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Exploring factors affecting the relationship between light consumption and GDP based on DMSP/OLS nighttime satellite imagery

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ABSTRACT

We consider night light as a type of consumer goods and propose a model for factors affecting the relationship between night lights and GDP. It is then decomposed into agricultural and non-agricultural productions. Further, the model is modified to determine how the factors affect residents' propensity to consume lights. Models are tested with time-fixed regression on a set of 15-year panel data of 169 countries globally and regionally. We find that light consumption propensity is affected by GDP per capita, latitude, spatial distribution of human activities and gross saving rate, and that light consumption per capita has an inverted-U relationship with GDP per capita.

1. Introduction

Gross Domestic Product (GDP) is a crucial indicator in many societal studies and an important reference for political decision making. However, it is inadequately measured all over the world (Feige & Urban, 2008). In the least-developed countries, there are no usable national GDP data; in undemocratic regimes, statistical data are unreliable for probable unreal declaration by local governments; even in developed economies, measurement errors inevitably exist, with shadow economies ignored. Furthermore, GDP figures become more uncertain when converted into international dollars to be comparable with that in other countries. In response, many methods have been adopted in the past decades to estimate more accurate GDP, including the cash-demand approach (Tanzi, 1983), the consumer expenditure approach (Crohan & Smith, 1986) and the recently developed MIMIC approach (Schneider et al., 2010).

The method of remote sensing was not introduced to estimate GDP until Elvidge et al. (1997) found a strong positive relationship between GDP and night lights observed from outer space, which was detected by the US Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS). The data are collected every day between 9 p.m. and 10 p.m. local time (Elvidge et al., 1999). Since 1992, annual cloud-free composites with background noise and fires removed have been made by NOAA-NGDC and can be downloaded by the public for free; consequently, night lights data has been attracting growing research interests in various domains (Cinzano & Elvidge, 2004; Small et al., 2011; Sutton, 2003).

As many earlier papers have stated, the data set acquired by satellites has several advantages in estimating GDP, one of which is its objectivity clear of statistical errors (Ghosh et al., 2009), and another its spatially specific resolution without segmentation by administrative boundaries (Zhao et al., 2011). Its high-frequency accessibility also makes it a better measure compared to the statistical method carried out yearly. Ebener et al. (2005), Doll et al. (2006), Sutton et al. (2007), Elvidge et al. (2009a, 2009b) and Ghosh et al. (2009) estimated GDP values or indicators of relative poverty at both national and sub-national scales based on night lights data. Earlier in 2002, Sutton and Costanza (2002) took nighttime imagery as a proxy of GDP to evaluate global ecosystem service.

However, relationships between GDP and night lights are not yet clear, and this uncertainty may lead to erroneous results when doing estimation. To solve the problem, Elvidge et al. (2009a, 2009b) introduced the population factor acquired by LandScan (a series of spatially disaggregated global population count data sets by Oak Ridge National Laboratory) into the estimation; Ghosh et al. (2010) grouped all countries into 36 categories based on ratios of night lights and GDP and did regression within the groups to reduce the estimation error; Henderson et al. (2011) amended the estimation by combining statistical data together with night lights. These methods were effective but did not focus on and reveal the nature of why relationships between GDP and night lights vary from country to country. It is obvious that

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how much night lights are consumed by residents in a certain country is not merely determined by its GDP; rather, if we take night lights as normal goods (in economics, normal goods are any goods for which demand increases when income increases and falls when income decreases but price remains constant), the relationships are deeply affected by consumer preferences, just as other goods discussed in economics are. Albeit consumer preferences, specifically residents' light consumption propensity, seem too complicated to analyze in a microscopic view, at the national level, different natural and social factors such as latitude, per capita income and domestic saving rate may statistically link to different consumption tendencies. Therefore, what we discuss in this paper is how these factors work with or regulate the oversimplified relationships between GDP and night lights, based on which GDP estimation using night lights would be more reliable and reasonable.

Because DMSP/OLS has no on-board calibration, annual composites in different years or taken by different satellites could not be compared directly with each other (Table 1). Elvidge et al. (2009a, 2009b) developed the second-order regression model to intercalibrate individual composites via an empirical procedure, in which Sicily was chosen as the reference area, with F121999 used as the reference composite. Data from other satellite years were adjusted to match the F121999 data range, assuming that night lights in the reference area have been largely stable over time. Although the calibration is valid, having successfully obtained a convergence of values in years where two satellite products are available, there are still two debatable issues:

a) The assumption that lighting for the reference area, Sicily, has been largely stable over time is not convincing as the author has discussed in his paper.
b) Any unnecessary calibration to the original images would bring new errors. Hence, if having an alternative to control systematic errors brought by satellites in some circumstances, we should turn to that. As to topics of GDP or other macro variable regression, time-fixed panel data models commonly applied in econometrics would be a better choice, or at least a choice.

Despite the fact that GDP and light consumption are strongly correlated, contributions of agricultural and non-agricultural productions to light consumption have not been studied quantitatively. In some studies, night lights were viewed only as urban things, as the authors believe that activities in rural areas without light produced cannot be captured by the satellites (Ghosh et al., 2010; Han et al., 2012). In other studies, night lights were implicitly considered as a reflection of all sectors of an economy, and the data set can be used to estimate total GDP (Doll et al., 2000, 2006). Which is closer to the real world? In our view, not only do industrial and servicing productions have immediate relationships with night lights, but also agricultural production is linked to night lights indirectly. What night lights represent is consumption rather than production. (Although this argument might be a little coarse for DMSP/OLS data sets, as gas flares, lights reflected by snow, and other light sources are all mixed with the true light consumption in the data sets, we believe it is generally reasonable.) That means both agricultural and non-agricultural productions reflect themselves in night lights indirectly to some extent. What proportions they separately contribute is one of the topics in this paper.

The study presented here contains three major parts: part A, factors affecting the relationship between light consumption and GDP; part B, contributions of agriculture and non-agriculture to global light consumption; part C, factors affecting light consumption per capita. Correspondingly, we first raise a model for light consumption and GDP with three other explanatory variables in consideration. Secondly, GDP is broken down into agricultural production and non-agricultural production to detect what proportions they separately contribute to light consumption. Thirdly, we develop a quadratic model for light consumption per capita to discover how factors, especially GDP per capita, affect residents' propensity to consume lights. After that, a set of 15-year panel data from 1995 to 2009 of 169 countries all over the world is used both globally and regionally in time-fixed regressions to test the models above. At the end, we offer some detailed discussion and some useful conclusions.

Table 1
Satellites at work from 1995 to 2009.
Source: NOAA-NGDC.

Year	Satellites at work			
1995	F12			
1996	F12			
1997	F12	F14		
1998	F12	F14		
1999	F12	F14		
2000		F14	F15	
2001		F14	F15	
2002		F14	F15	
2003		F14	F15	
2004			F15	F16
2005			F15	F16
2006			F15	F16
2007			F15	F16
2008				F16
2009				F16

2. Method

2.1. Theoretical model for factors affecting the relationship between light consumption and GDP

Several studies have proven that the amount of lights (sum of DN) in an area has a positive correlation with its GDP. Doll et al. (2000) tested the linearity of the log–log relationship between country-level PPP-GDP and total lit area all over the world using the data in 1994–1995, and the R-square of the regression model is 0.85. Ghosh et al. (2010) linearly regressed PPP-GDP and sum of lights globally in 2006 and got the R-square of 0.73.

Henderson et al. (2008) hypothesized that

$$light/area = \phi(GDP/area) = \beta \cdot (GDP/area)^{\alpha}. \tag{1}$$

Similarly, we also presume that amount of lights is an increasing function of corresponding GDP, and define it specifically as a power function, namely a log–linear relationship between GDP and amount of lights.

$$light = \phi(GDP) = k \cdot GDP^{\alpha}, \tag{2}$$

where parameter k is not a constant, but is determined by some factors other than GDP. A major concern in the study is the components of k. GDP per capita would be a probable factor, as a higher income per capita always leads to a higher consumption of normal goods, and light is seemingly a kind of normal goods. Latitude would also be a possible factor that affects parameter k for its potential influence on residences' demands for light. Another element that requires close attention is the degree of spatial concentration or dispersion of human activities, which is closely related to degree of urbanization. For example, even though Singapore and Vietnam have similar GDP, their concentration degree of light differs greatly, which may lead to different light consumptions in these two countries.

Hence, parameter k is decomposed into variables discussed above:

$$k = k_0 \cdot GDP\ percapita^{k_1} \cdot e^{k_2 \cdot CV} \cdot e^{k_3 \cdot latitude}, \tag{3}$$

where k_0 is a constant, *latitude* denotes the absolute value of average latitude for a country, CV is variation coefficient of lights in a country (derived by standard deviation of DN divided by mean of DN), which represents the degree of spatial concentration of human activities, and k_1, k_2 and k_3 are all coefficients of variables above. Take log, then the equation turns as follows:

$$\ln light = \alpha \cdot \ln GDP + \ln k_0 + k_1 \cdot \ln GDPpercapita + k_2 \cdot CV + k_3 \cdot latitude. \quad (4)$$

Considering that images obtained in different years or by different satellites contain repetitive errors, they cannot be compared directly. Therefore, time dummies are introduced into the model to exclude these interferences from what we focus on.

$$\ln light_{it} = \delta_t + \alpha \cdot \ln GDP_{it} + \ln k_0 + k_1 \cdot \ln GDPpercapita_{it} + k_2 \cdot CV_{it} + k_3 \cdot latitude_i + \varepsilon_{it}, \quad (5)$$

where i indexes country, t indexes year, δ_t is the time dummy and ε_{it} is random term. Later, we will make regressions with Eq. (5).

2.2. Contributions of agriculture and non-agriculture to global light consumption

Despite the fact that the model for relationship between light consumption and GDP is given as above, another issue of concern is what proportions of agricultural and non-agricultural productions contribute to global light consumption. It is a reasonable assumption that the relationship between light consumption and agricultural and non-agricultural productions observes Cobb–Douglas production function models as follows:

$$light = m \cdot Agri^{\beta} \cdot Nonagri^{\gamma}, \quad (6)$$

$$Agri + Nonagri = GDP, \quad (7)$$

where $0 < \beta < 1, 0 < \gamma < 1$. In this way, light consumption is decomposed into agricultural production and non-agricultural production. Parameter m here contains all residual information not explained by the two explanatory variables, among which we still select *latitude* (absolute value of average latitude) and CV (variation coefficient of lights) as the most important ones. The reason we don't take GDP per capita into m in Eq. (6) as we did to k in Eq. (3) is that GDP per capita has a high correlation with proportion of agricultural production to GDP in an economy. If it were introduced, multicollinearity would be brought out. So, parameter m is broken down as follows:

$$m = m_0 \cdot e^{m_1 \cdot CV} \cdot e^{m_2 \cdot latitude}, \quad (8)$$

where m_1, m_2 are coefficients of variables. As a result, light consumption can be expressed by the equation

$$\ln light = \beta \ln Agri + \gamma \ln Nonagri + \ln m_0 + m_1 \cdot CV + m_2 \cdot latitude. \quad (9)$$

Or, in a more complete format:

$$\ln light_{it} = \delta_t + \beta \ln Agri_{it} + \gamma \ln Nonagri_{it} + \ln m_0 + m_1 \cdot CV_{it} + m_2 \cdot latitude_i + \varepsilon_{it}. \quad (10)$$

2.3. Theoretical model for factors affecting light consumption per capita

In part A, we focused on how other variables regulate or influence the relationship between light consumption and GDP, with the goal of improving models for GDP estimation using night lights data. In this part, we are more curious about what factors on earth affect residents' propensity for light consumption and try to evaluate these influences.

Initially, we thought that light consumption per capita should be correlated to a nation's development level, namely GDP per capita, in some way. Probably the relationship is more than linear, thus is assumed to satisfy a quadratic equation:

$$lightpercapita = n + \delta GDPpercapita^2 + \omega GDPpercapita, \quad (11)$$

where δ and ω are coefficients that determine the shape of the parabola. Then *latitude* (absolute value of average latitude), CV (variation coefficient of lights) and *saving* (gross saving rate) are also put into the model as important explanatory variables:

$$lightpercapita = n_0 + \delta GDPpercapita^2 + \omega GDPpercapita + n_1 \cdot latitude + n_2 \cdot CV + n_3 \cdot saving, \quad (12)$$

where n_1, n_2, n_3 are coefficients of variables.

Or, in a more complete format:

$$lightpercapita_{it} = \delta_t + n_0 + \delta GDPpercapita_{it}^{\ 2} + \omega GDPpercapita_{it} + n_1 \cdot latitude_i + n_2 \cdot CV_{it} + n_3 \cdot saving_{it} + \varepsilon_{it}. \quad (13)$$

2.4. Panel data model for regression

Although Henderson et al. (2008) adopted country-fixed effects to control other factors varying by country, we don't use the effects because it is these factors that are being studied in this paper. Instead, time-fixed effects were considered for controlling any changes in satellites and their calibration in different years. Another problem is that there exists heteroskedasticity for standard errors in the regression, which eventually led us to Driscoll and Kraay (1998) standard errors for coefficients estimated by time-fixed effects regression (command "xtscc" with time dummies in Stata11.0). These standard errors are heteroskedasticity-consistent and robust to general forms of cross-sectional and temporal dependence when the time dimension becomes large.

Furthermore, countries are classified into seven regions as World Bank does to find whether regional differences exist. These regions are EAS (East Asia and Pacific), ECS (Europe and Central Asia), LCN (Latin America and Caribbean), MEA (Middle East and North Africa), NAC (North America), SAS (South Asia) and SSF (Sub-Saharan Africa). We need to mention that NAC includes only two countries, U.S. and Canada, which is too few to achieve statistical significance; therefore it is excluded from our study.

2.5. Data source and process

DMSP-OLS Nighttime Lights Time Series are the major data set in the study; we obtained them from National Geophysical Data Center at National Oceanic and Atmospheric Administration (http://www.ngdc.noaa.gov/dmsp). With ephemeral wildfires and clouds discarded, the data set contains only stable lights. These images are in 30 arc second grids. Each grid contains a digital number (DN), ranging from 1 to 63, indicating the average nighttime light intensity observed in a whole year.

As there exists over-saturation defect in some core urban areas for DMSP/OLS imageries, some correction methods, classified into four categories, were developed; however, all of them are not applicable for our national scale studies. The perfect approach is utilizing dynamic satellite gain settings conducted by NOAA (Elvidge et al., 1999; Ziskin et al., 2010), but is cost intensive and is available only for a very limited number of years. Another approach applied regression models assuming that the relationship between DN and cumulative DN was the same for non-saturation area and for saturation area in a given region (Letu et al., 2010). The assumption is reasonable in an urban area, but far from applicable for a national-scale correction. The third category of approach used NDVI data to fix DN, based on the rationale that urban features were inversely correlated with vegetation abundance. Because the intention of these approaches was to improve urban studies, their improvement was significant for urban areas, but also might bring distortion in rural areas, and the fixed data could not reflect light consumption straightforwardly anymore (Lu et al., 2008; Zhang et al., 2013). The last category of methods corrected saturated pixels via regression by each imagery and 1999 non-saturated OLS data (Letu et al., 2012), which seemed the most probable method to be adopted in our study. But based on our trial, the R-square was below 0.4, which indicated that it might need further study to be applicable on the world scale rather than a given city.

Since there are only around 17 countries, including Singapore and U.S., with a saturation area more than 1% of their whole lighted area, the saturation problem seems not serious enough to affect statistic results largely in our study, on which we would have a further discussion later in this paper. Consequentially, it is acceptable to use imageries without saturation-correction.

All data sets used and their detailed descriptions are listed in Table 2. We preprocessed imagery sequences in ArcGIS10.0 to acquire amount and CV of lights for each country, then set up panel data and did regression in Stata11.

3. Results

3.1. Theoretical model for factors affecting the relationship between light consumption and GDP

Globally, the country-level model (Eq. 5) fits very well with an R^2 of 0.9248 and $prob > F$ of 0.0000 (Table 3). The results show that light consumption has a strong positive correlation with GDP significantly and the elasticity α is 1.013, a little more than 1, which implies that GDP increasing 1% will lead to a 1.013% rise in light consumption, suggesting that a scale effect may exist. We can also gather from the regression results that if GDP is given, light consumption tends to be larger, with GDP per capita smaller, latitude larger or CV larger. It means that affluence decreases light consumption with the elasticity of -0.1171; if GDP is unchanged, countries located in high-latitude areas have a high propensity to use lights, and that agglomeration rather than homogeneous distribution creates more light consumption.

At a regional level, the results are similar to global study as a whole, with some subtle differences. For coefficients of In *GDP* all regions but ECS and MEA are between 1.0 and 1.2, while ECS is lower than 1.0 and MEA is higher than 1.2. For coefficients of In *GDPpercapita*, all but ECS and SAS are between -0.3 and 0.0, while ECS is lower than -0.4 and SAS is higher than 0.5. For latitude, only LCN has a negative coefficient, with others in the range of 0.01 and 0.05. For CV, SAS and SSF have negative coefficients while other regions being positive. It has also been recognized that goodness of fit for most regional regressions are higher than global analysis, except for SSF of 0.8306. One reasonable explanation for lower R-square of SSF is that national GDP statistics for some countries in SSF are not valid and are far from what GDP really is.

In addition, coefficients for time dummies, which control measurement errors caused by satellites, are also presented in Table 3.

3.2. Contributions of agriculture and non-agriculture to global light consumption

After we break GDP down into agricultural production and non-agricultural production, the goodness of fit is improved from 0.9248 to 0.9343 globally with no coefficient of any variable changed observably (Eq. 10, Table 4). Light consumption elasticity to agricultural production is 0.2661, while to non-agricultural production it is 0.7517. The sum of the two coefficients equals 1.0178, which connotes there exists a scale effect, similarly as what α denotes in part A. Then, we constrain $\beta + \gamma = 1$, eliminating the scale effect to directly observe the proportions agriculture and non-agriculture contribute to light consumption. As is shown in the table, agriculture is responsible for 25.42% of total light consumption and non-agriculture the remaining 74.58%.

3.3. Factors affecting light consumption per capita

The results show that our assumption that light consumption is a quadric function of GDP per capita is successful, with $\delta = 2.75 \times 10^{-11}$and $\omega = 4.72 \times 10^{-6}$globally and similar values regionally (Eq. (13), Table 5). In fact, δ and ω are of little meaning separately. But when combined, they determine the coordinates of the vertexes of these parabolas, which are quite meaningful to discover or predict how much at most light consumption per capita is or will be and its corresponding GDP per capita, given other parameters unchanged.

The absolute value of latitude has a positive effect on light consumption except for MEA. CV and gross saving rate significantly have a negative effect globally but seem to be controversial down to a regional level; both are positive for MEA, only CV is positive for EAS and ECS and only gross saving rate is positive for LCN and SSF. One reasonable explanation for MEA is that most countries in the region have the particularity of possessing abundant petroleum resources, which distorts the original relationships. The fact that gross saving rate is positive for LCN and SSF may be caused by their underdevelopment as a whole. In general, high saving rate means low overall consumption rate, for their complementation, and leads to less light consumption; but in the least-developed countries, high saving rates are always accompanied by relatively higher incomes, hence more light consumption. As mentioned above, CV is an index measuring spatial distribution of human activities. A higher CV connotes a larger spatial heterogeneity or a stronger agglomeration. Globally, the negative coefficient of CV demonstrates that agglomeration tends to reduce light consumption per capita and saves energy for our planet. But in EAS and ECS, it is the opposite.

4. Discussion

4.1. Panel regression could effectively control repetitive errors caused by satellites, while making them mixed with time sequential information

In all of Tables 3, 4 and 5, coefficients for time dummies are shown, from which we can find that years using the same satellites have much more similar values than years using different satellites. Take global

Table 2
Data sets descriptions and sources.

Data set	Data description	Data period	Data source
GDP	PPP in constant 2005 international dollars	1995–2009	World Bank Open Database
GDP per capita	PPP in constant 2005 international dollars	1995–2009	World Bank Open Database
Agriculture, value added	% of GDP	1995–2009	World Bank Open Database
Gross savings	% of GDP	1995–2009	World Bank Open Database
DMSP-OLS Nighttime Lights Time Series: Average Visible, Stable Lights, and Cloud Free Coverages	Spatial resolution is 30 arc second, spanning -180 to 180° longitude and -65 to 75° latitude.	1995–2009 (A total of 27 images, different images in the same year were made an average for panel regression.)	NOAA-NGDC
Global countries boundary map	ESRI SHP format	2010	ESRI

Table 3
Global and regional panel regression results for light consumption.

Region		Global	EAS	ECS	LCN	MEA	SAS	SSF
R^2		0.9248	0.9440	0.9189	0.9528	0.9411	0.9878	0.8306
prob > F		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of groups		169	21	46	29	19	8	44
Number of obs		2504	315	685	435	272	113	654
lnGDP		1.013***	1.007***	0.9332***	1.014***	1.244***	1.192***	1.066***
lnGDPpercapita		−0.1171***	−0.1926***	−0.4597***	−0.1276***	−0.2919***	0.5976***	−0.04916***
Latitude		0.03135***	0.03240***	0.04328***	−0.004928***	0.01042***	0.04116***	0.03719***
CV		.00004510***	.0005263	.0002344***	.0003815***	.00002640***	−.004492***	−.0004376
cons		−12.31***	−11.86***	−7.669***	−11.32***	−15.62***	−22.14***	−14.23***
F12	1995	–	–	–	–	–	–	–
	1996	−0.02720***	−0.005002***	−0.02163***	−0.01793***	−0.03871***	−0.06683***	−0.03491***
F12	1997	−0.1639***	−0.1222***	−0.1656***	−0.1321***	−0.09714***	−0.2987***	−0.2103***
F14	1998	−0.07293***	−0.006625***	−0.01540***	−0.05411***	−0.1178***	−0.2523	−0.1325***
	1999	−0.1271***	−0.1356***	−0.1301***	−0.04477***	−0.07435***	−0.2419***	−0.1777***
F14	2000	−0.08083***	−0.06690***	−0.06332***	−0.01788***	−0.01697***	−0.2561***	−0.1294***
F15	2001	−0.08995***	−0.06266***	−0.09057***	0.002859***	−0.03210***	−0.3207***	−0.1184***
	2002	−0.09579***	−0.02612***	−0.1012***	−0.0002074	−0.02010***	−0.3794***	−0.1021***
	2003	−0.3067***	−0.2799***	−0.2413***	−0.2224***	−0.1688***	−0.6555***	−0.3597***
F15	2004	−0.2547***	−0.1933***	−0.2670***	−0.1636***	−0.1498***	−0.5631***	−0.2394***
F16	2005	−0.3303***	−0.3193***	−0.2291***	−0.2708***	−0.2215***	−0.7519***	−0.3755***
	2006	−0.3369***	−0.3166***	−0.2724***	−0.2480***	−0.2179***	−0.8673***	−0.3454***
	2007	−0.3125***	−0.2610***	−0.2381***	−0.2277***	−0.2232***	−0.9353***	−0.3190***
F16	2008	−0.2459***	−0.2060***	−0.1464***	−0.1534***	−0.2248***	−0.9366***	−0.2355***
	2009	−0.3127***	−0.3025***	−0.2404***	−0.1632***	−0.3172***	−1.120***	−0.2912***

*** Significant at the 1% level.

regression in Table 3 as an example: The coefficient of dummy 1996 is −0.02720, while it is quite close to 0 of dummy 1995, which shares the same satellites of F12 with 1996; meanwhile, the coefficient of dummy 1999 is −0.1271, which differs greatly from −0.3172 of 2009, which uses F16 other than F12 or F14 (Fig. 1). This partially proves that with time dummies, the panel data model could effectively control repetitive errors caused by satellites. It suggests that it is not necessary to calibrate images before regression.

However, this method is limited due to its inevitable shortcomings: As measurement errors were separated from explanatory variables and stored in time dummies, information for real changes along time is mixed up with measurement errors and can hardly be told apart.

Table 4
Global regression results for contributions of agriculture and non-agriculture to light consumption.

Scenario		Regression with GDP in part A	Regression with agricultural production and non-agricultural production (no restriction)	Regression with agricultural production and non-agricultural production (force $\beta + \gamma = 1$)
R^2		0.9248	0.9343	–
prob > F		0.0000	0.0000	0.0000
Number of groups		169	162	162
Number of obs		2504	2307	2307
lnGDP		1.013***	–	–
lnAgri		–	0.2661***	0.2542***
lnNonAgri		–	0.7517***	0.7458***
lnGDPpercapita		−0.1171***	–	–
Latitude		0.03135***	0.03015***	0.03105***
CV		.00004510***	0.00003120***	0.00003090***
cons		−12.31***	−12.64***	−12.26***
F12	1995	–	–	–
	1996	−0.02720***	−0.02545***	−0.02473
F12 F14	1997	−0.1639***	−0.1647**	−0.1636**
	1998	−0.07293***	−0.0723***	−0.0706
	1999	−0.1271***	−0.1320***	−0.1302*
F14 F15	2000	−0.08083***	−0.0749***	−0.0735
	2001	−0.08995***	−0.0846***	−0.0830
	2002	−0.09579***	−0.0631***	−0.0606
	2003	−0.3067***	−0.2655***	−0.2622***
F15 F16	2004	−0.2547***	−0.2181***	−0.2141***
	2005	−0.3303***	−0.3008***	−0.2968***
	2006	−0.3369***	−0.3099***	−0.3049***
	2007	−0.3125***	−0.2797***	−0.2741***
F16	2008	−0.2459***	−0.2141***	−0.2089***
	2009	−0.3127***	−0.3035***	−0.2977***

*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

Table 5
Global and regional panel regression results for light consumption per capita.

Region		Global	EAS	ECS	LCN	MEA	SAS	SSF
R^2		0.5473	0.6354	0.5728	0.5430	0.5357	0.9316	0.8324
prob > F		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of groups		157	20	45	29	16	6	39
Number of obs		2143	274	642	424	203	86	484
GDPpercapita^2		−2.75E−11***	−2.57E−11***	−5.36E−11***	−1.55E−10***	−1.07E−10***	−2.24E−09***	−1.53E−10***
GDPpercapita		4.72E−06***	2.77E−06***	6.07E−06***	5.88E−06***	7.41E−06***	1.98E−05***	5.66E−06***
Latitude		0.00228***	0.000536***	0.0101***	0.000184***	−0.00117***	0.000629***	0.000166***
CV		−3.13E−05**	8.06E−06	4.58E−05***	−3.63E−05***	1.33E−04***	−3.45E−05***	−3.78E−05***
Saving		−0.000244***	−0.000311**	−0.00147***	0.000144***	0.00145***	−0.0000232	0.0000512**
Cons		−0.0216***	0.00707***	−0.383***	0.00247**	0.0142	−0.0256***	−0.00355***
F12	1995	–	–	–	–	–	–	–
	1996	−0.00217***	−0.000988***	−0.00155***	−0.000530***	−0.00302***	−0.00110***	−0.000230***
F12 F14	1997	−0.0140***	−0.00505***	−0.0302***	−0.00444***	−0.00767***	−0.00288***	−0.00112***
	1998	−0.00678***	−0.00307***	−0.0114***	−0.00170***	−0.00445***	−0.00244***	0.000186**
	1999	−0.0107***	−0.00600***	−0.0217***	−0.000970***	−0.00745***	−0.00267***	0.000769***
F14 F15	2000	−0.00776***	−0.00541***	−0.0137***	0.000874***	−0.0116***	−0.00313***	0.000765***
	2001	−0.0111***	−0.00256**	−0.0230***	0.00200***	−0.0106***	−0.00375***	0.000803***
	2002	−0.0139***	−0.00132*	−0.0350***	0.00253***	0.00305***	−0.00445***	0.000226*
	2003	−0.0181***	−0.00630***	−0.0353***	−0.00601***	−0.00841***	−0.00580***	−0.00146***
F15 F16	2004	−0.0191***	−0.00534***	−0.0400***	−0.00458***	−0.00896***	−0.00544***	−0.00120***
	2005	−0.0196***	−0.00813***	−0.0335***	−0.00814***	−0.0215***	−0.00753***	−0.00235***
	2006	−0.0214***	−0.00693***	−0.0389***	−0.00616***	−0.0240***	−0.00775***	−0.00251***
	2007	−0.0184***	−0.00565***	−0.0303***	−0.00505***	−0.0256***	−0.00790***	−0.00218***
F16	2008	−0.0146***	−0.00354***	−0.0221***	−0.00151***	−0.0193***	−0.00811***	−0.00202***
	2009	−0.0223***	−0.00548***	−0.0372***	−0.00553***	−0.0231***	−0.00917***	−0.00179***

*** Significant at the 1% level.
** Significant at the 5% level.
* Significant at the 10% level.

Consequently, this method is not suitable for situations in which we want to have knowledge of time trends.

4.2. Relationship between light consumption and GDP is not straightforward, but rather is significantly affected by other factors and varies by region

If we simplify Eqs. (5) to (14) as below, $R^2 = 0.8722$ would be derived from global regression, compared with 0.9248, which we have acquired before in part A with the same samples.

$$\ln light_{it} = \delta_t + \alpha \cdot \ln GDP_{it} + \ln k_0 + \varepsilon_{it}. \tag{14}$$

This comparison illustrates more convincingly that GDP per capita, latitude and spatial distribution of human activities play important roles in explaining light consumption, with which we could have a better understanding of how light consumption reflects GDP.

It is found that higher GDP per capita reduces light consumption, more largely in more affluent ECS, while relatively lightly in poorer SSF. These results are interesting, indicating that influence of GDP per capita on the light consumption may vary at different affluence levels. This inference is proved by regression results in Section 3.3 and will be discussed more deeply in Section 4.4. Higher-latitude countries tend to have higher light consumption. This may be attributed to a large base of installed outdoor lighting to compensate for short day lengths, or to a shared habit of not saving energy for residents suffering from extreme cold weather. There is also a seemingly reasonable explanation that light reflection by bright snow is stronger. Although this argument is not supported by results of regressions in SAS and SSF, as there is little snow in these regions, we cannot deny

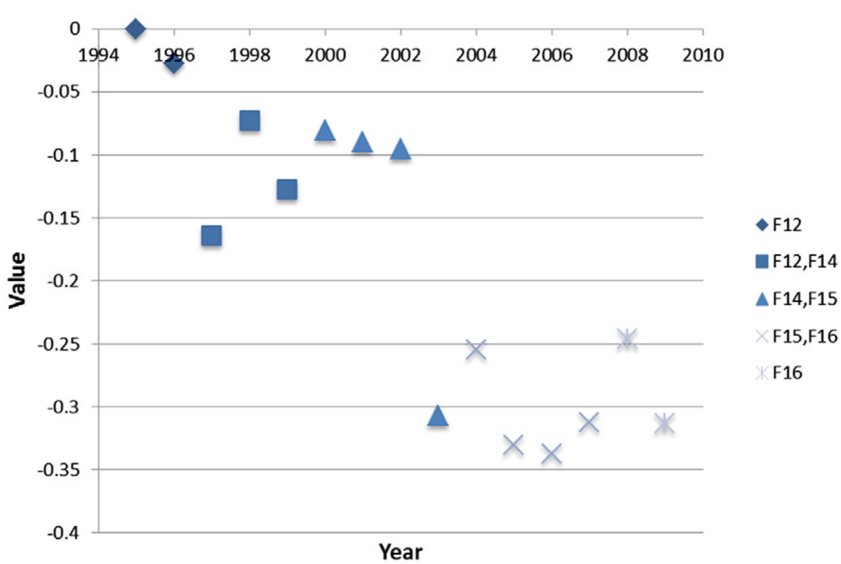

Fig. 1. Relationship between coefficients of time dummies and corresponding satellites.

Table 6
Global panel regression results for light consumption per capita and GDP per capita.

R^2		0.4192
prob > F		0.0000
Number of groups		173
Number of obs		2566
GDPpercapita^2		−5.79E−11***
GDPpercapita		7.23E−06***
cons		−0.0117***
F12	1995	–
	1996	−0.00174***
F12	1997	−0.0119***
F14	1998	−0.00568***
	1999	−0.00886***
F14	2000	−0.00591***
F15	2001	−0.00891***
	2002	−0.0118***
	2003	−0.0168***
F15	2004	−0.0187***
F16	2005	−0.0206***
	2006	−0.0227***
	2007	−0.0208***
F16	2008	−0.0170***
	2009	−0.0213***

*** Significant at the 1% level.

this plausible explanation. In fact, we would find it do\work significantly later in Section 4.4. CV has a positive effect globally, namely agglomeration rather than homogeneous distribution creates more light consumption. Elvidge et al. (2012) did more detailed work in providing a spatial depiction of differences in development within countries, similar to CV here but far more precise and meaningful. Further studies combining this depiction with national GDP may lead to some more inspiring discoveries.

Although this research just aims to detect the relationship between GDP and light consumption rather than perform a GDP estimation, it enlightens us that it is necessary to consider latitude, spatial inequity and affluence if more accurate GDP estimations are needed from night light imageries. It might also greatly help GDP estimation on a subnational and even a gridded scale with Eq. (5). Both night light imageries and latitude are easy to obtain and objective; gridded population data set by LandScan is available and widely used (GDP per capita equals GDP divided by population). This method would diminish errors in GDP estimation on various scales.

4.3. Both agricultural and non-agricultural production contribute to light consumption, with different proportions

As the results have shown, agricultural production and non-agricultural production are separately responsible for global light consumption 25.42% and 74.58% respectively. What we would place emphasis on is that night lights are typical kinds of consumptions among various ones, and thus are reflections of consumption level for residents of a country, and indirectly rather than directly related to GDP. Hence, both agricultural and non-agricultural productions contribute to night lights, which is opposed to the viewpoint that agriculture value is undetected in night lights data because it produces no light.

4.4. Factors affecting light consumption per capita are meaningful but need more research

When it comes to factors affecting light consumption per capita, GDP per capita, gross saving rate, CV and latitude are all important, among which GDP per capita has the most explanatory power and the most significant meaning. So we tried to ignore other factors to excavate the relationship merely between light consumption per capita and GDP per capita, for which Eq. (13) was simplified into Eq. (15):

$$lightpercapita_{it} = \delta_t + n + \delta_2 GDPpercapita_{it}^2 + \omega_2 GDPpercapita_{it} + \varepsilon_{it}. \tag{15}$$

Regression result and fitted curve are presented below (Table 6, Fig. 2).

The curve seems like an inverted "U" shape, which is generally called Kuznets curve in the realm of economics. A Kuznets curve was first raised to depict a hypothesis that as a country develops, market forces at first increase economic inequality, and then decrease it after a certain average income is attained (Kuznets, 1955). Decades later, an environmental Kuznets curve was adopted to describe a relationship between environmental quality and economic development: Environmental degradation tends to worsen as modern economic growth occurs until

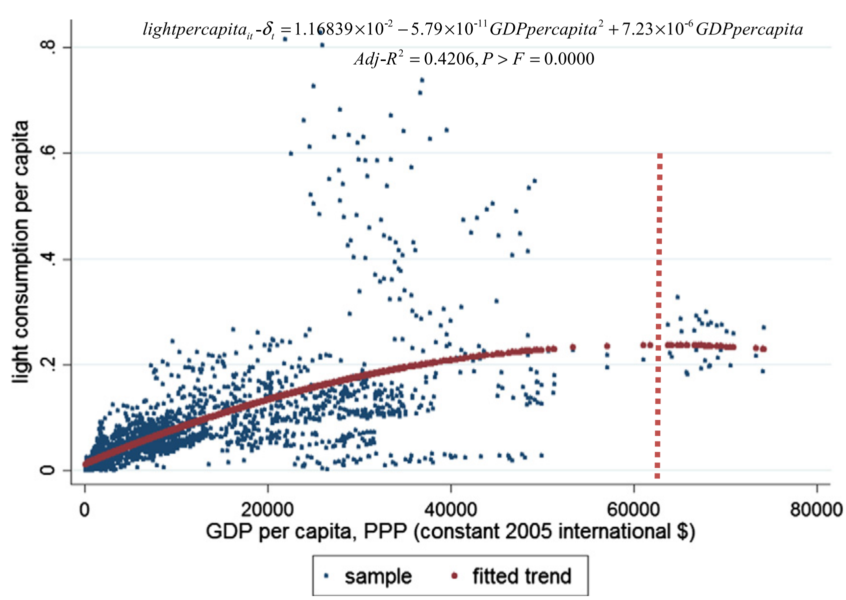

Fig. 2. Relationship between light consumption per capita and GDP per capita (using all samples). *Notes*: Light consumption per capita in all years was adjusted to year 1995 using coefficients of time dummies in Table 6.

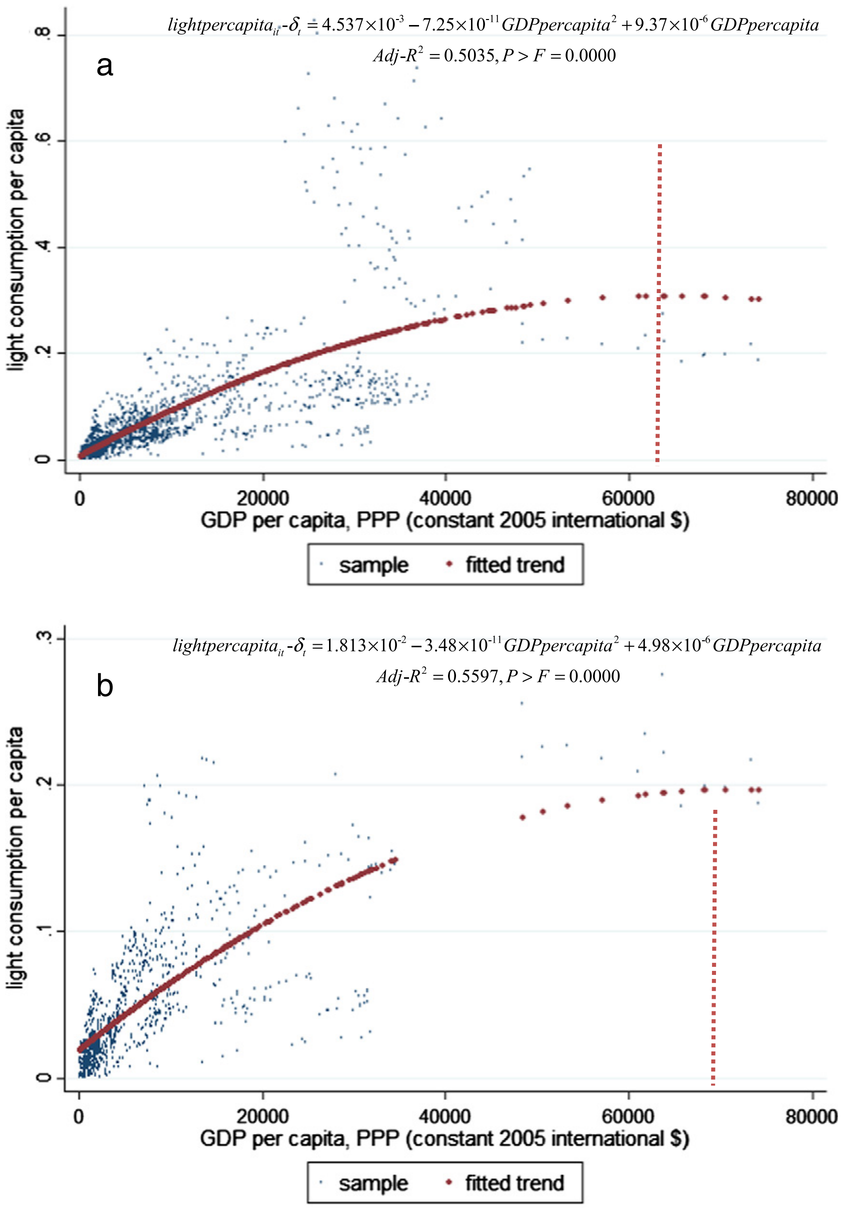

Fig. 3. a. Relationship between light consumption per capita and GDP per capita (using 2080 samples for countries where saturated area was less than 0.5% of their whole lighted area ($DN > 0$)). *Notes*: Light consumption per capita in all years was adjusted to year 1995 using coefficients of time dummies in Table 6. b. Relationship between light consumption per capita and GDP per capita (using 1082 samples for countries where saturated area was less than 0.01% of their whole lighted area ($DN > 0$) and simultaneously saturated pixels in which were less than 10). *Notes*: Light consumption per capita in all years was adjusted to year 1995 using coefficients of time dummies in Table 6.

average income reaches a certain point over the course of development, which was supported by some evidence that the inverted U-shaped relationships did exist in air and water pollution (Grossman & Krueger, 1996; Shafik, 1994). Results in this paper implicitly show that Kuznets curve may be suitable to represent relationships between domestic consumption and economic development as well.

We calculated the equation of symmetry axis of the gotten parabola, which is $GDPpercapita = 6.24 \times 10^4$. It reveals that statistically light consumption per capita increases along with GDP per capita if it is below 62.4 thousand dollars (2005 constant), and decreases instead if GDP per capita is above that value. The discovery may offer a valuable reference for other related studies and help in political decision making.

As in some developed countries or regions, i.e. Singapore, Hong Kong, Kuwait and U.K., saturated pixels account for significant proportions (more than 3%) of their whole lit area ($DN > 0$), there exists a probable problem: The inverse “U” shape might be a phenomenon biased by the data for over-saturated pixels uncorrected. To test the result, we did two more regressions in the same format. One is for those countries where the saturated area was less than 0.5% of their whole lighted area ($DN > 0$), and the other is more strictly for countries that meet two conditions simultaneously, that saturated area was less than 0.01% of the whole lighted area and that saturated pixels were less than 10. The results are shown in Fig. 3.

Although parameters for the three equations differ slightly due to different samples used in regressions, shapes of these curves (Figs. 2, 3a, b) are quite similar, and their symmetry axes are all between 60,000 and 70,000 constant 2005 international $. The results are intuitive to understand that the inverse “U” shape is not just a bias caused by saturation, or at least not mainly caused by saturation. Factually, some of the most affluent countries, including Denmark, Luxembourg and Switzerland, have few saturation pixels. However, to get more accurate discoveries, saturation correction is still needed.

It can be noticed that there exist some outliers between $20,000 GDP per capital and $50,000 GDP per capital in Figs. 2 and 3a: they have much higher y-values than normal, while most of them have been excluded in Fig. 3b. More detailed study found that points with quite high y-values are samples of Finland, Norway, Iceland, Canada, Sweden and Ireland. This indicate that light reflection by bright snow or ice may contribute to night lights in these 6 high-latitude countries. More studies are needed to examine the inference and these outliers should be handled with prudently. In addition, there might be some other unobservable factors influencing light consumption per capita, as the R^2 of most of regional regressions in Table 5 are below 0.6. Attempting to discover these missing factors would be a meaningful and interesting task.

5. Conclusion

DMSP/OLS supplies us valuable data to examine topics on relationships between light consumption and other natural and social variables. In this paper, we tested some models to analyze factors affecting the relationship between global and regional light consumptions and GDP using time-fixed panel regressions.

It is concluded that the way GDP affects light consumption nationally depends on many other significant factors whose effects vary slightly across regions, with GDP per capita being negative, latitude positive and the spatial agglomeration degree of human activity strength positive in general. Estimating GDP from night lights data should take these factors into consideration.

GDP was broken down into agricultural and non-agricultural productions, which improved the regression, and we reached a conclusion that both agricultural and non-agricultural productions are reflected by night lights; they are separately responsible for 25.42% and 74.58% respectively.

A multivariate quadratic model was raised to study factors affecting light consumption per capita and it is found that latitude had a positive effect, while gross saving rate and spatial agglomeration degree of human activity strength had a negative effect globally; at the regional level, the relationship is a little complicated because of different reasons. We also found that statistically, light per capita increases along with GDP per capita if it is below 62.4 thousand dollars (2005 constant), and decreases instead if GDP per capita is above that value, in the format of an inverted-U curve.

In addition, it has been proved that time-fixed panel regression could effectively control repetitive errors caused by satellites, though it has the shortcoming of making these errors mixed with time-sequential information.

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