Normalized US hurricane damage estimates using area of total destruction, 1900−2018

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Hurricanes are the most destructive natural disasters in the United States. The record of economic damage from hurricanes shows a steep positive trend dominated by increases in wealth. It is necessary to account for temporal changes in exposed wealth, in a process called normalization, before we can compare the destructiveness of recorded damaging storms from different areas and at different times. Atmospheric models predict major hurricanes to get more intense as Earth warms, and we expect this trend to eventually emerge above the natural variability in the record of normalized damage. However, the evidence for an increasing trend in normalized damage since 1900 has been controversial. In this study, we develop a record of normalized damage since 1900 based on an equivalent area of total destruction. Here, we show that this record has an improved signal-to-noise ratio over earlier normalization schemes based on calculations of present-day economic damage. Our data reveal an emergent positive trend in damage, which we attribute to a detectable change in extreme storms due to global warming. Moreover, we show that this increasing trend in damage can also be exposed in existing normalized damage records by looking at the frequency of the largest damage events. Our record of normalized damage, framed in terms of an equivalent area of total destruction, is a more reliable measure for climate-related changes in extreme weather, and can be used for better risk assessments on hurricane disasters.

hurricane | damage | tropical cyclone | loss | normalization

Hurricanes are the costliest natural disasters in the United States (1). The damage costs from Hurricane Katrina have been estimated to be $125 billion (2), which was 1% of gross domestic product (GDP) for the entire United States in 2005 (3). A better understanding of hurricane-related damage and its costs over time is clearly of immense societal importance.

Climate model projections of near-term and future warming scenarios indicate an increasing intensity of hurricanes in the North Atlantic with medium confidence (4), and that the most intense hurricanes will become more frequent and even intensify further (5–8). Damage has a nonlinear relationship with hurricane intensity (9–12), and total damage has been dominated by the most extreme events. By simple extrapolation, we therefore expect an increasing trend in hurricane damage to eventually emerge in the records. However, a trend may be difficult to discern with any statistical confidence, because damage is dominated by only a few particularly intense hurricanes.

The economic damage from tropical storms over the last century shows a rapid increase, but most of that increase can be attributed to increased wealth exposure. We cannot directly compare the damage from the 1926 Great Miami hurricane with that from Hurricane Irma in 2017 without considering the increased amount of valuable property exposed. The loss record must be "normalized" in order to make past events comparable to the present. Pielke and Landsea (13) pioneered the use of "loss normalization" on hurricane damage. They found that the trend in damage disappears after normalization and concluded that the apparent rising losses were entirely due to changes in society. This conclusion has been challenged on statistical grounds because it relies on a simple least-squares trend of highly skewed nonnormal data (14). Some authors have found no evidence for a trend in normalized damages (12, 15, 16), whereas other authors find an increasing trend (14, 17).

Traditional normalization schemes (13, 15, 16) do not attempt to account for changes in vulnerability, which would result in reduced losses from protection measures, stricter building codes, and other adaptations. Several recent studies attempt to address this by allowing for losses having an elasticity with wealth or population (14, 17–20). However, the resulting elasticities of these studies are contradictory, suggesting that this approach is highly uncertain.

In this paper, we foster a normalization technique framing losses in terms of a more physically appreciable quantity: an equivalent area of total destruction (ATD). This approach accounts for increases in wealth, population, and spatial differences in exposure. Our approach, however, still does not account for changes in vulnerability, and this must be kept in mind when assessing long-term trends.

Methods

We aim at normalizing economic base damage (B_i) to adjust for change in exposure that has happened since the time of hurricane landfall (t_i). The conventional approach to damage normalization (2, 13, 15, 16) adjusts for change in wealth (W). We write the normalized damage (ND) as

$$\begin{aligned}\mathrm{ND}_i &= B_i\frac{W(t_{now},\Omega_i)}{W(t_i,\Omega_i)} = B_i\frac{\mathrm{WPC}(t_{now})/I(t_{now})}{\mathrm{WPC}(t_i)/I(t_i)}\frac{I(t_{now})}{I(t_i)}\frac{P(t_{now},\Omega_i)}{P(t_i,\Omega_i)}\\ &= B_i\frac{\mathrm{WPC}(t_{now})}{\mathrm{WPC}(t_i)}\frac{P(t_{now},\Omega_i)}{P(t_i,\Omega_i)},\end{aligned}$$

where I is an inflation adjustment, WPC is wealth per capita, and P is the population in the region Ω_i considered to be local to the ith landfall. This normalization scheme adjusts damage with the ratio of change in estimated local wealth ($W = \mathrm{WPC}\cdot P$), and thus aims at quantifying how much damage the same hurricane would cause today.

Neumayer and Barthel (21) noted that a problem with the conventional normalization scheme is that it adjusts for temporal changes in wealth, but

Significance

We present an approach to normalize hurricane damage, where damage is framed in terms of an equivalent area of total destruction. This has some advantages over customary normalization schemes, and we demonstrate that our record has reduced variance and correlates marginally better with wind speeds and pressure. That is, it allows us to better address climatic trends. We find that hurricanes are indeed becoming more damaging. The frequency of the very most damaging hurricanes has increased at a rate of 330% per century.

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fails to adjust for spatial differences. The concentration of wealth varies substantially between rural and urban areas. This led them to design a different normalization scheme where they calculate an actual-to-potential-loss ratio (APLR),

$$\mathrm{APLR}_i = \frac{B_i}{W(t_i, \Omega_i)},$$

where W is the estimated wealth in the region Ω_i. The advantage of this scheme is that it accounts for an additional stochastic source of variance related to the location of landfall (21). APLR adjusts for levels of exposed wealth across time and space, whereas the conventional approach only accounts for the temporal changes in exposed wealth.

In this paper, we build upon the Neumayer and Barthel (21) methodology but frame the results in terms of an equivalent ATD. We calculate ATD_i by multiplying APLR with the area of the exposed region Ω_i. We write

$$\mathrm{ATD}_i = \frac{\mathrm{Area}(\Omega_i) \cdot B_i}{W(t_i, \Omega_i)},$$

such that the area of destruction is normalized by the actual-to-potential-loss ratio. By framing the damage in terms of an area, we make the normalization more robust to how the region Ω_i is defined.

There is no unique way to define the region Ω_i, and different authors have used different approaches. Regional wealth will scale roughly with the areal extent of the region considered. Pielke et al. (15) chose Ω_i as the affected counties reported by the National Oceanic and Atmospheric Administration Coastal Services Center, which may vary substantially in size between events. ND is robust to these differences in areal extent, as these differences would tend to cancel out in the wealth ratio. Neumayer and Barthel (21) realized that the APLR scales with area, and that it is necessary to consistently use the same area to ensure that the most destructive hurricanes, with a large regional impact, is rated with a higher APLR than those of less destructive events. They used a 100 km × 100 km square centered at the landfall location. Our ATD normalization approach combines the most desirable properties of the 2 other normalizations as it adjusts for geographic wealth variations as in APLR, but still allows us to use the actual region of exposure for each event as in ND. Now, we could define Ω based on the estimated wind field, when data are available (as in ref. 22), or we could define it from the area that contributed to losses for each event. Our objective is to construct an independent record that can be compared to storm characteristics data such as wind speed, and therefore we cannot impose correlations by including the same data in our normalization. We therefore let the region depend only on the landfall location. Here, we simply define Ω to be the 10,000-km^2 land-covered area nearest the location of landfall. We motivate this choice by the typical spatial scale of the hurricane-force wind field of major hurricanes, and by considering maps of destruction for recent large events.

All 3 normalization schemes (ND, APLR, and ATD) rely on an estimate of the regional wealth. Ideally, the measure of wealth should be in the same form as the reported base damage. If B is purely insured losses, then it would preferable that W was purely based on insured stock at risk. In this paper, we have to make do with available data, which are limited for the early part of the record. We follow Pielke and Landsea (13), and approximate regional wealth by assuming that national wealth is distributed according to population density. We express this as follows:

$$W(t, \Omega) = \mathrm{WPC}(t) \cdot P(t, \Omega).$$

The specific datasets used for WPC and P are presented in *Data*. With this approximation, ATD becomes inversely proportional to the average population density within the region, which is relatively constant even for large changes in the size of Ω. A step by step summary of our implementation of the ATD normalization scheme is outlined in *SI Appendix*.

All 3 normalizations adjust damage for temporal variability in wealth. We therefore expect the normalized data to have a reduced spread compared to the original base damage. A more useful normalization would account for more of the variance. We also know that there is a relationship between pressure, wind speed, and damage. We therefore use these considerations to gauge the usefulness of different normalizations. A "better" normalization will tend to have reduced spread and a more evident relationship between wind speed and damage. These 3 measures of normalized damage are close to log-normally distributed (e.g., ref. 23); we therefore quantify the spread from the variance of the logarithm of the normalized damage records. Authors have proposed both power-law relationships (10–12) and exponential relationships (9) between wind speed and damage. Therefore, we use the Spearman rank correlation coefficient as a clarity measure of the wind–damage relationship.

We estimate trends in the normalized data using several methods. We use ordinary least squares (OLS) linear regression on annually aggregated values (13, 15, 16). We estimate the statistical significance and confidence intervals using a standard bootstrap method (24). OLS regression is somewhat problematic on highly skewed data (14), as a few extreme events will dominate the fit. Estrada et al. (14) used Box–Cox regression to address the skewness problem, where the residual misfit is evaluated in a transformed space that is closer to normal. Unfortunately, the damage record misses some minor events in the early part of the twentieth century (25), which clearly will introduce a bias in trend estimates. The OLS fits, on the other hand, are largely unaffected by missing minor storms, as the residual sum of squares will be dominated by major events. Box–Cox regression would, by design, allow minor storms to have more influence on the trend, and would therefore be more affected by this bias. As an alternative method for estimating the trend, we examine the frequency of hurricane events above a damage threshold. We estimate the trend in annual count data using Poisson regression. This approach is insensitive to the shape of the distribution, and, by choosing a sufficiently high threshold, at the expense of diluting the data, we can exclude the records of the smallest storms where frequencies may have been biased by missing events (25).

Data. The direct economic damages from tropical storms making landfall in the United States have historically been published in *Monthly Weather Review* articles reported in current dollars (26). In more recent decades, damage has been estimated using private insurance losses, and the flood losses from the National Flood Insurance Program (26). These *base damage* estimates for all tropical storms since 1900 have been compiled by Pielke et al. (15), and updated by the ICAT catastrophe insurance company (2). We use the ICAT dataset for the base damage record. The database is missing records for some minor landfalling hurricanes in the early part of the twentieth century, but should be complete with respect to the most damaging events (25). The ICAT dataset also holds the Normalized Damage following the Pielke et al. (15) approach, and we will use this for comparison to our dataset. Two events in the ICAT dataset have zero normalized damage, which we interpret to be due to truncation errors. These events are excluded from the analysis. One concern with all normalization methods is that the base damage dataset is not homogeneous throughout time. To assess the robustness, we also apply the ATD normalization to 2 other datasets in *SI Appendix*: the Weinkle et al. (16) dataset, and the US Billion-Dollar Weather and Climate Disasters dataset (27).

The US population distribution is taken from Fang and Jawitz (28). This dataset contains 1-km^2 decadal population maps for the conterminous United States from 1790 to 2010 using parsimonious models based on natural suitability, socioeconomic desirability, and inhabitability. We use their most detailed model, as this accounts for socioeconomic desirability and its relative importance, which are factors we judge to be particularly useful near the coast.

We follow Pielke et al. (15) and use the Current-Cost Net Stock of Fixed Assets and Consumer Durable Goods (29) as an estimate of national wealth. This record spans from 1925 to 2015. The wealth record shows a close correspondence with the Nominal GDP from Johnston and Williamson (3). We therefore use a scaled version of the Nominal GDP to estimate wealth prior to 1925 and after 2015 (Fig. 1). We divide wealth with the total population to obtain WPC.

Each damage record is linked to the corresponding storm track in the International Best Track Archive for Climate Stewardship (IBTrACS; ref. 30). We extract the US landfall positions as the track location nearest the coast line on the landfall date. IBTrACS also provides additional weather data such as the wind speed and pressure at landfall.

Results

We have calculated the ATD for all events in the ICAT dataset (Dataset S1). We ranked the events according to ATD, and a subset of the most damaging events is shown in Table 1. The hurricanes with the greatest ATD are Katrina (2005) and Harvey (2017), which both resulted in an ATD greater than 5,000 km^2. The ATD normalization has a reduced spread relative to the ND normalization (Table 2), and marginally higher rank correlation with wind speeds than ND (Table 2).

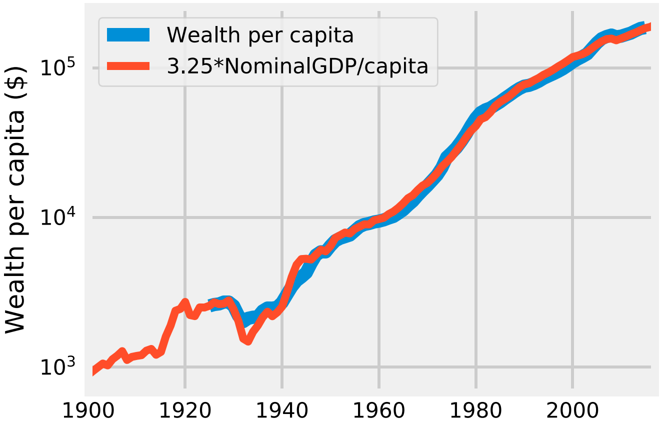

Fig. 1. WPC derived from the Current-Cost Net Stock of Fixed Assets and Consumer Durable Goods (29) compared to the scaled Nominal GDP per capita from Johnston and Williamson (3) which we use to extend WPC.

We aggregate normalized damage by year in Fig. 2 *A* and *B*. Using bootstrapping, we find a significant positive trend in ATD of 1,093 km^2 per century ($P < 0.01$) (Fig. 2*A* and Table 2). Regional variability in wealth will tend to mask any potential signal, and we find that the positive trend is obscured and not statistically significant in ND (Table 2; $P = 0.23$). The positive trend is more clear in the frequency of events above a threshold, regardless of what threshold is chosen (Fig. 2 *C* and *D*). We observe that the frequency plots of ND and ATD appear visually similar (Fig. 2 *C* and *D*). There is an increasing trend in the frequency for all magnitudes ranging from 1.3× to 3.2× per century, with the largest trends associated with the most-damaging storms.

Discussion

We hypothesized that the ATD should have smaller spread than the ND normalization, as it adjusts for the additional source of variance associated with the spatial differences in wealth. We find that this is indeed the case. The difference in variance is 0.46, which we note is 29% of the present day's spatial variance in regional wealth [$var(\log(W(t_{now}, \Omega_i))) = 1.59$]. The reduction in variance is a substantial improvement, as 2σ corresponds to a factor 2.5 change. By removing the stochastic component associated with a rural vs. urban landfall, we have increased the chances of exposing signals in the noise. This is demonstrated by the improved rank correlation with both wind speed and pressure (Table 2).

It is of great concern whether there is an increasing trend in hurricane damage. Pielke and coworkers (13, 15, 16) report that there is no trend in conventionally normalized damage. The ATD exposes an emergent positive trend in hurricane damage which was hidden in the spatial "noise" of the ND (Fig. 2 and Table 2). The observed increasing trend in hurricane damage seen in ATD is consistent with our expectations that the major hurricanes will become stronger in a warming climate. We have some doubts about using OLS on highly skewed data but have used it here to facilitate comparison with published literature. An alternative method is to look at the frequency of damage events above a threshold. We find positive trends for all magnitudes in both ND and ATD, and most are significant (Fig. 2 *C* and *D*). A few minor events may be missing in the earliest part of the record which will bias the frequency trends for small magnitudes. Pielke (25) argues that no moderate storms with ND > $1 billion are missing in the entire record, and here we correspondingly argue that no events with ATD > 50 km^2 are missing. We therefore disregard the frequency trend estimates below these thresholds. The most damaging storms have been increasing by a factor of 3.3% per century, whereas moderate storms have been only been increasing at a rate of 1.4× per century (Fig. 2*C*). This pattern is consistent with modeling which finds that warming is associated with more-frequent and even stronger major hurricanes in the Atlantic (4–8). This conclusion is robust to the choice of input dataset (*SI Appendix*).

The similarity between the frequency plots for ND and ATD may be surprising considering the reduced spatial noise in the ATD record. However, hurricane damage events span several orders of magnitude, which means that multiplicative errors can be quite high without causing large reshuffling in the ranking of events. This also means that the frequency plots like those in Fig. 2 *C* and *D* are robust with respect to changes in normalization.

Table 1. The 20 storms with the greatest ATD

Storm	Landfall date	Base damage (Mill. USD)	ND (Mill. USD$_{2018}$)	ATD (km^2)
Harvey	2017 Aug 26	125,000	132,690	11,835
Katrina	2005 Aug 29	125,000	148,240	7,621
Great Miami	1926 Sep 18	76	242,750	3,931
Carla	1961 Sep 11	325	22,270	3,728
Galveston	1900 Sep 09	30	171,510	2,826
Rita	2005 Sep 24	18,500	23,110	2,697
Storm 2 in 1919	1919 Sep 14	20	18,460	2,387
Storm 7 in 1948	1948 Sep 22	12	5,890	2,329
Irma	2017 Sep 10	50,000	52,970	2,315
Galveston	1915 Aug 17	50	121,200	2,215
Hazel	1954 Oct 15	281	36,450	2,069
Irene	2011 Aug 27	13,500	17,160	1,925
Wilma	2005 Oct 24	19,000	33,410	1,825
Isabel	2003 Sep 18	5,500	11,010	1,804
Lake Okeechobee	1928 Sep 17	25	63,830	1,799
Hugo	1989 Sep 22	7,000	27,430	1,781
Ivan	2004 Sep 16	20,500	36,910	1,689
Betsy	1965 Sep 10	1,281	17,750	1,633
Opal	1995 Oct 04	4,700	16,510	1,489
Floyd	1999 Sep 16	6,500	16,030	1,418

The full dataset can be found in Dataset S1. Mill. USD, million US dollars.

Table 2. Summary statistics of ATD and ND_{ICAT}

	Period	ATD	ND_{ICAT}
var(log(·))	Full	5.88	6.34
C(·,wind)	Full	0.63	0.62
C(·,pressure)	Full	−0.68	−0.68
C(·,wind)	1980–2018	0.63	0.60
C(·,pressure)	1980–2018	−0.70	−0.67
OLS trend	Full	1,093 km^2/cen	$8 billion/cen
(Fig. 2 *A* and *B*)		(459 to 1,757)	(−10 to 26)

ATD correlates slightly better with wind and pressure at landfall than ND, and has reduced variance. The spearman rank correlation is denoted with C. Ranges are 5 to 95% uncertainties from bootstrapping; cen, century.

Conclusion

We have developed a normalization scheme for hurricane losses based on the concept of an equivalent ATD (Fig. 2). Contrary to the conventional ND, this ATD normalization adjusts for spatial variability in wealth. This leads to reduced scatter in the normalized series, and slightly improved correlations with winds (Table 2). The reduced noise exposes an increasing trend in ATD that was otherwise barely detectable in ND using OLS on annually aggregated data (Fig. 2 *A* and *B* and Table 2). The increasing trend is even more evident when using a more appropriate statistical method which is insensitive to the skewness of the distribution (Fig. 2 *C* and *D*). We avoid statistical challenges associated with missing small events, and the highly skewed distribution, by examining the frequency of events above a range of thresholds. The rate of major damage events is increasing significantly in both ATD and ND (Fig. 2 *C* and *D*). There is evidence that the proportion of strong hurricanes has increased (8, 31). This is also consistent with numerical modeling simulations, which generally indicate an increase in mean hurricane peak intensity and the frequency of very intense hurricanes in a warming world (32–34). Furthermore, projected changes in hurricane tracks or hurricane areas of occurrence show some related features, most pronounced in the western North Pacific (34). Some studies project either poleward or eastward expansion of hurricane occurrence (7). A poleward expansion of the latitude of maximum hurricane intensity is consistent with the detected observed signals (35, 36) and with a Hadley circulation expansion (37).

In accordance, we find that the frequency of the most damaging storms is increasing at a higher rate than that of moderately damaging storms (Fig. 2 *C* and *D*). This conclusion is robust to alternative base damages data (*SI Appendix*). The increasing rate of the strongest storms is statistically significant. We find that our approach is very robust to details of the normalization scheme, as is evident from the similarity between Fig. 2 *C* and *D*.

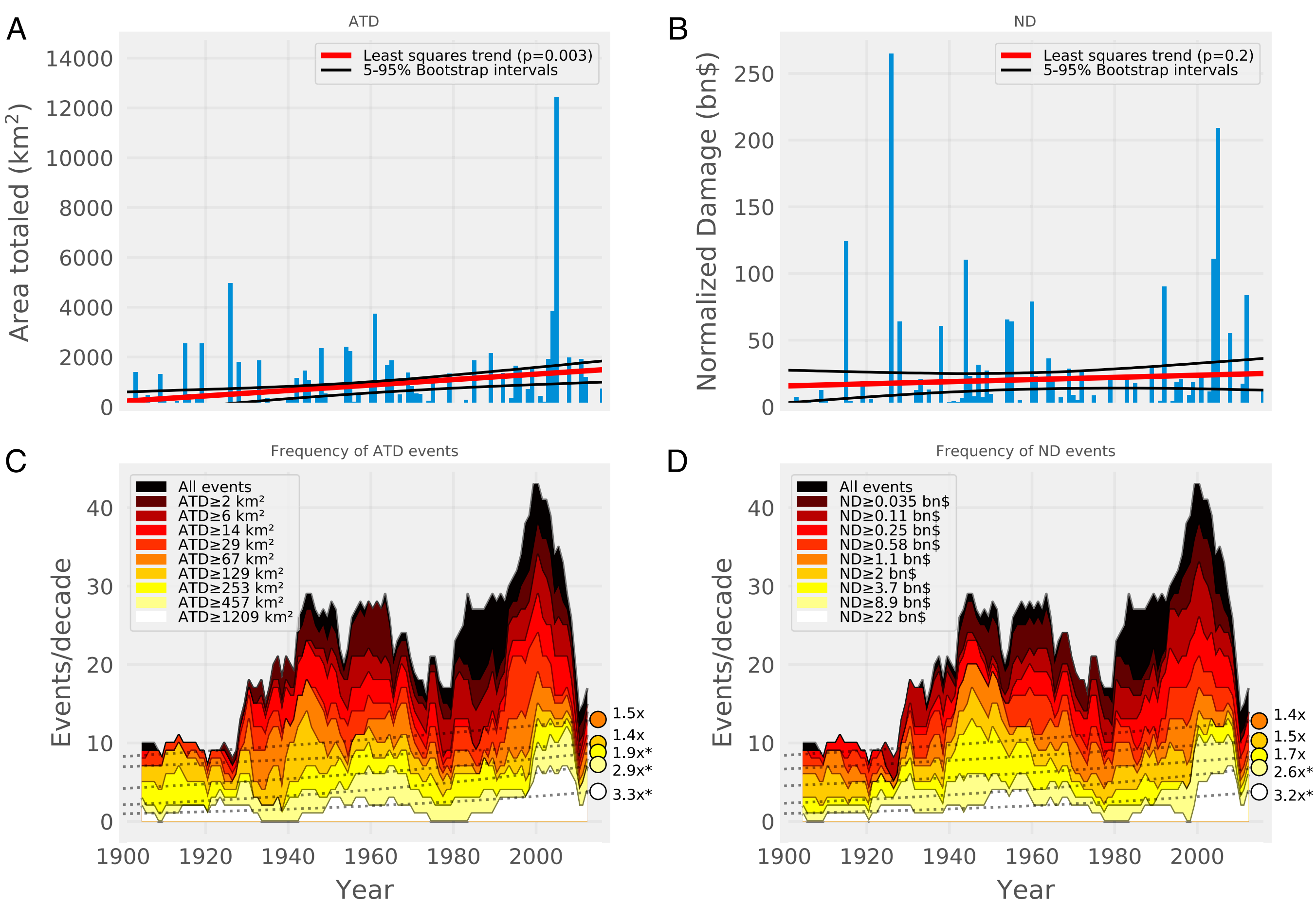

Fig. 2. Comparison of hurricane losses normalized using 2 different normalization techniques. (*A*) ATD, losses framed as an ATD. (*B*) ND, conventional normalized damage from ICAT. Red shows the OLS linear trends of the data; bn, billion. (*C* and *D*) The corresponding decadal frequency of normalized damage events above different thresholds for (*C*) ATD and (*D*) ND. Dotted lines show trend in frequency from Poisson regression. The relative frequency increase per century is shown as numbers on the right. Asterisks indicate the trend is significantly greater than one ($P < 0.05$).

We note that the framing of damage in terms of an equivalent ATD is transferable to other types of natural disasters. This adjusts damage for temporal and spatial changes in wealth. The ATD does not adjust for changes in vulnerability, which therefore has to be considered separately.

We acknowledge that the ATD could be further refined by explicitly considering the size of the wind field of the individual hurricanes when choosing the exposed region (see, e.g., ref. 20). The estimated regional wealth can also be modeled in more detail rather than using a single country-wide estimate of wealth per capita. In this paper, however, we have clearly been limited by the available data in the early 20th century.

Data Availability. The damage data are available in Dataset S1.

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