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Monitoring Economic Development from Space: Using Nighttime Light and Land Cover Data to Measure Economic Growth

SOUKNILANH KEOLA [a], MAGNUS ANDERSSON [b] and OLA HALL [b,*]
[a] *Japan External Trade Organization, Japan*
[b] *Lund University, Sweden*

Summary. — This study demonstrates estimations of economic activities on global, national, and subnational levels using remote sensing data, with a focus on developing economies. It extends a recent statistical framework which uses nighttime lights to estimate official income growth by accounting for agriculture and forestry which emit less or no additional observable nighttime light. The study argues that nighttime lights alone may not explain value-added by agriculture and forestry. By adding land cover data, our framework can be used to estimate economic growth in administrative areas of virtually any size.

Key words — remote sensing, economic growth, land cover, MODIS, gross domestic product, gross regional product

1. INTRODUCTION

The problem of measuring economic growth has stimulated research in economics and economic geography for many decades (Barro, 1991; Gallup, Sachs, & Mellinger, 2009; Maddison, 1995). The traditional approaches of estimating growth aim to measure changes in economic activities at national or global scales. However, the subnational dimensions of change in economic activities are also important, particularly in order to understand the interactions between local progresses/failures and those at higher geographical scales. In fact, development issues operate at intrinsically different spatial and temporal scales. Despite continuous revisions of knowledge, methodologies, and techniques for measuring income and economic activity using conventional ground survey-based data, reliable yearly statistics at the national level are often a luxury. Many poor countries lack both the resources and the capacity to acquire such reliable data, despite decades of international statistical support. The UN Statistical Commission has supported a standardized system of national accounts (SNA) since 1953, yet even today many developing countries do not regularly produce the full SNA due to capacity and cost constraints. A number of studies have actually pointed out potentially serious measurement errors in growth figures, particularly in developing and emerging economies (Henderson, Storeygard, & Weil, 2012; Johnson, Larson, Papageorgiou, & Subramanian, 2013; Nordhaus, 2006; Ravallion & Chen, 1999).

Since the early days of satellite remote sensing, its accessibility, quality, and scope have been continuously improving, making it a rich data source with a wide range of applications. Although there are a few examples of remote sensing to be found in the social sciences, developments have, on the whole, been less pronounced than in the natural sciences (Hall, 2010). This has historically been attributed to (a) the need for inhouse remote sensing expertise which is rarely found in social science departments, (b) the fact that many of the variables of interest in contemporary social science research are not directly observable from space, and (c) the very high costs for data acquisition.

Satellite remote sensing missions are generally designed for specific applications, often earth sciences related, such as vegetation classification and weather forecasting. The Defense-Meteorological Satellite Program-Optical Line Scanner (DMSP-OLS), launched in the early 1970s, was designed to observe clouds at night for weather forecasting purposes. However, its sensor was soon found to be very good at detecting the presence of light at night on Earth (Croft, 1978). The DMSP-OLS sensor is sensitive enough to detect street lights and even saury fishing vessels at sea (Saitoh *et al*., 2010). The lighting detected by the DMSP-OLS is largely the result of human activities, emitted from settlements, shipping fleets, gas flaring or fires from swidden agriculture. Therefore, nighttime light imagery serves as a unique view of the Earth's surface which highlights human activities (Figure 1).

Recent studies conducted by economists have paid more attention to artificial nighttime light data and efforts have been made to associate these observations with economic growth in order to cope with estimation errors (Chen & Nordhaus, 2011; Doll, Muller, & Morley, 2006; Ebener, Murray, Tandon, & Elvidge, 2005; Elvidge *et al*., 1997; Ghosh, Powell, Elvidge, & Baugh, 2010; Henderson *et al*., 2012; Sutton & Costanza, 2002). These studies have made attempts to advance research in two directions: (a) estimation of a consistent and objective level of economic activities, such as PPP, real GDP, and nominal GDP, and (b) disaggregation of these measures into smaller administrative/non-administrative areas where official statistics are otherwise lacking or unavailable. While these existing studies pushed literature forward greatly by showing potential applications of remote sensing data in economics, the remote sensing data accumulated since 1970s are tremendous and many more uses remain to be explored. The main limitations of these existing studies is their overdependence on nighttime lights and therefore their tendency to underestimate economic activities that emit less or no additional nighttime light as they grow. This is particularly troublesome in

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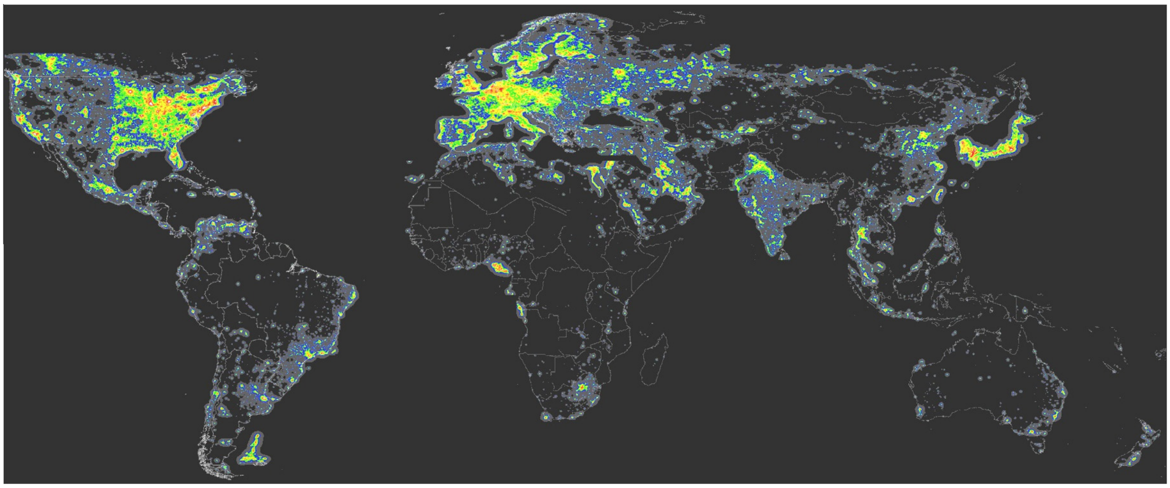

Figure 1. *A global view of nighttime lights year 2012 from the DMSP (Defense Meteorological Satellite Program).*

developing economies which often have a larger share of agriculture or forestry and therefore weaker linkages with nighttime lights.

The principle aim of this paper is to explore another potential remote sensing data source, namely land cover. The rest of this paper is structured as follows. Section 2 summarizes applications of remote sensing data in economic analysis thus far, before discussing some potential improvements. Section 3 reviews the data used in the analysis conducted in this paper, with a particular focus on remotely sensed land cover data. Section 4 sets estimation models by extending a framework developed by Henderson *et al.* (2012) and discusses the estimated results. Section 5 concludes.

2. REMOTE SENSING DATA AND ECONOMIC ANALYSIS

Our principle aim is to estimate economic growth using data observed from space. In this section we consider, in publishing order, selected studies that use remote sensing data to analyze economic activities on the ground and examine their methodologies, results, advantages, and drawbacks in turn. Croft (1978) was among the first to point out that nighttime light reflects human economic activities on the ground. This led Elvidge *et al.* (1997) to estimate population, GDP (PPP $), and electricity usage in lit areas. Through a single year cross-sectional analysis of 21 countries coefficients of log–log, or growth rate relationship, between population, GDP, and electricity and area lit were found to be very high (0.920, 1.159, and 1.178, respectively). Using area lit instead of sum of observed light intensity makes Elvidge *et al.* (1997) unique from most of the later studies. This study reveals that a statistically significant relationship between nighttime light and activities on the ground can be established. Its biggest drawback, however, lies in its inability to account for the fact that activities may also spread upward as well as outward.

Sutton and Costanza (2002) instead use the sum of the intensity of nighttime light to estimate GDP or, as they term it, a measure of marketed economic output and land cover to estimate ESP (Ecosystem Services Product), a type of non-marketed value. However, as they try to establish country-specific coefficients between nighttime light and GDP (PPP $) using single-year data, the relationship is a ratio generated by simple division. These country-specific coefficients are then used to produce one square kilometer GDP for each country. It is obvious that this will produce many sub-national administrative areas without GDP, as there are many areas without observed nighttime lights. Nevertheless, the introduction of ESP to account for economic activities that may not be captured by nighttime lights is highly suggestive. Using coefficients determined at the country-level on finer sub-national administrative areas is, as stated by the authors, an improvement to the general body of research on the subject.

Doll *et al.* (2006) estimate the relationship between the sum of nighttime light and the available Gross Regional Product (GRP) of 11 countries in the EU and states in USA. The elasticity of GRP on the sum of nighttime light is estimated to be between 0.049 and 0.210 in these regions, excluding outliers. Outliers are generally capitals or large cities that have different or higher elasticity when compared to the remaining domestic regions. The elasticity of these outliers is determined separately from the rest of the regions within each country. Only the Netherlands and Greece are found to have one consistent elasticity applicable nationwide. This shows that elasticity of nighttime light and GRP varies in most countries. For this reason, it is important to be cautious when using nighttime lights to directly estimate the level of GRP of a sub-national region without official data.

Ghosh *et al.* (2010) divide economic activities into commerce/industry and agriculture. They assume that agriculture does not emit observable nighttime light. They try to overcome the limitation of single-year cross-sectional data by grouping together countries and sub-national administrative areas by ratios of the sum of nighttime lights and value-added. Cross-sectional regression is used to determine specific coefficients for each group. Non-lit area is accounted for by grid population data from Landscan.[1] The population grid is used to assign agricultural output to sub-national geographic areas. Apart from limitations coming from a single-year analysis, this study is also limited because assigning agricultural value-added according to a population grid at a one square kilometer scale is not likely to adequately reflect the reality. In most societies besides subsistent societies, a small number of people work in agriculture to produce food not only for themselves but also for the population of other towns and cities.

Single-year analysis is common among the studies discussed so far. In addition to the high cost to acquire processed data in

Table 1. *Selected literature on GDP and nighttime light relationships*

Authors	DV	EV	Spatiotemporal Scope
Elvidge *et al.* (1997)	Population, GDP PPP, GWH	Area Lit	1994 or 1995 21 countries
Sutton and Costanza (2002)	GDP PPP, ESP	Night-time Light Sum, Land Cover	1995, World
Doll *et al.* (2006)	GRP	Night-time Light Sum	2003, 11 EU members and states in USA
Ghosh *et al.* (2010)	GDP PPP	Night-time Light Sum, Agricultural Share	2005 or 2006 World
Henderson *et al.* (2012)	GDP	Night-time Light Sum	1992–2009 World

DV: dependent variable, EV: explanatory variable.

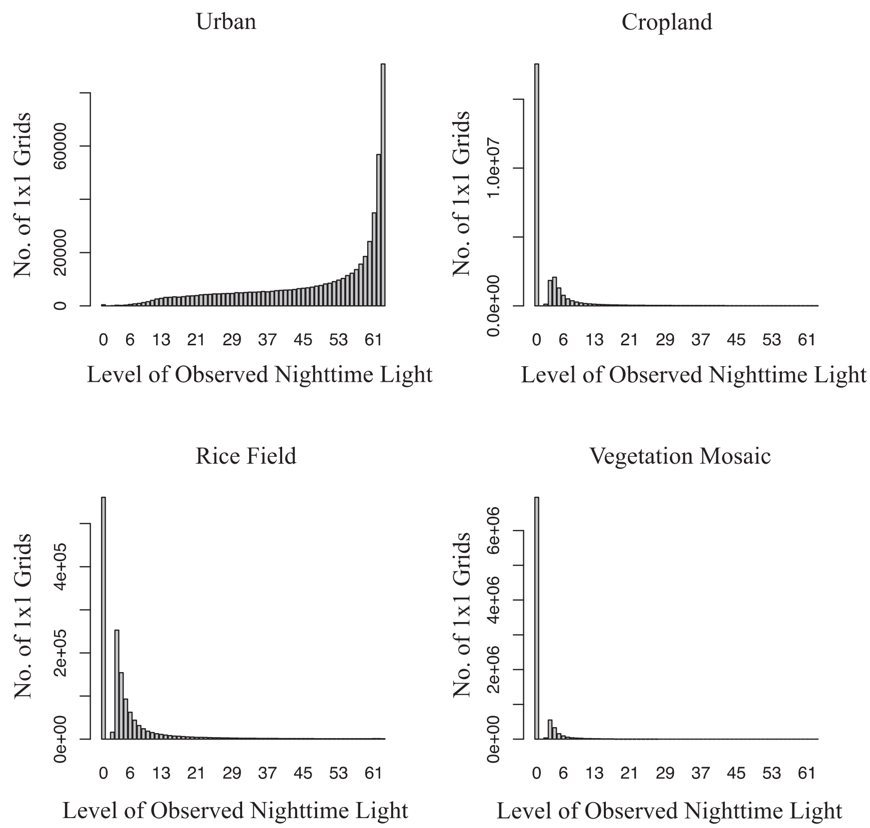

Figure 2. *The causal relationship between agriculture and nighttime light. Cross-tabulation between nighttime lights and four land cover classes (Urban, Cropland, Rice field and Vegetation mosaic.*

the past, the fact that nighttime light data should not be compared between different years is likely to be the main obstacle to a time-series analysis. This is not to say that night-time light data must not be compared over time. Levels of night-time light between 0 and 63 depend on sensor settings that vary over time, across satellites and due to the age of the satellite (Henderson *et al.*, 2012). Henderson *et al.* (2012) deal with this limitation by introducing time-variant effects in panel analysis. Moreover, panel analysis makes it possible to take into account differences among countries. Multi-year analysis in particular allows one to limit analysis on growth without having to deal explicitly with scale invariability. We extend the statistical framework of Henderson *et al.* (2012) to account for agriculture, which we demonstrate emits less or no observable nighttime light as it grows. We also make use of many direct and indirect suggestions offered in these existing studies (Table 1).

(a) *How nighttime light reveals less about agriculture and forestry*

With a few exceptions, nighttime lights have been the prime remote sensing data used in economic analysis. Henderson *et al.* (2012) show that growth of nighttime lights can be used to estimate growth across administrative boundaries and national borders. However, it cannot be assumed that all types of economic activities emit more nighttime lights as they grow. While this assumption may hold for industry and services, where concentration or clustering of activities in certain places is possible, it holds less strength in agriculture and forestry.

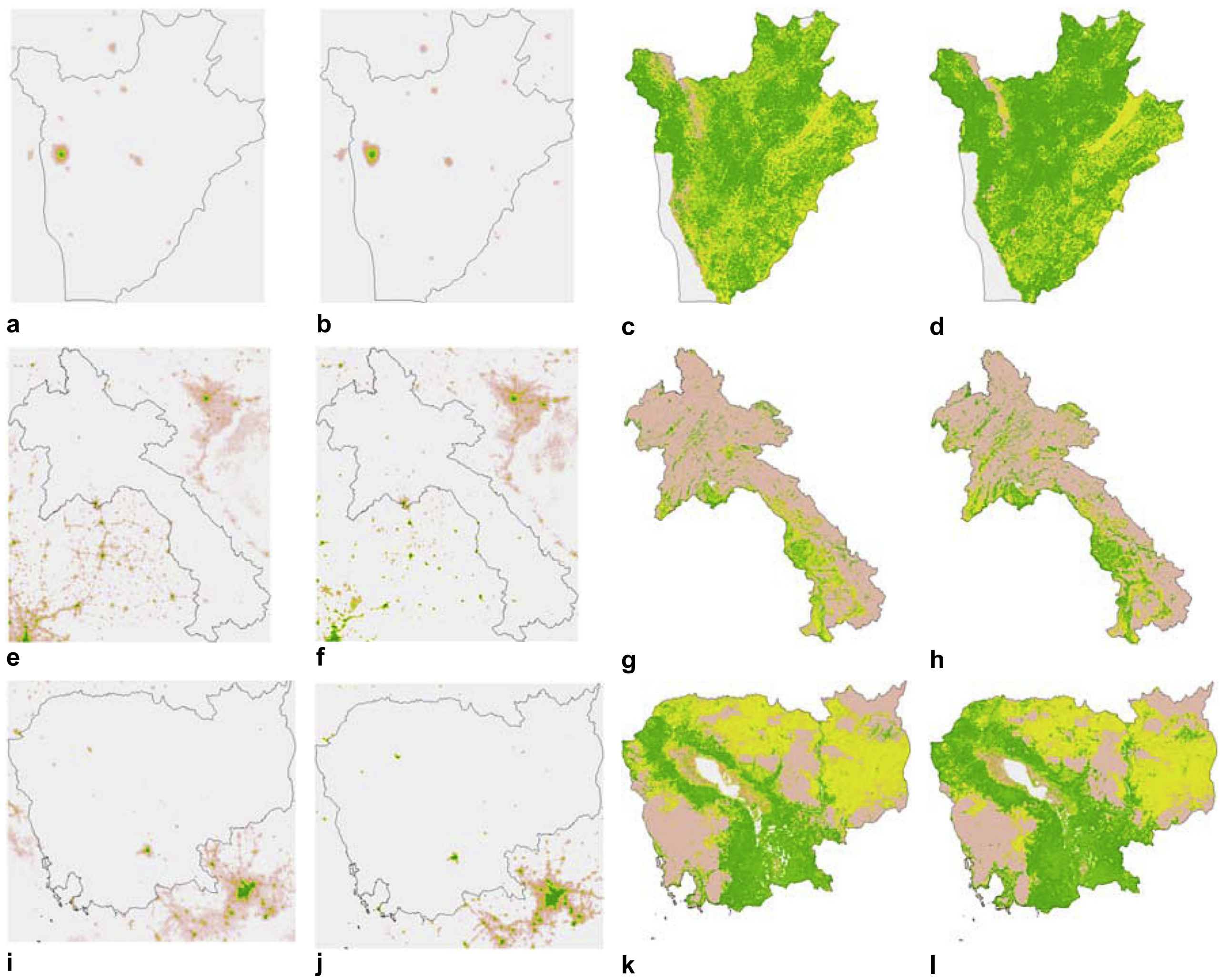

Figure 3. *DMSP-OLS night-time light and MODIS land cover for three different countries with a high dependence on agriculture for the year 2001 and 2009. Nighttime light for Burundi 2001 and 2009. (a and b) and MODIS land cover for matching year (c and d). Lao People's Democratic Republic (e–h). Cambodia (i–l).*

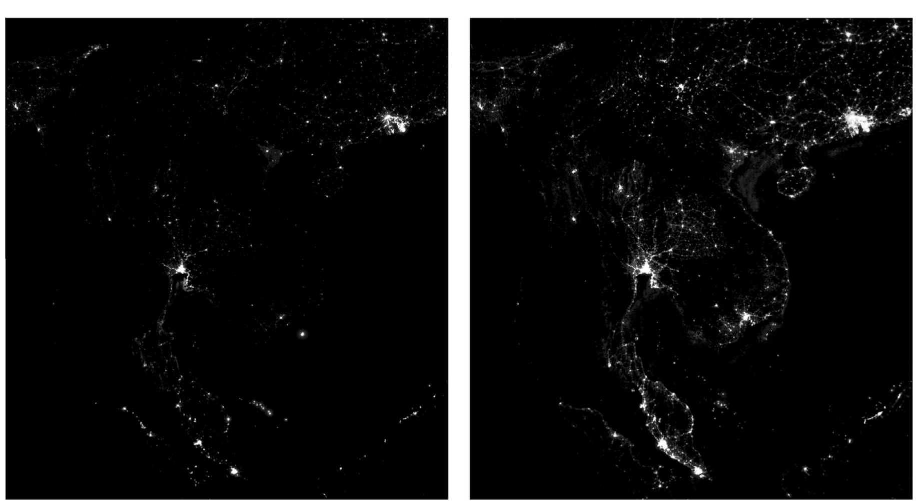

Figure 4. *Changes in night-light intensity 1992–2009 for South East Asia. Note the expansion in and around the Hong Kong, Guangzhou and Macau area in the top-right of the figures. The area north-east of Bangkok is a good example of how powerful infrastructure development is depicted in DMSP-OLS data. Also, note the coast bound development of Malaysia's west coast.*

Table 2. *Nighttime light data for selected countries 1992–2009 average*

	Cambodia	Lao PDR[a]	Vietnam	Burundi	Myanmar	Mongolia
DN0	98.92%	98.53%	74.60%	98.63%	98.39%	99.69%
DN1-2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
DN3-5	0.37%	0.61%	11.35%	0.38%	0.59%	0.18%
DN6-10	0.40%	0.56%	9.10%	0.57%	0.66%	0.08%
DN11-20	0.16%	0.18%	2.85%	0.19%	0.23%	0.03%
DN21-62	0.15%	0.13%	2.02%	0.22%	0.13%	0.03%
DN63	0.00%	0.00%	0.08%	0.00%	0.00%	0.00%
Gini(DN)	0.994	0.991	0.848	0.992	0.990	0.998
Pop. density	78.97	26.60	274.53	335.84	78.33	1.69
Percent urban	19.56	30.83	29.15	10.14	31.00	65.54
GDP per capita, PPP 2005 ($)	1882.09	2002.11	2610.56	473.92	–	3608.60
GDP per capita, 2000 ($)	587.99	561.52	775.76	150.28	–	1249.14

[a] Lao People's Democratic Republic.

Table 3. *Elasticity of nighttime light on GDP by agricultural share*

Agricultural share	Elasticity	Degree of freedom
Less than 10%	0.67453(***)	1324
From 10% to 20%	0.392780(***)	652
From 20% to 30%	−0.408595(***)	377
From 30% to 40%	−0.50387955(**)	272
From 40% to 50%	0.02351645	132
More than 50%	0.03823986	68

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Notes: All specifications include country- and year-fixed effects.

Productivity of agriculture is generally measured by output per area. In this section, we show from nighttime light and land cover data that growth of agriculture cannot be satisfactorily explained by growth of nighttime light.

Looking directly at the causal relationship between agriculture and nighttime lights can be a good way to support this claim. One way to do this is by examining land cover and nighttime lights to see whether or not places categorized as agricultural land emit light at night. We map nighttime light with land cover data on a cell-by-cell basis. The results seen in Figure 2 show the relationship between major agricultural land types and nighttime light.

As one might expect, nighttime light is mostly observed in areas categorized as urban. The number of urban areas that do not emit nighttime light is merely 0.07%. On the contrary, cells categorized as cropland, paddy field, and other vegetation mosaic emit no or marginal levels of nighttime light. The number of lit grid cells in areas with agriculture related land cover decreases sharply for higher levels of nighttime light intensity. For levels of observed nighttime lights greater than 5, the percentage of lit grids becomes 1%, 4%, and 6% for vegetation mosaic, cropland, and paddy field respectively. These figures become 0.3%, 0.7%, and 1.3% for grids with nighttime lights greater than 10. We cannot conclude that agriculture does not emit observable nighttime light at all but, based on our analysis, there are signs telling us that, geographically, agricultural activities are conducted in areas that emit marginal or no nighttime light.

In addition to the inference problem in using nighttime lights to estimate agriculture and forestry, there also exists one rational reason to look beyond nighttime lights. Henderson *et al.* (2012) cite the limitations arising from administrative/national boundaries as one of the important reasons to use nighttime lights. In other words, socio-economic data are usually made available by authorities of different administrative areas with varied capacities. Nighttime light observed objectively from space can be used as a proxy for socio-economic data. However, it is obvious that a critical quality of such a proxy is *ubiquitousness*. In other words, ideally, it must be able to be observed from almost anywhere on Earth. Figure 4 depicts well how land cover becomes a better proxy if one is to use remote sensing data to estimate subnational growth in developing countries. We know that there are economic activities, mostly agriculture and forestry in Burundi, Lao PDR and Cambodia, but nighttime lights are mostly only observed in the capital cities of these countries (Figure 3a,b,e,i,j). We argue that while nighttime light is a good start, one needs to look beyond it in order to develop potential applications of remote sensing data in socio-economic analysis.

3. DATA

In this section we describe our two datasets: DMSP-OLS nighttime lights and MODIS land cover, MCD12Q1 in particular.

(a) *DMSP nighttime lights*

The United States Air Force has operated their Defense Meteorological Satellite Program (DMSP) for more than 40-years. The program is based on a series of orbiting satellites whose primary function is to monitor weather. The daytime records of the sensor are exclusively sunlight reflected from clouds or the Earth's surface and thus, of limited use outside of weather forecasting. When the Earth's surface is at night, however, the electromagnetic energy sensed by the system is mostly a product of human light emitting activities (Figure 1). Croft (1978) was, to the best of our knowledge, the first to acknowledge that nighttime light data could be used to measure economic activity. The DMSP Operational Line Scan (OLS) sensors operate at an altitude of 830 km with a sun synchronous near polar orbit and a revisiting time of 101 min. The OLS is an oscillating scan radiometer which generates images with a swath width of approximately 3,000 km. With fourteen orbits per day, each OLS is capable of generating global daytime and nighttime coverage of the earth every 24 h.

Images are processed at the National Oceanic and Atmospheric Administration's (NOAA) National Geophysical Data Center (NGDC). Processing removes pixels for observations of the moon lit half of the lunar cycle, locations where the sun sets late in the summer (e.g., the Scandinavian countries),

Table 4. *Estimated results for non-agriculture on national level*

	Estimate	Std. error	t-value	Pr(>|t|)
Log(light/area)	0.27017(***)	0.01186	22.77145	5.86E-105
Factor(year)1993	−0.04306(**)	0.01553	−2.77273	5.60E-03
Factor(year)1994	−0.01984	0.01544	−1.28477	1.99E-01
Factor(year)1995	−0.04798(**)	0.01583	−3.03062	2.46E-03
Factor(year)1996	−0.01336	0.01589	−0.84086	4.01E-01
Factor(year)1997	0.09536(***)	0.01531	6.22743	5.50E-10
Factor(year)1998	0.09244(***)	0.01559	5.92842	3.46E-09
Factor(year)1999	0.11988(***)	0.01565	7.66104	2.57E-14
Factor(year)2000	0.07957(***)	0.01661	4.79105	1.75E-06
Factor(year)2001	0.16760(***)	0.01576	10.63241	6.97E-26
Factor(year)2002	0.13892(***)	0.01673	8.30320	1.60E-16
Factor(year)2003	0.26638(***)	0.01544	17.24853	2.93E-63
Factor(year)2004	0.31940(***)	0.01560	20.46861	1.49E-86
Factor(year)2005	0.34499(***)	0.01593	21.65791	6.89E-96
Factor(year)2006	0.39151(***)	0.01637	23.92323	1.17E-114
Factor(year)2007	0.41664(***)	0.01713	24.31711	4.81E-118
Factor(year)2008	0.46222(***)	0.01713	26.98443	7.31E-142
Factor(year)2009	0.47414(***)	0.01684	28.15954	8.37E-153

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Total sum of squares: 172.76.
Residual sum of squares: 45.998.
R-Squared: 0.73374.
Adj. R-Squared: 0.68453.
F-statistic: 404.631 on 18 and 2643 DF, p-value: <2.22e-16.
Notes: All specifications include country- and year-fixed effects.

Table 5. *Estimated results for agriculture on national level*

	GDPA (1)	GDPA (2)	GDPA (3)	GDPA (4)	GDPA (5)	GDPA (6)	GDPA (7)	GDPA (8)
Nighttime light	0.028							
	(0.019)							
Forest (L1–L5)		−0.046**						−0.045**
		(0.017)						(0.016)
Grassland (L10)			−0.010					
			(0.015)					
Cropland (L12)				0.044*				
				(0.019)				
Cropland/natural vegetation mosaic (L14)					0.020			
					(0.021)			
L12 + L14						0.140***		
						(0.032)		
L10 + L12 + L14							0.173***	0.173***
							(0.042)	(0.042)
Observation	1047	1048	1048	1048	1048	1048	1048	1048

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Standard errors are in the brackets.
Notes: All specifications include country- and year-fixed effects.

places with auroral activity (high latitude regions), and areas covered with clouds. The remaining observations for each operating satellite sensor are averaged to produce an annual dataset. The operational temporal resolution is then one year. Images from the system have been openly available since 1973 but were periodically overwritten to free storage capacity. Data are digitally archived and available only since 1992. The processed data are distributed to the public through NOAA or NGDC Internet portals.

The intensity of lights is coded in a grid format as six-bit digital numbers (DN). The range is between 0 (no light) and 63. A very small number of pixels are censored 63, according to Henderson *et al.* (2012), see Table 2. The spatial resolution is 30 arc-sec or 0.86 square kilometers at the Equator. Our area of investigation is between 65 degrees south and 75 degrees north latitude. The exclusion of high latitude zones affects a very small number of inhabited locations and is necessary due to auroral activity and the fact that the sun sets later than over-pass time. In essence, we have followed the setup of Henderson *et al.* (2012). The average number of valid nights of data for each satellite year is 39.2 and datasets currently exist for 30 satellite years.

In 1994, NGDC began producing annual global cloud-free composites of nighttime lights (Elvidge *et al.*, 1997). These

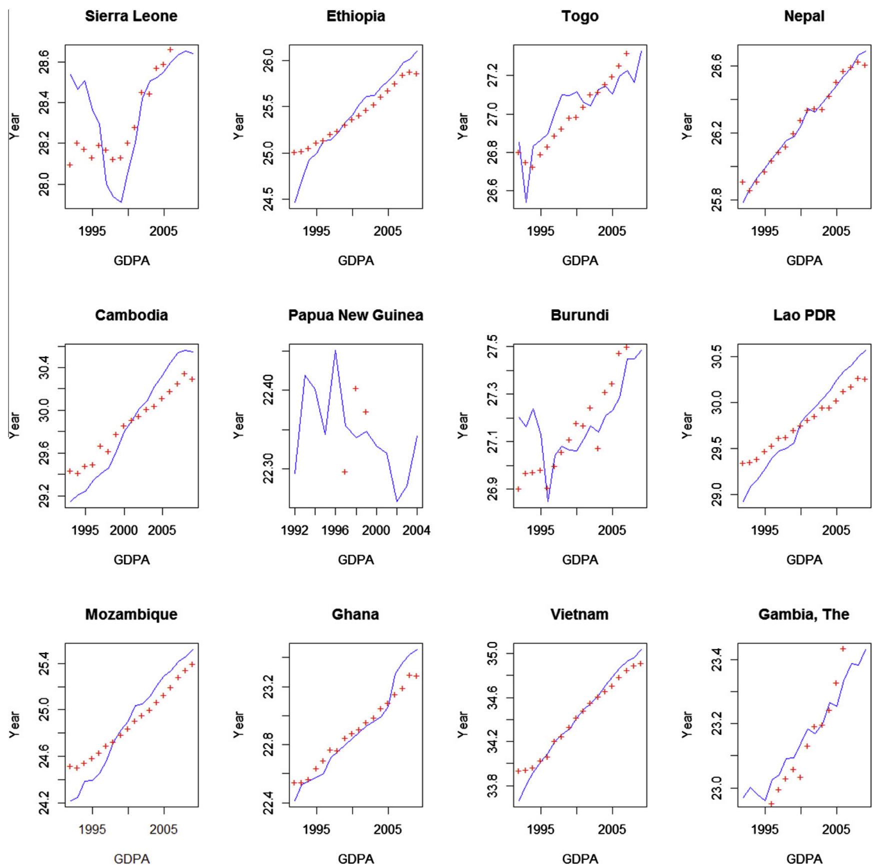

Figure 5. *Fit of non-agriculture's GDP for selected countries with large agricultural sector. Source: World Development Indicators and Estimated by Authors. Note: Natural log of real GDP in local currency. Real line represents official figures, crossed line is authors' estimations.*

products have been used for a multitude of applications including, for example, spatial modeling of population density and economic activity, quantification and comparison of global urban land uses, discrimination of urban and rural population distributions, estimation of infrastructure density, and assessment of losses of agricultural land. The OLS detects radiances down to the $5E^{-10}$ W $cm^{-2}sr^{-1}$ range which makes it possible to detect artificial sky brightness and most types of bulbs used for external lightning (Elvidge, 2007). In Figure 4 we provide an example from South East Asia that illustrates the spread and intensification of nighttime lights for the period during 1992–2009. The usefulness of DMSP-OLS data is evident, as it clearly reveals urban sprawl, infrastructure development and general economic expansion.

The shortcomings reported for the technical equipment are coarse spatial resolution, lack of on-board calibration, lack of systematic in-flight gain changes, limited dynamic range, six-bit quantification, and signal saturation in urban centers (Elvidge, 2007).

(b) *MODIS land cover data*

Over the past several years, researchers have increasingly turned to remotely sensed data to improve the accuracy of datasets that describe the geographic distribution of land cover at regional and global scales. *Land cover* is the physical material at the surface of the Earth. *Land use* is a description of how people utilize the land. There are two primary methods for capturing information on land cover: field surveys and analysis of remotely sensed imagery. For global analysis remote sensing is evidently the only feasible way to proceed. Land cover can be determined based on the physically derived spectral and spatial properties of, for example, maize, asphalt, and water. Land uses are more difficult to determine as they are established based on the human use of land. As an example, while land cover may be identified remotely as "asphalt" based on spectral characteristics, the land use could be anything from a road to a playground. Many remote sensing classification systems mix land cover types with land use.

There exist several global land cover datasets, many of which are based on spatially and temporally heterogeneous map and atlas data. Since the early 1990s, global remotely sensed land cover datasets derived from the low-resolution NOAA-AVHRR sensor have been produced. The current generation of global land cover datasets includes the GLC2000, a detailed dataset produced from 14 months of pre-processed daily global data acquired by the Vegetation instrument onboard SPOT 4. The project is a European Commission initiative in collaboration with a network of partners around the world. GlobCover was an ESA initiative that began in 2005. The aim of this project is to develop global land cover maps using as input observations from the 300 m MERIS sensor on board the ENVISAT satellite mission. ESA makes available land cover maps which cover 2 periods: December 2004–June 2006 and January–December 2009.

The Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's spacecraft Terra and Aqua produces several interesting suites of imagery with global coverage and high spatial and temporal resolution. Terra MODIS and Aqua MODIS view the Earth's entire surface every 1 to

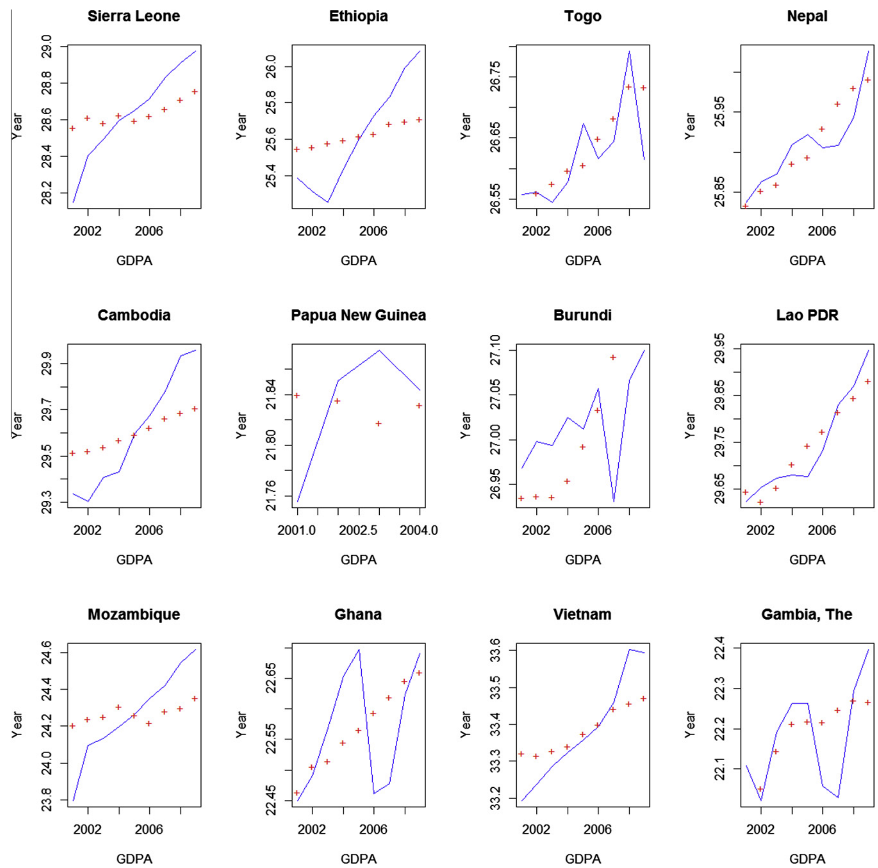

Figure 6. *Fit of agriculture's GDP for selected countries with large agricultural sector. Source: World Development Indicators and Estimated by Authors. Note: Natural log of real GDP in local currency. Real line represents official figures, crossed line is authors' estimations.*

2 days and observations are averaged over 8 or 16 days. The MODIS instrument provides high radiometric sensitivity (12 bit) in 36 spectral bands ranging in wavelength from 0.4 to 14.4 μm. Two bands are imaged at a nominal resolution of 250 m, five bands at 500 m and the remaining 29 bands at 1 km. MODIS land products are received, distributed, and archived at the Land Processes Distributed Active Archive Center (LP DAAC), a component of NASAs Earth Observing System (EOS) Data and Information System (EOSDIS). MODIS land cover products are produced from supervised classification, unlike GlobCover and GLC2000, which are produced mainly from unsupervised classification. MDC12Q1 is the MODIS yearly land cover product and exists in two versions, an older version (V005, 2001–2007) and a more recent version (V051, 2001–2010). Data are presented in tiles of approximately ~1200 × 1200 km (~10° × 10° at the Equator) with 500 m nominal spatial resolution.

As we aim to use nighttime lights and land cover to estimate growth, it goes without saying that we need a land cover dataset with similar spatial and temporal resolution. We have determined that, among the land cover datasets currently available without a fee, MDC12Q1 suits our purpose the most.

MDC12Q1 includes five layers based on different classification systems:

17-class International Geosphere-Biosphere Programme classification
14-class University of Maryland classification
10-class system for MODIS LAI/FPAR algorithm
8-biome classification by Running
12-class plant functional type classification by Bonan

Data are produced on a calendar year basis and the inputs to the classification algorithm are no fewer than 135 different features including, for example, spectral and temporal information from MODIS bands 1–7, Enhanced Vegetation Index and Land Surface Temperatures. Approximately 1,860 sites around the world are used as training data for the classification algorithm. Sites are selected to ensure geographic and ecological variability. They are manually delineated in Landsat imagery and are generally between 0.2 and 80 km^2. Results are quantitatively assessed based on a 10-fold cross validation. As our aim is to capture the economic growth generated by the agricultural sector, we have extracted the classes of most relevance. They are IGBP class 10 (grasses/cereals), 12 (croplands), and 14 (cropland/natural vegetation mosaic). The overall classification accuracy of the selected classes is 72.5% which can be considered as normal.

4. ESTIMATION AND RESULTS

Our basic estimation strategy follows that developed by Henderson *et al.* (2012). Their framework can be shown as Eqn. (1):

$$\gamma_{jt} = \hat{\psi} x_{jt} + c_j + d_t + e_{jt} \tag{1}$$

where $\ldots \gamma_{jt}$ is the true GDP of country j at time t. x_{jt} is the level of observed nighttime light in the corresponding country and at the corresponding time. c_j, d_t, and e_{jt} denote country effect, year effect, and error term, respectively. The assumption for this model is then that, no matter the type of economic

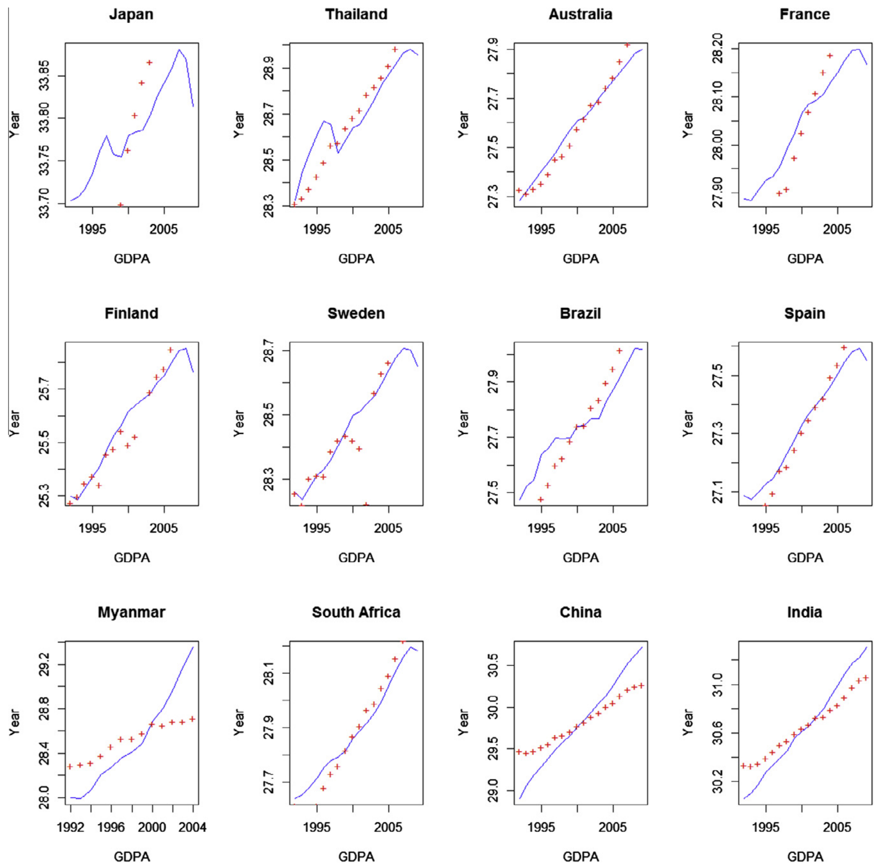

Figure 7. *Fit of non-agriculture's GDP for selected countries. Source: World Development Indicators and Estimated by Authors. Note: Natural log of real GDP in local currency. Real line represents official figures, crossed line is authors' estimations.*

activities on the ground, their aggregated growth results in the same percentage growth of nighttime light observed by satellite plus country-invariant, time-invariant effects and an error term. The basic regression analysis assumption requires that the error term be a random variable with a mean of zero. However, we have shown through gridded data of land cover and nighttime lights that it is possible for agriculture's value-added to increase without emitting more observable nighttime light into space. If this is the case, then the error term is actually dependent on the agricultural share as the higher the agricultural share the higher the error term. Randomness of the error term from independent variables is one of the important assumptions of regression analysis. It is therefore desirable to exclude activities that can grow without emitting more nighttime light. Table 3 shows the elasticity of nighttime lights on GDP for groups of countries according to agricultural share. Elasticity becomes negative for countries with an agricultural share between 20% and 40%. The relationship becomes insignificant for countries with an agricultural share equal to or more than 50%. Negative elasticity is unnatural because richer people can afford more not less nighttime lights. Given this unstable relationship, we argue that nighttime light is not a good predictor of growth of agricultural value-added.

It is noteworthy that agriculture is often not completely independent from non-agriculture. Apart from being consumed outright, agricultural products can also be inputs to non-agricultural sectors. If most non-agricultural activities emit nighttime light as they grow, agricultural growth may somehow be captured on the 'macro' level. In fact, Henderson *et al.* (2012) partly base justification of their framework on this mechanism. This seems to work reasonably at the country-level. However, limiting predictors to nighttime lights poses two major drawbacks. First, they cannot account for areas without observable nighttime light. Henderson *et al.* (2012) show how to analyze growth in cross-border areas without taking administrative borders into account. Obviously, such a framework cannot quantify growth of regions, international or domestic, without observed nighttime light. It can, at best, generate the same growth rate from differences of time-invariant effects among non-lit regions. Second, it would be a loss of opportunity not to explore other readily available remote sensing data. Nighttime light introduced remote sensing into economics and it is to the benefit of everyone involved to expand this in all possible directions.

(a) *Extended estimation framework and results*

This paper makes full use of the statistical framework and estimation strategy proposed by Henderson *et al.* (2012). However, we have revised the assumption that all economic growth is captured by growth in observed nighttime light. Our revised assumption is that nighttime lights observed from space are the result of growth in only the non-agricultural sector. We therefore divide the equation of Henderson *et al.* (2012) into non-agricultural (Eqn. 2) and agricultural (Eqn. 3) parts. Based on our discussion in previous sections, we

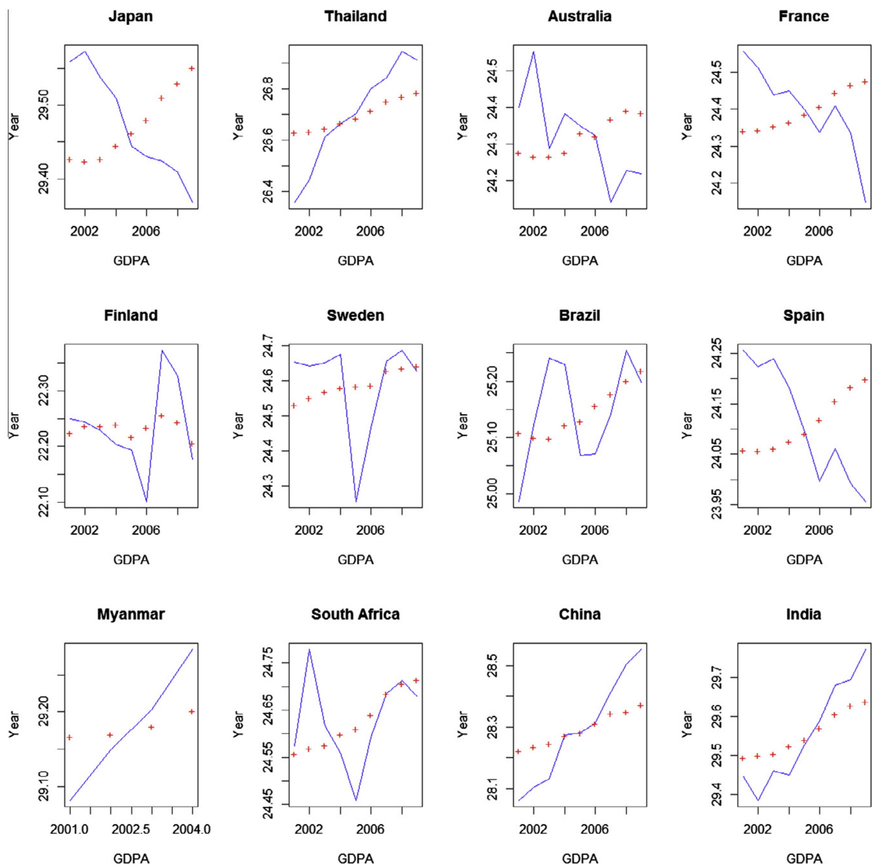

Figure 8. *Fit of agriculture's GDP for selected countries. Source: World Development Indicators and Estimated by Authors. Note: Natural log of real GDP in local currency. Real line represents official figures, crossed line is authors' estimations.*

introduce MODIS land cover product MCD12Q1. The biggest difference between land cover and nighttime light data is that there are many different classifications of the former.

$$\gamma_{jt}^{na} = \hat{\psi}^{na} x_{jt}^{na} + c_j^{na} + d_t^{na} + e_{jt}^{na} \tag{2}$$

$$\gamma_{jt}^{a} = \left(\hat{\psi}^{a1}\hat{\psi}^{a2}\ldots\hat{\psi}^{an}\right)\begin{pmatrix} l_{jt}^{a1} \\ l_{jt}^{a2} \\ \vdots \\ l_{jt}^{an} \end{pmatrix} + c_j^{a} + d_t^{a} + e_{jt}^{a} \tag{3}$$

(b) *Regression results*

We first show the estimated results of Eqn. (2) in Table 4. Table 4 is mostly a replication of Henderson *et al.* (2012), but shows non-agriculture growth instead of overall GDP growth. The elasticity on overall growth of GDP with respect to nighttime light is 0.27, close to the value of 0.3 found by Henderson *et al.* (2012). We take this as evidence that the growth of nighttime light, observed from space, is largely the result of expansion of non-agricultural growth on the ground.

Next is Eqn. (3). Land cover data used in our analysis are only available from 2001, so estimation of growth from agriculture is done for a period approximately half the length of that used for non-agriculture growth. Table 5 shows several combinations of land cover as predictors of agriculture growth. First, nighttime light is rejected as a significant estimator of value-added in agriculture and forestry. This holds for all specifications in Table 5. Second, forest area has negative impacts on agriculture and forestry. In other words, agriculture and forestry value-added can grow by reducing forest area. Cutting down trees reduces forest area, while their commercial value increases forestry's value-added. Forest area reduction through expansion of agricultural land also increases agricultural output. The coefficient of forestry is about -0.04 and is stable across all specifications.

The category cropland (L12) alone does not explain agriculture's value-added significantly. We argue that two limitations of categorical remote sensing data may be responsible for this. First, in categorical remote sensing, a certain area, in this case one square kilometer, needs to be categorized to one predefined category. However, many medium- and small-scale farmers have cropland hardly larger than one square kilometer. So, categorical errors inevitably exist. Smaller agricultural fields in developing countries may be mistaken for grassland or the like. Second is another categorical error but one that arises from a different source. Remote sensing at a global scale can only be achieved through automatic or semi-automatic categorization using a limited sample obtained from ground-based surveys. Areas are categorized automatically based on their spectral properties (color, reflectance etc.) which are used to place them into categories. It is not difficult to imagine that such sample data are much less readily available for developing countries. We argue that one way to overcome the effects of these categorical errors is to group similar categories together. This works for forest and also for agricultural land. When cropland (L12) is grouped with cropland/natural

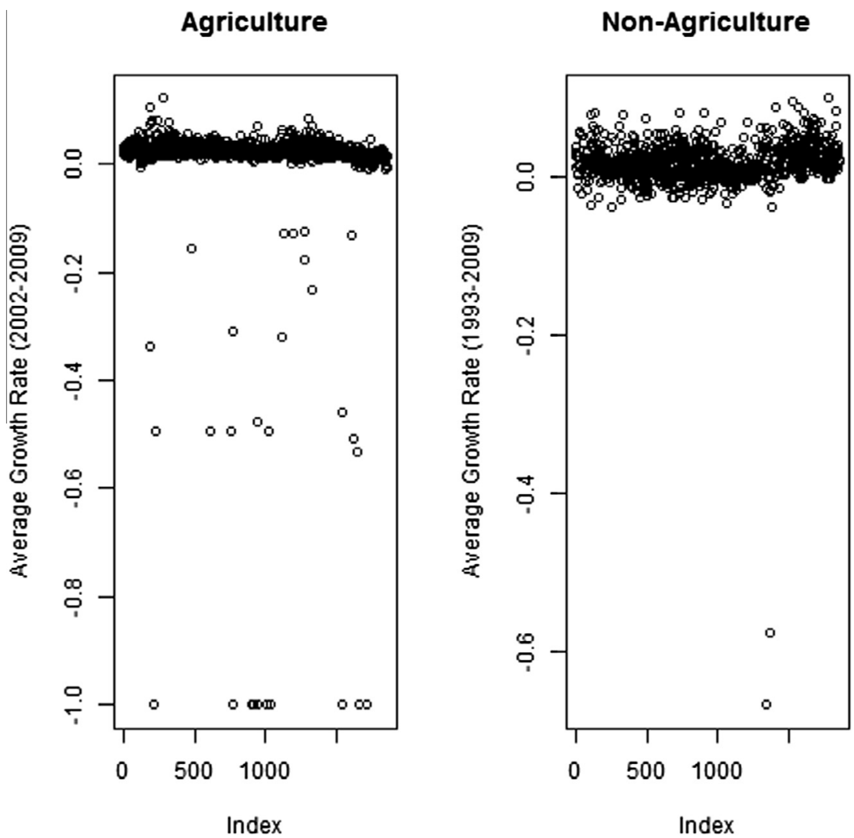

Figure 9. *Average growth of agriculture and non-agriculture on district level in Indochinese Peninsula (Cambodia, Lao PDR, Myanmar, Vietnam, Thailand). Source: Estimated by Authors.*

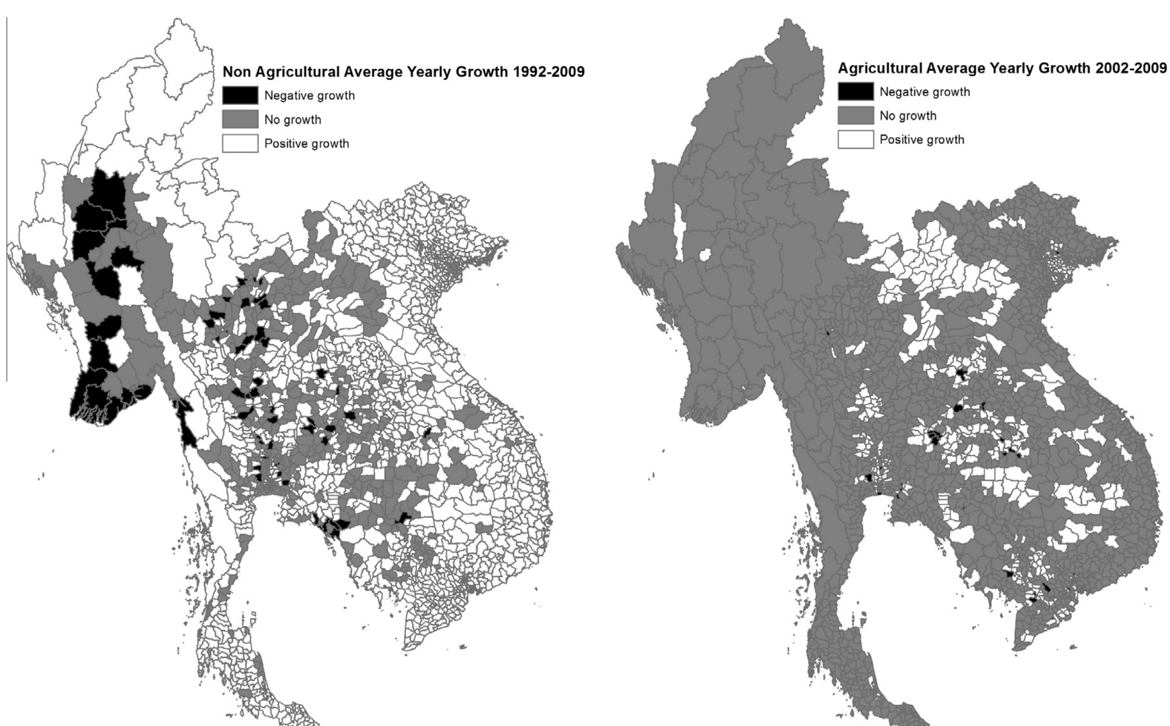

Figure 10. *Average growth of agriculture and non-agriculture on district level Indochinese Peninsula (Cambodia, Lao PDR, Myanmar, Vietnam, Thailand). Source: Estimated by Authors.*

vegetation mosaic (L14), they show positive impacts on value-added in agriculture and forestry. In the last specification, we determine group L10, L12 and L14 to generate agricultural land.

(c) *Estimating growth of agriculture and non-agriculture on national levels*

In this section we estimate growth of agriculture and non-agriculture in a selection of countries to evaluate the performance of our models. Figures 5–8 show these growth figures in countries with a large agricultural share and in selected industrialized and developing countries. The fit of non-agriculture and agriculture for countries with a large agricultural share is in Figures 5 and 6. The fit for non-agriculture is sufficiently good for most of the selected countries. While large fluctuations of agriculture value-added are not captured well, land cover data are able to predict the agriculture's growth trend well (Figure 6). Predictions of non-agriculture are even better for selected industrialized countries (Figure 7). On the contrary, the fit for agriculture is relatively poorer for higher income countries (Figure 8) which can be mentioned as a weakness of this framework. While expanding agricultural land is generally required in order to increase production in developing countries, the same is not true in developed countries. There, it is often possible to change production levels without affecting the amount of agricultural land. It is therefore more difficult for land cover data to predict agriculture's output for developed countries. In other words, unlike nighttime light data, land cover data are one-dimensional categorical data. Nighttime light data provide information in two dimensions. Area lit increases with new nighttime emissions in previously dark places and light intensity increases when additional light sources emerge on top of existing sources.

(d) *Estimating growth of agriculture and non-agriculture on sub-national levels*

Estimation of growth on the national level can be done through many existing frameworks. The advantage of our framework is the ability to estimate growth figures in regions of virtually any shape and size. We achieve this by, as discussed, including land cover data, which are much more ubiquitous than nighttime light data. This allows us to estimate growth within areas where nighttime lights are not observable from outer space. Figure 9 shows growth figures by administrative level 2 (equivalent with district level) in the Indochinese Peninsula. Among 3,538 districts in five countries, namely Cambodia, Lao PDR, Myanmar, Vietnam and Thailand, about 92% exhibit positive average growth in agriculture during 2002–09, while about 86% do so in non-agriculture during 1992–2009. A larger portion of level 2 administrative areas show negative average growth in non-agriculture because of a sharp drop off in 2008 and 2009. The geographical distribution of this is shown in Figure 10. High agricultural growth concentrates in Northern Lao PDR, Cambodia, and Northeastern Thailand. There is additionally some geographically scattered growth in Western and Northern Vietnam. The relatively high growth in the agricultural sector on district levels in Northern Lao PDR follows observations from the ground reported by Andersson, Engvall, and Kokko (2010). The rapid expansion is reported to be related to Chinese investments providing capacity to clear and prepare land previously used as forest land to be agricultural land. In contrast, non-agriculture has grown faster in Vietnam and Western Cambodia.

5. CONCLUSION

Monitoring of economic activities should provide longitudinal information in a standardized and regular manner at different geographical scales. Planning and directions of public investment are dependent on accurate statistical measurements. In many developing countries, survey data on economic activity are released at an interval of 5–10 years. Based on the information provided, stakeholders are enabled to make decisions and identify areas with large variation in production and productivity and target these areas through directed investments. Estimates should therefore be provided as early as possible during the economic cycle and updated periodically over time.

This article presents a model for estimating agricultural and non-agricultural economic growth on national and sub-national levels using satellite data. The application of remote sensing data in economic analysis is in the very early stages and has largely been limited to observations of nighttime light. We have contributed to the literature through better accounting for agriculture by means of land cover observations. The inclusion of land cover data significantly improves our model's estimates for agriculturally dominated regions on a global scale. Yet we acknowledge the limitations of categorical data on an annual time scale. The classes provided in the IGBP-classification protocol do not cover the geographic and ecological variability in global land cover, the temporal-spatial separation of classes is ambiguous and this is compounded by the inclusion of mixture classes (Friedl *et al.*, 2010). Furthermore, for more than forty years the design of the OLS has not changed significantly and OLS data have relatively coarse spatial resolution, limited dynamic range, and lack in-flight calibration (Elvidge, Baugh, Zhizhin, & Hsu, 2013).

Despite the limitations mentioned above, this article provides advancement on how to monitor economic development from space. First, our study provides a global model with a unique spatial and temporal perspective of change in economic activities. Second, it provides a truly geographical perspective with high spatial resolution of observations together with global coverage that permits analysis at a multitude of scales. The model output can be aggregated to arbitrary geographical spatial units such as nations but, more importantly, it can also be used for studying functional regions that challenge administrative borders as shown in the spatial analysis of agricultural and non-agricultural growth in the Indochinese Peninsula.

Our ongoing work includes tests with well-known remotely sensed vegetation indices with improved spatial (250 m) and temporal (monthly) resolution. Here, the problem becomes how to separate human-induced and economically relevant changes from natural and seasonal fluctuations in vegetation. In addition, in 2011 NASA and NOAA launched the Suomi National Polar Partnership (SNPP) satellite carrying the first Visible Infrared Imaging Radiometer Suite (VIIRS) instrument. The VIIRS collects low light imaging data and has several improvements over the OLS' capabilities which will be of great interest for future research in this vein.

NOTE

1. http://web.ornl.gov/sci/landscan/.

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