BLINDED BY THE LIGHT: MONITORING LOCAL ECONOMIC DEVELOPMENT OVER TIME WITH NIGHTLIGHT EMISSIONS

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ABSTRACT

Nighttime light (NTL) emissions are widely used across disciplines to map the spatial distribution of a variety of socio-economic variables. For economic studies, NTLs allow to proxy for levels of economic indicators at the country level as well as the local level. Further, multi-temporal differences in NTL intensity are also related to GDP differences on the country level. In this study, we investigate if this relation in temporal differences also holds for the local level. We test this with DMSP as well as VIIRS NTLs data from 2010-2015 in Nigeria, Tanzania, and Uganda. Even though we successfully map local levels of socio-economic status with NTLs, we find multi-temporal changes in NTLs at this local level to be uncorrelated with socio-economic development over time. We conclude that luminosity values based on current DMSP and VIIRS sensors are *no silver bullet* in measuring local economic changes over time and should, if at all, only be used with caution for this.

Index Terms— Nighttime Lights, Change Detection, Poverty Mapping, Sustainable Development Goals

1. INTRODUCTION

Nighttime lights (NTLs) have proven to be a powerful tool to measure socio-economic outcomes in a number of countries and continents. Particularly, NTLs can be used to augment or replace economic data which is often lacking or of low quality or resolution in low- and middle-income countries [1]. This is because a strong relation between NTLs and GDP and other economic indicators at high levels of spatial aggregation has been discovered [2, e.g.]. Further, it has also been shown that national GDP growth over time can be measured with multi-temporal differences in NTL [2]. And, NTLs have also been related to sub-national and regional economic development as well as levels of local human development in household surveys [3, 4, 5].

Because of its abilities and availability, luminosity has established itself as a widely used data source in economic studies. Most contributions within economics which use NTLs tend to rely on multitemporal comparisons of luminosity [6, p. 177] and predict changes in economic output at scales *down to the household level with NTLs* [6, p. 187]. This is because many of these studies try to determine factors that influence growth or monitor progress in alleviating poverty. For both of these goals, reliable information about the change in human development is crucial.

While the correlation of NTL emissions and local economic status at the household level is well-established [1, 3], it is unclear if a relation between temporal changes in NTLs and local changes in human development exists. Recently, Yeh et al. (2020) [7] concluded that NTL images over time as input to a convolutional neural network model were unable to discover changes in economic development on the ground. This is, however, far from how nighttime lights are used in practice in economics. There, temporal differences in NTLs are frequently applied as a *linear predictor* for changes in economic development or the direction of changes in NTLs direction is interpreted.

In this paper, we therefore address the question how reliable these measures of local economic growth based on multi-temporal NTLs are. We test the predictive power of temporal differences in NTLs for local growth in average wealth and income with a longitudinal time-series dataset. This dataset consists of local household clusters of about 10km $\times$ 10km in size in the countries of Uganda, Tanzania, and Nigeria. The data are available over the time period from 2010 to 2015. With this analysis, we aim to eliminate the current uncertainty of the use of temporal NTLs on the local level that might limit further studies of human development.

2. DATA

We rely on survey data to measure household wealth and consumption. Specifically, we use the Living Standards Measurement Survey (LSMS) conducted by the World Bank in sub-Saharan Africa in cooperation with national statistical offices. The LSMS data provide longitudinal measurements of the same households over time ('Panel data') and have also been used successfully for poverty mapping with nighttime lights [1]. We restrict our sample to Nigeria, Uganda, and

Tanzania because these three are the only countries that have a longitudinal component and include wealth as well as consumption data. Households are surveyed in geographic clusters of 10km $\times$ 10km in size where all households in a cluster share the cluster centroids as coordinates. The main period of analysis in our study is 2010 to 2015 which is determined by the availability of surveys. In total, we rely on seven surveys: Two from Tanzania in 2010/11 and 2012/13, two in Uganda in 2012/13 and 2014/15, and three in Nigeria in 2010/11, 2012/13 and 2014/15.

Total consumption expenditures per person in real local prices are directly provided in the LSMS data. Hence, the data is already adjusted for inflation. We follow Jean et al. (2016) [1] by converting the consumption expenditures from local currencies to US-$ and taking logs to make our results comparable to theirs. For wealth, we generate an index from survey responses about asset ownership following the Demographic and Health Surveys (DHS) methodology [8]. The wealth index is the result of taking the first principal component of these responses and normalizing the component within each country around mean 0 with standard deviation 1. In total, we collect information from 378 clusters with an average size of 7.86 households in Tanzania, 168 clusters with a size of 7.99 households in Uganda, and 449 clusters with 8.98 households per cluster in Nigeria. Finally, we average the standardized household level human development indicators per cluster.

The timeframe of our study from 2010-15 allows testing the local change detection abilities of two different sources of NTLs. Hence, we separate the analysis period by sensor. For years in our panel dataset until 2013, we rely on annual stable lights DMSP-OLS V4 composites. While it would be possible to use data points for Tanzania in conjunction with pre-2010 DMSP data, we restrict the scope on DMSP values from the F18 satellite. Otherwise, the DMSP values could hardly be compared across time since they stem from different satellites. For years from 2013 on we use the newer generation of NTL imagery from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day–Night Band (DNB) from the Suomi National Polar-orbiting Partnership (Suomi NPP). Hence, we base our analysis of Uganda and Nigeria on VIIRS and DMSP data. For Tanzania, however, we only rely on DMSP since there are no longitudinal cluster observations available after 2012.

We follow previous contributions [1, 3] and average the NTL intensity across a cluster. We take logs of NTLs and add a constant before the log transformation which is common practice in economic studies of NTLs to not lose observations with zero NTL intensity [3]. As a constant, we use an incremental unit on the respective NTL scale. As DMSP values are integers, we add 1 in this case and 0.01 for VIIRS data which are continuous. Then, we take temporal differences of these log mean NTL intensity per cluster values to investigate if they can predict changes in the development outcomes.

3. METHODS

At first, we aim to verify previous results that NTLs are a good linear predictor of local human development [1, 3] - a necessary requirement for the ability to estimate changes over time. To be consistent with [1, 3], we similarly test this ability with a linear regression. This relation is commonly tested with a regression because NTLs are used directly as a *linear* proxy for a variety of economic indicators in the literature [6]. Formally, we estimate all clusters together in a pooled setup:

$$D_{t,i} = \beta_0 + \beta_1 * NTL_{t,i} \tag{1}$$

where $D_{t,i}$ is the average *level* of the human development indicator of interest in cluster i and year t. Note that the unit of $D_{t,i}$ is log(US-$) for consumption. Further, $D_{t,i}$ has only a relative interpretation for wealth and can not be interpreted in absolute terms. $NTL_{t,i}$ as the explanatory variable is the log of mean NTL intensity in cluster i and the year of analysis t. Similarly, the ability of temporal differences in NTLs for the explanation of multi-temporal changes in economic indicators is also typically tested in a linear regression [2, 6]. Therefore we test if differences in NTLs can explain changes in local human development in a linear regression of differences:

$$\Delta D_{t,i} = \beta_0 + \beta_1 * \Delta NTL_{t,i} \tag{2}$$

Here, $\Delta D_{t,i} = D_{t,i} - D_{t-1,i}$ and similarly $\Delta NTL_{t,i} = NTL_{t,i} - NTL_{t-1,i}$. One time period is about 2-3 years if not mentioned otherwise based on the intervals of our survey data. If differences in NTLs are indeed a good predictor of multi-temporal changes in local development, we would expect a positive and statistically significant slope β_1 as well as a high share of explained variance R^2 by the regression.

However, a positive relation in changes could exist but might not necessarily be linear. Hence, we further test if just the direction of change in NTLs can be indicative of the direction of change in human development. We count the number of times when temporal changes in NTLs and human development do and do not share the same direction. We refer to this as alignment of directions.

4. RESULTS

Table 1 presents the results of estimating equation (1) and (2). Panel 1 shows specifications for log DMSP-OLS nightlight data which includes Tanzania, Nigeria, and Uganda. In Panel 2, log mean NTL intensity per cluster based on VIIRS data is used as the explanatory variable based on data from Nigeria and Uganda only. We first estimate equation (1) with wealth and consumption as an indicator of development in columns (1) and (2).

In all 4 regressions of columns (1) and (2), a positive and significant coefficient is visible. For DMSP (Panel 1), human development tends to increase as NTL emissions increase.

Table 1. Regressing Local Econ. Dev. on NTLs

	(1) Wealth$_t$	(2) Consump.$_t$	(3) Δ Wealth$_t$	(4) Δ Consump.$_t$
Panel 1: Log DMSP as NTLs				
DMSP	0.20***	0.14***		
	(0.01)	(0.01)		
Δ DMSP			0.01	-0.15***
			(0.05)	(0.05)
N	1990	1990	995	995
R^2	0.401	0.348	0.000	0.010
Panel 2: Log VIIRS as NTLs				
VIIRS	0.21***	0.20***		
	(0.01)	(0.01)		
Δ VIIRS			-0.04	0.17***
			(0.03)	(0.05)
N	1234	1234	617	617
R^2	0.283	0.321	0.003	0.025

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are in brackets.

The explanatory power of the regression is between 35% and 40 % for DMSP which is in line with previous results [1, 3] on the cluster level. Our results for DMSP are slightly above the range of R^2 between 30% and 37% obtained for the same task with DHS survey data and DMSP lights [9].

The coefficient of determination for VIIRS (Panel 2) data is slightly below DMSP values and ranges between 28% and 32%. Note that these values are not directly comparable to estimations with DMSP on the left since they refer to different countries and time periods. The number of observations is slightly lower in the right column because for Tanzania we used only DMSP values. Still, there is a strong positive association also with VIIRS data between cluster wealth as well as consumption with NTLs.

Therefore, we can clearly confirm the spatial relation between human development indicators and NTL intensities at the local level. This is in line with previous results in the literature. After demonstrating a strong spatial correlation of NTLs and local development in our data for the same year, we now proceed to estimate our main research question: To what extent are these correlations also visible in multi-temporal changes of these variables at the local level. The results of estimating equation (2) for the full sample are displayed in Columns (3) and (4).

For all four estimations of equation (2), the coefficients do not point towards a strong positive relationship. The coefficient for wealth and DMSP (Panel 1, column (3)) is virtually zero. For DMSP and Consumption (Panel 1, column (4)) and VIIRS and wealth (Panel 2, column (3)) the coefficient even turns negative. The only coefficient with a significant and positive slope can be observed for VIIRS and consumption

Table 2. Share of direction alignment of temporal changes in NTLs and local development

	$Align$	$\overline{Align}$	$\Delta NTL = 0$	Total
DMSP	24.8%	32.5%	42.7%	100%
	(494)	(646)	(850)	(1990)
VIIRS	48.5%	51.5%	0%	100 %
	(598)	(636)	(0)	(1234)
Total	33.9%	39.8%	26.3%	100%
	(1092)	(1282)	(850)	(3224)

Absolute counts are in brackets.

(Panel 2, column (4)). However, the share of explained variation is low at 2.5%. Hence, changes in local development are measured in this case unrelated to differences in DMSP as well as in VIIRS data. Further, this finding is homogeneous for both variables, wealth and income.

Since NTL emissions are commonly used as a *linear* predictor for socio-economic indicators in economics [6], our primary goal is to identify if they can be used as a *linear* predictor for multi-temporal changes on the local level as well. Table 1 underlines that this does not seem to be possible in our sample. However, multi-temporal differences in NTLs and local development might be related in a positive yet non-linear fashion. To test if a different functional form might discover a potential positive relation, we further test in how many clusters the direction of changes align for NTLs and local development.

Table 2 explores the alignment of directions in our full sample. The values represent the relative counts of direction alignment of clusters split by sensor. Both indicators of development and all three countries are included in these counts. For both sensors, there are more points where directions do not align compared to where they do. This even holds when excluding the points with no change for DMSP NTLs which has two consequences:

1. A binary classifier that would predict the direction of changes in development identical to the direction of change in NTLs would perform *worse than randomly guessing*.

2. This classifier could, in fact, improve its performance by predicting a positive development for all clusters with decreasing NTLs and vice versa.

This finding adds to our conclusion that multi-temporal changes in NTL emissions are an unreliable predictor of multi-temporal changes in economic development on the local level. If not even the direction in these changes align, our findings are also not driven by the functional form of equation (2) but are rather the result of a general absence of a relation, at least over the analyzed time frame.

5. DISCUSSION

Our results show that NTL emissions and local economic development are correlated, but multi-temporal differences in these variables show no correlation. While we can not conclusively determine what drives this pattern, there could be several possible explanations: First, infrastructure is comparatively sluggish, and economic development may be delayed, possibly longer than our monitoring period. Secondly, it seems likely that the emission of local lights might not be primarily a function of local variables. Decisions that affect local lights could largely be made on the level of administrative units such as provinces or even on the country level. These decisions might eventually also influence local development. Therefore, we may find no direct response in NTLs to multi-temporal changes in local development because this might not be what fundamentally drives nightlight activity. Third, the average values of NTLs may differ significantly from one year to the next even if they are from the same sensor. This might induce noise into the observations of our panel and make the task of taking differences in NTLs as an indicator of local growth fundamentally difficult at this spatial level. In this case, the approach of multi-temporal comparisons of NTLs down to the household level, which is frequently applied in economics, is potentially misleading. Hence, results obtained based on multi-temporal comparisons of local NTLs should only be interpreted with caution.

6. CONCLUSION

We explored if multi-temporal differences in NTLs can predict multi-temporal changes in average household human development indicators in regions of 10 km * 10 km size. For this purpose, we relied on longitudinal LSMS data about household consumption and wealth. The data from Tanzania, Uganda, and Nigeria between 2010 and 2015 was combined with VIIRS and DMSP-OLS nighttime light emissions from the respective years. We found that temporal differences in NTLs and multi-temporal changes in local development over time are unrelated. We observe this finding despite a high correlation of local development and nightlights in the same year in our data as shown in previous studies. Our outcomes were virtually identical for the VIIRS as well as the DMSP sensors and also for consumption as well as wealth as indicators of local development. Finally, we outlined that predicting the direction of economic development over time based on the multi-temporal change of NTLs in the same timespan would actually be worse than randomly guessing the direction of development change in our sample. This implies that the application of temporal differences in NTLs as a proxy for local growth in economics may be unreliable and misleading.

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