

Understanding the Impact of Windstorms on Economic Activity from Night Lights in Central America

Oscar A. Ishizawa

Juan Jose Miranda

Hongrui Zhang



WORLD BANK GROUP

Social, Urban, Rural and Resilience Global Practice Group

June 2017

Abstract

Central America is particularly prone to tropical storms and hurricanes. The prevailing conditions of poverty and socioeconomic inequality in most countries of the region make their exposed population especially vulnerable to those adverse natural events. This paper quantifies the causal effects of hurricane windstorms on economic growth using night lights in the Central America region at the highest spatial resolution data available (1 square kilometer). The paper uses a unique data set of monthly night lights data to capture the temporal disaggregation of hurricanes. Hurricanes in Central America are often localized events and tend to make landfall during the final months of the year

that are better captured through monthly—rather than yearly—frequency data. The results suggest that major hurricanes show negative effects up to 12 months after the hurricane strikes (between -2.6 to -3.9 percent in income growth at the local level). After that, the analysis finds positive effects during the second year and the first half of the third year as evidence of post-disaster recovery (from 2.5 to 3.6 percent in income growth). The paper contributes to the literature on natural disasters by providing robust estimates of the causal effects of major hurricane windstorms on Central America, which are negative (in the short term) and positive (two years after hurricanes hit).

This paper is a product of the Social, Urban, Rural and Resilience Global Practice Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at <http://econ.worldbank.org>. The authors may be contacted at oishizawa@worldbank.org and jjmiranda@worldbank.org.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

Understanding the Impact of Windstorms on Economic Activity from Night Lights in Central America¹

Oscar A. Ishizawa² Juan Jose Miranda³ Hongrui Zhang⁴
The World Bank

JEL Classifications: O11, O44, Q51, Q54, R11

Keywords: Hurricanes, Natural Disasters, Central America, Economic Growth, Night Lights

¹ This work was funded by The World Bank's Global Facility for Disaster Reduction and Recovery Program (Trust Fund # TF018258). We thank Eric Strobl and Stephane Hallegatte for helpful comments and suggestions, Xijie Lv and Nour Khater for outstanding research assistance. The views expressed here do not necessarily reflect those of the World Bank or their member countries. All errors and opinions are our own.

² Social, Urban, Rural and Resilience Global Practice (GSURR): oishizawa@worldbank.org.

³ Environment and Natural Resources Global Practice (GENDR): jjmiranda@worldbank.org.

⁴ International Monetary Fund – Economic Research Department: hzhang3@imf.org.

1. INTRODUCTION

Due to its geographical location, Central America is particularly prone to tropical storms and hurricanes formed in the North Atlantic and East Pacific basins, which occur mostly in the second half of the year. The prevailing conditions of poverty and socioeconomic inequality in most countries of the region make their exposed population especially vulnerable to those adverse natural events. A report by the United Nations Development Programme (UNDP), with data on tropical cyclones from 1980-2000, revealed that three of the six countries in Central America have extremely high mortality risk. In fact, Honduras and Nicaragua reported the highest numbers of people killed per million exposed to tropical cyclones during that period of analysis (UNDP, 2004). Economic risks from hurricanes are also relatively high in the region. According to Dilley et al. (2005), the economic risk from adverse natural events is especially high in El Salvador (96.4% of GDP at risk), Guatemala (92.2%), Costa Rica (86.6%), Nicaragua (67.9%), and Honduras (56.6%).

This mixture of high exposure and high vulnerability naturally exacerbates the potential destructiveness of hurricanes. Their capacity to wreak havoc along their path and cause extensive physical damages and human fatalities in the region is well documented. In 1998, Hurricane Mitch caused about 14,600 deaths, directly affected around 6.7 million people, and was responsible of more than US\$ 8.5 billion in damages in Nicaragua, Honduras, Guatemala, and El Salvador. More recently, in October 2011, Tropical Depression 12-E hit the coasts of El Salvador and Guatemala, causing damage in most of the countries in the region, which totaled almost US\$1 billion (CEPAL, 2011).

Hurricanes can be also a significant disruptive force to economic activity in Central America. Honduras's economy, for instance, fell into recession in 1999, the year after hurricane Mitch hit the country. But how much of the drop in economic growth was triggered by Mitch is unclear⁵, which underlines the difficulty to identify and quantify the causal effects of natural disasters. Most empirical works rely on self-reported monetary damages to capture the potential destructive power of natural hazards, but as several studies noted, the use of that information could lead to biased estimates (Cavallo et al., 2013)⁶. To overcome this problem, recent papers make use of windstorm models to reconstruct historical hurricanes and their trajectories, in an attempt to generate fully exogenous measures of hurricane intensity.

Specifically for Central America, Strobl (2012), and Ishizawa & Miranda (2016) combine damage indexes, produced by a wind field model, with Gross Domestic Product (GDP) data to quantify the causal effects of hurricanes on growth. A shortcoming of that approach, however, is the need to match high-spatial resolution data (i.e., 1 km²) generated by the model with traditional macroeconomic data (low-spatial resolution). As Ishizawa & Miranda (2016) recognize, when fully exogenous proxies of hurricane intensity are aggregated at a higher geographical level, exposure of assets and population need to be considered to reduce measurement errors, which ends up weakening the exogeneity assumption of the proxies.

Another major issue could also arise from the use of aggregated economic data to estimate the impact of hurricanes. Bertinelli & Strobl (2013), for example, find evidence for the Caribbean that aggregated analyses (e.g., at the national or regional level) tend to underestimate the impact of hurricanes on economic growth, while also suggesting that the effects can vary largely across space. Recent papers deal

⁵ A before-after assessment of the economic effects caused by hurricane Mitch was conducted by the UN Economic Commission for Latin America and the Caribbean, shortly after the disaster (ECLAC, 1999). The report compares the economic situation of Honduras before and after hurricane Mitch, but does not provide estimates of causal effects.

⁶ Poor countries tend to report larger damages due to their weaker socioeconomic conditions. Hence, self-reported damages are not an appropriate proxy for hurricane intensity.

with these concerns by using nocturnal light emissions from human activities as a proxy for local economic activity (e.g., Elliot et al, 2015 for coastal areas of China), which are available at a high-spatial resolution.

Built on the contributions of recent studies, this paper also uses a fully probabilistic windstorm model and night lights data to quantify the causal effects of hurricane windstorm on economic growth at the local level in the Central America region. The novelty, however, is the use of monthly frequency data instead of yearly frequency. We argue that not only spatial disaggregation is relevant for the analysis⁷; temporal disaggregation could be as well. The reasons are twofold. First, because hurricanes are local events that cause different effects across space, and are considered sudden-onset hazards, typically arriving with a few days warning and lasting for a few days (Hsiang & Jina, 2014), thus it is possible that the short-term effects on economic activity would be “aggregated out” when yearly frequency data is used. This point is especially worth considering in the Central American region, where hurricanes tend to make landfall during the final months of the year. Also, hurricanes of lower intensity may cause temporary effects on economic activity that are hard to notice in annual data. Second, the lack of a proper response to natural disasters in some developing countries, whether it is due to the limited financial resources, or because policy makers tend to prioritize short-term gains rather than addressing the fundamental causes of vulnerability, could make the short-term effects persist over time, and therefore, drive the long-run outcomes. In that sense, we contribute to the existing literature of natural disasters not only by providing robust estimates of the causal effects of hurricane windstorm on Central America, but also a better understanding of how those effects evolve after the event.

Overall, this paper finds robust evidence that hurricanes affect significantly the intensity of night lights. For locations that were hit by major hurricanes, we estimate a negative impact of 17% in the first 12 months after the event, followed by a recovery period of about 18 months that roughly offsets the initial drop. We also find hurricanes of mild intensity (i.e., of category 1 to 3 severity) to have significant, but short-lived, effects on night lights, suggesting that temporal aggregation could make it less likely to spot those effects. To translate those findings into economic terms, we first estimate the elasticity of real GDP with respect night lights of the Central America region. We then use the estimated elasticity to calculate the impact on income growth at the local level for a given change in night lights⁸. Our findings suggest a drop between -2.6% and -3.9% in income growth in the first year after the event, followed by a post-disaster recovery of similar magnitude in a longer period.

The remainder of the paper proceeds as follows. Section 2 describes thoroughly the night lights data used in this study as well as the main characteristics of the windstorm hazard model. Potential issues regarding the use of night lights data as a proxy for economic activity are discussed extensively. A brief description of the hurricane data and our proxy for potential damage from hurricanes is also included in this section. Section 3 explains our empirical approach, and Section 4 turns to the results. The several robustness tests to validate our main findings are presented in Section 5. Finally, Section 6 concludes the paper.

⁷ Elliot et al. (2015) demonstrated that the effects of a natural disaster could be “aggregated out” in more aggregated data. They used three alternative dependent variables: (1) aggregated night lights data at the county-city level, (2) real GDP/km² at the city level, and (3) normalized GDP by population at the city level; but found no significant effect of their potential typhoon destruction index.

⁸ Since the elasticity is calculated at the country level, we assume it does not differ much at the local level.

2. DATA AND STATISTICS

To quantify the impact of hurricane strikes on local economic activity in Central America, we used two main sets of data: (1) night lights data as a proxy for local economic activity, and (2) hurricane windstorm hazard data derived from a novel wind field model developed by the World Bank Group (WBG) Latin-American and the Caribbean Disaster Risk Management (DRM)⁹.

2.1. Night Lights Data

Since the 1970s, night light imagery has been captured and produced by satellites from the United States Air Force Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS), with the digital archive of this product beginning in 1992. The program was initially designed to monitor the global distribution of clouds and cloud top temperatures for weather forecasting purposes. But because clouds are difficult to observe at night, satellites were then equipped with onboard sensors that are capable of spotting moonlight that is reflected off of clouds. It did not take long for scientists and researchers to learn that these sensors were also good at detecting the lights emanating from different human activities: city lights, gas flaring, burning agricultural fields and even fishing vessels at sea (Keola et al. 2014; Mellander et al. 2015).

Specifically, those satellites have a 101 minute, sun-synchronous¹⁰ near-polar orbit at an altitude of about 830km above Earth's surface, providing coverage for every location on the planet twice a day, at some moment between 8:30 pm and 10:00 pm local time. Raw daily night light imageries are processed by scientists at the National Oceanic and Atmospheric Administration (NOAA), who developed a method to remove cloud obscured pixels, as well as sources of transient lights such as the bright half of the local cycle, auroral activity, forest fires, and other events, delivering yearly cloud-free night light composites that essentially capture nocturnal human activity¹¹.

NOAA distributes yearly frequency cloud-free night light composites (simple averages across daily values) to the public, with a spatial resolution of 30 arc-second output pixel (around 1 km² at the equator). Each pixel measures the intensity of lights normalized across satellites as a digital number (DN) that ranges from 0 (no light) and 63 (top-coded maximum light). Figures 1 and 2 show the nightlight intensity in Central America for 1993 and 2013, respectively. This DN, however, is not necessarily a perfect reflection of the so called true radiance due to mainly sensor saturation or top-coding, as pointed out frequently in the literature (Elvidge et al., 2007; Letu et al., 2010; Henderson et al., 2012; Huang et al., 2014). Because a high gain setting is applied to the sensors for the purpose of better cloud detection (i.e., dim lighting), DNs of light images are saturated in the bright cores of cities. In practice, this means the sensors are not able to register the intensity of night lights once it crosses the top-coded value of 63. Thus, night lights emanated from the center of big cities such as San José and Guatemala City are classified as the same level of intensity as the lights from their peripheries. As Mellander et al. (2015) noted in their research on

⁹ This research has been funded by the World Bank through a Global Facility for Disaster Reduction and Recovery (GFDRR) grant (TF014499) from the Government of Australia (AusAid) under the CAPRA Probabilistic Risk Assessment Program (P144982).

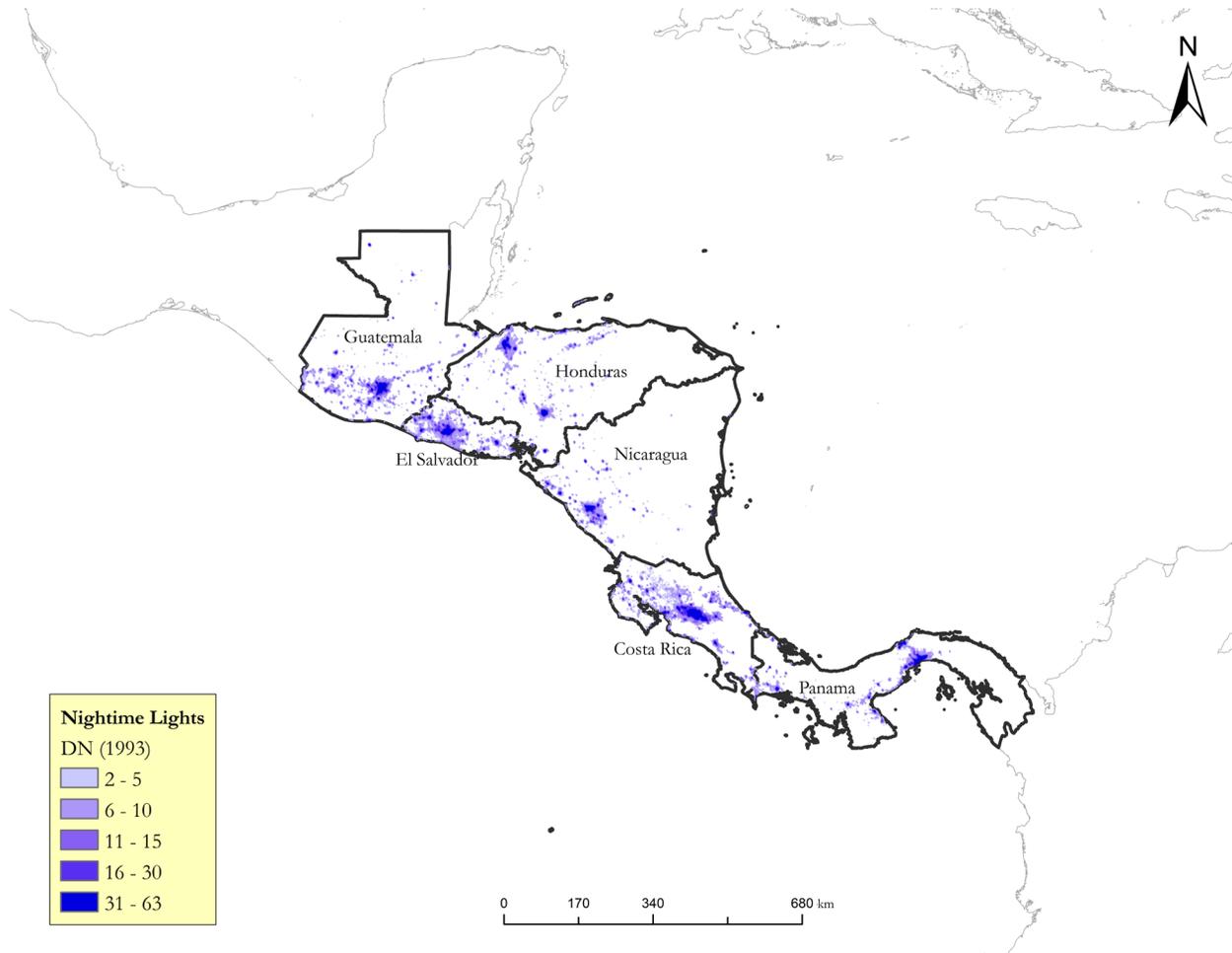
¹⁰ Remote sensing satellites typically fly in one of two orbits: geostationary or sun-synchronous. In the first case, satellites monitor the same area of the Earth's surface at all times, while a sun-synchronous orbit means that satellites can observe the entire Earth's surface at roughly the same time each day, and orbit several times per day, conditioning on their altitude.

¹¹ For further details on the filtering process, see Elvidge et al. (1997).

the statistical relationship between night lights and economic activity at a micro-level, the saturation issue could lead night lights to underestimate the activity from most densely populated cities.

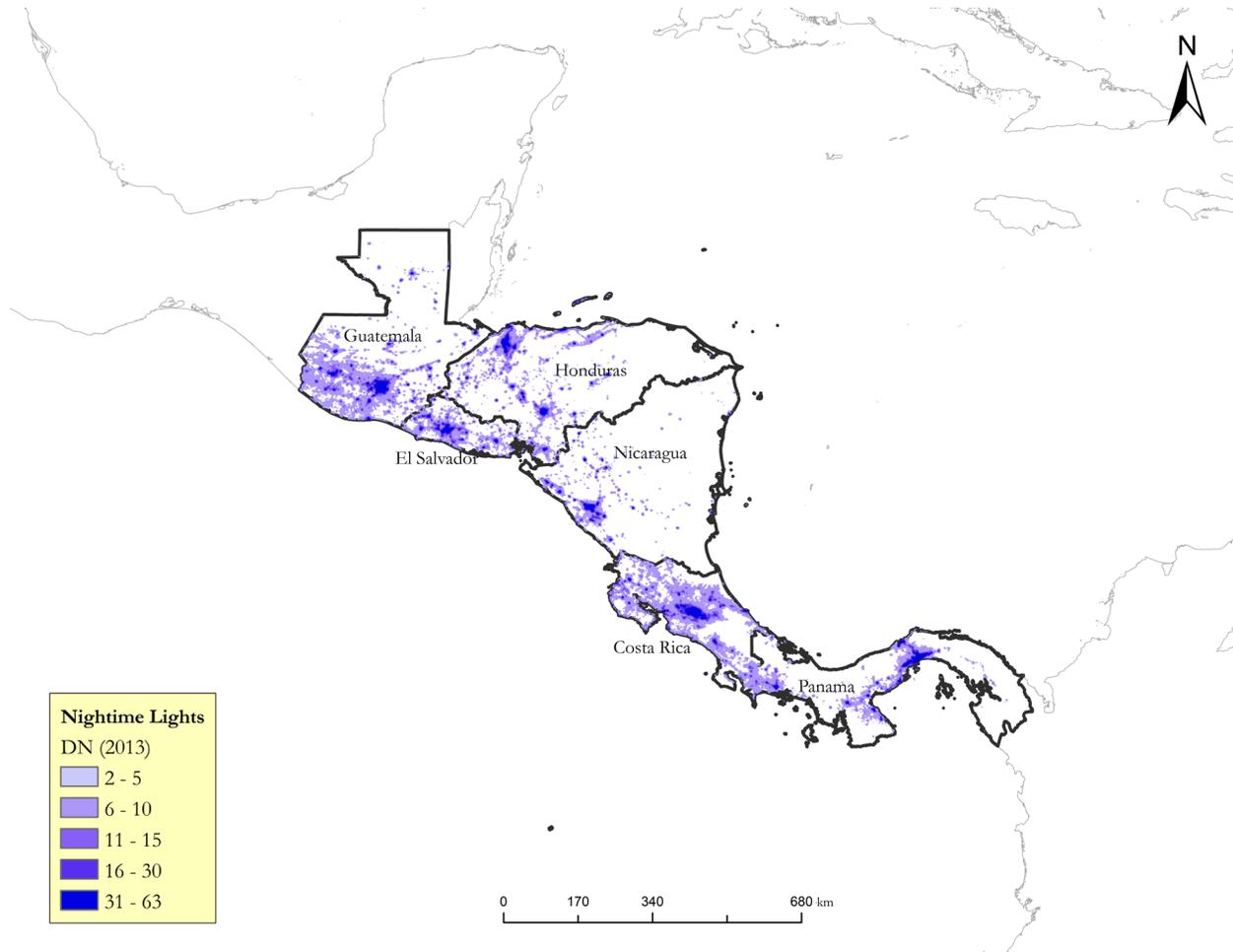
The problem of saturation has been extensively discussed by remote sensing scientists, and different approaches have been proposed or used to overcome it. Letu et al. (2012), for instance, explain the issue thoroughly and propose a correction method of the stable light image that uses the DMSP-OLS radiance calibrated images;¹² while Elvidge et al. (2007) argue that most shortcomings related to the DMSP-OLS sensor can be overcome by Nightsat, a new satellite sensor for night-time lighting developed by the authors. Similarly, other scientists have proposed algorithms to address the saturation phenomenon (Zhang et al., 2013; Raupach et al., 2010; Lo, 2001).

Figure 1. Night light imagery for Central America in 1993



¹² The radiance-calibrated night-time lights dataset is one of the five main datasets derived from the DMSP-OLS database. A summary of those datasets and their main differences can be found in Huang et al. (2014).

Figure 2. Night light imagery for Central America in 2013



Economists, who usually use night lights as a proxy for economic activity, have as well paid great attention to night light saturation in urban centers (e.g., Doll et al., 2006; Keola et al., 2015). Henderson et al., (2012) tested whether sensor saturation impairs the capacity of night lights to predictive GDP and, through a fixed-effects specification for a panel of 188 countries over 17 years, found that the estimate of the elasticity of night lights with respect to GDP and the R^2 remain unchanged after controlling by the number of pixels that are top-coded. We follow this approach to examine to what extent saturation weakens the suitability of night lights as proxy of local economic activity in Central America.

For this study, we use imagery recorded by satellite F10 for the period 1992-1994, F12 for 1994-1999, F14 for 1997-2003, F15 for 2000-2007, F16 for 2004-2009, and F18 for 2010-2011, covering six Central American countries: Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua and Panama. There are other studies that use yearly frequency night lights data to gauge the damaging effects of hurricane strikes on local economic activities (e.g., Bertinelli & Strobl, 2013; Elliott et al., 2015); but so far as we are aware, this paper is one of the first studies to use and exploit monthly frequency data¹³, provided by NOAA, in the analysis to better characterize those effects (Table 1).

¹³ We re-run our main specifications detailed in Section 3 with yearly frequency data and find results that are fairly consistent with our key findings. Results are available upon request.

Table 1. Sample of night lights data (1992-2013)

Satellite	Yearly frequency	Monthly frequency	
	Coverage	Coverage	Missing
F10	1992-1994	Apr-1992 / Sep-1994	Jul-Aug 1992
F12	1994-1999	Oct-1994 / Dec-1999	None
F14	1997-2003	Apr-1997 / Dec-2003	None
F15	2000-2007	Jan-2000 / Dec-2007	None
F16	2004-2009	Jan-2004 / Dec-2009	None
F18	2010-2013	Jan-2010 / Dec-2013	Jun-2011

Nevertheless, it is important to acknowledge that there are potential drawbacks associated to times series data of night lights. First, the lack of inter-satellite calibration could make comparisons of raw DNs to be troubling, especially for periods where two sets of composites (from overlapping satellites) are available, even though both datasets (yearly and monthly frequency) have been adjusted using Elvidge et al.'s (2009) invariant region and quadratic regression method. Economists commonly deal with this problem by taking simple averages of overlapping night light values across satellites (Henderson, et al., 2012; Bertinelli & Strobl, 2013; de Janvry et al., 2016) or simply using information from the most recent satellite (Elliott et al., 2015). Here we opt for a different approach: for each pixel we take weighted average of values from overlapping satellites, with the number of cloud-free nights (CFN) in a given year or month used as weight. We also use two additional approaches for our robustness check: values captured by the most recent satellites, and mixed values from both new and old satellites¹⁴.

Another concern is related to our decision to use monthly frequency data. Given that each DN is a simple average of all daily cloud-free night light values, monthly DNs are then evidently derived from a smaller set of information than yearly DNs. In fact, the average number of daily CFN used to produce each monthly DN is only 5, raising the risk of measurement error. Chen & Nordhaus (2011), in this regard, argue that using night lights as a proxy of local economic activity could have indeed considerable measurement error. We considered this problem in our regression analysis by controlling for differences in the number of daily cloud-free nights. Though we did find those differences to be statistically significant in explaining the variations of night lights, our estimates of the impact of hurricanes remained fairly unchanged;¹⁵ which implies the errors are not systematically correlated with our proxy for hurricane damage. In other words, we should not expect areas where night lights are poorer proxies are also those likely to have been hit by hurricanes (Bertinelli & Strobl, 2013). Thus, even if the inclusion of CFN does not completely clear out the problem of measurement error, it will only inflate the standard errors but not bias our estimates of the impact of hurricane strikes on local economic activity.

¹⁴ Our main findings remain unchanged if we use simple averages instead of weighted averages. We believe the latter approach is better because it gives more weight to DNs that are calculated with a larger set of observations.

¹⁵ Results that exclude CFN in the specification are available upon request.

Table 2. Night lights data for Central American countries, 1992-2013 average

DN	Costa Rica	El Salvador	Guatemala	Honduras	Nicaragua	Panama
0	57.7%	43.2%	78.1%	85.0%	94.0%	88.2%
(0, 3)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
[3, 6)	21.6%	24.5%	12.4%	8.3%	3.0%	5.3%
[6, 11)	13.8%	20.9%	6.3%	4.4%	1.9%	3.9%
[11, 21)	3.8%	6.7%	1.8%	1.2%	0.7%	1.3%
[21, 63)	2.7%	4.5%	1.2%	1.0%	0.5%	1.3%
63	0.3%	0.2%	0.1%	0.0%	0.0%	0.1%
Avg. DN	3.92	5.62	1.86	1.32	0.58	1.30
Avg. DN (excluding 0)	9.27	9.90	8.52	8.80	9.62	11.03
Number of pixels (M)	1,362	549	2,939	3,012	3,407	2,030
Area (km ²)	51,100	21,040	108,890	112,490	130,370	75,420
Pop. density (per km ² , 2015)	94	296	153	72	51	53
GDP per capita, PPP (2015 \$)	15,595	8,620	7,722	5,095	5,200	22,237

Table 2 shows the frequency distribution of DNs across pixels for Central American countries, along with information on land areas and GDP per capita at PPP. Most countries have a large size of their land areas or pixels¹⁶ with no artificial lights (i.e., have a DN value of 0) for the entire sample window of 22 years. In countries relatively more exposed to hurricane strikes such as Guatemala, Honduras and Nicaragua, more than three-quarters of their pixels are unlit. Following Bertinelli & Strobl (2013) and Elliott et al. (2015), who also use night lights data to study the economic impact of tropical storms on local activity, we assume there is no economic activity in pixels that have a DN value of 0 for our entire sample period, and exclude them in our econometric analysis (about 64% of the total sample). We also exclude pixels that reported intermittently positive DN values in a few months but stayed unlit for the rest of the sample window (19% of the sample), as they might likely be light overflow areas (Cao et al., 2016)¹⁷. This gives a sample size of around 21 million valid observations.

Table 2 also provides the number of top-coded pixels (i.e., have a DN value of 63) as well as the mean DN across our sample. It reveals that the percentages of censored pixels are zero or close to zero, suggesting that night light saturation in urban centers might not be a major issue in Central America. In contrast, the average value of DN across the six countries does show some variance. El Salvador, for instance, has the highest average DN in the region with 5.62, followed by Costa Rica with 3.9. Interestingly, Panama, the country with the highest income level, only has an average DN of 1.3, which is similar to that of Honduras, the poorest in the region according to the World Bank. Of course, this apparently weak correlation between the intensity of night lights and income levels can be explained in part by the inclusion of unlit pixels, which penalizes countries with low population density and large land areas, as it is the case of Nicaragua. But even if that is taken into account, night lights might not be a reliable proxy for income levels due to cultural differences in the use of lights and light saturation in large cities (Ghosh et al., 2010). Instead, night lights data work better as a proxy of economic growth (Henderson et al., 2012). For this reason, our empirical strategy (to be further discussed in the next section) centers on the variations in

¹⁶ The number of pixels of a country is fairly proportional to its land areas.

¹⁷ Intermittent pixels are more common in monthly frequency data, and some might well reflect new but temporal economic activity (e.g., a pixel that changes from unlit to lit) or hurricane strikes (e.g., from lit to unlit), so excluding those cases could be problematic. However, we identify only a small portion of the sample that could fit those two cases (3% each). In addition, our main results do not change when we use 12-month moving average of night lights, in which intermittent pixels are less prevalent.

night light intensity across pixels and over months, after controlling by time-invariant and time-specific effects, to isolate the impact of hurricanes on local economic activity.

2.2. Night Lights as Proxies of Local Economic Activity

Night lights data offer unique advantages to researchers, which can be summarized into three categories: 1) access to information that is hard to obtain at large scale and low marginal cost; 2) higher degree of spatial resolution than traditional data; 3) usually full geographic coverage (Donaldson & Storeygard, 2016). And since a digital archive of night light imagery was made available in 1992 by Chris Elvidge and his team at NOAA's National Geophysical Data Center, a growing number of remote sensing scientists and economists have exploited those advantages with applications of the data that range from monitoring human settlements, estimating demographic and socioeconomic parameters (e.g., population density, electricity consumption, GDP, income per capita), to gauging impacts from natural disasters (Huang et al., 2014). More recently, economists have used night lights as a proxy for economic activity to study civil conflict at the sub-national level in Africa (Harari & Ferrara, 2013), the influence of ethnic institutions on regional development within African countries (Michalopoulos & Papaioannou, 2013), policies of regional favoritism (Hodler & Raschky, 2014), differences in well-being across ethnic groups around the world (Alesina et al., 2016), and the role of transport costs in shaping city-level income in Africa (Storeygard, 2016).

In this paper we use night lights data derived from imageries captured by the DMSP-OLS to proxy changes in economic activity at the local level. Our approach is, of course, built upon preceding studies that have examined the relationship between night lights and economic activity at different levels of aggregation. At the country level, Henderson et al. (2012), for example, use a slightly unbalanced panel of 188 countries over 18 years to evaluate the accuracy of night lights as a proxy of the different dynamics of economic activity: annual growth, expansions and recessions, fluctuations around a growth path, and long-term growth. Overall, they find that changes in the intensity of night lights are a good predictor of economic growth, and demonstrate, in a similar fashion as Chen & Nordhaus (2011), the usefulness of night lights data at the sub-national level for lower middle income countries with relatively low capacity in producing statistics, which are probably the cases of Guatemala, Honduras and Nicaragua, based on World Bank's Statistical Capacity Indicator.

Several studies have shown night lights to be a good proxy for economic activity at finer geographic levels too. Doll et al. (2006) found the sum of night lights to be strongly correlated with the regional GDP of 11 European Union countries and the US GDP at the state level; and Ghosh et al. (2010) estimated a moderately strong relationship between the sum of light values and the official GDP at the sub-national level for China, India, Mexico and the US. Even at a micro-level, Mellander et al. (2015), who used a georeferenced residential and industrial dataset for Sweden, found a moderate correlation between night lights and wage density (i.e., income per km²). More closely related to our study are the papers of Bertinelli & Strobl (2013) and Elliott et al. (2015), who used night lights data as a proxy of economic growth to assess the local economic impact of hurricanes and typhoons in the Caribbean and China, respectively. But unlike those papers that did not put the accuracy of night lights as a proxy for economic activity under scrutiny, we did perform our own tests.

Specifically, we examine to what extent changes in the intensity of night lights are temporally and spatially correlated with local economic growth in the Central America region. For starters, we follow Henderson et al.'s (2012) econometric approach to evaluate the relationship between artificial night lights and real GDP over time, given by Equation 1:

$$z_{it} = \psi x_{it} + e_{it}, \quad (1)$$

where z_{it} is real GDP and x_{it} is the intensity of night lights (DN). Both variables are expressed in log-levels, so ψ is the elasticity of real GDP with respect to night lights. The analysis was conducted at the country level due to the lack of reliable disaggregated GDP data for all six countries.

GDP data are retrieved from two sources. Annual data are taken from version 9.0 of the Penn World Tables (PWT); and quarterly data are retrieved from each country's statistical agency. Night lights data are then aggregated and merged to each GDP dataset in order to estimate the coefficients of the different model specifications used by Henderson et al. (2012), which include year and country fixed effects to control for differences in sensor settings across satellites, energy cost, and technological advance over time, as well as cultural differences in the use of night lights across countries.

Table 3 presents the results for a balanced panel of 6 Central American countries observed at an annual frequency over a period from 1992 to 2013. Column 1 shows the estimates for our baseline specification: annual growth. The coefficient on night lights (ψ), that is the elasticity of night lights to GDP, is positive and highly significant, and the within- R^2 is 0.942¹⁸. In column 2, we include country time trends to test whether night lights can predict fluctuations of GDP around a growth path. Again, we estimate a highly significant elasticity in the order of 0.23, and a within- R^2 of 0.986. This result is crucial because our main interest in the present paper is to see whether short-term deviations of GDP from a country's growth path are explained by hurricane strikes (Figure 3).

Table 3. Night lights and economic growth (annual data)

Dependent variables	Annual growth (1)	Annual fluctuations (2)	Annual growth (3)	Annual fluctuations (4)	Long-term growth (5)	Expansions & recessions (6)
ln (lights/area)	0.1834*** [0.0686]	0.2326*** [0.0567]	0.1581*** [0.0104]	0.2276*** [0.0569]	0.3264*** [0.0910]	
+ Δ ln (lights/area)						0.2467** [0.1046]
- Δ ln (lights/area)						-0.2186** [0.1039]
ln (count top-coded + 1)			0.0104 [0.0064]	0.0035 [0.0033]		
Observations	132	132	132	132	72	132
R^2 (within country)	0.942	0.986	0.943	0.986	0.299	0.146

Note: Sample of 6 countries from 1992 to 2013. All specifications except (5) include country and year fixed effects. Specification (5) uses demeaned variables, and (6) takes 10-year difference.

*** Significant at the 1 percent level.

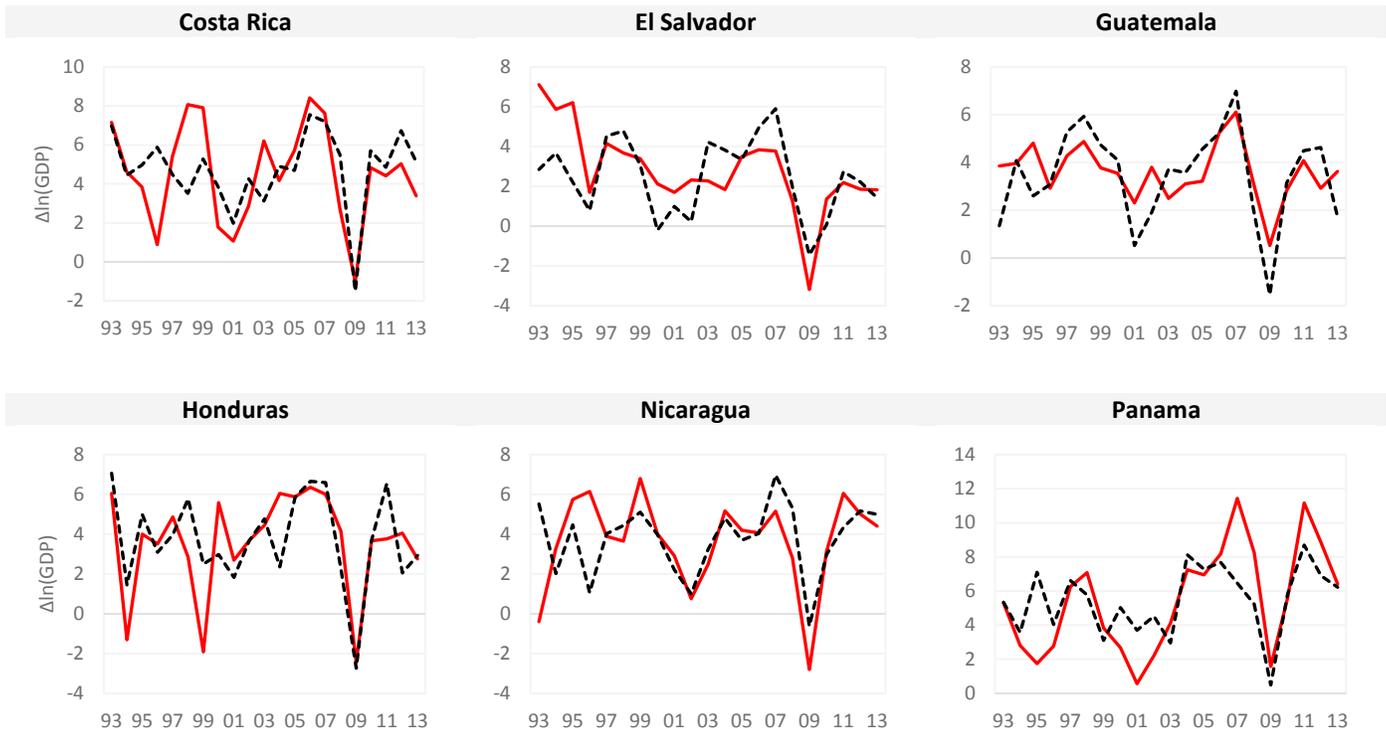
** Significant at the 5 percent level.

* Significant at the 10 percent level.

¹⁸ The R-squareds shown in Table 3 are high but not too different from those reported by Henderson et al. (2012) for low-middle income countries (0.903), and de Janvry et al. (2016) for Mexico (0.947).

In columns 3 and 4 of Table 3 we add controls for the number of top-coded pixels to investigate the phenomenon of sensor saturation, and find no evidence that it could lead night lights to underestimate economic activity from densely populated cities. It is true that the estimate of ψ drops from 0.18 to 0.16 in our baseline specification, but it remains more or less unchanged in our preferred specifications (2) and (4). In column 5 we evaluate whether changes in night lights are correlated with long-term growth, by regressing the change in log GDP on the change in log night lights for all 10-year differences between 1992 and 2013. And, similar to previous results, we find an estimate elasticity that is positive and significant at the 1 percent level. The difference, however, is that the coefficient is noticeably higher in this formulation, which implies night lights are better at predicting long-term economic growth as Henderson et al. (2012) suggested. Finally, in the last column, we explore the ratchet issue, that is whether night lights are capable of predicting economic expansions and recessions¹⁹. To do so, we first demean the data by regressing GDP and night lights on year and country fixed effects, so the resulting negative and positive residuals of night lights can be tested as proxies of economic downturns and expansions, respectively. We then regress the GDP residuals on both the positive and negative residuals in absolute value. The coefficients, as shown in column 6, are fairly similar, meaning that night lights do capture economic downturns and expansions.

Figure 3. Model predictions compared to observed GDP growth (Specification 2)



Finally, we follow Janvry et al.'s (2016) approach to further examine the spatial correlation between night lights and household's characteristics that are linked to income. Because changes in luminosity are driven, at least in part, by some indoor use of lights, some household's characteristics could be strongly correlated with night lights. Take the example of access to electricity. If the number of households with electricity in

¹⁹ Henderson et al. (2012) raise the concern that some lights growth might be derived from new lighting installations, meaning that some lights could be nondecreasing and incapable of capturing economic downturns.

a particular location increases over time, then the intensity of night lights associated with that location should also increase to reflect higher coverage. Here we examine that expected relationship.

Unfortunately, household-level data are limited or nonexistent in some Central American countries; and they are often not harmonized within the region, so cross-country comparisons could be challenging. We use data from the Integrated Public Use Microdata Series (IPUMS) International, a project of the University of Minnesota dedicated to collect and distribute census data from around the world. The data from IPUMS are harmonized but only available in some years for Costa Rica (2000, 2011), El Salvador (1992, 2007) and Panamá (2000, 2010). They are representative at the second level administrative unit (e.g., municipality in El Salvador), so night lights data are aggregated at that level.

Given the limitation of the data, we pick a handful of characteristics as dependent variables: number of households with access to electricity, has basic home appliance such as TV and refrigerator, has flush toilet, and possess car. We then regress the change in log of those variables on the intensity of night lights (DN) with ordinary least squares to obtain the coefficients (Table 4). The results reveal that the coefficients are positive and highly significant except for specification (5), and the R^2 range from 5% to 25%.

Table 4. Night lights and household characteristics

Dependent variables	$\Delta \ln$ (electricity) (1)	$\Delta \ln$ (TV) (2)	$\Delta \ln$ (flush toilet) (3)	$\Delta \ln$ (refrigerator) (4)	$\Delta \ln$ (autos) (5)
\ln (lights/area)	0.1923*** [0.0256]	0.1696*** [0.0239]	0.1203** [0.0550]	0.1309*** [0.0343]	0.0546 [0.0428]
Observations	188	188	133	133	187
R^2	0.251	0.219	0.049	0.103	0.015

Note: Cross-sectional sample only includes Costa Rica (2000, 2011), El Salvador (1992, 2007), and Panama (2000, 2010). Standard errors, clustered by the second administrative level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

2.3. The Hurricane Windstorm Model

A frequent difficulty in the modeling of windstorms is to incorporate the different ways in which tropical storms and hurricanes can disrupt economic activity and cause damage to people and property. Strobl (2012) discusses the characterization of windstorm damage, and argues that though destruction from hurricanes is usually caused by extreme winds, flooding and excess rainfall, and/or storm surge, all those forms are in fact correlated with wind speeds. In the same line of thinking, Ishizawa & Miranda (2016) explain that what makes hurricanes destructive is the strong wind speed coming in contact with some exposed stationary objects (e.g., bridges, buildings and cars.) that cannot safely absorb the energy carried in the moving air.

Following those studies, we use wind speed to characterize the potential damage of hurricane strikes in Central America. Specifically, we use a spatial hurricane windstorm model, developed by the WBG Latin-American and the Caribbean Disaster Risk Management (DRM) team and especially calibrated for the Central America region, to estimate surface gust wind speeds at a height of 10 meters for any affected places during the passing of a hurricane, with a resolution of 1 km², which is the same as the night lights data. This hurricane windstorm hazard model, described in full details in Pita et al. (2015), is capable not

only of producing local sustained wind speed data for all historic hurricanes in our sample window (1992-2011), but also estimating their trajectories and maximum sustained wind speeds (MSWS), which is our proxy for potential damage from hurricanes (PDH). In other words, it is capable of producing a fully exogenous measure of hurricane intensity and its potential destructive power at a fine-grained geographical level.

Like other wind field models used in recent studies (Bertinelli & Strobl, 2013; Elliot et al., 2015), this model is based on Holland's (1980) analytical model, which stands out for its reduced number of parameters and its accuracy in predicting the observed tracks and wind fields. To be specific, the model estimates the geographical distribution of the tangential gradient wind speeds (wind gusts) at a height of 10 meters, where wind speeds do the most damage, with a spatial resolution of 1 km². Put differently, the wind speed experienced at any location due to an observed hurricane is given by Equation 2.

$$V_g = \frac{V_T \sin(\varphi) - f \times r}{2} + \sqrt{\left(\frac{V_T \sin(\varphi) - f \times r}{2}\right)^2 + \left(B \times \frac{\Delta p}{\rho}\right) \left(\frac{RMW}{r}\right)^B \exp\left[-\left(\frac{RMW}{r}\right)^B\right]} \quad (2)$$

where:

- V_g is the sustained wind speed at a height of 10 meters at a spatial-resolution of 1 km²;
- B is Holland's shape parameter;
- Δp is the deficit of central and outer peripheral pressure in Pascal;
- ρ is the air density at the gradient height (kg/m³);
- RMW is the radius of maximum winds (m);
- r is the radius of any location to the center of the storm (m);
- V_T is the hurricane translation speed measured in m/s;
- f is the Coriolis parameter (1/sec); and
- φ is the angle between the North and the storm heading.

As mentioned before, the parameters in Equation 2 have been calibrated for the Central American region with observed tropical storm and hurricane activity in the East Pacific and North Atlantic basins. Different sources were used: the Global Land Cover Dataset 2000 for terrain roughness; the Shuttle Radar Topography Mission database for topography characteristics; the methodology proposed by the American Society of Civil Engineers in 1994 to estimate speed-up occurring in escarpments and ridges; and Vickery & Skerlj's (2005) estimation method to get the wind gusts factors.

In terms of accuracy and applicability, the estimates were benchmarked against the tracks and wind fields of several historical events. For instance, to evaluate the precision of the synthetic events and trajectories generated by the model, the estimated values on wind speed and trajectory for Hurricanes Mitch (1998) and Stan (2005) were compared with the values collected by the NOAA aircraft. Additionally, in-situ measurements recorded during the passing of Hurricane Jeanne and Frances in 2004 over Florida were evaluated against the predicted values by the model. In essence, in all the validation performed by Pita et al. (2015), the model was capable of producing estimates that were consistent with the observed storm activities, making it a reliable tool to identify windstorm hazard, and generate a fully exogenous measure of hurricane intensity in the Central America region at a high spatial resolution.

Of course, this study is not the first to take advantage of this novel model to generate windstorm hazard data. Ishizawa & Miranda (2016), for example, applied the same model to gauge the socioeconomic impact of hurricanes in Central America at the macro and micro levels. But unlike that study, this paper does fully exploit the advantages and features offered by a probabilistic hurricane windstorm model. First, instead of aggregating the data generated by the model at the country and sub-national level as Ishizawa

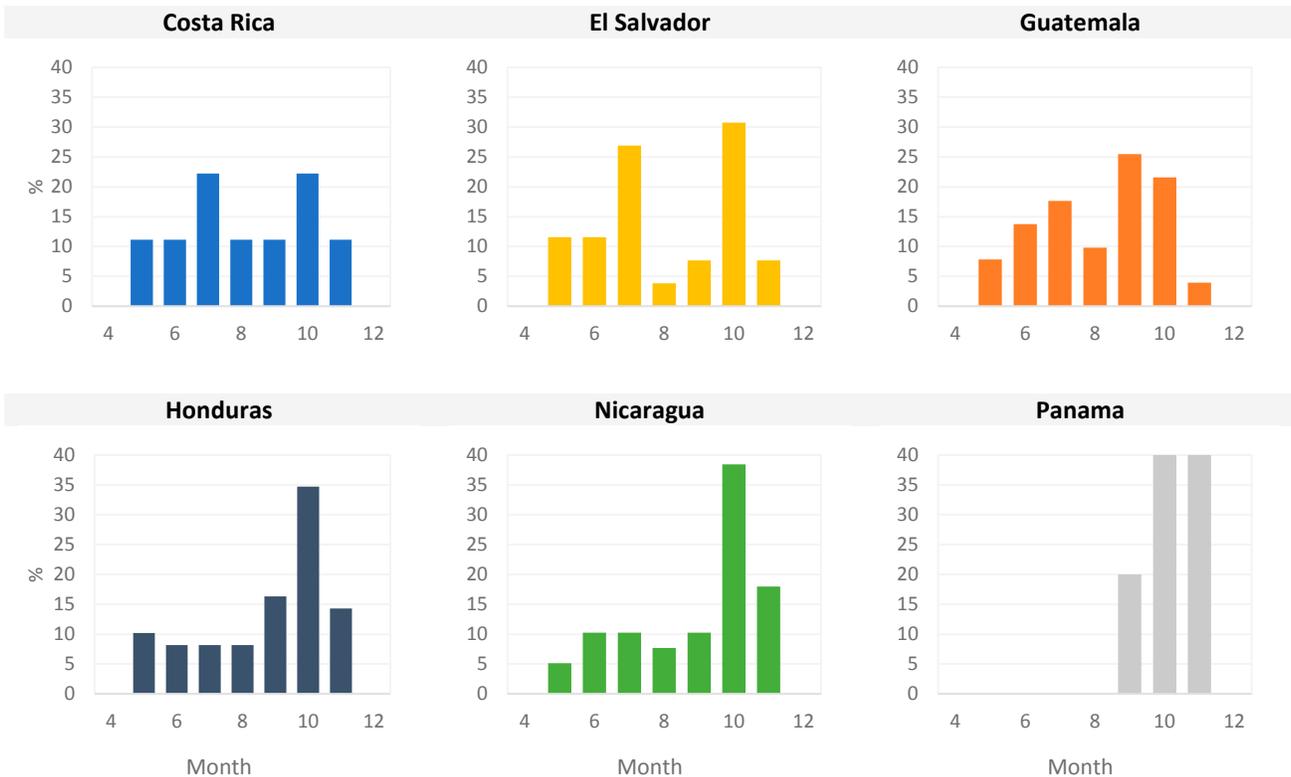
& Mirada (2016), we use the wind speed data at the highest spatial resolution (i.e., 1 km²): not only do the night lights data have the same resolution²⁰, but also spatial aggregation can create spurious causal relations. A result pointing to a statistically significant impact of hurricane winds on income, obtained from a country-level analysis, can be due to aggregation effects rather than a causal effect. By the same token, fine-grained data can provide useful information for causal inference as they enable us to fully exploit exogenous spatial variations in wind speed during the passage of hurricanes. Furthermore, when wind speed data are aggregated at a higher level, exposure of assets and population needed to be taken into account for the estimation of damages (Ishizawa & Miranda, 2016), which in turn put into question the exogeneity of wind speed as an instrument of potential damage.

Another common issue in studies that make use of a wind field model is the temporal mismatch between economic data and wind speed data. National accounts data and household surveys are often gathered and released on a yearly or quarterly basis, while most recent wind field models are often able to estimate wind speeds for any affected places at any point in time during the passing of a hurricane (e.g., monthly data). Studies that use night lights as a proxy of economic activity often face the same problem because they use NOAA's yearly frequency cloud-free night light composites, which are free to the public. This temporal mismatch could be problematic, particularly in the Central America region, where hurricanes tend to make landfall during the final months of the year (Figure 4). And because hurricanes are often localized events, their contemporaneous negative effects, if any, may well not be strong enough to put a dent in a country's yearly GDP growth nor change its trajectory, especially when the economy is in an expansionary phase. Also, the negative effects could linger throughout the first quarter of the following year²¹, or there could be multiple hurricanes in a given year. In any cases, the overall economic impact of hurricane strikes would be underestimated. We avoid those potential issues by matching wind speed data with monthly night lights data, so that regardless of the timing of the events, night lights will be able to pick up the immediate and short-to-medium term impact.

²⁰ In other words, we do not face the problem of spatial mismatch between night lights data and wind speed data.

²¹ Clear empirical evidence supporting long-term economic impact of hurricanes is rather limited. Most studies only find contemporaneous negative impact of hurricane strikes on economic activity (Bertinelli & Strobl, 2013; Ishizawa & Mirada, 2016).

Figure 4. Historical occurrence of hurricanes by month



2.4. Hurricane Data, Wind Speed Estimates and Potential Damage

During our sample period of 1992-2011, 70 hurricanes in the Central American region were registered by the National Hurricane Center (NHC) in the North Atlantic Hurricane database (HURDAT) and the Eastern North Pacific Tracks File. For all those hurricanes, we make use of our windstorm hazard model to simulate the MSWS experienced by the affected areas at a resolution of 1 km². The resulting wind speed data are then merged with night lights data.

Table 5 shows the number of hurricanes that have hit the region from 1992 to 2011. Records reveal that Guatemala and Honduras are the most prone to hurricane strikes. Out of the 70 hurricanes recorded by NHC, about 50 struck or affected those two countries, based on our windstorm hazard model's estimates. In contrast, Costa Rica and Panama have only witnessed 9 and 5, respectively, over a period of 20 years. Keep in mind that our model considers the possibility that hurricanes can strike a particular country with a certain wind speed without making landfall there or passing through it. For example, hurricane Mitch did not pass through Panama in 1998, but some areas of the country did experience winds up to 25 km/h, according to our model. Table 5 also shows the distribution of hurricanes by category of potential damage for each countries of the region. The hurricanes are classified into six categories based on the Saffir-Simpson Hurricane Wind Scale (SS), which uses sustained wind speed as a measurement of potential damage. Thus, a Category 1 hurricane, which is the least destructive in the SS scale, features sustained

wind speed of 74 to 95 mph (119 to 153 km/h), while a Category 5 hurricane, the most destructive, has sustained wind speed above 157 mph (250 km/h)²².

Table 5. Sample of hurricanes (1992-2011)

Country	Hurricane category (Saffir-Simpson Scale)						Total
	(0)	(1)	(2)	(3)	(4)	(5)	
Central America	26	8	8	9	10	9	70
Costa Rica	4	1	1	2	1	0	9
El Salvador	9	4	2	2	7	2	26
Guatemala	18	6	5	6	8	8	51
Honduras	21	4	5	5	8	6	49
Nicaragua	15	4	5	5	5	5	39
Panama	1	1	0	1	0	2	5

It is commonly assumed in recent papers that there is a wind speed threshold in which a tropical cyclone will cause devastating damage, implying that the relationship between MSWS and the economic losses on the ground is non-linear. Strobl (2012) and Bertinelli & Strobl (2013), for example, consider the category 3 as the cutoff point in the SS scale²³, and input estimated wind speed below 111 mph (178 km/h) as 0 in their regression analysis. However, one problem with that assumption is that the SS scale, which has been shown to be a useful tool for alerting about the potential impact of hurricanes in the US²⁴, might not adequately gauge economic damage in lower-middle-income countries such as El Salvador, Guatemala, Honduras and Nicaragua²⁵, where high poverty incidence and fragile dwellings are prevalent (Ishizawa & Miranda, 2016)²⁶. One way to deal with this problem is to set a lower wind speed threshold. Elliot et al. (2015), for instance, use a threshold of 93 km/h for coastal areas of China. Another way is to consider several groups of analysis with different thresholds. We follow the second approach and evaluate two groups: (1) hurricanes Category 1 or higher (threshold of 74 mph); and (2) hurricanes of Category 3 or higher (111 mph).

²² Sustained wind speed between 96 and 110 mph (154-177 km/h) are assigned to Category 2; 111-129 mph (178-208 km/h) to Category 3; 130-156 mph (209-251 km/h) to Category 4. Tropical cyclones with wind speed below 74 mph are classified as tropical storms (39-73 mph or 63-118 km/h) and tropical depressions (≤ 38 mph or ≤ 62 km/h). We group them as Category 0.

²³ According to the NHC, during the passage of a Category 3 hurricane, “well-built framed homes may incur major damage or removal of roof decking and gable ends. Many trees will be snapped or uprooted, blocking numerous roads. Electricity and water will be unavailable for several days to weeks after the storm passes.” Further explanation of the potential damages associated with each category can be found at <http://www.nhc.noaa.gov/aboutshws.php>.

²⁴ Pielke et al. (2008) investigated the economic damage caused by hurricanes from 1990-2005 in the United States, and found that of the total damage, around 85% is accounted by hurricanes of categories 3 to 5.

²⁵ World Bank’s classification.

²⁶ According to the Socio-Economic Database for Latin America and the Caribbean (SEDLAC), developed by the World Bank, the percentage of dwellings of low-quality materials in the Central America region reach as high as 46% in Guatemala, 31% in El Salvador, 15% in Nicaragua, and 14% in Honduras.

Figure 5. Central America's hurricane track by intensity

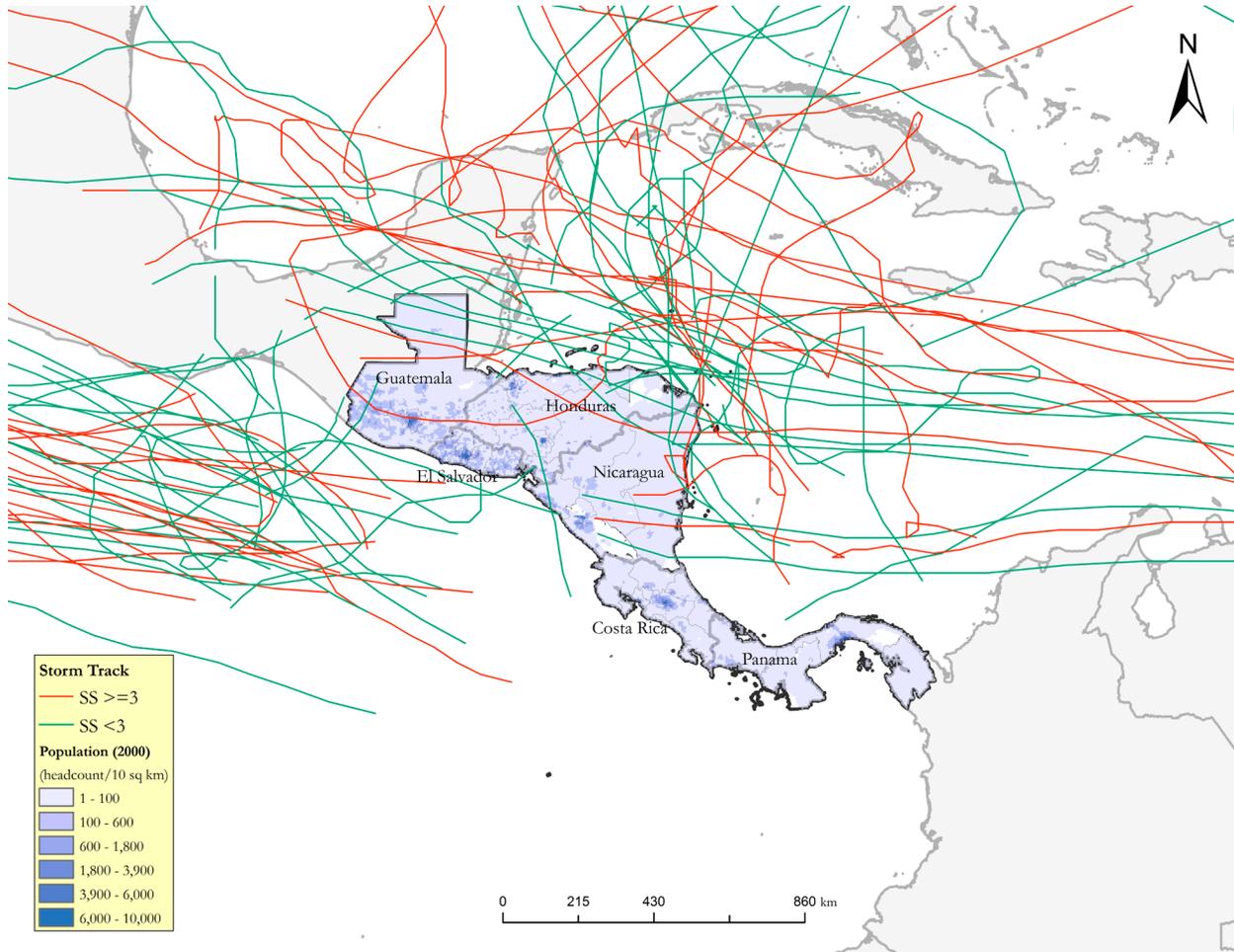


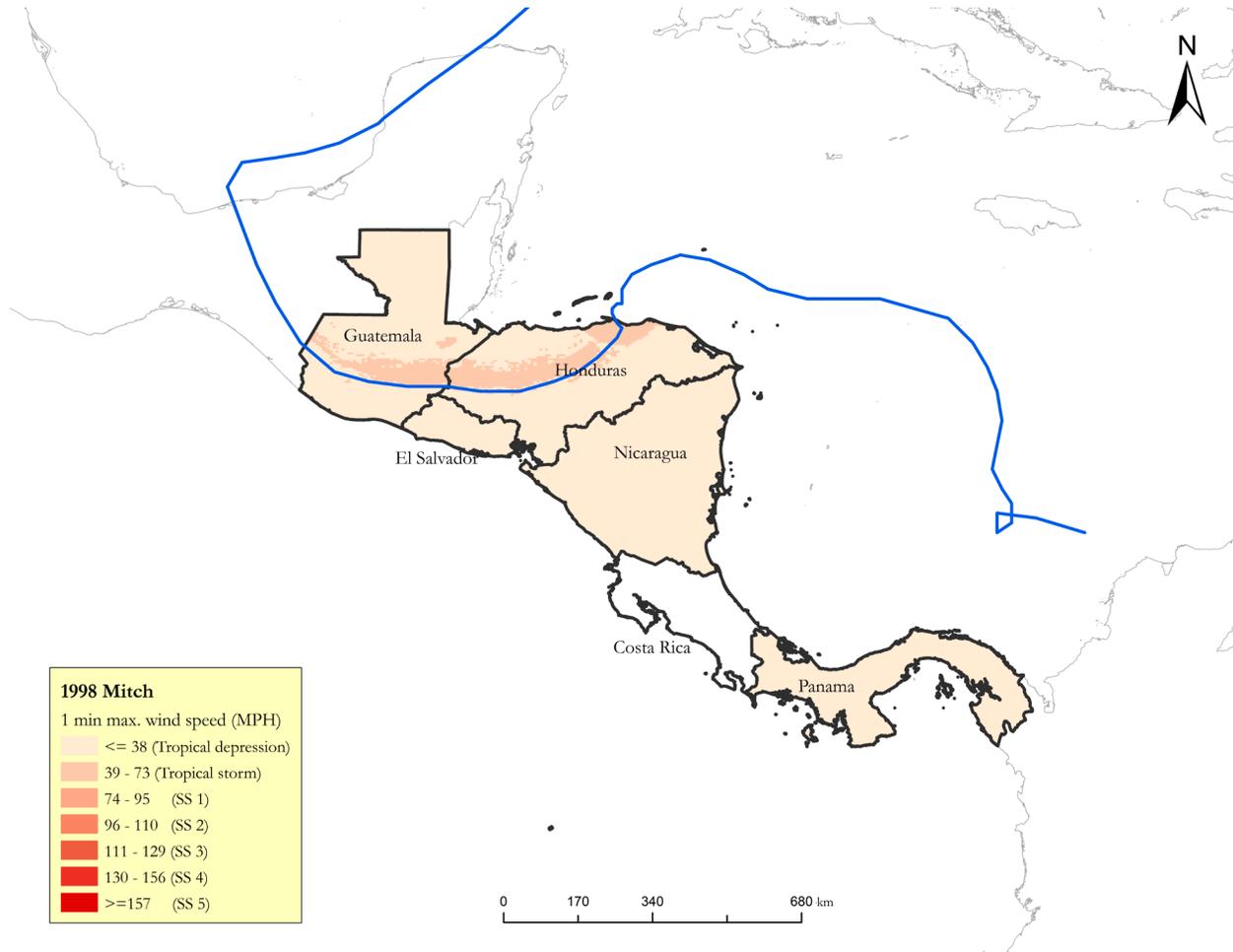
Figure 5 depicts the tracks of the 70 hurricanes in our sample period, classified by their intensity and along with the population distribution based on data from 2000. The first point to highlight here is the fact that few hurricanes are classified as Category 3 or higher (28 out of the 70). Second, those hurricanes of high intensity affected mostly Guatemala (22) and Honduras (19). Although both countries face similar risks of hurricane damage, an important distinction is that, due to their geographic locations, Guatemala is more prone to cyclones originated in Eastern North Pacific Ocean, and Honduras usually face hurricanes originated from the North Atlantic Ocean. Third, and more importantly, we need to distinguish between the scale assigned to a hurricane and the estimated MSWS with which that particular event hit the affected areas during its passing. It is not unlikely that a hurricane reaches category 3 over the open sea²⁷, but losses strength by the time it makes landfall. In that case, its intensity might decrease even more as it moves further inland, and ends up striking the exposed areas with a MSWS far below 111 mph, which is the commonly used threshold for a hurricane to inflict extensive economic damage. Hence, our proxy for potential damage from hurricane (PDH) is defined as follows:

$$PDH_{i,j,t} = \begin{cases} MSWS_{i,j,t}, & MSWS_{i,j,t} \geq \rho \\ 0, & MSWS_{i,j,t} < \rho \end{cases} \quad (3)$$

²⁷ Then that hurricane would be classified as Category 3 in the SS scale.

where MSWS is the maximum sustained wind speed generated by hurricane j at locality or pixel i in month t , and ρ is the threshold, which takes the value 74 mph for group 1, and 111 mph for group 2. The assumption behind Equation 3 is that economic damage occurs when the wind experienced by a locality is equal or above the threshold, otherwise it would be zero.

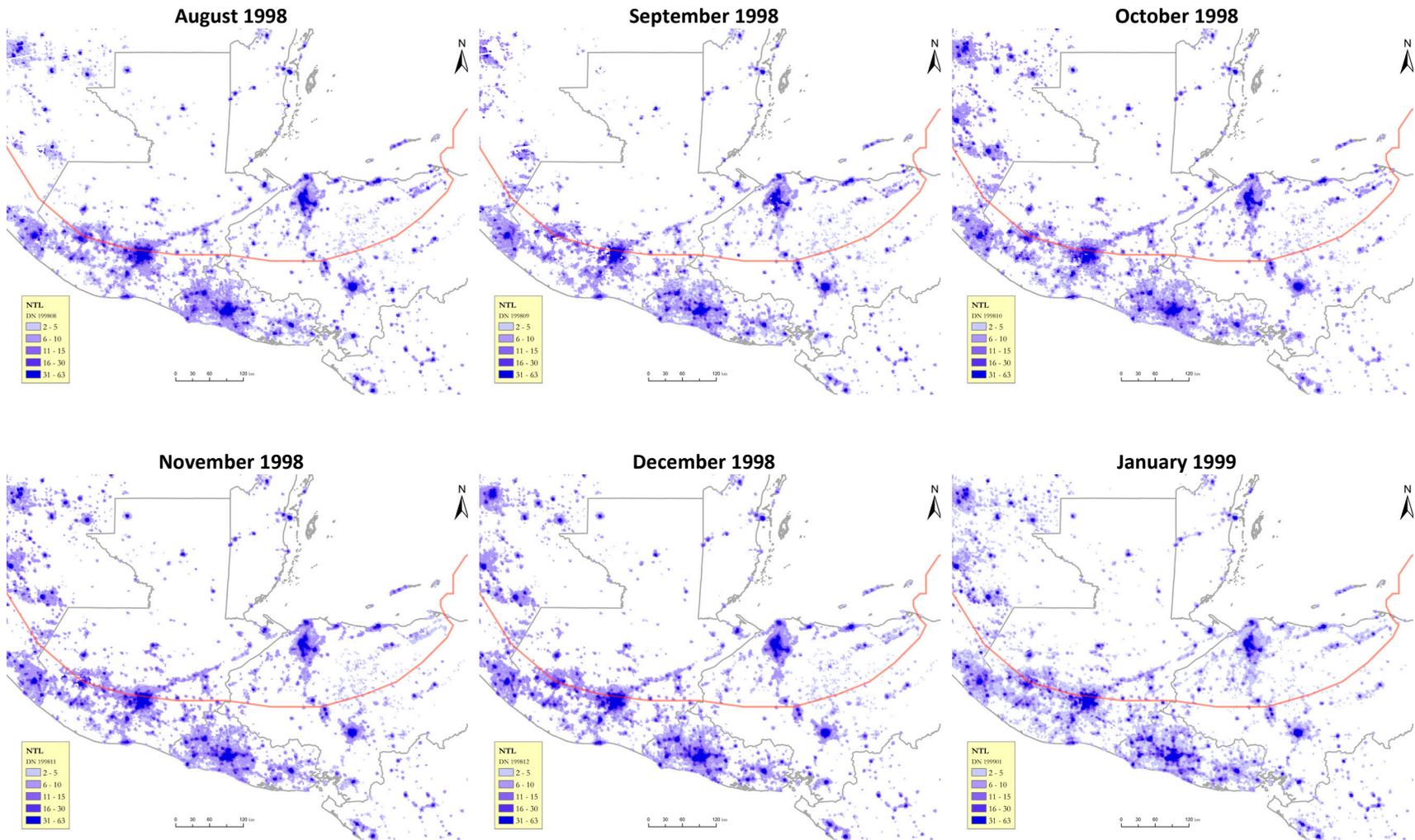
Figure 6. Trajectory of hurricane Mitch and its maximum sustained wind speed



With this consideration in mind, our sample of category-3 (or higher) hurricanes narrows down to only 4 events: Joan-Miriam (1988), Cesar (1996), Mitch (1998), and Felix (2007). Of those 4, only Mitch struck populated areas or exposed assets in Honduras (i.e., pixels with $DN > 0$) with wind speeds equal or above 111 mph, according to our windstorm hazard model. Figure 6 shows the specific trajectory and intensity of hurricane Mitch. The limitation of having only one event of Category 3 or higher in our second group of analysis is that any result we could draw from our econometric analysis will be entirely associated with Mitch. In that sense, a good understanding of the developments of hurricane Mitch in Honduras is necessary for us to put the results into context and read them properly.

Finally, by combining hurricane-generated wind speed data with night lights data, we can assess the effects of hurricane strikes on night lights intensity and local economic activity. A visual representation of how hurricanes affect luminosity over time is shown in Figure 7, which depicts the effects of the passing of hurricane Mitch in Honduras and Guatemala. It shows a noticeable reduction in lights intensity in the first two months after the event (i.e., Dec 1998 and Jan 1999).

Figure 7. Night lights intensity in Honduras and Guatemala before, during and after the passing of hurricane Mitch, Oct 22 - Nov 9, 1998



3. EMPIRICAL APPROACH

The identification of the causal effect of hurricanes on economic activity is challenging. Most empirical works rely solely on the Emergency Events Database (EM-DAT), which provides self-reported information on disaster losses such as the direct monetary damage and the number of people killed, to define their independent variables (Cavallo & Noy, 2011). The problem, as Hsiang & Jina (2014) noted, is that these self-reported damages tend to be larger among poor countries, which in turn have weaker conditions for economic growth. Therefore, the estimated impact of hurricane could be confounded by those economic conditions, undermining not only the quality of the estimates but also their validity.

We overcome this issue by using an objective and fully exogenous measure of potential destruction from hurricane (PDH). Specifically, we use a probabilistic windstorm hazard model to reconstruct the path and intensity of every hurricane recorded in Central America during 1992-2011. Our focus is on the maximum sustained wind speed (MSWS) that the affected areas (at a resolution of 1 km²) experienced during the passing of hurricanes, which serves as our proxy for PDH. Since MSWS is calculated using meteorological data that, in principle, are objectively collected and independent of a country's economic conditions, our proxy would not have the same issue as variables built from the EM-DAT²⁸.

On a more fundamental level, we argue that, given the nature of hurricanes, the MSWS can be treated as exogenous shocks. Hurricanes are considered sudden-onset hazards²⁹, normally arriving with a few days warning, producing extreme winds along its path, and lasting for a few days as well. Their formation, path, and intensity are “stochastic and difficult to predict more than a few days in advance” (Hsiang & Jina, 2014, p. 8). Hence, this randomness can be a source of exogenous temporal variation of the potential damage from hurricanes (proxied by the MSWS) within a particular location, giving us the confidence that the estimated effects are causal.

That being said, our identification strategy is akin to that of recent work on the economic impact of storms: exploit the random temporal variation in exposed intensity within a particular location (Bertinelli & Strobl, 2013; Hsiang & Jina, 2014; Elliot et al., 2015; Ishizawa & Miranda, 2016). The analysis is based on a pixel-by-month of light intensity (DN) panel, comprising the territory of 6 countries of the region over a 238-month period. Our benchmark specification is given by Equation 4:

$$\Delta \ln DN_{it} = \alpha + \sum_{L=0}^k \beta_L PDH_{it-L} + CFN_{it} + \mu_i + \gamma_T + \theta T + \varepsilon_{it}, \quad (4)$$

where $\Delta \ln DN_{it}$ is the natural-log difference of observed night light intensity between month t and month $t - 12$ in location i (i.e., the 12-month growth rate); PDH_{it-L} is our proxy for potential damage from hurricane in location i on month $t - L$, defined in Equation 3; CFN_{it} is the number of cloud-free night observations used to produce DN_{it} ; μ_i is a pixel-specific fixed-effect; γ_T is a year fixed-effect; θT is a linear time trend (year); and ε_{it} is the random error term. Notice that the number of lags (k) is not set in the equation. In theory, we can set any number, but as the number of lags increases, the estimation

²⁸ Noy (2009) emphasizes that a measure of potential damage constructed from only the physical characteristics of the disaster (e.g., sustained wind speed) would possibly avoid the endogeneity issue. Of course, transformations of the measure can sometimes undermine the exogeneity assumption. For example, Ishizawa & Miranda (2016) built hurricane damage indexes at the national level by combining MSWS (a fully exogenous measure) and population density (strongly correlated with economic activity) in order to reduce measurement error of MSWS. So the resulting index would not be fully exogenous. We do not face the same trade-off because we use only sustained wind speed as our damage index.

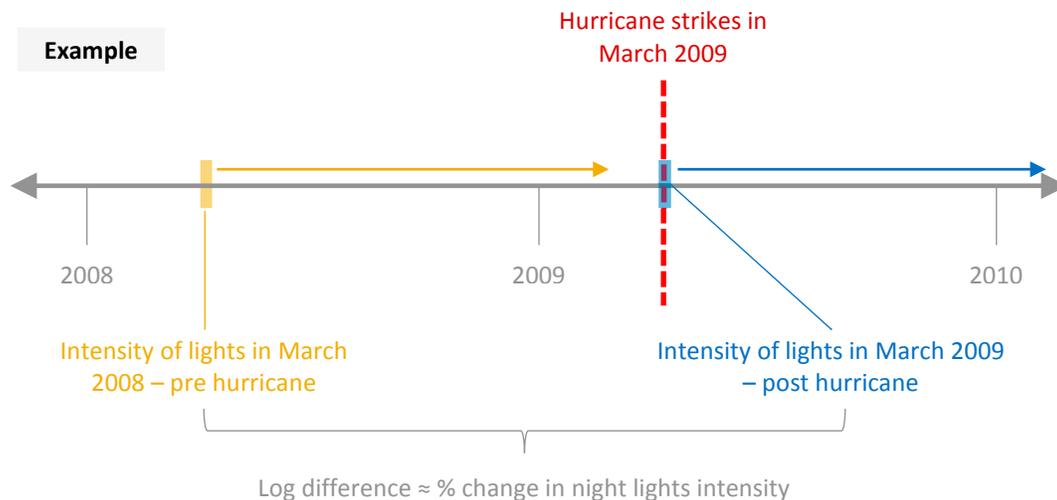
²⁹ Hurricanes, cyclones and typhoons are typically classified as rapid onset events, in contrast to sea-level rise or drought, which are considered as low onset events.

also becomes computationally more demanding, so we set $k = 12$ for our benchmark specifications. Figure 8 shows a graphical representation of the dependent variable in equation (4).

The inclusion of μ_i is to control for unobserved time-invariant effects that might bias our estimates of the causal effects of hurricane strikes on local economic activity (β). Particularly, we consider the possibility that locations that are often exposed to hurricanes have developed characteristics like proper disaster awareness and mitigation capacity, which are possibly invariant in the short-to-medium term (Bertinelli & Strobl, 2013). We also include year fixed effects (γ_t) and a regional time trend (θ_t) to account for the lack of calibration across satellites, and common factors to all countries, respectively.

One concern in this specification is the issue of cross-sectional and temporal dependencies in large-scale panel datasets. As Hoechle (2007) explains, actual information of microdata panels is often inflated since observations are likely to be spatially and temporally correlated, leading to biased standard errors and possibly inaccurate statistical inference if we use the standard fixed-effects estimator³⁰. The use of panel clustered standard errors could mitigate the issue to some extent as they are robust to heteroscedasticity and autocorrelation. However, in the words of Vogelsang (2012), “the validity of panel clustered standard errors requires that individuals in the cross-section be uncorrelated with each other, i.e. no spatial correlation in the cross-section.” (p. 303). We can, of course, have standard errors clustered at the country level and assume that pixels (locations) between clusters are uncorrelated. The drawback of that approach is that we have only 6 countries in the sample, which will necessarily overinflate the standard errors for Equation 4. Instead, we use standard errors proposed by Driscoll and Kraay (1998), who demonstrated their robustness to very general forms of spatial and temporal correlation in the panel³¹.

Figure 8. Graphical representation of the dependent variable



³⁰ We also obtain standard errors from a traditional fixed-effects estimator. For a damage threshold of 111 mph, almost all coefficients on PDH (β_t) remain statistically significant. However, for a threshold of 74 mph, the traditional estimator, which ignores spatial correlation, seems to lead to overly optimistic standard errors.

³¹ “[Driscoll-Kraay] standard errors are computed by taking cross-section averages of products of the regressors and residuals and then computing a HAC [heteroscedasticity autocorrelation consistent] estimator with those cross-section averages.” (Vogelsang, 2012, p. 304). We use a Stata implementation of Driscoll and Kraay’s covariance matrix estimator, developed by Hoechle (2007), that make use of pooled ordinary least squares and fixed-effects regression. The estimator is adjusted for use with unbalanced panels.

Another concern is the arbitrary definition of the dependent variable. As we argued before, monthly night lights data are potentially subject to measurement error, so taking 12-month growth rates will likely amplify the problem by creating artificial variations in the intensity of night lights. Though it might not bias our estimates because we control for CFN and there are no compelling reasons to expect the measurement errors are systematically correlated with PDH³², it might overinflate the standard errors and, therefore, lead to incorrect statistical inferences. Thus, as part of our robustness checks, we use several definitions (e.g., moving averages) to make sure our results are robust. We also evaluated simple averages –as the literature suggests using yearly night lights– however for monthly datasets, results are more erratic and volatile.³³

4. RESULTS AND DISCUSSION

4.1. Basic Results

Table 6 displays the results for our benchmark specifications. We start in columns 1 y 2, which report the estimates for a damage threshold of 74 mph. The coefficients on *PDH* in both specifications reveal that contemporaneous effects of hurricane strikes (i.e., within the same month) on night lights intensity are negative but statistically not significant. The negative effects begin to be highly significant one month after the event, and further intensify in the following. Our estimates suggest that the luminosity of a particular location hit by sustained wind speeds of 74 mph decreases by 12% to 15% on average in the first two months following the event. We find no significant effects beyond the second month, except for months 11th and 12th, though the positive sign on PDH_{t-12} requires further explanation as it may highlight the presence of measurement error or point to the beginning of the recovery phase. We will explore the dynamics of the longer-term effects of hurricanes in Section 4.2.

The previous results are insightful and shed light on the validity of the damage threshold commonly used in the literature. Most recent papers assume that extensive damage only occurs when wind speed reaches 111 mph. That assumption is based on Pielke et al. (2008), who finds that 85% of the economic damage caused by hurricanes in the United States from 1990-2005 was accounted by those of categories 3, 4 and 5. Our findings challenge the validity of that assumption. First, we find the negative effects of hurricanes to be significant but short-lived, so temporal aggregation (e.g., yearly frequency data) could make it hard to spot those short-lived effects, and wrongfully validating that threshold³⁴. Second, the proposed threshold could be adequate for high income countries, but it does not hold in the Central America region, adding more evidence to what Ishizawa & Miranda (2016) already found.

³² The coefficients (β_L) remain virtually unchanged when CFN is excluded in the benchmark specification, suggesting that potential measurement error is not systematically correlated with PDH.

³³ Results available upon request.

³⁴ We use yearly frequency night lights data to corroborate our main results. We find no significant effects of hurricane strikes on night lights for a threshold of 74 mph, underling the importance of temporal disaggregation in the analysis. Results are available upon request.

Table 6. Fixed-effects panel regressions: impact of hurricane strikes on night lights intensity

	MSWS \geq 74 mph		MSWS \geq 111 mph	
	Dummy variable (1)	Wind speed (2)	Dummy variable (3)	Wind speed (4)
PDH_{t-L}				
$L = 0$	-0.0047 [0.0622]	-0.0145 [0.0723]	-0.1664*** [0.0240]	-0.1309*** [0.0197]
$L = 1$	-0.1406** [0.0596]	-0.1607** [0.0683]	-0.1127*** [0.0224]	-0.0699*** [0.0184]
$L = 2$	-0.1819*** [0.0358]	-0.2055*** [0.0342]	-0.1314*** [0.0227]	-0.0982*** [0.0186]
$L = 3$	0.0417 [0.0813]	0.0402 [0.0942]	-0.1030*** [0.0297]	-0.0891*** [0.0244]
$L = 4$	0.0902 [0.0909]	0.0854 [0.1107]	-0.4312*** [0.0288]	-0.3393*** [0.0236]
$L = 5$	-0.0436 [0.0340]	-0.0536 [0.0346]	-0.1985*** [0.0293]	-0.1677*** [0.0240]
$L = 6$	-0.0613 [0.0866]	-0.0657 [0.0971]	0.1524*** [0.0290]	0.1045*** [0.0237]
$L = 7$	-0.0599 [0.1250]	-0.0706 [0.1490]	-0.0163 [0.0251]	-0.0212 [0.0204]
$L = 8$	0.0374 [0.0565]	0.0502 [0.0667]	---	---
$L = 9$	0.0287 [0.0454]	0.0412 [0.0575]	---	---
$L = 10$	0.1377 [0.0945]	0.1312 [0.1259]	-0.3335*** [0.0298]	-0.2763*** [0.0243]
$L = 11$	-0.2516*** [0.0415]	-0.2951*** [0.0422]	-0.4549*** [0.0288]	-0.3627*** [0.0236]
$L = 12$	0.1073** [0.0554]	0.1135* [0.0692]	-0.0498* [0.0289]	-0.0506** [0.0237]
CFN_{it}	0.0067*** [0.0022]	0.0067*** [0.0022]	0.0067*** [0.0022]	0.0067*** [0.0022]
Observations	21,766,078	21,766,078	21,766,078	21,766,078
R^2 (within country)	0.0244	0.0244	0.0244	0.0244

Note 1: Sample of 6 countries from 1992 to 2011, excluding pixels with DN=0 throughout the entire sample window. All specifications include pixel-level, year fixed effects, and linear time trend (year). Driscoll and Kraay Robust Standard Errors in parenthesis.

Note 2: MSWS is expressed in 100 mph. PDH takes different forms: in (1) and (3) PDH is a dummy variable that takes the value 1 if MSWS \geq 0.74 or MSWS \geq 1.11, respectively; while in (2) and (4) PDH takes the actual values of MSWS.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Columns 3 and 4 of Table 6 report the results for a threshold of 111 mph (i.e. hurricanes of category 3 or higher in the Saffir-Simpson Scale). As we mentioned before, those results are entirely associated with

the developments of hurricane Mitch in Honduras because it is the only event that has hit populated areas with sustained wind speed higher than 111 mph. The extensive damage caused by hurricane Mitch in Honduras has been well-documented. Mitch hit Honduras and other areas of Central America, especially Nicaragua, from 25 October to 1 November 1998, affecting 6.2 inhabitants (76.6% of the population) and causing economic damages of over US\$3.7 billion (ECLAC, 1999) or around two-thirds of the country's GDP in 1997.³⁵ While the objective of this paper is to understand the dynamics and magnitude of the effects of hurricane strikes on economic activity in Central America, we are aware of the limitation of the data, and the difficulty to generalize our findings to all countries of the region.

That being said, Table 6 reports all the coefficients on PDH except for months 8 and 9 because of missing night lights data between June and July 1999 (probably owing to late sunset during summer months). In contrast to the previous results, there is a contemporaneous negative effect on night lights intensity, and the effects are statistically significant in almost all the 12 months following hurricane Mitch. Based on our estimates, a particular location hit by sustained wind speeds of 111 mph could, on average, experience a drop of 17% in the intensity of night lights in the first 12 months following the event.

While the magnitude of the impact (i.e., size of the coefficients) fluctuates over time, it falls substantially one year after the event, pointing to a possible reversal of the sign on PDH. If so, it would provide evidence to support or rule out the four competing hypotheses, proposed in the literature, that describe how GDP respond to natural disasters in the long-run: “creative destruction”, “build back better”, “recovery to trend”, and “no recovery”³⁶. Another observation here is the positive and statistically significant effect of hurricane strikes on the intensity of night lights in month 6. Although it is likely owing to an unusual spike in reconstruction activities, it is hard to pin down the exact reason. In fact, we investigate whether there is a similar pattern in international aid flows and government spending, but find no clear evidence to support that hypothesis.

4.2. Longer-term Effects

In this section we explore the longer-term effects of hurricane strikes on the growth of night lights, by expanding our window of analysis to 3 years³⁷. A simple way to estimate the coefficients would be to set the number of lags to 36 in Equation 4. However, given the size of the dataset (more than 21 million observations), that strategy would be inefficient, time-consuming, and computationally too demanding. A more appropriate strategy would be to split the lagged values of PDH that we are interested into three

³⁵ For a comprehensive assessment of the damage caused by hurricane Mitch in Honduras, see ECLAC (1999).

³⁶ These hypotheses are explained thoroughly in Hsiang & Jina (2014, p. 6-7). To sum up, the “creative destruction” hypothesis argues that natural disasters boost economic growth immediately because domestic demand for goods and services can increase rapidly on the back of higher demand for labor to substitute lost capital, and because large flows of international aid can help stimulate growth. In contrast, the “build back better” hypothesis postulates that the economy slips into recession initially due to capital losses, but as firms replace their lost assets with new ones, a country's long-run growth should rise. On the pessimistic side, the “recovery to trend” hypothesis argues that the impact of catastrophes on economic growth should be temporal, and the economy should gradually bounce back to its pre-disaster trend. Finally, the “no recovery” hypothesis theorizes that economic growth stays permanently lower than its pre-disaster trend, even though output might keep growing in the long-run.

³⁷ We need to be aware that attributing changes in the intensity of night lights to events that occurred in the distant past can be challenging to say the least. As we move further away from the event in time, it becomes more and more likely that some unobserved heterogeneities across locations and countries will vary in time. Therefore, fixed-effects estimates might not be unbiased. As the recovery phase can last many years after the hurricane, we assume the bulk of the reconstruction activities take place in the first 3 years.

partitions and estimate each of them independently (Equation 5). By doing so, we only need to estimate the coefficients for the last two partitions (i.e., $j \in \{13, 25\}$), given that when $j = 0$, Equations 5 and 4 are identical.

$$\Delta \ln DN_{it} = \alpha + \sum_{L=j}^{j+11} \beta_L PDH_{it-L} + CFN_{it} + \mu_i + \gamma_T + \theta T + \varepsilon_{it}, \quad \forall j \in \{0, 13, 25\} \quad (5)$$

An immediate concern about that strategy is that the arbitrary exclusion of lagged values of PDH in the specifications may lead to omitted-variable bias, thus over or underestimating β_L . We think, however, the concern is misplaced because hurricanes are stochastic events and independent to each other. In other words, the correlation between, let's say, PDH_{t-1} and PDH_{t-3} is close to zero, so even if significant lagged values of PDH are left out, the fixed-effects estimator would remain unbiased.

The estimated coefficients on the lags on PDH are exhibited in Table 7. Columns 1 and 3 show that, when the threshold is set to 74 mph, meaning that below which no damage occurs, the longer-term effects of hurricane strikes on night lights intensity (proxy for local economic activity) are in general not significant. There are, however, a handful of coefficients that are statistically significant. But the lack of a clear pattern in terms of magnitude and sign possibly suggests some unobserved effects were not properly captured by our model. Overall, our findings support the general belief that low-intensity hurricanes do not cause extensive nor lasting impact on a country's local economic activity. Nonetheless, we do find significant impact in the first two months after the event. Those short-lived effects are difficult to catch if low-frequency data (e.g., annual) are used.

A clear contrast can be observed in columns 2 and 4 of Table 7. When the threshold is set to 111 mph, we find positive and statistically significant effects during the second year and the first half of the third after the events. Interestingly, this temporary rebound in night lights is only fairly similar to the overall negative effects during the first year in terms of size, meaning that affected places are able to return to their pre-hurricane trajectory. However, we find no significant nor consistent effects during the second half of the third year. In fact, our estimates suggest the strength of the rebound reaches its peak at the end of the second year, and gradually wanes thereafter.

Given the lack of evidence of a strong and sustained recovery phase in the Central American region, it is probably reasonable to rule out the optimistic hypotheses: "creative destruction" and "build back better". We, however, cannot conclude which of the two remaining hypotheses (i.e., "recovery to trend" and "no recovery"³⁸). The night lights of the affected locations did experience a temporary rebound, but with no evidence of longer-term recovery attributed to the disaster, it is very difficult to tell whether the rebound was enough to return the night lights to their pre-hurricane trajectory.

³⁸ As we explained before, the "no recovery" hypothesis does not argue against the existence of a rebound. It argues that the rebound is not strong enough for post-disaster output to return to its pre-disaster trajectory.

Table 7. Fixed-effects panel regressions: longer-term impact of hurricane strikes on night lights intensity

	≥ 74 mph Wind speed (1)	≥ 111 mph Wind speed (2)		≥ 74 mph Wind speed (3)	≥ 111 mph Wind speed (4)
	<i>Left Panel</i>			<i>Right Panel</i>	
PDH_{t-L}			PDH_{t-L}		
$L = 13$	-0.0460 [0.0571]	-0.0055 [0.0220]	$L = 25$	0.1377*** [0.0510]	0.1478*** [0.0293]
$L = 14$	0.1687*** [0.0363]	0.1112*** [0.0226]	$L = 26$	-0.0833*** [0.0313]	0.0682** [0.0292]
$L = 15$	-0.1189 [0.0743]	0.1008*** [0.0267]	$L = 27$	-0.0128 [0.0503]	0.0439* [0.0243]
$L = 16$	-0.0171 [0.0791]	0.2056*** [0.0270]	$L = 28$	-0.0589 [0.0724]	0.1383*** [0.0236]
$L = 17$	0.1241*** [0.0419]	0.2674*** [0.0265]	$L = 29$	-0.0980 [0.0663]	0.1145*** [0.0243]
$L = 18$	0.0777 [0.0574]	0.0019 [0.0265]	$L = 30$	-0.0711 [0.0500]	0.1497*** [0.0233]
$L = 19$	0.0809 [0.0621]	0.1652*** [0.0264]	$L = 31$	-0.0593 [0.0466]	0.0491** [0.0218]
$L = 20$	-0.0833 [0.1247]	--	$L = 32$	-0.0393 [0.0406]	0.0965*** [0.0227]
$L = 21$	-0.1672*** [0.0204]	--	$L = 33$	-0.0089 [0.0355]	-0.0136 [0.0230]
$L = 22$	-0.0866 [0.0868]	0.2563*** [0.0264]	$L = 34$	-0.0195 [0.0289]	0.0188 [0.0216]
$L = 23$	0.0508 [0.0344]	0.1000*** [0.0264]	$L = 35$	-0.1631 [0.1178]	0.0441* [0.0234]
$L = 24$	-0.0107 [0.0718]	0.0766*** [0.0264]	$L = 36$	0.0762 [0.0786]	0.0279 [0.0230]
CFN_{it}	0.0046**	0.0046**	CFN_{it}	0.0039	0.0039
Observations	21,203,506	21,203,506	Observations	21,257,821	21,257,821
R^2 (within country)	0.0251	0.0250	R^2 (within country)	0.0244	0.0244

Note 1: Sample of 6 countries from 1992 to 2011, excluding pixels with DN=0 throughout the entire sample window. All specifications include pixel-level, year fixed effects, and linear time trend (year). MSWS is expressed in 100 mph. Driscoll and Kraay Robust Standard Errors in parenthesis.

*** Significant at the 1 percent level.

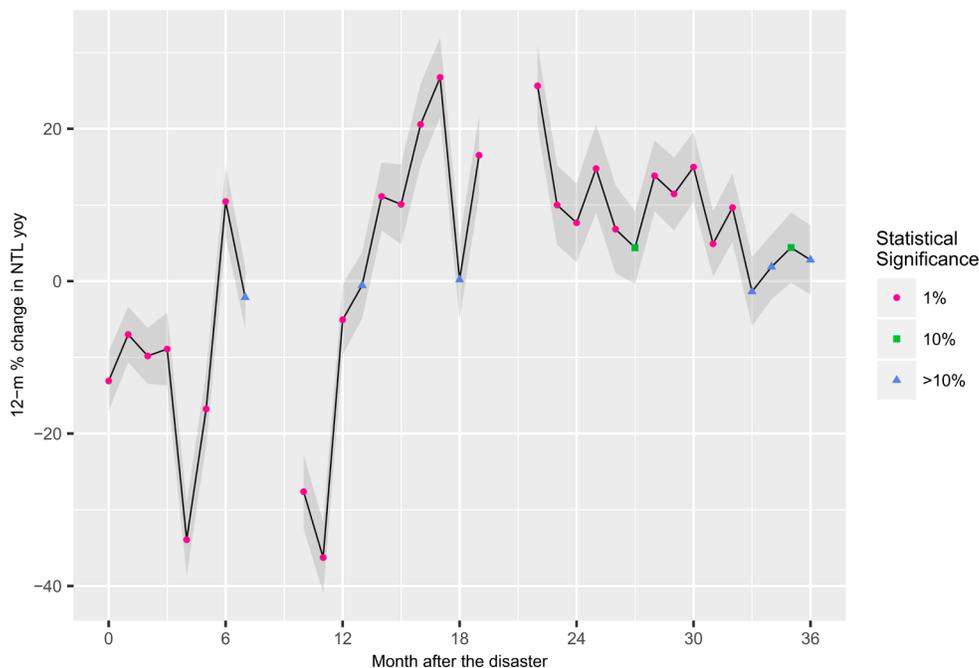
** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 9 is a summary of Table 6 (columns 3 and 4) and Table 7 (columns 2 and 4). It draws the point estimates from each regression within a 95% confidence interval. The markets show whether the specific month coefficient was at least statistically significant at different level of significance. This figure clearly shows that the impact of major windstorms on night lights show systematic negative effects up to 12 months after the hurricane strikes. After this period, the recovery period starts. These results, however,

are not tangible in economic terms. The next section translates our night light findings into economic terms.

Figure 9. Main results: marginal impact of hurricane strikes on night lights over time (threshold = 111 mph)



4.3. Impact on Economic Growth

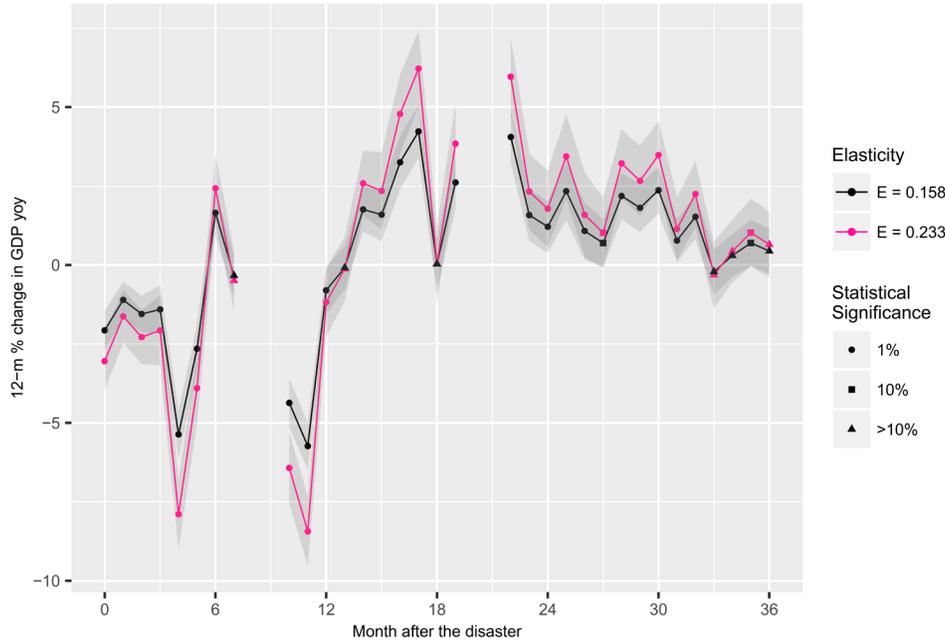
While the primary interest of this paper is to assess the impact of hurricanes on local economic activity in Central America, the absence of disaggregated data at the local level make it difficult, if not impossible, to quantify the impact directly. To overcome it, we use nocturnal light emissions from human activity as proxy for local economic activity. So far, we have discussed the effects of hurricanes on night lights. The next step is to translate our previous findings into economic terms. To do so, we follow the approach of Henderson et al. (2012), and use the elasticity of real GDP with respect to night lights (ψ) to establish a direct link between changes in luminosity and economic output (or income) at the local level for the Central America region. As detailed in section 2, our estimates of the elasticity (ψ) range from 0.16 to 0.23, depending on which specification is used³⁹. Those values are similar to other estimates for Mexico (between 0.11 and 0.25, de Janvry et al., 2016), and the world (between 0.18 and 0.29, Henderson et al., 2012).

Figure 10 shows the estimated impact of hurricane strikes on income growth at the local level during the first three years after the disaster for a threshold of 111 mph. As mentioned before, the negative effects on income growth are concentrated in the first year. The overall negative impact on growth is estimated to be in range of -2.4% to -3.5% for hurricanes that strike with PDH of 111 mph. If we take the mean of nonzero PDH (i.e., 122 mph), our calculations suggest an impact on income between -2.6% and -3.9%. To put things into context, Honduras, the most affected country during the passing of hurricane Mitch in late 1998, fell into recession the following year, and its GDP growth plummeted to -1.9% from 2.9% in 1998.

³⁹ We assume the country-level elasticity does not differ much from the local-level elasticity.

Even though the plunge in growth might not have been prompted entirely by hurricane Mitch, or might vary across space, our estimates seem to reflect reasonably well the magnitude and timing of the impact.

Figure 10. Average impact of hurricane strikes on income growth over time (threshold = 111 mph)



A temporary recovery phase begins in the second year as the positive effects of the recovery efforts start to outweigh the lasting negative effects. We estimate a boost that ranges between 2.5% and 3.6% in income growth in the second year for hurricanes that hit with PDH of 122 mph. In the third year, the impulse to income growth that is attributed to post-disaster efforts weakens significantly, especially during the second half of the year. Our assessments suggest a boost to growth that ranges between 1.4% and 2.1%. Again, Honduras saw a sharp rebound in its GDP growth (7.2%) in 2000, but it was short-lived as well as growth cooled down to only 2.7% in 2001.

5. ROBUSTNESS CHECKS

We have raised throughout this paper questions and potential concerns regarding the validity of empirical findings presented here. So in this section we explain the many robustness tests that have been conducted in order to rule out or weaken the possibility that the results are explained by factors other than the causal impact of hurricane strikes. Our focus is on the findings obtained for a threshold of 111 mph.

5.1. Measurement Error

We have discussed in section 2 the issues related to measurement error in night lights data. One potential problem is the lack of inter-satellite calibration, which could make comparisons of DNs across time periods to be problematic, particularly when two satellites overlap and produce two different sets of composites. The results presented in section 4 are based on an approach that uses the number of CFN (i.e., number of daily observations) as weights to compute the monthly DNs (“weighted satellites”). Therefore, we use two

alternative approaches to test the robustness of these results. The first uses only DNs captured by the most recent satellite (“new satellites”), and the second approach prioritizes the new satellite when the values of DN are different than zero, otherwise, it uses values gathered by the old satellite (“mixed satellites”). As expected, almost all coefficients on PDH stay highly significant and have the same sign as those shown in section 4 (Table 8).

Table 8. Fixed-effects panel regressions: impact of hurricane strikes on night lights (threshold = 111 mph)

	Weighted Satellites (1)	New Satellites (2)	Mixed Satellites (3)		Weighted Satellites (4)	New Satellites (5)	Mixed Satellites (6)
	<i>Left Panel</i>				<i>Right Panel</i>		
PDH_{t-L}				PDH_{t-L}			
$L = 0$	-0.1309*** [0.0197]	-0.1845*** [0.0462]	-0.1581*** [0.0356]	$L = 13$	-0.0055 [0.0220]	-0.0772*** [0.0286]	-0.0291 [0.0250]
$L = 1$	-0.0699*** [0.0184]	0.0275 [0.0457]	-0.0261 [0.0356]	$L = 14$	0.1112*** [0.0226]	0.3632*** [0.0280]	0.2799*** [0.0253]
$L = 2$	-0.0982*** [0.0186]	-0.3523*** [0.0465]	-0.3327*** [0.0356]	$L = 15$	0.1008*** [0.0267]	-0.0123 [0.0175]	0.0008 [0.0182]
$L = 3$	-0.0891*** [0.0244]	-0.1034*** [0.0274]	-0.0778*** [0.0207]	$L = 16$	0.2056*** [0.0270]	0.0807*** [0.0178]	0.0629*** [0.0187]
$L = 4$	-0.3393*** [0.0236]	-0.3291*** [0.0278]	-0.3098*** [0.0207]	$L = 17$	0.2674*** [0.0265]	0.2037*** [0.0209]	0.2254*** [0.0193]
$L = 5$	-0.1677*** [0.0240]	-0.1022*** [0.0274]	-0.1040*** [0.0207]	$L = 18$	0.0019 [0.0265]	-0.0596*** [0.0175]	-0.0632*** [0.0177]
$L = 6$	0.1045*** [0.0237]	0.1568*** [0.0288]	0.1584*** [0.0207]	$L = 19$	0.1652*** [0.0264]	0.0659*** [0.0185]	0.0580*** [0.0183]
$L = 7$	-0.0212 [0.0204]	--	0.1433*** [0.0215]	$L = 20$	--	--	--
$L = 8$	---	--	--	$L = 21$	--	--	--
$L = 9$	---	--	--	$L = 22$	0.2563*** [0.0264]	0.1988*** [0.0186]	0.1319*** [0.0182]
$L = 10$	-0.2763*** [0.0243]	0.0755** [0.0327]	-0.0159 [0.0207]	$L = 23$	0.1000*** [0.0264]	0.1256*** [0.0205]	0.0936*** [0.0193]
$L = 11$	-0.3627*** [0.0236]	-0.0752** [0.0302]	-0.1343*** [0.0207]	$L = 24$	0.0766*** [0.0264]	-0.1417*** [0.0178]	-0.1394*** [0.0180]
$L = 12$	-0.0506** [0.0237]	0.0633** [0.0276]	-0.1225*** [0.0207]				
CFN_{it}	0.0067*** [0.0022]	0.0101** [0.0039]	0.0101** [0.0036]	CFN_{it}	0.0046** [0.0022]	0.0077* [0.0040]	0.0078* [0.0036]

Note 1: Sample of 6 countries from 1992 to 2011, excluding pixels with DN=0 throughout the entire sample window. All specifications include pixel-level, year fixed effects, and linear time trend (year). Driscoll and Kraay Robust Standard Errors in parenthesis.

Note 2: MSWS is expressed in 100 mph.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure 11. Marginal impact of hurricane strikes on night lights over time (threshold = 111 mph)

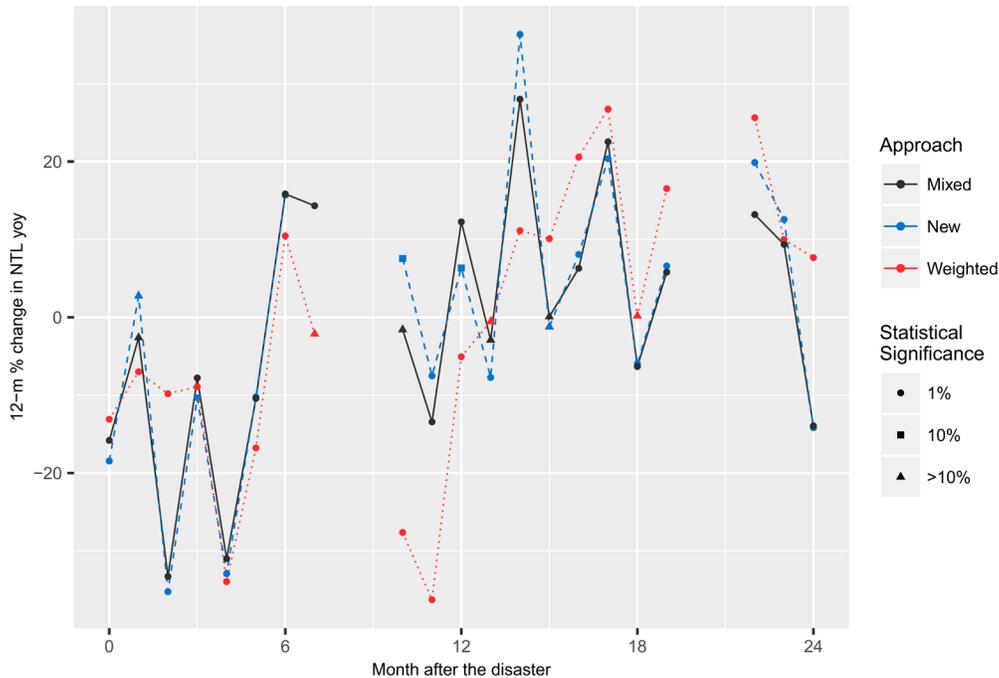


Figure 11 compares the coefficients on PDH of the three different approaches. Overall, all three approaches tell the same history, though some differences are fairly evident. First, the estimated coefficients of the alternative approaches are less stable. Second, the rebound in the second year of the post-disaster period seems to be less steady, though the aggregated effect is still positive. We strongly prefer the “weighted satellites” approach because it uses a larger set of information⁴⁰. Therefore, not only does it smooth the transition between old and new satellites⁴¹, and compensate for sensor degradation, it could also reduce measurement errors.

Another problem is associated with measurement errors is the use of monthly frequency data. Compared to yearly frequency data, the risks of measurement error are higher since for a given month the monthly DN are obtained from a smaller set of observations. And if the errors turn out to be systematically correlated with PDH, our proxy for hurricane damage, then estimates of the causal impact of hurricanes on local economic activity could be biased. One way to rule out that concern is to exclude the number of daily of cloud-free nights (CFN) from Equation 4 (i.e., our benchmark specification) and re-estimates the coefficients on PDH⁴². If the errors are not systematically correlated with PDH, then the coefficients would stay unchanged. Hence, we re-run our main specifications without CFN and compare the coefficients on PDH with those shown in Table 6. The results are reported in Table 9. In effect, the two set of coefficients are fairly similar in both significance and magnitude, indicating that the measurement errors, if any, are not systematically correlated with PDH.

⁴⁰ Two overlapping satellites do not pass over the same location at the same time.

⁴¹ This possibly explain the high volatility in the estimated coefficients of the other two approaches.

⁴² Another approach is to regress directly CFN on MSWS: if hurricane wind speeds are uncorrelated with the number of cloud-free nights, meaning that the quality of night lights data does not depend on the intensity of hurricanes strikes, then it is less likely the potential measurement errors could be systematically correlated with PDH. We regressed CFN on MSWS and tested different specifications, but did not find MSWS to be statistically significant in explaining CFN.

Table 9. Fixed-effects panel regressions: impact of hurricane strikes on night lights (threshold = 111 mph)

	Dummy variable		Wind speed	
	CFN not included (1)	CFN included (2)	CFN not included (3)	CFN included (4)
PDH_{t-L}				
$L = 0$	-0.1575*** [0.0238]	-0.1664*** [0.0240]	-0.1237*** [0.0195]	-0.1309*** [0.0197]
$L = 1$	-0.1195*** [0.0238]	-0.1127*** [0.0224]	-0.0754*** [0.0195]	-0.0699*** [0.0184]
$L = 2$	-0.1349*** [0.0238]	-0.1314*** [0.0227]	-0.1010*** [0.0195]	-0.0982*** [0.0186]
$L = 3$	-0.0892*** [0.0272]	-0.1030*** [0.0297]	-0.0779*** [0.0224]	-0.0891*** [0.0244]
$L = 4$	-0.4365*** [0.0272]	-0.4312*** [0.0288]	-0.3435*** [0.0224]	-0.3393*** [0.0236]
$L = 5$	-0.1913*** [0.0272]	-0.1985*** [0.0293]	-0.1619*** [0.0224]	-0.1677*** [0.0240]
$L = 6$	0.1529*** [0.0272]	0.1524*** [0.0290]	0.1049*** [0.0224]	0.1045*** [0.0237]
$L = 7$	-0.0358 [0.0228]	-0.0163 [0.0251]	-0.0369** [0.0187]	-0.0212 [0.0204]
$L = 8$	--	---	--	---
$L = 9$	--	---	--	---
$L = 10$	-0.3637*** [0.0272]	-0.3335*** [0.0298]	-0.3005*** [0.0224]	-0.2763*** [0.0243]
$L = 11$	-0.4664*** [0.0272]	-0.4549*** [0.0288]	-0.3717*** [0.0224]	-0.3627*** [0.0236]
$L = 12$	-0.0519* [0.0272]	-0.0498* [0.0289]	-0.0524** [0.0224]	-0.0506** [0.0237]
CFN_{it}		0.0067*** [0.0022]		0.0067*** [0.0022]
Observations	21,766,078	21,766,078	21,766,078	21,766,078
R^2 (within country)	0.0228	0.0244	0.0244	0.0228

Note 1: Sample of 6 countries from 1992 to 2011, excluding pixels with DN=0 throughout the entire sample window. All specifications include pixel-level, year fixed effects, and linear time trend (year). Driscoll and Kraay Robust Standard Errors in parenthesis.

Note 2: MSWS is expressed in 100 mph. PDH takes different forms: in (1) and (2) PDH is a dummy variable that takes the value 1 if MSWS ≥ 1.11 , respectively; while in (3) and (4) PDH takes the actual values of MSWS.

*** Significant at the 1 percent level.

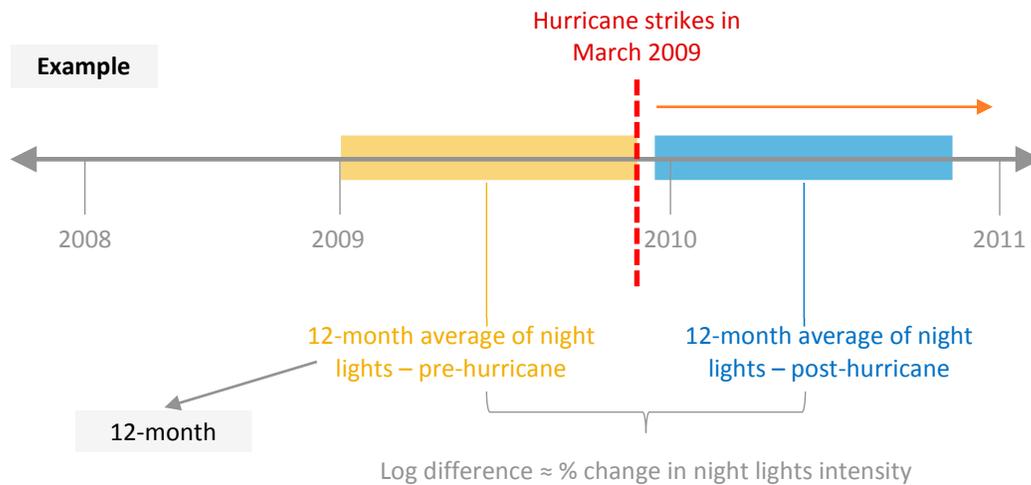
** Significant at the 5 percent level.

* Significant at the 10 percent level.

5.2. Specification Tests

Another major concern is whether the findings are robust to the definition of the dependent variable. As we alert in section 3, using 12-month growth rates of night lights may amplify potential measurement errors by creating variations in night lights that do not reflect changes in nocturnal human activity. Though the issue is unlikely to bias our estimates of the causal effects of hurricanes on night lights because there are no compelling reasons to believe the measurement errors are systematically correlated with PDH; it could lead to invalid statistical inferences by inflating the standard errors. One approach to ease the issue is to use moving averages. Specifically, the dependent variable is defined as the log difference between the average DNs for the 12 months before the hurricane and the 12-month average at various points after the disaster (Figure 12). Thus, any potential measurement errors in a particular month would be smoothed out.

Figure 12. Graphic representation of the alternative dependent variable



We report the new coefficients on PDH in Table 10. The first thing to notice is that all coefficients are highly significant and negative. In other words, the significance of the causal effects of hurricane strikes on local economic activity, reported in section 4, is robust to a different definition of the dependent variable. More importantly, those new results are completely consistent with the previous ones: (i) the negative effects are more intense during the first year of the post-disaster period; (ii) there is a temporary rebound during the second year that sends the affected locations back to their pre-disaster level, though it weakens over time.

Table 10. FE panel regressions: impact of hurricane strikes on night lights (alternative dependent variable)

	≥ 111 mph Wind speed (1)
PDH _{t-L}	
L = 12	-0.3552*** [0.1080]
L = 15	-0.2966*** [0.0993]
L = 18	-0.3835*** [0.0684]
L = 21	-0.1945*** [0.0558]
L = 24	-0.0913*** [0.0326]

Note 1: Sample of 6 countries from 1992 to 2011, excluding pixels with DN=0 throughout the entire sample window. All specifications include pixel-level, year fixed effects, and linear time trend (year). MSWS is expressed in 100 mph. Driscoll and Kraay Robust Standard Errors in parenthesis.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

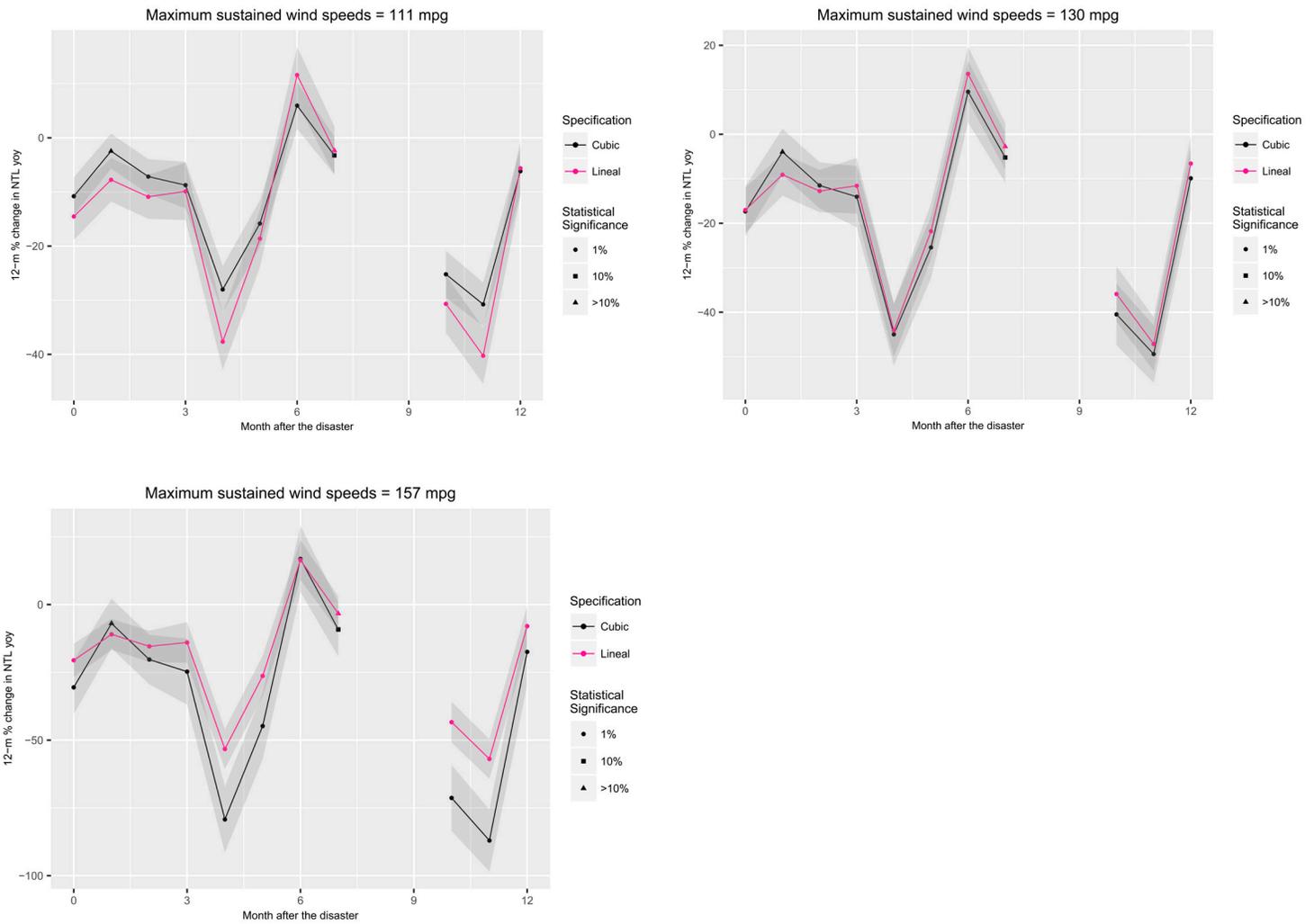
Also related to the specification of the model, our main results are too robust to the assumption of non-linearity between night lights and hurricane intensity. As some recent studies point out, economic damage caused by hurricanes and the maximum recorded wind speeds follow a cubic relationship. Thus, to test whether our results are sensitive to the linearity assumption, we redefine our proxy of potential damage from hurricane (PDH) as in Equation 6, and estimate again the coefficients for our benchmark specification (i.e., Equation 4).

$$PDH_{i,j,t} = \begin{cases} MSWS_{i,j,t}^3, & MSWS_{i,j,t} \geq 111 \\ 0, & MSWS_{i,j,t} < 111 \end{cases} \quad (6)$$

Figure 13 depicts the average effects of hurricane strikes on luminosity over time for cubic MSWS, and compares them with our benchmark results. In terms of significance, the non-linearity assumption hardly changes our benchmark results: the effects on lights intensity are statistically significant in almost all the 12 months following the event. In terms of effect size, however, there are interesting differences. When MSWS is set to 111 mph⁴³, assuming a linear relationship yields lightly larger effects on night lights. Both specifications give the same results if MSWS is 130 mph; but as wind speed increases beyond that level, a cubic relationship produces ever-larger effects. Although those findings strongly suggest that use of cubic MSWS is appropriate, they do not claim that a linear relationship fails to capture the effects properly as the true form is unknown. In fact, both specifications yield similar estimated effects for major hurricanes such as Mitch, which hit with an average MSWS of 124 mph.

⁴³ Since the coefficients on PDH of both specifications cannot be compared directly, we set different levels of wind speed and compare the average impacts instead.

Figure 13. Average impact of hurricane strikes on night lights: cubic MSWS



6. CONCLUDING REMARKS

Given the recurrence of hurricanes in Central America, it is important to understand the full extent of their influence on the region’s economic growth. Built on the contributions of recent studies, this paper uses a fully probabilistic windstorm model and monthly frequency night lights data to quantify the causal effects of hurricane windstorm on economic growth in the region. To our knowledge, this is one of the first studies that uses monthly nightlight images. Because hurricanes are local events that cause different effects across space, and are considered sudden-onset hazards, our empirical approach exploits the random temporal variation in exposed intensity within a particular location.

Our findings shed light on the short and long term impacts of major hurricanes. Importantly, our results point out an important issue not discussed before. Yearly nightlight data hide the short-term and long-term dynamics of the recovery phase. First, we find that the negative effects of hurricane strikes on economic activity are concentrated in the first year, with an estimated impact that ranges between -2.4% and -3.5% in GDP growth. Second, a temporary recovery phase begins in the second year as the positive effects of the recovery efforts start to outweigh the lasting negative effects. We estimate a boost to GDP

growth that ranges between 2.5% and 3.6% in the second year. Third, during the third year, the impulse to GDP growth that is attributed to post-disaster efforts weakens significantly, especially during the second half of the year. Our results are robust to different robustness checks.

There are, however, some important issues not addressed in this paper. Most importantly we do not address and evaluate what are the major driving forces of recovery. We observed a quick and rapid recovery after the 12 months, but we do not have the data to explore causal links differentiating investment types. Exploring these issues warrants further research.

7. REFERENCES

- Alesina, A., Michalopoulos, S., & Papaioannou, E. (2016). Ethnic Inequality. *Journal of Political Economy*, 124(2), 428-488.
- Bertinelli, L., & Strobl, E. (2013). Quantifying the Local Economic Growth Impact of Hurricane Strikes: An Analysis from Outer Space for the Caribbean. *Journal of Applied Meteorology and Climatology*, 52, 1688-1697.
- Cao, Z., Wu, Z., Kuang, Y., Huang, N., & Wang, M. (2016). Coupling an Intercalibration of Radiance-Calibrated Nighttime Light Images and Land Use/Cover Data for Modeling and Analyzing the Distribution of GDP in Guangdong, China. *Sustainability*, 8(108), 1-18.
- Cavallo, E., & Noy, I. (2011). Natural Disasters and the Economy: A Survey. *International Review of Environmental and Resource Economics*, 5(1), 63-102.
- Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic Natural Disasters and Economic Growth. *The Review of Economics and Statistics*, 95(5), 1549-1561.
- CEPAL. (2011). *Resumen Regional del Impacto de la Depresión Tropical 12-E en Centroamérica*. Mexico, D.F.: Comisión Económica para América Latina y el Caribe .
- Chen, X., & Nordhaus, W. (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, 108(21), 8589-8594.
- de Janvry, A., del Valle, A., & Sadoulet, E. (2016). *Insuring Growth - The Impact of Disaster Funds on Economic Reconstruction in Mexico*. Washington, DC: The World Bank .
- Dilley, M., Chen, R., Deichmann, U., Lerner-Lam, A., Arnold, M., Agwe, J., . . . Yetman, G. (2005). *Natural Disaster Hotspots - A Global Risk Analysis*. Washington, DC: The World Bank.
- Doll, C., Muller, J.-P., & Morley, J. (2006). Mapping regional economic activity from night-time light satellite imagery. *Ecological Economics*, 57, 75-92.
- Donaldson, D., & Storeygard, A. (2016). The View from Above: Applications of Satellite Data in Economics. *Journal of Economic Perspectives*, 30(4), 171-198.
- Driscoll, J., & Kraay, A. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80(4), 549-560.
- ECLAC. (1999). *Honduras: Assessment of the Damage Caused by Hurricane Mitch, 1998*. New York: Economic Commission for Latin America and the Caribbean.
- Elliott, R., Strobl, E., & Sun, P. (2015). The Local Impact of Typhoons on Economic Activity in China: A View from Outer Space. *Journal of Urban Economics*(88), 50-66.
- Elvidge, C., Baugh, K., Kihn, E., Kroehl, H., Davis, E., & Davis, C. (1997). Relation between satellite observed visible-near infrared emissions, population, economic activity and electric power consumption. *International Journal of Remote Sensing*, 18(6), 1373-1379.
- Elvidge, C., Cinzano, P., Pettit, D., Arvesen, J., Sutton, P., Small, C., . . . Ebener, S. (2007). The Nightsat mission concept. *International Journal of Remote Sensing*, 28(12), 2645-2670.
- Elvidge, C., Ziskin, D., Baugh, K., Tuttle, B., Ghosh, T., Pack, D., . . . Zhizhin, M. (2009). A Fifteen Year Record of Global Natural Gas Flaring Derived from Satellite Data. *Energies*, 2, 595-622.
- Ghosh, T., Powell, R., Elvidge, C., Baugh, K., Sutton, P., & Anderson, S. (2010). Shedding Light on the Global Distribution of Economic Activity. *The Open Geography Journal*, 3, 148-161.
- Harari, M., & La Ferrara, E. (2013). *Conflict, Climate and Cells: A Disaggregated Analysis*. London: Centre for Economic Policy Research.
- Henderson, V., Storeygard, A., & Weil, D. (2012). Measuring Economic Growth from Outer Space. *American Economic Review*, 102(2), 994-1028.
- Hodler, R., & Raschky, P. (2014). Regional Favoritism. *Quarterly Journal of Economics*(129), 995-1033.
- Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal*, 7(3), 281-312.

- Holland, G. (1980). An Analytic Model of the Wind and Pressure Profiles in Hurricanes. *Monthly Weather Review*, 108, 1212-1218.
- Hsiang, S., & Jina, A. (2014). *The Causal Effect of Environmental Catastrophe on Long-run Economic Growth: Evidence from 6700 Cyclones*. Cambridge: National Bureau of Economic Research.
- Huang, Q., Yang, X., Gao, B., Yang, Y., & Zhao, Y. (2014). Application of DMSP/OLS Nighttime Light Images: A Meta-Analysis and a Systematic Literature Review. *Remote Sensing*, 6, 6844-6866.
- Ishizawa, O., & Miranda, J. (2016). *Weathering Storms - Understanding the Impact of Natural Disasters on the Poor in Central America*. Washington, DC: Policy Research Working Paper.
- Keola, S., Andersson, M., & Hall, O. (2015). Monitoring Economic Development from Space: Using Nighttime Light and Land Cover Data to Measure Economic Growth. *World Development*, 66, 322-334.
- Letu, H., Hara, M., Tana, G., & Nishio, F. (2012). A Saturated Light Correction Method for DMSP/OLS Nighttime Satellite Imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 50(2), 389-396.
- Letu, H., Hara, M., Yagi, H., Naoki, K., Tana, G., Nishio, F., & Shuhei, O. (2010). Estimating energy consumption from night-time DMSP/OLS imagery after correcting for saturation effects. *International Journal of Remote Sensing*, 31(16), 4443-4458.
- Lo, C. (2001). Modeling the population of China using DMSP operational linescan system nighttime data. *Photogrammetric Engineering & Remote Sensing*, 67(9), 1037-1047.
- Mellander, C., Lobo, J., Stolarick, K., & Matheson, Z. (2015). Night-Time Light Data: A Good Proxy Measure for Economic Activity? *PLoS ONE*, 10(10), 1-18.
- Michalopoulos, S., & Papaioannou, E. (2013). Pre-colonial Ethnic Institutions and Contemporary African Development. *Econometrica*, 81(1), 113-152.
- Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*(88), 221-231.
- Pielke, R., Gratz, J., Landsea, C., Collins, D., Saunders, M., & Musulin, R. (2008). Normalized Hurricane Damage in the United States: 1900-2005. *Natural Hazards Review*, 9(1), 29-42.
- Pita, G., Gunasekera, R., & Ishizawa, O. (2015). *Windstorm Hazard Model for Disaster Risk Assessment*. Working Paper.
- Raupach, M., Rayner, P., & Paget, M. (2010). Regional variations in spatial structure of nightlights, population density and fossil-fuel CO₂ emissions. *Energy Policy*, 38, 4756-4764.
- Storeygard, A. (2016). Farther on down the road: transport costs, trade and urban growth in sub-Saharan Africa. *Review of Economic Studies*, 83(3), 1263-1295.
- Strobl, E. (2012). The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the Central American and Caribbean regions. *Journal of Development Economics*(97), 130-141.
- UNDP. (2004). *Reducing Disaster Risk: A Challenge for Development*. New York: United Nations Development Programme.
- Vickery, P., & Skerlj, P. (2005). Hurricane Gust Factors Revisited. *Journal of Structural Engineering*, 131(5), 825-832.
- Vogelsang, T. (2012). Heteroskedasticity, autocorrelation, and spatial correlation robust inference in linear panel models with fixed-effects. *Journal of Econometrics*(166), 303-319.
- Wu, J., He, S., Peng, J., Li, W., & Zhong, X. (2013). Intercalibration of DMSP-OLS Night-Time Light Data by the Invariant Region Method. *International Journal of Remote Sensing*, 34(20), 7356-7368.
- Zhang, Q., Schaaf, C., & Seto, K. (2013). The Vegetation Adjusted NTL Urban Index: A new approach to reduce saturation and increase variation in nighttime luminosity. *Remote Sensing of Environment*, 129, 32-41.