



# WORKING PAPER

## Syria in the Dark: Estimating the Economic Consequences of the Civil War through Satellite-Derived Night Lights

Giorgia Giovannetti and Elena Perrai<sup>1</sup>

EMNES Working Paper No 29 / February, 2020

### Abstract

The Syrian Civil War begun in 2011 and is still wreaking enormous damages on the country's economy, with a significant toll measured in deaths, migration, and the destruction of Syria's historical heritage and physical infrastructure. This paper examines the impact of the War on Syria's economy from the perspective of outer space, by-passing the issue of data availability due to the inaccessibility of the war-ravaged territory. The study's contribution to literature is threefold: first, we estimate the elasticity of Gross Domestic Product (GDP) growth to variation in Night Lights for a balanced panel of 13 Middle Eastern and North African countries. This is in order to obtain alternative measurements of GDP growth and loss potentially overcoming issues resulting from governmental distortion of official statistics in wartime; secondly, we calculate the loss in Syrian GDP after 2011 according to this methodology. We obtain more pessimistic estimates than those reported by international organisations. Finally, extrapolating GDP loss from a spatial analysis of Night Lights reduction, we provide long-term projections for the country's economy and estimate the window for GDP recovery to pre-war levels. We discuss geo-political implications which could prevent our projections from happening.

**Keywords:** Syria, War, GDP estimates, Night Lights

---

<sup>1</sup> The authors thank the participants in the June 27-28<sup>th</sup> 2019 EMNES Annual Conference in Brussels at CEPS, for having contributed to this working paper. Their comments and suggestions have vastly enhanced the analysis of this project.

## 1. Introduction

The Syrian Conflict is still far from an end, but its consequences are already unsustainable. Since the start of the war, 13.1 million people have required humanitarian assistance, 6.5 million are in a situation of “food insecurity” (United Nations Office for the Coordination of Humanitarian Affairs, 2016), and 80% of the population has plunged into poverty and their life expectancy has been reduced by 20 years (Syrian Centre for Policy Research, 2015). The need for collecting accurate and valuable data from zones of conflict and war is crucial towards guiding interventions to help people receive immediate assistance and aid. Furthermore, they represent an irreplaceable and vital source of information to address the resolution process in each particular context (European Survey Research Association, 2017). Nevertheless, areas of conflict, violence, injury and disease represent an obstacle to the traditional process of assembling information. Collecting data in real time when infrastructure, administrative systems, and hospitals are not operational and law enforcement is weak or absent, is a difficult challenge. At the same time, when data exists, relying on national statistics could be unwise due to the risk of bias and lack of accuracy.

The lack of data is not confined to war zones and areas of conflict, but also concerns most of the developing world. This “data market failure” constitutes one of the main hurdles in identifying, understanding and accurately targeting active interventions to regions where they are most needed (Jean et al., 2016). The United Nations have called for a “data revolution” aimed at filling the gap in the data collection process amongst developed and developing countries (Independent Expert Advisory Group on a Data Revolution for Sustainable Development, 2014).

In the developing world and in countries devastated by conflicts, in particular, household surveys present two main challenges: on one hand their cost is often prohibitive and, on the other hand, data collection often encounters institutional frictions, since “governments often see little benefit in having their lacklustre performance documented” (Jean et al., 2016). However, reliance on good data is of a paramount importance to pursue solid economic and social policies<sup>2</sup>. Due to these costs, alternative methods to collect data have been proposed. The most popular new sources of information are based on social media, mobile phone networks and remotely sensed satellite data (Jean et al., 2016).

These new techniques exploit the intuition of using tools of the digital millennium. The idea is to observe and analyse phenomena from afar, without compromising quantitative precision. The use of alternative methods helps overcome the problems of accessibility and danger, but it does entail a trade-off: traditional collection methods help obtain not just quantitative data, but also qualitative information about the context in which the data is collected. However, this process is not always immune from bias, since human interaction and perceptions naturally influence the results, even when following rigid behavioural protocols. On the other

---

<sup>2</sup> Hence, it is necessary to consider a fundamental trade-off between high quality data and its availability. Sometimes, it could be required to find the best sub-optimal solution, in terms of quality and availability.

hand, remotely sourced data presents the main drawback of being removed from the context under analysis – which is fundamental to understand the direct and indirect influences of external and internal factors.

In this article, we aim to compare the official statistics on macroeconomic indicators with remotely sensed proxies. The employment of selected Night Lights has the potential to overcome issues linked to government incentives to manipulate and distort official statistics during time of War. At the same time, this comparison allows us to test the accuracy and the precision of the economic projections provided by international organisations and to evaluate the robustness of their estimates compared to the use of alternative data sources<sup>3</sup>. We use the change in Night Lights over time as a proxy of GDP growth to: (1) Obtain a measure of the elasticity of GDP to Night Lights for a sample of 13 selected Middle Eastern and North African (MENA)<sup>4</sup> countries (Section 5); (2) Increase the confidence in estimates of GDP loss during the war, by constructing upper and lower bounds for the drop in Syrian GDP after 2011 (Section 5.1); (3) Compare our estimates to official projections, namely Gobat and Kostial (2016) and the Penn World Tables (Feenstra et al., 2013) (Section 5.1); (4) Produce projections of different scenarios for Syrian GDP recovery, estimating the approximate window in which Syrian GDP will bounce back to its pre-war levels (Section 6).

Night Lights have already been tested in conflict analysis: Henderson et al. (2012) illustrate the 1993-1994 Rwandan genocide through the reduction in the country's luminosity. They find that the reaction of Night Lights to the conflict event is less pronounced than the reaction observed in gross domestic product statistics. Our study finds the opposite; the drop-in luminosity is larger than the official estimates of GDP growth, suggesting a deeper recession. Therefore, our study expands existing literature on remotely sensed measurements of economic activity, by restricting Henderson et al. (2012)'s cross-country analysis to a selected panel of developing countries, located in the Middle East and North Africa. We also find higher elasticities of GDP to Night Lights, which may be indicative of the need for future research in this area; consequently, for the first time, we estimate the economic destruction witnessed in Syria through Night Lights imagery, providing a more pessimistic scenario than the one reported by official statistics.

The remainder of the paper proceeds as follows: Section 2 reviews literature on the use of Night Lights as a proxy of economic activity; Section 3 presents the data and the methodology employed in the analysis; Section 4 reports an exploratory spatial analysis of the decrease in luminosity experienced in Syria after 2011; in Section 5, we estimate the elasticities of GDP to Night Lights for our selected panel and compare these estimates with official statistics for the case of Syria; Section 6 is comprised of projections for Syrian GDP recovery to its pre-war levels, offering alternative scenarios based on our econometric estimates; Section 7 provides the conclusion.

---

<sup>3</sup> The macro-level design of our study does not encounter the contextual problems of obtaining qualitative information at the micro level, thus sidestepping the main disadvantage of employing remotely sourced data

<sup>4</sup> The explanation of the countries' selection is reported in section 5 and in the Appendix

## 2. Night Lights as a Proxy of Economic Activity: Review of the Literature

The DMSP/OLS is a long-term operational meteorological programme of the US DoD (Department of Defense), developed in the 1960s. Its original goal was collecting and disclosing data on worldwide cloud cover, on a daily basis, and giving data for strategic and tactical weather predictions to support US military operations (Earth Observation Portal, 2002). The scientific community quickly understood the potential of using this data source. Researchers apply this data to a number of fields: “With a few exceptions, Night Lights have been the prime remote sensing data used in economic analysis” (Keola et al., 2015). Croft (1978) is amongst the first to have exploited the opportunity of using Night Lights data in economic analysis, highlighting its capacity for giving a representation of the level of human economic activities through the luminosity in urban settings, gas flares and fires.

Elvidge et al. (1997) focus on the relation between Night Lights (hereafter NTLs), population, economic development and electric power consumption, finding a statistically significant relationship among NTLs and economic activity; Doll et al. (2000) use NTLs’ data to map global socio-economic and CO<sub>2</sub> emissions. Sutton and Costanza (2002), on the other hand, use the sum of the intensity of NTLs to calculate an approximation of GDP. Ghosh et al. (2010) used regression models to analyse and create a disaggregated map of economic activities, taking into account the link between the sum of NTLs and the official measurement of economic level, both at sub-national and national levels. Along similar lines, Chand et al. (2009) use NTLs to show the spatial and temporal changes in electric power consumption patterns in India from 1993 to 2002. Their results suggest that changes in luminosity reflect socio-economic and energy utilisation developments. Townsend and Bruce (2010) use NTLs as a proxy of electric consumption, showing its spatial distribution throughout Australia, for the period 1997-2002. The estimated correlation between night light data and electric power consumption is high and significant (R squared of 0.93).

Zhou et al. (2015) and Gibson et al. (2014) use NTLs to estimate urban expansion and Gibson et al. (2014) analyse the relation between economic growth and China’s urban land area developments from 1993 to 2012. In line with this, Mellander et al. (2015), by the use of correlation analysis and geographically weighted regressions, inspect how NTLs could represent a good proxy to estimate population and its density.

NTLs have also been employed to assess regional inequalities. Mveyange (2015) finds a significant positive relationship amongst regional inequalities visible through the luminosity emitted by NTLs and African income. Lee (2018) studies the effect of the economic and political sanctions imposed on North Korea, through the regional inequalities reflected by luminosity trends, whilst Smith and Wills (2016) propose a poverty measure by combining NTLs with gridded population data, thereby devising a new and strategic way to assess poverty levels in remote and inaccessible areas. They compute the ratio between population density over unlit areas, starting from the intuitive assumption that illumination is a basic human need. Jean et al. (2016) use high-resolution daytime satellite imagery to estimate socio-economic data,

such as average household expenditure and average household wealth at a “cluster level”. Their study is a further counterproof of the use of NTLs in mapping the spatial distribution of economic well-being across, in this case, African countries, allowing access to poverty levels and its geographical distribution.

Amaral et al. (2005), propose a methodology to single out human presence and activities in the Brazilian Amazon region, using NTLs. The usefulness of their results reflects two main considerations: the first concerns the continental dimensions of Amazonia and the difficulties in tracing human presence. The other is in regard the absence of dynamic demographic information, as the census is only available every 10 years. Other sources of indirect data collection which have been used in developing countries and war zones are social media and mobile phone networks (Flowminder Foundation, 2018). These types of data provide several advantages; firstly, the objectivity and the immediate capacity to be available on a daily frequency; secondly, this data helps overcome the problem of reaching inaccessible and dangerous zones.

Building on this, Chen and Nordhaus (2011) question whether luminosity could incorporate crucial information for improving economic output data at a regional level in developing countries. They investigate if NTLs could represent a valuable proxy of traditional output measures. They find that luminosity could be considered a good proxy for countries with weak statistical and administrative systems, whilst they can deviate and not be very precise for developed countries. Not surprisingly, NTLs *in primis* reflect investment in physical capital and infrastructure, but they do not otherwise capture the value added from the service economy, which is one of the main pillars of developed economies’ growth. Furthermore, NTLs data is a sub-optimal source of data, since they are a tool that indirectly analyses phenomena for which we cannot reach an appropriate degree of data precision. Henderson et al. (2012) report the main difficulties in recording the precise value of GDP in developing countries.

### 3. EMPIRICAL STRATEGY and Data Sources

The empirical strategy adopted in the paper follows the procedure of Henderson et al. (2012). First of all, we aim at estimating the coefficients which measure the responsiveness of a GDP variation to a change in NTLs. Then, we aim to compare the official projections of GDP loss, estimated by Gobat and Kostial (2016) and Feenstra et al. (2013), with those calculated through our elasticities of GDP to NTLs. The projections of Gobat and Kostial (2016) rely on data from the Syrian authorities, the Syrian Centre for Policy Research and World Bank. Nevertheless, as they point out, the important role played by the informal sector, the difficulty of traceability and the unreliability of the administrative sectors in a state in which the rule of law breaks down, render the estimates significantly uncertain. The Penn World Table version 9.0 (Feenstra et al., 2013) is, instead, a dataset that covers 182 countries between 1950 and 2014, with information on levels of income, output, input and productivity. However, the standard collection process may have to overcome enormous challenges, especially in contexts such as the one that we aim to analyse.

Without compromising quantitative precision, NTLs represent an alternative tool which links spatial analysis with economic estimations, allowing us to produce more solid and realistic projections. Then, in order to compare official estimates of war-torn Syrian GDP recession with experimental estimates inferred from NTLs Data, we use the following data sources:

1. Night Lights Data derived by National Oceanic and Atmospheric Administration, (hereafter, NOAA) (2013). This dataset comprises 22 years (1992-2013) of satellite observations of the spectral bands of the Earth at night, allowing for identification of urban agglomerates, physical infrastructure, roads and rural human settlements. The Defense Meteorological Satellite Program Operational Line Scanner (DMSP-OLS) was first developed for meteorological application, such as research into the distribution of global cloud cover and its characteristics (Huang et al., 2014). However, since the digitalisation of the archive, started in 1992, the Night Lights composites have been exploited by social scientists for different applications, mainly related to the detection of human activity on the Earth's surface. The dataset has a resolution of 30x30 arc-seconds (approximately 1Kmx1Km at the equator) and it is constituted by the aggregation of 9 OLS satellites (F10-F18) with different calibration and sensors. Three types of images are produced for each year: Average Visible Lights, Cloud Free Lights and Stable Lights. In line with previous research (e.g. Elvidge et al. (1997), Henderson et al. (2012)), we use the Stable Lights dataset. The Stable Lights images associate with geo-referenced 1Kmx1Km squares on the Earth's surface, the frequency of light detection, "normalised by the number of cloud-free observations" (Huang et al., 2014)<sup>5</sup>. Each pixel is coded from 0-63 according to its luminosity level. We

---

<sup>5</sup> National Geophysical Data Centre (NGDC), together with NOAA clean the data from "strong sources of natural light such as forest fires, auroral activity, late sunsets and the bright half of the lunar cycle to produce observations of man-made outdoor and some indoor use of light" (Walters et al., 2019) .

aggregate average pixel luminosity at the country-level, as in Henderson et al. (2012) and construct a variable of average luminosity as a proxy of aggregate GDP.

2. The Penn World Tables version 9.0 (Feenstra et al., 2013) from which we derive the real GDP calculated using national accounts statistics. We compute its fall from 2010 to 2014.
3. The estimates of the fall in GDP calculated by the International Monetary Fund in Gobat and Kostial (2016)
4. Data from the World Bank's Development Indicators database (The World Bank, 2017), for population density and growth.

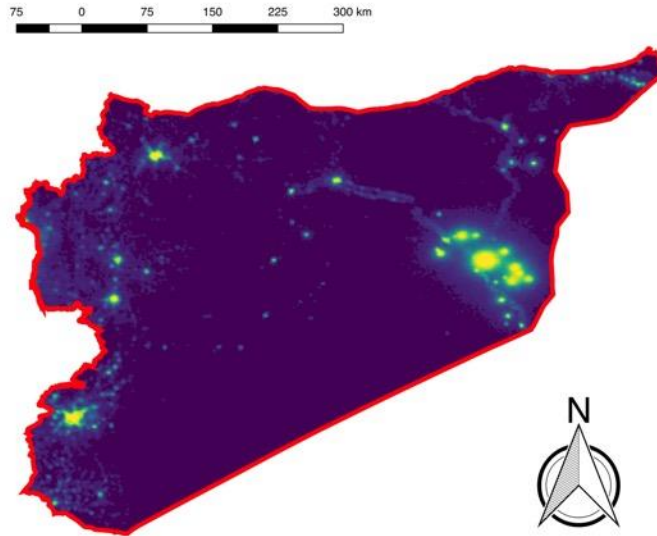
By applying official and experimental data, we highlight the importance of using alternative data sources in conflict areas, where the quality of official accounts is mired by the political instability and the inaccessibility of data sources for data collection processes at micro and macro levels.

## 4. Exploratory Spatial Analysis

We exploit Geographic Information Systems, hereafter GIS, to visualise and investigate the dynamics of NTLs from 1992 to 2013, two years after the onset of the War. QGIS 2.18 is an open source application which is used in spatial econometrics for analysing geo-coded spatial data. We use it to create our final dataset and preemptively visualise the drop in NTLs over the period under consideration. First of all, we show the luminosity of Syria for four selected years in our dataset: 1992, 2000, 2010, and 2013. The pictures below show that, after a period of relative increase in luminosity from 1992 to 2010 in the main cities of Aleppo and Damascus, there is a sharp decline in NTLs from 2010 onwards. Furthermore, from 1992 to 2000, another important consideration can be inferred by inspecting the luminosity around the basin of the Euphrates River. In particular, what emerges is that there has been a substantial decrease in luminosity. The reason for this drop could be retraced to several and interconnected factors. The first one can be found in the process of urbanisation within the country and the consequent exploitation of water resources, due to the focus on water-intensive crop production to meet the demands of food and agricultural products in the cities. As a reflection of this increased pressure on water resources the riverbed dried up for most of the summer months (Nouar Shamout and Lahn, 2015). Limiting the causes of the reduction in luminosity to the scarcity of water resources, due to the mismanagement of the Syrian government, would be misleading. Indeed, the control of the Euphrates River has been the cause of tensions across the Middle East, in particular for three key countries: Turkey, Syria and Iraq. Across these three countries, the river represents a vital source of water for 27 million people. The past and current hydro-engineering projects in the three riparian states that account in total for around 32 dams and barrages, are one of the crucial determinants of water stress in the region. In the dispute over control of water-resources, Turkey plays a central role, since about 90% of the Euphrates' total annual flow originates on Turkish soil. In light of this fact, in 1996 Iraq and Syria complained about the consequences of the construction of the Birecik dam in Turkey, which resulted in reduced water levels and more polluted water due to Turkish irrigation activities (W. Al-Muqdadadi et al. 2016).

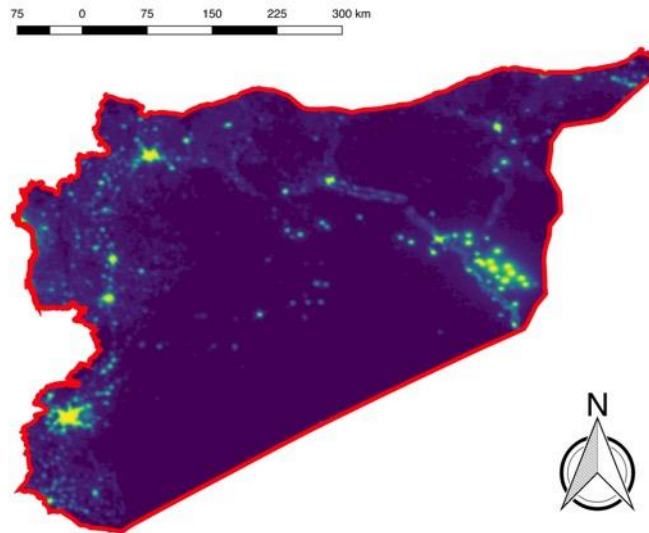


**Figure 1: Syrian Night Lights – 1992**



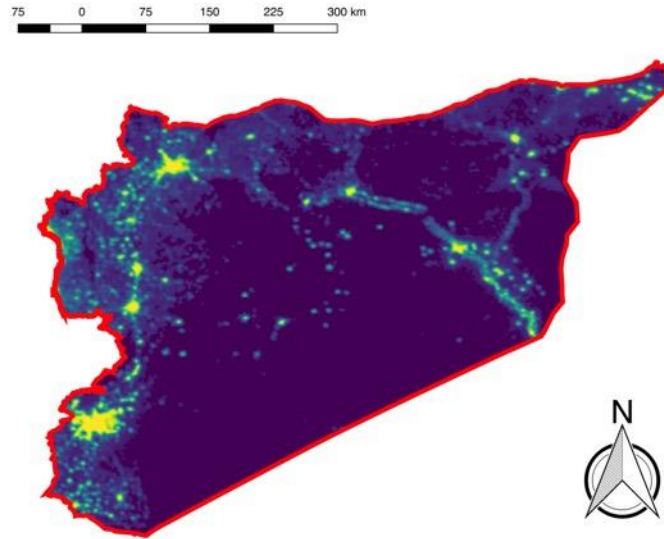
**Source:** *Authors' Elaboration on NOAA (2013).*

**Figure 2: Syrian Night Lights – 2000**



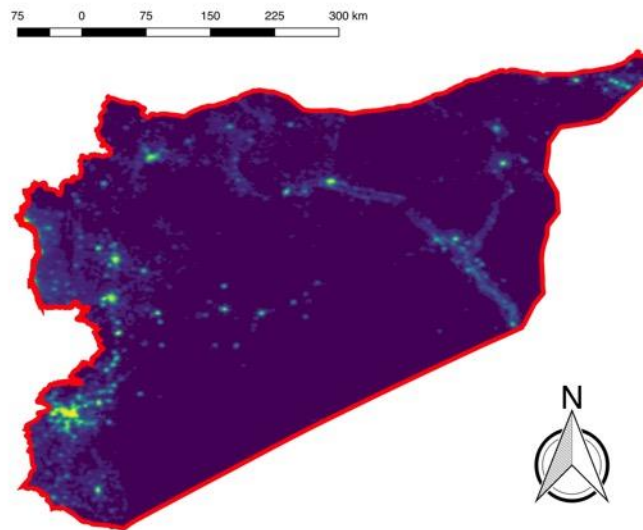
**Source:** *Authors' Elaboration on NOAA (2013).*

**Figure 3: Syrian Night Lights – 2010**



*Source: Authors' Elaboration on NOAA (2013)*

**Figure 4: Syrian Night Lights – 2013**



*Source: Authors' Elaboration on NOAA (2013)*

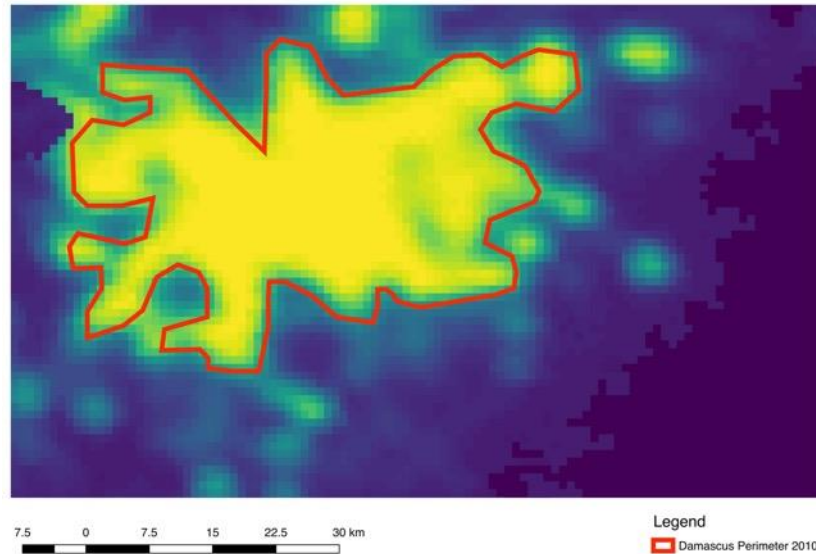
Comparing Figure 1 with Figure 4, we notice a drastic decline in luminosity, possibly as an effect of the Civil War. Li and Li (2014) state that NTLs “can be a useful source for monitoring humanitarian crises”. Following this insight, we analyse the impact of the War through the loss in luminosity.

As expected, the conflict and the bombings destroyed a large portion of the Syrian infrastructure. Since NTLs detect human settlements, urbanisation, economic activity and population density, their drastic decrease is a clear indicator of the

destruction caused by the War. The average digital number for luminosity, calculated over the whole Syrian territory, drops by 64.06%, from 5.64 in 2010 to 2.027 in 2013<sup>6</sup>.

Focusing on Damascus, the effect of the conflict is even more visible. The reduced luminosity is stark, by comparing Figure 5 (2010) with Figure 6 (2013).

**Figure 5: Damascus Night Lights - 2010**

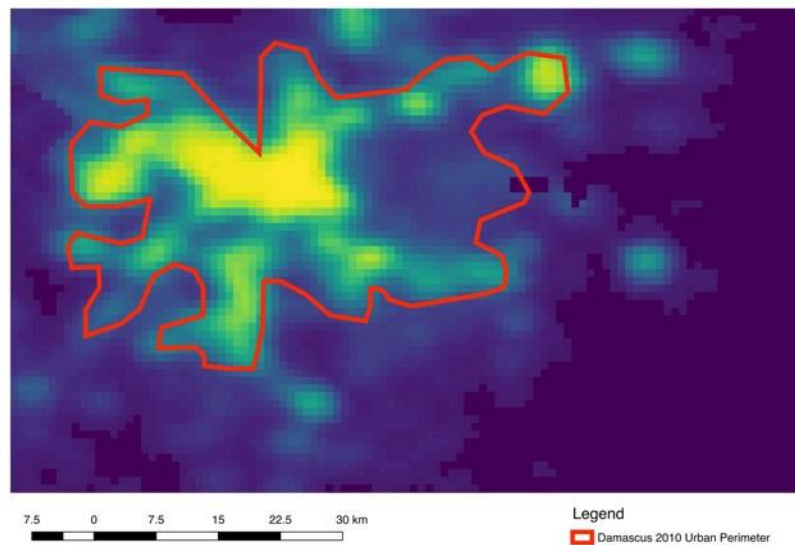


**Source:** *Authors' Elaboration on NOAA (2013).*

---

<sup>6</sup> More precisely, luminosity decreases by 19.3% from 2010 to 2011, 21.53% from 2011 to 2012 and 43.26% in the final period under analysis

**Figure 6: Damascus Night Lights - 2013**



**Source:** *Authors' Elaboration on NOAA (2013).*

The decline in just three years is 43.13% (from 56.97 to 32.39).

## 5. Econometric estimation of the elasticity of GDP to Night Lights

In line with Henderson et al. (2012), we estimate the coefficients which measure the change in GDP induced by a change in NTLs on a balanced panel of 13 MENA countries:

$$GDP_{it} = \alpha + \beta_1 NightLights_{it} + \beta_2 X_{it} + \lambda_t + \delta_i + \epsilon_{it} \quad (1)$$

where:  $GDP_{it}$  is the natural logarithm of the GDP for country  $i$  in year  $t$ ,  $NightLights_{it}$  is the natural logarithm of the average digital number, extracted from NOAA (2013), for country  $i$  in year  $t$ ,  $X_{it}$  is a vector of demographic covariates, namely population density and population growth, for country  $i$  in year  $t$ ,  $\lambda_t$  are year-specific fixed effects,  $\delta_i$  are country-specific fixed effects, and  $\epsilon_{it}$  it is a stochastic error term. We use a FE regression on the grounds that time-invariant unobserved heterogeneity could affect our estimates; in addition, as pointed out by Henderson et al. (2012), FE regression allows us to overcome measurement problems, related to the variation over time of satellite sensor settings, which could alter the comparison of raw digital numbers of estimated NTLs. These considerations find validation in the result of the test of over-identifying restrictions for fixed effects vs random effects, reported in Table 1.

To explore the possibility of a non-linear association between GDP and NTLs, we also include in equation (1) the squared natural logarithm of the average digital number for Night Lights:

$$GDP_{it} = \alpha + \beta_1 NightLights_{it} + \beta_2 NightLights_{it}^2 + \beta_3 X_{it} + \lambda_t + \delta_i + \epsilon_{it} \quad (2)$$

Furthermore, in line with Henderson et al. (2012) we test a fixed-effects two stage least squares Instrumental Variable (IV) specification, defined as follows:

$$GDP_{it} = \alpha + \beta_1 NightLights_{it} + \lambda_t + \delta_i + \epsilon_{it} \quad (3)$$

where  $NightLights_{it}$  is determined in the first stage by:

$$NightLights_{it} = \gamma + \theta X_{it} + u_{it} \quad (4)$$

where  $X_{it}$  is an Instrumental Variable, in this case represented by demographic characteristics. This specification tests for the non-random distribution of Night Light intensity by regressing NTL on population density and growth, which we assume are correlated to luminosity and its measurement error, but not necessarily to the measurement error of GDP. The use of IV allows us to separate the effects of population indicators on NTLs from the effect of NTLs on GDP. In the first stage (equation 4) we regress NTLs on demographics, in order to explain the portion of measurement error in NTLs which does not affect the measurement of GDP. In the second stage (equation 3), the IV procedure regresses GDP on the “purified” NTLs from the first stage, allowing us to obtain an unbiased measure of the elasticity of GDP to NTLs.

Differently from Henderson et al. 2012, we are interested in running analysis that considers a selected pool of countries from the Middle East and Northern Africa (MENA). The reasons underlying this choice must be retraced in geo-political and historical considerations. We seek to estimate the elasticity of GDP to NTLs for this

particular sample, as a simple cross-country, worldwide estimation could lead to bias arising from uneven socio-economic characteristics. By restricting the analysis to MENA countries which haven't experienced shocks in their post-1992 GDP trends, we are confident that our estimates of elasticity are appropriate to infer the decrease in Syrian GDP after the 2011 war. The Middle East has been the theatre of a number of tensions and conflicts in recent decades. Ignoring to take this into account could drive the analysis to erroneous estimations. However, it is equally true that this geo-political environment is a *unicum* for its intrinsic determinants and characteristics. Since Syria is completely immersed in this context and bears its own consequences, it would be tantamount to being inadvisable not to consider these determinants.<sup>7</sup>

Table 1 reports the results: Column (1) is the baseline fixed-effects specification; Column (3) demographic covariates for population density and population growth are added to our specification; Column (2) and (4) include the quadratic term; Column (5) reports the results for the IV estimate. All models include year-and-country specific fixed effects for 13 selected countries (Middle East and North Africa).

**Table 1: Estimates of the elasticity of GDP to Night Lights**

Elasticity of GDP to Night Lights					
Variables	(1) FE	(2) FE-sq	(3) FE	(4) FE-sq	(5) IV
Night Lights	<b>0.397**</b> (0.177)	<b>0.256***</b> (0.0566)	<b>0.404***</b> (0.117)	<b>0.251***</b> (0.0495)	<b>0.352**</b> (0.175)
Squared NTL		0.185** (0.0698)		0.151** (0.0521)	
Population Density			0.000342** (0.000135)	0.000103 (8.40e-05)	
Population Growth			0.0393** 0.0139	0.0298*** 0.00627	
Constant	11.00***	10.51***	10.82***	10.54***	
	0.249	0.262	0.199	0.184	
Year FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	286	286	286	286	286
R-squared	0.850	0.925	0.908	0.951	0.849
Number of countries	13	13	13	13	13
Test of Over-identifying Restrictions: fixed vs random effects Sargan-Hansen statistic: 24.517 Chi-sq(1) p-value=0.0000***					
Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1					

**Sources:** Authors' estimation

<sup>7</sup> For additional information regarding the choice of the donor pool of countries, see the Appendix.

Table 1 shows that our elasticity estimates range from 0.251 to 0.404, values slightly higher, but in line, with Henderson et al. (2012). Higher numerical values could be driven by the exclusion from our sample of high GDP countries, for which the relationship between NTLs and GDP is less pronounced. Our estimated elasticities are all  $< 1$ , meaning that the reaction of GDP to an increase in luminosity is positive, but incomplete. This seems to confirm the capacity of NTLs to predict investment in infrastructure and physical capital, but not to reflect value added sectors such as services, high-tech, trade *et similia*.

## 5.1 Upper and Lower Bounds and Comparison with Official Estimates for Syrian GDP Fall

Table 2 reports two official estimates of the decline in Syrian GDP after the onset of the 2011 Civil War. The first two rows respectively present the estimated values by Gobat and Kostial (2016), covering the 2011-2015 period, and by Feenstra et al. (2013), covering the period 2011-2014. These values are projections.

The DMSP/OLS satellite annual composites are only available up to 2013, when they were superseded by the Suomi VIIRS Satellite, for which only monthly composites are available. Since intercalibration between the DMSP/OLS and the Suomi VIIRS satellites is beyond the scope of this paper (see Li et al. (2017)), we rely on the DMSP/OLS to construct our observational estimates of GDP decline, based on NTLs' decrease adjusted with the estimated elasticity values (Section 5).

Row 3 in Table 2 reports the “raw” decrease in NTLs, accounting for 19% in the first year, 22% in the second, and 43% in the third, thus portraying a more catastrophic scenario than that projected by official sources. This scenario assumes a quite extreme hypothesis, namely that the elasticity of GDP to NTLs is exactly one. We decide to report this case in order to have a more comprehensive range of scenarios. Furthermore, as evidenced by Henderson et al. (2012, p: 1004), raw NTLs may be a purer indicator of the destruction of physical capital and of physical infrastructure, giving a more vivid picture of the drastic decline in economic performance. As an aside, it may be interesting for future research to investigate if these projections were more in line with actual results than the others, suggesting that “raw” NTLs may be a more efficient tool to analyse drastic loss in economic performance than elaborated extrapolations and standard measurements.

Rows (4-8), weighted respectively according to columns (1)-(5) in Table 1, instead, are more in line with Gobat and Kostial (2016) and Feenstra et al. (2013), but consistently underestimate the GDP decrease observed in 2012, accounting for about half of the official projections. These estimates are extrapolated by multiplying the elasticities,  $\hat{\epsilon}$ , of GDP to NTLs of Table 1 in each specification with the “raw” decrease in NTLs, following the procedure of Henderson et al. (2012):

$$\widehat{GDP}_{LOSS} = \hat{\epsilon} * NTL_{RAW}$$

Row (9) reports a weighted average of the fall in GDP reported in Feenstra et al. (2013) and of the NTLs' loss estimated in Row (3). The coefficients used to calculate the weighted average have been inferred from Henderson et al. (2012), according to the following formula:

$$\widehat{GDP}_{LOSS} = \lambda GDP_{EST} + (1 - \lambda) NTL_{RAW}$$

where:  $\widehat{GDP}_{LOSS}$  is the estimated loss in GDP for the country under analysis,  $GDP_{EST}$  is the value of the GDP, as reported in the national statistics, and  $NTL_{RAW}$  is the average digital number representing luminosity. The parameter  $\lambda$  is 0.484, according to Henderson et al. (2012). This technique allows us to obtain composite estimates of



economic mass, which are able to correct for the measurement errors which are usually observed in “bad data countries”.

As we can observe from Table 2, the NTLs’ loss calculated via the weighted combination of GDP data and raw NTLs gives values that are in between the projections by Feenstra et al. (2013) and the raw loss calculated on QGIS. We have obtained different scenarios for the decline in Syrian GDP after 2011. In Section 6, we impute data for 2014-2018, based on the average GDP fall for each scenario and we assume that the War ends in 2019, to offer three different indicative projections for post-war GDP recovery.

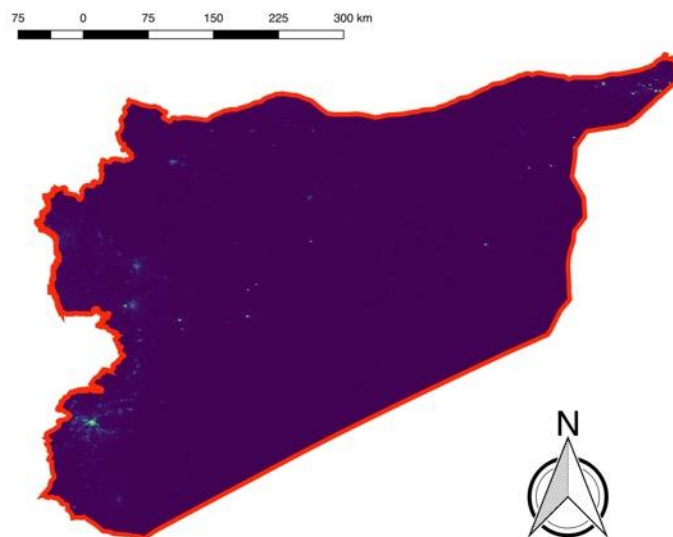
**Table 2: Comparison of Different Estimates of GDP Decrease in Syria after 2011**

Estimate	2011	2012	2013	2014	2015
(1) Gobat and Kostial (2016)	-0.06	-0.21	-0.17	-0.17	-0.15
(2) Feenstra et al. (2013)	-0.06	-0.22	-0.25	0.00	
(3) NTLRAW	-0.19	-0.22	-0.43		
(4) NTL <sub>FE(1)</sub>	-0.08	-0.09	-0.17		
(5) NTL <sub>FEsq(2)</sub>	-0.05	-0.06	-0.11		
(6) NTL <sub>FE(3)</sub>	-0.08	-0.09	-0.17		
(7) NTL <sub>FEsq(4)</sub>	-0.05	-0.05	-0.11		
(8) NTL <sub>IV</sub>	-0.07	-0.08	-0.15		
(9) NTL <sub>WEIGHTED</sub>	-0.13	-0.22	-0.34		

**Source:** Authors’ estimation

We tend to be sceptical about the optimistic scenarios since, as reported in Li et al. (2017), illumination in Syria’s major cities has dropped by 65-99%, with “Aleppo, Dar’a, Deir ez-Zor and Idlib losing 89%, 90%, 96%, and 99% of their city lights between March 2011 and January 2017, respectively”. This also confirms Henderson et al. (2012)’s conjecture about the better predictive capacity of the weighted combination of identifying the real path of GDP decline. Moreover, we have extrapolated the monthly composite image of Syrian NTLs from the Suomi VIIRS satellites, which we could not implement in our quantitative analysis, due to inter-calibration issues. Nonetheless, we investigate the data for descriptive purposes, in order to explore whether our previous intuitions were plausible. As we can observe from Figure 7, there is almost no light in Syria in 2018, confirming the destruction of the country’s physical infrastructure.

**Figure 7: Syrian Night Lights- February 2018**

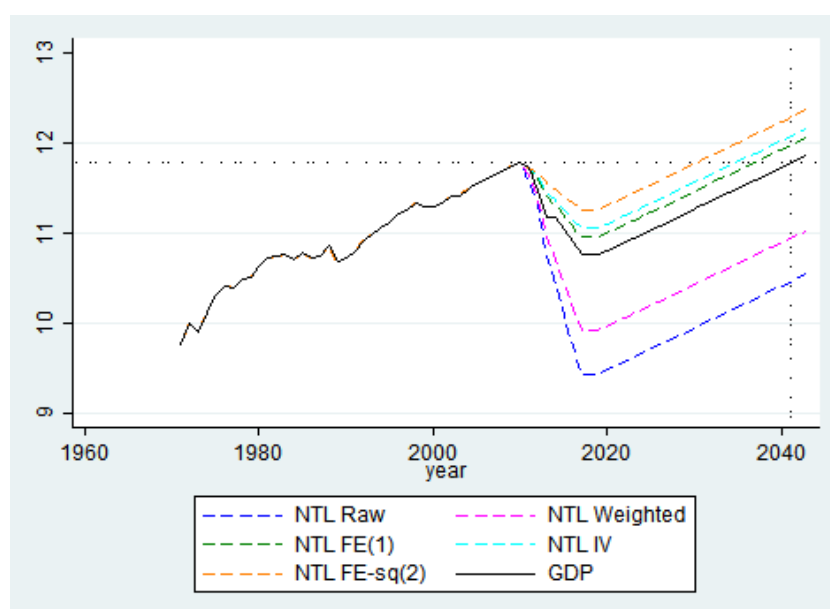


**Source:** Authors' elaboration.

## 6. A simple exercise on Syrian Recovery

In order to have an idea of the magnitude of the consequences of the Syrian Civil War and the recovery timeframe needed to return to pre-War economic levels, we construct a simple framework with alternative hypothetical scenarios. We assume that the post-Syrian War re-building period will begin in 2020 and the economy will grow at the long-term GDP trend growth rate of 4.72%. We extrapolate the long-term trend rate of growth for Syria's GDP by applying a Hodrick-Prescott filter (Hodrick and Prescott, 1997) to the Syrian GDP time series from 1992 to 2010. We also assume that Syrian GDP is stable from 2018 to 2020, consistent with Gobat and Kostial (2016) and with a “buffer period” for growth preceding the rebuild.

**Figure 8: Projections for Syrian GDP Recovery.**



**Source:** Authors' elaboration.

We impute data for 2014-2018 by assuming a constant decrease in GDP and in NTLs, each of them at its own 2010-2013 average de-growth rate. This analysis allows us to infer scenario-specific timeframes for recovery.

Under the “optimistic scenarios” of Section 5.1, the fall in GDP is estimated as the fall in NTLs, weighted by the elasticity parameters from: (1) Fixed Effects without covariates,  $\hat{\epsilon} = 0.397$ ; (2) Fixed Effects with squared NTLs,  $\hat{\epsilon} = 0.256$ ; (3) Instrumental Variables,  $\hat{\epsilon} = 0.352$ . Figure 8 shows that, under these three hypothetical configurations, GDP bounces back to its pre-war levels after 10-17 years.

Under the “pessimistic scenarios”, GDP decline is estimated as: (4) Raw decrease in average luminosity; (5) Weighted combination of the decrease in average

luminosity and the fall in GDP. In these two projections, GDP reaches its pre-war level in 2060 and 2070, respectively<sup>s</sup>.

The current GDP series, computed using the same assumption of 2014-2018, decrease at its average rate and 2020-onwards increase at its long-term trend rate, moving closer to the optimistic rather than the pessimistic scenario: indeed, it reaches its pre-war level in 2041 (the red dotted line on the x-axis), 21 years after the date we established as the end of the conflict.

The conflict only seems to have intensified after 2013, hence we cannot discard our assumptions as hyperbolic about the sustained 2014-2018 GDP decrease at the average 2010-2013 rate. If anything, these assumptions seem slightly conservative; however, the pessimistic scenario also relies on the correspondence between NTLs and GDP decline ( $NTL_{RAW}$ ) and on the accuracy of the weighted measure of GDP, proposed by Henderson et al. (2012). We assert that the damages presented in the two pessimistic scenarios cannot be pre-emptively ruled out.

A note of caution is due to the fact that these projections are based on further binding assumptions, as in Gobat and Kostial (2016): (1) The Syrian territory regains political and economic unity after 2020; (2) The economy grows at its long-term trend growth rate each year after 2020.

The first assumption seems unlikely to be sustained. The country is now fragmented into three main zones of influence; those held by government forces, the rebel Syrian opposition and Kurdish militia. The fragmentation, besides being due to the war, mirrors the original ethnic composition of Syria and has become increasingly polarised, due to the economic and political interests at stake. This makes it “increasingly difficult to envisage the reconstitution of the pre-uprising central Syrian state”, with scholars calling for a solution based on a “transitional decentralised state”. Regional self-sufficiency will likely play a part in the post-war stabilisation of the country (Yazigi, 2014).

The second assumption is also likely to be violated, since after a period of conflict there are two other plausible and opposite scenarios: (1) A quick growth spurt, similar to the one observed in Lebanon after 1989, resulting from the reconstruction of the physical infrastructure of an entire country; (2) A stagnation period, due to the absence of investment, international aid, or to a chaotic socio-political environment. Hence, our assumption mediates between the two and offers an alternative framework for evaluating the long-term damages wreaked on the Syrian economy, quantifying the amount of investment and stability needed for human well-being, in order to recover to its pre-war levels.

---

<sup>s</sup> More projections are available on request: (1) projections for FE with demographics; (2) projections for FE with demographics and squared Night Lights; (3) projections which extend up to 2075.

## 7. Conclusions

This article investigated the economic consequences of the Syrian Civil War on Syrian GDP. We compared official projections of GDP decline with estimates obtained through non-conventional economic approach. We employed Night Lights extrapolated from NOAA's (2013) satellite data, to calculate the average rate of decrease in luminosity, in order to have an approximation of the "real" fall in GDP. The use of Night Light data springs from the necessity to overcome data quality and availability problems, particularly relevant in war zones.

The "space perspective" allows us to approach the devastating economic consequences of the War from an innovative point of view, giving insight for further research in this field. Our estimates suggest that the scenario reported by the official statistics is optimistic. As reported in Table 2, our estimate of GDP decline, using NTLs, are significantly higher, accounting for 43% in 2013 when employing raw NTLs and 34.4% by using the weighted combination proposed by Henderson et al. (2012), whilst official statistics report 17% (Gobat and Kostial, 2016) and 25% (Feenstra et al., 2013), respectively. This comparison highlights the magnitude of data discrepancies, in a context in which reliable statistics are difficult to be collected.

Bearing in mind all the possible limitations of our research, we believe that this could be a first contribution towards understanding the scale of the conflict and the period required for a full recovery.

## 8. References

1. Amaral, Silvana et al. (2005). "Estimating population and energy consumption in Brazilian Amazonia using DMSP night-time satellite data". In: *Computers, Environment and Urban Systems* 29.2, pp. 179–195. issn: 01989715. doi: 10.1016/j.compenvurbsys.2003.09.004.
2. Al-Muqdad et al. (2016). "Dispute over Water Resource Management- Iraq and Turkey". In: *Journal of Environmental Protection*, 7, 1096-1103.
3. Chand, T. R. et al. (2009). "Spatial characterisation of electrical power consumption patterns over India using temporal DMSP-OLS night-time satellite data". In: *International Journal of Remote Sensing* 30.3, pp. 647–661. issn: 01431161. doi: 10.1080/01431160802345685
4. Chen, X. and Nordhaus, W. D. (2011). "Using luminosity data as a proxy for economic statistics". In: *Proceedings of the National Academy of Sciences* 108.21, pp. 8589– 8594. issn: 0027-8424. doi: 10.1073/pnas.1017031108. url: <http://www.pnas.org/cgi/doi/10.1073/pnas.1017031108>.
5. Croft, T. A. (1978). "Night-time Images of the Earth from Space". In: *Scientific American* 239, pp. 86–98. doi: 10.1038/scientificamerican0778-86.
6. Doll, Christopher N. H., Muller, Jan-Peter, and Elvidge, Christopher D. (2000). "Night- time Imagery as a Tool for Global Socioeconomic Mapping Parameters and Green- house Gas Emissions". In: *AMBIO: A Journal of the Human Environment* 29.3, pp. 157–162. issn: 0044-7447. doi: <http://dx.doi.org/10.1579/0044-7447-29.3.157>. url: <http://www.bioone.org/doi/full/10.1579/0044-7447-29.3.157>.
7. Earth Observation Portal (2002). DMSP (*Defence Meteorological Satellite Programme*). url: <https://directory.eoportal.org/web/eoportal/-/dmsp>.
8. Elvidge, C. D. et al. (1997). "Relation between satellite observed visible near-infrared emissions, population, economic activity and electric power consumption". In: *International Journal of Remote Sensing* 18.6, pp. 1373–1379. issn: 13665901. doi: 10.1080/014311697218485.
9. European Survey Research Association (2017). *Survey research in Conflict Areas: Learnings from Case Studies*. url: <https://www.europeansurveyresearch.org/conference/programme2017?sess=34&day=4> (visited on 03/12/2018).
10. Feenstra, Robert C., Inklaar, Robert, and Timmer, Marcel (2013). *The Next Generation of the Penn World Table*. Working Paper 19255. National Bureau of Economic Research. doi: 10.3386/w19255.
11. Flowminder Foundation (2018). *WorldPop Database*. url: <http://www.flowminder.org/publications/worldpop-open-data-for-spatial-demography>.

12. Ghosh, Tilottama et al. (2010). “Shedding Light on the Global Distribution of Economic Activity”. In: *The Open Geography Journal* 3, pp. 148–161. issn: 18749232. doi: 10.2174/1874923201003010147.
13. Gibson, John, Li, Chao, and Boe-Gibson, Geua (2014). “Economic growth and expansion of China’s urban land area: Evidence from administrative data and night lights, 1993-2012”. In: *Sustainability (Switzerland)* 6.11, pp. 7850–7865. issn: 20711050. doi: 10.3390/su6117850.
14. Gobat, Jeanne and Kostial, Kristina (2016). “Syria’s Conflict Economy”. In: *IMF Working Paper*, p. 29. url: <https://www.imf.org/external/pubs/ft/wp/2016/wp16123.pdf>.
15. Henderson, J. Vernon, Storeygard, Adam, and Weil, David N. (2012). “Measuring economic growth from outer space”. In: *American Economic Review* 102.2, pp. 994–1028. issn: 00028282. doi: 10.1257/aer.102.2.994. arXiv: arXiv:1011.1669v3.
16. Hodrick, Robert J and Prescott, Edward C (1997). “Postwar US Business Cycles: An Empirical Investigation”. In: *Journal of Money, Credit and Banking* 29.1, pp. 1–16. issn: 00222879. doi: 10.2307/2953682.
17. Huang, Qingxu et al. (2014). “Application of DMSP/OLS night-time light images: A meta-analysis and a systematic literature review”. In: *Remote Sensing* 6.8, pp. 6844–6866. issn: 20724292. doi: 10.3390/rs6086844.
18. Independent Expert Advisory Group on a Data Revolution for Sustainable Development (2014). *A World that Counts: Mobilising the Data Revolution for Sustainable Development*. Tech. rep.
19. Jean, Neal et al. (2016). “Combining satellite imagery and machine learning to predict poverty”. In: *Science* 353.6301, pp. 790–794.
20. Keola, Souknilanh, Andersson, Magnus, and Hall, O L A (2015). “Monitoring Economic Development from Space: Using Night-time Light and Land Cover Data to Measure Economic Growth”. In: *World Development* 66, pp. 322–334. issn: 0305-750X. doi: 10.1016/j.worlddev.2014.08.017. url: <http://dx.doi.org/10.1016/j.worlddev.2014.08.017>.
21. Lee, Yong Suk (2018). “International isolation and regional inequality: Evidence from sanctions on North Korea”. In: *Journal of Urban Economics* 103, pp. 34–51. issn: 00941190. doi: 10.1016/j.jue.2017.11.002.
22. Li, Xi and Li, Deren (2014). “Can night-time light images play a role in evaluating the Syrian Crisis?” In: *International Journal of Remote Sensing* 35.18, pp. 6648–6661. issn: 13665901. doi: 10.1080/01431161.2014.971469.
23. Li, Xi et al. (2017). “Inter-calibration between DMSP/OLS and VIIRS night-time light images to evaluate city light dynamics of Syria’s major human settlement during Syrian Civil War”. In: *International Journal of Remote Sensing* 38.21, pp. 5934–5951. issn: 13665901. doi: 10.1080/01431161.2017.1331476.

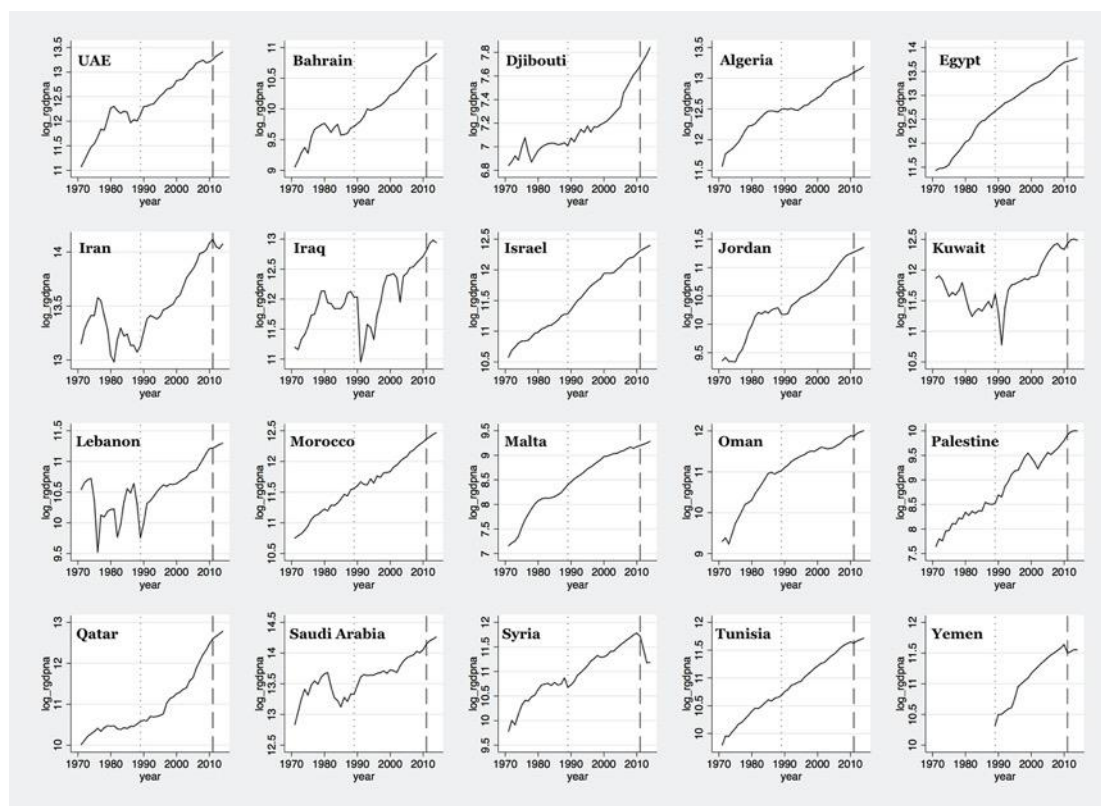
24. Mellander, Charlotta et al. (2015). “Night-time light data: A good proxy measure for economic activity?” In: *PLoS ONE* 10.10, pp. 1–18. issn: 19326203. doi: 10.1371/journal.pone.0139779.
25. Mveyange, Anthony (2015). *Night lights and regional income inequality in Africa*. isbn: 9789292309749.
26. M. Nouar Shamout, Glada Lahn (2015) “The Euphrates in Crisis: Channels of Cooperation for a Threatened River”. Research Paper: Energy, Environment and Resources.
27. NOAA (2013). *DMSP-OLS Night-time Lights*. Tech. rep. Image and data processing by NOAA’s National Geophysical Data Centre. DMSP data collected by US Air Force Weather Agency.
28. Smith, Brock and Wills, Samuel (2016). “Left in the Dark? Oil and Rural Poverty”. In: October, pp. 1–41.
29. Sutton, P. C. and Costanza, R. (2002). “Global estimates of market and non-market values derived from night-time satellite imagery, land cover, and ecosystem service valuation”. In: *Ecological Economics* 41.3, pp. 509–527. issn: 09218009. doi: 10.1016/S0921-8009(02)00097-6.
30. Syrian Centre for Policy Research (2015). *Syria: Confronting Fragmentation! Impact of Syrian Crisis Report*. Tech. rep., p. 67.
31. The World Bank, World Bank (2017). World Development Indicators. url: [http:// data.worldbank.org/indicator/SP.DYN.LE00.FE.IN](http://data.worldbank.org/indicator/SP.DYN.LE00.FE.IN).
32. Townsend, Alexander C. and Bruce, David A. (2010). “The use of night-time lights satellite imagery as a measure of Australia’s regional electricity consumption and population distribution”. In: *International Journal of Remote Sensing* 31.16, pp. 4459– 4480. issn: 01431161. doi: 10.1080/01431160903261005.
33. United Nations Office for the Coordination of Humanitarian Affairs (2016). *About the Crisis*. url: [www.unocha.org/syrian-arab-republic/syria-country-profile/ about-crisis](http://www.unocha.org/syrian-arab-republic/syria-country-profile/about-crisis) (visited on 03/12/2018).
34. Walters, L., Bittencourt, M, and Chisadza, C. (2019). Public Infrastructure Provision and Ethnic Favouritism: Evidence from South Africa. AidData Working Paper #84. Williamsburg, VA: AidData at William & Mary.
35. Yazigi, Jihad (2014). *Syria’s War Economy*. Tech. rep. January. European Council on Foreign Relations, p. 8. url: [http://mediterraneanaffairs.com/wp-content/ uploads/2015/07/ECFR97{\\\_}SYRIA{\\\_}BRIEF{\\\_}AW.pdf](http://mediterraneanaffairs.com/wp-content/uploads/2015/07/ECFR97{\_}SYRIA{\_}BRIEF{\_}AW.pdf).
36. Zhou, Yuyu et al. (2015). “A global map of urban extent from nightlights”. In: *Environmental Research Letters* 10.5. issn: 17489326. doi: 10.1088/1748-9326/10/5/ 054011.
- 37.



## 9. Annexes

In order to select the appropriate countries to be included in our donor pool, we decide to pre-emptively test the potential candidates for our donor pool, by visually examining their GDP trends for the period 1971-2014, reported in Figure 9. This inspection allows us to identify eventual shocks which could alter our estimations.

**Figure 9: GDP Trends for all the potential donor countries.**

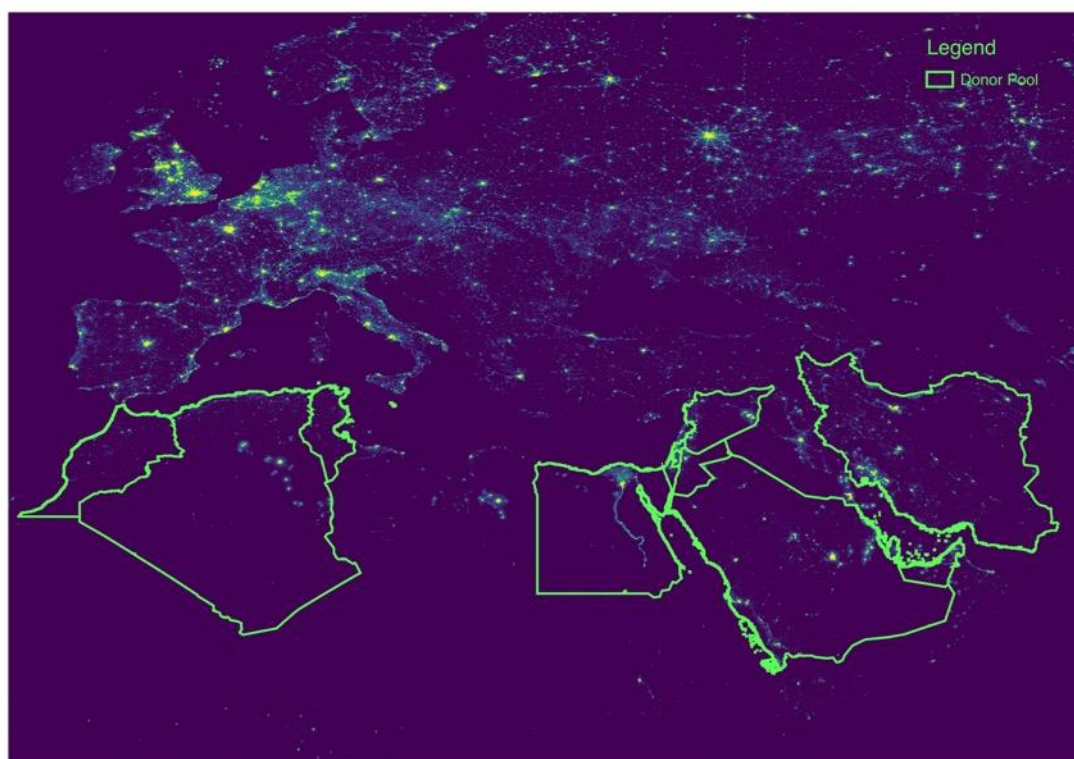


**Source:** Authors' elaboration.

As expected, multiple countries have suffered from large shocks to their GDP growth in the period under consideration. The obvious examples are Iraq and Kuwait, which withstood the dramatic Gulf War, beginning in 1991. Iraq's path also suffers from the subsequent second Gulf War, which began in 2004, making it an implausible candidate to be included in our donor pool. Several countries, namely Iran, Lebanon and Qatar suffer from non-monotonic growth paths for the years preceding 1989. Indeed, in 1978, Iran experienced the Iranian Revolution and, from 1980 to 1988, it fronted up to Saddam Hussein's aggression. From 1989, with the advent of the Ayatollah regime, economic growth was more stable and it did not suffer any major war-related shocks. Lebanon's experience is somewhat similar, with almost two decades of civil and trans-boundary upheaval happening between 1975 and 1989, after which economic growth stabilised, even though the political and social environment

has remained flammable. Saudi Arabia, instead, has experienced strong fluctuations due to the volatility of gas and oil prices in the 1980s, as did all the OPEC member states but, at the beginning of the 1990s, its economy started to grow again, even reaching dramatic pace after 2000. In addition, Yemen experienced a slight drop in GDP after 2009, which could interfere with our estimations. All the other countries appear not to suffer from major shocks during the whole sample period. Bearing in mind these considerations, we decide to exclude the following countries from our analysis: Iraq, Kuwait, Lebanon, Palestine (due to its continuous tension with Israel) and Yemen. In addition, we drop from our potential donor pool: Djibouti and Oman, because of their dimensions, which are not significant in terms of luminosity emitted and Libya, due to the tensions and its subsequent civil war experienced from 2011 onwards. After this pre-emptive analysis, we have narrowed down the donor pool to the following states: United Arab Emirates, Bahrain, Algeria, Egypt, Iran, Israel, Jordan, Morocco, Malta, Qatar, Tunisia and Saudi Arabia.

**Figure 10: MENA NTLs 1992.**



**Source:** Authors' elaboration. Note: the Hala'ib Triangle is disputed between Egypt and Sudan. Any conflict of attribution is not the authors' responsibility but rather mediated by the dataset providers



## 10. About EMNES

The Euro-Mediterranean Network for Economic Studies (EMNES) is a network of partner and associate research institutions and think tanks working on the Mediterranean region. EMNES aims to provide a renewed vision for socio-economic development in the Mediterranean region, mainly focusing on employment creation, social inclusion, and sustainable development.

EMNES' areas of research include the role of institutions and institutional reforms, macro-economic policies, private sector and micro, small and medium sized enterprises and employment creation, role of education, innovation, skill mismatch and migration, finance, regulation and the real economy and regional integration.

EMNES will produce books, studies, scientific and policy papers and will disseminate through the organisation of annual conferences, and workshop meetings in the region, bringing together leading senior and junior researchers, academics, policy makers and representatives in civil society, to discuss and debate optimal policies for the future of the region.

EMNES is built on four core principles: independence, excellence, policy relevance and deep knowledge on Euro-Mediterranean affairs.

### **EMNES' Network Partners**

- Centre for European Policy Studies (CEPS) (Belgium)
- Euro-Mediterranean University (EMUNI) (Slovenia)
- Free University of Berlin (FUB) (Germany)
- Institut Tunisien de la Compétitivité et des Etudes Quantitatives (ITCEQ) (Tunisia)
- Institut des Hautes Etudes Commerciales (IHEC) (Tunisia)
- Euro-Mediterranean University of Fes (UEMF) (Morocco)
- Institut Agronomique et Vétérinaire Hassan II (IAV) (Morocco)
- University of Cairo- Faculty of Economics and Political Science (FEPS) (Egypt)
- Yarmook University (YU) (Jordan)
- Euro-Mediterranean Economists Association (EMEA) (Spain)
- Forum for Euro-Mediterranean Innovation in Action (FEMIA) (France)
- Institute of Computers and Communications Systems - E3M lab, National Technical University of Athens (ICCS) (Greece)
- Istanbul Policy Center - Sabanci University (IPC) (Turkey)
- Institute of Studies for the Integration of Systems (ISINNOVA) (Italy)
- University of Barcelona Regional Quantitative Analysis Group (UB-AQR) (Spain)
- Centre International de Hautes Etudes Agronomiques Méditerranéennes - Istituto Agronomico Mediterraneo di Bari (CIHEAM) (Italy)
- Fondazione Eni Enrico Mattei (FEEM) (Italy)
- International Institute for Cooperatives Alphonse & Dorimène Desjardins at HEC Montreal (Canada)

EMNES funding: European Commission and EMNES' partners.

### **Disclaimer**

The EMNES' documents are produced with the financial assistance of the European Union within the context of the EU project "Support to economic research, studies and dialogue of the Euro-Mediterranean Partnership" under contract number ENPI/2014/354-488. The contents of EMNES' documents are the sole responsibility of the authors and can under no circumstances be regarded as reflecting the position of the European Union.