A Statistical Analysis of North Indian Ocean Cyclones

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Abstract: A tropical cyclone is a large-scale weather system characterized by a low-pressure center and rotating winds. These cyclones can bring destructive winds and heavy rainfall and pose a critical threat to coastal regions by forming over warm ocean waters near the equator. This paper focuses on tropical cyclones generated in the North Indian Ocean Basin (Bay of Bengal and Arabian Sea sub-basins), which typically form during the pre-monsoon and post-monsoon seasons and mainly impact the countries India, Bangladesh, Myanmar, and Sri Lanka.

This project analyzes tropical cyclones in the North Indian Basin through global and basin-specific visualizations. We further explore modeling techniques such as two nonparametric models for joint modeling of wind direction and wind speed of cyclones and compare them. Besides, an independent parametric joint model of wind speed and wind direction is also employed by taking the von Mises distribution to fit wind direction and the Gaussian distribution to fit wind speed, and we compare the effectiveness of these models. Additionally, spatial point pattern analysis is conducted on cyclone origin points to identify clustering and spatial patterns. We also discuss Kernel density estimation of the spatial point pattern of the originating point of cyclones.

This study enhances the understanding of cyclones in the North Indian Basin and provides insights into their modeling and spatial characteristics.

Keywords and phrases: Tropical cyclones, Non-Parametric Kernel Density, Non-Parametric Johnson-Wehrly model, von Mises distribution, Spatial point pattern, Kernel smoothing.

1. Introduction

Tropical cyclones are widely acknowledged as the most formidable meteorological phenomena with far-reaching implications. For countries surrounding the North Indian Ocean, these cyclones have been extensively studied by researchers such as Girishkumar and Ravichandran (2012) and Nath et al. (2015), who have underscored their substantial impacts on vast geographical extents. Historical evidence establishes that these cyclones have been a recurring menace to the coastal communities of the Bay of Bengal and the Arabian Sea. Furthermore, empirical analysis conducted by Belanger et al. (2012) confirms the profound consequences endured by these coastal nations in the face of tropical cyclones. While the Northern Indian Ocean (NIO) is known to be a favorable region for the development of tropical cyclones, it actually accounts for only a small portion of the world's total cyclone activity. According to studies by Mohapatra, Bandyopadhyay and Tyagi (2014) and Shaji, Kar and Vishal (2014), the NIO serves as a breeding ground for tropical cyclones. However, these cyclones represent only approximately 7% of the total tropical cyclones worldwide, as reported by Mohapatra, Bandyopadhyay and Tyagi (2014) and Sahoo and Bhaskaran (2016). Thus, the annual human and financial costs associated with tropical cyclones (TCs) making landfall along the coastlines of the Northern Indian Ocean (NIO) can be extremely high. These costs refer to the damages and losses incurred by communities and economies in the affected regions. Tropical cyclones have the potential to cause widespread destruction, including loss of life, infrastructure damage, displacement of populations, and economic setbacks. The magnitude of these costs can be substantial and have significant impacts on the affected areas (Haggag and Badry, 2012).

This paper provides an in-depth examination of tropical cyclones worldwide, with a specific emphasis on the NIO Basin. It presents a comprehensive analysis of descriptive features observed in cyclones occurring globally since 1980, investigating their behavior, intensities, and impacts. In addition, two non-parametric models called the Non-Parametric Kernel Density (NP-KD) model and the Non-Parametric Johnson-Wehrly (NP-JW) model for jointly modeling storm speed and storm direction by Han et al. (2018) are discussed here. Furthermore, we have done independent parametric modeling by estimating the parameters using the Maximum likelihood estimation technique by motivating from Carta, Ramirez and Bueno (2008). The paper also delves into the spatial point pattern technique concerning the originating point of cyclones. It discusses the kernel density estimation of the spatial point pattern of the cyclogenesis locations, exploring its spatial distribution. This research enhances tropical cyclone understanding, encompassing characteristics, modeling, and spatial patterns in the North Indian Ocean Region. Identifying cyclone-prone areas aids targeted disaster management, while joint modeling reveals intensity and trajectory insights, enabling effective risk mitigation. These findings inform policy and urban planning, fostering resilient coastal regions, safeguarding lives, and improving well-being.

In section 2, we detailed the appropriate statistical methodology employed in this study. We explained the specific approaches and techniques utilized to analyze the data and address the research objectives outlined in this paper. Moving on to section 3, we provided an overview of the data utilized in this research. We discussed the data sources, collection methods, and relevant characteristics necessary for our analysis. The data was then analyzed using the statistical methodology discussed insection 2 and we presented and discussed the findings obtained from our analysis. We elaborated on the outcomes, trends, and patterns identified through the application of the statistical methodology to the data. These results provide insights into the characteristics and behaviors of tropical cyclones in line with the objectives of this study. In section 4, we have thoroughly examined and presented all the outcomes obtained from our analysis. Finally, in section 5, we offered concluding remarks summarizing the key findings and implications of our study. We highlighted the contributions of our research, discussed any limitations or future research directions, and emphasized the importance of the statistical methodology in enhancing our understanding of tropical cyclones.

2. Methodology

In this study, our primary focus is on tropical cyclones that occurred in the Northern Indian (NI) Basin between the years 1980 and 2022.Our main focus is on exploring the joint probability density function (PDF) of wind speed and wind direction. In this regard, we use two non-parametric models (NP-KD and NP-JW) and one simple parametric model ignoring the dependence between the variables. Later, we have done a spatial point pattern analysis of originating points of the cyclones.

2.1. Non-Parametric Kernel density model (NP-KD Model):

Let $(v_1, \theta_1), (v_2, \theta_2), \ldots, (v_n, \theta_n)$ be a random sample drawn from an unknown bivariate population. The joint PDF of wind speed and wind direction is given by

$$f_{V,\Theta}(v,\theta) = \sum_{i=1}^{n} K_{V,\Theta}(v,\theta), \tag{2.1}$$

where the bivariate kernel $K_{V,\Theta}(v,\theta)$ can be expressed as the product of univariate kernels as $K_{V,\Theta}(v,\theta) = K_V(v) \cdot K_\Theta(\theta)$, where

$$K_V(v) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(v-\mu_v)^2}{2\sigma^2}\right), \ K_\Theta(\theta) = \frac{1}{2\pi I_0(\kappa)} \exp\left(\kappa \cos\left(\theta - \mu_\theta\right)\right). \tag{2.2}$$

In this equation, σ and κ are the two bandwidth parameters associated with the tensor product kernel function and the term $I_0(\kappa)$ corresponds to the modified Bessel function of the first kind and order zero. For wind speed (v), non-parametric models typically utilize the univariate Gaussian function, and for angular data like wind direction of cyclones (θ), the von Mises kernel function is employed for fitting purposes. Thus,

$$\hat{f}_{V,\Theta}(v,\theta) = \frac{1}{(2\pi)^{3/2} I_0(\kappa)\sigma} \sum_{i=1}^{n} \exp\left(-\frac{(v-v_i)^2}{2\sigma^2}\right) \exp\left(\kappa \cos\left(\theta - \theta_i\right)\right) \tag{2.3}$$

is the estimated joint PDF of wind speed and wind direction, based on the NP-KD model as described in Han et al. (2018).

2.2. Non-Parametric JW Model

The NP-JW model is an extension of the classical JW model (Johnson and Wehrly (1978)) that combines wind speed and wind direction data into a joint PDF as described in Han et al. (2018). The expression of the JW model is

$$f_{V,\Theta}(v,\theta) = 2\pi g(\zeta) f_V(v) f_\Theta(\theta) \quad 0 \leq \theta < 2\pi, -\infty \leq v < \infty, \tag{2.4}$$

where $f_V(v)$ and $f_\Theta(\theta)$ are the PDFs of wind speed and direction, respectively. Here ζ represents the circular variable between the wind speed and direction, defined as

$$\zeta = \begin{cases} 2\pi \left[F_V(v) - F_\Theta(\theta)\right], & F_V(v) \geq F_\Theta(\theta) \\ 2\pi \left[F_V(v) - F_\Theta(\theta)\right] + 2\pi, & F_V(v) < F_\Theta(\theta), \end{cases} \tag{2.5}$$

where $F_V(v)$ and $F_\Theta(\theta)$ are the distribution functions of wind speed and direction, respectively, and $g(\zeta)$ represents the PDF of ζ. In the NP-JW model, the wind speed and direction data are fitted using univariate Gaussian and von Mises kernel functions, respectively. By estimating the PDFs, the corresponding distribution functions for wind speed and direction are computed.

2.3. Joint density of Wind speed and wind direction of cyclones using a conditional approach :

The joint PDF for wind speed and wind direction, incorporating the von Mises distribution for wind direction and the Gaussian distribution for wind speed given wind direction, can be expressed as

$$\begin{aligned} &f\left(S, \Theta; \mu_S, \sigma_S, \mu_\Theta, \kappa\right) \\ &= \frac{1}{2\pi I_0(\kappa)} \exp\left(\kappa \cos\left(\Theta - \mu_\Theta\right)\right) \frac{1}{\sigma_S\sqrt{2\pi}} \exp\left(-\frac{\left(S-\mu_S\right)^2}{2\sigma_S^2}\right), \end{aligned}$$

where $0 \leq \theta < 2\pi, v \in \mathbb{R}$. Here, S represents the wind speed, Θ represents the wind direction, μ_S represents the mean wind speed, σ_S represents the standard deviation of the wind speed,

μ_Θ represents the mean wind direction, and κ represents the concentration parameter of the von Mises distribution. The parameters can be estimated using maximum likelihood estimation.

2.4. Spatial Point Pattern Analysis :

Spatial point patterns refer to the arrangement or distribution of individual points or events in a geographical space. They are commonly used in various fields, including ecology, geography, urban planning, and epidemiology, to study the spatial characteristics and underlying processes of point occurrences(Baddeley, Rubak and Turner (2015)).

A spatial point pattern typically consists of a set of individual points that represent the locations of specific events or objects. Here we made a spatial point pattern of originating points of Cyclones in the NIO Basin since 1980. We here also discussed Kernel density estimation.

2.4.1. Kernel density estimation :

Suppose the n observed data points be denoted as $\boldsymbol{u}_1, \boldsymbol{u}_2, \ldots, \boldsymbol{u}_n \in \mathcal{D} \subset \mathbb{R}^2$, where $\mathcal{D}$ denotes the study domain. Then, the kernel density is the weighted average of the kernels centered at each data point, with the weights representing the contribution of each data point to the density estimation. A common choice for the kernel function is the Gaussian kernel given by

$$K(\boldsymbol{u}; h) = \frac{1}{\sqrt{2\pi h^2}} \exp\left(-\frac{\|u\|^2}{2h^2}\right), \tag{2.6}$$

where u is a variable and h is the bandwidth, a smoothing parameter that influences the smoothness of the estimated density as described in Sheather (2004),Scott (2015).

To estimate the PDF $\hat{f}(\boldsymbol{u})$ at a point $\boldsymbol{u}$, we compute the weighted average of the kernels centered at each data point, with the weights representing the contribution of each data point to the density estimation. This can be expressed as

$$\hat{f}(\boldsymbol{u}) = \frac{1}{n} \sum_{i=1}^{n} K\left(\boldsymbol{u} - \boldsymbol{u}_i; h\right). \tag{2.7}$$

KDE provides a flexible and versatile way to estimate the probability density function from a set of observed data points, allowing for the exploration and analysis of the underlying distribution without assuming a specific functional form.

3. Data and exploratory analysis

Our analysis focused on examining the track data of tropical cyclones in the North Indian Ocean region, which includes the Arabian Sea and the Bay of Bengal. We obtained this data from the International Best Track Archive for Climate Stewardship (IBTrACS), hosted by the National Climatic Data Center (NCDC) at `www.ncdc.noaa.gov/oa/ibtracs/`. The study period for our analysis spanned from 1980 to 2022, allowing us to investigate cyclone patterns and trends over a considerable timeframe. To visualize the cyclone trajectories in the North Indian Ocean region during this period, we created a figure (fig. 1) that displays the paths followed by the cyclones.

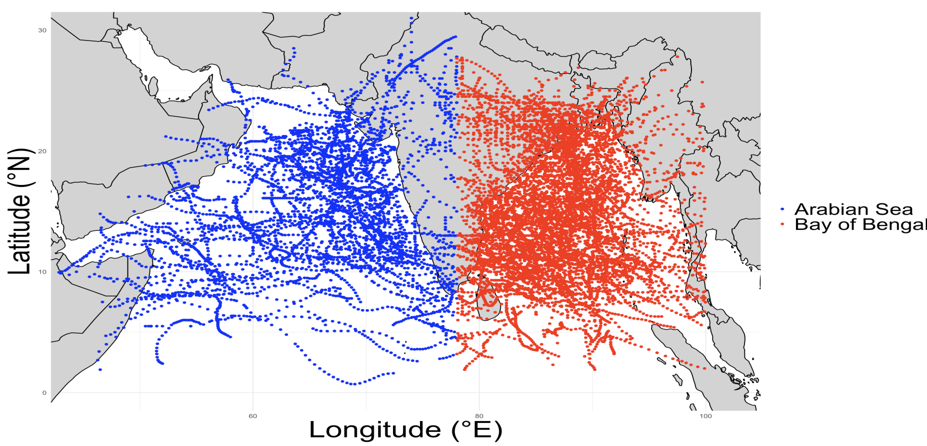


Fig 1: Contour plot of Joint Density of Storm Speed and Storm Direction

From our analysis, we observed that the Arabian Sea experiences a lower frequency of cyclones compared to the Bay of Bengal. The approximate ratio between the two regions is 1:4, indicating that the Bay of Bengal has a significantly higher occurrence of cyclones. Furthermore, by examining fig. 2, we identified a notable increase in the occurrence of cyclones generated in the North Indian Ocean region since 1990.

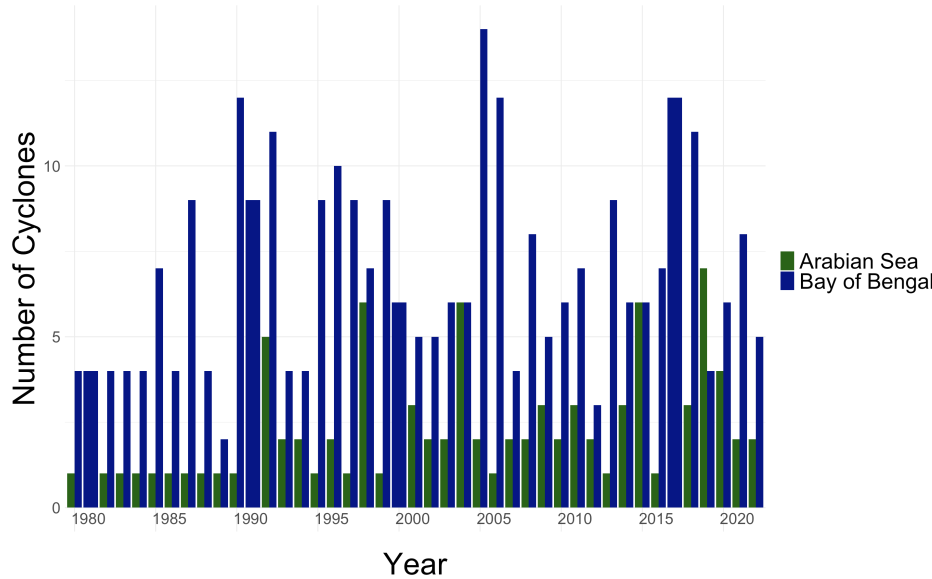


Fig 2: Contour plot of Joint Density of Storm Speed and Storm Direction

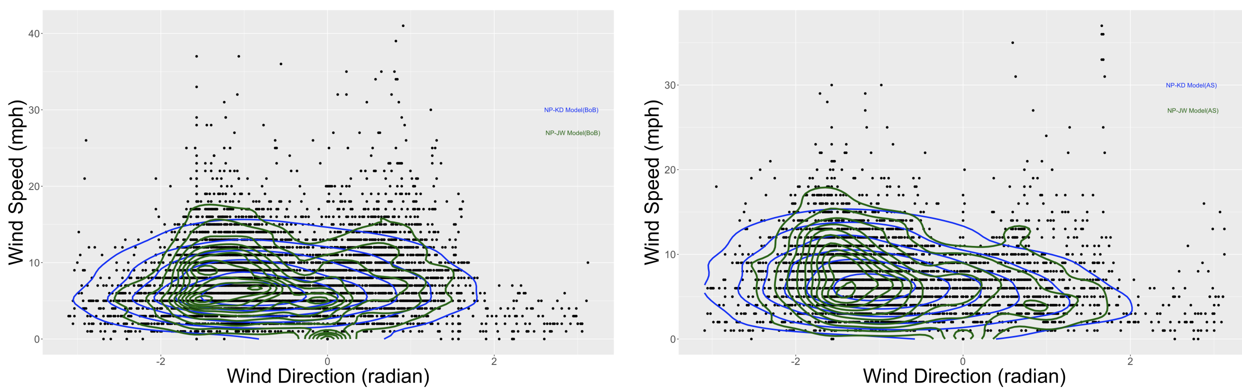
This finding suggests that the frequency of cyclones in this region has been rising over the past few decades. Overall, our analysis of the tropical cyclone data in the North Indian Ocean region provides valuable insights into the frequency and trends of cyclone occurrences. The observed disparity in cyclone frequency between the Arabian Sea and the Bay of Bengal, as well as the increasing trend in cyclone occurrence since 1990, highlight the dynamic nature of this region's climate and the potential implications for affected coastal areas.

3.1. Wind speed and wind direction modelling

Our main focus is on exploring the joint probability density function (PDF) of wind speed and wind direction. In this regard, we use two non-parametric models (NP-KD and NP-JW) and one simple parametric model ignoring the dependence between the variables.A description of the methodologies used in these methods has been provided in Section 2.

3.1.1. Non-parametric Models:

The joint density contour plots(fig. 3) generated by both the NP-KD and NP-JW models exhibit a single cluster, which closely aligns with the points on the scatter plot. This alignment indicates a good fit between the models and the observed data. It is important to note that the NP-KD model outperforms the NP-JW model to some extent in accurately capturing the joint distribution. The superiority of the NP-KD model can be attributed to its ability to determine the optimal bandwidth. The bandwidth selection plays a crucial role in kernel density estimation as it controls the smoothness of the estimated density. By finding the optimal bandwidth, the NP-KD model effectively captures the mode of the joint distribution, resulting in a clear identification of a single cluster. This feature was previously discussed in the work by Han et al. (2018) Han et al. (2018), indicating the strengths of the NP-KD model in capturing the joint behavior of wind speed and wind direction.



(a) Contour plot comparison(BoB) (b) Contour plot comparison(AS)

Fig 3: Contour plots for NP-KD and NP-JW models across the sub-basins.

Moreover, when analyzing the cyclone formation patterns in both the Bay of Bengal and Arabian Sea sub-basins (as depicted in fig. 3), a similar pattern emerges. This suggests that there are no distinct characteristics specific to any particular region within the Bay of Bengal and Arabian Sea sub-basins in terms of cyclone behavior. The behavior of cyclone formation appears to be consistent across these sub-basins, indicating a lack of significant differences between the two regions.

3.1.2. Joint parametric modeling of storm speed and storm direction

The contour plot presented illustrates the joint density of storm speed and storm direction, revealing an elliptical shape. An important observation from the plot is that the variability in the data is more pronounced in the wind speed dimension compared to the wind direction dimension. In other words, storm speeds exhibit a higher degree of variability compared to storm directions. Furthermore, the contour plot in Figure 4 shows that the data does not display multiple modes or distinct clusters. Instead, the density distribution appears to be concentrated within a single elliptical shape. This indicates that there is no clear separation or distinct grouping of data points based on storm characteristics. The absence of multiple modes suggests a lack of distinct subpopulations or categories within the data, suggesting a relatively homogeneous behavior in terms of storm speed and direction.

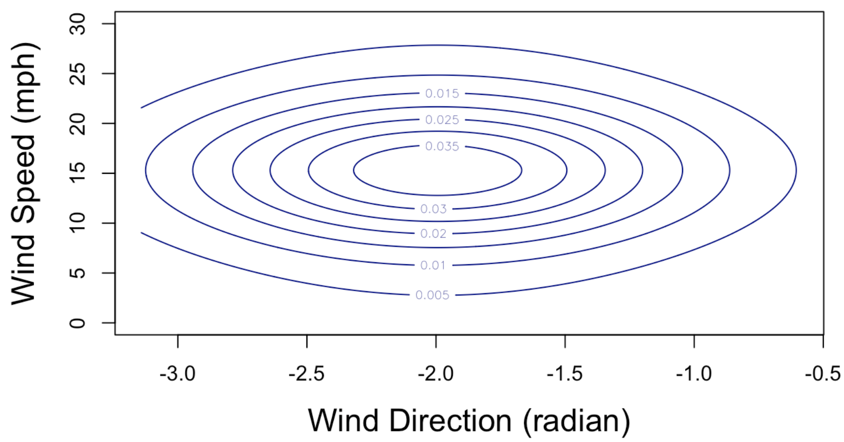


Fig 4: Contour plot of Joint Density of Storm Speed and Storm Direction

This observation implies that storm events within the analyzed dataset tend to exhibit consistent behavior in terms of their speed and direction. While there is variability in storm speeds, there is no clear separation of storms into different groups based on their characteristics. This suggests a relatively uniform distribution of storm events across the range of both speed and direction, with no distinct subpopulations or clusters. Understanding the distribution and characteristics of storms is crucial for various applications, such as risk assessment, planning, and mitigation strategies. The presented analysis provides insights into the joint behavior of storm speed and direction, highlighting the variability and relative homogeneity in their distribution. These findings contribute to a better understanding of storm patterns and can aid decision-making processes related to storm-related activities and infrastructure planning.

3.2. Cyclogenesis point pattern analysis

We have made an intriguing discovery concerning a spatial point pattern, which refers to the distribution and arrangement of points within a geographic or spatial domain. In our study, we have identified a point pattern that exhibits two clusters, primarily concentrated near the Arabian Sea and the Bay of Bengal sub-basins.

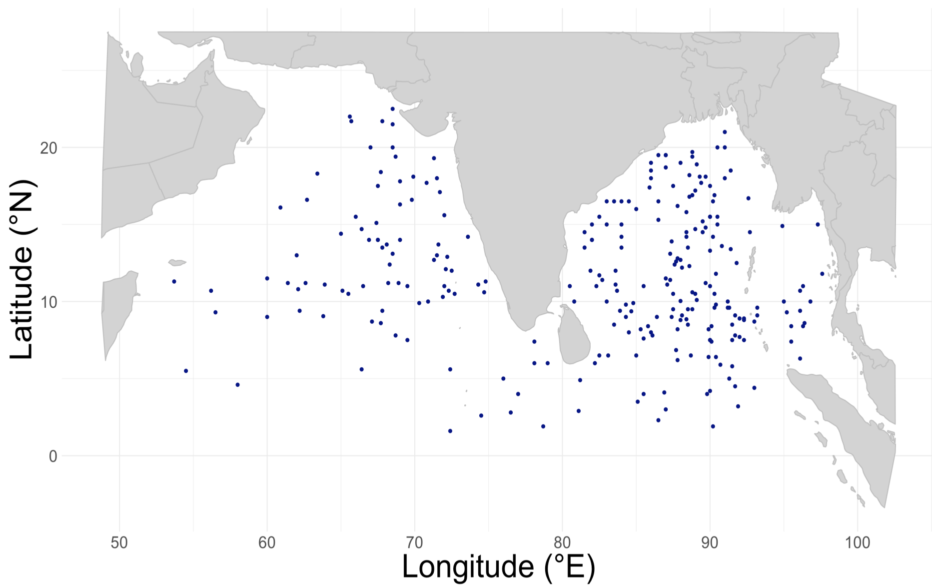


Fig 5: Originating locations of cyclones in NIO Basin

This particular pattern reveals the presence of two distinct groupings of points, with each cluster being noticeably prominent in its respective surrounding region. However, it is important to note that the density of the cluster is higher in the Bay of Bengal region compared to the Arabian Sea region. This distinction is clearly evident in the visualization shown in fig. 5. To further analyze and quantify the density differences, we examined kernel density estimation. The kernel density within the Bay of Bengal Basin was found to be consistently higher on average compared to the Arabian Sea region. This observation is clearly depicted in the heatmap of the kernel density shown in fig. 6. Moreover, based on our analysis, there is a significant likelihood of cyclone development in the coastal region of

Tamilnadu, as well as its surrounding areas within the Bay of Bengal basin. Similarly, the coastal region of Kerala and its neighboring coastal areas demonstrate a higher tendency for cyclone occurrence.

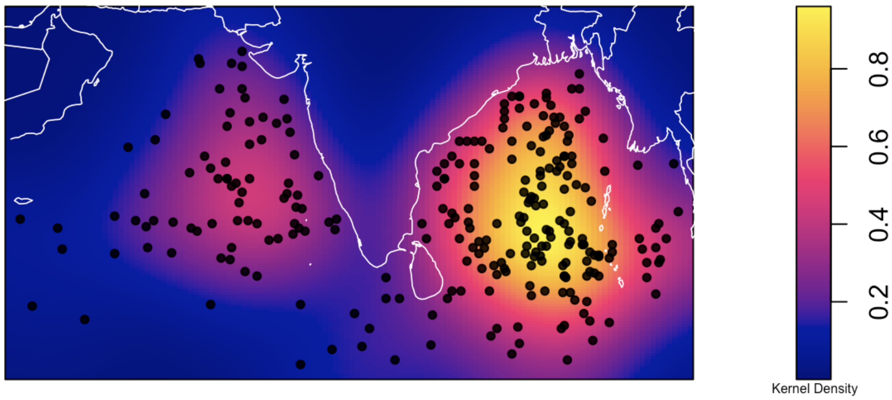


Fig 6: Heat map of Kernel density

Overall, our findings indicate a distinct spatial point pattern characterized by clusters, with the Bay of Bengal region, exhibiting a denser concentration of points compared to the Arabian Sea region.

4. Results and discussions

The analysis of cyclones in the North Indian Ocean (NIO) region over a period of 42 years (1980-2022) revealed interesting findings regarding their distribution and characteristics. We discussed two non-parametric models, namely NP-KD and NP-JW (Han et al. (2018), Johnson and Wehrly (1978)) and also a parametric model, to study the joint modeling of wind speed and wind direction of cyclones in NIO Basin. Joint modeling can improve cyclone forecasting capabilities. Incorporating both wind speed and wind direction information allows for more accurate prediction of cyclone tracks, intensities, and potential impacts. This is particularly useful for generating probabilistic forecasts that provide a range of possible outcomes. Joint modeling also contributes to climate studies by providing insights into the long-term behavior and trends of cyclones. It helps in identifying changes in the joint distribution of wind speed and wind direction over time, which can provide valuable information on shifts in cyclone characteristics due to climate change or other factors. The joint density contour plots of the NP-KD and NP-JW models for the joint modeling of wind speed and wind direction exhibited a single visible cluster. This finding suggests that the majority of cyclones in the North Indian Ocean region display a distinct and cohesive behavior in terms of their wind speed and wind direction characteristics. The contours in the density contour plots closely matched the scatter plot points, indicating a good fit for both models. This implies that the chosen non-parametric models effectively captured the underlying joint distribution of wind speed and wind direction in cyclones. The contours revealed the areas of higher density where cyclones tend to exhibit specific combinations of wind speed and wind direction. The agreement between the contour plots and scatter plot points indicates that the chosen non-parametric models accurately captured the joint behavior of wind speed and wind direction in cyclones. The close match between the contours and scatter plot points suggests that the models were able to estimate the underlying probability density function well. This indicates that the joint modeling approach successfully captured the joint distribution of wind speed and wind direction in cyclones, providing valuable insights into their behavior and characteristics in the North Indian Ocean region. However, the NP-KD model outperformed the NP-JW model in terms of fitting the joint distribution. This suggests that the NP-KD model, with its optimal bandwidth selection, effectively captured the predominant cyclone formation cluster, consistent with previous studies in Han et al. (2018). This pattern was observed in both the Bay of Bengal and Arabian Sea sub-basins. Furthermore, the observed pattern of cyclone formation in the Bay of Bengal and Arabian Sea sub-basins was similar. This suggests that the joint distribution of wind speed and wind direction exhibits consistency across these two regions within the North Indian Ocean basin. The similarity in the pattern of cyclone formation implies that there may be common underlying mechanisms or environmental factors influencing cyclone development in both sub-basins. This finding adds to our understanding of the spatial characteristics of cyclones in the region and can be valuable for forecasting and risk assessment purposes.

When analyzing the parametric joint density of storm speed and storm direction in cyclones, we observed an elliptical shape in the contour plot. This indicates that the joint distribution of these variables can be well approximated by an elliptical or bivariate normal distribution. Notably, the variability was found to be more pronounced in the wind speed dimension compared to the wind direction dimension. This suggests that cyclone speeds tend to vary more widely than their directions within the North Indian Ocean (NIO) region. The elliptical shape of the contour plot indicates the relationship between storm speed and storm direction, showing how changes in one variable may correspond to changes in the other. Importantly, the data did not exhibit multiple modes, implying that there is a relatively uniform distribution of cyclone characteristics in the NIO region. This suggests that cyclones in the NIO region do not exhibit distinct subgroups or categories based on their storm speed and storm direction. Instead, the distribution appears to be more continuous and spread out, without clear separation into different clusters or modes. The observation of a relatively uniform distribution indicates that cyclone characteristics in the NIO region exhibit a wide range of storm speeds and storm directions without distinct concentration points or preferred modes. This finding provides insights into the overall behavior of cyclones in the region and can contribute to our understanding of their variability and potential impacts. Understanding the joint distribution of storm speed and storm direction is crucial for various applications, including cyclone forecasting, risk assessment, and disaster management. By examining the elliptical shape, variability, and lack of multiple modes in the parametric joint density, we gain valuable insights into the statistical characteristics of cyclones in the NIO region.

This spatial clustering suggests that these regions are more prone to cyclone formation compared to other areas within the NIO Basin. The presence of clusters indicates the existence of localized factors or conditions that favor cyclone development in these specific areas. These factors may include sea surface temperature, atmospheric instability, moisture content, and other meteorological variables that contribute to cyclone formation and intensification. Additionally, the kernel density estimation provided insights into the density of cyclones within the NIO Basin. The analysis revealed that the Bay of Bengal Basin exhibited a higher cyclone density on average compared to the Arabian Sea sub-basin. This means that the Bay of Bengal experiences a higher frequency of cyclone activity compared to the Arabian Sea. From a meteorological perspective, this disparity in cyclone density can be attributed to various factors. The Bay of Bengal Basin is influenced by the southwest monsoon winds, which bring moist air over warm sea surface temperatures, creating favorable conditions for cyclone development. The presence of the Himalayan mountain range to the north of the Bay of Bengal also plays a role in influencing atmospheric dynamics, potentially enhancing cyclone formation. On the other hand, the Arabian Sea sub-basin experiences a different atmospheric environment. It is influenced by the northeast monsoon winds and is relatively less affected by the mountainous terrain. These factors contribute to a lower average cyclone density in the Arabian Sea compared to the Bay of Bengal. Understanding the spatial distribution and density of cyclones in the NIO Basin is crucial for meteorological forecasting, hazard assessment, and disaster management. It helps in identifying regions that are more vulnerable to cyclones and enables the implementation of targeted mitigation measures and preparedness strategies in those areas. Overall, the spatial point pattern analysis and kernel density estimation provide meteorological insights into the clustering of cyclone origins in the NIO Basin and the discrepancy in cyclone density between the Bay of Bengal and the Arabian Sea sub-basins. These findings provide valuable insights into the distribution, clustering, and characteristics of cyclones in the NIO region. Understanding the spatial and temporal patterns of cyclone formation can contribute to better forecasting, risk assessment, and disaster management strategies in vulnerable coastal areas. Further research could explore additional factors influencing cyclone formation and investigate long-term trends in cyclone behavior in the NIO region.

5. Conclusion

This study aimed to investigate various joint modeling techniques for wind speed and wind direction of cyclones in the North Indian Ocean (NIO) Basin, while also examining the spatial point pattern of cyclone origination over a 42-year period from 1980 to 2022. The main findings are summarized as follows:

- 1. Descriptive analysis of cyclones in the NIO Basin revealed higher cyclone-prone areas and clusters of cyclone origination points. The study observed an overall increase in cyclone formation over the years, with a significant rise starting from 1990.
- 2. Non-parametric models for joint modeling of wind speed and wind direction were explored for cyclones in the Bay of Bengal and Arabian Sea sub-basins. The performances of these models were compared using contour plots. Additionally, a parametric joint modeling approach for wind speed and wind direction was examined independently.
- 3. Spatial point pattern analysis of cyclone origination points in the NIO Basin provided insights into cyclone clusters and prone areas. Kernel density estimation highlighted the most densely populated cyclone areas. The study identified a significant likelihood of cyclone development in the coastline region of Tamil Nadu and its surroundings in the Bay of Bengal basin. Similarly, Kerala's coastline region and its neighboring coastal areas exhibited a higher tendency for cyclones.

These findings have significant meteorological implications and can contribute to improving cyclone forecasting and preparedness in coastal areas. By understanding the cyclone-prone regions and clusters, authorities can enhance early warning systems, evacuation plans, and disaster management strategies. The insights gained from the joint modeling techniques for wind speed and wind direction can lead to more accurate predictions of cyclone behavior, enabling timely and targeted interventions to mitigate potential risks. Ultimately, these advancements in cyclone modeling and understanding of spatial patterns can help save lives and protect coastal communities from the devastating impacts of cyclones in the North Indian Ocean region.

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