Forecasting Rogue Waves in Oceanic Waters

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2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA) | 978-1-7281-8470-8/20/$31.00 ©2020 IEEE | DOI: 10.1109/ICMLA51294.2020.00105

***Abstract*— We present a novel approach for the prediction of Rogue Waves in oceans using Machine Learning methods. Since the ocean is composed of many wave systems, the change from a bimodal or multimodal directional distribution to unimodal one is taken as the warning criteria. Further, we explore various features that help in predicting Rogue Waves. The analysis of the results shows that the Spectral features are significant in predicting Rogue Waves. Finally, we propose a Random Forest Classifier based algorithm to predict Rogue Waves in oceanic conditions. For a range of windows, the proposed algorithm has accuracies between 89.57% and 91.81%, and the balanced accuracies between 79.41% and 89.03%. Moreover, we have also introduced the publicly available buoy dataset, which can serve as a benchmark dataset.**

***Keywords*— rogue waves, nonlinear waves, spectral methods, random forest, machine earning**

I. Introduction

Rogue Waves are studied using various nonlinear equations, which assume that wave energy gets focused on these events and generates nonlinearity [1, 2]. Rogue Waves are observed in hydrodynamics [3], optics [4], quantum mechanics [5], Bose-Einstein condensates [6], and finance [7]. They are mainly studied analytically using the spectral algorithms applying some deterministic equations like the nonlinear Schrodinger equation [8]. Rogue Waves may be needed in fiber optics to satisfy certain energy levels and to locate the information using matched filtering but they are dangerous in oceans and present a danger to the safety of marine operations. Examples of these events include the sinking of Prestige [9], El Faro [10], and damage to the Draupner platform [11]. To prevent these accidents, an early detection system with precise emergence time of these events is needed.

There are various methods for the early detection of nonlinear waves. For example, spectral techniques can be used by measuring the super-continuum patterns in the Fourier spectra before the Rogue Waves form. However, checking the Fourier spectra solely would fail to give any clue about the expected emergence point (or time) of a rogue wave in a chaotic wave field. Although spectral methods have also been proposed to include the time-dependent information about the waves [12], the prediction time is only in the order of seconds, which is not useful for avoiding exposure to the large waves. Later, Birkholz *et al.* [13] proposed a Grassberger-Procaccia nonlinear time series algorithm for the prediction of Rogue Waves and have slightly improved the time scale. Likewise, AD Cattrell [14] suggested that Machine Learning/statistical methods could be used to predict Rogue Waves using characteristic wave parameters.

To achieve the goal of forecasting Rogue Waves, it is necessary to develop statistics based computational approaches that can reliably and rapidly identify and forecast Rogue Waves in chaotic wave fields like the oceans. In contrast with the deterministic equations, such statistical methods can be employed for predicting a wide range of instabilities and can also help simulate the physics of the equations without computing a set of equations periodically. Some of the classical nonlinear evolution equations include nonlinear Schrodinger equation [15], Korteweg-de Vries equation [16], Kadomtsev-Petviashvili equation [17], Zakharov equation [18] and fully nonlinear potential systems [19]. However, such equations only describe a specific instability, and using a set of equations every time to forecast Rogue Waves is not possible for a continental/planetary scale prediction. Since the ocean waves are often bimodal/multimodal due to the presence of many wave-systems, it is assumed that Rogue Waves are more likely to occur when the distribution turns unimodal. Afterward, we used various Machine Learning classifiers to forecast Rogue Waves.

II. Possible causes of Rogue Waves

Various methods for the formation of Rogue Waves have been explored in the literature. Some of them include (a) Linear Superposition, (b) Nonlinear effects, and (c) wind-wave interactions.

A. Linear Superposition and weakly nonlinear effects

The most widely used theory for describing statistics of the surface gravity waves is the Gaussian theory, which assumes that waves are a linear phenomenon. However, the theory fails to account for nonlinear effects. This theory attributes the formation of large waves to linear superposition of waves. Three mechanisms have been proposed to explain how superposition occurs. First, the waves of different scales and frequencies propagate at different speeds. Besides, waves of the same scale propagate with different speeds depending on their steepness. The waves can intersect and pile-up resulting in a higher surface elevation. The wavefields with the same frequency and same steepness can be focused and superposed if they come from different angles [1]. This phenomenon is also known as wave focusing. While focusing is mostly linear, the last stage of the focused-wave dynamics demonstrates various nonlinear behaviors when the steepness is large enough [2]. Wave focusing due to directionality has been found to be a regular cause for wave breaking in wave tanks, which is associated with large waves [19]. If the waves of the same scale come from different directions, then a superposition of only two waves is needed to double wave height and steepness. These conditions can produce regular events with the height being the summation of two wave heights [20] or, at certain angles, activate some mechanisms of wave instability [21]. Linear superposition of waves is most likely at small angles (which is not too dangerous) or at angles close to 180 degrees, which have been shown to be dangerous even at low significant wave heights [20]. Thus, linear superposition remains one of the most likely mechanisms behind the formation of large waves in the oceans.

B. Nonlinear effects

A thorough description of different aspects of large waves has been provided by Kharif *et al.* [3]. The authors present various possible causes behind Rogue Waves like wave focusing and higher-order nonlinearities. One of the most studied higher-order instability in wave systems is the Benjamin-Feir instability (also called modulational instability) due to third-order quasi-resonant interactions between the free waves when the initial spectra represent narrowband long-crested conditions [22]. The likelihood of this mechanism is quantified by the Benjamin-Feir Index (BFI) [23]. Favorable conditions for the instability can be generated mechanically in wave tanks [11] or simulated numerically [1]. Miguel Onorato [24] provided the first experimental evidence that nonlinear wave statistics, mainly in the wave tanks and shallow water conditions, depend on BFI. Likewise, from the results of Petrova and Guedes Soares [25], it is known that, in general, the wave nonlinearity increases with the distance from the wavemaker on experiments on the wave tank. Numerical studies [26] analyzing the effect of the directionality show that the wave trains become increasingly unstable towards long-crested conditions. However, the initial requirements for the instability make this mechanism unlikely to be the primary cause for most extreme wave occurrences in oceanic conditions, characterized by the broader spectra and directional spread [27]. It is important to note that the nonlinear statistics of the following sea states observed are usually lower than the mixed crossing seas with identical initial spectra. The results for the distribution of the wave heights corroborate the conclusion of Rodriguez [28] that the existence of two wave systems of different dominant frequencies but similar energy contents result in the reduction of probability of wave height higher than the mean, and the effect becomes more significant as the intermodal distance increases. The higher-order wave nonlinearity is reported to increase significantly with the observed probability of occurrence of large wave events. It is also observed that the high-frequency spectral counterpart for both following and crossing seas shows a decrease in peak magnitude and downshift of the peak with the distance, as well as a reduction of the spectral tail when modulational instability takes place [29]. It is possible to conclude that when the free wave interactions become relevant, higher-order models are more likely to predict Rogue Waves than the strictly linear ones. It suggests the presence of nonlinear waves which occur due to various nonlinear interaction between the wave components also contribute to the formation of large waves. The result is well confirmed by a recent numerical experiment by Manolidis *et al.* [30].

C. Wind-wave interactions

During storms, locally generated wind waves combine with the long period ocean swells to produce bimodal waves. Wind waves are characterized by one spectral peak with one significant wave height and one peak period. A bimodal (double-peaked) spectrum is usually formed through the combination of swell from a distant storm and locally generated wind sea. Transformations of these wave systems can be described in terms of wave crests, troughs, and wave height distributions. Longuet-Higgins [31] proposed the Rayleigh distribution of wave heights, and several modifications have been made to the low wave-height exceedance distributions. Specifically, a depth modified version of the Rayleigh distribution was proposed by Battjes and Groenendijk [32], which is applied only to the unimodal waves. Similarly, Rodriguez [28] studied the wave height probability distributions using extracted gaussian bimodal waves from numerical simulations. The study classifies bimodal seas as wind-dominated, swell-dominated, and mixed-sea conditions. Likewise, Petrova and Guedes Soares applied a linear quasi-deterministic theory to compare the energies from wind and swell seas using a simplified Sea-

Swell energy ratio (SSER) on the assumption of wave nonlinearity [33]. Moreover, Norgaard and Lykke Anderson developed a slope dependent version of Rayleigh distribution based on an Ursell number criterion [34].

III. Identification of Rogue Waves from normal sea state

Ocean waves generally consist of more than one wave system, identified as swell and sea component. To calculate the unimodal sea state, we calculate the kurtosis and skewness from the Discrete FFT derived from the time series data at each frequency band. The assumption is that when the energy gets focused, nonlinear effects occur, and a rogue wave is more likely to occur. The focusing can sometimes generate unimodal distributions when the initial conditions are bimodal/multimodal which is reflected in skewness and kurtosis.

The estimate of the kurtosis and skewness [35] is based on integration over the frequency band 0.025 Hz to 0.580 Hz on the bulk Fourier moments a_1, b_1, a_2, b_2 weighted by the energy density. Note that Fourier moments refer to the coefficients of sines and cosines, which are calculated from the waves after Fourier transform.

$$\begin{bmatrix} a_1 \\ b_1 \\ a_2 \\ b_2 \end{bmatrix} = \frac{1}{E^b} \int_{0.025}^{0.580} \left(df\, E_r(f) \begin{bmatrix} a_1(f) \\ b_1(f) \\ a_2(f) \\ b_2(f) \end{bmatrix} \right) \tag{1}$$

where E^b is the variance with

$$E^b = \int_{0.025}^{0.580} df\, E_r(f) \tag{2}$$

afterward, we calculate

$$\theta = tan^{-1}(\frac{b_1}{a_1}) \tag{3}$$

$$m_1 = ({a_1}^2 + {b_1}^2)^{1/2} \tag{4}$$

$$m_2 = a_2 \cos(2\theta) + b_2 \sin(2\theta) \tag{5}$$

$$n_2 = b_2 \cos(2\alpha) - a_2 \sin(2\alpha) \tag{6}$$

$$skewness = \gamma = \frac{-n_2}{\{(1-m_1)/2\}^{3/2}} \tag{7}$$

$$kurtosis = \delta = \frac{6 - 8m_1 + 2m_2}{\{2(1-m_1)\}^2} \tag{8}$$

In (1), the bulk Fourier moments are derived from calculating the skewness and kurtosis. We take the integration of the Fourier moments multiplied by energy [36] and bandwidth. It is then normalized by dividing it with variance calculated in (2). Afterward, we use (3) to (6) to find different parameters, which are used to calculate skewness and kurtosis. Subsequently, we calculate the skewness and kurtosis in (7) and (8), respectively. Finally, the criteria suggested by Kuik *et al.* [35] is used to determine the unimodal distribution.

It is known that the skewness and kurtosis are very sensitive to the secondary directional peaks and thus can be used to identify bimodal/multimodal distribution from a unimodal one. Although the Kuik *et al.* derived the equations on the assumption of the unimodal distribution and described the two peaked spectra as a warning criterion, we use the same criteria because of its model-free attributes but define the warning criteria as to when a unimodal distribution arises. The criteria are given in (9) and (10).

$$kurtosis < 2 + |skew|\ and\ |skew| \le 4 \tag{9}$$

$$kurtosis < 6\ and\ |skew| > 4 \tag{10}$$

IV. Computational methods for prediction of Rogue Waves

A. Dataset

The historical dataset of the oceanic waves around the United States is collected via the Coastal Data Information Program (CDIP) buoys and is available at the NOAA website [37]. We used the data from January 2007 to October 2019 for the study. From the total data, we retain 754490 positive points and 189345 negative points for the benchmark dataset. Note that the data was shuffled before the training phase to avoid any bias arising due to data collection.

For the forecasting of Rogue Waves, we divide 106 minutes (min) to four different steps of size 26.67 min (1600s) each referred hereafter as a time window. The 26.67 min interval corresponds to the time for which the waves contain at least 100 wave samples, are somewhat stationary, and predictions can be made. The 106 min total time is the setup of the study and may be extended.

B. Features

After applying Fast Fourier Transform (FFT) on the directional spreading function [38], the resulting frequency band with bandwidth $bd_{1,n}$, energy $e_{1,n}$, and mean wave direction $deg_{1,n}$, we get $a_{1,n}$, $b_{1,n}$, $a_{2,n}$, $b_{2,n}$ per frequency band n. The information can be summarized with (11).

$$C = \begin{bmatrix} bd_{1,1} & e_{1,1} & deg_{1,1} & a_{1,1} & b_{1,1} & a_{2,2} & b_{2,2} \\ bd_{1,2} & e_{1,2} & deg_{1,2} & a_{1,2} & b_{1,2} & a_{2,2} & b_{2,2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ bd_{1,n} & e_{1,n} & deg_{1,n} & a_{1,n} & b_{1,n} & a_{2,n} & b_{2,n} \end{bmatrix} \tag{11}$$

We calculate the direction shape features from array C. Rather than taking the values of the components directly from C, We sought to calculate various features due to two reasons: (a) to decrease the number of features and (b) to measure the interactions between various frequency components of waves.

Let **X** be a subset of array C, which has $n = 64$ rows and $m = 6$ columns.

$$\mathbf{X} = \begin{bmatrix} e_{1,1} & deg_{1,1} & a_{1,1} & b_{1,1} & a_{2,1} & b_{2,1} \\ e_{1,2} & deg_{1,2} & a_{1,2,} & b_{1,2} & a_{2,2} & b_{2,2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ e_{1,n} & deg_{1,n} & a_{1,n} & b_{1,n} & a_{2,n} & b_{2,n} \end{bmatrix} \quad (12)$$

The features used in this paper were derived from the Fourier spectra of the Directional Spreading Function after Discrete Fast Fourier Transform. It is important to note that the buoys do not always measure the same frequency components. It is thus necessary to derive the features that are adaptable to varying frequency components length. Likewise, these features also help reduce the number of features significantly. The following features were derived from the four Fourier moments.

$$\sum_{i}^{n-1} mean(\sum_{j=i+i}^{n} minkowski(X[:i], X[:j], k) \quad (13)$$

$$\sum_{i}^{n-1} mean\_c(\sum_{j=i+1}^{n} mean\_c(X[i:j])) \quad (14)$$

$$\sum_{i}^{n-1} mean\_c(\sum_{j=i+1}^{n} median\_c(X[i:j])) \quad (15)$$

$$\sum_{i}^{n-1} mean\_c(\sum_{j=i+1}^{n} median\_c(X\_R[i:j])) \quad (16)$$

$$\sum_{i}^{n-1} mean\_c(\sum_{j=i+1}^{n} mean\_c(X\_R[i:j])) \quad (17)$$

$$\frac{1}{n}\sum_{i=1}^{n} kurtosis_i \quad (18)$$

$$\frac{1}{n}\sum_{i=1}^{n} skewness_i \quad (19)$$

$$\frac{1}{n}\sum_{i=1}^{n} e_{1,i} \quad (20)$$

$$\frac{1}{n}\sum_{i=1}^{n} deg_{1,i} \quad (21)$$

where $mean\_c$ and $median\_c$ refer to column-wise mean and median respectively of the array derived from Fourier coefficients at different frequencies. Likewise, X_R refers to the array reversed in order, $minkowski$ refers to the Minkowski distance function. In (13), we calculate the mean Minkowski distances between various frequency components, which helps identify various interactions between the frequency components. It is used because it is the generalization of Euclidean and Manhattan distances. The values of k used are 0 and 1. The value of i and j vary from 0 to 64 and cover the frequency bands in the spectra from 0.025 Hz to 0.580 Hz. Likewise, (14), (15), (16), and (17) capture the information about the general shape of the directional distribution. It is done by measuring the average mean and median, which helps identify skewed distributions. The main intuition behind the features is that Rogue Waves occur due to various linear/nonlinear interactions between waves, and thus, measuring how the mean and median fluctuates between different frequency components interact should capture more information about the Rogue Waves.

Moreover, it is to be noted that when modulational instability occurs, it is characterized by the spreading of the initial narrowband spectra. In such cases, when the wave-wave interactions occur, it is common to observe that one wave system grows at the expense of another. Thus, these features should be helpful in identifying various nonlinearities in the oceans.

Equation (18) and (19) define the normalized kurtosis and skewness of the directional wave distribution. The equations for calculating individual skewness and kurtosis per frequency are given by (7) and (8). Likewise, (20) refers to the normalized sum of energy, and (21) refers to the normalized sum of directions of different frequency components of Fourier spectra.

C. Results

In this section, we present the results of the experiments that were carried out in this study. All the methods were implemented using Python language. The Scikit-learn library [39] was used for implementing the Machine Learning algorithms. 10-fold cross-validation was used for testing the classifiers. The window size of 26.67 mins is a standard for most NOAA buoys for data archiving. We test Logistic Regression (LogReg), K Nearest Neighbor (KNN), Random Forest (RF), and Extra Trees (ET) for each window and compare the performance.

1) Search for the best classifier for the time window 0-26.67 min

TABLE I: PERFORMANCE OF CLASSIFIERS FOR 0-26.7 MIN

Methods	LogReg	KNN	RF	ET
Sensitivity (Sens)	0.9125	0.9233	**0.9474**	0.9339
Specificity (Spec)	0.7570	0.7259	0.8332	**0.8405**
Balanced Accuracy (Bal ACC)	0.8347	0.8246	**0.8903**	0.8872
Accuracy (ACC)	0.8663	0.8646	**0.9135**	0.9061
FPR	0.2429	0.2741	0.1667	**0.1594**
FNR	0.0874	0.0766	**0.0526**	0.0660
Precision (Prec)	0.8988	0.8885	**0.9308**	0.9327
F1	0.9056	0.9055	**0.9390**	0.9333
MCC	0.6768	0.6685	**0.7908**	0.7751

Bold indicates the best performance.

From Table I, we can see that Random Forest performs the best with a Sensitivity of 0.9474, Specificity of 0.83332, Balanced Accuracy of 0.8903, Overall Accuracy of 0.9135, FPR of 0.1667, FNR of 0.0526, Precision of 0.9308, F1

0.9390, and MCC of 0.7908. Although Extra Tree performs better than the Random Forest Classifier on False Positive Rate and Specificity, we choose Random Forest Classifier because it performs best on all other metrics. The best parameters for each classifier are given in Table II.

TABLE II: CLASSIFIER PARAMETERS FOR 0-26.7 MIN

Methods	**Best Parameters**
LogReg	C=10
KNN	trees=1300
RF	max_depth=50, min_samples_split=5, n_estimators=1000
ET	n_estimators=1000

LogReg = Logistic Regression, KNN = K Nearest Neighbors, RF = Random Forest, and ET = Extra Tree.

2) Search for the best classifier for time window 26.67 min to 53.34 min

TABLE III: PERFORMANCE OF CLASSIFIERS FOR26.6-53.3 MIN

Methods	LogReg	KNN	RF	ET
Sens	0.7755	0.9544	**0.9621**	0.9452
Spec	**0.7943**	0.6369	0.6816	0.6957
Bal ACC	0.7849	0.7956	**0.8219**	0.8205
ACC	0.7796	0.8851	**0.9009**	0.8907
FPR	**0.2056**	0.3630	0.3183	0.3042
FNR	0.2244	0.0455	**0.0378**	0.3042
Prec	**0.9310**	0.9039	0.9154	0.9175
F1	0.8461	0.9285	**0.9324**	0.6947
MCC	0.49339	0.6434	**0.6947**	0.6687

Bold indicates the best performance.

From Table III, we note that Random Forest performs the best with a Sensitivity of 0.9621, a specificity of 0.6816, Balanced Accuracy of 0.8219, Overall Accuracy of 0.9009, FPR of 0.3183, FNR of 0.0378, Precision of 0.9154, F1 of 0.9324, and MCC of 0.6947. Note that Logistic Regression has the highest Precision and Sensitivity among all the models tested and has the lowest False Positive Rate. However, we choose Random Forest Classifier because it beats all the other classifiers in other metrics. The best parameters for each classifier are given in Table IV.

TABLE IV: CLASSIFIER PARAMETERS FOR 26.7-53.3 MIN

Methods	**Best Parameters**
LogReg	C=1
KNN	trees=1200
RF	max_depth=40, min_samples_split=10, n_estimators=800
ET	n_estimators=1000

3) Search for the best classifier for time window 53.34 mins to 80.01 min

TABLE V: PERFORMANCE OF CLASSIFIERS FOR 53.3-80 MIN

Methods	LogReg	KNN	RF	ET
Sens	0.7699	0.9529	**0.9591**	0.9437
Spec	**0.7941**	0.6144	0.6555	0.6614
Bal ACC	0.7820	0.7837	**0.8073**	0.8020
ACC	0.7750	0.8822	**0.8957**	0.8847
FPR	**0.2058**	0.3855	0.3444	0.3385
FNR	0.2300	0.0470	**0.0408**	0.0562
Prec	**0.9340**	0.9034	0.9133	0.9134
F1	0.8441	0.9275	**0.9356**	0.6664
MCC	0.4815	0.6206	**0.6664**	0.6366

Bold indicates the best performance.

From Table V, we observe that Random Forest outperforms all other classifiers with a Sensitivity of 0.9591, Specificity of 0.6555, Balanced Accuracy of 0.8073, Overall Accuracy of 0.8957, FPR of 0.3444, FNR of 0.0408, Precision of 0.9133, F1 of 0.9356, and MCC of 0.6664. We note that Logistic Regression, however, has the highest Specificity and Precision and has the lowest False Positive Rate. However, it does not outperform Random Forest on all the other metrics. Thus, we choose Random Forest as the best classifier. The best parameters for each classifier are given in Table VI.

TABLE VI: CLASSIFIER PARAMETERS FOR 53.3-80 MIN

Methods	**Best Parameters**
LogReg	C=0.1
KNN	trees=1000
RF	max_depth=10, min_samples_split=2, n_estimators=200
ET	n_estimators=1000

4) Searching for the best classifier for time window 80.01 min to 106.58 min

TABLE VII: PERFORMANCE OF CLASSIFIERS FOR 80-106.6 MIN

Methods	LogReg	KNN	RF	ET
Sens	0.7657	0.9539	**0.9699**	0.9685
Spec	**0.7915**	0.6093	0.6182	0.6203
Bal ACC	0.7709	0.7816	**0.7941**	0.7944
ACC	0.7709	0.8840	**0.9181**	0.9172
FPR	**0.2084**	0.3906	0.3817	0.3800
FNR	0.2343	0.0461	**0.0300**	0.0315
Prec	0.9352	0.9056	**0.9363**	0.9361
F1	0.8420	0.9291	**0.9528**	0.9522
MCC	0.4706	0.6172	**0.6493**	0.6462

Bold indicates the best performance.

Table VII shows that Random Forest performs the best with a Sensitivity of 0.9699. Specificity of 0.6182, Balanced Accuracy of 0.7941, Overall Accuracy of 0.9181, FPR of 0.3817, FNR of 0.0300, Precision of 0.9363, F1 0.9528 and MCC of 0.6493. Logistic Regression has the highest Specificity and has the lowest False Positive Rate. However, it does not outperform Random Forest on all the other metrics. Thus, we choose Random Forest as the best classifier. The best parameters for each classifier are given in Table VIII.

TABLE VIII: CLASSIFIER PARAMETERS FOR 80-106.6 MIN

Methods	Best Parameters
LogReg	C=1
KNN	trees=1300
RF	max_depth=20, min_samples_split=2, n_estimators=1000
ET	n_estimators=1200

We observe from the above results that the performance of the classifiers increases when more features from the Fourier Spectra are included. We note that Logistic Regression, which is a weakly nonlinear model, can predict Rogue Waves from the normal waves with a considerable degree of accuracy. The results validate the conclusions of Petrova and Soares that weakly nonlinear models are still helpful to predict nonlinear effects [40] although nonlinear methods like ET and RF have better prediction performance. Likewise, since the Random Forest algorithm is very robust to noise compared to Extra Trees Classifier, it performs the best for all time windows explored in the paper. Moreover, as the prediction time for forecast increases, the Balanced Accuracy also decreases. It suggests that more features are required to forecast Rogue Waves for longer time frames.

V. CONCLUSIONS

In this paper, we explored some Machine Learning methods for forecasting rogue waves in oceanic waters rather than using deterministic equations. Instead of using the individual moments per frequency components from the buoy data, we derived various features, which measure interactions between various frequency components of a wave system. The features allowed us to capture wave information with fewer components. Among the Machine Learning classifiers tested, although RF outperforms all the other algorithms, its performance is similar to ET. We attribute the superior performance of these methods to the underlying tree-based algorithms, which capture nonlinear interactions between the features and also robustness to noise due to the averaging of the variance errors in RF. Moreover, since Random Forest uses a greedy algorithm to select the best split instead of randomly like in ET, it performs slightly better than ET.

With the use of model-free evaluation criteria, various Spectral Features, and Machine Learning methods, the warning time for Rogue Waves has been improved from the scale of seconds/minutes to a scale of hours. Our future work will focus on extending the forecasting time and improving accuracies.

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