Coastal wetlands reduce property damage during tropical cyclones

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Coastal wetlands dampen the impact of storm surge and strong winds. Studies on the economic valuation of this protective service provided by wetland ecosystems are, however, rare. Here, we analyze property damage caused by 88 tropical storms and hurricanes hitting the United States between 1996 and 2016 and show that counties with more wetland coverage experienced significantly less property damage. The expected economic value of the protective effects of wetlands varies widely across coastal US counties with an average value of about \$1.8 million/km^2 per year and a median value of \$91,000/km^2. Wetlands confer relatively more protection against weaker storms and in states with weaker building codes. Recent wetland losses are estimated to have increased property damage from Hurricane Irma by \$430 million. Our results suggest the importance of considering both natural and human factors in coastal zone defense policy.

ecosystem services | economic valuation | climate change

Traditional defensive measures against storm surge include building levees and sea walls. However, such structures can fail (1), and there are concerns about negative impacts of such structures on the local environment (2). Planners are looking at coastal wetlands as potential natural levees for storms due to their ability to reduce water velocity and wave turbulence (3). Moreover, wetlands accumulate sediments providing protection against rising sea levels and local subsidence (4, 5).

Policymakers are often skeptical about employing wetlands as storm buffers, and hesitant to preserve or restore wetland systems as part of a storm defense strategy. Previous work has focused on mechanisms by which wetland plants attenuate storm surge (3–7). Surprisingly few studies address the economic value of this protective service. These studies, which we build on, tend to be limited to a particular type of wetland, such as mangrove forests (8–11), a few specific disasters (8–10), or specific regions [i.e., certain tropical countries (8–11) and Louisiana (12–15)]. The exception is the influential US national study (16), which finds that 1 km^2 of wetlands produce on average \$3.3 million annually in storm protection services. However, this study is limited by the coarse data employed and imprecise measure of the storm impact region.

Here, we estimate the economic value of coastal wetlands in storm protection by analyzing all 88 tropical cyclones (of which 34 made landfall as hurricanes) impacting the counties along the entire Atlantic and Gulf Coasts of the United States between 1996 and 2016 (*SI Appendix*, Figs. S1 and S2). Tropical storms are defined as tropical cyclones with maximum sustained winds of 34 to 63 kt, while hurricanes are those with at least 64 kt (17). Among the 232 coastal counties experiencing at least tropical-storm–level winds, 203 experienced property damage at least once, and 38% of counties suffered damage when hit by tropical-cyclone winds (*SI Appendix*, Tables S1 and S2). Many tropical cyclones hitting the United States are below hurricane strength—the focus of most previous work (8–16). We show wetlands reduce property damage proportionately more at the lower end of the tropical cyclone classification scale, although the absolute magnitude of damage reduction is larger at the high end of the scale.

By using all of the tropical storms and hurricanes affecting the United States since 1996, when consistently defined county estimates of property damage become available, we avoid sample selection bias issues, whereby damage data were generally available earlier only for more destructive storms. Areas subject to flood risk in a county are more accurately estimated, based on local elevation data and detailed information on individual storm trajectories that more precisely spatially delineate storm paths and wind speeds at different distances and directions from the eye (see Fig. 1 for the example of Hurricane Katrina). Wetland coverage varies over time and space within a county due to natural or anthropogenic factors (2). It also effectively varies because each storm's flooding area is a function of 1) storm path and 2) wind intensity. State characteristics remaining unchanged over time and year-level economic shocks potentially influencing property damage are controlled by using a fixed-effects statistical framework.

Annual expected property damage caused by tropical cyclones depends on the following: first, the probability that a county experiences tropical cyclones of different wind velocities—the wind velocity, in turn, determines the area likely to be flooded by storm surge; second, the probability that, on experiencing a given wind speed, damage is nonzero. These relationships are described by the following:

$$\mathrm{E}(\mathrm{D}|X_{-v}) = \int P(D>0|v,X_{-v})E\left(D|v,X_{-v},D>0\right)f(v)dv,$$

where D represents a county's property damage when experiencing wind speed v during a tropical cyclone, $f(v)$ represents the

Significance

With rising sea levels and increasingly intense storms associated with climate change, there is substantial interest in alternative defensive measures for protecting low-lying coastal communities against coastal flooding. Coastal wetlands are known to dampen storm surge and wind impacts, but policymakers have doubts about employing wetlands as natural levees due to lack of empirical evidence of effectiveness. Using detailed geospatial data, we explore a comprehensive set of natural and human factors to examine the role of coastal wetlands in reducing tropical-cyclone–related property damage. Using all 88 tropical storms and hurricanes hitting the United States between 1996 and 2016, the expected economic value of the protective effects of wetlands is estimated for all counties along the Atlantic and Gulf Coasts.

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Data deposition: All data and code (csv files and Stata code) necessary for replication of the results in this paper have been deposited at GitHub, https://github.com/fangsun/wetland/tree/master/PNAS_wetland.

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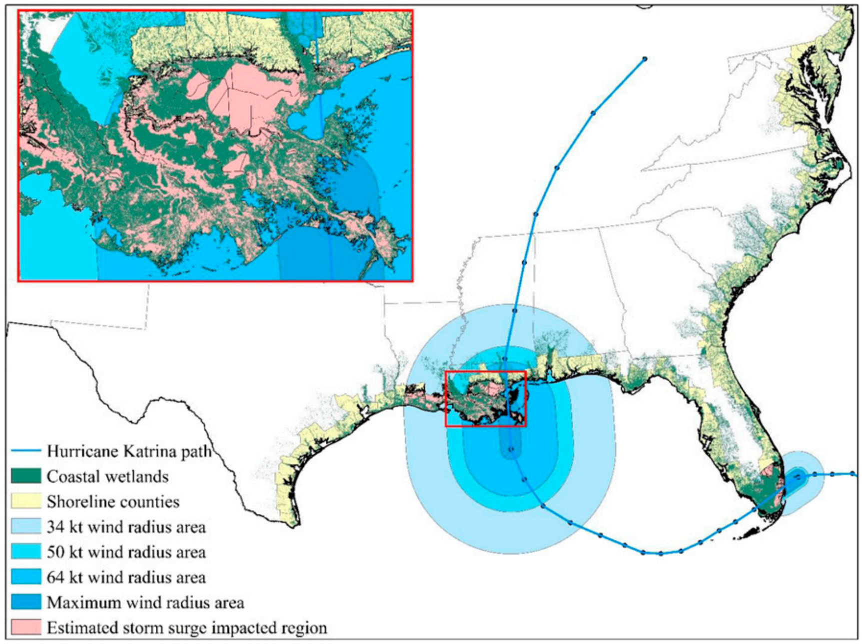

Fig. 1. Coastal wetland distribution and estimated storm surge area near Hurricane Katrina landfall.

annual probability of experiencing wind speed v, and X_{-v} represents other factors affecting property damage besides wind intensities. Applying the damage function approach developed by Barbier (11), coastal wetlands may influence property damage during storms in two ways: first, through the likelihood of a county experiencing damage in a storm surge; second, if damage occurs, the amount.

Results

Coastal wetland coverage is associated with statistically significant reductions in cyclone-related property damage. A loss of 1 km^2 of wetland coverage increases the predicted probability of experiencing property damage during storms by 0.02% ($P < 0.05$) in a county with the average wetland coverage, wind speed, and flooding area (*SI Appendix*, Table S3). For coastal communities suffering from property damage from a storm, a 1% loss of coastal wetlands is associated with a 0.6% increase in property damage ($P < 0.01$), controlling for storm-specific characteristics, property value under flooding risk, state-specific time-invariant determinants of property damage, and year-level shocks (Table 1 and *SI Appendix*, Fig. S3). Coefficient estimates of wind, potential storm surge area, property value under flooding risk, and being located to the right-hand of the storm path are positive and significant. The wind effect is particularly large (a 1% increase increases damage by 7%) and counties on the storm path's right side experience 140% ($P < 0.01$) more property damage than those on the left.

Coastal wetlands' protective effects are nonlinear in wind intensity, conditional on damage. This may be because once wetland vegetation is fully saturated with water, wave dissipation effects are weaker (18, 19). To detect this type of nonlinearity, wetland effects are decomposed by the wind speeds experienced by a county. Wetlands are effective against storms of all different magnitudes. The elasticity of property damage with respect to wetlands is −0.58 for a tropical storm (a 1% decrease in wetlands is associated with a 0.58% reduction in property damages), −0.55 for a category 1 hurricane, −0.40 for a category 2 hurricane, and −0.35 for a category 3 to 5 hurricane (Fig. 2*A* and *SI Appendix*, Table S4). This pattern is consistent with laboratory experiments (6). The preventative effect is especially strong for tropical storms, which happen twice as often as hurricanes. However, because property damage is rapidly increasing in storm strength, the absolute magnitude of damages prevented is predicted to be largest for major hurricanes.

Saltwater wetlands are located closer to the shore than freshwater wetlands (*SI Appendix*, Fig. S4), providing the first line of defense against storm surges. Nevertheless, freshwater wetlands typically have more coverage than saltwater wetlands, providing a wider buffer zone, as freshwater wetlands constitute about 85% of total coastal wetland coverage. We find significant reductions in property damage for both freshwater and saltwater wetlands. The difference between their contributions is small and not significantly different from zero (Fig. 2*B*; column 3 of Table 1). This is not surprising since storm surge can extend miles inland and encompass both types of wetlands.

Forested wetlands, having rougher woody vegetation, may provide a more effective buffer than emergent or scrub/shrub wetlands (5, 11, 14, 15). Costanza et al. (16) did not find significant evidence that forested wetlands reduced economic losses, perhaps due to data limitations. We find forested and nonforested wetlands play similarly protective roles (estimated elasticities are −0.58 and −0.56, respectively). We cannot reject the hypothesis that forested wetland reduces damage more than nonforested wetlands, as suggested by simulation studies (14, 15), although our result is consistent with that of Gedan et al. (5), who survey field observation studies and find mangroves and marshes confer comparable wave attenuation.

Coastal states take different strategies in terms of disaster relief and preparedness. Some adopt more stringent building codes, e.g., requiring building on stilts or setting a minimum construction elevation, while others do not. To investigate whether state-level policy factors induce heterogeneity in wetland protective effects, coastal states were separated into two groups based on being above or below the median assessment score for strictness of the residential building code and enforcement system (*Materials and Methods*). Virginia, Florida, South Carolina, and New Jersey rank as the top four states, while Texas, Mississippi, Alabama, and Delaware have no mandatory statewide building code directed toward storm damage prevention. Wetland effects on property damage reduction are significantly lower in states with

Table 1. Conditional damage model estimates

	(1)	(2)	(3)	(4)	(5)
	Log(damage)	Log(damage)	Log(damage)	Log(damage)	Log(damage)
Log(wetland)	−0.5756***	−0.5752***	−0.5805***	−0.5598***	−0.8055***
	(0.1840)	(0.1718)	(0.1836)	(0.1805)	(0.2029)
C1 hurricanes × log(wetland)		0.0261			
		(0.0769)			
C2 hurricanes × log(wetland)		0.1724*			
		(0.1029)			
C3-C5 hurricanes × log(wetland)		0.2251*			
		(0.1208)			
Saltwater wetlands × log(wetland)			0.0073		
			(0.0409)		
Forested wetlands × log(wetland)				−0.0198	
				(0.0390)	
Strict building code × log(wetland)					0.3011*
					(0.1545)
Log(wind)	7.1885***	6.4122***	7.1928***	7.1953***	7.1929***
	(0.5653)	(0.9744)	(0.5683)	(0.5668)	(0.5668)
Right	0.8821***	0.8749***	0.8828***	0.8880***	0.8825***
	(0.3129)	(0.3200)	(0.3147)	(0.3183)	(0.3128)
Log(storm area)	0.4793**	0.4767**	0.4811**	0.4595**	0.4558*
	(0.2249)	(0.2180)	(0.2248)	(0.2235)	(0.2293)
Log(property at risk)	0.3205***	0.3135***	0.3190***	0.3194***	0.3179***
	(0.0622)	(0.0599)	(0.0638)	(0.0624)	(0.0617)
Adjusted R^2	0.52	0.53	0.52	0.52	0.52

SEs (in parentheses) are clustered two ways at the county and storm levels. n = 946. All models include state and year fixed effects. *$P < 0.10$, **$P < 0.05$, and ***$P < 0.01$.

more stringent building codes and enforcement systems, suggesting that building codes are a partial substitute for wetlands in terms of storm protection (stricter code estimate, −0.50; less strict code estimate, −0.81), although wetlands still have a sizable effect even with stricter building codes (Fig. 2*D* and *SI Appendix*, Table S4).

The estimated storm protection effects of wetlands are broadly robust to the statistical model used (*SI Appendix*, Alternative Specifications; *SI Appendix*, Tables S5–S8) and do not change substantially when time trends are included instead of year fixed effects or whether the two largest disasters, Hurricanes Katrina and Sandy, are excluded. As additional robustness checks, we examine models that include different types of manmade storm defenses (levees, hard structures such as sea walls, and beach nourishment); different treatments of the property value at risk, which might be important due to the collapse of real estate markets during the Great Recession; and different substate regional indicator variables instead of state fixed effects. The

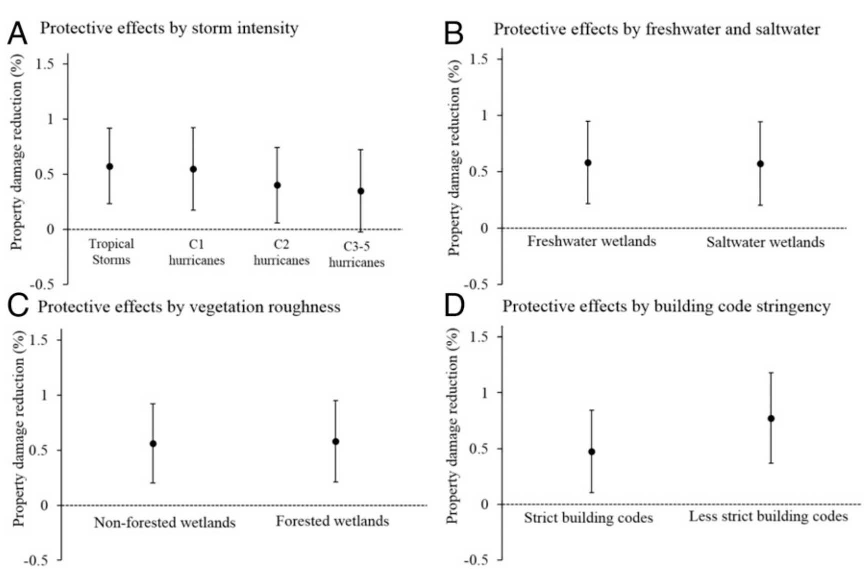

Fig. 2. Elasticity of property damage with respect to coastal wetland coverage by (*A*) storm intensity, (*B*) wetland type, (*C*) vegetation roughness, and (*D*) building code stringency. Each panel shows percent reduction (with 95% confidence interval) in property damage per 1% increase in wetland coverage. Regression coefficients correspond to models estimated in *SI Appendix*, Table S4, columns 2 to 5.

results of these models have estimated wetland impacts that are not statistically different from that of our primary specification.

We estimate the marginal value of coastal wetlands for storm protection for each shoreline county along the Atlantic and Gulf Coasts. Assuming the local probability of experiencing different tropical cyclone intensities provided in ref. 20 follows a gamma distribution, estimated annual marginal values range from less than \$800 to \$100 million per km^2, with an average of about \$1.8 million and a median value of \$91,000 (Fig. 3 and *SI Appendix*, Table S9). The heterogeneity in the storm protection value of wetlands (*SI Appendix*, Figs. S5 and S6) across counties is due to the property values at risk, local wetland coverage, coastline shape, local elevation, building codes, and the probability of experiencing different wind intensities. The low valued wetlands tend to be located in more rural, less populated counties, while the converse is true for more highly valued wetlands.

The marginal value of coastal wetlands for storm protection over a fixed time period, the relevant quantity for benefit–cost assessments involving development projects, can be estimated by discounting the future annual value of wetlands over the desired time frame assuming the current annual marginal value remains constant. Using a discount rate of 2.8% (21), expected storm protection services provided by 1 km^2 of coastal wetlands over a 30-y (100-y) period are on average worth about \$36 million (\$60 million). The median value is \$2 million (\$3 million).

Discussion

Estimates of the marginal economic value of wetland services in protecting property value can serve many purposes. Federal, state, and local agencies responsible for wetland management could employ our estimated expected marginal value when determining the amount and the optimal site of required compensatory mitigation. To achieve the goal of "no net loss" in both wetland acreage and function, section 404 of the Clean Water Act requires development projects that could have adverse impacts on wetlands to offset wetland loss by restoring, creating, enhancing, or preserving wetlands within the same watershed (22). To determine the amount of compensatory mitigation for each project, the Army Corps of Engineers conducts a case-by-case evaluation and sets a compensatory mitigation ratio. The expected marginal value of wetlands in reducing storm damages estimated in this study should be useful to a federal agency making such assessments, as well as serving as an input to risk models of the National Flood Insurance Program. One of our main findings is that location is a crucial factor in the storm protection services provided by wetlands. This should be accounted

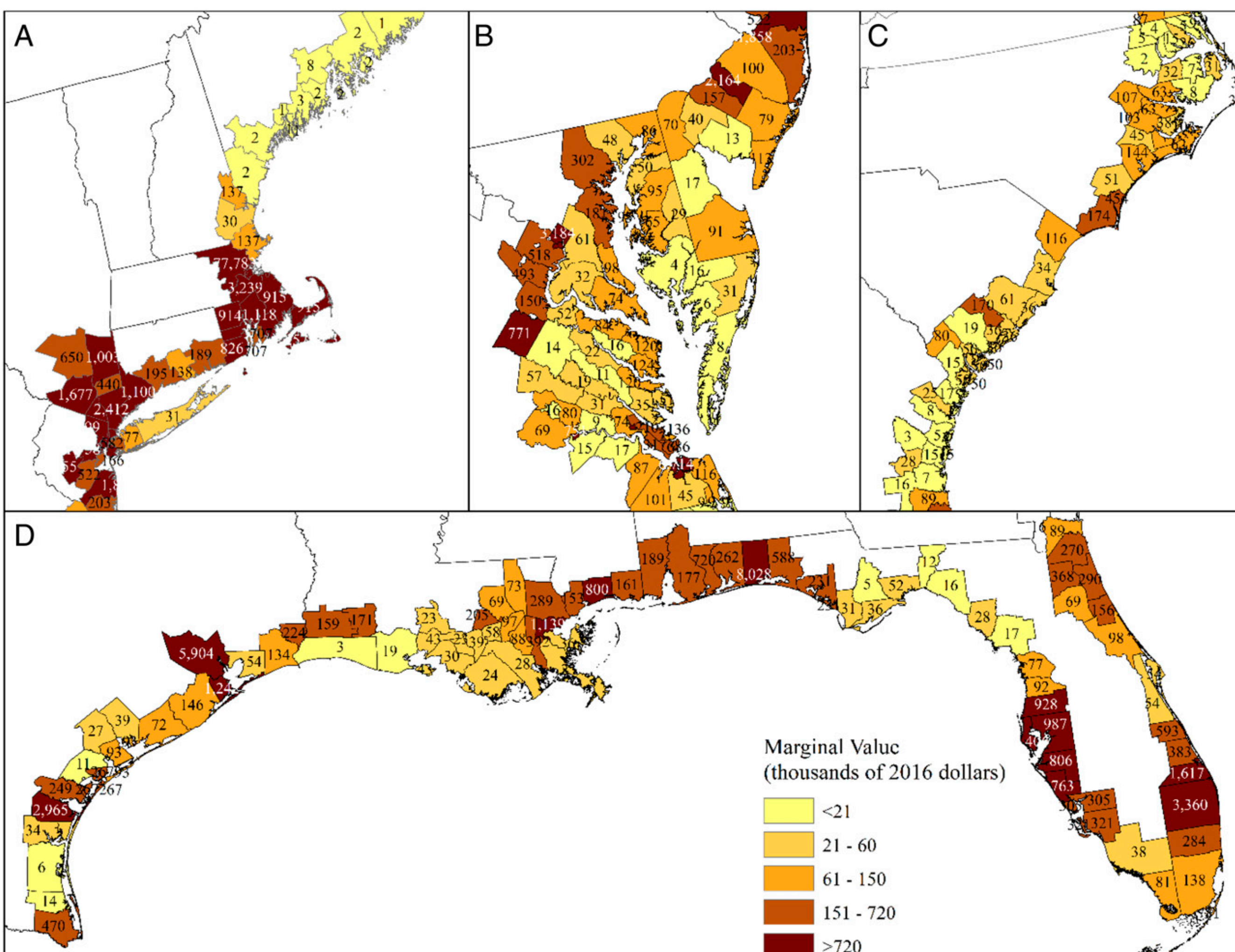

Fig. 3. Annual county-level marginal value of coastal wetlands for storm protection in (*A*) northeastern coastal counties, (*B* and *C*) eastern and southeastern coastal counties, and (*D*) coastal counties from Texas to Florida.

for when evaluating off-site compensatory mitigations since even relatively small differences in location between the wetlands lost and the new wetlands created can substantively influence the storm protection services provided. Furthermore, a replacement wetland may take decades to fully develop the functions provided by the original wetlands. The approach developed here, for a given discount rate, can be used to obtain a consistent estimate of the economic value of the storm protection service lost during the time it takes for the new wetland to fully reach the capacity of the lost wetland.

Our model can be used to estimate property damage under different wetland loss scenarios. To illustrate this use, we consider the question of how much property damage from Hurricane Irma, in 2017, which occurred just outside of our sample period, might have been prevented if there had been no loss of wetlands in Florida between 1996 and 2016. In the 19 coastal counties that experienced tropical-storm–level wind speeds when Hurricane Irma made landfall, wetland coverage was reduced by 2.8% between 1996 and 2016. Absent this reduction in wetlands, we estimate property damage in these counties would have been lower by about $430 million (*Materials and Methods*). This is substantial for a single storm. For comparison, the Federal Emergency Management Agency spent $10 billion on preventative hurricane, storm, and flood mitigation programs from 1989 to 2017 (23). This suggests that wetland preservation is likely to be a comparatively effective way of protecting coastal communities against tropical cyclones. Restoring wetlands may also be a cost-effective policy, but that action needs to consider the time path noted earlier for such wetlands to provide storm protection services. The interaction between building codes, restrictions on building in high-risk locations, and wetland coverage locations deserves further attention from a policy perspective.

Our model can also be used to predict the storm protection value of coastal wetlands in the context of different climate change scenarios. This can be done in a straightforward manner for the winds associated with tropical cyclone activity by simply replacing the actual wind distribution at each location with the forecast wind distribution based on a particular climate change scenario and reintegrating property damages estimates over the desired spatial locations and time frame. It is also possible to use our model to look at the interaction between changing sea levels and wetlands in coastal counties by holding the estimated parameters constant and substituting in a new detailed topographic map of areas at risk under different storm conditions. With projections of rising sea levels and increasingly intense storms associated with climate change (24), low-lying coastal communities are likely to become more vulnerable to flooding. Model-based estimates can be calculated for the economic value of preventing future property damage under specific climate change and mitigation scenarios under different assumptions about wetland coverage.

It is important to recognize storm protection for property is just one of the ecological services that wetlands provide. Other ecosystem services delivered by wetlands include habitat for fish and wildlife; filtration of industrial, residential, and agricultural runoff; outdoor recreational opportunities; and carbon sequestration—all of which we do not value here. These services are at the heart of the current controversy over the US Clean Water Act (22, 25). While we have provided comprehensive estimates for a major component of wetland services, having values for the entire suite of these services is needed for effective policy decisions (26), particularly when unmonetized benefits of wetland services are likely to be ignored.

Materials and Methods

Data. Information on data sources can be found in *SI Appendix, Data*.

Data Availability. All data and code necessary for replication of the results in this paper are available for download at GitHub.

Construction of Potential Flooding Area for Each Storm. For each tropical cyclone, the maximum sustained wind speed experienced by each affected county was estimated based on distance from the storm center and the radii of different wind intensities. Potential flooding areas for each tropical cyclone wind category are estimated based on local elevation since inland penetration of storm surge is highly dependent on local topography. For each county, we map the area below each elevation from 0 to 8 m in 0.5-m increments. We then compare the area with the Storm Surge Inundation Map developed by National Oceanic and Atmospheric Administration Map (27), which provides the flooding inland extent for different hurricane categories based on simulated storms, taking into account local topography, elevation, and other environmental features. We select the elevation for which these two maps coincide the closest. For tropical storms and category 1 hurricanes, we select locations with elevation below 1 to 1.5 m as the potential flooding areas. For category 2 to category 5 hurricanes, we choose elevations ranging from 2 to 8 m to create the flooding areas. The estimated storm surge impact region for a specific storm is the intersection of the potential flooding areas and the areas exposed to at least tropical storm strength wind. The property value at risk for flooding is the value of total housing, estimated based on US Census Bureau block group housing value data, within the flood risk area.

Regression Models. To estimate the marginal effects of coastal wetlands in storm protection along both the extensive and intensive margins, we employ a Cragg lognormal hurdle model (28, 29) that consists of two parts: a probit model estimating whether coastal wetlands reduce the likelihood that a county experiences damage in a storm, and a conditional damage model estimating to what extent coastal wetlands reduce property damage when damage occurs. The two models can be expressed as follows:

$$P(damage_{csht} > 0|X) = \Phi(\gamma_0 + \gamma_1 wetland_{csht} + \gamma_2 wind_{csht} + \gamma_3 stormarea_{csht} + \gamma_4 riskproperty_{csht} + \gamma_5 right_{csht} + \eta_{csht}), \quad [1]$$

$$\ln(damage)_{csht} = \beta_0 + \beta_1 \ln(wetland)_{csht} + \beta_2 \ln(wind)_{csht} + \beta_3 \ln(stormarea)_{csht} + \beta_4 \ln(riskproperty)_{csht} + \beta_5 right_{csht} + \gamma_s + \lambda_t + \varepsilon_{csht}, \quad [2]$$

where $damage_{csht}$ is the property damage caused by tropical cyclone h in year t in county c of state s, and X is a vector of all of the regressors in the probit model. $wetland_{csht}$ is the coastal wetland area in county c within the estimated storm surge impact region of storm h, $wind_{csht}$ is the maximum sustained wind speed experienced by the county, and $stormarea_{csht}$ is the area of each county within the potential storm surge impact zone. $riskproperty_{csht}$ controls for the total property value under the risk of coastal flooding for each county. Counties with more property value within the potential flooding areas are likely to experience greater losses because the property to be potentially destroyed is of greater value. To control for the location of a county relative to the storm track, an indicator variable, $right_{csht}$, is included in the model. $right_{csht}$ equals 1 if a county is located to the right of the storm path, and 0 otherwise. Coastal flooding impacts are expected to be greater on the right side of the storm path since tropical cyclones rotate counterclockwise in the Northern Hemisphere with strong winds pushing water onshore to the right of the storm path, while blowing water away from the coast to the left (30). γ_s is a state fixed effect, which captures state-specific characteristics that are fixed across time. One example is the shape of the coastline of each state, which is relatively stable over time—a state with a coastline curved inward may experience higher surge levels (thus, more damage) when a tropical cyclone makes landfall, compared to states with a convex coastline (31). γ_s also includes factors such as each state's historical exposure to storm surges and residents' culture and attitudes toward storms. λ_t is a year fixed effect, which mainly picks up year specific factors that affect all counties in the United States. η_{csht} and ε_{csht} are error terms, which capture random components with limited long-term forecast in advance such as tides, very specific storm track, wind gusts, and rainfall. β_1 is the coefficient of interest, which captures the elasticity of storm damage to existing wetland coverage when a county suffers from positive property damage.

Our model relies on estimation techniques designed for panel data. With panel data, one needs: a long enough time dimension; a large enough number of units along the individual unit or spatial dimension; and for the product of these two dimensions, the number of individual observations, to

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be reasonably large. When either dimension gets to be too small, key statistical quantities of interest, and particularly fixed effects, are unreliably estimated in the specific sense that they are not consistent estimates of quantities. Our number of individual observations is more than 900, and substantially larger than that used in past studies. Our number of time periods, 21 y, is also larger than that in many environmental impact studies using panel data. Less obvious is the fact that our panel dataset is unbalanced. In the conditional damage model, an observation is only generated if tropical storm winds hit a particular county. Because we have far more tropical storms than previously used and these storms often hit multiple states, there are plentiful observations to get consistent state-level fixed effects for all of the states hit except for New Hampshire, Maine, and Connecticut, which were not hit by many storms. However, this is not the case for individual counties. Forty counties were hit only once. Adding county-level fixed effects causes these counties to drop out of the sample because the fixed effect is effectively equal to the residual. There are another 64 counties that are hit twice. The county fixed-effect estimate for these counties is unreliable as it is simply the average of the two residuals for that county. It is only when the number of observations on which the fixed effect is based gets reasonably large that fixed-effect estimates become well defined with the signal clearly standing out from the noise of the error term. Alternative specifications using county-level and substate-level fixed effects defined in two different ways are explored in *SI Appendix*, Alternative Specifications, State-level and Sub-State-level Fixed Effect Models.

Potential Endogeneity. The main source of random variation that statistically identifies the impact of wetlands in storm protection is the storm-specific track for each tropical hurricane. Each storm track (including specific path, radius, and intensity) puts a different set of wetlands, even within the same county in the same year, into play exogenously and at different intensity. This means that, even for the same property, if a storm of a specified intensity approaches from a different angle or the track shifts a mile or two in one direction, there might be a different set of wetlands providing protective services. Exogeneity follows from the assumption that, at the time a particular storm track becomes manifest, the structures at risk have already been built and any wetlands providing protective services are in place. The identifying assumption is that, unlike say a localized pressure zone in front of a storm, which can shift its track, the configuration of wetlands in front of a storm does not influences its exact path up until the time the storm hits that area. It is important to recognize that this source of identifying variation does not allow us to address the issue of how the structures came to be located where they are at the time a tropical storm threatens the area. Hence that question is not the subject of investigation in this paper.

In addition to exploiting random variation in storm tracks, there is also variation in $wetland_{csht}$ that comes from two other sources: 1) natural processes such as sunshine, precipitation, nutrition in the water, and coastal erosion, which all can influence wetland distributions; 2) human activities including constructing structures, dredging, filling wetland, and building canals and levees. These alterations to the hydrologic systems influence the amount of sediments and nutrition brought to wetlands, thus influencing wetland productivity. (1) is due to exogenous natural factors; endogeneity concerns are therefore focused on (2). There may be concern that there are places where wetlands are being drained on a large scale to build structures. While this did take place in the more distant past, it is not a major issue in the wake of the 1988 Bush Administration "no net loss" of wetland coverage and function policy. To achieve this goal, the Environmental Protection Agency (EPA) finalized the Clean Water Act section 404 and required permits for projects with potential negative impacts on wetlands. Furthermore, the 1990 Memorandum of Agreement between the EPA and the Department of the Army established a three-part process, the mitigation sequence, that must be followed to offset impacts to wetlands (32). The import of these regulations during our study period (1996 to 2016) is that while there is some amount of building of new structures on wetlands in coastal areas, they almost always involve at most a small number of structures and the restoration of a close-by wetland within the same watershed. Some states are better at enforcing laws with respect to wetland loss, but this is picked up in state fixed effects. National enforcement efforts have some variation over time, but this is picked up in year fixed effects.

The potential for endogeneity naturally arises in any consideration of property damage, due to moral hazard and other concerns. This is largely due to locational and insurance decisions. However, the housing units at risk have already been built at their particular location when a storm strikes; each tropical cyclone's path is exogenous, providing the randomly assigned wind treatment. In addition, our damage measure includes total losses, not just insured losses, and there are reasons to expect the two measures to be quite different—for example, the probability of households in areas at high risk of coastal flooding having flood insurance was found to be only about 63% (33). Furthermore, the government strongly favors an ex post response to property damage, even though ex ante actions are considerably more effective, a contradiction largely driven by political considerations (23).

Another possible source of possible endogeneity is that units in areas at high risk of being hit by tropical cyclones may be better built or located in areas that are better protected by wetlands and other natural defenses against storm surge and flooding, although ex ante the opposite scenario is also plausible. To a large extent, this should be captured by the property value at risk. Also, state fixed effects capture time-invariant state-level factors influencing damages. The model results shown in *SI Appendix*, Table S6, column 2, go even further by including county level fixed, suggesting that, if anything, our main estimates for the marginal value of wetlands may be underestimated.

Marginal Value of Wetlands in Storm Protection. Let D_{csht}, W_{csht}, V_{csht}, S_{csht}, P_{csht}, and R_{csht} refer to $damage_{csht}$, $wetland_{csht}$, $wind_{csht}$, $stormarea_{csht}$, $riskproperty_{csht}$, and $right_{csht}$, and let α stand for $\beta_0 + \gamma_s + \lambda_t$. Based on the conditional damage model, the expected damage to a county when the wind speed is v, conditional on experiencing property damage, will be (omitting subscripts):

$$\mathrm{E}(\mathrm{D}|\mathrm{v}, X_{-v}, \mathrm{D}>0) = W^{\beta_1} v^{\beta_2} S^{\beta_3} P^{\beta_4} e^{\alpha} E(e^{\varepsilon}). \quad [3]$$

The underlying statistical framework here is a survival model where the expected value depends on both the estimated regression parameters and the estimated variance. There are two standard approaches to obtaining the estimate of $\mathrm{E}(e^{\varepsilon})$. First, we can assume the residuals are normally distributed, effectively treating the regression model as the maximum-likelihood estimator, which can be sensitive to outliers. Second, we can estimate this quantity by bootstrapping the empirical residual distribution of the observed data. This latter approach is more flexible and, in this instance, more conservative. It produces an estimated value of 10.81 for $\mathrm{E}(e^{\varepsilon})$, and estimates of marginal wetland values that are 17% lower than those obtained under the assumption that the error terms are normally distributed. We report the more conservative estimates. The annual expected property damage due to tropical cyclones to a shoreline county can be calculated by integrating the expected property damage over all of the possible storm wind speeds that could affect the county:

$$\mathrm{E}(\mathrm{D}|X_{-v}) = \int E\left(D\middle|v, X_{-v}, D>0\right) P\left(D>0\middle|v, X_{-v,}\right) f(v) dv. \quad [4]$$

The marginal value of wetlands in storm protection will be $\partial \mathrm{E}(\mathrm{D}|X_{-v})/\partial W$, which can be expressed as follows:

$$\int \left[\frac{\partial E(D|v, X_{-v}, D>0)}{\partial W} P(D>0|v, X_{-v}) + \frac{\partial P(D>0|v, X_{-v})}{\partial W} E(D|v, X_{-v}, D>0)\right] f(v) dv. \quad [5]$$

This can be estimated using the expression:

$$\int \hat{D}\left(\frac{\widehat{\beta_1}}{W} P\left(\widehat{D>0}|v, X_{-v}\right) + \frac{\partial P\left(\widehat{D>0}|v, X_{-v}\right)}{\partial W}\right) f(v) dv, \quad [6]$$

where $\hat{D}$ is the predicted property damage when county c experiences a storm with wind speed v based on the estimation results of the model in Eq. **2**. In a few instances, the predicted value exceeds total property value under risk. To control the overprediction problem, $\hat{D}$ is capped by the total property value under flooding risk for each wind category. $P(\widehat{D>0}|v, X_{-v})$ and $\partial P(\widehat{D>0}|v, X_{-v})/\partial W$ are the predicted likelihood of a county experiencing damage when hit by wind velocity v and the estimated marginal effect of wetlands in reducing the probability of suffering property damage based on the estimation results of the model in Eq. **1**.

The annual distribution of wind speeds projected for each county from ref. 20 is assumed to follow a gamma distribution, and we impose 152 kt as the upper bound wind force (strongest wind speed recorded post World War II in the United States, which was during Hurricane Camille in 1969). The Landfalling Hurricane Probability Project estimated the probability of one or more events bringing three wind intensities, i.e., $P(v \geq 34$ kt), $P(v \geq 65$ kt), and $P(v \geq 100$ kt), for 11 coastal regions covering all counties in our analysis. These 11 coastal regions group counties based on the frequency of major hurricane landfalls from 1900 to 1999. For each region, using these points on the cumulative distribution function of wind speeds, the parameters of the best fit gamma probability distribution function of wind speeds are backed out using the minimum distance estimation method (34). The R-squared reported is the average over regressions from 11 different wind regions (20). As a robustness check, Weibull and log-normal distributions are fit for each county as well. These have slightly lower R^2 compared with that of the gamma distribution and generate similar estimates for the marginal value of wetlands (*SI Appendix*, Table S10).

The annual expected property damage due to tropical cyclones to a shoreline county can be calculated by integrating the expected property damage over all of the possible storm wind speeds that could affect the county. It would be straightforward to use alternative projections for future wind intensities in the modeling framework put forward here.

The marginal value of coastal wetlands across time is estimated by discounting the future annual value of wetlands to the current period. Assuming that the annual marginal value of wetlands for storm protection stays the same in the future, then the formula can be expressed as follows:

$$\sum_{t=0}^{T}\frac{1}{(1+r)^t}\frac{\partial E(D|X_{-v})}{\partial W}, \quad [7]$$

where r is the discount rate and t refers to year.

Wetland Loss in Florida and Hurricane Irma. The expected change in property damage can be forecasted under different wetland loss scenarios for a given storm. Hurricane Irma made landfall in Florida on September 10, 2017, as a category 4 hurricane (35) and influenced 19 coastal counties at its landfall locations (*SI Appendix*, Fig. S7). Since the storm path and wind speed radius data from refs. 36 and 37 have not been updated, we estimated wind intensity experienced by each affected county using Hurricane Irma Advisory Archive data from the National Hurricane Center (35). We used our usual methodology for the remaining explanatory variables. Total property damage caused by Hurricane Irma is also not yet known; therefore, we predict it using the model for two different scenarios: first, using 2010 coastal wetland coverage; second, using coverage in 1996, that is, assuming no loss. From 1996 to 2010, the total wetland coverage within the potential flooding area was reduced by about 500 km^2 (from 17,900 to 17,400 km^2), a loss about 2.8% of wetland coverage in 1996. The forecasted property damage is \$19.07 billion based on the wetland coverage in 1996 and \$19.50 billion based on the wetland coverage in 2010. Thus, our model predicts that property damage caused by Irma would have been reduced by \$430 million, if the 500 km^2 of wetlands lost between 1996 and 2010 had been maintained.

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Supporting Information

Coastal wetlands reduce property damage during tropical cyclones

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This PDF file includes:

Data
Alternative Specifications
Figs. S1 to S8
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SI Text

Data

Coastal wetlands. Included in this study are saltwater and freshwater wetlands located within the coastal watershed boundary of U.S. states (*1*). The wetland coverage data is extracted from digital land cover maps provided by the NOAA Coastal Change Analysis Program (*2*). These land cover maps are created based on 30-meter Landsat imagery and are updated every five years since 1996. Wetlands are classified to palustrine and estuarine wetlands based on the salinity level where they located, and each group is further categorized based on their vegetation types – forested, scrub/shrub, and emergent wetlands. Fig. S8 shows the distribution of wetland changes during 1996 to 2010 in the typical flooding area when a tropical storm or Category 1 Hurricane hits a county. This analysis includes counties with more than a de minimis [over .2 km^2 (50 acres)] coastal wetland coverage within the flooding area during a Category 5 hurricane.

Tropical cyclones. Storm trajectories, intensities and radii of various wind speeds are collected from the International Best Track Archive for Climate Stewardship Dataset (*3*) and the Extended Best Track Dataset (*4*).

Storm damage. Storm property damage for each coastal county is from the Storm Event Database, which is an official publication by the National Weather Service (NWS) of NOAA (*5*). To ensure that the database is as accurate as possible, NWS has established detailed instructions on collecting statistics on property damage. Though NWS uses the best available information, measurement error in estimating disaster damage is no doubt present. From a statistical perspective, random measurement error in the dependent variable does not bias OLS estimates of the impact of wetlands on storm protection. This type of measurement error will make estimates less precise, reducing the power of statistical tests. A constant percentage underestimate will be absorbed into the constant term. Difficulties can arise if there is consistent underestimation of damages whose magnitude is tied to covariates in the model. Over time, NWS has improved data quality control procedures for damage estimation accuracy over time. NWS goes through considerable effort to obtain estimates of both insured and uninsured loss. Large uninsured losses and, particularly those requiring building permits, are generally included. Smaller uninsured losses may be under counted. To the extent that the magnitude of underestimation has change over time this should be captured by year fixed effects (Table S4 Column 1) or time trend (Table S4 Column 2). Note that the cost of economic disruption included in (*6*) is not covered here. These costs tend to be inaccurately estimated and, given the need to evacuate people in the face of high winds and large scale loss of utility services, may not be heavily influenced by wetland coverage. There are also injuries and deaths associated with tropical cyclones but again these are less clearly tied to wetland coverage than evacuation success. To the extent economic disruption cost and direct harm to people are influenced by wetland coverage, our estimates will represent a lower bound.

Property value. The property values were estimated from two sources: the 2000 and 2010 Censuses and annually released ACS 5-Year Estimates from 2005-2014. The 2000 U.S. Census data is retrieved from the IPUMS National Historical Geographic Information System (*7*), while the rest of the housing data is from the U.S. Census Bureau Topologically Integrated Geographic Encoding and Referencing (TIGER) Product (*8*). The main advantage of using these datasets is that they collect housing values and the number of housing units at the census block group level, which allows us to estimate the total property value under coastal flooding risk in each block group, then aggregate to the county level during each storm event. For each of the ACS 5-Year Estimates, data is collected during a 60-month time period. For example, the 2010-2014 ACS 5-Year Estimates data was collected between January 1st, 2010, and December 31st, 2014. For each ACS 5-Year Estimates dataset, we assign the housing data to the mid-year, for example, we use ACS 2010-2014 data as the housing data for 2012. For years with no Census or ACS 5-Year Estimates data available, we interpolate the housing value based on the annual growth rate of the state-level House Price Index (HPI) from the Federal Housing Finance Agency (*9*), which is based on housing transaction data.

Elevation. Elevation data is based on the National Elevation Dataset (NED) produced by the United States Geological Survey (*10*).

Storm probability. Annual storm probability data for each coastal county is collected from the United States Landfalling Hurricane Probability Project (*11*).

Building codes. The stringency of building codes for Atlantic and Gulf Coast states is measured based on an assessment report by the Insurance Institute for Business and Home Safety in 2015 (*12*). This report ranks hurricane-prone states on a scale of 0-100 based on the effectiveness of the states' residential building code adoption and enforcement systems. The building code stringency dummy variable "code" equals to 1 for states with an assessment score above the median score and 0 otherwise.

Levee. The length and age of levees in each coastal county along the Atlantic and Gulf Coast is collected from the National Levee Database (NLD) published by the U.S. Army Corp of Engineers (*13*). NLD is a congressionally authorized database that documents U.S. levees.

Hard Shoreline Structures. The length of shorelines armored with man-made storm defensive structures for each coastal county is estimated by (*14*), based on the Environmental Sensitivity Index (ESI) geo-databases from the NOAA Office of Response and Restoration. Hard shoreline structures include seawalls, bulkheads, and riprap structures (revetments, breakwaters, groins/jetties).

Beach Nourishment. The information of beach nourishment projects during our study period is collected from a comprehensive beach nourishment database in the U.S. through the Program for the Study of Developed Shorelines (PSDS) at Western Carolina University (*15*). The volume of sediment emplacement in each nourishment episode is aggregated to the county-year level and merged to our county-storm year level dataset.

Alternative Specifications

Time Trends, Dropping Largest Storms, a More General Functional Form and Selection Bias

Estimation results of Eq. (2), as well as a few alternative specifications are shown in Table S5. Adding linear and quadratic time trends as controls instead of time fixed effects does not substantively change the estimation of the protective effects of wetlands (Column 2). Figure S2 reflects one important feature of tropical cyclones – a highly skewed distribution of outcomes (*16*). To check whether the regression results in Table 1 are driven primarily by only a few extremely large disasters, observations corresponding to the highest and second highest damage storms are dropped (Columns 3-4). The coefficient estimates remain stable across the columns, suggesting that the main regression results are not largely driven by a few devastating storms.

The appropriateness of the log-log damage model specification was checked by estimating a Box-Cox model (*17*). We found that the null hypothesis of a log-log specification cannot be rejected (P=0.88). To check for whether it was necessary to account for possible correlation, conditional on included covariates, between the first and second stages of the Cragg lognormal hurdle model, we estimated a Heckman model which allows for potential correlation between the two stages. We can not reject the null hypothesis using a Wald test that the error terms of the two stages are independent (P=0.55). Hence, we use the Cragg lognormal hurdle model as our main model in the analysis.

State-level and Sub-State-level Fixed Effect Models

To capture the observed and unobserved features specific to a county, county fixed effects are included in the model instead of state fixed effects (Table S6 Column 2). The identifying variation comes from within-county differences in wetland coverage across storms, induced by differences in the flooding area at risk. The elasticity of property damage with respect to wetlands changes to -1.69. That is, rather than controlling for time invariant factors that may affect damage at the state level, when we attempt to more precisely control for such factors at the county level, the wetland effect becomes larger. While this may suggest the elasticity in the main specification is underestimated, the sample is effectively different because many counties appear only for one storm and, more generally, the identification of the county-level fixed effects is tenuous (with state-level fixed effects, New Hampshire is the only state that effectively drops out of the model).

A very optimistic rule of thumb is that at least five observations per estimated parameter (e.g., fixed effects) are needed before there is a reasonable chance that the parameter is consistently estimated. Dropping counties that are hit less than five times drops out 24% of the sample. The more frequently advanced 10 observation rule of thumb drops out 76% of the sample if our fixed effects are at the county level. We do have some confidence in county-level fixed effects because when we drop out counties with fewer than five observations, we get very similar estimates (Table S6 Columns 3 and 4) to our models using the full sample with state fixed-effects (Table S6 Column 1) and with county-fixed effects (Table S6 Column 2). At the more standard ten or more observations per parameter (*18*), we only have 19 counties left, and much of the variation in wetlands is lost. Thus, while we think there is some statistical support from the county-level fixed effects models (Table S6 Columns 2 and 4) for the hypothesis that the protective effect of wetlands is considerably larger than that from our state-level fixed effects model (Table S6 Column 1), that estimate is underpowered. There may be utility in using the estimate based on controlling for county-level fixed effects as an upper bound for the protective role of wetlands with respect to property damage.

The only definitive way to resolve this conflict between the influence of wetlands controlling for state-level and county-level fixed effects is with a substantial amount of additional data. Since we include all tropical storms during 1996 to 2016, the only realistic way for this to happen is by augmenting the current sample with the set of future U.S. tropical storms that occur over next ten years or so.

We take an intermediate strategy of including sub-state fixed effects by placing counties in groups. Adjacent counties are not necessarily alike due to county boundaries sometimes defining abrupt shifts in ecological conditions or population characteristics, so there is no single defensible strategy for defining subregions. That said, we pursue two reasonable versions of this strategy to check the robustness of our main results and to shed some light on the state versus county fixed effects conflict for our wetland impact estimate. Both support the magnitude of the wetlands estimate using state-level fixed effects. The first test is done by noting that two states, Florida and Texas, have much longer coastlines than the remaining states and have long recognized regional differences that can be used. It is reasonable to expect there maybe unobserved characteristics that are very different in far western Florida compared to Miami, or along the Gulf coast compared to the Atlantic coast. A natural test then is to divide Florida into three regions: Florida Panhandle, East Florida Gulf Coast and East Florida Atlantic Coast. Texas is similarly divided into West Texas (Cameron to Jackson) and East Texas (Matagorda to Orange). For the remaining states, there is still a single state dummy. This allows us to capture substate variation in fixed characteristics, at a level between state fixed effects and county fixed effects. The estimated wetland effect is a bit smaller, but not statistically different, than our original estimates (Table S6 Column 1) using these sub-state dummies instead of the state-level dummies (Table S6 Column 5).

For the second test, the 17 coastal states analyzed in the main model are categorized into 25 sub-state regional dummies based on their probability of being stricken by a tropical cyclone in any particular year. These sub-state dummies are constructed as follows. Hurricane frequency data is collected from the Landfalling Hurricane Probability Project which categorizes the entire US coastline into 11 regions of contiguous counties based on frequency of intense or major hurricane landfalls during the 20th century (*11*). Since these regions may cross state borders, we interact them with state dummies, which leaves us with 25 hurricane frequency-by-state regions. In addition to capturing sub-state regional variation, it also controls for fixed characteristics common to all counties with different probabilities of being hit by a storm (e.g., high likelihood counties may take common approaches to storm defense, regardless of their state). The estimate of the wetland effect is a bit smaller, but not statistically different, than our original estimate using this second set of sub-state dummies (Table S6 Column 6).

Other Coastal Defensive Measures

Wetlands are not the only coastal defense against property damage from tropical cyclones. We investigate whether inclusion of other man-made coastal defensive measures in the model changes the estimated protective effects of wetlands. We first look at the most common hard structure to protect against water damage – levees – and ask whether incorporating the extent of levee system as a control variable influences our estimated wetland coefficient. To do this, we collected the length of levees in each coastal county along the Atlantic and Gulf Coast from the National Levee Database (*13*). There are about 3171 miles of levee systems in the coastal counties. Palm Beach County and Miami-Dade County of Florida, and Plaquemines Parish and Lafourche Parish of Louisiana rank as the top four counties in terms of the total length of levees while about 60% of coastal counties do not have any levee systems.

The first important stylized fact to note is that almost all levee systems were built much earlier than our study period (1996-2016), with an average age about 45 years old among those with age information available in the database. Effectively, we have a county-level cross section of levee lengths, where some of levees may not be relevant if they are located far enough inland from the coast. Since the levee system is essentially static in our representation, it will also be picked up to some extent in the state fixed effects. The relevant part of the levee system also enters into the SLOSH map based on which we calculate the area at risk of flooding. Both of these considerations suggest that we might not expect to see the addition of a county level levee variable play much of a role in terms of changing the estimated wetland impact coefficient. We test this in two ways.

First, we estimated an expanded model that includes the log of the total levee length (+1) in each county as an additional control variable (Table S7 Column 2). The impact of levee length on property damage is quite small and not statistically significant. The coefficient on wetlands is virtually unchanged.

Second, we test whether presence of a levee system in the county rather than the number of miles of levee improves the fit of the model or substantively influences the estimated wetland coefficient. This test is performed by inclusion of an indicator variable for whether the county has a levee system (about 60% do) and an interaction of this indicator variable and the log of wetlands which allows wetlands to play a different role in counties with levee systems. Results in Table S7 Column 3 show that neither of these two additional variables accounting for the role of levees approaches statistical significance and the coefficient on wetlands is almost the same as in our main specification.

While levees are likely to be the most important man-made coastal defense measure since they line the coastal rivers, which are often the major path for large scale storm surge events, they are not the only one. About 90% of coastal counties in the conditional damage model are armored with some type of man-made storm defensive structures. These are seawalls, bulkheads, and riprap structures (revetments, breakwaters, groins/jetties) according to (*14*) who recently assembled a cross-sectional database of these structures. For an average coastal county in our analysis, 15% of the length of its shorelines is equipped with hard structures (with a median of 11%). Again, the limitation of this dataset is that it represents a single recent cross-section.

In Table S7, Column (4) shows that the new variable representing the share of the shoreline armored with hard structures in each county is insignificant. The coefficient on wetlands has increased about 20% in magnitude but is not statistically different from that in our main specification. A variant of this model that includes an interaction with wetlands is insignificant and produces in little change in the estimated wetland coefficient.

Another man-made coast defense is known as beach (re-) nourishment, whereby sand is brought to a beach to replace sand lost to erosion and storms. In Table S7, the model in Column (5), a variable for the total volume of sand (measured in cubic yards) added in beach nourishment episodes during the specific year. Unlike the previous variables, this one has both cross sectional and time series variation. The difficulty with the time series variation is that the rate at which sand is lost over time is likely to be beach specific. The results here show that the log of the quantity of sand (+1) put on beaches in the county is insignificant and the coefficient on wetlands is almost identical to that in our primary model specification.

The last column of Table S7 includes a set of variables representing levees, hardened shorelines and beach nourishment projects. The results here suggest that none of the variables in this set are statistically significant individually nor as a set. The coefficient estimate on wetlands is a little over 20% higher than the base model suggesting the possibility that inclusion of these factors produces a somewhat larger estimate of the protective effective of wetlands but the difference between this estimate and our base model is not statistically different.

Use of Alternative Property Value Series

Census and ACS housing value data have been used in the empirical literature on a wide range of research topics and form the basis of the capital value of the U.S. housing stock in national income accounts. However, housing values recorded in the Census and ACS are homeowner self-reported data. The accuracy of homeowner-reported housing value has been examined by researchers since the 1950s. Several studies examine the self-reported home value bias by comparing housing sales pricing data with owner-assessed home values from national representative surveys such as Survey of Consumer Finance (*19*), Census (*20*), and American Housing Survey (*21-25*). Most of these studies find that homeowners provide good quality estimates of the value of their homes but that these home value estimates are larger by about 2% to 8% than estimates derived from repeated sales data. This should provide an upper bound on potential overall bias, since dwelling units in worse internal condition and with negative externalities like traffic noise and bad neighbors that require physical verification sell more often, and hence are include in the repeat-sales index more often than other properties. (*21*) shows that indexes based on the Census owner-assessed value estimates tend to closely track the Case-Shiller repeat home sales indices on a percent change basis. (*20*) finds that homeowners tend to rely on somewhat outdated information, which is not surprising given the lag period between the listing of a home at a price and its eventual sale price. This leads to reported home values potentially lagging behind market prices during housing booms and reported home values that are potentially higher than that reflected by sales prices during housing busts. Our current method, by using Census block group level data, provides high level spatial resolution for property values. Its weakness is being relative unresponsive temporally to market sales information when markets are quickly moving up and, particularly down, during an illiquidity crisis in the housing market.

As noted above, we examine alternative sources of housing price information and perform additional statistical tests to examine the robustness of our conclusions to allowing our home value at risk measure to become more responsive to boom-bust cycles. We consider three specific robustness checks. First, to investigate whether the recession during our study period influences our estimates on wetland effects, we drop the official NBER Great Recessions dates of 2007-2009 and find the coefficient on wetlands is stable (Table S8 Column 2).

We can also investigate whether property value under flooding risk has a different impact on property damage depending on housing boom and bust. We run a model where we include an additional interaction term: property value under flooding risk interacted with an indicator of whether the storm happens during the 2006-2012 housing bust (Table S8 Column 3). The interaction term, while negative in sign, is not statistically significant, suggesting there is no evidence that the property value at risk effect is different in this time period. Moreover, the coefficient estimate for the wetland effect is very close to that in our primary specification.

As a third robustness check, we use an alternative method to calculate the change in housing prices over time. Using the 2000 Census estimates as the cross-sectional base at the Census block level, we scale these estimates annually to reflect changes in the county-level annual Housing Price Index growth rate. This method effectively substitutes greater spatial information over time at the Census block group level for greater temporal resolution at the county level. The county-level HPI index was recently released by the Federal Housing Finance Agency and is a broad measure of the movement of single-family house prices in the United States (*26*). The HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales or refinancing on the same properties. The mortgage information used for it is repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac.

The HPI is available on a much more spatially disaggregated level, counties, than the better-known Case-Shiller repeat sales home price index, which is available only nationally and in 20 metropolitan areas. Its drawback is that while a large part of the housing market goes to Fannie Mae and Freddie Mac, not all of it does. The subset of houses that do not may appreciate differently. Relative to the ACS, the county-level HPI data allows for housing values to change more frequently (annually rather than a five-year average) and accounts for the role that liquidity effects had on current housing sales prices.

For each county, we use housing value collected from the 2000 Census as the base value and estimate the housing value for other years based on the HPI annual growth rate of the county. A small number of counties have missing HPI data in a specific year due to having too few transactions. We impute annual HPI growth rate in such cases using the average annual HPI growth rate of the neighboring coastal counties within the same state, weighted by the length of their border with the county. For each county-by-storm observation, we calculate the total property value under coastal flooding risk, using the newly estimated property value and the number of properties within the potential flooding area. The wetland storm protection effects do not change much after adopting the new method of estimating property value under flooding risk (Table S8 Column 4).

To conclude here, we find that neither dropping the Great Recession, allowing the housing bust period to behave differently nor substituting the trend in housing prices reflected by the HPI for that reflected in the ACS substantively changes either our wetland impact or property value at risk coefficients. In retrospect, the reason for this result is clear. The different time series for housing value are highly correlated because spatial variation in population and average housing price is the dominate source of variation in the property at risk variable. Our time fixed effects are picking up the large national swing in housing values.

Fig. S1. Paths of tropical cyclones hitting the United States (1996-2016).

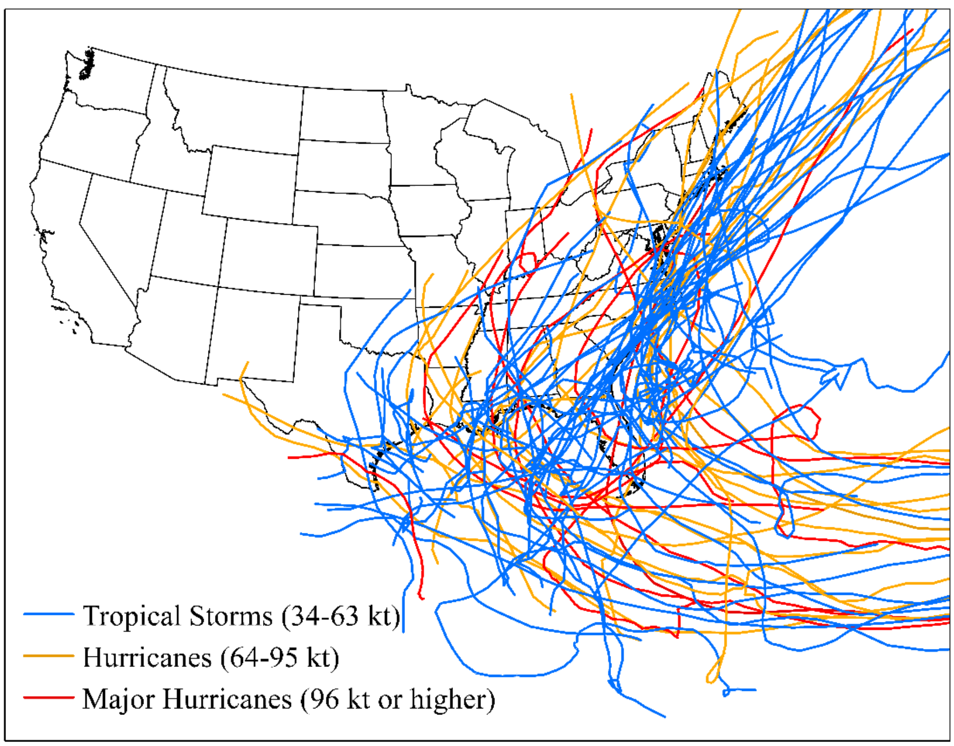

Fig. S2. Property damage to U.S. shoreline counties during tropical cyclones from 1996 to 2016.

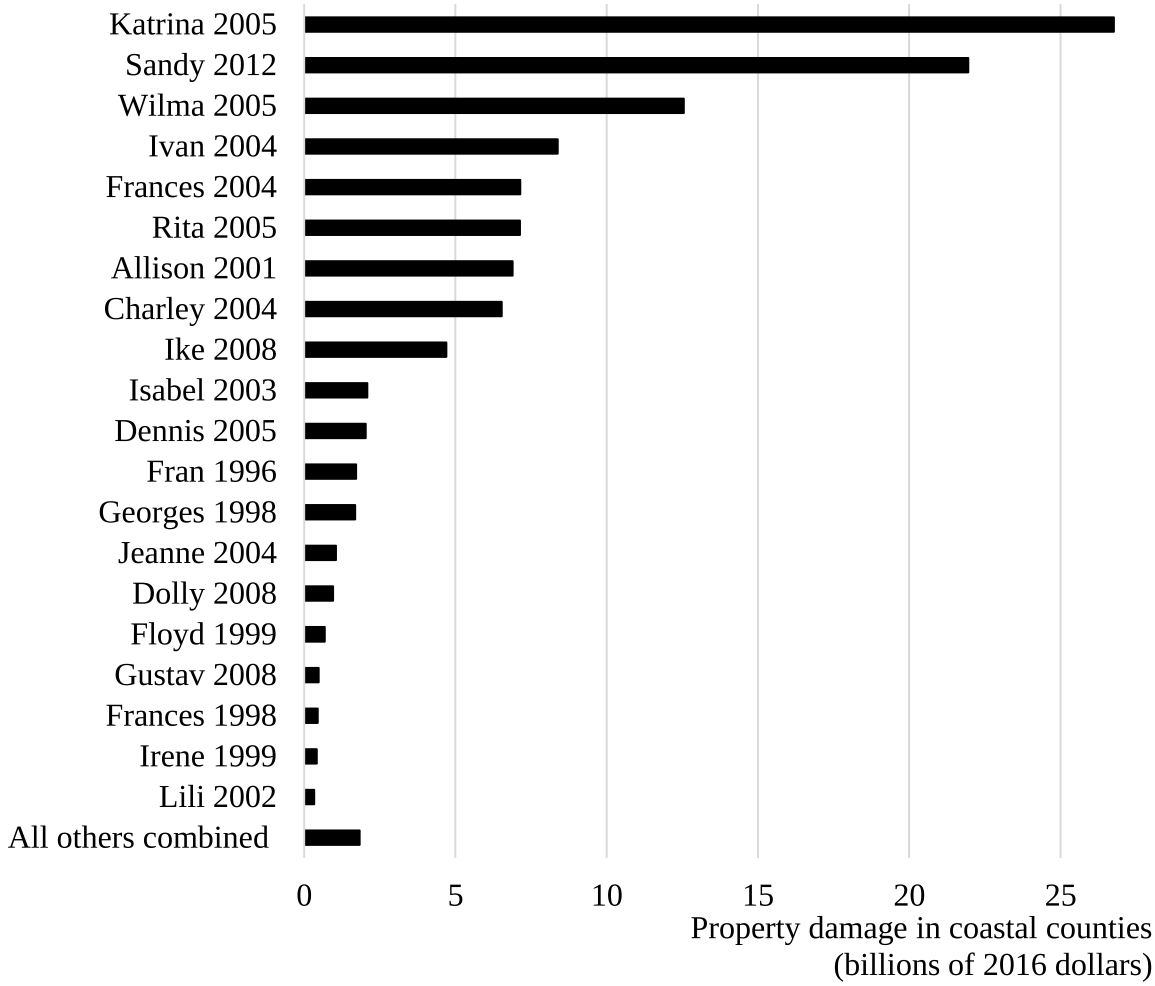

Fig. S3. Observed vs. predicted log property damage for each observation in the conditional damage model, Eq. (2).

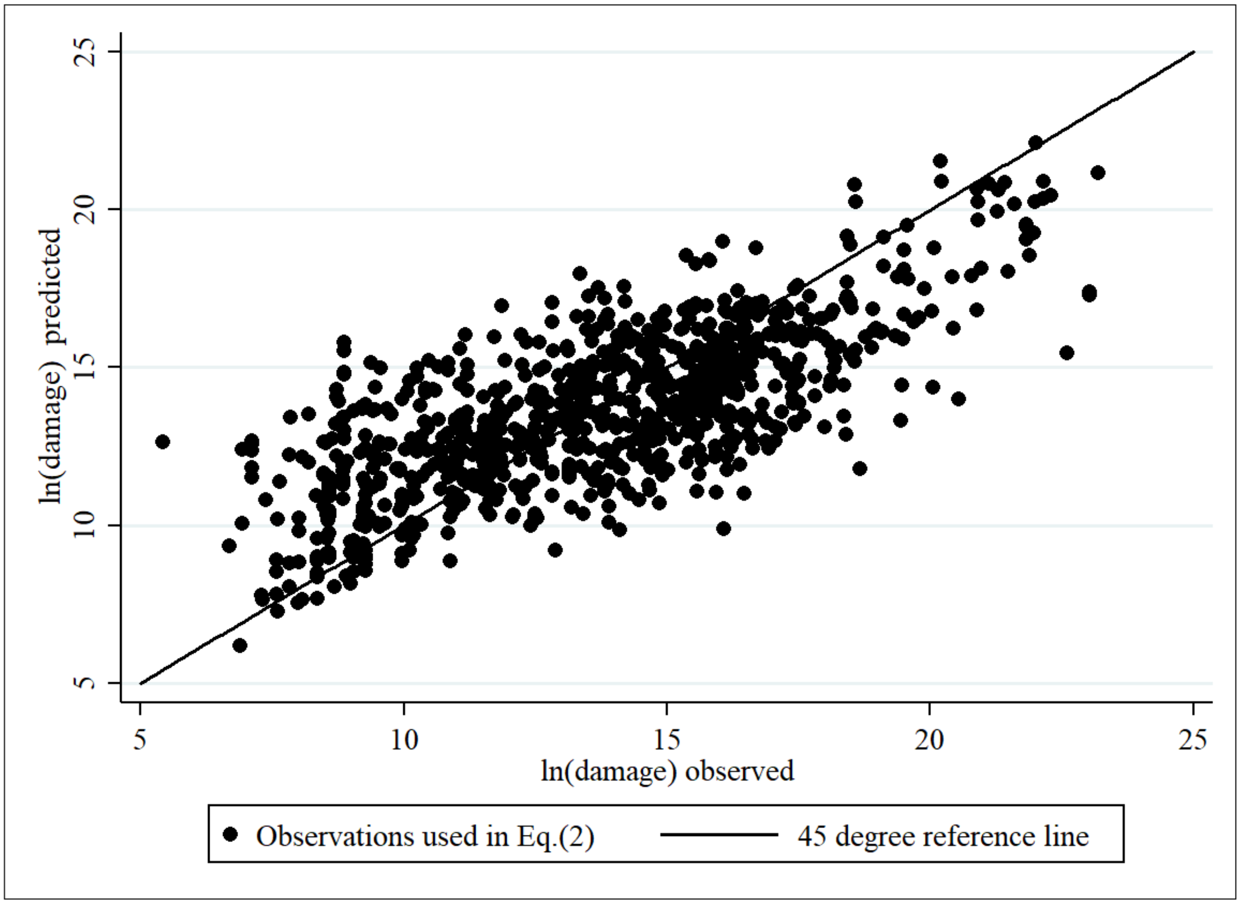

Fig. S4. Coastal wetland coverage along the Atlantic and Gulf Coasts (2010).

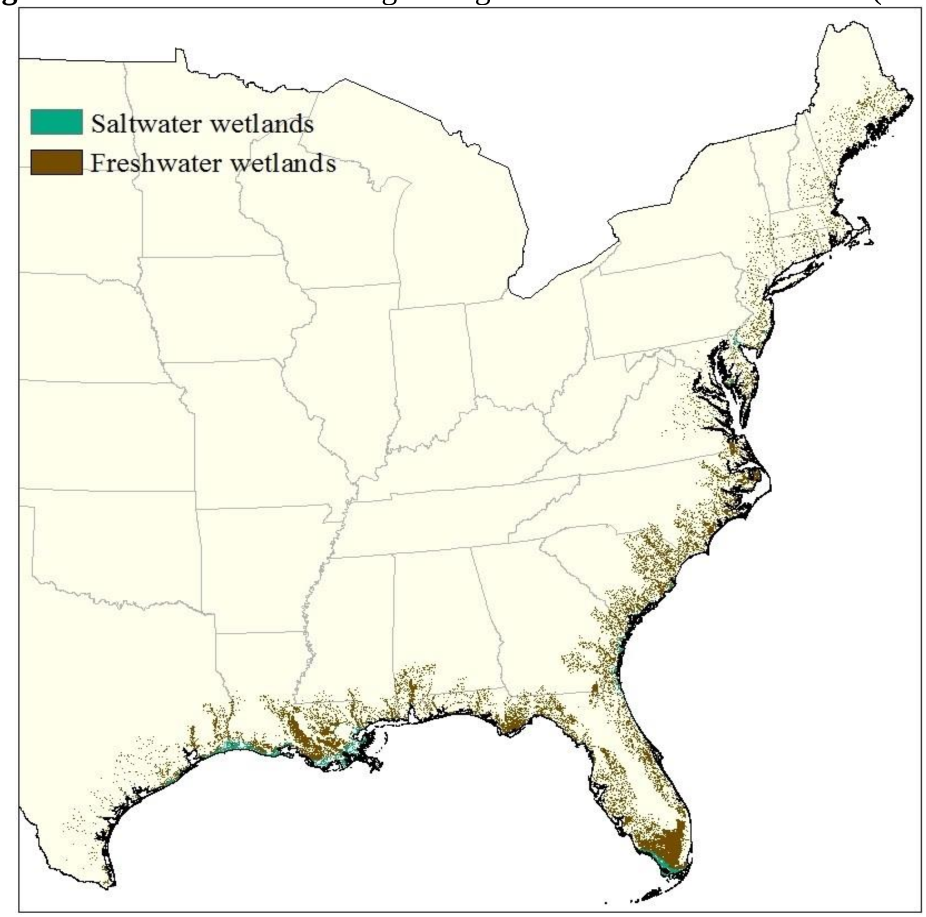

Fig. S5. Annual county-level wetland values for storm protection services along Atlantic and Gulf Coasts.

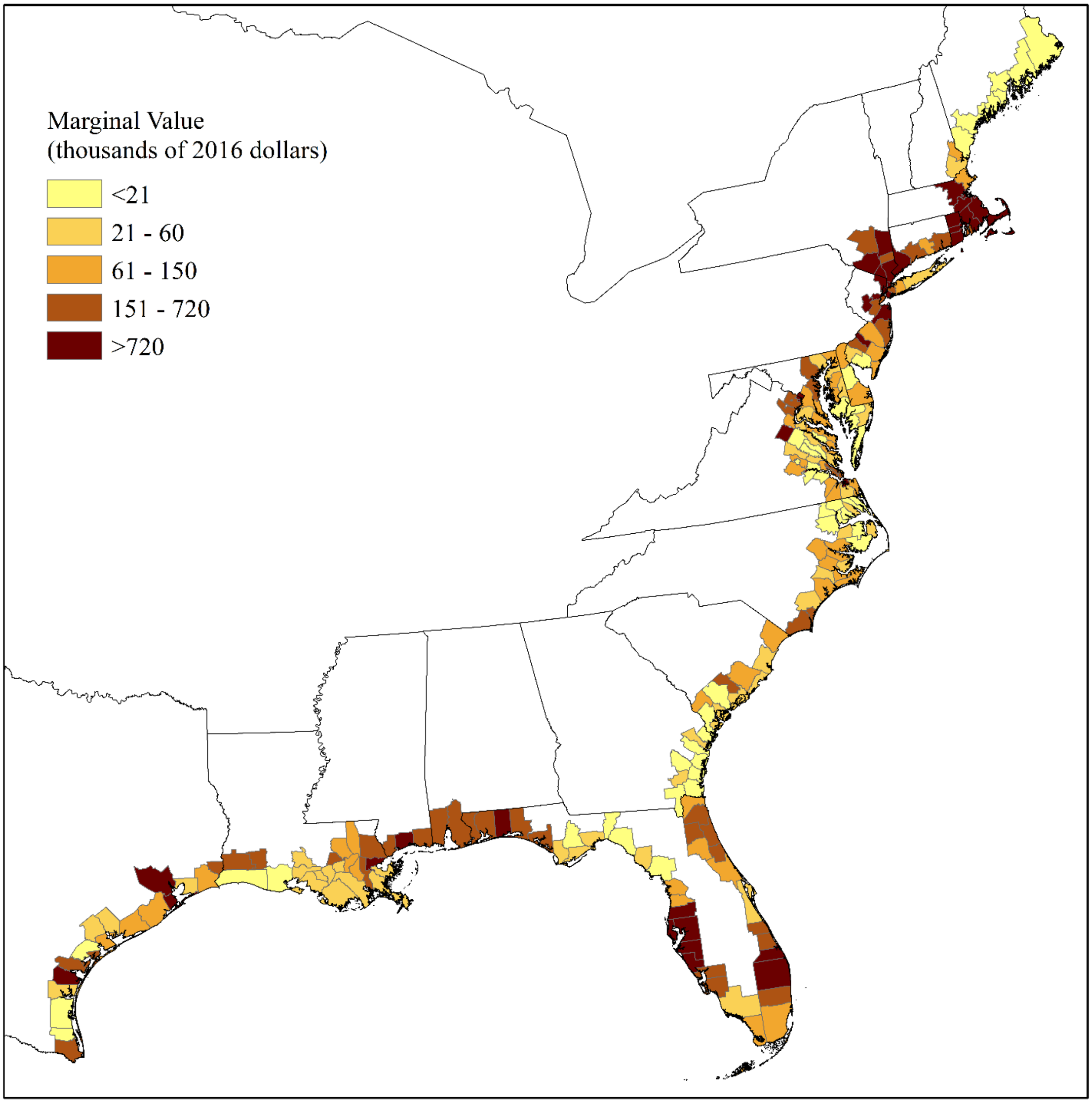

Fig. S6. Kernel density plot of log of county level marginal wetland value.

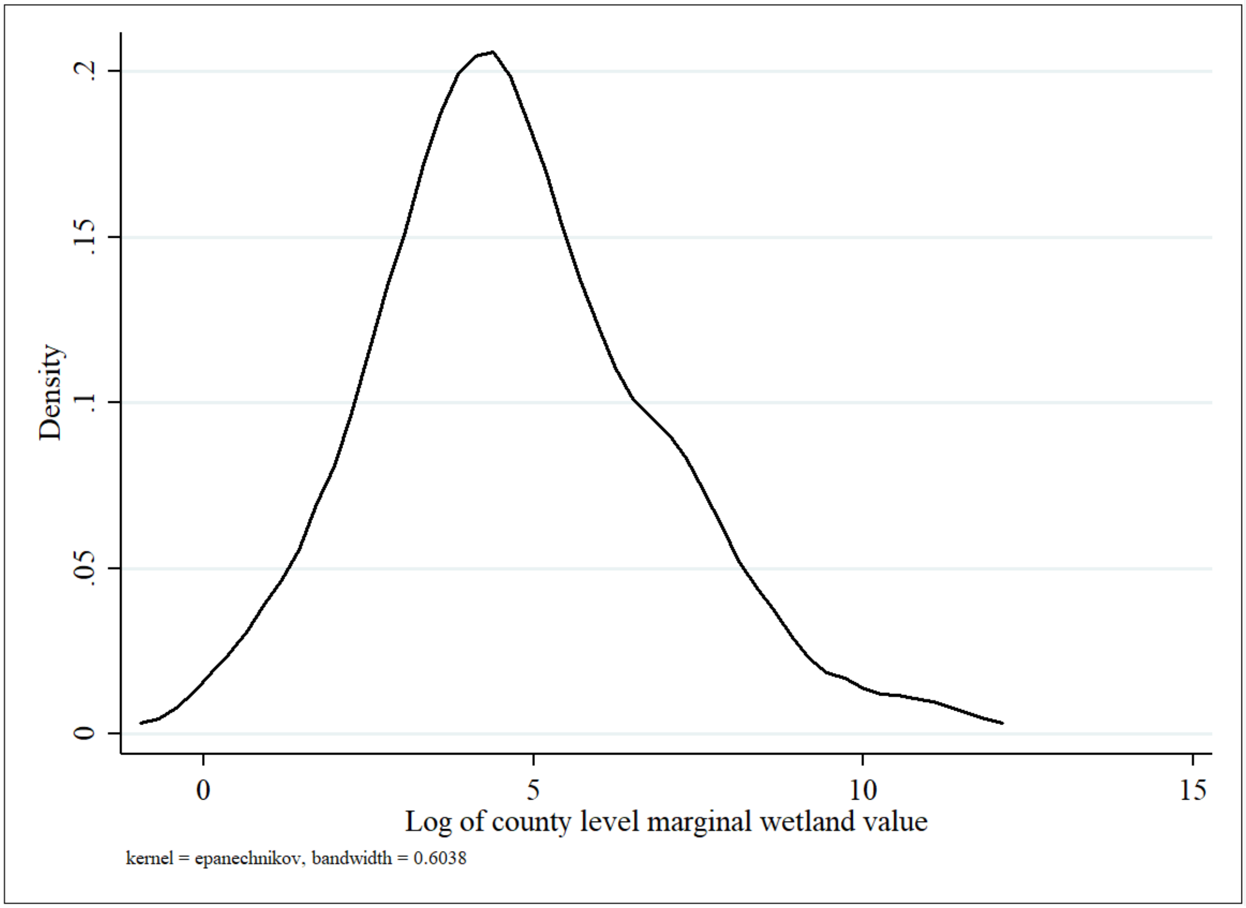

Fig. S7. Coastal wetlands distribution and storm surge area near Hurricane Irma landfall.

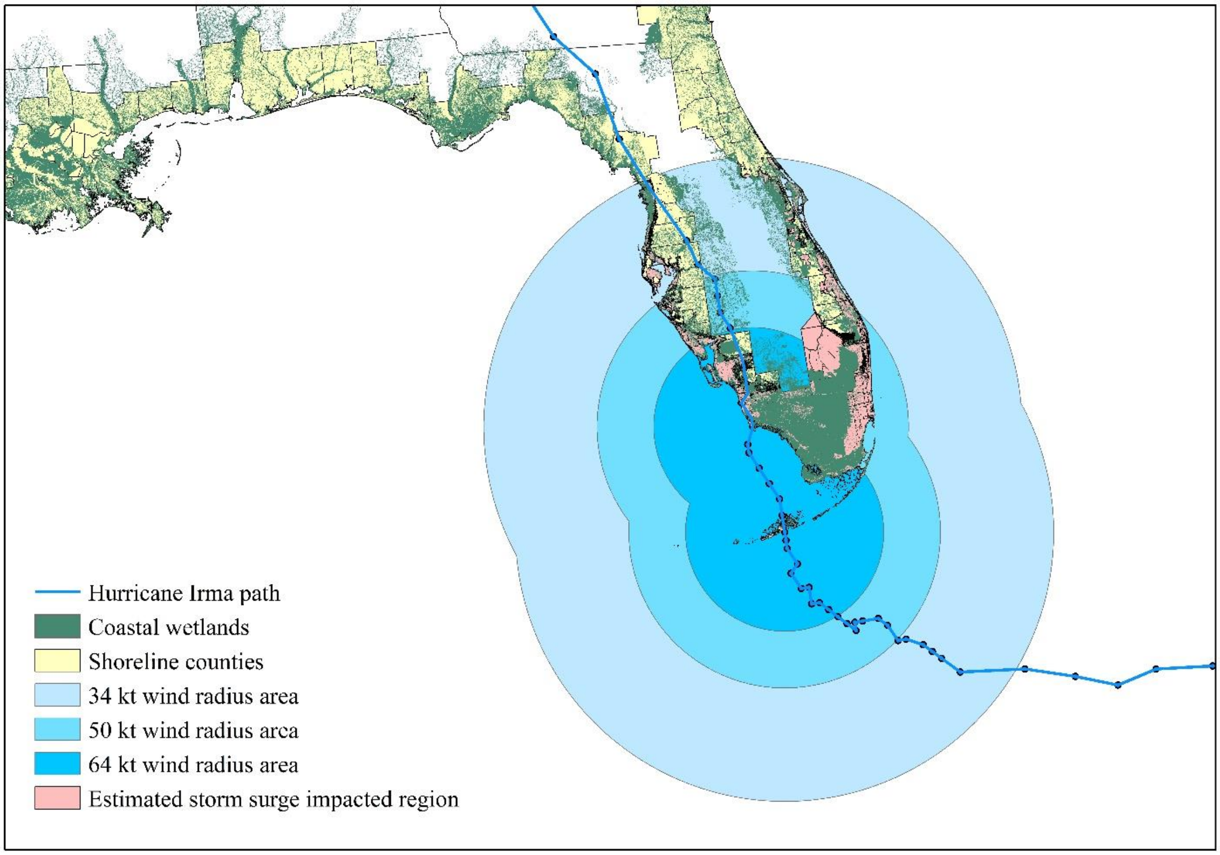

Fig. S8. Coastal Wetland Change in Counties along Atlantic and Gulf Coasts (1996-2010).

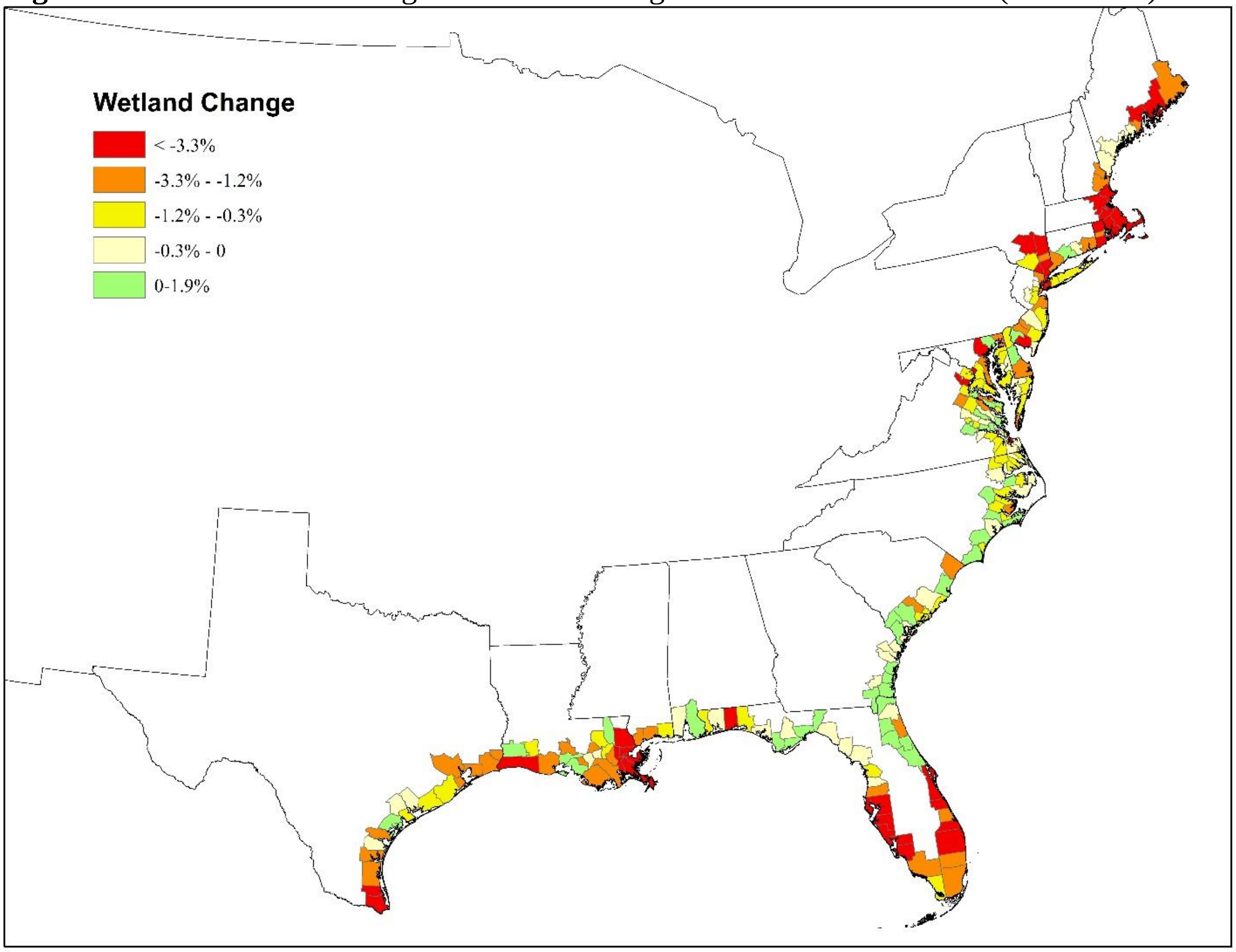

Table S1. Variable definitions and summary statistics of the conditional damage model.

Variable	Description	Units	Mean	SD	Min	Max
Property damage	County property damage during a storm.	Millions of 2016 dollars	122.75	792.22	0.00	12340.91
Wind	Maximum sustained wind speed experienced by a county.	knots	56.22	16.40	34.00	125.00
Storm area	Potential storm surge area.	km^2	620.76	906.76	0.92	5178.02
Wetland	Coastal wetland coverage within the estimated storm surge area of a county.	km^2	377.63	593.99	0.30	3636.25
Property at risk	Total amount of property value under the risk of flooding during a storm.	Millions of 2016 dollars	5437.80	16998.40	0.77	193456.90
Right	0-1 dummy variable, equal to 1 if a county is located to the right side of the storm path and 0 otherwise.		0.54	0.50	0	1
Freshwater wetlands	0-1 dummy variable, equal to 1 if freshwater wetlands are dominant within the storm surge area of a county and 0 otherwise.		0.66	0.47	0	1
Saltwater wetlands	0-1 dummy variable, equal to 1 if saltwater wetlands are dominant within the storm surge area of a county and 0 otherwise.		0.34	0.47	0	1
Forested wetlands	0-1 dummy variable, equal to 1 if forested wetlands are dominant within the storm surge area of a county and 0 otherwise.		0.41	0.49	0	1
Non-forested wetlands	0-1 dummy variable, equal to 1 if emergent and shrub wetlands are dominant within the storm surge area of a county and 0 otherwise.		0.59	0.49	0	1
Tropical storms	0-1 dummy variable, equal to 1 if a county experienced tropical storm level wind intensity (34-63 knots) and 0 otherwise.		0.70	0.46	0	1
Category 1 hurricanes	0-1 dummy variable, equal to 1 if a county experienced Category 1 level wind intensity (64-82 knots) and 0 otherwise.		0.22	0.41	0	1
Category 2 hurricanes	0-1 dummy variable, equal to 1 if a county experienced Category 2 level wind intensity (83-95 knots) and 0 otherwise.		0.06	0.24	0	1
Category 3-5 hurricanes	0-1 dummy variable, equal to 1 if a county experienced Category 3-5 level wind intensity ($\geq$ 96 knots) and 0 otherwise.		0.02	0.15	0	1
Strict building codes	0-1 dummy variable, equal to 1 if observation is in a state with above median building code assessment score and 0 otherwise.		0.81	0.40	0	1
Less strict building codes	0-1 dummy variable, equal to 1 if observation is in a state with below median building code assessment score and 0 otherwise.		0.19	0.40	0	1

Table S2. Summary statistics for property damage across different tropical cyclone classes.

	Observations			For counties experiencing property damage				
Cyclone Class	Total	Without damage	With damage	Median	Mean	Min	Max	SD
Tropical Storm	1164	855	309	0.03	25.56	0.00	6845.40	389.64
C1 Hurricane	506	242	264	0.78	90.98	0.00	10497.57	913.36
C2 Hurricane	536	306	230	5.36	77.80	0.01	3189.76	302.88
C3 Hurricane	252	126	126	8.34	475.13	0.01	12340.91	1462.66
C4 Hurricane	25	7	18	3.51	364.68	0.06	3827.71	1051.08

Sample is comprised of 2,483 county by storm observations, of which 947 observations (38% of total observations) experienced property damage (millions of 2016 dollars).

Table S3. Probit model assessing effect of wetlands on reducing probability of experiencing property damage during a tropical cyclone hitting the U.S. from 1996 to 2016. **P*<0.10, ***P*<0.05, ****P*<0.01. Robust standard errors are given in parenthesis.

	(1) Prob(damage)
Wetland	-0.001^{**} (0.0003)
Wind	0.035^{***} (0.0026)
Storm area	0.001^{***} (0.0002)
Property at risk	-0.000 (0.0000)
Right	0.492^{***} (0.0554)
Constant	-2.414^{***} (0.1373)
Log-likelihood	-1403.412
N	2483

Table S4. Conditional damage model estimates (with the marginal effects of wetlands reported in the table). Standard errors (in parentheses) are clustered two-ways at the county level and storm level. **P*<0.10, ***P*<0.05, ****P*<0.01.

	(1) log(damage)	(2) log(damage)	(3) log(damage)	(4) log(damage)	(5) log(damage)
log(wetland)	-0.5756***				
	(0.1840)				
Tropical storms × log(wetland)		-0.5752***			
		(0.1718)			
C1 hurricanes × log(wetland)		-0.5491***			
		(0.1876)			
C2 hurricanes × log(wetland)		-0.4029**			
		(0.1724)			
C3-C5 hurricanes × log(wetland)		-0.3501*			
		(0.1873)			
Freshwater wetlands × log(wetland)			-0.5805***		
			(0.1836)		
Saltwater wetlands × log(wetland)			-0.5731***		
			(0.1863)		
Non-forested wetlands × log(wetland)				-0.5598***	
				(0.1805)	
Forested wetlands × log(wetland)				-0.5796***	
				(0.1857)	
Strict building codes × log(wetland)					-0.5044**
					(0.1979)
Less strict building codes × log(wetland)					-0.8055***
					(0.2029)
Right	0.8821***	0.8749***	0.8828***	0.8880***	0.8825***
	(0.3129)	(0.3200)	(0.3147)	(0.3183)	(0.3128)
log(wind)	7.1885***	6.4122***	7.1928***	7.1953***	7.1929***
	(0.5653)	(0.9744)	(0.5683)	(0.5668)	(0.5668)
log(storm area)	0.4793**	0.4767**	0.4811**	0.4595**	0.4558*
	(0.2249)	(0.2180)	(0.2248)	(0.2235)	(0.2293)
log(property at risk)	0.3205***	0.3135***	0.3190***	0.3194***	0.3179***
	(0.0622)	(0.0599)	(0.0638)	(0.0624)	(0.0617)
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	946	946	946	946	946
Adjusted R^2	0.52	0.53	0.52	0.52	0.52

Table S5. Regression results for alternative specifications of the conditional damage model. Standard errors (in parentheses) are clustered two-ways at the county and storm level. *P<0.10, **P<0.05, ***P<0.01. Column 2 includes both linear and quadratic time trends, the coefficients of which are significant different from zero jointly at the 95% confidence level.

	(1) Base Model	(2) Add time trends	(3) Drop Katrina	(4) Drop Katrina & Sandy
log(wetland)	-0.5756***	-0.6149***	-0.5733***	-0.6089***
	(0.1840)	(0.1659)	(0.1890)	(0.1936)
log(wind)	7.1885***	7.2137***	7.0594***	7.0405***
	(0.5653)	(0.6587)	(0.5858)	(0.6182)
Right	0.8821***	0.6610*	0.8151**	0.7844**
	(0.3129)	(0.3668)	(0.3151)	(0.3340)
log(storm area)	0.4793**	0.5448***	0.4775**	0.4772*
	(0.2249)	(0.1980)	(0.2283)	(0.2397)
log(property at risk)	0.3205***	0.2835***	0.3110***	0.3068***
	(0.0622)	(0.0736)	(0.0622)	(0.0664)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	Yes
County FE				
Time trends		Yes		
N	946	946	920	866
Adj. R^2	0.52	0.48	0.50	0.50

Table S6. Regression results for alternative specifications of the conditional damage model with county-level or sub-state-level fixed effects. Standard errors (in parentheses) are clustered two-ways at the county and storm level. *P<0.10, **P<0.05, ***P<0.01.

	(1) Base Model	(2) County FE	(3) Drop County Hit <5 Times (State FE)	(4) Drop County Hit <5 Times (County FE)	(5) Sub-State FE (FL, TX)	(6) Sub-State FE (landfall probability)
log(wetland)	-0.5756***	-1.6945*	-0.5778***	-1.7495*	-0.4821***	-0.4726**
	(0.1840)	(0.9116)	(0.1922)	(0.9100)	(0.1505)	(0.2060)
log(wind)	7.1885***	7.5881***	7.4167***	7.7629***	7.2548***	7.2085***
	(0.5653)	(0.5715)	(0.5428)	(0.5493)	(0.5252)	(0.5473)
Right	0.8821***	1.0383***	0.8877**	0.9301**	0.9472***	0.9349***
	(0.3129)	(0.3250)	(0.3549)	(0.3756)	(0.3069)	(0.3213)
log(storm area)	0.4793**	1.5418	0.4225	1.4809	0.3516**	0.3500
	(0.2249)	(1.0237)	(0.2702)	(1.0176)	(0.1704)	(0.2403)
log(property at risk)	0.3205***	0.0709	0.2737***	0.0953	0.2720***	0.3248***
	(0.0622)	(0.2674)	(0.0729)	(0.2955)	(0.0566)	(0.0585)
State FE	Yes		Yes			
County FE		Yes		Yes		
Sub-State FE					Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	946	906	715	715	946	946
Adjusted R^2	0.52	0.49	0.52	0.50	0.53	0.53

Table S7. Regression results for alternative specifications of the conditional damage model with other coastal defensive measures. All models include state-level and year-level fixed effects. Standard errors (in parentheses) are clustered two-ways at the county and storm level. *P<0.10, **P<0.05, ***P<0.01.

	(1) Base Model	(2) Levee Length	(3) Levee Indicator	(4) Hard Shoreline	(5) Beach Nourishment	(6) All Man-made Defensive Measures
log(wetland)	-0.5756***	-0.5757***	-0.5878**	-0.6959***	-0.5686***	-0.7015***
	(0.1840)	(0.1829)	(0.2279)	(0.2556)	(0.1843)	(0.2635)
log(wind)	7.1885***	7.1885***	7.1885***	7.1673***	7.1894***	7.1652***
	(0.5653)	(0.5658)	(0.5667)	(0.5649)	(0.5652)	(0.5663)
log(storm area)	0.4793**	0.4798**	0.4848**	0.5703**	0.4713**	0.5647**
	(0.2249)	(0.2210)	(0.2322)	(0.2577)	(0.2262)	(0.2548)
log(property at risk)	0.3205***	0.3207***	0.3205***	0.3618***	0.3273***	0.3725***
	(0.0622)	(0.0646)	(0.0637)	(0.0764)	(0.0663)	(0.0829)
Right	0.8821***	0.8821***	0.8834***	0.8824***	0.8846***	0.8855***
	(0.3129)	(0.3130)	(0.3135)	(0.3113)	(0.3134)	(0.3117)
log(levee length + 1)		-0.0012				0.0209
		(0.0650)				(0.0693)
Has Levee × log(wetland)			0.0155			
			(0.1112)			
Has Levee			-0.0708			
			(0.5405)			
Share of Hard Shorelines				-0.7988		-0.9074
				(0.8199)		(0.8782)
log (Beach Nourishment + 1)					-0.0079	-0.0100
					(0.0238)	(0.0243)
N		946	946	946	946	946
Adjusted R^2		0.52	0.52	0.52	0.52	0.52

Table S8. Regression results for alternative specifications of the conditional damage model. Standard errors (in parentheses) are clustered two-ways at the county and storm level. All models include year-level and state-level fixed effects. In Columns 1-3, property at risk is estimated using the same method as in the original paper. In Column 4, property at risk is estimated based on county-level HPI annual growth rate. *P<0.10, **P<0.05, ***P<0.01.

	(1) Base Model	(2) Drop Recession 2007-2009	(3) Housing Bust Indicator	(4) Newly Estimated Property Value
log(wetland)	-0.5756***	-0.5494**	-0.5354***	-0.5742***
	(0.1840)	(0.2208)	(0.1705)	(0.1862)
log(wind)	7.1885***	6.7809***	7.1939***	7.2629***
	(0.5653)	(0.6255)	(0.5670)	(0.5484)
log(storm area)	0.4793**	0.4353*	0.4315**	0.4237*
	(0.2249)	(0.2574)	(0.2078)	(0.2319)
log(property at risk)	0.3205***	0.3719***	0.3729***	0.3429***
	(0.0622)	(0.0614)	(0.0751)	(0.0702)
Bust × log(property at risk)			-0.1596	
			(0.1357)	
Right	0.8821***	1.1591***	0.9211***	0.8891***
	(0.3129)	(0.3288)	(0.3157)	(0.3124)
N	946	822	946	946
Adjusted R^2	0.52	0.49	0.52	0.53

Table S9. Annual, 30-year and 100-year marginal value of coastal wetlands for storm protection for Atlantic and Gulf shoreline counties (thousands of 2016 dollars per km^2).

County	Annual	30-year	100-year
Alabama			
Baldwin	177	3,552	5,908
Mobile	189	3,803	6,325
Connecticut			
Fairfield	1,100	22,122	36,792
Middlesex	138	2,772	4,610
New Haven	195	3,930	6,536
New London	189	3,797	6,316
Delaware			
Kent	17	351	584
New Castle	70	1,403	2,334
Sussex	91	1,834	3,050
District of Columbia			
District of Columbia	3,184	64,060	106,540
Florida			
Bay	231	4,643	7,722
Brevard	54	1,083	1,801
Broward	284	5,718	9,511
Charlotte	305	6,132	10,199
Citrus	77	1,546	2,571
Clay	368	7,410	12,325
Collier	38	764	1,271
Dixie	28	570	949
Duval	270	5,441	9,049
Escambia	720	14,484	24,089
Flagler	156	3,142	5,226
Franklin	36	733	1,220
Gulf	31	615	1,022
Hernando	92	1,857	3,089
Hillsborough	987	19,847	33,009
Indian River	593	11,919	19,824
Jefferson	12	242	402
Lee	321	6,452	10,731
Levy	17	341	566
Liberty	5	92	153
Manatee	806	16,207	26,954
Martin	1,617	32,535	54,110
Miami-Dade	138	2,776	4,616
Monroe	81	1,628	2,707
Nassau	89	1,788	2,973
Okaloosa	8,028	161,493	268,584
Palm Beach	3,360	67,599	112,425
Pasco	928	18,668	31,048
Pinellas	2,406	48,412	80,515
Putnam	69	1,381	2,296
Saint Johns	290	5,829	9,695
Saint Lucie	383	7,711	12,825
Santa Rosa	262	5,277	8,777
Sarasota	763	15,355	25,538
Taylor	16	329	548
Volusia	98	1,976	3,286
Wakulla	52	1,047	1,741
Walton	588	11,828	19,672
Georgia			
Brantley	28	565	940
Bryan	25	507	843
Camden	7	140	232
Charlton	16	325	541
Chatham	17	341	568
Glynn	15	298	496
Liberty	8	160	267
McIntosh	5	107	178
Wayne	3	58	97
Louisiana			
Ascension	205	4,117	6,847
Assumption	39	791	1,316
Calcasieu	159	3,203	5,327
Cameron	3	66	111
Iberia	43	865	1,439
Jefferson	392	7,889	13,120
Jefferson Davis	171	3,443	5,727
Lafourche	28	573	953
Livingston	69	1,380	2,295
Orleans	1,139	22,905	38,094
Plaquemines	23	454	755
Saint Bernard	36	721	1,199
Saint Charles	88	1,769	2,942
Saint James	58	1,167	1,941
Saint John the Baptist	97	1,947	3,238
Saint Martin	23	457	760

Saint Mary	30	594	988
Saint Tammany	289	5,806	9,655
Tangipahoa	73	1,473	2,450
Terrebonne	24	480	798
Vermilion	19	383	637
Maine			
Cumberland	2	37	62
Hancock	2	39	65
Knox	2	50	83
Lincoln	3	52	86
Sagadahoc	1	19	31
Waldo	8	158	263
Washington	1	14	24
York	2	47	79
Maryland			
Anne Arundel	181	3,646	6,063
Baltimore	302	6,066	10,089
Calvert	98	1,963	3,265
Caroline	29	593	987
Cecil	86	1,735	2,885
Charles	32	653	1,086
Dorchester	4	71	118
Harford	48	966	1,606
Kent	50	1,009	1,679
Prince George's	61	1,227	2,041
Queen Anne's	95	1,919	3,192
Saint Mary's	74	1,490	2,477
Somerset	6	113	188
Talbot	65	1,298	2,159
Wicomico	16	318	529
Worcester	31	615	1,024
Massachusetts			
Barnstable	915	18,405	30,610
Bristol	1,118	22,487	37,399
Dukes	2,578	51,856	86,244
Essex	137	2,752	4,577
Middlesex	77,783	1,564,761	2,602,406
Nantucket	2,330	46,869	77,950
Norfolk	3,239	65,163	108,376
Plymouth	915	18,409	30,617
Suffolk	15,019	302,147	502,511
Mississippi			
Hancock	153	3,085	5,131
Harrison	800	16,098	26,773
Jackson	161	3,232	5,376
New Hampshire			
Rockingham	30	600	998
Strafford	137	2,764	4,597
New Jersey			
Atlantic	79	1,598	2,658
Bergen	1,699	34,173	56,834
Burlington	100	2,005	3,335
Camden	2,164	43,525	72,388
Cape May	113	2,267	3,770
Cumberland	13	254	422
Gloucester	157	3,156	5,249
Hudson	31,456	632,802	1,052,434
Middlesex	522	10,501	17,465
Monmouth	1,858	37,375	62,160
Ocean	203	4,075	6,778
Salem	40	801	1,333
Somerset	100,155	2,014,829	3,350,930
Union	11,758	236,540	393,397
New York			
Bronx	1,984	39,903	66,365
Dutchess	1,003	20,180	33,562
Kings	6,202	124,757	207,487
Nassau	77	1,557	2,589
New York	27,139	545,955	907,997
Orange	1,677	33,738	56,112
Putnam	440	8,843	14,707
Queens	582	11,711	19,477
Richmond	166	3,340	5,556
Rockland	1,035	20,830	34,643
Suffolk	31	620	1,031
Ulster	650	13,084	21,760
Westchester	2,412	48,514	80,686
North Carolina			
Beaufort	63	1,259	2,093
Bertie	2	36	60
Brunswick	174	3,499	5,819
Camden	5	95	158
Carteret	62	1,243	2,067
Chowan	19	379	630
Craven	103	2,072	3,446
Currituck	9	179	298
Dare	31	618	1,027
Gates	4	71	118

Hertford	5	110	182
Hyde	8	160	265
Jones	45	900	1,496
New Hanover	454	9,140	15,202
Onslow	144	2,900	4,824
Pamlico	38	757	1,259
Pasquotank	26	517	859
Pender	51	1,030	1,713
Perquimans	15	307	511
Pitt	107	2,156	3,586
Tyrrell	7	136	227
Washington	32	644	1,071
Rhode Island			
Bristol	1,033	20,775	34,551
Kent	2,814	56,600	94,133
Newport	707	14,219	23,647
Providence	4,914	98,861	164,418
Washington	826	16,609	27,623
South Carolina			
Beaufort	50	997	1,658
Berkeley	61	1,235	2,054
Charleston	36	720	1,198
Colleton	19	375	624
Dorchester	170	3,427	5,700
Georgetown	34	680	1,132
Hampton	80	1,603	2,666
Horry	116	2,328	3,871
Jasper	15	303	504
Texas			
Aransas	267	5,378	8,944
Brazoria	146	2,931	4,875
Calhoun	93	1,873	3,115
Cameron	470	9,462	15,736
Chambers	54	1,084	1,802
Galveston	1,242	24,990	41,562
Harris	5,904	118,764	197,521
Jackson	39	779	1,296
Jefferson	134	2,698	4,488
Kenedy	6	123	204
Kleberg	34	693	1,152
Matagorda	72	1,440	2,394
Nueces	2,965	59,642	99,193
Orange	224	4,515	7,508
Refugio	11	217	361
San Patricio	249	5,007	8,327
Victoria	27	548	911
Willacy	14	290	483
Virginia			
Accomack	8	155	258
Alexandria	40,812	821,025	1,365,475
Arlington	8,042	161,785	269,071
Caroline	14	287	478
Charles City	9	183	304
Chesapeake	45	909	1,511
Chesterfield	69	1,393	2,317
Essex	22	435	724
Fairfax	518	10,425	17,338
Gloucester	35	711	1,182
Hampton	686	13,791	22,936
Hanover	57	1,153	1,918
Henrico	80	1,608	2,675
Hopewell	751	15,104	25,119
Isle of Wight	87	1,751	2,912
James City	74	1,494	2,485
King and Queen	11	221	368
King George	52	1,050	1,746
King William	19	389	648
Lancaster	124	2,491	4,142
Mathews	51	1,026	1,706
Middlesex	120	2,421	4,027
New Kent	31	626	1,041
Newport News	317	6,378	10,608
Norfolk	6,714	135,072	224,643
Northampton	11	213	354
Northumberland	120	2,407	4,003
Poquoson	136	2,743	4,562
Portsmouth	3,118	62,720	104,311
Prince George	15	302	503
Prince William	493	9,917	16,492
Richmond	16	314	523
Spotsylvania	771	15,514	25,803
Stafford	150	3,014	5,013
Suffolk	101	2,042	3,396
Surry	17	333	553
Virginia Beach	116	2,326	3,869
Westmoreland	84	1,686	2,805
Williamsburg	1,418	28,530	47,448
York	210	4,224	7,025

Table S10. Summary statistics of the estimated marginal value of wetlands in storm protection for each coastal county based on the best fit gamma distribution, log-normal distribution and Weibull distribution (thousands of 2016 dollars).

Best fit wind probability distribution	R-squared	Mean MV	Median MV	SD MV	Min MV	Max MV
Gamma	0.9995	1785	91	9085	0.7	100155
Log-normal	0.9982	1727	90	8558	0.7	91551
Weibull	0.9980	1769	93	8873	0.7	96335

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