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Improving GDP estimates using night-time lights

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1 INTRODUCTION

Human activities release traces into the environment. In this regard, we often think of air or water pollution but, usually, little attention is paid to light pollution. Namely, the light emitted by human economic activities that have characterised modern economic production since the second industrial revolution.

Most human economic activities produce light. For instance, using a car to drive to work or to visit a tourist destination produces light pollution. Similarly, building a bridge, a skyscraper, or an airport increases the amount of light emitted of a country.

For many years, measuring light sources' intensity was impossible, especially with proper spatial geolocalisation. The first attempts have been made with photos taken from aeroplanes that, however, had very little quality and impossible precise localization in the space. With the production of specialised satellite modules in the 1960s, the effective measurement of the spatial distribution of night-time lights and their reflectance intensity became possible. With later technology advances, high-frequency publication and very high image resolution have been achieved.

This thesis aims to study the relationship between economic activity and light pollution production using satellite images of the Suomi NPP and NOAA-20 satellites. In particular, I will focus on studying the relationship between night-time lights and GDP, their causal link and the many economic applications. I will show the intriguing properties that satellite imagery have in estimating economic variables, such as their almost global coverage, their exogenous nature with respect to official GDP measurement and the high frequency of the data publication. Finally, in chapter 4 I will combine the official GDP measurements with night-time lights information obtained from the satellites to create a better GDP estimate with a lower measurement error.

As per past literature, night-time lights are strongly correlated with many economic variables. However, handling such data is not straightforward; the relationship between the two is not linear and changes over time. This relation depends on the characteristics of the countries, on their share of the agriculture sector and on the level of economic development in the region.

The Defence Meteorological Satellite Program (DMSP) is a US military programme that, since the 1960s, has been involved in the launch into orbit of satellites to acquire environmental earth data. The project is jointly managed by the United States Space Force and the National Oceanic and Atmospheric Administration. For more than ten years, i.e. from the 1960s until 1972, the operation remained highly classified due to the very high technology involved. Moreover, the tense period of the Cold War certainly played an important role as the DMSP satellites collected photos twice a day for each area of the world. As of December 1972, the mission was declassified and began to be opened to the non-military scientific community.

The DMSP-OLS satellite was equipped with sensors capable of measuring day and night visible and near-infrared light. The collected images were used to observe meteorological systems and cloud coverage. While recognising cloud bodies from daytime images was quite simple, doing so with night-time images entailed obvious complications. Therefore, the sensor was equipped with a 'Photomultiplier Tube' (PMT) capable of enhancing the light captured, thus producing images of the globe of night-time lights. From the comparison of the images from different times and, thus, from the presence or absence of light pixels attesting, as mentioned, human settlements and water surfaces, it could be stated that a certain area was covered or not by clouds.

For the purposes of this thesis, I will only use the data from night-time measurements. Such images are much easier to study in economic analysis without losing the instrument's effectiveness. Namely, there is no need to analyse complex images of the earth's surface during the day when it is sufficient to analyse night-time light sources. Furthermore, night-time data do not suffer from the intense light distortions caused by the sun.

Since the night-time light monitoring system has been operating, DMSP sensors have been the leading technology adopted. However, today, the data produced by DMSP has some limitations due to outdated technology, i.e. poor resolution, six-bit quantisation, saturation on the brightest lights, lack of in-flight calibration, and production of files with a lack of spectral layers suitable for discriminating different light sources.

A significant advance in the field was achieved when the Visible Infrared Imaging Radiometer Suite (VIIRS) was launched into orbit in October 2011 by the Suomi National Polar-Orbiting Partnership (Suomi NPP). The new type of sensor mounted on the satellite has overcome many of the problems of the old generation. Compared to DMSP-OLS, night-time light data imagery obtained by NPP-VIIRS has a finer spatial resolution ($742mt \times 742mt$ vs $5km \times 5km$ at nadir) and higher radiometric resolution (quantisation of 14 bits vs 6 bits). Moreover, an onboard calibration system has been implemented to enhance the quality of NPP-VIIRS night-time data. Replication code for this thesis is uploaded in a GitHub repository.[1]

1 `https://github.com/nbadino/Master-Thesis`

2

WHY NIGHT-TIME LIGHTS

Before proceeding with the data analysis, it is first necessary to dwell on the causal relationship between night-time lights and the economy. The first connection that needs to be made concerns the physical source of night-time lights which is simply light bulbs that run on electricity. Apart from naturally occurring night-time lights, it should be no surprise that electricity consumption (EC) is the primary cause of human light production observed from satellites (NTL).

$$\mathrm{EC} \longrightarrow \mathrm{NTL}$$

Figure 1: Causal structure between electricity consumption and night-time lights.

Even if the direction of causation is unclear in the literature, GDP and electricity consumption are strictly connected, and the latter causes night-time lights.

$$\begin{tikzcd} & \mathrm{GDP} \\ \mathrm{EC} \arrow[r] \arrow[ur, dashed, leftrightarrow] & \mathrm{NTL} \end{tikzcd}$$

Figure 2: Causal structure between GDP and night-time lights.

However, the connection between these two variables needs to be investigated more accurately. Electricity consumption enters fully into the production function of a country, i.e. it tells us the aggregate of how many industrial machines are currently running, how many electric motors are switched on, or how much air conditioning is used. While electricity consumption gives us an aggregate of the energy consumed in a country, night-time lights give us a particular portion of it. That is, that component of the consumed electricity that produces illumination. Moreover, the connection between the amount of light emitted and its distribution in space tells us a lot about the well-being of a country. Observing the lights emitted by North Korea, one is surprised by the very small amount of light emitted at night, so much so that South Korea looks like an island. Yet, assuming one can know the country's energy consumption, which is not disclosed, it is plausible that North Korea consumes far more energy than many other developing countries with more night-time lights. Although studies on this are few, it is likely that in North Korea, almost all of the available energy is used in war industries or propaganda activities, resulting in an extreme contraction of consumption due to home light rationing and brutal control of citizens' life.[1,2] Therefore, even if military production fully enters into GDP, night-time lights allow us to study the actual energy used by the population and thus discriminate the economic well-being from the regime's propaganda parades and the enormous amount of energy that is forcibly subtracted from the population and conveyed to weapon production. In other words, it is plausible to assume that night-time lights tell us more about the consumption component of the gross domestic product and of the population's living standards. Or, looking at the investment side, about the part that has a close connection with the

1 https://www.dailynk.com/english/north-koreas-electricity-situation-worsens-compared-to-last-year/

2 https://www.cia.gov/the-world-factbook/countries/korea-north/

population's consumption, namely: airports, theatres, highways or street lighting.

Finally, as an obvious consequence, past literature has shown that night-time lighting is strongly affected by the consumption preferences of the living population of a country (Cinzano et al., 1999). In this sense, Falchi et al., 2016, highlighted that Italy and South Korea are the most light-polluted countries in the world. This is undoubtedly due to their high living standards but also to country-specific characteristics such as consumption choices and spatial population distribution.

2.1 ECONOMIC CONNECTIONS

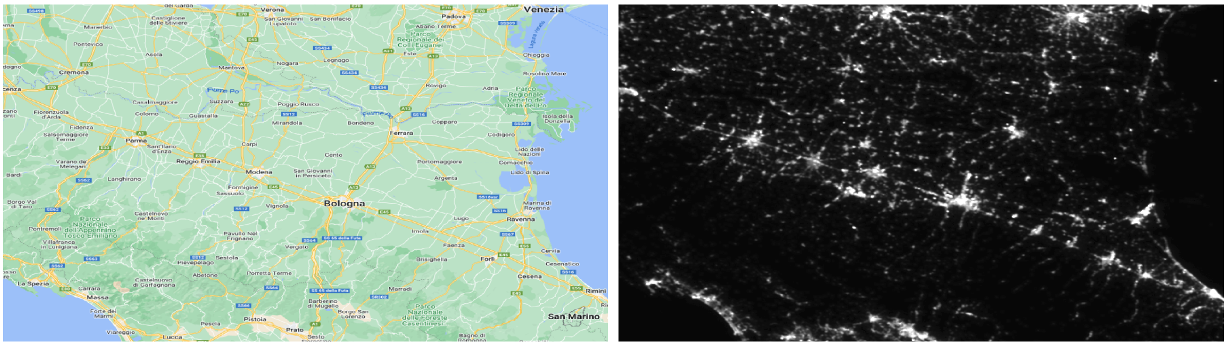
As previously stated, economic production is deeply involved with electricity consumption. From the elementary national income identity in a closed economy:

$$Y = C + I + G \tag{1}$$

It is straightforward to see that each element on the right-hand side has a strict relation with night-time lights. For instance, after a growth in disposable income, individuals may decide to use the car more, maybe to reach an outdoor concert or visit a nearby city. These are all events that produce light consumption. On the investment side, similar behaviour can be assumed. Due to increased taxation flows, governments may decide to build new infrastructures such as bridges, ports or railways, causing new massive light production. For these reasons, night-time lights can be used as a proxy for GDP.

2.1.1 *Roads*

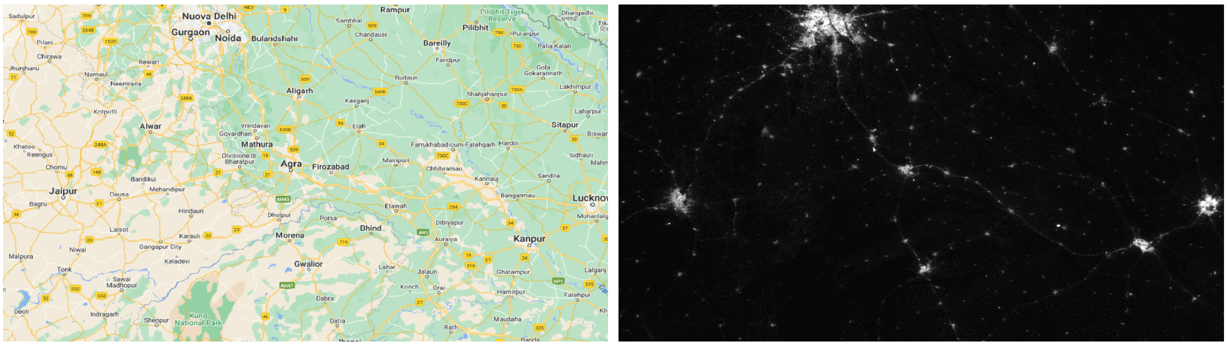
Roads and highways provide valuable information on investment and consumption within a country. The set of new infrastructure is part of the investment component, which is an important determinant of GDP. The same can be sustained with the upgrade to new lighting technology dismissing the old one, as in the case of led street lamps. At the same time, road traffic tells us a lot about the movement of people and thus the consumption component. Queues and traffic tell an eloquent story about the dynamism of a country and the number of people moving at a certain time.



(a) Google Maps (b) Night-time lights

Figure 3: North Italy roads - A1 and A14 highways connecting Bologna and Modena with Milan.

Observing night-time lights, the lines of communication between cities or towns can be studied in depth. Figure 3 shows an extract of the main communication line in northern Italy, namely the A1 and A14 motorways connecting the cities of Bologna and Modena with Milan, some of the country's most productive areas. Figure 4, on the other hand, shows an excerpt of the roads connecting New Delhi in India and peripheral cities.

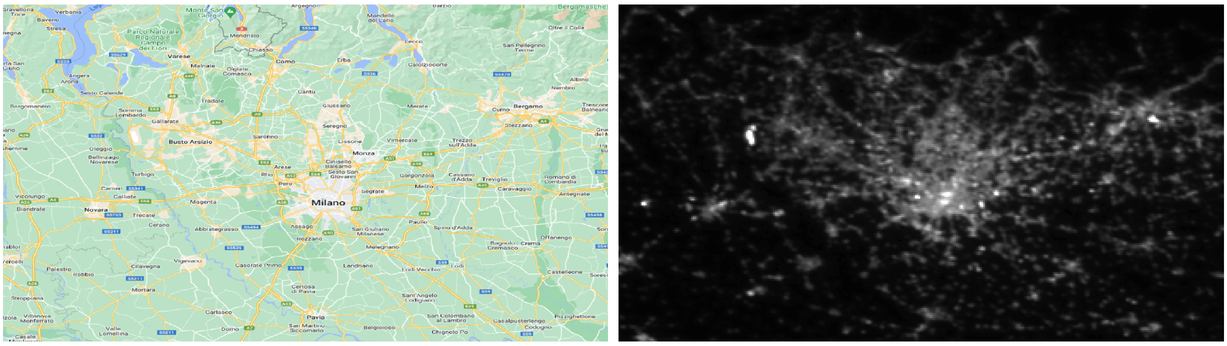


(a) Google Maps (b) Night-time lights

Figure 4: New Delhi periphery roads.

2.1.2 *Cities*

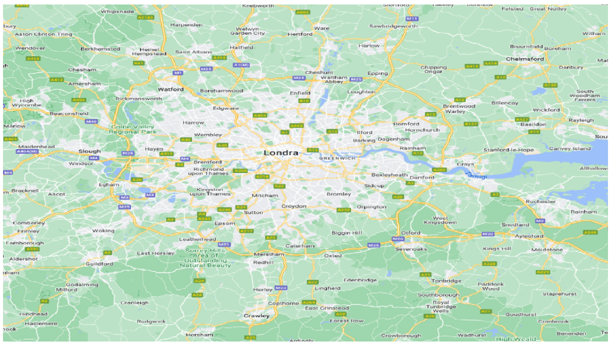
Cities are the primary producers of night-time lights. Studying satellite imagery, the geographical distribution of urban settlements and some of the brightest elements of the cities can be observed, such as major roads, airports and ports. Cities' night-time lights can be a proxy for many economic-related variables. That is population concentration, city dynamism and traffic. It can also be assumed that brighter cities are more economically active and have the resources to maintain such electrical consumption.



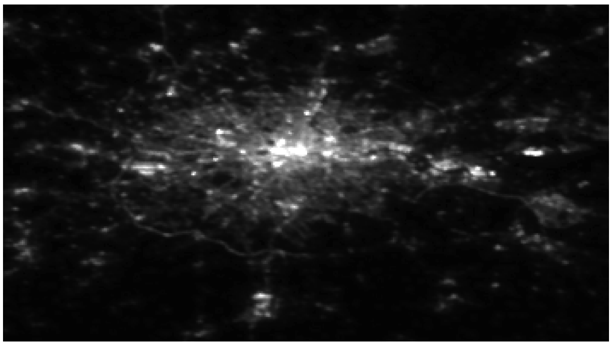
(a) Google Maps (b) Night-time lights

Figure 5: Milan - Italy.

Figure 5 shows the city of Milan and Figure 6 shows London. They are both characterized by well-known web shapes. It can be recognized some roads connecting points of interest of the cities and the main airports of both cities can be easily individuated.



(a) Google Maps

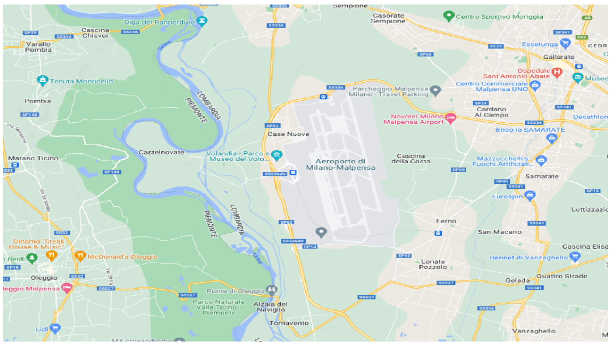


(b) Night-time lights

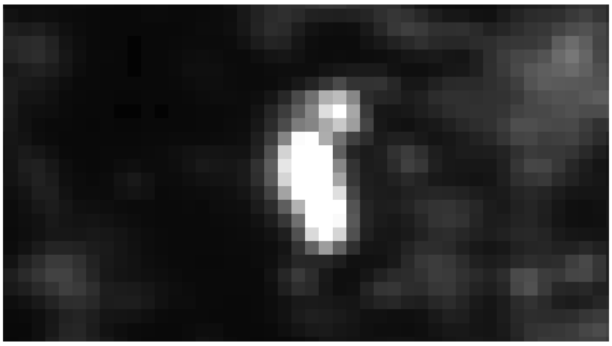
Figure 6: London - United Kingdom.

2.1.3 *Airports*

Airports are usually the brightest part of the cities. In Figure 7 and in Figure 8 two of Europe's busiest airports. The intense night-time lighting is influenced by the traffic and by the dimensions of the airport.

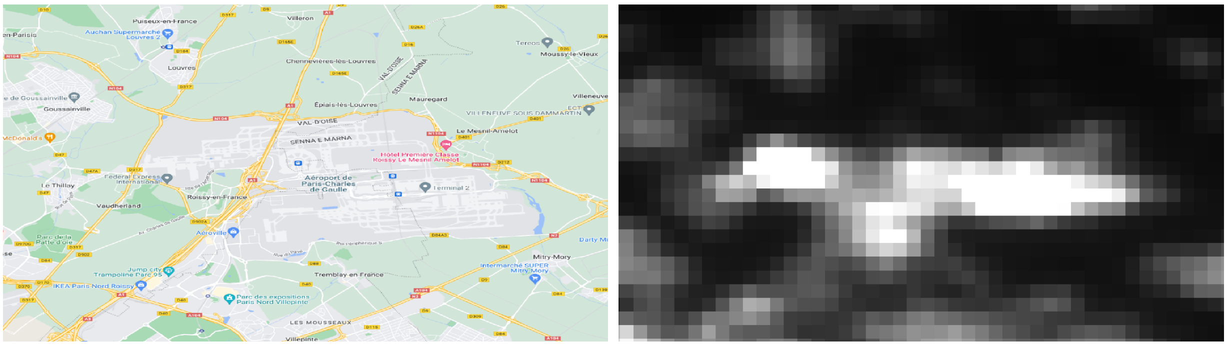


(a) Google Maps



(b) Night-time lights

Figure 7: Malpensa Airport, Milan - Italy.

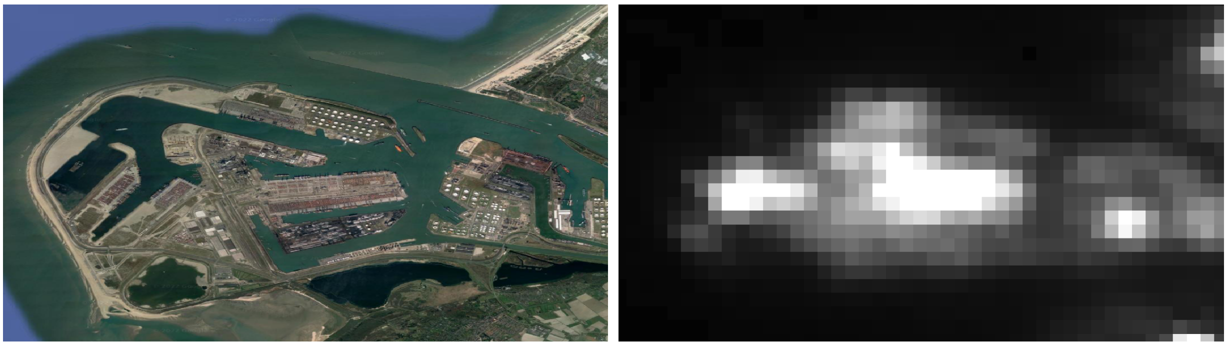


(a) Google Maps (b) Night-time lights

Figure 8: Charles De Gaulle Airport, Paris - France.

2.1.4 *Ports*

In Figure 9, the port of Rotterdam which is one of the largest European commercial ports. The port infrastructure is the main driver of night-time lighting, however docked ships are also a main source.



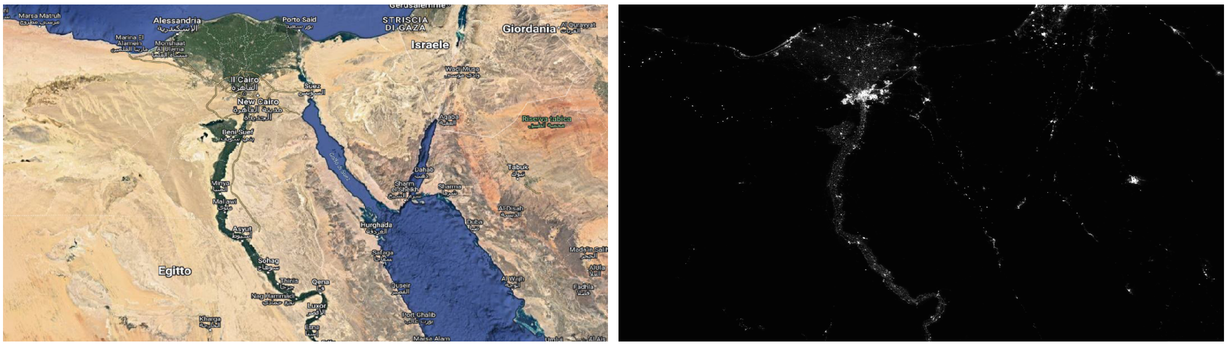
(a) Google Maps (b) Night-time lights

Figure 9: Rotterdam port - Netherlands.

2.1.5 *Human settlements*

Figure 10 shows the night-time lights image of the Nile river in Egypt. This image is particularly fascinating as it shows a well-known fact in historiography: populations tend to settle around water sources.

In particular, observing the river delta, it is possible to see how human activities are concentrated, in a web fashion, around its distributaries. Indeed, it is unsurprising that most of Egypt's gross domestic product is concentrated around its primary water source.



(a) Google Maps (b) Night-time lights

Figure 10: Nile river, Egypt.

2.2 WHY NIGHT-TIME LIGHTS SHOULD BE ADOPTED

The employment of night-time lights makes it possible to estimate economic variables under special conditions in situations where we cannot obtain data or have no guarantee of its truthfulness. Night-time lights have several interesting properties that have allowed their usage in economic literature.

EXOGENOUS NATURE: Night-time lights' measurement errors are independent of economic variables' ones (Hu and Yao, 2022). This is a crucial property, as it will be shown in the next chapters, that allows them to be used as an alternative measure of the economy to improve the estimates of the standard ones. In addition, official growth estimates or forecasts pass through government institutes that may have an interest in manipulating data for their political agenda. Night-time lights observable by satellites are much more challenging to manipulate.

In this regard, a recent working paper (Martinez, 2018), forthcoming in the Journal of Political Economy in 2022, shows how autocratic states tend to overstate their growth estimates. Martinez argues that "Since governments themselves usually produce these estimates, they face a recurring temptation to exaggerate just how well the economy is doing". His results show that the elasticities of night-time lights on GDP are systematically larger in the most authoritarian regimes and that the overestimation averages 35%.

WORLDWIDE COVERAGE: night-time lights imagery are captured daily for every area worldwide. This makes it possible to conduct economic estimations in every area of the globe, including countries lacking statistical institutions or areas affected by natural disasters or wars.

For instance, using data from Project Black Marble, researchers from NASA's Goddard Space Flight Center (GSFC) and the Universities Space Research Association (USRA) analysed the consequences of the Russian invasion of Ukraine on city lights.[3] Similarly, Li et al. (2018) studied the dynamics of night-time lights during the Iraqi civil war.

HIGH-FREQUENCY DATA: data on night-time lights are published daily. As I will show later, for this time span there are substantial data cleaning

3 https://earthobservatory.nasa.gov/images/150002/tracking-night-lights-in-ukraine

problems; however, these images lend themselves to daily analysis. Given the long process of estimating official GDP, it can be argued that estimating economic variables through night-time lights leads to high-frequency data. Unfortunately, little has been written about the applicability of economic variables estimated with night-time lights to high-frequency studies. However, also as a result of recent developments in sensor technology (VIIRS), it is possible to consider using these data for policy evaluation analyses.

HIGH-RESOLUTION DATA: As I will show in more detail in the following section, the night-time light data is high-resolution data. Namely, we can obtain information for areas of approximately $500mt \times 500mt$. Using these data to study economic variables allows us to reconstruct economic data and allocate information in space. For instance, it is possible to reconstruct geographic maps by calculating the GDP produced in each square kilometre of a country and thus perform zonal statistics in very small areas. With the high-frequency nature of data, it is possible to monitor a restricted area and observe what happens over time or how the economy of the area evolves following the adoption of a certain policy.

3 THE DATA

Night-time lights data are released by NASA and the EOG project of the Colorado School of Mines. Data is published with different timeframes, i.e. nightly, monthly and yearly. As I will illustrate in this chapter, the data need to be cleaned before being used, and the two sources use different data cleaning algorithms; NASA has a faster publishing rate. New data is released each night just over an hour after the satellite took the imagery. On the other hand, the EOG data, from the analysis I have carried out, implements a more effective data cleaning algorithm. Moreover, NASA files are published in tiles, small portions of space that must be processed before they can be used. Each tile must be geolocalised in space according to the order in which the tile is positioned.

3.1 DEALING WITH SATELLITE DATA

Night-Time light data are distributed in georeferenced *.tif* images, which are images that contain map projection information, namely the coordinate reference system. *Raster* files are $n \times k$ matrices that divide the observation surface into rectangular pixels.

With night-time lights, each cell of the raster matrix contains the reflectance measured in that specific portion of the globe. Depending on the sensor's technology mounted on the satellite, the pixels will capture smaller portions of the globe, producing higher resolution images.

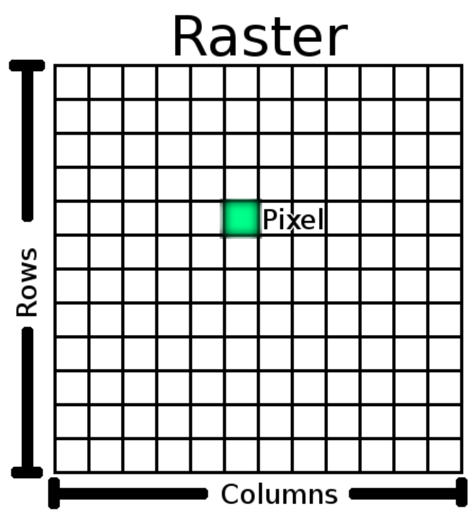


Figure 11: Raster representation - Source: Qgis Documentation.

Given the circular motion of the satellite orbit, the resolution is measured in *arc/seconds*. Regarding the two main technologies in the night-time lights industry, the VIIRS sensor data has a resolution of 15 arc/seconds (circa 500 metres at the equator), while the previous DMSP sensor data is about 30 arc/seconds (circa 1000 metres at the equator). The geographic reference system divides the Earth into 360 equal segments called degrees. Each degree contains 60 minutes and, therefore, 3600 seconds. An arc-second is the geographical distance measured on the surface of the Earth after one second's rotation, or 1/3600th of a degree. At the equator, one arc/second of latitude corresponds in metres to one arc/second of longitude. However, the further one moves towards the poles, the equivalent of one arc/second in longitude decreases while latitude remains stable.

To perform *zonal statistics*, i.e. statistics of delimited areas of the globe, it is necessary to delimit the raster files with another file that contains georeferenced information about geographical boundaries. For

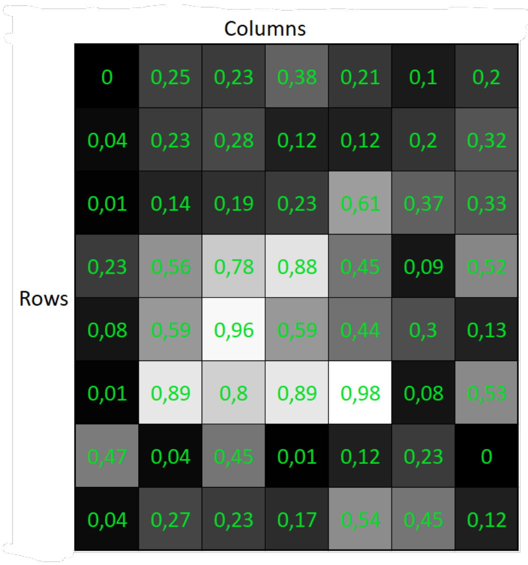


Figure 12: Night-time raster representation.

this purpose, most of the time, *Shapefiles* or *GeoJson* are used, which are called "polygon files". These files contain information about the boundaries of the geographical regions to be studied. As with raster files, polygon files can also have different resolutions. In this thesis, I will use the data with the highest possible resolution distributed by GADM. GADM is a

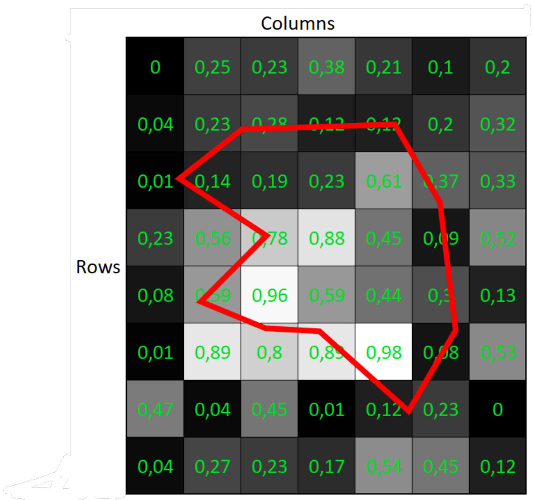


Figure 13: Night-time lights extraction process representation.

free open-access database of global administrative areas that publishes high-quality border data. The geographical area to be studied is obtained from the intersection of the raster file and the polygon file such that a statistical function can be applied. For this thesis, I will make use of summation, but spatial variance can be used as well. Given a $m \times n$ raster file, the summation is defined as:

$$\text{TotNTL} = \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij}. \quad (2)$$

An important consideration must be made regarding the data extraction process. It is legitimate to ask how to deal with pixel values only partially contained within the geographical boundaries of interest as in Figure 13. In this thesis, I will use the R package *exactextractr*, which is the most refined package for data extraction. This package, unlike *raster* and *terra* alternatives, extracts values by weighting them for effective coverage. A final note on the analysed data is the weight they occupy on the disk. An annual panel analysis of 11 years results in a data volume of around 120 gigabytes multiplied by 12 (i.e. around 1.5 terabytes) if the analysis is carried out with monthly data. This results into long analysis processes and so high computing power is needed.

3.2 DATA PROBLEMS

Managing satellite data is complex. One of the difficulties is dealing with some capturing issues that, without correction, may give biased data. For this reason, research on the best algorithms for cleaning and producing data does not stop, and new types of algorithms are constantly updated. The three main problems we face are:

1. **Cloud Coverage:** As argued earlier, one of the many purposes of night-time lights was to study the presence of clouds. It is, therefore, not surprising that, if only interested in the dynamics of the emitted night-time illumination, the complete or partial overlay of clouds may result in missing or dirty data. The data published by both NASA and EOG also include detailed information on the areas where clouds were present at the time of the capture. It is up to the researcher to choose whether the amount of daily data without cloud cover is sufficient for her purposes. A possible solution is to use the information on the areas covered by clouds from other periods. To do this, the time window of analysis must be increased. Several algorithms have been developed to aggregate daily data into monthly or annual surveys. The operation is not complex and works as follows, given several daily surveys in one layer of raster information and another layer with the different cloud cover of the respective days, the algorithm takes only the values of the non-covered or partially covered areas and through a statistical function (mean or median most of the time) reconstructs a complete image. Although very rare, a particular area may be covered for a whole month by clouds that prevent a correct representation of the actual light emitted. For this reason, it is necessary to consider the percentage of cloud-free observations of that month. Otherwise, data would be biased and annual aggregates may have to be used.

2. **Natural lights:** when measuring night-time lights, the presence of natural lights is a problem. Nat-

ural lights include sunlight, moonlight, reflections, burning biomass and other ephemeral events. Dealing with these problems is much more complex than with cloud coverage. Different strategies have been adopted. The most common of the strategies is cleaning through data aggregation, as seen above. This is because some of these natural lights have a seasonal nature. For instance, some areas of Northern Europe in the summer months suffer from overexposure to light at night, and the resulting images have entire areas burnt out. This kind of problem can be solved satisfactorily by aggregating an entire year's daily images. On the other hand, other natural light sources have no seasonal character, namely, among the others, burning biomass and reflections. In this case, the remote sensing literature has treated these problems as outliers and proposed some solutions. For instance, the first version of EOG data used a histogram-based technique in which the tails were cut off. This data was further cleaned by eliminating background noise by identifying a minimum threshold in the neighbourhood of each pixel.

3. **Stray Lights:** In optics, stray lights are defined as instrumental noise in optical systems due to unwanted light, namely reflections or lens imperfections. Again, various algorithms have been created to deal with this issue. EOG publishes two types of data, "vcm" is the raw non-stray light corrected data, while "vcmsl" is the cleaned data.

The data I will use in this thesis are those of the EOG project. In the last years, they adopted three versions of the cleaning algorithm, V1.0, V2.0, and V2.1, which have gradually become more and more sophisticated in handling the issues mentioned above. Version 2.0 of the algorithm updates the threshold detection used to eliminate the light background in a sophisticated manner. Without intending to be exhaustive, the new algorithm calculates the median of the maximum values of the multiyear time series, weighted for cloud-free observations. A scattergram of the observations is then created by plotting the percentage of cloud free versus the data range, and a gamma curve was fit to lie above the scattergram noise levels. Gamma curves are usually adopted in optics applications. In this case, the gamma curve sets a threshold for each globe observation for each cloud-coverage level.

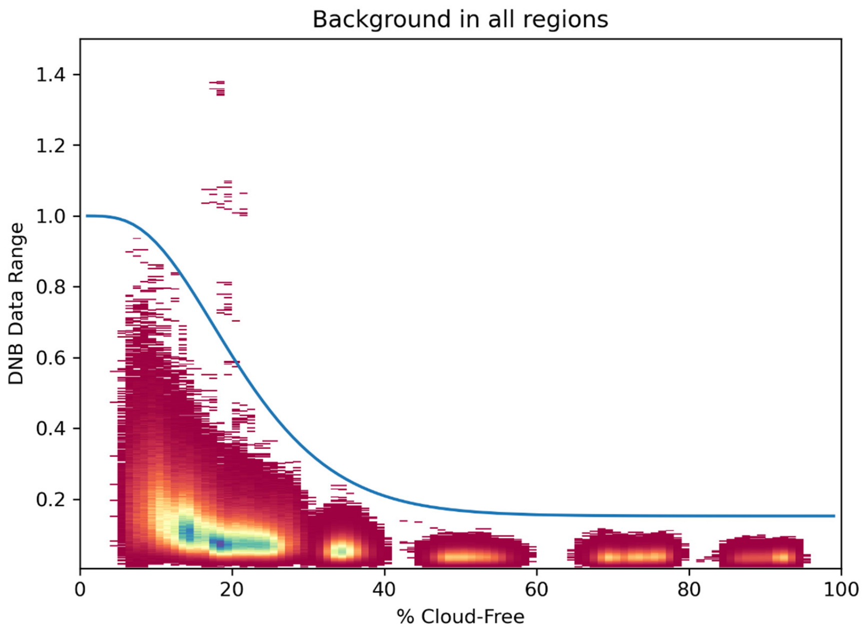


Figure 14: Scattergram and gamma curve - (Elvidge et al., 2021).

Finally, much noise was caused by the Aurora Borealis. Increasing the threshold too much would have resulted in a significant loss of information in other areas of the globe. Therefore, a *manual* approach was adopted by overlaying a layer on the residual noise in the north and south aurora zones. As mentioned earlier, although these algorithms (Elvidge et al., 2021) constitute state-of-the-art in the field, they do not correct for some peculiar events. When analysing the data, I found some anomalies. If I extract the maximum observable values, I find very high values in Russia in the middle of nature partly caused by gas flaring, a phenomenon due to the high quantity of natural gas processing plants in the region. This phenomenon is particularly relevant for the purpose of this thesis because it causes huge light concentrations that leads to pixels 200 times brighter than the most populated capitals in the world. These points are few, but they take high values, and the sum extraction process leads to very different results in some countries. In the following sections, I will try to deal with this problem. Finally, after analysing the data, I found that between 2016 and 2017 there is a big jump in the levels of night-time lights for many countries in the world. The reason seems to be that as of 12 January 2017, the EOG team changed the methodology for converting the raw data to radiance data. Specifically, the dark offset term used in converting the raw counts to radiance was changed from a dark ocean view to a space view, resulting in a slight upward radiance shift per each data point. This was first documented by Elvidge et al. (2020) in which this change was quantified as an increase in the radiance of about $0.125nw/cm^2/sr$. This upward shift led to an overall radiance increase of up to 20% in some countries. Since the shift of radiance occurred in the conversion from raw data to radiance data and since I only had access to the latter, I was unable to harmonise the pre-2017 data with the post-2017 data. However, because in this thesis I work with growth rates and not levels, this did not pose any particular problem and dropping the 2017 growth rates observations was sufficient.

3.3 OUTLIERS

A quick analysis of the data shows that the brightness of a city of 500,000 to 1 million inhabitants reaches maximum values of between 100 and $250nW/cm^2/sr$. The city of Milan, one of the brightest places in Italy, reaches maximum values of $130/140nW/cm^2/sr$ in the centre and around $200nW/cm^2/sr$ at its airports. Other European cities have similar characteristics, with London reaching maximums of $200/240nW/cm^2/sr$ in the area around Piccadilly and Oxford Circus, and Paris and Rome reaching values of no more than $120/150nW/cm^2/sr$ in the centre. American cities, which are generally considered brighter, reach higher values. The brightest point in New York is the block between the Rockefeller centre and Time Square, which reaches a peak of about $420nW/cm^2/sr$. These values are similar with the largest world capitals, which are generally considered bright. Dubai is generally less bright than New York except for the pixel containing the Burj Kalifa, the world's tallest skyscraper, which reaches brightness levels of over $500nW/cm^2/sr$. Asian cities are all comparable with New York but, in the vast majority of cases, emit lower light peaks. Hong Kong, for example, does not exceed $220nW/cm^2/sr$, Shenzen $100nW/cm^2/sr$, very similar to Milan, while Tokyo, the brightest of the Asian cities, barely exceeds $400nW/cm^2/sr$.

The brightest city in the world is undoubtedly Las Vegas, the average value in the city centre is around

$1,000nW/cm^2/sr$ in an area of about 11 square kilometres. In addition, the pixel containing The Luxor Hotel Casino reaches a peak of $6,000nW/cm^2/sr$. The reason is quickly stated, the pyramid-shaped hotel emits a beam of light at its apex that is directed towards the sky. I conjecture that these values may be considered too extreme to have an economic relevance on GDP and that perhaps they should be handled as outliers. But they are not alone.

Russia is one of the countries whose images suffer most from extreme values. Looking at night-time images of Russia, multiple pixels with values totally out of scale can be observed. Namely, pixels with values of more than $10,000nW/cm^2/sr$ in the middle of nowhere, tens of kilometres away from population centres. Studying point by point, I found two interesting phenomena. The first confirmed, as mentioned before, that Russia is indeed dotted with gas flares, which are fields with vents burning day and night. The second is that, surprisingly, these flames are exceeded in light output by building similar to sheds in the middle of the steppe. I cross-referenced OpenStreetMap data and some Google searches, discovering that such sheds are indeed greenhouses with controlled environment agriculture. They consist in transparent structures with artificial illumination to boost plants growth. Russia's solid agricultural vocation, with limited energy costs, has led to the flourishing of many greenhouses heated and illuminated by thousands, but perhaps millions, of light bulbs turned on day and night. The transparent roofs with the huge amount of light make these greenhouses some of the brightest places on Earth. This kind of greenhouse can also be found outside Russia because all countries with high latitudes need to compensate for the lack of daylight, especially during the win-

Figure 15: Netherlands' greenhouses with controlled environment agriculture - Tom Hegen (2019).

ter. To my knowledge, greenhouses never appear in the literature, even though it is a significant problem that needs to be addressed when dealing with nighttime lights for economic applications. In 2021, the total light emitted by Russia cleaned by these two phenomena was about 20% less than the un-cleaned imagery. A vast difference that, however, seems to be extremely invasive for Russia only. In other European countries, this phenomenon is much more limited. In Italy, for example, such outliers cannot be observed, not even in Spain, France and Germany. The only exception is the Netherlands, which has several greenhouses of the same Russian technology, albeit in smaller quantities. Concerning gas flares, on the other hand, I found no outliers in Europe with the same Russian magnitude. On the contrary north African countries, endowed with well-known oil deposits, are full of them.

Dealing with these outliers raises some critical economic questions. Greenhouses and gas flares enter directly into the GDP count. It is, therefore, questionable whether it is correct to eliminate or keep them. However, it is unrealistic to think that a pipeline vent in Siberia that emits as much light as an average European metropolis has the same impact on GDP. Therefore, I decided to clean the data from outliers but keep the original data, which will be compared on the following pages.

3.3.1 *Outlier Removal strategies*

Several strategies are adopted to deal with outliers:

1. Spatial correction: the algorithm checks each pixel and compares it with the surrounding area, usually 3×3 or 5×5 pixels. If the value of

the pixel is several orders of magnitude higher than the average of the surrounding area, the pixel is recognised as an outlier and is removed

2. Statistical correction: a predetermined percentile of the data distribution is removed. (For data from Russia, tests suggest the removal of the 0.001 tail)

3. Manual correction: By looking at the values of cities and the central infrastructure of a country (airports, first of all), it is possible to derive a maximum threshold beyond which all other data are outliers. As far as Russia is concerned, the maximum value observed in cities is less than 500, while all values above are greenhouses or gas flares.

For reasons of computational power, in this thesis, I will use the third approach since it appears to be sufficient. Moreover, power and RAM at a server level are required to manipulate this type of data.

4 THE MODEL

Economists, since the seminal work of Chen and Nordhaus, 2011, the successive work of Henderson, Storeygard, and Weil, 2012 and the more recent paper of Hu and Yao, 2022 dealt with night-time lights using latent variable models with measurement error. I decided to base the work of this thesis on the framework built from the papers just mentioned.

Official GDP estimates are plagued by a non-negligible statistical error due to the difficulty of estimation and the limited statistical capacity of many countries. Let y be the "true" real GDP, y^{NA} the real GDP as measured in the national accounts, and NTL the sum of night-time lights measured from outer space. For a generic country we can assume that the GDP measured by the national accounts is equal to the true GDP value plus an error component:

$$y^{NA} = y + \varepsilon^{NA}. \tag{3}$$

Moreover, assume that night-time lights are produced by "true" GDP as in the following relation:

$$\mathsf{NTL} = \beta y + \varepsilon^{NTL}. \tag{4}$$

This thesis aims to construct a better estimate of GDP through the additional information from night-time lights.

It should be noted that the error terms of equation 3 and 4, ε^{NA} and ε^{NTL}, have a peculiar relation. They are, respectively, the error terms of national accounts GDP estimate and of night-time lights measurement.

That is, for the component concerning official estimates, the errors of national statistical systems in estimating all production components of complex national economic systems and, for night-time lights, the difference between the light actually emitted by human activities and the light captured by the sensor. An interesting property of using information from outer space is that the measurement errors of GDP and of night-time lights do not depend on each other. The underlying idea is that the error from official GDP estimation, which is mainly due to economic reasons, is uncorrelated with the error of measurement of night-time lights from outer space, which is due to optical or physical reasons. So:

$$cov(\varepsilon^{NA}, \varepsilon^{NTL}) = 0. \tag{5}$$

It should be noted that equation 4 represents a production relationship between the true GDP and night-time lights. As previously shown, the lights produced overnight in a country are strictly connected to GDP. However, the purpose of this thesis is to construct an improved estimate of GDP through night-time lights' additional information. Thus, the first step of this model is estimating national accounts GDP through night-time lights. The simplest predictive relation can be written as:

$$y^{NA} = \gamma NTL + \varepsilon. \tag{6}$$

Note that γ from equation 4 is $\frac{cov(y^{NA}, NTL)}{var(NTL)}$. Using equations 15b and 15c, the relation between γ and β is:

$$\text{plim}\,(\hat{\gamma}) = \frac{1}{\beta}\left(\frac{\beta^2\sigma_y^2}{\beta^2\sigma_y^2 + \sigma_{NTL}^2}\right). \tag{7}$$

The true GDP cannot be observed so the β parameter cannot be calculated unless, as I am going to show, some assumptions are taken.

It is possible to construct an improved measure of GDP through the linear combination (as shown in equation 8) of the GDP predicted with night-time lights and the official GDP such that the resulting optimal composite estimate will have a lower error than either separately.

$$\hat{y} = \lambda \cdot y^{NA} + (1-\lambda) \cdot \hat{y}^{NA}. \tag{8}$$

The weight λ minimizes the variance of the measurement error in the estimate relative to the true value of GDP growth. As long as the weight of $\hat{y}^{NA}$, that is $(1-\lambda)$, is greater than zero, the use of night-time lights improves our ability to measure true GDP. Optimal λ is obtained by:

$$\lambda^{\star} = argmin\left(var(\hat{y} - y)\right). \tag{9}$$

Now, note that, thanks to the assumption taken in equation 5, the variance term can be decomposed as follows:

$$\begin{aligned} &var(\hat{y} - y) = \\ &\qquad = var(\lambda(y^{NA} - y) + (1-\lambda)(\hat{y}^{NA} - y)) \\ &\qquad = \lambda^2\sigma_{NA}^2 + (1-\lambda)^2 var(\hat{y}^{NA} - y). \end{aligned} \tag{10}$$

Past literature, using 6 and 4 rewrite $var(\hat{y}^{NA} - y)$ as follows:

$$\begin{aligned} &var(\hat{y}^{NA} - y) = \\ &\qquad = var(\hat{\gamma}NTL - y) = var(\hat{\gamma}\beta y + \hat{\gamma}\varepsilon^{NTL} - y) \\ &\qquad = (\hat{\gamma}\beta - 1)^2\sigma_y^2 + \hat{\gamma}^2\sigma_{NTL}^2. \end{aligned} \tag{11}$$

However, this procedure seems to be suspicious because $\hat{\gamma}$, which is a random variable, is taken out of the variance operator as if it were a constant. Future work will have to go deeper into these passages.

Using equation 7 we obtain:

$$var(\hat{y}^{NA} - y) = \frac{\sigma_y^2 \sigma_{NTL}^2}{\beta^2 \sigma_y^2 + \sigma_{NTL}^2}. \tag{12}$$

Substituting this in the original equation we get:

$$\begin{aligned} var(\hat{y} - y) &= \\ &= \lambda^2 \sigma_{NA}^2 + (1-\lambda)^2 \frac{\sigma_y^2 \sigma_{NTL}^2}{\beta^2 \sigma_y^2 + \sigma_{NTL}^2}. \end{aligned} \tag{13}$$

Finally, solving for the λ, which minimizes the variance, the following is obtained:

$$\lambda^\star = \frac{\sigma_{NTL}^2 \sigma_y^2}{\sigma_{NA}^2 (\beta^2 \sigma_y^2 + \sigma_{NTL}^2) + \sigma_{NTL}^2 \sigma_y^2}. \tag{14}$$

Note that $\lambda^\star$ is a function of four unknown parameters, but the observed data provide only three sample moments:

$$var(y^{NA}) = \sigma_y^2 + \sigma_{NA}^2 \tag{15a}$$

$$var(NTL) = \beta^2 \sigma_y^2 + \sigma_{NTL}^2 \tag{15b}$$

$$cov(NTL, y^{NA}) = \beta \sigma_y^2 \tag{15c}$$

Substituting equation 15 moments in the equation 14 and rearranging, we get:

$$\lambda^\star = \frac{\phi var(y^{NA}) var(NTL) - cov(y^{NA}, NTL)^2}{var(y^{NA}) var(NTL) - cov(y^{NA}, NTL)^2}. \tag{16}$$

where:

$$\phi = \frac{\sigma_y^2}{\sigma_y^2 + \sigma_{NA}^2}. \tag{17}$$

Equation 17 is the ratio of signal to total variance in measured GDP, or also known as attenuation bias.

4.1 SOLVING THE IDENTIFICATION PROBLEM

As just shown, λ^* is a function of four unknown parameters but observed data provide only three sample moments. In order to solve the identification problem, many strategies may be adopted. Past literature used information from IMF and World Bank on the quality of national statistical institutes. The idea is that countries with less developed statistical institutes produce GDP estimates with a bigger measurement error. Thus, the set of countries can be sorted by their statistical institutions quality and divided into n groups, and the last term of equation 15a can be let vary:

$$var(y_n^{NA}) = \sigma_y^2 + \sigma_{NA,n}^2. \tag{18}$$

with $n = (1, ..., N)$.

In a two groups case, in which countries are divided in good and bad data countries we get four equations with five unknowns (β, σ_y^2, σ_{NTL}^2, $\sigma_{NA,g}^2$, $\sigma_{NA,b}^2$). Where $\sigma_{NA,g}^2$ and $\sigma_{NA,b}^2$ are, respectively, the variances of the measurement errors for good and bad data countries. The fifth element required to identify the system is the ϕ_g for good data countries, which is obtained by making an assumption on its value, as I will show in the next section. This lets me to close the model and to estimate the true GDP variance along with the remaining unknowns.

4.1.1 *Data*

In order to estimate the parameters, a source of information on statistical institutes quality is needed. Past literature had some difficulties to reconstruct such information. This is because, at the time, a single index wasn't produced, and information had to be merged and harmonized from different sources (mainly from World Bank, IMF and Penn World Table). For example, the World Bank used to produce a statistical capacity index only for developing countries, thus requiring to obtain information from developed countries elsewhere. From 2021 the World Bank started to produce a statistical performance index for 174 countries (Dang et al., 2021). The new index has worldwide coverage and is a much-improved version of the previous one. To my knowledge, such an index has never been used in the night-time lights GDP estimation literature. The information obtained from the World Bank is a time series of 4 years, from 2016 to 2019. So in my model, unfortunately, I will not let the index of statistical performance to vary over time even though the model can be easily extended in this sense. I believe that for analyses of small periods, in my case 9 years, this assumption is not too strong. Henderson, Storeygard, and Weil (2012), and Chen and Nordhaus (2011), although they analyse much larger periods than in this thesis, also have the same problem and keep the parameters on statistical capacity fixed over time. Hence, the index I will use in the model is calculated through an arithmetic average of the four available observations.

I proceed dividing countries into four groups (A, B, C, D) according to their statistical performance, and then I have all the elements to close the analysis. The first step is to estimate GDP through night-time light proxy. I use a fixed effect panel-data model with clustered standard errors with years dummy in order to control for year-specific measurement error of night-time lights, as suggested by past literature (Henderson, Storeygard, and Weil (2012), Beyer, Hu, and Yao (2022)). As national account GDP growth rates, I use gross domestic product based on purchasing power parity published by the World Bank after testing other official measures like constant prices GDP growth rate, local currency unit at constant prices and at current prices. Regressions results are summarised in the appendix.

After estimating the model, a GDP measure $\hat{y}^{NA}$ can be constructed using only night-time lights information. Finally, I proceed with the estimation of the remaining parts of the model. The model can be closed after making an assumption on the ϕ_A, the attenuation bias for countries with high statistical capacity. Ideally, if we were perfectly capable of measuring the true GDP, the signal would equal one. So, it can be assumed that for countries with high-quality statistical institutions, ϕ_A has a value near one. On the other hand, it can be expected that in countries where the national statistical system is more lacking, σ^2_{NA} is higher, and so the resulting ϕ is lower.

With ϕ_A fixed by assumption, the variance of y is obtained by combining equations 17 with 18:

$$var(y) = \frac{\phi_A}{var(y_A^{NA})}. \tag{19}$$

Once $var(y)$ is obtained, ϕ_B, ϕ_C and ϕ_D can be calculated as follows:

$$\phi_n = \frac{var(y)}{var(y_n^{NA})}. \tag{20}$$

with $n = (B, C, D)$.

With $var(y)$ known, the β parameter of equation 4 can be obtained after inverting 15c:

$$\beta = \frac{cov(NTL, y^{NA})}{\sigma_y^2}. \tag{21}$$

Finally, λ^* for each country group can be calculated from 14.

Attenuation bias						Optimal weight		
ϕ_A	ϕ_B	ϕ_C	ϕ_D	β	λ_A	λ_B	λ_C	λ_D
1	0.56	0.45	0.16	1.33	1.00	0.55	0.44	0.16
0.9	0.51	0.41	0.15	1.48	0.89	0.49	0.39	0.14
0.8	0.45	0.36	0.13	1.66	0.79	0.43	0.34	0.12
0.7	0.39	0.32	0.12	1.9	0.68	0.37	0.30	0.11
0.6	0.34	0.27	0.10	2.22	0.58	0.32	0.25	0.09

Table 1: Results for different values of fixed ϕ_A.

It is important to notice that the estimation of all parameters relies on the initial assumption of ϕ_A parameter. Thus, in table 1 I show how the model's parameters change with different assumed values of ϕ_A. When ϕ_A is fixed to 1, λ_A is 1, while it drops to 0.55 for the B group, to 0.44 to the third and to 0.16 to the fourth. The lambdas obtained are the optimal weights of equation 14 that minimize the variance of the measurement error in the estimate relative to the true value of income.

For $\lambda = 1$ equation 14 reduces to $\hat{y} = y^{NA}$, thus additional information from outer space is not needed to improve national accounts estimate of gross national product. This is the case of countries with perfect statistical institutions.

For $\lambda = 0$ equation 14 reduces to $\hat{y} = \hat{y}^{NA}$. This is the case of countries with nonexistent or very lacking statistical performances. Thus, GDP estimated from night-time light is the only source of information to estimate true GDP. $\phi_A = 1$ is too strong an assumption, so I will opt for a less extreme value of 0.9 that is usually taken in the literature (Henderson, Storeygard, and Weil (2012), Chen, Qiao, and Zhu (2021)).

With $\phi_A = 0.9$ the resulting lambdas are $\lambda_A = 0.89$, $\lambda_B = 0.49$, $\lambda_C = 0.39$ and $\lambda_D = 0.14$. The results obtained are quite extreme for country group D; national accounts GDP enters in equation 14 only with a weight of 0.14. This is due to the high variance of such group respect to the others. It is now possible to reconstruct true GDP as in equation 14.

4.2 DESCRIPTIVE ANALYSIS OF THE IMPROVED GDP

Previous night-time lights literature has given much attention to the misestimation of GDP. In particular, two very interesting topics are the informal economy estimation and the study of which countries are overstating their official GDP. Regarding the estimation of the informal economy, the paper by Ghosh et al. (2009) is a seminal paper on the subject. On the other hand, the papers by Martinez (2018) and Clark, Pinkovskiy, and Sala-i-Martin (2017) are two of the best-known papers on the study through night-time lights techniques of possible GDP overestimation. The approach used in this thesis is rough because it does not consider the different production functions between countries. In fact, it is conceivable that the elasticity between GDP and lights in a developed country differs from that in a developing country. Let's assume that observable night-time lights consist of two components:

$$\mathrm{NTL}_{total} = \mathrm{NTL}_{citizens-life} + \mathrm{NTL}_{production} \tag{22}$$

The last component of the RHS is peculiar to the specific production function of the country. It depends on different levels of development of the country or different sector shares. Even if higher lights still mean higher GDP, elasticities may significantly vary between countries. The first component of the RHS is relative to the quantities of night-time lights emitted by something it can be identified with the life of citizens. It means consumption relative to city life or installed capital that produces light, such as street lamps. This component is strictly connected with country and citizens' well-being. Moreover, it actually depends on the last component of the RHS because with high production, countries can permit to use more light in the activities of the first term. I believe this is why night-time lights are still a precise tool to predict GDP even between countries with very different production systems.

In figure 16 are plotted the growth rates of the improved estimate of GDP obtained through the model explained in chapter 4 and the official growth rates of GDP for France. As one could expect the differences

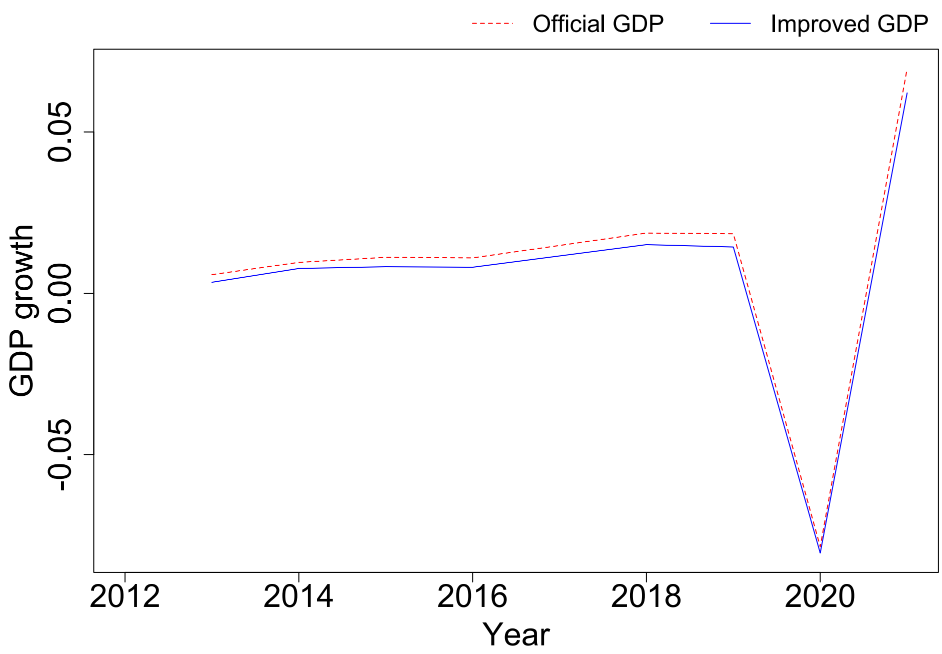


Figure 16: France.

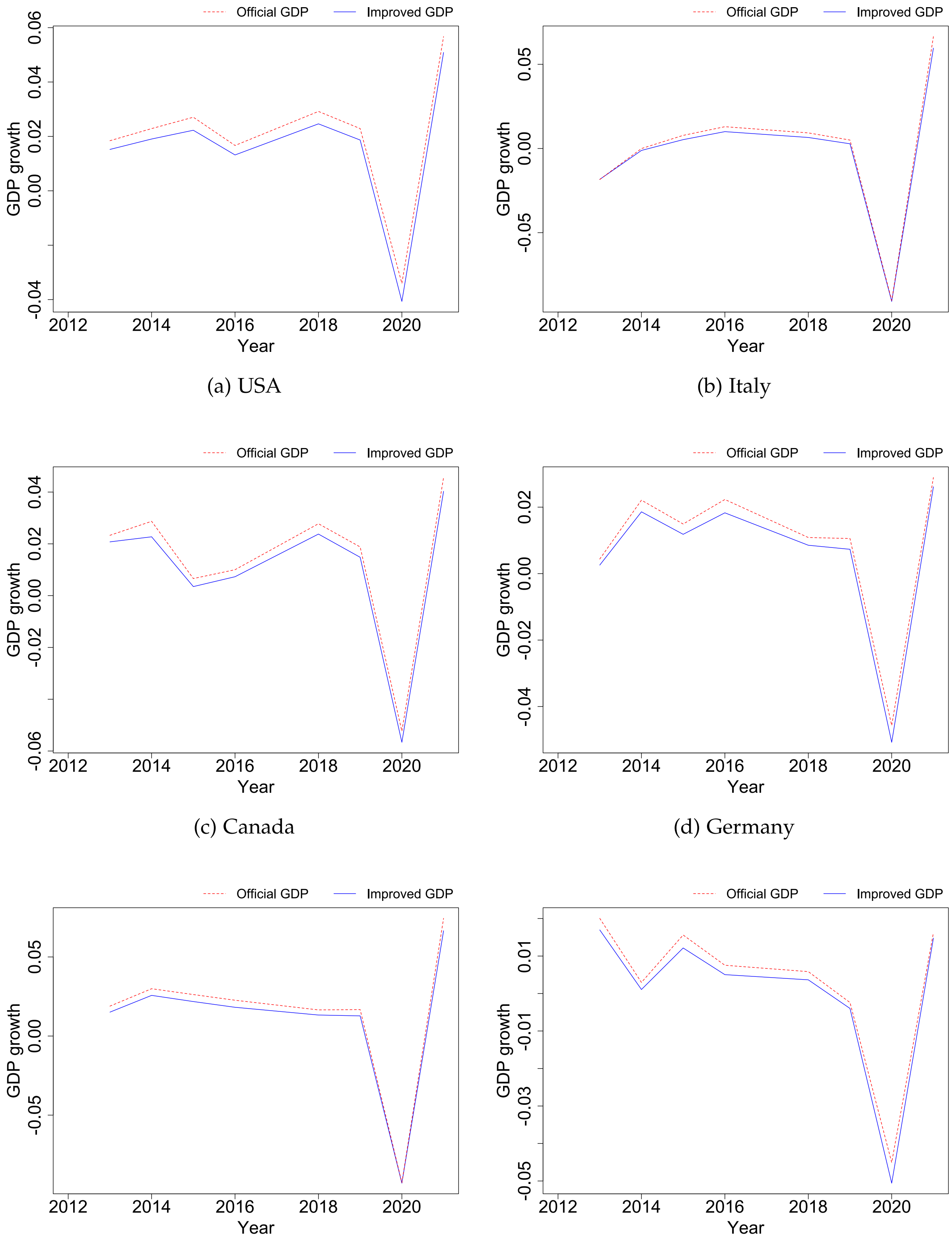
are negligible. Moreover, the improved GDP sees the same effect of COVID-19 to the french economy as the national account estimates.

In figure 17 the rest of the G7 countries' curves are plotted and the results are analogous to what said for

France. Night-time lights improved estimate is very similar to the official one estimate for the COVID-19 period. For G7 countries the biggest difference is in 2014 for Canada in which the improved estimate is lower than the official one suggesting that official GDP may be slightly overstated. However, further work on this is needed to understand better the reasons for such differences, which may be the result of street lights conversion to LED technology. A quick search on the web seems to confirm this theory.

The behaviour of less developed countries is expectably different. As it can be seen in figure 18, developing countries tend to have more difficulties in estimating true GDP. From the plot, Congo seems to have official GDP values constantly higher than the improved estimates. For Libya, on the other hand, the curves are more similar. Concerning Lebanon, what can be seen is that the official estimates are generally more optimistic than the improved ones. The same can be said for Morocco whose official GDP values are consistently above the improved ones.

Generally speaking, the differences between the two curves may have different interpretations. First, the reason may be a very fast structural change in the economic system as suspected for Canada. As previously stated, country-specific different production functions have a strong influence on night-time lights. In fast developing countries, the changes in the economy may be the result of an evolving economic framework that may produce more or fewer night-time lights per unit of additional GDP. Second, as past literature has shown, some countries may miscalculate their own national statistics for political interests. In figure 19 are plotted the two curves of China and India, which allegedly, according to a part of literature (Martinez, 2018), may have over-



(a) USA

(b) Italy

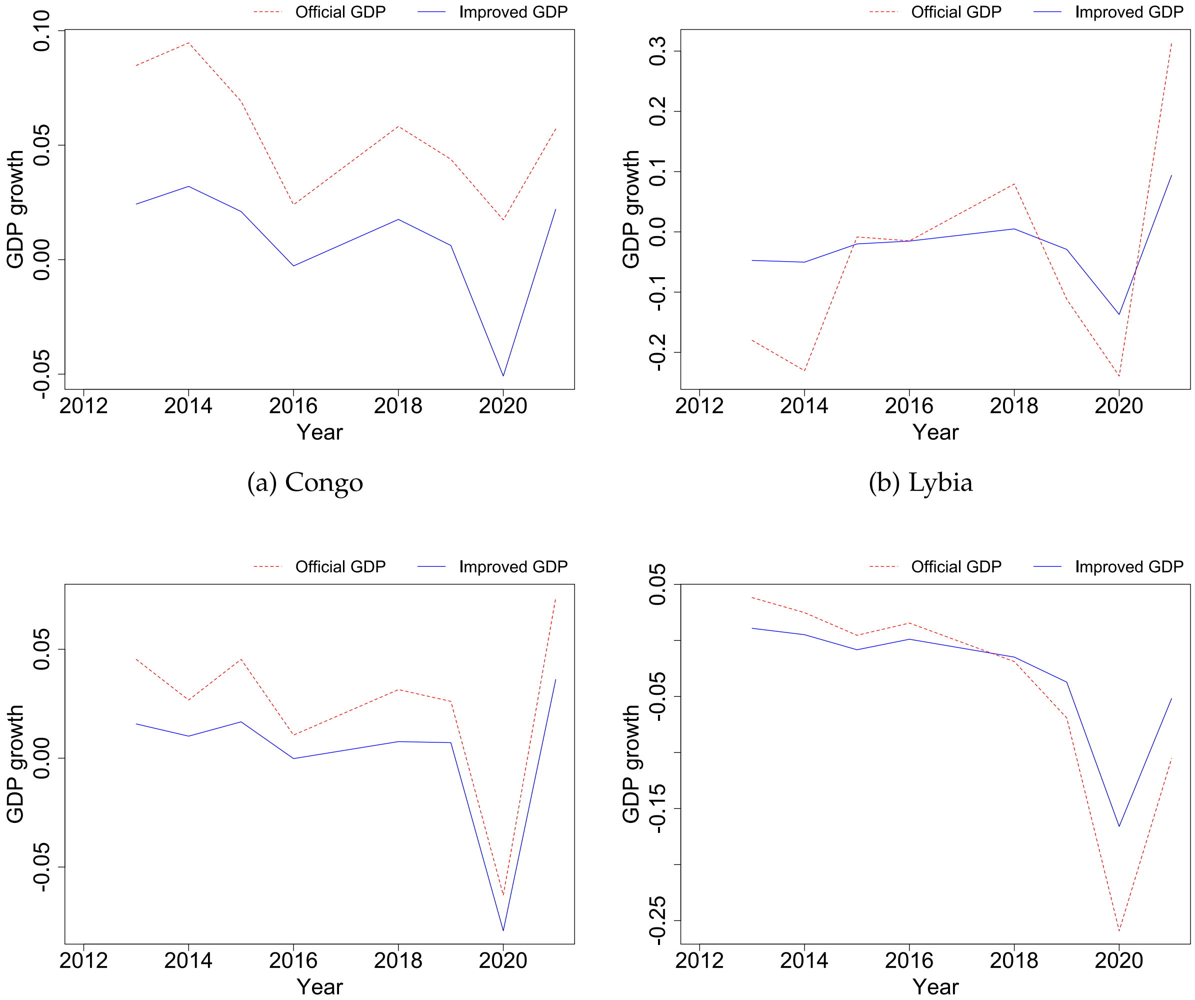
(c) Canada

(d) Germany

(e) United Kingdom

(f) Japan

Figure 17: G7 countries.



(a) Congo

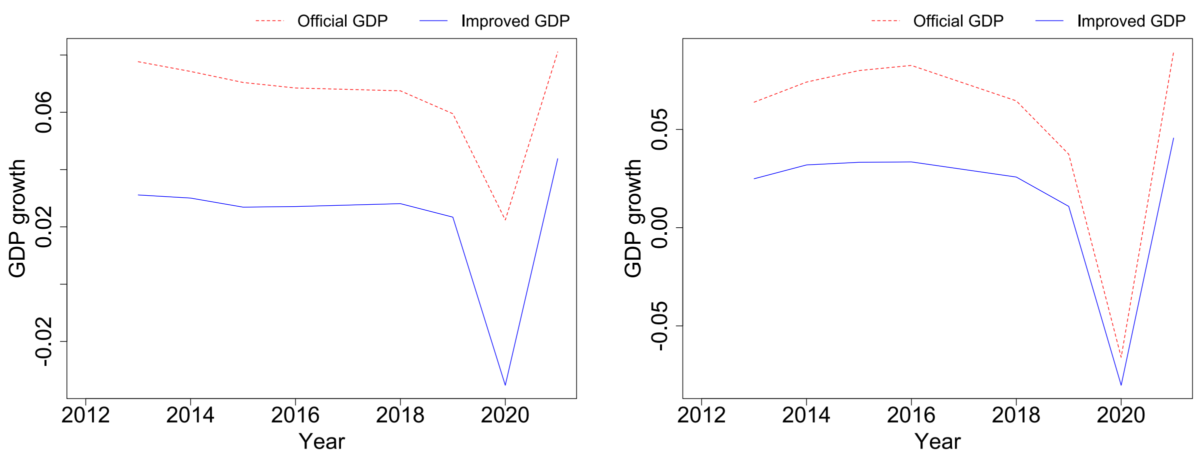
(b) Lybia

(c) Morocco

(d) Lebanon

Figure 18: Developing countries.

stated their past GDP growth estimates. Concerning India, it is very interesting to note that, according to the measure proposed in this thesis from 2013 until 2019, the official GDP estimates seem overstated. In 2020, on the other hand, the two measures are very similar, although the curve of the official measures always remains above the GDP improved with night-time lights. For China, for the entire period analysed, the official estimates are much higher compared to the proposed improved measures. Differently from



(a) China

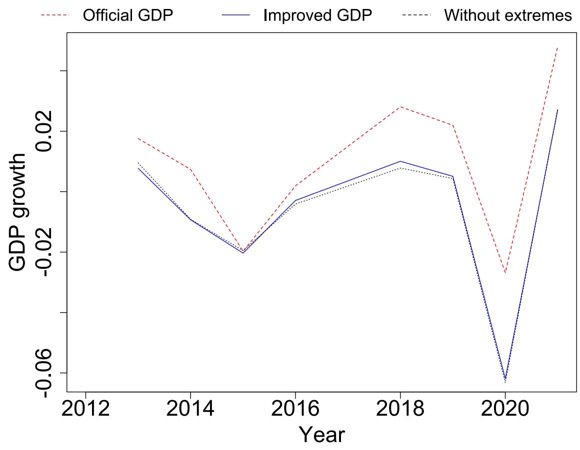
(b) India

Figure 19: China and India - differences.

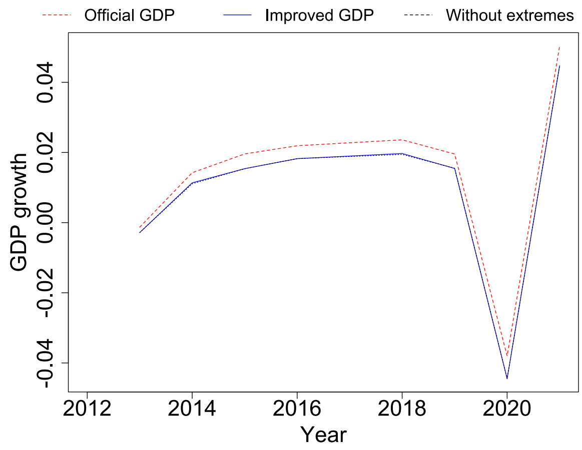
India, over the COVID period, the Chinese official measures seem to underestimate the fall in GDP by about three percentage points compared to what the improved estimate with satellite information reveals. However, in future work, confidence intervals should be constructed to verify that the observed differences are statistically significant.

4.3 RESULTS OF EXTREME VALUES REMOVAL

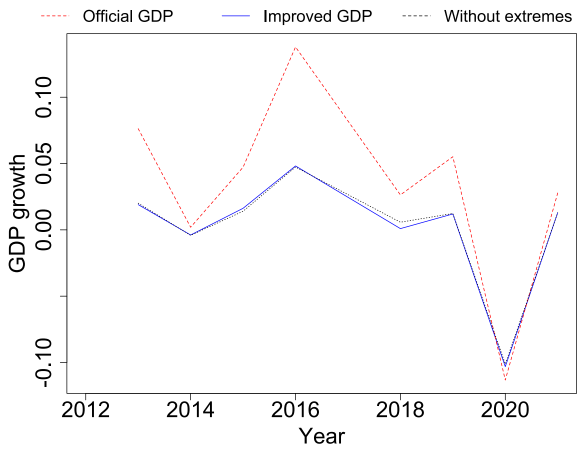
As previously stated, some observations have extremely high values in several countries. In this section, I want to see what happens if these values are removed and what the consequences are in the countries that are most affected. I remove the values greater than $800nW/cm^2/sr$ through *data clamping* of the raster files. The table 4 in the appendix shows the observations with a difference of more than 5% of the data clamped with respect of the original files. As can be seen, these are mostly countries with a strong extracting vocation. In particular, it can be seen that in 2013, 41% of Iraq's night lighting was composed of gas flares, a share that tends to decrease to 27% in more recent years. The Netherlands also has a strong component of lights from extreme observations. Unlike most of the other countries in the table, these extreme values derive from the strong component of modern greenhouses, which, as previously seen, emit a large amount of light. Since I use growth rates in this thesis, I am not very interested in the shares of extreme lights in relation to the total but rather in how they vary over time and whether they alter the improved measure of GDP proposed above. Figure 20 shows four countries with a high proportion of extreme lights with respect to the total. The red and blue lines, as seen before, are the official GDP and the GDP increased by night-time lights, respectively. The black line, on the other hand, is the GDP increased by night lights by removing the extreme observations. As can be seen from the graphs, the black line tends to assume values very similar to the red one. This means that the extreme values remain constant over time and do not change abruptly. Therefore, while in levels these extreme values are of



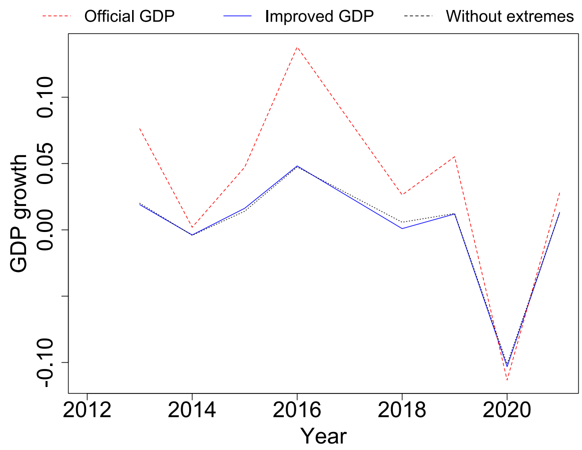
(a) Russia



(b) Netherlands



(c) Kazakhstan



(d) Iraq

Figure 20: Comparison of improved estimates with and without extreme values correction.

great importance since in some cases they make up to 40% of the total of the lights observed by satellite, using growth rates their importance is less relevant.

5 CONCLUSIONS

In this thesis, I have shown some interesting properties of night-time lights that make them a unique source of information. Night-time lights are a very interesting tool for economic analysis and, due to their interesting properties, they lend themselves to being used in conjunction with more standard economic tools in sub-optimal contexts. The advancement of remote sensing technology may lead to further improvements in economic applicability in the future. In this sense, NASA's black marble project is already producing very high-resolution tiles with a resolution of less than 30 meters. Even if they have not been made public yet, they may be used, in the future, for new economic applications.

In chapter four, I proposed a model for reconstructing an improved GDP estimate by combining information from national statistical institutes and night-time lights. Unfortunately, the temporal availability of the data chosen for this study doesn't allow us to make a long-run analysis and study how the trend of the difference between true and official GDP changes over time. In a recent study of Li et al. (2020), a 27 years dataset of night-time lights observations was reconstructed, harmonizing the data of past with new satellite technology. However, the resulting quality is remarkably lower than the new technology standing alone. There is, thus, a trade-off between data quality and data availability. Data on national statistical capacity is still scarce. Future work will concern the construction of an index with a longer time period so that it can be let vary with respect to time in order to get better estimates. In this thesis, I found that when growth rates are taken into account, extreme values from greenhouses or gas flares do not heavily influence the final result. However, if interested in values in levels, it is necessary to take these phenomena into account and understand the connection with production. With my model, I obtained results consistent with the literature concerning the possible overestimation of GDP for some countries. Additionally, the optimal combination proved to be quite sensitive to COVID-19 economics' implications. In conclusion, future work should focus on a more precise production function of night-time lights taking into account the distribution of sectors in the economy.

A

APPENDIX

A.1 PANEL DATA REGRESSION

Panel regressions with different estimates of GDP growth at current prices, local unit currency at constant prices, local unit currency at current prices and purchasing power parity adjusted.

Table 2: Panel data regressions results

	Current prices	LUC constant	LUC current	PPP
sum_growth	0.08^{**}	0.08^{**}	0.05	0.06^{**}
	(0.03)	(0.03)	(0.08)	(0.02)
factor(year)2013	-0.02^{**}	-0.02^{**}	-0.08^{***}	-0.02^{**}
	(0.01)	(0.01)	(0.02)	(0.01)
factor(year)2014	-0.01	-0.01	-0.08^{***}	-0.01^{*}
	(0.00)	(0.00)	(0.02)	(0.00)
factor(year)2015	-0.01^{**}	-0.01^{**}	-0.10^{***}	-0.01^{**}
	(0.00)	(0.00)	(0.02)	(0.00)
factor(year)2016	-0.01^{*}	-0.01^{*}	-0.08^{***}	-0.01^{**}
	(0.00)	(0.00)	(0.02)	(0.00)
factor(year)2018	-0.01^{***}	-0.01^{***}	-0.07^{***}	-0.01^{***}
	(0.00)	(0.00)	(0.02)	(0.00)
factor(year)2019	-0.02^{***}	-0.02^{***}	-0.07^{***}	-0.02^{***}
	(0.00)	(0.00)	(0.02)	(0.00)
factor(year)2020	-0.09^{***}	-0.09^{***}	-0.15^{***}	-0.10^{***}
	(0.01)	(0.01)	(0.02)	(0.01)
Num. obs.	1605	1607	1629	1523
Num. groups: country	206	207	210	193
R^2 (full model)	0.47	0.47	0.38	0.47
R^2 (proj model)	0.33	0.33	0.05	0.34
Adj. R^2 (full model)	0.38	0.38	0.28	0.39
Adj. R^2 (proj model)	0.32	0.32	0.05	0.34

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

A.2 COUNTRY DATA QUALITY GROUPS

Table 3: Data quality country groups

Group A	Group B	Group C	Group D
Armenia, Australia, Austria, Canada, Switzerland, Chile, Czechia, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Greece, Hungary, Ireland, Italy, Japan, South Korea, Lithuania, Latvia, Mexico, Netherlands, Norway, New Zealand, Poland, Portugal, Slovakia, Slovenia, Sweden, Turkey, United States	Albania, Argentina, Azerbaijan, Belgium, Bulgaria, Belarus, Bolivia, Brazil, Colombia, Costa Rica, Cyprus, Dominican Republic, Ecuador, Egypt, Georgia, Guatemala, Honduras, Croatia, Indonesia, India, Iceland, Israel, Kazakhstan, Kyrgyzstan, Sri Lanka, Luxembourg, Moldova, North Macedonia, Malta, Montenegro, Mongolia, Mauritius, Malaysia, Peru, Philippines, Russia, Rwanda, Singapore, El Salvador, Serbia, Thailand, Tunisia, Tanzania, Uganda, Ukraine, Uruguay, Vietnam, South Africa	Afghanistan, Angola, United Arab Emirates, Burundi, Benin, Burkina Faso, Bangladesh, Bahrain, Bahamas, Bosnia Herzegovina, Belize, Bhutan, Botswana, China, Côte d'Ivoire, Cameroon, Cape Verde, Algeria, Ethiopia, Fiji, Ghana, Guinea, Gambia, Iran, Jamaica, Jordan, Kenya, Cambodia, Kuwait, Laos, Lebanon, Liberia, St. Lucia, Lesotho, Morocco, Madagascar, Maldives, Mali, Myanmar (Burma), Mozambique, Mauritania, Malawi, Namibia, Niger, Nigeria, Nicaragua, Nepal, Oman, Pakistan, Panama, Paraguay, Qatar, Saudi Arabia, Senegal, Sierra Leone, São Tomé Príncipe, Suriname, Eswatini, Togo, Tajikistan, Trinidad Tobago, Uzbekistan, St. Vincent Grenadines, Venezuela, Samoa, Zambia, Zimbabwe	Congo - Brazzaville, Djibouti, Micronesia (Federated States of), Gabon, Guinea-Bissau, Guyana, Haiti, Iraq, Kiribati, Libya, Marshall Islands, Papua New Guinea, Sudan, Solomon Islands, South Sudan, Chad, Turkmenistan, Vanuatu, Yemen

A.3 EXTREME VALUES REMOVAL RESULTS

Table 4: Percentage differences after removing raster values greater than 5%

Country	Year	% diff	Country	Year	% diff	Country	Year	% diff
COG	2013	13	IRQ	2021	27	NLD	2021	12
COG	2019	11	KAZ	2013	27	OMN	2013	8
COG	2020	16	KAZ	2014	37	OMN	2014	8
COG	2021	12	KAZ	2015	33	OMN	2015	6
DZA	2013	18	KAZ	2016	22	OMN	2016	7
DZA	2014	17	KAZ	2018	10	OMN	2018	5
DZA	2015	15	KAZ	2019	8	OMN	2019	5
DZA	2016	17	KAZ	2020	6	OMN	2020	5
DZA	2018	13	KAZ	2021	6	PNG	2014	11
DZA	2019	14	KWT	2013	7	QAT	2013	5
DZA	2020	14	KWT	2014	11	RUS	2013	12
DZA	2021	8	KWT	2015	8	RUS	2014	11
EST	2014	6	KWT	2016	8	RUS	2015	9
EST	2015	7	LBY	2013	10	RUS	2016	11
EST	2016	6	LBY	2014	7	RUS	2018	16
EST	2021	6	LBY	2015	8	RUS	2019	17
FIN	2015	6	LBY	2016	6	RUS	2020	20
FIN	2016	6	LBY	2018	10	RUS	2021	18
FIN	2018	8	LBY	2019	14	TCD	2013	24
FIN	2019	7	LBY	2021	15	TCD	2014	17
FIN	2020	12	MEX	2021	6	TCD	2015	14
FIN	2021	10	NER	2014	6	TCD	2016	16
GAB	2021	5	NGA	2013	10	TCD	2018	6
IRN	2013	12	NGA	2014	8	TKM	2013	20
IRN	2014	13	NGA	2015	12	TKM	2014	14
IRN	2015	13	NGA	2016	7	TKM	2015	12
IRN	2016	17	NGA	2018	13	TKM	2016	14
IRN	2018	15	NGA	2019	9	TKM	2018	10
IRN	2019	11	NGA	2020	6	TKM	2019	9
IRN	2020	9	NGA	2021	7	UKR	2013	5
IRQ	2013	41	NLD	2013	14	UKR	2014	6
IRQ	2014	41	NLD	2014	17	UKR	2015	7
IRQ	2015	43	NLD	2015	17	UKR	2016	7
IRQ	2016	44	NLD	2016	16	UKR	2018	6
IRQ	2018	32	NLD	2018	16	VUT	2016	25
IRQ	2019	31	NLD	2019	14			
IRQ	2020	27	NLD	2020	13			

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