Trends in U.S. Atlantic Tropical Cyclone Damage, 1900–2022

H. E. WILLOUGHBY,[a] J. I. HERNANDEZ,[a] AND ANDREW PINNOCK[b]

[a] Florida International University, Miami, Florida
[b] Broward County Environmental Monitoring Laboratory, Davie, Florida

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ABSTRACT: A series of papers published since 1998 assert that U.S. tropical cyclone (TC) damage, when "normalized" for individual wealth, population, and inflation, exhibits no increase attributable to anthropogenic global warming (AGW). This result is here questioned for three reasons: 1) The then-year (no demographic or economic adjustments) U.S. TC damage increases 2.5% yr^{-1} faster than U.S. then-year gross domestic product. This result, which is substantially due to the faster growth of assets in hurricane-prone states, shows that TC impacts on the total U.S. economy double every generation. 2) Fitting of an exponential curve to normalized damage binned by 5-yr "pentads" yields a growth rate of 1.06% yr^{-1} since 1900, although causes besides AGW may contribute. 3) During the twenty-first century, when the Atlantic multidecadal oscillation (AMO) was in its warm phase, the most damaging U.S. TCs struck at twice the rate of the warm AMO of the twentieth century and 4 times the rate of the entire twentieth century, both warm and cool AMO phases. A key unanswered question is as follows: What will happen when (and if) the AMO returns to its cool phase later in this century?

SIGNIFICANCE STATEMENT: U.S. hurricane damage, normalized for changes in inflation, population, and wealth, increases by approximately 1% yr^{-1}. For 1900–2022, 1% yr^{-1} is equivalent to a factor of >3 increase, substantially but not entirely, attributable to climate change. The incidence of the most damaging tropical cyclones (TCs) approximately doubled in the twenty-first century compared with climatologically analogous periods of the twentieth century. These results contradict the previously published work that introduced normalization and found zero trend in normalized damage but are consistent with physical reasoning and modeling studies.

KEYWORDS: Hurricanes/typhoons; Trends; Damage assessment; History

1. Introduction

Hurricane Irma of 2017 (Fig. 1) had 59 m s^{-1} (115 kt; 1 kt $\approx$ 0.51 m s^{-1}) winds as it approached Cudjoe Key, Florida, on its way to a second U.S. landfall at Marco Island (Cangialosi et al. 2021). It subsequently moved inland, northward, parallel to the west coast of the peninsula, and weakened before ultimate dissipation over the Mississippi Valley. Earlier, before landfall in Cuba, it had sustained two episodes of winds > 70 m s^{-1} (140 kt) for a total of almost 3 days. Irma, along with other recent category 5 hurricanes (e.g., Maria 2 weeks later, Michael of 2018, and Dorian of 2019), raises the questions: Are tropical cyclones (TCs) in the Western Hemisphere becoming more threatening? If so, are they causing a detectable increase in U.S. damage? Can this increase be attributed to anthropogenic global warming (AGW)?

The primary destructive or lethal weather elements in landfalling TCs are wind, inland flooding, and coastal storm surge. Their relative roles are treated in more detail below. It is generally conjectured that TCs have become more threatening as Earth has warmed since 1900. The financial records of U.S. damage are less definitive because of diverse provenance, large dynamic range, and changes due to inflation, increasing population, and growing per capita wealth. Indeed, there is a substantial argument that, normalized for economic factors, U.S. hurricane damage has remained constant (e.g., Weinkle et al. 2018; hereafter WK18).

The counterargument begins with the observation that a moist adiabatic originating in the TC boundary layer produces TCs' low hydrostatic surface pressures (Holland 1997; Miller 1958) and that the tropical seas are warming both at the surface and throughout the oceanic mixed layer. These results were confirmed and extended by the theoretical insight that hurricanes are classical heat engines operating between a warm reservoir at the sea surface and a cold reservoir at the tropopause (Emanuel 1986, 1988, 2005). The effects of warming seas are often limited by the upwelling of cold water from below the thermocline, environmental wind shear, eyewall replacements, or too-short storm life cycle duration. Thus, thermodynamic models define the minimum central pressure attainable for preexisting thermodynamic conditions. At any given time, the minimum pressure will be greater than or equal to this minimum. The thermodynamic theories are the basis for the expectation that AGW will cause more severe hurricane impacts. This view is broadly consistent with published meteorological or climatological assessments of the peril (e.g., Emanuel 2005, 2008, 2017, 2021a,b; Webster et al. 2005; Patricola and Wehner 2018; Knutson et al. 2019, 2020; Walsh et al. 2019; Guzman and Jiang 2021; Zhu et al. 2021). There remain, however, emphatic exceptions to this consensus (e.g., Landsea 2005; Pielke 2005; Maue 2011).

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Corresponding author: Hugh Willoughby, willough@fiu.edu

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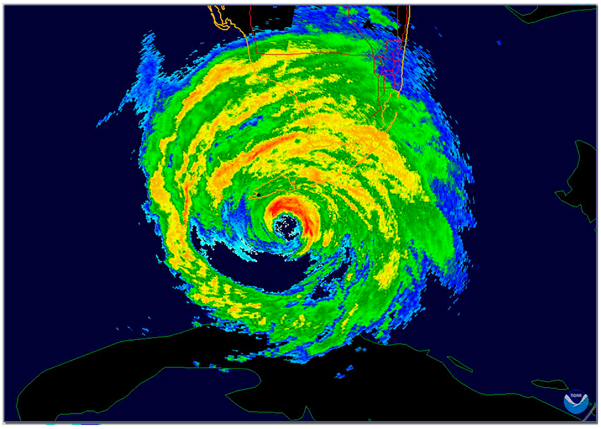

FIG. 1. WSR-88D radar image from the National Weather Service's Key West Forecast Office. It shows Hurricane Irma as it approached the Florida Keys at 1004 UTC 10 Sep 2017. At landfall, Irma's maximum wind was 115 kt or 59 m s^{-1}. In total, Irma caused \$50B in U.S. nominal damage (NOAA/NWS image).

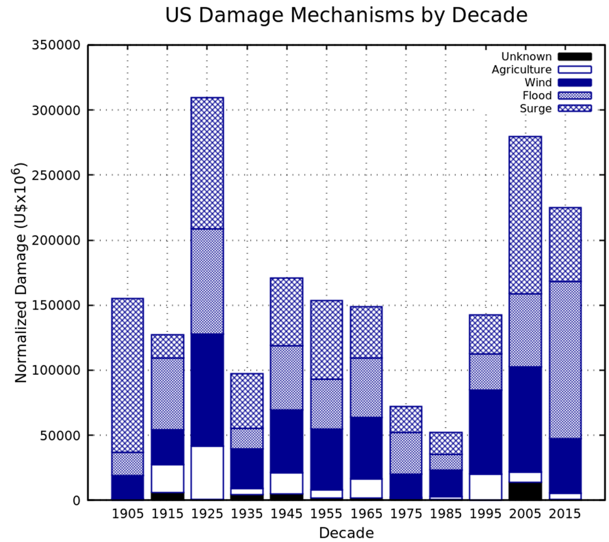

FIG. 2. Causes of U.S. normalized TC damage in millions of dollars aggregated by decade. Years on the abscissa are the midpoints of the decadal intervals.

Economic normalization (WK18; Pielke and Landsea 1998, 1999; Pielke et al. 2008; hereafter PL98; PL99; PA08) approximates the contemporary cost of past damaging TCs. The normalized damage D_N is calculated by adjusting the cost of the damage when it occurred D_Y (in economic jargon the "nominal" or "then-year" damage) for inflation I_{NY}, changes in local county-level population P_{NY}, and changes in nominal, national per capita real wealth W_{NY} between the year when the storm occurred and the reference year:

$$D_N = I_{NY} P_{NY} W_{NY} D_Y.$$

The term D_N approximates past TCs' cost if they had made landfall in a recent reference year for all damaging U.S. TCs since 1900. Normalization provides valuable insight into the decadal-to-century-scale variations of the hurricane peril.

This paper seeks to verify or refute the idea that AGW has no effect on normalized TC damage. It addresses the following topics: Section 2 discusses causes of TC damage, growth of the U.S. national economy, population growth of hurricane-prone states, and environmental factors other than AGW that influence Atlantic TC climatology. Section 3 treats the normalized damage dataset, its history, and its application. Section 4 adds the 2018–22 to the original dataset from contemporary sources. Section 5 analyzes then-year and normalized TC damage data to reveal century-scale trends. Section 6 treats the occurrence of the most destructive TCs to reveal a possible tipping point near the turn of the twenty-first century. Section 7 summarizes the results.

2. Context

a. Causes of TC damage

Figure 2 shows the estimates of causes of TC-related damage in the United States (1900–2017) by decade based on normalized damage (WK18) and online individual storm or seasonal reports (AOML and NOAA 2022). Of necessity, the estimates are subjective. The effects of wind and freshwater flooding are roughly equal (27% and 28% of the 118 year total); storm surge is somewhat greater than either (35% of the total); and there are much smaller contributions from agricultural and unknown losses (8% and 2%). The theoretical and modeling links between AGW and increasing wind, freshwater flooding, and storm surge are easier to establish than the connection between AGW and the cost of damage.

b. Growth of the U.S. economy

U.S. nominal gross domestic product (GDP) from 1900 to 2022 provides perspective into hurricane impacts relative to the size of the U.S. economy (Fig. 3; data from Williamson 2024). Annual U.S. nominal GDP measures the dollars paid for all "final use" goods and services within the United States during a given year. At the risk of repetition, "nominal GDP" means that there is no correction for inflation and is not per capita. It represents the total prices paid at the contemporary value of the currency (e.g., Krugman and Wells 2013). It measures economic activity, not accumulated wealth or real-estate values. It also measures resources available to repair TC damage at the time it occurred. The semilogarithmic plot in Fig. 3 shows that nominal GDP grew at an average rate of 6.45% yr^{-1}. This plot represents a least squares fit to the logarithm of GDP. In statistical terminology, it is the "minimum-variance unbiased estimator" for both the slope and the intercept. By way of comparison with an economist's determination, it does not start in a base year (in this case 1900) and apply percentage changes. Here, the intercept is the logarithmic geometric mean GDP and mean year. As a result, the curve starts below the observed GDP data in the prosperous early twentieth century and grows somewhat faster than the usually cited century-scale value (~6%), but it

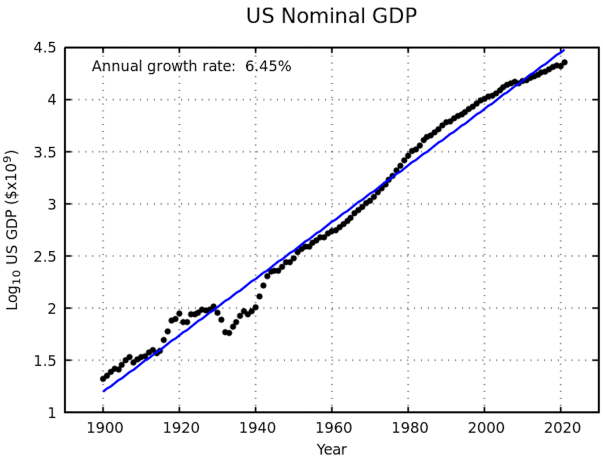

FIG. 3. Common logarithm of the U.S. nominal GDP plotted as a function of years 1900–2022 and fitted with a 6.45% annual rate trend line.

follows the data more closely throughout the 1900–2022 interval because it has 2 degrees of freedom instead of one.

The actual GDP grew faster than the century-scale mean rate in the prosperous years before 1929, decreased—because of deflation and declining real productivity (Galbraith 1972)—during the Great Depression (1929–39), then fluctuated about the mean trend—somewhat slower in the immediate post-World War II years, then faster than the century-scale mean (1960–70), about the same rate (1980–2000), and somewhat slower in the twenty-first century. Here, the interest is in changes on the multidecadal-to-century time scale. Since the exponential growth of a quantity is proportional to the quantity itself, we can use GDP as a proxy, albeit an imperfect one, for the growth of total U.S. wealth. To be sure, taking logarithms minimizes substantial fluctuations, but to a first approximation, GDP grew at a rate of 6.45% yr^{-1} between 1900 and 2022, with a doubling time of 11.1 yr.

c. Populations of hurricane-prone states

A key factor in the normalization is population. Figure 4 uses the 1900–2020 decadal census data to analyze population growth rates for Atlantic and Gulf of Mexico coastal states. All population figures are expressed as multiples or fractions of the states' populations in the 1960 census. The population of the entire U.S. grew at a rate of 1.35% yr^{-1} or a factor of 4.34, 1900–2020. The two most rapidly growing states were Florida (3.43% yr^{-1} or a factor of 40.7 since 1900) and Texas (2.07% yr^{-1} or a factor of 9.6). These figures contrast with the mid-Atlantic states (Georgia, South Carolina, North Carolina, Virginia, Maryland, and Delaware), which grew somewhat faster than the national figure (~1.5% yr^{-1} or a factor of 4.5–5), and the northern Gulf of Mexico (Louisiana, Alabama, and Mississippi) and northeastern Atlantic coastal states (New Jersey, New York, Connecticut, and Massachusetts), which generally grew at rates comparable to or somewhat slower than the national figures (~1% yr^{-1} or a factor of <4). Since, for example, six of the 10 most destructive TCs of the twentieth century

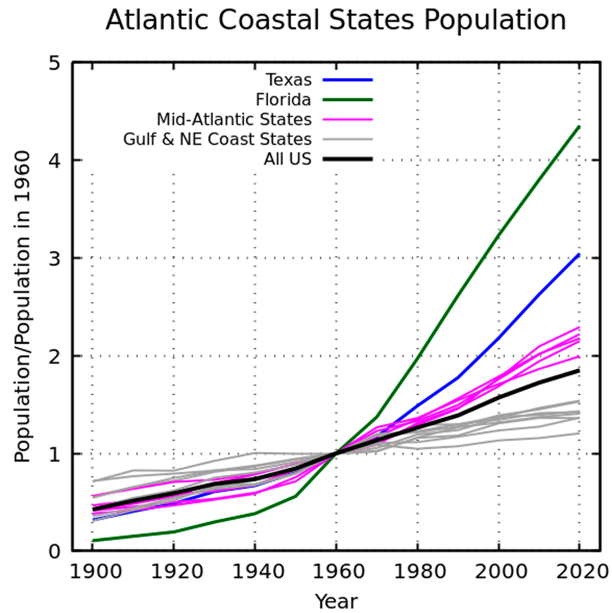

FIG. 4. Populations of Atlantic and Gulf of Mexico coastal states, 1900–2020, scaled by their values in 1960.

struck Florida or Texas, which had by far the greatest population growth, this effect is at least partially responsible for the large growth of nominal damage since the early twentieth century.

d. Factors affecting TC occurrence

In the early twentieth century, Earth's surface temperature increased by 0.3°C and then declined slightly between 1940 and 1970. After 1970, it increased by another 0.7°–0.8°C above the midtwentieth-century mean (Hansen et al. 2010; Lindsey and Dahlman 2023). Thus, one might naively expect TC activity to increase monotonically, at least after 1970. One explanation for why it does not is El Niño (Gray 1984; Pielke and Landsea 1999; Klotzbach 2011) in which an equatorial Kelvin wave (Matsuno 1966) warms the eastern Pacific Ocean, causing increased vertical wind shear over the tropical Atlantic and suppression of hurricanes on a time scale of 1–3 years. Indeed, three of the very suppressed episodes were the extreme El Niño events of 1982–83, 1997–98, and 2014–16 (Ren et al. 2018).

Another contributor may be the Atlantic multidecadal oscillation (AMO) between favorable (warm) and unfavorable (cool) conditions for hurricane formation and intensification (Kerr 2005). The AMO was initially thought to be a vacillation of the Atlantic meridional overturning circulation (AMOC; Broecker 2010) between warm and cool surface waters with 20–43 years in each phase. The warm phase correlates with low shear and more major hurricanes, and the cool phase correlates with high shear and fewer major hurricanes (Goldenberg et al. 2001).

The AMO was in its warm phase in the earliest years of the twentieth century, cool from about 1903 until the mid-1920s, then warm until the early 1960s, cool until 1995, and finally warm since. The role, even the existence, of the AMO has been intensely debated (e.g., Mann and Emanuel 2006; Enfield and Cid-Serrano 2010), but its signal has been traced using tree-ring data for more than five centuries in the past (Gray et al. 2004). It is correlated with twentieth-century U.S. rainfall and runoff (Enfield et al. 2001). A recognizable signature of the AMO arose spontaneously in a 1400-yr oceanic simulation (Knight et al. 2005), and specified AMO sea surface temperatures reproduce many features of North American and western European summertime climate (Sutton and Hodson 2005).

More recent work questioned the dynamics of the AMO. For example, Mann et al. (2020) found no intrinsic AMO-like oscillation in the CMIP5 model results. Clement et al. (2015) questioned the role of AMOC in the AMO because an AMO-like SST distribution arose in a model with prescribed meridional heat transport, and Booth et al. (2012) attributed most of the AMO-like variability to natural and anthropogenic aerosols. Nonetheless, the results at hand require consideration of the potential effects of the AMO, controversial though the underlying physics may be, on decadal- to century-scale analyses of TC damage.

3. Original dataset 1900–2017

Normalization of TC damage has a pedigree that spans a quarter of a century. It began with PL98, covering the years 1925–95, and offered the significant scientific conclusion that major hurricanes (Saffir–Simpson categories 3, 4, and 5) constitute 21% of U.S. damaging TCs but inflict 83% of U.S. normalized damage. It was also the first to assert zero increase in damage beyond what could be accounted for by the normalizing factors: inflation, local population, and individual wealth. This assertion was probably correct at the time since it was articulated at the end of the mid-1960s to mid-1990s cool phase of the AMO. PL99 extended the normalized damage dataset to 1925–97 and used it to demonstrate a significant reduction in normalized damage during El Niño events. Katz (2002) used the PL99 data to show the U.S. losses by TC followed lognormal distributions and the numbers of TCs during individual seasons followed Poisson distributions, leading to compound distributions by seasons. In PA08, the record was extended to include 1900–2005. This work confirmed the dominance of damage due to major hurricane landfalls. It asserted no trend in normalized damage but identified the decade 1996–2005 as the second most damaging in the record, after 1925–35. Willoughby (2012) used the data of PA08 to show that different lognormal distributions fitted seasons in which at least one major hurricane made landfall and no major hurricanes made landfall. He also showed that truncating the data file at the year 2000 produced a ~10% reduction in mean normalized damage. Combining the different distributions produced a negatively skewed lognormal distribution for seasons 1900–2008. Other investigators added local housing units (Collins and Lowe 2001) and area of total destruction (Grinsted et al. 2019) to the local population as additional bases for normalization.

The International Catastrophe Insurance Managers (2018) dataset was downloaded from the ICAT (LLC) Damage Estimator website. It continued the established philosophy and format of PL98, PL99, and PA08 in an online damage estimator using the data from the group led by Pielke. It updated the database to include 1900–2017 with damage normalized to 2018 and formed the basis of the Grinsted et al. (2019) analysis. Generally, the data in ICAT represent each TC as single entry, even when the TC makes multiple landfalls. There are a few exceptions: Diane of 1955, Betsy of 1965, and Andrew of 1991 (but not Katrina of 2005). The second ranked landfall invariably caused much less damage, so each entry in ICAT is treated as a "damaging TC." It is the version of normalized damage data that are used here. It is, unfortunately, no longer available online from ICAT.

The WK18 analysis of 1900–2017 used normalized damage based on a different, "later version" of the same database. The present authors downloaded it from the supplementary data for the online version of WK18, but did not use it except for replication of the results of section 6. WK18 contained some unexplained "anomalies." The number of damaging TCs was reduced from 250 in ICAT to 198 in WK18. Thirty-nine "normalized damage" values were introduced into WK18 without nominal damage to be normalized. Except for Claudette of 2003, all these anomalous TCs occurred between 1901 and 1969. These TCs were as follows: two unique values of normalized damage: \$4.768B and \$4.458B and four groups of identical normalized damages: six with \$1.658B, four with \$0.774B, seven with \$0.679B, and 20 with \$0.287B. The explanation for these additions was that the new values represented landfalling TCs without reported nominal damage and so were assigned the median damage for similar TCs. They constituted almost 20% of the WK18 database, but did not contribute to the tail of the distribution.

Other anomalies were also concerning. WK18 presented low estimates of the then-year damage due to three of the most damaging twenty-first-century TCs: \$82B for Katrina of 2005; \$60B for Harvey of 2017; and \$35B for Irma of 2017. The NHC's best estimates and ranges are \$125B for Katrina, \$97.4B–\$145.5B (Knabb et al. 2023); \$125B for Harvey, \$90B–\$160B (Blake and Zelinsky 2018); and \$50B for Irma, \$37.5B–\$62.5B (Cangialosi et al. 2021). In all three cases, ICAT agreed with NHC. Despite ICAT's informal provenance, the present authors chose it for consistency with a quarter century of previously published research and with the National Hurricane Center's official damage estimates.

4. Extended dataset 1900–2022

Damage 1900–2022 data for this study are the then-year and normalized damage 1900–2017 ICAT dataset extended to 2018–22 with then-year damages from NHC's archived Tropical Cyclone Reports (NHC and NOAA 2023) to produce extended (I)CAT (XCAT). Normalized damages for 2019–22 are then approximated by "discounting" the then-year damages in the NHC reports to 2018 with $D_{2018} = D_Y(1 - 0.0645)^{Y-2018}$, where Y denotes the year when the damage occurred. These data are adjusted to 2018 because 2018 is the normalization year for the latest available version of ICAT. The magnitudes of the adjustments to D_Y for 2019, 2020, 2021, and 2022 were factors of

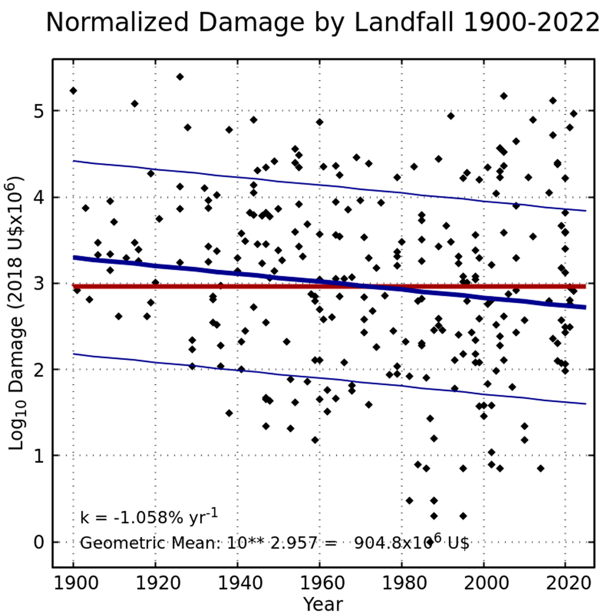

FIG. 5. Scatterplot of common logarithmic normalized XCAT damage by TC as a function of year, 1900–2022. The heavy, dark-red curve is the geometric mean; the heavy, dark-blue curve is the fitted logarithmic-linear trend, and the lighter dark-blue curves are plus and minus the residual RMS error.

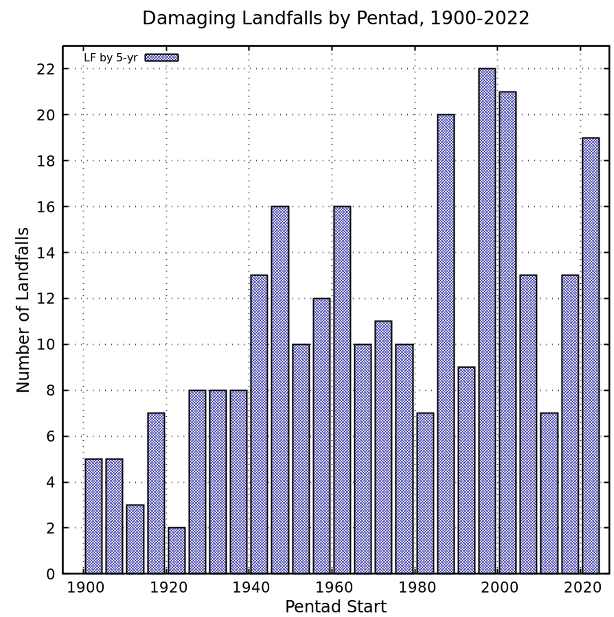

FIG. 6. Damaging U.S. TC by pentad, 1900–2022, from XCAT.

0.9355, 0.8752, 0.8187, and 0.7659, respectively. XCAT encompasses 1900–2017 damage data from ICAT and 2018–22 from the discounted then-year data. It contains 275 damaging U.S. Atlantic TCs.

Figure 5 shows a scatterplot of common logarithmic, normalized XCAT data by landfall as a function of time to illustrate the challenges presented by historical normalized damage data. The data have a dynamic range of five orders of magnitude. They exhibit nonconstant logarithmic variance which compromises the fitting of a meaningful linear trend. Other related difficulties are a scarcity of landfalls below the logarithmic mean before 1940 and an excess of small impacts after 1980. This feature causes the spurious downward trend in the fitted line. The geometric mean is about three common logarithmic units, or about \$1B, and the RMS error is plus or minus one common logarithmic unit corresponding to a range of \$0.1B–\$10B. Many of the small impacts are more than one or two orders of magnitude below the geometric mean, and so have negligible impact on the century-scale variation of total damage. The next section will propose a strategy of overcoming these challenges to obtain a credible decadal-to-century-scale TC damage trend.

5. Analysis by 5-yr pentads

The solution to the difficulty presented in Fig. 5 is the judicious binning of the damage. If the bins are too narrow, they present the possibility of zero binned value and undefined logarithmic values. If the bins are too wide, they smooth out trends. Since the longest interval of zero reported damage is 3 years, pentads (5-yr bins), are a logical choice. The 25 pentads are 1900–04, 1905–09 … 2015–19, and 2020–25. Because the XCAT dataset ends in 2022, the last pentad represents only three hurricane seasons.

Figure 6 shows damaging U.S. TCs by pentad. The average is about 11 TCs per pentad. Before 1940, damaging TCs struck at an average rate of 5.75 per pentad. After 1940, damaging TCs struck at an average rate of 13.47 per pentad. Thus, the eight pentads in 1900–39 clearly experienced fewer recorded damaging TCs than expected because of incomplete reporting, inconsistent combining of multiple landfalls into a single TC, limited warming of the planet before 1920, or the cool AMO, 1902–24. The lack of small-impact TCs before 1940, as shown in Fig. 5, supports the first two of these possibilities. Since most of them caused damage one or two orders of magnitude smaller than the bin total, the reduction in the pentad total is small, though real.

The logarithm of nominal damage aggregated by pentad appears in Fig. 7. A linear function of time was fitted to the logarithm of the aggregated data to generate an exponential. The result exhibits an increase of 9.19% yr^{-1} for 1900–2022. This rate of increase is ~2.74% yr^{-1} faster than that of GDP and is different from zero at $p < 0.001$ by randomization and F tests.[1] The pentads before 1925 show much more volatility than subsequently, consistent with the discussion of Fig. 6. The 1900–04, 1915–19, and 1925–29 pentads extend farther above the 1900–2022 trend line than any other pentad. They

[1] Here and elsewhere, the randomization test was implemented by generating 5000 random permutations of the pentad orders, recomputing the trends, and counting the fraction with tendencies that exceeded the actual value. The F test is implemented in the R package (e.g., Teetor 2011) and applied to the common logarithms of the pentad values.

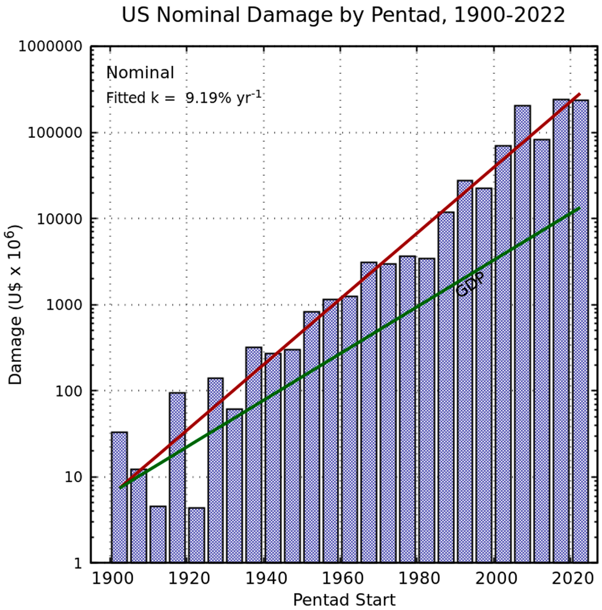

FIG. 7. U.S. logarithmic nominal TC damage aggregated by pentad. A 9.19% yr^{-1} trend line is fitted to these data, and a 6.45% yr^{-1} GDP trend line appears for comparison.

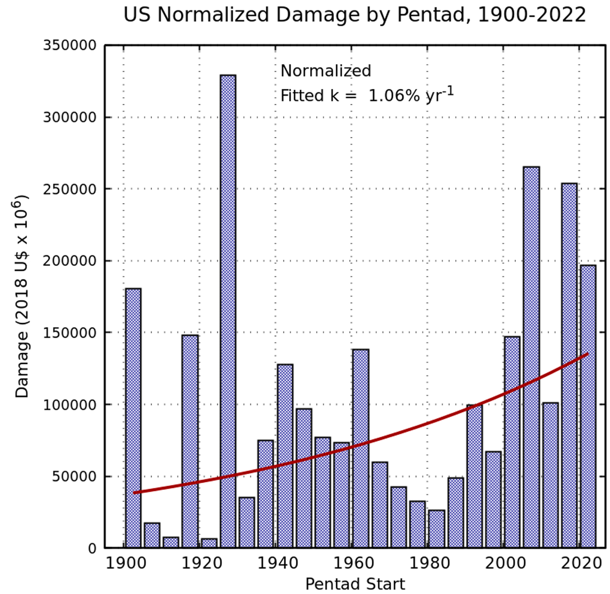

FIG. 8. Values of U.S. hurricane damage (2018 U$ $\times 10^6$) aggregated by pentad, 1900–2022, normalized to 2018 with an exponential 1.06 yr^{-1} trend superimposed.

contained the 1900 and 1915 Galveston hurricanes and the 1926 Miami Hurricane. By contrast, the 1910–14 and 1920–24 lie furthest below the trend line ostensibly because of the 1903–24 cool AMO. The 1935–39 pentad marks the beginning of bars that track the trend line more closely. In that context, it is important to recognize that Fig. 7 is a semilogarithmic plot that spans more than five orders of magnitude, so that large financial impacts appear as small wiggles. Nevertheless, it shows that the impact of TCs on the entire U.S. economy doubles in about a generation. Organizations (e.g., FEMA, Red Cross, and windstorm insurers) that respond to local hurricane disasters but draw their resources from the national economy claim an increasing portion of the total U.S. productivity.

If, on the other hand, we examine normalized damage from XCAT (Fig. 8), which responds to the local county-level population, the growth rate by pentad is 1.06% yr^{-1} (different from zero at $p = 0.059$ and 0.061 by randomization and F tests, respectively). Although these p values do not meet the usual 0.05 threshold for rejection of the null hypothesis, they do show that there is only a 1/17 probability that the growth of normalized damage is due to chance. The 23 years since 1999 are largely responsible for the increase. In this context, it is important to recognize that the last pentad represents only 2020–22, not 2020–24.

A reasonable concern is that the XCAT record before 1940 may be unrepresentative of the later data. Figure 6 shows that many fewer landfalls occurred before 1924 and somewhat fewer before 1940. In Fig. 7, the 1905–09, 1910–14, and 1915–19 pentads are far below the normalized damage trend line. Somewhat offsetting this concern is the presence before 1929 of the first, fifth, and sixth of the 25 pentads ranked by normalized damage. Recomputation of the trend line beginning in 1910, 1920, 1930, and 1940 yielded essentially the same slope ($\sim$1% yr^{-1}), although the randomization-test significance was degraded for 1940 and subsequently. Similarly, terminating the trend computation in 2017, as WK18 did, also yielded 1% yr^{-1} growth, consistent with these results. An earlier calculation that used XCAT 1900–2021 produced 0.94 yr^{-1} with $p = 0.092$. The last pentad in the present calculation contains only 3 years, including Hurricane Ian. Thus, the $\sim$1% yr^{-1} trend is robust in the face of reasonable truncations of XCAT.

The 1900 and 1915 Galveston hurricanes and the 1926 Miami Hurricane are extreme outliers. In XCAT, the Galveston hurricanes caused \$30M and \$50M in nominal damage, primarily by storm surge, or \$172B and \$121B normalized to 2018. One might not expect the damage to be so great from similar storms striking in the twenty-first century because of the construction of the seawall on Galveston Island after 1900 and raising and strengthening it after 1915 and ICAT's normalization of the damage using the population of Galveston and Harris (Houston) counties. It is true that there was considerable damage on the mainland in both storms (Garriott 1900; Frankenfield 1915), but the locus of total devastation was the city of Galveston (26% population growth 1900–2010). By contrast, most of the "local" population growth since 1900 was in Harris County (a factor of 64) and in mainland Galveston County (i.e., not only on Galveston Island, a factor of 6.6).

There are no a priori reasons to doubt the big peak in the normalized damage stemming from the Miami Hurricane of 1926 (Mitchell 1926), except that it is big and caused primarily by an increase in population. The 1926 hurricane made landfall over the urban center. It caused \$243B in damage normalized to 2018. Hurricane Andrew (Mayfield et al. 1994) made landfall 30 km south of the city. A contemporary news article (Doig 1992) states that Andrew inflicted \$20B in nominal damage. Moving the template of damage northward over the fixed pattern of assets to obtain the maximum possible loss yielded the result that if Andrew had made landfall at the same position as the 1926 hurricane it would have caused \$62B in then-year damage. Adjusting the number proportional to the change in nominal GDP to 2018 yields \$315B. The 1926 hurricane was less intense, but much larger, than Andrew (Landsea et al. 2004). Thus, the normalized figure is reasonable or possibly conservative. Despite the foregoing misgivings about the 1900 and 1915 hurricanes' damage figures, all three TCs are retained for consistency with previous studies.

Additional factors besides AGW may contribute to the trend shown in Fig. 8. These include more complete accounting for TC damage after the midtwentieth century, incomplete reporting in the early twentieth century, concentration of affluence in urban and coastal settings, and dominance of the warm AMO during the twenty-first century in contrast with the twentieth century's mix of AMO phases. By way of perspective, 1.06% yr^{-1} compounded over 122 years produces growth by a factor of 3.6, but not all of the growth may be attributable to AGW.

6. The most damaging TCs

BIG20, the 20 most destructive individual TCs in XCAT, caused \$1863B in U.S. normalized loss. The threshold for inclusion in the BIG20 was \$31B. The total BIG20 damage is 63.6% of the \$2.648B XCAT total. Twenty TCs are 7.27% of the 275 TCs recorded in XCAT. This disproportionate contribution of a few landfalls to the total agrees, in principle, with the statements that 20% of the TCs are responsible for 80% of the losses (PL98; PA08).

Examination of the BIG20 was motivated by the observation that their damage is well represented by a Pareto (power-law) distribution (Hernandez 2014; Dey and Das 2016):

$$P_N = P_1\left(\frac{D_1}{D_N}\right)^X,$$

where P_N is the fitted probability of loss D_N due to Nth event in the Pareto tail, P_1 is the fitted probability of the first (smallest) BIG20 event causing loss D_1 (\$31.1B in Tropical Storm Diane of 1955), and $X = 1.430$ is the fitted Pareto exponent. If the Pareto TCs were uniformly distributed in time, an occurrence of damage $\geq D_1$ would be expected approximately every 6 years. Thus, the BIG20 represents the "tail risk" of infrequent but costly events.

Figure 9 illustrates the individual BIG20 events, AMO phase, El Niño years, and years with zero reported U.S. Atlantic TC damage for 1900–2022. Chronologically, the first three BIG20 TCs, the Galveston hurricanes of 1900 and 1915, and the Miami Hurricane of 1926, ranked second, fifth, and first in terms of normalized damage. The third and fourth ranked TCs are Katrina of 2005 and Harvey of 2017. The BIG20 TCs at landfall are one CAT 5 TC, eleven CAT 4s,

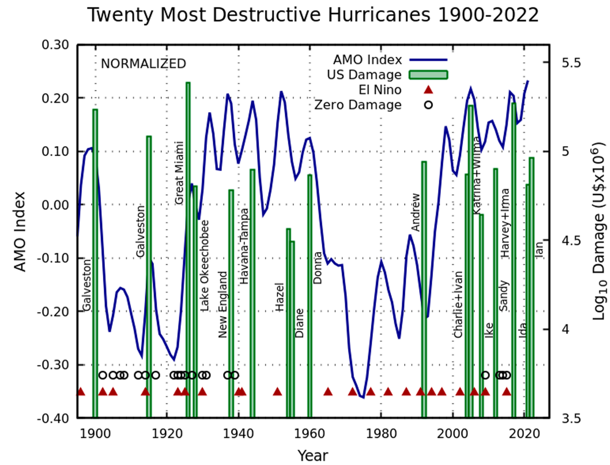

FIG. 9. The 20 most destructive U.S. landfalling TCs, 1900–2022 (green bars), the AMO index (blue curve), El Niño years (red triangles), and years with zero TC impact (circles).

five CAT 3s, one each of CATs 2 and 1, and a single tropical storm (Diane of 1955). It is remarkable that 10 of the 20 struck between 1900 and 1999 and the other ten struck after 2000 or later. Half of the most destructive TCs made landfall in the last 19% of the years.

The 1900–01, 1926–62, and 1995–99 warm AMO phases experienced eight BIG20 TCs (including the 1900 Galveston Hurricane) in 44 years. Only two BIG20 TCs struck during the 56 years of the cool AMO phases (1902–24 and 1963–94). During 23 years of warm AMO during the twenty-first century (2000–22), ten BIG20 TCs struck the United States. Thus, a transition to more frequent damaging storms appears to have happened in the late twentieth century or the early twenty-first century. This observation is intriguing, but is it statistically significant? Should the division be marked by 1995 when the AMO returned to its warm phase or by 2004 when the warm phase appeared dramatically as damaging TCs? A reasonable (and easily remembered) compromise is the year 2000, halfway between these two milestones.

The null hypothesis here is that the numbers of BIG20 destructive TCs (successes in statistical jargon) during the warm AMO phase of the twenty-first century (W21), the warm phase of the twentieth century (W20), and the cool phase of the twentieth century (C20) are described by binomial distributions (Fraser 1958; Berman 2023a,b) with the same annual probability (1/123) but different durations. Thus, the probability that a given BIG20 TC struck during W21 is 0.187; during W20, it is 0.358; and during C20, it is 0.455. The term $N_T = 20$ is the total number of destructive TCs (Bernoulli tries). The term N_A is the number of BIG20 destructive TCs in each AMO phase, and N_E is the number of expected BIG20 TCs (binomial means) in each phase. The term N_A = 10, 8, and 2 and N_E = 3.7, 7.2, and 9.1 for W21, W20, and C20, respectively. Figure 10 illustrates N_A/N_T and the distributions of binomial probabilities: 0.002 that $N_A \geq 8$ for W21; 0.429 that $N_A \geq 8$ for W20; and 0.001 that $N_A \leq 2$ for C20. These binomial probabilities are insensitive to the transition between

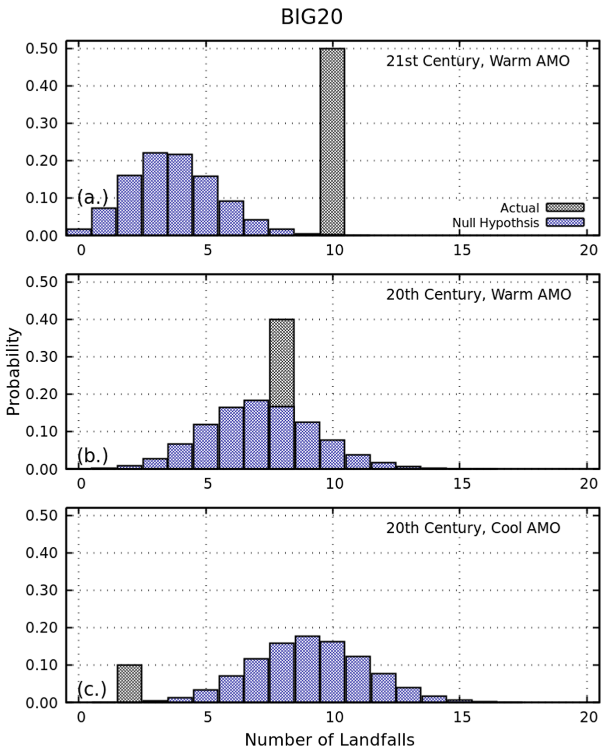

FIG. 10. The BIG20, null hypothesis, binomial distributions, and N_A/N_T by the AMO phase: (a) twenty-first-century warm AMO, (b) twentieth-century warm AMO, and (c) twentieth-century cool AMO.

C20 and W21 occurring in 1995, 2000, or 2004. Thus, the twenty-first-century warm AMO has many more of the BIG20 events than expected, and the twentieth-century cool AMO has many fewer. By contrast, there is no reason to doubt the null hypothesis for W20. In quantitative terms, the twenty-first-century BIG20 TCs experienced a statistically significant factor of 2.35 increase in BIG20 TCs relative to the climatologically similar epoch of the twentieth century.

In Table 1, foregoing calculation was repeated for the BIGn, the n most destructive TC in terms of normalized damage. The results were consistent, a more than doubling of damaging TCs in the twenty-first century, with $p = 0.013$–0.002. Only for BIG10 was the null hypothesis accepted at $p = 0.099$. A key advantage of the BIG20 and similar metrics is that they reduce the impact of outliers through the use of rankings rather than amounts of damage.

The BIG10–BIG40 TCs account for 46.2%–80.5% of the total normalized damage in XCAT. The most damaging TC is the 1926 Miami Hurricane ($242.8B). The least damaging TCs are BIG10, Donna of 1960 ($73.4B); BIG20, Dianne of 1955 ($31.1B); BIG30, Alicia of 1983 ($22.3B); and BIG40, Frederic of 1979 ($17.1B). The total-sample arithmetic-mean annual normalized damage was $42B, $26B, and $10B for W21, W20, and C20, respectively.

Replicating Table 1 using the WK18 dataset yielded consistent results with somewhat reduced significance because of the smaller sample size. Based on WK18, p values for the

TABLE 1. BIG10–BIG40 TCs of the twenty-first and twentieth centuries by the AMO phase. The null hypothesis is that damaging TCs by the AMO phase follow binomial distributions with probabilities proportional to the phase durations. The term N_A is the actual value for each AMO phase; N_E is the binomial mean; and p is the probability under the null hypothesis of N_A or more during the warm AMO phases and of N_A of fewer during the cool AMO.

AMO	W21			W20			C20		
Duration		23			44			56	
Probability		0.187			0.358			0.455	
Variable	N_A	N_E	p	N_A	N_E	p	N_A	N_E	p
BIG10	4	1.9	0.099	4	3.6	0.507	2	4.4	0.094
BIG15	7	2.8	0.013	6	5.4	0.462	2	6.8	0.010
BIG20	10	3.7	0.002	8	7.2	0.429	2	9.1	0.001
BIG25	11	4.7	0.003	10	9.0	0.402	4	11.4	0.002
BIG30	13	5.6	0.002	10	10.8	0.676	7	13.6	0.011
BIG40	15	7.5	0.004	15	14.3	0.601	10	18.2	0.015

BIGn occurrences were <0.04 for W21 and C20 for BIG15–BIG40, but not significantly different from chance expectations for BIG10 or for W20 in BIG15–BIG40. By contrast, replication of the normalized damage tendency by pentad (e.g., Fig. 8) with WK18 yields a growth rate of 0.656% yr^{-1} or a factor of 2.24, 1900–2022. However, the p value = 0.23 so this result may be attributed to chance. A landmark paper by Grinsted et al. (2019) pioneered alternative normalization by area of total destruction. They fitted statistically significant increases to the numbers of the most destructive TCs, 1900–2017, by Poisson regression but did not deconvolute the effects of AGW and AMO phases. An essential advantage of the BIGn strategy by rank is that it is easily replicated.

To summarize, during the warm AMO of the twenty-first century the BIG20 TCs were more than twice as frequent as during the warm AMO of the twentieth century and 4 times more frequent than during the entire (warm and cool AMO) of the twentieth century. The latter figure is consistent with the factor of 3.6 increase in the fitted trend, 1900–2022. This pattern provides perspective on the exchange between Emanuel (2005), Landsea (2005), and Pielke (2005). It is also manifest in Fig. 8. The cool AMO of 1903–24 was "bookended" by the fifth and first ranked pentads and contained the destructive 1915–19 pentad (sixth rank) but also contained the three least destructive pentads. The 1926–62 warm AMO was much more destructive than the 1963–95 cool AMO. The interaction between the AMO and AGW may have tended to obscure any trend (Vecchi et al. 2021). The five twenty-first-century pentads were ranked seventh, second, tenth, third, and fourth in terms of normalized damage. The twenty-first century was unique because it experienced two BIG20 landfalls during the same year on three occasions. Was the increase in BIG20 TCs due to AGW crossing a tipping point, or was it due to AGW's effect emerging from the cool AMO's masking?

Figure 11 shows the tracks of the warm AMO TCs from HURDAT (Landsea and Franklin 2013). Only four of the 10 W21 TCs exhibited Cape Verde tracks. Similarly, only two of the Cape Verde TCs and two others reached maximum

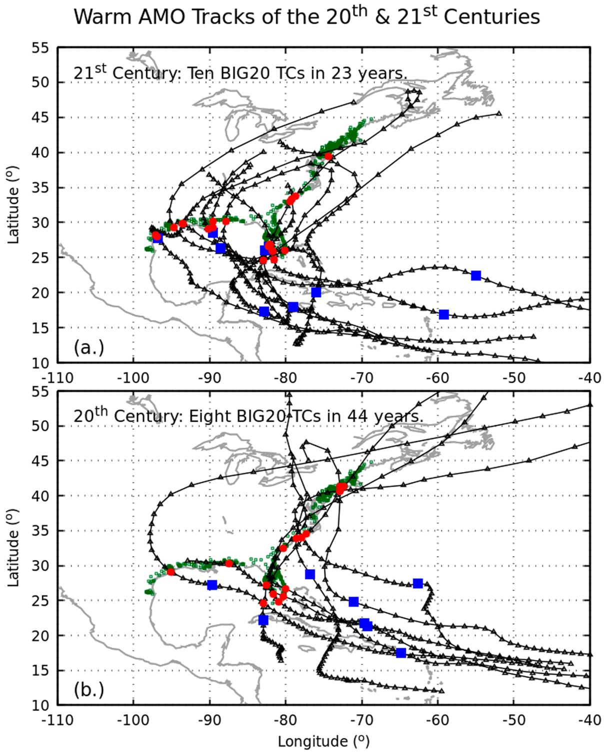

FIG. 11. Tracks of the (a) 10 W21 TCs and (b) eight W20 TCs. Blue squares indicate the positions of maximum intensity; red circles indicate U.S. landfalls; and black triangles indicate storm positions at 6-h intervals.

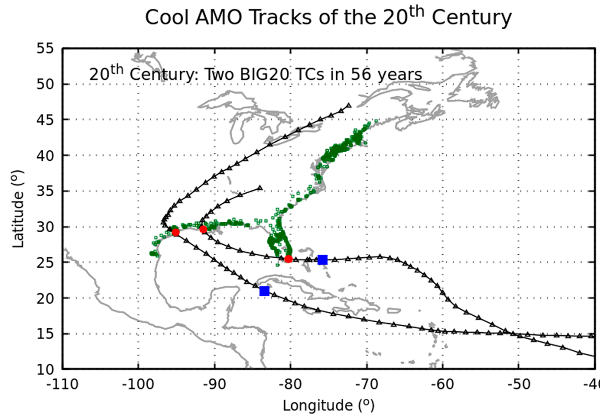

FIG. 12. Tracks of the two C20 TCs, Galveston of 1915 and Andrew of 1992. Maximum intensity and landfall positions are indicated as in Fig. 11.

intensity east of 80°W, and a total of eight struck U.S. Gulf of Mexico shores (Fig. 11a). Their dominant threat was to the Gulf Coast rather than the Eastern Seaboard. In contrast, six of the eight W20 TCs reached maximum intensity west of 80°W. They exhibited a preponderance of Cape Verde tracks and a dominant threat to the U.S. Eastern Seaboard and peninsular Florida. Two of the eight attained maximum intensity west of 80°W, and only one (the Galveston Hurricane of 1900) reached maximum intensity in the Gulf of Mexico. Seven of them impacted Florida or the U.S. Atlantic seaboard. All BIG20 TCs reached maximum intensity south of 30°N and half of them south of 25°N. Figure 12 shows that both C20 TCs (Galveston 1915 and Andrew) were Cape Verde hurricanes that attained maximum intensity east of 95°W long before final landfall on the U.S. northern Gulf of Mexico coast.

7. Conclusions

A key result presented here is that, between 1900 and 2022, the then-year damage from TCs increased at a rate of 9.19% yr^{-1} (Fig. 7). No adjustments were made for inflation, population, or individual wealth. The arithmetic data were, however, binned by pentads, so that seasons with zero reported damage could be included in the exponential fit. During the same interval, the U.S. gross domestic product (GDP) increased at a rate of 6.45% yr^{-1}. Thus, the nominal impact of TCs upon the nation's economy increased at 2.74% yr^{-1}, equivalent to a generational (~25 years) doubling time.

The data supporting the assessment of hurricanes' century-scale threat to the U.S. economy pose challenges. The numbers have inconsistent provenance, large dynamic range, and uneven reporting. During the early twentieth century, there was a dearth of damaging TCs compared with the remainder of the record, but some of the TCs before 1940 were extremely destructive when normalized to the twenty-first century. An exponential curve fitted to the normalized data from all recorded individual damaging TCs exhibits a −1.058% annual rate of growth (i.e., a decrease; Fig. 5). This spurious result is primarily due to underreporting of small-impact events early in the record. Published normalization of past nominal damage has been interpreted as demonstrating a zero trend (e.g., WK18). These interpretations may have stemmed, in part, from an overemphasis on the 80% of small values that inflicted 20% of the damage instead of focusing on the 20% of the "outliers" that inflicted 80% of the damage.

Fitting an exponential to the normalized damage data since 1900 binned by pentads yields 1.06% yr^{-1} increase or a factor of 3.6 since 1900. The p value determined for the fit was 0.059, so the probability that the 1.06% normalized trend arose by chance is 1/17. Still, it is possible that other economic, demographic, or AMO-related factors besides AGW contributed to the increase.

Additional evidence supporting a real increase is the observation that of the twenty most damaging TCs (BIG20) to strike the United States since 1900, ten struck in the 23 years after 1999 when the AMO was in its warm phase. During the twentieth century, when the AMO was in the warm phase for 44 years, eight of the BIG20 TCs struck. Under the null hypothesis that the annual probability of a BIG20 TC landfall is 1/123, the probability of 10 BIG20 TCs making landfall in the twenty-first century is 0.002. The damaging landfall rate of BIG20 TCs after the year 2000 is 2.33 times the expected rate based on twentieth-century warm AMO experience. These results are robust for the 15, 25, 30, and 40 most damaging TCs ($p \leq 0.01$), but not for the most damaging 10. Is this the signature of crossing a tipping point? Or is it to be expected if the climate change signal is beginning to emerge from the noise of the steady-state twentieth-century regime obscured by the changing phase of the AMO?

The XCAT dataset presents challenges for fitting a century-scale trend because they are actually a series of step functions: A big jump caused by the 1900 Galveston Hurricane, followed by a profound lull from 1902 to 1925 (except for the 1915 Galveston Hurricane), and then another big jump due to the 1926 Miami and 1928 Lake Okeechobee hurricanes, followed by the warm AMO phase that lasted until the mid-1960s, another deep lull that extended for the rest of the twentieth century, and finally by the very destructive twenty-first century. It is these abrupt, step function transformations rather than a gradual increase that are responsible for the trend. The twenty-first-century warm AMO was marked by a doubling of the incidence of the most damaging TCs with respect to the twentieth-century warm AMO and a quadrupling with respect to the entire twentieth century. The latter comparison is consistent with the 1900–2022 fitted-exponential increase by a factor of 3.6. Reasonable questions are as follows: What will happen when the AMO returns to the cool phase? Indeed, will the AMO cool phase return at all on a warming globe (e.g., Ditlevsen and Ditlevsen 2023)? These questions emphasize the need for a more comprehensive understanding of the AMO.

These results contradict the forceful statement that there is no evidence of an AGW effect on hurricane losses near the start of the third decade of the twenty-first century (Weinkle et al. 2018). Earlier studies (e.g., Pielke and Landsea 1998; Pielke et al. 2008) are more difficult to challenge, coming as they did soon after the 1963–95 cool phase of the AMO. Nothing in the foregoing should be interpreted as discrediting the normalization of TC damage for changing demographic and economic conditions. It is a vital record and should be updated frequently and maintained rigorously and transparently.

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Data availability statement. The ICAT database of nominal and normalized damage data was accessed from the ICAT website which is no longer available online. The versions of ICAT and XCAT used here are available from the corresponding author. The current version of the HURDAT data on Atlantic hurricane tracks and intensities is available from the U.S. National Hurricane Center at https://www.nhc.noaa.gov/data/#hurdat.

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