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Continental United States Hurricane Landfall Frequency and Associated Damage: Observations and Future Risks

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Capsule Summary

While United States landfalling hurricane frequency or intensity shows no significant trend since 1900, growth in coastal population and wealth have led to increasing hurricane-related damage along the United States coastline.

Keywords

Hurricanes, tropical cyclones, climate change, FEMA, flood insurance

Abstract

Continental United States (CONUS) hurricane-related inflation-adjusted damage has increased significantly since 1900. However, since 1900 neither observed CONUS landfalling hurricane frequency nor intensity show significant trends, including the devastating 2017 season.

Two large-scale climate modes that have been noted in prior research to significantly impact CONUS landfalling hurricane activity are El Niño-Southern Oscillation on interannual timescales and the Atlantic Multi-decadal Oscillation on multi-decadal timescales. La Niña seasons tend to be characterized by more CONUS hurricane landfalls than do El Niño seasons, and positive Atlantic Multi-decadal Oscillation phases tend to have more CONUS hurricane landfalls than do negative phases.

Growth in coastal population and regional wealth are the overwhelming drivers of observed increases in hurricane-related damage. As the population and wealth of the US has increased in coastal locations, it has invariably led to the growth in exposure and vulnerability of coastal property along the US Gulf and East Coasts. Unfortunately, the risks associated with more people and vulnerable exposure came to fruition in Texas and Florida during the 2017 season following the landfalls of hurricanes Harvey and Irma. Total economic damage from those two storms exceeded $125 billion. Growth in coastal population and exposure is likely to continue in the future, and when hurricane landfalls do occur, this will likely lead to greater damage costs than previously seen. Such a statement is made recognizing that the vast scope of damage from hurricanes often highlight the effectiveness (or lack thereof) of building codes, flood maps, infrastructure, and insurance in at-risk communities.

1. Introduction

Among weather-related disasters, landfalling tropical cyclones (TCs) are a leading cause of economic damage in the continental United States (CONUS) and globally.[1] The very active and destructive 2017 Atlantic hurricane season resulted in an excess of $125 billion in damage in the CONUS (Aon Benfield 2018). Landfalling TCs also accounted for eight of the top ten costliest United States (US) insured losses from natural disaster events according to Aon Benfield through 2017. CONUS landfalling hurricane damage has risen dramatically since the start of the 20th century after adjusting historical losses for inflation (Pielke et al. 2008). However, because property and wealth exposed to hurricane impacts accumulates in exposed coastal locations, inflation adjustments alone cannot entirely capture the increased potential for losses if those same storms were to impact at today's levels of development.

Several studies have examined trends in CONUS hurricane losses since 1900 by normalizing historical damage to modern-day values by adjusting for inflation, population and various individual wealth metrics, as well as other factors (Pielke and Landsea 1998; Pielke et al. 2008; Schmidt et al. 2009; Nordhaus 2010; Bouwer and Wouter Botzen 2011; Neumayer and Barthel 2011; Barthel and Neumayer 2012). These studies have typically shown no significant trend in CONUS landfalling normalized damage once societal change is considered (Pielke et al. 2008). This result is expected as landfalling CONUS hurricanes have not increased in frequency or intensity since 1900 through 2017 (as shown below), meaning that an unbiased normalized loss record would be expected to show the same (lack of) trend. Independent climate and

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[1] http://www.aonbenfield.com/catastropheinsight

economic data indicate that the primary source of the increase in damage caused by hurricanes in recent decades is due to increases in exposure along the United States East and Gulf Coasts (Pielke et al. 2008; Bouwer and Wouter Botzen 2011).

This manuscript has three primary themes. Following a discussion of data sources, we examine trends in both CONUS landfalling hurricanes as well as CONUS normalized damage from 1900-2017. We then re-examine the relationship between El Niño - Southern Oscillation (ENSO) and CONUS landfalling hurricanes (Bove et al. 1998; Klotzbach 2011) along with the relationship with associated normalized damage (Pielke and Landsea 1998). This section also updates the impact that the phase of the Atlantic Multi-decadal Oscillation (AMO)[2] has on CONUS landfalling hurricanes and damage (Landsea et al. 1999). The manuscript then examines potential future CONUS landfalling hurricane damage through analyses of current and projected trends in coastal exposure and finishes with a discussion and conclusions.

2. Data and Methodology

CONUS hurricane landfall data are extracted from the Atlantic Oceanographic and Meteorological Laboratory's (AOML) website from 1900-1960 and 1983-2016 (http://www.aoml.noaa.gov/hrd/hurdat/UShurrs_detailed.html). For the period from 1961-1982 where the National Hurricane Center's (NHC's) hurricane database (HURDAT2) reanalysis project (Landsea and Franklin 2013) is not yet complete, we calculated hurricane landfall

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[2] We note that there remains vigorous scientific discussion as to the origins of the AMO, with some arguing that the Atlantic Meridional Overturning Circulation is the primary driver (Grossmann and Klotzbach 2009; Yan et al. 2017), while others argue that sulfate aerosols (Booth et al. 2012) or stochastic mid-latitude atmospheric forcing play a greater role (Clement et al. 2015).

locations directly from hurricane tracks plotted from HURDAT2 with landfall intensities constrained to be the same Saffir-Simpson scale category as listed on the AOML website: http://www.aoml.noaa.gov/hrd/hurdat/All_United States_Hurricanes.html. Landfall locations and intensities for the 2017 Atlantic hurricane season were taken from NHC operational advisories. Multiple landfalls by an individual TC were counted separately as long as they traveled over the open ocean for at least 100 miles between their individual landfalls. In the case of 2017, all three CONUS hurricanes (Harvey, Irma and Nate) made multiple landfalls, but the second landfall was less than 100 miles from the first one, and consequently, each storm was counted once in this analysis.

Base damage adjusted for inflation and normalized damage estimates for historical CONUS landfalling TCs were taken from the ICAT Damage Estimator (http://www.icatdamageestimator.com/) which is based on Pielke et al. (2008). Damage values in the ICAT database through 2016 were adjusted to 2017 dollars using the methodology of Pielke et al. (2008). The 2017 damage total was taken from individual storm estimates determined by Aon Benfield (Aon Benfield 2018).

The definition of ENSO events used here is the August-October-averaged Oceanic Niño Index (ONI). The ONI is the official index used by the National Oceanic and Atmospheric Administration (NOAA) to define ENSO events. We calculate the ONI from the NOAA Extended Reconstructed SST version 4 (Huang et al. 2015). The August-October ONI is defined to be the August-October average of Niño 3.4 (5°S-5°N, 170°-120°W; Barnston et al. 1997) sea surface temperature (SST) anomalies calculated from 30-year centered base periods updated every five years. Any August-October-averaged ONI greater than 0.5°C was classified as El Niño, an anomaly less than -0.5°C was classified as La Niña, and all other seasons were classified as ENSO neutral. A total of 29 years were classified as El Niño, 29 years were classified as La Niña, and the remaining 60 years were classified as ENSO neutral.

Our definition of the AMO classified seasons using the same approach used in Klotzbach and Gray (2008) whereby 1900-1925 and 1970-1994 were classified as negative AMO periods while 1926-1969 and 1995-2017 were classified as positive AMO periods. There is considerable uncertainty as to whether the Atlantic has in recent years reverted to a negative AMO phase (Klotzbach et al. 2015), but given the very active 2017 Atlantic hurricane season that has just occurred, we prefer to extend the positive AMO phase through to the present recognizing that such a classification remains provisional. However, the results displayed for the AMO throughout the manuscript would not show significant differences were the 2013-2017 period to be reclassified as a negative AMO phase.[3]

Statistical significance for trends in both landfall frequency as well as normalized damage were evaluated using a t-test. All statistical significance tests must exceed a 5% level to be considered significant. For the remainder of the document, significant/insignificant trends refer to those which either exceeded or failed to exceed the 5% level. Each year was counted as an individual degree of freedom, since there is little auto-correlation between one year's Atlantic hurricane activity (r=0.11) or damage (r=0.22) and that experienced the following year. Monte Carlo simulations were conducted to determine differences in mean and median values between climate modes and CONUS hurricane landfalls and damage. A total of 1000 random time series with the same number of years as the climate mode being investigated were drawn from the full

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[3] For example, the average positive (negative) AMO number of CONUS landfalling hurricanes per year is 1.94 (1.53) when treating 2013-2017 as a continuation of a positive AMO phase, while the average number is 2.00 (1.50) when treating 2013-2017 as a new negative AMO phase.

118-year dataset. For example, in the case of both El Niño and La Niña, one thousand 29-year time series of the full 118-year time series were drawn. If the observed value was either greater than the 95th percentile or less than the 5th percentile of the randomly-drawn values, the difference from the mean value of all seasons was said to be significant at the 5% level. However, such simple statistics should be interpreted with caution as climate variables may or may not exhibit stationarity, and the textbook notion of observations serving as a sample from a population may not accurately represent out-of-sample climate processes (Saunders et al. 2017).

3. Trends in Continental United States Landfalling Hurricanes and Normalized Hurricane Damage

We begin by examining the long-term trend in CONUS landfalling hurricanes and damage since the start of the 20th century. Inflation-adjusted CONUS hurricane losses show a significant increasing trend since 1900 (Fig. 1). However, there is an insignificant trend in CONUS landfalling hurricanes from 1900-2017 (Fig. 2a). When we only examine hurricanes that made landfall at major hurricane strength (Saffir-Simpson Category 3-5) (one-minute sustained winds >=96 kt), which are responsible for greater than 80% of all normalized tropical cyclone-related damage (Pielke and Landsea 1998), we find a similar insignificant trend (Fig. 2b). We therefore conclude that the large increase in observed hurricane-associated inflation-adjusted CONUS damage (Pielke et al. 2008) is primarily due to increases in exposure as opposed to increasing frequency or intensity of hurricanes making CONUS landfall.

We next employ the same methodology used in Pielke et al. (2008) to examine trends in CONUS hurricane damage since 1900 normalized to 2017 values, noting that there is currently an effort underway by Pielke and colleagues to comprehensively update Pielke et al. (2008). The long-term normalized hurricane damage record also shows no significant trend. One of the most notable items is the extreme year-to-year variability in the time series (Fig. 3). For example, the most damaging normalized CONUS landfalling hurricane is the Great Miami Hurricane of 1926 which is estimated to result in >$210 billion in damage, were it to occur in 2017. If the normalization is unbiased, then no significant trend in CONUS normalized hurricane damage since 1900 is expected, consistent with no significant trend in landfalling hurricanes or major hurricanes.

The fact that climate trends and normalization trends both show no significant increases or decreases provides an indication that the normalization methodology is, in aggregate, unbiased.[4] In other words, the adjustments to economic data result in a time series with statistical properties that correspond with those of the climate time series, as would be expected from an unbiased normalization. Climate data provide an independent check on the normalization time series.

4. Relationships between Large-Scale Climate Modes and Continental United States Landfalling Tropical Cyclone Frequency and Damage

a. ENSO

We next examine how ENSO is related to the frequency and intensity of CONUS landfalling hurricanes. About 1.75 times as many hurricanes make CONUS landfall in La Niña

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[4] It is of course possible that there are numerous biases that are insignificant, or cancel out each other.

seasons compared with El Niño seasons (Fig. 4a), although Jagger and Elsner (2006) found that the strongest storms making CONUS landfall occur in El Niño seasons. We find similar ENSO-related modulation in both Florida and East Coast landfalls as well as Gulf Coast landfalls. The La Niña/El Niño ratio is slightly larger for major hurricane landfalls than for all hurricane landfalls (Fig. 4b), which is also in keeping with prior research (Bove et al. 1998; Klotzbach 2011), although we note that the increase in hurricane landfalls observed in La Niña seasons from that observed in all seasons does not meet the 5% significance level. The stronger modulation of stronger hurricane activity is in keeping with physical reasoning, since more conducive environments are necessary to sustain major hurricane intensity as opposed to Category 1-2 hurricane intensity. Gray (1984) documented that vertical wind shear in the Caribbean and further east into the tropical Atlantic increased in El Niño seasons, creating conditions that were detrimental for TC formation and intensification. Tang and Neelin (2004) showed that El Niño also increases upper tropospheric temperatures in the tropical Atlantic, thereby stabilizing the air column and suppressing deep convection. El Niño has also been shown to be associated with a weaker subtropical high, promoting recurvature of TCs and reducing frequency of CONUS hurricane landfall (Colbert and Soden 2012).

CONUS normalized hurricane damage shows a large increase in La Niña seasons compared with El Niño seasons, with neutral ENSO conditions having larger median damage than El Niño seasons but less than La Niña seasons (Fig. 5a). Normalized damage in El Niño seasons is significantly less than the median damage incurred in all seasons, while the observed median damage in La Niña seasons is significantly more than the median damage incurred in all seasons. The reduction in normalized damage in El Niño seasons and the increase in normalized damage in La Niña seasons is significant for Florida and the East Coast. The significance level of the reduction for Gulf Coast damage in El Niño is unable to be determined precisely as ~25% of all Monte Carlo simulations for Gulf Coast damage returned a median damage of $0. Note that the combined Florida and East Coast and Gulf Coast median damage values do not sum to the CONUS total in Figure 5, since median values are being plotted (as opposed to mean values).

Since 1900, a total of 37 years have had over $10 billion in normalized damage. Only four of those years were classified as El Niño seasons: 1965, 1969, 1972, and 2004. Two of these seasons (1969 and 2004) would qualify as weak El Niño seasons using the current operational definition of NOAA for ENSO strength as their ONI values were <1°C. Both 1965 and 1972 would qualify as strong El Niño seasons. As would be expected given the volatile nature of the normalized damage time series, the standard deviation of the damage is much larger than the median value (Fig. 5b). These conclusions are consistent with those of Pielke and Landsea (1999) using 21 years of additional data.

b. AMO

Our focus now turns to the AMO (Goldenberg et al. 2001) and its relationship with CONUS hurricane landfall frequency. Klotzbach and Gray (2008) demonstrated a significant modulation in both basin-wide as well as Florida and East Coast landfalling hurricane frequency. We find similar results, with a significant increase in both CONUS as well as Florida and East Coast landfalling hurricanes in positive AMO phases (Fig. 6a) and a significant decrease in negative AMO phases from the average of all hurricane seasons. Little signal is observed for hurricanes making landfall along the Gulf Coast. This is likely due to different formation mechanisms for Florida and East Coast versus Gulf Coast systems. Hurricanes making landfall in Florida and along the East Coast often form from Cape Verde hurricanes or develop in the

Caribbean, which are areas where the AMO plays a significant role (Klotzbach and Gray 2008) (Fig. 7). Hurricanes making landfall along the Gulf Coast can form from these mechanisms but can also form in either the Bay of Campeche or in the Gulf of Mexico. TCs forming in the Gulf of Mexico or in the subtropical Atlantic are not as significantly modulated by the AMO (Goldenberg et al. 2001).

When examining CONUS major hurricane landfalls, we find a significant modulation between positive and negative AMO phases for Florida and East Coast landfalls, while we continue to find very little difference for the Gulf Coast (Fig. 6b). The difference in CONUS landfalls between AMO phases also is not statistically significant. Median United States normalized hurricane damage shows statistically significant modulations by the AMO, with ~9 times as much median damage in a positive AMO season compared with a negative AMO season (Fig. 8a). The difference is also significant for Florida and the East Coast, with over $800 million in median damage for Florida and the East Coast in a positive AMO compared with $69 million in a negative AMO. While the differences in median damage are considerable for the Gulf Coast as well ($105 million for positive AMO vs. $4 million in negative AMO), these differences are not statistically significant. As was the case with ENSO, the standard deviation of year-to-year normalized damage by AMO phase is quite large, indicating the high levels of volatility in the normalized damage time series (Fig. 8b).

5. Background Factors for Continental United States Landfalling Hurricane Damage

a) Population and Housing

With the historical hurricane landfall and financial cost trends established, the focus can now shift towards the future and what trends may be experienced in the decades to come given observed socioeconomic and demographic shifts. Of particular interest to many sectors – including local, state, and federal government agencies as well as the insurance industry – is the continued pattern of population increases along coasts, and in turn, greater exposures to hurricanes.

Decadal data from the US Census Bureau from 1900 to 2010 shows that the population of the US grew from 132 million to 309 million, equal to an annual growth rate of 2.8%. However, when breaking the country into six distinct regions (Atlantic, Gulf Coast, Non-Coastal South, Midwest, West, Coastal West) (Fig. 9a), there are vastly different annual growth rates and total counts of residents since 1940 across each of these regions (Fig. 9b). This is particularly true during the past ~50 years. Partial decadal census data from 2010 to 2016 shows a continuation of these trends, with the US population now estimated at 323 million.

From 1970 to 2016, regional annual rates of growth were: West (3.9%), Gulf Coast (2.7%), Coastal West (2.1%), Non-Coastal South (1.2%), Atlantic (0.8%), and Midwest (0.4%). The national growth rate was 1.3%. When breaking down the data into raw totals, during the 47 years from 1970-2016, the actual population increase was as follows: Gulf Coast (+33.7 million), Atlantic (+26.5 million), Coastal West (+25.1 million), West (+16.7 million), Midwest (+11.4 million), and Non-Coastal South (+6.4 million). This indicates that over 60 million more people are now living in states directly exposed to TC landfall than in 1970.

In the years since the last official decadal census in 2010, an even more pronounced trend of coastal growth has occurred as some of the greatest rates of population growth were found in particularly vulnerable hurricane landfall locations. Of the top 20 fastest-growing counties from 2010-2016, 13 were in hurricane-prone states – including 12 in either Florida or Texas (Table 1). While much of the growth is occurring in ocean-bordering counties – which are most prone to high-impact damage at the point of TC landfall – a significant portion of growth is found in areas further inland. This means that there is an increased risk of exposed inland population and property to be impacted by hurricanes in their weakening or post-tropical phases. Recent examples such as Hurricane Irma (2017), Hurricane Sandy (2012) and Hurricane Ike (2008) highlighted damage from high winds, prolonged rainfall and flooding, and severe convective storms that were recorded well inland from the initial landfall location.

Unsurprisingly, the growth in population has directly correlated to an accelerated rate of exposure[5] increase in these same areas. Further analysis using housing count data from the US Census Bureau shows that annual national housing units grew from 37 million (1940; first year of data collection) to 136 million (2016). This corresponds to a national average annual growth rate of 3.5% during the 77-year period.

Similar to the trends seen with population, there has been a wide spread of housing unit growth rate and aggregated count among the six identified regions since 1970 (Fig. 10). The regional annual rate of housing count growth was as follows: West (5.5%), Gulf Coast (3.8%), Coastal West (2.4%), Non-Coastal South (2.2%), Atlantic (1.6%), and Midwest (1.3%). The national rate during this time was 2.1%. The higher rate of growth for housing count versus population suggests that more people have bought multiple properties during this time, increasing the volume and scope of exposure. In addition, US Census Bureau data shows that there has been a slow decline in the average number of people per household from 3.14 in 1970

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[5] For this exercise, an “exposure” is defined as any public, residential, and commercial building or other physical structure as well as the wealth that it contains.

to 2.53 in 2016, providing another possible explanation for the increase in housing units. Further studies have shown that household composition and structure has also continued to evolve over time. For instance, the number of households identified as “Family” in US Census Bureau surveys conducted between 1940 and 2010 has shown a decrease from 90% to 66%, while “Non-Family” households increased from 10% to 34% (Jacobson 2012).

When breaking down the data into raw totals, from 1970-2016, the actual regional housing unit increase was Atlantic (+18.1 million), Gulf Coast (+16.3 million), Midwest (+11.0 million), Coastal West (+9.9 million), West (+7.7 million), and Non-Coastal South (+4.0 million). Most strikingly, the two most vulnerable regions for hurricane landfall – Atlantic and Gulf Coast – combined for over 34 million new homes, or 51% of all new housing units during this time.

One final metric regarding housing units examined here is the actual size of single-family homes. Since the US Census Bureau first started collecting data on single-family home size, the average home has grown from 1,660 square feet (1973) to 2,640 square feet (2016), or by 59%. The two regions – as defined by the US Census Bureau – that have noted the greatest growth in size are the Northeast and South (Fig. 11). Larger homes often require greater cost and more material to build. When a hurricane makes landfall, the combined costs to rebuild or fix a home – plus higher costs often associated with demand surge at construction and home retail sectors – often enhance the final damage bill beyond a home’s original value.

An important point regarding housing unit exposure and financial losses in TC-prone areas is the quality of construction and efficiency of building codes. Damage assessments conducted by one of this paper’s authors (S. Bowen) following Hurricanes Harvey, Irma, and Maria in 2017 found that structures either built to modernized code and/or with proper elevation in areas identified in the most current FEMA flood zones often reported minimal damage. In Texas, the worst flood damage from Harvey often occurred to older-built structures constructed at ground level; while in Florida, structures built prior to current stringent codes developed after Hurricane Andrew (1992) performed much more poorly in areas where Irma's radius of maximum winds occurred. Many other studies have delved more deeply into the positive impact of improved building codes over time with respect to hurricane-force winds, notably in Florida (Done 2017). Simply put, when homes and structures are built properly to recommended modernized guidelines in TC or flood-risk areas, the magnitude of damage can be reduced. Future work with academia and private sector groups will prove critical to continued improvements in future building codes and their enforcement. One particular private sector group conducting such studies, the Insurance Institute for Business and Home Safety (IBHS), is an insurance industry organization that focuses entirely on independent scientific research to "identify and promote the most effective ways to strengthen homes, businesses and communities against natural disasters and other causes of loss".[6]

b) Wealth

Another data metric highlighting the expectation of greater future TC-related catastrophe losses is the general increase in wealth. Using available data from the US Bureau of Economic Analysis (BEA; 1980-2016), nationwide Gross Domestic Product (GDP) has trended upwards at an annual average of 2.8%. Using the "real" inflation-adjusted BEA dataset, with losses

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[6] The Insurance Institute for Business and Home Safety (IBHS), headquartered in Tampa, FL, has an entire research center in Richburg, SC dedicated to testing residential and commercial construction materials, practices and systems.

indexed/chained to 2009 dollars, the BEA cites GDP growth from $6.1 trillion (1987) to $16.3 trillion (2016). Index/chained datasets help provide a more accurate picture of the economy and better capture changes in spending patterns and prices (Landefeld et al 2003). Similar to population count and exposure growth, the increases in GDP are more pronounced in certain states and regions of the country. For this study, we are particularly interested in the performance of GDP growth since the start of the most recent positive AMO phase in 1995 (Fig. 12).

The breakout of regional growth during the 22-year timeframe included Coastal West (+3.3%), Gulf Coast (+3.2%), West (+3.1%), Atlantic (+2.5%), Non-Coastal South (+2.5%), and the Midwest (+2.0%). The national average was 2.7%. When focusing specifically on three states historically prone to landfall events, we find that the annual rate of growth is higher than the US average: Texas (+4.0%), North Carolina (+2.9%), and Florida (2.8%). This further supports the claim that the accelerated economic growth in these states would additionally lead to more expensive damage and rebuilding costs. The population, housing, and wealth dataset analyses put into strong context the current and future TC risk, and are essential data points for the many public and private agencies that are responsible to warn, protect and assist in recovery.

c) Insurance

Beyond analyzing the overall economic cost of TCs in the US, another important measure that helps explain the growth of exposure, population and wealth are the claims paid by public and private insurance entities. Insured losses are the portion of economic damage that is covered by insurance. A public insured loss is identified as a claim paid via the Federal Emergency Management Agency’s National Flood Insurance Program (NFIP) or the US Department of

Agriculture's Risk Management Agency crop insurance program. Private insured losses are claims paid directly by corporate, for-profit entities.

Losses resulting from TC damage did not become significant for the insurance industry in the US until the 1950s (Fig. 13). This coincided with the first introduction of homeowners insurance in September 1950 by the Insurance Company of North America in which a singular policy would protect against "loss caused by fire, theft, lightning, wind, explosion, hail, riot, vehicle damage, vandalism and smoke" (Carr 1967). Hurricanes Carol and Hazel – both of which led to notable damage across the Northeast and Mid-Atlantic – combined to cause $258 million in nominal insurance payouts in 1954 ($2.3 billion; inflation-adjusted to 2017). TC landfalls often drive growth in property and casualty insurance take-up rates, defined as the percentage of eligible people or properties in which active insurance policies are held, and premiums as homeowners and businesses recognize the need to protect themselves should disaster strike.

In the next several decades, numerous significant hurricane landfalls such as Betsy (1965), Hugo (1989), Andrew (1992), and the 2004/2005 hurricane seasons all led to greater public and private insurance industry response to the peril. Hurricane Betsy caused extensive damage in Louisiana and was thought to be the first nominal billion-dollar TC event in the US – earning the name "Billion-Dollar Betsy" (Sugg 1966). Much of the damage was caused by coastal and inland flood inundation. At the time, no defined flood insurance program existed, and since private insurers viewed flood as too risky, the federal government established the National Flood Insurance Program (NFIP) to provide an alternative to disaster assistance to meet the escalating costs of home, building and content repairs (FEMA 2002). It was often considered by the public that wind was the primary threat from hurricanes, but Betsy helped change the narrative. Andrew, in particular, changed how the private insurance industry market viewed hurricane risk, especially in the state of Florida. Some of the profound changes that Andrew made for the insurance industry included more carefully assessed and managed coastal exposure, greater use of global reinsurance capital (reinsurance can be simply defined as insurance for insurance companies), major growth in the sophistication and usage of catastrophe modeling, and increased focus on modernized and enforced building codes (McChristian 2012).

At the end of 2016, there were roughly 5.1 million NFIP active policies in place in the US, the fewest number since 2005. By the start of the 2017 Atlantic hurricane season, that total had dipped slightly below 5.0 million. Historically, there was a gradual rise in policies from the late 1970s into the late 2000s following notable hurricane landfalls (Fig. 14a). With an extended stretch of lessened hurricane landfalls (and no major (Category 3+) hurricane landfalls in more than a decade) (Hall and Hereid 2015), there was a steady drop in national NFIP coverage as well as total insured value (TIV) (Fig. 14b) prior to the 2017 season. State-level data from FEMA indicates that the number of NFIP policies often increase following major events. Following the 2004/2005 seasons, the number of NFIP “earned contract counts” in Florida increased from 1.28 million in 2004 to a peak of 1.51 million in 2007. That number dropped to under 1.25 million by 2016.

With costly coastal exposures continuing to increase along the Gulf Coast and East Coast, this enhances the risk of greater spikes in catastrophe loss on an economic basis when the next hurricanes come ashore. For NFIP, flood payout spikes coincide with hurricane landfalls (Fig. 14c).

With more housing units and fewer NFIP policies in place, this leads to the likelihood of a greater portion of the economic cost not being covered by insurance during future events. A large portion of hurricane damage is often flood-related, and in the case of 2017’s Hurricane

Harvey, only 30% of that storm's impacts – estimated USD100 billion economic loss – were covered by insurance given high coastal and inland flood inundation throughout southeast Texas (Aon Benfield 2018). Less than 20% of homeowners in Texas' Harris County had active NFIP policies in place at the time of landfall, and given Harvey's remarkable flood footprint, much of the damage occurred in areas outside of the demarcated 100 or 500-year flood zones[7]. To put recent NFIP trends into perspective, we use the state of Florida as an example. At the end of 2011, Florida had active NFIP policies in place with a total insured value of $471 billion. By the middle of 2017, a decline in active policies also coincided with TIV dropping to $422 billion despite hundreds of thousands of new single-family homes being built during that time. Table 2 provides regional breakouts of 2017 NFIP policies and TIV.

Using data as of early 2017, 14 of the top 20 states receiving the greatest amount of NFIP payouts are found in ocean-bordering states prone to hurricane landfall (Fig. 15). For greater context, the five Gulf Coast states have received more than 60% (or $34.5 billion) of all nominal NFIP payouts. The payouts are somewhat unsurprising given that more than 84 percent – or nearly 4.2 million – of all NFIP policies currently in place are found in the Gulf Coast and Atlantic. The TIV of these active policies in the Gulf Coast and Atlantic covers $1.05 trillion (85%) in residential and commercial property assets. Whether fully insured or not, this further highlights the growing risk in these states given the tremendous aggregated value of properties located in hurricane-prone locations.

These data strongly suggest that the combination of increased population, greater exposure, the quality of building construction and further modifications of building codes have –

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[7] To view address-level FEMA flood zone mapping, visit the FEMA Flood Map Service Center: https://msc.fema.gov/portal/search

and will continue – to play a significant role in rising damage associated with TCs in the CONUS. Any increase in landfalling TC frequency or intensity (e.g., Knutson et al. 2010, Walsh et al. 2015) would expectedly combine with these socioeconomic and demographic factors to cause even greater losses.

6. Discussion and Conclusions

We have investigated trends in CONUS hurricane activity since 1900 and found no significant trends in landfalling hurricanes, major hurricanes or normalized damage, consistent with what has been found in previous studies. CONUS landfalling hurricane activity is, however, influenced by El Niño-Southern Oscillation on the interannual timescale and by the Atlantic Multi-decadal Oscillation on the multi-decadal timescale.

Despite a lack of trend in observed CONUS landfalling hurricane activity since 1900, large increases in inflation-adjusted hurricane-related damage have been observed, especially since the middle part of the 20th century. We demonstrate that this increase in damage is due strongly to societal factors, namely increases in population and wealth along the US Gulf and East Coasts.

These findings have practical significance. Prior to the very active and costly 2017 season, the CONUS enjoyed an eleven-year major hurricane drought (Hall and Hereid 2015; Hart et al. 2016), and during this period, there were sizable growth patterns in coastal population, vulnerable coastal exposures, housing size, and nominal wealth in the most hurricane-prone areas of the country.

When the major hurricane drought came to an end in 2017, Texas and Florida recorded aggregated economic damage losses in excess of $125 billion. In total, economic damage in CONUS during the 2017 season was among the costliest ever recorded on a nominal, inflation-adjusted and normalized basis. It is further expected that future catastrophe losses resulting from landfalling storms will be even more financially significant for local, state and federal government agencies and the insurance industry if proper steps are not taken to reduce the current vulnerabilities of property and other exposures. The conclusion of greater future losses stands regardless of any changes in future hurricane frequency or intensity associated with changes in the climate behavior of hurricanes. Even if future hurricane frequency were to lessen, even one storm in an otherwise quiet year can result in unprecedented damage (e.g., Hurricane Andrew in 1992).

Losses from future hurricanes have significant potential to dwarf those of the past based on societal change alone. Event losses will be even greater with potential increases in storm intensity (Knutson et al. 2010, Walsh et al. 2015) as well as flood-related impacts associated with an accelerated rate of sea level rise (Mousavi et al. 2011) and/or increased amounts of rainfall (Emanuel 2017). This highlights the continued importance of modernized and consistent building codes across hurricane-prone states, updated flood maps, and improved coastal/inland infrastructure given assumed impacts in the future.

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Table 1. Top 20 US counties in terms of population growth from 2010-2016. Bold-faced counties are in states that are prone to hurricane impacts.

Ranking	County	State	2010	2011	2012	2013	2014	2015	2016	Raw # Change	% Change
1	**Harris**	Texas	*4,108,308*	*4,179,717*	*4,259,206*	*4,346,883*	*4,441,928*	*4,533,341*	*4,589,928*	*481,620*	*10.35%*
2	Maricopa	Arizona	3,825,616	3,870,806	3,942,959	4,011,219	4,083,931	4,161,637	4,242,997	417,381	8.78%
3	Los Angeles	California	9,825,473	9,888,476	9,953,555	10,015,436	10,066,615	10,112,255	10,137,915	312,442	2.92%
4	San Diego	California	3,104,346	3,140,692	3,181,513	3,218,419	3,258,856	3,290,245	3,317,749	213,403	5.99%
5	King	Washington	1,937,786	1,972,444	2,008,763	2,045,874	2,078,886	2,114,256	2,149,970	212,184	9.11%
6	**Bexar**	Texas	*1,723,006*	*1,755,342*	*1,788,530*	*1,822,056*	*1,858,749*	*1,895,482*	*1,928,680*	*205,674*	*10.01%*
7	**Miami-Dade**	Florida	*2,507,362*	*2,573,361*	*2,607,979*	*2,641,273*	*2,667,299*	*2,692,593*	*2,712,945*	*205,583*	*7.39%*
8	**Dallas**	Texas	*2,372,450*	*2,407,305*	*2,452,421*	*2,479,810*	*2,512,281*	*2,545,775*	*2,574,984*	*202,534*	*7.31%*
9	Clark	Nevada	1,953,216	1,966,295	1,995,815	2,025,096	2,064,899	2,109,289	2,155,664	202,448	7.99%
10	**Tarrant**	Texas	*1,817,687*	*1,848,347*	*1,882,352*	*1,912,501*	*1,944,512*	*1,981,410*	*2,016,872*	*199,185*	*9.01%*
11	Riverside	California	2,202,226	2,236,146	2,264,919	2,291,452	2,322,455	2,352,892	2,387,741	185,515	6.84%
12	**Travis**	Texas	*1,030,569*	*1,061,858*	*1,096,122*	*1,120,948*	*1,149,668*	*1,174,818*	*1,199,323*	*168,754*	*14.00%*
13	**Orange**	Florida	*1,148,716*	*1,169,806*	*1,202,048*	*1,225,366*	*1,253,631*	*1,284,864*	*1,314,367*	*165,651*	*11.85%*
14	**Broward**	Florida	*1,753,125*	*1,787,889*	*1,816,552*	*1,840,051*	*1,865,385*	*1,887,281*	*1,909,632*	*156,507*	*7.65%*
15	Orange	California	3,017,647	3,053,884	3,084,935	3,112,576	3,134,438	3,156,573	3,172,532	154,885	4.60%
16	**Collin**	Texas	*788,741*	*814,607*	*837,229*	*858,098*	*885,175*	*913,079*	*939,585*	*150,844*	*15.76%*
17	**Fort Bend**	Texas	*590,433*	*606,962*	*625,796*	*653,252*	*684,646*	*713,849*	*741,237*	*150,804*	*20.90%*
18	**Hillsborough**	Florida	*1,233,839*	*1,271,205*	*1,281,677*	*1,293,189*	*1,317,116*	*1,347,077*	*1,376,238*	*142,399*	*9.18%*
19	**Wake**	N. Carolina	*906,949*	*929,208*	*952,296*	*973,920*	*997,897*	*1,021,974*	*1,046,791*	*139,842*	*12.68%*
20	**Denton**	Texas	*666,736*	*685,376*	*707,475*	*728,282*	*752,820*	*778,491*	*806,180*	*139,444*	*16.76%*

Table 2. NFIP policies in place by US region, the percentage of total NFIP policies in each US region, the total insured value (TIV) of NFIP policies by US region and the percentage of total insured value of NFIP policies by US region.

Region	Policies per Region	% NFIP Policies	TIV per Region (bn USD)	% TIV
Atlantic	1,231,707	25.0%	310	25.2%
Coastal West	310,757	6.3%	86	7.0%
Gulf Coast	2,925,909	59.4%	737	59.9%
Midwest	210,513	4.3%	42	3.4%
Non-Coastal South	80,969	1.6%	17	1.3%
West	160,696	3.3%	38	3.1%
Other US Territories	6,918	0.1%	1	0.1%
Total	4,927,469	100%	1023	100%

FIGURE CAPTIONS

Fig. 1. CONUS total inflation-adjusted economic losses from TC landfalls (1900-2017). The dotted line represents the linear trend over the period. The p-value for the linear trend is <0.01 indicating that the trend is significant.

Fig. 2. (a) CONUS landfalling hurricanes by year from 1900-2017 and (b) CONUS landfalling major hurricanes by year from 1900-2017. The dotted lines represent linear trends over the period. P-values for the linear trends are 0.33 (landfalling hurricanes) and 0.61 (landfalling major hurricanes) indicating that neither of these trends are significant.

Fig. 3. Normalized CONUS landfalling hurricane damage from 1900-2017. The dotted line represents the linear trend in CONUS hurricane normalized damage during the period of record. The p-value for the linear trend is 0.86 indicating that the trend is not significant.

Fig. 4. (a) Mean annual CONUS landfalling hurricanes by ENSO phase from 1900-2017 and (b) mean annual CONUS landfalling major hurricanes by ENSO phase from 1900-2017. Differences that are significant at the 5% level are plotted with diagonal hatching.

Fig. 5. (a) Median and (b) standard deviation of annual CONUS normalized hurricane damage by ENSO phase. Differences in the median that are significant at the 5% level are plotted with diagonal hatching. The * in panel a in the El Niño bar in the Florida and East Coast column indicates that this difference is significant at the 5% level (the hatching would not display since the value is so small).

Fig. 6. (a) Mean annual CONUS landfalling hurricanes by AMO phase from 1900-2017 and (b) mean annual CONUS landfalling major hurricanes by AMO phase from 1900-2017. Differences that are significant at the 5% level are plotted with diagonal hatching.

Fig. 7. (a) Named storm formation location for all Gulf Coast landfalling hurricanes from 1900-2017, and (b) named storm formation location for all Florida and East Coast landfalling hurricanes from 1900-2017.

Fig. 8. (a) Median and (b) standard deviation of annual CONUS normalized hurricane damage by AMO phase. Differences that are significant at the 5% level are plotted with diagonal hatching. The * in panel a in the negative AMO bar in the Florida and East Coast column indicates that this difference is significant at the 5% level (the hatching would not display since the value is so small).

Fig. 9. (a) CONUS map showing six regions as defined in this manuscript and (b) CONUS decadal population by region (1940-2016).

Fig. 10. CONUS decadal housing unit count (in millions) by region (1940-2016).

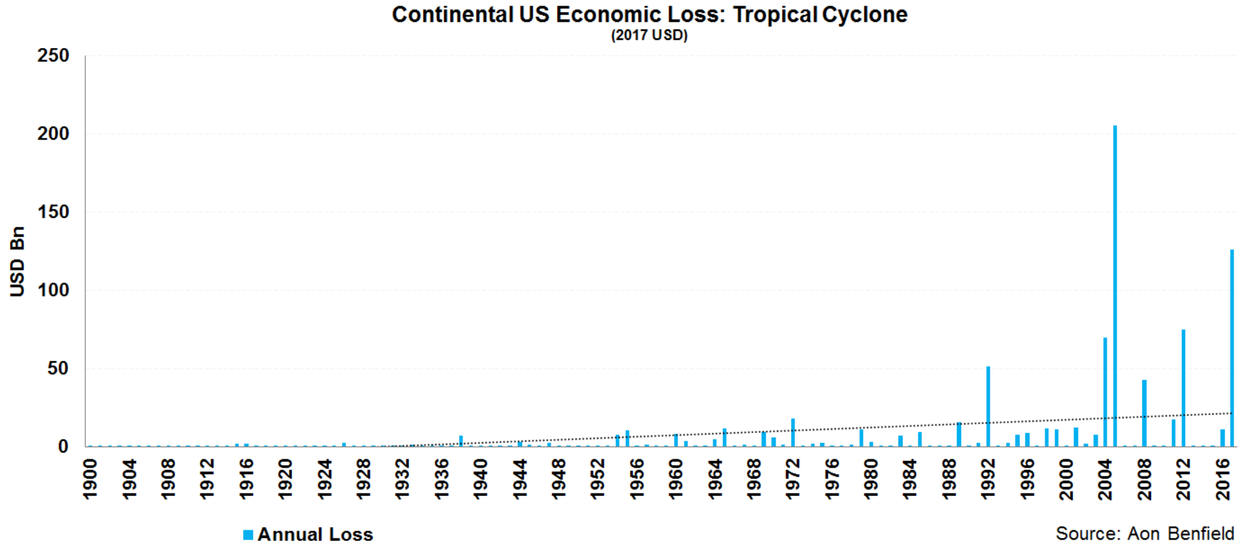
Fig. 11. Average size of a CONUS single-family home by region as defined by the US Census Bureau (1973-2016).

Fig. 12. Real GDP growth by region (1995-2016).

Fig. 13. CONUS total inflation-adjusted insured losses from TC landfalls (1900-2017). The dotted line represents the linear trend over the period. The p-value for the linear trend is <0.01 indicating that the trend is significant.

Fig. 14. (a) Annual NFIP policies in place (1978-2017), (b) total insured value of NFIP coverage (nominal values, 1978-2017) and (c) calendar year NFIP payouts from 1978-2016 (2017 $).

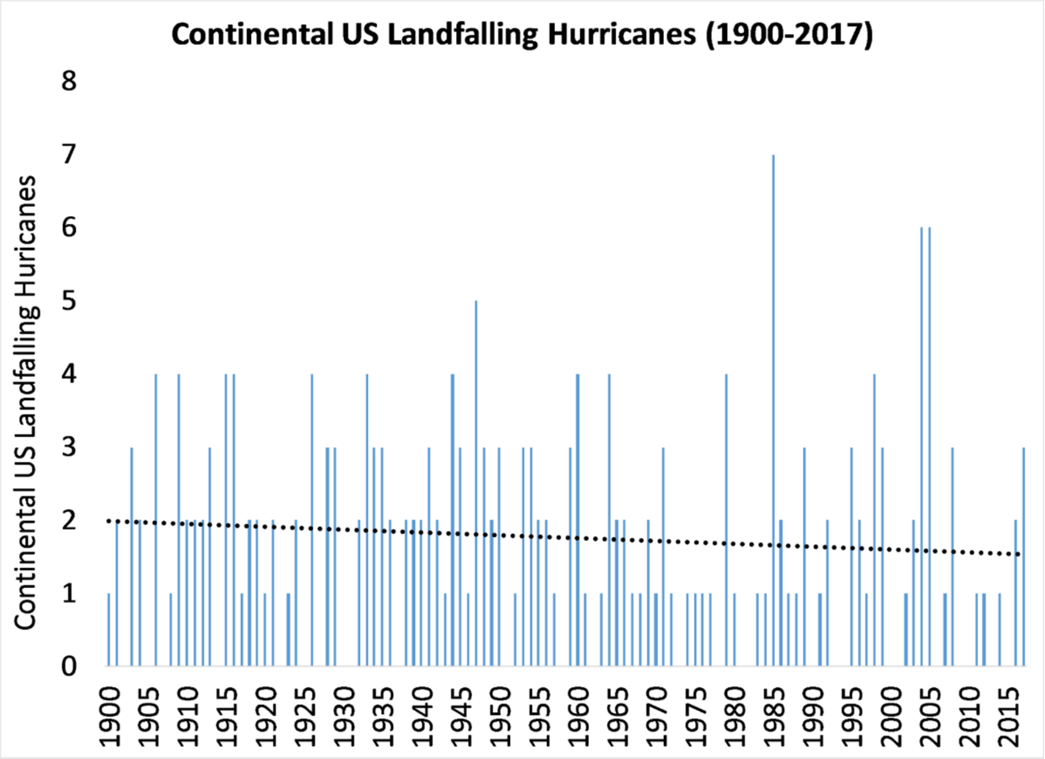
Fig. 15. Top 20 states for NFIP payouts (1978-2015; inflation-adjusted to 2017 USD).



Source: Aon Benfield

Fig. 1. CONUS total inflation-adjusted economic losses from TC landfalls (1900-2017). The dotted line represents the linear trend over the period. The p-value for the linear trend is <0.01 indicating that the trend is significant.

(a)


Continental US Landfalling Hurricanes (1900-2017)
Continental US Landfalling Huricanes
0
1
2
3
4
5
6
7
8
1900
1905
1910
1915
1920
1925
1930
1935
1940
1945
1950
1955
1960
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010
2015

(b)

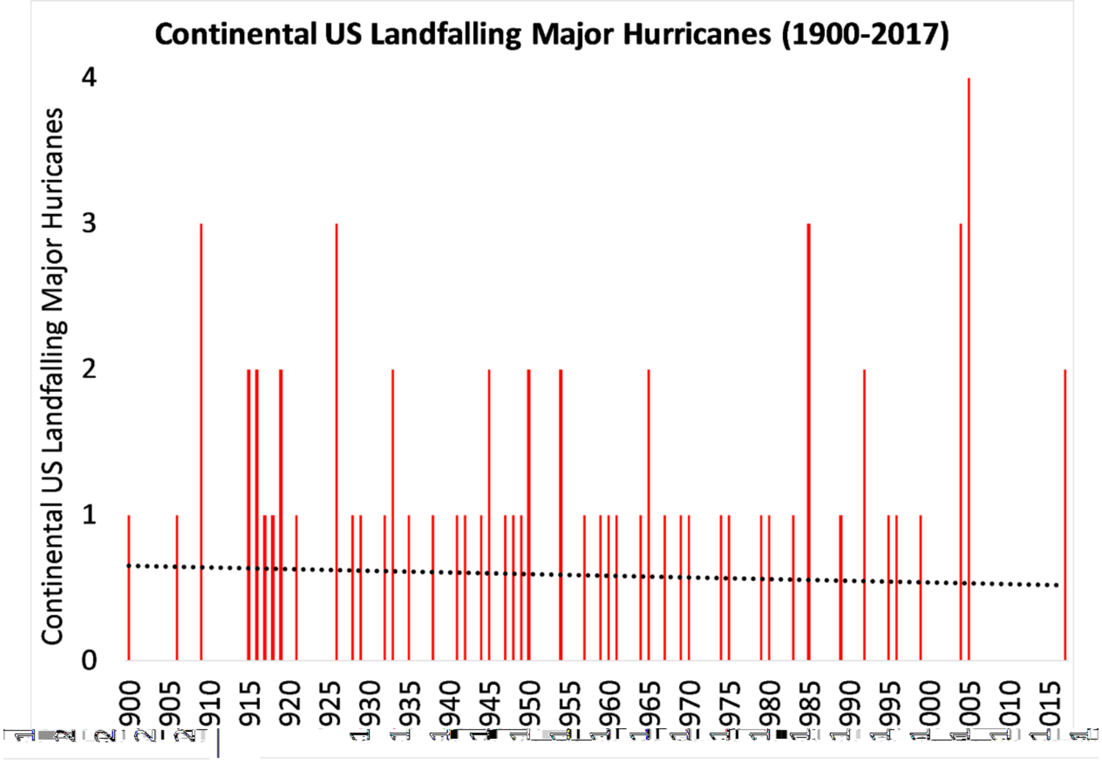

Continental US Landfalling Major Hurricanes (1900-2017)
Continental US Landfalling Major Huricanes
0
1
2
3
4
900
905
910
915
920
925
930
935
940
945
950
955
960
965
970
975
980
985
990
995
000
005
010
015

Fig. 2. (a) CONUS landfalling hurricanes by year from 1900-2017 and (b) CONUS landfalling major hurricanes by year from 1900-2017. The dotted lines represent linear trends over the period. P-values for the linear trends are 0.33 (landfalling hurricanes) and 0.61 (landfalling major hurricanes) indicating that neither of these trends are significant.

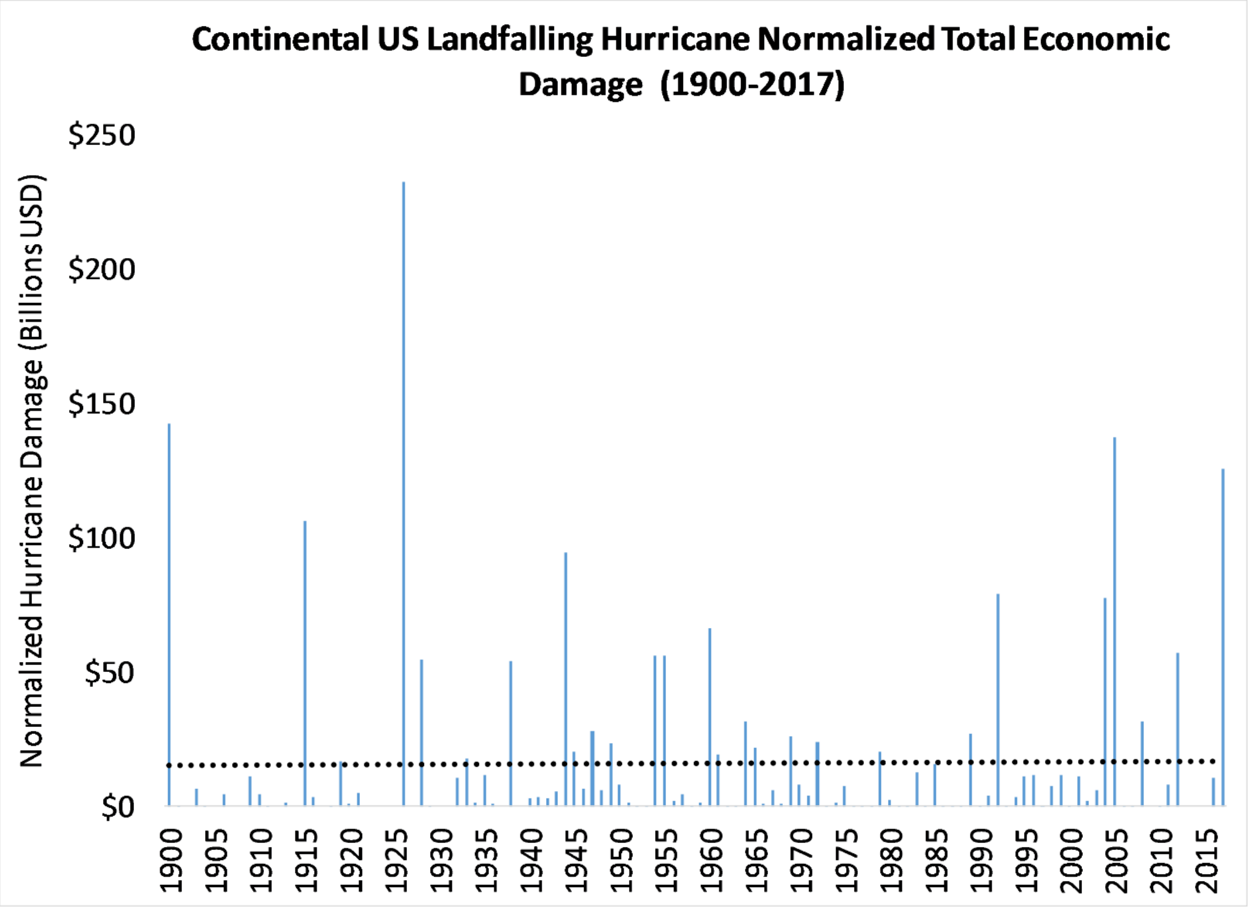
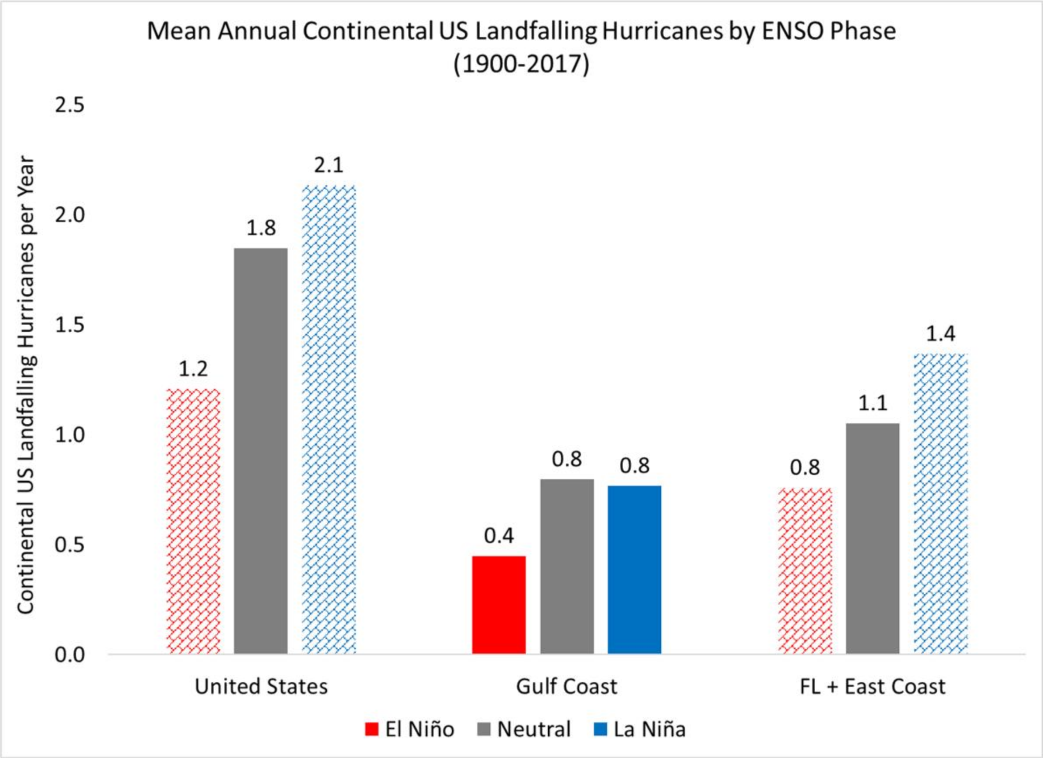
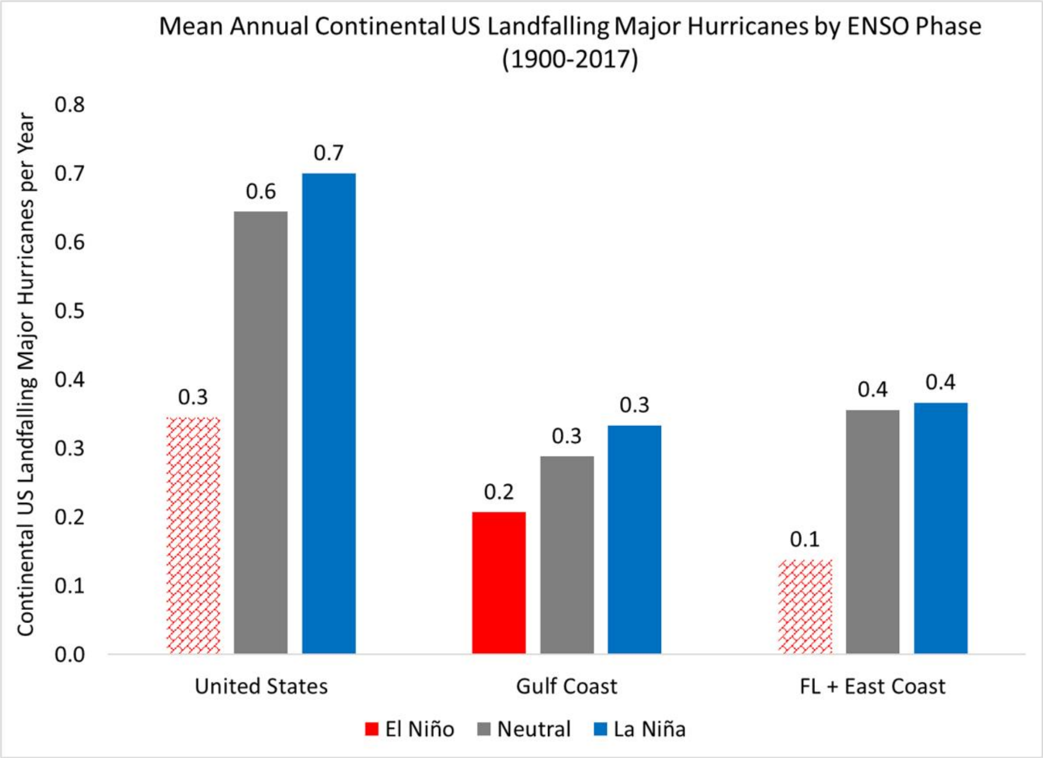


Fig. 3. Normalized CONUS landfalling hurricane damage from 1900-2017. The dotted line represents the linear trend in CONUS hurricane normalized damage during the period of record. The p-value for the linear trend is 0.86 indicating that the trend is not significant.

(a)


Mean Annual Continental US Landfalling Hurricanes by ENSO Phase
(1900-2017)
Continental US Landfalling Hurricanes per Year
2.5
2.0
1.5
1.0
0.5
0.0
1.2
1.8
2.1
0.4
0.8
0.8
0.8
1.1
1.4
United States
Gulf Coast
FL + East Coast
El Niño
Neutral
La Niña

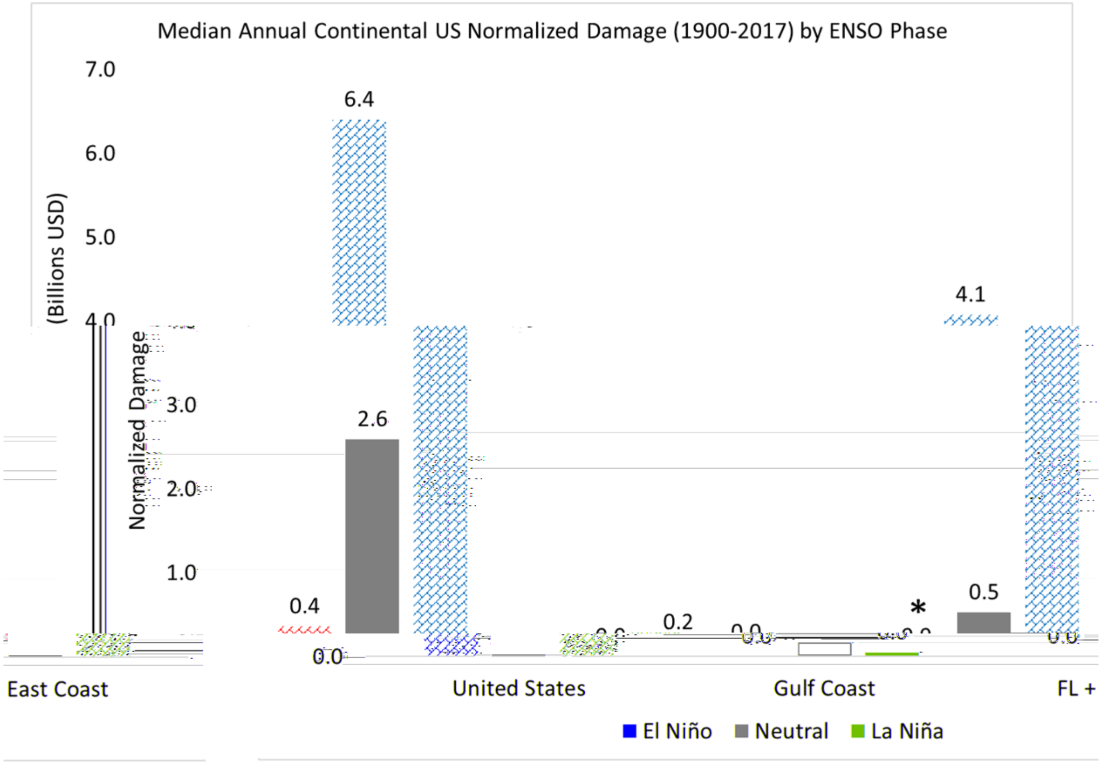
(b)


Mean Annual Continental US Landfalling Major Hurricanes by ENSO Phase
(1900-2017)
Continental US Landfalling Major Hurricanes per Year
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.3
0.6
0.7
0.2
0.3
0.3
0.1
0.4
0.4
United States
Gulf Coast
FL + East Coast
El Niño
Neutral
La Niña

669

Fig. 4. (a) Mean annual CONUS landfalling hurricanes by ENSO phase from 1900-2017 and (b) mean annual CONUS landfalling major hurricanes by ENSO phase from 1900-2017. Differences that are significant at the 5% level are plotted with diagonal hatching.

(a)


Median Annual Continental US Normalized Damage (1900-2017) by ENSO Phase
Normalized Damage (Billions USD)
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
6.4
2.6
0.4
0.2
0.0
4.1
0.5
*
United States
Gulf Coast
FL + East Coast
El Niño
Neutral
La Niña

(b)

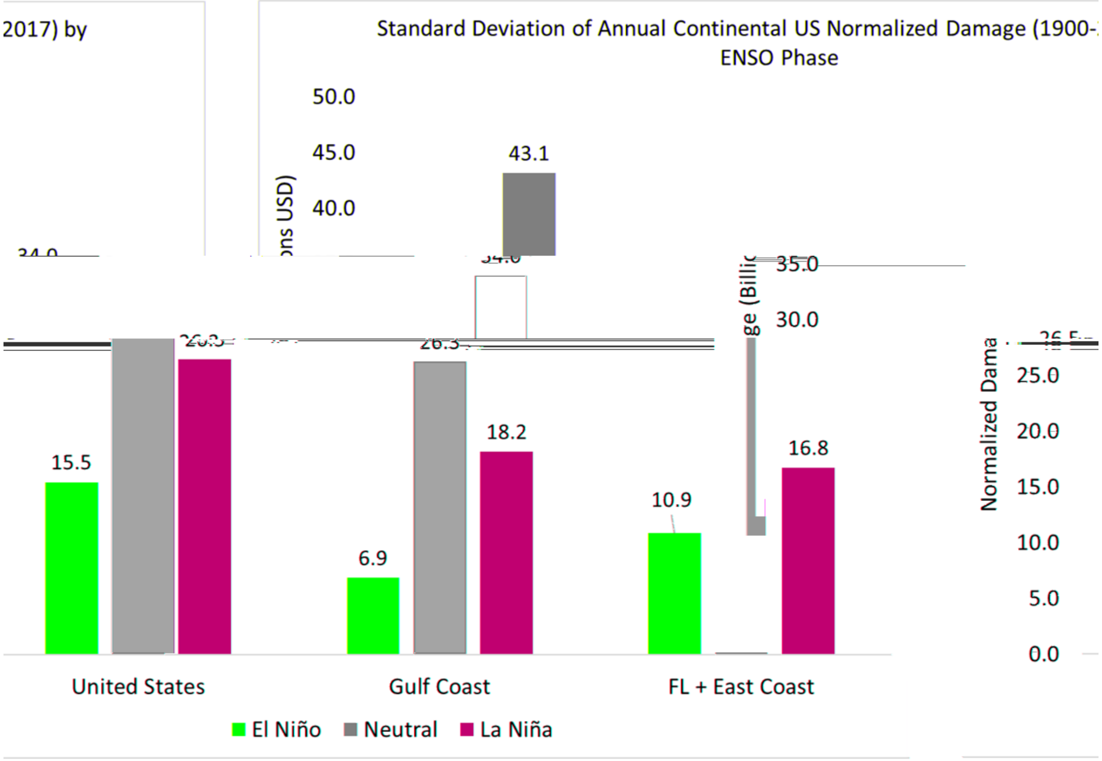
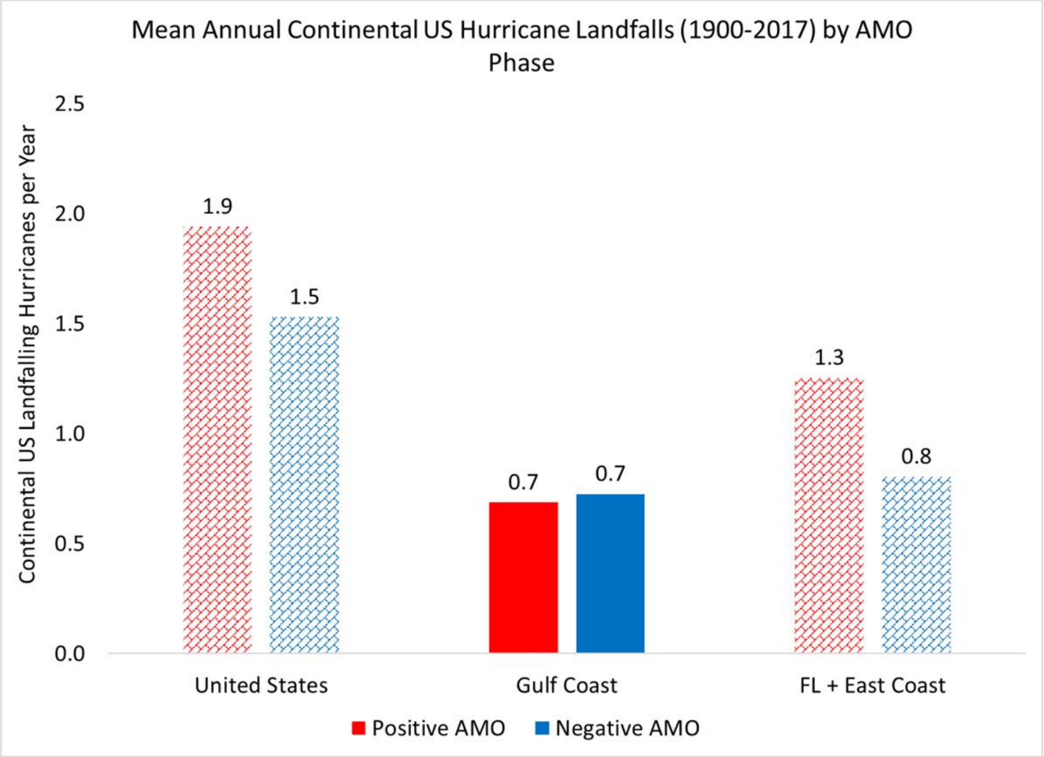

Standard Deviation of Annual Continental US Normalized Damage (1900-2017) by ENSO Phase
Normalized Damage (Billions USD)
50.0
45.0
40.0
35.0
30.0
25.0
20.0
15.0
10.0
5.0
0.0
43.1
34.0
26.5
26.3
15.5
6.9
18.2
10.9
16.8
United States
Gulf Coast
FL + East Coast
El Niño
Neutral
La Niña

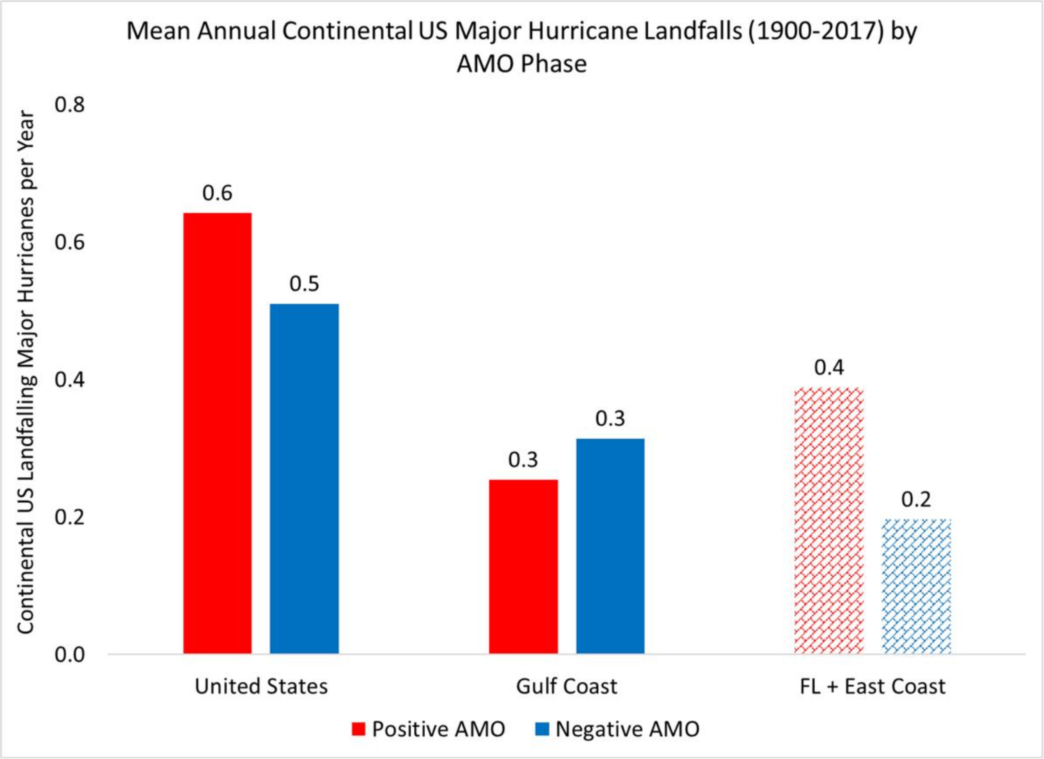
Fig. 5. (a) Median and (b) standard deviation of annual CONUS normalized hurricane damage by ENSO phase. Differences in the median that are significant at the 5% level are plotted with diagonal hatching. The * in panel a in the El Niño bar in the Florida and East Coast column indicates that this difference is significant at the 5% level (the hatching would not display since the value is so small).

(a)



Mean Annual Continental US Hurricane Landfalls (1900-2017) by AMO Phase
Continental US Landfalling Hurricanes per Year
2.5
2.0
1.5
1.0
0.5
0.0
1.9
1.5
0.7
0.7
1.3
0.8
United States
Gulf Coast
FL + East Coast
Positive AMO
Negative AMO

(b)



Mean Annual Continental US Major Hurricane Landfalls (1900-2017) by AMO Phase
Continental US Landfalling Major Hurricanes per Year
0.8
0.6
0.4
0.2
0.0
0.6
0.5
0.3
0.3
0.4
0.2
United States
Gulf Coast
FL + East Coast
Positive AMO
Negative AMO

Fig. 6. (a) Mean annual CONUS landfalling hurricanes by AMO phase from 1900-2017 and (b) mean annual CONUS landfalling major hurricanes by AMO phase from 1900-2017. Differences that are significant at the 5% level are plotted with diagonal hatching.

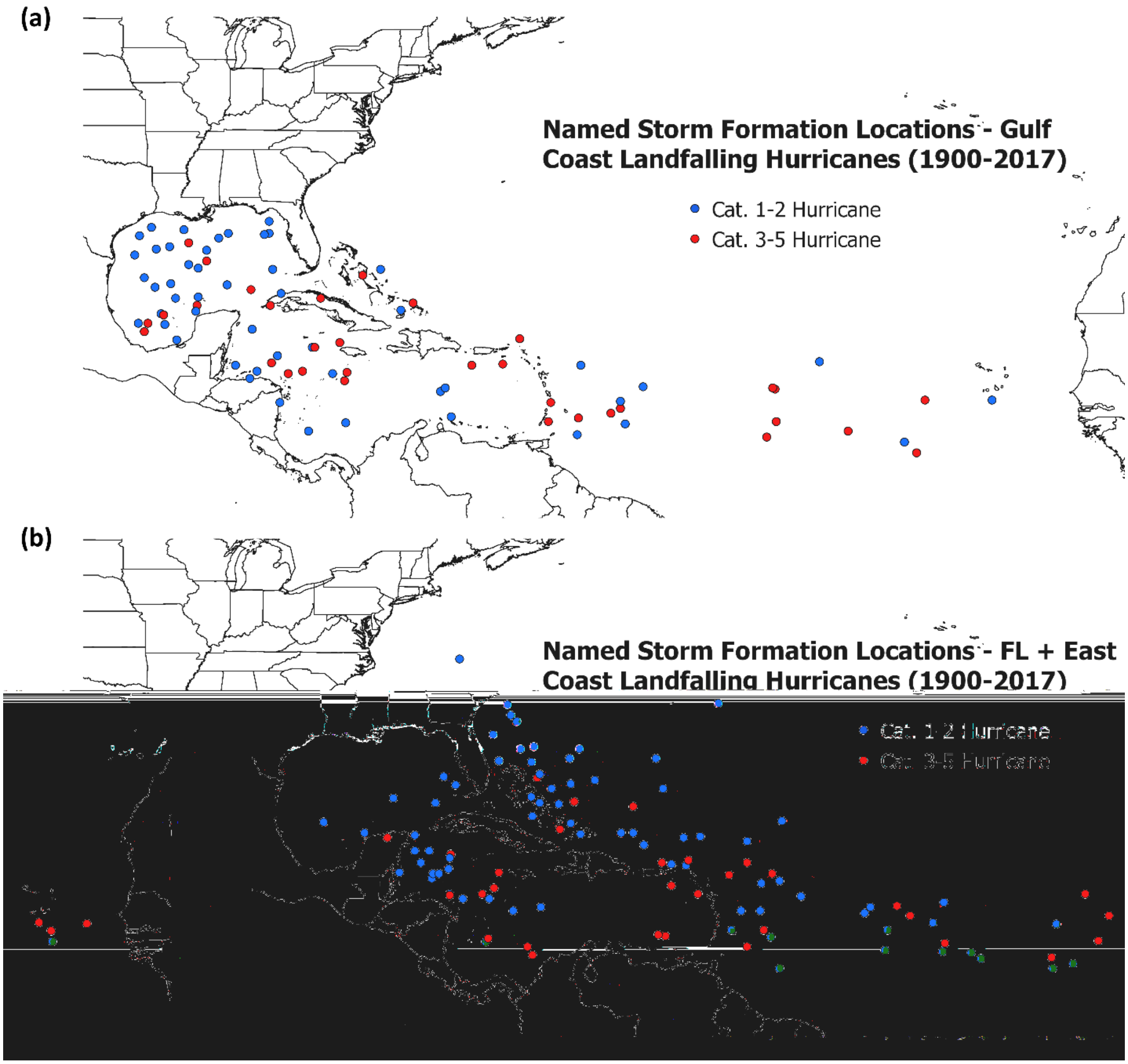
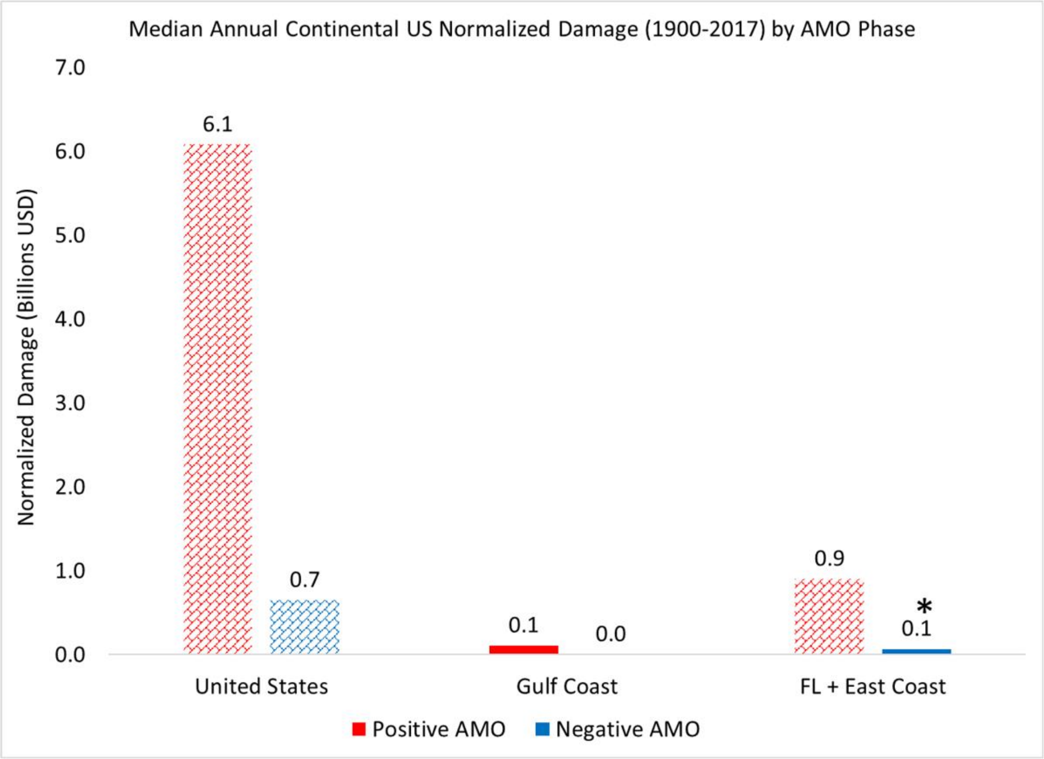


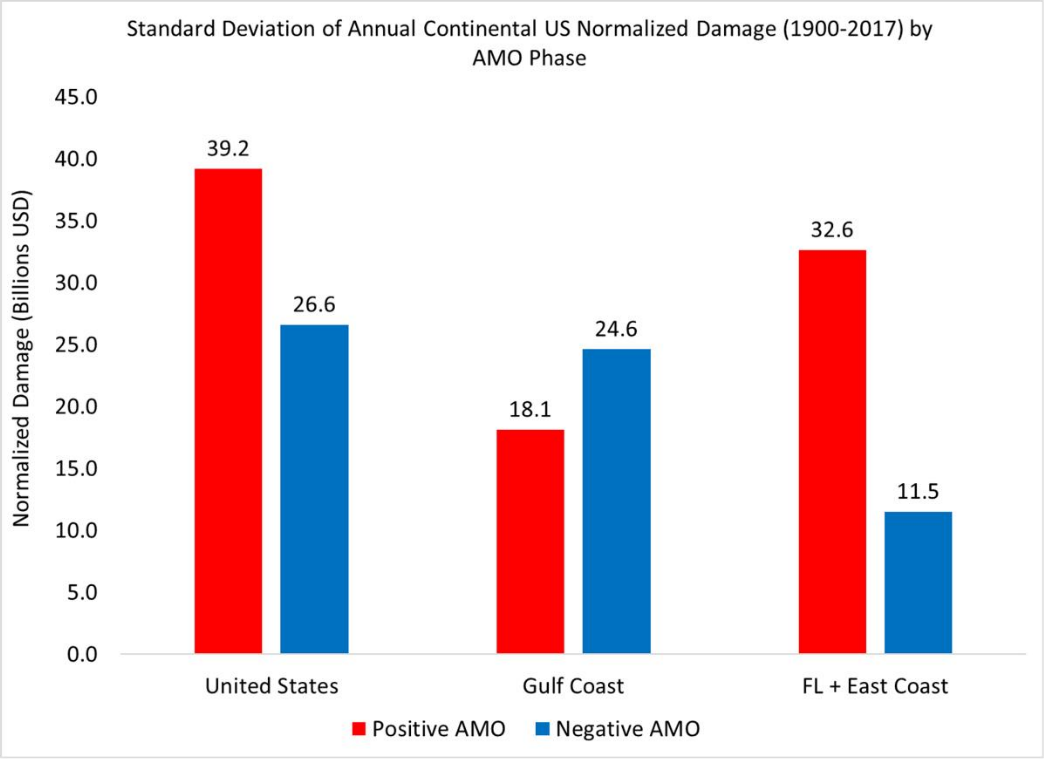
Fig. 7. (a) Named storm formation location for all Gulf Coast landfalling hurricanes from 1900-2017, and (b) named storm formation location for all Florida and East Coast landfalling hurricanes from 1900-2017.

(a)



Median Annual Continental US Normalized Damage (1900-2017) by AMO Phase
Normalized Damage (Billions USD)
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
6.1
0.7
0.1
0.0
0.9
*
0.1
United States
Gulf Coast
FL + East Coast
Positive AMO
Negative AMO

(b)

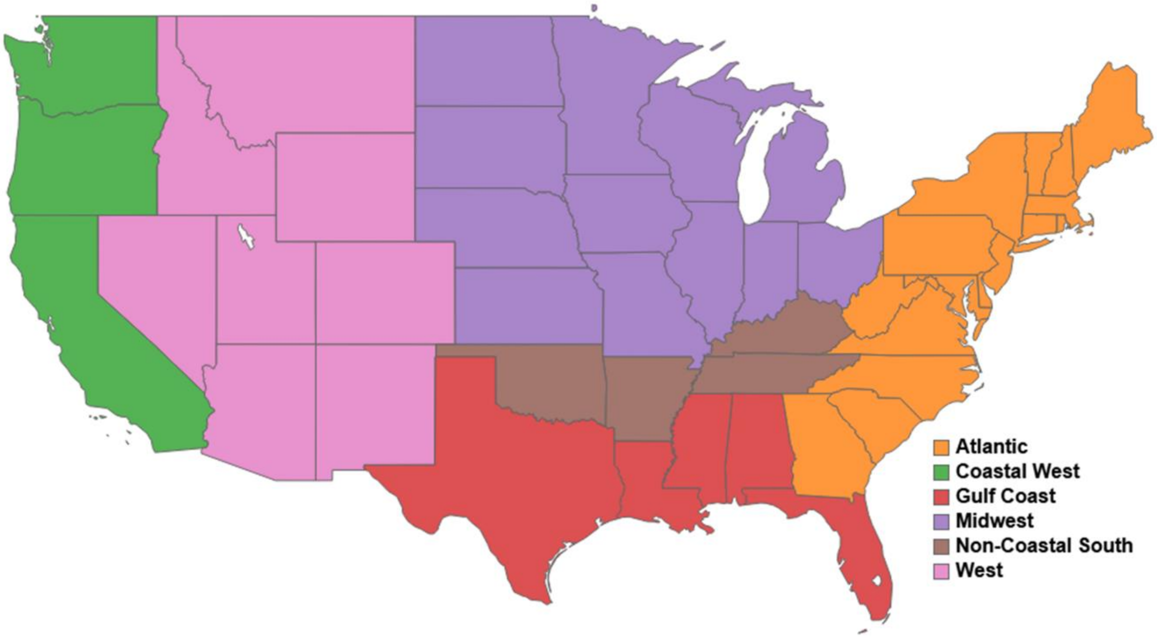


Standard Deviation of Annual Continental US Normalized Damage (1900-2017) by AMO Phase
Normalized Damage (Billions USD)
45.0
40.0
35.0
30.0
25.0
20.0
15.0
10.0
5.0
0.0
39.2
26.6
18.1
24.6
32.6
11.5
United States
Gulf Coast
FL + East Coast
Positive AMO
Negative AMO

690

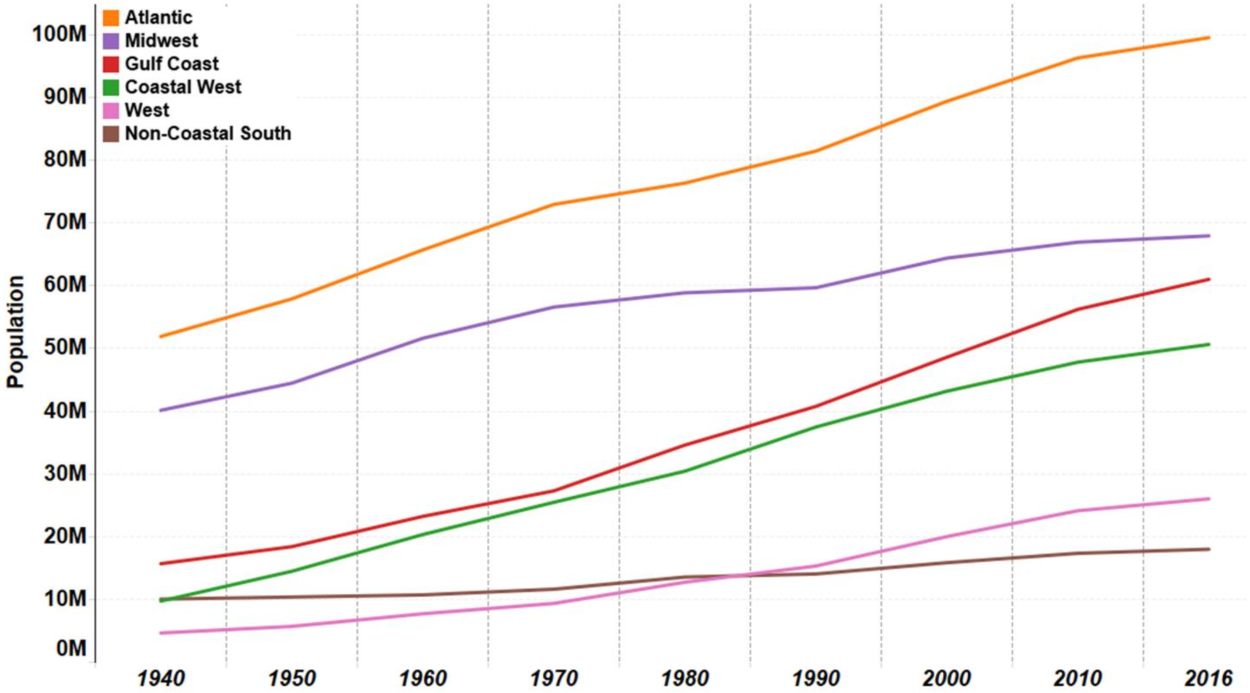
Fig. 8. (a) Median and (b) standard deviation of annual CONUS normalized hurricane damage by AMO phase. Differences that are significant at the 5% level are plotted with diagonal hatching. The * in panel a in the negative AMO bar in the Florida and East Coast column indicates that this difference is significant at the 5% level (the hatching would not display since the value is so small).

(a)



🟧 Atlantic
🟩 Coastal West
🟥 Gulf Coast
🟪 Midwest
🟫 Non-Coastal South
West

(b)



Atlantic
Midwest
Gulf Coast
Coastal West
West
Non-Coastal South
100M
90M
80M
70M
60M
50M
40M
30M
20M
10M
0M
Population
1940
1950
1960
1970
1980
1990
2000
2010
2016

Fig. 9. (a) CONUS map showing six regions as defined in this manuscript and (b) CONUS decadal population by region (1940-2016).

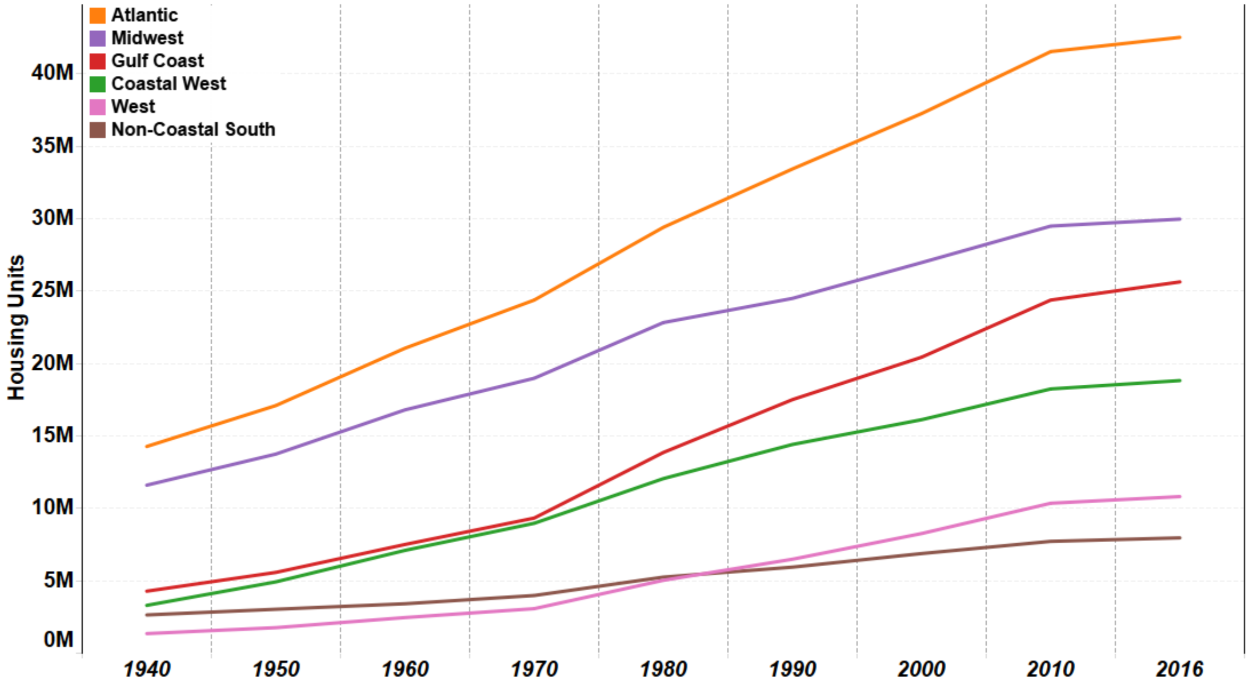


Fig. 10. CONUS decadal housing unit count (in millions) by region (1940-2016).

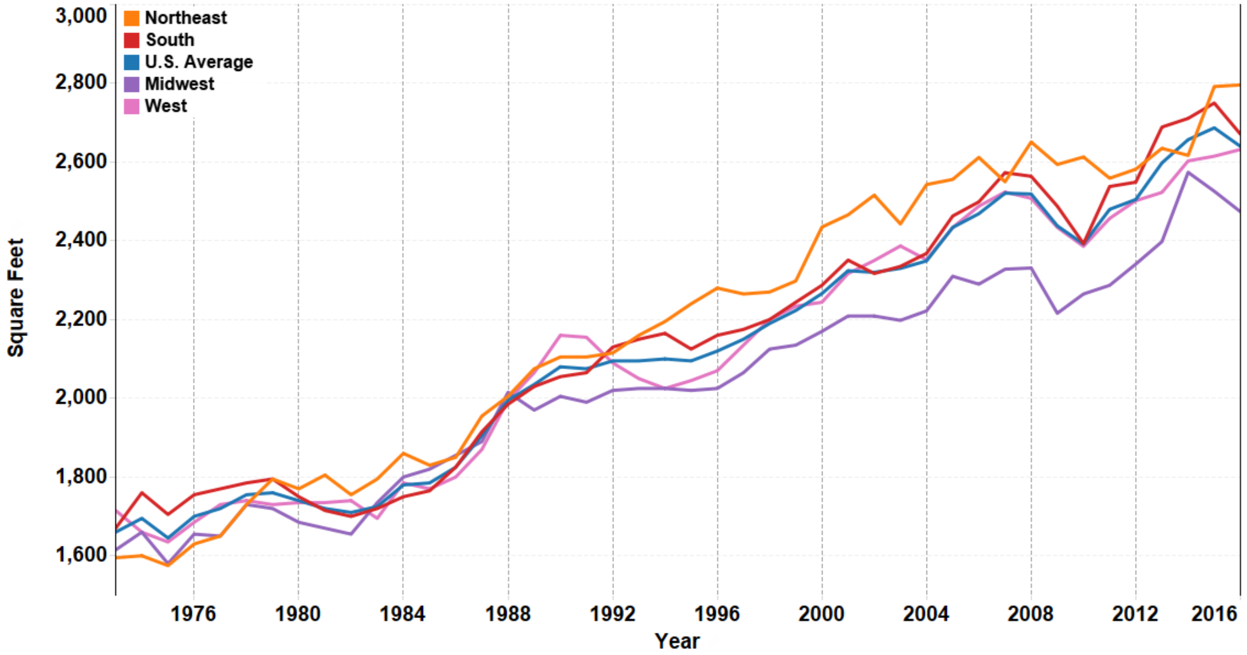
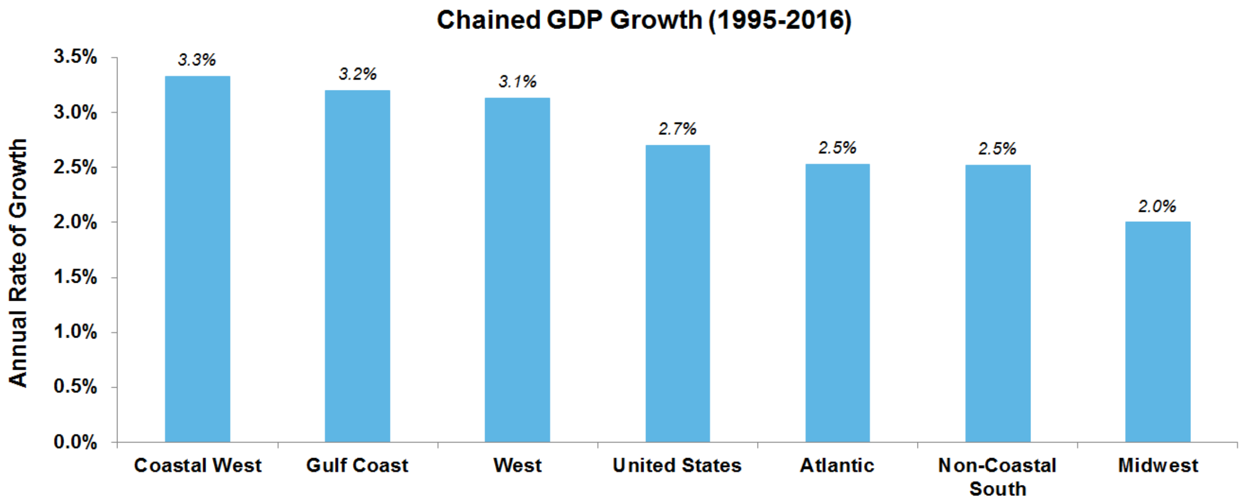
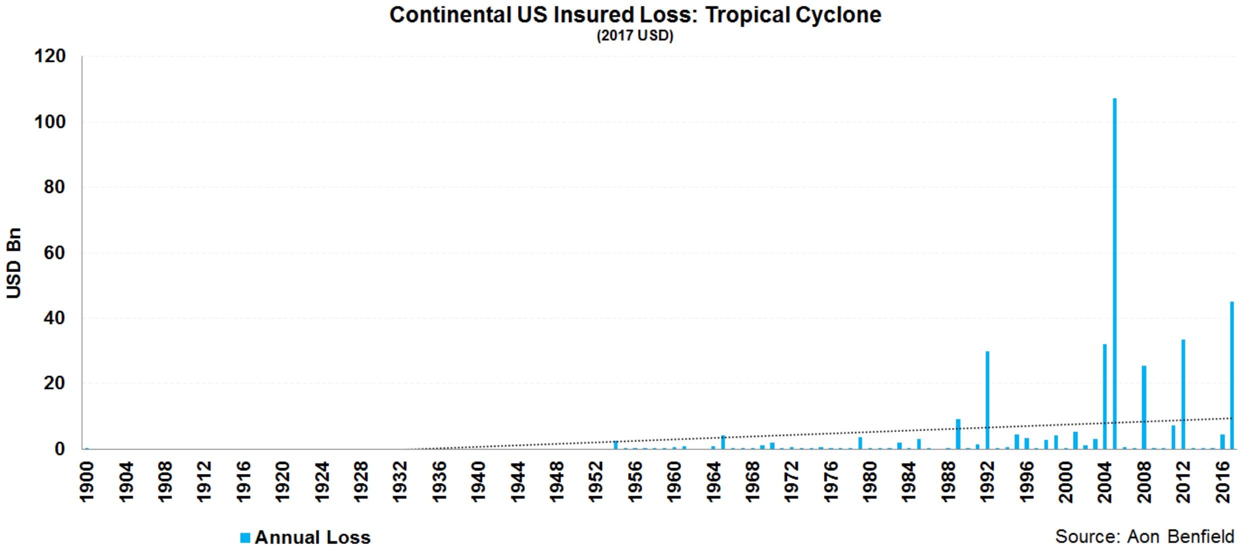


Fig. 11. Average size of a CONUS single-family home by region as defined by the US Census Bureau (1973-2016).



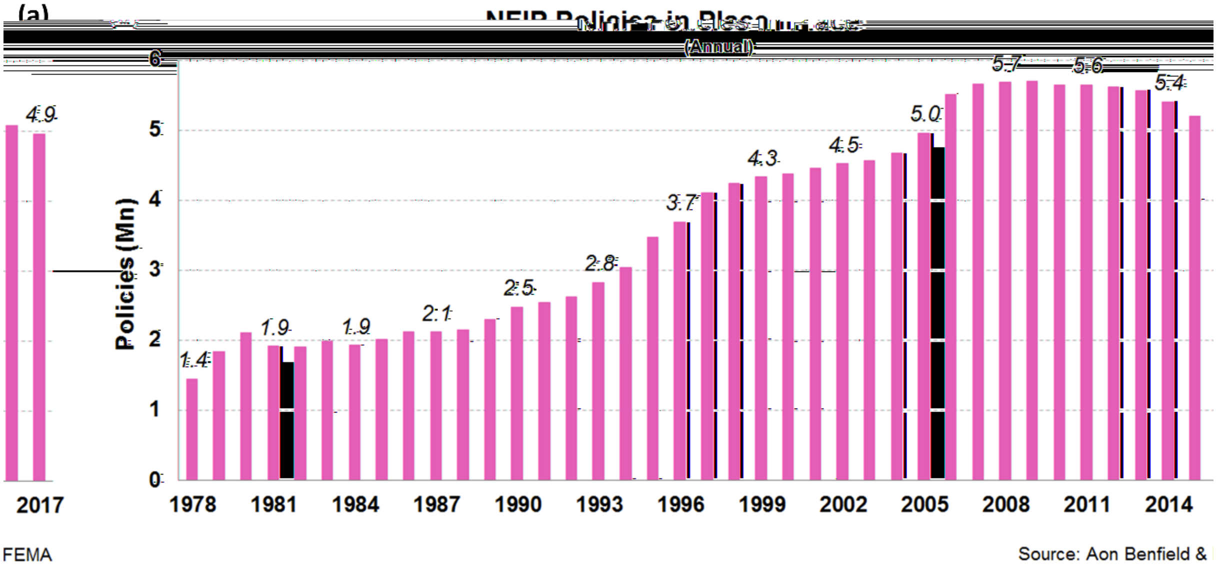
Source: Aon Benfield & US Bureau of Economic Analysis

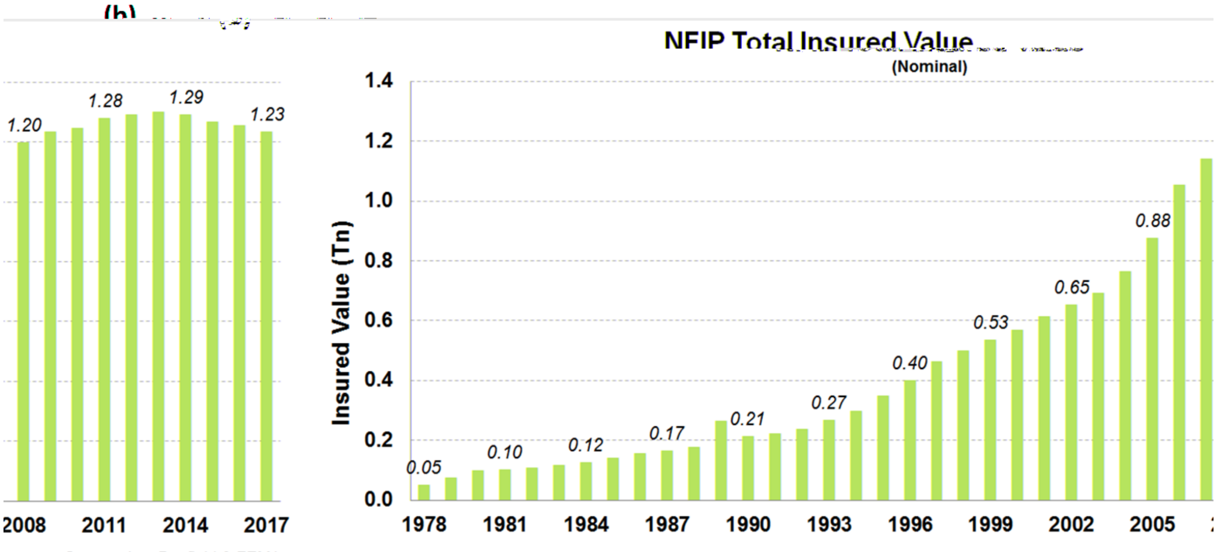
Fig. 12. Real GDP growth by region (1995-2016).



Source: Aon Benfield

Fig. 13. CONUS total inflation-adjusted insured losses from TC landfalls (1900-2017). The dotted line represents the linear trend over the period. The p-value for the linear trend is <0.01 indicating that the trend is significant.


(a)
NFIP Policies in Place
(Annual)
Policies (Mn)
0
1
2
3
4
5
6
1.4
1.9
1.9
2.1
2.5
2.8
3.7
4.3
4.5
5.0
5.7
5.6
5.4
4.9
1978
1981
1984
1987
1990
1993
1996
1999
2002
2005
2008
2011
2014
2017
Source: Aon Benfield &
FEMA


(b)
NFIP Total Insured Value
(Nominal)
Insured Value (Tn)
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
0.05
0.10
0.12
0.17
0.21
0.27
0.40
0.53
0.65
0.88
1.20
1.28
1.29
1.23
1978
1981
1984
1987
1990
1993
1996
1999
2002
2005
2008
2011
2014
2017
Source: Aon Benfield & FEMA

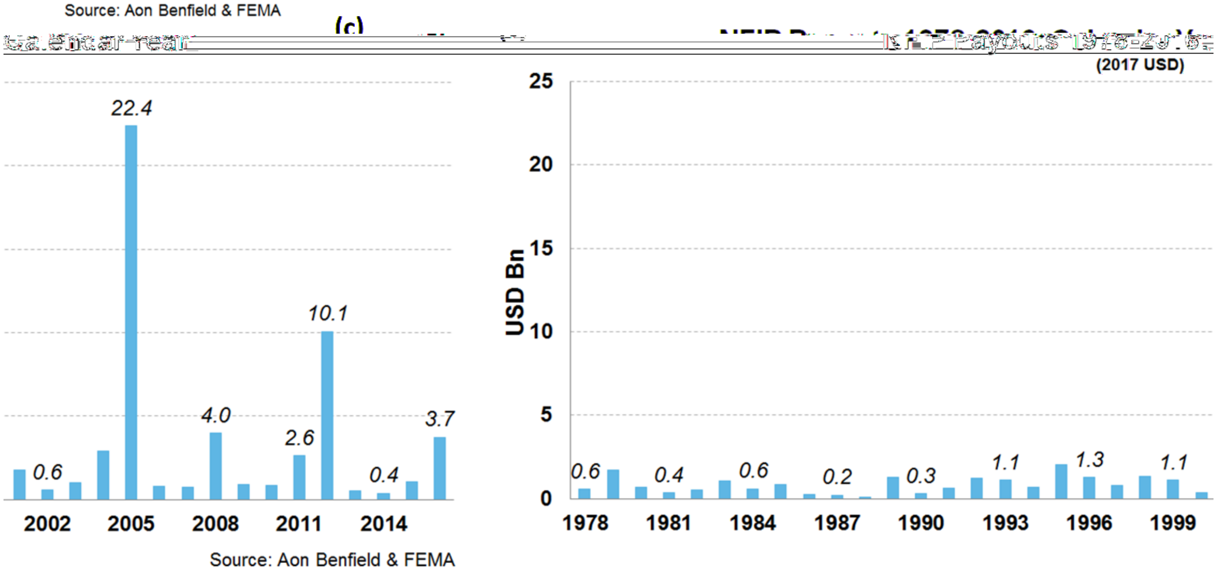
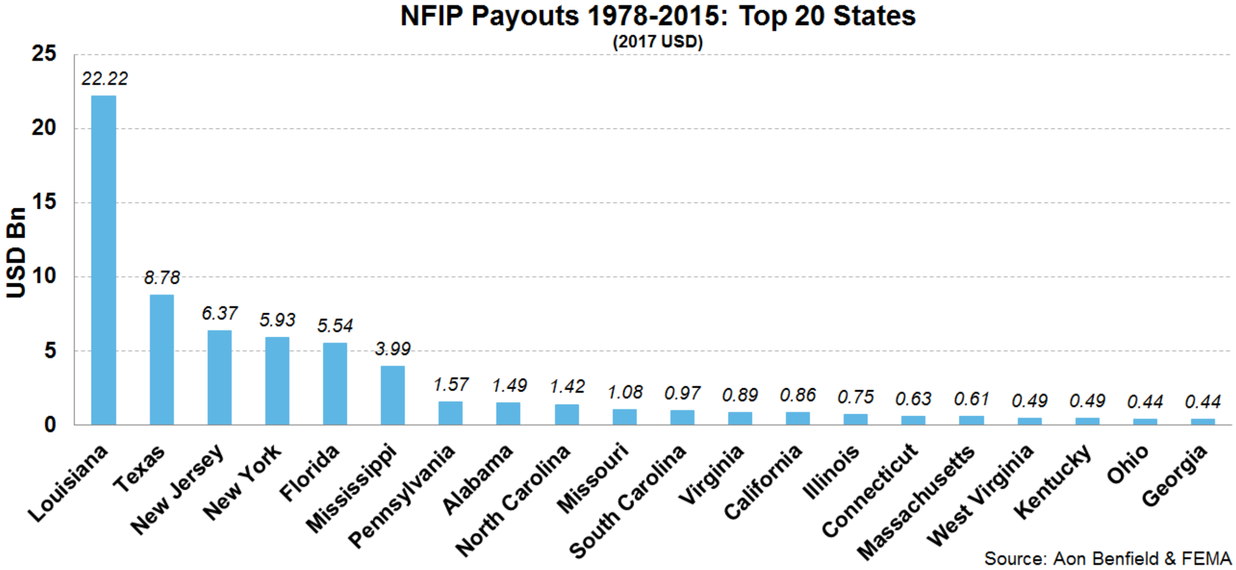

(c)
NFIP Payouts 1978-2017
(2017 USD)
USD Bn
0
5
10
15
20
25
0.6
0.4
0.6
0.2
0.3
1.1
1.3
1.1
0.6
22.4
4.0
2.6
10.1
0.4
3.7
1978
1981
1984
1987
1990
1993
1996
1999
2002
2005
2008
2011
2014
Source: Aon Benfield & FEMA

Fig. 14. (a) Annual NFIP policies in place (1978-2017), (b) total insured value of NFIP coverage (nominal values, 1978-2017) and (c) calendar year NFIP payouts from 1978-2016 (2017 $).



Source: Aon Benfield & FEMA

Fig. 15. Top 20 states for NFIP payouts (1978-2015; inflation-adjusted to 2017 USD).