Control of salinity stratification on recent increase in tropical cyclone intensification rates over the postmonsoon Bay of Bengal

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Keywords: tropical cyclone, intensification rate, salinity stratification, barrier layer

Abstract
This study explores the variability of tropical cyclone (TC) intensification rates (IRs) in the postmonsoon Bay of Bengal (BoB) for the satellite period of 1980–2015. It is found that both number of rapid intensification (RI) events and magnitude of IRs show a robust increase, with a northeastward shift of intensification events. Analyses show that the temporal variability of sea surface temperature dominated the IR variability during 1980–1997. However, the thick barrier layer in the northern BoB was considerably responsible for IR variability during 1998–2015, which significantly contributed to the IR increase. Due to more intensification events occurring over the northeastern region in two recent decades, the thick barrier layer with strong salinity stratification in the northern BoB limits TC-induced sea surface cooling and in turn favors TC intensification. This study has an important implication that air–sea coupled climate model need to realistically simulate upper ocean salinity variability on projecting TC intensity change over the BoB.

1. Introduction

Intensity variability of tropical cyclones (TCs), especially for the rapid intensification (RI), is notoriously arduous to forecast (Lee et al. 2016, Mei and Xie 2016, Balaguru et al. 2018, Bhatia et al. 2019), which makes coastal habitat and the economy more vulnerable to TCs. Previous studies showed that the TC intensification rates (IRs) have increased over most global basins during the past three decades (e.g. Kishatwal et al. 2012, Mei and Xie 2016, Balaguru et al. 2018, Bhatia et al. 2019). The enhanced TC IRs can strikingly skew the distribution of TC intensity to the high intensity side (Kishatwal et al. 2012, Lee et al. 2016). Both observations and numerical simulations exhibit upward trends in the number and proportion of intense TCs globally (e.g. Knutson et al. 1998, Webster et al. 2005, Oouchi et al. 2006, Elsner et al. 2008, Bender et al. 2010, Emanuel 2013, Bengtsson et al. 2016). More intense TCs may result in heavier losses and damage. It is thus necessary to understand the factors and multi-scale processes responsible for TC intensification so as to better forecast TC intensity.

Although the Bay of Bengal (BoB) only accounts for 5% of global TC genesis on annual average, much less than the Pacific and Atlantic basins, it has formed the majority of the deadliest TCs during the past 500 years (Mohanty et al. 2013). Due to the simple geography and dense population along the coast of BoB, the damage tends to be considerable when TCs make landfall (Needham et al. 2015). For instance, cyclone Phailin intensified rapidly from category 1 to category 5 during 10–11 October 2013. It reached its maximum intensity of exceeding 70 m s⁻¹ and made landfall at the Odisha state of India as a category 3 TC on 12 October 2013 (Osuri et al. 2017, Qiu et al. 2019). According to the reports of Odisha, the natural catastrophe killed 22 people, devastated 2 million hectares of agricultural land and 2 million houses, and produced vast other damage (Osuri et al. 2017). Hence, it has significant socioeconomic implications to better understand the mechanisms of TC intensification in the BoB.

During the summer monsoon season, the BoB receives a large quantity of freshwater from rainfall and river runoff (Vinayachandran et al. 2002, Thadathil et al. 2007). The freshwater shoals the mixed layer (ML), which tends to induce the barrier layer (BL) formation above the top of the thermocline (Lukas and Lindstrom 1991, Sprintall and Tomczak...
1992). The BL in the northern Bay can persist into the postmonsoon (October–December) season (Thadathil et al 2007). The thin ML and subsurface warm water within the BL have a great impact on air–sea interaction. Previous studies have reported that the BL can weaken sea surface temperature (SST) cooling, enhance enthalpy flux exchange from ocean to air, and favor TC intensification (e.g. Wang et al 2011, Balaguru et al 2012, Grodsky et al 2012, Wang and Han 2014, Yan et al 2017, Rudzin et al 2018, Hlywiak and Nolan 2019). Case studies about the TCs over the northern Bay showed that the persistence of BL significantly inhibits sea surface cooling (e.g. Wang and Han 2014, Qiu et al 2019). Sengupta et al (2008) found that the postmonsoon TCs over the northern BoB do notmarkedly cool SST, compared to the premonsoon TCs. The difference is significantly related to deep thermal stratification with a strong upper ocean freshening over the postmonsoon BoB, and 40% of the cooling reduction is caused by the salinity stratification (Neetu et al 2012).

In this study, we find that the magnitude of TC IRs has markedly increased in the postmonsoon BoB in two recent decades, which has not been thoroughly discussed in previous studies. We explore the mechanisms accounting for the variability and especially highlight the importance of BL with strong salinity stratification in the northern BoB. The rest of the paper is organized as follows. Section 2 introduces the datasets and methods used in this study. Section 3 describes the spatial and temporal variations of IRs and analyzes the environmental factors responsible for the variability. Summary and discussions are presented in section 4.

2. Data and Methods

TC data used in this study for the satellite period of 1980–2015 are from the Joint Typhoon Warning Center (JTWC) best-track dataset (Chu et al 2002), which provides 6-hourly locations with 1 min averaged maximum sustained wind speeds. The JTWC expanded its area of responsibility into the BoB from 1971 (Guard et al 1992, Chu et al 2002). Satellites have been used to estimate TC intensity through applying the Dvorak technique (Dvorak 1972) by JTWC since the 1970s. In 1984, the improved Dvorak technique used a quantitative infrared method (Dvorak 1984) which gave a more reasonable measurement of the maximum sustained wind speed. Knaff et al (2010) pointed out that intensity estimated by the Dvorak technique is stable, robust and less sensitive to the infrared satellite image resolution. Consequently, TC intensity estimate for the satellite era is reliable. The IR is defined as an increase of the maximum sustained wind speed in the following 24 h at a given location (Xu et al 2016). Each IR is called an intensification event, and the IR being equal to or higher than 30 knots is usually termed an RI event (e.g. Kaplan and Demaria 2003, Wang et al 2015, 2017). We only consider the intensification events occurring during the intensification period (from achieving 34 knots for the first time to peak intensity) of the TC intensified over the BoB. The track locations over land are excluded from the analysis. After the above selection, in general, RI corresponds to the 90% percentile of 24 h intensity changes. However, the sample size of RI events is too small in the postmonsoon BoB. We therefore choose the upper quartile of 24 h intensity variability, corresponding to 20 knots, and define it as strong intensification events.

Monthly wind, relative humidity, and relative vorticity with a 0.5° × 0.5° grid for the months of October–December during 1980–2015 are obtained from ERA-Interim (Dee et al 2011). Considering the effect of upper ocean thermlhaline structure on TC intensification, we use the monthly temperature and salinity from the Simple Ocean Data Assimilation (SODA) product version 3.4.2 (Carton and Giese 2008) to compute tropical cyclone heat potential (TCHP; Leipper and Volgenau 1972) and barrier layer thickness (BLT; de Boyer Montégut et al 2007). The SODA product has a 0.5° × 0.5° grid spatial resolution and 50 vertical levels, with a roughly 10 m resolution in the upper 100 m and a resolution of 20 m in the upper 200 m. TCHP and BLT are calculated as follows:

\[
TCHP = \int_{Z_{26}}^{0} \rho c_p (T - 26) \, dz 
\]

where Z26 is the depth of 26 °C isotherm, ρ is the seawater density, \(c_p\) is the specific heat capacity of seawater, and \(T\) is the oceanic temperature. Barrier layer (BL) usually refers to the zone between the base of mixed layer and the base of isothermal layer, and the BLT is correspondingly defined as the isothermal layer depth (ILD) minus the mixed layer depth (MLD). The ILD is the depth where the temperature decreases 0.2 °C compared to the reference depth of 10 m. The MLD denotes the depth where the potential density \(\sigma_{θ}\) increases from the reference depth by a threshold (de Boyer Montégut et al 2007):

\[
\Delta \sigma_{θ} = \sigma_{θ}(T_{10}, S_{10}, P_{0}) - \sigma_{θ}(T_{10}, S_{10}, P_{0}) 
\]

where \(T_{10}\) and \(S_{10}\) are the temperature and salinity of seawater at the depth of 10 m, and \(P_{0}\) is the pressure at sea surface. The climatological SODA BLT gives a reasonable estimation in the spatial distribution, compared to that derived from monthly BLT data produced by the French Research Institute for Exploration of the Sea (Ifremer; figure S3 (available online at stacks.iop.org/ERL/15/094028/mmedia); de Boyer Montégut et al 2007, Mignot et al 2007).

Daily Optimum Interpolation Sea Surface Temperature (OISST; Reynolds et al 2007) on a 0.25° spatial resolution for the period September 1981 to
2015 obtained from the National Oceanic and Atmospheric Administration (NOAA) are used to estimate pre-storm SST and cold wake. The OISST used here only incorporates the Advanced Very High Resolution Radiometer infrared satellite SST data (AVHRR-only OI SST). Some discussions about the choice of AVHRR-only OI SST are included in Text S1. Although no daily SST data are obtained for the months of October–December of 1980, no TCs actually meet our aforementioned criteria in October–December 1980. The pre-storm SST is defined as the averaged SST value within a $1.5^\circ \times 1.5^\circ$ box on the storm’s center of 4 d prior to each intensification event. The post-storm SST is defined as the same as the pre-storm SST but for the value 2 d after the passage of the storm’s center. The cold wake is thus calculated as the post-storm SST minus pre-storm SST (Foltz et al 2018). The initial intensity is considered as the TC intensity at each intensification event location, and the translation speed is calculated over the 12 h period centered on each location (Foltz et al 2018).

Following (Vincent et al 2012), the Cooling Inhibition (CI) index which is used to measure the influence of upper ocean on the amplitude of cold wake is calculated as follows:

$$\Delta E_p (\Delta T) = g \int_{h_m}^{h_0} \left[ \rho_i (\Delta T) - \rho_i (z) \right] gzdz$$

$$CI = \left[ \Delta E_p (\Delta T) \right]^{1/3}$$

(3)

where $\Delta T$ is the given SST reduction ($-1$ °C chosen in the present study), $h_m$ is the mixing depth necessary to produce a $\Delta T$ surface cooling, $\rho_i$ is the initial unperturbed density profile, $\rho_f$ is the final density considered to be homogeneous down to the depth $h_m$, $g$ is the acceleration due to gravity, and $z$ is the depth. The Wind Power index (WPI) is calculated to represent the strength of TC forcing and includes the effect of translation speed and intensity (Vincent et al 2012). For a given location, the WPI is simplified as follows:

$$WPI = \left( \frac{V_{max}}{U_0} \frac{U_0}{V_{max}} \right)$$

(4)

where $V_{max}$ is the maximum sustained wind speed, $U$ is the translation speed, and $V_{max0}$ and $U_0$ are the maximum sustained wind speed of 17 m s$^{-1}$ and translation speed of 3 m s$^{-1}$ for a weak TC, respectively.

The probability distribution functions (PDFs) of IRs are estimated using the Monte Carlo method. We randomly choose a half of the samples, generate a PDF, and then repeat for 10 000 times. The mean PDF and standard deviations for each bin are computed across the various PDFs (Balaguru et al 2012, 2016a, 2018). If not specified in the following, the significance test is based on a two-tailed Student’s t test.

### 3. Results

#### 3.1. Temporospatial changes in intensification rates

According to the criteria in section 2, 40 TCs during 1980–2015 in the postmonsoon BoB are chosen for the analysis. 21 TCs form during 1980–1997 (epoch-I), and 19 TCs form during 1998–2015 (epoch-II). The number of intensification events is nearly the same in the two periods. However, the number of strong intensification events rises from 23 (1.28 per year) in epoch-I to 38 (2.11 per year) in epoch-II, increasing by 65%. The frequencies of RI events display significant difference in the two periods. Only 5 RI events (0.28 per year) occur during epoch-I, whereas 24 RI events (1.33 per year) appear during epoch-II. This indicates a dramatic increase of nearly four times during epoch-II, compared to epoch-I (table 1). Correspondingly, the number and proportion of category 3–5 TCs during epoch-II are twice as many as during epoch-I (table 1). We further calculate the PDFs of IRs for the two periods using the Monte Carlo method. The PDF for epoch-I is skewed to the right compared to that for epoch-II (figure 1(a)). The average IR magnitude ascends from 11.2 kt per 24 h for epoch-I to 16.5 kt per 24 h for epoch-II, with an increase by 47%. The difference between the average IR magnitudes for two periods is statistically significant at the 99% confidence level. The above results suggest that the RI events become more frequent, along with the increasing IR in two recent decades.

Next, we attempt to detect whether there is a trend in the IR. The temporal evolution of seasonal average IR is presented in figure 1(b). The trend is 2.0 kt per 24 h per decade from 1980 to 2015 but not prominent (p-value = 0.16). However, excluding weak intensification events, the trend of average IR for the strong intensification event is statistically significant at the 95% level (p-value = 0.02), with the value of 4.4 kt per 24 h per decade. The ratios of the RI events and strong intensification events to all intensification events are also estimated (figure 1(c)). The trend of the RI ratio is 0.0643 per decade, statistically significant at the 90% confidence level (p-value = 0.07), and the trend of the strong IR ratio is similar to the trend of the RI ratio. Before 1995, most TCs have no RI occurrence, and the seasonal average IR remains nearly constant. However, the probability of RI occurrence, as well as the IR magnitude, increases since 1995.

Occurrence locations of the RI events also exhibit significant spatial change in the postmonsoon BoB. The RI events mostly occur over the southwestern BoB during epoch-I but shift to the northeastern BoB during epoch-II. Due to the small sample size of RI events, we thus consider spatial variability of the strong intensification events. In epoch-I, the strong intensification events scatter around 85.6°E, 12.4°N but move northeastern to near 90.4°E, 14.6°N in epoch-II (figure 2). The spatial variability...
Table 1. TC, category 3–5 TC, intensification event, strong intensification event, and RI event number during 1980–1997 and 1998–2015. The number inside the parentheses indicates the annual mean.

|                | 1980–1997 | 1998–2015 | Total  |
|----------------|-----------|-----------|--------|
| TC             | 21(1.17)  | 19(1.06)  | 40(1.11) |
| category 3–5 TC| 3(0.17)   | 6(0.33)   | 9(0.25)  |
| Intensification event | 128(7.11) | 130(7.22) | 258(7.17) |
| Strong intensification event | 23(1.28)  | 38(2.11)  | 61(1.69)  |
| RI event       | 5(0.28)   | 24(1.33)  | 29(0.81)  |

Figure 1. (a) The PDFs of IR for 1980–1997, 1998–2015, and their difference, respectively. The error bar indicates the standard deviation of each bin. (b) Temporal evolution of seasonal average IR during 1980–2015 in the postmonsoon BoB. The blue (red) solid line indicates the average magnitude of IR during 1980–1997 (1998–2015), with the mean values enclosed (see legend). The gray (red) dashed line denotes the trend of seasonal average IR (averaged strong IR). (c) Variation of ratio between the RI events and strong intensification events to all intensification events with time. The gray (yellow) dashed line denotes the trend of the RI (strong intensification) event ratio.

is statistically significant at the 99% confidence level using the nonparametric permutation test.

3.2. Influences of environmental factors
The SST, relative humidity at 600 hPa, relative vorticity at 850 hPa, and vertical wind shear between 200 and 850 hPa, together constituting the Genesis Potential Index, are conventionally used to diagnose TC genesis (e.g. Camargo et al. 2007). However, they have been used to investigate TC intensification in many previous researches (e.g. Girishkumar et al. 2014, Balaguru et al. 2016b, Foltz et al. 2018). These parameters that represent the large-scale atmospheric and oceanic conditions are critical for TC development and intensification (e.g. Wang et al. 2015, 2017). In addition, the pre-existing warm subsurface water and thick BL can decrease TC-induced sea surface cooling and therefore favor TC intensification (e.g. Lin et al. 2009, Balaguru et al. 2012). Thus, the TCHP and BLT are also important for the TC intensification. We next attempt to investigate the influences of the six large-scale environmental factors on the IR variability. A stepwise regression is performed onto the environmental factors averaged over a 1.5° × 1.5° box centered on each intensification event location. This method works in the way that the term with smallest (largest) p-value of the F statistics less (greater) than 0.05 will be added to (removed from) the multi-linear model to minimize rms error. The procedure will end when no additional term can be added or removed from the model (Li and Zhou 2012). The regression equations, squares of multiple correlation coefficient, and p-values for the period of 1980–2015, epoch-I, and epoch-II are presented as follows, respectively.

For the period of 1980–2015:

\[
IR = 3.12(SST) + 0.45(BLT) + 0.23(Humidity) - 400658.16(Vorticity) - 88.05
\]

\(R^2 = 0.25, p < 0.01\)

For the period of 1980–1997:

\[
IR = 3.99(SST) - 101.77
\]

\(R^2 = 0.09, p < 0.01\)

For the period of 1998–2015:

\[
IR = 0.63(BLT) - 0.68(Shear) + 0.37(Humidity) - 445215.96(Vorticity) - 1.36
\]

\(R^2 = 0.41, p < 0.01\)
During epoch-I, the IR variability is less sensitive to the large-scale environmental parameters except that the SST explains 9% of variance in the IRs. In contrast, the variance explained by the linear model for epoch-II is nearly 41%, which is statistically significant at the 99% level based on the F test. Semipartial correlations between the IRs and environmental factors show that the BLT and relative humidity are the most important two factors for the IR variability during epoch-II (figure 3(a)).

The shift of TC tracks tends to make TCs experience different environmental parameters. In addition to the temporal variability of large-scale environmental parameters, the nonuniform spatial distributions of environmental parameters associated with changes in prevailing TC tracks can therefore affect TC intensity (Wu and Wang 2008, Kossin and Camargo 2009, Wu et al 2015, 2018). Thus, the nonuniform spatial distributions and temporal variations of these factors can potentially modulate IR variability. To further clarify the respective influences of spatial distributions and temporal variations of the dominant environmental parameters during the two periods, we calculate the average of environmental factor anomalies and their climatology over a $1.5^\circ \times 1.5^\circ$ box centered on each intensification event location and correlations with IRs, respectively. During epoch-I, the IR variability is more sensitive to the temporal variability component of SST but not to the spatial variability of SST associated with the location change of the intensification events (figures 3(b) and (e)). However, the IR variability for epoch-II is primarily affected by the spatial variability of BLT associated with location change of the intensification events and temporal variability of relative humidity (figures 3(c), (d), (f) and (g)). The spatial change of relative humidity seems to act as a negative effect on the IR variability (figure 3(g)). We can obtain the same result that the IR variability in epoch-II is significantly correlated with the climatological BLT from another two datasets (table S1), including the European Center for Medium-Range Weather Forecasts (ECMWF) Ocean Reanalysis System 5 (ORAS5; Zuo et al 2017) and the Met Office Hadley Center EN4.2.1 objective analysis (Good et al 2013), suggesting that our results are not dependent on datasets. As stated earlier, the RI events and strong intensification events displace to the northeastern BoB in epoch-II. Moreover, the number of intensification events decreases over the western Bay and increases over the eastern Bay (figure S2). Consequently, due to the nonuniform spatial distribution of BLT (figure S3), the thick BL in the northeastern Bay may exert a critical effect on the IR variability in epoch-II.

3.3. Control of salinity stratification on IR increase

Previous studies showed that BL can reduce the amplitude of cold wake through limiting the entrainment of cold thermocline water into mixed layer (e.g. Wang et al 2011, Yan et al 2017, Qiu et al 2019). Weak cold wake usually increases the enthalpy flux exchange from ocean to air and therefore favors TC intensification (Balaguru et al 2012). To further ascertain
the influence of BLT on the IR variability, we calculate the cold wakes induced by TCs for epoch-I and epoch-II, respectively. The IR generally increases with the weakening of cold wake, and it is more evident for the 75th percentiles of IRs (figure S4). It reveals that the IR tends to be higher when the cold wake is weaker. A similar result has been documented by (Mei et al 2012) and (Vincent et al 2014) for the global TCs. On average, the cold wake for epoch-II is pronouncedly weaker than that for epoch-I (figure S5(a)). In addition to the upper ocean thermohaline structure, translation speed and intensity of a TC can partly determine the magnitude of TC-induced cooling. A slow translation speed with a high intensity can cause a strong cold wake (Mei et al 2012, Vincent et al 2012). However, the translation speed is slower, and the initial intensity is higher in epoch-II than in epoch-I (figures S5(b) and (c)). The BLTs associated with the intensification events shift are thicker during epoch-II than during epoch-I (figure S5(d)). The results indicate that BLT probably exerts a great effect on the weakening of cold wake and leads to the IR increase in epoch-II. To integrate the effect of translation speed and initial intensity, we choose WPi as the metric of TC forcing strength (Neetu et al 2012, Vincent et al 2012). The slope of cold wakes against WPi is −0.36 °C, whereas the slope reduces by a half in epoch-II (figures 4(a) and (b)). This also illustrates that the cold wake is much weaker in epoch-II than in epoch-I for a given WPi. The influence of BLTs on cold wakes is further examined by dividing the BLTs into two parts according to the median of all BLTs (which is 8.3 m). The slopes for the two parts are similar in epoch-I, while the slope for the thick BLTs is gentler than that for the thin BLTs in epoch-II. The correlation coefficient between the BLTs and cold wakes is 0.27 in epoch-II. When WPi is more than 3, the correlation coefficient reaches 0.50 in epoch-II. These correlations are statistically significant and much larger than in epoch-I.
Figure 4. (a), (b) Scatterplots of WPis versus cold wakes for the period of 1980–1997 and 1998–2015. The red (blue) solid line denotes the average cold wake in each bin (bin size: 1), and the error bars indicate the upper and lower quartiles of cold wakes for each bin with the BLT larger (less) than 8.3 m. The red (blue) dashed line indicates the least-squared fit when the BLT is larger (less) than 8.3 m, and the black dashed line is the least-squared fit for all BLT. (c), (d) Scatterplots between BLTs and cold wakes for the period of 1980–1997 and 1998–2015. The red (blue) line indicates the least-squared fit for all WPi (WPi larger than 3).

Figure 5. Scatterplots between IRs and (a), (d) CI, (b), (e) ClSO, and (c), (f) Cl - ClSO for the period of 1980–1997 and 1998–2015, respectively. The upper (lower) panel denotes the period of 1980–1997 (1998–2015). The black lines indicate the least-squared fits.
(figures 4(c) and (d)). Above results reveal that the BLs largely restrict the cold wake magnitude during epoch-II, especially when TC forcing is stronger.

In order to further assess the effect of ocean stratification, we use CI to describe the oceanic inhibition to a storm-induced cooling (Vincent et al 2012). In order to isolate the effect of salinity, the $CI_{S0}$ is calculated with constant salinity profile of 34.30 psu (the mean of the upper 200 m salinity in the postmonsoon BoB), representing the contribution of temperature stratification on the CI, and the $CI - CI_{S0}$ thus denotes the contribution of salinity stratification. The spatial pattern shows that the maximum value of CI resides at the northern rim of the Bay, whereas the smallest CI distributes in the southwestern region (figure S6(a)). $CI - CI_{S0}$ exhibits a northeast-southwest decreasing pattern (figure S6(c)) and accounts for more than 25% of the total CI in the northeastern BoB (figure S6(d)). The nonuniform spatial pattern of salinity-induced CI makes the IRs more likely to be affected by the salinity stratification due to the northeastward shift of intensification events in epoch-II. Indeed, the scatterplot of CIs against the IRs shows that the CI explains higher IR variability in epoch-II than in epoch-I. The temperature-induced CI ($CI_{T0}$) accounts for lesser IR variance during epoch-II. In contrast, the correlation coefficient between the salinity-induced CIs ($CI - CI_{S0}$) and IRs reaches up to 0.47, with statistical significance at the 99% confidence level (figure 5). Comparing the two periods, CI has a large difference of 5.35 ($J m^{-2} 1/3$) for the RI events, which is significant at the 99% confidence level (figure S7(a)). The difference of CI is considerably small for the non-RI events. The temperature and salinity-induced CI are significantly different for the RI events as well (figures S7(b) and (c)), and salinity-induced CI accounts for ~57% of the total CI difference. These results suggest that the RI events may be sensitive to the salinity stratification. Due to the northeastward shift of intensification events, more intensification events enter the high salinity stratification region and are more likely to turn into RI events. This consequently leads to the increase in the IR magnitude and number of RI events during epoch-II.

The robustness of the relationship between IRs and upper ocean salinity stratification in epoch-II is also confirmed by the correlation between the IRs and salinities at different depths. Ocean temperature and salinity over the upper 100 m considerably explain the IR variability in epoch-II (figure S8). The surface salinity shows a strong negative correlation with the IRs, indicating that fresher surface water may be more conductive to TC intensification. The correlations are mostly not significant in epoch-I. This also supports that the salinity BL is one of the dominant factors on the IR variability in epoch-II.

4. Conclusions and discussions

In this study, we analyze the IR variability in the postmonsoon BoB during the period of 1980–2015. Our results show that the number of RI events increases nearly four times during the period of 1998–2015 (epoch-II) than during the period of 1980–1997 (epoch-I). The magnitude of IR significantly increases in epoch-II, which is consistent with the observation that the TC intensity increases in the postmonsoon BoB (Balaguru et al 2014). Spatially, the RI events mostly occur over the southwestern BoB during epoch-I but shift northeastward during epoch-II. Regression analysis shows that the oceanic factor that most explains IR variability changes from SST in epoch-I to BLT in epoch-II. Due to the northeastward shift of intensification events, the thick BL with strong salinity stratification in the northeastern Bay strongly restricts TC-induced cooling through limiting cold thermocline water into the mixed layer, which is more conductive to TC intensification in epoch-II. Therefore, the observed weaker cold wake in epoch-II contributes to the increase in the magnitude of IR and number of the RI events. This study also suggests that TCs shifting into the northern BoB is more likely to experience a rapid intensification and obtain a higher intensity.

Since the strong relationship between the upper ocean salinity stratification and postmonsoon TC intensification during the recent two decades, the upper ocean salinity may have an important implication for TC intensity forecasting. TCs, especially for the intense TCs, are highly sensitive to the near surface salinity. The freshening of the upper ocean tends to intensify the intense TCs (Balaguru et al 2016a). Nevertheless, the Coupled Model Intercomparison Project phase 5 (CMIP5) models perform poorly in reproducing the seasonal and interannual variability of sea surface salinity (SSS) in the BoB. The CMIP5 models overestimate the SSS about 1.5 psu due to the negative bias of precipitation over the BoB (Fathrio et al 2017). Therefore, the results should be interpreted with caution when using the CMIP5 models to project the future TC intensity variability in the postmonsoon BoB.

In this study, we emphasize the importance of salinity stratification on the IR increase over the postmonsoon BoB in the recent two decades. However, other atmospheric and oceanic factors may also affect the IR variability. In fact, the upward trend of SST and downward trend of vertical wind shear have been found in the BoB during the past three decades (Balaguru et al 2014, Balaji et al 2018), which may contribute the IR increase as well. The contributions of various environmental factors to the IR variability have not been quantified in the present study. The respective roles of anthropogenic climate change and natural variability to the changes of IRs are still unknown.
These topics need to be further clarified in future work.

Acknowledgments

This study is supported by the National Natural Science Foundation (41776004), the China Ocean Mineral Resources Research and Development Association Program (DY135-E2-3-02), the Opening Project of Key Laboratory of Marine Environmental Information Technology, Joint Advanced Marine and Ecological Studies (JAMES), the Fundamental Research Funds for the Central Universities (2019B62914), and the Postgraduate Research & Practice Innovation Program of Jiangsu Province (SJKY19_0416).

Data availability statement

The data that support the findings of this study are openly available. The Joint Typhoon Warning Center best track data is available at www.metoc.navy.mil/jtwc/jtwc.html?north-indian-ocean; ERA-interim can be downloaded from www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets-era-interim; SODA is obtained from www.atmos.umd.edu/~ocean/; OSI SST is available at www.esrl.noaa.gov/psd/data/gridded/data.noaa.oisst.v2.highres.html

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