Quantifying the Local Economic Growth Impact of Hurricane Strikes: An Analysis from Outer Space for the Caribbean

LUISITO BERTINELLI

Centre de Recherche en Économie Appliquée, University of Luxembourg, Luxembourg, Luxembourg

ERIC STROBL

Ecole Polytechnique, Paris, France

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ABSTRACT

Studies of the impact of hurricanes on economic activity typically are restricted to a very aggregate level of analysis because of the lack of spatially disaggregated data. In this paper nightlight satellite imagery is employed as a measure of local economic activity in conjunction with a local proxy for potential hurricane destruction generated from a wind field model to statistically assess the impact of hurricane strikes on local economic growth. The regression results suggest that on average hurricane strikes reduce income growth by around 1.5% at the local level, with no effect beyond the year of the strike. This estimated impact from localized data is more than 2 times that implied by aggregate analyses.

1. Introduction

Hurricanes are usually associated with a considerable amount of economic losses that are often believed to leave long-lasting and devastating impacts on affected communities, particularly in developing countries. Appropriately alleviating the potential short- and long-term negative consequences of these losses and helping the local communities to quickly recover then crucially rests, in part at least, on the ability to accurately quantify the true impact. This has, however, remained a considerable challenge so far, as economic losses due to hurricanes have typically been presented by estimates of total physical damage.[1] There are, however, a number of concerns in using such figures as proxies for the actual economic impact of tropical storms. First, they tend to be fairly roughly estimated, relying on insurance claims or, as is more often the case for developing countries, on potentially biased estimates by the local government, the media, or international organizations. Perhaps more important, damage itself only measures direct losses and arguably constitutes a small portion of the total economic effect, which includes the usually much larger subsequent disruption to economic activity (see Hallegate and Przyluski 2010). There are now a handful of studies that have examined the impact of hurricanes on economic activity, but these have solely focused on very aggregate impacts—typically at the national or, in a few cases, at a fairly large regional level—because of the lack of appropriate, more disaggregated data.[2] The very nature of the storms themselves, however, as well as local community characteristics means that the economic impact, both direct and indirect, can vary widely across space.

In this paper we set out to rectify these weaknesses by taking an alternative approach to measuring the impact of hurricanes on local economies. To be more specific, we avail ourselves of time-varying estimates of nightlight intensity as captured by satellite images to measure

[1] See, for instance, the widely used ‘‘EM-DAT’’ database or Pielke et al.’s (2008) study of the United States.

[2] See Hsiang (2010) and Strobl (2012) for examples of studies of the impact of hurricanes on economic activity at the national level in the Caribbean Sea region and Nordhaus (2006) and Strobl (2011) for examples at the 1° latitude × 1° longitude and/or county level for the United States.

Corresponding author address: Luisito Bertinelli, CREA, University of Luxembourg, 162A, Av. de la Faïencerie, 1511 Luxembourg, Luxembourg.
E-mail: luisito.bertinelli@uni.lu

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the extent of local economic activity within the Caribbean Sea region and then estimate how this intensity was affected after a hurricane strike. To measure the local potential destructiveness of hurricanes, we employ a wind field model on historical hurricane tracks to calculate an approximation of the severity of the winds experienced at the geographical level of the nightlights' spatial units. Combining these potential destruction data series with the nightlight data provides us with a locally detailed time-varying dataset with which we can statistically estimate the effect of hurricane strikes on local economic activity.

We are, of course, not the first to use nightlight imagery as a proxy for local economic activity but follow the contributions of Chen and Nordhaus (2011) and Henderson et al. (2011), among others, who propose an empirical framework to employ nightlight imagery when data on income are not available or are of poor quality.[3] It can be argued that the Caribbean region serves as a natural case study for our analysis in that it is frequently hit by hurricanes. Moreover, there are no comprehensive income data available at the local level, limiting previous studies to aggregate analysis. For instance, Strobl (2012) uses country-level data to estimate the economic-growth impact of hurricane strikes in the region and finds an effect of 0.7% for an average hurricane, whereas Hsiang (2010) finds no impact on aggregate production in the Caribbean.[4]

The remainder of the paper is organized as follows. In the next section we describe our datasets, and in section 3 we provide some summary statistics. In section 4 we provide our regression analysis. We give conclusions in section 5.

2. Data and methods

a. Nightlight data

As a proxy for economic activity at the local level, we resort to data derived from satellite images of nightlight. To be more specific, in the early 1960s the U.S. military launched a weather satellite program that was intended to provide weather and climate data, among other cloud-cover imagery, to improve the effectiveness of military operations. Since the 1970s, this Defense Meteorological Satellite Program (DMSP) has been declassified and is instead mostly used to produce ground-level nighttime imagery, and the digital archive of this product extends back to 1992. In terms of coverage, each DMSP satellite has a 101-min near-polar orbit at an altitude of about 800 km above Earth's surface, providing global coverage 2 times per day, at the same local time each day.[5] In the late 1990s, the National Oceanic and Atmospheric Administration developed a method to generate "stable, cloud-free nightlight data sets by filtering out transient light, such as produced by forest fires, and other random noise events occurring in the same place less than three times" from these raw data [see Elvidge et al. (1997) for a comprehensive description]. The resulting images are percentages of nightlight occurrence for each pixel per year normalized across satellites to a scale ranging from 0 (no light) to 65 (maximum light). The spatial resolution of the original pictures was about 0.008° on a cylindrical projection (i.e., with constant areas across latitudes), which was later converted to a polyconic projection, leading to squares of about 1 km^2 near the equator. To get yearly values, simple averages across daily (filtered) values of grids were generated.

The annual nightlight data captured by these satellites essentially capture nocturnal human activity, such as electrified human settlements and gas flares, and we take this as a proxy for economic wealth. As an example, we depict in Fig. 1 nightlights for a selected number of Caribbean islands (Cuba, the Dominican Republic, and Jamaica) in 2003. Note in this regard that the brightly lit areas correspond to centers of economic activity (i.e., to the capital cities of the islands). The same relationship holds at the country level, where, for instance, the Bahamas, as one of the wealthiest islands in the region, is the country that is most lit. This is shown across the Caribbean in Fig. 2, in which the scatterplot of the logged values of nightlights per square kilometer relative to that of gross domestic product (GDP) per square kilometer across islands depicts a clear positive relationship between these two indicators. It is this positive relationship, thoroughly analyzed by Chen and Nordhaus (2011) and Henderson et al. (2011), that we use as our basis for employing nightlights as a proxy for local economic activity.

b. Hurricane data and the wind field model

While the extent of potential damage caused by hurricanes may depend on many factors, such as flooding,

[3] Other relevant references in this regard are Elvidge et al. (1997), Sutton and Costanza (2002), and Ghosh et al. (2010).

[4] Important is that the author does find that if one disaggregates production by industry level then there can be significant, but fairly heterogeneous, impacts.

[5] Note that to date there have been five DMSP satellites that cover the following subperiods: satellite *F10* for 1992–94, *F12* for 1994–97, *F14* for 1997–2003, *F15* for 2000–07, and *F16* for 2004–09. To handle the data during overlapping periods, we have taken, for each cell, simple averages of nightlight values across satellites.

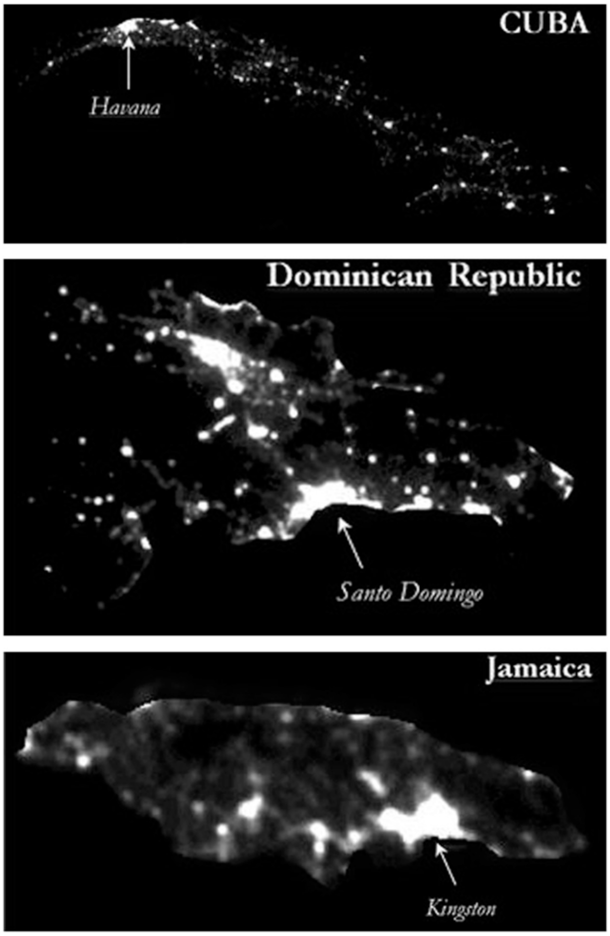

FIG. 1. Nightlight maps for Cuba, the Dominican Republic, and Jamaica (2003).

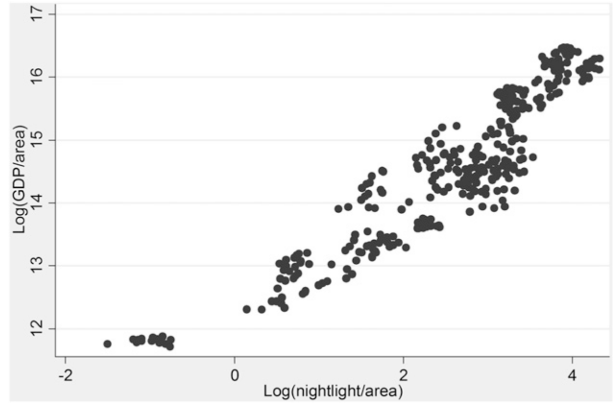

FIG. 2. Income–nightlight relationship.

rainfall, and storm surge, it is typically measured in terms of wind speed because of a lack of data availability on these other factors. To be specific, our hurricane potential damage index is based on being able to estimate local wind speeds at any particular locality over or nearby which the tropical storm passes. To do so, we rely on the meteorological wind field model developed by Boose et al. (2004), which provides estimates of wind velocity of any point relative to the eye of the hurricane. This model, which is based on Holland's (1980) well-known equation for cyclostrophic wind and sustained wind velocity at any point P, is estimated as

$$V_s = F[V_m - S(1 - \sin T)(V_h/2)] \times \{(R_m/R)^B \exp[1 - (R_m/F)^B]\}^{1/2}, \quad (1)$$

where V_m is the maximum sustained wind velocity anywhere in the hurricane, T is the clockwise angle between the forward path of the hurricane and a radial line from the hurricane center to the point of interest P, V_h is the forward velocity of the hurricane, R_m is the radius of maximum winds, and R is the radial distance from the center of the hurricane to point P. Of the remaining ingredients, F is the scaling parameter for effects of surface friction, S the scaling parameter for asymmetry due to the forward motion of the storm, and B the scaling parameter controlling the shape of the wind profile curve. The peak wind gust velocity at point P can then be estimated with

$$V_g = GV_S, \quad (2)$$

where G is the gust wind factor.

As noted by Emanuel (2005), both the monetary losses in hurricanes as well as the power dissipation of these storms tend to rise roughly as the cube of the maximum observed wind speed.[6] As a consequence, he proposes a simplified power dissipation index (PDI) that can serve to measure the potential destructiveness of hurricanes as

$$\mathrm{PDI} = \int_0^\tau V^3\,dt, \quad (3)$$

where V is the maximum sustained wind speed and τ is the lifetime of the storm as accumulated over time intervals t. Here, we modify this index to obtain an index of potential damage of a hurricane at a particular spatial locality. To be more precise, the total destruction due to a hurricane/storm r in country i at locality j in year t is

$$\mathrm{HD}_{i,j,r,t} = \sum_0^\tau V^3_{i,j,r,s} \quad \text{if} \quad V \geq 178\,\mathrm{km\,h^{-1}}. \quad (4)$$

[6] There are physical energy dissipation grounds for using wind speed to the cubic power; see, for instance, Andrews (2010).

The index in (4) can then be used to calculate annual total destruction in locality j by aggregating all of its values over a year t. Note that we only consider wind speeds above 178 km h^{-1}, that is, those that would fall above the category-3 cutoff point on the Saffir–Simpson hurricane scale and are believed to cause more extensive damage.

To calculate local and potential damage estimates due to hurricanes as in (4), we first need to estimate the local wind speeds experienced by relevant localities from (1) and (2). In this regard we assume values for the scaling parameters F, S, B, and G and of R_m as suggested by Boose et al. (2004).[7] For the remaining data on the position of the hurricane eye, maximum wind speed, bearing, and velocity, we take information from the North Atlantic Hurricane database (HURDAT), maintained by the National Hurricane Center. These data consist of 6-hourly positions and corresponding intensity estimates in terms of maximum wind speed of tropical cyclones in the North Atlantic basin since 1851 and is the most complete and reliable source of North Atlantic Ocean hurricanes (Elsner and Jagger 2004). Since storms may travel a considerable distance within 6 h, we linearly interpolated the given positions of the hurricane center to obtain 3-hourly track data. In choosing all possible positions for which to calculate wind speeds experienced (i.e., the points P in our analysis), we compiled the location of the center of each nightlight cell within the Caribbean region.

c. *Regression specification*

Our main goal is to statistically estimate the impact of hurricane destruction on local economic activity, and we do so with the following regression specification:

$$\Delta \log(\text{nightlight}_{i,t-1\rightarrow t}) = a + \beta \text{HD}_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{5}$$

where the left-hand side is the *growth* rate of observed nightlight (i.e., the log difference) between period $t-1$ and period t in grid cell i, HD is the value of our hurricane potential destruction index at grid cell i at time t, β is our coefficient of interest, μ are gridcell-specific time-invariant effects, λ are year-specific effects common to all cells, and ε is the error term. Note that by allowing for μ we are taking account of the possibility that some areas that are more prone to hurricanes may have implemented or may be characterized by certain (time invariant over our sample period) disaster mitigation measures that could reduce the effect of a hurricane whenever it strikes. Not considering this in the estimation of (5) could potentially bias the estimated coefficient β by creating a correlation between the unexplained error term and HD. Our approach is to eliminate this by using a fixed-effects estimator that essentially transforms all variables into deviations from their means and hence purges μ from the specification.[8] We also allow for year-specific effects λ that are common to all localities such as, for instance, changes in satellites and their quality over time. Standard errors for (5) were calculated using the Driscoll and Kraay (1998) nonparametric covariance matrix estimator, which produces heteroscedasticity-consistent standard errors that are robust to very general forms of cross-sectional as well as temporal dependence. Note also that we could have also defined our dependent variable as the value of nightlights in levels. Panel unit root tests consistently indicated that the nightlight data were nonstationary in levels and only stationary in first differences, however, and thus there was a statistically based preference for the use of the latter. In this regard it is noteworthy that, by focusing on the growth rate of nightlights, our specification captures the *short-run* effect of the exogenous hurricane shock.[9]

[7] In particular, F is assumed to take on values of 1.0 and 0.8 for points on water and land, respectively, while for G we assume respective values of 1.2 and 1.5 for these surface types. Parameters S and B are assumed to be 1.0 and 1.3, respectively. One should also note that, while the radius of maximum winds R_m (i.e., the distance between the center of the cyclone and its band of strongest winds) is considered to be an important parameter in tropical cyclone forecasting, historical hurricane best-track data generally do not provide estimates of this factor. We thus assume it to take on the value of 50 (km), which corresponds to the average value found for hurricanes with central pressures falling between 909 and 993 hPa (see Hsu and Yan 1998).

[8] See Wooldridge (2010, chapter 4). Note also that the use of linear regression for determining causality is not without its critics. One criticism cast against this technique is the often lack of exogeneity of regressors, which could bias the estimated coefficients. In our case, the *ex ante* potential destruction due to hurricanes as measured by the hurricane event itself is clearly exogenous in contrast to *ex post* measures of actual losses. Even apart from this point, however, linear regression analysis implicitly makes assumptions about the functional form of the relationship and the distribution of the unexplained error term. Here, we follow the empirical economic-growth literature and assume that these assumptions are reasonable.

[9] The standard empirical economic-growth literature, which is based on the idea that economies converge toward steady-state development paths in the long run, tends also to include the lagged-level value of the economic-activity variable as an additional regressor to capture such convergence. In our case in which our grid cells do not actually constitute economic units but rather are an arbitrary spatial breakdown of the economy, this approach would arguably not be appropriate. Moreover, within our fixed-effects estimator, including a lagged dependent variable would induce further endogeneity issues; see Islam (1995).

TABLE 1. Descriptive statistics (by country; 1993–2009).

	Share of unlit grid cells	Avg nightlight value ($\neq 0$)	Annual growth of GDP/area (%)
Anguilla	0.05	12	8.08
Antigua and Barbuda	0.39	8	4.65
Aruba	0.09	23	2.42
Bahamas	0.72	8	2.95
Barbados	0.02	28	2.43
Bermuda	0.38	19	3.41
Cayman Islands	0.14	15	3.49
Cuba	0.58	5	4.95
Dominica	0.38	4	1.76
Dominican Republic	0.51	8	5.62
Grenada	0.23	8	3.81
Guadeloupe	0.09	15	3.58
Haiti	0.79	8	0.23
Jamaica	0.09	9	0.96
Martinique	0.03	19	2.99
Netherlands Antilles	0.33	15	0.89
Puerto Rico	0.01	26	2.46
St. Kitts and Nevis	0.10	11	4.44
St. Lucia	0.14	10	2.45
St. Vincent and the Grenadines	0.44	5	3.94
Trinidad and Tobago	0.11	17	6.23
Turks and Caicos Islands	0.67	9	9.72

3. Descriptive statistics

The nightlight and hurricane-track data provide us with a sample window of 18 yr that covers the 1992–2009 period. In terms of the cross-sectional dimension, the Caribbean region is divided into slightly more than 300 000 grid cells spread across 22 countries, a list of which can be found in Table 1. A main feature of these nightlight data is the high number of unlit areas. Indeed, about 65% of all observations in our sample of Caribbean countries are unlit,[10] and 44% of all of our grid cells are unlit throughout the whole period under scrutiny. For our empirical analysis, we thus make the assumption that these cells contain no economic activity and drop all cells with no lights over our sample period. This leaves us with about 140 000 grid cells constituting about 1.6 million observations. Table 1 provides the number of unlit cells as well as the average value of nightlight across our sample.

In terms of hurricane activity over our sample period, there were 85 hurricanes in the Caribbean, of which 41 were of categories 3–5 on the Saffir–Simpson hurricane scale (see Table 2).[11] Countries in our sample were hit

TABLE 2. Number of tropical storms (1993–2009).

Tropical storm category and wind range (km h^{-1})	Frequency
Tropical depression (0–62)	13
Tropical storm (63–117)	55
Hurricane: category 1 (118–153)	33
Hurricane: category 2 (154–177)	11
Hurricane: category 3 (178–208)	13
Hurricane: category 4 (209–251)	20
Hurricane: category 5 ($\geq$252)	8

on average every 6–7 yr by a hurricane of intensity 3–5, although with substantial variation across islands.

Before turning to the regression analysis, we first provide some illustrative examples regarding the possible relationship between growth in nightlights and hurricane destruction for the particularly hurricane-prone year of 2005. To be specific, during this year four category-5 hurricanes are estimated to have caused at least some damage according to our index. As a matter of fact, three of these are ranked in the top 10 of the most intense hurricanes ever registered (viz., Katrina, Rita, and Wilma) and are well known to have caused large degrees of damage across the Caribbean. In particular, Wilma, the most intense Atlantic Ocean hurricane ever recorded, caused numerous fatalities and inflicted severe damage in Haiti, Jamaica, and Cuba. Katrina, in contrast, only affected the Bahamas in the Caribbean, and Hurricane Rita hit the Bahamas and Cuba and, to a lesser extent, the Turks and Caicos Islands. In Table 3 we depict the average growth rates of nightlights for these countries in 2005 as well as the average growth rates for all years in which there was no positive value of potential destruction according to our index. As can be seen, for the countries in the year affected, average nightlight growth figures are about −7% as compared

TABLE 3. Annual nightlight growth (by country; 2005).

	Annual nightlight growth during 2005 (%)	Annual nightlight growth during all years except when a category-5 hurricane made landfall (%)
Bahamas	−8.5	3.8
Grenada	−10	4.3
Jamaica	−6.8	0.8
Cuba	−25	4.1
Haiti	−3.8	2.8
Trinidad and Tobago	−6.5	5.7
Turks and Caicos	−3.3	6.4

[10] Even for the United States, the number of unlit areas is about 68%; see Henderson et al. (2011).

[11] We consider all hurricanes that came within 500 km of any of the Caribbean countries.

TABLE 4. Grid-level growth regressions for 22 Caribbean countries. The column contents are described in the text. The dependent variable is $\log(\text{nightlight})_t - \log(\text{nightlight})_{t-1}$. Boldface indicates significance at the 1% level. These are fixed-effects regressions, using Driscoll-Kraay standard errors (given in parentheses).

	Column 1	Column 2	Column 3
HD_t	**−0.524** (0.106)	**−0.511** (0.105)	**−0.518** (0.105)
HD_{t-1}		0.178 (0.127)	0.171 (0.125)
HD_{t-2}			−0.092 (0.140)
Time dummies	Yes	Yes	Yes
R squared	0.23	0.23	0.23
No. of obs	1 590 338	1 590 338	1 590 338
No. of grids	139 058	139 058	139 058

with 4% for the unaffected years, with large differences across countries.

4. Regression results and discussion

a. Basic results

Table 4 displays results for our baseline specification (5). In column 1, the negative and statistically significant coefficient on HD shows that there is a contemporaneous negative effect of hurricane strikes on the growth of nightlights. Taking the mean of (nonzero) HD and multiplying this by the estimated coefficient suggests that growth of nightlights will decrease by 3.4% (i.e., more than 2 times the absolute value of the annual average nightlight growth rate over all lit areas) as a result of hurricane damage. The corresponding figure for a hurricane strike 1 standard deviation above its mean implies a reduction in nightlight growth by 6.7%. In columns 2 and 3 of Table 4 we successively add lagged values of hurricane strikes to investigate whether there are longer-term effects. Our data, however, do not confirm this hypothesis, because none of the lagged hurricane values displays a statistically significant coefficient. Note that a similar result was found by Strobl (2012) using country-level data.

One concern, as highlighted by Chen and Nordhaus (2011), comes from the fact that gridcell-level nightlight intensity may have considerable measurement error in terms of acting as a proxy for local economic activity. Note in this regard that measurement error in the dependent variable—as nightlight intensity is used here—will only cause a reduction in precision (i.e., will inflate the standard errors) but will not cause inconsistent or biased estimates of the coefficients of the regressors, as long as the measurement error is not systematically related to the explanatory variables. This is unlikely be a problem in the current context. To be more specific, there is no a priori reason to believe that areas where nightlights are relatively poorer proxies of economic activity are also those likely to have experienced a potential hurricane "shock" after controlling for all time-invariant differences across cells via cell-level fixed effects. Nor, in a similar line of reasoning, would one expect any time-varying portion of measurement error in our hurricane destruction proxy to be systematically related to the time-varying measurement error in our economic-activity proxy.

A potential issue with using wind speed as a proxy for potential destruction due to hurricanes is that, because of lack of alternative data, we are in essence employing it also to capture damage other than that due to the direct destructive power of the wind, such as storm surge. Although the extent of storm surge and the wind speed of a hurricane are certainly related and wind speed is often used to capture the damage due to storm surge (see, e.g., Emanuel 2011), it is certainly an imperfect proxy. In this regard note that the extent of storm surge at a particular location will depend on a number of local factors, including local bathymetry and land use, that cannot be represented by using the storm's wind speed as a proxy. There unfortunately are no comprehensive data for these other factors for the Caribbean, and therefore we are unable to model storm surge directly. Nonetheless, in a case study of storm surge in coastal plains, Nicholls (2006) has noted that it decays quickly as it moves inland. A number of studies have thus used distance to the coastline as a proxy for the likely importance of storm surge (see, e.g., Brecht et al. 2012). We follow this approach by similarly investigating whether for a given wind speed the impact of hurricanes diminishes the farther the cells are from the shoreline. To this end, we first classified nightlight observations according to their center's distance to the shoreline. Note in this regard that in the Caribbean the distribution of distances of cells to the coast ranges from 0 to ~150 km, with almost 90% of the observations within 40 km. To have similar sample sizes, we thus divided our cells into four subsamples corresponding to the quartiles of distances, that is, into categories of distances of 0–5.4, 5.4–14, 14–27.1, and greater than 27.1 km, respectively. For each of these groups we then created dummy variables and "interacted" (multiplied) these with (by) our hurricane destruction index, to then be included in our regression equation in place of the hurricane index itself. The resultant regression coefficients for each interaction term can then be viewed as the effect of hurricanes on nightlights with the corresponding distance quartile. As can be seen in Table 5, these results suggest that the destructiveness of hurricanes indeed decreases with distance to the shore, becoming statistically insignificant for the most inland regions (i.e., beyond 27.1 km). The size of the

TABLE 5. Grid-level growth regressions for 22 Caribbean countries, controlling for urban build up and distance to the shore. The column contents are described in the text. The dependent variable is $\log(\text{nightlight})_t - \log(\text{nightlight})_{t-1}$. Boldface and italics indicate significance at the 1% and 5% levels, respectively. These are fixed-effects (country) regressions, using Driscoll-Kraay standard errors (given in parentheses). The urban and built-up data are taken from the North America Land Cover Characteristics Data Base, version 2.0.

	Column 1	Column 2	Column 3	Column 4
HD_t		−**0.687** (0.247)	−*0.598* (0.272)	−**0.556** (0.196)
HD_t × first-quartile shore distance	−**0.607** (0.083)			
HD_t × second-quartile shore distance	−**0.477** (0.092)			
HD_t × third-quartile shore distance	−**0.449** (0.116)			
HD_t × fourth-quartile shore distance	−0.598 (0.418)			
Distance to urban build up (km)		10	20	50
Time dummies	Yes	Yes	Yes	Yes
R squared	0.23	0.20	0.22	0.24
No. of obs	1 590 338	307 169	666 465	1 229 579
No. of grids	139 058	21 910	53 717	110 551

estimated coefficients suggests that an average hurricane strike reduces nightlight growth by 4.5%, 3.2%, and 2.8% for the first, second, and third quartiles, respectively.

Another issue with regard to using nightlight images as proxies for economic activity is that these may capture different aspects depending on the land use of the grid cell in question. For instance, the sectoral composition of urban sectors tends to consist more of manufacturing and services sectors, whereas rural areas are more likely to be agriculturally based. In this regard, Hsiang (2010) has shown, using country-level data, that the services sector is more negatively affected than are other sectors in the economy in the Caribbean. Since we cannot classify the source of the nightlights directly using the available gridded data, we instead examine this potential difference by classifying our cells into urban and rural, where it seems reasonable to assume that urban areas are more likely to cover manufacturing and services and rural areas correspond more to the agricultural sector. To do so, we used the 2000 global land cover 1-km gridded spatial dataset (http://edc2.usgs.gov/glcc/nadoc2_0.php),[12] which divides the global land area into 22 land-use categories at the 1-km^2 level. We take those categories referring to urban and built-up areas to identify urban centers and then add different-sized buffer zones around these to classify our cells into urban and nonurban. In Table 5 we reran specification (5) for the *urban*-cells sample using buffer zones of 10, 20, and 50 km. The estimated coefficients suggest that an average hurricane reduced nightlight growth in these areas by 3.4%, 3%, and 3.1%, respectively. Note that running our specification on the nonurban sample of the databases for 10-, 20-, and 50-km buffer zones led to an average 3.5% reduction in the *nonurban* cells. More important, these estimates were not statistically different from those for the urban cells, suggesting that differences in sectoral composition do not induce differences in the impact of hurricanes on economic activity when nightlights serve as its proxy.

Last, we also investigated whether there may be spillover effects between units of observations where the effect of hurricanes may also have an impact on neighboring localities.[13] In this regard we reran our benchmark model but averaged the local hurricane destruction index by its value in cell *i* and that in cells neighboring to *i* in any year. Results for different levels of contiguities are displayed in Table 6. In column 1 the hurricane index is averaged over its own cell and the four neighboring cells (i.e., north–south and east–west), whereas in column 2 the four diagonal neighboring cells are included.[14] Noteworthy is that the results are only slightly larger than our previous estimates, indicating little evidence of spillovers. For example, an average annual nonzero hurricane strike would reduce nightlight growth by 3.7% (3.8%) when

[12] Data for urban and built-up areas are part of the 1-km-resolution global land cover characterization, collected jointly by the U.S. Geological Survey, the University of Nebraska—Lincoln, and the European Commission's Joint Research Centre. At the time of writing, a detailed description of the data could be found online as mentioned in the text.

[13] One may, for instance, expect the existence of an input–output relationship between nearby producers in Caribbean islands, such that final users of certain inputs are affected by destruction of production capacities of input suppliers. In a similar way, power plants hit by hurricane landfall may face a halt in their production, affecting areas that are not immediately affected by the hurricane.

[14] To be more particular, we based our contiguity measures on both rook and queen polygon adjacency. The main difference between these methods is that the former (rook) uses only common boundaries to define neighbors whereas the latter (queen) includes all common points (boundaries and vertices). See Cressie (1993) for an in-depth treatment of spatial data.

TABLE 6. Grid-level growth regressions for 22 Caribbean countries, including neighborhood effect. The dependent variable is log $(\mathrm{nightlight})_t - \log(\mathrm{nightlight})_{t-1}$. These are fixed-effects (country) regressions, using Driscoll-Kraay standard errors (given in parentheses). Boldface indicates significance at the 1% level. The urban and built-up data are taken from the North America Land Cover Characteristics Data Base, version 2.0.

	Four neighbors	Eight neighbors
HD_t	−**0.622** (0.139)	−**0.632** (0.142)
Time dummies	Yes	Yes
R squared	0.24	0.24
No. of obs	1 214 832	1 196 595
No. of grids	136 404	137 662

destruction in the four (eight) neighboring cells is also taken into account.[15] This result may not be surprising given the high level of correlation of wind speed estimates at spatially very disaggregated levels.

b. *Impact on economic growth*

We have thus far provided an estimate of the impact of hurricane landfall in terms of the units of nightlights. It is arguably of greater interest to know the impact of hurricane strikes on the growth rate of local economic activity measured in more common economic units, in particular if one wants to compare it with other studies using more aggregate and/or actual income data. To translate our nightlight measures into economic values, we follow Chen and Nordhaus (2011) and Henderson et al. (2011) and estimate the following specification:

$$\Delta \log(\mathrm{GDP}_{i,t-1\rightarrow t}) = \delta + \gamma\Delta \log(\mathrm{nightlight}_{i,t-1\rightarrow t}) + \eta_i + \tau_t + \omega_{it}, \quad (6)$$

where the left-hand side represents GDP growth between period $t-1$ and period t in grid cell i and the right-hand side is the growth rate of observed nightlight. Our coefficient of interest is given by γ, the inverse elasticity of nightlights with respect to GDP. Here, η, τ, and ω represent gridcell-specific time-invariant effects, year-specific effects that are common to all cells, and an error term, respectively.

To estimate (6) for all countries in our sample, we take GDP data for Caribbean countries from the Penn World Table (PWT; https://pwt.sas.upenn.edu/php_site/pwt_index.php), which is also the source of the GDP data for Henderson et al. (2011), and supplement these with data on GDP from Bulmer-Thomas (2012) for the five countries/regions that are not covered in the PWT. To generate a nightlight measure at the country level, we, similar to the method of the previous authors, aggregate grid-level data and divide these results by their total area.[16] Annual growth figures of GDP/area over our period of observation are provided in the last column of Table 1. Using these data to estimate (6) with a fixed-effects estimator, including year dummies and clustering standard errors at the country level, produced a statistically significant coefficient of 0.28 on the aggregate nightlight variable, hence again attesting to the strength of nightlights as a measure of economic activity. Note that the larger coefficient relative to that found by Henderson et al. (2011) (0.44) is due to our subsample covering just the Caribbean rather than all developing countries. We can infer the economic growth impact of hurricane strikes by multiplying these coefficients by those obtained in Table 4. To be more specific, this suggests that growth of income would decrease by 1.5% and 3% following a hurricane for the average nonzero HD and HD of 1 standard deviation above mean value, respectively.

It is important to emphasize that our estimated "economic" impact is nearly double that found by Strobl (2012). To investigate whether this is due to the differences in our country and time samples and/or aggregation bias, we also performed a number of country-level regressions, the results of which are depicted in Table 7. We simply regressed GDP growth on our measure of hurricane destruction, aggregated to the country level. As expected, one finds a negative and significant coefficient. In terms of the quantitative effect, taking the mean of (nonzero) hurricane years in Caribbean countries multiplied by the estimated coefficient suggests

TABLE 7. Country-level regressions of GDP growth–nightlight for 22 Caribbean countries. The dependent variable is $\log(\mathrm{GDP/area})_t$. Boldface indicates significance at the 1% level. Robust standard errors, clustered at the country level, are shown in parentheses.

$\log(\sum \mathrm{nightlight})_t$	**0.444** (0.141)
Time dummies	Yes
No. of obs	351
R squared	0.79
No. of countries	22

[15] Note that using different levels of spatial aggregation on the left-hand-side and right-hand-side variables might induce biases in our estimation results. We therefore clustered our error term at the appropriate level for each of the two specifications, thus taking account of the correlation structure of error terms across observations.

[16] Note that, taking the simple average of nightlight grids by countries, we end up with very similar values, and the correlation coefficient between the two series is 0.94, with a significance p value of lower than 1%.

TABLE 8. Country-level regressions of GDP growth–hurricanes for 22 Caribbean countries. The column contents are described in the text. The asterisk and italics indicate significance at the 10% and 5% levels, respectively. Robust standard errors, clustered at the country level, are shown in parentheses. Hurricane variables have been multiplied by 10^{10} to ease the readability of the estimated coefficients.

	Column 1	Column 2
	Dependent variable: $\log(\mathrm{GDP/area})_t - \log(\mathrm{GDP/area})_{t-1}$	Dependent variable: $\log(\sum\mathrm{nightlight})_t - \log(\sum\mathrm{nightlight})_{t-1}$
$\sum(\mathrm{HD/area})_t$	−0.794* (0.420)	*−1.48* (0.546)
Time dummies	Yes	Yes
No. of obs	329	328
R squared	0.19	0.52
No. of countries	22	22

a decrease of 0.7% in GDP growth, which is essentially identical to that found by Strobl (2012) in his aggregate analysis using a longer time period. We next reran our estimation measuring the impact of hurricanes on nightlights, but at the country rather than the grid level, the results of which can be found in the second column of Table 8. As expected, we find again a negative and significant coefficient. Multiplying this coefficient by the average annual (nonzero) value of potential hurricane destruction and converting the result into GDP growth units as above, our result implies a reduction of 0.5% in GDP growth. This is again consistent with the undervaluation found above and points toward the importance of estimating the impact of hurricane shocks at the most disaggregated level possible.

5. Conclusions

Studies of the economic-growth impact of hurricanes have typically been restricted to aggregate/national analysis because of a lack of comprehensive data at the localized level, although it can be argued that tropical storms are very local phenomena that have widely differing effects across space. In this study, we propose a new approach to circumventing this problem by employing nightlight imagery in conjunction with a hurricane model and hurricane-track data to estimate the impact at a spatially very detailed ($1\,\mathrm{km}^2$) level. Our results show that aggregation tends to underestimate the effect of hurricanes on economic growth. Moreover, there may be some heterogeneity across spatial areas in terms of this impact.

For future research, there are a number of important improvements to our analysis that would be possible with greater data availability. For instance, one drawback of our study is that, because the nightlight data that we use are annual, we have not been able to examine the very-short-term (i.e., intra annual) impacts of hurricane strikes. One would suspect that such higher-frequency data would produce a more pronounced impact. Furthermore, our approach does not identify the channels through which hurricanes cause a reduction in economic growth since our measure of economic activity will only capture the total net effect. Classifying local areas by the nature of their economic activity through, for instance, detailed information on land use and type of economic activity conducted could provide insight into this ''black box.'' Related to this point, a clearer understanding of how growth in nightlights is specifically related to economic growth would allow one to gauge what is included in our measured effect.

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