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# Understanding the Recent Increase in Landfalling Tropical Cyclones Over Florida's Gulf Coast

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**Key Points:**

- The Gulf Coast of Florida has seen an increased incidence of tropical cyclones (TCs) over the past two decades
- Climate modes explain a significant amount of variance in TC activity along Florida's Gulf Coast, but not along the Atlantic Coast
- The control exerted by climate modes on Gulf Coast TCs, in combination with decadal trends in those modes, are likely responsible

**Supporting Information:**

Supporting Information may be found in the online version of this article.

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## Abstract

Unlike Florida's Atlantic Coast, the Gulf Coast of Florida has seen heightened tropical cyclone (TC) activity in recent decades with several destructive landfalls. Here, we attempt to understand this regional contrast using a suite of observations for the period 1979–2024. First, we demonstrate that while the El Niño Southern Oscillation (ENSO), the Atlantic Multidecadal Oscillation (AMO) and the North Atlantic Oscillation (NAO) can explain ∼23% of the interannual variability in landfalls over the Gulf Coast, the variance explained by them for the Atlantic Coast is statistically insignificant. Next, we show that this striking difference may be attributed to the regional patterns of wind shear, steering flow and air-sea thermodynamic state excited by those modes of variability. The differential control exerted by ENSO, AMO, and NAO on landfalling Florida TCs, in combination with decadal trends in those modes, is likely responsible for the observed increases in landfalls over Florida's Gulf Coast.

## Plain Language Summary

In recent decades, Florida's Gulf Coast has been hit by more tropical cyclones (TCs) than usual, while the Atlantic Coast of Florida has been relatively quiet. In this study, using an analysis of observations spanning the 46-year period 1979 to 2024, we attempt to explain the stark difference between the two coasts. We found that natural modes of variability, such as the El Niño Southern Oscillation (ENSO), the Atlantic Multidecadal Oscillation (AMO), and the North Atlantic Oscillation (NAO), can explain a significant amount of year-to-year changes in TC activity along Florida's Gulf Coast. On the other hand, these climate oscillations are unable to explain changes in TC activity along the Atlantic Coast of Florida. This is because while the effects of these modes of variability on the storm environment align together to favor Gulf Coast hurricanes, they compete with each other for Atlantic Coast TCs. These results, in combination with long-term trends in the climate oscillations, likely explain the cause behind the increased TC activity along Florida's Gulf Coast over the past two decades. The findings from our study have profound implications for TC predictability at seasonal-to-decadal timescales along Florida's coastline.

## 1. Introduction

Historically, Florida is the most tropical cyclone(TC)-prone state in the US (Blake et al., 2007) with about 40% of all US TCs making landfall in that state (Blake et al., 2011). Over the last century, of the 4 storms that have made landfall over the contiguous US at Category 5 strength, three have done so over Florida. The Labor Day Hurricane of 1935 made landfall over the Florida Keys with 160 kt winds and caused catastrophic destruction with a record storm surge that exceeded 6 m (Landsea et al., 2014; Needham & Keim, 2012). Later, Hurricane Andrew struck south Florida near Miami-Dade county in 1992 at Category 5 strength (Willoughby & Black, 1996) and was the costliest US TC at that time. More recently, Huricaner Michael (2018) also made a destructive landfall over the Florida Panhandle with near 140 kt winds and caused severe damages to Mexico Beach and Panama City (Kennedy et al., 2020), including to nearby Tyndall Air Force Base (Achenbach et al., 2018). Besides these, other notable storms that inflicted substantial damages over the last few years include Hurricane Ian (2022) (Bucci et al., 2023), Hurricane Idalia (2023) (Cangialosi & Alaka, 2024), Hurricane Helene (2024) (Hagen et al., 2025) and Hurricane Milton (2024) (Beven et al., 2025), all of which made landfall over Florida at Category 3 or 4 strength. Several factors, such as having a long coastline and being located in the western subtropical Atlantic surrounded by warm ocean waters, act together to make Florida highly vulnerable to TCs.

Florida's coastline, which is the longest in the conterminous US, can be divided into two distinct parts: the Gulf Coast, which borders the eastern Gulf waters, and the Atlantic Coast, which leads into the open Atlantic Ocean

(Zhu et al., 2021). When we consider Category 3 or higher intensity TCs over the past 20 years, 8 storms have made landfall over Florida (https://www.aoml.noaa.gov/hrd/hurdat/All_U.S._Hurricanes.html). Interestingly, out of these 8 storms, none made landfall on Florida's Atlantic Coast, with all of them making landfall on the Gulf Coast instead. Even when we include weaker storms, 14 out of 19 Florida TCs made landfall over the Gulf Coast between 2004 and 2024. However, the potential reasons for the skewness in Florida landfalls toward the Gulf Coast in this period are unclear, even though the Gulf Coast experiences a relatively greater threat from TCs on average (Brettschneider, 2008).

Further, past studies have shown the important role played by various modes of natural variability, such as the El Niño Southern Oscillation (ENSO), the Atlantic Multidecadal Oscillation (AMO) and the North Atlantic Oscillation (NAO) in US landfalling TCs (Klotzbach et al., 2018). For instance, conditions become more favorable for US landfall during La Niña years compared to El Niño years, primarily due to changes in vertical wind shear over the tropical Atlantic (Bove et al., 1998; Gray, 1984; Klotzbach, 2011; Pielke & Landsea, 1999; Xie et al., 2002). Similarly, Atlantic TC activity and conterminous US landfall probabilities increase during the positive phase of the AMO when sea surface temperatures (SSTs) over the North Atlantic are warmer and the wind shear is reduced over the Main Development Region (MDR, approximately 80°W–20°W, 10°N–20°N) (Bell & Chelliah, 2006; Goldenberg et al., 2001; Klotzbach & Gray, 2008; Klotzbach et al., 2018). However, whether these modes of variability exert a different degree of control on TCs making landfall over Florida's Gulf and Atlantic Coasts, and whether such differences can explain those in TC activity observed between the two coasts in recent years remains unknown. In this study, we examine TC landfalls over Florida's Gulf and Atlantic Coasts and attempt to explain the differences using modes of climate variability that are well-known to influence Atlantic TC activity.

## 2. Methods

### 2.1. Data

Atlantic TC track information for the 46-year period 1979–2024 is obtained from the National Hurricane Center's Best Track data (HURDAT2) (Landsea & Franklin, 2013). We analyze the data to determine the track location and intensity of TCs, using the location information to identify where landfall occurs. The monthly Oceanic Niño Index (ONI) and the AMO index are obtained from NOAA and used to represent ENSO and the AMO, respectively. Although we use the ONI to examine ENSO's influence in this study, sensitivity tests with other indices of ENSO suggest that our results are robust and not overly dependent on the exact choice of the index. Besides ENSO and the AMO, we also include the North Atlantic Oscillation (NAO) in our analysis. The NAO index is based on Jones et al. (1997). We calculate climate index averages over July–October. For each of these climate oscillations, all years are considered in our analysis rather than applying predefined thresholds to separate distinct phases. This approach allows for a continuous examination of year-to-year variability rather than dividing data into discrete categories. Monthly SST, sea-level pressure, air temperature, specific humidity and winds for the same 46-year period are obtained from the European Center for Medium-Range Weather Forecasts (ECMWF) Reanalysis version 5 (ERA5) (Hersbach et al., 2020). These data are used to examine the storm environment and how it is affected by various climate modes. We selected the years 1979–2024 for our study primarily because the advent of satellite observations makes TC track information as well as reanalysis data more reliable over this period, allowing for more robust assessments of storms and their ambient environment (Bhatia et al., 2019; Emanuel, 2010; Hersbach et al., 2020).

To understand the role of external forcing in the variability of observed TC landfall, TC track data are obtained from 5 fully-coupled climate models belonging to the High Resolution Model Intercomparison Project (High-ResMIP) (Haarsma et al., 2016) and used to examine historical TC landfalls. The various models used are: CNRM-CM6-1-HR [1], EC-Earth3P-HR [2], HadGEM3-GC31-HH [1], HadGEM3-GC31-HM [3] and MPI-ESM1-2-XR [1]. For each model, the number of ensembles used is indicated in the brackets. The models selected have a horizontal atmospheric resolution of 50 km or higher (Roberts et al., 2020). Tracks from the "hist-1950" simulations covering the 36-year period 1979–2014 are used. Also, TC tracks from the "highres-future" simulations are used to project Florida's TC landfalls into the future. These tracks cover the 36-year period 2015–2050 under the SSP5-8.5 scenario, where the radiative forcing from greenhouse gases is expected to reach 8.5 $Wm^{-2}$ by the end of the century (O'Neill et al., 2016). The TC tracks from HighResMIP that we use in this study are based on TempestExtremes (Ullrich & Zarzycki, 2017), a scale-aware feature tracking software that operates on the model's native grid.

TC track data based on the Risk Analysis Framework for Tropical Cyclones (RAFT) (Balaguru et al., 2023; Xu et al., 2024) are also obtained to understand how landfall probabilities over Florida may change in the future. RAFT is a hybrid model that combines physics, statistics and advanced artificial intelligence to generate large ensembles of TCs consistent with a given climate. For further details regarding the methodology of RAFT and validation, please refer to Balaguru et al. (2023), Xu et al. (2024), Lipari et al. (2024), and Rice et al. (2025). RAFT has been combined with 9 fully-coupled earth system models belonging to Coupled Model Intercomparison Project Phase 6 (CMIP6) (Eyring et al., 2016) to generate TC tracks for historical (1980–2014) and future (2066–2100) periods. The future period here is also based on the SSP5-8.5 emissions scenario. We chose SSP5-8.5 for consistency with HighResMIP future simulations, and additionally because it serves as a useful stress test, allowing a clearer separation of external forcing signals from natural variability. Statistical bias correction has been applied to the CMIP6-forced RAFT TC data to ensure that the effects of systematic coupled model biases are suppressed (Cannon et al., 2015; Gori et al., 2022). For further details regarding the various CMIP6 models used, see Lipari et al. (2024) and Rice et al. (2025). With over 430,000 TC tracks generated for each of the historical and future periods, RAFT offers a robust pathway for projecting the spatial distribution of landfall probabilities (Balaguru et al., 2023; Lipari et al., 2024; Rice et al., 2025).

### 2.2. Calculations

To separate Florida landfalls between the Gulf and Atlantic coasts, we follow the method of Zhu et al. (2021) that is adopted from the National Oceanic and Atmospheric Administration (NOAA). In this approach, a straight line that connects 82.69°W at the northern Florida border with 80.85°W at the southern tip of Florida is used to split the coastline into the Gulf and Atlantic sections. The approximate Gulf-Atlantic section split in the Florida Keys is on the western tip of Long Key. We define the first instance when the center of the storm comes ashore along either of Florida's coasts as landfall. While in observations, we use the landfall flag provided in HURDAT2, we use a land-sea mask to determine land crossing in models.

To understand the influence of various climate modes on cyclogenesis for Florida's landfalling storms, we use the Dynamic Genesis Potential Index (DGPI) (Murakami & Wang, 2022). The DGPI is estimated as

$$DGPI = (1 + 0.1 \times V_s)^{-2} + \left(5.5 - \frac{du}{dy} \times 10^5\right)^{2.3} + (5 - 20 \times w)^{3.4} \left(5.5 + |\zeta \times 10^5|\right)^{2.4} e^{-11.8} - 1 \quad (1)$$

Here, $V_s$ is the vertical wind shear estimated between 200 and 850 hPa, $\frac{du}{dy}$ is the meridional shear of the zonal wind at 500 hPa, $w$ is the vertical velocity at 500 hPa and $\zeta$ is the absolute vorticity at 850 hPa. Unlike traditional genesis potential indices which include thermodynamic factors (Emanuel & Nolan, 2004), the DGPI is based on dynamical parameters and has been shown to better represent interannual variations (Wang & Murakami, 2020) and future changes in cyclogenesis (Murakami & Wang, 2022).

Similarly, the potential intensity (PI) framework is used to understand the influence of the air-sea thermodynamic state on Florida's landfalling TCs. Following Emanuel (1999), the PI is computed as

$$PI^2 = \frac{C_k}{C_d} \frac{SST - T_o}{T_o} (K_s - K_a) \quad (2)$$

Here, $C_k$ is the exchange coefficient for enthalpy, $C_d$ is the coefficient of drag, $T_o$ is the outflow temperature, $K_s$ is the enthalpy at the sea surface and $K_a$ is the enthalpy in the ambient boundary layer. Both PI and shear are used however to understand the influence of the environment on the intensification of landfalling Florida storms. The environmental steering flow, estimated as the sum of 0.2 times the winds at the upper-level (200 hPa) and 0.8 times the winds at the lower-level (850 hPa) (Emanuel et al., 2006), is used to determine the potential role of steering winds in influencing Florida TC landfalls. The time series of various climate indices were normalized by computing their Z-score before using them for regression analysis.

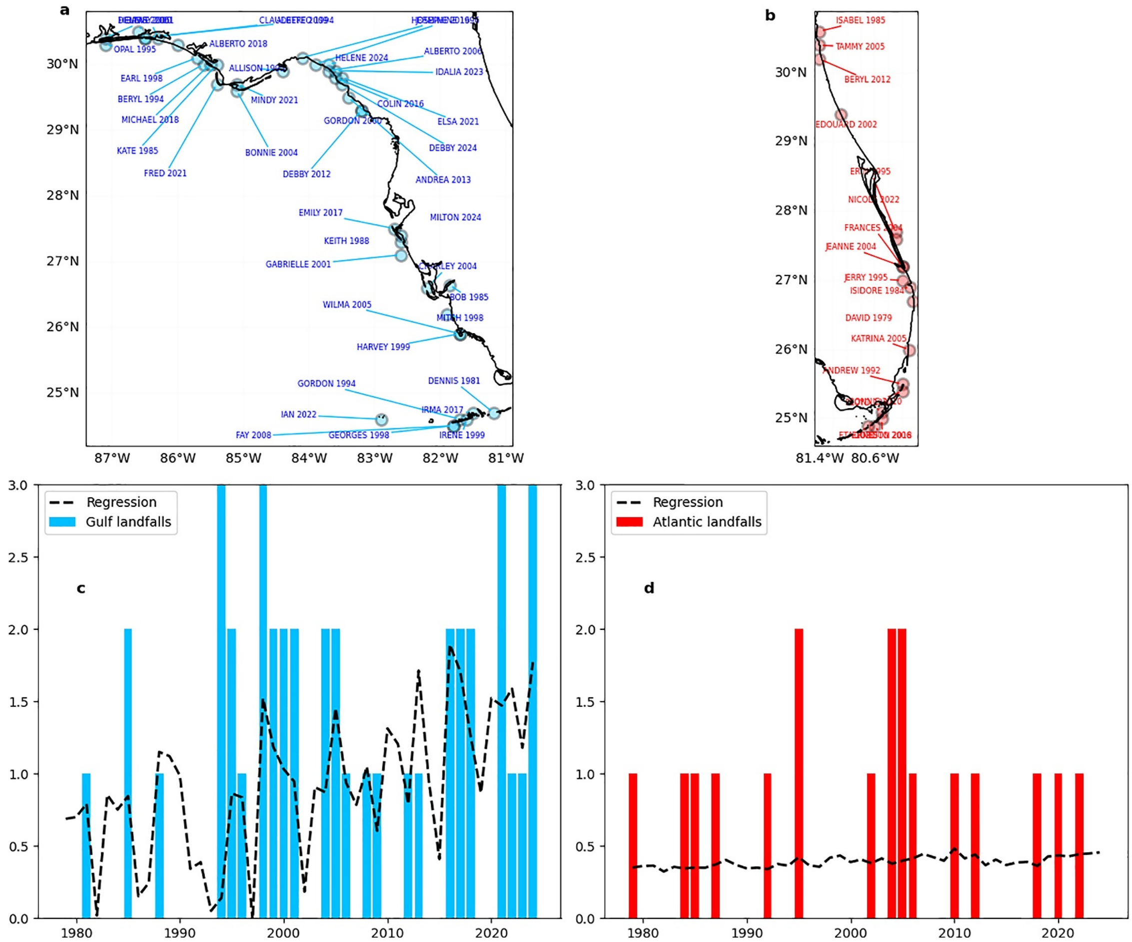


**Figure 1.** Locations of named storm landfalls along Florida's (a) Gulf and (b) Atlantic Coasts. Time series of annual TC landfalls for the (c) Gulf and (d) Atlantic Coasts of Florida. In panels (c, d), the linear regression using ENSO, AMO and NAO indices as predictors are shown (dashed-line). The analysis is for the period 1979–2024.

## 3. Results

### 3.1. TC Observations

We begin by examining historical Florida landfalls over the 46-year period 1979–2024 (Figure 1). During this period, there were 60 landfalls in total over Florida with 42 of them over Florida's Gulf Coast (Figure 1a) and the remaining 18 over the Atlantic Coast of Florida (Figure 1b). This suggests that, on average, the likelihood of a TC making landfall over the Gulf Coast is roughly twice that of the Atlantic Coast. Note that only those storms that made landfall as at least tropical storms (i.e., $\geq$34 kt) are considered in our analysis. While TC landfalls over the Gulf Coast are mainly clustered around the Panhandle region and parts of southwest Florida, most Atlantic Coast landfalls have occurred in southeast Florida. Histograms of TC landfalls for the Gulf and Atlantic Coasts are shown in Figures 1c and 11d, respectively. The Gulf Coast experienced fewer TC landfalls in the 1980s and early 1990s with noticeably increased activity since the mid-1990s. The linear trend is significant at the 95% level based on the non-parametric Mann-Kendall test. When a 1-2-1 filter (Emanuel, 2005) is applied to smooth the time series, a Theil-Sen slope of 0.02 per year is obtained while maintaining a significance level of 95%. In contrast, for the Atlantic Coast, TC landfalls appear to be fairly consistent over time. The linear trend is insignificant with a p-value close to 0.9. Smoothing this timeseries does not increase the significance of the results. These findings are in broad agreement with our earlier observation related to Florida TC landfalls.

To understand this contrast in TC landfalls between the Gulf and Atlantic Coasts of Florida, we develop multivariate linear regression models using the ENSO, AMO, and NAO indices as predictors. First, a regression model is developed to predict landfalls for the Gulf Coast. The linear model (dashed line in Figure 1b) explains ~23% of

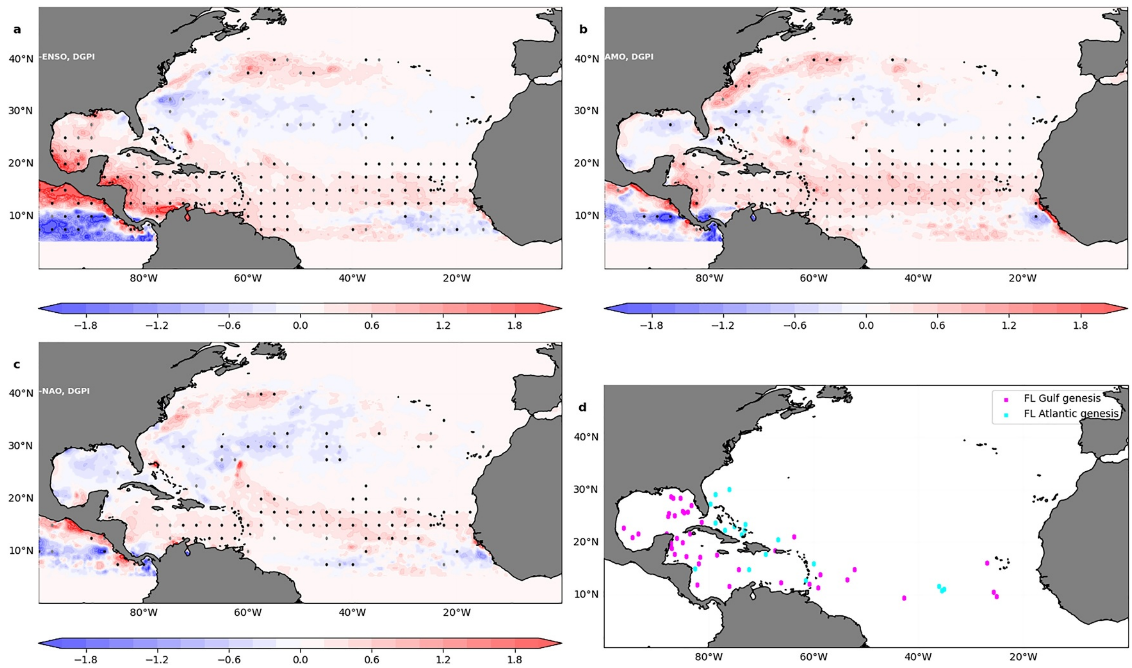


**Figure 2.** Spatial maps of regression coefficients for DGPI regressed onto (a) ENSO, (b) AMO and (c) NAO. Note that for both ENSO and the NAO, negative values of the corresponding indices are used for ease of comparison with the AMO. In panels (a–c), the black and gray dots indicate locations where the regression coefficients are significant at the 95% and 90% level, respectively, based on the Wald test. (d) Locations of cyclogenesis for historical TCs making landfall over Florida's Gulf (magenta) and Atlantic (cyan) Coasts. The analysis is for the period 1979–2024. All parameters are averaged over June–October.

the variance in the interannual landfalls for the Gulf Coast, significant at the 95% level. Out of the three modes, the AMO is the most significant predictor with a significance level exceeding 95%, followed by ENSO with a p-value of 0.06. The significance level for the NAO is just under 90% with a p-value of 0.13. However, when a similar regression model is used to predict landfalls for the Atlantic Coast, the variance explained is 0.3% and is statistically insignificant. This differing influence of ENSO, AMO and the NAO on TC landfalls between the two coasts is striking. Further, over the 46-year period, both the AMO and the NAO exhibit significant linear trends. While the AMO has trended positive, the NAO has trended negative. Therefore, these linear trends in modes of variability, in combination with the influence they exert on TC landfalls over the Gulf Coast, may explain the recent observed increase in Gulf Coast TCs. This leads us to the following important question: How do ENSO, the AMO and the NAO affect Florida's Gulf and Atlantic landfalling TCs differently?

### 3.2. Cyclogenesis

To address this, we now examine the influence of ENSO, the AMO and the NAO on various dynamic and thermodynamic parameters that may affect Florida's landfalling TCs, starting with cyclogenesis. Figure 2 shows the climate modes regressed on the DGPI, an index of environmental cyclogenesis favorability (Murakami & Wang, 2022; Wang & Murakami, 2020). The regression coefficients are significant and positive for both ENSO (Figure 2a) and the AMO (Figure 2b), and cover much of the Atlantic TC main development region (MDR). Note that for both ENSO and the NAO, a negative value of the index is used for ease of comparison with the AMO. This indicates that during either a La Niña (Figure 2a) or a positive AMO phase (Figure 2b), the environment in the tropical Atlantic becomes more favorable for TC formation, consistent with several previous studies (Camargo et al., 2007; Klotzbach, 2011; Klotzbach & Gray, 2008; Klotzbach et al., 2015, 2018; Pielke & Landsea, 1999).

On the other hand, the influence of the NAO on TC genesis appears to be relatively weak (Figure 2c). Considering the locations of cyclogenesis for Florida's landfalling TCs (Figure 2d), it is clear that Gulf landfalling storms tend to originate farther west in the basin compared to Atlantic landfalling storms. While some Atlantic landfalling storms form in the MDR, they mainly originate in the tropical Atlantic to the east of Florida and to the north of the islands of the Greater Antilles. On the other hand, while a few Gulf landfalling storms form over the eastern MDR, a majority of them form over the Caribbean Sea and the eastern Gulf. Next, for each mode of variability, we

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compute the difference in means for the regression coefficients between Gulf and Atlantic landfalling storms, estimated near their respective genesis locations. However, these differences are statistically insignificant, suggesting that ENSO, the AMO and the NAO exert a similar influence on cyclogenesis for Gulf and Atlantic landfalling TCs.

### 3.3. Storm Intensification

Having considered their potential influence on cyclogenesis, we now examine the impact of various modes of variability on the intensification of Florida landfalling TCs (Figure 3). Specifically, we examine how ENSO, the AMO and the NAO affect vertical wind shear and PI, two environmental parameters that play a pivotal role in storm development and intensification (DeMaria & Kaplan, 1994; Emanuel, 1999; Emanuel et al., 2004). During a La Niña (Figure 3a) or a positive AMO (Figure 3c) period, the vertical wind shear decreases substantially in the western MDR and over a broad band extending toward the African coast between 10°N and 20°N (Bove et al., 1998; Gray, 1984; Klotzbach, 2011; Pielke & Landsea, 1999; Xie et al., 2002). To the north of this region, wind shear increases in the subtropics, especially near Florida's Atlantic Coast. This opposing response of wind shear in the tropics and subtropics has been discussed previously (Kossin, 2017). Compared to wind shear differences during a La Niña or a positive AMO period, a weaker decrease in wind shear is seen over the MDR during a negative NAO phase (Figure 3e). Also, a relatively stronger increase in wind shear is seen during a negative NAO phase in regions close to the US coast.

To quantify the relative significance of these changes in wind shear on Florida's landfalling TCs, we estimate the regression coefficients along the tracks of Gulf (Figure 3g) and Atlantic (Figure 3h) landfalling storms and compute the difference in means between the two (Table S1 in Supporting Information S1). For the case of ENSO, the means for Gulf and Atlantic landfalling TCs are −0.44 and −0.27, respectively, a difference that is statistically significant at the 95% level. This suggests that while both Gulf and Atlantic landfalling storms experience reduced wind shear during La Niña, the effect is relatively stronger for Gulf landfalling TCs. This difference can be understood by considering the spatial distribution of Florida landfalling TCs (Figures 3g and 3h). The Atlantic landfalling storms experience reduced wind shear in the MDR (Figure 3a). But subsequently, they may encounter enhanced shear conditions as they approach Florida's Atlantic Coast. In other words, some of the effects of reduced shear in the MDR may be negated by the high shear conditions closer to Florida. On the contrary, the Gulf landfalling TCs predominantly go through the Caribbean Sea where the reduction in wind shear is the strongest (Figure 3a). Also, the increase in wind shear they experience in the Gulf is relatively weaker than that experienced by Atlantic landfalling storms.

The AMO modulation of environmental conditions are broadly similar to those of ENSO (Figure 3c). The mean values of along-track regression coefficients for Gulf and Atlantic landfalling storms are −0.50 and −0.43, respectively, with a significance exceeding the 90% level ($p$-value of 0.08). This suggests two things. First, on average, the impact of the AMO on tropical Atlantic wind shear is slightly stronger than that of ENSO. Second, as is the case during La Niña, Gulf landfalling storms experience lower wind shear conditions compared to Atlantic landfalling storms during a positive AMO period. However, when a similar analysis is carried out for the NAO (Figure 3e), no significant difference between Gulf and Atlantic landfalling TCs is obtained. The mean values for Gulf and Atlantic landfalling TCs are −0.16 and −0.18, respectively, and their difference is statistically insignificant.

When it comes to the thermodynamic state, more favorable PI conditions prevail in the tropical Atlantic during a La Niña, a positive AMO or a negative NAO phase (Figures 3b–3f). However, unlike wind shear, the modes of variability appear to influence PI conditions for Gulf and Atlantic landfalling storms similarly, especially for ENSO and the NAO. A mean regression coefficient of 0.18 is obtained for both Gulf and Atlantic landfalling storms associated with ENSO. Similarly, the mean regression coefficients for Gulf and Atlantic landfalling storms associated with the NAO are 0.49 and 0.48, respectively, and are statistically indifferent. For the case of the AMO however, the mean values for Gulf and Atlantic landfalling storms are 0.73 and 0.64, respectively, with a difference that is statistically significant at the 95% level. This indicates that the influence of the AMO on tropical Atlantic PI is stronger and that a positive AMO phase favors Gulf landfalling storms more. The results from the PI analysis are summarized in Table S2 in Supporting Information S1.

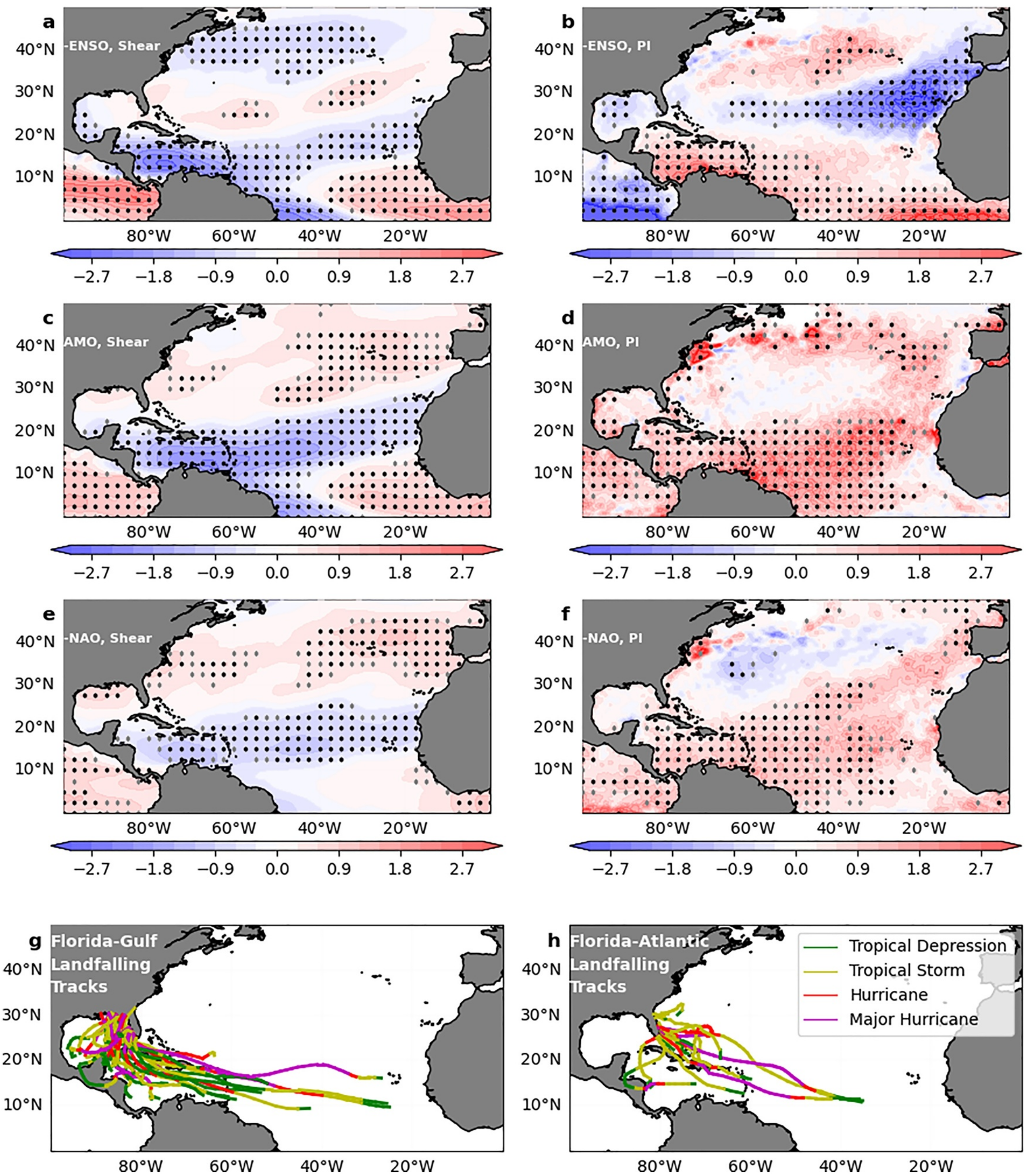


**Figure 3.** Spatial maps of regression coefficients for vertical wind shear regressed onto (a) ENSO, (c) AMO, and (e) NAO. Spatial maps of regression coefficients for PI regressed onto (b) ENSO, (d) AMO, and (f) NAO. Note that for both ENSO and the NAO, negative values of the corresponding indices are used for ease of comparison. In panels (a–f), the black and gray dots indicate locations where the regression coefficients are significant at the 95% and 90% level, respectively, based on the Wald test. Tracks of historical TCs that made landfall over Florida's (g) Gulf and (h) Atlantic Coasts. In panel (h), the legend indicates the intensity category during a storm's lifetime. The analysis is for the period 1979–2024. All parameters are averaged over June–October.

### 3.4. Steering Flow

So far, we have seen that both vertical wind shear, and to a certain degree, PI, tend to become more favorable for Gulf landfalling storms when compared to Atlantic landfalling storms during a La Niña or a positive AMO phase. Finally, we examine the influence of various modes of variability on steering flow, and consequently on Florida landfalling TCs (Figure 4). Climatological average steering flow patterns for June–November (Figure S1 in Supporting Information S1) provide a useful baseline for comparison against phase-specific anomalies. Average steering flow tends to deter landfall along Florida's Atlantic Coast, with anomalies associated with climate

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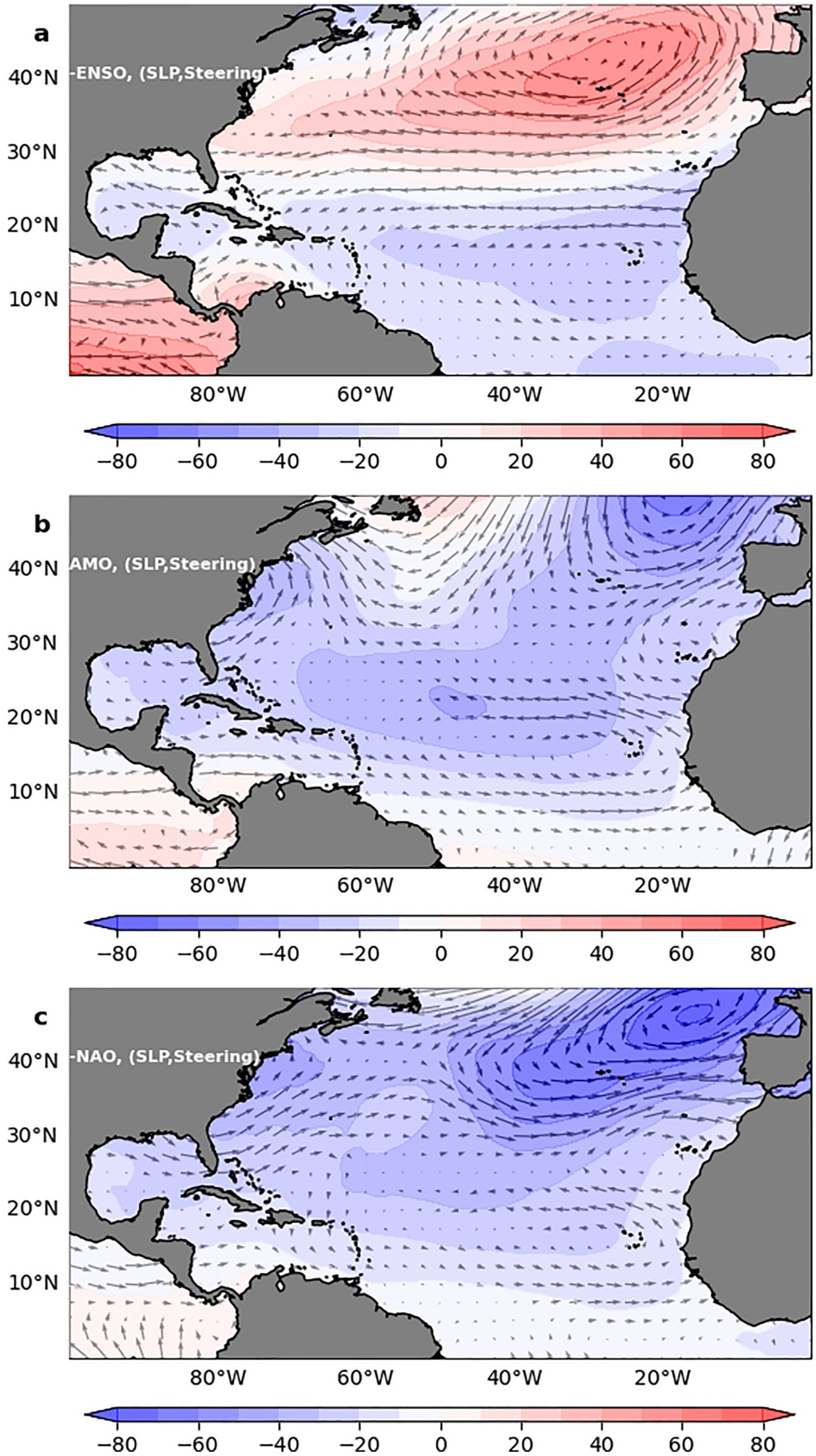


**Figure 4.** Spatial maps of regression coefficients for steering flow (vectors) and sea-level pressure (colored) regressed onto (a) ENSO, (b) AMO, and (c) NAO. Note that for both ENSO and the NAO, the negative values of the corresponding indices are used for ease of comparison. All parameters are averaged over June–October. The analysis is for the period 1979–2024.

oscillations either enhancing or suppressing landfall likelihood. For instance, during a La Niña phase, easterly steering flow anomalies prevail in the tropical Atlantic (Figure 4a), which enhance the climatological westward steering flow (Figure S1 in Supporting Information S1) and makes conditions more favorable for US landfall along the Atlantic Coast. This is in broad agreement with several previous studies that noted the increased US landfall probability during a negative ENSO phase (Bove et al., 1998; Klotzbach, 2011; Pielke & Landsea, 1999). However, while the easterly steering flow change is more favorable for landfall over Florida's Atlantic Coast, it is less conducive for a landfall on Florida's Gulf Coast as the tracks may be steered farther west in the Gulf. During a positive AMO, while easterly steering flow is generated between 20°N–30°N in the North Atlantic, as during La Niña, the steering flow response near the US coast is very different (Figure 4b). Anomalous southwesterly steering flow that is nearly parallel to the US East Coast is generated during a positive AMO phase, which enhances the climatological steering flow over that region (Figure S1 in Supporting Information S1) and tends to make landfall less favorable for Florida's Atlantic Coast. Weak westerly steering flow is generated in the eastern Gulf during a positive AMO, which may favor landfall over the Gulf Coast of Florida. The steering flow during a negative NAO phase is broadly consistent with that during a positive AMO near the US coast (Figure 4c). Similar to the positive AMO, a negative NAO phase produces anomalous southwesterly steering flow that is parallel to the US East Coast, amplifies the climatological unfavorable steering and is less conducive for landfall over Florida's Atlantic Coast. In the Gulf however, westerly steering flow is generated that is more conducive for a landfall over Florida's Gulf Coast.

## 4. Discussion

Based on an analysis of various climate modes and their impact on the large-scale storm environment, we have attempted to explain the stronger incidence of TC landfalls over Florida's Gulf Coast relative to Florida's Atlantic Coast in recent decades (summarized in Table S3 in Supporting Information S1). First, our analysis reveals that cyclogenesis for Florida's Gulf and Atlantic landfalling storms is affected similarly by various climate modes. Next, turning our attention to TC intensification and steering, we find that while La Niña makes the storm environment relatively more conducive for intensification of Gulf landfalling TCs, the steering flow changes induced by La Niña favor landfall over Florida's Atlantic Coast. This suggests a competing influence of ENSO for Gulf and Atlantic landfalling storms. During a positive AMO phase however, the large-scale environment relevant for TC intensification becomes relatively more favorable for Gulf landfalling storms. Also, the steering flow becomes more favorable for Gulf landfalling storms and less favorable for Atlantic landfalling storms during a positive AMO. Finally, during a negative NAO phase, the steering flow becomes less favorable for a landfall over Florida's Atlantic Coast and more favorable for a Gulf Coast landfall. These results, in concert with the positive and negative trends in the AMO and the NAO, respectively, over the period 1979–2024, can potentially explain the heightened TC activity over Florida's Gulf Coast in recent decades. Also importantly, they reveal that for the Atlantic Coast, the opposing effects of wind shear, PI and steering flow associated with the AMO and the NAO on landfalling TCs may suppress predictability for this region.

These results have substantial implications for TC landfall seasonal-to-decadal predictability over Florida, and potentially other regions. They suggest that basin-scale predictions based on indices of natural variability may not be adequate to understand their impacts at the regional or local scales. Future studies using high-resolution numerical models are needed to further improve our understanding of how different modes of variability may affect the large-scale storm environment, and thereby, the local scale TC risk. In our study, although we found that the AMO may have played an important role in the increased TC landfalls over Florida's Gulf Coast, we note that much of our study period coincides with the warm phase of the AMO, which might limit the extent to which we can account for the AMO's influence on Florida TCs. While past research has demonstrated the AMO's influence on Atlantic TC activity (Goldenberg et al., 2001; Vimont & Kossin, 2007), its irregular periodicity and potential overlap with external forcings may introduce uncertainties about its exact influence on Atlantic TCs (Alexander et al., 2014; Gray et al., 2004; Mann & Emanuel, 2006; Srokosz & Bryden, 2015). An additional limitation of this study is the sole focus on landfalling TCs, excluding storms near the coast that do not make landfall but may still cause significant damages. For instance, Hurricane Matthew (2016) was a powerful storm that stayed offshore but still had substantial impacts over eastern Florida. Future studies could incorporate such storms when exploring landfall frequency.

One factor that we did not consider explicitly in our study is seasonality. Examining monthly distributions of landfalls for Florida's Gulf and Atlantic Coasts (not shown), we find that they are broadly similar with Atlantic landfalls being roughly half of Gulf landfalls during a given month. This is especially the case during the peak season months of August–September and late season months of October–November. However, during the early season months of June–July, Florida landfalling TCs are skewed toward the Gulf Coast with few landfalls for the Atlantic Coast. This is likely due to the warmer SSTs in the Gulf relative to the MDR during the early TC season, consistent with data indicating a higher tendency for storms to form and impact the Gulf during this period https://www.nhc.noaa.gov/climo/. This aligns with findings from Elsner et al. (2000), who observed Gulf Coast landfalls to occur earlier in the season compared to Atlantic Coast landfalls over the period 1801–1998. Considering that both coasts experience landfalls during the later part of the season when climate oscillations such as ENSO may manifest more profoundly, it is likely that the seasonality of TC landfalls may play a role in the translation of impacts from climate modes onto TCs.

Through our analysis in this study, we have obtained evidence to link the recent increase in TC landfalls over Florida's Gulf Coast to natural variability in the climate system. However, the potential role of external forcing was not explored. To address this question, we analyzed TC track data from a suite of historical fully-coupled climate model simulations from HighResMIP (Figure S2 in Supporting Information S1). Although the models underestimate the mean magnitudes of landfall, they are able to simulate the relatively higher landfall probability for the Gulf Coast, consistent with observations. When trends were computed however, no significant trends were obtained for Gulf Coast landfalls, suggesting that external forcing is less likely to play a role in the observed signal. Finally, to understand how TC landfalls over Florida may change in the future, we examined TC tracks from HighResMIP future climate simulations (Figure S3 in Supporting Information S1). Under the SSP5-8.5 emissions scenario, HighResMIP suggests a broad increase in Florida TC landfalls for the period 2015–2050 relative to 1979–2014, although sample size limitations preclude an examination of the spatial distribution of those changes. To overcome this, we next analyzed projections of future TC landfalls using RAFT. Over the historical period (1980–2014), despite some underestimation of the number of Florida landfalls when compared with best track data, the model realistically captures the relative proportion of Gulf and Atlantic landfalls (Table S4 in Supporting Information S1). Under the SSP5-8.5 emissions scenario in a future period (2066–2100), the model projects an overall increase in Florida landfalls with a similar percentage increase for Florida's Gulf and Atlantic Coasts, with the Atlantic Coast experiencing a larger relative increase. Interestingly, future increases are concentrated primarily along the Florida Panhandle and in southeast Florida (Figure S4 in Supporting Information S1). While prior work (Balaguru et al., 2023) links these landfall changes to steering flow shifts driven by projected sea surface warming in the eastern tropical Pacific (Xie et al., 2010), it remains unclear whether such changes in steering may lead to a clustering of TC landfalls over a particular region. Further studies examining how the complex interplay between natural variability and external forcings may shape future TC landfall changes are needed.

## Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

## Data Availability Statement

The analysis presented in this study are based on TC best track data from https://www.nhc.noaa.gov/data/hurdat/hurdat2-1851-2024-040425.txt, ERA5 reanalysis data (Hersbach et al., 2020, 2023). Monthly ONI, AMO, and NAO indices are available from https://psl.noaa.gov/data/timeseries/month/DS/ONI/, https://www.ncei.noaa.gov/pub/data/cmb/ersst/v5/index/ersst.v5.amo.dat and https://crudata.uea.ac.uk/cru/data/nao/, respectively. RAFT TC track data are available via Balaguru et al. (2022). TC tracks detected in HighResMIP simulations are based on Roberts (2019). The python code to compute Potential Intensity is based on Gilford (2021) and is archived at Gilford (2020). All figures in this study were generated using open-source Python libraries, including Matplotlib, Numpy, Scipy, and Cartopy.

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