Quantifying the Economic Damage due to Hurricane Strikes:

An Analysis from Outer Space for the Caribbean Region

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Abstract

Hurricanes are well known to cause considerable amount of damage in the Caribbean, a region that is highly susceptible to these phenomena and largely consists of small island developing economies. However, data constraints have limited the quantification of the damage to only very sparse and rough figures. In this paper we set out to quantify the economic damage due to hurricane strikes in the region using alternative data sources. Our innovation in this regard to use night lights data derived from satellite images the capture the extent of economic activity locally and then measures its changes after a hurricane strike. We proxy the potential damage due to a hurricane by using destruction index derived from actual hurricane track and a wind field model. Our results indicate that during our sample period 1992-2003 hurricanes significantly affected the extent to which economic activity as captured from outer space.

1. Introduction

Natural disasters are generally associated with considerable economic losses. Particularly alarming in this regard is not only the fact that the last three and a half decades have witnessed an increase in the number of such occurrences, but also that developing countries seem to be those bearing the brunt of these events and ultimately the economic consequences, thus possibly further adding to the perceived gap between the 'rich' and the 'poor'. For example, between 1970 and 2002, out of a total number of 6436 natural disasters 77 per cent have taken place in the developing world. Moreover, the reoccurrence of such extreme events often tends to be concentrated in particular geographic areas, striking certain countries again and again, often with great severity. For instance, since 1984 Dominica has been struck by 9 different hurricanes, while Hurricane Georges caused losses of around 400 million US$, constituting over 140 per cent of GDP, in the Caribbean islands of St. Kitts and Nevis in 1998.[1]

Nevertheless, while the above cited figures do give some indication as to the impact of hurricanes on local economic activity, they can at best be considered very rough figures based on varying sources and hence are unlikely to be consistent across events. More systematic evidence on how much damages due to extreme events actually translate into economic losses is as of date sparse, and the few estimates that exist vary considerably. For instance, Raddatz (2007) investigated the role that external shocks played in a panel of low-income countries and found that climatic disasters can

[1] Rasmussen (2004).

only account for 13.9 per cent of the total volatility due to external shocks. In contrast, Noy (2008) finds that natural disasters will typically cause a drop in output of 9 percentage points in developing countries, while Strobl (2009), specifically examining Caribbean countries, finds that an average sized hurricane causes output growth to fall by 0.84 percentage points. Arguably, there are a number weaknesses with the studies just cited. Firstly, they all estimate the impact of hurricane destruction at the net aggregate country level. While Strobl (2009) does use a population weighted aggregation of local destruction, his results can nevertheless only arrive at an average country level impact, and hence cannot say anything about local destruction. Moreover, all of these studies use GDP per capita as their dependent variable, which will invariably be net of any disaster aid and relief and hence not provide a true measure of destruction. Moreover, the accuracy of GDP data across countries may introduce considerable measurement error into their estimates.

In this paper we attempt to address these weaknesses by taking a different approach to measuring the impact of hurricanes on local economies. More specifically, we avail of time varying estimates of night light intensity as captured by satellite images to measure the extent of local economic activity within the Caribbean region, an area traditionally prone to hurricane strikes, and estimate how this intensity was affected after a hurricane strike. To measure the local destructiveness of hurricanes we, as in Strobl (2009), use actual historical data tracking the movement of tropical storms across the affected region and employ a wind field model on these hurricane `tracks' that allows us to calculate an approximation of the severity of winds experienced at a detailed geographical level of the countries potentially affected. Combining these two data series together then provides us with a locally detailed panel data with which we can econometrically estimate the effect of hurricane strikes on local economic activity.

The remainder of the paper is organized as follows. In the next section we describe our data sets and provide some summary statistics. In Section III we provide our econometric analysis. Finally, we conclude in the last section.

2. Data and descriptive statistics

Hurricane strikes

A tropical cyclone is a meteorological term for a storm system which forms almost exclusively in tropical regions of the globe. Tropical storms in the North Atlantic and the North East Pacific region, as we study here, are referred to as hurricanes if they are of sufficient strength[2] and their season can start as early as the end of May and last until the end of November. In terms of its structure, a hurricane will typically harbor an area of sinking air at the center of circulation, known as the 'eye, where weather in the eye is normally calm and free of clouds, though the sea may be extremely violent.[3] Outside of the eye curved bands of clouds and thunderstorms move away from the eye

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[2] Generally at least 119 km/hr.

[3] National Weather Service (October 19, 2005). Tropical Cyclone Structure. JetStream - An Online School for Weather. National Oceanic & Atmospheric Administration.

wall in a spiral fashion, where these bands are capable of producing heavy bursts of rain, wind, and tornadoes. Hurricane strength tropical cyclones are normally about 483 km wide, although this can vary considerably.

Damages due to hurricanes typically take a number of forms. Firstly, their strong winds may cause considerable structural damage to crops as well as buildings. Secondly, the heavy rainfall can result in extensive flooding and, in sloped areas, landslides. Finally, the high winds pushing on the ocean's surface cause the water near the coast to pile up higher than the ordinary sea level, resulting in storm surges. The flooding inland due storm surges generally occurs as early as 3-5 hours before arrival of hurricane and is often its most damaging aspect, causing severe property damage and destruction and salt contamination of agricultural areas.[4] One may also want to note that hurricanes lose their strength as they move over land.

While the extent of potential damages caused by hurricanes may depend on many factors, such as slope of the continental shelf and the shape of the coastline in the landfall region in the case of storm surges, it is typically measured in terms of wind speed. A popular classification has been the Saffir-Simpson (SS) Scale, where values from 1 through 5 correspond to wind speeds of 119-153 km/hr, of 154-177 km/hr, of 178-209 km/hr, of 210-249 km/hr, and 250+ km/hr, respectively. In this regard, it is

[4] Yang (2007).

generally agreed that considerable damages only occur once a hurricane reaches a strength of 3 on the SS scale in approaching the coast and/or making landfall.[5]

Our hurricane wind damage index is based on being able to estimate local wind speeds at any particular locality where a hurricane strength tropical storm directly passes over or nearby. To do so we rely on the meteorological wind field model developed by Boose et al (2004)[6], which provides estimates of wind field velocity at any point relative to the 'eye' of the hurricane. This model, based on Holland's well known equation for cyclostrophic wind and sustained wind velocity[7], estimates wind speed at any point P to be:

$$V = GF\left[V_m - S(1-\sin(T))\frac{V_h}{2}\right]\left[\left(\frac{R_m}{R}\right)^B \exp\left(1-\left[\frac{R_m}{F}\right]^B\right)\right]^{\frac{1}{2}} \quad (1)$$

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, R is the radial distance from the center of the hurricane to point P, and G is the gust wind factor. The relationship between these

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[5] For instance, for the United States Pielke et al (2008) that over 85% of total damages are due to hurricanes of strength 3 and above, although these have only comprised 24 per cent of all U.S. landfalling tropical cyclones. Similarly Vickery et al (2006) show using the loss functions of the HAZUS-MH model that loss ration is minimal for wind speeds below 177 km/hr.

[6] This wind field model was, for instance, verified by the authors on data for Puerto Rico.

[7] See Holland (1980).

parameters and P are depicted in Figure 1. The remaining ingredients, F, S, and B, are scaling parameter for surface friction, asymmetry due to the forward motion of the storm, and the shape of the wind profile curve, respectively.

If we take as a given that the power dissipation, and hence subsequent damage, of a hurricane is intrinsically related to its wind speed, then we can propose the following index, *WIND*, of total destruction due of a storm r over its life time τ in any country i at time t:[8]

$$WIND_{i,r,t} = \left(\sum_{j=1}^{J} \int_{0}^{\tau} V_{jt}^{\lambda} w_{i,j,r,t} \, dr \right) \quad \text{if } V_{jt} > 177 \text{ km/hr (SS} \geq 3\text{) and zero otherwise} \qquad (2)$$

Where V are estimates of local wind speed at localities j, J is the set of localities j within country i, w are weights assigned according to characteristics of the locality to capture the 'potential' damage there, and λ is a parameter that relates local wind speed to the local level of damage.[9] In terms of the weights w we use the time varying share of population of each individual locality j at t-1, where the underlying argument is that, even if severely damaged by hurricane winds, sparsely populated areas are unlikely to

[8] In essence this is a modified version of Emanuel's (2005) proposed destruction index.

[9] Dilley et al (2005) use a wind field model, albeit a different one, and intra-national population figures to identify local tropical cyclone hazard areas across the globe. In his study of the impact of hurricane events on international financial aid flows, Yang (2007) uses the wind field model employed by Dilley et al (2005) to calculate out local hurricane speeds and time invariant population weights to generate an index of hurricane severity. Our approach in modeling hurricane destruction differs in two regards to these studies. Firstly, we base our destruction measure on a statistically based equation of power dissipation and damages. Secondly, in terms of implementation, we use time varying rather than time invariant population shares. Moreover, we experiment with using local land cover type to capture differences in 'potential' local damage.

play a significant role in the overall macroeconomic impact of a hurricane for a country in any year. In this regard, it has been noted by McGranaham et al (2007) that in developing countries a significant share of the population tends to live in coastal areas, especially in small island countries, which are of course more vulnerable to tropical storm incidence. Alternatively we will also experiment with using the land use type of areas *j* to create weights *w*. One should note that in (2) we focus only on wind speeds that cause significant damages, i.e., on those that that are of least strength 3 on the SS scale, as discussed above.

An important input variable to (2) is λ, i.e., the parameter that links wind speed to its level of destruction. In this regard Emanuel (2005) noted that both the monetary losses as well as the power dissipation of hurricanes tend to increase as the cube of the maximum observed wind speed rises, and hence argues that the destructiveness of a hurricane can roughly be measured by the cubic value of its maximum observed wind speed.[10] However, it should be noted that his proposed 'cubic' relationship between monetary damages and wind speed is based only on a few rudimentary calculations by Southern (1979).

In contrast Nordhaus (2006) conducts a more comprehensive statistical analysis and shows that data for the US suggests that the relationship between wind speed and damages is more closer to the eighth power. More specifically, he takes data on total costs and maximum wind speeds for a set of 20th century hurricanes and regresses the

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[10] This cubic 'regularity' is based on a some figures contained in Southern, R. (1979).

log of the cost per hurricane normalized by US GDP on the logged maximum wind speed and finds a coefficient of around 8 on wind speed. However, arguably total US GDP is unlikely to be a good normalization for costs, since hurricanes typically only affect areas close to the coast which constitute only a small proportion of the US. Moreover, the relative local wealth that was affected is likely to have changed substantially over the period as coastal communities have grown in size and income.[11] Given that many of the latter hurricanes in the 20th century were particularly strong, neglecting these features is likely to bias his estimate of λ upward.

In order to address the shortcomings of Nordhaus' (2006) estimates, we instead regressed the log of the normalized cost values calculated by Pielke et al (2008) - who normalized hurricane damages with regard to changes in inflation, population, and wealth of only the counties affected - on the log of maximum observed wind speeds of the hurricanes in Nordhaus' data set, and found that the resultant coefficient implies that costs rise to the 3.8th not the 8th power of wind speed.[12] Given that Emmanuel's (2005) proposed cubic relationship is not based on any comprehensive statistical analysis and Nordhaus' (2005) statistical analysis does not take into account the local nature of natural disasters, we thus here take our estimate of 3.8 as the relatively more accurate proxy of λ and assume that is also applicable to the LAC region.[13]

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[11] See Rappaport and Sachs (2003).

[12] Our regression also includes a set of time dummies. Detailed results are available upon request.

[13] Unfortunately no data exists to perform a similar estimation for the CAC region.

For data on hurricanes in the CAC region[14] we rely on two data sources, the North Atlantic Hurricane database (HURDAT) and the Eastern North Pacific Tracks File, maintained by the National Hurricane Center. The HURDAT database consists of six-hourly positions and corresponding intensity estimates in terms of maximum wind speed of tropical cyclones in the North Atlantic Basin over the period 1851-2006 and is the most complete and reliable source of North Atlantic hurricanes.[15] The Eastern North Pacific Tracks File similarly consists of six-hourly positions and corresponding wind speeds of tropical cyclones, albeit in the Eastern North Pacific Basin, which is the portion of the North Pacific Ocean east of 140W, and is available from 1949 onwards. [16] Given the sample period of our economic data (which starts earliest for some countries in 1950), we limit our use of these data to the period from 1950 onward. We linearly interpolated the positions and wind speeds between the six hourly data to obtain three hourly track data since hurricanes can move considerable distance in just a few hours.[17]

We depict all hurricane tracks in the region since 1950 in Figure 2, where straight segments indicate when the hurricane was of at least SS strength 3. As can be seen, throughout the region there has been considerable tropical storm activity with

[14] The CAC region consists of 31 countries/territories. We list these in Table 1.

[15] While due to differences in data collection methods for periods prior to the 1960s some weak tropical storms may be missed, in terms of cyclones that reached hurricane density the data set can be considered essentially to be exhaustive. For a detailed description see Elsner (2003) and Jagger and Elsner (2004).

[16] As with HURDAT, in terms of tropical storms that reached hurricane intensity the data can be viewed as essentially exhaustive; see Jarvinen et al (1998).

[17] One should note that interpolating the track data to obtain more frequent observations of the tropical cyclone is standard in the literature; see, for instance, Jagger and Elsner (2006).

577 tropical storms having navigated the region. However, one may want to note that a large part of this activity has been at a level deemed not (relatively) important in terms of potential damages caused as suggested by the Saffir-Simpson scale.

Nightlight

The Defense Meteorological Satellite Program (DMSP) has produced ground-level night time imagery since the 1970s. The digital archive of such data extends back to 1992, and leaves us with a comprehensive and continuous data set of night light intensity updated since then. Each DMSP satellite has a 101 minute near-polar orbit at an altitude of about 800km above the surface of the earth, providing global coverage twice per day, with typical passes occurring between 8.30 and 9.30 PM. Night light data captured by these satellites represents essentially human activity, such as electrified human settlements, gas flares and heavily lit boats. The issues due to transient light has been resolved in the late 1990s by the National Oceanic and Atmospheric Administration. They developed a methodology to generate "stable, cloud-free night light 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, are removed (see Elvidge et al. (1997) for a comprehensive description). Resulting images are percentages of nightlight occurrences for each pixel. These percentages have then be normalized across satellites (whose sensor setting vary) to a scale ranging from 0 (no light) to 65 (maximum light).

The spatial resolution of the original pictures was about 0.008degrees on a cylindrical projection (i.e. with constant areas across latitudes) and has only thereafter been converted to a polyconic projection, leading to squares of about 1sqkm. In order to get yearly values, simple average across values of daily squares have been taken.

In Figure 3, we have represented nightlight over some Caribbean islands, namely Cuba, the Dominican Republic and Jamaica for the year 2003. Lid areas clearly correspond to more centers of economic activity, of which capital cities are pinpointed. An interesting feature is also the area that is totally dark. These represent for instance 64 per cent in Cuba, and 59.5 per cent over the whole Caribbean's. These figures can be compared to those put forward by Henderson et al (2009) for the US: 67.7 per cent. However, given the far larger population density of the Caribbean's compared to the US (by approximately a factor of 6), the difference can be attributed to lower living standards for the latter. Finally, the most lid of the Caribbean islands are the Bahamas, which happen to be the wealthiest nation in terms of GDP per capita.

3. Econometric Results

In this section, we will analyze the local impact of hurricane strikes on the development level of Caribbean islands. Denoting the level of development by NL (i.e. nightlight) and by HD the hurricane destruction measure as developed in the previous section, we rely on simple cross-country, time-varying growth regression:

log(NL)= f(log(HD)),

where f' is expected to be positive. Given the panel nature of our data, we will be able to control for time-invariant as well as area specific (time varying) effects. Furthermore, we allow the error generating process to take very general forms of cross-sectional and temporal dependence. In particular, spatial dependence might be an issue as we are relying on nightlight data, disaggregated at a very fine geographical scale, raising thus suspicion on the existence of spatial dependence among observations. The Driscoll and Kraay (1998) standard errors takes account of this, by estimating standard errors using nonparametric techniques.

Our panel spans the period 1992 to 2003, excluding 1993 and 1994, as no significant strikes have hit the Caribbean nations during these two years. Our panel is furthermore unbalanced in the cross-sectional dimension, as hurricane strikes do not always happen in all locations. As we are interested in the local impact of hurricane strikes, we drop territories which are not hit at time t (i.e. across years, this corresponds to about keeping slightly less than 7 per cent, or more than 780.000 observations).

In Table 1, we estimate the above specification, relying on a log-linear function. Unreported year-specific time dummies are added throughout the regressions, unless otherwise mentioned. The first column suggests a negative and significant impact of hurricane strikes on development, measured by night light intensity. Specifically, a one standard deviation increase in hurricane strikes would induce a subsequent nightlight reduction of about 3 per cent. This figure may however be underestimated due to the contemporaneous nature of the estimation in column 1. We may actually expect direct and above all indirect effects of hurricanes to show into night light only with some lag. This is confirmed in column 2 of the result table, with a 4.5 per cent effect. In column 3, we introduce 3 lags. Interestingly, we can see that the impact is really important during the first lag, reduces subsequently and becomes marginally insignificant 3 years after hurricane strike. Note that estimations in columns 2 to 3 are performed on shrinking samples, as introducing lags in hurricane strike measures reduces our sample by the corresponding number of periods. However results remain qualitatively similar if we restrict our sample for all regressions on the observations of column 3, as can be retrieved in columns 4 to 6 in the same table. Given sample sizes, this should not affect the accuracy of the results.

In Table 2, we further report results, when taking account of the distance of each observation to the shore. Climatologist have long observed that hurricane's strength decreases when they hit on land. The explanation for this comes from the fact that to build up and gain in strength, hurricane need a warm layer of water on top of the oceans. If these climatic conditions are not met, the hurricane's wind speed tend to diminish. So as to take account of this, we have computed the shortest distance of each grid to the sea, and interacted the log of these figures with our hurricane variable. Column 1 results support the expected effect, i.e. the further away from the sea, the lower the marginal effect of hurricanes on nightlight and thus, on development. Column 2 even reinforces this result and shows that hurricanes' destructive power reduce more than proportionally with distance. Distance is measured here in degrees, so a one-standard deviation distance to the sea (representing slightly less than 20km) would reduce hurricanes' destructive power by about 28 per cent.

Section 4. Conclusion

In this paper we investigated the local economic impact of hurricane strikes in the Caribbean region using satellite derived proxy of local economic activity and hurricane destruction measures derived from hurricane track data and a wind field model. Our estimates show a significant statistical impact of hurricanes on annual night light intensity. The next step will be to translate the estimates into actual wealth figures by using country wide and local estimates of income and estimating their relations ship to night light intensity.

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Table 1: Econometric results (dependent variable: log(1+nightlight))

	(1)	(2)	(3)	(4)	(5)	(6)
log(HD)	-0.032**		-0.060***	-0.012		-0.063***
	(0.012)		(0.016)	(0.008)		(0.014)
log(HD_{t-1})		-0.044***	-0.120***		-0.036*	-0.115***
		(0.016)	(0.029)		(0.020)	(0.039)
log(HD_{t-2})			-0.064***			-0.056***
			(0.006)			(0.011)
log(HD_{t-3})			-0.009			
			(0.017)			
Sample	full	full	full	restr.	restr.	restr.
Time dum.	Yes	Yes	Yes	Yes	Yes	Yes
R^2 within	0.10	0.04	0.20	0.20	0.20	0.21
Obs.	742732	409913	100902	100902	100902	100902
# grids	123090	117304	58490	58490	58490	58490

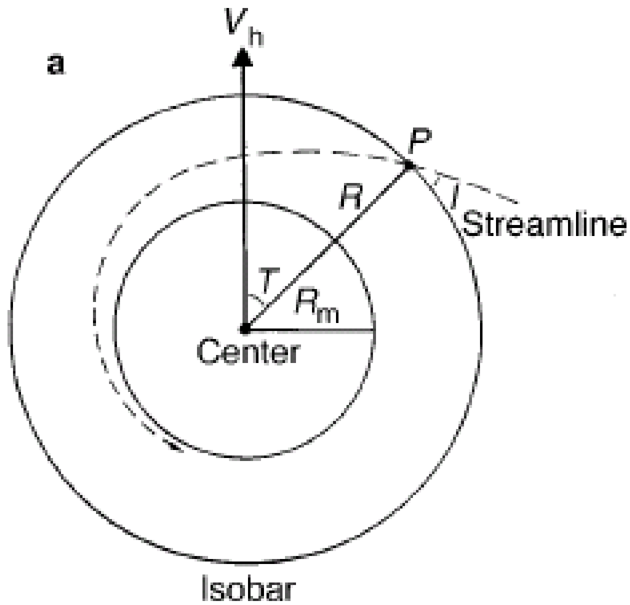
Notes: dependent variable. *log*(1+nightlight); Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 2: Econometric results (dependent variable: log(1+nightlight))

	(1)	(2)
log(HD_{t-1})	-0.038**	-0.013*
	(0.018)	(0.008)
log(HD_{t-1})· *log*(dist. to shore)	0.003**	0.026***
	(0.001)	(0.003)
log(HD_{t-1})· *log*(dist. to shore)^2		0.004***
		(0.001)
Time dum.	Yes	Yes
R^2 within	0.04	0.04
Obs.	409913	409913
# grids	117304	117304

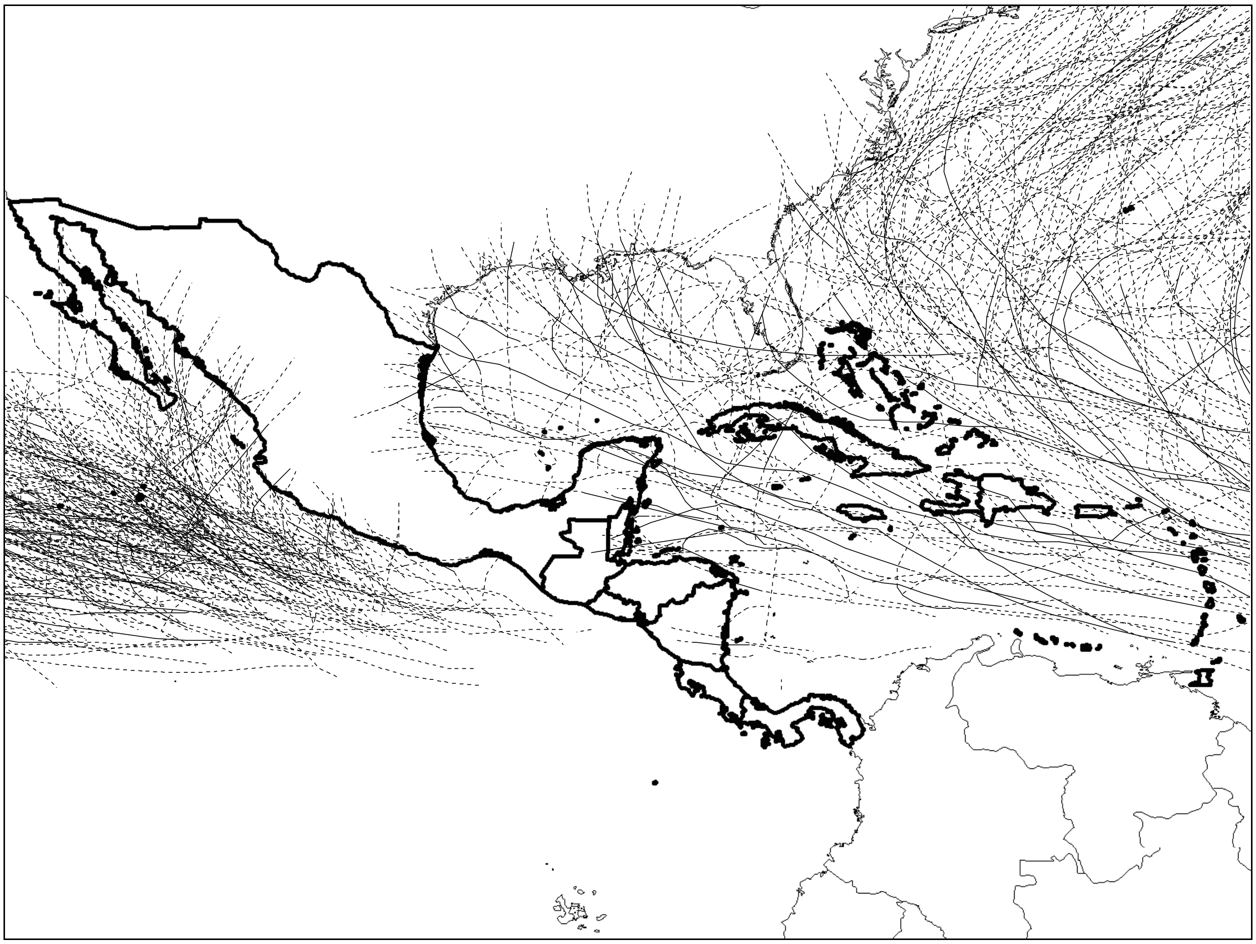
Notes: dependent variable. *log*(1+nightlight); Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1: Wind Field Model Structure

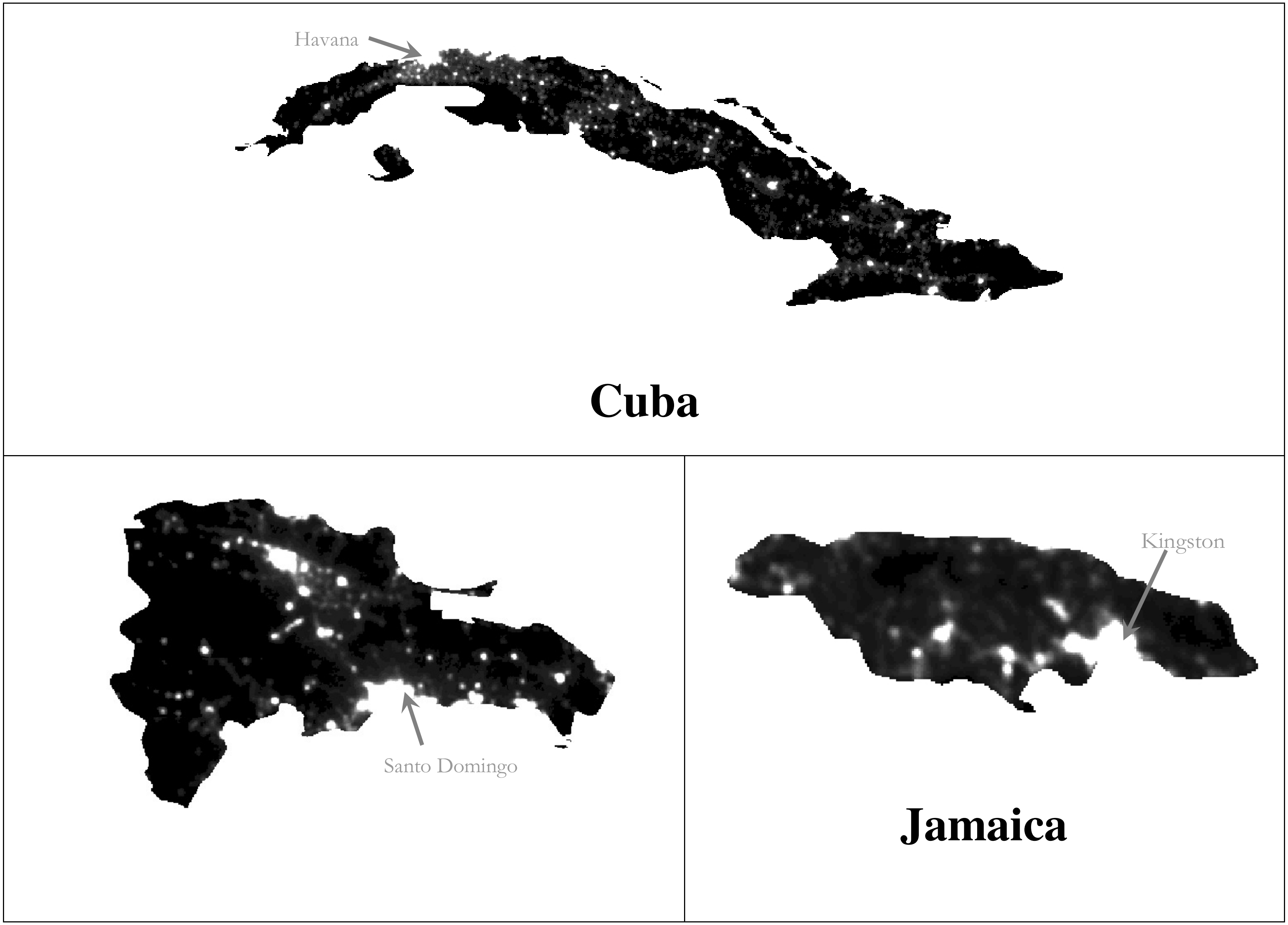


Source: Boose et al (2001)

Figure2: Hurricanes Since 1950



Notes: (1) Darker outlines indicate CAC region countries/territories. (2) Solid portion of hurricane tracks indicates times when the storm was classified as of at least SS strength 3, otherwise of hurricane strength 1 or 2.


Havana
Cuba
Santo Domingo
Kingston
Jamaica

Dominican Republic	

Figure 1: Nightlight data 2003