile, bright areas expanded beyond the 17-km danger zone, notably in Tanauan, Calamba, Malvar, Mataas na Kahoy, and Lipa City.

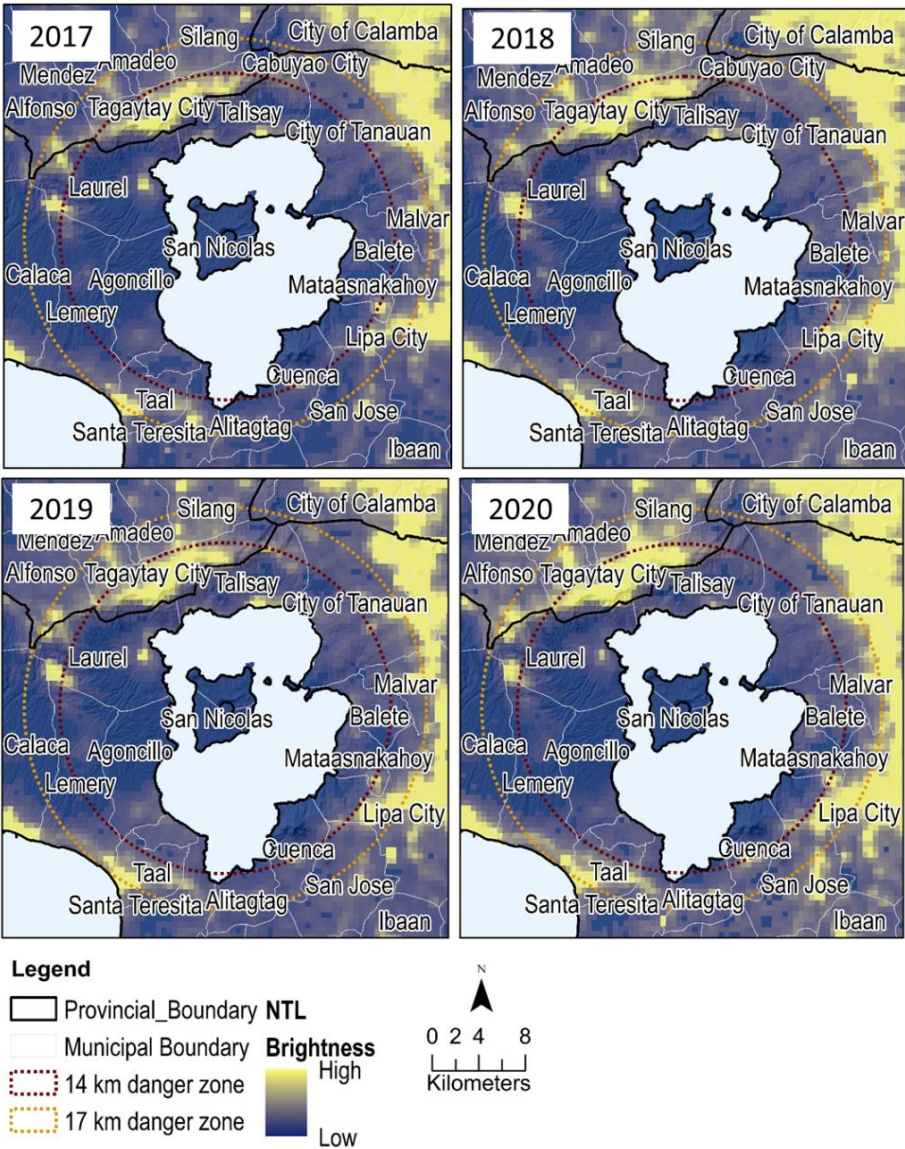


Figure 38. Pre-processed NTL data for January 2017 to January 2020 (Del Castillo, et al., 2025).

Being established as a suitable indicator of economic activity in terms of GDP Chapter 4, NTL data was used as an indicator of economic activity. However, due to differing data scales, this study conducted separate analyses for temporal and spatial dimensions to maximize the level of spatial and temporal details from each data. It analyzed the spatial distribution of impacts using the monthly NTL data at the

municipality level through NTLC mapping, involving NTLC computation and aggregation.

$NTLC_p$ which represents the change in emitted light brightness per pixel p was computed by subtracting the average NTL per pixel for January 2017, January 2018, and January 2019 from the NTL in January 2020 $NTL_{p,2020}$ (Equation 30). This process is similar to change detection methods employed in another study (Beyer, et al., 2021).

$$NTLC_p = NTL_{p,2020} - \left(\frac{NTL_{p,2017} + NTL_{p,2018} + NTL_{p,2019}}{3} \right)$$

Equation 30

The sum of NTLC per municipality $NTLC_m$ was computed using zonal statistics to determine the municipality with the greatest NTL reduction. $NTLC_m$ was computed from the total pixels n in municipality m (Equation 31). The resulting value allows comparison of economic impacts across municipal units.

$$NTLC_m = \sum_{p=1}^n NTLC_p$$

Equation 31

The differences between pre- and post-eruption NTL were plotted per pixel to locate areas with economic activity reduction. Figure 39 presents the NTL reduction as blue and the NTL increase as yellow. The majority of the area within the 14-km danger zone experienced decreased brightness. Specifically, intense dimming was observed on the shores of Talisay and Laurel, and moderate dimming was observed in Agoncillo, Tanauan, and San Nicolas. Clusters of dimmed spots were observed between the 14-km and 17-km danger zones. Isolated dimmed pixels were also scattered outside the 17-km danger zone, which predominantly had increased brightness.

Spatial analysis revealed uneven NTL reduction, matching the 17-km danger zone, ashfall extent, and built-up areas. The most intensely dimmed spots (Figure 39) are within the 17-km danger zone. Within this zone, the dimming concentrated in and around built-up areas (see land cover map in Del Castillo, et al. 2020) within the ash-covered coasts north and west of Taal Lake (see ashfall extent map in Merin, et al., (2021)). Although agricultural losses have been reported (NEDA IVA, 2020), NTLC was not able to detect these impacts (Del Castillo, et al., 2025).

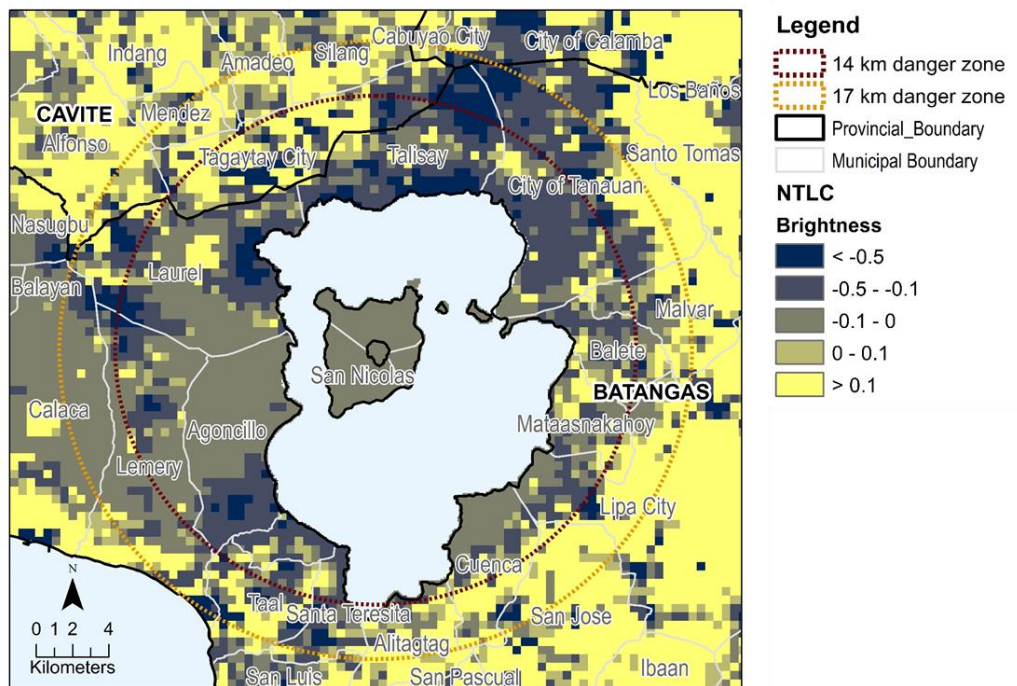


Figure 39. Computed NTLC map (Del Castillo, et al., 2025).

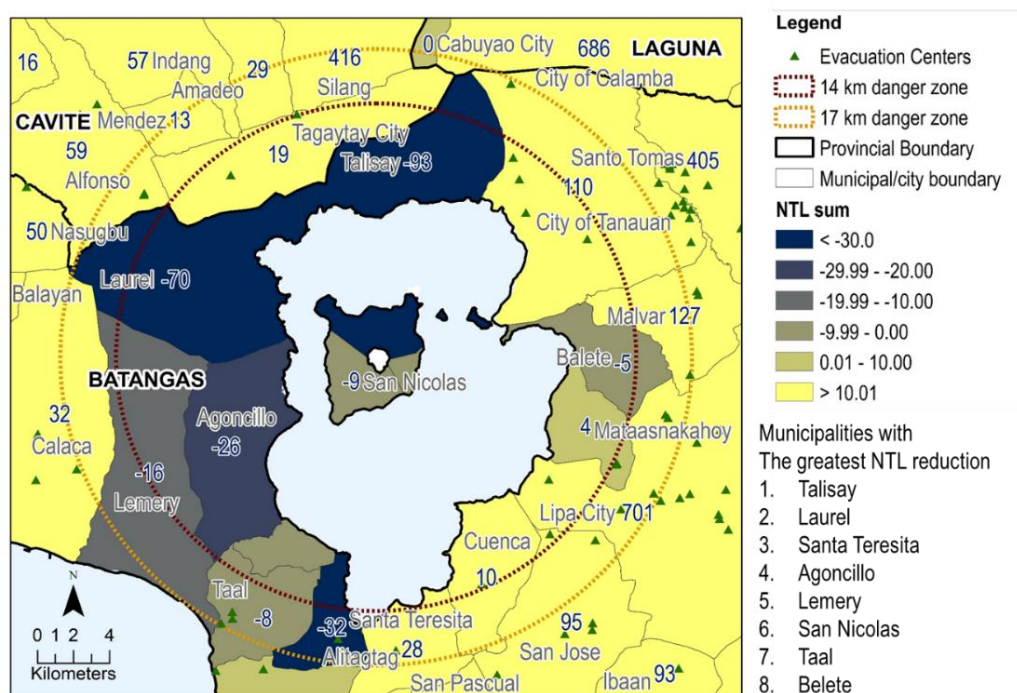


Figure 40. NTLC per municipality and location of evacuation sites. Annotated in numbers are the NTLC sum (Del Castillo, et al., 2025).

Municipal NTLC values were summed to identify the most affected areas, with negative sums indicating dimming and positive sums suggesting increased brightness. As shown in Figure 40, Talisay, Laurel, and Santa Teresita experienced the greatest NTL reduction, followed by Agoncillo, Lemery, San Nicolas, Taal, and Balete. All other municipalities saw an overall NTLC increase. (Del Castillo, et al., 2025).

The identified municipalities appear reasonable as they generally coincided with the government reports (NEDA IVA, 2020) except for two inconsistencies. First, the overestimated NTLC value in Santa Teresita was mainly due to an anomalous cluster of pixels with high NTL values in the January 2017 image which elevated the pre-eruption brightness leading to a substantial NTL reduction in 2020. As the anomaly happened in 2017, it was unrelated to the eruption. Second, false negatives were observed upon comparison with a government report (NEDA IVA, 2020). NEDA identified 15 affected municipalities: Agoncillo, Alitagtag, Balete, Cuenca, Laurel, Lemery, Lipa City, Malvar, Mataasnakahoy, San Nicolas, Santa Teresita, Taal, Talisay, Tanauan, and Tagaytay. This method could not detect almost half of those municipalities (Alitagtag, Cuenca, Lipa City, Malvar, Mataasnakahoy, Tanauan, and Tagaytay) due to a possible overall increased NTL emission from evacuation sites in those municipalities. Nevertheless, the NTLC map and most affected municipalities identified using this method showed that NTL can be used to map volcanic eruption impacts by capitalizing on spatially detailed data.

6.5 Conclusion

This chapter covered the paper of Del Castillo, et al. (2025). In this paper, they analyzed how the economic impacts of Taal Volcano eruption are distributed across space and time using daily ECL and monthly NTL data (Del Castillo, et al., 2025). The study computed ECL and NTLC as indicators of economic activity reduction, estimating a total economic loss of approximately 4 billion PhP based on daily ECL. This estimate aligned with reports and literature, confirming the method's reliability.

The results revealed fluctuating economic impacts with spatial variability. The temporal analysis identified two ECL peaks and two recovery valleys, aligning with power outages, restoration, road closures, earthquakes, affected populations, evacuees, and aid distribution (Del Castillo, et al., 2025). This alignment demonstrated the data's ability to capture ground conditions. The study also highlighted the importance of rapid lifeline restoration and timely financial support for recovery. Beyond estimating total losses, the study emphasized the dynamic nature of economic impacts, influenced by

hazards such as earthquakes, infrastructure damage, and population displacement—factors often overlooked due to data limitations. The findings demonstrated EC data's potential to bridge this gap. However, challenges remain, particularly in the spatial and sectoral granularity of EC data. More frequent updates with finer resolution and classification would enhance real-time impact monitoring. Further research is needed to explore how improved monitoring can minimize losses and accelerate recovery (Del Castillo, et al., 2025).

Spatial analysis identified significant NTL reductions where ashfall overlapped with built-up areas, highlighting the most affected municipalities and areas within them (Del Castillo, et al., 2025). This finding could be used for reconstruction planning and support prioritization (Del Castillo, et al., 2025). This information can guide reconstruction planning and aid prioritization. Since NTLC maps align with past eruption damage, such as in 1911 (Maso 1911), reconstruction efforts should avoid these high-risk zones. The NTLC map can also support assistance fund applications, which are typically based on the state of calamity declarations covering entire administrative units. This broad coverage may lead to disproportionate aid distribution. By revealing uneven impacts within municipalities, the NTLC map can help direct aid to those most affected (Del Castillo, et al., 2025).

The results apply only to non-agricultural economic activities, which use little energy and emit minimal nighttime light (Del Castillo, et al., 2025). Additionally, the study captures only immediate impacts, as the method cannot estimate the effects of multiple hazards. Due to scale differences, EC was used for temporal analysis and NTL for spatial analysis. Future research could extend the study period for long-term impact assessment, use higher-resolution data with sectoral classification, and explore integrating EC with NTL data (Del Castillo, et al., 2025).

In conclusion, EC and NTL data offer effective remote methods for analyzing the spatiotemporal distribution of immediate economic impacts from volcanic eruptions. This approach provides crucial information for response and recovery planning, even during ongoing hazards. With high-frequency EC and high-resolution NTL data, impact estimates can overcome spatiotemporal blindness (Del Castillo, et al., 2025).

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Discussion and Conclusion

7.1 Summary of the study and research findings

Economic impact estimates often suffer from spatiotemporal blindness due to data limitations. Lacking spatiotemporal dimensions, estimates have reduced capacity to inform disaster management, leading to mismatched, disproportionate, and delayed support. To address this problem, this research aimed to develop a method to estimate the economic impacts of disasters using EC and NTL.

Chapter 2 summarized studies focusing on the use of EC and NTL as economic activity indicators and disaster impact estimators. Consulting the literature pointed out the methodological, and application gaps that this research can address. The literature review then focused on two key points. The first point delved into the studies focusing on the use of EC and NTL as economic activity indicators and their application for determining disaster impacts. This review pointed out gaps in terms of analysis scale and limited application of EC and NTL in estimating the impacts of disasters, particularly, volcanic eruptions, especially in the Global South countries like the Philippines. Further, this review noted the analysis period focusing mostly on immediate impacts and the need for methods applicable for long-term assessment. The second section then focused on the problem of baseline determination. This section discussed possible methods and their limitations. This highlighted the need for a method to estimate a baseline using EC and NTL data that can be flexibly applied for a short-term small-scale and a long-term large-scale hazard. Overall, the literature review identified the research gap which is a lack of method to estimate a baseline that can be applied across multiple scales. This research gap led to the formulation of the research question: how to estimate a counterfactual based on EC and NTL to compute for the multi-scale economic impacts of disasters?

Chapter 3 discussed the methodology development. In this chapter, the idea of the counterfactual-based economic impact estimation was introduced. Then, the process of estimating economic impacts based on EC and NTL datasets was explained. This process entailed the generation of pre-disaster EC and NTL regression models. These pre-disaster EC and NTL models were then used to estimate the counterfactual EC and NTL. The economic impact can then be computed as the difference between the actual and the

counterfactual values. Impacts can be estimated in terms of GDP by computing the GDP loss. To compute for GDP loss, a counterfactual GDP was estimated based on the counterfactual EC and NTL. This process is limited to the spatiotemporal scale of GDP. To maximize the resolution and frequency of NTL and EC datasets, economic impact indices can be computed. This chapter introduced three indices: the EAR, ECL, and NTLC.

The method was then employed in three case studies to determine how it would performed using real-world data of actual disasters occurring across varying scales. Chapter 4 determined whether EC and NTL can be appropriate economic activity indicators and used them to estimate the impacts of COVID-19 at the national quarterly scale covering the multiple years based on the contents of Del Castillo, et al., (2024). Establishing EC and NTL as substitutes for GDP in estimating economic activity opens up avenues to further their use, taking advantage of their frequency and resolution, particularly in examining the spatial and temporal dimensions of economic impacts. Further, this chapter addresses the current limitation in literature mostly focusing on the immediate impacts of a dynamic and long-term hazard. Due to the limitation of GDP data to national quarterly and regional annual scales in the Philippines, the analysis entailed EC and NTL data aggregation to match the scale of GDP data. Pre-pandemic regression models were then generated to estimate GDP based on EC and NTL datasets, adding dummy variables to control for seasonal variations. The results showed that EC and NTL data can be a suitable economic activity estimator. The models estimated 89.1% of the pre-pandemic NTL and 99.3% of EC were then used to estimate the counterfactual EC and NTL. These counterfactual EC and NTL were then inputted into the pre-pandemic GDP model to estimate the counterfactual GDP. Then, the economic losses due to COVID-19 in terms of GDP were estimated by subtracting the actual from the counterfactual. Results showed that the Philippines lost 2.9 and 3.2 trillion PhP in 2020 and 2021, respectively, due to COVID-19 with the highest losses experienced during the lockdown in Q2 of 2020 and the period with the highest COVID-19 cases during Q2 and Q3 of 2021. This chapter established EC and NTL as suitable proxies for GDP in the Philippines allowing its use to analyze the spatiotemporal distribution of impacts.

Chapter 5 focused on the use of NTL to determine the spatiotemporal distribution of COVID-19 impacts based on Del Castillo, et al., (2024). Analyzing the spatiotemporal distribution can generate insights to formulate region-specific strategies enhancing disaster management. Further, studies covering longer-term COVID-19 impacts at the subnational level to monitor its impacts and guide decisions and policies are integral but

come in short supply. This analysis then contributes to filling this gap by developing a method estimating NTL which allows a longer analysis period and enables regional impact comparison. This chapter then employed spatial regression models to estimate the pre-pandemic NTL based on mean temperature, maximum rainfall, and built-up area. This model explained 81.6% of the pre-pandemic NTL and was used to estimate the counterfactual NTL. Then, the EAR index was introduced. This index estimates the regional monthly economic impacts, revealing the spatiotemporal distribution of COVID-19 covering three years. The results revealed that economic impacts concentrate on the urban regions. Increased EAR initially inflicted the highly urbanized regions. As the EAR declined in these highly urbanized regions, its burden transferred to the urbanizing regions revealing dynamic fluctuations across time.

Chapter 6 also focused on the spatiotemporal distribution of economic impacts based on the study of Del Castillo, et al., (2024). Unlike COVID-19, the Taal Volcano eruption in 2020 covered a much smaller area and lasted for a short duration. This chapter then filled the research gap in the application of EC and NTL data to estimate the economic impacts of a volcanic eruption and the limited research covering the Global South. This chapter demonstrated the use of daily EC data to analyze the impacts per day and the use of NTL to determine the impact distribution within cities. In this chapter, a regression model estimating daily EC before the eruption was generated based on temperature and dummy variables controlling for the temporal variations. A model estimating 90.5% of the pre-eruption EC was used to determine the counterfactual EC from which the ECL was derived to indicate the daily economic impacts. The results estimated an average EC loss of 79.8 GWh, representing 1.6% of the counterfactual EC in the Luzon grid by the end of the 18-day analysis period. This translates to roughly 3.99 billion PhP of economic impacts in the non-agricultural sector. The daily economic impacts based on ECL revealed two loss peaks coinciding with the power outage decreasing energy demand and the influx of affected population, evacuees, earthquake occurrences, and road closures. Results also showed recovery after major assistance distribution. Then, the NTL index was computed using the average pre-eruption and post-eruption NTL values to map out the areas most affected by the eruption. Further, by aggregating the NTLC, the worst-affected municipalities were identified, most of which are located in the northwestern shores of Taal Lake. This chapter demonstrated an alternative method that uses high-frequency EC to reveal temporal fluctuations of immediate non-agricultural economic impacts and map out the worst-affected areas.

7.2 Implications of research

This study found that EC and NTL can strongly estimate economic activities in terms of GDP. The regression model results showed that EC and NTL can estimate 98.3% and 84.9% of GDP before 2020. This result is comparable with the results of Beyer, et al., (2021) which modeled India's GVA based on EC ($R^2=0.953$) and NTL ($R^2=0.775$). Further, this result aligns with the numerous studies investigating the relationship of EC and NTL with GDP. However, unlike the result of Beyer, et al., (2021) where they found that NTL became insignificant when combined with EC, this study found that combining EC and NTL can slightly improve the model's predictive power. This approach then can lead to different possibilities and explanatory variable combinations as it is highly data-dependent. Nevertheless, the results demonstrated that EC and NTL can significantly measure economic activities in terms of GDP in the Philippines. This result opens up opportunities for their use in estimating economic activities and disaster impacts at a finer scale. Further, although the results are only limited to the Philippines, the method can be applied to other study sites and hazard types. This study notes that in the absence of high-resolution and high-frequency economic data, EC and NTL can serve as suitable proxies to reveal spatial and temporal patterns of impacts which provide pertinent information guiding disaster management.

Leveraging on the previous point, this thesis was able to estimate COVID-19 impacts amounting to 2.9 trillion PhP in 2020 and 3.2 trillion PhP in 2021 and that of Taal Volcano eruption in 2020 costing 3.99 billion PhP. Both estimates coincide with the estimates reported in the literature. Literature reported 2.1 trillion PhP (Yu, et al., 2020) and 4.3 trillion PhP (National Economic and Development Authority, 2021) losses due to COVID-19 in 2020. Another set of studies reported 3.5 billion PhP (Santos, et al., 2023) and 8.4 billion PhP (NEDA IVA, 2020) losses due to the Taal Volcano eruption. The main difference between this study's and the literature's findings was the inclusion and exclusion of certain sectors. As the study of Yu, et al., (2020) and Santos, et al., (2023) implemented the Input-Output methods which can capture economic interdependencies across sectors, their analysis includes the agricultural sector. However, the results are often lower than the government reports probably due to the use of pre-pandemic datasets as inputs to the models. Government estimates also cover agricultural damages which this study was unable to capture. However, government estimates did not include household losses. This study supplements this shortcoming as EC and NTL datasets cover residential sectors. Hence, this study has demonstrated that the use of EC and NTL in estimating economic impacts through a counterfactual-based approach can complement other

methods like Input-Output or survey-based estimates and yield reasonable overall estimates. This is parallel to the findings of Beyer, et al, (2021) and the rest of the studies using EC and NTL in estimating economic activities and economic impacts. Further, this method enabled a longer-term impact analysis without the need for onsite investigation in hazardous areas during disaster situations. This method opens up doors to using EC and NTL in crafting informed region-specific strategies to manage disasters beyond the immediate impacts. Specifically, this method can complement change detection methods and other impact estimation methods in monitoring impact levels across time and space to evaluate intervention success.

The third point revolves around the analysis of the spatiotemporal distribution of impacts arising in insights and points for consideration in disaster risk management. This third point can be discussed on two levels. On the research level, this thesis demonstrates the use of EC and NTL to determine the impacts of two hazards with varying scales. This research fills the gap in multi-scale disaster economic impact estimation. It demonstrated the flexibility of EC and NTL datasets to be used for large-scale long-term hazards to a small-scale short-term hazard. Owing to their high frequency and high-resolution and scalability, the analysis scale can be adjusted to the hazard scale. This way, disaster economic estimates of small-scale hazards need not depend on macro-level quarterly or annual data which could dilute the impacts. This research enabled the analysis of spatial distribution and temporal dynamics of economic impacts in greater detail and extended the analysis scope across space and time. With this method, impacts can be monitored until recovery or beyond, assuming no other hazards occur.

On the societal level, the spatiotemporal analysis of COVID-19 impacts highlighted the separation between urban and rural regions. These results aligned with the literature (Carvalho, et al., 2021; Hamman, et al., 2023) indicating that urban regions tend to suffer more economic losses due to COVID-19. Further, in the Philippines, a study (Shinozaki & Rao, 2021) highlighted that the impacts are more likely to happen in highly urbanized regions like NCR. However, these studies focused on the initial impacts. Extending the analysis period to more than one year revealed the subsequent impacts of case surges and protocol adjustments as regions struggle to recover. This is a part of the story often left untold but which the affected had to endure. Specifically, this research demonstrated that the pandemic resulted in higher impacts initially inflicting the highly urbanized regions and eventually transferring to the urbanizing regions. This finding then raises the question of how to interpret the impacts. On the one hand, absolute losses, measured in monetary units, tend to be higher in urban regions due to their higher income base. Though absolute

losses may be higher in these highly urbanized regions, these losses may constitute a smaller proportion of their economy leaving greater room for recovery. On the other hand, urbanizing regions may suffer comparatively smaller absolute losses than highly urbanized regions. However, this smaller absolute loss can make up a significant proportion of the economy, substantially harming their economic trajectory and leaving them less able to cope and recover. This lower capacity to recover then translates to a greater need for support due to their more significant proportionate loss.

The transfer of impacts from the highly urbanized regions to the urbanizing regions found in Chapter 5 asks the question of whether to act based on absolute losses or proportionate losses. From the perspective of a disaster manager, responding based on absolute losses could lead to an urban-centered response, despite the greater need in urbanizing regions. This then implies that an urban-centered response can obstruct the support to the urbanizing regions which have a greater need for support. It would then be imperative to also consider the economic trajectory of a region in disaster management as this will ensure the equitability of support distribution. Through the use of counterfactual estimates, this thesis was able to compute the economic trajectory. Then, researchers, governments, disaster managers may use this counterfactual-based approach as well as the economic impact indices introduced in this thesis to estimate economic impacts taking into consideration the economic trajectory over the long run to monitor recovery, determine resilience, and more urgently, to distribute support more equitably.

Having this multi-scale economic impact analysis capacity can benefit researchers, policymakers, emergency managers, and recovery planners. Disaster loss and damage researchers can adapt and improve the methods to analyze the spatiotemporal dimensions, track the recovery status, and monitor the non-agricultural impacts of various types of disasters. National and local governments and emergency managers could use the results of this analysis to proportionately and promptly allocate financial support to the affected areas, taking into consideration the economic trajectory for equitable resource distribution.

7.3 Current limitations and recommendations

This research was conducted using only Philippine data. This means that it would be important to test the relationship of NTL and EC with economic activity indicators like GDP again when conducting the method for another country, especially in the Global South. Future research can test this relationship for other countries and for other hazards. A general model covering the Global South can be generated. Although the results of this thesis are only valid for the Philippines, the process can be adapted for other sites.

The presence of clouds, especially during monsoon season tends to affect the consistency of NTL data across time. Future research may remove the data from monsoon seasons for better results. Another possible solution would be combining multiple sources of NTL data taken at various times to fill in the cloud pixels could improve the detection of light during monsoon seasons.

One specific limitation regarding the sectoral disaggregation of NTL data was the lack of comprehensive land use data and coarse NTL resolution could result in mixed light source detection. This land use data may not be complete but it is the up-to-date and comprehensive data available at the time of analysis. Further, NTL data was only able to detect economic activities at night. As the VIIRS data is being captured at 1:30 am, the bulk of economic activities occurring during the day were not captured. This gap further supports the need for using EC and NTL datasets together because they complement each other, providing the information that the other one lacks. Future research may use comprehensive detailed land use data and higher resolution NTL data to better disaggregate the sources of NTL.

EC data for Luzon was used even though the affected area only composed a small portion of it. It was assumed that any changes in EC were due to the eruption. Future research could use finer resolution EC (regional monthly) to isolate the impacts of the affected area.

EC data is limited to detecting static economic activities. Hence, it could not measure mobile activities like that of the transport sector. Other datasets like mobility data must be used to estimate the impacts on the transport sector. Further, the introduction of work-from-home arrangements is a confounding factor that was not included in the models. Due to work-from-home arrangements, the actual economic activity was transferred even

though the commercial and industrial EC dropped. This means that the estimated commercial and industrial loss may be larger than the actual loss. Further research can be done to measure the effect of work-from-home arrangements on the residential EC and household consumption to account for the transfer of economic activity during the pandemic.

Other factors affecting energy consumption and NTL emissions such as power interruption or special events were not included in the models. If it is possible to obtain data on power interruptions, it can be incorporated into the models for future research.

This method is suitable for estimating the losses of non-agricultural sectors. It could not estimate agricultural sector impacts because this sector neither release substantial nighttime light nor rely on electricity for operation. Future research can correlate the non-agricultural GVA instead of the total GDP for better correlation and use multispectral images to estimate agricultural damage and use multispectral daytime imageries for agricultural loss estimation.

The method is suitable for measuring the effects of one hazard. It cannot be used for multi-hazard impact assessment. It cannot distinguish the impacts of one hazard from another. The model requires a cutoff date which is the date of hazard occurrence. This current model assumes that the changes in the actual data are due to the hazard that occurred on the cutoff date. In the case of long-term hazards like COVID-19, other disasters occurred during the pandemic, hence, the effects of these minor disasters were included in the estimates. Future research could focus on designing a model to handle multiple hazards.

7.4 Future research directions

Beyond the above-mentioned future research recommendations, this research can expand in several directions. The first direction is to lengthen the study period. The method could be used for long-term monitoring of impacts to track recovery trends and determine community resilience. Traditional methods and economic impact datasets tend to be limited to immediate impacts and the actual recovery status is often left to the projected values without accounting for the actual changes as they occur. Monitoring the impacts could reveal insights that can guide authorities as to how fast or slow the community is recovering. With this, they can evaluate the effectiveness of response and recovery measures in near-real time.

A second direction would be to expand the study site, possibly covering several countries. Aside from the COVID-19 pandemic, another possible hazard to study would be the long-term and wider effects of climate change or sea level rise. Given the global scope of the NTL data and the national scale availability of EC data, the impacts of these hazards can be mapped and monitored across time. This would give strong evidence for investing in cleaner energy, mitigating infrastructures, and adaptation measures.

A third direction would be to disaggregating the impacts across sectors, specifically for the informal sector. The impacts of the informal sector are often not recorded in disaster reports. Though, this information would be pertinent in alleviating poverty due to recurring disasters. In the coming years, finer-resolution NTL datasets could be available from sources other than VIIRS. Finer-resolution NTL could be used to better ascertain the economic impacts in the informal sector.

7.5 Concluding remarks

This research developed a method to estimate the economic impacts based on EC and NTL. This method estimated a counterfactual which served as a baseline for computing the economic impacts. This counterfactual approach enabled a longer-term and more detailed impact assessment across space and time. These datasets and methods used in this thesis have opened up a door toward expanding the scope of economic impact estimation and a more detailed spatiotemporal distribution analysis for measuring, mapping, and monitoring the impacts. The economic impact analysis was performed on three case studies covering multiple scales demonstrated the flexibility of EC and NTL data to yield information that can aid disaster management. This information aids in addressing the blind spots in economic impact estimation. EC and NTL can be used as “*corrective lenses*” to improve the current view and understanding of economic impacts.

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