Predictability of Tropical Cyclone Rapid Intensification based on Statistical Approach

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Abstract
This study investigated the spatial and temporal characteristics of rapid intensification (RI) in the Vietnam East Sea (VES) and evaluated the predictability of RI using statistical methods. For the purpose of the RI study, this work focused on a dataset of TCs that reach storm level higher, or having a maximum intensity of at least 34 knots (kn) during their existence. The results show that the annual TC activity in the VES is characterized by a dominance of strong TCs (Category 12 and above) and a significant occurrence of RI-TCs accounting for 73.7% and 23% of the total respectively. Remarkably, RI-TCs were consistently observed in 26 out of the 31 years studied, with a tendency to occur during the latter months of the year.

Additionally, approximately 20% of these RI-TCs underwent RI near the Vietnam Coastal region. Given the increasing demand for accurate RI forecasts, four probability models namely Linear Discriminant Analysis (LDA), Logistic Regression (LogR), Naïve Bayes Classifier (Bayes) and Ensemble, using predictors from the SHIPS dataset, are developed to evaluate the predictability of the RI forecast. Among the predictors used, thermodynamic factors such as COHC, vertical wind shear (SHRD) and current TC states (PER) play crucial roles in constructing the RI probability models. Verification indices such as POD, FAR, CSI and BSS, indicate significant improvements in RI forecasting over the VES when utilizing the probability models, especially with the ensemble method.

Keywords: Rapid intensification, Probability models, TCs, Vietnam East Sea.

Introduction
Intensity forecasts of tropical cyclones (TCs) have been challenging tasks. Forecasting rapid intensification (RI) is even more complicated because the RI process is a multi-scale interaction process[11]. Overall, this process is modulated by large-scale environmental forcing, thermodynamics of the ocean and inner core processes of the TC[27]. Studies have investigated the synoptic flow patterns associated with RI to identify favorable environments for RI development. In particular, Chen et al[2] identified certain thresholds for sea surface temperature (SST), vertical wind shear (VWS), low-level relative humidity (RH) and 200 hPa relative eddy angular momentum flux convergence that proved effective for RI classification in the Vietnam East Sea (VES, which also called the South China Sea).

Shieh et al[24] studied Severe Typhoon Vicente (1208) in the VES and found that the passage of an upper-tropospheric (UT) "inverted" trough significantly influenced the RI process. The tropical upper-tropospheric trough enhanced the upper-level poleward and equatorial outflow of severe typhoon vicente. The passage of the trough also lowered VWS. Vicente underwent RI in a strong divergence and low VWS environment without a significant increase in SST and tropical cyclone heat potential (TCHP). Additionally, Mercer and Grimes[18] pointed out that mid and upper-level temperature fields, near-surface and upper-level geopotential height and near-surface relative humidity were the best classifiers for RI/non-RI, based on three reanalysis datasets: the NCEP/NCAR reanalysis dataset (NNRP – 11), the NCEP-DOE Reanalysis II dataset (DOE – 12) and the 20th-century Regional Reanalysis dataset (20th – 13) along with the NHC Atlantic Hurricane database for 1985 to 2009.

Besides the large-scale atmospheric circulation, the thermodynamic processes of the ocean have also been widely studied to understand the mechanisms of RI in TCs. A study by Gray[7] highlighted the significance of SST as one of the most important factors for TC formation. Warmer SSTs create favorable thermodynamic conditions for TC development as supported by the maximum potential intensity (MPI) theories proposed by Emanuel[4,5] and Holland.[8]

However, in the case of the Western North Pacific (WNP), studies by Knaff et al[14] and Zeng et al[31] demonstrated a weaker correlation between SST and MPI. Specifically, even though SST decreases for stronger intensities, the relationship is less significant. Instead, studies by Shay et al[23] and Chih and Wu[3] showed that the total heat content of the upper ocean, known as the tropical cyclone heat potential (TCHP) or ocean heat content (OHC), which considers the underlying oceanic thermal structure, is a more indicative factor than SST. The RI of TCs showed statistically significant differences in the upper OHC but was not sensitive to SST. This discrepancy is due to the stronger

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impact of entrainment mixing and upwelling processes on the upper OHC compared to their effects on SST.

The results suggest that MPI and SST may be inadequate for classifying or predicting TC intensity accurately. Furthermore, several studies have shown that the presence of oceanic eddies is often associated with RI. For instance, Shay et al[23] proposed that a warm core eddy in the Gulf of Mexico played a role in the RI of Hurricane Opal in the Atlantic. In the northeastern Tropical Pacific, Oropeza and Raga[19] investigated the role of oceanic eddies in the rapid and/or explosive deepening of TCs during the period 1993-2009. Their results indicated that oceanic eddies play a vital role in the intensification and RI of TCs.

Lin et al[17] analyzed observations of category 5 cyclones including Hurricane Katrina (2005), Rita (2005), Mitch (1998) and Supertyphoon Maemi (2003) to assess the importance of the background climatological upper ocean thermal structure on the sea surface height anomaly features. The results showed that when the background warm layer is deep, it is not critical for a TC to pass over positive features, as the background itself is already sufficient to limit the self-induced cooling negative feedback during intensification.

Previous studies have demonstrated the crucial role of inner-core processes in tropical cyclone intensity change. Recent studies by Knaff et al[15,16], Weatherford[28], Kieper and Jiang[12], Xu and Wang[30] and Carrasco et al[1] have highlighted the significant contributions of TC size and inner-core size to the intensification process. These findings suggest that smaller storms and those with the coldest brightness temperatures near the center are more likely to experience rapid intensification. Consequently, inner-core information has been used as a valuable predictor in discriminating rapid intensification in studies by Knaff et al[15] and Tam et al.[27]

Accurate forecasts of RI are of practical importance for society due to their detrimental impacts on coastal livelihood and properties[21,24]. Numerous studies have evaluated the skill of RI forecasts using both statistical and dynamical approaches in basins worldwide including the Atlantic and WNP. Indeed, the feasibility of statistical prediction for RI-TCs has been demonstrated in several studies. These studies have shown that it is possible to develop statistical models based on various environmental predictors to forecast the probability of RI events. Kaplan et al[10] developed a rapid intensity index (RII) for the Atlantic and eastern North Pacific basins. The RII utilizes linear discriminant analysis with large-scale predictors from the Statistical Hurricane Intensity Prediction Scheme (SHIPS) to estimate the probability of RI over the succeeding 24 hours.

The results showed that the probabilistic RII forecasts outperformed climatology in both basins. However, the RII exhibited modest probability of detection (POD) values ranging from 15% to 73% and relatively high false alarm rate (FAR) values ranging from 53% to 83%, indicating the difficulty of predicting RI, particularly in the Atlantic basin. The authors suggested that incorporating more detailed inner-core information may improve the skill of the RII due to its reliance on large-scale predictors. Rozoff and Kossin[23] incorporated data from the SHIPS dataset into logistic regression and naive Bayesian models to build probabilistic predictions of rapid intensity change in tropical cyclones over the North Atlantic and eastern North Pacific Ocean basins. The results demonstrated that the logistic regression and Bayesian probabilistic models outperformed climatology and the linear discriminant analysis probabilistic models. Additionally, combining the probabilities from the logistic regression, Bayesian and SHIPS-RII models through a simple average yielded better performance than any individual model. For the rapid intensification threshold of 25 kn/24hr, the Brier skill scores of the three-member ensemble were 33% and 52% higher than the existing SHIPS-RII scores in the North Atlantic and eastern North Pacific respectively.

Vietnam, situated on the western margin of the WNP with a coastline of over 3,000 km, experiences significant impacts from TCs activity in the VES. Many studies[15,26,27] have evaluated the skills of RI forecasts for the WNP. Therefore, given the demand for RI information in Vietnam, this study aims to investigate: 1) the characteristics of RI and 2) the predictability of RI based on a statistical approach for the VES.

Material and Methods

TC Data: The WNP TC best track data from the Joint Typhoon Warning Center (JTWC) over the VES, limited to the range of longitude from 100°E to 120°E and latitude from 5°N to 23°N in 31-year period from 1990 to 2020 were used in this study. JTWC data were obtained directly on the homepage https://www.metoc.navy.mil/jtwc/jtwc.html?western-pacific including TC central position, minimum sea level pressure (P_{min}) and maximum sustained wind (V_{max}) information for each storm reaching tropical depression. The maximum wind speed here is the 1-minute average wind and the data are formatted with time steps six-hourly to ensure uniform ΔV calculation over time of change Δt. Furthermore, to reduce the uncertainty in detecting weak TCs such as tropical depressions[14], the study only considers TCs that reach storm level higher or having a maximum intensity of at least 34 knots (kn) during their existence.

RI definition: Previous studies[9,10,15,25] have used the 95th percentile of ΔVs as the threshold for identifying RI. In line with these studies, the 95th percentile of ΔVs within a 24-hour period is utilized to identify observed RI-TCs. These results will be employed to investigate the characteristics of RI-TCs over the VES. Additionally, since we use the observed RI-TC as predictand to train our probability models, its definition significantly influences the performance of RI forecasts. Therefore, we adopt the 95th percentiles of ΔVs at different time intervals such as 12, 24, 36 and 48 hours, for defining RI to assess the role of

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predictors and to evaluate the performance of probability models. To provide clarity, the values of the 95th percentiles of ΔVs at 12, 24, 36 and 48 hours are +15kn, +25kn, +35kn and +45kn respectively.

Construction of RI probability models: Construction of the RI forecast follows the same approach as previous studies[9-11]. In the development phase, we use predictors from the SHIPS dataset (RAMMB)[20] which describe the environmental conditions and information about the current TC state to forecast the probability of RI. The selected predictors are based on previous studies[15,16,27]. A list of predictors is shown in table 1.

This study uses probability models such as Linear Discriminant Analysis (LDA), Logistic Regression (LogR), Naïve Bayes Classifier (Bayes) and Ensemble which have been previously demonstrated as skillful in RI forecasting[9-11,27]. The first three models (LDA, LogR and Bayes) are individually used to generate statistical forecasts of RI occurrence based on the provided predictors. The specific methodologies for these models can be found in the previous studies[9-11,27]. The ensemble method is defined as the simple ensemble mean of the RI probability results from the three mentioned models (LDA, LogR and Bayes).

The performance of the probability models was assessed using several metrics including POD (Probability of Detection), FAR (False Alarm Rate), CSI (Critical Success Index) and BSS (Brier Skill Score), on training data (from 1990 to 2020) and testing data (from cross-validation). The BSS is given by the formula BSS = 1 - (BS_f / BS_r) where BS_f represents the Brier Score of the forecasts and BS_r represents the Brier Score of the reference[29]. In this study, the reference for BSS calculation is the climatology of observed RI events.

Results and Discussion

Spatial and Temporal Distribution of RI-TCs: Figure 1 shows the variations in the number of TC activities across different categories and periods within the VES region from 1990 to 2020. On average, approximately 9 TCs occur annually in the VES. About 73.7% of these TCs reach category 12 or higher on the Beaufort scale (i.e. V_{max} above 64kn). Specifically, around 4.4 TCs per year fall within the category 12-13 range (i.e. V_{max} from 64kn to 80kn) and approximately 2.3 TCs per year are classified above category 13 (i.e. V_{max} above 80kn). Approximately 2.1 TCs per year underwent rapid intensification (RI) identified using the 95th percentile of ΔVs (change in wind speed) within 24 hours. These RI-TCs account for approximately 23% of the total TC activity in the region.

Additionally, RI-TCs were documented in 27 out of the 31 years and TCs reaching above category 13 were observed in 26 out of the 31 years. This indicates the dominant occurrence of strong TCs and RI-TCs within the VES. Figure 2a shows the probability of TC occurrences in different categories for each month throughout the year. The results indicate that TC activity in the VES is concentrated from June to December with a particularly notable concentration in July, August and September.

The occurrence probability for each of these months is approximately 83%. In terms of temporal distribution, stronger TCs tend to occur in the later months of the year. Specifically, TCs in category 12-13 show a concentration from July to September while TCs classified above category 13 exhibit a higher occurrence probability from September to November.

Additionally, the occurrence probability of RI-TCs is notably higher from July to September compared to other months. The occurrence probability of RI-TCs remains consistently higher than that of TCs classified above category 13 throughout most months of the year, except for October, November and December. Notably, the occurrence probability of both RI-TCs and TCs with intensities above category 13 is highest in September with a value of 45%.

Table 1
List of predictors

S.N.	Predictor	Definition
Environmental predictors		
1	COHC	Ocean heat content evaluated at the point closest to the TC (equals to 0 if SST is below 26 C)
2	D200	200 hPa divergence averaged over 1000 km radial distance from the TC centre
3	SHRD	200–850 hPa space mean vertical wind shear averaged 200-800 km radial distance from the TC centre
4	VMPI	Maximum potential intensity from Kerry Emanuel equation, as a function of SST at the storm center and the current intensity
5	RHHI	300–500 hPa RH averaged 200-800 km radial distance from the TC centre
6	TADV	The temperature advection between 850 and 700 hPa averaged from 0 to 500 km Estimated from the geostrophic thermal wind (deg per sec*106)
Best-track/advisory-based predictors		
7	PER	Persistence: previous 12 hr intensity change
8	CI	Current intensity

Figure 2b shows the proportions of RI events among TCs categorized below category 12, category 12-13 and above category 13. The results indicate that approximately 69% of RI events occur with TC intensities classified above category 12. This suggests the importance of considering TCs categorized with higher intensity levels when analyzing RI occurrences.

Figure 3 shows the best tracks of RI-TCs activity in the VES with denoted points where RI occurred each month from June to November, spanning the years 1990 to 2020. Overall, the results indicate a southward shift in the tracks and landing sites of tropical cyclones over time. Between June and September, the majority of TCs occurred north of 12°N in the VES, with landfalls predominantly observed in the North Central region of Vietnam. However, during October and November, there was a noticeable shift in the favorable areas for TC formation, moving southward below 18°N. Consequently, the landing sites became concentrated in the South Central region. Figure 3 also illustrates that approximately 34.5% of the locations where rapid intensification occurs within the boundaries of the VES during the peak TC months (from June to November).

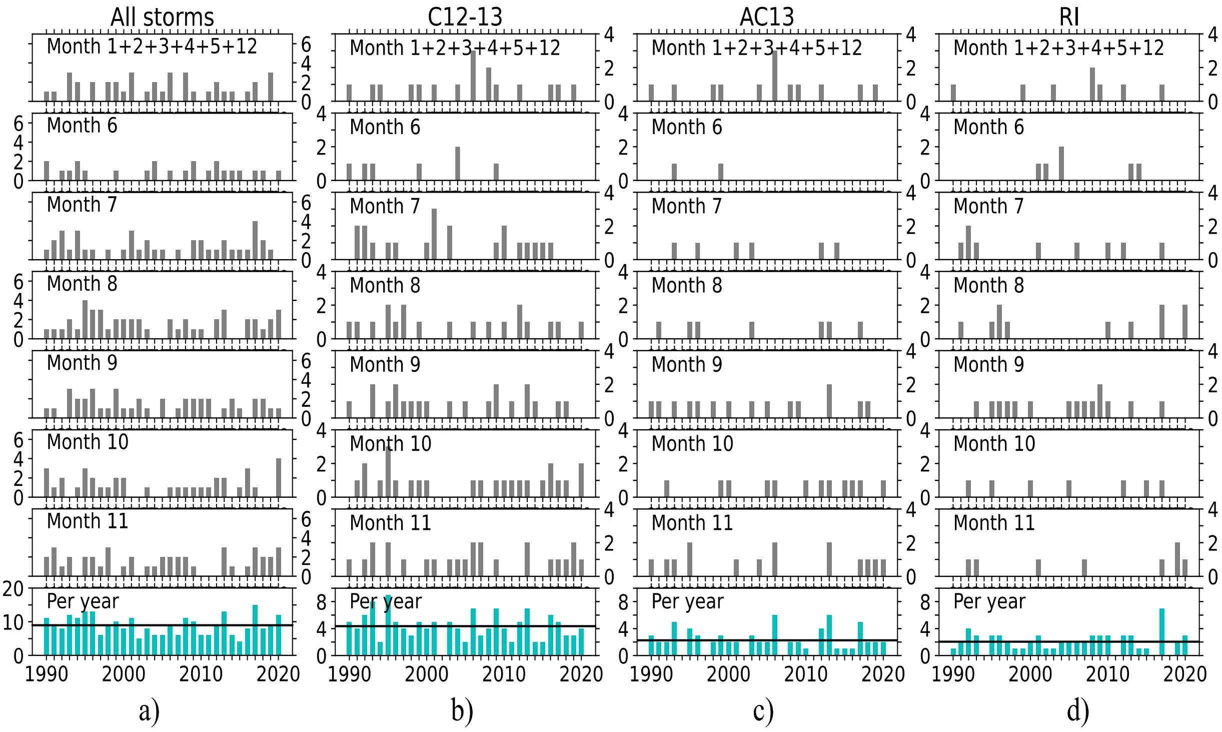

Figure 1: Number of TCs activities in the VES across all categories (column a), Category 12-13 (C12-13, column b), above Category 13 (AC 13, column c) and rapid intensification (RI, column d) for the period 1990-2020, divided into December to May (row 1), June (row 2), July (row 3), August (row 4), September (row 5), October (row 6), November (row 7) and the entire year (row 8) from 1990 to 2020.

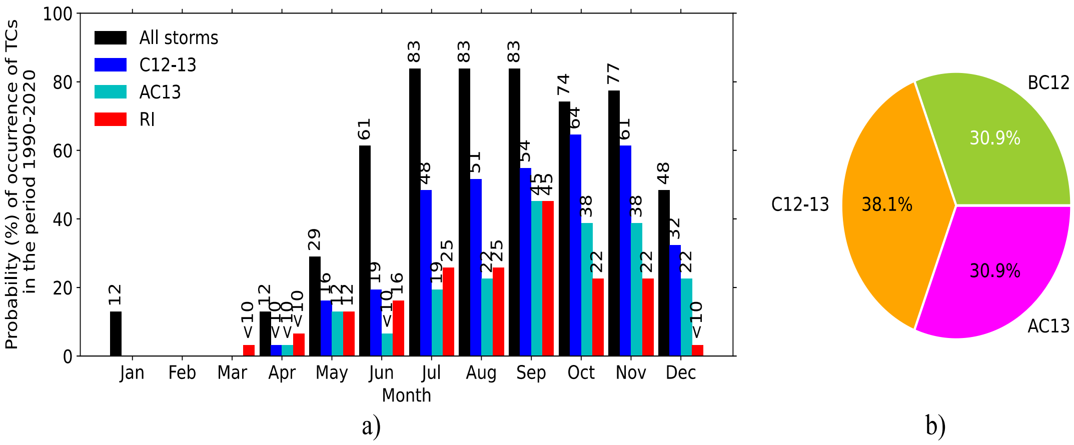

Figure 2: a) Probability of TC occurring at Category 12-13 (C12-13), above Category 13 (AC13) and RI for the period 1990-2020 (b) Percentage of RI occurring at below Category 12 (BC12), Category 12-13 (C12-13) and above Category 13 (AC13) for the period 1990-2020

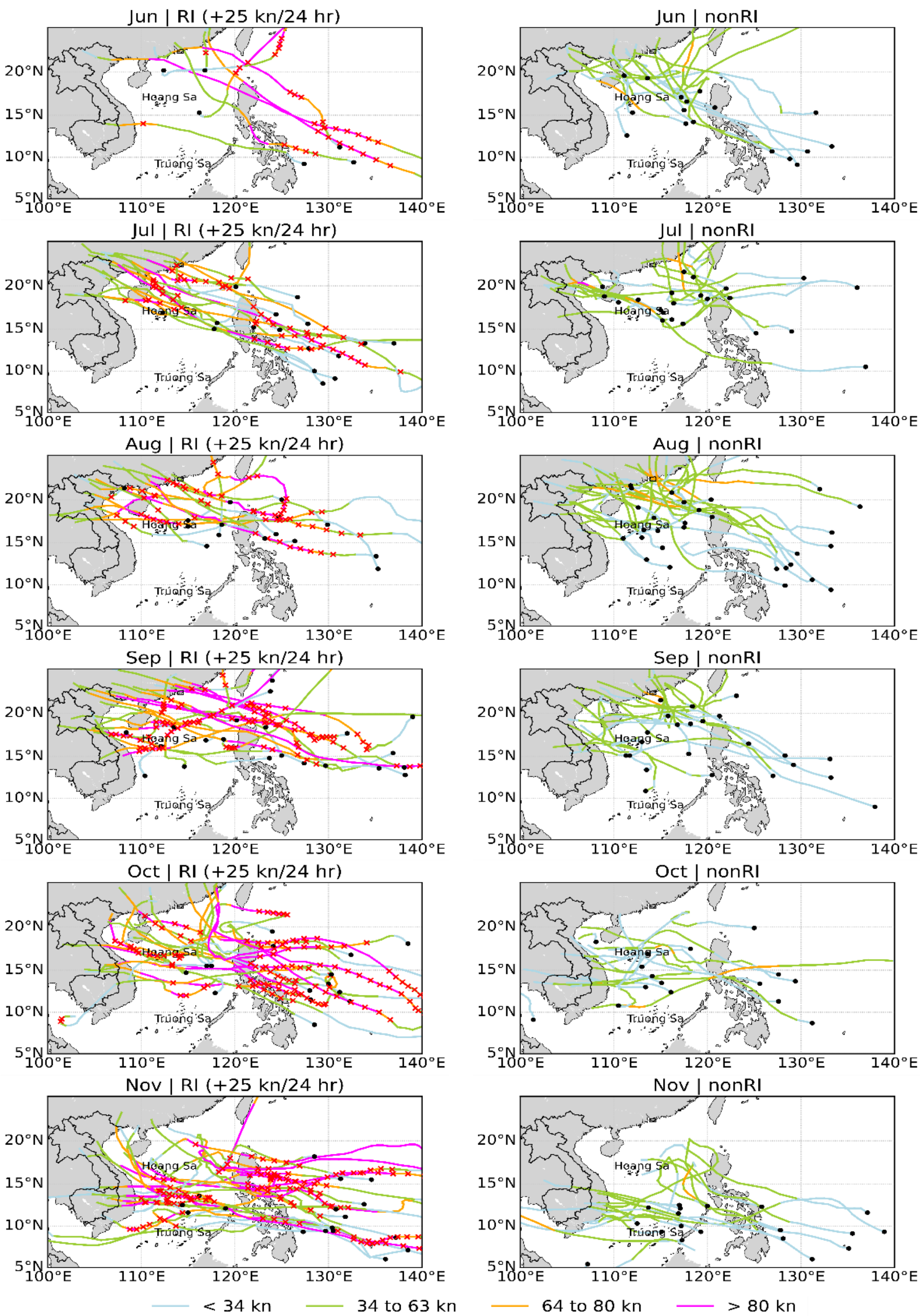

Figure 3: Best track of RI-TCs (left) and non-RI-TCs (right) in VES from June to November over the period 1990-2020. RI event symbol (×, red), forming point (•, black)

This suggests that the VES provides favorable conditions for the RI of TCs. Notably, among RI-TCs activity in the VES, approximately 20% experience RI near the Vietnam Coastal region, specifically in the western area around the longitude of 110°E. The concentration of RI events within the VES region, especially near the Vietnam Coastal region, highlights the necessity of enhancing knowledge and forecasting capabilities to minimize the impact of RI-TCs on vulnerable coastal areas.

Predictability of RI forecasts over the VES

RI predictors: Given the high demand for RI forecasts, the primary objective of this study is to assess the predictability of RI of TCs over the VES using statistical methods. The predictors used in this study were obtained from the SHIPS dataset and have been used in previous studies[10,15,16,27] to develop statistical models for forecasting the RI of TCs.

Analyzing these predictors could provide information about favorable conditions for the occurrence and development of RI events, specifically atmospheric conditions (e.g. D200, SHRD, VMPI, RHHI, TADV), oceanic factors (COHC) and TC current-state information (PER, CI). It is noted that an observed RI event is defined when the maximum sustained wind speed of a TC intensifies by at least 25 knots within 24 hours. The results from table 2 indicate that high ocean heat (e.g. COHC), low wind shear (e.g. SHRD) and high divergence at the high level (e.g. D200) are favorable for enhancing convective processes. The increased convective activity of TCs is reflected by higher moisture at the mid-level (e.g. RHHI). The release of latent heat from convective processes serves as an energy source for intensification, as evidenced by the high values of VMPI, PER and VMAX. The results are qualitatively in line with previous studies[6,10,27] on favorable conditions for RI occurrence. Furthermore, table 2 shows that the difference in means of all selected predictors between RI and non-RI events is statistically significant at the 99.9% level as determined by the t-test. This implies that all selected predictors have the potential to distinguish and identify RI events, making them valuable in constructing RI probability models, particularly for the VES region. Therefore, all predictors were used to develop probability models of RI-TC occurrence in this study.

To objectively evaluate the contribution of predictors in forecasting RI events, we calculated relative weights associated with each predictor in those three statistical models for various RI definitions. Figure 4 shows the diverse relative weights of each predictor between four RI definitions (e.g. +15kn/12hr, +25kn/24hr, +35kn/36hr and +45kn/48hr) and among three probability models (e.g. LDA, LogR and Bayes).

Table 2
Mean and SD of RI and Non-RI, with threshold +25 kn/24 hr

Predictor	Unit	RI (mean)	RI (SD)	Non–RI (mean)	Non–RI (SD)	RI - Non–RI (mean)	Significance level
COHC	kJ/cm^2	92.5	24.9	72.5	28.2	+20.0	99.9^{th}
D200	10^{-7} s^{-1}	71.7	42.6	53.2	37.6	+18.5	99.9^{th}
SHRD	kn	11.4	5.7	15.2	7.4	-3.8	99.9^{th}
VMPI	kn	147.5	10.6	140.2	17	+7.3	99.9^{th}
RHHI	%	68.7	11.3	64	12.9	+4.7	99.9^{th}
TADV	deg 10^6	-0.4	4.5	0.6	6.1	-1.0	99.9^{th}
PER	kn	10.4	7.9	2.9	9.3	+7.5	99.9^{th}
VMAX	kn	57.6	21.5	53.4	28.6	+4.2	99.9^{th}

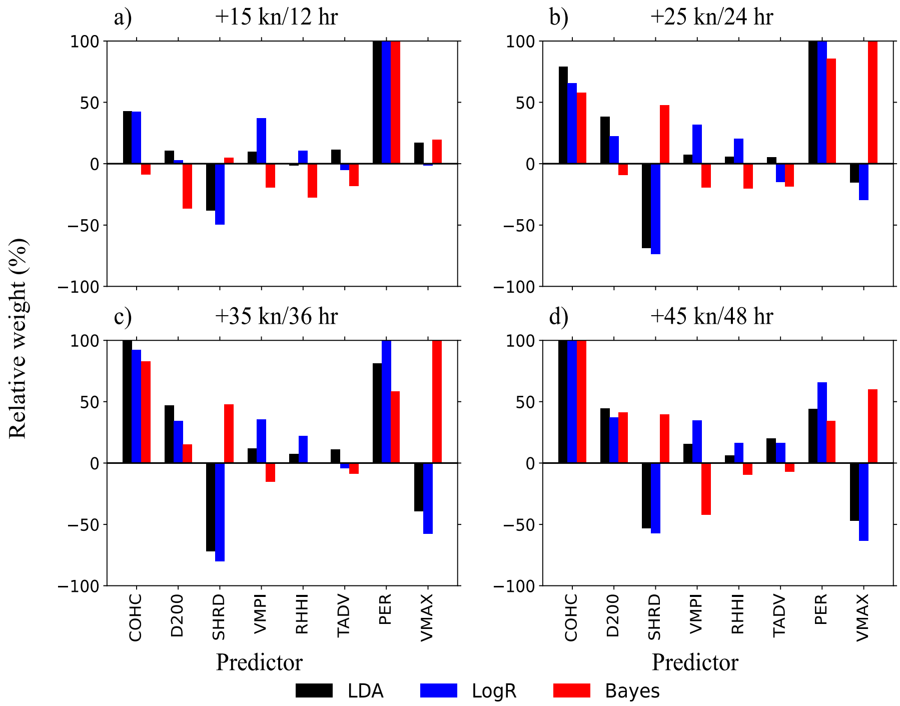

Figure 4: The relative weights for each RI predictors based on training data for different RI definition including a) +15kn/12hr; b) +25kn/24hr; c) +35kn/36hr; d) +45 kn/48hr

Overall, among the eight predictors used to construct RI probability models, PER, COHC and SHRD have emerged as playing significant roles compared to the other predictors. Their importance is evident from the notably high magnitudes of their relative weights, even when considering variations in the definition of RI events (Fig. 4).

The relative weights of the thermodynamic predictors (e.g. COHC), the vertical wind shear (e.g. SHRD) and current TC states (e.g. PER) consistently appear higher, approximately twice as much as the other predictors across all four RI definitions. This suggests that for the VES, thermodynamic conditions and vertical wind shear are vital factors influencing the occurrence of RI. Additionally, the change in TC intensity over 12 hours (e.g. PER) shows the highest correlation with COHC compared to other predictors (not shown). This indicates that the thermodynamic condition, as represented by COHC, is the most crucial factor for RI processes and the primary predictor for developing RI forecasts in the VES.

Evaluation of RI probability models: Four probability models including LDA, LogR, Bayes and Ensemble were used to predict the RI over the VES based on the predictors from the SHIPS dataset. Figure 5 shows the probability distributions of RI and non-RI cases for the four RI probability models based on training data (from 1990 to 2020) and testing data (from cross-validation). Overall, the probability distributions from each model are consistent between the two types of datasets for both RI and non-RI cases. This suggests that all models are highly stable for RI forecasting. Besides that, there is agreement among the four probability models regarding the distribution of non-RI events.

The frequency of non-RI events is predominantly found at small probabilities with over 80% occurrence at probability levels less than 0.2. However, the shapes of the RI probability distribution vary among the four models. The results obtained from the LDA model show some similarities to those derived from the LogR model and ensemble model, particularly with a higher frequency observed around probabilities ranging from 0.1 to 0.4.

In contrast, the Bayes model demonstrates improved forecasting performance in capturing the occurrence of higher probabilities of RI. However, the Bayes model has the highest frequency at a probability value of 0, indicating a relatively higher frequency of non-RI cases predicted by the model compared to other models. The differences observed in the probability distributions generated by each model highlight the importance of selecting the optimal threshold for the forecasted probability to define the occurrence of RI for each specific model. Choosing the appropriate threshold is crucial in correctly identifying RI events and minimizing errors such as misses and false alarms in the RI forecasts.

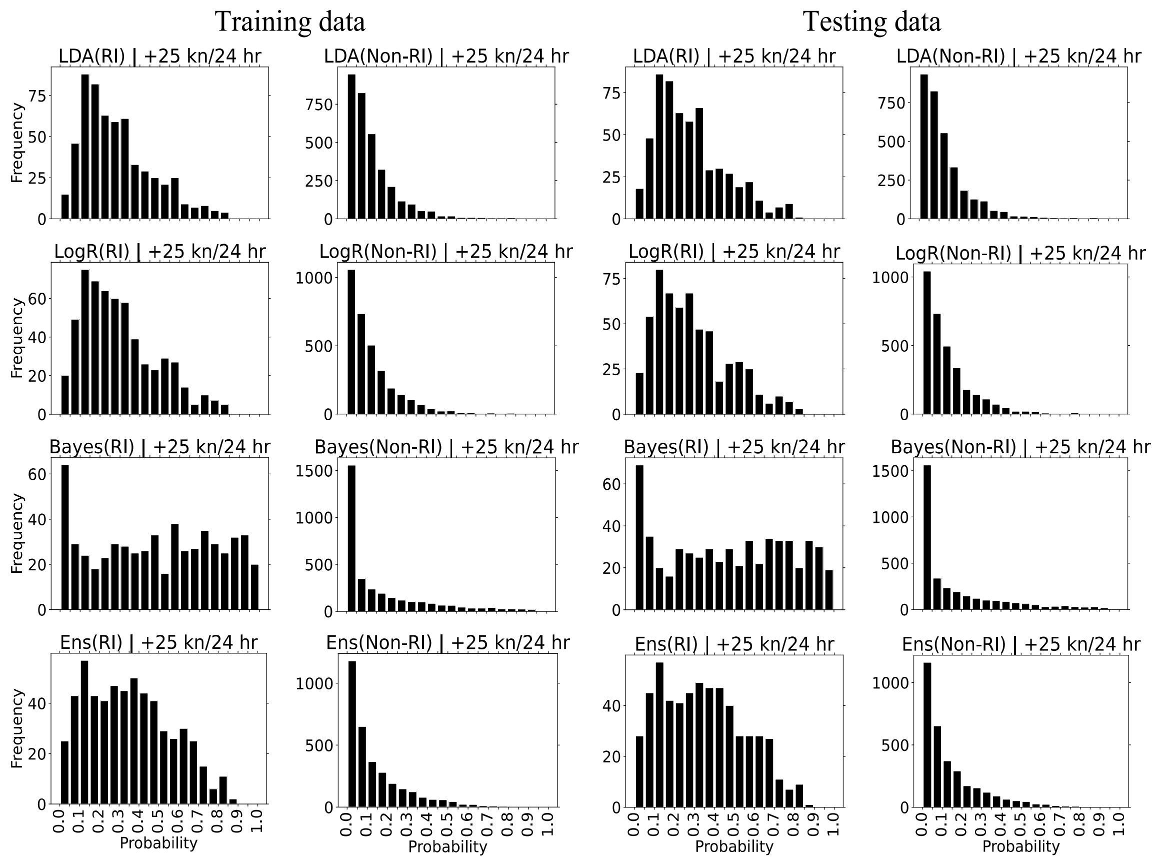

Figure 5: The probability distributions of RI (column 1 for training data and column 3 for testing data) and non-RI cases (column 2 for training data and column 4 for testing data) based on LDA (row 1), LogR (row 2), Bayes (row 3) and Ensemble (row 4).

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Figure 6 displays the performance of four models (LDA, LogR, Bayes and Ensemble) for different RI thresholds, ranging from 0 to 1.0. The RI threshold refers to the minimum forecasted probability indicating the occurrence of RI. The models were trained on data from 1990 to 2020 and tested using cross-validation. The distribution of verification indexes (POD, FAR and CSI) based on the different RI thresholds shows similarities between the training and testing data. This indicates that the models exhibit stability and reliability in predicting RI events, as their performance remains consistent across different datasets.

The performance of the LDA and LogR models, as measured by POD, FAR and CSI, is quite similar at all RI thresholds. This similarity is reflected in the high consistency of the probability distribution for RI and non-RI events from these models (Figure 5). For all models, the POD values tend to decrease as the RI threshold increases. When comparing the models, the LDA and LogR models have a higher POD than the Bayes and Ensemble models at low RI thresholds (below 0.15). Conversely when using a high threshold to indicate the occurrence of RI, the Bayes and Ensemble models have higher PODs than the LDA and LogR models.

Regarding FAR values, both the Bayes and Ensemble models show a decreasing trend as the RI threshold increases, indicating that these models perform better at avoiding false predictions as the threshold becomes stricter. In contrast, the LDA and LogR models show a decreasing trend in FAR values as the RI threshold increases, but once the chosen threshold exceeds 0.5, the FAR tends to increase. This suggests that the Bayes and Ensemble models are better than the LDA and LogR models when selecting a high RI threshold (e.g. above 0.5) to reduce false predictions.

The distribution of CSI points reveals that the performance of each model heavily depends on the probability threshold used to indicate the occurrence of RI events. Overall, the CSI values for all four models range from 0 to 0.3. The forecasts based on the LDA and LogR models show high CSIs when the RI threshold is around 0.2.

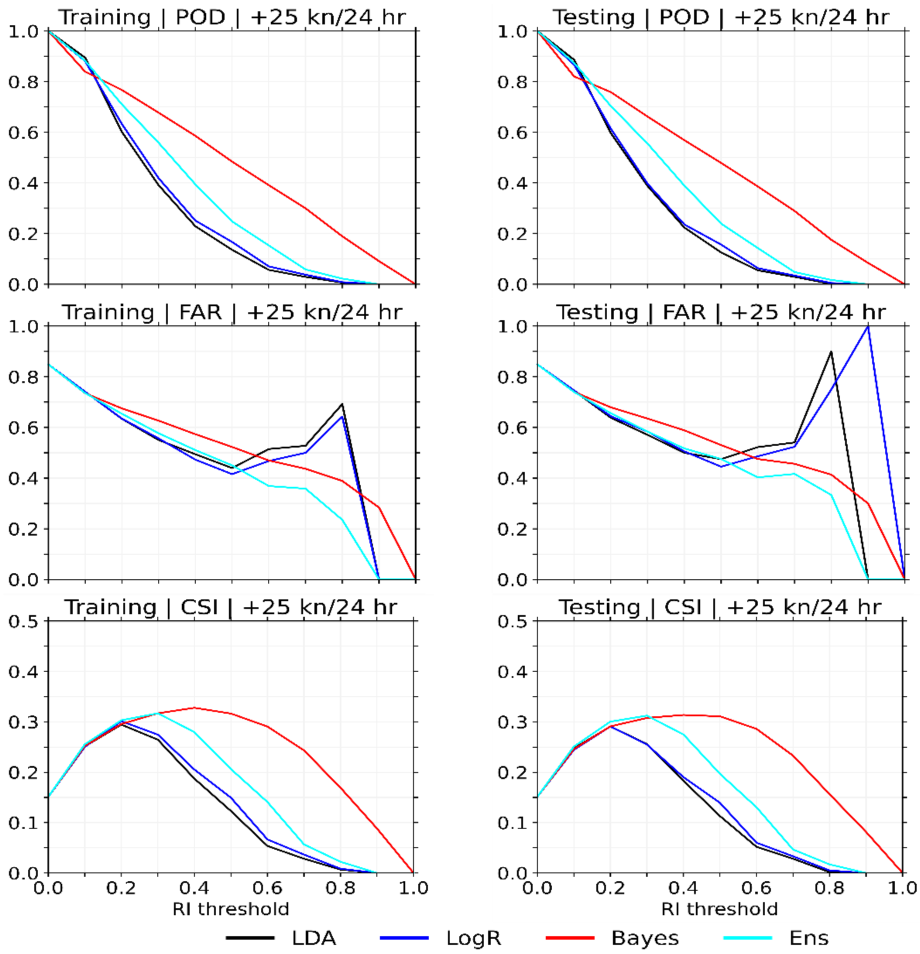

Figure 6: The performance of LDA (black line), LogR (blue line), Bayes (red line) and Ensemble (cyan line) for different RI thresholds (minimum probability to indicate the occurrence of RI) based on training data (1990-2020). Noted that observed RI event is defined when the maximum sustained wind speed of a TC intensifies by at least 25 knots within 24 hours.

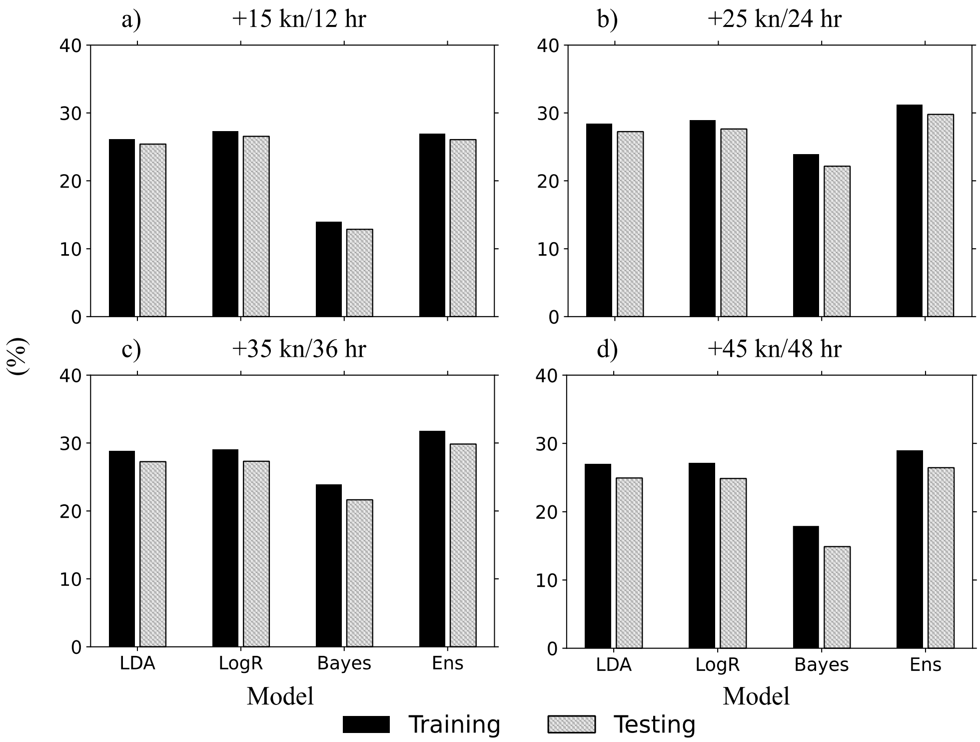

Figure 7: The BSS values for the RI forecasts are based on 4 models including LDA, LogR, Bayes and Ensemble, with different observed RI definitions. Specifically, observed RI event is defined when the maximum sustained wind speed of a TC intensifies by at least a) +15kn/12hr; b) +25kn/24hr; c) +35kn/36hr; d) +45kn/48hr.

In contrast, the ensemble model demonstrates high CSIs over a wide range of RI thresholds, specifically from 0.2 to 0.4. Similarly, the Bayes model shows high CSIs across a broader range of RI thresholds, specifically from 0.3 to 0.6. This suggests the consistent performance of the ensemble and Bayes models in correctly predicting the occurrence of RI events across different RI thresholds.

It is noted that the performance of RI probability models depends on the specific definitions of observed RI events. Therefore, the BSS is calculated for different observed RI definitions in both the training and testing datasets to evaluate the models' ability to predict RI occurrences. These RI definitions differ based on the minimum increase in the maximum sustained wind speed required to identify RI occurrences, specifically, the thresholds considered are +15kn/12hr, +25kn/24hr, +35kn/36hr and +45kn/48hr. Figure 7 shows that all probability models including LDA, LogR, Bayes and Ensemble, demonstrate good performance compared to climatology forecasts in predicting the occurrence of RI regardless of the specific RI definition. This is reflected by the positive BSS values (above 20% in Fig. 7) obtained for both the training and testing data as well as for different RI definitions.

Furthermore, the forecasts generated by the ensemble model have the highest BSS (approximately 30%) compared to those from the LDA, LogR and Bayes models. This suggests that the ensemble model provides more accurate and skillful predictions of RI events. For the Bayes model, despite its strengths in detecting RI events (shown by the verification indexes such as POD, FAR and CSI), the BSS values are lower due to its high extreme probability distributions (Fig. 5) when compared to other models.

Conclusion

The study uses the 95th percentile of ΔVs (change in wind speed) within 24 hours to identify observed RI-TCs in the VES. The results show that the annual TC activity in the VES is characterized by a dominance of strong TCs (Category 12 and above) and a significant occurrence of RI-TCs, which account for 73.7% and 23% of the total respectively. RI-TCs are consistently observed in 26 out of the 31 studied years and tend to occur in the latter months of the year, indicating their high-frequency occurrences in the VES region.

Additionally, around 20% of these RI-TCs experience RI near the Vietnam Coastal region, specifically in the western area around the longitude of 110°E. The high frequency and concentration of RI events within the VES region, particularly near the Vietnam Coastal region, emphasize the importance of enhancing knowledge and forecasting capabilities to minimize the impact of RI-TCs on vulnerable coastal areas. Given the increasing demand for accurate RI forecasts, this study employed four probability models namely LDA, LogR, Bayes and Ensemble, utilizing predictors from the SHIPS dataset, to assess the predictability of RI over the VES. The results demonstrate that the selected predictors which describe atmospheric conditions (e.g. D200, SHRD, VMPI, RHHI, TADV), oceanic factors (COHC) and information about the current state of the tropical cyclones (PER, CI), are consistent with previous studies[6,10,27] in representing the favorable conditions for RI occurrences over the VES.

While all the predictors show the potential to distinguish and identify RI events, the study finds that vertical wind shear (e.g. SHRD), current TC state (e.g. PER) and especially the thermodynamic predictor (e.g. COHC) play pivotal roles as primary predictors in developing RI forecasts for the VES. Furthermore, a previous study[11] highlights that the relative weight of PER and SHRD is important for RI forecasting in other regions such as the Atlantic and eastern North Pacific basins. This suggests that certain predictors may exhibit similar importance and influence on RI events across different geographical locations.

The performance of four models (LDA, LogR, Bayes and Ensemble) in predicting the occurrence of RI is evaluated using both training data (from 1990 to 2020) and testing data (from cross-validation), employing verification indexes such as POD, FAR and CSI. The results demonstrate that the distribution of these verification indexes is similar between the training and testing data, indicating the stability of these models in predicting RI events. Notably, the results highlight that the performance of probability models significantly depends on the selection of RI thresholds (i.e. the minimum forecasted probability to indicate the occurrence of RI).

Overall, the POD and FAR values tend to decrease as the RI threshold increases for almost all models. This implies that as the threshold becomes stricter, these model performances are better at avoiding false predictions. Furthermore, the CSI values for all four models range from 0 to 0.3. The LDA and LogR models have an optimal threshold of around 0.2 while the Ensemble and Bayes models exhibit wider ranges of optimal RI thresholds, namely 0.2 to 0.4 and 0.3 to 0.6 respectively.

Additionally, positive BSS values above 20% were obtained for both the training and testing data in different cases of defining the observed RI-TCs (e.g. the values of the 95th percentiles of ΔVs at 12, 24, 36 and 48 hours are +15kn, +25kn, +35kn and +45kn respectively). The forecasts generated by the ensemble model have the highest BSS (approximately 30%) compared to those from the LDA, LogR and Bayes models. This indicates that all used probability models, especially the Ensemble method, offer substantial advancements in RI forecasting over the VES compared to climatology-based predictions.

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