Recent Trends in Tropical Cyclones Over the Arabian Sea and the Vulnerability of India's West Coast

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Abstract The IPCC's sixth assessment report emphasizes the increase in the frequency of stronger Tropical Cyclones (TC, category 3–5) over the last four decades. The Northern Indian Ocean (NIO) exhibits identical trends. The Arabian Sea (AS) has become a breeding ground for TCs that have wreaked havoc on Oman, UAE, Iran, Muscat, and India's west coast in recent years. The west coast of India is extremely vulnerable to TCs due to its unique coastal topography and population density. Most of the research on the North Indian Ocean is focused on Bay of Bengal (BoB) TCs, which necessitates rigorous studies in AS. The focus of this study is to improve our understanding of TC activity over AS by analysing the frequency of TCs and explaining observed higher intensity TCs in terms of Accumulated Cyclone Energy (ACE) and Power Dissipative Index (PDI) over the last 39 years. Energy metric analysis confirms the increasing intensity of TCs in AS. Annual ACE and PDI have been increasing in recent years primarily due to monsoon and post-monsoon TCs. While pre-monsoon TCs show a decreasing trend. The effect of El-Nino Southern Oscillation (ENSO) on TCs in AS is found to be negligible. The study also attempts to ascertain the vulnerability of western coastal districts to TCs using housing damage risk data Vulnerability Atlas of India. Ahmedabad and Vadodara in Gujarat, Thane and Mumbai Suburban in Maharashtra, Dakshin Kannada in Karnataka, and Malappuram, Ernakulam, and Thiruvananthapuram in Kerala are among the most vulnerable districts along India's western coast.

Keywords Tropical Cyclone · Accumulated Cyclone Energy · Power Dissipative Index · Vulnerable Districts · Arabian Sea

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1 Introduction

Tropical cyclones (TCs) are one of the most frequently occurring hydrometeorological disasters in tropical and subtropical latitudes, wreaking havoc on sea-based regions and the coast (Wahiduzzaman and Yeasmin 2019). Numerous dangers accompany TCs, including wind (Zhou et al. 2018), storm surges (Kohn et al. 2018), and widespread rainfall events (Knutson et al. 2019). TCs are the most destructive natural disasters on the North Indian Ocean's rim, claiming thousands of lives and causing billions of dollars' worth of property damage (Alam and Collins 2010; Girishkumar and Ravichandran 2012). Around 40% of the world's population lives within 100 kilometers of the coast (Barua et al. 2021) making the coastal region extremely vulnerable to TC events. India's coastline is approximately 7516 kilometres long and forms part of the coastal zone along with NIO (encompassing the Arabian Sea (AS) and the Bay of Bengal (BoB)). NIO accounts for 7% of global TC activity (Singh et al. 2001). Due to India's narrow continental shelf, flat coastal topography, high population density, geographical location, and physiological characteristics, it is extremely vulnerable to cyclones and related dangers (NDMA 2017; Kumar 2020).

In developing countries such as India, the coastline population is growing primarily due to urbanization of rural areas. In a climate change scenario, TCs and their associated storm surges pose significant challenges particularly affecting the coastal community (Rao et al. 2020). According to recent IPCC reports, the proportion of stronger TCs (Category 3–5) has increased over the last four decades, and the average maximum wind speed of a tropical storm in the Atlantic and Pacific Oceans will increase by 2–11% over the next century (IPCC 2021, 2013). Numerous studies have revealed a global increase in the frequency and strength of TCs. The North Atlantic Ocean is observed to have the greatest increase in TC frequency and intensity among the ocean basins (Deo et al. 2011; Elsner et al. 2008; Webster et al. 2005; Walsh et al. 2016). Other basins, such as the north and south Indian oceans, and the south-western Pacific oceans, have also seen an increase in the frequency of TCs (Deo et al. 2011). Recent research on TCs in the NIO corroborates the IPCC's findings. Deo and Ganer (2014) finds that the intensity of tropical cyclones in the NIO has increased over the last 15 years. Sahoo and Bhaskaran (2016) determined that the accumulation of cyclone energy in the BoB has increased significantly since 1980. Singh et al. (2000) reports an increase in the prevalence of TCs in BoB, but not in AS. Balaguru et al. (2014) finds that the intensity of post-monsoon TCs in BoB has increased in conjunction with rising sea surface temperature and upper ocean heat content. Many more studies have shown an increase in TCs in NIO (Balaji et al. 2018; Deshpande et al. 2021; Bhardwaj et al. 2019; Sattar and Cheung 2019). Singh et al (2020) had discovered the unusual tracks of TCs over AS and rapid intensification is a result of warm ocean.

The majority of NIO research is focused on BoB TCs, which are known for their cyclone activity and damage to the Indian coast. In comparison to AS, TCs are approximately four to five times more abundant in BoB (Bhardwaj et al. 2019) approximately 10%–20% with a mean frequency of 1.33TCs each year (Soltanpour et al. 2021). Following the history of AS TCs, the first cyclone to make landfall on the Somalia coast was a very severe cyclonic storm (VSCS) in AS in 1994. Though the possibility of a cyclone making landfall over the AS coast is scarce, several strong TCs have recently approached these coastlines, including Gonu (2007), Nilofar (2014), Chapla (2015), Megh (2015), Mekunu (2018), Maha (2019) and Kyarr (2019). In 2007, super cyclone (SuCS) Gonu made two landfalls after passing through the Gulf of Oman, the first near Muscat and the second on Iran's southern coasts. Gonu caused over USD 4 billion in damage and killed 78 people (IMD 2008), whereas cyclones Phet and Megh (IMD 2016) killed 47 and 18 people, respectively (Bandyopadhyay et al. 2011). A few TCs had a significant impact on the low-lying coastlines of Oman, the United Arab Emirates (UAE), and Iran's (Vieira et al. 2021). SuCS Kyarr (2019) dumped 25mm of rain over Maharashtra, wreaking havoc on the agriculture sector (IMD 2021). The track of all TCs detected in AS during the study period is depicted in supplemental figures (Fig S1). Researchers (e.g., Deshpande et al. 2010; Mukhopadhyay et al. 2011; and Osuri et al. 2012) have built atmospheric models to aid in forecasting TCs over the AS. Some publications have recently identified an increase in the intensity of TCs in the AS basin during the last few decades. Murakami et al. (2013) predicted a significant increase in TC frequency over AS based on simulations using the Japan global model. According to Murakami et al. (2017), anthropogenic forcing accelerated the growth of extremely severe cyclonic storms (ESCS) over AS. Studies on AS (Evan and Camargo 2011; Murakami et al. 2017; Chowdhury et al. 2020) indicate that TCs have become more intense and frequent in recent years, implying that AS should be given increased attention due to its potential to affect many countries along the coast. Regardless of the magnitude of the AS TCs' impact, the basin has received significantly less attention than the BoB basin. While AS TCs are investigated in conjunction with BoB as a component of NIO TCs, only a few studies have examined AS as a source of TCs on its own (Zhang and Villarini 2019).

The present study examines trends in the frequency of TCs across the AS from 1982 to 2020 and attempts to gain a better understanding of the distribution and trends of the intensity of TCs (Accumulated Cyclone Energy, ACE and Power Dissipative Index, PDI). We further classified districts on India's west coast according to their housing vulnerabilities to TCs.

This paper is divided into five sections. Following the introduction in Sect.1, Sect.2 describes the data sources and methodologies used to analyze the cyclone parameters and classify cyclone vulnerable areas. The analysis result and trends in TCs over AS is described in Sect.3 and discussed in line with the existing literature in Sect.4. Sect. 5 summarizes the study findings.

2 Data and Methodology

The AS TCs are examined in this study over 39 years from 1982-2020. This is a significant and stable period, as it is the post geostationary satellite era (Deshpande et al. 2021). The frequencies of tropical cyclones are derived from the Indian Meteorological Department's Cyclone e-Atlas (IMD). The storm's intensity (maximum sustained wind speed) and details about the cyclone's origin and landfall are derived from IMD's best-track data for cyclonic storms (version 2.0/2011 version) (<https://rsmcnewdelhi.imd.gov.in>). As this study is concerned with the disaster potential of TCs, systems with a maximum sustained wind speed of less than 34 knots are excluded (Bhardwaj et al. 2019). The categories used in this study are based on those used by the IMD (Singh et al. 2016). To calculate the roof type vulnerability and wall type vulnerability, housing risk data is collected from the Vulnerability Atlas of India (BMTPC 2019).

2.1 Accumulated Cyclone Energy and Power Dissipative Index

ACE, introduced by Bell et al. (2000) is a measure of TC energy and is considered as a measure of storm kinetic energy. It accounts for the combined duration and strength of the TC. It is defined as the sum of the squares of the 6-hourly maximum sustained wind speed (knots) of the storm. In the present study, it is calculated by adding up squares of the six-hourly maximum sustained surface wind speed (knot) and dividing by 10^4 to make it an index for easier interpretation (Camargo and Sobel 2005).

$$ACE = \sum V_{max}^2 (10^4 kt^2)$$

where V_{max} is maximum sustained wind squared at all 6-hourly periods obtained from IMD best track data.

To characterize the destructive potential of TCs PDI (Emanuel 2005) is used in this study and is calculated as,

$$PDI = \sum V_{max}^3 (10^6 kt^3)$$

This index is analogous to ACE and is approximately proportional to the budgetary damage generated by TC. Both energy metrics consider the collective effect of frequency, intensity, and duration of all the TCs for a particular year. ACE ($10^4 kt^2$) accounts for both the strength and duration while PDI ($10^6 kt^3$) underlines more on TC intensity.

2.2 Mann–Kendall test and Sen’s Slope Estimator

The non-parametric Mann-Kendall test (Mann 1945; Hoeffding 1957) is employed to detect a monotonic upward or downward trend in the time series of AS cyclone frequency. The detail of the analysis is given in supplementary information. The value of Z (normalized MK statistics) determines an upward or downward trend. If Z yields a positive value, then there is an increasing trend in the time series and if Z yields a negative value, which means there is a downward trend. Sen’s slope estimator reveals the steepness of the trend.

2.3 Calculation of the vulnerability of a location

Indian Ministry of Housing and Urban Affairs’ Building Materials and Technology Promotion Council (BMTPC 2019) published the third edition of the Vulnerability Atlas of India, which includes a Cyclone Occurrence Map of Coastal India based on maximum/estimated 3-minute average maximum sustained wind. Additionally, the atlas illustrates the housing risk associated with various locations based on the wall and roof types.

Housing damage risk tables were created by BMTPC (2019) by linking dwelling types, hazard intensities on the map, and damage risk levels. The districts susceptible to AS TCs in the coastal states of Kerala, Karnataka, Goa, Maharashtra, Gujarat, Daman & Diu, and Lakshadweep are classified based on the style of the house. Two types of vulnerabilities occur depending on the type of house: 1) Roof type vulnerability and 2) Wall type vulnerability. Districts from western coastal states that fall into the four proneness categories (as per RSMC reports) were chosen for categorization. RSMC calculates the proneness based on the frequency of total cyclones, total severe cyclones, actual/estimated maximum wind speeds, probable maximum storm surge associated with cyclones, and probable maximum precipitation.

The vulnerability atlas is used to identify the number of houses with lightweight sloping roofs (L), heavyweight sloping roofs (H), and flat roofs (F), and a weighted average is calculated for each district to calculate roof type vulnerability (RTV). Because the level of resistance varies for different types of walls under different wind conditions, the study assigns different weights to each wall type when evaluating RTV. A level roof is given a 0.5 weight, a lightweight sloping roof is given a 1.5 weight, and a heavyweight sloping roof is given a weight of 1.

$$\text{Roof type vulnerability (RTV)} = \frac{((R1 \times L \times 1.5) + (R2 \times H \times 1) + (R3 \times F \times 0.5))}{(R1 + R2 + R3)}$$

where, $R1$, $R2$ and $R3$ are the percentages of houses with L, H and F roof types respectively. L, H and F here denote the number of houses with respective roof types. The RTV for each district is calculated and divided by, 10^5 to construct an index for easy comprehension. According to the RTV values, the districts are classified as high risk, medium risk, or low risk.

To calculate wall type vulnerability, the number of houses with mud and unburnt brick walls (A1), wood walls (C2) and other materials (X) are identified from the data (BMTPC 2019). The weighted average of this data gives wall type vulnerability of a district.

$$\text{Wall type vulnerability (WTV)} = \frac{((W1 \times A1) + (W2 \times C2) + (W3 \times X))}{(W1 + W2 + W3)}$$

where, W 1, W 2 and W 3 are the percentage of houses with A1, C2 and X wall types respectively. A1, C2 and X here denote the number of houses with respective wall types. To produce an index for easier comprehension, the WTV for each district is calculated and divided by, 10^4 . According to the WTV values, the districts are classified as high risk, medium risk, or low risk. Table 1 shows the risk levels for RTV and WTV.

3 Results and Discussion

3.1 Frequency of TCs (1982-2020)

The frequency of all TCs from 1982-2020 are depicted in figure 1 for five distinct storm types: CS, SCS, VSCS, ESCS, and SuCS. 45 TCs formed in AS during the period. AS is found to be active in most years with at least one TC and up to five TCs per year while it did not experience TCs in years 1983, 1984, 1986–1991, 1997, 2000, 2005, 2008, 2013, 2016, and 2017. BoB is known to have the highest concentration of TCs in the NIO basins. However, there have been some recent years in which AS TCs outnumbered BoB TCs (2001, 2004, 2014, 2015, and 2019) as well as years in which both AS and BoB TCs had an equal share of NIO TCs (1993, 1994, 1998, 2007, 2011 and 2012). During this period 17(38%) of the 45 TCs that formed are CS, 10(22%) are SCS, 7(16%) are VSCS, 9(20%) are ESCS, and 2(4%) are SuCS.

The trend line in figure 1 shows that the number of TCs in AS has been increasing over time. To ascertain the recent trend in TC frequency, we divide the 39-year period into two segments: the bygone era (BE), 1982–2000 and the modern era (ME), 2001-2020. Figure 2a illustrates the frequency of TCs in BE and ME. ME has 31 total TCs, compared to 14 in BE, a 54.8% increase. It is concerning to note that ME had two SuCS, whilst BE had none. From BE to ME, VSCS indicates a maximum rise of 60%. From BE to ME, ESCS exhibits a 50% growth. In comparison to BE, ME had a 58% rise in CS. SCS indicates a minimum of a 33% increase from BE to ME when compared to other categories. As observed from Fig 2a, the number of cyclones intensifying to VSCS or higher has increased.

Figure 2b illustrates the seasonal distribution of TCs over AS. The occurrence of TCs is demonstrated to be negligible in January and February. The cyclone season in AS begins in the pre-monsoon season (March-April-May); May (9) has the highest occurrence of tropical cyclones during the pre-monsoon season. March and April are devoid of TC incidents. Monsoon season (June-September) is responsible for a sizable portion of the annual TC frequency. Cyclones occur most frequently during the monsoon season in June (10) and September (4). July and August have no TC events.

Post-monsoon season TCs contribute the most to the annual frequency of TCs during (October to December). TCs are most prevalent in October (12), followed by November (8) and December (2). Thus, the AS is most active during the post-monsoon and monsoon seasons, particularly in May, June, October, and November.

To establish the trend in the frequency of TCs over AS, the Mann-Kendall (MK) test is used. The results of the MK test to determine the frequency of cyclones over AS are reported in Table 2. The MK test validates the existence of a nonlinear increasing trend in the annual frequency of TCs in AS with a 95% confidence level. The annual frequency of TCs has a Z value of 2.4004 and a p-value of 0.016. The considerable annual increase in the frequency of higher category TCs is due to an increase in the frequency of ECSC ($Z=2.0987$ and $p = 0.035$). This conclusion is consistent with recent ESCS events such as Nilofar (2014), Chapla (2015), Megh (2015), Mekunu (2018), and Maha (2019). The MK test did not reveal any significant trends in the frequency of CS, SCS, VSCS, or SuCS because the p-values for any of these categories are more than 0.05. Thus, the MK test indicates that the annual frequency and frequency of ESCS have a substantial upward trend, whereas the other four categories exhibit no monotonic trend.

3.2 Arabian Sea and Bay of Bengal comparison

Figure 3 shows the frequency of TCs by category in AS and BoB from 1982 to 2020. Figure 3a illustrates the frequency of CS. Both basins are trending down in the frequency of CS, with BoB experiencing a greater decline. The frequency of SCS is depicted in Figure 3b; a sharp decline in the frequency of BoB SCS can be observed. AS SCS also exhibits a downward trend. Figure 3c illustrates VSCS, which depicts the frequency of higher intensity TCs. Surprisingly, while the frequency of VSCS appears to be decreasing for BoB, it appears to be increasing for AS. After 2010, the AS VSCS slope exhibits a more pronounced increase. In terms of ESCS frequency, AS has a significantly increasing trend, whereas BoB TCs do not (Figure 3d). SuCS frequency is shown in Figure 3e, which is stationary in both AS and BoB. Super cyclones were confined to BoB; there were no super cyclones in AS until after 2007. In the six years from 2014 to 2020, five ESCS and four VSCS occurred in AS, out of a total of nine ESCS and seven VSCS over 39 years. During this period, AS was also struck by two SuCS, transforming it into a hotspot for strong cyclonic activity. The declining trend in CS and SCS in BoB and AS suggests an increased proclivity for TCs intensification, which increases the frequency of VSCS, ESCS, and SuCS.

3.3 TC Energy Metrics

Table 3 shows the basic statistical values of ACE and PDI in the AS from 1982 to 2020. The ACE (PDI) value ranges from 0 to $51.22 \times 10^4 \text{kt}^2$ ($44.56 \times 10^6 \text{kt}^3$). Annual mean values for the ACE and PDI are 5.05 (SD = 9.85) and 3.91 (SD = 8.50), respectively. Additionally, Table 3 contains data for the pre-monsoon, post-monsoon, and monsoon seasons. The post-monsoon values of ACE and PDI exhibit significant variations, with SDs of 7.25 and 6.71, respectively. Annual ACE has the least dispersion around the mean, with a coefficient of variance of 1.95, while pre-monsoon PDI has the most dispersion, with a coefficient of mean of 3.31. This indicates that there is considerable uncertainty regarding cyclones' pre-monsoon damage potential.

The ACE and PDI time series for all TCs are shown in Figure 4. Both the ACE and PDI trendlines in Fig 4a demonstrate an increasing trend in the annual values of the parameters. The rising trend can be confirmed with 95% confidence, and the ACE slope is 0.368 ± 0.13 and that of PDI is 0.305 ± 0.12 . This conclusion is comparable to the rising trend in the frequency of higher category TCs reported in Section 3.1. To examine variations over time, the ACE and PDI values for BE and ME are plotted.

The values of ACE and PDI are observed to increase during ME. The ACE plots for BE and ME are shown in Figures 4b and 4c, and the PDI plot is given in the supplementary figures (Fig S2). It is determined that the maximum value of ACE (PDI) during BE is $11.29 \times 10^4 \text{kt}^2 (11.11 \times 10^6 \text{kt}^3)$, whereas the maximum value of ACE (PDI) during ME is $51.22 \times 10^4 \text{kt}^2 (44.56 \times 10^6 \text{kt}^3)$. These findings indicate that the energy of TCs has recently increased, as has their destructive potential. The slope of the pre-monsoon ACE (PDI) is decreasing in ME, whereas the post-monsoon ACE (PDI) exhibits a significant upward slope of 0.757 ± 0.35 (0.689 ± 0.33). The annual increase in ACE (PDI) levels in AS is attributed to post-monsoon ACE (PDI) values.

The non-parametric MK test and Sen's slope estimator are used to analyze ACE and PDI trends in the data. The MK test results are summarized in Table 4. The MK trend test demonstrates a 95% statistically significant increase in annual ACE and PDI. Annual ACE and PDI both exhibit a significant upward trend, with magnitudes of 0.0436 and 0.017 (Sen's slope estimator values), respectively. The significant increase in annual ACE (PDI) is associated with an increase in VSCS and ESCS in AS, which is evident in ACE from 2014 to 2020. Pre-monsoon and post-monsoon seasons also exhibit a rising trend, but this is not statistically significant. The MK test, on the other hand, indicates a positive trend for both ACE and PDI during the monsoon season with a 95% confidence interval.

As a result of an increase in post-monsoon and monsoon season TC activity, the energy metric of TCs in AS has been increasing over the study period. Increases in these characteristics indicate that the wind speed, duration, and severity of TCs in AS, as well as their destructive potential, have increased over the study period. Sen's slope estimator estimates for annual ACE (0.044) and PDI (0.016) suggest that the MK test's substantial positive trend is critical. Sen's slope estimator for seasonal values of ACE and PDI was zero, indicating a negligible slope in their trend lines, even though several of the parameters exhibit a significant trend in the MK test.

3.4 Monsoon and TCs

The monsoon season is well-known for depressions and deep depressions. The present study finds that there are more TCs in AS during the monsoon (JJAS), particularly in June, during ME than BE. Supplementary figures (Fig S3) explain the increase in ACE and PDI values in AS during the monsoon season. The number of TCs (6), ACE (slope = 0.127 ± 0.16), and PDI (slope = 0.068 ± 0.13) increase more rapidly during ME than during BE. Also the MK test for seasons showed a significant positive trend in monsoon values of ACE and PDI. As discussed in sections 3.1 and 3.2, monsoon TCs contributed a significant amount to annual TC frequency, ACE, and PDI during this period, and this trend is expected to continue in the future, as illustrated in figure 5. ACE and PDI are depicted in Figures 5a and 5c in BE, respectively, while 5b and 5d depict ACE and PDI in ME. ACE and PDI values in BE have been increasing since 1998, but the increase has been gradual. ACE and PDI values, on the other hand, exhibit a steeper increasing trend with more abrupt values in ME.

3.5 Influence of ENSO on AS TCs

ENSO events have remote controls on the climate of many places over the globe. The present study analyzes the effect of ENSO events on AS TCs. Over the course of 39 years, the analysis identified 13 El- Nino years (1982, 1986, 1987, 1991, 1994, 1997, 2002, 2004, 2006, 2009, 2014, 2015, 2018), 13 La-Nina years (1983, 1984, 1988, 1995, 1998, 1999, 2000, 2007, 2010, 2011, 2016, 2017, 2020), and 13 neutral years (1983, 1984, 1988, 1995, 1998, 1999, 2000, 2007, 2010, 2011, 2016, 2017, 2020). During this period, 17 (38%) of the 45 TCs were formed during El Nino years, 16 (35%) during neutral years, and 12(27%) during La Nina years. There is no discernible pattern to these occurrences.

The Nino 3.4 values were then correlated with the frequency of TCs, ACE, and PDI to determine if there is a correlation between Nino 3.4 sea surface temperature anomaly and AS TCs. There was no correlation between Nino 3.4 values and TC parameters that was statistically significant (at the 95% significance level). Pearson's correlation coefficient of TC frequency (0.075), ACE (0.142), and PDI (0.131) are not statistically significant. This concludes that the ENSO events have no discernible effect on the frequency of TCs, ACE, or AS PDI. Examination of ENSO demonstrates that we cannot attribute the occurrence of active TC in AS solely to this large-scale climate variability. Additionally, the distribution of TCs is random. For example, the most active TC year in AS was 2019 with five TCs, a neutral year; 2018 was another active year in AS with three TCs, an El-Nino year; and 1998 was a La-Nina year in AS with three TCs, also a neutral year. The characteristics of SSTAs and TCs are depicted in Figure 6.

3.6 Vulnerability of districts in the west coast of India based on roof and wall types

The vulnerability of each district in the western coastal states using the RTV and WTV indices is depicted in Figure 7. The districts in the west coast that are being considered are listed in Table S2 of supplementary materials. The RTV and WTV indices for each district are calculated, and the districts are classified accordingly.

Gujarat: Gujarat is a large state with cyclone-prone districts. Gujarat's coastal districts are classified as P2 (highly prone) and P3 (moderately prone) hazard prone districts (Mohapatra 2015). Ahmedabad, Surat, Rajkot, and Vadodara are classified as moderately vulnerable, whereas Junagadh, Kutch, Bhavnagar, Amreli, Jamnagar, Anand, Navsari, Valsad, Bharuch, and Porbandar are classified as lowly vulnerable according to the type of roofing material used.

Ahmedabad, Bhavnagar, Anand, and Vadodara, according to WTV, are moderately vulnerable due to the type of wall. Junagadh, Kutch, Amreli, Jamnagar, Surat, Valsad, Bharuch, Porbandar, and Rajkot all have a low vulnerability level. The proportion of houses with unburned brick walls, wood walls, and other lightweight materials is greater in moderate-risk districts than in low-risk districts. Ahmedabad and Vadodara districts face a moderate risk when compared to the rest of Gujarat's coastal districts.

Maharashtra: The RSMC classifies Maharashtra's coastal districts as P3 districts, which means they are moderately prone to cyclones. Thane and Mumbai Suburban are considered high-risk areas by the RTV index. Mumbai Suburban has a very high RTV index value (10.7). Ratnagiri is the next most vulnerable. Other coastal districts such as Sindhudurg and Raigarh exhibit low vulnerability as indicated by the RTV index. Districts are classified differently in the WTV index. According to the WTV index, Thane and Raigarh are highly vulnerable, while Mumbai suburban and Ratnagiri are moderately vulnerable, and Sindhudurg is exhibit very low vulnerability. In summary, Thane and Mumbai Suburban are Maharashtra's most vulnerable districts.

Goa: The RSMC classifies Goa as cyclone-prone in the P3 category. Apart from that, this study discovers that both North and South Goa fall into the low vulnerability category according to the RTV and WTV indices. There is only a very slight difference in index values between North and South Goa.

Karnataka: Udupi, Uttar Kannada, and Dakshin Kannada are the three coastal districts in Karnataka. On the RSMC's cyclone proneness map, all these districts are classified as P3. All three districts are classified as low vulnerability districts by the RTV. However, Dakshin Kannada is classified as having moderate vulnerability in the WTV classification, making it the most vulnerable district in Karnataka.

Kerala: Nine of Kerala's fourteen districts are coastal. This fact increases the state's vulnerability to hazards associated with cyclones. However, the RSMC classifies the districts of Kozhikode, Malappuram, Thrissur, Kannur, Kollam, Alappuzha, and Thiruvananthapuram as P3 (moderately prone). Ernakulam and Kasaragod are classified as P4 areas (less prone). Malappuram and Ernakulam are classified as moderately vulnerable districts by the RTV index, whereas the remaining districts are classified as less vulnerable. The WTV index classifies Thiruvananthapuram as moderately vulnerable, while the remaining districts are classified as less vulnerable.

Daman and Diu, Lakshadweep: Daman is classified as a P3 vulnerability by the RSMC, while Lakshadweep and Diu are classified as P2 vulnerabilities. These areas have a significantly lower population and housing density than India's western coast states. As a result, both the WTV and RTV indices used in this study classify the vulnerability of these union territories as low risk.

4 Discussion

Our study on the TCs over a period of 39 years, from 1982 to 2020 reveals an increase in the frequency and intensity of TCs over the Arabian Sea. This study demonstrates that the frequency of TCs is increasing as they are becoming more intense as explained in section 3.1. We find that in ME the number of TCs belonging to higher categories (VSCS, ESCS and SuCS) are remarkably large. The frequency of VSCS is observed to increase by 60% during ME. It is also identified via MK test that there is a significant upward trend in the frequency of ESCS and this is evident in recent occurrences of TCs in AS from 2014 to 2020. This result is consistent with a trend toward stronger storms projected by Knutson et al. (2010), who predicted a 2-11 percent increase in storm intensity by 2100. According to Knutson et al. (2013) and Kossin et al. (2013), the frequency of category 4-5 systems may increase by approximately 40% by 2100. Sahoo and Bhaskaran (2018) finds that out of four to five TCs occurring in NIO one or two are very severe. Many studies (Deshpande et al. 2021; Murakami et al. 2017; Balaguru et al. 2014) reveals an abrupt shift toward intensification of TCs in the NIO, resulting in an increase in the number of VSCS storms in the NIO basins over the course of cyclone seasons especially in BoB. This study makes a similar finding in AS, indicating that AS is as significant globally as any other ocean basin.

Our study demonstrates that the frequency of VSCS and ESCS is significantly higher in AS than BoB. Some numerical model simulations, suggest that the frequency of global TCs is expected to decrease, not increase, in 21st century (Knutson et al. 2010). Our study observes a decline in the frequency of CS and SCS but clear increase in the frequency of higher category TCs in both AS and BoB. We observed that ME witnessed consecutive ESCS incidents in 2015. Chowdhury et al. (2020) observed that warm ocean surface resulted in back-to-back occurrence of TCs over AS which is in line with our observation. Even though this study observes two SuCS in ME, we cannot make any conclusions because the number of SuCS is extremely small in comparison to the number of individual TCs in cyclone seasons.

This study found a significant rise in ACE and PDI in AS during the period. The increase is more pronounced after 2010, implying that the strength and destructive potential of TCs have increased significantly over the years. This rise in ACE is coherent with the findings of Deshpande et al. (2021) who finds a significant increasing trend in the intensity, frequency, and duration of cyclonic storms over NIO. Sahoo and Bhaskaran (2016) report that PDI of TCs in BoB is sixfold that of the past decade. Surprisingly, this study observes a decline in ACE and PDI values during pre-monsoon in ME and a steep increase in post-monsoon values of the parameters. Monsoon values exhibit a similar trend to post-monsoon values, though they are less steep. Thus, the annual increase in ACE and PDI values are attributed to post-monsoon and monsoon values of these parameters. We also observe that during ME the TCs in monsoon shows abrupt values for ACE, PDI and the frequency. The increase is more gradual during BE. Such unprecedented occurrences amplify the risk associated with TCs and vulnerability. Muni Krishna (2009) predicted that the decreasing trend in tropical easterly jet because of warming ocean would facilitate the formation of hurricane intensity TCs in NIO during summer monsoon. Our findings corroborate this prediction.

May, June, October, and November are the most active TC months in AS, according to our results. Evan and Camargo (2011) hypothesized that TCs in May and June in AS were associated with the early and late onset of the southwest monsoon, respectively. Studies such as Sattar and Cheung (2019), cover the pre-monsoon season from June to August, this study adheres to the traditional division of months into pre-monsoon, monsoon, and post-monsoon.

We also observe that ENSO events have negligible effect on TC frequency, ACE and PDI values in AS. Bhardwaj et al. (2019) and Girishkumar and Ravichandran (2012) and observes that in BoB Nino 3.4 sea surface temperature anomalies are negatively correlated with TC parameters. Camargo and Sobel (2005) observe a positive correlation between ENSO indices and western north Pacific basin TC parameters. We observe random TC events during various ENSO indices in AS. This could be because TCs are inexplicable in terms of a single mode of climate variability. Numerous climate variables are at work during a cyclone.

Rao et al. (2020) demonstrate that the Indian peninsula is affected by the intensification of TCs. In comparison to India's west coast, almost every state on the east coast is extremely vulnerable to cyclones (Mohapatra et al. 2012). Many studies have highlighted disaster-prone districts on India's east and west coasts (Mohapatra et al. 2012; Mohapatra 2015). RSMC has compiled a list of Indian districts that are prone to cyclones. According to RSMC, 72 districts that border the Indian coast have been divided into four proneness categories, with 33 districts and three union territories located on the west coast (Mohapatra 2015). This classification was made solely based on hazard, without regard for the vulnerability of a location. Additionally, studies examined the vulnerability of districts such as Orissa (Dube et al. 2000; Mohanty et.al 2020), Andhra Pradesh (Raghavan and Rajesh 2003), Tamil Nadu (Jeganathan and Andimuthu 2013) and West Bengal (Gayathri et al. 2015). It should be emphasized that these studies focus exclusively on India's eastern coastal states (Rao, 2020). Only Gujarat, on the west coast, is known to be particularly prone to cyclones. Our study concentrates on vulnerability of western coast of India and observe that Gujarat's Ahmedabad and Vadodara districts, Maharashtra's Thane and Mumbai Suburban districts, Karnataka's Dakshin Kannada district, and Kerala's Malappuram, Ernakulam, and Thiruvananthapuram districts are the most vulnerable districts along the country's western coast. It is worth noting that some districts classified as highly prone in the RSMC list fall into the less vulnerable category according to the RTV and WTV indices. This discrepancy arises because RSMC considered only the hazard aspect of TC events. The vulnerable districts according to our classification are densely populated and rapidly urbanizing, which contributes to a locality's increased risk during TC event.

5 Conclusion

In recent years, the Arabian Sea has become a hotspot for TCs, with dire socioeconomic consequences for India's west coast. The purpose of this study is to gain a better understanding of tropical cyclone activity over AS by analyzing the frequency of TCs and explaining observed higher intensity TCs in terms of accumulated cyclone energy and power dissipative index. Our major findings are as follows:

- The frequency analysis of TCs reveals an increase in the annual frequency of TCs over AS from 1982 to 2020. Between BE and ME, VSCS increases by 60% and ESCS by 50%. Additionally, the frequency of CS and SCS has decreased over time, indicating a shift in AS towards higher intensity TCs.
- Energy metric analysis confirms the increasing intensity of TCs over AS. It is discovered that the increase in post-monsoon and monsoon TCs contributes to the annual TC parameter increase. Increases in these characteristics indicate that the wind speed, duration, and severity of storms are increasing. The pre-monsoon parameters of TCs show a decreasing trend during ME, whereas the monsoon values show an increasing trend (June).
- Monsoon TCs contributed a significant amount to annual TC frequency, ACE, and PDI during this period, and this trend is expected to continue.
- The effect of ENSO events on TC activity in AS and conclude that ENSO has a negligible effect on TC activity in AS. Also, the TCs occurrence show a random distribution over El-Nino, La-Nina and neutral years.
- Analysis for vulnerable districts revealed that Gujarat's Ahmedabad and Vadodara, Maharashtra's Thane and Mumbai Suburban, Karnataka's Dakshin Kannada, and Kerala's Malappuram, Ernakulam, and Thiruvananthapuram are among the most vulnerable districts along India's western coast.

The study indicates that the strength and frequency of TCs in AS are expected to increase in the future. This scenario will exacerbate the vulnerability of countries such as India, the UAE, Oman, Iran, Muscat and even Somalia. The risk of damage to a location can be mitigated to a certain extent by using proper building materials, which minimize a house's vulnerability, thereby reducing the vulnerability of a district. The long-term goal of the study is to develop a disaster mitigation strategy for India's coastal regions.

6 Abbreviations

TC, Tropical cyclone; NIO, North Indian Ocean; AS, Arabian Sea; BoB, Bay of Bengal; ACE, accumulated cyclone energy; PDI, power dissipative index; ME, modern era; CS, cyclonic storm; SCS, severe cyclonic storm; VSCS, very severe cyclonic storm; ESCS, extremely severe cyclonic storm; SuCS, super cyclonic storm; RSMC, regional specialized meteorological centre; IMD, Indian Meteorological Department; MK Test, Mann-Kendall Test; BMTPC, Building Materials and Technology Promotion Council; RTV, roof type vulnerability; WTV, wall type vulnerability; BE, bygone era

7 Competing interests

The authors declare that they have no competing interests.

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9 Authors' contributions

Stefy Thomas conceptualized, carried out data analysis and drafted the manuscript. Lekshmy P.R. supervised and mentored the study by holding regular discussions. The authors read and approved the final manuscript.

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Table 1 Level of risk for different roof types and wall types as calculated and classified in the study

Roof type vulnerability index values	Level of risk	Wall type vulnerability index values	Level of risk
0-3	Low	0-10	Low
3-6	Medium	11-20	Medium
6 and above	High	21-30	High

Table 2 MK test results for frequency of TCs over the Arabian sea from 1982-2020. There is a significant positive trend in the frequency of total TCs and the frequency of ESCS.

Frequency	MK		Inference
	p-value	z-value	
Total TC	0.016	2.400	Significant positive trend
CS	0.07	1.8072	No monotonic trend
SCS	0.635	0.4735	No monotonic trend
VSCS	0.057	1.9031	No monotonic trend
ESCS	0.035	2.0987	Significant positive trend
SuCS	0.134	1.4963	No monotonic trend

Table 3 Basic statistics of ACE and PDI over the AS from 1982-2020. The table gives the basic statistics of total ACE and PDI, pre-monsoon, post-monsoon and monsoon values of ACE($10^4 kt^2$) and PDI ($10^6 kt^3$).

	Total		Pre-monsoon		Post- monsoon		Monsoon	
	ACE	PDI	ACE	PDI	ACE	PDI	ACE	PDI
Minimum	0	0	0	0	0	0	0	0
Maximum	51.22	44.56	13.78	12.05	37.02	34.83	14.20	11.55
Range	51.22	44.56	13.78	12.05	37.02	34.83	14.20	11.55
Median	0.650	0.23	0	0	0	0	0	0
Mean	5.06	3.91	1.05	0.85	2.67	2.12	1.338	0.93
SE.mean	1.58	1.36	0.52	0.45	1.16	1.07	0.527	0.41
CI.mean.0.95	3.19	2.75	1.05	0.91	2.35	2.17	1.067	0.84
Variance	97.18	72.25	10.42	7.85	52.53	44.98	10.84	6.65
Standard Deviation	9.86	8.5	3.23	2.80	7.25	6.71	3.29	2.58
Coefficient of variance	1.95	2.18	3.07	3.31	2.71	3.15	2.46	2.76

Table 4 Results of MK test performed for annual and seasonal values of ACE and PDI. A significant positive trend is observed both in annual values of ACE and PDI. The same can be observed in monsoon values of both ACE and PDI.

Parameter	MK Z value	P-value	Sen's Slope	Inference
ACE	2.407	0.016	0.044	Significant positive trend
Pre monsoon	0.472	0.637	0	No significant trend
Post monsoon	1.875	0.061	0	No significant trend
Monsoon	2.154	0.031	0	Significant positive trend
PDI	2.358	0.018	0.016	Significant positive trend
Pre monsoon	0.472	0.637	0	No significant trend
Post monsoon	1.743	0.081	0	No significant trend
Monsoon	2.124	0.034	0	Significant positive trend

Supplementary Files

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