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ORIGINAL PAPER

Exposure of US counties to Atlantic tropical storms and hurricanes, 1851–2003

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Abstract Exposure of counties in the continental United States to tropical storm and hurricane conditions was determined using the historic record of storm tracks for the period 1851–2003. Two approaches were used to determine exposure: (1) cumulative number of hits, with a hit occurring when the storm's path crosses a county and (2) cumulative exposure factor, which describes how much of the county has been exposed to tropical storm, hurricane, and intense hurricane-force winds. In both approaches the top 10 counties in terms of cumulative exposure are in coastal Florida, North Carolina, and Louisiana. An explanatory model was developed to describe the patterns in the documented exposure, which included distance to coast, latitude, longitude, size, and shape of the counties. Multivariate linear regression confirmed that much of the spatial variability in exposure to storm conditions can be explained with these simple parameters.

Keywords Hurricanes · Tropical storms · Exposure · Counties · GIS

1 Introduction

The 2004 and 2005 hurricane seasons have highlighted the vulnerability of the United States to Atlantic hurricanes. Hurricane losses in the United States are significant and increasing (Pielke et al. 2008; Jain et al. 2005). Planning for the possible impacts of hurricanes requires a careful analysis of the exposure of the population, the built environment, and the economic system to hurricane conditions. The hazards posed by tropical storms and hurricanes result from three factors: wind, storm surge, and rain. The storm surge hazard is mostly limited to coastal areas of low-lying elevation, while the wind and rain hazard can reach far inland. Much of the current research on hurricanes has emphasized developing estimates for landfall probability for different storm categories and determining temporal trends in storm frequency and intensity. Probability is expressed as a

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percentage or mean return period in years. Gray and Klotzbach (2005), for example, developed a methodology to model the hurricane landfall probability for 55 different regions on the Gulf and Atlantic Coasts. Davidson and Lambert (2001) used the mean return period in the development of a Hurricane Disaster Risk Index for coastal counties. The emphasis on the coastal areas and the point of landfall, however, overlooks the fact that the effect of a tropical storm or hurricane can reach far inland and includes areas far away from the point of landfall. For example, the impacts caused by hurricanes Katrina and Wilma in 2005 covered large areas, some of which were far inland. While it is well established that tropical storms and hurricanes weaken in strength after making landfall (Kaplan and DeMaria 1995), the use of the point of landfall as the only area being affected by the storm is insufficient for hazard evaluations. This is recognized by the National Hurricane Center's inland wind model and the maximum envelope of winds (MEOW) (NHC 2005), but this model has not received widespread use in the analysis of historical storm records.

The data on historical storms and hurricanes has been widely used for the analysis of temporal trends in their frequency and intensity. It has only been fairly recently, however, that the historical record for storms in the period from the mid-1800s to early 1900s has been reconstructed. This has already led to some new findings. For example, the busiest hurricane season on record for the continental United States is 1886 when seven hurricanes made landfall (AOML 2005). It has also lead to a longer time record for use in the activity cycles of hurricane activity. A comprehensive review of historical hurricane analysis, including a discussion of different temporal scales of variability in hurricane activity, is provided by Murnane and Liu (2004). Specifically for the Atlantic storms and hurricanes, there is now wide agreement on the fact that the El Nino Southern Oscillation (ENSO) is a strong controlling factor in the formation of North Atlantic hurricanes. Years with a La Nina dominant pattern are more likely to have an increased number of hurricanes (Bove et al. 1998; Elsner and Bossak 2004). There is also evidence to suggest that there are (multi) decadal trends in hurricane activity and that we are currently experiencing a rise in Atlantic hurricane activity. However, there is no wide agreement on the exact nature of the trends and their causes, although much of the research seems to suggest a 25- to 40-year activity cycle, with an upswing in frequency starting in 1995 (Goldenberg et al. 2001; Landsea et al. 1996; Elsner and Bossak 2001). There is even less agreement on the potential influence of global warming, although recent findings suggest that global warming is not likely to result in an increase in storm frequency but in intensity (Knutson and Tuleya 2004; Webster et al. 2005; Emanuel 2005).

What is clear from the research on Atlantic hurricane activity is that the number of storms and hurricanes that form every year is relatively low (in terms of sample size for statistical analysis) and the number that makes landfall is even lower, which makes is imperative that any attempt to look at spatial patterns in storm tracks uses the most comprehensive time record for which reliable tracks are available. At present, the reconstruction of the historical tracks of Atlantic storms and hurricanes has been completed as far back as 1851. Efforts to go back even further are underway but have not yet led to a set of reliable tracks for use in spatial–temporal analysis with any degree of reliability (Bossak 2003).

The objective of this research is to determine spatial patterns in the exposure of US counties to Atlantic tropical storms and hurricanes based on best available historical records. "Exposure" is defined here as being in the path of a tropical storm or hurricane, looking at both the actual storm track (the "eye") and the area within a certain distance of the storm track that experiences sustained tropical storm or stronger winds.

Much of the decision-making, planning, and response to tropical storms and hurricanes making landfall in the US occurs at the level of the county, which therefore presents a logical unit of analysis. Analysis at the level of States is deemed too coarse to reveal relevant spatial patterns, and grouping of counties into coastal segments, which has been used in several other studies looking at hurricane landfall, is arbitrary at best.

The concept of "landfall" is also expanded in this study to include the entire track of each storm over land, not just the point of landfall itself; therefore, this study looks at overall exposure, not just the coastal storm surge. While coastal areas commonly experience the largest impacts due to the combined effects of coastal storm surge, rain-induced flooding, and wind damage, damage to inland areas can be very devastating as well.

This research only deals with exposure, not vulnerability or risk in general. So only the spatial pattern in the occurrence of tropical storms and hurricanes is examined, not the on-the-ground characteristics that may determine the actual impact from an event. In addition to looking at the spatial patterns in exposure, an explanatory model is developed for the spatial pattern in the occurrence of tropical storms and hurricanes. The model is based on the assumption that the amount of exposure of a county can be predicted using the following variables:

- Distance to coast—the closer to the coast, the higher the exposure;
- Latitude—the further south, the higher the exposure;
- Longitude—the further east, the higher the exposure;
- Size—the larger the surface area of the county, the higher the exposure;
- Shape—the more elongated the shape of the county in one or more directions, the higher the exposure.

The null-hypothesis here is that after correcting for these variables, the exposure basically becomes equal. The expectation, however, is that selected areas will come out where the exposure is not equal after this normalization, for example, the inland counties of Florida. Still, the variables are expected to explain much of the spatial variability in the exposure.

2 Methods

2.1 Data sources

Historical storm tracks were obtained from the National Oceanic and Atmospheric Administration (NOAA) Coastal Services Center. These historic tracks contain the six-hourly (0000, 0600, 1200, 1800 UTC) center locations and intensities for all subtropical depressions and storms, extratropical storms, tropical lows, waves, disturbances, depressions and storms, and all hurricanes, from 1851 through 2003. Original data was obtained in geographic coordinates (NAD1983). The tracks represent the most accurate data available for this time period but are not considered pin-point accurate and should therefore only be used in county-level or regional analysis. Specific accuracy information can be found in Neumann et al. (1999). The over-water portions of storm tracks before 1944 are subject to considerable uncertainties, but these portions were not considered in this analysis.

A subset of these tracks was created with only the tropical storms and hurricanes. A tropical storms is defined as a tropical cyclone in which the maximum sustained surface wind speed ranges from 39 to 73 miles per hour (mph) (63–117 kilometer per hour (kph)). When winds in a tropical cyclone equal or exceed 74 mph (119 kph), it is called a hurricane. Hurricanes are further designated by categories on the Saffir–Simpson scale.

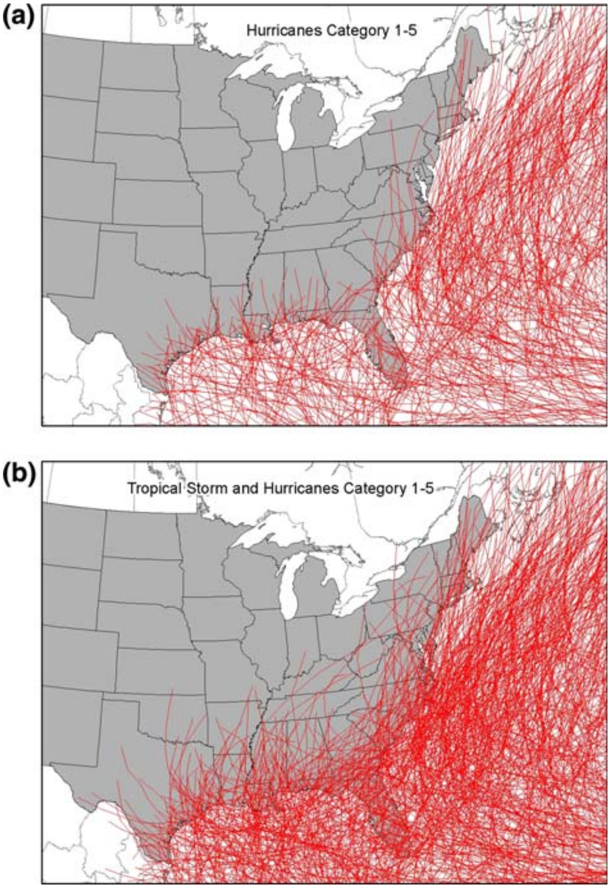

Fig. 1 Historic Atlantic hurricane and tropical storm tracks, 1851–2003

Hurricanes in categories 3, 4, 5 are known as major hurricanes or intense hurricanes. Figure 1a shows the tracks of all hurricanes, while Fig. 1b shows all tropical storms and hurricanes for the period 1851–2003. Over this time period, a total of 1,255 storms reached tropical storm strength or greater of which 466 storms made landfall in the US. A total of 778 storms reached hurricane strength of which 249 made landfall in the US.

Boundaries of US counties with a detailed coastline were obtained from Geographic Data Technology (2004). The accuracy of this data corresponds to a map scale of 1:100,000. Original data was obtained in geographic coordinates (NAD1983).

2.2 Exposure of counties to storms

The historic storm tracks were split into three sub-sets: (1) all tropical storms and hurricanes, (2) only hurricanes, and (3) major hurricanes (categories 3, 4, and 5). These three sets of tracks were compared with the current boundaries of the US counties, and for each county a determination was made of how many times a county was hit. A “hit” occurs when the storm track (a polyline) crosses the boundary of the county (a polygon). A single storm only results in a single hit for one county, even when it crosses the boundary

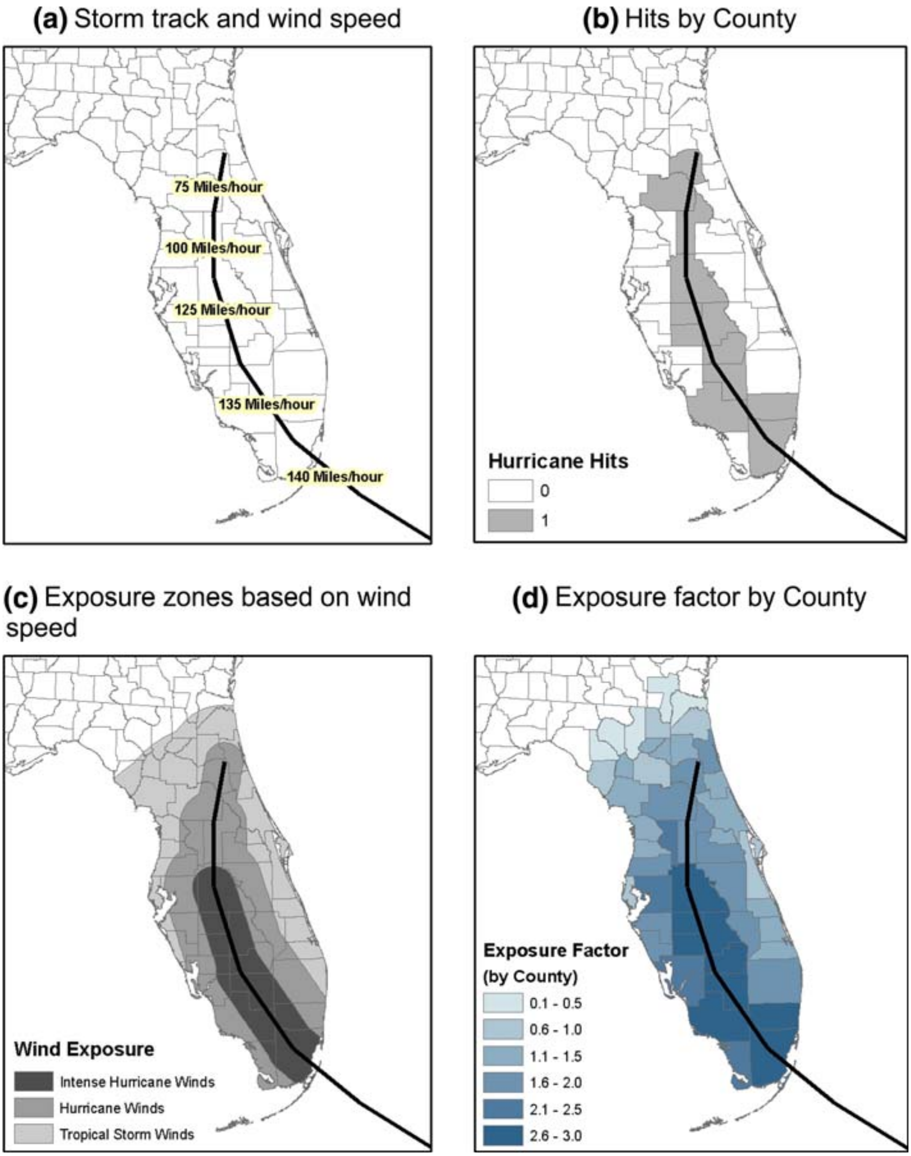

Fig. 2 Illustration of exposure analysis for unnamed hurricane, 12–16 September 1945

multiple times and/or changes category within the county boundary. This was accomplished using the Intersect function of ArcGIS 9 (ESRI 2005), followed by a Dissolve on the fields for unique storms and counties.

As an example of this methodology, Fig. 2a shows the path of the unnamed hurricane in September 1945 which made landfall in South Florida as a category 4 hurricane, moved across the State of Florida, gradually diminishing in strength to a category 1 hurricane. Figure 2b shows which counties scored a single hit as a result of this one storm.

This procedure was repeated for every storm, and the cumulative number of hits for each county over the period 1851–2003 for each of the three subsets of storms was determined, and the results tabulated and mapped.

Determining the “hits” by county is computationally simple but may not provide a very realistic description of exposure to storm conditions for a particular county. As can be seen from Fig. 2a and b, a “hit” occurs simply when the track crosses the county boundary, without considering the actual area being exposed to storm conditions within that county. In addition, counties in close proximity to the track which are likely to experience storm conditions do not score a hit. Added to this is the limited accuracy of the storm track data—a position is recorded only every 6 h with straight line segments drawn between them, and every 6 h location is only accurate to within several kilometers.

Therefore, a second analysis technique is used to determine the exposure of counties to storm conditions. Each storm track is buffered by a certain distance, based on the reported maximum wind speed. Figure 3 shows the buffer distances used. These values are based on the methodology developed by Gray and Klotzbach (2005). A brief summary is provided here. Maximum sustained winds of every intensity tropical cyclone are assumed to extent out to a radius of 30 km from each cyclone center. Beyond 30 km, the maximum intensity is assumed to gradually decrease with distance following a simple decay function. As the storm strength increases, the extent of damaging winds is also assumed to increase. The extent of three levels of intensity is considered: tropical storm-force winds (maximum sustained winds of 40 mph (64 kph) or greater), hurricane-force winds (maximum sustained winds of 75 mph (121 kph) or greater), and intense hurricane-force winds (maximum sustained winds of 115 mph (185 kph) or greater). This results in the three curves in Fig. 3.

For example, a storm with a maximum sustained wind speed of 100 mph (161 kph) at its center will be buffered by 160 km to identify the area that could experience tropical storm-force winds and by 53 km to identify the area that could experience hurricane-force winds. Since the maximum sustained wind speed of a storm will change along its track, the buffer distance also changes.

Fig. 3 Exposure zone distances by wind speed

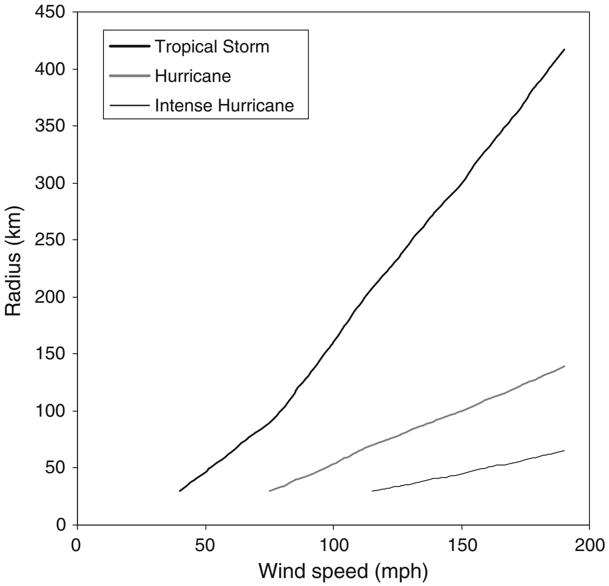

Figure 2c shows an example of these three different exposure zones for tropical storm-force winds, hurricane-force winds, and intense hurricane-force winds for the unnamed hurricane in September 1945.

For each hurricane the three (or fewer) exposure zones are compared to the current boundaries of the US counties. For every county a determination is made how much area is covered by each of the exposure zones. These areas are added together and divided by the area of the county, resulting in a factor that expresses the exposure to storm conditions. Figure 2d shows the results for the unnamed hurricane in September 1945. The maximum value of 3.0 occurs when a county falls completely inside the intense hurricane exposure zone, but any value between 0.0 and 3.0 is possible.

As can be seen from the results in Fig. 2d, the number of counties affected by storm conditions is much larger than when considering only the direct hits. This is obviously a direct result of the use of a buffering distance. The exposure pattern also shows a more gradual pattern between high and low exposure, reflecting both proximity to the storm track and the intensity of the storm. This is a direct result of the use of a variable distance buffer based on the maximum sustained wind speed and the calculation of the exposure based on the ratio of the exposed area to the area of the county.

The cumulative exposure for each county over the period 1851–2003 was determined by repeating the steps above for each storm and summing the results by county. This exposure analysis was completed only for the hurricanes.

2.3 Development of an explanatory model

To test the hypothesis that the exposure to storm conditions can partly be explained by a set of simple spatial parameters, the following characteristics of each US county were determined:

- Latitude—determined as the latitude of the centroid of the county (units in decimal degrees);
- Longitude—determined as the longitude of the centroid of the county (units in decimal degrees);
- Distance to the coast—determined as the Euclidean distance of the centroid of the county to the coastline (units in kilometers). The coastline was derived from the combined boundaries of the US counties;
- Size—area calculated in an Albers equal area projection (units in square kilometers);
- Shape index—determined as the perimeter of the envelope of the county boundary divided by the square-root of the area of the county (dimensionless). The envelope of the county was determined in geographic coordinates, but the perimeter of this envelope was calculated in an Albers equal area projection. The use of the square-root of the area assures the shape index is not scale-dependent. The resulting ratio between perimeter and the square-root of the area was multiplied by 0.25 to assure a perfectly square county would have a shape index of 1.0.

Figure 4 shows the results of the shape index for a number of selected counties as an example of the methodology. Palm Beach County is almost perfectly square and has a shape index of 1.04; Polk County is a bit more elongated and has a shape index of 1.22; Monroe County includes the Florida Keys and has a shape index of 2.93. What this implies is that Monroe County, relative to its size, is almost three times more likely to get hit by a storm track based on its shape.

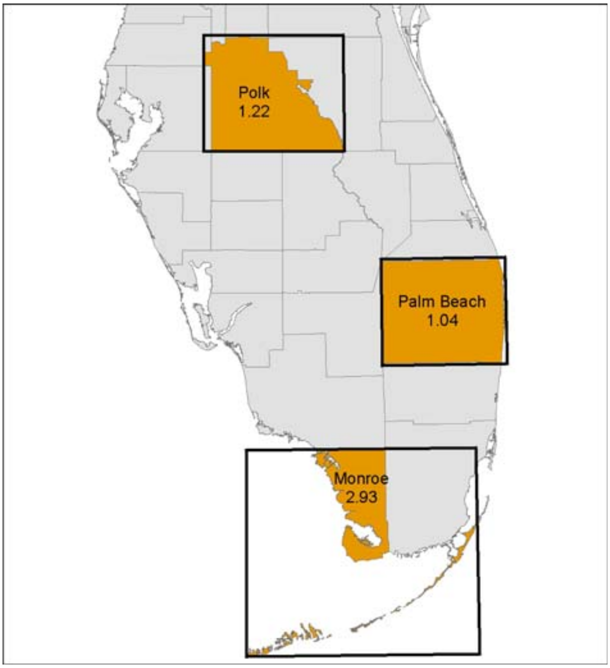

Fig. 4 Shape index for selected counties

Multivariate linear regression was used to determine how much of the variability in storm exposure can be predicted with the set of simple spatial parameters. Two analyses were run:

1. *Explanatory model for the number of hits.* The cumulative number of hits was the dependent variable, and the five parameters listed above (latitude, longitude, distance, area, and shape index) were the independent variables. This analysis was run for the hits from tropical storms and hurricanes combined as well as for the hits from only hurricanes. Sample sizes were 1,237 and 560, respectively. Only 147 counties were hit by a major hurricane which was considered an insufficient sample size for this analysis.
2. *Explanatory model for cumulative exposure factor.* The cumulative exposure factor was the dependent variable, and latitude, longitude, and distance to coast were the dependent variables. Because of the nature of the exposure factor, the geometric properties of the county polygons (area and shape) have no influence on the exposure factor and are therefore not considered in this analysis.

Initial exploration of the regression analysis indicated that the relationship between storm exposure and distance to coast may not be best represented by a linear relationship, but the use of various logarithmic and power functions did not result in any improvements in the regression results, including no substantial changes in the pattern of the regression residuals.

Both regular and stepwise multivariate linear regression techniques were employed to confirm the strongest explanatory model.

3 Results and discussion

3.1 Number of hits by county

Figure 5 shows the number of hits by county for the three subsets of storms. Tables 1–3 show the top 10 counties with the most number of hits for the three subsets of storms.

For the major hurricanes, counties in Florida come out at the top of the list, with the southern tip of Florida being the major hotspot. Many coastal counties did not experience a hit because the total number of major hurricanes that made landfall was relatively small. The results also reveal a number of areas where counties far inland were hit, since a few major hurricanes did not diminish in strength until far inland.

For all hurricanes, several hotspots can be identified, including much of Florida, southern Louisiana, and the coastal Carolinas. Only a handful of coastal counties did not experience a hit, while a very large number of inland counties did.

For all tropical storms and hurricanes, the same general hotspots emerge. All coastal counties have experienced at least one hit, as well as a very large number of counties far inland. Several inland counties in Florida, Georgia, and the Carolinas received substantially larger number of hits than their coastal neighbors.

3.2 Exposure factor by county

Figure 6 shows the results by county for the cumulative exposure to hurricanes, expressed as a dimensionless exposure factor. As described in the Sect. 2, this exposure factor considers the storm intensity by buffering the storm track based on the maximum wind speed.

When comparing Figs. 5b–6, several patterns emerge. First, the number of counties affected is much greater. Only 560 counties were hit by the tracks of all hurricanes, but 1,126 counties were exposed to tropical storm-force winds or greater from the same hurricanes. This is a direct result of the buffering of the storm tracks based on wind speed. Second, the pattern in Fig. 6 reveals a very strong relationship between cumulative exposure and distance to coast, which is not as clearly visible in Fig. 5b. This is a direct result of considering the storm's intensity in determining exposure: as hurricanes make their way inland, their strength diminishes rapidly even though they remain at hurricane strength.

Table 4 reports the top 10 counties with the highest cumulative exposure. From these top 10, no less than nine also appear on the top 10 of the hurricanes hits, suggesting a strong agreement in the major hotspots despite the observed differences in the overall spatial pattern.

3.3 Regression results for number of hits by county

The results of the multivariate regression results for the number of hits by county are shown in Tables 5 and 6.

The regression results suggest that a substantial amount of variability in the hits can be explained by the relative simple factors of latitude, longitude, distance to coast, area, and shape. Adjusted R^2 values for the two sets of storm considered are 0.629 and 0.507, respectively.

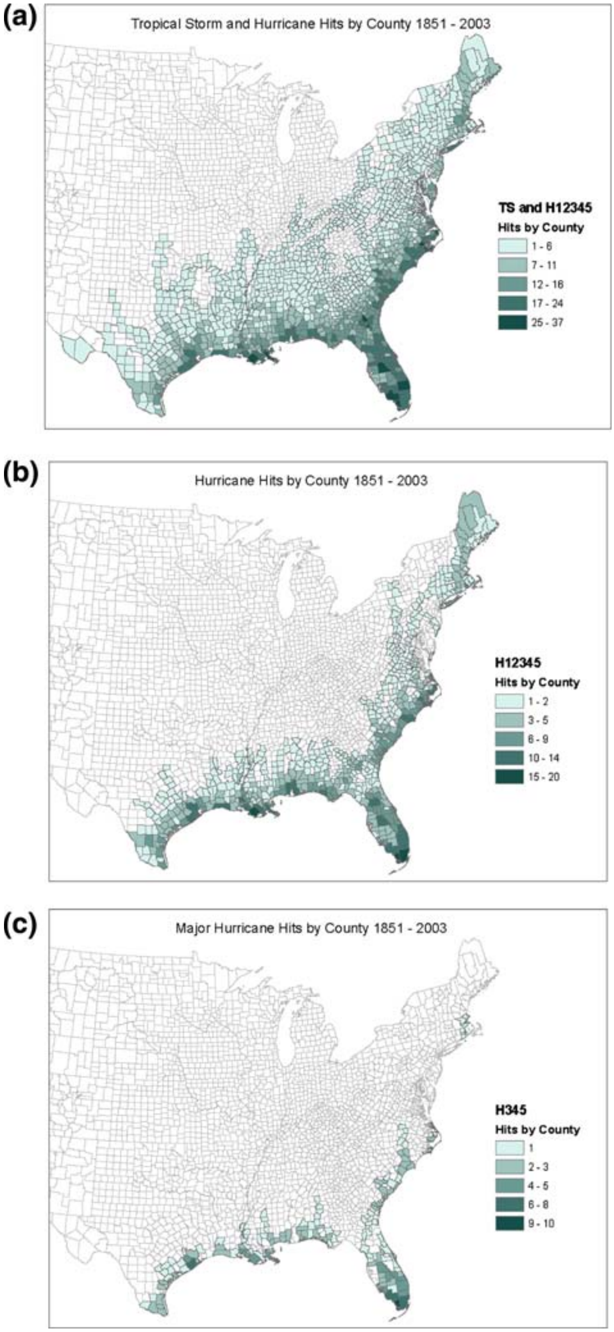

Fig. 5 Storm hits by county, 1851–2003

Size, shape, and longitude have a positive regression coefficient, while latitude and distance to the coast have a negative coefficient, all of which are according to the research hypothesis. Note that longitude values are negative, so a positive coefficient implies the

Table 1 Top 10 counties with the most number of hits from tropical storms and hurricanes, 1851–2003

Rank	County	Number of hits
1	Monroe, FL	37
2	Dare, NC	34
3	Palm Beach, FL	31
4	Ware, GA	29
5	Carteret, NC	29
6	Collier, FL	28
7	Craven, NC	28
8	Plaquemines, LA	27
9	Terrebonne, LA	26
10	Polk, FL	26

Table 2 Top 10 counties with the most number of hits from hurricanes, 1851–2003

Rank	County	Number of hits
1	Monroe, FL	20
2	Miami-Dade, FL	17
3	Terrebonne, LA	16
4	Plaquemines, LA	14
5-tie	Palm Beach, FL	13
5-tie	Carteret, NC	13
6-tie	St. Mary, LA	12
6-tie	Dare, NC	12
7-tie	Bay, FL	11
7-tie	Brazoria, TX	11
7-tie	St. Martin, LA	11
7-tie	Lafourche, LA	11
7-tie	Mobile, AL	11
7-tie	Polk, FL	11
7-tie	Broward, FL	11
7-tie	Collier, FL	11
7-tie	Hyde, NC	11

Table 3 Top 10 counties with the most number of hits from major hurricanes, 1851–2003

Rank	County	Number of hits
1	Monroe, FL	10
2	Collier, FL	8
3	Miami-Dade, FL	7
4	Brazoria, TX	6
5-tie	St. Mary, LA	5
5-tie	Terrebonne, LA	5
5-tie	Lee, FL	5
5-tie	Polk, FL	5
5-tie	Broward, FL	5
5-tie	Highlands, FL	5

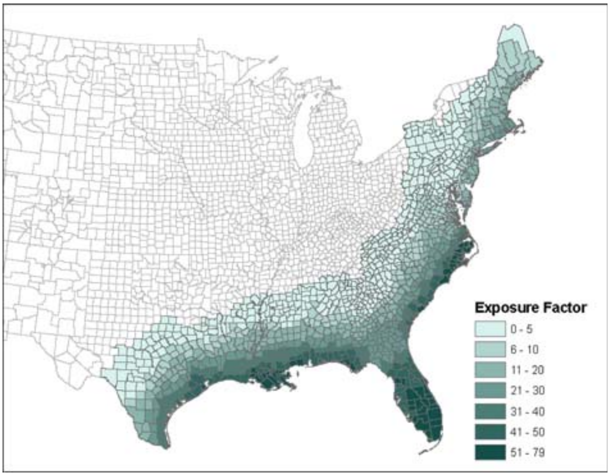

Fig. 6 Exposure to hurricanes by county, 1851–2003

dependent variable increases eastwards. Stepwise regression using the five variables confirms that all the five variables considered add to the explanatory power of the regression.

The explanatory power of the model can be considered quite strong, in particular given the relative simple and linear nature of the constructed model. As expected, proximity to the Atlantic Basin comes out as being very significant (as expressed in latitude, longitude, and distance to coast), but both county shape and area contribute to overall explanatory power of the model.

The residuals of the two regression models were mapped to determine any patterns in the remaining variability. Figures 7 shows these residuals for the two set of storms considered. The units are in number of hits: negative values indicate the predicted number of hits was higher than the observed number, while positive values indicate the predicted number of hits was lower than the observed number.

Some interesting patterns emerge from the analysis of the residuals. First, a number of coastal areas in Louisiana, Georgia, Florida, and the Carolinas have experienced many more hits than predicted. For these areas the predicted hits are around 10–20, while the actual number of hits for several of these counties fall in the 20–30 range. Second, many of the coastal counties of Texas have experienced much lower hits than predicted. Most storm tracks indeed do not reach this far west and including longitude in the analysis does not completely account for this. Third, some counties far inland that experienced only a single hit have a high positive residual since a negative number of hits was predicted, primarily driven by latitude and distance to coast. Fourth, some of the counties with the highest positive residuals are inland counties within close proximity to the coast—this is particularly true in Florida where the majority of the inland counties have a positive residual. This suggests that distance to coast is not a very good predictor for these areas. This corresponds to observations of storm events; many of the storms making landfall on the Atlantic or Gulf Coast of Florida make their way across the entire State while maintaining tropical storm or hurricane strength.

Table 4 Top 10 counties with the highest exposure factor to hurricanes, 1851–2003

Rank	County	Cumulative exposure factor
1	Miami-Dade, FL	78.56
2	Broward, FL	75.23
3	Carteret, NC	74.44
4	Monroe, FL	73.54
5	Palm Beach, FL	72.24
6	Martin, FL	72.05
7	Dare, NC	70.06
8	Hyde, NC	66.89
9	St. Lucie, FL	66.69
10	Plaquemines, LA	66.23

Table 5 Regression results for tropical storms and hurricanes for cumulative number of hits

Variable	Standardized coefficient	*t*-Value	*p*-Value
Distance to coast	−0.167	−6.572	<0.001
Latitude	−0.868	−27.319	<0.001
Longitude	0.629	17.742	<0.001
Size	0.241	13.262	<0.001
Shape	0.159	8.378	<0.001
(Constant)	–	22.404	<0.001
Adjusted R^2	0.629	*N*	1,237

Table 6 Regression results for hurricanes for cumulative number of hits

Variable	Standardized coefficient	*t*-Value	*p*-Value
Distance to coast	−0.256	−7.239	<0.001
Latitude	−0.693	−13.137	<0.001
Longitude	0.364	6.679	<0.001
Size	0.304	10.097	<0.001
Shape	0.282	8.721	<0.001
(Constant)	–	8.886	<0.001
Adjusted R^2	0.507	*N*	560

3.4 Regression results for exposure factor by county

The results of the multivariate regression results for the cumulative exposure by county are shown in Table 7.

The regression results suggest that a substantial amount of variability in the hits can be explained by the relative simple factors of distance to coast, latitude, and longitude. The adjusted R^2 value for the 1,126 counties is 0.725.

Latitude and distance to the coast have a negative coefficient, while longitude has a positive coefficient (longitude values are negative, so a positive coefficient implies that

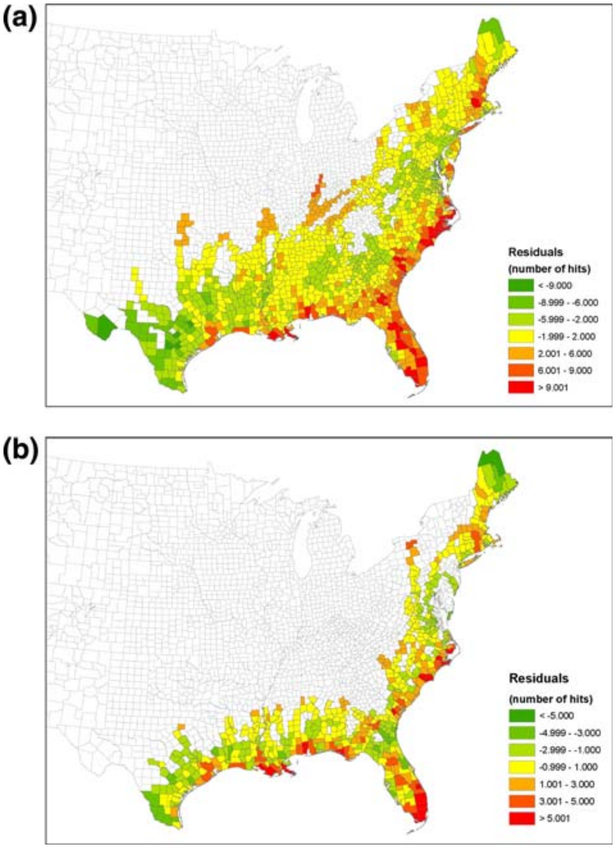

Fig. 7 Residuals from multivariate linear regression for number of hits by county, for topical storms and hurricanes (**a**) and hurricanes (**b**)

Table 7 Regression results for hurricanes for cumulative exposure factor

Variable	Standardized coefficient	*t*-Value	*p*-Value
Distance to coast	−0.544	−28.835	<0.001
Latitude	−0.785	−27.705	<0.001
Longitude	0.378	12.448	<0.001
(Constant)	–	22.969	<0.001
Adjusted R^2	0.725	*N*	1,126

cumulative exposure increases eastwards), all of which are according to the research hypothesis. Distance to the coast and latitude are the strongest variables in terms of how much of the variability they explain. Longitude explains much less of the variability, but its addition to the regression model does improve the overall fit. Stepwise regression using the three variables confirms that all the three variables considered add to the explanatory power of the regression.

The explanatory power of the model using only three variables is quite high. The model confirms the expectation that in general proximity to the Atlantic Basin results in higher

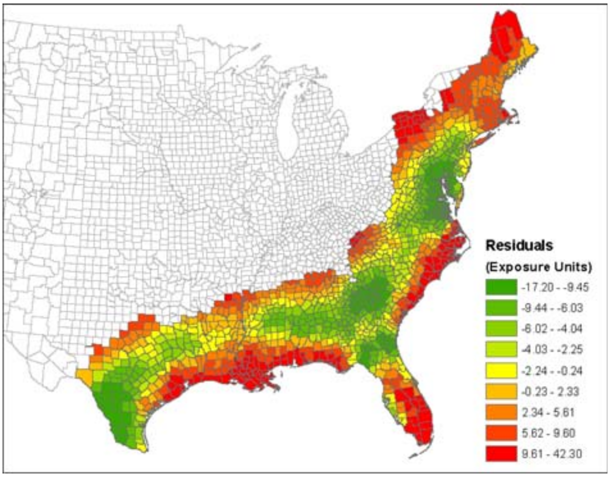

Fig. 8 Residuals from multivariate linear regression for cumulative exposure to hurricanes by county

exposure estimates. More importantly, however, the results indicate that a relatively simple linear model using only geographic factors explains 73% of the variability in exposure estimates. The explanatory power is also substantially higher when using the exposure factor estimates for hurricanes (73%) instead of a simple count of hurricane hits (51%).

The residuals of the regression model were mapped to determine any patterns in the remaining variability. Figure 8 shows these residuals. The units are in dimensionless exposure units. Negative values indicate the predicted exposure was higher than the observed exposure, while positive values indicate the predicted exposure was lower than the observed exposure.

Some interesting patterns emerge from the analysis of the residuals. First, the pattern of the residuals for the exposure has a much smoother look than that of the hits, i.e., there is much greater spatial autocorrelation in this dataset. This is a direct result of using buffer distances around the storm tracks, which in many cases exceed the extent of single counties. Second, some very strong patterns emerge in the location of high and low residual values. Some very high residual values are observed for inland counties, at the outer edge of the extent of the exposure zones. While the exposure values are quite low for these inland areas (usually less than 1.00), the predicted exposure values are negative, based on their distance to the coast and latitude. Three coastal areas with very high positive residuals also emerge: coastal Louisiana, southern Florida, and coastal North Carolina. Predicted exposure values for these areas are in the 30–50 range, while observed values are in the 50–80 range. Interestingly, these areas all appear to represent “exposed” coastal zones, i.e., the general shape of the coastline at a regional level is convex (as opposed to concave). Several concave coastal areas (Chesapeake Bay area, coastal Georgia, and the Gulf Coast of North-Central Florida) come out as the areas with some of the strongest negative residuals. This pattern can be explained by the fact that in general storms will quickly diminish in strength after making landfall. More exposed coastal areas can be hit from many directions by a hurricane directly from open water, while less exposed coastal areas are somewhat protected by neighboring landmasses and may be exposed only after a hurricane has traveled some distance over land.

A few other smaller patterns emerge as well. Some of the lowest residuals are observed in the counties surrounding Chesapeake Bay. Relative high exposure values are predicted for these areas based on the distance to the coast (which uses the outline of Chesapeake Bay). This suggests the use of distance to coast for these areas may need some revision, recognizing the fact that not all coastlines should be considered equal. Another smaller pattern is the occurrence of high residual values in the counties in upper New York, Vermont and Maine. These areas are far inland and at high latitudes, resulting in large negative predicted values.

4 Conclusions

The analysis presented in this study is unique in the fact that it uses a long historical record of Atlantic tropical storms and hurricanes and considers the entire path of the storms after making landfall.

Two approaches were used to determine the exposure of US counties to storm conditions: (1) cumulative number of hits, with a hit occurring when the storm's path crosses a county and (2) cumulative exposure factor, which describes how much of the county has been exposed to tropical storm, hurricane, and intense hurricane-force winds.

In both approaches to determining exposure, the top 10 counties in terms of cumulative exposure over the time period considered are in coastal Florida, North Carolina, and Louisiana.

An explanatory model was developed to describe the patterns in the documented exposure. For the cumulative number of hits, explanatory variables included distance to coast, latitude, longitude, size, and shape. Multivariate linear regression confirmed that exposure increases as a county is closer to the coast, eastwards, southwards, and with larger values for area and shape index. For tropical storms and hurricanes combined, the five variables explain 63% of the variation in the number of hits, while for only hurricanes the five variables explain 51% of the variation in the number of hits. Analysis of the residuals reveals that several coastal and near-coastal counties in Louisiana, Florida, and the Carolinas experienced many more hits than predicted. Residual analysis also reveals high spatial variability due to the relative low number of storms that made it far inland.

For the cumulative exposure, explanatory variables included distance to coast, latitude, and longitude. Multivariate linear regression confirmed that exposure increases as a county is closer to the coast, eastwards, and southwards. The three variables explain 73% of the variation in the cumulative exposure factor. Analysis of the residuals reveals that some "exposed" areas of the coast (i.e., convex shape) experience higher exposure. Residual analysis also reveals much less spatial variability compared to using the number of hits resulting from a more realistic model of the exposure based on storm intensity.

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