CML for RI

The Development of a Consensus Machine Learning Model for Hurricane Rapid Intensification Forecasts with HWRF Data

Mu-Chieh “Laura” Ko[1,2,3], Xiaomin Chen[2,4], Miroslav Kubat[3], and Sundararaman Gopalakrishnan[2]

1 Cooperative Institute for Marine and Atmospheric Studies, University of Miami
2 NOAA/OAR/Atlantic Oceanographic and Meteorological Laboratory
3 Electrical and Computer Engineering, University of Miami
4 Northern Gulf Institute, Mississippi State University, Stennis Space Center

Abstract

This study focuses on developing a consensus machine learning model (CML) model for tropical cyclone (TC) intensity probabilistic forecasting, especially for rapid intensification (RI). This CML model is built based on six classical machine learning models with the input data extracted from a high-resolution hurricane model, the Weather Research and Forecasting (HWRF) system. The input data contains 20 to 34 RI-related predictors extracted from the 2018 version of HWRF (H218). This study found that TC inner-core predictors can be critical for improved RI predictions. Inner-core relative humidity is identified as one of the most influential predictors in our input dataset. Moreover, the importance of performing resampling on an imbalanced input dataset is also emphasized in this paper. Edited Nearest Neighbor and Synthetic Minority Oversampling Technique used for resampling can improve Probability of Detection (POD) by about 10% for the RI class. This paper also shows that the CML model built based on the rebalanced input data has satisfactory performance on RI predictions. CML can reach about 47% POD but with less than 50% false alarm ratio (FAR), while the HWRF system had only 15% POD and 40% FAR. The CML model was further tested with the HWRF data from 2019. The performance was slightly degraded compared to the results with H218, possibly due to limited training data. The results indicate that, with proper and sufficient training data, CML has the potential to provide reliable probabilistic RI forecasts during a hurricane season.

Abstract

This study focuses on developing a consensus machine learning model (CML) model for tropical cyclone (TC) intensity probabilistic forecasting, especially for rapid intensification (RI). This CML model is built **based on six classical machine learning models** with the input data extracted from a high-resolution hurricane model, the Weather Research and Forecasting (HWRF) system. The input data contains **20 to 34 RI-related predictors extracted from the 2018 version of HWRF (H218).** This study found that TC inner-core predictors can be critical for improved RI predictions. Inner-core relative humidity is identified as one of the most influential predictors in our input dataset. Moreover, the importance of performing resampling on an imbalanced input dataset is also emphasized in this paper. Edited Nearest Neighbor and Synthetic Minority Oversampling Technique used for resampling can improve Probability of Detection (POD) by about 10% for the RI class. This paper also shows that the CML model built based on the rebalanced input data has satisfactory performance on RI predictions. CML can reach about 47% POD but with less than 50% false alarm ratio (FAR), while the HWRF system had only 15% POD and 40% FAR. The CML model was further tested with the HWRF data from 2019. The performance was slightly degraded compared to the results with H218, possibly due to limited training data. The results indicate that, with proper and sufficient training data, CML has the potential to provide reliable probabilistic RI forecasts during a hurricane season.

Abstract

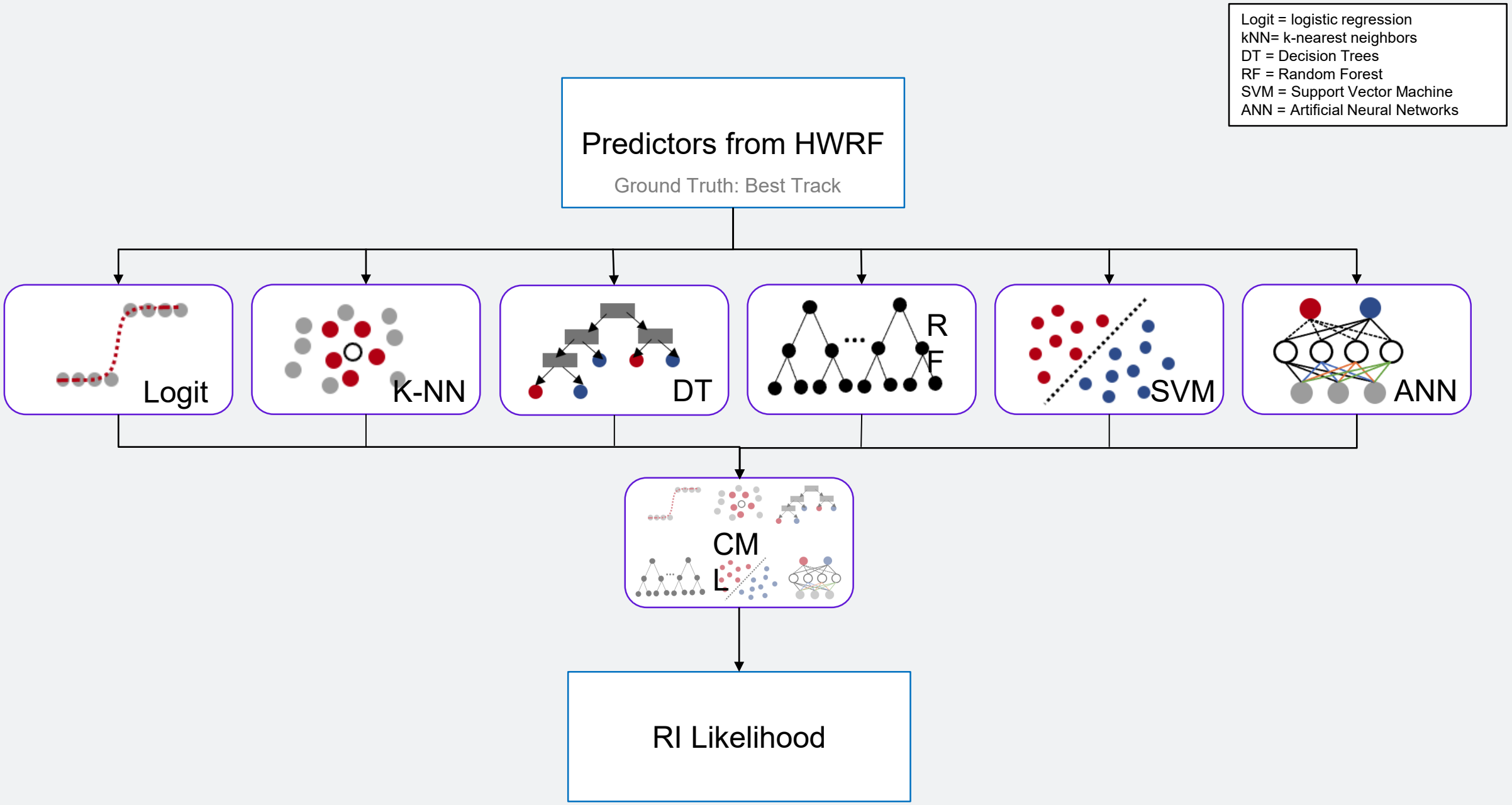
This study focuses on developing a consensus machine learning model (CML) model for tropical cyclone (TC) intensity probabilistic forecasting, especially for rapid intensification (RI). This CML model is built **based on six classical machine learning models** with the input data extracted from a high-resolution hurricane model, the Weather Research and Forecasting (HWRF) system. The input data contains **20 to 34 RI-related predictors extracted from the 2018 version of HWRF (H218).** This study found that TC **inner-core predictors can be critical** for improved RI predictions. Inner-core relative humidity is identified as one of the most influential predictors in our input dataset. Moreover, the importance of performing resampling on an imbalanced input dataset is also emphasized in this paper. Edited Nearest Neighbor and Synthetic Minority Oversampling Technique used for resampling can improve Probability of Detection (POD) by about 10% for the RI class. This paper also shows that the CML model built based on the rebalanced input data has satisfactory performance on RI predictions. CML can reach about 47% POD but with less than 50% false alarm ratio (FAR), while the HWRF system had only 15% POD and 40% FAR. The CML model was further tested with the HWRF data from 2019. The performance was slightly degraded compared to the results with H218, possibly due to limited training data. The results indicate that, with proper and sufficient training data, CML has the potential to provide reliable probabilistic RI forecasts during a hurricane season.

Abstract

This study focuses on developing a consensus machine learning model (CML) model for tropical cyclone (TC) intensity probabilistic forecasting, especially for rapid intensification (RI). This CML model is built **based on six classical machine learning models** with the input data extracted from a high-resolution hurricane model, the Weather Research and Forecasting (HWRF) system. The input data contains **20 to 34 RI-related predictors extracted from the 2018 version of HWRF (H218).** This study found that TC **inner-core predictors can be critical** for improved RI predictions. Inner-core relative humidity is identified as one of the most influential predictors in our input dataset. Moreover, the importance of performing **resampling** on an imbalanced input dataset is also emphasized in this paper. Edited Nearest Neighbor and Synthetic Minority Oversampling Technique used for resampling can improve Probability of Detection (POD) by about 10% for the RI class. This paper also shows that the CML model built based on the rebalanced input data has satisfactory performance on RI predictions. CML can reach about 47% POD but with less than 50% false alarm ratio (FAR), while the HWRF system had only 15% POD and 40% FAR. The CML model was further tested with the HWRF data from 2019. The performance was slightly degraded compared to the results with H218, possibly due to limited training data. The results indicate that, with proper and sufficient training data, CML has the potential to provide reliable probabilistic RI forecasts during a hurricane season.

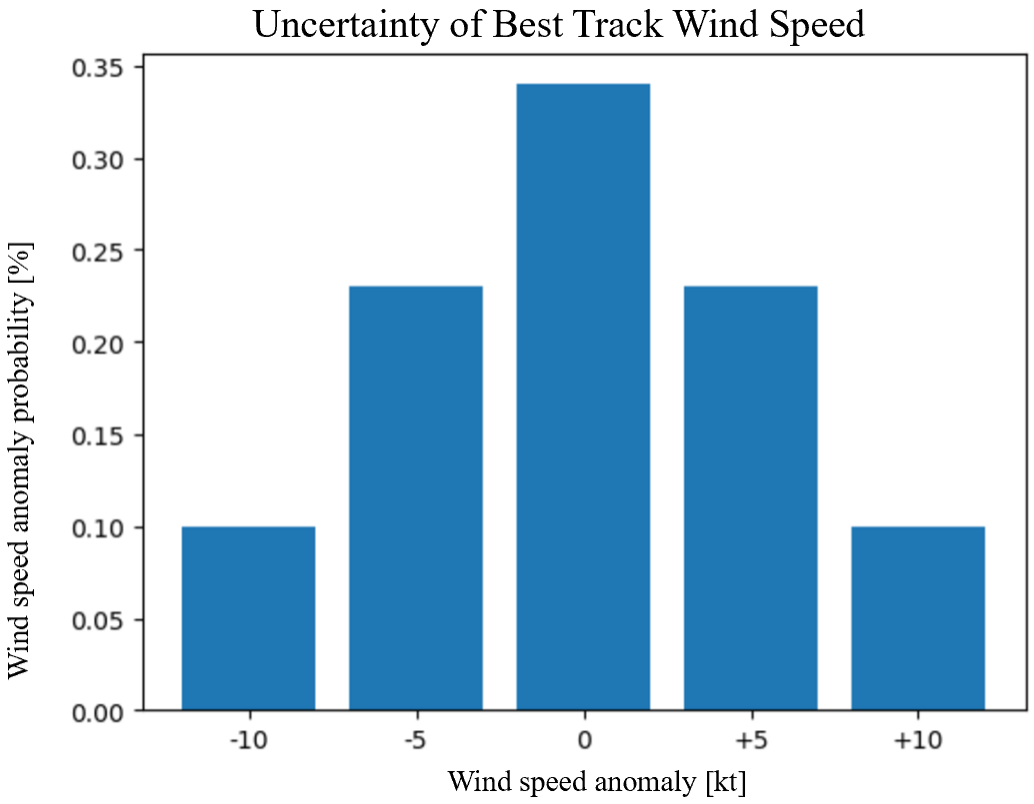
Abstract

This study focuses on developing a consensus machine learning model (CML) model for tropical cyclone (TC) intensity probabilistic forecasting, especially for rapid intensification (RI). This CML model is built **based on six classical machine learning models** with the input data extracted from a high-resolution hurricane model, the Weather Research and Forecasting (HWRF) system. The input data contains **20 to 34 RI-related predictors extracted from the 2018 version of HWRF (H218).** This study found that TC **inner-core predictors can be critical** for improved RI predictions. Inner-core relative humidity is identified as one of the most influential predictors in our input dataset. Moreover, the importance of performing **resampling** on an imbalanced input dataset is also emphasized in this paper. Edited Nearest Neighbor and Synthetic Minority Oversampling Technique used for resampling can improve Probability of Detection (POD) by about 10% for the RI class. This paper also shows that the CML model built based on the rebalanced input data has satisfactory performance on RI predictions. **CML can reach about 47% POD but with less than 50% false alarm ratio (FAR)**, while the HWRF system had only 15% POD and 40% FAR. The CML model was further tested with the HWRF data from 2019. The performance was slightly degraded compared to the results with H218, possibly due to limited training data. The results indicate that, with proper and sufficient training data, CML has the potential to provide reliable probabilistic RI forecasts during a hurricane season.


Logit = logistic regression
kNN= k-nearest neighbors
DT = Decision Trees
RF = Random Forest
SVM = Support Vector Machine
ANN = Artificial Neural Networks
Predictors from HWRF
Ground Truth: Best Track
Logit
K-NN
DT
RF
SVM
ANN
CML
RI Likelihood

Best Track Uncertainty

- Based on Torn and Snyder (2012), best track has uncertainty on the wind speed values
- We use this uncertainty to create the probability ground truth for wind speed change profiles
- 30-kt intensity changes:
  [W, N, I, RI] = [0, 0, 0.33, 0.67]



CLAT	Shear S	CAPE up Shear	Land
CLON	Shdir S	CAPE down Shear	D200
dINT12	Shdir M	HLCY up Shear Helicity	C850
RMW	Shear D	HLCY down Shear Helicity	dTemp 500hPa warm core
SST	Shdir D	RH 750-500	WV#1 Wind field

SHX	Ro Rossby Number	INRH 900-400
LHX	MSE	INRH up shear
CB Convective bursts	Tilt	PS Precip symmetricity
POT	RH 850-700	Shear M
dTemp 350hPa warm core	RH 500-300	

Inner-core features

Experiment 1: 20 features from f000
Experiment 2: 20 features from f006
Experiment 3: 34 features from f006

Inner-core Feature

- Inner-core RH (INRH)

AGU100 ADVANCING EARTH AND SPACE SCIENCE

Geophysical Research Letters

RESEARCH LETTER
10.1029/2019GL083667

Key Points:
- The nearly saturated lower-middle troposphere in the inner core region precedes the tropical cyclone (TC) rapid intensification in shear
- The moistening of the inner core region is achieved by a competition between surface heat fluxes, radiation, and ventilation effects
- Vortex alignment benefits the moistening of the TC inner core by reducing ventilation effect

Supporting Information:
- Supporting Information S1

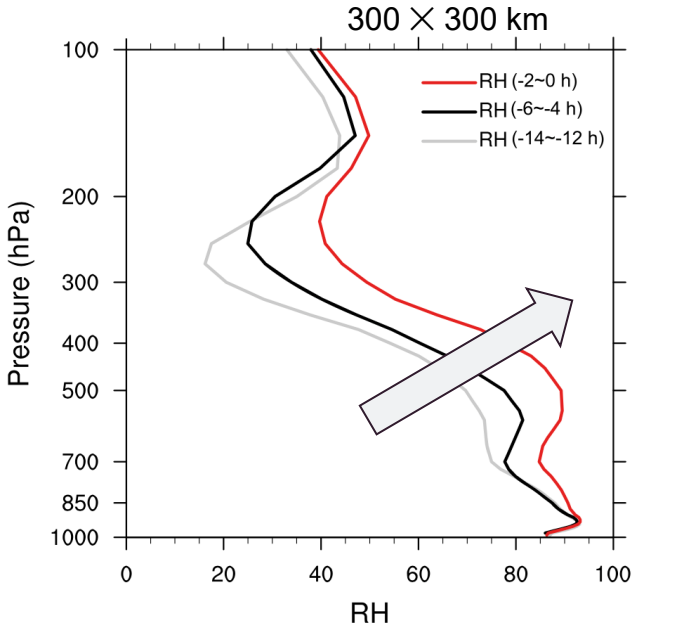
Correspondence to:
X. Chen,
xiaomin.chen@noaa.gov

A Thermodynamic Pathway Leading to Rapid Intensification of Tropical Cyclones in Shear

Xiaomin Chen[1], Jun A. Zhang[1,2], and Frank D. Marks[1]

[1]NOAA/AOML Hurricane Research Division, Miami, FL, USA, [2]Cooperative Institute for Marine and Atmospheric Studies, University of Miami, Miami, FL, USA

Abstract Understanding physical processes leading to rapid intensification (RI) of tropical cyclones (TCs) under environmental vertical wind shear is key to improving TC intensity forecasts. This study analyzes the thermodynamic processes that help saturate the TC inner core before RI onset using a column-integrated moist static energy (MSE) framework. Results indicate that the nearly saturated inner core in the lower-middle troposphere is achieved by an increase in the column-integrated MSE, as column water vapor accumulates while the mean column temperature cools. The sign of the column-integrated MSE tendency depends on the competition between surface enthalpy fluxes, radiation, and vertical wind shear-induced ventilation effect. The reduction of ventilation above the boundary layer due to vertical alignment is crucial to accumulate the energy within the inner core region. A comparison of the RI simulation with a null simulation further highlights the impact of vortex structure on the thermodynamic state adjustment and TC intensification.

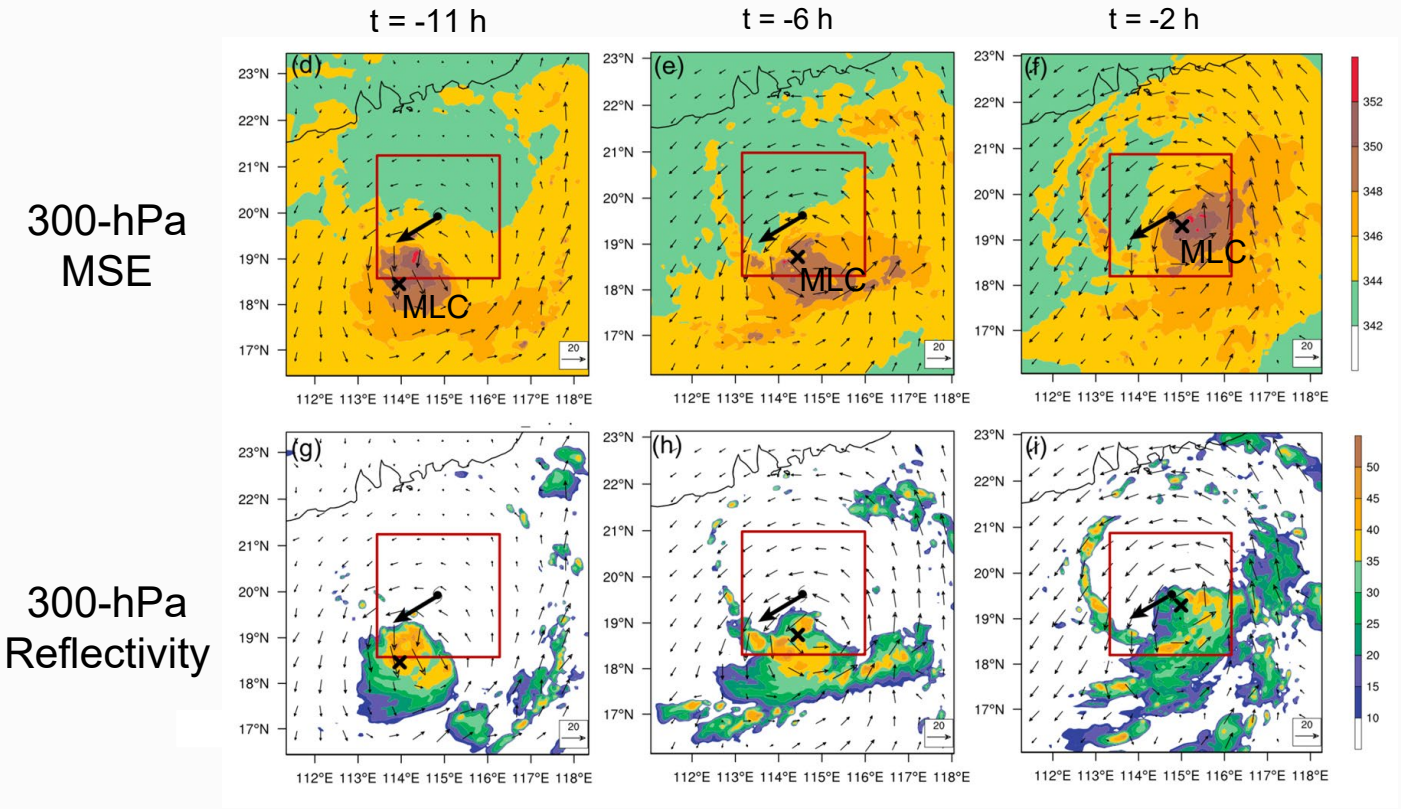


- The formation of a nearly-saturated mesoscale core is an important precondition for RI onset **(X. Chen et al. 2019)**

Inner-core Feature

- MSE
- Tilt

(X. Chen et al. 2019)



- Under vertical wind shear, a nearly-saturated core forms when mid-level moisture (high-MSE region) is aligned with low-level circulation.

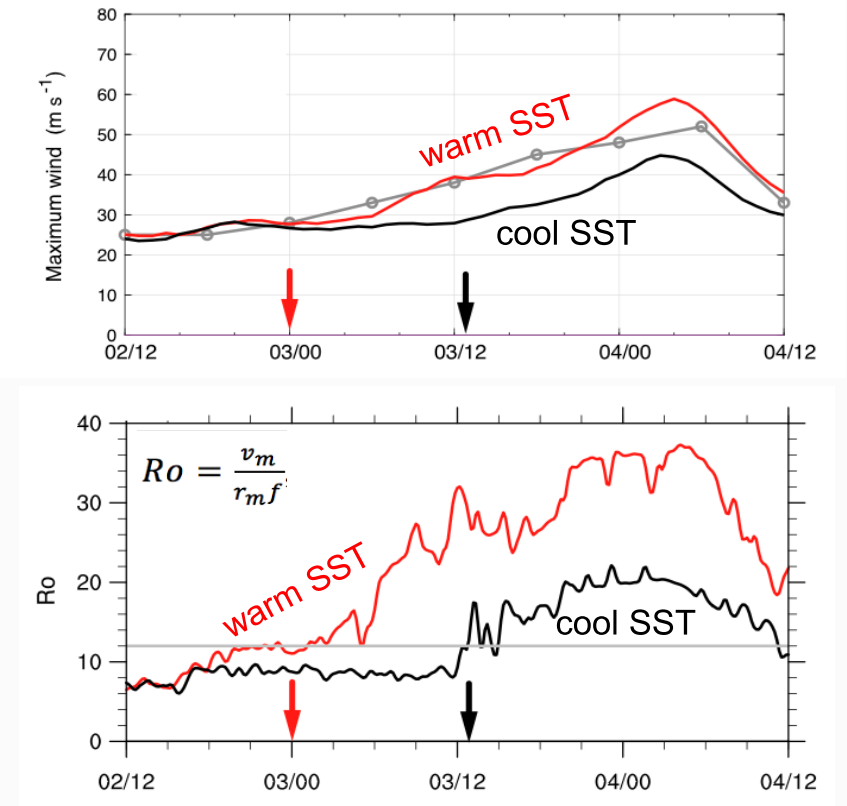
- The increase of column-integrated MSE precedes RI onset.

Inner-core Feature

- Local Rossby number (Ro)

(X. Chen et al. 2018, 2021, JAS)

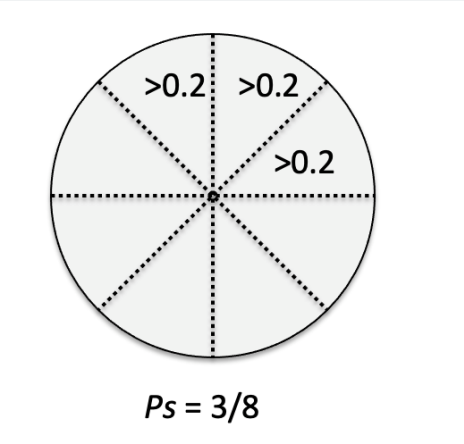
RI onset timing differs with different SSTs



- Effective RI indicator for all experiments: R_0>12 (near surface), i.e., the formation of a compact/strong inner-core

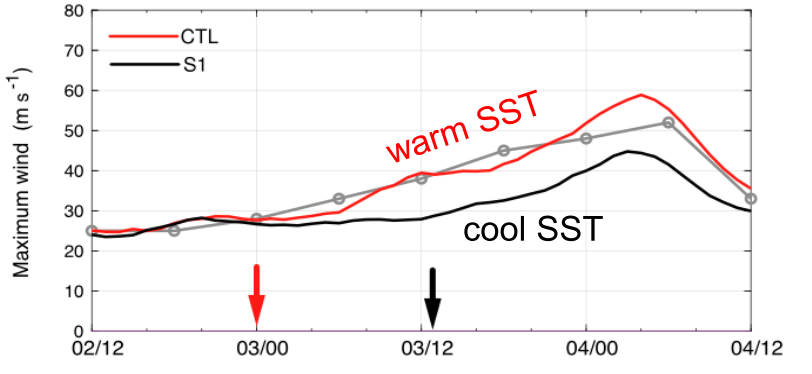
Inner-core Feature

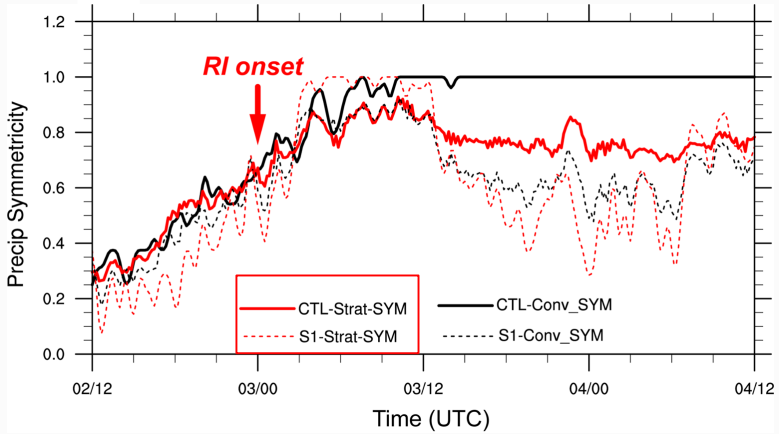
- Precipitation symmetricity (PS)



(X. Chen et al. 2018, 2021, JAS)

RI onset timing differs with different SSTs





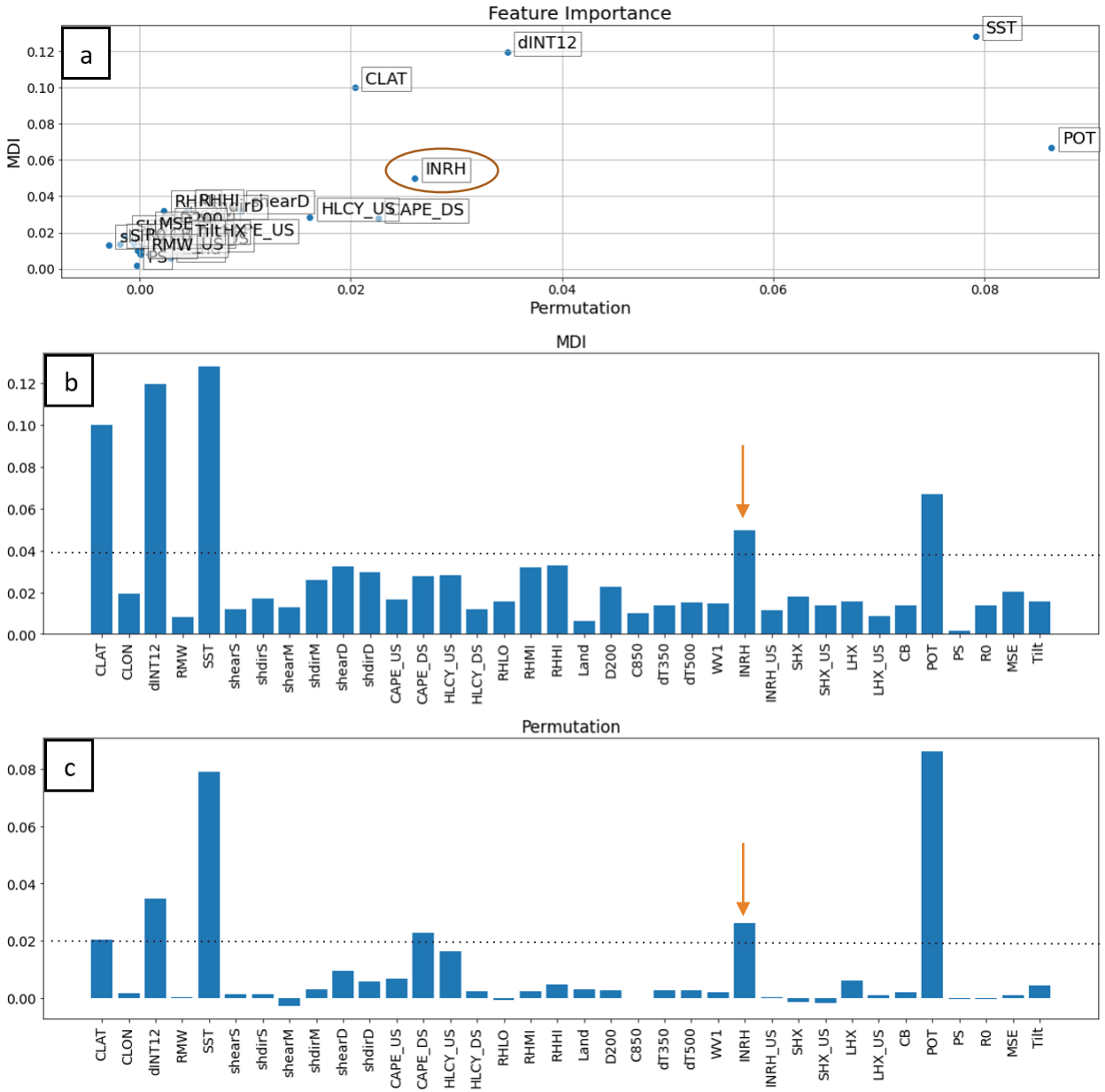
solid: warm SST
dash: cool SST

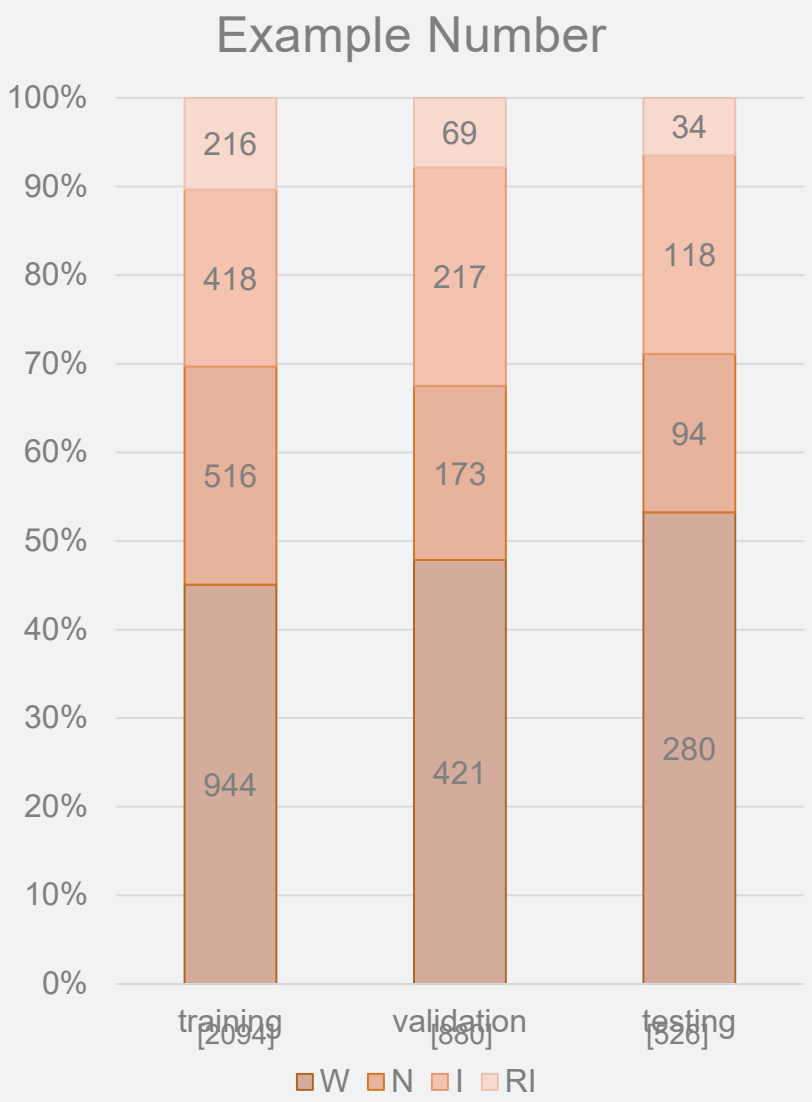
Red: stratiform precip symmetricity

- Early-RI TCs have notably higher symmetricity of stratiform precipitation (~0.2) than late-RI TCs.
- For simplicity, we use the surface rain rate (0.5 mm/hr) as a proxy in this study.

Feature Importance

- SST
- POT
- dINT12
- CLAT
- INRH

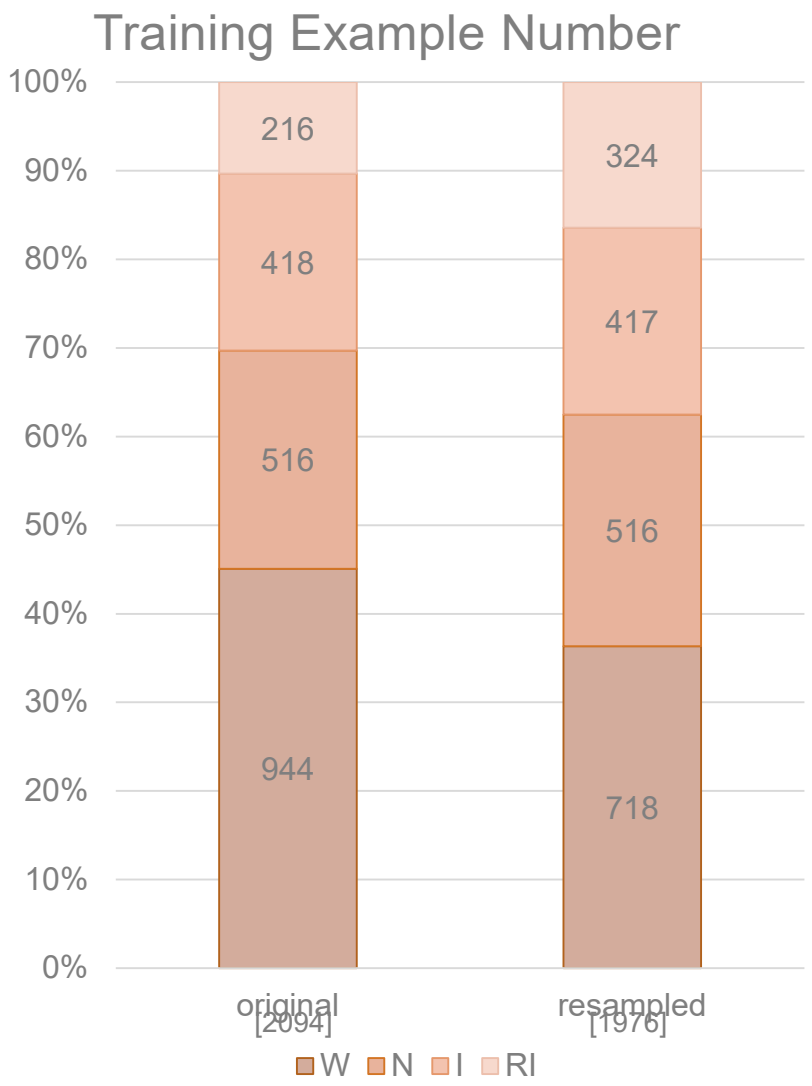



Example Number
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
216
418
516
944
69
217
173
421
34
118
94
280
training
[2094]
validation
[880]
testing
[526]
W
N
I
RI

Input data

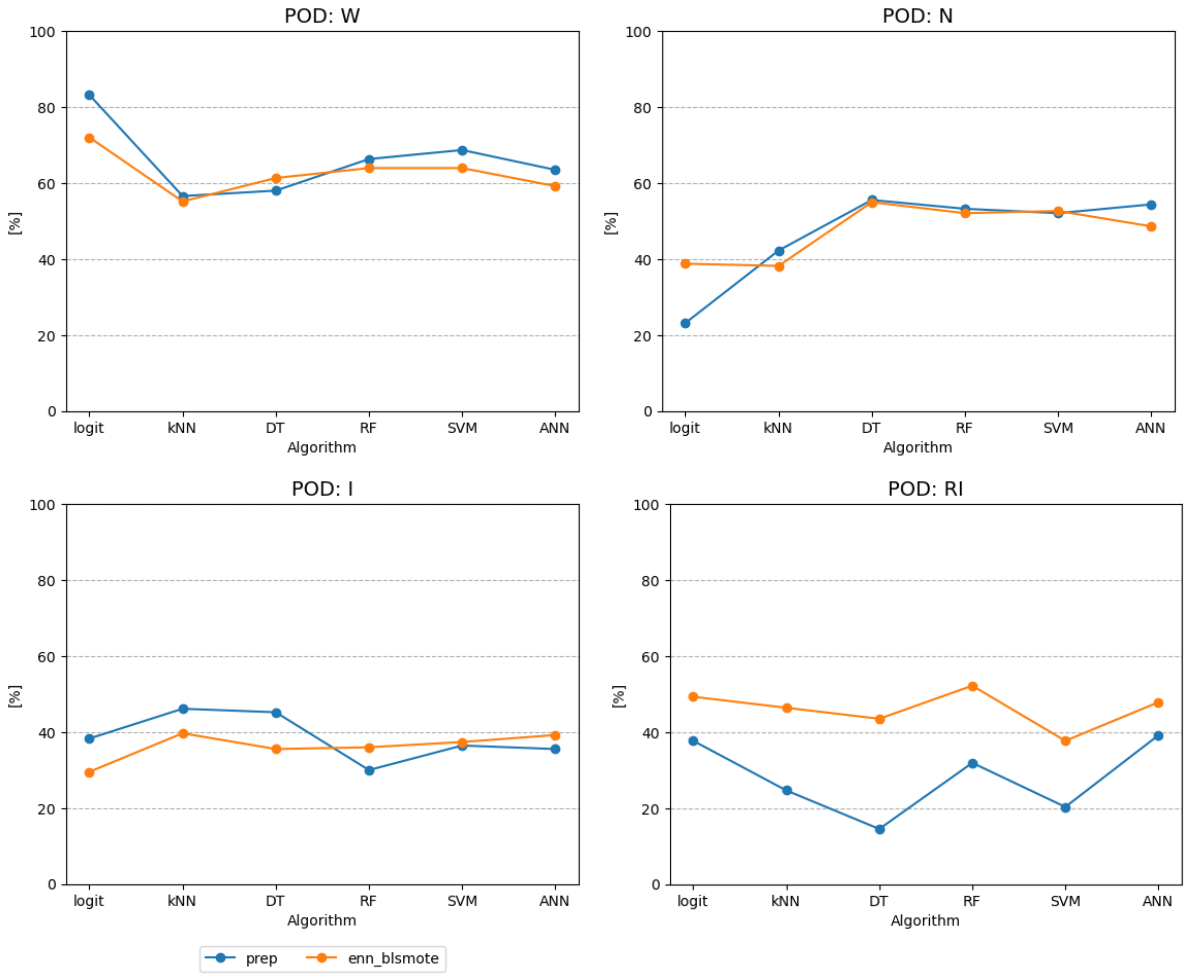
Resampling

- Resampling is important for imbalanced-class problem
- Edited Nearest Neighbor to undersample (Silson 1972)
  use 5-NN to detect data noise in the majority set (def: 3+ NNs are from different classes)
- Boulder-line SMOTE to upsample (Han et al. 2005)
  use 10-NN to detect boulderline samples (def: 6-9 NNs are from the majority set), and 5-NN in the minority set to create synthetic data



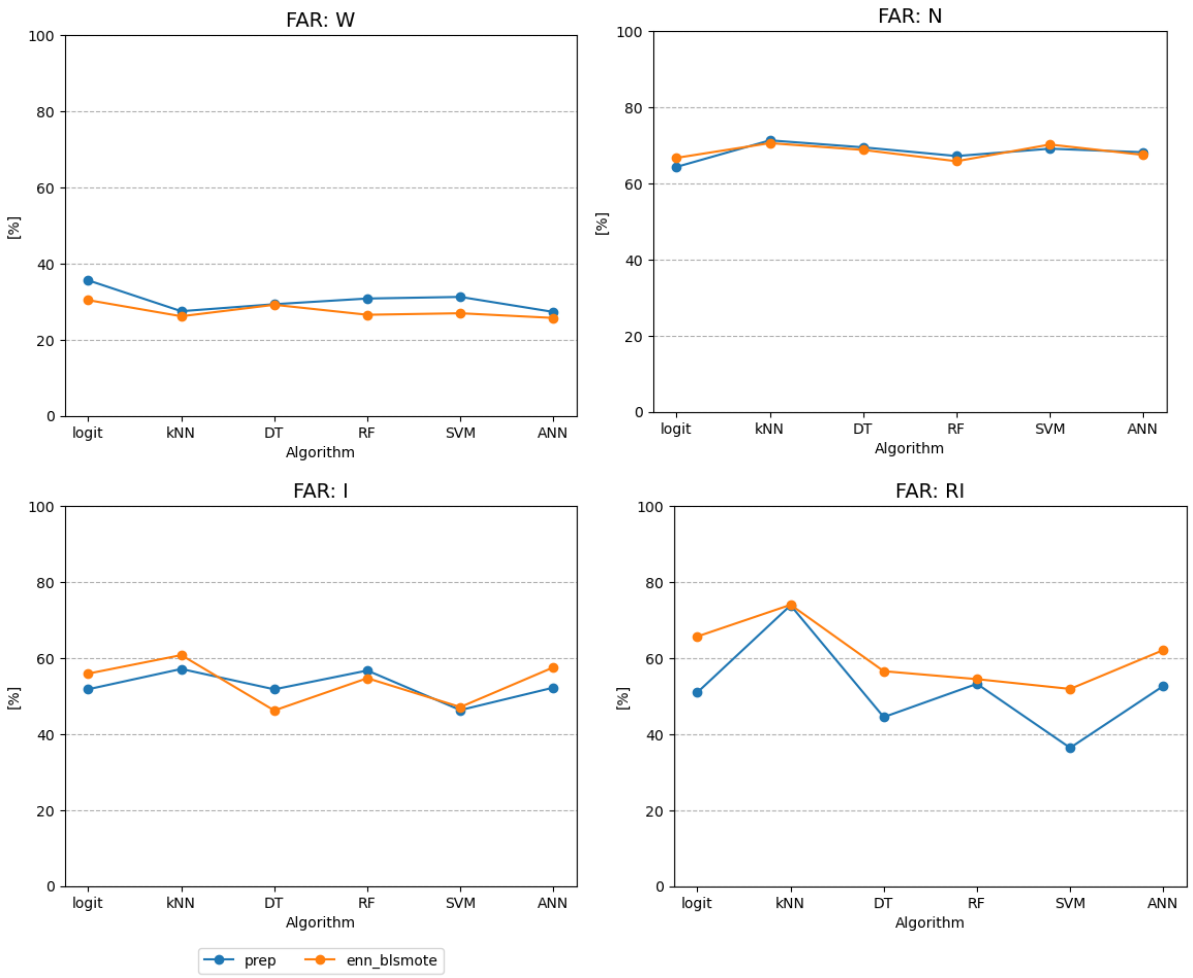
Resampling

- Resampling is important for imbalanced-class problem
- Edited Nearest Neighbor to undersample (Silson 1972)
  use 5-NN to detect data noise in the majority set (def: 3+ NNs are from different classes)
- Boulder-line SMOTE to upsample (Han et al. 2005)
  use 10-NN to detect boulderline samples (def: 6-9 NNs are from the majority set), and 5-NN in the minority set to create synthetic data
- Rebalancing the dataset increase the performance on predicting RI



Resampling

- Resampling is important for imbalanced-class problem
- Edited Nearest Neighbor to undersample (Silson 1972)
  use 5-NN to detect data noise in the majority set (def: 3+ NNs are from different classes)
- Boulder-line SMOTE to upsample (Han et al. 2005)
  use 10-NN to detect boulderline samples (def: 6-9 NNs are from the majority set), and 5-NN in the minority set to create synthetic data
- Rebalancing the dataset increase the performance on predicting RI



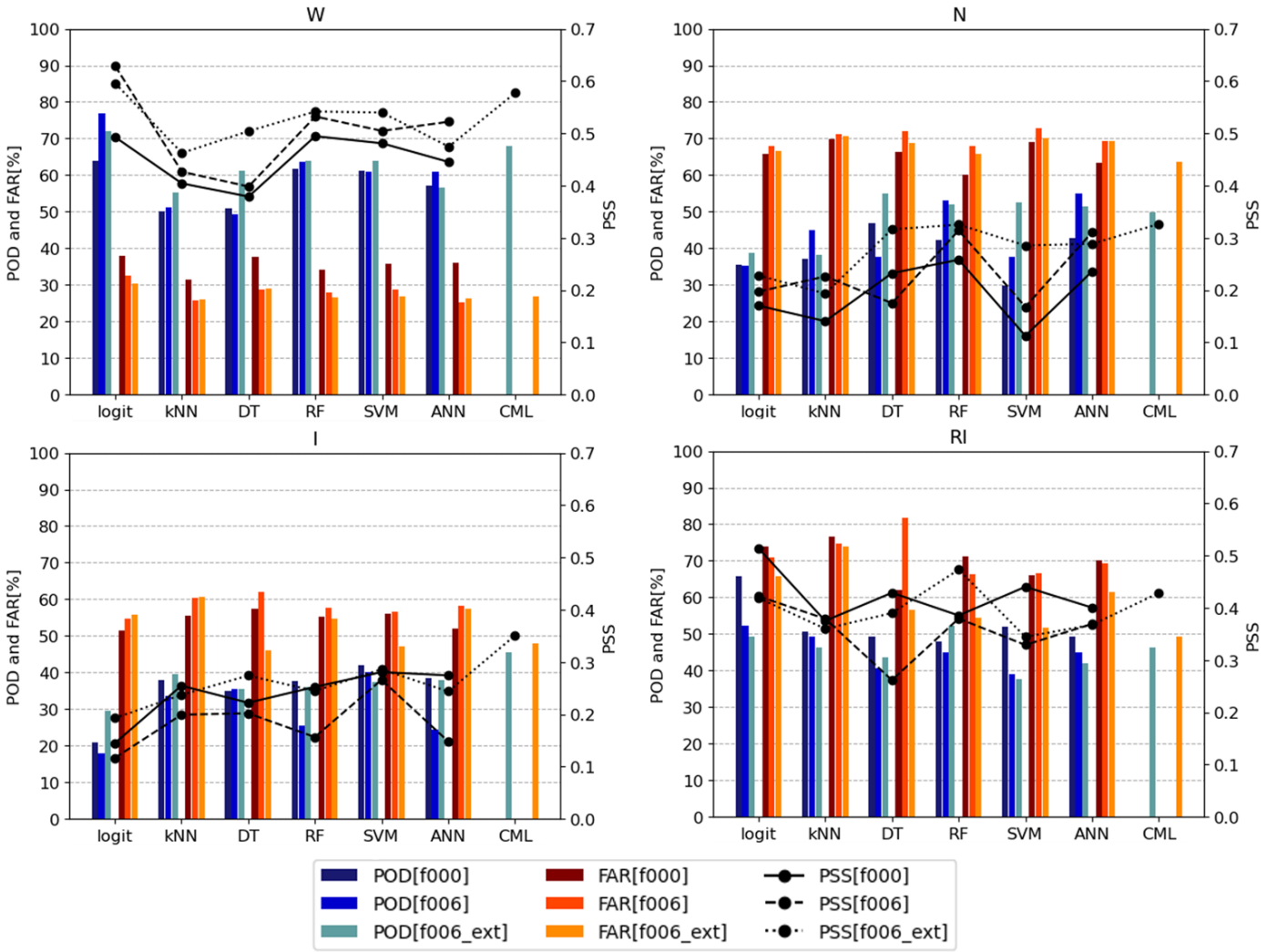
Validation Result

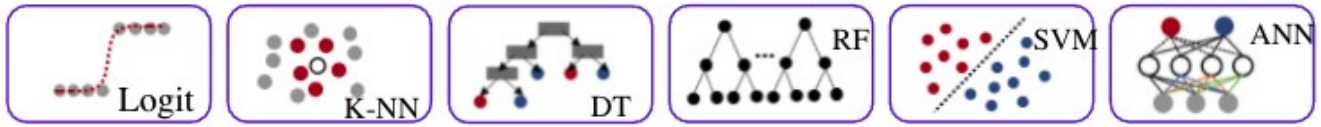
- Training: H218 retrospective run (2015-2017)
- Validating: H218 real-time run (2018)

- Analysis data conveys better information to ML models than forecast data

- Increase feature space can decrease FAR

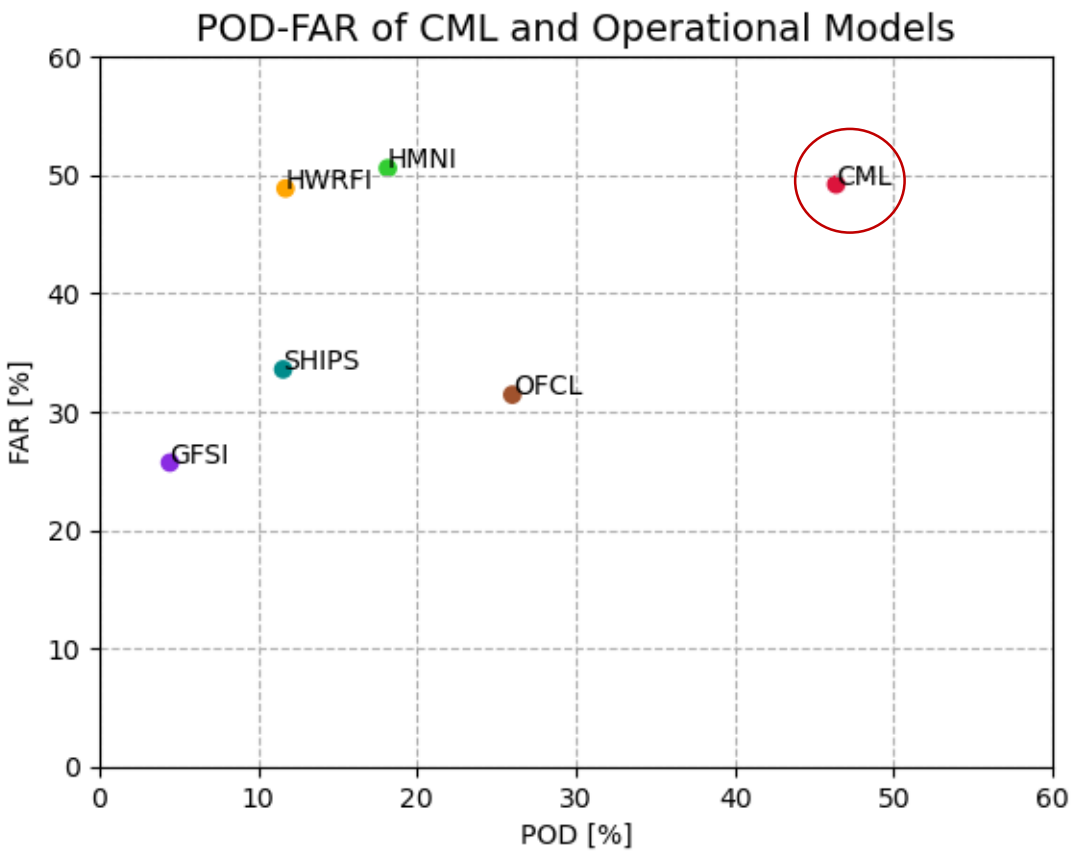
- CML is the best across all the classes





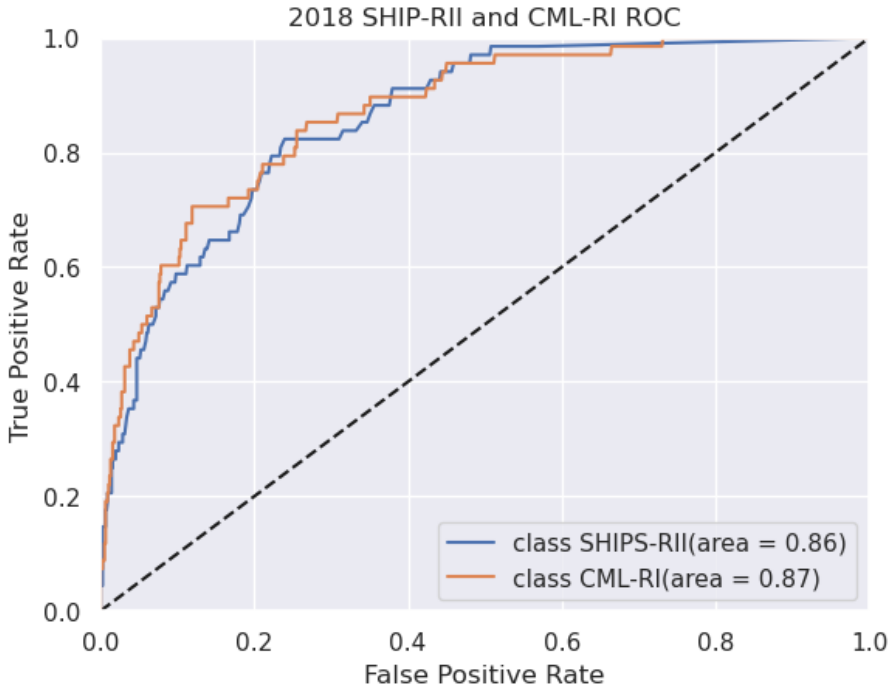
Validation Result

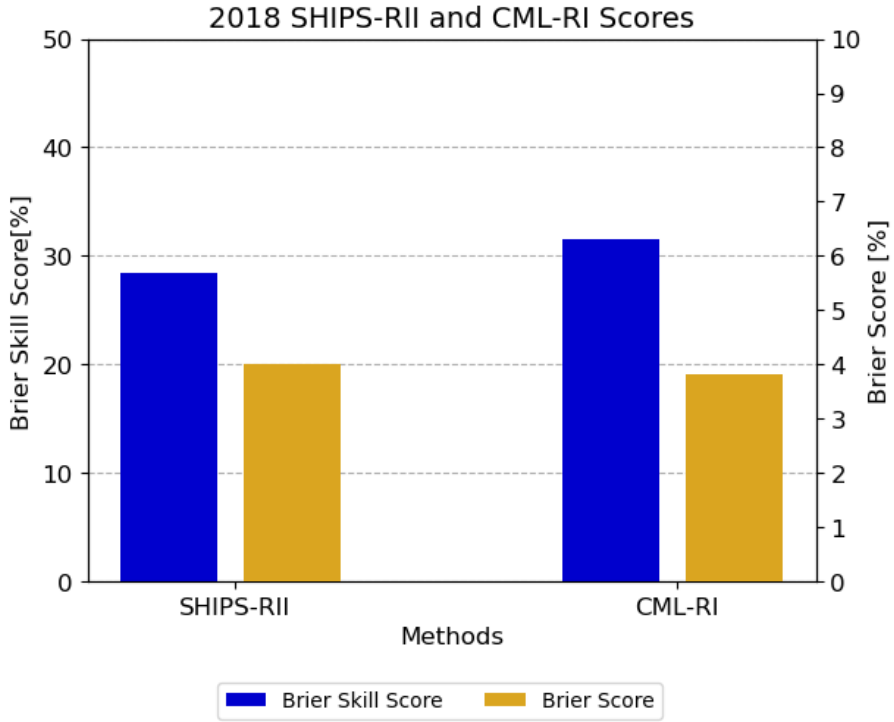
- Compare to other operational models: CML has high POD, but still high FAR
- Further expand feature space may help



Validation Result

- The CML-RI performance is comparable to SHIPS-RII



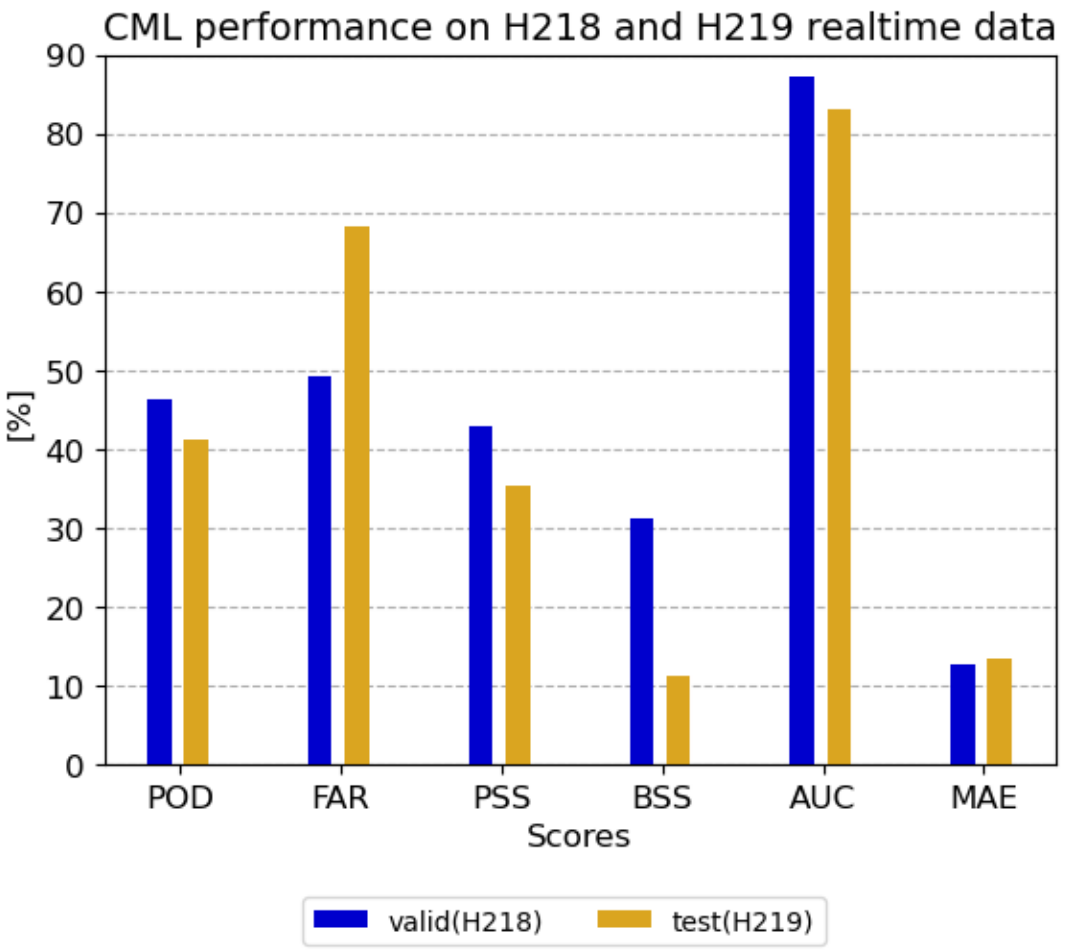


Testing Result

- Training: H218 retrospective run (2015-2017)
- Testing: H219 real-time run (2019)

- The 3-year of training data may not be sufficient enough to cover the full range of RI profile

- HWRF annual updates may have also contribute to the decrement of the performance. Including the retrospective run of the year may be key to avoid the impact from the annual updates



Conclusion

- Inner-core features are important to RI forecasts
- Resampling can increase POD rate while maintaining the FAR
- Increasing feature space can lower FAR
- CML method is better than any individual classical ML methods

Future Work

- Deep learning method (resources?)
- Acquiring a larger dataset (retrospective run over several years and from various HWRF versions) may enhance the ML prediction
- Adding more predictors
- Basin separation (AL, EP, CP, etc.)

Prediction \ Observation	POS	NEG
POS	(a)	(b)
NEG	(c)	(d)

POD = a/(a+c)

Hit rate; Recall

The percentage of correctly predicted observation events

FAR = b/(a+b)

= 1-Precision

The fraction of predictions that did not occur

Prediction	Observation POS	Observation NEG
POS	(a)	(b)
NEG	(c)	(d)

POD = a/(a+c)

POFD = b/(b+d)

False alarm rate
The forecast events that did not occur

PSS = POD-POFD

Pierce's Skill Score
Show the accuracy of predicting both "yes" and "no" events