Università degli Studi Firenze
DISEI
Dipartimento di Scienze per l'Economia e l'Impresa

Working Papers - Economics

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

Giorgia Giovannetti and Elena Perra

Working Paper N. 05/2019

DISEI, Università degli Studi di Firenze
Via delle Pandette 9, 50127 Firenze (Italia) www.disei.unifi.it

Syria in the Dark:

Estimating the Economic Consequences of the Civil War through Satellite-Derived Night-Time Lights

Giorgia Giovannetti[a,b], Elena Perra[a,c,*]

[a] *University of Florence, Department of Economics and Management*
[b] *European University Institute, Robert Schuman Centre for Advanced Studies*
[c] *University of Trento, Doctoral School of Social Sciences*

Abstract

The Syrian Civil War has begun in 2011 and is still wrecking enormous damages on the country's economy, with an impressive toll measured in deaths, migration, and the destruction of the Syrian historical heritage and physical infrastructure. This paper examines the impact of the War on Syria's economy from the perspective of outer space, to bypass the issue of data availability due to the inaccessibility of the war-ravaged territory. The estimates obtained in this way are more pessimistic than the ones reported by international organisations. Starting from our estimates, we provide long-term projections for the country's economy, and estimate the window for GDP recovery at the pre-war levels. We discuss geo-political implications which could prevent our projections from happening.

Keywords:
Syria, War, GDP estimates, Night-Lights
JEL: E01, O15, C82, H56

---

1. Introduction

The Syrian Conflict is still far from an end, but the 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 Center for Policy Reseach, 2015). The need of collecting accurate and valuable data from conflict and war zones is crucial to guide interventions to help people receiving assistance, aid in the real time. 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, in conflict areas, violence,

*Corresponding author. *Email address:* `elena.perra@unitn.it`
The authors thank Prof. D. Romano for his comments on a previous draft of this work.

injuries and diseases represent an obstacle to the traditional collection process. Collecting data in real time when infrastructure, administrative systems, and hospitals are not operational and the law enforcement is weak or absent, is a difficult challenge. At the same time, when data exists, relying on national statistics could be deviant due to the risk of bias and lack of accuracy.

The lack of data is not confined to war zones and conflicts areas, but 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 among 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 often "governments 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[1]. 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 the tools of the digital millennium. The idea is to observe and analyse phenomena from afar, without compromising quantitative precision. The use of alternative methods allows to overcome the problems of accessibility and dangerousness, but entails a trade-off: the traditional collection methods allows to obtain not just quantitative data, but also qualitative information about the context in which the data are collected. However, this operation is not always immune from bias, since human interaction and perceptions naturally influence the results, even when following rigid behavioural protocols. On the other hand, remotely sourced data present the main drawback of being removed from the context under analysis, which is fundamental in order to understand the direct and indirect influences of external and internal factors.

[1]Hence, it is necessary to consider a fundamental trade-off between high quality data and their availability. Sometimes, it could be required to find the best sub-optimal solution in terms of quality and availability.

1.1. Data Quality in the Analysis of the Syrian Civil War

In this article, we aim to compare the official statistics on macroeconomic indicators with remotely sensed proxies. The employment of selected Night-Time Lights has the potential to overcome issues linked to the government incentives to manipulate and distort official statistics in a 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 to the use of alternative data sources[2].

Night Lights have been already tested in conflict analysis: Henderson *et al.* (2012) illustrate the 1993-1994 Rwandan genocide through the drop in the country 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.

2. Data Sources

In order to compare official estimates of War-led Syrian GDP recession with experimental estimates inferred from Night-Lights Data, we use the following data sources:

1. Night Lights Data, derived by 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 firstly developed for meteorological application, such as research on the distribution of the 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

[2] 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.

associate to geo-referenced 1Kmx1Km square on the Earth's surface the frequency of light detection, "normalised by the number of cloud-free observations" (Huang *et al.*, 2014). Each pixel is coded from 0-63 according to its luminosity level. We 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 mined by the political instability, and the inaccessibility of data sources for data collection processes at the micro and macro levels.

3. Exploratory Spatial Analysis

We exploit the Geographic Information Systems, hereafter GIS, to visualise and investigate the development of the Night Lights 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 pre-emptively visualise the drop in the Night Lights 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, there is a sharp decline in the Night Lights from 2010 onwards.

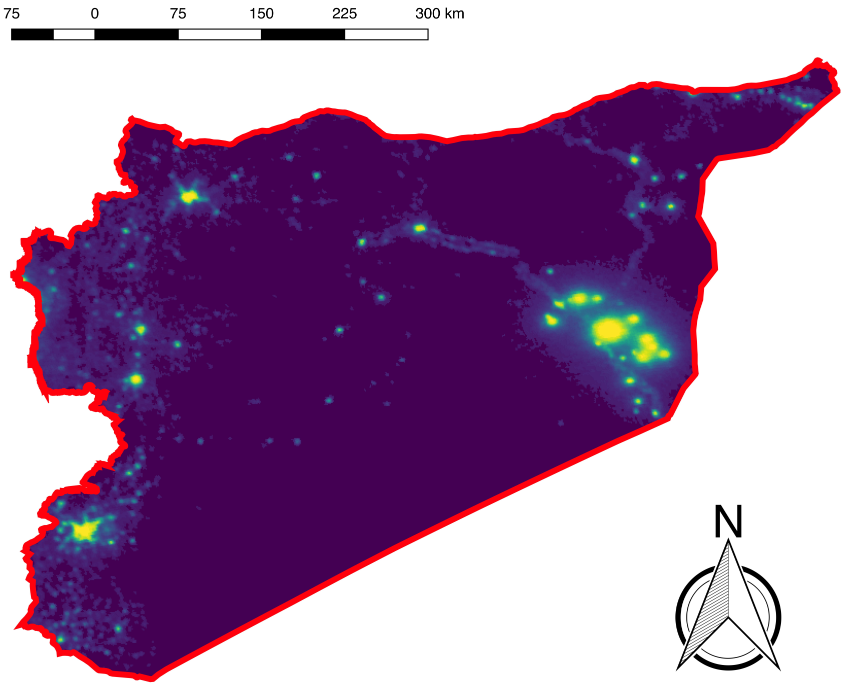

Figure 1: Syrian Night Lights - 1992. Source: Authors' Elaboration on NOAA (2013)

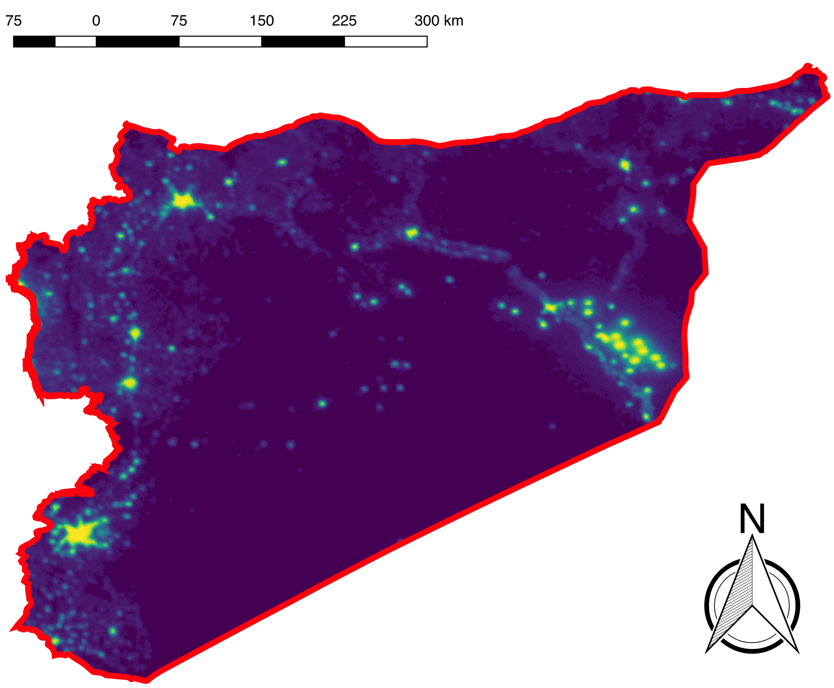

Figure 2: Syrian Night Lights - 2000. Source: Authors' Elaboration on NOAA (2013)

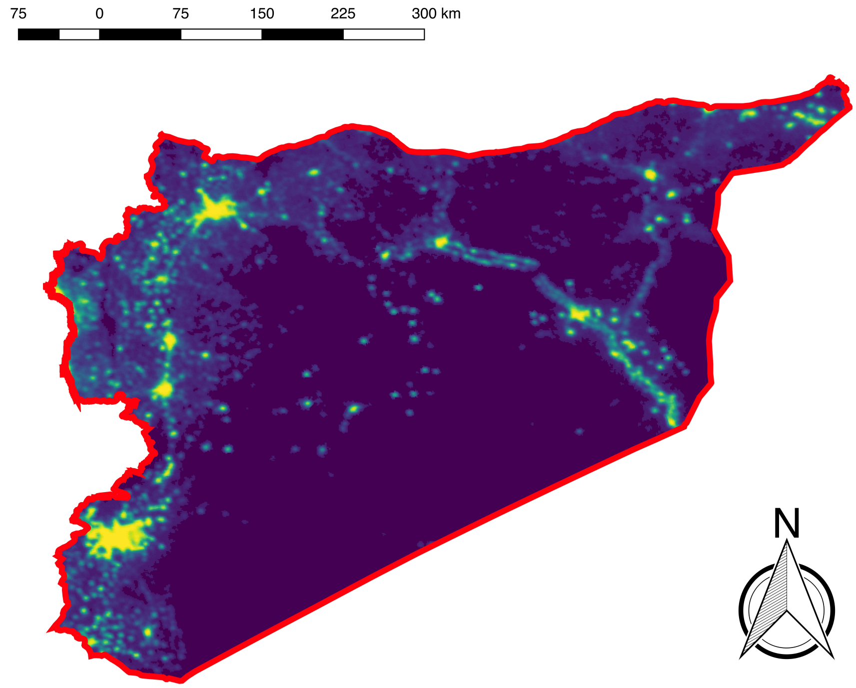

Figure 3: Syrian Night Lights - 2010. Source: Authors' Elaboration on NOAA (2013)

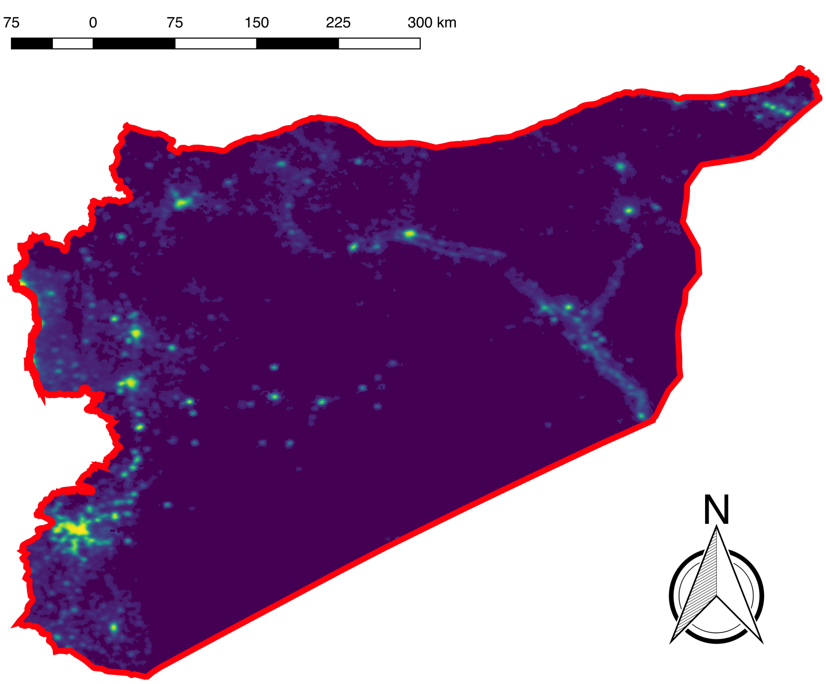

Figure 4: Syrian Night Lights - 2013. Source: Authors' Elaboration on NOAA (2013)

Comparing Figure 1 with Figure 4 we notice a drastic decline in luminosity, possibly as effect of the Civil War. Li and Li (2014) state that Night Lights "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 Syrian Infrastructures. Since the night lights reflect human settlements, urbanisation, economic activity and population density, their drastic decrease is a clear indicator of the damages of 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.[3].

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

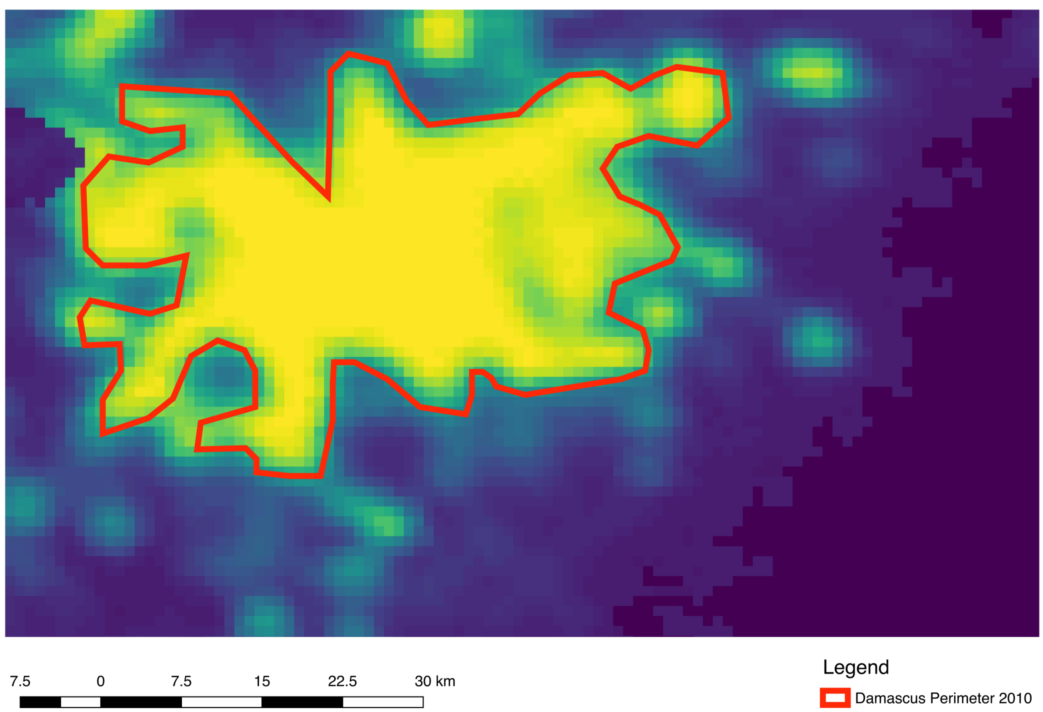

Figure 5: Damascus Night Lights - 2010. Source: Authors' Elaboration on NOAA (2013)

[3]More precisely, luminosity decreases by 19.3% from 2010 to 2011, 21.53% from 2011 to 2012, and 43.26% in the last period under analysis

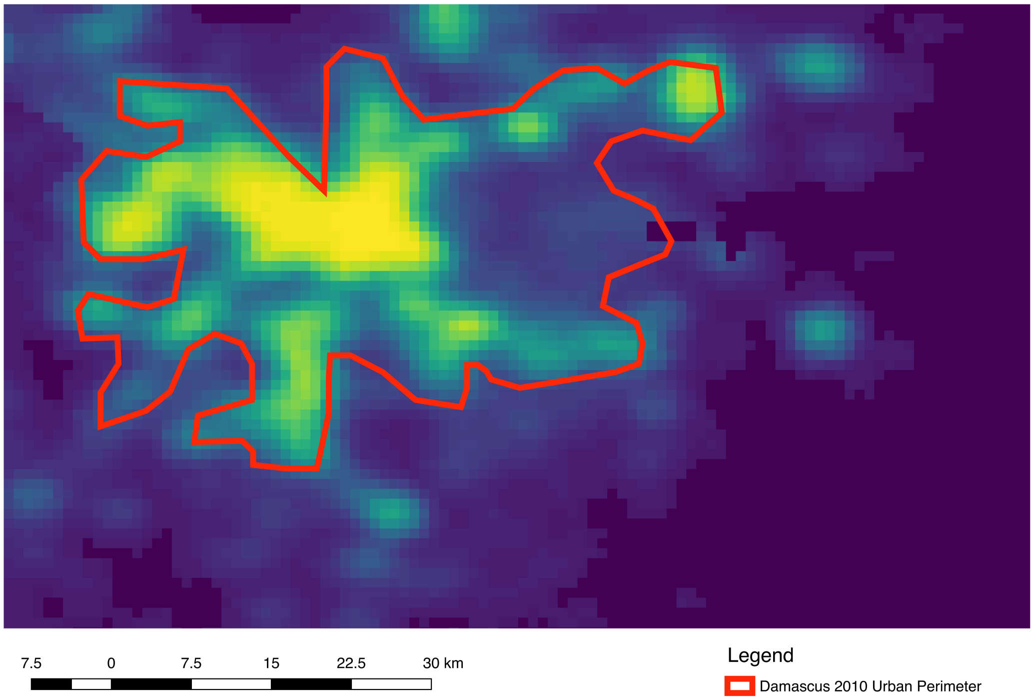

Figure 6: Damascus Night Lights - 2013. Source: Authors' Elaboration on NOAA (2013)

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

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

The DMSP/OLS is a long-operational meteorological programme of the US DoD (Department of Defence), developed in the 1960s. The original goal was collecting and disclosing data on worldwide cloud cover, on a daily basis and giving data for strategic and tactical weather prediction to support US military's operations (Earth Observation Portal, 2002). The scientific community quickly understood the potentiality of using this data source. Researchers apply these data to a number of fields, as reported by Huang *et al.* (2014). "With a few exceptions, Night Lights have been the prime remote sensing data used in economic analysis" (Keola *et al.*, 2015). Croft (1978) is among the first to have exploited the opportunity of using Night Lights data in economic analysis, highlighting their capacity of 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, population, economic development and electric power consumption, finding a statistically significant relationship among NTLs and Economic activity; Doll *et al.* (2000) use night lights data to map global socio-economic and CO2 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 night lights and official measure of economic level both at sub-national and national grade. Along similar lines, Chand *et al.* (2009) use NTLs to show the spatial and temporal changes in the electric power consumption patterns in India from 1993 to 2002. Their results suggest that luminosity changes reflects 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 among Economic growth and China's urban land area developments from 1993 to 2012. In line with that, Mellander *et al.* (2015) by the use of correlation analysis and geographically weighted regressions, inspect how night lights could represent a good proxy to estimate population and its density.

NTL has also been employed to assess regional inequalities. Mveyange (2015) finds a significant positive relationship among regional inequalities visible through the luminosity emitted by the NLT 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 and Smith and Wills (2016) propose a poverty measure by combining night lights with gridded population data, therefore 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 counter-proof of the use of night lights to map the spatial distribution of economic well-being across, in this case, African countries, allowing inference on poverty levels and its geographical distribution.

Amaral *et al.* (2005), propose a methodology to single out the human presence and activities in the Brazilian Amazon region, using NTLs data. The usefulness of their results reflects two main considerations: the first concerns the continental dimensions of Amazonia, and the difficulties to trace human presence, the other regards the absence of dynamic demographic information, as the census is available only every 10 years. Other sources of indirect data collection which have been used in developing countries and war zones are: social media, mobile phone networks (Flowminder Foundation, 2018), satellite data such as Night Lights (Jean *et al.*, 2016). These types of data provide several advantages. First the objectivity and the immediate capacity to be available on a daily frequency. Besides, these data allow to 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 night lights could represent a valuable proxy of traditional output measures. They find that luminosity could be considered a good proxy for countries with a weak statistical and administrative systems, while they can be deviant and not very precise for Developed Countries. Not surprisingly, Night Lights *in primis* reflect investment in physical capital and infrastructure, but do not capture as well the value added from the services economy, which is one of the main pillars of developed economies growth. Furthermore, night lights data are a sub-optimal source of data, since that they represent a tool to indirectly analyse phenomena for which we cannot reach the appropriate degree of data precision. Henderson *et al.* (2012) report the main difficulties in recording the precise value of Gross Domestic Product in Developing Countries. 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 (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 6);
3. Compare our estimates to official projections, namely Gobat and Kostial (2016) and the Penn World Tables (Feenstra *et al.*, 2013) (Section 6);
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 7).

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 Night Lights:

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

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, λ_t are year-specific fixed effects, δ_i are country-specific fixed effects, and ϵ_{it} is a stochastic error term. We use a FE regression on the ground that time-invariant factors could affect our estimates; in addition, as pointed out by Henderson *et al.* (2012), FE regression allows us to overcome measurement problems, related with the variation over time of satellites' sensor settings, which could alter the comparison of raw digital numbers of estimated Night Lights.

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

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

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

$$GDP_{it} = \alpha + \beta_1 NightLights_{it} + \lambda_t + \delta_i + \epsilon_{it} \tag{3}$$

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

$$NightLights_{it} = \gamma + \theta X_{it} + u_{it} \tag{4}$$

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 Night Lights from the effect of Night Lights on GDP. In the first stage (equation 4) we regress Night Lights on demographics, in order to explain the portion of measurement error in Night Lights which does not affect the measurement of GDP. In the second stage (equation 3), the IV procedure regresses GDP on the "purified" Night Lights from the first stage, allowing us to obtain an unbiased measure of the elasticity of GDP to NTLs.

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).

Elasticity of GDP to Night Lights

	(1)	(2)	(3)	(4)	(5)
VARIABLES	FE	FE-sq	FE	FE-sq	IV
Night Lights	**0.397****	**0.256*****	**0.404*****	**0.251*****	**0.352****
	(0.177)	(0.0566)	(0.117)	(0.0495)	(0.175)
Squared NTL		0.185**		0.151**	
		(0.0698)		(0.0521)	
Population Density			0.000342**	0.000103	
			(0.000135)	(8.40e-05)	
Population Growth			0.0393**	0.0298***	
			(0.0139)	(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

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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

Table 1 shows that our elasticity estimates range from $\epsilon = 0.251$ to $\epsilon = 0.404$, 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*.

6. Upper and Lower Bounds and Comparison with Official Estimates for Syrian GDP Fall

Table 2 reports two official estimates of Syrian GDP fall after the onset of the 2011 Civil War. The first two rows present respectively 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 sub-sided 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 fall, 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. 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.

Row (9) reports a weighted average of the GDP fall 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 fron Henderson *et al.* (2012), according to the following formula:

$$GDP_{TRUE} = \lambda GDP_{EST} + (1 - \lambda) NTL_{RAW}$$

where: GDP_{TRUE} is the "real" value of the 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 λ is 0.484, according to Henderson *et al.* (2012). This technique allows 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 GDP fall in Syria after 2011. In Section 7, 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.

Estimate	2011	2012	2013	2014	2015
(1) Gobat and Kostial (2016)	-0.06	-0.21	-0.17	-0.15	-0.15
(2) Feenstra *et al.* (2013)	-0.06	-0.22	-0.25	0.00	-
(3) NTL_{RAW}	-0.19	-0.22	-0.43	-	-
(4) $NTL_{FE(1)}$	-0.08	-0.09	-0.17	-	-
(5) $NTL_{FEsq(2)}$	-0.05	-0.06	-0.11	-	-
(6) $NTL_{FE(3)}$	-0.08	-0.09	-0.17	-	-
(7) $NTL_{FEsq(4)}$	-0.05	-0.05	-0.11	-	-
(8) NTL_{IV}	-0.07	-0.08	-0.15	-	-
(9) $NTL_{WEIGHTED}$	-0.13	-0.22	-0.34	-	-

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

We tend to be skeptical 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 light s between March 2011 and January 2017, respectively". Besides, this confirms Henderson *et al.* (2012)'s conjecture about the better predictive capacity of the weighted combination to recreate the real path of GDP loss.

Moreover, we have extrapolated the monthly composite image of Syrian Night Lights from the Suomi VIIRS satellites, which we could not implement in our quantitative analysis due to intercalibration 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 physical infrastructure of the country.

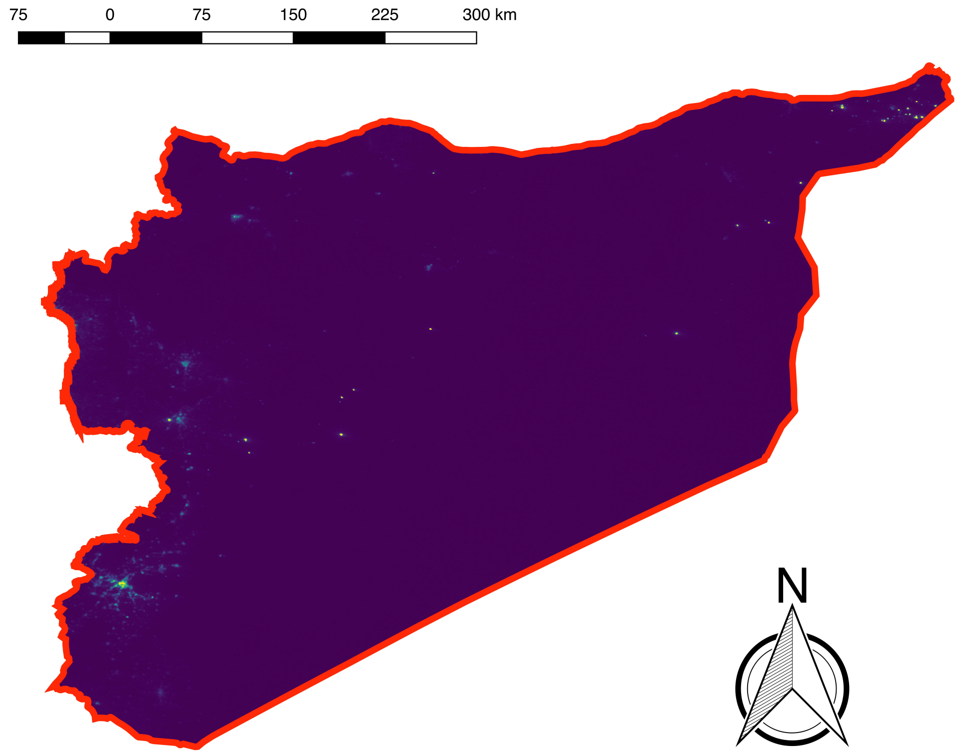

Figure 7: Syrian Night Lights - February 2018. Source: Authors' elaboration

7. A simple exercise on Syrian Recovery

In order to have an idea of the magnitude of the consequences of 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 GDP long-term 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, consistently with Gobat and Kostial (2016) and with a "buffer period" for growth preceding the rebuild.

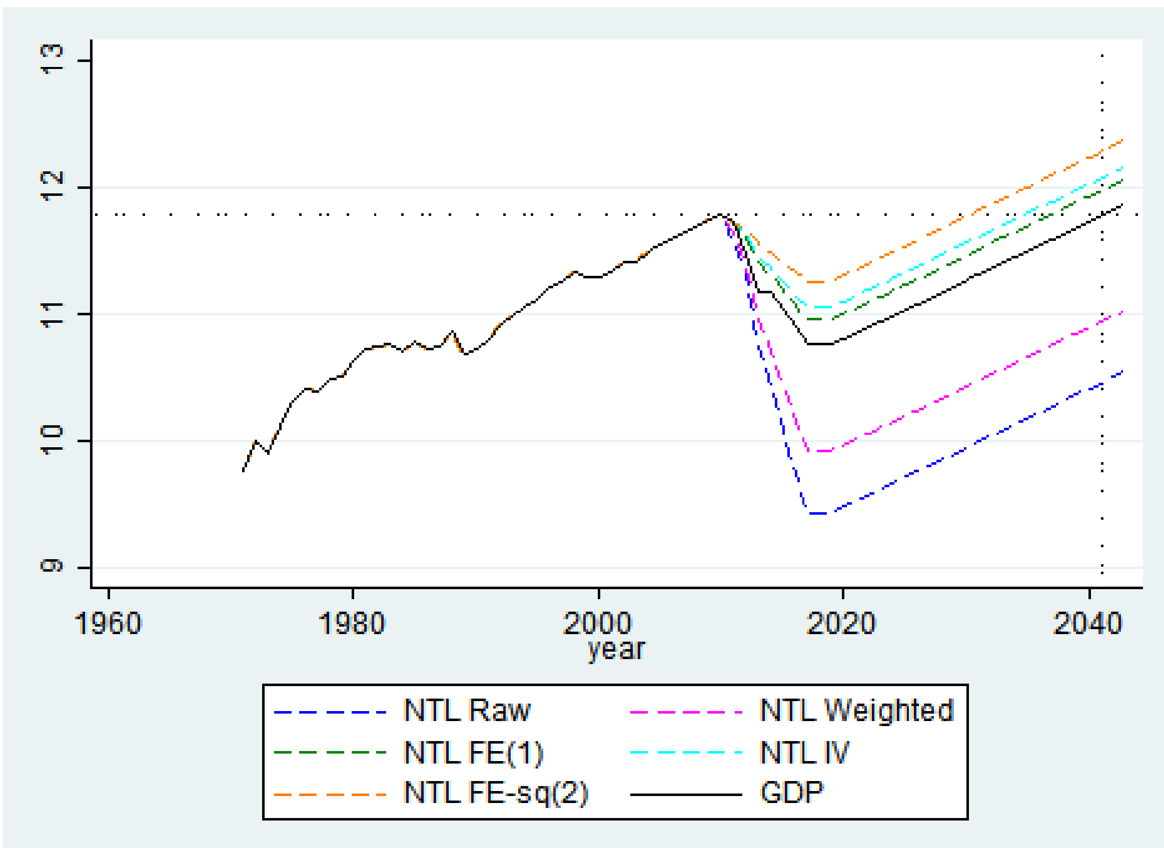

Figure 8: Projections for Syrian GDP Recovery. Source: Authors' elaboration

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 6, GDP fall is estimated as the fall in Night Lights, weighted by the elasticity parameters from: (1) Fixed Effects without covariates,

$\epsilon = 0.397$; (2) Fixed Effects with squared Night Lights, $\epsilon = 0.256$; (3) Instrumental Variables, $\epsilon = 0.352$. 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 fall 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 [4].

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, falls 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 about the sustained 2014-2018 GDP decrease at the average 2010-2013 rate as hyperbolic. If anything, these assumptions seem slightly conservative; however, the pessimistic scenario also relies on the correspondence between Night Lights and GDP fall (NTL_{RAW}) and on the accuracy of the weighted measure of GDP proposed by Henderson *et al.* (2012). We claim 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 hold. The country is now fragmented in three main influence zones: the government forces, the rebel Syrian opposition and the 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 spur, similar to the

[4] 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.

one observed in Lebanon after 1989 due to 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 to evaluate the long-term damages wrecked on the Syrian economy, quantifying the amount of investment and stability needed for human wellbeing to recover to its pre-war levels.

8. Conclusions

This article investigated the economic consequences of Syrian Civil War on Syrian GDP. We compared official projections of the GDP fall with estimates obtained through non-conventional economic approach. We employed Night-time Lights extrapolated from NOAA (2013)'s satellite data to calculated the average rate of decrease in luminosity, in order to have an approximation of the "real" GDP fall. 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 on this field. Our estimates suggest that the scenario reported by the official statistics is optimistic. As reported in Table 2, our estimated of GDP fall using Night Lights are significantly higher, accounting for 43% in 2013 when employing raw NTL and 34.4% by using the weighted combination proposed by Henderson *et al.* (2012), while official statistics reports 17% (Gobat and Kostial, 2016) and 25% (Feenstra *et al.*, 2013), respectively. This comparison highlights the magnitude of the discrepancies of data in context in which reliable statistics are difficult to be collected.

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

Bibliography

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.

Chand, T. R. *et al.* (2009). "Spatial characterization 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.

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.

Croft, T. A. (1978). "Nighttime Images of the Earth from Space". In: *Scientific American* 239, pp. 86–98. DOI: 10.1038/scientificamerican0778-86.

Doll, Christopher N. H., Muller, Jan-Peter, and Elvidge, Christopher D. (2000). "Night-time Imagery as a Tool for Global of Socioeconomic Mapping Parameters and Greenhouse 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.

Earth Observation Portal (2002). *DMSP (Defense Meteorological Satellite Program)*. URL: https://directory.eoportal.org/web/eoportal/-/dmsp.

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.

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).

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.

Flowminder Foundation (2018). *WorldPop Database*. URL: http://www.flowminder.org/publications/worldpop-open-data-for-spatial-demography.

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.

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.

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.

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.

Hodrick, Robert J and Prescott, Edward C (1997). "Postwar U . S . Business Cycles : An Empirical Investigation". In: *Journal of Money, Credit and Banking* 29.1, pp. 1–16. ISSN: 00222879. DOI: 10.2307/2953682.

Huang, Qingxu *et al.* (2014). "Application of DMSP/OLS nighttime light images: A meta-analysis and a systematic literature review". In: *Remote Sensing* 6.8, pp. 6844–6866. ISSN: 20724292. DOI: 10.3390/rs6086844.

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.

Jean, Neal *et al.* (2016). "Combining stallite imagery and machine learning to predict poverty". In: *Science* 353.6301, pp. 790–794.

Keola, Souknilanh, Andersson, Magnus, and Hall, O L A (2015). "Monitoring Economic Development from Space : Using Nighttime 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.

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.

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.

Li, Xi *et al.* (2017). "Intercalibration 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.

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.

Mveyange, Anthony (2015). *Night lights and regional income inequality in Africa*. ISBN: 9789292309749.

NOAA (2013). *DMSP-OLS Night-time Lights*. Tech. rep. Image and data processing by NOAA's National Geophysical Data Center. DMSP data collected by US Air Force Weather Agency.

Smith, Brock and Wills, Samuel (2016). "Left in the Dark ? Oil and Rural Poverty". In: October, pp. 1–41.

Sutton, P. C. and Costanza, R. (2002). "Global estimates of market and non-market values derived from nighttime 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.

Syrian Center for Policy Reseach (2015). *Syria: Confronting Fragmentation! Impact of Syrian Crisis Report*. Tech. rep., p. 67.

The World Bank, World Bank (2017). *World Development Indicators*. URL: http://data.worldbank.org/indicator/SP.DYN.LE00.FE.IN.

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.

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 (visited on 03/12/2018).

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.

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.