The Use of Synthetic Hurricane Tracks in Risk Analysis and Climate Change Damage Assessment

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ABSTRACT

Because of the lack of data on past hurricanes, empirical evaluations of the statistics needed for risk management are very uncertain. An alternative strategy is to use a hurricane model to produce large sets of synthetic hurricane tracks. This method provides, for 11 regions of the U.S. Atlantic and Gulf Coasts, the annual landfall probabilities of hurricanes from each category of the Saffir–Simpson scale. This model can be used to investigate the future of hurricane risks. As a first step, the model is run with a 10% increase in potential intensity. Annual landfall probabilities increase in all regions, especially for the strongest hurricanes. The vulnerability of each U.S. coastal county is then calibrated using data on past hurricanes and their normalized economic losses. Annual hurricane damages increase by +54% in response to a 10% increase in potential intensity, meaning that the average normalized losses caused by hurricanes would increase from approximately $8 billion to about $12 billion per year. These results suggest that hurricane losses are very sensitive to changes in potential intensity and may rise significantly in response to climate change. This paper calls, therefore, for taking into account hurricane damages in the analysis of climate policies, even though other factors like population evolution, economic growth, and preparedness may remain the main drivers of hurricane damages.

1. Introduction

Socioeconomic damages caused by hurricanes, and more generally by extreme weather events, have risen steadily for decades (Munich Re 2006). Despite numerous studies on this topic, the role of climate change in this evolution is still unclear. Of course, it is unquestionable that socioeconomic drivers, like economic growth and changes in the localization of assets and population, have been the main factors of the observed increase in economic losses (Pielke and Landsea 1998). After the unprecedented 2004 and 2005 hurricane seasons in the North Atlantic Ocean, however, some have argued that climate change has started to significantly modify hurricane characteristics (Emanuel 2005a,b; Webster et al. 2005). This claim has been heatedly contested (e.g., Landsea 2005; Pielke 2005; Pielke et al. 2005), and no definitive answer can currently be provided. This uncertainty on the causes of the current evolution of disaster losses translates into an even larger uncertainty concerning the future evolution of disaster losses: Will hurricanes become more intense in a warmer world? Will hurricanes more often reach places currently spared and therefore less prepared? Will climate change be responsible for a significant increase in hurricane damages in the future? These uncertainties make the design of long-lived infrastructure much more difficult and, therefore, can provoke significant losses in case of inadequate design and ill adaptation to climate conditions (Hallegatte 2006).

For hurricanes, the shortness of data series, and their often poor quality, explains why most of these questions cannot be answered with certainty. Even for the North Atlantic and the U.S. coastline, on which I will focus in this paper, high-quality data on hurricane properties are very recent, and the rarity of the most extreme events makes landfall statistics uncertain. Together, these two constraints make it very difficult to develop empirical statistics on the most powerful storms, on which risk analysis and protection measures

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must, nevertheless, be based. To improve risk management, therefore, there is an increasing need for new methodologies to overcome the data scarcity issue and to supplement traditional statistical approaches.

Two of such new methodologies can be found in the literature. The first one is based on advanced statistical analyses, which are able to cope, to a certain extent, with the rarity of the considered events. Examples of such works are Casson and Coles (2000), Vickery et al. (2000), Katz (2002), Coles and Simiu (2003), Jewson et al. (2006), and Jagger and Elsner (2006). These authors produce statistics of return levels, sometimes as a function of large-scale conditions [El Niño, North Atlantic Oscillation, Atlantic multidecadal oscillation, etc.]. This approach can also be used to forecast hurricane losses as a function of large-scale parameters (e.g., Jagger et al. 2007).

The current paper follows an alternative way, using synthetic hurricane tracks generated by a hurricane model based on the physical mechanisms, which drive hurricane tracks and intensity. This approach differs, therefore, from statistical models that only consider observed hurricane properties. The idea is to compensate for the shortness of the data series through understanding of the involved physical mechanisms. In this paper, the analysis is based on Emanuel's model (see Emanuel 2006; Emanuel et al. 2006). From this model, useful risk analysis statistics can be derived. If the model that generates the tracks is considered to be accurate enough, that is, if the understanding and modeling of the most important physical mechanisms are good enough, using synthetic tracks provides a potentially infinite synthetic-hurricane dataset and allows the computation of probabilities of occurrence for major events. These probabilities could then be used to help design protection infrastructures.

The second issue is the potential impact of climate change on these statistics. Because the track model can be run in a different environment (Emanuel 2006), synthetic tracks can be produced in what we expect to be the future climate, and corresponding changes in risk statistics can be evaluated. From there, and using vulnerability indices derived from the consequences of past hurricanes, it is possible to assess how climate change may influence economic losses from hurricanes. This is a major advantage when compared with purely statistical models, the results of which cannot be easily extrapolated to the different large-scale environment of a changed climate.

Section 2 of this paper presents both the datasets and methods used in the analysis. Section 3 focuses on the statistics of hurricane power at landfall, both to validate the model against observed statistics and to assess how hurricanes may become more or less destructive in the future. Section 4 looks at landfall location statistics, in order to assess the ability of the model to reproduce observations. Joint probability of landfall location and landfall power are presented in section 5. Local damage functions, linking hurricane power at landfall with corresponding socioeconomic losses, are calibrated in section 6, and these functions are used to assess how economic damages from hurricane may evolve on the U.S. Atlantic and Gulf Coasts. Conclusions and proposed future research are presented in section 7.

2. Datasets and methods

The U.S. Atlantic and Gulf Coasts are represented by a piecewise linear function of 107 points corresponding to the 106 coastal counties of the U.S. Atlantic and Gulf Coasts, referenced by their longitude and latitude.

The cyclone historical data are the "historical best tracks" from the hurricane database (HURDAT), developed by the National Hurricane Center, between 1950 and 2004, with 570 tracks and 217 landfalls. No wind speed adjustment has been made, contrary to what is done by Emanuel (2005a). For the Atlantic basin, HURDAT is the best database on hurricane tracks, and data from 1950 onward are considered to be fairly good. This database provides, with 6-h sampling, the position and speed of the eye and the maximum wind speed.

The synthetic tracks used in this study are those described in Emanuel (2006). They are based on two models, which are comprehensively described in Emanuel et al. (2006). The first is a hurricane track model, in which the hurricane eye is moved according to environmental winds, constructed to conform to observed statistics of winds, plus a correction for "beta drift" (Holland 1983). This model is sometimes referred to as the "beta and advection model" (BAMS; Marks 1992). The second model is a hurricane intensity model (Coupled Hurricane Intensity Prediction System; Emanuel et al. 2004) that gives the evolution of hurricane intensity according to environmental factors—namely, potential intensity [which summarizes the effect of sea surface temperature (SST) and tropospheric temperature profile], depth of the ocean mixing layer, and thermal stratification of the ocean below the ocean mixing layer. This model is run quasi operationally at the National Hurricane Center and Joint Typhoon Warning Center and gives forecasts comparable in skill to other forecast methods (Emanuel and Rappaport 2000). Note that in this modeling framework, tracks are independent of intensities, except in that each track ends when the intensity—predicted by the intensity model—falls below a critical value.

An important feature of these tracks is that storm genesis is not modeled. As a consequence, historical statistics of genesis are used to initiate the tracks and no influence of climate change on genesis can, so far, be investigated with this tool.

Two sets of tracks are used. First, I use a set of 3000 tracks (with 1862 landfalls), which was produced using climatological large-scale climate conditions. This set is referred to as present climate (PC). I assume that climate conditions were constant over the 1950–2004 period, even though SST increased by about 0.5K.

Second, I use another set of synthetic tracks, which was produced assuming a 10% increase in potential intensity, when compared with climatological climate conditions. Such an increase in potential intensity, together with other environmental changes and with a large uncertainty, is expected at the end of this century (Emanuel 2005b). This set also contains 3000 tracks, with 1912 landfalls, and is hereinafter referred to as modified climate (MC). Since only potential intensity is changed, and since potential intensity is an input of the intensity model only, tracks in the MC set are unchanged relative to the PC tracks, except that they can be shorter or longer. A comprehensive description and validation of these synthetic tracks are provided in Emanuel (2006).

Since my interest lies in landfall characteristics, the landfall position(s) and characteristics (maximum wind and minimum sea level pressure) have been calculated from all track files (HURDAT and synthetic PC and MC). A landfall is defined as the hurricane trajectory crossing the coastline, with the hurricane going from sea to land. In the historical series and synthetic data, some hurricanes make multiple landfalls. An issue is that hurricane intensity can change very rapidly around landfall. As a consequence, the 6-h time-step sampling of the HURDAT database creates a large uncertainty for landfall characteristics; As an example, Andrew (1992) made landfall as a category-5 hurricane at approximately 0900 UTC (see http://www.nhc.noaa.gov/1992andrew_add.html) but was a category-4 hurricane at 0600 and 1200 UTC, the times of the two observations available in HURDAT. In my analysis, therefore, Andrew is improperly recorded as a category-4 landfall. To avoid making an exception for a single storm, I did not change the Andrew's record, but this problem is likely to occur also for other storms. This issue of rapidly changing hurricane intensity at landfall exists also but is less problematic for synthetic tracks that are sampled with a 2-h time step. For simplicity, I retained the wind speed values just preceding landfall as the landfall values.

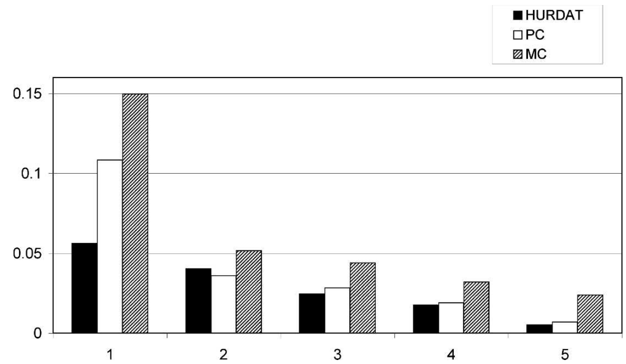

FIG. 1. Probability, for a given storm, of making landfall as a hurricane of categories 1–5, estimated from HURDAT and from synthetic tracks for the PC and an MC.

3. Landfall power statistics

The statistics for hurricane power at landfall are used to assess the model ability to reproduce hurricane strength at landfall and to assess how these statistics might change in a modified climate.

a. Current climate

Figure 1 shows the probability that any given storm will make landfall as a hurricane in categories 1–5, in the Saffir–Simpson scale, according to historical data and the model.

To translate this probability into the probability of occurrence of an event (here, the annual probability of occurrence of landfall for a hurricane of category n), it is necessary to take into account the genesis probability, calculated from historical data, and to assume that hurricane genesis and trajectories are independent. With these hypotheses, the hurricane landfall can be modeled through a Poisson process and the annual probability of occurrence of a hurricane of category $n(P_n)$ is linked to the probability, for any given storm, of making landfall as a hurricane of category $n(Q_n)$, by the following relationship:

$$P_n = 1 - \exp(NQ_n), \qquad (1)$$

where N is the average number of storms per year. The annual probabilities of occurrence of landfall of a hurricane of category $n(P_n)$ are reproduced in Fig. 2.

One can see in Figs. 1 and 2 that the model reproduces fairly well the probability of making landfall as a hurricane of any category, except for category-1 hurricanes. In this validation process, however, data scarcity is a major concern, since any discrepancy between observed and model values may be due to the small number of hurricanes in the historical database. To assess to what extent any discrepancy can be attributed to data

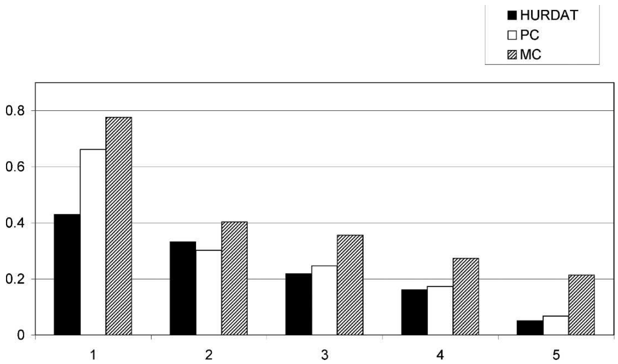

FIG. 2. Annual probability of landfall of a hurricane of a given category, estimated from HURDAT and from synthetic tracks for the PC and MC.

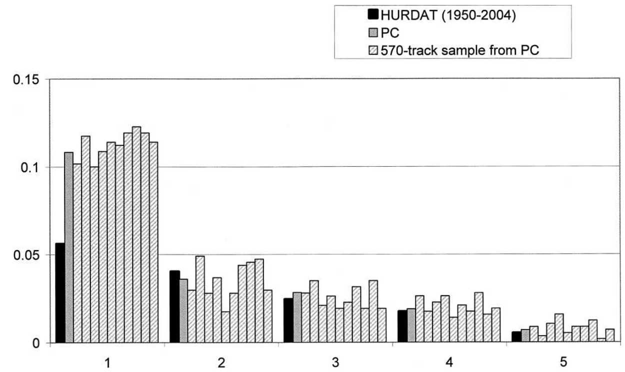

FIG. 3. Same as in Fig. 1, but from HURDAT, the synthetic tracks in PC, and 10 samples of 570 synthetic tracks.

availability, several subsets of hurricane tracks are extracted from the entire set of synthetic tracks. Each subset contains the same number of tracks as the historical dataset (i.e., 570 tracks from 1950 to 2004).

Figure 3 shows the historical empirical probabilities, for a given storm, of making landfall as a hurricane of categories 1–5, along with probabilities derived from the entire set of synthetic tracks and from the ten 570-track subsets. One can see that the uncertainty in landfall probability is much larger for the strongest storms than for category-1 storms, which is logical since weak storms greatly outnumber strong storms, making their statistics much less uncertain. The historical probability is within the range of the probabilities derived from the subsets of synthetic tracks for all categories but category 1, for which the model deviates considerably from observations. The model, therefore, produces too many weak hurricane landfalls. Note that the problem concerns the landfalls, not the total number of weak hurricanes, since the simulated number of category-1 hurricanes is correct (655 out of 3000 tracks, i.e., 21.8%, while there are 132 such hurricanes out of 570 tracks in HURDAT between 1950 and 2004, i.e., 23.2%). As a consequence, it is likely that the landfall statistics discrepancy arises from the track model. This hypothesis is supported by the analysis of the model tracks for weak hurricanes,[1] which are skewed toward the coast, probably because of an overly large western drift in the track model for weak hurricanes. The fact that weak storms are not well structured might explain why the beta advection model is less suitable to assess their tracks and has lower skill than statistical models (e.g., Markov chain models; see Emanuel et al. 2006). Consequently, the model is considered to be unable to reproduce the trajectory for weak storms. Strong storm tracks, on the other hand, are well reproduced.

This problem with weak storms does not prevent the approach from providing interesting insights, because 1) the methodology can be reapplied as soon as improved models are available, 2) climate change is expected to influence hurricane damages more through changes in hurricane intensity than through modifications in track distribution; the track bias for weak storms, therefore, should not influence my results much, and 3) the model reproduces well the track and intensity for the strongest hurricanes, which represent by far the largest threat to human societies (e.g., 85% of hurricane damages are caused by hurricanes from categories 3, 4, and 5; Pielke et al. 2008). In the rest of this paper, because of this model mismatch and the fact that weak hurricanes do not cause much damage, I will focus on hurricanes in categories 2–5.

b. *Modified climate*

To estimate how these landfall power statistics may change in the future because of climate change, I carry out the same analysis with the synthetic tracks generated assuming a 10% increase in potential intensity (MC). In this case, the landfall probability is slightly increased (1912 landfalls for 3000 tracks in PC, as compared with 1862 landfalls for 3000 tracks in MC). Since tracks are independent of potential intensity except for their ending, it means that the larger potential intensity allows storms to persist longer, such that some, which would have dissipated over the ocean with a lower potential intensity, are instead able to reach the coast. Also, the average maximum wind speed at landfall is increased by 13%, from 60 to 69 kt (1 kt $\approx$ 0.5 m s^{-1}). As a consequence, the probability of making landfall as a hurricane (with maximum winds exceeding 64 kt) in-

[1] Because of length constraints, this analysis was not reproduced here.

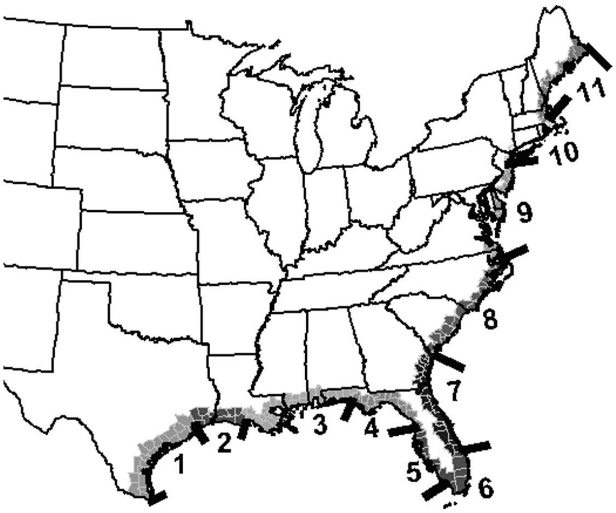

FIG. 4. Map of the 11 regions along the U.S. East and Gulf Coasts.

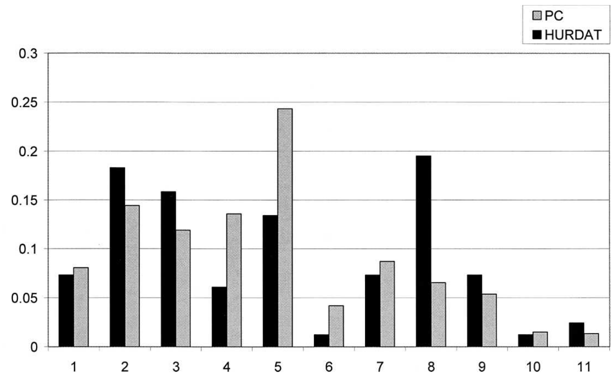

FIG. 5. Distribution of hurricane landfalls for each of the 11 regions, estimated from HURDAT and from synthetic tracks for the PC.

creases by 53% (909 hurricane landfalls, as compared with 596).

Figures 1 and 2 show that the more powerful the hurricane, the larger the increase in probability: the annual probability of landfall is increased by 17% for category-1 hurricanes, by 33% for category-2 hurricanes, by 44% for category-3 hurricanes, by 58% for category-4 hurricanes, and by 215% for category-5 hurricanes. Note that these increases are of the same order of magnitude as the difference observed—during the 1899–2004 period—between years that are warmer than average and years that are colder than average (Jagger and Elsner 2006). The nonlinearity of these changes is a clear illustration of the multiplicative effect of extreme events: a limited change in the characteristics of the mean (+13% in average maximum wind speed at landfall) can have a dramatic impact on the distribution tail (+215% increase in category-5 landfall probability). As a consequence, the annual probability that a category-5 hurricane will landfall along the U.S. Atlantic and Gulf Coasts rises dramatically, from 7% to 21%.

Moreover, because socioeconomic impacts of hurricanes are highly nonlinear with respect to hurricane intensity, such an evolution may translate into an even larger change for hurricane damages, justifying the investigation of this issue that is carried out in section 6.

4. Landfall location statistics

Having focused on hurricane power at landfall, I now investigate the ability of the model to reproduce landfall locations. To do so, I calculate the landfall probabilities for each "region." The regions are those defined in the United States Landfalling Hurricane Probability Project (see http://www.e-transit.org/hurricane/welcome.html). Region 1 is near the Mexican border; region 11 is near the Canadian border (see Fig. 4). I look only at the storms that make landfall as hurricanes (those that make landfall as tropical storms, i.e., with a maximum wind below 64 kt, are disregarded).

Figure 5 provides the distribution of hurricane landfalls in each of the 11 regions, calculated from historical data[2] and from synthetic tracks of the PC. The model reproduces surprisingly well the orders of magnitude and the main characteristics of landfall distributions, even though there are large discrepancies for some regions: The model greatly overestimates the probability of hurricane landfall in regions 4, 5, and 6 (western and southern Florida) and underestimates the probability for region 8 (South and North Carolina). To assess how much of this discrepancy arises from data scarcity and how much arises from model errors, I make use again of the ten 570-track samples, and I calculate—for each sample—the empirical distribution of hurricane landfalls in each region (Fig. 6).

This approach provides an approximation of the error made when using historical data to evaluate landfall probabilities. The results of the model are judged to be adequate for this study, even though empirical probabilities are outside of the range of sample-based probabilities for region 3 (slightly), and for regions 4, 5, and 8.

5. Joint landfall intensity–landfall location statistics

The most interesting statistic for risk management and protection design is, for each region, the probabil-

[2] The number of events used to calculate the empirical probabilities lies between 1 in region 10 and 16 in region 8.

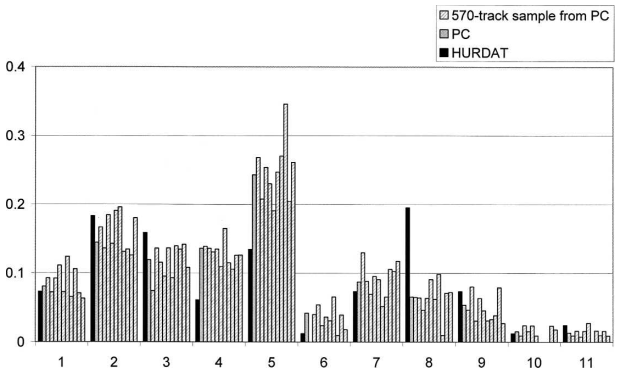

FIG. 6. Distribution of hurricane landfalls in each region, estimated from historical data, from the synthetic tracks for the present climate and from 10 samples of 570 synthetic tracks.

ity of landfall of a hurricane of a given category. This probability is extremely difficult to derive from historical data because of the shortness of the data series. Therefore, models can also be used, as proposed in Emanuel et al. (2006).

a. Present climate

I calculated first the empirical joint probability of landfall region and landfall category, derived from historical data. It represents the probability, for an existing storm, of making landfall in a given region as a hurricane of a given category. For instance, the probabilities that an existing storm makes landfall as a category-4 or -5 hurricane in the New Orleans region (see Fig. 4) are, respectively, 0.18% and 0%. These figures translate [see Eq. (1)] into annual probabilities of landfall of a category-4 or -5 hurricane for this region of, respectively, 1.8% and 0% (see Table 1).

My dataset contains 217 landfalls, which is obviously not sufficient to calculate joint probabilities for the 55 groupings (5 categories × 11 regions). To overcome this difficulty, I assume that the model is able to reproduce the behavior of hurricane tracks well enough, and I use the larger number of synthetic tracks to compute the joint probabilities. Table 1 summarizes these results, through the annual landfall probability of hurricanes of different categories, in each region, calculated from the synthetic track. For instance, the annual probability of landfall of a category-5 hurricane in the New Orleans, Louisiana, region is estimated by the model at 0.3%. For comparison purposes, empirical probabilities calculated from the HURDAT database are also reproduced in parentheses in Table 1.

b. Modified climate

The same joint probabilities, but for the synthetic tracks of MC with increased potential intensity, are reproduced in Table 2. All probabilities increase, but the increase is very dependent on localization and category. Again, the most extreme events are very sensitive to the change in potential intensity: the more powerful the hurricanes, the larger the increase in frequency. In the New Orleans region (region 3), the annual probability of landfall of a category-5 hurricane soars from 0.3% to 3%. Such a trend, obviously, would drastically change the optimal design of a flood protection system (see Hallegatte 2006). Table 2 shows that most regions would have a probability larger than 1% of experiencing a category-5 hurricane every year.

A large increase in the probability of rare, large-scale events may cause enormous socioeconomic damages. This possibility leads us to investigate the link between hurricane power and socioeconomic losses.

TABLE 1. Annual probability of landfall of a hurricane of each category, in the 11 regions, for the present climate, according to the synthetic tracks; the values calculated from the HURDAT data are in parentheses. Regions 4 and 5 have a landfall probability of a category-5 hurricane that is larger than 1%.

	Category				
Region	1	2	3	4	5
1	8.91% (1.75%)	2.63% (0%)	1.00% (5.26%)	2.96% (3.51%)	0.00% (0.00%)
2	17.03% (15.79%)	3.28% (1.75%)	2.63% (0.00%)	3.28% (5.26%)	0.66% (3.51%)
3	11.60% (12.28%)	4.88% (1.75%)	3.60% (7.02%)	2.31% (1.75%)	0.33% (0.00%)
4	14.22% (3.51%)	5.51% (1.75%)	3.60% (3.51%)	1.00% (0.00%)	1.32% (0.00%)
5	22.12% (3.51%)	6.45% (7.02%)	7.38% (3.51%)	5.19% (3.51%)	3.60% (1.75%)
6	4.24% (0.00%)	1.98% (0.00%)	1.65% (1.75%)	0.33% (0.00%)	0.00% (0.00%)
7	6.14% (3.51%)	4.88% (3.51%)	3.92% (0.00%)	1.32% (3.51%)	0.66% (0.00%)
8	5.82% (10.53%)	1.32% (14.04%)	2.96% (3.51%)	2.31% (0.00%)	0.33% (0.00%)
9	7.07% (3.51%)	2.63% (7.02%)	0.66% (0.00%)	0.00% (0.00%)	0.00% (0.00%)
10	2.31% (0.00%)	0.66% (1.75%)	0.00% (0.00%)	0.00% (0.00%)	0.00% (0.00%)
11	1.32% (1.75%)	1.00% (1.75%)	0.33% (0.00%)	0.00% (0.00%)	0.00% (0.00%)

TABLE 2. Annual probability of landfall of a hurricane of each category, in the 11 regions, for the MC. Regions 1–5 and region 7 have a landfall probability of a category-5 hurricane that is larger than 1%.

	Category				
Region	1	2	3	4	5
1	13.93%	2.96%	2.96%	3.92%	1.98%
2	22.89%	7.38%	5.82%	3.28%	3.60%
3	15.63%	5.82%	6.76%	2.96%	2.96%
4	20.55%	7.07%	6.76%	3.28%	2.31%
5	26.90%	9.82%	10.42%	6.45%	9.52%
6	6.45%	3.60%	1.65%	1.00%	0.00%
7	7.07%	3.92%	2.96%	5.51%	2.31%
8	6.76%	3.28%	3.60%	4.24%	0.33%
9	9.82%	5.19%	1.32%	0.33%	0.00%
10	2.96%	0.33%	0.00%	0.33%	0.00%
11	2.96%	0.66%	0.33%	0.33%	0.00%

6. Assessment of economic losses

a. Calibration

I investigate here the relationship between economic losses and maximum wind speed at landfall. Since population and economic growth are the main long-term drivers of hurricane losses, I use normalized losses, in which the effect of these two drivers has been removed. Such normalized losses have been produced for the 1900–2005 period by Pielke et al. (2008).

As a first step, I assume that a simple relationship links maximum wind speed at landfall and normalized economic losses:

$$L = \alpha(s)W^3, \tag{2}$$

where L measures the normalized economic losses (in millions of U.S. dollars), W is the maximum wind (m s^{-1}), s is the linear coordinate along the coast, and $\alpha(s)$ is a parameter that measures the local vulnerability at the location s. This function shape is supported by the shape of the amount of energy dissipated by hurricanes (see Emanuel 2005a) and is roughly consistent with empirical damage functions (e.g., Munich Re 2002). One shortcoming of this function is that economic losses can rise indefinitely as wind speed increases, while actual damages are limited, in each location, by the total value of assets at risk (see Nordhaus 2006).

The parameter $\alpha(s)$ is calibrated for each of the 106 counties along the U.S. East and Gulf Coasts. To do so, I select, for each county, the set of hurricanes that made landfall in this county. When this set is not empty, I fit the parameter $\alpha(s)$ that links maximum wind at landfall and normalized recorded losses (through the minimization of the squared differences).

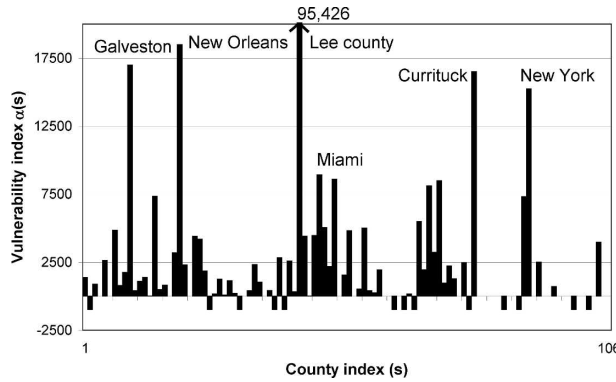

FIG. 7. Historical local vulnerability coefficients, county per county. The negative bars represent the counties for which no data are available.

Figure 7 reproduces this vulnerability $\alpha(s)$ for all counties. In counties where no hurricanes made landfall (13 counties), shown in Fig. 7 by negative bars, the vulnerability is taken as the average vulnerability of all the counties for which I have data. Note that what I call *the vulnerability of county A* can be better defined as *the vulnerability of the U.S. economy to a hurricane making landfall in county A,* since this vulnerability also takes into account the losses that occurred in other counties after a landfall in county A.

According to my method, the largest vulnerability along the U.S. coastline is in Lee County, Florida, in which a weak hurricane (maximum wind = 64 kt) made large damages in 1944 (normalized losses: \$36 billion). The second largest vulnerability is in the Orleans County (city of New Orleans), Louisiana, in which a weak tropical storm made significant damages in 1955 (normalized losses of \$3.5 billion for maximum winds of only 40 kt). Two other landfalls in 1900 and 1945 with no damages make the vulnerability in Orleans County lower than in Lee County, however. The year 2005 is not included in the analysis, so Hurricane Katrina is not taken into account in this vulnerability assessment. Using the vulnerability assessed from the 1900–2004 period, Eq. (2) provides an estimation of the economic losses due to Hurricane Katrina (125 kt) at about \$36 billion, while recorded losses (from wind damages only) are approximately \$50 billion.

The third largest vulnerability is in Galveston County, Texas, where two hurricanes caused large damages: a hurricane with a recorded maximum wind of 125 kt caused damages amounting to \$73 billion (normalized) in 1900, and a hurricane with recorded maximum winds of 105 kt caused \$57 billion of damages in 1915. The vulnerability of Galveston County is lower than

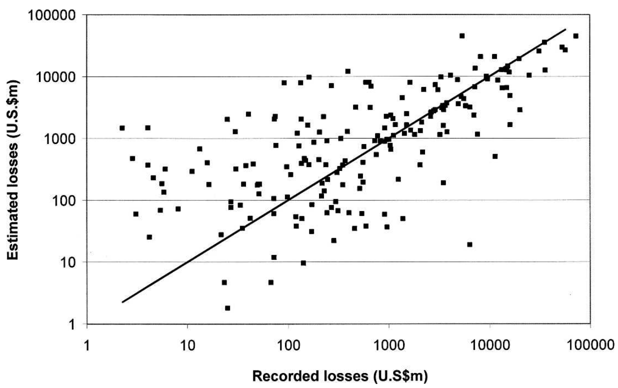

FIG. 8. Each point represents a historical hurricane landfall. The abscissa is the recorded normalized economic losses due to landfall. The ordinate is the normalized economic losses estimated from the maximum wind speed at landfall and the estimated local vulnerability. Both axes are in logarithmic scales.

that for Lee County and Orleans County because it experienced seven other hurricane landfalls after 1915, which produced only "limited" damages (between \$2 million and \$5 billion).

The fourth most vulnerable county is Currituck County, in North Carolina, where Hurricane Doria made landfall as a tropical storm (with 55-kt winds) in 1967, generating normalized damages amounting to \$3 billion. The fifth most vulnerable place is New York County, New York, where Hurricane Agnes, though weak at landfall, caused large losses in 1972 (normalized losses: \$10 billion).

This vulnerability assessment, even though far from perfect, nonetheless gives some interesting results. The economic losses estimated from these vulnerabilities are roughly consistent with historical records (see Fig. 8), with a correlation of 0.78. The results support the choice of my wind-speed-to-loss relationship. The large variability in recorded economic losses arises from 1) hurricane characteristics other than wind speed (e.g., the amount of precipitation, which is to a large extent independent of wind speed), and 2) the precise landfall position and time, because counties are not spatially homogenous and mitigation measures change vulnerability over time. Indeed, measuring actual vulnerability would require much smaller geographical and temporal units, which is impossible with available data.

One should mention that these vulnerability coefficients have the same problem as the normalized economic losses from Pielke and Landsea (1998) and Pielke et al. (2008): they do not take into account mitigation actions and, therefore, probably overestimate current vulnerability.

To investigate this issue, I look at how the vulnerability of a county evolves when this county experiences a hurricane landfall. To do so, I consider the vulnerability of each county s, as estimated by Eq. (2) for each landfall independently. This process leads to a series of vulnerability $\alpha(s, 1), \alpha(s, 2), \ldots, \alpha(s, n_s)$, where n_s is the number of landfalls in the county s between 1900 and 2004.

In the data, the picture is mixed. On the one hand, $\alpha(s, n)$ is found to increase 70 times out of 125 pairs of landfalls, meaning that $\alpha(s, n + 1)$ is larger than $\alpha(s, n)$ 70 times and lower 55 times. Vulnerability, therefore, is found to increase more often than to decrease with time. On the other hand, the average value of $Ln[\alpha(s, n + 1)/\alpha(s, n)]$, which measures the relative change in vulnerability, is found to be -0.44, meaning that the vulnerability is, on average, reduced by 36% after each landfall. It seems, therefore, that there is a broad tendency to reduce vulnerability after a landfall occurs. The small amount of data makes it difficult to go further in this direction and it will be necessary to look at detailed case studies to decide whether reconstruction after a hurricane landfall reduces vulnerability or not. However, it seems that vulnerability evolves with time, probably toward a reduction of vulnerability in most but not all cases. This complex evolution makes it very difficult to interpret any trend (or absence of trend) in normalized economic losses (Pielke 2005).

b. Validation

To validate the ability of this method to assess hurricane losses, these vulnerabilities were applied to the synthetic tracks produced for the PC to assess, for each synthetic hurricane that makes landfall, the corresponding economic losses. The mean economic losses are estimated at \$1578 million per landfall and \$980 million per track. These values are slightly less than historical economic records (respectively \$1833 and \$1005 million). The reasons for this discrepancy could be as follows: 1) inaccuracy in the hurricane track and intensity models, 2) the lack of vulnerability data in some place, 3) the role of other factors like rainfall and early warnings, 4) the fact that a county is too large as a geographical unit to assess homogenous vulnerability, and 5) the fact that historical series are only one realization of the random process and that recorded damages differ from mean damages. To assess to which extent the difference is a statistical artifact due to the sampling effect, I calculate the mean damages from the 10 samples of 570 tracks extracted from the PC simulations. The mean damages per track and per landfall are reproduced in Fig. 9. This figure shows that ob-

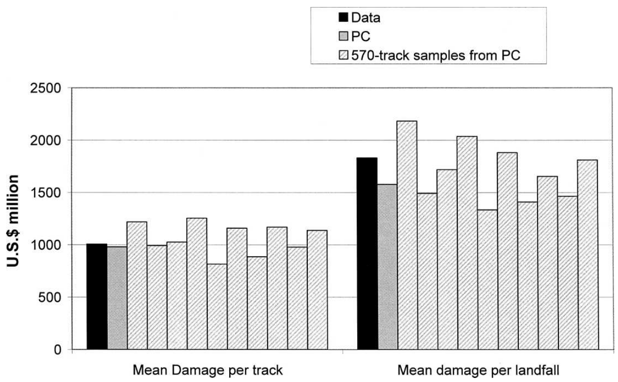

FIG. 9. Mean damage per track and per landfall from historical data, from synthetic tracks generated for the present climate, and from the ten 570-track samples extracted from the PC synthetic tracks.

served damages are within the range predicted by the model.

c. Hurricane damages in a modified climate

The same analysis is carried out with the synthetic tracks produced in a modified climate in which the potential intensity is increased by 10%. Synthetic tracks can be used, because most of the biases of the intensity and track models (like the role of asymmetry and other structural details of the storm, problems in track simulation for weak storms, or systematic biases due to convection parameterizations, etc.) are due to factors that are not expected to change significantly in the future.

When potential intensity is increased by 10%, the mean economic losses are estimated at $2375 million per landfall and $1514 million per track, as compared with $1578 and $980 million for the synthetic tracks in PC. Assuming 1) that the bias in my methodology is unchanged in the future, 2) that no adaptation is undertaken, and 3) that no change in hurricane genesis takes place, a 10% increase in potential intensity is found to cause a 54% increase in the mean normalized economic losses due to hurricane landfall on the U.S. Atlantic and Gulf Coasts. Since observed annual damages from hurricane are currently about $8 billion, such an increase would translate into hurricane losses amounting to, on average, $12 billion per year.

Considering that climate change is expected to make potential intensity increase significantly (Emanuel 2005b), this result suggests the possibility of a large increase in hurricane risks in the future. It has to be mentioned, however, that climate change will also influence other environmental parameters, with various effects (see Emanuel 2006): the expected increase in vertical wind shear could reduce mean hurricane intensity; the expected change in ocean thermal structure may, on the other hand, increase hurricane intensity; and a significant sea level rise would make vulnerability rise in low-lying areas. Also, the change in normalized losses will translate into total economic losses that will depend on other factors like population and asset values in coastal areas and on prevention measures that can be implemented (e.g., land use management, improved building norms, warning and evacuation systems, and flood protection systems).

7. Conclusions

Data on hurricanes are scarce and, until recently, were of poor quality. Even though systematic reanalyses of past hurricanes will bring a welcome improvement (Landsea 2005), there is no way to totally overcome the shortness of historical data series. It is, however, possible to build hurricane models and to use them to learn more about hurricane statistics. This approach was proposed by Emanuel et al. (2006), and has been followed in this paper, using Emanuel's model and the synthetic tracks and intensities it produces. The synthetic tracks and intensities are found consistent with historical landfall locations and strengths, except that weak hurricanes (tropical storms and category-1 hurricanes) make landfall more often than in the real world. Then, joint probabilities of landfall position and power at landfall are calculated. These probabilities, when translated into annual probability of occurrence, provide the information needed for risk management and the design of protection infrastructures.

Such an approach also allows us to assess how climate change might modify hurricane risks. To do so, I used synthetic tracks produced assuming a 10% increase in potential intensity. Landfall probabilities calculated from these modified climate synthetic tracks indicate that all hurricane landfall probabilities increase, and the more powerful the hurricanes, the larger the increase in frequency. The number of regions in which the annual probability of a category-5 hurricane landfall is larger than 1% rises from 2 to 6 (out of 11 regions). As an example, the annual probability of a category-5 hurricane landfall over the New Orleans region would increase from 0.3% to 3%. Overall, the annual probability of a category-5 hurricane landfall on the U.S. Atlantic and Gulf Coasts soars from 7% to 21%, meaning that, if potential intensity increases by 10%, the United States would have to cope with a category-5 hurricane landfall every 5 yr on average.

Translating these changes in probabilities into economic losses is a very tricky task. A rough assessment can be carried out, however, based on past hurricane damages. To do so, I calibrated, over each county of the U.S. Atlantic and Gulf Coasts, a simple relationship linking the maximum wind speed of hurricanes and the economic losses they generated, normalized to remove the influence of population and economic growth. Using this relationship, a 10% increase in potential intensity is found to cause a 54% increase in annual direct economic losses due to hurricane landfall on the U.S. Atlantic and Gulf Coasts. If genesis is unchanged, it would make annual mean economic losses from hurricanes on the U.S. Atlantic and Gulf Coasts rise from about $8 billion per year today to about $12 billion per year.

This estimate is only a first insight into the influence of climate change on hurricane risk, for at least two reasons. First, there are large uncertainties related to climate change: its influence on potential intensity is not fully understood yet; it will cause other environmental changes that will also influence hurricanes; and the response of hurricanes to these changes is still disputed. These uncertainties are illustrated by the differences in predictions by, among numerous others, Suji et al. (2002), Knutson and Tuleya (2004), Chauvin et al. (2006), and Emanuel (2006).

Second, the vulnerability data used to calibrate the damage function are very uncertain, and could be improved using geographic data (e.g., assessing the influence of local elevation and value at risk on vulnerability). The method proposed by this paper, however, is a first step and suggests the possibility of a large increase in hurricane risk, when compared with previous estimates that suggested only moderate increases in hurricane damages (e.g., Cline 1992; Fankhauser 1995; Tol 1995; Nordhaus 2006).

It is likely that population change, economic growth, and asset location will remain the main drivers of hurricane losses in the future (e.g., Pielke et al. 2008). This does not mean, however, that the increase in hurricane risk due to climate change can be neglected in the analysis of climate policies. In particular, according to my results, additional hurricane damages due to climate change may be a noticeable component of the total climate change cost and significant relative to mitigation costs.[3] It is, therefore, necessary to take hurricane risk into account when assessing the benefits of climate policies.

The 54% increase of hurricane direct economic losses found in this study hides another important component of hurricane damages. Indeed, as shown in Pielke and Pielke (1997), RMS (2005), Hallegatte et al. (2007), or Hallegatte (2006), total socioeconomic damages (including indirect impacts) can be much larger than direct losses. Indirect impacts are in fact highly nonlinear and involve a large set of complex processes like indirect economic impacts (demand surge, losses in tax revenues, losses of wages, reconstruction delays, etc.); lost lives and injuries; and economic and social destabilization. Some additional research is necessary to understand these indirect impacts and to assess how local economies would react to a 54% increase in annual direct hurricane losses.

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[3] For instance, Tulkens and Tulkens (2006) summarize the results from 20 different models, which estimate as between $0 and $240 billion per year the cost of respecting the Kyoto protocol in the United States.

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