Report

Robert Costanza, Octavio Pérez-Maqueo, M. Luisa Martinez, Paul Sutton, Sharolyn J. Anderson and Kenneth Mulder

The Value of Coastal Wetlands for Hurricane Protection

Coastal wetlands reduce the damaging effects of hurricanes on coastal communities. A regression model using 34 major US hurricanes since 1980 with the natural log of damage per unit gross domestic product in the hurricane swath as the dependent variable and the natural logs of wind speed and wetland area in the swath as the independent variables was highly significant and explained 60% of the variation in relative damages. A loss of 1 ha of wetland in the model corresponded to an average USD 33 000 (median = USD 5000) increase in storm damage from specific storms. Using this relationship, and taking into account the annual probability of hits by hurricanes of varying intensities, we mapped the annual value of coastal wetlands by 1km × 1km pixel and by state. The annual value ranged from USD 250 to USD 51 000 ha^{-1} yr^{-1}, with a mean of USD 8240 ha^{-1} yr^{-1} (median = USD 3230 ha^{-1} yr^{-1}) significantly larger than previous estimates. Coastal wetlands in the US were estimated to currently provide USD 23.2 billion yr^{-1} in storm protection services. Coastal wetlands function as valuable, selfmaintaining "horizontal levees" for storm protection, and also provide a host of other ecosystem services that vertical levees do not. Their restoration and preservation is an extremely cost-effective strategy for society.

INTRODUCTION

Globally, since 1900, 2652 windstorms (including tropical storms, cyclones, hurricanes, tornadoes, typhoons, and winter storms) have been considered disasters. Altogether, they have caused 1.2 million human deaths and have cost USD 381 billion in property damage (1). Of these, hurricanes, cyclones, and tropical storms have resulted in USD 179 billion in property damage (47% of the total from all windstorms) and the loss of 874 000 human lives (73% of the total from all windstorms). The impact of cyclones and hurricanes over the last decades has increased, owing to an increase in built infrastructure along the coasts, an increased frequency of category 4 and 5 hurricanes (2), and an upward trend in tropical cyclone destructive potential (3). Coastal wetlands reduce the damaging effects of hurricanes on coastal communities by absorbing storm energy in ways that neither solid land nor open water can (4). The mechanisms involved include decreasing the area of open water (fetch) for wind to form waves, increasing drag on water motion and hence the amplitude of a storm surge, reducing direct wind effect on the water surface, and directly absorbing wave energy (5, 6). Since marsh plants hold and accrete sediments (7), often reduce sediment resuspension (8), and consequently maintain shallow water depths, the presence of vegetation contributes in two ways: first by actually decreasing surges and waves, and also by maintaining the shallow depths that have the same effect. While few experimental studies or modelling efforts have specifically addressed the effect of coastal marshes on storm surges, anecdotal data accumulated after Hurricane Andrew in 1992 in Louisiana suggested that storm surge was reduced about 4.7 cm km^{-1} of marsh (3 inches $mile^{-1}$ of marsh) (9).

Coastal wetlands may also protect coastal communities from other types of damages. For example, there is evidence that decreasing mangrove area in Thailand has led to larger damages from all coastal natural disasters, including wind storms, floods, and tsunamis (10). There is also evidence that property damage and loss of human lives from the 2004 tsunami that hit Southeast Asia was ameliorated by coastal ecosystems (11). While this relationship has been questioned for tsunamis, which are able to devastate even tall coastal forests (12), the evidence for the role of coastal wetlands for protection from damages due to hurricanes is more compelling.

METHODS

We estimated the value of coastal wetlands for hurricane protection in the US using two basic steps. In step 1 we used a multiple regression analysis using data on 34 hurricanes that have hit the US since 1980 with relative damages as the dependent variable and wind speed and wetland area as the independent variables. In step 2 we used a version of the relationship derived in step 1, combined with data on annual hurricane frequency to derive estimates of the annual value of wetlands for storm protection. This analysis allows us to estimate how this value varies with location, area of remaining wetlands, proximity to built infrastructure, and storm probability. These two steps are briefly described in turn below. Some of the more technical details are explained in the notes at the end of the paper in order to improve readability.

In step 1 we assembled available data on the major hurricanes (those considered "disasters") that have hit the Atlantic and Gulf coasts of the US since 1980 and for which data on total damages were available (34 of the total of 267 storms) (1). We originally intended to perform a global analysis, but after looking at the available global land use data and doing some preliminary analysis, we decided that its quality and coverage of coastal areas, and in particular coastal wetlands, was too poor to be usable. We were, however, able to find suitable coastal land use data for the US (with some caveats—see below) so we limited our study to the US.

We combined data on the tracks of the US hurricanes and their wind speeds with data on storm damages and spatially explicit data on gross domestic product (GDP) and coastal wetland area in each storm's swath (Fig. 1). The following datasets were assembled for the analysis: *i)* tracks of all hurricanes striking the US from 1980 to 2004, which included wind speed (13). Of these, only 34 hurricanes had sufficient information on damages to include in the regression analysis. All of the storms were used to estimate the strike frequencies, since this did not require damage information. *ii)* Nighttime light imagery of the US (14). A 1 km resolution GDP map was prepared by using a linear allocation of the national GDP to the light intensity values of the nighttime image composite (15). This technique has been shown to be very accurate in allocating GDP spatially, and correlates well with state totals derived independently. While not perfect, GDP is a good proxy for

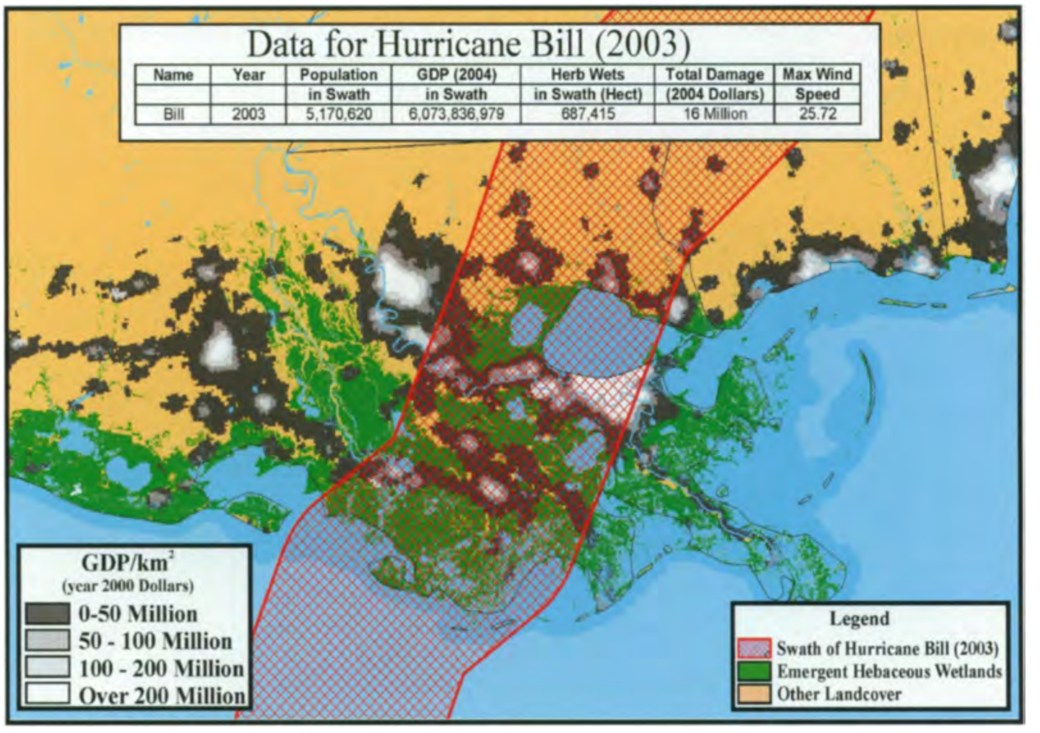


Figure 1. Typical hurricane swath showing GDP and wetland area used in the analysis.

economic activity and built infrastructure, and it is the only measure we could derive at the high spatial resolution needed for this study. GDP was adjusted to the year of each hurricane using data on national GDP by year (16). *iii)* The 30 m resolution National Landcover dataset, which included mapping of both herbaceous and forested wetlands (17). In our analysis, we ended up using only the area of coastal herbaceous wetlands (marshes), since the area of forested wetlands and other land use types were found not to correlate with relative damages (see Results below). Wetland area for Louisiana was adjusted for years other than the year 2000 (the year of the land use data) to take into account the recent extremely high rate of coastal wetland loss of 65 km^2 yr^{-1} (6). We made this adjustment because Louisiana was the only area to have lost significant coastal wetlands over the period of analysis and we suspected that this rate of loss would significantly affect storm protection characteristics. *iv)* Total damage information for 34 hurricanes considered to be "disasters" from the Emergency Events Database (1). The damage included both direct (e.g., damage to infrastructure, crops, and housing) and indirect (e.g., loss of revenues, unemployment, and market destabilization) consequences on the local economy. We adjusted the damage data for inflation to convert them to 2004 USD based on the US Department of Commerce implicit Price Deflator for Construction (http://www.bea.gov).

100 km wide × 100 km inland hurricane swaths were then overlaid on the spatially explicit GDP and wetland cover (herbaceous and forested wetlands were measured separately) to obtain GDP and wetland area in each swath (Fig. 1). The 100 km × 100 km swath was used as an approximate average spatial extent in order to standardize the calculations, and since we did not have explicit data on the size of the swath of each storm. This width of the swath was derived from visual observations of storm extents based on cloud cover. It would be difficult to explicitly map the extent of the storm's influence without knowing the complete wind and storm surge fields, which were not available for all the storms. We also varied this assumption and tried 60 km and 140 km wide swaths, but these did not improve the results. The 100 km distance inland is a bit more arbitrary, as is any definition of the "coastal zone," but this distance seemed to include the major elements of interest for our study and was consistent with the width of the hurricane swath we were using.

The GDP calculated within each hurricane swath and the reported total economic damage (TD) were used to generate a ratio (TD/GDP) which was used to represent the relative economic damage caused by each hurricane (18).

We completed step 1 of the analysis by deriving from the regression equation the total expected damages and avoided damages per hectare of wetlands from storms of a given wind speed, GDP in swath, and wetland area in swath. For step 2 of the analysis, we assembled data on storm frequency by state and by pixel from historical storm tracks. This was necessary in order to derive a proxy for the annual probability of being struck by hurricanes in specific storm categories, and these probabilities were needed to derive annual (as opposed to by storm) total damage and avoided damage estimates by state and by pixel.

RESULTS

For step 1, using ordinary least squares (OLS) we fit nine alternative multiple regression models using the natural logs of wind speed and area of coastal herbaceous and forested wetlands as the independent variables and TD/GDP as the dependent variable (19).

The final model we used was

$$\ln(TDi/GDPi) = \alpha + \beta 1 \ln(g_i) + \beta 2 \ln(w_i) + u_i \qquad \text{Eq. 1}$$

where TDi = total damages from storm i (in constant 2004 USD); GDPi = gross domestic product in the swath of storm i (in constant 2004 USD; the swath was considered to be 100 km wide by 100 km inland); g_i = maximum wind speed of storm i (in m sec^{-1}); w_i = area of herbaceous wetlands in the storm swath (in ha); and u_i = error.

This model had an adjusted R^2 of 0.604 and was highly significant. The best fit coefficients for the model are shown in Table 1 (21, 22, 24). The data used in the model are included in Table 2.

As expected, increasing wind speed increased relative damages (TD/GDP), while increasing herbaceous wetland area decreased them. Figure 2 shows the observed vs. predicted

Table 1. Regression model coefficients including lower and upper 95% confidence intervals.

Parameter	Coefficient	Lower 95% CI	Upper 95% CI	Standard Error	t	P
α	−10.511	−20.06	−3.36	3.29	−3.195	0.003
β_1	3.878	2.45	5.34	0.706	5.491	<0.001
β_2	−0.77	−1.06	−0.247	0.16	−4.809	<0.001

relative damages from the model, with each of the hurricanes identified.

It was unexpected that forested wetlands did not improve the model. Part of the explanation for this is that our land use database did not distinguish between coastal forested wetlands (i.e., mangroves) and inland riparian forested wetlands. We would expect mangroves to have a significant storm protection effect, relative to inland riparian forest. Since mangroves occur in the US to a significant extent only in southern Florida, their positive effect was no doubt out-weighted by the lack of effect of riparian forested wetlands elsewhere. In future studies we hope to obtain better data that can differentiate mangroves from riparian forested wetlands.

We can rearrange equation (1) to estimate the total damages from hurricane i as:

$$TD_i = e^{\alpha} \times g_i^{\beta_1} \times w_i^{\beta_2} \times GDP_i \qquad \text{Eq. 2}$$

One can clearly see from this form of the relationship the relative influence of GDP, wind speed and wetland area on total damages. Total damages vary linearly with GDP, as one might expect since the more infrastructure there is to be damaged the more damage one can expect. TD also varies as the β_1 power of wind speed. The value of β_1 from Table 1 indicates that total damages increase as the 3.878 power of wind speed, fairly consistent with the well-known relationship that the power in wind varies as the cube of speed. The value of β_2 in Table 1 of −0.77 indicates that total damages decrease quite rapidly with increasing wetland area.

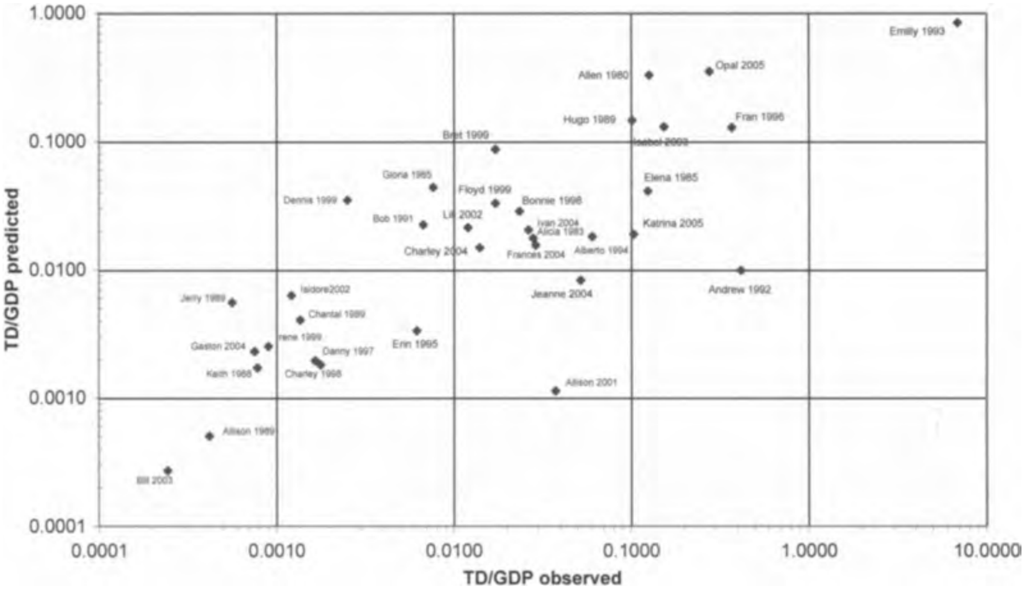
The difference in TD_i with a loss of an area a of wetlands (i.e., the "avoided damage" per unit area of wetland) is then:

$$\Delta TD_i = MV_i = e^{\alpha} \times g_i^{\beta_1} \times \left[(w_i - a)^{\beta_2} - w_i^{\beta_2}\right] \times GDP_i \qquad \text{Eq. 3}$$

Table 2. Maximum wind speed, herbaceous wetland area, gross domestic product (GDP), total damage and calculated marginal value (MV) (per ha of wetland) for storm protection for each hurricane used in the regression analysis. Lower and upper 95% confidence intervals on the marginal values are also shown.

Hurricane	Year	States hit	Max wind speed (m sec^{-1})	Herbaceous wetland area in swath (ha)	GDP in swath hit year (2004 USD millions)	Observed total damage (2004 USD millions)	Estimated MV ha^{-1} (2004 USD ha^{-1})	MV lower 95% CI (2004 USD ha^{-1})	MV upper 95% CI (2004 USD ha^{-1})
Alberto	1994	GA, MI, FL, AL	28.3	4466	5040	305	15 607	1254	59 663
Alicia	1983	TX	51.4	93 590	100 199	2823	14 449	5316	22 146
Allen	1980	TX	84.9	26 062	13 151	1674	127 090	29 204	283 261
Allison	1989	TX, LA, FL, NC, PA, VA	23.1	167 494	149 433	63	348	85	938
Allison	2001	TX, LA, FL, NC, PA, VA	25.7	100 298	185 610	6995	1611	377	4042
Andrew	1992	FL, LA	69.4	901 819	83 450	34 955	699	318	1247
Bill	2003	LA, MS, AL, FL	25.7	642 544	70 669	17	23	8	54
Bob	1991	NC, ME, NY, RI, CT, MA	51.4	68 465	122 358	829	30 683	9982	48 743
Bonnie	1998	NC, SC, VA	51.4	49 774	15 840	373	6984	2008	11 585
Bret	1999	TX	61.7	29 695	2043	35	4557	1119	8368
Chantal	1989	TX	36.0	104 968	81 319	111	2400	763	4351
Charley	1998	TX	25.7	55 126	18 775	33	470	90	1254
Charley	2004	FL	64.3	358 778	483 281	6800	15 347	7918	24 062
Danny	1997	OH, PA, IL, NY, NJ	36.0	271 317	66 711	111	367	158	622
Dennis	1999	NC	46.3	22 752	17 669	45	20 704	4199	40 396
Elena	1985	FL, AR, KY, SD, IO, MI, IN, MO	56.6	50 568	14 240	1774	8835	2629	14 698
Emily	1993	NC	51.4	615	6	38	5795	272	24 748
Erin	1995	FL, AL, MS	41.2	264 226	132 138	821	1278	610	1967
Floyd	1999	NC, FL, SC, VA, MD, PA, NJ, NY, DE, RI, CT, MA, VT	69.4	188 637	420 940	7259	56 214	26 075	93 566
Fran	1996	NC, SC, VA, MD, VA, PA, OH, Washington DC	54.0	9 033	10 471	3900	114 389	16 760	259 346
Frances	2004	FL, NC, SC, OH	64.3	340 051	150 986	4400	5272	2710	8270
Gaston	2004	VA, SC, NC	30.9	100 502	82 063	62	1439	402	2999
Gloria	1985	NC, NY, CT, NH, ME	64.3	87 863	188 531	1451	72 229	27 350	119 390
Hugo	1989	SC	72.0	32 906	13 684	1391	46 288	11 868	89 485
Irene	1999	FL	46.3	692 219	114 903	104	319	179	488
Isabel	2003	NC, MD, VA, Washington DC	72.0	37 942	35 068	5406	92 176	24 987	175 244
Isidore	2002	LA, MS, AL, TN	56.6	574 157	64 990	79	547	296	830
Ivan	2004	AL, LA, MS, FL, PA, MD, NJ, OH, NC, VA, GA, TN	74.6	504 033	226 150	6000	6996	3204	12 550
Jeanne	2004	FL	56.6	404 769	133 657	7000	2088	1148	3096
Jerry	1989	TX	38.6	98 540	86 173	49	3717	1209	6450
Katrina	2005	AL, LA, MS, GA, FL	78.2	708 519	214 277	22 321	4363	1847	8429
Keith	1988	FL	33.4	222 324	55 856	44	328	126	594
Lili	2002	LA	64.3	224 504	24 439	295	1779	881	2798
Opal	1995	FL, GA, AL	66.9	7261	12 652	3521	465 730	64 749	1 111 043
		Mean	52	218 995	99 905	3561	33 268	7356	71 962
		Median	53	100 400	75 994	825	4914	1231	8398
		S.D.	17	243 111	110 816	7001	83 466	13 403	196 765

Figure 2. Observed vs. predicted relative damages (TD/GDP) for each of the hurricanes used in the analysis.



If a is small relative to w, this represents the estimated "marginal value" (MV) per unit area of coastal wetlands in preventing storm damage from a specific hurricane. Table 2 lists MV_i for each of the 34 hurricanes in the database for unit areas of 1 ha. The values range from a minimum of USD 23 ha^{-1} for Hurricane Bill to a maximum of USD 465 730 ha^{-1} for Hurricane Opal, with an average value of just over USD 33 000 ha^{-1}. The median value was just under USD 5000 ha^{-1}, indicating a quite skewed distribution, mirroring the skewed distribution of damages. For each hurricane, we also calculated an upper and lower bound on the marginal value estimate by applying the formula for marginal value to each combination of regression parameters and taking the 95th percentiles (as reported in Table 1).

Equation 3 allows one to estimate the avoided damages from any area of wetlands (a) up to the total area of wetlands in the swath. For example, one might be interested in the "average" value of a larger area of wetlands, say half the wetlands in the swath. This could be estimated by using $a = ½$ of the total area of wetlands in the swath in Eq. 3 and then dividing the result by ½ the total area of wetlands in the swath. The average values per hectare calculated in this way (using 50% of the wetland area) are consistently 1.8 times higher than the marginal values.

For step 2, we then estimated the *annual* value of coastal wetlands for storm protection. This required an estimate of the annual probability of being hit by hurricanes of various intensities. We used data on historical frequencies by state as proxies for these probabilities. Data for each of the 19 states in the US that have been hit by a hurricane since 1980 (267 total hits) were used to calculate the historical frequency of hurricane strikes by storm category (26). We calculated the average GDP and wetland area in an average (100 km × 100 km) swath through each state using our Geographic Information System database. We then calculated the annual expected marginal value (MV) for an average hurricane swath in each state using the following variation of Eq. 3:

$$MV_{sw} = \sum_{c=1}^{5} p_{c,s} \times e^{\alpha} \times g_c^{\beta_1} \times \left[(w_{sw} - 1)^{\beta_2} - w_{sw}^{\beta_2}\right] \times GDP_{sw} \quad \text{Eq. 4}$$

where s = state; sw = average swath in state s; g_c = average wind speed of hurricane of category c; $p_{c,s}$ = the probability of a hurricane of category c striking state s in a given year; GDP_{sw} = the GDP in state s in the average hurricane swath; w_{sw} = the wetland area in state s in the average hurricane swath. We then estimated total annual value of wetlands for storm protection as the integral of the marginal values over all wetland areas (i.e., the "consumer surplus") (27). We can then estimate the average annual value per wetland hectare per state as

$$AV_s = TV_s / w_s \quad \text{Eq. 5}$$

The estimated annual marginal value in an average swath (MV_{sw}), the total value (TV_s) for all the state's wetlands, and the average annual value per hectare (AV_s) of coastal wetlands for each state estimated in this way are shown in Table 3.

Using this technique, the mean annual marginal value per hectare in a typical swath across states (MV_{sw}) was almost USD 40 000 ha^{-1} yr^{-1}, with a range from USD 126 ha^{-1} yr^{-1} (for Louisiana) to USD 586 845 ha^{-1} yr^{-1} (for New York) and a median value of USD 1700, indicating a quite skewed distribution. MV varied inversely with wetland area (Fig. 3A), indicating that the per hectare value of wetlands increases as they become more scarce. The expected mean of the total annual values by state (TV_s) integrating over all the state's wetlands, for the 19 states (assuming a lower bound cut-off for the integration of k = 5000 ha) was USD 1.2 billion yr^{-1}, with a median of USD 140 million yr^{-1}, again reflecting a skewed

Hurricane Katrina approaching the coast of Louisiana in August, 2005.

Table 3. Coastal wetland area in each state, mean wetland area and gross domestic product (GDP) in the average 100 km swath, estimated annual storm probabilities by category, and calculated marginal value per average swath (MV_{sw}), total value for the state (TV_s) under 3 assumptions for the lower area cut-off value for the integration (27) and average annual value per ha (AV_s).

State	Wetlands within 100 km of coast by state W_s (ha)	Wetland area in average swath W_{sw} (ha)	GDP in average swath (USD millions y^{-1})	Probability of state being hit by a storm of the given category in a year by storm category				
				1	2	3	4	5
Alabama	16 759	6388	9499	7.14%	3.25%	3.90%	0.00%	0.00%
Connecticut	21 591	12 601	65 673	2.60%	1.95%	1.95%	0.00%	0.00%
Delaware	33 964	12 089	10 488	1.30%	0.00%	0.00%	0.00%	0.00%
Florida	1 433 286	186 346	70 491	27.92%	20.78%	17.53%	3.90%	1.30%
Georgia	140 556	29 120	7356	7.79%	3.25%	1.30%	0.65%	0.00%
Louisiana	1 648 611	370 299	36 250	11.04%	9.09%	8.44%	2.60%	0.65%
Maine	60 388	15 500	14 670	3.25%	0.65%	0.00%	0.00%	0.00%
Maryland	60 511	16 011	21 924	0.65%	0.65%	0.00%	0.00%	0.00%
Massachusetts	49 352	16 801	67 266	3.25%	1.30%	1.95%	0.00%	0.00%
Mississippi	25 456	6048	3890	1.30%	3.25%	4.55%	0.00%	0.65%
New Hampshire	19 375	9905	23 051	0.65%	0.65%	0.00%	0.00%	0.00%
New Jersey	69 001	21 864	78 703	1.30%	0.00%	0.00%	0.00%	0.00%
New York	5306	2117	90 770	3.90%	0.65%	3.25%	0.00%	0.00%
North Carolina	64 862	21 295	13 023	13.64%	8.44%	7.14%	0.65%	0.00%
Pennsylvania	7446	2994	93 117	0.65%	0.00%	0.00%	0.00%	0.00%
Rhode Island	3638	1759	12 810	1.95%	1.30%	2.60%	0.00%	0.00%
South Carolina	107 894	39 177	15 367	12.34%	3.90%	2.60%	1.30%	0.00%
Texas	448 621	79 110	63 661	14.94%	11.04%	7.79%	4.55%	0.00%
Virginia	71 509	23 588	27 786	5.84%	1.30%	0.65%	0.00%	0.00%
Mean	225 691	45 948	38 200	6.39%	3.76%	3.35%	0.72%	0.14%
Median	60 388	16 011	23 051	3.25%	1.30%	1.95%	0.00%	0.00%
S.D.	475 157	89 175	31 083	7.01%	5.25%	4.39%	1.40%	0.35%

State	Annual expected marginal value per average swath MV_{sw} (USD ha^{-1} yr^{-1})	Total annual value per state (TV_s) for k = 10 000, 5000, and 1000 (USD millions y^{-1})			Average annual value of wetlands per ha per state (AV_s) at k = 5000 (USD ha^{-1} yr^{-1})
		k = 10 000	k = 5000	k = 1000	
Alabama	14 155	40.9	133.6	749.5	7970.4
Connecticut	14 428	263.2	615.4	2705.2	28 503.5
Delaware	222	3.7	8.7	38.6	255.8
Florida	1684	6453.9	11 293.6	40 010.3	7879.5
Georgia	630	72.3	140.0	542.2	996.2
Louisiana	126	1665.7	2883.2	10 107.2	1748.8
Maine	715	21.3	46.5	196.0	770.1
Maryland	445	14.3	30.9	129.4	510.4
Massachusetts	8422	301.2	643.3	2673.1	13 035.3
Mississippi	7154	17.8	59.0	341.5	2316.1
New Hampshire	1095	10.7	28.1	131.7	1451.2
New Jersey	583	37.0	74.8	298.9	1083.5
New York	586 845	79.5	271.2	3473.3	51 106.9
North Carolina	5072	304.1	617.5	2477.0	9519.6
Pennsylvania	11 651	4.1	14.1	141.3	1890.4
Rhode Island	95 193	7.7	26.3	377.0	7239.1
South Carolina	1281	265.0	498.0	1880.0	4615.3
Texas	3901	3087.1	5547.2	20 144.4	12 365.0
Virginia	1555	115.6	230.8	914.1	3227.6
Mean	39 745	671.8	1219.1	4596.4	8236.0
Median	1684	72.3	140.0	749.5	3227.6
S.D.	134 195	1594.0	2788.8	9848.0	12 418.4
	Totals	12 765.0	23 162.0	87 330.7	

distribution across states (see note 24 for an explanation of k, table 3 also lists totals for other values of k). The total annual value summed over all states was USD 23.2 billion yr^{-1} (at k = 5000). TV_s generally increased with total area of wetlands in the state (Fig. 3B). Differences by state in both Figures 3A and 3B reflect the relative amounts of coastal infrastructure vulnerable to damage and relative storm probabilities. For example, Louisiana has the most wetlands, but less vulnerable infrastructure than Florida and Texas, while New York, Massachusetts, and Connecticut had fewer wetlands but more vulnerable infrastructure. The mean AV_s by state was a little over USD 8000 ha^{-1} yr^{-1}, with a range from around USD 250 $ha^{-1}yr^{-1}$ (for Delaware) to just over USD 51 000 ha^{-1} yr^{-1} (for New York) and a median value of just over USD 3200 ha^{-1} yr^{-1}.

Our final analysis in step 2 involved using spatially explicit data on historical storm tracks to estimate probabilities of being hit by storms of a particular category for each pixel along the coast. For this analysis we had data on fewer storms (a total of 52), resulting in frequencies that did not match the state level frequencies exactly, and were distributed across the states. The advantage is that it allowed us to map wetland storm protection values at much higher spatial resolution. For this application, a circle with radius 50 km was drawn around each 1 km × 1 km pixel within 100 km of the coast, the wetland area and GDP in the circle was measured, and Eq. 5 was applied, with the result for each pixel multiplied by the area of wetland in the pixel divided by the area of wetland in the 50 km radius circle. Figure 4 maps the total value per 1 km × 1 km pixel estimated in this

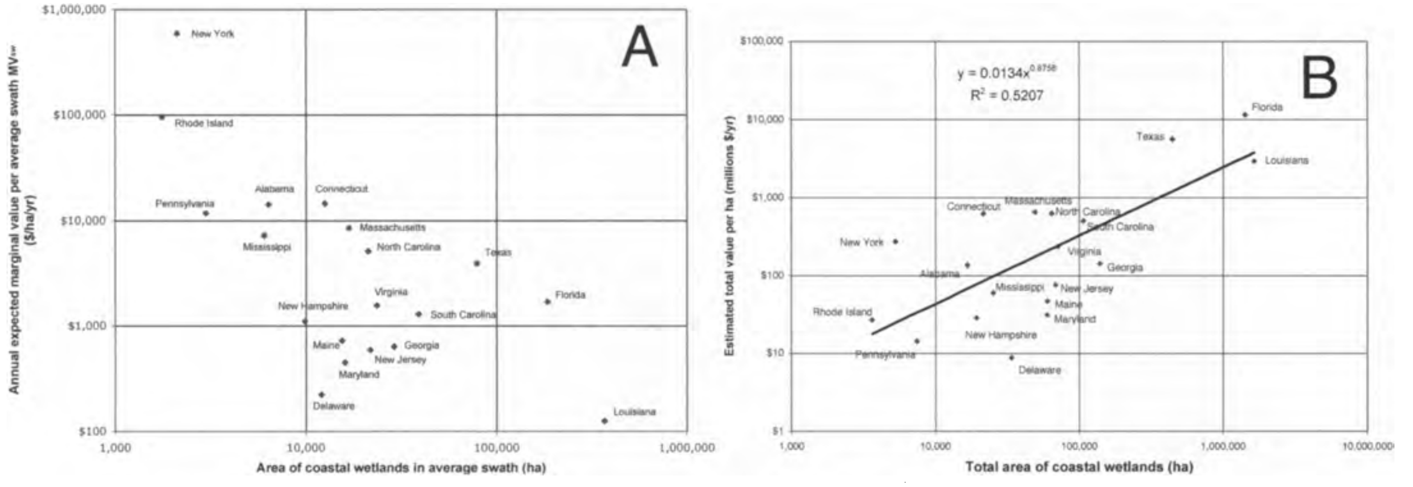


Figure 3. Area of coastal wetlands in the average hurricane swath vs. the estimated marginal value per ha (MV_{SW}) (A) and in the entire state (B) vs. the total value (TV_S) of coastal wetlands for storm protection.

way. Finally, we summed over all pixels in each state to yield estimates comparable with the "state level" analysis discussed earlier. The state totals aggregated from the "pixel level" analysis had an adjusted R^2 of 0.88 compared with the state totals from the "state level" analysis. Figure 4 shows wetlands of particularly high storm protection value density at the intersection of high storm probability, high coastal GDP, and high wetland area. For example, Southeast Florida, coastal Louisiana, and parts of Texas all show high values. Connecticut, Massachusetts, and Rhode Island also show fairly high values, due largely to the very high levels of coastal GDP in those states.

DISCUSSION

There have been many previous estimates of the value of coastal wetlands (10, 28–30) but estimates of the value for hurricane protection have been few. Barbier (10) recently estimated the value of mangroves in Thailand for protection against coastal natural disasters (including tsunamis, wind storms, and floods) using a similar avoided damages approach (what he calls the

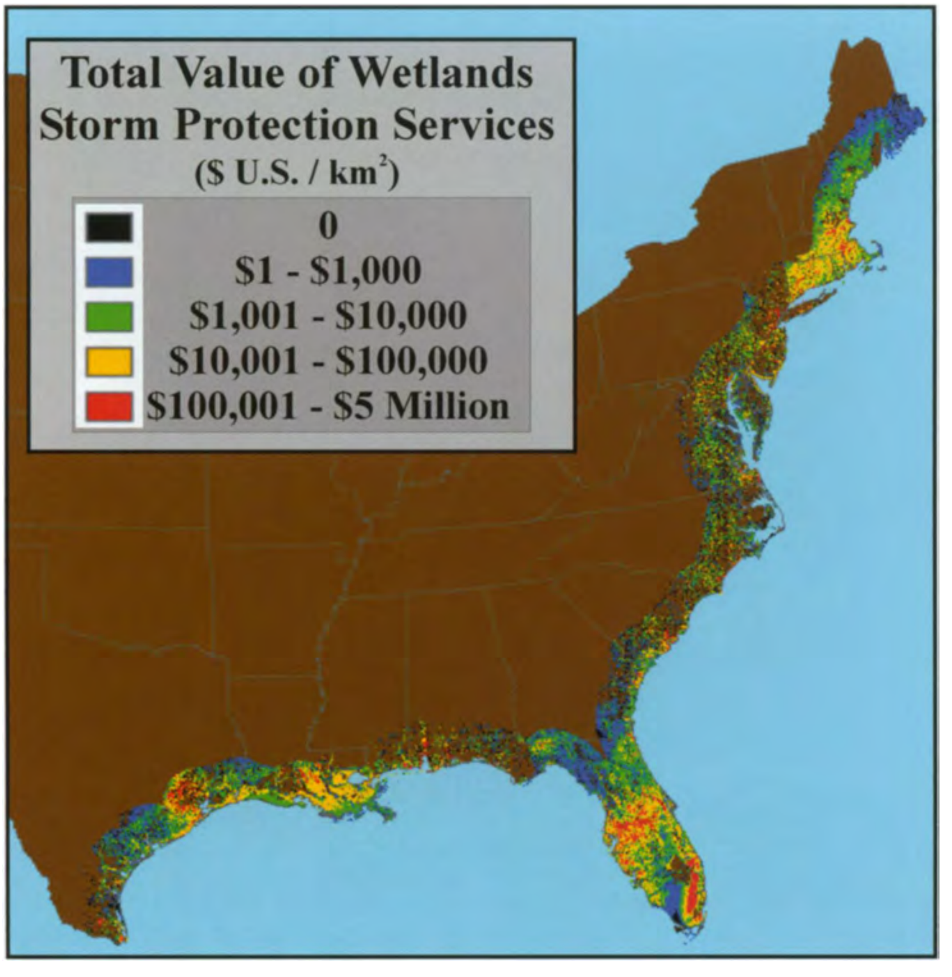


Figure 4. Map of total value of coastal wetlands for storm protection by 1 km × 1 km pixel.

Expected Damage Function, or EDF approach). The data for his application were much less spatially explicit than that used in the current study, and the form of the equation and the statistics involved were somewhat different because of the nature of the data. He derived a value of USD 5850 ha^{-1} for mangroves.

Farber (31) and Costanza et al. (28) used a method similar to (but less spatially explicit) than the one used in this study to estimate the value of coastal wetlands for hurricane protection. They dealt only with hurricanes striking Louisiana and estimated an annual average value of hurricane protection services of about USD 1000 ha^{-1} yr^{-1} (converted into 2004 USD). Our current analysis included a much larger database of more recent hurricanes covering the entire US Atlantic and Gulf coasts and was able to utilize much more spatially explicit data on hurricane tracks, wetland area, and GDP. Our corresponding estimated value for Louisiana was about USD 1700 ha^{-1} yr^{-1}, somewhat larger than the previous estimate, but still fairly consistent. Our current study allows one to assess not only the value of wetlands for storm protection, but how that value varies with location, area of remaining wetlands, proximity to built infrastructure, and storm probability, thus providing a richer and more useful analysis of this important ecosystem service. It also allows us to state the ranges of values that would result from varying parameter assumptions and the confidence intervals on the estimates.

The results also allow straightforward assessments of the impacts of changes to wetlands. For example, Louisiana lost an estimated 480 000 ha of coastal wetlands prior to Katrina (2005) and 20 000 ha during hurricane Katrina itself (6). The value of the lost storm protection services from these wetlands can be estimated as the average value per hectare in Louisiana (USD 1700 ha^{-1} yr^{-1} from Table 3) times the area, yielding approximately USD 816 million yr^{-1} for services lost from wetlands lost prior to Katrina and an additional USD 34 million yr^{-1} for wetlands lost during the storm. Converting this total of USD 850 million yr^{-1} to present value terms using a 3% discount rate implies a lost value for just the storm protection service of this natural capital asset of USD 28.3 billion, and the lost storm protection value due to wetlands lost during Katrina of USD 1.1 billion.

If the frequency and intensity of hurricanes increases in the future, as some are predicting as a result of climate change, then the value of coastal wetlands for protection from these storms will also increase. Coastal wetlands provide "horizontal levees" that are maintained by nature and are far more cost-effective than constructed levees. The experience of hurricane Katrina provided a tragic example of the costs of allowing these natural capital assets to degrade. Coastal wetlands also provide a host of other valuable ecosystem services that constructed levees do not. They have been estimated to provide about USD 11 700 ha^{-1} yr^{-1} (in 2004 USD) in other ecosystem services (excluding storm protection) (32), and experience (including the current study) has shown that as we learn more about the functioning of ecological systems and their connections to human welfare, estimates of their value tend to increase. Investing in the maintenance and restoration of coastal wetlands is proving to be an extremely cost-effective strategy for society.

References and Notes

1. Emergency Events Database (http://www.emdat.be): this data set defined a hurricane to be a disaster if it satisfied at least one of the following criteria: *i)* 10 or more people killed; *ii)* 100 or more people affected, injured, or homeless; *iii)* declaration of a state of emergency and/or an appeal for international assistance.
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18. Pearson's coefficients showed insignificant collinearity between the analyzed variables. In addition no other land use areas covaried with either herbaceous or forested wetlands, which were also not correlated with each other.
19. We tested various log-log formulations using maximum likelihood and Akaike's Information Criterion (AIC) corrected for small sample size. Our theoretical assumption was that TD should be proportional to GDP and thus we used ln(TD/GDP) as the dependent variable. We did compare this to models with ln(TD) as the dependent variable and ln(GDP) as one of the independent variable. However, these models did not have a sufficient increase in likelihood to merit the additional degree of freedom as measured by AIC. The addition of forested wetlands to the model also did not improve the model, but the addition of herbaceous wetlands yielded the best model reducing the AIC_c by 2.91 versus a model with just wind speed. The AIC evidence ratio implies that the model with wetlands included has an 81% chance of being the correct model versus a model with wetlands omitted. We also tested the model using a recently available alternative data set for hurricane damages from Pielke et al. (20). This data set normalized damages for wealth and population by county. Using this data set gave us very similar results, however, so we decided to report our results using the original damage data set.
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21. A 95% confidence interval was generated for each of the parameter estimates as well as the adjusted R^2 measure using a 10 000 iteration bootstrap analysis. The adjusted R^2 interval was (0.342, 0.832). The intervals for the other parameters are listed in Table 1. The coefficient for wind speed (β_1) was significant 99.94% of the time, while the coefficient for wetlands (β_2) was significant 93.04% of the time.
22. One potential problem with this formulation is endogeneity. If wetland area and GDP are *negatively* correlated (as one might expect if urban area and wetland area were "competing" for the same fixed landscape area), then this could cause bias in the estimate of the coefficient for wetlands or spurious correlation. For example, it might be the case that high wetland area correlates with lower GDP, which correlates with less TD. We tested for the possibility that the reduction in damage attributable to herbaceous wetlands was spurious and caused by an endogenous relationship with GDP. GDP and herbaceous wetland area (all variables assumed log-transformed) were actually positively (and weakly) correlated ($r = 0.19$). However, as hypothesized, the partial correlation coefficient of total damage upon herbaceous wetlands controlling for GDP and wind speed was negative ($r = -0.34$, $p = 0.05$) (23). Controlling for the relationship with GDP demonstrates that the perceived effect of herbaceous wetlands upon hurricane damage is not spurious but rather is partially suppressed (statistically) because of the positive correlation between GDP and wetlands. Further, if an endogenous relationship with GDP were causing a spurious effect of herbaceous wetlands upon total damage, a similar relationship should have been seen with other undeveloped land covers. However, the addition of other land cover types (e.g., forested wetlands and forest) did not improve any of the models we tested.
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24. A second potential problem with the formulation used is selection bias. It might be the case that we are using data that is selectively gathered from locations where recorded damage is greater, probably due to a higher intensity of GDP. In these places, since storm protection services are proportional to total damage (more potential damage to mitigate), they could be disproportionately high leading to overestimates of the average values. However, unlike the case of selection bias in typical valuation studies (see 25) in damage mitigation studies we find that selection bias tends to cause underestimates of value. We tested this by creating a Monte Carlo simulated data set using a log-log formulation and comparing regression results when the data was restricted to samples with damages above a given percentile. The higher the percentile, the lower the estimated damage mitigation of wetlands implying our estimates are conservative.
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27. While residual analysis suggests little correlation between wetland area and model error and we have several data points with low wetland area, the log-log formulation makes marginal value calculations at low wetland areas problematic because values go to infinity as area goes to 0. For this reason, we capped increases in marginal value in our calculations for wetland areas below a certain number, k. In other words, in the integration we used the marginal value at k for all wetland areas less than k rather than

allowing it to climb to infinity. Given model fit across the range of areas, we believe this yields a conservative value estimate. If the model diverges from reality at some lower threshold of wetlands, then for hurricanes with wetland area below that threshold, observed damage should have been below the predicted. However, of the four hurricanes with the least wetland area, three have observed damages higher than the model prediction, and the hurricane with the lowest amount of herbaceous wetland, Emily, is an outlier for which total damage was strongly underestimated. We used $k = 5000$ (The minimum area of wetlands in any state in our sample was 3638 ha for Rhode Island. 5000 ha is thus just within the range of our data.) but also report values in Table 3 using $k = 10\,000$ and $k = 1000$ to demonstrate sensitivity to this assumption. TV increases as k decreases, but in all cases, limiting the integration in this way leads to conservative estimates.

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Robert Costanza is Gordon and Lulie Gund Professor of Ecological Economics and Director, Gund Institute for Ecological Economics. His address: Gund Institute for Ecological Economics, Rubenstein School of Environment and Natural Resources, University of Vermont, Burlington, VT 05405, USA.
E-mail: Robert.Costanza@uvm.edu

Octavio Perez-Maqueo is a fulltime researcher in Applied Ecology. His address: Instituto de Ecología A.C., km 2.5 antigua carretera a Coatepec no. 351, Congregación El Haya, Xalapa, Ver. 91070, México.
E-mail: maqueo@ecologia.edu.mx

M. Luisa Martinez is a fulltime researcher in Functional Ecology. Her address: Instituto de EcologÚa A.C., km 2.5 antigua carretera a Coatepec no. 351, Congregación El Haya, Xalapa, Ver. 91070, México.
E-mail: marisa.martinez@inecol.edu.mx

Paul C. Sutton is an associate professor of Geography and Environmental Science. His address: Department of Geography, University of Denver, Denver, CO 80208, USA.
E-mail: psutton@du.edu

Sharolyn J. Anderson is an assistant professor of Geography and Environmental Science. Her address: Department of Geography, University of Denver, Denver, CO 80208 USA.
E-mail: sharolyn.anderson@du.edu

Kenneth Mulder is an assistant professor at Green Mountain College. His address: Green Mountain College, 1 College Circle, Poultney, VT 05764, USA.
E-mail: mulderk@greenmtn.edu