Spatial Variability of Tropical Cyclone Heading Angles: Implications for Probabilistic Coastal Hazard Assessment

Emily Cheng[a], Ziyue Liu[b,c], Michelle T. Bensi[b]
[a]Department of Computer Science, University of Maryland, College Park, MD, USA. echeng15@umd.edu
[b]Department of Civil and Environmental Engineering, University of Maryland, College Park, MD, USA. ziyue20@terpmail.umd.edu; mbensi@umd.edu
[c]Edwardson School of Industrial Engineering, Purdue University, West Lafayette, IN, USA. liu4205@purdue.edu

Abstract: Tropical cyclones (TCs) cause significant damage to coastal communities and infrastructure. Probabilistic coastal hazard assessments provide information on the frequency and severity of coastal hazards (typically represented as hazard curves) and serve as a key input to probabilistic risk assessments for coastal hazards. The Joint Probability Method (JPM) serves as a foundational tool for the probabilistic assessment of TC-induced hazards, especially for storm surge. Among the critical TC parameters used in the JPM, including central pressure deficit, forward velocity, radius of maximum wind, and heading angle, the heading angle is a circular variable and represents the direction of TC approach. It exhibits statistical properties that differ fundamentally from those of linear parameters. Existing studies have begun to explore the impact of incorporating circular statistics into the JPM framework for modeling the heading angle in regional case studies. However, the circular statistical characteristics of the heading angle across multiple geographic regions have not been systematically investigated. In this study, we investigate the circular statistical properties of the heading angle across multiple study regions using different TC data sampling methods. We focus on the variability of the heading angle's marginal distributions and its statistical dependence on other linear TC parameters. The results provide new insights into regional variability and dependence structures among TC parameters and highlight the importance of properly accounting for circular variables in probabilistic TC hazard modeling. These findings contribute to improving the accuracy and robustness of JPM-based assessments of TC-induced coastal hazards.

1. INTRODUCTION

Tropical cyclones (TCs) pose significant hazards and threaten coastal critical infrastructure, causing substantial damage to communities worldwide. Consequently, the probabilistic analysis of TC-induced coastal hazards has become a critical research topic. The Joint Probability Method (JPM) has become a foundational tool for the probabilistic assessment of coastal hazards, particularly those associated with storm surges [1-4]. [5] developed the Coastal Hazard System (CHS) framework that integrates the JPM for the probabilistic estimation of TC-induced coastal hazards. In the framework, a JPM integral equation is used to compute the annual exceedance frequency of a coastal response exceeding a given threshold. The JPM incorporates key TC parameters, including central pressure deficit (ΔP), forward velocity (V_{f}), radius of maximum wind ($R_{\max}$), landfall heading angle (Θ), and landfall location, to characterize the probability distribution of hazard responses such as storm surge.

Among these parameters, ΔP, V_{f}, $R_{\max}$ and Θ are collectively referred to as TC atmospheric parameters and are assumed to be statistically dependent. Notably, the storm heading angle Θ is a circular variable, defined on a periodic domain. Previous statistical approaches that treat Θ as a linear variable can introduce artificial discontinuities and sensitivity to the choice of directional convention (e.g., shifting the reference angle). The practical consequences of such misspecification are non-trivial because biases in the marginal distribution of Θ or in its dependence structure with other TC parameters propagate directly into the JPM integral, potentially distorting exceedance frequency estimates for storm surge and other coastal hazards. Critically, the direction and magnitude of this bias can vary by region, motivating the need for a systematic, multi-region investigation of how Θ behaves statistically and how it relates to other TC atmospheric parameters.

To address this issue, [6] incorporated circular statistical methods within joint distribution models to more appropriately represent the periodic nature of Θ. The study focused on the New Orleans region and examined the sensitivity of hazard estimates to the inclusion of circular statistical features, focusing on Θ's marginal distribution and its correlation with the three linear TC atmospheric parameters ΔP, V_{f}, and $R_{\max}$. Its results indicated that, in the New Orleans region, incorporating circular properties of Θ had a limited impact on probabilistic hazard estimates.

However, it remains unclear whether these findings generalize across regions with different storm-track characteristics and coastal geometries. In particular, both the relationship between Θ and other TC parameters and the sensitivity of these relationships to the TC data sampling method may vary depending on storm evolution and regional dynamics. In this study, we build on the work of [6] to investigate the circular statistical features of Θ across multiple study sites (i.e., coastal reference locations (CRLs)) using different TC data sampling methods. We focus on investigating how both the marginal distribution of Θ and its dependence with linear TC atmospheric parameters (ΔP, V_{f}, and $R_{\max}$) vary across regions and sampling methods.

In this study, we use the HURDAT2 database [7, 8], supplemented with data imputation techniques [9, 10], as the historical TC dataset. Statistical analyses are conducted across multiple CRLs along the U.S. coastline, as shown in Figure 1.

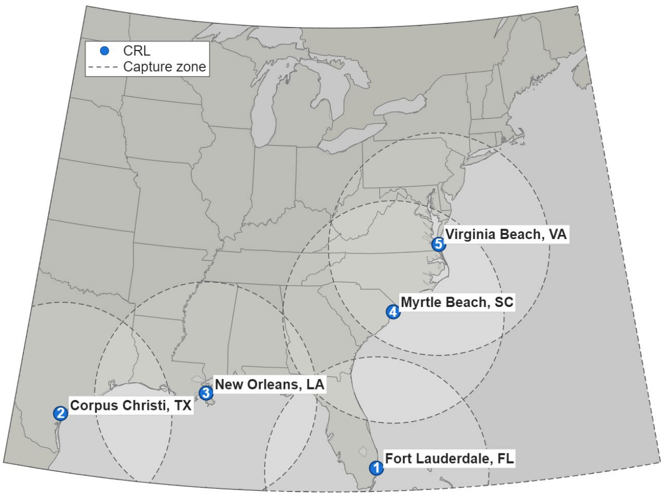
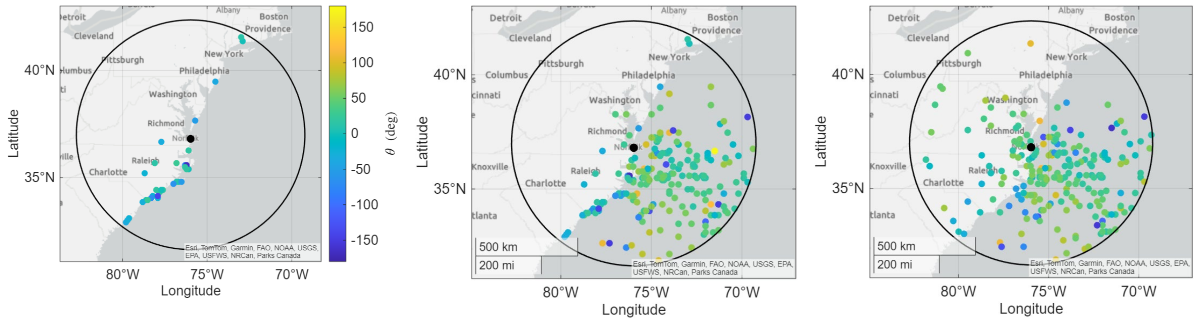


Figure 1: CRLs Used in This Work. Each CRL is associated with a 600 km radius capture zone

We compare three TC data sampling methods. In **Case 1**, only TC data points at landfall locations within the capture zone of each CRL are considered. In **Case 2**, the data points at landfall locations and the closest over-water points of bypassing TCs within the capture zone are extracted. In **Case 3**, we adopt the method introduced in the USACE CHS framework [11], in which the TC data point with the maximum intensity index is used. Figure 2 shows the sampling points extracted using the three different sampling methods for the Virginia Beach location (CRL 5 in Figure 1). Note that in Figure 2-a (Case 1), some data points extend inland. This is caused by the 6-hour temporal resolution of the HURDAT2 dataset, which may not capture the exact coastline crossing time. Although the temporal resolution of historical TC datasets can be improved through interpolation [12], this study deliberately employs the original data without interpolation to maintain consistency in the statistical analysis. Cases 2 and 3 yield a greater number of sampled points, as they incorporate non-landfall TC data within the capture zone.

In this study, due north is defined as 0° and Θ is expressed in the range $[-180°, 180°]$ with clockwise rotation taken as the positive direction.



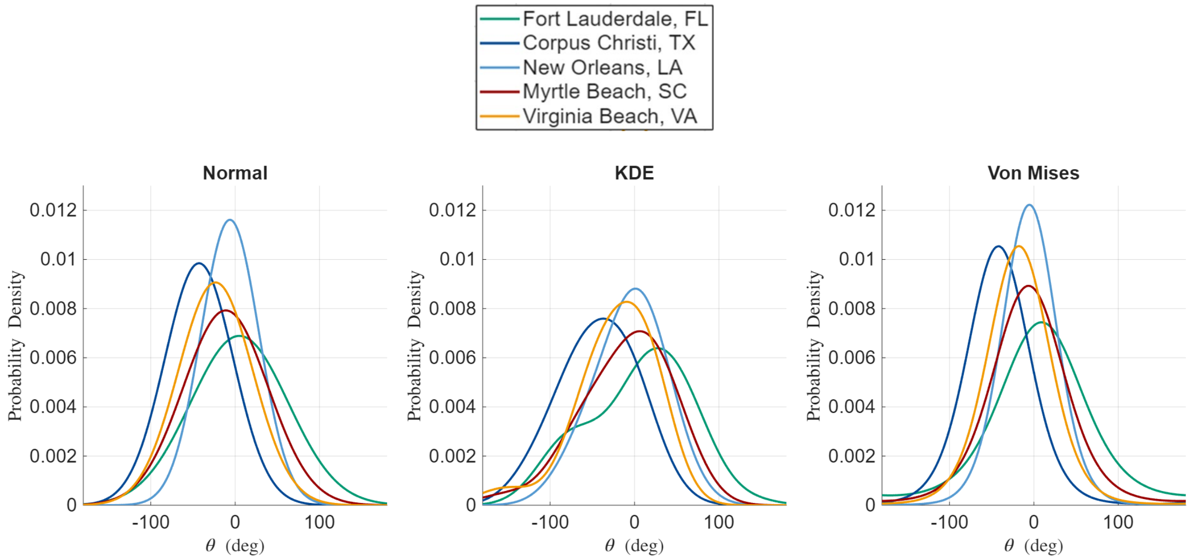
(a) Case 1 **(b) Case 2** **(c) Case 3**

Figure 2: Sampling points, colored based on heading angle, at Virginia Beach, VA (black dot)

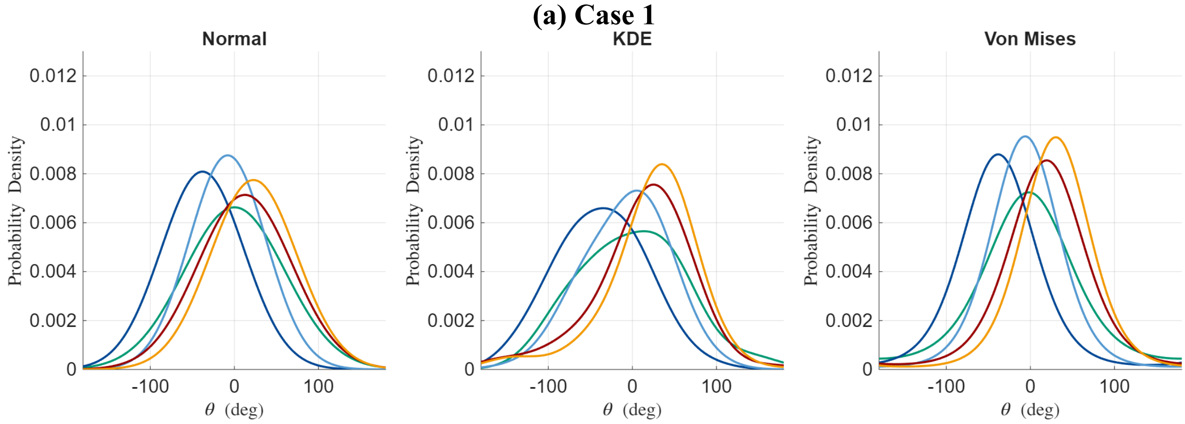
2. MARGINAL ANALYSIS

For each TC data sampling case and CRL, marginal distribution analyses are conducted using three representative distribution models. First, the normal (Gaussian) distribution is used due to its simplicity and its widespread use in previous studies (e.g., [13]). However, the normal distribution is defined on a linear domain and therefore has limited capability to represent circular variables with inherent periodicity. Second, a nonparametric kernel density estimation (KDE) approach is employed, offering greater flexibility in capturing complex distributional shapes; nevertheless, standard KDE formulations are also defined on a linear domain and thus do not inherently account for the periodic nature of circular data. To address these limitations, the von Mises distribution is additionally considered. The von Mises distribution, often referred to as the "circular normal" distribution, is specifically formulated for circular data defined on a periodic domain.

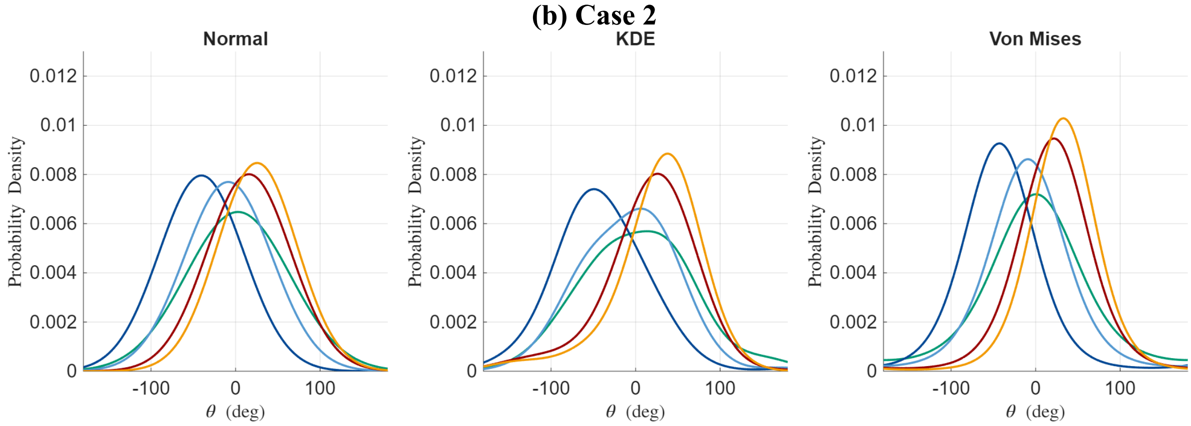
We compared the fitted marginal distributions of Θ across different CRLs under each sampling case and distribution type. The results of these marginal analyses are presented in Figure 3. It can be observed that, for a given sampling case and distribution type, the marginal distributions vary substantially among CRLs, indicating strong spatial variability in the distribution of Θ. In addition, noticeable differences in the modal peaks are evident between Case 1 and the other two sampling cases. These discrepancies reflect the influence of the sampling strategy on the representation of Θ. In contrast, the difference between Case 2 and Case 3 is relatively small, suggesting that these two methods yield more consistent representations of Θ. Overall, the choice of sampling method has a more pronounced impact on the fitted distributions than the choice of distribution model itself.



(a) Case 1



(b) Case 2



(c) Case 3

Figure 3: Fitted Marginal Distributions Among CRLs

3. DEPENDENCE ANALYSIS

The dependence among TC atmospheric parameters is critical for quantifying the resulting hazards [14], [15]. In this study, we focus on the dependence between Θ and the other three linear TC atmospheric parameters (ΔP, V_{f}, and $R_{\max}$). As in [6], to characterize this dependence, we employ the circular-linear correlation coefficient ρ_{cl} introduced by [16]:

$$\rho_{\mathrm{cl}} = \sqrt{\frac{r_{cx}^2 + r_{sx}^2 - 2r_{cx}r_{sx}r_{cs}}{1 - r_{cs}^2}} \tag{1}$$

where r_{sx} is the Pearson's ρ between $\sin\theta$ and x; r_{cx} is the Pearson's ρ between $\cos\theta$ and x; r_{cs} is the Pearson's ρ between $\sin\theta$ and $\cos\theta$; and x is a linear variable (ΔP, V_{f} and $R_{\max}$). ρ_{cl} provides a measure of the strength of association between the linear variable and the circular variable, indicating the extent to which higher values of the linear variable are systematically associated with a specific angle.

Figure 4 presents the ρ_{cl} values between Θ and each linear variable, calculated for each CRL under the three sampling cases. For ΔP, Fort Lauderdale has the strongest dependence in Cases 1 and 3, while Fort Lauderdale and Virginia Beach have similar correlations for Case 2. For V_{f}, Myrtle Beach and Virginia Beach generally exhibit stronger correlations than the other CRLs, particularly in Case 1. The results for Cases 2 and 3 are again relatively similar, suggesting that the V_{f}-based dependence is less sensitive to the sampling differences between them. In contrast, the dependence associated with $R_{\max}$ varies more among both CRLs and sampling cases. This indicates that $R_{\max}$-based dependence is more sensitive to the choice of sampling case than ΔP and V_{f}.

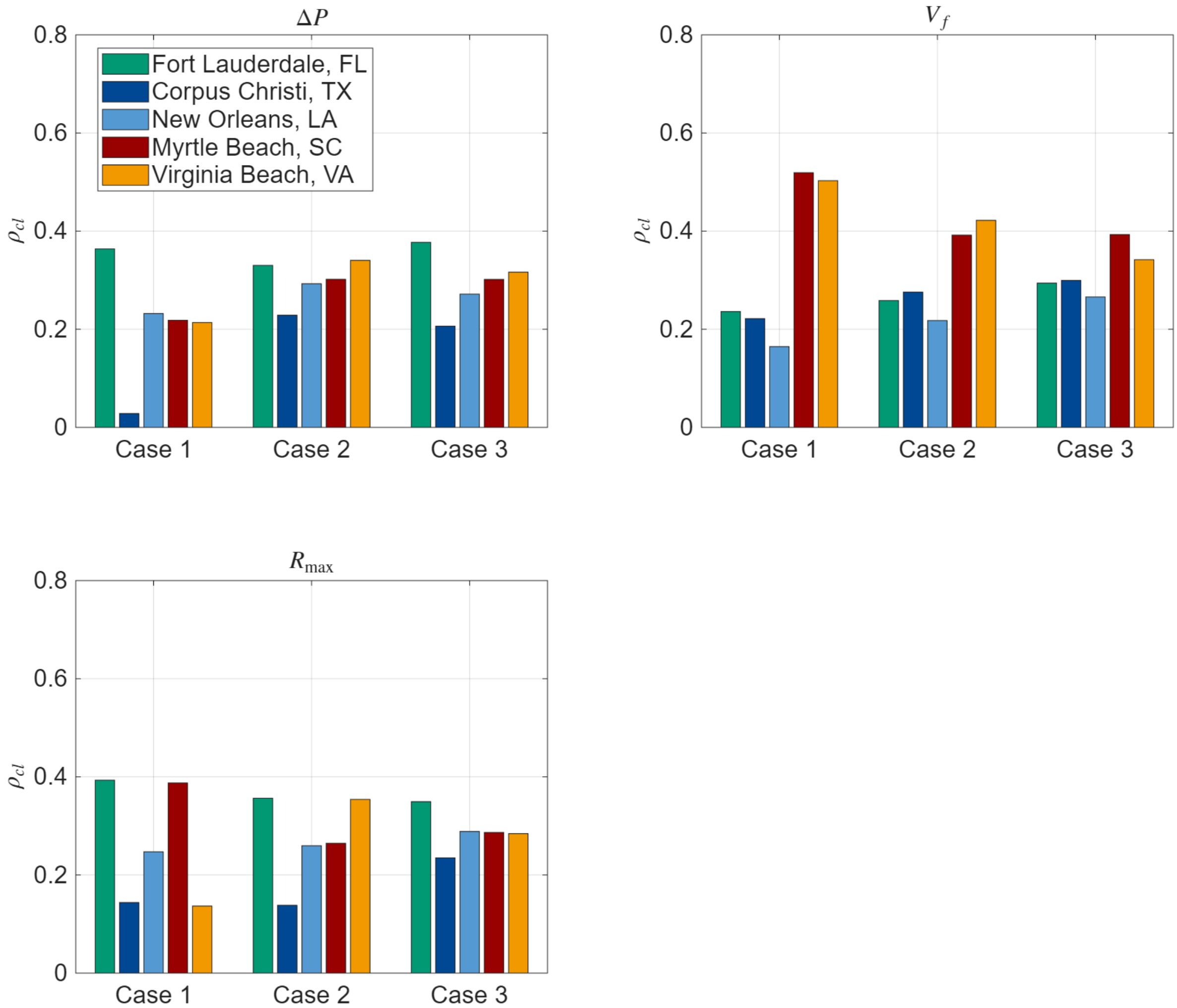
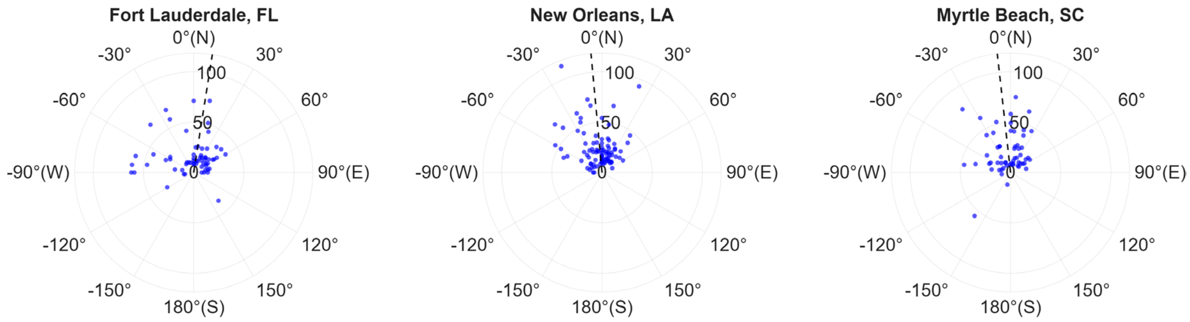
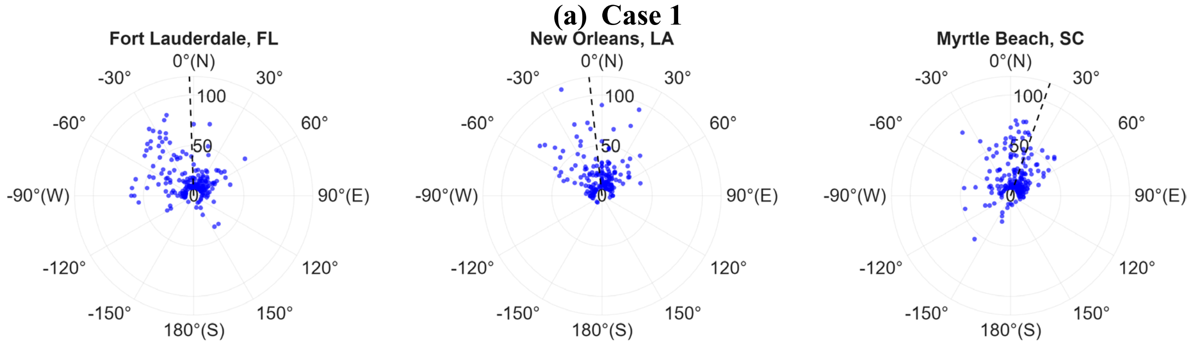


Figure 4: ρ_{cl} calculated between Θ and each linear variable for each CRL and sampling case

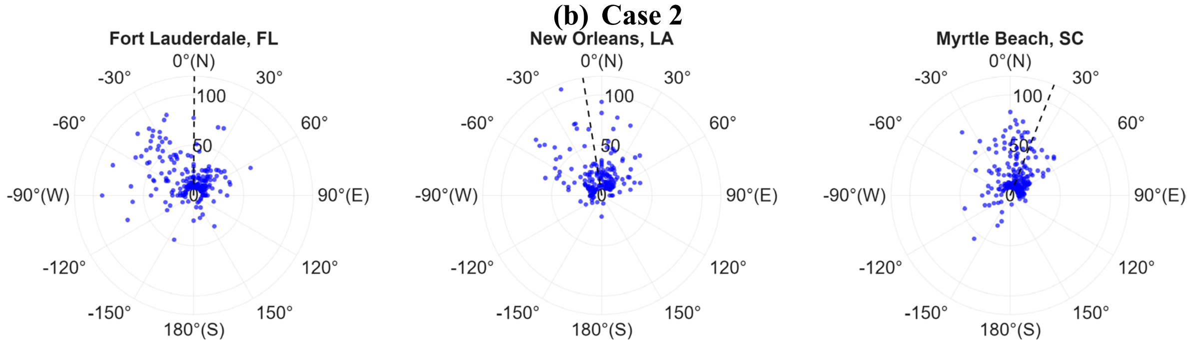
To directly visualize the dependence between Θ and ΔP, Figure 5 presents polar scatter plots for selected CRLs with the angle representing Θ and the radial distance representing ΔP. It can be observed that the samples are not uniformly distributed over the full angular range. In addition, most points are concentrated near the center of the plots, indicating that the majority of samples correspond to relatively low or moderate ΔP values. High ΔP events, represented by points farther from the center, occur less frequently and tend to appear within specific directional sectors. For Fort Lauderdale and New Orleans, high ΔP values are mainly associated with directions between the northwestern and northern sectors. Especially for Fort Lauderdale in Cases 2 and 3, a clear cluster of relatively high ΔP values is concentrated around -30°. This direction differs from the calculated circular mean value of Θ, which is closer to $0°$. Overall, Figure 5 indicates that the dependence between Θ and ΔP is directional and site-specific.



(a) Case 1



(b) Case 2



(c) Case 3

Figure 5: Polar scatter plots of Θ and ΔP (hPa, represented by the radial axis) in selected CRLs. The dashed line indicates the mean value of Θ

4. CONCLUSION

In this study, we investigate the statistical behavior of TC heading angle Θ along the U.S. North Atlantic coastline, a key factor in quantifying TC-induced hazards that pose significant threats to coastal critical infrastructure. Our analysis leverages an imputed historical TC dataset and encompasses multiple CRLs along the coastline.

Both marginal distribution analyses of Θ and dependence analyses between Θ and the three linear TC atmospheric parameters ΔP, V_{f} and $R_{\max}$ are conducted. The marginal analysis indicates that, at each CRL, the estimated distributions are highly sensitive to the TC data sampling method. In addition, substantial spatial variability is observed among different CRLs. The dependence analysis reveals moderate to strong circular-linear correlations between Θ and the three linear TC atmospheric parameters. These correlations are also sensitive to both the sampling method and the selected CRL. Notably, the dependence associated with $R_{\max}$ appears to be more sensitive to the sampling method than those associated with ΔP and V_{f}. In addition, the clustering of high ΔP values may occur around directional angles that differ from the mean Θ calculated from historical data. This study provides the basis for future work to investigate the differences between the angular clustering associated with high ΔP, V_{f}, and $R_{\max}$ values and the corresponding historical mean angles.

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