BAMS
Article

Normalized Hurricane Damage in the United States: 1900–2022

Joanne Muller,[a] Kaylee Mooney,[a] Steven G. Bowen,[b] Philip J. Klotzbach,[c] Tynisha Martin,[a] Tom J. Philp,[d,e] Dhruvkumar Bhatt,[a] Richard S. Dixon,[f] and Senthil B. Girimurugan[g]

KEYWORDS: Coastal meteorology; Hurricanes/typhoons; Anthropogenic effects/forcing; Damage assessment; Economic value; Vulnerability

ABSTRACT: Since 1900, landfalling hurricanes have been the costliest of all weather-related disasters to afflict the contiguous United States. To provide a present-day (2022) reevaluation of this risk, this study employs an improved normalization approach to better understand potential economic event losses in the context of contemporary societal conditions. The updated methodology identifies impacted coastal counties using the newly available radius of maximum winds at landfall. Hurricane Katrina is the most expensive hurricane since 1900, with a likely 2022 normalized cost of $234 billion. Combined losses from the 50 most expensive hurricane events are ∼ $2.9 trillion in normalized economic losses. The study also explores some "analog storms" where comparisons can be made between two historic storms with similar landfall locations. For example, category 5 Andrew (1992) has lower 2022 normalized losses than category 4 Great Miami (1926), at $125 billion versus $178 billion, most likely due to the significantly different radius of maximum wind size (10 vs 20 n mi; 1 n mi = 1.852 km). As with previous studies, we conclude that increases in inflation, coastal population, regional wealth, and higher replacement costs remain the primary drivers of observed increases in hurricane-related damage. These upsurges are especially impactful for some coastal regions along the U.S. Gulf and Southeast Coasts that have seen exceptionally high rates of population/housing growth in comparison to countrywide growth. Exposure growth trends are likely to continue in the future and, independent of any influence of climate change on tropical cyclone behavior, are expected to result in greater hurricane-related damage costs than have been previously observed.

SIGNIFICANCE STATEMENT: Normalization takes historical estimates of damage arising from landfalling hurricanes since 1900 and adjusts these to estimate the damage that would be caused if these events were to recur in 2022, given changes in inflation, coastal population, and wealth. Our updated normalization approach improves upon previous methodologies by allowing for greater consistency through time. This updated normalization finds that Hurricane Katrina is the costliest hurricane since 1900, causing an estimated $234 billion if it were to reoccur in 2022.

DOI: 10.1175/BAMS-D-23-0280.1
Corresponding author: Joanne Muller, jmuller@fgcu.edu

Supplemental information related to this paper is available at the Journals Online website: https://doi.org/10.1175/BAMS-D-23-0280.s1.
Manuscript received 31 October 2023, in final form 25 August 2024, accepted 21 October 2024

AFFILIATIONS: [a] Department of Marine and Earth Sciences, The Water School, Florida Gulf Coast University, Fort Myers, Florida; [b] Gallagher Re, Rolling Meadows, Illinois; [c] Department of Atmospheric Science, Colorado State University, Fort Collins, Colorado; [d] Department of Philosophy, London School of Economics, London, United Kingdom; [e] Maximum Information, London, United Kingdom; [f] CatInsight, London, United Kingdom; [g] Department of Mathematics, College of Arts and Sciences, Florida Gulf Coast University, Fort Myers, Florida

1. Introduction

Of all recorded weather disasters in United States (U.S.) history, hurricanes have caused the most property destruction and loss of life. The risk is particularly serious for coastal communities, such as those in Florida and the Gulf of Mexico, which over the last few decades have seen rapid increases in assets at risk (e.g., exposure) (Klotzbach et al. 2018). As a result, hurricane damage has increased substantially over the last 120 years, with a particularly rapid increase since the turn of the twenty-first century. Directly comparing historical hurricane losses is meaningless without considering these background changes in society, such as property values that are exposed. To bring historical losses into a comparable state, it is possible to adjust historic storm losses based on monthly changes in inflation as seen in the U.S. Consumer Price Index, which is the methodology used by NOAA/NCEI (2024). While this type of adjustment analysis is useful for accounting for how much damage incurred at the time of an event would cost today, and while such data do inherently capture changes in population or exposure and macroeconomic metrics such as inflation with time, more detailed, geographic-specific methodologies exist.

In seeking to better understand how the risk has changed over time, our study builds on previous efforts, particularly those of Pielke and Landsea (1998), who introduced a loss normalization methodology to estimate the direct economic losses if historical hurricane events were to impact today's exposure. To this end, they used inflation, wealth, and population measures to adjust nominal damage estimates from the historical catalogue of contiguous United States (CONUS) hurricanes (1925–95). Collins and Lowe (2001) also normalized landfalling hurricane losses from 1900 to 1999 using inflation, wealth, and importantly, housing units (HUs) as normalizing factors. Pielke et al. (2008) updated normalized loss estimates from 1900 to 2005 using both the Pielke and Landsea (1998) and Collins and Lowe (2001) approaches. Weinkle et al. (2018) updated estimates of normalized losses using both methods, finding the 2017 normalized losses from CONUS hurricanes since 1900 to sum to \$2 trillion or ~\$17 billion annually over the 118-yr period. As with other studies, these normalized losses showed no obvious trends over time, mirroring the results of Klotzbach et al. (2018), who found no trends in landfalling hurricanes or major hurricane frequency.

There have been further normalization studies, such as those of Neumayer and Barthel (2011) and Grinsted et al. (2019), who sought to identify changes in spatial, not just temporal, wealth. For example, Grinsted et al. (2019) looked at the "area of total destruction," which defined the area impacted and population wealth within that area rather than the per capita wealth of entire counties. This methodology did not, however, allow for a housing unit adjustment, as employed by Collins and Lowe (2001). Martinez (2020) developed a normalization that considered building cost inflation. Martinez found that recent damage from individual hurricanes was considerably less than the costliest storms in the early twentieth century and attributed this to a combination of better forecasts, recent hurricanes not directly striking large and vulnerable exposures and adaptation through improved building techniques and the construction of sea walls (Martinez 2020). Since the above studies were published, population and exposure along the coastlines of Florida and Texas have continued to increase in tandem with high levels of inflation. There have also been several major landfalling hurricanes (category 3+) and an important economic reanalysis by NOAA of the nominal loss record for prominent historic storms such as Hurricane Katrina.

This study updates the Pielke and Landsea (PL) and Collins and Lowe (CL) studies. In particular, it features as follows:

1) An updated normalization dataset to 2022.
2) A revised normalization method using the newly available landfalling radius of maximum wind (RMW) to identify impacted coastal counties for landfalling hurricanes in HURDAT2.
3) Open access provided for all raw data and calculations via GitHub.

2. Methodology

We used two existing normalization methods in this study, which we evolved to more precisely and transparently determine counties affected by historical hurricanes. The original Pielke and Landsea (1998) normalization was the baseline method used in Pielke et al. (2008) and presented most recently in Weinkle et al. (2018). Our calculations using this underlying methodology are referenced throughout as PL22. We also used the Collins and Lowe (2001) normalization method that was also used as an alternative method in both Pielke et al. (2008) and Weinkle et al. (2018). Our calculations using this methodology are referenced throughout as CL22. Details of both methodologies are provided below.

a. Pielke–Landsea (2022) normalization method. The general formula for the PL22- normalized losses is

$$D_{2022} = D_y \times \times I_y \quad \mathrm{RWPC}_y \times P_{2022/y},$$

where D_{2022} is the normalized damage in 2022 U.S. dollars, D_y is the reported damage in landfall-year U.S. dollars, I_y is an inflation adjustment, RWPC_y is the real wealth per capita adjustment, and $P_{2022/y}$ is the county population adjustment. Previous normalizations have used the terms damage and loss interchangeably; thus, any reference to either within this paper is one and the same.

The reported damage in landfall-year (D_y) is taken from a newly constructed dataset that sources the base economic damage for storms between 1900 and 1979 from the original reports (see data availability statement and GitHub repository). These damage records are mostly sourced from *Monthly Weather Review* discussions of each storm, while several storms have updated damage numbers due to incomplete reporting of the original damages in *Monthly Weather Review*. Within this dataset, each storm has an individual citation to the damage estimate source. We then use National Centers for Environmental Information (NCEI) for storms from 1980 onward. NCEI disaggregated damage (for multiple landfalling storms) is sourced from the individual National Hurricane Center tropical cyclone reports. Because there is not one agency reporting on hurricane damages through time, uncertainty arises in the consistency of the historical damage estimates between 1900 and 2022. For example, the *Monthly Weather Review* estimates (1900–79) represent a highly variable and subjective combination of losses from the American Red Cross, the U.S. Office of Emergency Preparedness, insurance companies, and press reports (Blake et al. 2011). NCEI (1980–2022) has more detailed reporting efforts that likely include more complete flood attribution to the overall damage estimate using National Flood Insurance Plan (NFIP) claims data. While it is difficult to determine how flood damage was handled in early *Monthly Weather Review* estimates, it is clear that such water-related damage was included in many event totals. It is important that users of this dataset be aware of the uncertainty through time, and for this reason, authors refrain from trendline analysis in this study. Please see the GitHub repository for more information on the damage dataset explanation and raw, disaggregated damage data for each storm, with individual citations. The reader is referred to README GitHub for details on "damage estimates through time." For some storms, often those occurring after 2018, damage data are sometimes available for the coastal landfall state, as well as inland states separately. In this case, and the case of multiple landfalling storms, we normalized each state damage estimate separately and aggregated data to get a total normalized loss for each storm (see below for the population and housing unit adjustment).

To adjust for inflation, the implicit price deflator for gross domestic product (IPDGDP) for the years 1900–2022 was used. We used calculations from Johnson and Williamson (2023), which was based on data from the U.S. Department of Commerce's Bureau of Economic Analysis (BEA). The inflation factor I_y is the ratio of the 2022 GDP deflator to the GDP deflator of the year that the hurricane made landfall.

To adjust for real national wealth, we used the estimate of current-cost net stock of fixed assets and consumer durable goods between 1925 and 2022 (U.S. Bureau of Economic Analysis 2023). Adjustment factors are needed to consider national wealth without the influence of inflation and population. The population of the country was used because wealth per capita is estimated for the entire United States. Years between the census years were linearly interpolated from the decadal U.S. Census Bureau data between 1900 and 2000, while annual data were available between 2000 and 2022 (U.S. Census Bureau 2022). Using the same approach as Pielke et al. (2008), wealth from 1900 to 1924 was estimated to increase by 3% per year based on the lower of the average annual change in wealth from 1925 to 2005 (6%) and from 1925 to 1928 (3%). Because real GDP increased by ~3% per year for 1900–24, and wealth typically increases at a faster rate than GDP, the assumption for pre-1924 changes in wealth are likely conservative (Johnston and Williamson 2006). The fixed assets ratio, $V_{2022/y}$, is the ratio of fixed assets in year 2022 to year y, with the year y denoting the year of the hurricane landfall. Because the wealth data are reported in billions of landfall-year dollars for the entire nation, these data are adjusted for inflation and population. Wealth is disaggregated to a noninflated real per capita metric to allow the independent roles of inflation, wealth, and population to be distinguished.

To adjust for population, we use data from the U.S. Census for the counties impacted by each hurricane. The county population factor, P_y, is a ratio of the county population in 2022 to the year of the hurricane's landfall (interpolated and extrapolated census data also used here). To determine the coastal counties impacted by historic storms, we employed a new method. We took the newly released landfalling RMWs for each historic hurricane from HURDAT2 (Colón-Burgos and Landsea 2023; Landsea et al. 2013) and input these RMWs into Environmental Systems Research Institute (ESRI)'s ArcGIS Pro software (Fig. 1). RMWs are available for all top 50 storms except for Tropical Storm Allison. This RMW was sourced from the 6-hourly position prior to landfall in the Extended Best Track (Demuth et al. 2006). We follow the landfall definition as established by the National Hurricane Center (NHC) as "the intersection of the surface center of a tropical cyclone with a coastline" (latitudes and longitudes obtained from HURDAT2) (Landsea et al. 2013). Using the spatial tools in ArcGIS Pro, we identified coastal counties that fell within the RMW field for each historic storm. If the storm had multiple landfalls, and loss estimates were provided for those multiple landfalls, we included each landfall using this method. To deal

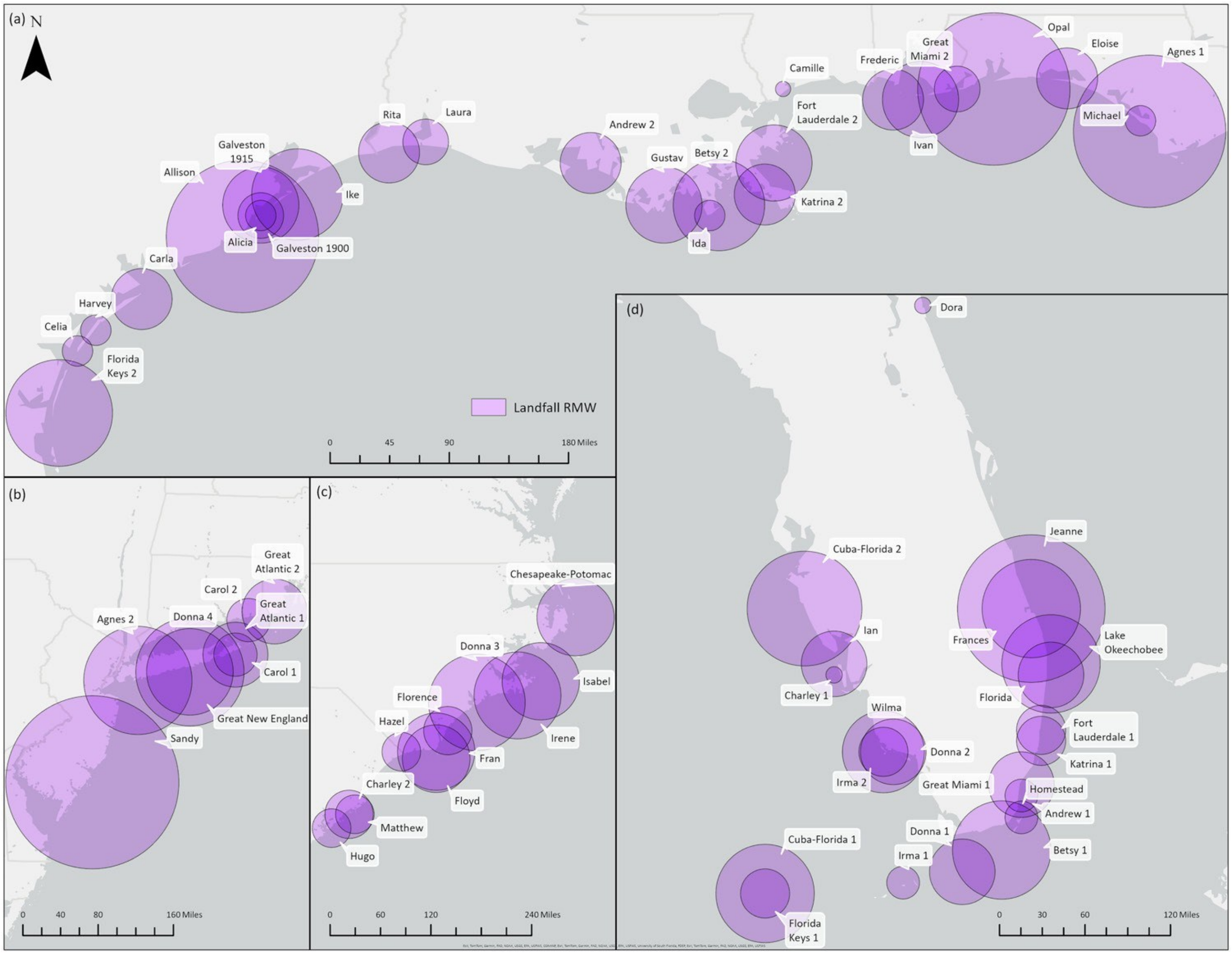


Fig. 1. Landfalling RMWs for the top 50 CONUS landfalling historic hurricanes. The regions displayed are the (a) northern Gulf Coast, (b) Northeast United States, (c) Southeast United States, and (d) Florida.

with issues introduced by complex coastline shapes over small spatial scales, we define multiple landfalls only by the number of distinct loss records per storm from our updated loss tables (GitHub repository).

The updated PL22 and CL22 normalizations using the new RMW method to determine coastal counties have some trade-offs. For example, for a storm like Harvey where the majority of the losses did not occur in the landfall counties, our population and housing unit adjustments may not reflect well the population and housing units' changes in the counties where the damage occurred. Weinkle et al. (2018) classified "rain event" storms, and for these storms, the entire state population, or housing unit, adjustment was applied, rather than just the landfall counties. We have kept our methods standard across all storms in order to avoid subjectivity.

In addition, for stronger storms, such as categories 4–5 hurricanes, it is likely that the damaging wind field extends beyond the RMW, and therefore may include additional counties to those used in this set of 2022 normalizations. There are possible ways of addressing this issue in the normalization. For example, for an arbitrary RMW of 1.5 or 2 times the RMW could be applied to model the NHC's terminology of "direct landfall" (2 × RMW on the righthand side of the storm versus 1 × RMW on the left-hand side of the storm). In the supplemental documents and GitHub repository, we discuss the methodology for this and the subsequent normalized results. However, within the paper itself, we use 1 × RMW only to identify coastal counties. We do this in order to avoid subjectivity, because without reliable and long-term wind radii data, we would have to address this with an arbitrary adjustment (like the one used above) or a subjective model (parametric wind profile, or model simulation with subjective estimates of the wind field). All of these approaches would be moving toward modeling and away from a purely observational data methodology. Therefore, for this current study, we use the 1 × RMW method for all storms, but note that there are grounds for improvement that will be explored in future work. We also note that giving users full access to raw data and code and therefore the option to select the best methodology for their use case may be the best way forward.

If multiple landfall and loss estimates are available, we normalize the loss for each landfall, and then aggregate all losses, to generate the total loss per storm. We do not include losses in U.S. territories (e.g., Puerto Rico, U.S. Virgin Islands). For very recent storms (Laura, Michael, Ida, and Ian) and older storms [Cuba–Florida (1944), Agnes (1972)] where damage estimates are also available for inland states, we use the population adjustment for the entire state. This allows us to capture a total loss number by aggregating the landfalling state loss estimate and the inland state loss estimates. Finally, for a small number of storms, namely, Great Atlantic (1944), Carol, and Sandy, loss estimates are provided for states in which "landfall" did not occur. For example, Sandy made landfall in New Jersey, but approximately half of the losses were in New York State. In this case, similar to above, we use the population adjustment for the entire state for non-landfalling states.

By way of example, Fig. 2a illustrates our updated PL normalization in the case of Hurricane Alicia (Fig. 2a). Alicia's Texas damage estimate from 1983 was $3 billion. Wealth in 2022 was $93.6 trillion and was $12.6 trillion in 1983. The ratio of 2022 to 1983 was 7.40. The inflation adjustment for 1983 was 2.48, so the inflation-corrected wealth adjustment (i.e., real wealth) for 1983 = 7.40/2.48 = 2.98. Finally, to adjust the inflation-corrected wealth adjustment for the change in U.S. wide population, we use the U.S. population in 1983 and 2022 which is estimated to be 233 195 025 and 335 990 029 people, or 1.44, respectively. The final wealth adjustment for 1983 is the real wealth adjustment of 2.98 corrected for the U.S. population change of 1.44, which equals 2.07. Therefore, each person in the United States has (on average) 2.07 times more wealth in 2022 than did each person in 1983.

Finally, we calculate the population adjustment by using coastal counties impacted by RMW. The RMW for Alicia was 10 nautical miles (n mi; 1 n mi = 1.852 km), only impacting Brazoria and Galveston Counties. Populations for Brazoria and Galveston were 184 143 and 213 333 (sum = 397 467) in 1983 and 388 181 and 357 117 (sum = 745 298) in 2022. We divide 745 298/397 467 = 1.87 to calculate the population adjustment. Our final calculation for Alicia is as follows: D_{2022} = 3 000 000 000 × 2.48 × 2.07 × 1.87. Therefore, the 2022 PL-normalized losses for Alicia are $28.8 billion. To better understand the effect of each adjustment, Fig. 2c shows the individual adjustments for Alicia in any given year between landfall in 1983 and 2022. For example, in the landfall year of 1983, the adjustments would be 3 000 000 000 × 1 × 1 × 1, in 2000, they would be 3 000 000 000 × 1.52 × 1.32 × 1.24 ($7.5 billion), and as mentioned above, in 2022, they would be 3 000 000 000 × 2.48 × 1.87 × 1.97 ($28.9 billion).

b. Collins and Lowe (2022) normalization method. A normalization methodology based on population could underestimate the magnitude of contemporary losses because in many exposed coastal locations, the amount of property at risk to damage has increased at a rate that exceeds local population growth (Collins and Lowe 2001). Collins and Lowe (2001) take

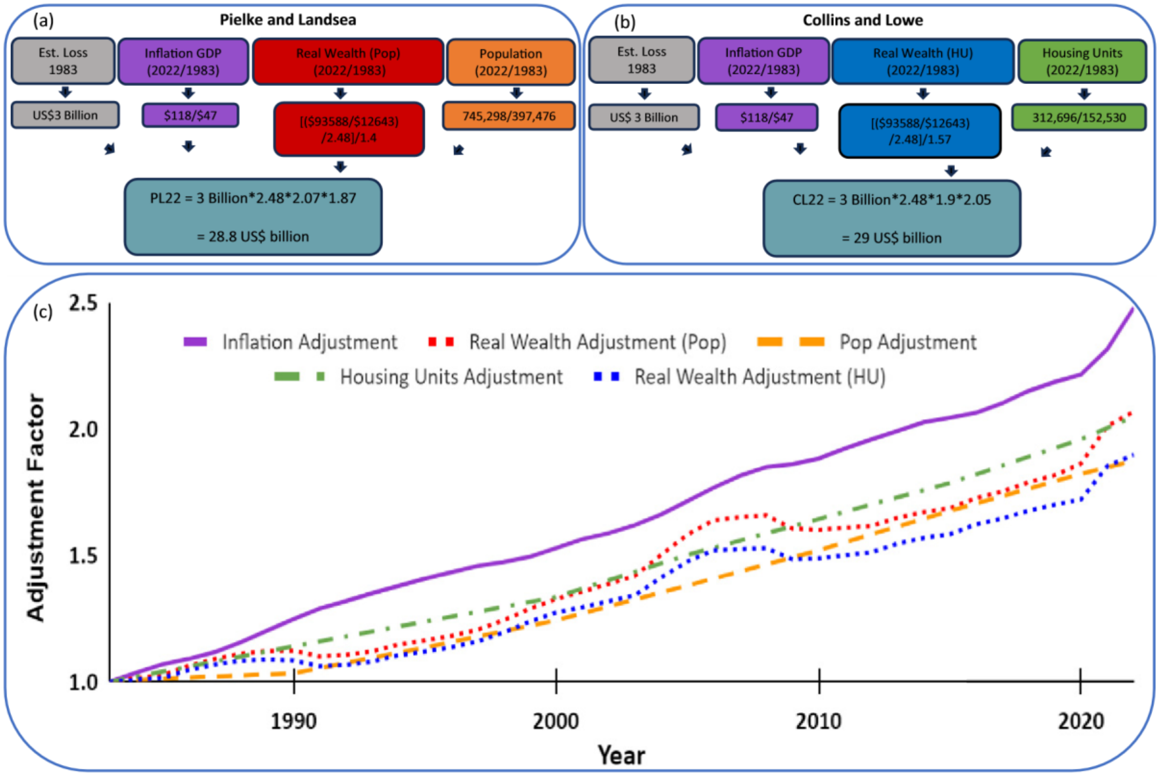


Fig. 2. Adjustments for Hurricane Alicia PL and CL normalization calculations. (a) Flowchart of adjustment factors used in the PL22 normalization. (b) Flowchart of adjustment factors used in the CL22 normalization. (c) Adjustments through time for Hurricane Alicia PL and CL normalization calculations. The GDP deflator used for the inflation adjustment in both PL22 and CL22 (year of normalization/1983) is displayed with the purple line. The Current-Cost Net Stock of Fixed Assets and Consumer Durable Goods (CCNSFACDG) (also adjusted for inflation and U.S. population) used for the real wealth per person adjustment in PL (year of normalization/1983) is displayed with the red dotted line. The county population (Pop) adjustment used in PL (year of normalization/1983) is displayed with the orange dashed line. The CCNSFACDG (also adjusted for inflation and U.S. HUs) used for the real wealth per HU adjustment in CL (year of normalization/1983) is displayed with the blue dotted line. The county HU adjustment used in CL (year of normalization/1983) is displayed with the green dashed line.

this into account using a housing unit adjustment, rather than a population adjustment. The general formula for the CL22-normalized losses is

$$D_{2022} = D_y \times \times I_y \quad \mathrm{RWHU}_y \times \mathrm{HU}_{2022/y},$$

where D_{2022} is the normalized damage in 2022 U.S. dollars, D_y is the reported damage in landfall-year U.S. dollars, I_y is the inflation adjustment, RWHU_y is the real wealth per housing unit adjustment, and $\mathrm{HU}_{2022/y}$ is the county housing unit adjustment.

The calculation of CL22 involves the same inflation adjustment as PL22. The wealth adjustment is different, as it corrects for national changes in housing units, rather than population. The final adjustment in CL22 is county housing units. As above with population, we use ArcGIS Pro to identify coastal counties that fall within the RMW field for each historic storm. For those coastal counties, we draw on U.S. Census information. Housing unit data are provided by decade in U.S. Census reports, and these numbers we manually entered from historic reports are not yet digitized and published by the agency in spreadsheet format. Linear interpolation was used between decadal counts (U.S. Census Bureau 2020). Finally, the housing unit adjustment was calculated based on the ratio of county housing units in 2022 to that of the year in which the storm originally made landfall.

Using Hurricane Alicia as example, the inflation adjustment is 2.48 (Fig. 2b). However, here we adjust the inflation-corrected wealth adjustment for the change in U.S. wide housing units in 1983 and 2022, which is estimated to be 92 510 204 and 145 322 999 units, or by a factor of

1.57 respectively. The final wealth adjustment for 1983 is the real wealth adjustment of 2.98, adjusted for the U.S. housing units of 1.57, which equals 1.89. Therefore, each housing unit in the United States has (on average) 1.89 times more wealth in 2022 than did each housing unit in 1983. Finally, we calculate the housing unit adjustment by using coastal counties impacted as above. Housing units for Brazoria and Galveston were 64 672 and 87 858 (sum = 152 530) in 1983 and 150 595 and 162 101 (sum = 312 696) in 2022. We divide the total 2022 housing units by the total of 1983 housing units (312 696/152 530 = 2.05) to calculate the housing unit adjustment. Our final calculation for Alicia is as follows: $D_{2022} = 3\,000\,000\,000 \times 2.48 \times 1.89 \times 2.05$. Therefore, the 2022 PL-normalized losses for Alicia are \$29 billion. Figure 2c also shows the CL individual adjustments for Alicia in any given year between landfall in 1983 and 2022. For example, in the landfall year of 1983, the adjustments would be $3\,000\,000\,000 \times 1 \times 1 \times 1$, in 2000, they would be $3\,000\,000\,000 \times 1.52 \times 1.27 \times 1.33$ (\$7.8 billion), and as mentioned above, in 2022, they would be $D_{2022} = 3\,000\,000\,000 \times 2.49 \times 1.71 \times 2.05$ (\$29 billion).

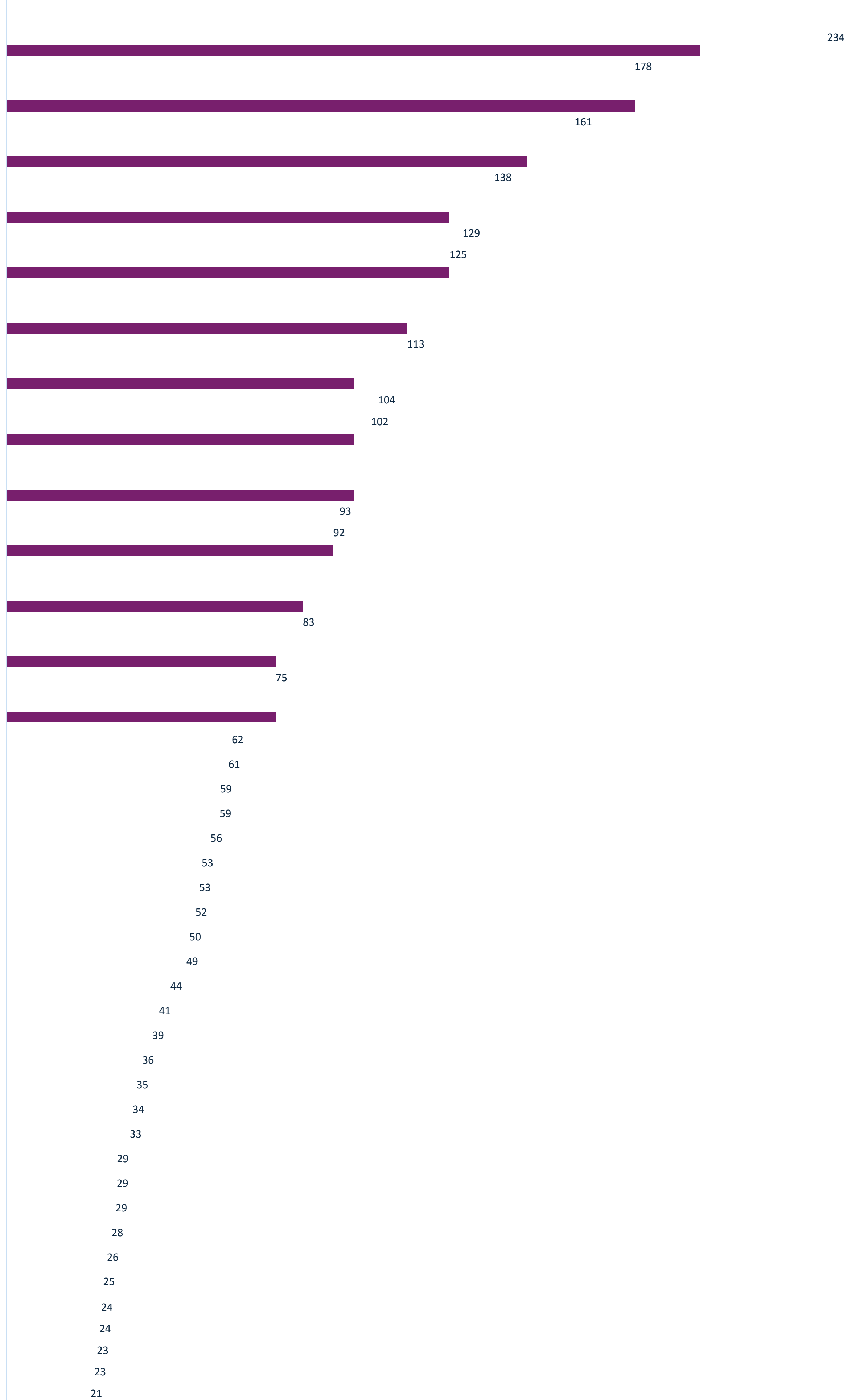
3. Results

Figure 3 shows the top 50 most damaging hurricane landfalls, ranked by 2022 normalized losses, using the Collins and Lowe approach and our RMW methodology (CL22). The top nine storms all have losses greater than \$100 billion (Fig. 3). The total normalized costs for the top 50 storms amount to \$2.9 trillion, with the top 10 storms on this list accounting for approximately half of that damage (\$1.4 trillion). The order of our top 10 storms is somewhat different to those of Weinkle et al. (2018) (see supplemental data Table 1 in the online supplemental material). Hurricane Ian (2022) also made our top 10 list. Ian had not occurred at the time of the Weinkle et al. (2018) study. Below we provide more detail on the top five most damaging hurricanes.

Hurricane Katrina is now ranked as the most damaging storm at \$234 billion in CL22-normalized losses (PL22 \$226). The population and housing units in counties affected by Katrina have decreased since landfall in 2005, and therefore, the increase in Katrina's normalized loss in comparison to Weinkle et al. (2018) is driven by different baseline damage estimates, inflation, and wealth factors. We use a baseline damage estimate of \$125 billion unadjusted (the same as listed in NCEI), which is compared to an \$82.2 billion unadjusted estimate used in Weinkle et al. (2018).

It is possible to compare our normalized losses with losses generated from a tropical cyclone (TC) catastrophe model; although models are private, some model developers publish results (please see supplemental material for "catastrophe models and their history"). In 2020, Swiss Re used their probabilistic tropical cyclone loss model (catastrophe model) to generate loss estimates for a Hurricane Katrina–like event with the observed wind and storm surge from 2005, however with 2020 exposure information and updated flood protection and vulnerability assumptions. They concluded that the total economic toll from such an event in 2020 could likely exceed \$175 billion (Schwartz 2020). This figure is higher than the 2005 Katrina economic losses (\$125 billion) despite the city having 80% of the population it did in 2005 (our normalization population and housing unit adjustments are <1). The catastrophe model, and our normalized results, illustrate that despite New Orleans' lower population and strengthened flood protection system, economic losses from natural hazards like Katrina are expected to continue to increase (Schwartz 2020).

The reason our normalized losses are higher than the 2020 Swiss Re estimate is due to small increases in inflation and wealth between 2020 and 2022, alongside an additional factor that is often referred to in catastrophe modeling as secondary uncertainty. Secondary uncertainty refers to the uncertainty in the damage estimation arising from impacts of a



234
178
161
138
129
125
113
104
102
93
92
83
75
62
61
59
59
56
53
53
52
50
49
44
41
39
36
35
34
33
29
29
29
28
26
25
24
24
23
23
21

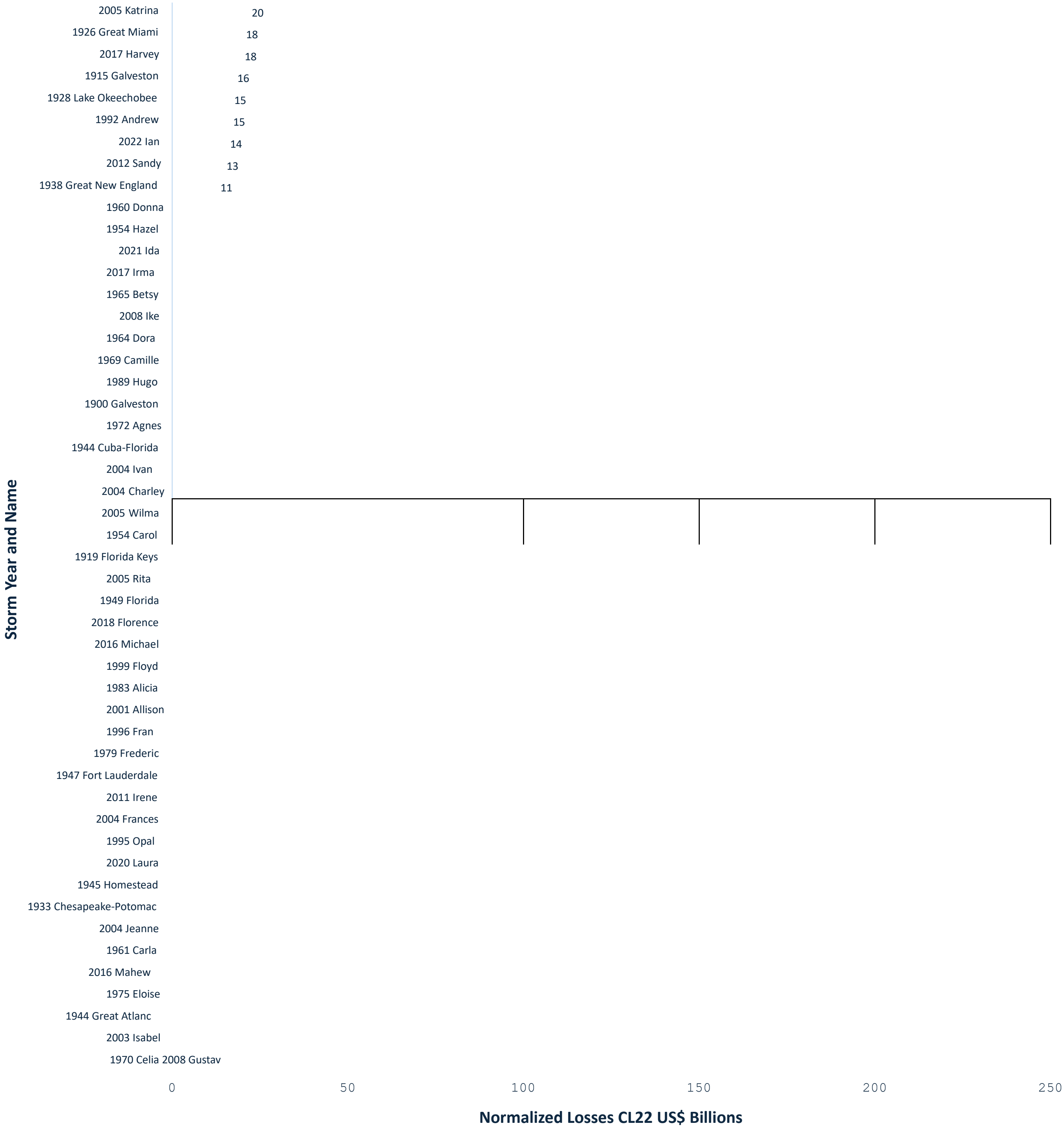


Fig. 3. 2022 normalized losses of the top 50 storms ranked by CL22.

single event and ultimately captures the inherent randomness in the system, reflecting the fact that small changes in hazard attributes can lead to very different loss outcomes. This is as opposed to primary uncertainty, which is more often defined as the uncertainty in the occurrence/frequency of the hazard event itself.

In the context of 2005 Hurricane Katrina, flood wall and levee failure were a major driver of overall losses (which resulted in flooding 80% of the city). Due to the strengthened flood system now in place post–Hurricane Katrina, the Swiss Re model is predicting a lower overall economic loss than that calculated by our normalized loss because our initial damage estimate only captures flood system failure, as opposed to the full distribution of potential outcomes if the flood system did not fail. Secondary uncertainty is a complex but important concept for understanding the limits of information that exist in historical loss records. Here, secondary uncertainty can lead to differences in normalized losses for individual events between studies and ultimately evidences why deriving trends from loss data of these rare, single events is fraught with difficulty.

The Great Miami hurricane is ranked second, but with lower CL22-normalized losses of \$178 billion (PL22 \$207 billion) in comparison to the previous CL17 estimate of \$208 billion in Weinkle et al. (2018). This may be due to the use of different population and housing unit adjustments. Our study uses Miami–Dade County given that the hurricane had an RMW of 20 n mi, consequently only impacting Miami–Dade County with its strongest winds. This county saw lower population and housing unit increases between 1926 and 2022 than did Broward County to the north. Note here that the PL22 normalization computes higher losses than the CL22 normalization. This is due to a higher population growth rate, in comparison to housing units growth rate in these counties since 1926.

The damage estimates for Hurricane Harvey make it the third costliest storm in this normalization (CL22 \$161 and PL22 \$165 billion). As with Hurricane Katrina, the county population and housing units have also decreased since Harvey's landfall, and therefore, like Katrina, it is the NCEI baseline, inflation, and wealth driving the difference in damage estimates [compared to the previous Weinkle et al. (2018) normalization] for Hurricane Harvey. It is also worth noting here that previous studies (Weinkle et al. 2018) have handled storms such as Harvey differently, due to the extreme precipitation associated with the storm. In these studies, population and housing unit adjustments were calculated for the entire state. While we agree with the theory behind this methodology, we choose to remain consistent with our methodology between storms, using the RMW at landfall to identify counties. More details on this choice are provided in the supplemental material.

The 1915 Galveston hurricane is the fourth costliest storm, with CL22-normalized losses of \$138 billion (PL22 \$158 billion). This hurricane had an RMW of 25 n mi, affecting three counties (Brazoria, Galveston, and Harris) that have seen major population increases between 1915 and 2022. Interestingly, the 1900 Galveston hurricane has moved out of the top 10 storms. These storms have similar tracks; however, the 1900 Galveston hurricane had a more westward landfall position and a smaller RMW (15 n mi) (Fig. 1). Our RMW adjustment factor includes only Brazoria and Galveston counties in the population and housing unit adjustment, normalizing this storm to CL22 \$53 billion (PL22 \$58 billion) making it now the 19th costliest storm. Indeed, the damage estimate from *Monthly Weather Review* states that "damage was from Galveston Island only. Other damage inland was noted, but not quantified" (Garriott 1900). This highlights the importance of landfall location and RMW, given that the 1900 Galveston and 1915 Galveston hurricanes had similar maximum sustained wind and minimum sea level pressures at landfall [120 kt (1 kt $\approx$ 0.51 m s^{-1}) and 936 hPa for the 1900 Galveston hurricane and 115 kt and 940 hPa for the 1915 Galveston hurricane]. See supplemental material for further discussion on Galveston 1900.

Large increases are also seen with the Okeechobee hurricane (RMW of 30 n mi) due to the major growth in Palm Beach, Martin, and Broward counties since 1928. We normalized here using the coastal counties at landfall, even though the highest death tolls were seen in Okeechobee County. This is also in line with the damage description in the *Monthly Weather Review* article that states "25 million in total property loss at West Palm Beach, Palm Beach, and other places in FL" (Mitchell 1928). Another historic report reflects: "Damage in coastal Palm Beach County was severe, especially in the Jupiter area where the eyewall of the hurricane persisted longer than at any other location because of where the storm crossed the coast. A storm surge around 10 ft with waves likely as high as 20 ft crashed into the barrier islands including Palm Beach." (UF Digital Collections 1928). Considering this, a 22CL $129 billion (PL22 $147) normalized loss for the Okeechobee hurricane may be reasonable.

See supplemental Fig. 2 for the top 50 most damaging hurricane landfalls using the Pielke and Landsea approach with our RMW (PL22) methodology. A comparison between the CL22 and PL22 and the CL17 and PL17 (Weinkle et al. 2018) normalization results can be found in supplemental Table 2. When comparing the results between the CL22 and PL22, we note small differences in 2022 normalized losses for many of the top 50 storms. However, for coastlines that have seen a more rapid growth in population than that of housing units, like the Florida, Southeast, New England, and Texas coastlines, we see higher normalized losses using the PL methodology. We see this, for example, with the 1926 Great Miami, the 1915 Galveston, the 1928 Lake Okeechobee, and the 1938 Great New England hurricanes, where the PL method yields normalized losses $18–28 billion greater than the CL-normalized losses. The opposite is true for coastlines like west Florida and the Carolinas, where housing unit growth has outpaced population growth. We see this, for example, with 1960 Donna and 1954 Hazel, where the CL method yields normalized losses $22–26 billion greater than the PL-normalized losses.

4. Discussion

a. Inflation. Inflation raises the nominal value of buildings, motor vehicles, and other fixed assets that insurers cover, pushing up claims to cover the cost of repairs. According to the Pew Research Center, the annual rate of inflation in the United States rose to 7% in November 2021 and 6.5% in 2022, which are the highest rates seen in almost four decades (U.S. Bureau of Labor Statistics 2021). The cumulative inflation rate increase between August 2018 and August 2022 was 17.5% (average inflation 4.1% per year). Therefore, recent inflation imparts a clear upward trend on the normalized loss calculations between the 2017 normalization (Weinkle et al. 2018) and our 2022 normalization (trends noted in Figs. 2 and 3).

b. Exposure. The 2022 normalization shows the importance of exposure in driving economic losses. Seven of the top eight storms that each exceed $100 billion in economic losses have all made landfall along coastlines in which the RMW encompasses greater than 1 million housing units (excluding Harvey) (Fig. 4a). Metropolitan areas that have been impacted by these costly storms include New Orleans, Miami, Galveston, West Palm Beach, Fort Myers, and coastal New Jersey. Substantial growth over the past 20 years is apparent for most south Florida coastal counties, as well as some counties in Texas and Alabama (Fig. 4b). More specifically, the largest relative increments between this study (2022) and the last study (2017) (Weinkle et al. 2018) are noted in regions that have also seen substantial population/ housing units increases (i.e., exposure) between 2017 and 2022 (supplemental Table 2 and Fig. 3). These increases have resulted in CL-normalized damage increases for recent hurricanes in these areas, for example, Hurricane Wilma ($44 billion in 2022 vs $32 billion in 2018) in Florida, Hurricane Ike ($61 billion in 2022 vs $35 billion in 2018) in Texas, and Hurricane Ivan ($50 billion in 2022 vs $27 billion in 2018) in Alabama.

What is also interesting here are high exposure coastal regions that have not seen significant losses since 1900. For example, both Tampa and Jacksonville are high exposure regions in the state of Florida that have seen rapid population growth through time but have not seen significant losses from a direct landfalling hurricane since 1900. This may be due to a combination of luck as well as atmospheric synoptic and historical climatological behavior.

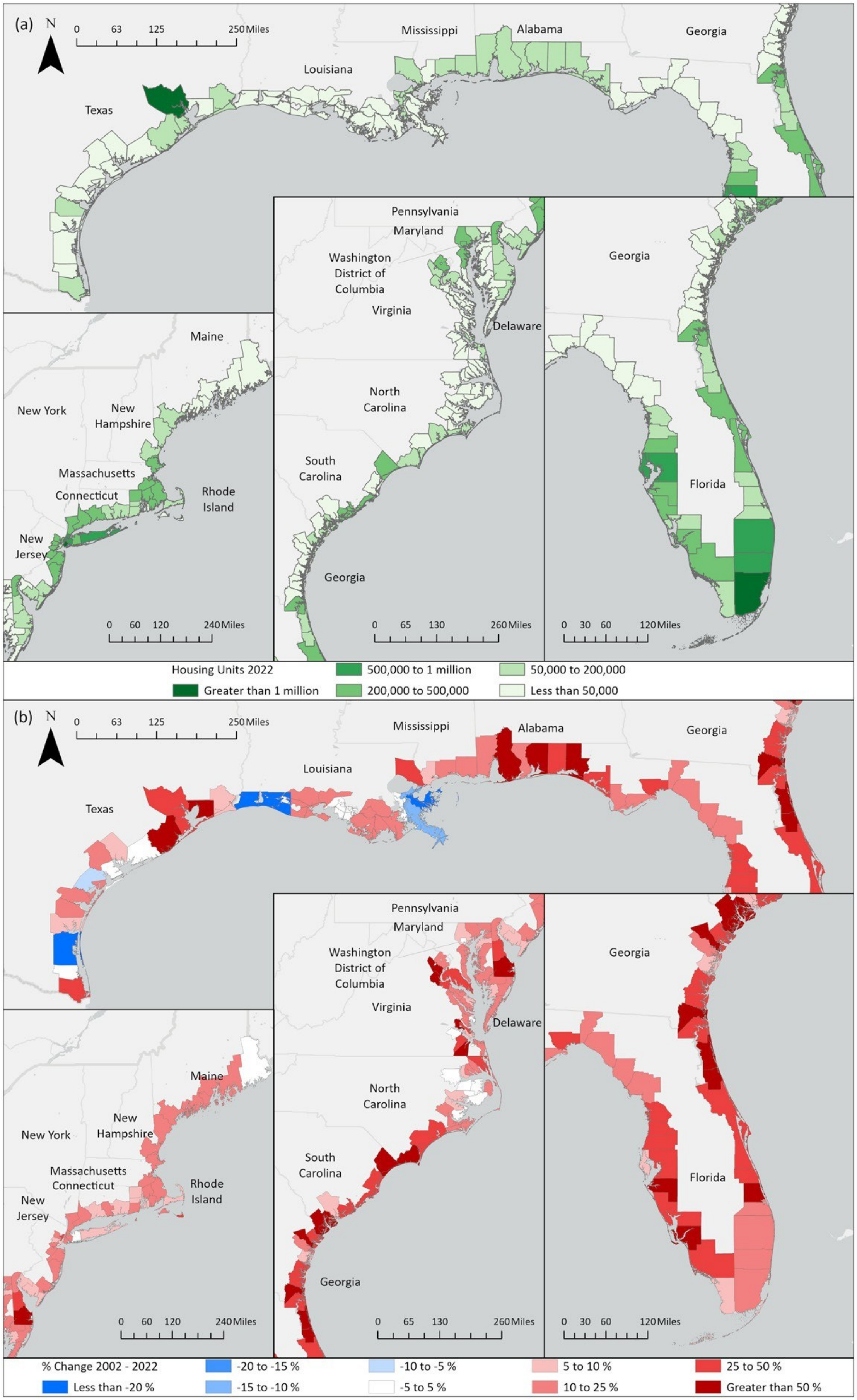


Fig. 4. (a) CONUS coastal county exposure (total county HUs) in 2022. Dark green indicates highest exposure. (b) Growing or declining trends between 2002 and 2022 (denoted as percentage increase or decrease). Blue colors indicate declining trends, and red colors indicate growing trends.

Jacksonville's location in northeast Florida may be less likely to get hit due to the typical steering around the western periphery of the Bermuda high being from south to north and disfavoring storm landfalls in that region climatologically. However, Jacksonville was directly impacted by category 2 Hurricane Dora in 1964. Dora had a small RMW of only 5 n mi, with a landfalling pressure of 966 hPa and sustained winds of 95 kt. If Dora was to make landfall today, it is estimated to cause ~$59 billion in damage—the 17th costliest normalized damage hurricane in our dataset (CL22).

Tampa has not had a direct landfall since the Tampa Bay hurricane in 1921, although several hurricanes have posed serious threats to Tampa in recent years, including Charley, Irma, Ian, and more recently Helene and Milton. Much of the Tampa metro area has a higher percentage of relatively (compared to many other regions of Florida) older building stock which has not been rebuilt due to a passing hurricane, plus the high susceptibility of storm surge potential given a gradual rise in the continental shelf along the west coast of Florida. The 1921 storm made landfall as a category 3, north of the populous Hillsborough County, with an RMW of 20 n mi, pressure of 958 hPa, and sustained winds of 100 kt. The unadjusted losses in 1921 were $3 million. Today, the outer edges of the 20-n mi RMW would likely affect northern Hillsborough County, making this now the 54th costliest hurricane at $7.3 billion in damage.

c. Analog storms. Analog storms, those with similar tracks/landfalls and intensities, allow for interesting comparisons (Fig. 5). Hurricanes Betsy (1965) and Ida (2021) were both category 4 storms that made landfall to the west of New Orleans, within 10 miles of each

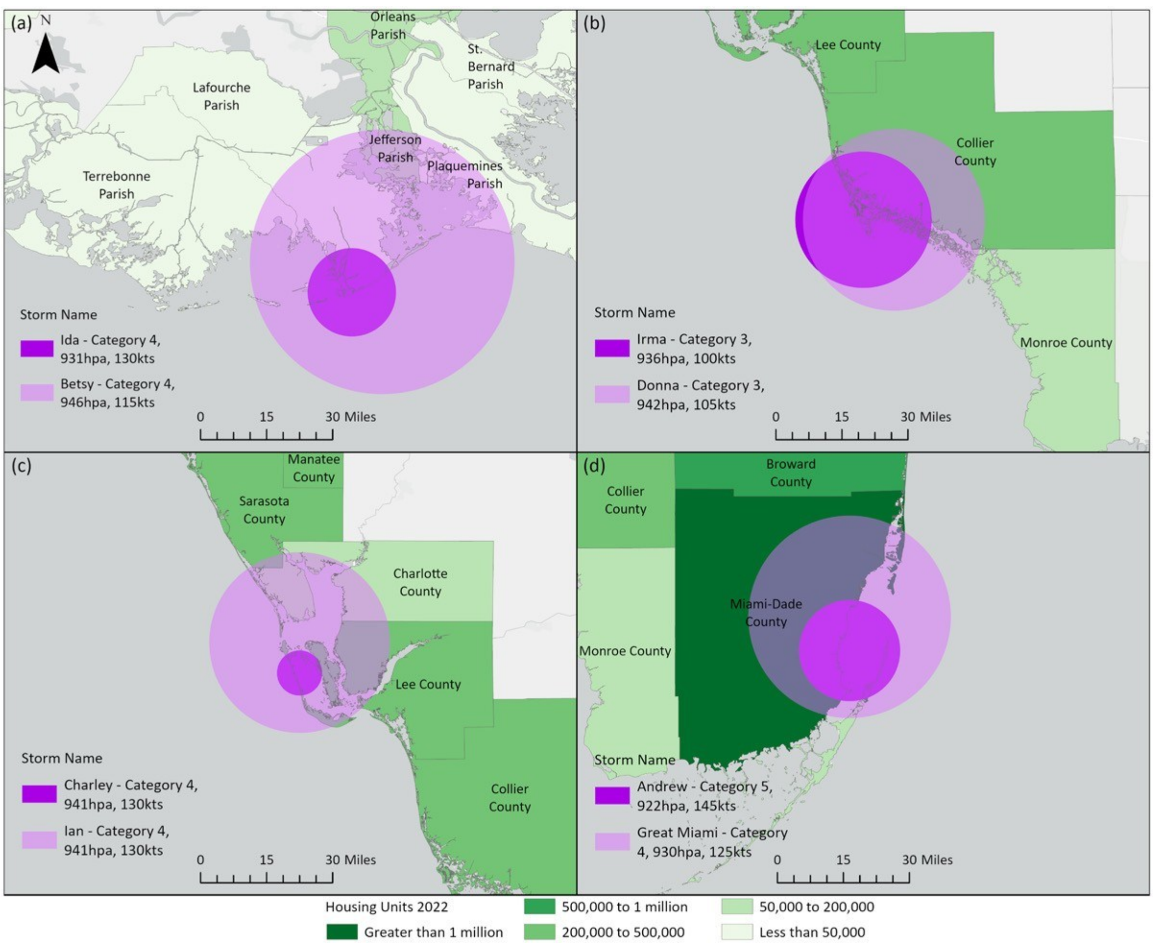


Fig. 5. Hurricane analog storm comparisons. (a) Betsy vs Ida RMWs with storm landfall characteristics, (b) Donna vs Irma RMWs with storm landfall characteristics, (c) Charley vs Ian RMWs with storm landfall characteristics, and (d) Great Miami vs Andrew RMWs with storm landfall characteristics.

other (Fig. 5a). Normalized losses for Betsy's landfall in LA are CL22 $62 billion and Ida's are CL22 $83 billion. Hurricane Ida was the stronger storm with a landfalling minimum sea level pressure of 931 hPa and maximum sustained winds of 130 kt, while Betsy made landfall with a minimum sea level pressure of 946 hPa and maximum sustained winds of 115 kt. However, Betsy had a much larger wind footprint (RMW of 30 n mi) than Ida (RMW of 10 n mi). After landfall, Ida weakened at a slower rate than Betsy. In an aggregate sense, the larger, slightly weaker Betsy that weakened faster post-landfall and the smaller, slightly stronger Ida that weakened slower post-landfall did comparable damage (within ~15% of each other).

As noted in Weinkle et al. (2018), Hurricanes Donna (1960) and Irma (2017) provide another opportunity to compare similar landfalling storms (Fig. 5b). Normalized losses for Donna are CL22 $93 billion and for Irma are CL22 $75 billion. Both storms made landfall as category 4 storms over the Florida Keys which then made landfall in Collier County at category 3 strength. Donna had a larger wind field (RMW 20 n mi in both Monroe and Collier County) than Hurricane Irma (RMW 10 n mi in Monroe and 15 n mi in Collier County), which may explain the difference in normalized losses for these storms. Category 4 Hurricane Ian had a similar track to category 4 Hurricane Charley (Fig. 5c), but Charley's loss estimates are significantly lower (CL22 $49 billion versus CL22 $113 billion). This is most likely due to Charley's small size, meaning Charley's RMW (5 n mi) did not impact the higher exposure areas in Lee County that were impacted by Ian's large RMW (20 n mi).

In addition, Charley's size and faster forward speed resulted in a storm surge that was much less than that of Ian. Maximum storm surge estimates from Charley ranged from 6 to 7 ft (Pasch et al. 2004), while Ian produced a catastrophic storm surge of 10–15+ ft along Fort Myers Beach. It is likely that the post–Hurricane Charley (2004) rebuild in Charlotte County resulted in lower losses from Hurricane Ian (2022), due to a greater number of houses built to stronger Florida building codes post-Hurricane Charley.

Perhaps, one of the most interesting comparisons can be seen between the Great Miami hurricane (1926) and Hurricane Andrew (1992) (Fig. 5d). Both storms had subsequent landfalls after Miami, but for the purposes of comparing these two storms, we report here only on the first landfall near Miami. Normalized losses for the first landfall of Great Miami are CL22 $154 billion and for Andrew are CL22 $121 billion (see GitHub for disaggregated losses). Both storms had similar tracks and landfalls along the Miami coastline. The Great Miami hurricane made landfall as a strong category 4 with a minimum sea level pressure of 930 hPa and maximum sustained winds of 125 kt, while Andrew made landfall as a category 5 with a minimum sea level pressure of 922 hPa and maximum sustained winds of 145 kt. Even though Andrew was more intense at landfall, the Great Miami hurricane had an RMW that was twice as large as that of Hurricane Andrew (20 vs 10 mi) and made landfall slightly farther north, closer to central Miami. Consequently, the RMW of Andrew did not track over downtown Miami, while the outer edge of the Great Miami hurricane did directly impact downtown Miami. This direct impact is likely why the normalized damage caused by the Great Miami hurricane is higher than that of Hurricane Andrew.

d. Vulnerability, rebuild culture, and climate change. The normalizations presented in this study provide sound estimates for normalized losses considering inflation, wealth, and exposure. However, these normalized losses do not account for vulnerability. Vulnerability considers intrinsic characteristics of a system that creates the potential for harm but are independent of the risk of any hazard or extreme event (Sarewitz et al. 2003). It is usually an independent component of catastrophe loss models (e.g., Verisk 2020; Risk Management Solutions 2019) through which the translation of hazard event severity into damage and/or loss can occur. Vulnerability, in the context of this research, might involve how the damageability of an asset for a given severity of the extreme event changes (most often reduces) with time due to improvements in building technology. Changes in vulnerability may arise from improved state-enforced requirements detailing how new buildings must be constructed. While building code changes seek to reduce vulnerability, this may increase over time if building maintenance is poor. The current CL and PL normalizations for hurricane losses assume housing structures to have the same vulnerability throughout time. We know that this is not the case. While not every state currently has building codes in place, the state of Florida does have some of the most stringent building codes in the United States [Insurance Institute for Business and Home Safety (IBHS) 2024]. For example, the Great Miami hurricane of 1926 incurred significant losses, but the changes in structural resilience that occurred since 1926 are not accounted for in this normalization. In this case, the current 2022 normalization assumes all housing structures existing in 2022 are built to the same structural integrity that they were in 1926. This is problematic considering buildings constructed since the implementation of Florida's stringent building codes translates to a much higher portion of properties that are not nearly as vulnerable as they were in 1926.

A normalization method that includes vulnerability was developed by Crompton (2011) and recently used in McAneney et al. (2019, 2022) to adjust Australian losses between 1966 and 2017 and New Zealand losses between 1968 and 2019. For example, the 2019 normalization method uses the number and nominal cost of new residential dwellings and post-1974 improvements in construction standards in tropical cyclone–prone Australia. McAneney et al. (2019) concluded that the rising cost of natural disasters was primarily driven by exposure. A vulnerability adjustment would allow for a more realistic picture of historic CONUS hurricane losses. We are currently developing vulnerability adjustments for all CONUS hurricane losses and will report on these in a future publication.

Another factor that might contribute to bottom-line nominal losses not considered in current normalization is rebuild culture. Economic demand surge after a natural catastrophe is the result of disruption to the local construction market. When a hurricane makes landfall, and there is a significant increase in the workload, prices can rise suddenly. For example, in Florida post–Hurricane Irma, the demand surge was calculated at 5% (Verisk 2020). It is impossible to unpick how much demand surge might have contributed to the normalized nominal losses reported in this study; however, we might assume that demand surge may underprice today's costs of the older storms in our top 50 list, due to greater populations today, in comparison to the past.

Finally, climate change and other human influences may have exerted some impact on recent hurricane losses as demonstrated in recent attribution studies (Reed et al. 2022; Strauss et al. 2021). While most of the loss increase to date is likely driven by increases in exposure, anthropogenic warming's contributions to sea level rise, increased extreme precipitation, and increased hurricane intensification rates (e.g., Knutson et al. 2019, 2020; Klotzbach et al. 2022) are likely to increase climate change's proportion of the impact to losses from future hurricanes. Incorporating terms which address climate change explicitly into the normalization methodologies would be highly desirable, from both private industry and societal perspectives. However, the contribution of anthropogenic global warming to future hurricane damage and loss remains an active area of research, and precisely how to incorporate climate change coherently in hurricane normalizations is unclear.

Acknowledgments. The authors would like to acknowledge immeasurable help from Eric Blake (National Hurricane Center) with historic damage details and understanding. We also thank Adam Smith [National Centers for Environmental Information (NCEI)] for help with economic loss methodologies and data. We also thank Delian Colón-Burgos and Dr. Chris Landsea for their assistance with RMW data. The authors thank the editor and the three reviewers for very helpful comments, edits, and suggestions that significantly improved the manuscript. J. Muller, K. Mooney, and T. Martin acknowledge support from the National Science Foundation (Award OCE:2322270). P. Klotzbach acknowledges support from the G. Unger Vetlesen Foundation.

Data availability statement. All raw datasets and dataset explanations and calculations for normalization are available in a GitHub repository (https://github.com/DrJoMuller/ Hurricane-Normalization-2022). Economic data will be updated annually from BEA (October annually for the previous year) and decadally for U.S. Census data (2030, 2040 etc.). Therefore, the updated 2023 normalizations will be available by February 2025.

References

Blake, E. S., C. W. Landsea, and E. Gibney, 2011: The deadliest, costliest, and most intense United States tropical cyclones from 1851 to 2010 (and other frequently requested hurricane facts). NOAA Tech. Memo. NWS NHC-6, 49 pp., https://www.nhc.noaa.gov/pdf/nws-nhc-6.pdf.

Collins, D., and S. P. Lowe, 2001: Validation dataset for US Hurricane Models. Casualty Actuarial Society, 34 pp., http://www.casact.org/pubs/forum/01wforum/ 01wf217.pdf.

Colón-Burgos, D., and C. W. Landsea, 2023: Expanding the Atlantic hurricane database: Adding in radius of maximum winds. *103rd Annual Meeting*, Denver, CO, Amer. Meteor. Soc., S254, https://ams.confex.com/ams/103ANNUAL/ meetingapp.cgi/Paper/417962.

Crompton, R. P., 2011: Normalising the Insurance Council of Australia natural disaster event list. Insurance Council of Australia by Risk Frontiers Rep., 9 pp.

Demuth, J., M. DeMaria, and J. A. Knaff, 2006: Improvement of advanced microwave sounder unit tropical cyclone intensity and size estimation algorithms. *J. Appl. Meteor. Climatol.*, **45**, 1573–1581, https://doi.org/10.1175/JAM 2429.1.

Garriott, E. B., 1900: Forecasts and warnings. *Mon. Wea. Rev.*, **28**, 371, https:// doi.org/10.1175/1520-0493(1900)28[425b:FAW]2.0.CO;2.

Grinsted, A., P. Ditlevsen, and J. Hesselbjerg Christensen, 2019: Normalized US hurricane damage estimates using area of total destruction, 1900–2018. *Proc. Natl. Acad. Sci. USA*, **116**, 23 942–23 946, https://doi.org/10.1073/pnas. 1912277116.

IBHS, 2024: Rating the states: 2024 Edition: An assessment of residential building code and enforcement systems for life safety and property protection in hurricane-prone regions. 25 pp., https://ibhs1.wpenginepowered.com/wp-content/uploads/RTS_2024.pdf.

Johnson, L., and S. H. Williamson, 2023: What was the U.S. GDP then? Measuring Worth, accessed 11 January 2023, https://www.measuringworth.com/datasets/ usgdp/result.php.

Johnston, L. D. and S. H. Williamson, 2006: The annual real and nominal GDP for the United States, 1790–present. Economic History Services, http://eh.net/ hmit/gdp/.

Klotzbach, P. J., S. G. Bowen Jr., R. Pielke, and M. Bell, 2018: Continental U.S. hurricane landfall frequency and associated damage: Observations and future risks. *Bull. Amer. Meteor. Soc.*, **99**, 1359–1376, https://doi.org/10.1175/ BAMS-D-17-0184.1.

——, K. M. Wood, C. J. Schreck III, S. G. Bowen, C. M. Patricola, and M. M. Bell, 2022: Trends in global tropical cyclone activity: 1990–2021. *Geophys. Res. Lett.*, **49**, e2021GL095774, https://doi.org/10.1029/2021GL095774.

Knutson, T., and Coauthors, 2019: Tropical cyclones and climate change assessment: Part I: Detection and attribution. *Bull. Amer. Meteor. Soc.*, **100**, 1987–2007, https://doi.org/10.1175/BAMS-D-18-0189.1.

——, and Coauthors, 2020: Tropical cyclones and climate change assessment: Part II: Projected response to anthropogenic warming. *Bull. Amer. Meteor. Soc.*, **101**, E303–E322, https://doi.org/10.1175/BAMS-D-18-0194.1.

Landsea, C. W., J. L. Franklin, and J. L. Beven, 2013: The revised Atlantic hurricane database (HURDAT2). United States National Oceanic and Atmospheric Administration's National Weather Service Rep., 6 pp., https://www.nhc. noaa.gov/data/hurdat/hurdat2-format-atlantic.pdf.

Martinez, A. B., 2020: Improving normalized hurricane damages. *Nat. Sustainability*, **3**, 517–518, https://doi.org/10.1038/s41893-020-0550-5.

McAneney, J., B. Sandercock, R. Crompton, T. Mortlock, R. Musulin, R. Pielke Jr., and A. Gissing, 2019: Normalised insurance losses from Australian natural disasters: 1966–2017. *Environ. Hazards*, **18**, 414–433, https://doi.org/10.1080/ 17477891.2019.1609406.

——, M. Timms, S. Browning, P. Somerville, and R. Crompton, 2022: Normalised New Zealand natural disaster insurance losses: 1968–2019. *Environ. Hazards*, **21**, 58–76, https://doi.org/10.1080/17477891.2021.1905595.

Mitchell, C., 1928: The West Indian Hurricane of September 10–20, 1928. *Mon. Wea. Rev.*, **56**, 347–350, https://doi.org/10.1175/1520-0493(1928)56<347: TWIHOS>2.0.CO;2.

Neumayer, E., and F. Barthel, 2011: Normalizing economic loss from natural disasters: A global analysis. *Global Environ. Change*, **21**, 13–24, https://doi. org/10.1016/j.gloenvcha.2010.10.004.

NOAA/NCEI, 2024: U.S. billion-dollar weather and climate disasters. Accessed 1 November 2024, https://www.ncei.noaa.gov/access/billions/events.

Pasch, R. J., D. P. Brown, and E. S. Blake, 2004: Tropical cyclone report, Hurricane Charley. NHC Tech. Rep., 23 pp., https://www.nhc.noaa.gov/data/tcr/AL032004_ Charley.pdf.

Pielke, R. A., Jr., and C. W. Landsea, 1998: Normalized hurricane damages in the United States: 1925–95. *Wea. Forecasting*, **13**, 621–631, https://doi.org/ 10.1175/1520-0434(1998)013<0621:NHDITU>2.0.CO;2.

——, J. Gratz, C. W. Landsea, D. Collins, M. A. Saunders, and R. Musulin, 2008: Normalized hurricane damage in the United States: 1900–2005. *Nat. Hazards Rev.*, **9**, 29–42, https://doi.org/10.1061/(ASCE)1527-6988(2008)9:1(29).

Reed, K. A., M. F. Wehner, and C. M. Zarzycki, 2022: Attribution of 2020 hurricane season extreme rainfall to human-induced climate change. *Nat. Commun.*, **13**, 1905, https://doi.org/10.1038/s41467-022-29379-1.

Risk Management Solutions, 2019: Like moths to the flame. *Exposure Magazine*, 1 August 2024.

Sarewitz, D., R. Pielke Jr., and M. Keykhah, 2003: Vulnerability and risk: Some thoughts from a political and policy perspective. *Risk Anal.*, **23**, 805–810, https://doi.org/10.1111/1539-6924.00357.

Schwartz, M., 2020: 15 years after Katrina: Would we be prepared today? Swiss Reinsurance Company, https://www.swissre.com/.

Strauss, B. H., and Coauthors, 2021: Economic damages from Hurricane Sandy attributable to sea level rise caused by anthropogenic climate change. *Nat. Commun.*, **12**, 2720, https://doi.org/10.1038/s41467-021-22838-1.

UF Digital Collections, 1928: 92 views. American Autochrome Company, accessed 1 November 2023, https://ufdc.ufl.edu/UF00001306/00001/images/0.

U.S. Bureau of Economic Analysis, 2023: Current-cost net stock of fixed assets and consumer durable goods [K1WTOTL1ES000]. Federal Reserve Bank of St. Louis, accessed 1 February 2024, https://fred.stlouisfed.org/series/K1WTO TL1ES000.

U.S. Bureau of Labor Statistics, 2021: Consumer price index summary. Economic News Release, accessed 26 December 2021, https://www.bls.gov/news. release/cpi.nr0.htm.

U.S. Census Bureau, 2020: Historical housing change data (1910–2020). Accessed 30 September 2023.

——, 2022: Historical population change data (1910–2020). Accessed 1 October 2023, https://www.census.gov/data/tables/time-series/dec/popchange-datatext.html.

Verisk, 2020: Insights into economic demand surge after Hurricanes Harvey and Irma, 2017 hurricane season review, October 2020. AIR Worldwide Corporation, 12 pp., www.air-worldwide.com/siteassets/Publications/White-Papers/documents/2017_hurricane_season_demand_surge_insights.pdf.

Weinkle, J., C. Landsea, D. Collins, R. Musulin, R. P. Crompton, P. J. Klotzbach, and R. Pielke Jr., 2018: Normalized hurricane damage in the continental United States 1900–2017. *Nat. Sustainability*, **1**, 808–813, https://doi.org/10.1038/ s41893-018-0165-2.