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"OPTIMAL" CONDITIONS FOR RAPID INTENSIFICATIONS OF TROPICAL CYCLONES WITH LIMITED FACTORS

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ABSTRACT

Rapid Intensifications (RI) of tropical cyclones (TC) provide major error sources in the challenging task of TC intensity forecasting. There are many factors affecting the RI processes of TCs, and identifying the combination of conditions most favorable to RI development is very time consuming when using traditional statistical data analysis methods. Data mining techniques have been implemented in the analysis of RI of TCs, and a simpler combined condition is identified, which gives a higher RI probability than a more complex condition from ordinary statistical analysis. Moreover, the data mining technique can be used to identify the "optimal" RI conditions when the number of affecting factors is given. The variation of RI probabilities with the factor numbers leads to a saturation stage, and individual cases are traced back for the cases with the globally most favorable RI conditions. In this paper, we will report the most recent findings through the data mining technique based on the data for SHIPS (Statistical Hurricane Intensity Prediction Scheme), an operational statistical-dynamical hurricane intensity forecasting model.

Key words: *hurricane intensity, rapid intensification, data mining, association rules.*

1. INTRODUCTION

Forecasting tropical cyclone (TC) intensity changes, rapid intensification (RI) in particular, is a challenge. As Kaplan and DeMaria [2003] defined, a TC undergoes RI if its intensity (defined by the maximum wind) has increased at least 30 knots (15.4 m/s) over a 24-hour period. The favorable factors for TC intensification have been broadly studied. Those factors include warm ocean eddies [Shay et al., 2000; Hong et al., 2000; Wu et al., 2007], the contraction of an outer eyewall [Willoughby et al., 1982; Willoughby and Black, 1996; Lee and Bell, 2007], an environment with low vertical shear [Gray, 1968; Merrill, 1988; DeMaria and Kaplan, 1994; DeMaria, 1996; Frank and Ritchie, 1999, 2001; Zeng et al., 2007, 2008], interactions between the upper-level trough and a TC [Molinari and Vollaro, 1989, 1990; DeMaria et al., 1993], dissipative heat [Jin et al., 2007] and even cloud microphysics [Wang, 2002] and isotopic concentrations [Gedzelman et al., 2003].

Most of the previous studies were largely focused on only one of three categories of factors: ocean characteristics, inner-core processes, and environmental interactions, and it is well known that intensity changes depend on a combination of those factors [Gray, 1968; Zhu et al., 2004]. Holliday and Thompson [1979] examined the rapidly intensifying northwest Pacific typhoons and observed that a sufficiently deep layer of warm water, the development at night time, and a smaller eye size were favorable for those RI typhoons. DeMaria and Kaplan [1994] studied Atlantic TCs and found that the TCs with a smaller size, with a greater potential to reach their maximum potential intensity, with a faster intensification history, and in an environment with low vertical shear and weak upper-level forcing exhibited the largest 48-hour

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intensification rates. In a study of the RI process of Hurricane Opal (1985), Bosart et al. [2000] concluded that its RI was a result of a combination of several factors: enhanced upper-level divergence, low vertical shear and the enhanced heat and moisture from a warm Gulf eddy. Jones et al. (2007) discussed the detailed environmental and inner-core conditions controlling TC intensity with Hurricane Erin (2001) which underwent two different phases in its life as an example. They further divided the contributions from different parameters into five categories; climatology, SST-Potential, shear, (other) environment, and microwave. One interesting finding is that the contribution from shear is weak when Erin is not intensifying but significantly increases during the intensifying phase.

Kaplan and DeMaria [2003] examined the large-scale characteristics of rapidly intensifying Atlantic TCs from 1989-2000 using the NHC HURDAT file and the SHIPS database, estimated the RI probability (RIP), and discussed the dependence of RI probability on a combination of factors.

Following Kaplan and DeMaria [2003, hereafter KD03], Yang, Tang & Kafatos [2007, hereafter YTK07] explored an association rule data mining algorithm [Agrawal et al., 1993] to search for condition combinations favoring the RI process. Compared to statistical analysis, the technique of association rules can explore associations among multiple conditions without extra effort because it examines all possible combinations of frequent condition sets automatically. It provides an as complete as possible picture of the dataset to scientists so that the connections among multiple conditions will not be overlooked by a theory-driven analysis approach. As a successful scientific data mining example, YTK07 not only identified the predictors giving an improved RI probability but also obtained this result with fewer predictors through a pruning process of association rules.

Since the association rule data mining technique provides a comprehensive picture of the connections among multiple conditions, one can search for the “optimal” conditions for RI in a given set of predictors. In other words, if a set of conditions controlling the TC intensity changes is given, one can identify the conditions giving the highest RI probabilities when the number of factors is given among the selected set. The “optimal” results will suggest conditions which may be sufficient to make TCs undergo a RI process although the conditions are not necessary for all RI cases.

2. DATA AND METHODS

2.1. Data Sets

The datasets for this study are the NHC HURDAT file [Jarvinen et al., 1984] and the SHIPS 1982-2003 database [DeMaria and Kaplan, 1994, 1999; DeMaria et al., 2005]. A detailed description of the variables in the HURDAT and SHIPS datasets can be found in KD03. The HURDAT file consists of 6-hr estimates of position and maximum sustained surface wind speeds for all named Atlantic TCs from 1851 to the present. The SHIPS database contains synoptic information for every 12-hr of all Atlantic TCs from 1982 to the present. In this study, the time period is limited to 1982-2003 due to the initial data availability. The authors noticed that the SHIPS database was recently updated to include information at 6-hr intervals (DeMaria et al., 2005).

Table 1. The eleven statistically significant predictors and the corresponding threshold values (reproduced based on Table 4 of KD03). The predictors DVMX, SHR, and SLYR in KD03 are renamed as PD12, SHRD, and PSLV here.

Name	Description	Threshold
PD12	Intensity change during the previous 12 hours.	4.6 m/s
SHRD	850-200 hPa vertical shear.	4.9 m/s
SST	Sea surface temperature.	28.4 ^{o}C
POT	Maximum potential intensity (MPI) – initial intensity	47.6 m/s
RHLO	850-700 hPa relative humidity.	69.7 %
LAT	Latitude	19.7 ^{o}N
LON	Longitude	63.2 ^{o}W
USTM	Zonal (u) component of storm motion.	-3.1 m/s
U200	200 hPa zonal (u) component of wind	-0.6 m/s
REFC	200 hPa relative eddy angular momentum flux convergence	0.9 m/s/day
PSLV	Pressure of the center of mass of layer for which the environmental winds best match the current storm motion.	583.4 hPa

The two datasets are merged based on the methodologies described in KD03 and YTM07. As in KD03, 11 independent predictors from the original 34 attributes were selected. These predictors are chosen because KD03 found that the mean initial conditions of these predictors for RI cases and non-RI cases are statistically different at least at the 95% significance level based on an unequal-variance, two-sided t test. In this work, the predictor (condition) set is limited to the 11 variables. To mine those attributes with the association rule algorithm, the continuous values of the attributes are converted into disjoint conditions, "High" or "Low" ranges. The initial threshold values are chosen to be the same as those provided in KD03, which was derived from the mean values of the RI samples [KD03]. Table 1 lists the predictors with the abbreviation names and the threshold values.

After the merging and discretizing process, one has 22 predictors (11 parameters with 2 value ranges) associated with each TC case at every 6h. The TCs are categorized into either rapidly intensifying cases (RI) or non-rapidly intensifying cases (non-RI) based on the RI definition proposed in KD03; at least 30 knots of intensity increase in 24 hours. The data sets are also cleansed by removing items with missing values. After the cleansing, there are a total of 5505 valid records with 265 RI cases for this study.

KD03 uses only SHIPS data from 1989 to 2000. Since we have more data from 1982 to 2003, we divided the data into 3 subsets: 1989-2000, 1982-1988, and 2001-2003, and include the three sub-periods and the whole period in the study, as in YTM07.

2.2. Association Rule Algorithm

An association rule, first defined for market basket analysis, is a rule like "Z <= X, Y," where items X and Y are called antecedents in the rule and Z is the consequent [Agrawal et al., 1993]. This rule expresses an association between items X, Y, and Z. It states that if a customer is picked randomly and the customer selected items X and Y, it is likely that the customer also selected item Z. The number of antecedents can range from one to the total number of items in a database.

For data mining with the 11 selected predictors and the "high" and "low" value divisions, the antecedents in this case are the 22 input features (11 variables with the "high" and "low" discretized values) and the consequent is "the TC underwent RI." Therefore a closed frequent condition set containing "RI" and other persistent and synoptic attributes indicates an association among these attributes and the future rapid intensification.

There are several parameters that measure the strength of an association rule. The most widely used parameters are support, which estimates the probability $P(\{X,Y,Z\})$, confidence, which estimates the probability $P(Z|\{X, Y\})$, and lift (Silverstein et al. 1998), which measures the strength of a rule defined as the ratio between the actual probability of the item set containing both the antecedent set and the consequent divided by the product of the individual probabilities of the antecedent set and the consequent, $P(\{X,Y,Z\})/[P(\{X,Y\})*P(Z)]$. An association rule is strong if it has a large support, a high confidence and a large lift.

The version of the association rule algorithm we used in this study is implemented by Borgelt [2008]. The support value in this implementation is defined as $P(\{X,Y\})$ instead of $P(\{X,Y,Z\})$, and this definition $P(\{X,Y\})$ is the same as those used in KD03 for description. Based on the definition above, one can tell that the confidence is actually the RI probability (RIP) corresponding to the selected conditions.

3. RESULTS AND DISCUSSION

As discussed above, the objective of this work is to identify the highest RI probability when the number of factors is fixed with a set of selected factors. Figure 1 shows the changes in highest RI probabilities with the number of the thresholds in the 22 predictor pool for different time periods. All data demonstrated the same trend: the highest RIP increases with the numbers of predictors initially but reaches the peak values when the number of predictors approaches five to seven (N=5-7). The highest RIP then decreases with further increases of the numbers of predictors. These results demonstrate that the multiple factors together are responsible for the RI process of TCs. However, the number of factors will saturate at certain numbers. After that, the impacts of individual factors may cancel each other out, or may be replaced by other factors.

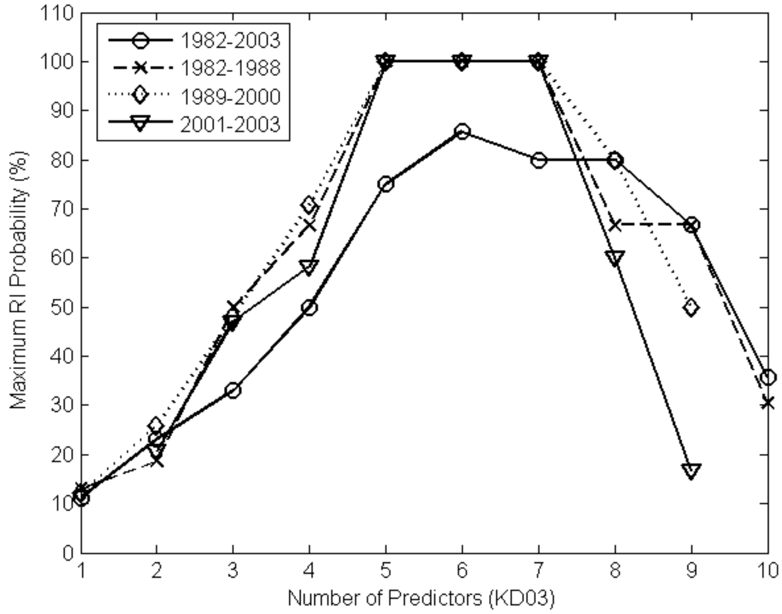

Figure 1. The highest RI probability for different number of thresholds and multiple time periods.

The most striking result in Figure 1 is that the data mining algorithms identify certain cases with a 100% RI probability. These "perfect" results take place only for the three specific subset periods but not for the whole period. This plausible result comes from the fact that the detailed "optimal" conditions for each subset period are different from each other, and as a result, the conditions and the RI probability for the whole time period are also different from those in individual time periods. For example, Table 2 lists the detailed conditions for the N=6 cases for different time periods. By carefully checking, one can see that no two groups give the same conditions although the RIP (confidence) is 100% for all three short periods.

Table 2. Optimal conditions when N=6 for different time periods. The numbers in parenthesis are the corresponding support and confidence values.

Periods	**Detailed Conditions for N=6**
1982-2003	LON=L,REFC=L,PD12=H,LAT=H,POT=H,PSLV=H (0.1, 85.7)
1982-1988	PD12=L,LAT=L,USTM=L,POT=L,SHRD=L,RHLO=H (0.2, 100.0)
1989-2000	POT=L,SHRD=L,PD12=H,USTM=H,RHLO=H,PSLV=H (0.2, 100.0)
2001-2003	PD12=L,LAT=L,POT=L,U200=L,SST=H,REFC=H (0.2, 100.0)

As in YTK07, the RIP variation with the number of predictors in a given group for the N=6 case is plotted in Figure 2. In this plot, the "optimal" conditions mined for the 1989-2000 time period is chosen. The relatively low RIP values for up to five predictors further demonstrated that the predictor combinations for optimal conditions for a given number of predictors change with the number. In addition, the results are sensitive to the subset periods as the RIP diversifies when all conditions are satisfied, from zero to 100%. Moreover, the case numbers are relatively small as shown by the support values in Table 2. Actually, the RI cases and the total cases satisfying all conditions for Figure 2 are 1/3 (1 RI cases in total of 3 cases) for the 1982-1988 sub-period, 7/7 for 1989-2000, 0/4 for the 2001-2003, and 8/14 for the whole time period, 1982-2003. To increase the confidence of the data mining results, we will focus on the results for the whole time period, 1982-2003, in which we have a total of 265 RI cases out of 5505 TC cases (YTK07), in the following sections.

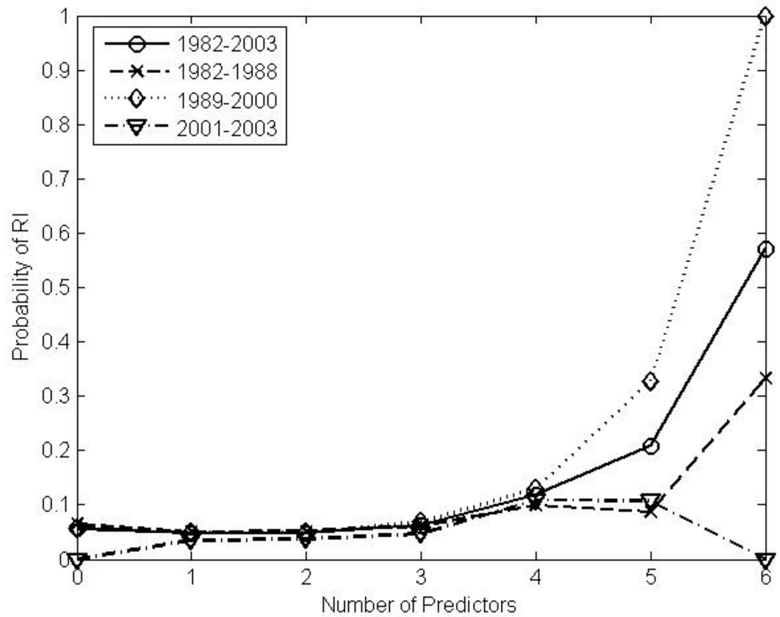

Figure 2. The RIP variation with number of threshold values chosen from the set which gives the highest RIP (100%) when all (N=6) are satisfied for the 1989-2000 time period. That is, the condition set is (PD12=L, LAT=L, USTM=L, POT=L, SHRD=L, RHLO=H), as given in Table 2.

Table 3 lists the optimal conditions for different numbers of thresholds (N) for the 1982-2003 period along with the RIP and support values. The RIP is also plotted in Figure 3 as the dashed line. By carefully studying the condition combination in Table 3, one may find that new conditions are simply added to the existing conditions to achieve the optimal condition combination when the number increases from one to three. In other words, when only one condition is satisfied, “PD12=H” gives the highest RIP. The optimal condition combination with N=2 is “PD12=H” and “SHRD=L,” and then adding “RHLO=H” gives the optimal conditions for N=3. This result shows that there exist dominant factors for RI process, and when they take effects together, the chances of RI is significantly higher.

Table 3. The “optimal” condition combination for the highest RI probabilities for the 1982-2003 period.

N	RIP	Conditions											Support
1	11.1			PD12=H									23.2
2	23.1			PD12=H					SHRD=L				6.5
3	33			PD12=H				RHLO=H	SHRD=L				1.7
4	50	LAT=L			POT=L				SHRD=L			USTM=H	0.4
5	75	LAT=L			POT=L	PSLV=H			SHRD=L			USTM=H	0.2
6	85.7	LAT=H	LON=L	PD12=H	POT=H	PSLV=H	REFC=L						0.1
7	80			PD12=H	POT=L	PSLV=H		RHLO=H	SHRD=L	SST=H		USTM=H	0.2
8	80	LAT=L	LON=H	PD12=H	POT=L	PSLV=H	REFC=L			SST=H		USTM=H	0.2
9	66.7	LAT=L		PD12=H	POT=H	PSLV=L	REFC=H	RHLO=L	SHRD=H	SST=H	U200=L		0.1
10	35.7	LAT=H	LON=H	PD12=L	POT=H	PSLV=L	REFC=L		SHRD=L	SST=H	U200=L	USTM=L	0.3

However, this incremental feature is not valid when N increases from three to four. Suddenly, the conditions reshuffle, and only "SHRD=L" remains in the new combination with N=4. In the mean time, the support (related to the case number) drops to quite a small number when compared with the corresponding values for cases with N=1-3. When the cases change from N=4 to N=5, the incremental feature reappears by adding "PSLV=H." But conditions reshuffle again when the cases change from N=5 to N=6.

As shown in Figure 3, when N increases from 6 to 7 and further, the RIP starts decreasing and the condition combinations listed in Table 3 show more changes in either parameters or parameter value ranges. Therefore, it is difficult to expect the combinations with large numbers of conditions (N>6) give much physical explanation to the TC intensification physics. As a result, the discussion in this paper is limited for up to six conditions (N=6), which also gives the highest RIP in all situations.

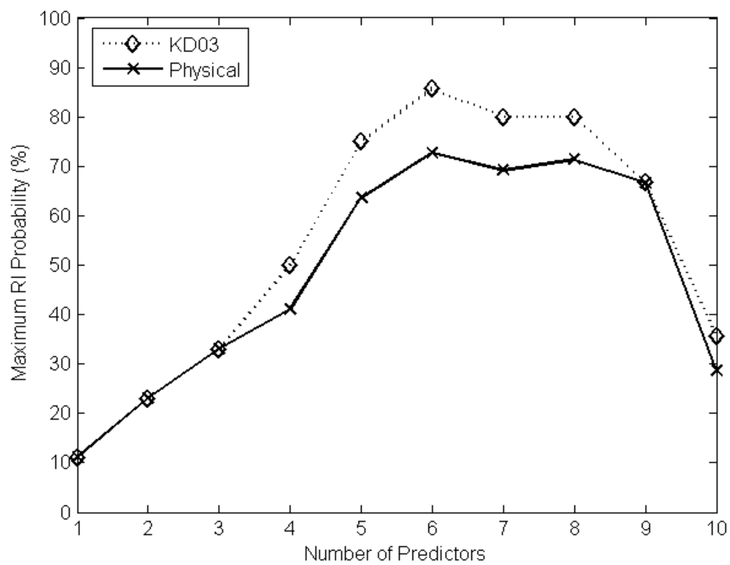

Figure 3. The highest RIP for different sets of thresholds.

Although the confidences of the mined rules or the RIP are high for most conditions as listed in Table 3, the supports or the case numbers are relatively low. For the highest RIP, 85.7% when six predictors are working together, we only have a 0.1% support or exactly seven cases satisfying the conditions, and six of them underwent RI. For all other cases with high RIP (>75%), the case number is at least ten.

The low support (sample size) for the highest RIP leads one to suspect the usefulness of mined results, or the representation of a general rule. To see if the result is of general value, we trace back the seven cases to the original data to identify the corresponding TC cases.

The seven cases are actually from four TCs as shown in Table 4. The cases for the same TCs at different times, i.e., for Hurricane Nana at 0h and 6h of October 17, 1990 and Hurricane Clau at 18h of September 5, 1991 and at 0h and 6h of September 6, 1991, took place in consecutive times. Therefore, it is expected that the conditions at the given time spans did not change much. The only case in which the TC did not undergo a RI process is the case for Hurricane Karl at 0h on September 24, 1998. However, the intensity of Karl increased from 35 knots to 50 knots in 24 hours and then to 75 knots in another 24 hours. Karl continued the intensification process after that until 0h on September 27 at 90 knots. Therefore, it is quite reasonable to say that the six conditions together are favorable to RI process in almost all cases. The fact that relatively large numbers of diversified TCs underwent RI when the above given conditions (the six predictor combination) were satisfied and the extreme high RIP lead us to believe that the results from data mining are significant. The results shed light for guiding future forecasting of RI processes.

Table 4. Specific TC cases satisfying the given condition combination (the case with N=6 in Table 3.)

TC Name	Year	Date	Hour
EARL	1986	9/11	6
NANA	1990	10/17	0
NANA	1990	10/17	6
CLAU	1991	9/5	18
CLAU	1991	9/6	0
CLAU	1991	9/6	6
KARL	1998	9/24	0

As discussed before, another interesting result is the dramatic condition changes from N=5 to N=6 as shown in Table 3. The condition shift is not only on the affecting parameters, but also on the value ranges associated with specific parameters. Up to N=5, “LAT=L” and “POT=L” are favorable conditions for RI process. However, when N=6, the opposite values, i.e., “LAT=H” and “POT=H” are favorable to the RI process. Physically, it is difficult to explain the role of latitude in TC intensification in general and its role is indirectly reflected in the SHIPS model [DeMaria and Kaplan, 1999]. For POT, “POT=H” should be the reasonable condition for TC intensification because the higher the gap between the current intensity and the maximum potential intensity, the more likely the TC intensifies. Then, why does the POT value range change from one optimal condition to the other? The most likely reason is that the results are sensitive to the threshold value dividing the “High” and “Low” values of POT.

In the data discretization process, the threshold value for POT is 47.7 m/s based on KD03. However, since RI is defined by a 30 knot (about 15 m/s) wind increase in 24 hours, a more logical threshold for POT should be 15 m/s. Therefore, with the same threshold values for other parameters except POT, the above data mining procedure is repeated to reveal the impact by changing the POT threshold value from 47.7m/s (KD03) to 15.0m/s (physical).

The results with the “physical” threshold values are shown in Figure 3 as the solid line and in Table 5. Clearly, there is no difference in the results for N=1-3 with either the KD03 thresholds or the physical thresholds. For N>3 cases, the largest RIP with the KD03 thresholds are higher than the corresponding values with the physical thresholds except for the case N=9. The overall trends of the RIP variation with N are the same, too. The detailed conditions in Table 5 show that POT=H is not an important factor for the RI process when the physical threshold value is used. This is because the POT values are in the high range for most cases when the lower physical POT threshold is used. This result and the result based on KD03 thresholds suggest that neither of the threshold values for POT is optimal, and a value between those two could give better results.

Table 5. The “optimal” condition combination for the highest RI probabilities for the 1982-2003 period with the physical threshold values.

N	RIP	Conditions											support
1	11.1			PD12=H									23.2
2	23.1			PD12=H					SHRD=L				6.5
3	33			PD12=H				RHLO=H	SHRD=L				1.7
4	41	LAT=L		PD12=H					SHRD=L			USTM=H	0.7
5	63.6			PD12=H		PSLV=L		RHLO=H	SHRD=L	SST=L			0.2
6	72.7	LAT=L		PD12=H		PSLV=H		RHLO=H			U200=L	USTM=H	0.2
7	69.2			PD12=H		PSLV=H	REFC=L		SHRD=L	SST=H	U200=L	USTM=H	0.2
8	71.4	LAT=H	LON=L	PD12=H	POT=H	PSLV=H	REFC=L			SST=H	U200=L		0.1
9	66.7	LAT=L	LON=H			PSLV=L	REFC=L	RHLO=L	SHRD=H	SST=H	U200=L	USTM=L	0.1
10	28.6	LAT=H	LON=L		POT=H	PSLV=H	REFC=L	RHLO=L	SHRD=H	SST=H	U200=H	USTM=H	0.3

4. DISCUSSION AND CONCLUSIONS

Since the association data mining technique provides an as complete as possible picture of the relevant dataset, this technique helps us to identify the combination of conditions most favorable to RI development among many factors affecting the RI processes of TCs. One mined condition combination giving the highest RIP for the whole data set covering 1980-2003 time period is (PD12=L, LAT=L, USTM=L, POT=L, SHRD=L, RHLO=H). Although the RIP is not a perfect 100%, the detailed information found by tracing back to individual TCs shows that the condition combination can be considered as a sufficient condition for the RI process. More physical studies should be carried out to investigate the complicated interactions among those favorable conditions.

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