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THE MACROECONOMIC IMPACT OF NATURAL DISASTERS IN DEVELOPING COUNTRIES: EVIDENCE FROM HURRICANE STRIKES IN THE CENTRAL AMERICAN AND CARIBBEAN REGION

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THE MACROECONOMIC IMPACT OF NATURAL DISASTERS IN DEVELOPING COUNTRIES:

EVIDENCE FROM HURRICANE STRIKES IN THE CENTRAL AMERICAN AND CARIBBEAN REGION*

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Abstract

In this paper we investigate the macroeconomic impact of natural disasters in developing countries by examining hurricane strikes in the Central American and Caribbean region. Our innovation in this regard is to employ a windfield model combined with a power dissipation equation on hurricane track data to arrive at a more scientifically based index of potential local destruction. This index allows us to identify potential damages at a detailed geographical level, compare hurricanes' destructiveness, as well as identify the countries most affected, without having to rely on potentially questionable monetary loss estimates. Combining our destruction index with macroeconomic data we show that the average hurricane strike caused output to fall by up to 0.8 percentage points in the region, although this crucially depends on controlling for local economic characteristics of the country affected.

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Section I: 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 severety. 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]

While cited damage figures due to extreme events are often impressively large, the overall macroeconomic impact, in particular with regard to economic output, may in principle not necessarily be quite that apparent for a number of reasons. Firstly, as argued by Horwich (2005), natural disasters are almost always localized events and may thus only affect a limited part of the whole economy. Additionally, natural disasters generally relate to a loss in the capital

[1] See Rasmussen (2004).

stock – generally of a physical nature although there may also be losses in human capital – in an economy. However, if the gross domestic product is taken as the measure of output, it may actually be enlarged by the "production of replacement capital and disaster-related rescue, [and] relief and clean-up activity" (Horwich, 2000, p. 524).[2] Although of course GDP may initially fall before such replacement capital, direct fund injections, and rescue and relief activity take place, this may at least in part be mitigated if physical assets are not the dominant resource and/or if resource substitution occurs. Moreover, as noted by Hallegate (2006), negative shocks such as natural disasters may serve as a catalyst for re-investment and upgrading of capital goods which in turn can boost an economy.[3]

Arguably, however, one would expect such a 'dampening' of the negative effects due to natural disasters to play less of a role in developing countries, and the evidence seems to support this. For instance, Horwich (2005) argues that the Kobe earthquake in Japan, which was the most severe earthquake of modern times to strike an urban area, had little observable macroeconomic consequences, while the 1988 earthquake in Armenia, which registered at a lower Richter scale, are believed to have had devastating effects on the economy.[4] Also, in a cross-country study Noy (2008) finds that any macroeconomic costs are almost entirely due the developing country group of their sample. Such a differential effect for

[2] Although pre-disaster components and GDP itself could fall before enough replacemtn capital becomes available.
[3] For a discussion on the growth implication derived from theoretical literature, see Noy (2008).
[4] International Monetary Fund (2001).

developing countries may not be that surprising. Firstly, as noted earlier, much of the extreme events seem to mainly take place in geographic regions where mostly developing countries are located. Also, many developing countries tend to be relatively specialized in production, with particular emphasis on agricultural activities, which is likely to be the sector most affected by natural disasters.[5] As a matter of fact, recent evidence seems to indicate that the extent of losses due to natural disasters is very much related to the level of development; see, for instance, Anbarci et al (2005), Kahn (2005), Toya and Skidmore (2007), and Noy (2008).

Nevertheless, evidence on how much damages due to extreme events actually translate into a fall in overall economic output 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 (which includes those due to tropical cyclones) can only account for 13.9 per cent of the total volatility due to external shocks – an arguably small figure when one considers that he finds that external shocks themselves can only explain 11 per cent of total output volatility in developing countries. Bluedorn (2005) studies the response of the current account to hurricane activity by partially constructing his own estimates of damage losses of hurricane strikes in Central America and the Caribbean, and his findings suggest that the median damaging hurricane strike will cause output to

[5] See Albala-Bertrand, J.M. (1993).

fall by only 0.3 percentage points.[6] In contrast, Noy (2008) finds that natural disasters will typically cause a drop in output of 9 percentage points in developing countries.

While the few studies investigating the macroeconomic impact of natural disasters should be applauded for their novel attempts in this regard, there are a number of reasons to be skeptical about the actual quantitative size of their estimates. Firstly, except for Bluedorn (2005), these studies tend to treat natural disasters as a homogenous group of extreme events affecting an assumed homogenous group of countries. Arguably, however, different types of natural disasters have different potential effects, while different geographical regions are subject to different probabilities of occurrence for these, and thus are likely to be affected non-homogenously as the level of readiness may depend on the (perceived) probability of incidence.[7] Secondly, current studies essentially have all relied on aggregate damage estimates, either in financial or human loss levels or in terms of identifying the occurrence. Typically, however, damage estimates, such as those provided by the well-known EM-DAT database, which is the main source of information for papers investigating national disasters across countries[8], come from different sources, the nature and quality of reporting may change over time, the costs may be exaggerated to attract international

[6] Calculation using Bludorn's (2005) estimated coefficient and the mean damages per GDP value for hurricanes in the region taken from the EM-DAT database.

[7] For example, tropical cyclones only affect certain regions of the world and mostly coastal areas of these, while for other regions being near fault lines increases the likelihood of an earthquake; see Woo (1998).

[8] Bluedorn (2005) uses the EM-DAT data, as well as other sources to compile information on losses due to hurricanes. For those hurricanes for which there was no information, he inferred costs from similar hurricane strikes.

emergency relief, and identified events are generally subject to some threshold level for inclusion. Finally, as noted earlier, natural disaster events tend to have very localized impacts so that aggregate figures give little indication what portion of a country's economy are actually affected.

The purpose of the current paper is to address these shortcomings not only by employing arguably more appropriate estimates of the potential destruction of natural disasters, but also by focusing on a particular region subject to a particular type of natural disaster to isolate more reliable estimates of their overall macroeconomic impact. More specifically, as in Bluedorn (2005), our geographical focus is on hurricane strikes in the Central American and Caribbean region, an area that has been and continues to be particularly vulnerable to hurricanes. For example, in the last 50 years over 80 hurricanes made landfall in the region. However, unlike the previous studies we, rather than using potentially measurement error prone indicators of economic damages to proxy the severity of a hurricane strike, resort to 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. These local wind estimates are then used in conjunction with a power dissipation index to proxy local potential destructiveness of hurricanes.

Employing this wind field model approach arguably allows us to arrive at a more scientifically based estimate of potential damage due to hurricanes in the region over time. With this in hand we are then able to more accurately show which hurricanes were the most damaging, and which sub-regions within countries have been historically most affected. Combining our destruction estimates with available macroeconomic data we estimate that a typical hurricane strike in the region causes a reduction in annual output growth of about 0.8 percentage points. We also show that it is crucial in this regard to take account of both the local population distribution as well as the land use of the area affected.

The remainder of the paper is as follows. In the next section we briefly describe the basic nature of hurricanes and their potential destructiveness. In Section III we outline the wind field model and power dissipation equation used to derive a local index of local destructiveness. Section IV describes our data sources. Some destruction estimates using our proxy are given in Section V. We econometrically investigate the macro-economic impact of hurricanes in the region in Section VI. Finally, concluding remarks are provided in the last section.

Section II: Some Basic Facts about Hurricanes and their Destructive Power

A tropical cyclone is a meteorological term for a storm system, characterized by a low pressure system center and thunderstorms that produces strong wind and flooding rain, which forms almost exclusively, and hence its name, in tropical regions of the globe.[9] Depending on their location and strength, tropical cyclones are referred to by various other names, such as hurricane, typhoon, tropical storm, cyclonic storm, and tropical depression. Tropical storms in the North Atlantic and the North East Pacific region, as we study here, are generally termed hurricanes if they are of sufficient strength.[10] 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.[11] Outside of the eye curved bands of clouds and thunderstorms move away from the eye wall in a spiral fashion, where these bands are capable of producing heavy bursts of rain, wind, and tornadoes. The typical structure of a hurricane is depicted in Figure 1. Hurricane strength tropical cyclones are typically about 483 km wide, although they can vary considerably. The season for hurricanes in the two regions can start as early as the end of May and last until the end of November.

Hurricane damages typically take a number of forms. Firstly, the strong winds associated with hurricanes may cause considerable structural damage to buildings as well as crops. Secondly, strong 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, and this effect combined with the low pressure at the center of the

[9] The term "cyclone" derives from cyclonic nature of such storms, with counterclockwise rotation in the Northern Hemisphere and clockwise rotation in the Southern Hemisphere.
[10] Generally at least 119 km/hr.
[11] National Weather Service (October 19, 2005). Tropical Cyclone Structure. JetStream - An Online School for Weather. National Oceanic & Atmospheric Administration.

weather system and the bathymetry of the body of water that results in storm surges are the most damaging aspect of hurricanes. In particular, storm surges can cause severe property damage and destruction and salt contamination of agricultural areas, where flooding on the coast may occur 3-5 hours before the arrival of the center of the hurricane.[12] 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. In this regard, a popular classification has been the Saffir-Simpson Scale, which classifies hurricanes into 5 different categories, where 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 are given values of 1, 2, 3, 4, and 5, respectively, on the scale. With regard to the extent of damages caused, it is generally agreed that damages from hurricanes of levels 1 and 2 are relatively minor.[13] In contrast, once a hurricane reaches a strength of 3 on the Saffir-Simpson scale, considerable damage is likely as it approaches the coast of an area and when it makes landfall.[14] For instance, storm surges are typically above

[12] Yang (2007).
[13] For instance, hurricanes of level 2 typically involve storm surges between 1.8-2.4 meters, damage to shrubbery and trees with some trees blown down, and damage to mobile homes, poorly constructed signs, and piers. For more details see http://www.nhc.noaa.gov/aboutsshs.shtml.
[14] 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. Relatedly 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.

between 2.7 (at level 3) and 5.5 (at level 5) meters, while terrain continuously lower than 1.5 meters above mean sea level may be flooded inland 13 km or more for hurricanes of level 3, and 20 km or more for maximum strength storms.

Section III: Hurricane Wind Damage Index

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 passes over or nearby. To do so we rely on the meteorological wind field model developed by Boose et al (2004).[15], which provides estimates of wind field velocity of any point relative to the 'eye' of the hurricane. This model is based on Holland's well known equation for cyclostrophic wind[16] and sustained wind velocity at any point P is estimated as:

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

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, and R is the radial distance from the center of the hurricane to point P. The relationship between these parameters and P are depicted in Figure 2. Of the remaining ingredients F

[15] This wind field model was, for instance, verified by the authors on data for Puerto Rico.
[16] See Holland (1980). One may want to note that Holland's model is an axisymmetric model in that the true asymmetric nature of a hurricane cannot be represented. There is, however, no consensus on how such asymmetry should be modeled; see Bao et al (2005).

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 via:

$$V_g = GV_S \tag{2}$$

where *G* is the gust wind factor.

The next step entails translating these wind field calculations into potential damage estimates. 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 rises. Consequently, he proposes a simplified power dissipation index that can serve to measure the potential destructiveness of hurricanes as[17]:

$$\text{PDI} = \int_0^{\tau} V^3 dt \tag{3}$$

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. In particular, we focus on speeds that cause significant damages, i.e., on those that that are of speed of at least strength 3 on the Saffir-Simpson scale, as discussed

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[17] This index is a simplified version of the power dissipation equation $PD = 2\pi \int_0^t \int_0^{r_0} C_{D\rho} |V|^3 rddt$ where the surface drag (C_D), surface air density (ρ), and the radius of the storm (r_0) are taken as given since these are generally not provided in historical track data. Emanuel (2005) notes that assuming a fixed radius of a storm is likely to introduce only random errors in the estimation. He similarly argues that surface air density varies over roughly 15%, while the surface drag coefficient levels off at wind speeds in excess of 30m/s, so that assuming that their values are fixed is not unreasonable.

above. More precisely, the total destruction due to a storm *r* in any locality *j* in country *i* at time *t* is:

$$\mathrm{WIND}_{i,j,r,t} = \int_0^{\tau} V_j^3 w_{i,j,r,t}\, dr \qquad \text{if } V_{jt} > 177 \text{ km/hr and zero otherwise} \qquad (4)$$

where *w* are weights assigned according to characteristics of the locality to capture the 'potential' damage there.[18] Given that we are mainly interested in measuring local destruction in its importance for the country *i* where the area is located, we use importance weights. In this regard we weight by the time varying share of population of each individual locality at *t-1*, where the underlying argument is that, even if severely damaged by hurricane winds, sparsely populated areas are unlikely to 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. Moreover, allowing the population density to vary over time allows one to control for the likely changes in the distribution in favour of such coastal

[18] 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 scientifically based equation of power dissipation. Secondly, in terms of implementation, we use time varying rather than time invariant population shares, as well as an indicator of land cover type, to be discussed later, to take account more accurately of the differences in 'potential' damage locally.

areas over our sample period.[19] Finally, we will also experiment with using weights that describe the land cover type of area *j*.

Section III: Data Sources

Our paper specifically focuses on hurricane activity within the Central American and Caribbean region, the members of which are depicted in non-gray colors in Figure 2. In total the region consists of 31 countries/territories, a list of which is given in Table 1. In order to conduct our empirical analysis of the effect of hurricane destruction on these we rely on information compiled from a number of data sources described below.

A. Hurricane Data

For data on hurricanes in the Central American and Caribbean region 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 (NHC). 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.[20] One may want to note that the data are considered to be particularly reliable beginning with 1944, the year in which aircraft reconnaissance information about the storms is

[19] For example, for the US it has been found by Rappaport and Sachs (2003) that coastal areas have increased their share of the population due to both productivity as well as quality of life effects. One would suspect that the latter would feature particularly in the CAC region where a large of economic activity depends on tourism particularly in coastal areas.
[20] Elsner and Jagger (2004).

available. Nevertheless, because satellite monitoring only began in the mid-1960s, a portion of the lifetime of some of the tropical cyclones, particularly in their early life far away from land and normal shipping routes, may be missing. However, since we are mainly interested in tropical cyclones that are likely to have caused significant damage, i.e., cyclones of hurricane intensity near to land, this is unlikely to be a problem for our use of the data. Given the sample period of our economic data (which starts earliest for some countries in 1950), we limit our use of the data to the period from 1950 onward.[21]

The Eastern North Pacific Tracks File also consists of six-hourly positions of tropical cyclones, albeit in the Eastern North Pacific Basin, which is the portion of the North Pacific Ocean east of 140W. The first wind data from aircraft reconnaissance in the Eastern North Pacific region were obtained in 1956, where, as with the HURDAT data, information for tropical cyclones prior to this were taken from ship observations. Similarly, satellite monitoring only was implemented in the mid-1960s.[22] However, as argued above, given that we are interested in tropical cyclones of hurricane intensity, in particular those that were close enough to any land area to cause any damage in the region, the lower completeness of the data in this earlier time period is unlikely to affect our results. We thus similarly use the track data starting from 1950.

We depict all tropical storm tracks in the region since 1950 in Figure 4, where the segments in red signify the part of tropical storms that reached at least

[21] See Elsner (2003).
[22] See Jarvinen et al (1998).

hurricane level of strength 3. As can be seen, throughout the region there has been considerable tropical storm activity with 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.

B. Population Data

The population data used in the analysis is derived from the Latin America and Caribbean Population Database (LAC), which provides data on the spatial distribution of the region for 2.5 minute grid cells for 1960, 1970, 1980, 1990, and 2000. The LAC was compiled from medium-scale maps at country and sub-national level, national population censuses and United Nations data for the smaller islands of the Caribbean.[23] Given that the date of censuses differed across countries and did not always coincide with the dates for which data was constructed, population projections for the required years were derived from an inter-censal growth rate between the next and the next to last enumeration for each administrative unit. The approach to then converting the administrative figures into gridded data was based on the assumption that population densities are strongly correlated with accessibility. More precisely, information on the transportation network consisting of roads, railroads and navigable rivers was combined with the location of urban centers to compute a simple measure of accessibility for each node in the transportation network. These accessibility

[23] One may want to note that particularly the small Caribbean islands lacked sub-national administrative units.

measures were then interpolated into a regular raster surface. Finally, population figures for each administrative unit are distributed in proportion to the accessibility index value of each grid cell. We use this regional breakdown as the benchmark geographical schemata for our analysis. One may want to note that this breaks the total Central American and Caribbean region into 137,820 individual locations.

In order to derive annual national population share figures for each grid cell for each country in our analysis, we use a similar inter-censal growth rate to interpolate data for years between the given values. For the years prior to 1960 (i.e., 1950-1959) and those after 2000 (i.e., 2001-2005) we simply assumed the same annual growth rate of the decade subsequent and prior to the period, respectively.

In Figure 5 we portray the population share of individual localities within countries as calculated from the LAC for 2000, where darker shading indicates a higher share. It becomes clear that the population within countries is fairly unevenly distributed. For example, for many of the Caribbean islands, as well as for some of the Central American countries, populations tend to be more concentrated in coastal areas, i.e., locations that are also more likely to suffer from hurricane strikes. One may also want to note that while the average change in share has been small (0.02 percentage points)[24], there is considerable variation (a standard deviation of 0.2 percentage points), with some cells altering their

[24] Although of course the number of grid cells is large so that large average changes are unlikely.

share by as much as 21 percentage points. Hence there is clearly also some time variation in the distribution of population in the region even at a very local level.

C. Land Cover Data

Our data source for classifying land cover type is the Global Land Cover 2000 data set (GLC 2000). The data classifies land cover across the globe into 22 distinct land cover categories based on 14 months (1 Nov. 1999 - 31 Dec. 200) of daily 1-km resolution satellite data acquired over the whole globe by the VEGETATION instrument on-board the SPOT 4 satellite and delivered as multi-channel daily mosaics ("S1" format). We first overlaid the data to the grids used for the population data described above. We then used land cover categories (i) urban built-up areas, (ii) cropland (upland cropland or inundated/flooded crops), (iii) mosaic of cropland / shrub or herbaceous cover, and (iv) mosaic of cropland / tree cover / other natural vegetation to define the cells as 'economic' areas (EA) and all other land cover categories to identify 'non-economic' (NEA) areas.[25] We depict the distribution of these our land cover classification in Figure 6, where the beige color portrays NEAs and greened colored are the non urban built up areas and green shading portrays all other EAs. The first thing to note is that the urban-built up areas constitute a minute portion of land cover and it is hence for this reason that we group them into the EA category. More generally, one can see that all countries contain significant proportions of both the NEA and the EA types.

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[25] These other areas include all other areas that were not 'built-up' or used for crops.

D. GDP Data

Our source of GDP per capita data is taken from the World Penn Tables (WPT), which provides annual economic data for a large number of countries. One may want to note that GDP data are not available for all countries for all years, so that any use of the WPT data in our analysis, i.e., the econometric part of our study, ultimately means working with an unbalanced panel. The years of data available per country, as well, as the average growth rate, where available, are given in Table 1.

Section IV: Hurricane Destruction Estimates

To calculate local and aggregate wind speed damage estimates due to hurricanes, we first need to estimate local wind speeds experienced by relevant localities. One should note that of all the parameters necessary to estimate (1) and (2) some are given by the hurricane best track data, while for others values need to be assumed as in Boose et al (2004). In particular, the raw hurricane data set provides values for maximum sustained wind velocity, V_m, at particular locations at particular time intervals and from these one can then estimate V_h, the forward velocity, and, relative to the point of interest P, the clockwise angle between the forward path of the hurricane T, and, R, the radial line from the hurricane center.

The scaling parameters, F, S, B, and G in (1) and (2) control for surface friction, forward motion of the hurricane, the shape of the hurricane, and the gust factor, respectively. Here we use the figures as suggested by Boone et al (2005). In particular, F is assumed to take on values of 1.0 and 0.8 for points on water and land respectively, while G uses respective values of 1.2 and 1.5 for these surface types. S and B are assumed to be 1.0 and 1.3, respectively. Finally, one should 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 parameter.[26] We thus assume this to take on the value of 50 (km), which corresponds to its average value found for hurricanes with central pressures falling between 909 and 993 hPa.[27]

With these parameter inputs in hand the wind field model in (1)-(2) enables us to estimate the wind intensity experienced by any location relative to the position and maximum wind speed of a hurricane (as given by the best track data). However, one may want to note that while the raw cyclone data provides six hourly positions of tropical cyclones, these storms may travel considerable distance within six hours. Thus in order to ensure that we do not neglect areas that may be affected but do not fall within any significant distance (in the sense of experiencing severe winds) in our six hour windows, we linearly interpolated the positions P and wind speeds between the six hourly data to obtain three

[26] This parameter is traditionally measured by reconnaissance aircraft in the Atlantic basin, so that there is no information in this regard for older hurricanes.
[27] See Hsu and Yana (1998). This roughly corresponds to the central pressures of tropical storms of hurricane strength, where central pressure is inversely related to strength.

hourly track data.[28] In choosing all possible positions for which to calculate wind speeds experienced, we compiled the location of the center of each grid cell used for the population data within our region of interest.

In terms of applying our wind field model to obtain local wind intensity estimates for the Central American and Caribbean region, we then followed each tropical cyclone over each point of the interpolated track and calculated the wind intensity relative to the center of each grid cells in the schemata provided by the population data as long as these fell within 500 km of the hurricane's location.[29] This provided us with a complete set of estimates of wind fields experienced by all spatially relevant localities relative to each position of each tropical cyclone. We were then able to calculate local destruction according to our index of (4).

We first depict all hurricane tracks that according to our wind damage index were associated with at least some damage in one of the countries in the CAC region in Figure 7, where the red portions of the tracks indicate when these reached strengths of at least 3 on the Saffir-Simpson scale. Accordingly, only 119 storms, i.e., 20 per cent of all tropical storms that occurred since 1950 in the North Atlantic and Eastern North Pacific, came within close enough distance and reached high enough strength to affect local areas of the countries in the CAC region.

[28] 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).
[29] Hurricanes have been observed to reach up to a maximum of size of 1000km in diameter.

As a demonstration of how our WIND index translates into estimates of local destruction for individual hurricane occurrences we next calculated and plotted its value over all affected localities for Hurricanes David and Gilbert in Figures 8 and 9, respectively, where shading moving from yellow to red indicates the rising scale of damages (measured in terms of their contribution on a national scale because of the population weights). One may want to note that these were two of the most destructive hurricanes in the region over our sample period. For instance, David, which struck in 1979, was a hurricane of strength 5 reaching up to 240 km/hr winds and is known to have been one of the most deadliest of the 20th century, killing at least 2,068 individuals, and causing torrential damages, particularly in the Dominican Republic. In contrast, Hurricane Gilbert was the second most intense hurricane ever observed in the Atlantic basin, wreaking havoc in the Caribbean and the Gulf of Mexico for nearly 9 days in 1988, killing a total of 341 people and causing about $9.4 billion (2006 USD) in damages over the course of its path.[30]

As can be seen from Figure 8, Hurricane David only made landfall at hurricane strength in the Dominican Republic, causing damages throughout the island. Noteworthy in this regard is that the extent of damages differed widely, where being close to the actual traveled track does not necessarily mean large destruction in terms of national importance because of a non-even spread of

[30] See http://en.wikipedia.org/wiki/Hurricane_Gilbert.

population densities.[31] One may also want to take note that while no other islands were directly struck, Hurricane David's winds were strong enough to affect many of these by simply passing by. Hurricane Gilbert, in contrast, made landfall at hurricane strength in both Jamaica and Mexico, but caused relatively little damages in other islands that it passed. Additionally, although damages due to Gilbert were highest in levels in Mexico, the large size of the country and hence lower population shares of the affected areas, which is taken account of in terms of our employed weighting scheme, implies that in terms of national importance the storm had a much larger impact on Jamaica.

Summing the values calculated from the WIND proxy over all hurricanes *r* can also serve to compare the destructiveness of hurricanes relative to each other in terms of the damages done across economies. We show the top twenty most destructive, their normalized levels (relative to the 20th ranked) of destruction, as well as the countries affected, listed in descending order of destruction, in Table 2. As can be seen, Hurricane Hugo, striking in 1989, was the most destructive storm over our sample period, affecting 9 countries, where St. Kitts and Nevis was the nation hit hardest. Moreover, compared to the hurricane ranked 20th (i.e., Hattie), it caused over ten times more destruction. In contrast, Hurricane David, whose track was shown above, while slightly less destructive, affected a larger number of countries.

[31] Most obviously, some areas, despite being very close to the actual track, were estimated to have zero damages because the local population was zero.

In Figure 10 we plot the degree of destruction suffered by individual localities in the region – i.e., summing WIND over *j* – where the scale increases as colors change from yellow to red. As can be seen, particularly the very small islands have suffered badly from hurricane strikes, which is not surprising given that much of their area can be considered coastal, and hence especially vulnerable to hurricanes, and the fact that a greater share of the population will be affected given their geographical size. The larger Central American countries, in contrast, suffered mostly in their coastal regions, which constitute a much smaller portion of their total area, and hence the level of destruction (as indicated by the yellow shading) has not been as severe as for some of the other territories in the area.

One can also use our index to compare the cumulative historical experience of countries within our sample period, by summing WIND over all *i*. The results of this are shown in Table 3, where we for each country within the CAC region list the number of hurricanes that affected it, as well as the normalized of destruction (relative to the one with the lowest non-zero value, i.e., Guatemala). Accordingly, the incidence of hurricanes varies widely across the CAC, as does the degree of destruction. Anguilla has, according to our index, suffered the most, nearly two thousand times that of Costa Rica. Other countries severely affected over our sample period were St. Kitts and Nevis, the Virgin Islands, the Cayman Islands, Antigua, Monsterrat, and Guadeloupe. One may want to note that although Mexico, being exposed to both the Eastern North

Pacific and North Atlantic hurricanes, was hit by the most hurricanes, the total destruction suffered, relative to other countries, was relatively minor given its large geographical area and lower population shares of individual localities.

Section V: Macroeconomic Impact

Our main econometric task is to investigate the macroeconomic impact of hurricane strikes in the Central American and Caribbean region using our index of destruction. To do so we take our panel of countries for which we also have macroeconomic data and specify a simple growth equation:

$$GROWTH_{i,t-1\to t} = \alpha + \beta_1 GDP\_CAP_{i,t-1} + \beta_2 WIND_{i,t} + \varepsilon_{i,t} \tag{5}$$

where *GROWTH* is the growth rate in GDP per capita over *t-1* to *t*, *GDP_CAP* is the log of initial GDP per capita at time *t-1*, *WIND* is our destruction proxy, summed over all hurricanes *r* and all regions *j*, and ε is an error term. In essence this is a simple growth equation that allows for some degree of convergence via the initial GDP per capita term, as commonly used in the empirical literature, although here over the short term, i.e., annual time intervals.[32]

One should also note that with the inclusion of the initial level of GDP per capita one could easily rewrite (5) to be a dynamic panel model with the lagged dependent variable as one of the regressors. However, it is well known that dynamic panel regressions are characterized by a systematic bias in the estimator of the coefficient on the lagged dependent variable, first identified by Nickell

[32] One may want to note that that Noy (2007) uses a similar set-up investigating the macroeconomic consequences of natural disasters affect using cost data from the EM-DAT database.

(1981). Furthermore, this potential bias in the convergence term may lead to a bias in other coefficients in the model. Thus standard panel estimator such as the Least Squares Dummy Variable (LSDV) or fixed effects estimator would be inappropriate. In order to correct for the bias we hence employ Bruno's (2005) bias correction LSDV estimator, which extends the original estimator by Kiviet (1995).[33] Standard errors on the coefficients are generated via bootstrapping methods. One may also want to note that we are implicitly assuming that our *WIND* index is exogenous. This seems fairly plausible since, apart from the population weighting scheme (defined in terms of the previous year), it is constructed from non-economic data.

We first started estimating (5) without including any hurricane destruction measure, just simply the convergence parameter and year dummies. As can be seen from the first panel in Table 4, initial GDP per capita has a negative a significant coefficient, indicating, as much of the convergence literature suggests, that there is some convergence towards a some growth path (although in the relatively short-term since our data is annual). Moreover, the rate of convergence implied by the parameter is roughly in line with what has been found in the convergence literature in terms of the per annum convergence rate.

[33] Another option would be to use now standard GMM estimator, such as that proposed by Arellano and Bond (1991) . However, as shown by Judson and Owen (1996), the corrected LSDV estimator is more efficient in a typical macroeconomic panel as we have here.

We next proceeded to add our *WIND* proxy, as shown in panel two of Table 4. As can be seen, the damage due to hurricane winds is estimated to have a negative and significant impact on economic growth in countries in the region. Taking the average destruction of a hurricane strike, for instance, the estimated size of the coefficient would imply a reduction in the growth rate by 0.5 percentage points, whereas the largest destruction in a country in any year over our sample period (which was in the Virgin Islands due to Hurricane Lenny in 1999) would have reduced economic growth by 7.3 percentage points. We also investigated whether there may be growth effects beyond a year, for which we show the results of including the *WIND* index lagged by a year. However, the insignificance of the lagged value, depicted in the third panel, suggests that any negative impact does not extend beyond the short term.[34]

An advantage of the *WIND* index is that it allows one not only to capture the effect on those localities where according to the track data the hurricane passed directly over, but also those which were within plausible distance to experience nevertheless losses, even to the extent that the hurricane may have never made landfall in the country concerned. To investigate how important it is to capture these aspects, we first created a simple zero-one dummy indicating whether there were any landfalls of hurricanes of at least strength three in the year - the results of this are shown in panel 4 of Table 4. However, the insignificant and positive coefficient suggests that such a landfall incidence

[34] We tried including up to four year lags, but these were always insignificant.

proxy is unlikely to be enough to capture the negative growth impact of hurricanes. Similarly using the number cells directly passed over in any year by hurricanes relative to the total number of cells in any country as a proxy for destructiveness shown in the fifth panel does not suffice in proxying hurricane damages.

Earlier on we made the argument that it may be important to control for the population share of localities in order to take account of its 'potential' destruction. To emphasize this point we instead used the simple area share of each locality as weights in (4) in the 6th panel in the regression results table. [35] Accordingly, our WIND proxy is now, compared to the results in the second row, although still negative, insignificant.

It is important to emphasize that once the wind speed for localities of destruction are estimated, the degree of destruction in our index depends essentially on two assumptions. First, it is only winds of at least strength of 178 km/hr that cause significant damage, as suggested by the Saffir-Simpson scale. Secondly, in line with the argument made by Emmanuel (2005), both power dissipation and the degree of destruction rise in cubed terms with wind speed experienced. To investigate whether it is indeed winds above hurricane three strength that cause significant damage at the macroeconomic level, we calculated the equivalent measure in (4) except using wind speeds of at least strength 1, i.e., the cut-off point for a tropical storm in the region to be considered a hurricane.

[35] One should note that although in a horizontal plane all grid cells are of the same area, given the curvature of the Earth's surface the actual area will vary with the longitude.

Also, we also experimented with not cubing the hurricane speeds (above strength 3) experienced by a grid cell.[36] However, as can be seen from the estimated coefficients in the 7th and 8th panels, both of these proxies, while still negative, are no longer significant. Thus, at least as discernable from our results, it seems indeed reasonable to assume that damages from hurricanes mostly start once winds experience at least a strength of 178 km/hr and increase in cubic fashion in speed above this threshold.

While the distribution of population may give some rough indication of the 'potential' damage that a area in a country may experience due to hurricane winds relative to other less populated areas, one problem with regard to adhering strictly to this proxy for developing countries in particular is that often large portions of economic output are agricultural, and agricultural areas are likely to be especially vulnerable to wind field destruction. But, if landholdings are relatively large and/or farm households are not particularly large, then sparsely populated areas may simply be areas where agricultural production is important. In other words, weighting by population may be underestimating the actual potential effect of hurricane damage.

In order to roughly address this issue we used our classification of individual cells into the economic (EA) and non-economic (NEA) areas, as defined in Section III, and re-calculated *WIND* in (4), giving a weighting of 1 to the EAs but zero to NEAs. In order to isolate the effect of this classification we

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36 Not cubing the measures that incorporates wind speeds above strength one also was insignificant.

first start off with using area rather than population weights. The results of employing these land cover weights are shown in panel 9 of Table 4. Accordingly, while the coefficient on our proxy is still negative, it is no longer significant. Thus solely controlling for land cover type is insufficient to capture local economic importance of locality. We next, in panel 10, used population rather than area weights in conjunction with our land cover type weights, depicted in the panel 10. *WIND* is now highly significant and moreover portrays a much larger quantitative effect than for the simple population weighted measure. For example, if one considers the mean of non-zero observations on WIND_EA, then this would indicate that the average destruction in these areas caused a fall in output growth by about 0.8 percentage points. Thus, our findings suggest that it is important to take both the population distribution as well as the land use into consideration when trying to measure hurricane destruction with our wind field model approach.

As a final exercise it is arguably instructive to investigate how the results from using our wind field model approach in modeling the macroeconomic impact of hurricanes would compare to using data commonly used as a measure of damages in the natural disasters literature, i.e., data from the EM-DAT database. In this regard, one should note that the EM-DAT database is the most comprehensive publicly available compilation of information on the natural disasters and their damages around the globe that have occurred since 1900. In particular, the database records natural disasters as those in which at least 10 people were killed, at least a 100 people were affected, and/or there was a call for international assistance or a declaration of state emergency. For each natural disaster the EM-DAT database records the total number of individuals killed, the number of persons affected, and the total value of damages due to the event. With regard to hurricane related natural disasters, the database isolates a category termed 'windstorms', which consists of natural disaster events relating to cyclones, hurricanes, storms, tornados, tropical storms, and typhoons and winter storms.

Before proceeding in using the EM-DAT data to estimate the macro-economic impact of hurricanes in the Central American and Caribbean region, it is important to point out that, while there is considerable merit in the quality and coverage of the data and hence its widespread use, there a number of shortcomings that need to be considered with regard to estimating damages. First of all, information used to collate the list of natural disaster events is taken from a number of sources and hence there may be some concern in terms consistency across sources and thus possibly across countries and time. Related to this there appears to be greater reporting of events over time and the likelihood that events recorded in earlier time periods are more likely to have exceeded the minimum specified criteria in the data.[37] Perhaps most importantly, one should note that damages reported in the data refer to `ex-post' measures in that they are damages due to events that have to meet the minimum

[37] See Ramcharan (2007).

criteria of impact, and hence cannot be used to measure the actual potential impact of a natural event, given that the probability of a potentially damaging event to become actually damaging may depend on a number of other country specific and local factors. This latter aspect may inherently introduce a sample selection bias into the issue of measuring damages due to natural disaster events such as hurricanes. For instance, it has been demonstrated that the extent of damages may depend on factors such as wealth and the level of human capital in a country; see Kahn (2005) and Toya and Skidmore (2007). It has also been pointed out that reporting of damages due to natural disasters may be subject to exaggeration to encourage greater flows of international financial aid; see Yang (2007). Finally, it has also been pointed out that the measure of damages in the EM-DAT base only includes direct losses due to the natural disaster events; see Noy (2008).

We these caveats in mind we proceeded to use information from the EM-DAT database to construct proxies of hurricane events to investigate their macroeconomic impact in the Central American and Caribbean region. In particular, we used those most commonly used and found to be significant in the natural disaster literature estimating cross-country effects, namely, total damages measured relative to GDP (of a year prior) and the number of persons killed relative to the population size (of a year prior).[38] We calculate these measures for the information provided in EM-DAT on hurricane events in the region.[39]

One may want to first remark that Bluedorn (2005) noted that for hurricane strikes the EM-DAT is particularly unsatisfactory, where there are several important hurricane strikes that have taken place in the region that are missing from the data set. We thus first calculated the number of hurricanes affecting each country over our sample period from EM-DAT and depict these for comparison reasons relative to that derived form our measure in Table 3. As can be seen, the EM-DAT number of significant hurricane strikes is lower than that derived from our wind field model for 24 out of 31 countries, in many cases by at least 50 per cent. There are also four countries for which the EM-DAT sources indicates a greater number of significant incidences of losses due to hurricanes, namely, St. Lucia, Panama, El Salvador, and Costa Rica. One may want to note that this does not mean that these hurricanes are missing from the best track data[40], but that the areas affected according to our time varying population data were essentially unpopulated and/or that wind speeds did not reach high enough strength to be considered significant. For the years and countries for which we had both GDP and damages estimates we also compared our cumulative country specific measure of destruction with that using damage data from the EM-DAT calculated as a ratio of GDP. The correlation coefficient

[38] See, for instance, Kahn (2005), Toya and Skidmore (2007), and Noy (2008).
[39] One may want to note that the database does not systematically record actual maximum wind speeds observed for any of these hurricanes.
[40] This was verified by looking at the raw track data.

of the ranking of countries, found to be 0.024, shows that there is little relationship between the relative rankings of the two measures. One may also want to note that if we compare our minimum non-zero destruction country (Costa Rica) with that country that which experienced the most destruction in this sub-sample (Anguilla), then the destruction in the latter was 1,831 times larger. A comparison of the same minimum and maximum affected countries (Turcs & Caicos Islands and Mexico, respectively) as found from the EM-DAT database, suggests that in contrast the latter experienced destruction 1,621,659 times larger.

Our results of including these EM-DAT measures of destruction are shown in the last two panels of Table 4 . As can be seen, while the coefficients are negative, they are statistically insignificant for both. Hence this provides some indication that, at least for hurricanes strikes in the CAC region, using EM-DAT data may not be appropriate.

Section VI: Concluding Remarks

While monetary losses due to natural disasters are often large, it is not clear to what extent such losses will translate into large reductions in countries' growth rates. In this paper we investigated the macroeconomic impact of natural disasters in developing countries by examining hurricane strikes in the Central American and Caribbean region since the 1950s. Our innovation in this regard is to develop a more scientifically based index of potential local destruction of hurricanes that employs a wind field model combined with a power dissipation equation using historical hurricane track data.

Our index allowed us to identify potential damages at a detailed geographical level, compare hurricanes' destructiveness, as well as identify the countries most affected without having to rely on potentially questionable monetary loss estimates. Combining this index with a macroeconomic data for a panel of countries in the area we estimate that the loss in output growth for an average hurricane is about 0.8 percentage points, but that the most destructive hurricane would have caused on average a reduction in the growth rate of about 7.6 percentage points.

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Table 1: Central American and Caribbean Region Countries/Territories, ISO Codes, and the Availability of Economic Data

CAC List:	ISOCDE:	Non-Missing GDP Data Minimum Year	Maximum Year	Non-missing Observatios
Aruba	ABW	---	---	0
Anguilla	AIA	---	---	0
Antigua	ATG	1970	2003	34
Bahamas	BHS	1970	2004	35
Belize	BLZ	1970	2004	35
Barbados	BRB	1960	2004	45
Costa Rica	CRI	1950	2004	55
Cuba	CUB	1970	2003	34
Cayman Islands	CYM	---	---	0
Dominica	DMA	1970	2003	34
Dominican Republic	DOM	1951	2003	53
Guadaloupe	GLP	---	---	0
Grenada	GRD	1970	2003	34
Guatemala	GTM	1950	2003	54
Honduras	HND	1950	2004	55
Haiti	HTI	1970	2000	31
Jamaica	JAM	1953	2003	51
St. Kitts & Nevis	KNA	1970	2003	34
St. Lucia	LCA	1970	2003	34
Mexico	MEX	1950	2004	55
Martinique	MTQ	---	---	0
Montserrat	MSR	---	---	0
Netherlands Antilles	ANT	1970	2003	34
Nicaragua	NIC	1950	2004	55
Panama	PAN	1950	2003	54
Puerto Rico	PRI	1970	2003	34
El Salvador	SLV	1950	2003	54
Turks & Caicos Islands	TCA	---	---	0
Trinidad &Tobago	TTO	1950	2003	54
St.Vincent & Grenadines	VCT	1970	2003	34
US Virgin Islands	VIR	---	---	0

Table 2: Top Ten Most Damaging Hurricanes

Name	Year	ND	Countries Affected (in descending order of damage)
HUGO	1989	10.05	KNA, MSR, VIR, GLP, ATG, AIA, DMA, PRI, MTQ
DAVID	1979	8.84	DOM, DMA, MTQ, VIR, PRI, GLP, LCA, MSR, BRB, KNA, HTI, ATG, BHS
DONNA	1960	7.72	TCA, ATG, AIA, KNA, MSR, GLP, CUB, VIR, DMA, BHS, PRI
LENNY	1999	7.11	VIR, AIA, KNA, PRI
IVAN	2004	6.72	CYM, JAM, ABW, ANT, GRD, CUB, TTO, VCT, MEX
LUIS	1995	5.93	AIA, ATG, KNA, MSR, GLP
INEZ	1966	3.54	MSR, GLP, DMA, ATG, KNA, VIR, PRI, DOM, HTI, CUB, MEX
ALLEN	1980	3.52	CYM, VCT, BRB, LCA, HTI, JAM, MTQ, CUB, MEX, GRD, DOM, DMA
CLEO	1964	3.22	HTI, GLP, MSR, DMA, KNA, ATG, DOM, VIR, JAM, MTQ, PRI, CUB, BHS
DOG	1950	3.19	AIA, ATG, KNA, LCA, MTQ, MSR, GLP, VCT
GILBERT	1988	2.00	CYM, JAM, HTI, MEX, CUB, DOM
FLORA	1963	1.89	CUB, GRD, HTI, TTO, DOM
BETSY	1965	1.79	BHS, TCA, DMA, BHS, GLP, VIR, MTQ, PRI, DOM
JANET	1955	1.72	BRB, GRD, BLZ, VCT, ABW, MEX, HND, GTM
FOX	1952	1.70	CYM, BHS, CUB
GEORGES	1998	1.69	MSR, ATG, GLP, KNA, PRI, VIR, DOM, AIA, CUB
ANDREW	1992	1.57	BHS
FRANCES	2004	1.38	TCA, BHS
KEITH	2000	1.10	BLZ, MEX
HATTIE	1961	1	BLZ, HND, GTM, MEX

Notes: ND refers to normalized (relative to Hurricane HATTIE) destruction.

Table 3: Cumulative Historical Destruction by Country/Territory

ISOCODE	# Hurricanes	ND	EM-DAT # Hurricanes
AIA	7	2278	3
KNA	9	2220	4
VIR	9	2172	4
CYM	9	2082	2
ATG	11	1959	4
MSR	10	1801	2
GLP	11	1713	5
BHS	20	1322	8
TCA	5	1138	0
JAM	7	1052	7
BLZ	8	986	7
DMA	7	986	5
PRI	10	918	4
DOM	13	774	9
HTI	10	663	10
CUB	21	637	10
MTQ	7	557	6
GRD	4	493	3
BRB	4	487	3
LCA	4	407	5
ABW	4	377	0
VCT	4	273	4
ANT	3	212	0
HND	11	175	7
TTO	2	95	2
MEX	42	61	18
NIC	7	31	6
GTM	7	3	5
CRI	1	1	5
PAN	0	0	2
SLV	0	0	4

Notes: (1) # Hurricanes indicates the number of hurricanes that had affected the individual countries/territories. (2) Normalization of destruction is done relative to CRI. (3) ND refers to normalized (relative to Hurricane HATTIE) destruction.

Table 4: Regression Results

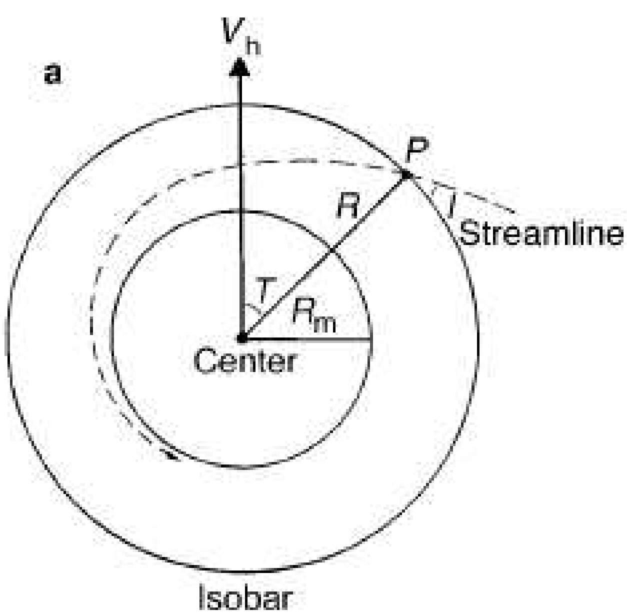
	Hurricane Proxy	β_{WIND}	*Std. Error*	$\beta_{GDP\_CAP(t-1)}$	*Std. Error*
(1)	*None*			-0.0260885*	*0.0106504*
(2)	*(Windspeed>178)^3 Population Weighted*	-5.08e-10*	*2.37e-10*	-0.0252828*	*0.0103694*
(3)	*(Windspeed>178)^3 Population Weighted*	-5.09e-10*	*2.46e-10*	-0.025109*	*0.010935*
	*(Windspeed>178)^3 Population Weighted(t-1)*HU*	-2.13e-11	*1.55e-10*		
(4)	*Landfall Dummy*	0.003629	*0.0047441*	-0.0261541*	*0.0107717*
(5)	*% of Grids with Landfalls*	-7.74e-08	*2.69e-07*	-0.026056*	*0.0107626*
(6)	*(Windspeed>178)^3 Area Weighted*	-4.88e-10	*2.57e-10*	-0.0253455*	*0.0104367*
(7)	*(Windspeed>118)^3 Population Weighted*	-2.11e-10	*1.45 e-10*	-0.0254827*	*0.010364*
(8)	*(Windspeed>178) Population Weighted*	8.35e-15	*1.79e-13*	-0.026056*	*0.0107638*
(9)	*(Windspeed>178)^3 Area Weighted, EA=1, NEA=0*	-4.96e-10	*6.41e-10*	-0.026052*	*0.0102181*
(10)	*(Windspeed>178)^3 Population Weighted* EA=1, NEA=0*	-8.80e-10**	*3.07e-10*	-0.0259452*	*0.0106592*
(11)	*COST/GDP(t-1)*	-384.2236	*2194.5*	-0.0258881*	*0.0106052*
(12)	*DEATHS/POP(t-1)*	-20.69586	*12.34383*	-0.0266218*	*0.0103922*

Notes: (1) # of observations and countries in all regressions are 969 and 23, respectively. (2) time dummies included. (3) ** and * are 1 and 5 per cent significance levels, respectively. (4) Standard errors are bootstrapped.

Figure 1: The Typical Structure of a Hurricane

Source: http://www.angryconservative.com/home/Portals/0/Blog/GlobalWarming

Figure 2: Wind Field Model Structure



Source: Boose et al (2001)

Figure 3: Caribbean and Central American (CAC) Region

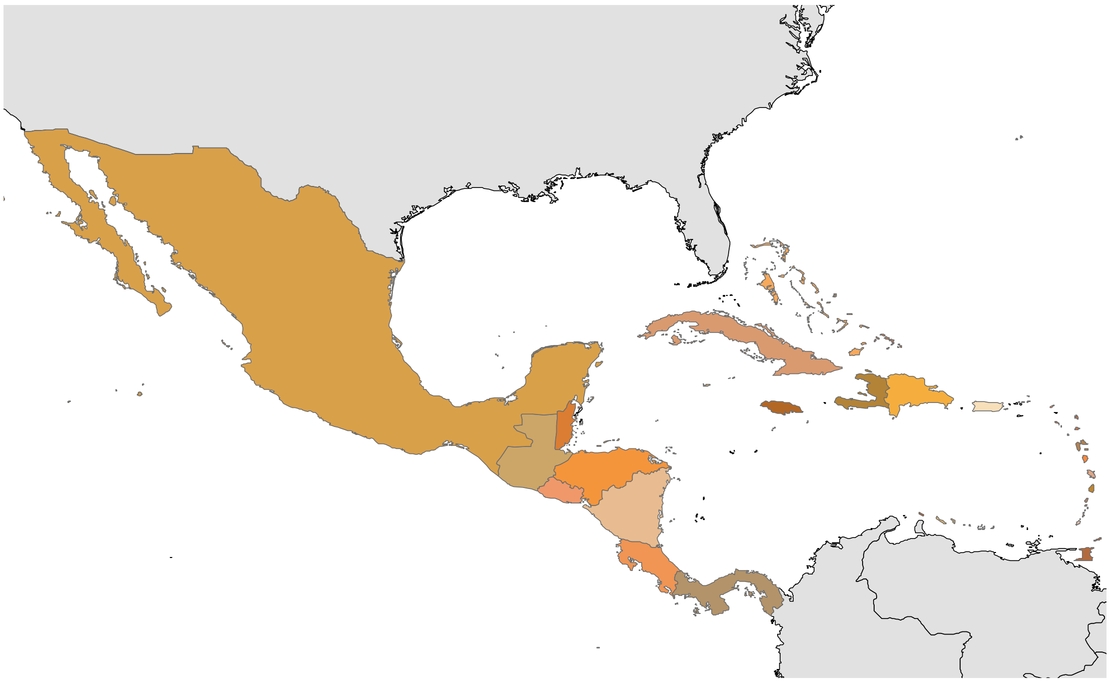
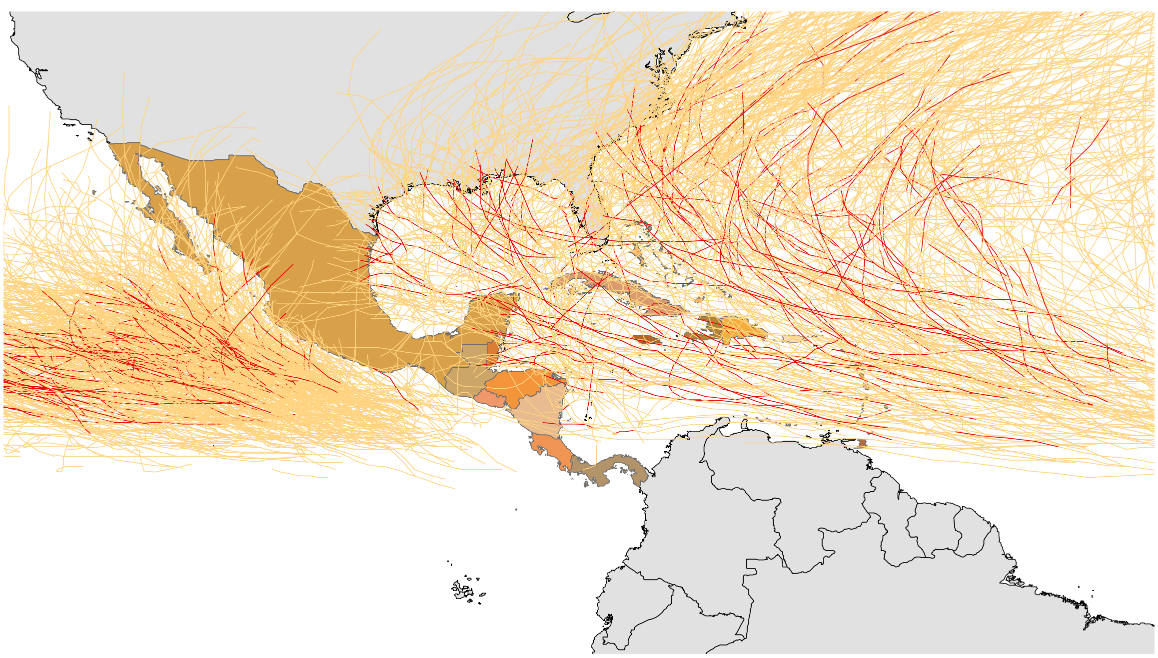
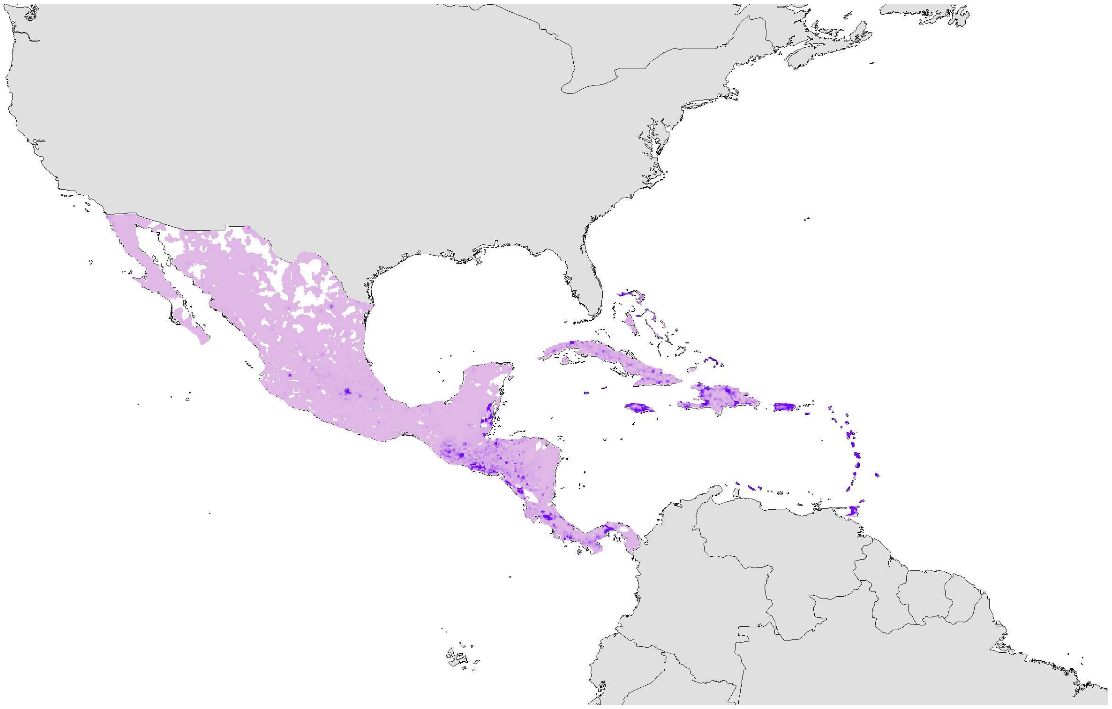


Figure 4: All Tropical Cyclone Activity Since 1950



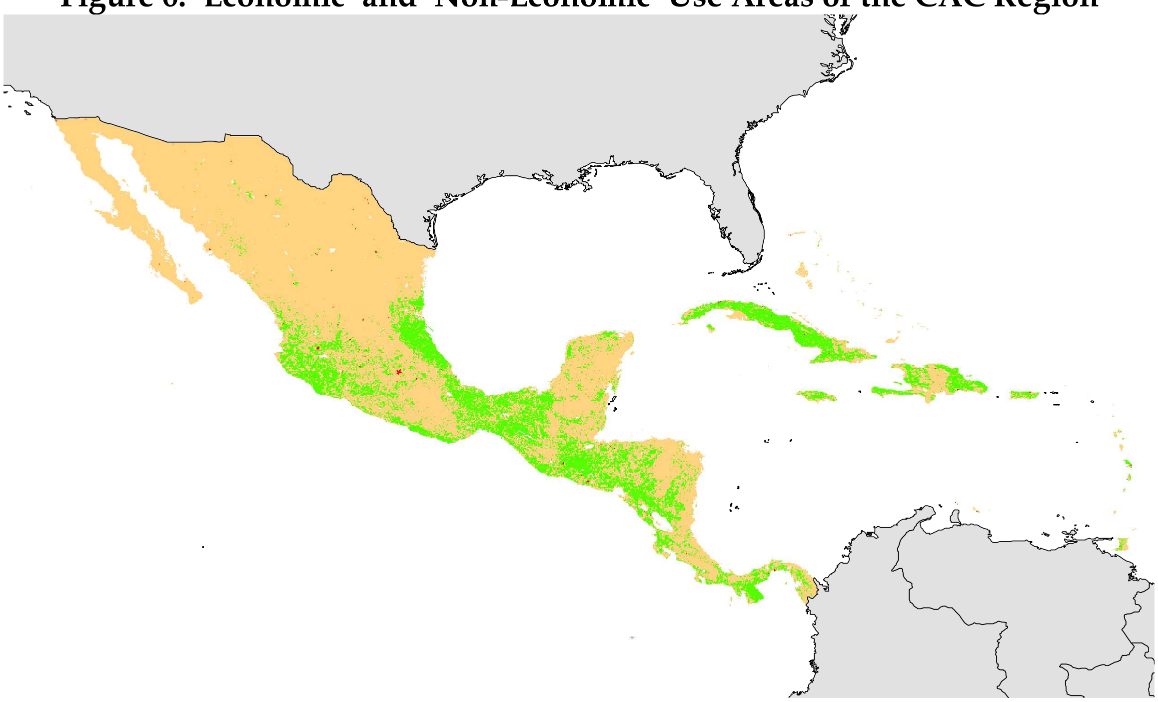
Notes: The red portion of the tracks constitute the segments of tropical storm tracks that reached at least hurricane intensity of level 3.

Figure 5: Population Share Distribution in 2000



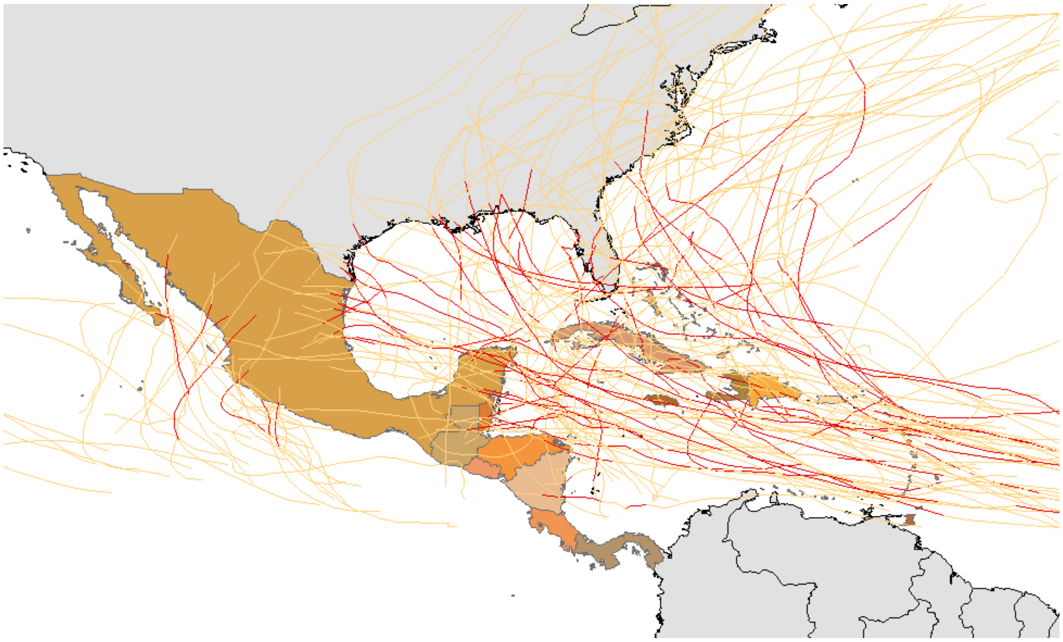
Notes: Share is measured in terms of local units in the national population, where darker shading indicates greater share.

Figure 6: 'Economic' and 'Non-Economic' Use Areas of the CAC Region



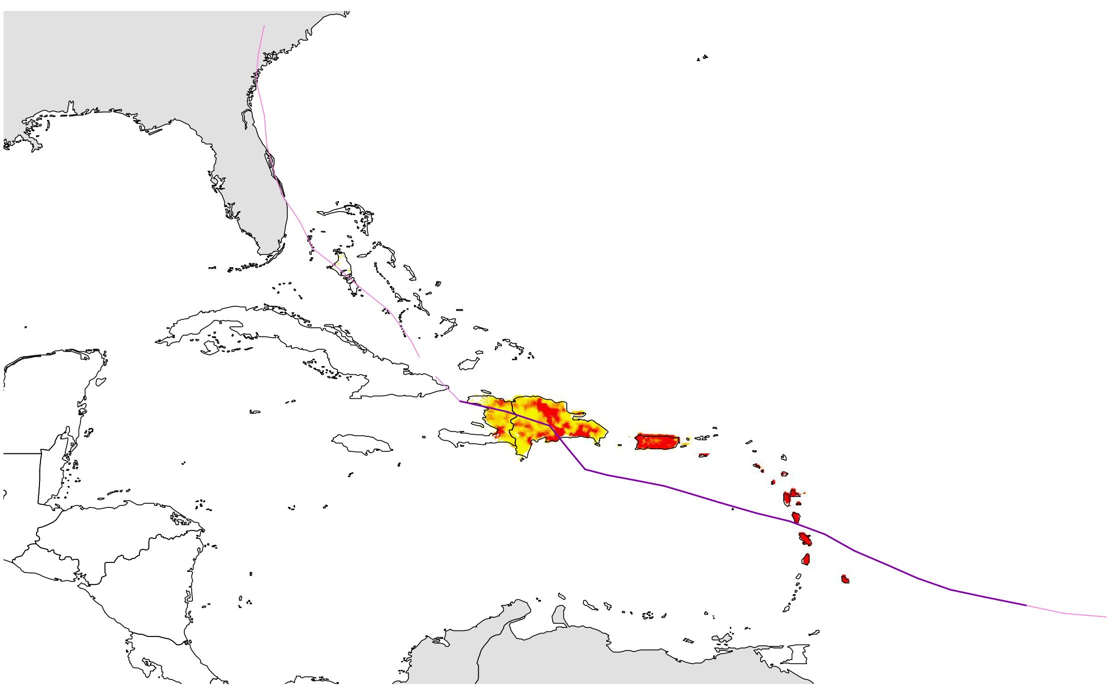
Notes: Beige colored areas are NEAs, while the portions constitute the urban built-up and green shading signifies all other EAs.

Figure 7: Relevant Hurricanes



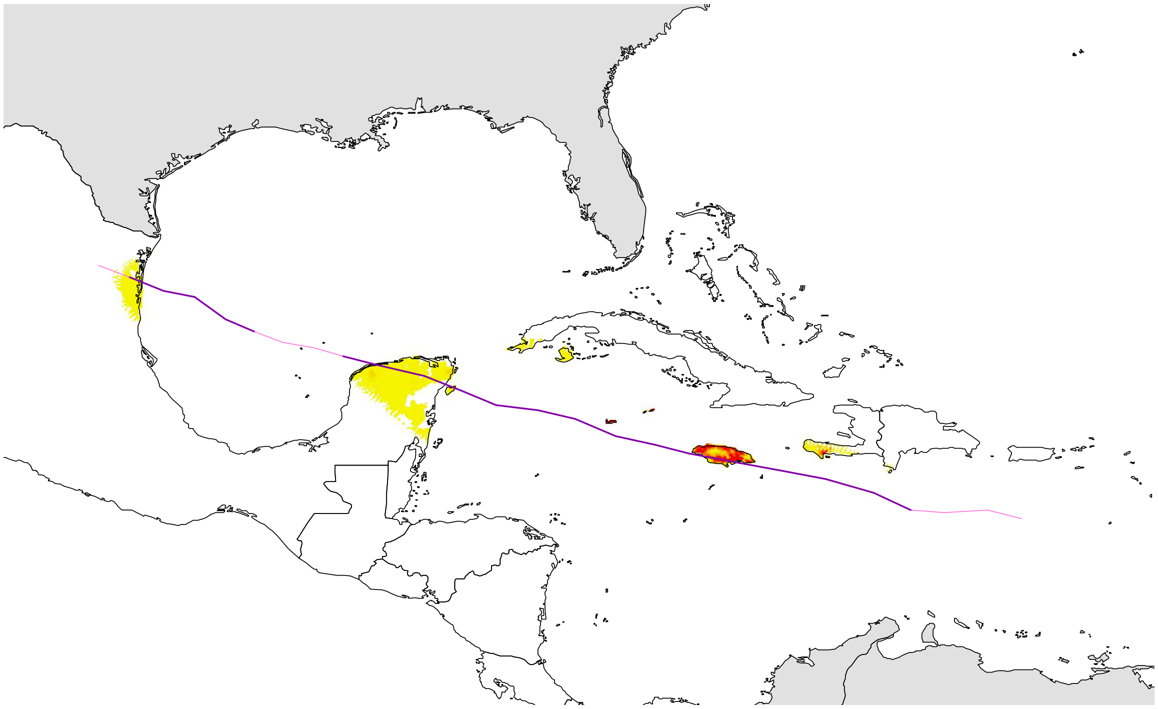
Notes: The red portion of the tracks constitute the segments of tropical storm tracks that reached at least hurricane intensity of level 3.

Figure 8: Hurricane David's Destruction Path



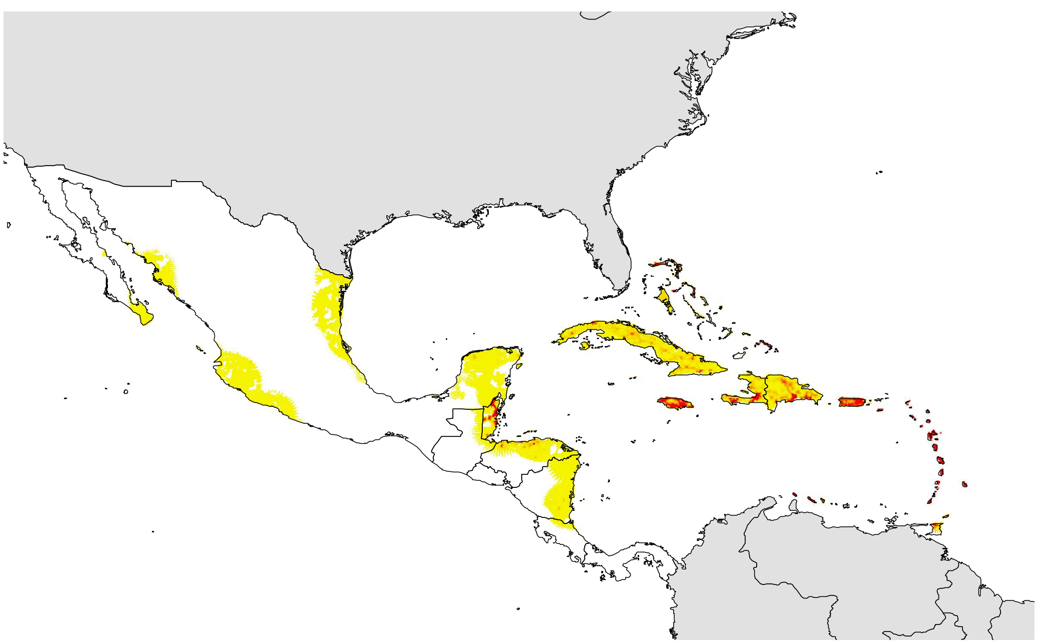
Notes: (1) The degree of destruction increases as the colour scheme changes from yellow to red. (2) Hurricane tracks of at least strength 3 are depicted in purple and those of strengths 1-2 as pink.

Figure 9: Hurricane Gilbert's Destruction Path



Notes: (1) The degree of destruction increases as the colour scheme changes from yellow to red. (2) Hurricane tracks of at least strength 3 are depicted in purple and those of strengths 1-2 as pink.

Figure 10: Local Degree of Destruction



Notes: The degree of destruction increases as the color scheme changes from yellow to red.