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Mangroves for Coastal Protection

Evidence from Hurricanes in Central America

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Abstract

This paper evaluates whether mangroves can mitigate the impact of hurricanes on economic activity. The paper assembles a new, regionwide panel data set that measures local economic activity using nightlights, potential hurricane damages using a detailed hurricane windstorm model, and mangrove protection by mapping the width of mangrove forests on the path to the coast. The results show that hurricanes have negative short-run effects on economic activity, with losses likely concentrated in coastal lowlands that are exposed to both wind and storm surge hazards. In these coastal lowlands, the estimates show that nightlights decrease by up to 24 percent in areas that are unprotected by mangroves. By comparison, the impact of the hurricanes observed in the sample is fully mitigated in areas protected by mangrove belts of one or more kilometers.

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Mangroves for Coastal Protection: Evidence from Hurricanes in Central America

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1 Introduction

More than 1.4 billion people live in coastal areas at risk of tropical cyclones (Dilley et al., 2005). Cyclone damage is expected to increase as a result of more frequent high-intensity storms created by climate change and increased exposure created by the ongoing movement of people and assets to high-risk coastal areas (Mendelsohn et al., 2012; Emanuel, 2011; Knutson et al., 2010). While interventions such as early warning systems may be cost effective in terms of saving lives (e.g., Das and Vincent, 2009), coastal defense interventions to protect assets and prevent disruptions to economic activity tend to be expensive to construct and maintain (e.g., seawalls or embankments) and can have adverse ecological side effects (Temmerman et al., 2013).

An alternative coastal defense intervention is the conservation and restoration of natural habitats that can provide protection against cyclones (Saleh and Weinstein, 2016). Mangrove forests have received considerable attention because their aerial root and canopy structure makes them capable of reducing wave action (Massel et al., 1999; Mazda et al., 2006; Barbier et al., 2008; Horstman et al., 2014), wind velocity (Das and Crépin, 2013), and storm surge (Krauss et al., 2009; Barbier et al., 2011; Zhang et al., 2012; Liu et al., 2013). While there is an ongoing debate on whether mangroves are effective at saving lives (Das and Vincent, 2009; Baird et al., 2009), relatively little is known about their value in terms of protecting assets and mitigating disruptions to economic activity.

Here we fill this gap by showing that mangroves can considerably mitigate the damage to economic activity created by hurricanes in Central America. We focus on this region because hurricanes occur frequently; its coastline is highly exposed to storm surge (Dilley et al., 2005), which is one of the most damaging features of hurricanes; and because coastal areas have historically sustained mangrove forests (Spalding et al., 1997) capable of providing protection.

Intuitively, because mangrove forests act as barriers to obstruct flow and buffer winds, protection is expected to increase with their density and width (Mazda et al., 1997). Mangroves in Central America may be particularly well suited for providing protection. Specifically, in terms of density, mangroves near the equator are characterized by dense above-ground biomass, and by less pronounced seasonal variation in their density (Koch et al., 2009). Moreover, the dense stilt root systems of the *Rhizophora* spp., which is commonly found in Central America, have been shown to be effective at dissipating wave energy (Horstman et al., 2014; Zhang et al., 2012) and withstanding storms (Dahdouh-

Guebas et al., 2005; Sandilyan and Kathiresan, 2015). In terms of width, mangrove belts are still found in the region despite significant deforestation (Spalding et al., 2010). Wide mangrove belts are likely to be an important feature of protection against storm surge as argued by Zhang et al. (2012).

To estimate whether mangroves can reduce hurricane damage, we divide Central America into one km^2 grid cells and construct a cell-year panel for the 2000 to 2013 period. The panel combines measures of economic activity, potential hurricane damage, and mangrove protection. Specifically, we use remote sensing data on nightlights to measure local economic activity. Nightlights have been shown to be a good proxy of economic activity (see Donaldson and Storeygard (2016) for a review), and their high spatial resolution is ideal because the economic impact of tropical cyclones has been shown to be highly localized (e.g., Bertinelli and Strobl, 2013; Elliott et al., 2015). We measure potential hurricane damages using predicted wind speed from the wind field model of Pita et al. (2015). The model is calibrated for Central America and has been validated with historical data. To translate wind speed into potential destruction, we use the damage function proposed by Emanuel (2011). To measure the degree of mangrove protection, we follow Das and Vincent (2009) and calculate the width of mangrove, as measured in 2000, along the closest path to the coast.

We estimate the causal impact of hurricanes on our proxy of economic activity by regressing nightlights on our damage index. The identifying assumption is that hurricane strikes are exogenous conditional on cell and year fixed effects. We then explore the heterogeneity in the impact of hurricanes by interacting our damage index with the predetermined width of mangrove on the path to the coast.

Our results fall into two categories. The first set of results show that, consistent with previous literature, hurricanes have negative short-run effects on economic activity. The estimated effect size suggests that a category three hurricane in the Saffir-Simpson scale can reduce our proxy of economic activity by 16%. We additionally document a 17% reduction in economic activity for coastal lowlands, which are at risk from both wind and storm surge damage.

The second set of results show that the impact of hurricanes, in storm surge prone areas, decreases as the width of mangrove increases. To ensure that the effect is driven by the mangrove vegetation itself, and not by other characteristics of the location of mangrove habitats, we further restrict our sample to cells that have been historically protected by mangrove habitats. Our preferred specification explores the impact of hurricanes in steps of one km mangrove width. We find that in areas with less than one km of mangrove width a category three hurricane can decrease nightlights by roughly 24%. By comparison areas with one or more km of mangrove width are unaffected by the hurricanes in our sample. To show that these findings are not driven by a mechanical relationship between mangrove width and distance to the coast, we additionally show that, in coastal lowlands, the impact of hurricanes does not decrease with distance to the coast in the absence of wide mangrove belts. Last, we present results from a counterfactual exercise showing that mangroves averted the loss of 2.5% of the initial economic activity in coastal Nicaragua. Nicaragua's coastlines were exposed to various hurricanes including the largest event in our sample, hurricane Felix.

Our findings contribute to several strands of literature. First, they contribute to the literature on coastal defenses by showing that in the coastal lowlands of Central America, mangroves protected vulnerable assets and economic activity from hurricanes. Our findings thereby demonstrate that in regions capable of supporting mangrove habitats, conservation efforts can offer an alternative to building coastal defenses or incentivizing the retreat from vulnerable areas. Second, our findings also contribute to the literature on the valuation of ecosystem services, and specifically to the valuation of the protective service of mangroves (see Barbier (2016) for a review). To our knowledge, this paper provides the first empirical estimates of the value of mangroves in terms of protecting economic activity in a region from several hurricanes. These estimates highlight that the value of mangrove protection is non-negligible, and should be accounted for in addition to other ecosystem benefits, such as carbon sequestration and biodiversity. Third, our results add corroborating empirical evidence to earlier case study papers which highlight that effective mangrove protection requires the preservation or restoration of wide mangrove belts (e.g., Zhang et al., 2012). Last, we add to the literature on the local economic impact of tropical cyclones by showing that, in consensus with past papers, cyclones have a negative short-run effect on economic activity (e.g., Elliott et al., 2015; Bertinelli et al., 2016; Ishizawa et al., 2017; Del Valle et al., 2018).

The paper is organized as follows. Section 2 describes the data. Section 3 presents the identification strategy and the results. Section 4 concludes.

2 Data

2.1 Nightlights

We measure local economic activity using imagery from four weather satellites that are part of the United States Air Force Defense Meteorological Satellite Program. These satellites record daily cloud formation by measuring the amount of moonlight reflected by clouds at night. On nights with no cloud cover, these satellites measure the light emissions from the earth's surface. Specifically, we use the annual composites produced by the National Oceanic and Atmospheric Administration (NOAA). These composites predominantly measure man-made lights because they only use information from cloud-free days and because NOAA's methodology filters transient sources of light.[1]

Nightlights provide a good proxy for economic activity because consumption of lights at night is likely to increase with income. Accordingly, nightlights have been extensively used to measure changes in economic activity (see Donaldson and Storeygard, 2016, for a literature review), including the downturns generated by hurricanes (Bertinelli and Strobl, 2013; Elliott et al., 2015; Bertinelli et al., 2016; Ishizawa et al., 2017; Del Valle et al., 2018).

Our nightlights data set is composed of 22 satellite-year composites for the period 2000-2013. Each composite covers Central America and contains information on 604,473 one-kilometer square grid-cells. Each cell records the intensity of nightlights, on a scale that ranges from zero (no light) to 63 (maximum light). In years with overlapping satellite coverage, we aggregate nightlights by taking cell-level weighted averages across satellites, where the weights are given by the number of cloud-free days.[2] We restrict the sample to cells that have non-zero nightlights in at least one year during our sample period. The resulting cell-year panel is composed of 212,072 cells which we observe for 13 years. The average value of nightlights in 2000 is 5.1 with a standard deviation of 8.4.

[1] The procedure to produce composites is described in detail in Elvidge et al. (1997).

[2] This method follows Ishizawa et al. (2017). Taking unweighted averages or using information only from the newest satellite produces very similar results. These results are available upon request.

2.2 Hurricane Damage

Hurricane Windstorm Model

To measure the distribution of surface winds from hurricanes in Central America during our sample period, we use the wind field model developed by Pita et al. (2015). This model uses an asymmetric Holland equation that has been specifically calibrated for Central America. The main model output is predicted wind speed in kilometers per hour (km/h) at the height of 10 meters for each cell and tropical storm that has since 2000 affected the following countries: Costa Rica, El Salvador, Honduras, Guatemala, Nicaragua, and Panama. Further details of the model can be found in supporting information.

Hurricane Destruction Index

To match the wind speed data set to our nightlight data, we construct a cell-year panel, that uses only observations from the hurricane with the highest recorded wind speed during a given year.[3] Approximately a quarter of the cells in our sample experience non-zero wind speed.

We convert wind speed into potential damage using the transformation and parameters proposed by Emanuel (2011). This transformation imposes a threshold below which damage is unlikely to occur, it guarantees that damage will approach unity for very high wind speeds, and it accounts for the physical property that wind power (the rate of increase of kinetic energy) from a hurricane is proportional to the third power of wind speed. The damage index f is given by:

$$f_{it} = \frac{\left[\frac{max(V_{it}-V_T,0)}{V_H-V_T}\right]^3}{1+\left[\frac{max(V_{it}-V_T,0)}{V_H-V_T}\right]^3} \tag{1}$$

where V_{it} represents wind speed in cell i and year t, V_T is the threshold below which damage is unlikely to occur, it is set just below severe gale speeds 50 knots ($\approx$ 92.6 km/h), and V_H is the wind speed at which half of all structures are expected to be destroyed 150 knots ($\approx$ 277.8 km/h). Additionally, because physical damages may be higher non-linear

[3]We also calculate a cell-year panel using the highest recorded wind speed in each cell-year, without taking into account the overall strength of the hurricane.

functions of wind and water stress, in the supporting information appendix we show that our results are also robust to following Nordhaus (2006) suggestion of an eighth-power relationship between maximum wind speed and damages.

Storm Surge Prone Area

The f damage index provides an informative measure of wind damages and potentially of overall damages because it is also correlated with damage from excess rainfall and storm surge. Nonetheless, because storm surge is often considered one of the most damaging aspects of hurricanes, we further investigate whether coastal lowlands are disproportionately affected by hurricanes. Specifically, we create a coastal lowland indicator variable identifying contiguous areas along the coast which are less than 10 meters above sea level.[4] This storm surge prone area is composed of 7,758 cells (3.6% of all cells). For each of these cells, we additionally calculate the shortest path (Euclidean distance) from the centroid of the cell to the coast. The average distance to the coast is 5.41 km.

2.3 Mangrove

Data on the distribution of mangroves come from two sources. The first is a collection of harmonized maps, 1960 to 1996, that was assembled for the Mangrove World Atlas (Spalding et al., 1997). We use this map to identify areas that have historically supported mangrove habitats. The second source is Giri et al. (2011), who use 1997 to 2000 Landsat data, together with supervised and unsupervised digital image classification, to construct a 30 square meter resolution map of the global distribution of mangrove. We use this second data set to precisely measure the presence of mangrove at the beginning of our sample period.

To rule out that any protection benefits of the mangrove are derived because mangroves grow in areas that are naturally more sheltered, for example, areas that lay in a steeper continental shelf, we begin by excluding from the analysis areas that have not historically supported mangrove habitats. Specifically, for every cell in the storm surge prone area we exclude cells that have no mangrove, as defined by Spalding et al. (1997), in their

[4] Nordhaus (2006) considers areas with elevation less than 8 meters as vulnerable to storm surge. We use a less stringent definition because Shuttle Radar Topography Mission (SRTM) elevation estimates below 10 meters are not considered reliable (McGranahan et al., 2007). We thank Eric Strobl for providing us with GIS boundaries for global coastal lowlands constructed from STRM data.

shortest path to the coast. We find that there are 3,853 cells (49% of cells in storm surge prone areas) with mangrove on their path to the coast.

Next, for each of the remaining cells, we calculate mangrove width in two steps. First, we identify the line segments along the shortest path to the coast that overlap mangrove forests as defined by Giri et al. (2011). Second, we sum the line segments to measure cumulative mangrove width on the shortest path to the coast. Figure 1 provides a visual representation of the mangrove width calculation in the North Caribbean Coast Autonomous Region in Nicaragua, where hurricane Felix made landfall. The dots are cell centroids, the black colored lines are the paths to the coast, and the green lines are the mangrove line segments that are summed to measure mangrove width. We find that in our sample the average mangrove width is 0.9 km, with a minimum of zero and a maximum of 10.11 km.[5]

3 Results

3.1 Impact of hurricanes on nightlights

To estimate the impact of hurricanes on economic activity, as measured by nightlights, we use the following two-way fixed effect specification:

$$NL_{it} = \alpha + \beta f_{it} + \pi_t + \mu_i + \varepsilon_{it} \tag{2}$$

where NL_{it} represents the nightlight intensity of cell i in year t, f_{it} is the damage index, π_t are year fixed effects, μ_i are cell fixed effects, and ε_{it} is the error term. The parameter β measures the impact of hurricanes on nightlights under the assumption that these shocks are exogenous. While certain areas of Central America may have a greater historical incidence of hurricanes leading, for example, to a relocation of economic activity or to investment in damage prevention, we account for this possibility by including cell fixed effects. We also account for time-varying common shocks and address the issue of over time comparability of nightlights by including year fixed effects. Equation 2 is estimated

[5]Figure S1 in the supporting information section overlays on figure 1 the maximum sustained wind speed from hurricane Felix

using ordinary least squares for the sample period 2001-2013.[6] To allow for correlation among nightlights across cells and over time, we cluster standard errors at the administrative level below the state, which is the municipalities for most countries.[7] Table 1 shows, consistent with previous literature, that hurricanes have considerable short-run negative effects on local economic activity. Column 1 presents the results from the specification in Equation 2. Our estimate of β is negative and statistically significant at the 5 percent level. The size of the coefficient indicates, for example, that nightlights in cells that experience category three hurricane winds ($f = 0.2$, wind speed of 208 km/h) decrease by 0.81 units ($\approx -4.055 \times 0.2$).[8] Since the average nightlights was 5.1 in 2000, this effect roughly corresponds to a 16% decrease in our proxy of local economic activity. The most affected cells in our sample experience an f of 0.23, the average f among impacted cells is 0.004.

Next in column 2, we investigate whether hurricanes have lasting effects on economic activity by introducing a lag of the f_{it} damage index, but find no evidence of effects beyond the year the hurricane occurs. Specifically, the estimated f coefficient is statistically significant and nearly identical to that of column 1, while the lagged coefficient is small and statistically indistinguishable from zero. This result is in line with previous literature which has highlighted that the negative effect of hurricanes on economic activity is relatively short-lived (e.g., Elliott et al., 2015; Del Valle et al., 2018).

Last in column 3, we estimate the impact of hurricanes in storm and non-storm surge prone areas. Specifically, we create dummy variables for each of these areas and we interact these variables with our damage index f. We then include the variables obtained in the previous step in place of f in Equation 2. The resulting coefficients can be interpreted as the effect of hurricanes on nightlights for each of these areas. The coefficient for non-storm surge prone areas is negative, but noisily estimated, we can neither rule out that it is statistically indistinguishable from zero or from the coefficient for storm surge prone areas. By comparison, the coefficient for storm surge prone areas is sharply estimated and clearly indicates that hurricanes have considerable negative effects in this area. Specifically, nightlights in cells in storm surge prone areas that experience category

[6]We exclude the year 2000 from our sample to interpret mangrove width in 2000 as a predetermined covariate in the next section.

[7]We also compute and find very similar results using standard errors clustered at the state level, and spatial heteroscedasticity and autocorrelation consistent errors as described in Conley (1999). The Conley errors are computed with 12 lags and a 500 km bandwidth.

[8]Hurricane wind speeds of category one (f=0.03, wind speed 153 km/h) or two (f=0.09, wind speed 177 km/h) would decrease nightlights by 0.12 and 0.37, respectively.

three hurricane winds ($f = 0.2$) are reduced by 0.88 units or 17%.

3.2 Mangroves reduce hurricane impact

We study the effectiveness of mangrove defenses by testing whether the impact of hurricanes on nightlights decreases as the level of mangrove protection increases. Our measure of mangrove protection for each cell is the width of mangrove in 2000 along the shortest path to the coast. We focus on storm surge prone areas because we have shown that hurricanes generate considerable damage in these areas, and because mangroves may be well suited to provide protection against wave action and storm surge. As described in the data section, to rule out that the reduction in damages is generated by the characteristics of the habitat, we further exclude from the sample cells that historically have not had mangrove on their path to the coast.

Because past literature has argued that wide mangrove belts are needed to protect against storm surge (e.g., Zhang et al., 2012), we conjecture that there may be a non-linear relationship between mangrove width and observed reduction in damages. Consequently, we begin exploring the heterogeneity of hurricane impact by estimating three different models. In each model we discretize mangrove width into various bins that correspond to its q-quantiles. For the first model we use q=2, we create a dummy variable for each bin and interact these variables with the f damage index. We then take the resulting variables and include them in Equation 2 in place of the f damage index. We repeat this procedure using q=3 and q=4.

Panel A in figure 2 plots the point estimates and 95% confidence intervals for each of these models. Panel B plots the distribution of mangrove width for each bin, the box represents the interquartile range, the whiskers are the minimum and the maximum, and the dot is the average value.

The top 2 rows plot the impact of hurricanes on nightlights for each bin of model 1 (q=2). In this model the bins correspond to cells with above and below median mangrove width (0.63 km) on their path to the coast. We find that in below median areas (cells with an average mangrove width of 0.21 km) hurricanes can considerably reduce nightlights. The estimated coefficient of -5.96 indicates that when a cell experiences, for example, category three hurricane winds ($f = 0.2$, wind speed of 208 km/h) nightlights would decrease by ≈ 1.2 units (-5.96×0.2) or a 23% reduction. By comparison the effect in above median areas (with an average of 1.6 km mangrove width) is small and statistically indistinguishable from zero. We additionally test and confirm that the effect of hurricanes is differential between the groups ($p-value < 0.001$). Taken at face value, the difference between these coefficients indicates that the reduction in damage from mangroves roughly corresponds to 5.6 nightlight units.[9]

The next seven rows plot coefficients for model 2 ($q = 3$) and model 3 ($q = 4$). The models consistently show a decreasing pattern of hurricane damage, with full mitigation of damages taking place in the last bin. That is, for model 2 the third tercile (mangrove width greater than 1 km and average width of 2 km), and for model 3 the fourth quartile (mangrove width greater than 1.26 km and average width of 2.3 km). As before, we additionally test and are able, in both cases, to reject the null hypotheses of equality between the last bin and the previous bin ($p-value < 0.001$). The estimated reduction in damages from mangroves is of a similar magnitude to that found in model 1.

On the whole, the previous models indicate that cells with 1 km or more of mangrove width along their path to the coast suffer considerably less damages from hurricanes. In the last three rows we summarize these findings estimating the impact of hurricanes on night lights for three groups of mangrove width: 0-1 km, 1-2 km, and 2 km or more. The estimated coefficients highlight that the benefits of mangrove protection occur among cells with one or more km of mangrove width in their path to the coast. Specifically, while category three hurricane winds ($f = 0.2$, wind speed of 208 km/h) would lead to a 24% decrease in economic activity in cells with less than 1 km of mangrove width, cells with more than 1 km mangrove width would experience no damage.

This finding is broadly consistent with other estimates of mangrove protection, which indicate, for example, that two to seven km of mangrove width would be needed to fully attenuate storm surge from the category one to three hurricanes that make up the bulk of our sample.[10] Moreover, our estimates suggest that this effect is economically relevant. A simple counterfactual simulation for coastal Nicaragua reveals that avoided losses from protection by mangroves account for up to 2.5% of the economic activity observed in Nicaragua's coast in 2000.[11]

[9]This test is performed by adding to Equation 2 an interaction term between the f damage index and a dummy variable for being above median mangrove width.

[10]This figure is derived by combining the predicted height of storm surge for this category of hurricane 1.2-3.6 meters (Simpson and Saffir, 1974) and Zhang et al. (2012) estimate for the Florida Gulf Coast suggesting that storm surge is reduced by 50 cm per km of mangrove width.

[11]See the supporting information appendix for a step by step description of this counterfactual calculation

Next, panel C in figure 2 plots distance to the coast for each model and bin. The figure reveals that while there are many observations with low values of mangrove width at long distances from the coast, it is still the case that on average a longer mangrove width also implies a longer distances to the coast. An important concern is that our heterogeneity results are not driven by mangrove protection, but rather by factors related to distance to the coast. These include, for example, greater exposure and presence of assets close to the coast, or factors not fully captured by our wind field model, such as the decay of storm surge as the hurricane moves inland.

To rule out these alternative explanations we conduct a placebo exercise where we test whether hurricane damage decreases with distance to the coast, after we exclude from the sample cells that are protected by mangrove (have long mangrove widths) on their path to the coast. We begin this exercise by performing an analogous calculation to that of figure 2 model 2 (terciles). The sample is the same as before but in this exercise we use the terciles of distance to the coast to construct the bins. The first 3 rows of panel A in figure 3 present the coefficients and 95% confidence intervals for this exercise. We find that, while noisily estimated, the group that is closest to the coast (first tercile) experiences the largest reduction in nightlights, and that the impact of hurricanes progressively decreases with distance to the coast. Importantly, as shown in panel B, the groups that experience smaller reductions in nightlights (second and third tercile of distance) are also characterized by average mangrove widths of 0.99 and 1.36 km.

In the next 3 rows, we repeat the previous exercise excluding from the sample cells that have mangrove widths on their path to the coast longer than 1.5 km. As can be seen in panels B and C, this exercise allows us to construct bins that have a very similar distribution in terms of distance to the coast, but that have on average less than 0.6 km of mangrove width on their path to the coast. Turning to the results in panel A, while some coefficients are noisily estimated, we no longer find evidence of a decreasing pattern of hurricane impact. In the next 6 rows we repeat this placebo exercise, and find very similar results, when we exclude cells with 1.25 and 1 km of mangrove width on their path to the coast. Taken together these results suggest that for our sample, where 95% of the observations are within 18 km of the coastline, the reduction in hurricane impact is not driven by distance to the coast but rather by the protection provided by the mangrove.

Last, table S1 in the supporting information shows that the result from our preferred specification (model 4 of figure 2) is robust. Specifically, we show that we find very similar results using a wide range of alternative assumptions for the inference of standard errors, the construction of the hurricane damage function, and the calculation of mangrove width. We additionally show that our results hold among the sample of most affected countries, and that they are not driven by differential policy responses captured using state-year fixed effects.

4 Conclusion

In this paper, we show that wide mangrove belts in Central America have the potential to mitigate the disruption to economic activity generated by hurricanes. We measure local economic activity using remote sensing data on nightlights; potential hurricane destruction using a damage index derived from a wind field model calibrated for Central America; and mangrove protection by calculating the cumulative width of mangroves along the closest path to the coast. Using these data, we estimate the impact of hurricanes on economic activity, under the assumption that hurricane strikes are exogenous conditional on cell and year fixed effects. We then explore, using a binning estimator, whether there is a negative, and plausibly non-linear, relationship between mangroves and hurricane damages.

We find that hurricanes have negative short-run effects on economic activity, with losses likely concentrated in coastal lowlands at risk of both wind and storm surge. Within the coastal lowlands, we further show that the impact of hurricanes declines with mangrove width, and specifically that the effect of hurricanes in our sample is entirely mitigated by one km or more of mangrove width. We additionally conduct various robustness checks and rule out that these findings are driven by the physical characteristics of the mangrove habitat or by the distance to the coast.

Our results are important for policy makers, because they highlight that mangrove conservation and restoration efforts can be used in coastal lowlands to protect economic activity against tropical cyclones. One important observation from this analysis, however, is that the benefit of protection is only accrued from wide mangrove belts. This observation implies that large-scale efforts will be required to achieve the benefits of mangrove protection.

Last, there are two important caveats of this analysis concerning the benefits of mangrove conservation and restoration over a longer time horizon. First, our estimates are likely to underestimate the protective value of mangroves in the long run because mangrove protection may entail benefits on outcomes such as lives saved, health, and human capital accumulation, which are not well captured by nightlights. Second, while climate change and the resulting intensification of storms may increase the value of conservation for protection purposes, areas designated for conservation or restoration must be carefully chosen given the threat of sea-level rise (Blankespoor et al., 2017). Consequently, an important avenue for future research is the identification of areas that should be prioritized for conservation or restoration.

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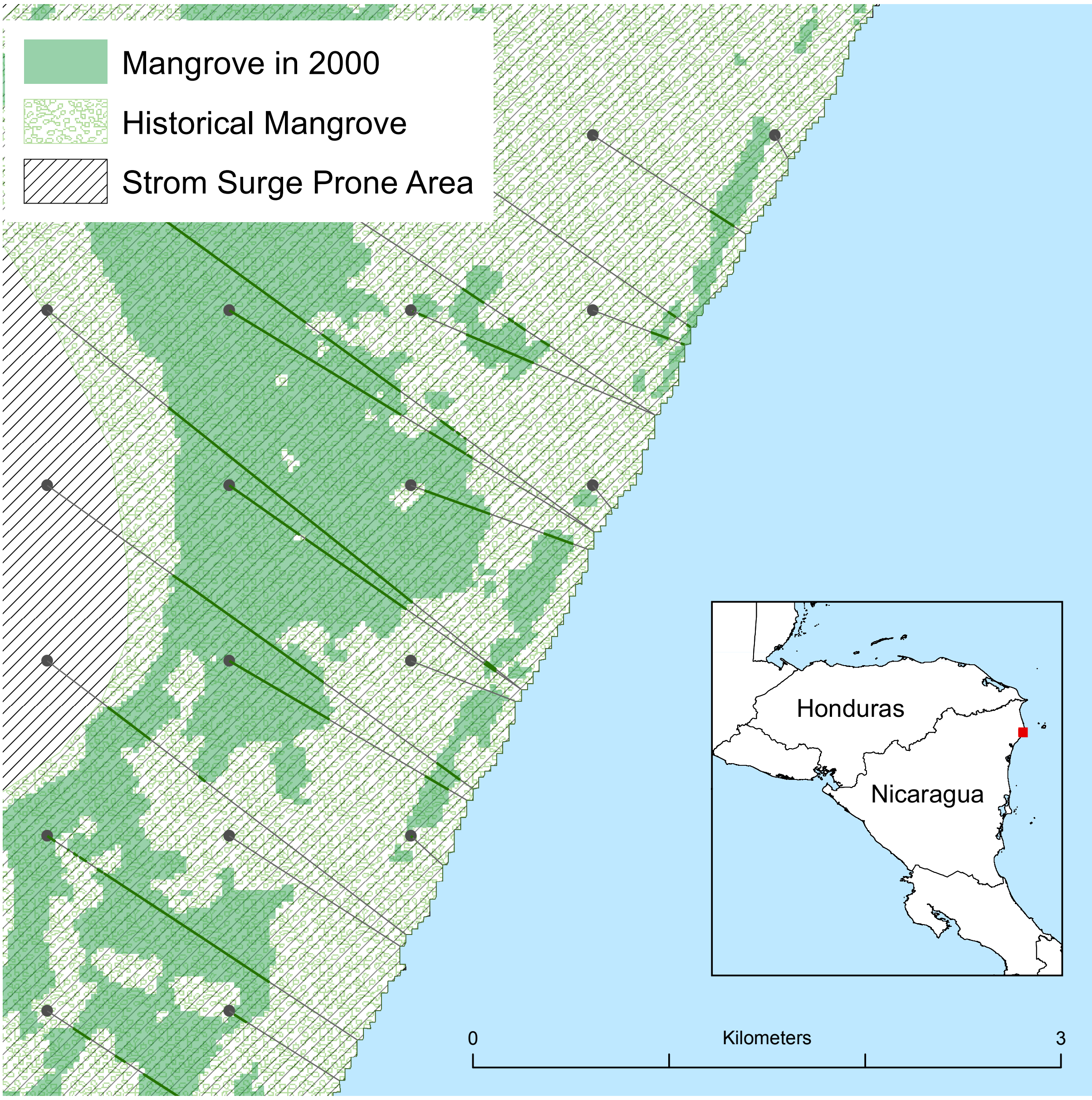
5 Table and Figures

Table 1: Impact of hurricanes on nightlights

	(1)	(2)	(3)
f	-4.055	-4.046	
	(1.693)	(1.765)	
$f(t-1)$		0.104	
		(1.543)	
f in non-storm surge prone areas			-2.574
			(6.648)
f in storm surge prone areas			-4.417
			(0.648)

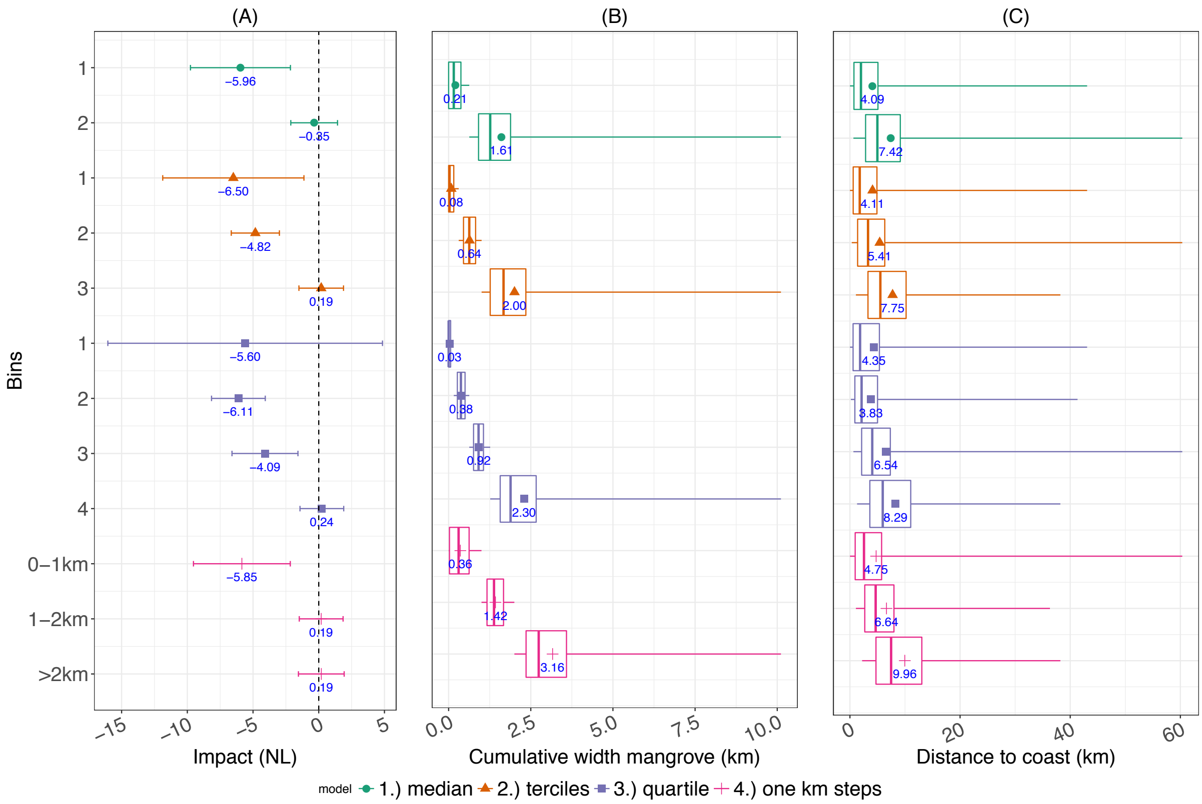
Notes: Dependent variable nightlights. Estimates from OLS regression, cell and year fixed effects included but not reported. Robust standard errors clustered at the municipal level in parentheses (1,056 clusters). The number of observations is 2,757,001 of which 100,854 are in storm surge prone areas. The average nightlights in the year 2000 is 5.1.

Figure 1: Distribution of the mangrove in the North Caribbean Coast Autonomous Region, Nicaragua



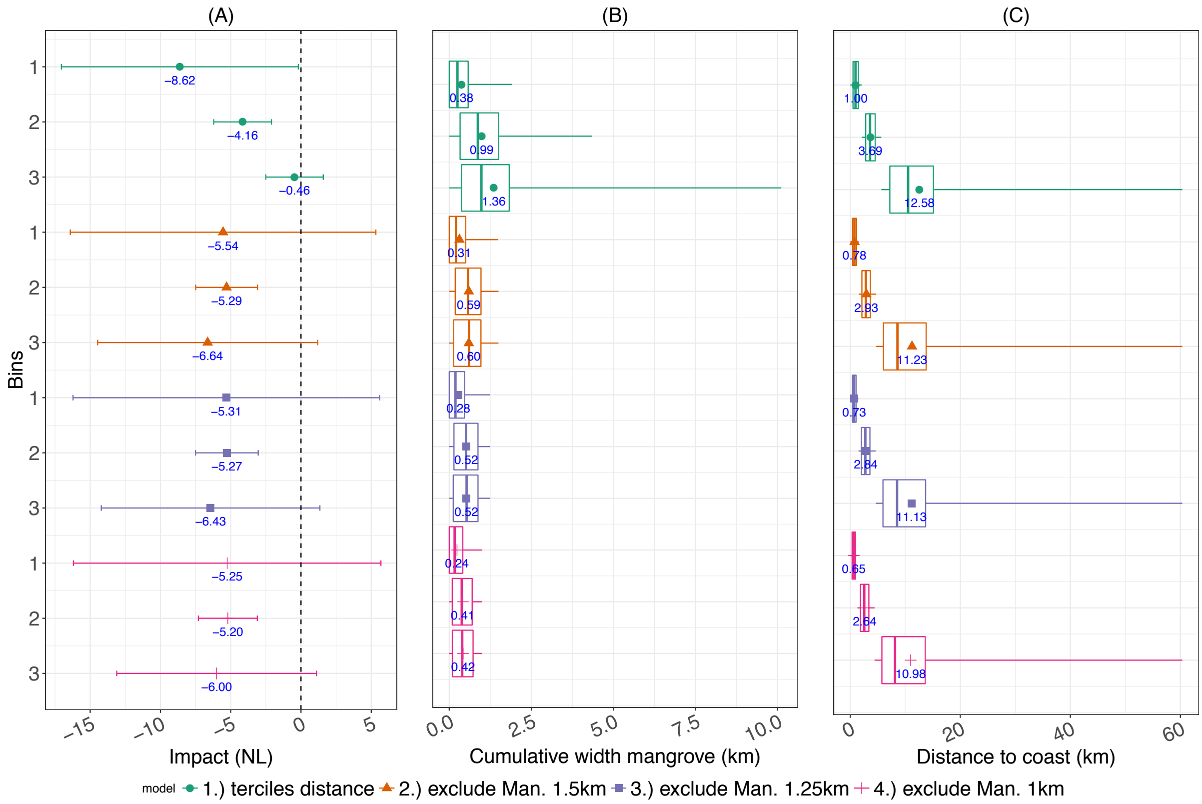
Notes: This map illustrates our calculation of mangrove protection in the area where hurricane Felix made landfall in 2007. Dots represent centroids of cells; lines show the shortest path to the coast; green line segments represent mangrove on the path to the coast.

Figure 2: Impact of hurricanes on nightlights by mangrove width



Notes: Panel (A) plots point estimates and 95% confidence intervals for four models. In models one to three we discretize the mangrove width variable into various bins that correspond to its q-quantiles and estimate the impact of hurricanes on economic activity for each bin. Model one uses q=2 and is labeled with dots. Model two uses q=3 and is labeled with triangles. Model three uses q=4 and is labeled with squares. Model four uses bins representing one km steps of mangrove width and is labeled with crosses. Panel (B) plots the distribution of mangrove width for each bin, and Panel (C) plots the distribution of distance to the coast for each bin. In panels (B) and (C) the box represents the interquartile range, the whiskers are the minimum and the maximum, and the symbol is the average value.

Figure 3: Impact of hurricanes on nightlights by distance to coast



Notes: Panel (A) plots point estimates and 95% confidence intervals for four models. In model one we discretize the distance to the coast variable into tercile bins and estimate the impact of hurricanes on economic activity for each bin. Models two two four, estimate model one excluding from the sample cells that are protected by mangrove on their path to the coast. Model two excludes cells with more than 1.5 km of mangrove width protection. Analogously, model three exclude cells with more than 1.25 km, and model four excludes cells with more than 1 km. Panel (B) plots the distribution of mangrove width for each bin, and Panel (C) plots the distribution of distance to the coast for each bin. In panels (B) and (C) the box represents the interquartile range, the whiskers are the minimum and the maximum, and the symbol is the average value.

Supporting Information

S1 Hurricane Windstorm Model

The local wind speeds experienced due to a hurricane are derived from a spatial hurricane windstorm model developed by the World Bank Group Latin America and the Caribbean Disaster Risk Management team (Pita et al., 2015). The model estimates maximum wind speeds at the height of 10 meters with a spatial resolution of 1 km^2 for observed hurricanes and tropical storms in Central America during our sample period. The structure of this wind field model is based on the well-known equation for cyclostrophic wind and sustained wind velocity by Holland (1980) and is calibrated for the Central America region. The model's accuracy of the simulated wind speeds has been tested and validated with observed data. The maximum sustained wind speed experienced in a particular location due to a hurricane is given by:

$$V = \frac{V_S \sin(\varphi) - f * r}{2} + \sqrt{\left(\frac{V_S \sin(\varphi) - f * r}{2}\right)^2 + \left(B \frac{\Delta p}{\rho}\right)\left(\frac{RMW}{r}\right)^B exp\left[-\left(\frac{RMW}{r}\right)^B\right]} \qquad (3)$$

where B is the Holland shape parameter, Δp is the deficit of central and outer peripheral pressure (Pa), ρ is the air density at the gradient height (kg/m^3), RMW is the radius of maximum winds (m), r is the radius of any location to the center of the storm (m), V_S is the hurricane translation speed measured (m/s), f is the Coriolis parameter (1/sec), and φ is the angle between the north and the storm heading.

The data source for the terrain roughness is the Global Land Cover Dataset 2000 and for the topography characteristics is the Shuttle Radar Topography Mission database. The method to estimate speed-up occurring in escarpments and ridges comes from the American Society of Civil Engineers in 1994 and to retrieve the wind gusts factors comes from Vickery and Skerlj (2005). For more detailed information about the hurricane windstorm model, see Pita et al. (2015).

S2 Implied monetary losses

To convert the benefit of mangrove protection (mitigation of hurricane damage), measured in nightlights, into rough monetary values, we begin by calculating a conversion factor between nightlights and economic activity as measured by Gross Domestic Product (GDP). Using World Bank data on GDP in Parity Purchasing Power (PPP) in 2011 international dollars, we derive average GDP and nightlights per km^2 for each country and year in our sample. Figure S2 presents a scatter plot of GDP and average nightlights per km^2. The figure reveals a clear positive linear relationship between the two variables. To estimate this relationship, while accounting for changes in the measurement of nightlights, we regress GDP on nightlights and year fixed-effects. The estimated coefficient indicates that a one unit increase in nightlights per km^2 is associated with a \$ 225,838 increase in GDP per km^2 (p-value < 0.001).[12] Figure S3 plots observed and predicted GDP using the product of nightlights and the estimated coefficient. Given that most observations are close to the 45-degree line, we conclude that this specification captures reasonably well the relationship between nightlights and GDP.

Next, we compute implied monetary losses in two steps. First, to derive observed total losses in terms of nightlights, we multiply each of the estimates from our preferred specification (model 4 of figure 2) by the sum of the f damage index for each group. Second, we recover monetary losses by multiplying the previous results with the conversion factor of nightlights to GDP. To compute counterfactual hurricane losses in the absence of mangrove protection, we focus on the two groups where we find that mangroves mitigate the impact of hurricanes (1-2 km and 2 km or more of mangrove width). Specifically, we modify the first step by multiplying the sum of f for each of these two groups by the reduction in nightlights estimated for the group not protected by mangrove (less than 1 km of mangrove width). To account for uncertainty in our estimates of damages and the conversion factor between night lights and GDP we draw coefficients from a normal distribution with mean equal to the estimated coefficient and standard deviation equal to the standard error. This procedure is then repeated 5,000 times, using a random draw of the coefficients each time.

To illustrate the value of mangrove protection, we perform this calculation for coastal Nicaragua, which was affected by various hurricanes including the largest event in our sample, hurricane Felix. Figure S4 plots the distribution of observed and counterfactual losses for each group with mangrove protection (1-2 km and 2 km or more of mangrove width). The counterfactual simulation suggests that average avoided monetary losses from mangroves are \$565,647 (std. dev. \$201,372) and \$403,769 (std. dev. \$143,743), respectively. Because the value of initially exposed economic activity protected by man-

[12] Standard errors are clustered at the country level. Because there are only 6 clusters, we also perform a wild cluster bootstrap (1000 iterations) procedure that yields a (p-value < 0.001).

groves amounted to roughly \$39 million,[13] the estimates from the counterfactual simulation indicate that average combined avoided losses in this area (\$969,416) is roughly equivalent to 2.5%.

[13] This can be calculated by summing nightlights in 2000 for this area and multiplying by the conversion factor.

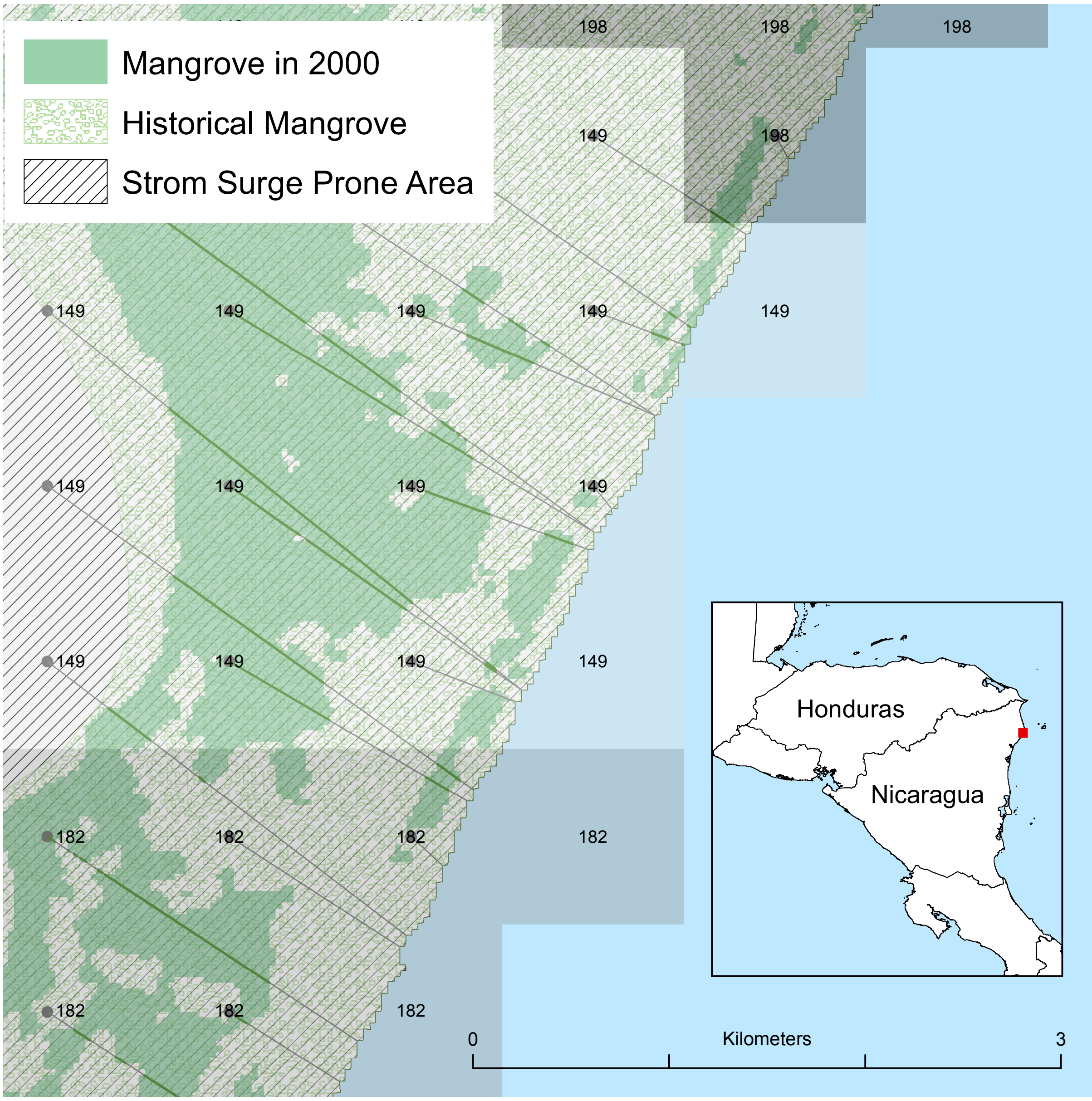
S3 Table and Figures

Table S1: Robustness Mangrove Protection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
f 0-1 km mangrove width	-5.849	-5.378	-1.768	-4.619	-1.89×10^{-17}	-9.049	-6.487	-5.852
	(1.860)	(1.875)	(0.640)	(1.807)	(5.22×10^{-18})	(1.899)	(2.946)	(1.861)
	[2.307]							
	{2.676}							
f 1-2 km mangrove width	0.185	0.188	0.022	-0.231	5.04×10^{-19}	-1.964	-0.793	0.166
	(0.842)	(0.842)	(0.277)	(0.883)	(2.91×10^{-18})	(0.825)	(2.419)	(0.842)
	[1.241]							
	{1.975}							
$f > 2$ km mangrove width	0.195	0.198	0.029	0.363	1.55×10^{-18}	-2.042	-0.828	0.254
	(0.879)	(0.879)	(0.291)	(0.830)	(2.91×10^{-18})	(0.863)	(2.419)	(0.857)
	[1.295]							
	{2.105}							
Observations	50,089	50,089	50,089	50,089	50,089	24,011	50,076	50,089
Implied mangrove protection, cat. 3	1.209	1.209	0.961	1.111	1.658	1.401	1.132	1.221
V threshold (km)	92.6	92.6	92.6	75.63	-	92.6	92.6	92.6
V half (km)	277.8	277.8	203.72	277.8	-	277.8	277.8	277.8

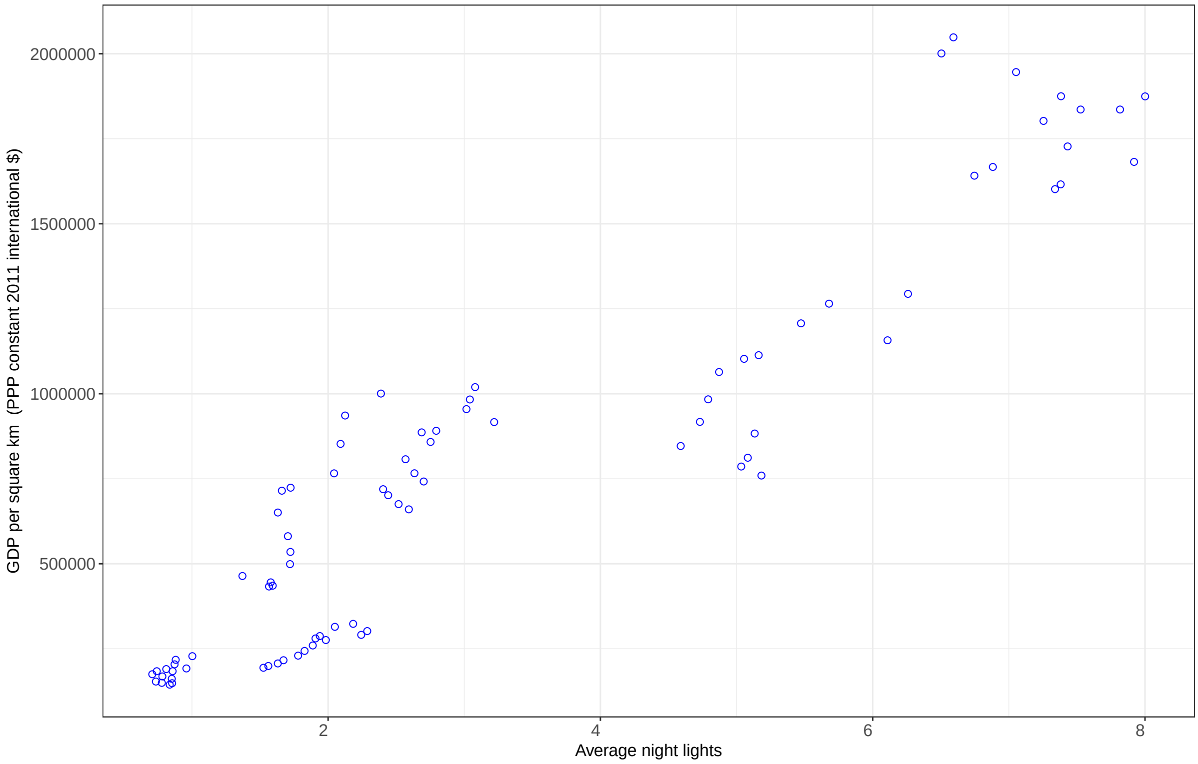
Notes: Dependent variable nightlights. Estimates from OLS regressions, cell and year fixed effects included but not reported. Mangrove protection is the difference in damage (measured in nightlights) between cells with more and less than 1 km of mangrove width when they are affected by a category three hurricane (209 km/h). Robust standard errors clustered at the municipal level in parentheses (120 clusters); clustered at state level (35 clusters) in brackets; Conley errors (12 lags and a 500 km bandwidth) in crochets. Column 2 uses the highest wind speed for every every cell-year regardless of whether is generated by the strongest storm in that year. Column 3 uses a lower v_h parameter as suggested by Emanuel (2011).Column 4 uses gale level winds to set a lower v_T parameter. Column 5 follows Nordhaus (2006) and uses wind to the power of 8 instead of the f damage index. Column 6 restricts the sample to countries that experience at least a category one hurricanes during our sample period (Guatemala, Honduras, and Nicaragua). Column 7 includes state-year fixed effects. Column 8 uses only dense mangrove (at least 50% forest cover) to calculate mangrove width on the path to the coast.

Figure S1: Distribution of the mangrove and hurricane Felix wind speed in the North Caribbean Coast Autonomous Region, Nicaragua



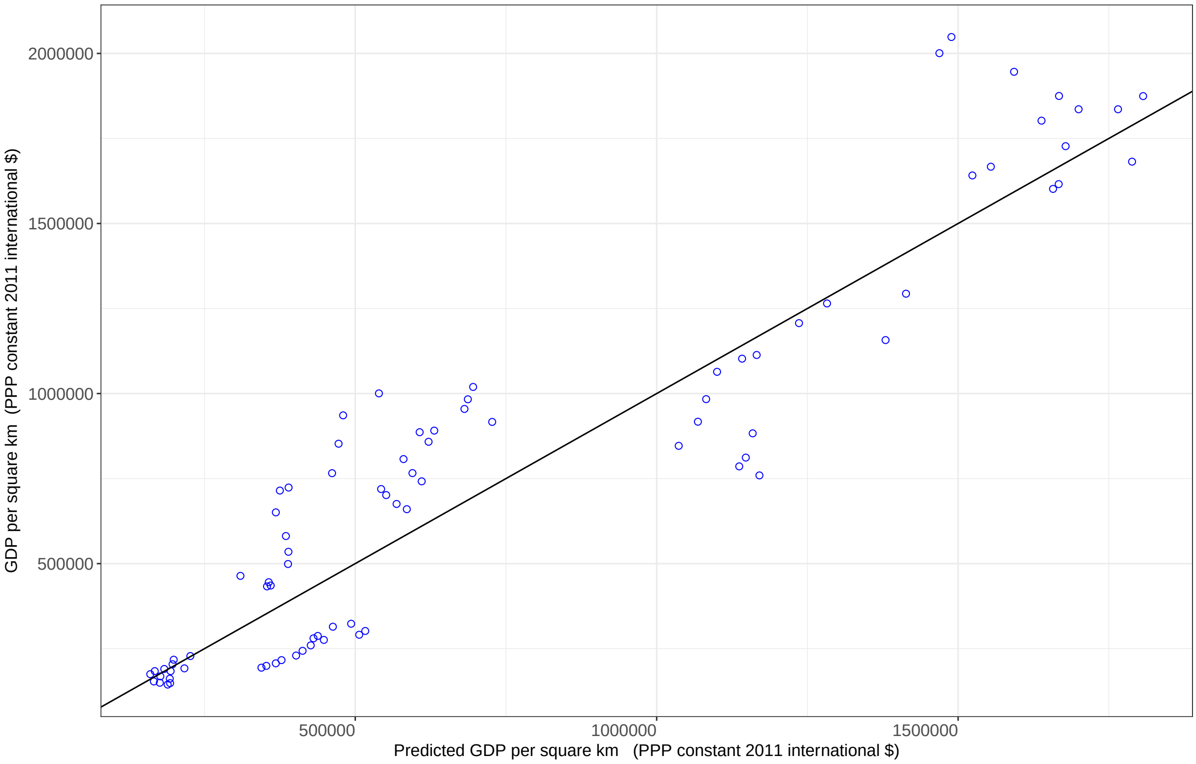
Notes: This map shows the maximum sustained wind speed in km/h experienced during hurricane Felix. Dots represent centroids of cells; lines show the shortest path to the coast; green line segments represent mangrove on the path to the coast.

Figure S2: GDP per km^2 and average nightlight intensity for each country and year



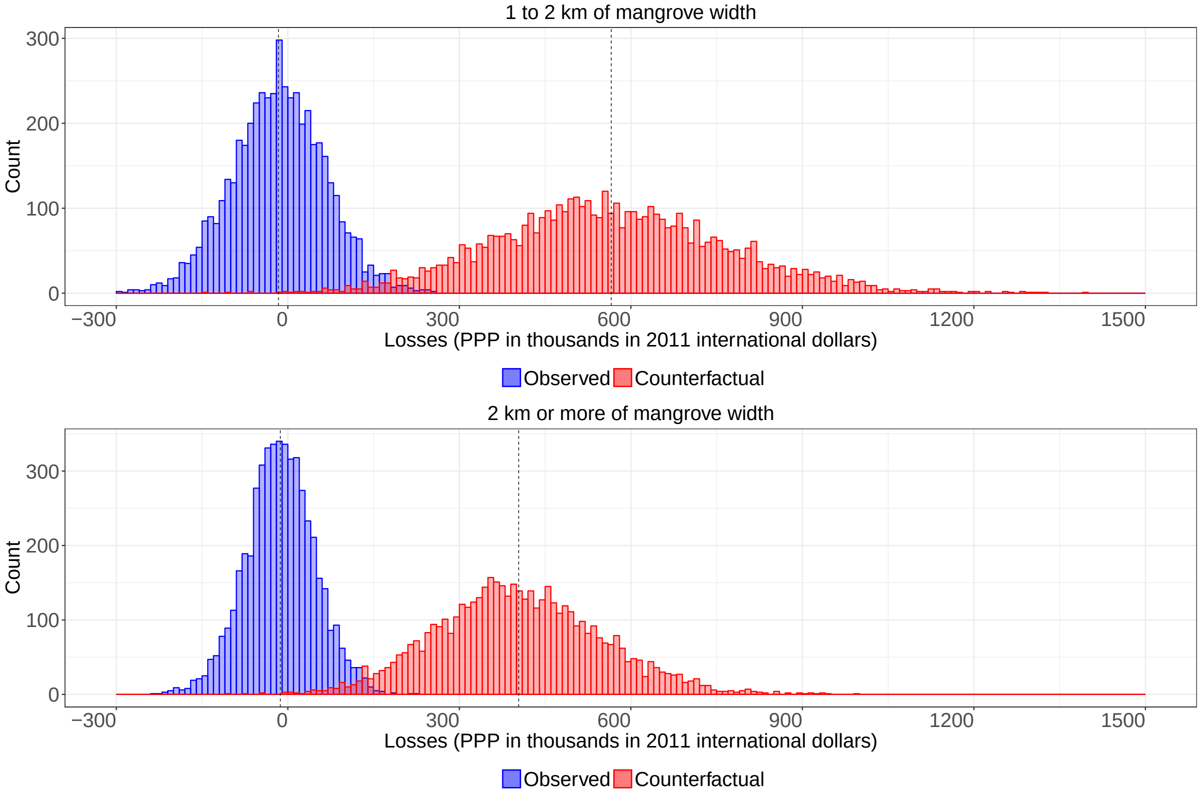
Notes: Scatter plot of the gross domestic product (PPP in 2011 international dollars) per km^2 and the average nightlight intensity per km^2 for each country and year (2000-2013).

Figure S3: Actual and predicted GDP per km^2 for each country and year



Notes: Scatter plot of the actual and estimated gross domestic product (PPP in 2011 international dollars) per km^2 for each country and year (2000-2013).

Figure S4: Distribution of observed and counterfactual monetary losses.



Notes: This figure plots, for two groups currently protected by mangroves in coastal Nicaragua (1-2 km and 2 km or more of mangrove width), the distribution of implied monetary losses both observed and counterfactual (had mangrove been absent). Observed losses are calculated by multiplying the estimates for each bin from our preferred specification (model 4 of figure 2) by the sum of the f damage index for each group. To express these losses in PPP 2011 international dollars, we then multiply the total losses in nightlight units previously derived by the nightlight to GDP conversion factor (see section S2 for further details). To account for uncertainty in both our estimates of damages and the conversion factor between nightlights and GDP, in each case we draw coefficients from a normal distribution with mean equal to the corresponding estimated coefficient and standard deviation equal to the standard error. This procedure is then repeated 5000 times, using a random draw of the coefficients each time. The resulting implied monetary losses are then plotted. The procedure to derive counterfactual losses is analogous, but we multiply the sum of f for each of these two groups by the reduction in nightlights estimated for the group not protected by mangrove (less than 1 km of mangrove width). The dashed lines represent the average for observed and counterfactual losses for each group.