Forecaster: *F*orecast *O*riented Featu*r*e *E*limination-based *C*lassification of *A*dverse *S*patio-*T*emporal *E*xt*r*emes

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Abstract. Accurate forecasting of extreme events in spatio-temporal systems is a highly underdetermined, yet very important problem. Physics-based models provide unreliable predictions for variables highly related to adverse extreme events, while statistical methods can often only predict linear system responses. In this paper, we propose Forecaster, an algorithm that constructs a forecast-oriented feature elimination-based ensemble of classifiers for robust forecasting of extreme events. In contrast to existing classification methods that predict the current system state, Forecaster predicts the *future* phase of the system based on the preceding multivariate data, and it is able to handle underdetermined problems. Forecaster supports nonlinear system behavior as well. Experimental results show that Forecaster increases prediction accuracy of traditional methods by up to 13% on two seasonal tropical cyclone prediction systems.

Keywords: Forecast-oriented Classification; Feature Elimination-based Ensemble; Extreme Event Prediction; Spatio-temporal Data Mining;

1 Introduction

Accurate forecasting of extreme events, such as hurricanes, droughts and earthquakes, is a paramount priority for our society. Their adverse nature can change the landscape of society by triggering abrupt changes in the landscape around them, defined by their catastrophic characteristics. For example, in Western Africa, periods of very low relative humidity (RH) often coincide with higher incidences of meningitis epidemics that affects more than 200,000 people throughout the African Sahel region annually [1]. Our ability to predict the occurrence of such events—ahead-of-time, with the lead-time of days, weeks, and even months—could translate to taking preventive measures to eliminate or

reduce the severity of the event. For instance, during anticipated low RH seasons in Western Africa, authorities must be able to coordinate vaccinations and relief efforts adequately to ensure potential problem areas are targeted, and thus prevent the misdistribution of such efforts.

Fortunately for society, while the adverse effects of extreme events are enormous, their occurrences are relatively rare. For example, Hurricane Katrina cost the United States of America over 80 billion dollars and over one thousand lives [17], yet only 92 hurricanes of great destructive magnitude have been reported to strike the United States from 1851-2004, of only 273 hurricanes reported overall during this same period [10].

While the rarity of occurrence of these extreme events is a blessing in the real sense, it is a curse from a statistical machine learning perspective, given the lack of an appropriate number of observational events to build models upon. This issue becomes worse if the characteristics of these events come into consideration, as these events can occur in different locations and different times of the year. Furthermore, these events can be influenced by multiple factors which may be nonlinearly correlated, bringing forth the challenges of multivariate, spatio-temporal, and inherently nonlinear problems. Thus, considering the fact of having only a handful of available observational events ($m \approx 100$'s) in high-dimensional spaces ($n \approx 10,000$'s), the existing machine learning methods easily become hardly suitable for dealing with such *underdetermined, or unconstrained, problems* ($m << n$).

Presently, physics-based models and simulations from first-principles have been making relatively reliable predictions at global spatial scale for ancillary variables, such as climatological factors including Sea Surface Temperature (SST), humidity profiles over land, or wind speed at different heights. However, they provide least reliable predictions for variables that are crucial for impact assessment for adverse extreme events including regional precipitation, hurricane intensity and frequency, droughts and floods. In fact, "The sad truth of climate science is that the most crucial information is the least reliable" [19].

As such, statistical methods have emerged to address this need. Unfortunately, because our quantitative knowledge about highly non-linear dynamic systems is very meager, modelers often resort to linear regression techniques, such as Least Absolute Deviation (LAD), Least Square Error (LSE), and Poisson regression, among others, to learn the linear system's response from various system predictands. For example, hurricane activity is modeled as an LAD regression model using observed or simulated system's parameters, such as SST, Sea Level Pressure (SLP), Vertical Wind Sheer (VWS), and others [9].

However, these models over-simplify the problem, given they only consider linear relations between the response variable and the predictands, thus only covering single linear-phase system behaviors. But complex dynamic systems often operate in multiple phases, described as having similar defining characteristics but whose feedbacks behave in non-linear fashion. Fig. 1 illustrates the abstract system's behavior driven by minimization of its Gibbs free energy [7] (solid blue lines in Fig. 1) that undergoes phase transition (at $Temp = Temp_m$)

with possibly nonlinear behavior (see, for example, Landau's theory of phase transitions [15]). Arguably, such a compromised representation (red dashed line in Fig. 1) in a form of a single-phase linear regression model would likely lead to a model with a poor predictive skill for the response variable. For example, hurricane activity is the climate system's response initiated by a liquid-vapor phase transition associated with non-linearly coupled fluctuations in the ocean and the atmosphere. Therefore, linear regression models, while insightful, still offer limited predictability (e.g., 62% prediction accuracy for the observed hurricane activity in North Atlantic region).

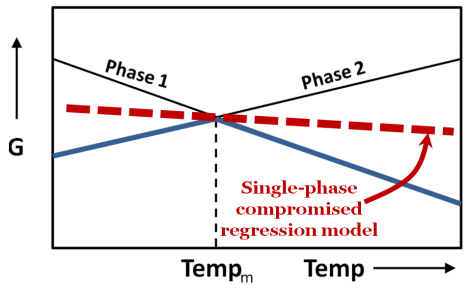


Fig. 1. A single-phase "compromised" linear regression model (dashed red line) for a multi-phase physical system that minimizes its Gibbs free energy (solid blue lines) at different phases.

While both regression- and physics-based approaches deserve their own merits, in this paper, we draw readers' attention to a slightly different, yet complementary, *supervised machine learning* problem. Namely, given a historic record about rarely occurring spatio-temporal extreme events of interest, can an algorithm learn the complex non-linear relationships between system parameters and the event's response variable, so that the algorithm can predict what phase the system will likely transition to in some future time and in some spatial region given the knowledge about the system's parameters defined over global spatial scales before the event's occurrence?

Slightly more formally, assume that the *multi-phase* system during the extreme event $e = (P, T_f, L_e)$ can be characterized by one of its phases, $P \in \{P_1, P_2, \ldots, P_s\}$ at some future time period T_f and in some event's spatial location region L_e. Can the algorithm A predict P given the system's state(s) $S(T, F, L)$ described by some spatio-temporal multivariate feature set F over space $L \supseteq L_e$ and time $T = (T_f - \Delta T, T_f)$? Note that the temporal resolution, ΔT, is domain-specific (e.g., 1–5 months for hurricanes). For the sake of simplicity, we assume that the number s of distinct system's phases/states is finite. For example, the hurricane activity can be characterized as being in one of $P = \{$above normal, normal, or below normal$\}$ phases during hurricane season $T_f = \{$July-November$\}$ in region $L_e = \{$North America$\}$. We call this problem a ***forecast-orientated classification of spatio-temporal extreme events***.

To address this problem, we propose an algorithm, called FORECASTER, that constructs feature elimination-based ensemble of classifiers for accurate and robust forecasting of adverse spatio-temporal extreme events. Unlike physical models, which often aim to track event development over a *fine-grain* spatio-temporal resolution, FORECASTER simplifies the problem by utilizing a *coarser-grain* spatial resolution, and takes an extended time frame into consideration, expanding to a larger scale, such as for seasonal forecasts, with aim to be able to work in lead-time. For example, for a climate-based problem of predicting hurricane activity, we would consider data from the effective hurricane season, spanning from June through November, and work to make such predictions a month(s) in advance.

Furthermore, unlike statistical models that infer linearity and aim to predict linear responses, FORECASTER's aim is to avoid such inference and treat the system as behaving nonlinearly. Moreover, unlike models such as the aforementioned regression techniques, the intent of our model is not to predict an actual numerical magnitude of the response, instead to seek proper classification into unambiguous groupings, or system's phases that provide enough information to make proper decisions, as many statistical models are ultimately being translated into such coarser scales [3] for impact assessment.

Finally, FORECASTER is different from traditional classification machine learning methods in a number of ways:

- FORECASTER forecasts the *future* phase of the system given its characteristics *prior* to the time-frame of interest unlike existing classification methods that predict what state the system *currently* belongs to, given its *current* characteristics.
- FORECASTER naturally supports multi-variate *spatio-temporal* data, which, to the best of our knowledge, no existing classification methodologies are particularly designed for.
- FORECASTER is optimized for dealing with highly underdetermined, or unconstrained, classification problems, for which most existing machine learning methods are hardly suitable.

We successfully apply FORECASTER to predicting seasonal tropical cyclone activity for two regions of interest: North Pacific and North Atlantic. Our experimental results show that FORECASTER is able to increase prediction accuracy of traditional regression-based methods by up to 13% for this problem.

2 Method

We address the aforementioned technical challenges through some key innovative steps underlying the FORECASTER methodology, summarized with its overview diagram in Fig. 2. Next, we describe each of these steps in more detail.

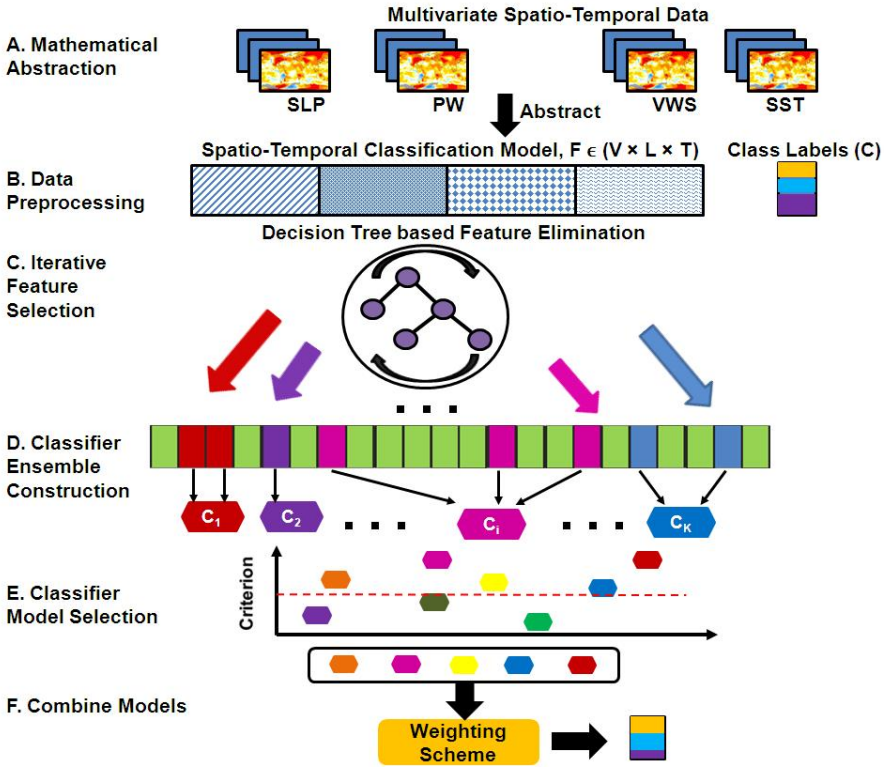


Fig. 2. FORECASTER's methodology overview.

2.1 Mathematical Abstraction

In traditional supervised classification, a model is learned from a matrix representation of the original data with m rows corresponding to a set E of observations, or events, and n columns corresponding to a set F of features that characterize each event. In addition, a column vector associates each event with its class from a finite set C of available classes. Once learned, the model predicts what class the target event defined over the same features F belongs to.

Both the forecasting nature of our problem and the multivariate spatio-temporal nature of the data necessitate a *mathematical abstraction* that could transform this data into a mathematical form suitable for a downstream machine learning task, in general, and *forecast-driven classification*, in particular.

More formally, let V be a set of variables (or factors) that characterize the system over spatial locations L and over time period T. For example, the climate system could be characterized by its climatological factors, such as SST, SLP, and VWS defined over spatial (latitude, longitude, altitude) grid points over a time period of 1948-2010 with monthly mean values.

In the context of the target extreme events, such as hurricanes or droughts, let us also assume that $T = T_1 \bigcup T_2 \bigcup \ldots \bigcup T_m$ is divided into m *coarse-grain* time intervals during which an extreme event e can occur over some spatial region $L_e \subseteq L$ with some probability. Let us further assume that each time interval $T_j \in T$ is partitioned into the *fine-* or *coarse-grain observable* $T_{j,o}$ time period and the *coarse-grain forecastable* $T_{j,f}$ time period ($T_j = T_{j,o} \bigcup T_{j,f}$ and $T_{j,o} = T_{i,o}, T_{j,f} = T_{i,f}, \forall i, j = \overline{1, m}$).

In the context of hurricane extreme events, for example, each time interval T_j may correspond to a calendar year that is further divided into a hurricane season $T_{j,f} = \{$July-November$\}$, for which hurricane activity, say in $L_e = \{$North Atlantic$\}$ region, is being forecasted based on the observed or simulated monthly means for climatological factors defined over the entire globe L during the hurricane pre-season, $T_{j,o} = \{$December-June$\}$.

Furthermore, suppose that each extreme event e can be classified based on some event-specific classification taxonomy, C. For example, seasonal hurricane activity, from the impact assessment perspective, could be broadly categorized as "above normal" (say, more than six hurricanes during the hurricane season), "normal," or "below normal" (say, less than three hurricanes in a season).

Based on the aforementioned notations, the mathematical form can then be defined as follows (Step **A**, Fig. 2). Let each row of the matrix correspond to each time interval $T_j, j = \overline{1, m}$, and let each column of the matrix correspond to a 3-tuple defined over $F = V \times L \times T_{*,o}$, where $T_{*,o}$ is replaced with $T_{j,o}$ for the corresponding row T_j. Thus, each (row, col) cell of the matrix if filled in with the value of the corresponding variable in V for column *col* defined at the corresponding spatial point in L and the corresponding time $T_{row,o}$.

Furthermore, let us assume that a set of known extreme events E is defined over some spatial region L_e, and the class label from C is assigned to each time interval T_j based on the accumulative statistics of the observed events over $T_{j,f}$ time period in region L_e.

Fig. 3 illustrates this mathematical abstraction using SST and VWS as variables, or predictands, defined over $T = (1970 - 1972)$ during the months of $T_{*,o} = \{$May, June$\}$ over (latitude, longitude) spatial grid points for the sea-level altitude. The class label is inferred based on the historical record of observed hurricanes in North America during $T_{*,f} =$ (July-November) hurricane season.

2.2 Data Preprocessing

Given the aforementioned mathematical abstraction of the original multivariate spatio-temporal data, the next step of the Forecaster algorithm is data preprocessing (Step **B**, Fig. 2) designed to improve the classifier performance. While the choice of which data preprocessing techniques to employ may be dependent on the type of data under consideration, for preprocessing multivariate, spatio-temporal data, Forecaster utilizes the following three techniques: *temporal deseasoning*, *spatial denoising*, and *descretization-based denoising*.

Temporal deseasoning: If temporal data can exhibit seasonality, such as winter, spring, summer, and fall, each variable's time series at each spatial location is

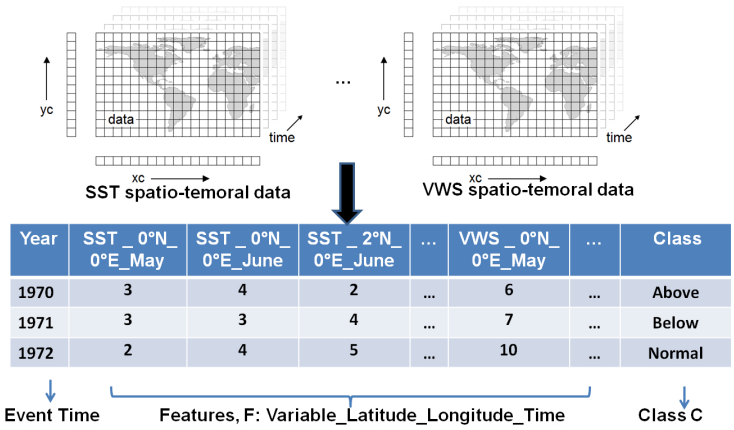


Fig. 3. A mathematical form for forecast-driven classification of hurricane events.

first transformed into the anomaly time series with zero mean and unit variance per season. This avoids learning a strong seasonality signal and also enables multiple variables with different scales of measurement to be combined into different columns of the same matrix.

Spatial denoising: Since the values of the variable at any location can vary across different time intervals T_j even at the same observational time period $T_{j,o}$, to lessen the affect of this variability, the anomaly time series at each location point is replaced with its mean anomaly time series taken over the points in the spatial "neighborhood" of this point. This transformation reduces the variance across different T_j time intervals, thus making the model inference more robust.

Descretization-based denoising: We use a discretization method by Fayyad and Irani [6] to further denoise continuous variables by discretizing their values into categorical intervals based on the entropy minimization heuristics. This technique has been found to be effective in classifying microarray data [21].

2.3 Iterative Decision Tree based Feature Elimination

While the mathematical form proposed in Section 2.1 seems to be suitable for direct use by almost any existing classification technique in machine learning, its highly underdetermined nature prevents this utilization and necessitates advancements that would enable Forecaster to deal with such unconstrained problems (i.e., when the size of the feature space $|F| = n$ is significantly larger than the number m of time intervals, $T_j, j = \overline{1, m}$) .

Forecaster tackles this problem by identifying multiple complementary sets of discriminatory features from F in order to build a robust ensemble of classifiers. The proposed methodology relies on the assumption that there are multiple disjoint sets of discriminatory features within the entire feature set, namely $F = F_1 \bigcup F_2 \bigcup \ldots \bigcup F_k, F_i \cap F_j = \emptyset$. By identifying these discriminatory feature sets, we can construct an ensemble of classifiers capable of producing an accurate and stable prediction (see Section 2.4).

Specifically, our methodology employs a *supervised, multivariate* feature selection method that *iteratively* selects feature sets until some *stopping criterion* is met (Step **C**, Fig. 2). Under this approach, each iteration produces a subset of features out of the current feature set, then removes these features from the set so that they cannot be selected again.

We use the CART-decision tree algorithm [2] to select a set of discriminatory features from the available feature space. Basically, CART builds a decision tree by choosing the locally best discriminatory feature at each split step based on the Gini Index Impurity Function [25]. To avoid overfitting, CART employs backward pruning to build smaller, more general decision trees. CART chooses features in a multivariate fashion, which allows the feature selection process to find a set of discriminatory features instead of considering one feature at a time.

Forecaster identifies a candidate set of discriminatory features by building a decision tree model M using CART, and extracting the features that belong to the internal nodes of M (Lines 3–4 in Algorithm 1). In subsequent iterations, it removes the set of discriminatory features F_M corresponding to the model M from the full feature set F (Line 12) before applying CART-based feature selection to the rest of the features (those that have not yet been identified as discriminatory features).

Stopping criterion: There are several different criteria that can be used to decide when to stop generating new sets of features (Line 2). Due to high dimensionality of our data, we set the threshold on the maximum number of iterations as the stopping criterion.

2.4 Ensemble of Classifiers

Given the set of discriminatory feature sets from Step C above, Forecaster builds an ensemble of classifiers (Step **D**, Fig. 2) from the set of selected classifier models (Step **E**, Fig. 2) whose predictions are then combined (Step **F**, Fig. 2) to make the final prediction.

Building an ensemble of classifiers: For each of the feature sets identified, we form a new data set D_{F_M} by restricting the original data to include only the selected features F_M. We then train a separate base classification algorithm A (e.g., decision tree, SVM, Naïve Bayes, etc.) on the restricted data set to construct a candidate classifier model M_A. The candidate classifier model M_A will only be included into the ensemble of classifiers if it meets the *model selection criterion* (Lines 5–11 in Algorithm 1). The resulting class prediction for the event with the unknown class label is based on the majority voting of the selected classifiers M_A's. While there are many different voting methods, one can use to combine predictions made by different classifiers in the ensemble (e.g., [24, 22]), we utilize a simple majority voting, since combining model predictions is outside the focus of the paper.

Classifier model selection: An important issue in building an ensemble of classifiers is how to select which of the candidate classifier models to add to the ensemble. One possibility is to use classifiers with low training error to form the ensemble, namely adding a classifier to the ensemble only if the training error of

Algorithm 1: Feature elimination-based ensemble of classifiers

Input:
D : a training dataset over a set of features F, and given class labels C
D': a test dataset over the same features as D, but without class labels
A : a basic classification algorithm like decision tree, SVM, and *etc.*
Output:
C': predicted class labels for the test set D'

```
Initialize Y = ∅;
while the stopping criterion is not met do
    Run CART-decision tree algorithm on D to get a pruned decision tree M;
    Let F_M be a set of all features that belong to the internal nodes of M;
    Let D_{F_M} be the restriction of D to the features in F_M;
    Construct a classifier model M_A by applying A to D_{F_M};
    if M_A meets the model selection criterion then
        Let D'_{F_M} be the restriction of D' to the features in F_M;
        Apply M_A to D'_{F_M} to produce predicted class labels C'_{M_A};
        Add C'_{M_A} to Y;
    end
    Remove features in F_M from F;
    Remove the data over feature F_M from D;
end
Predict the class labels C' based on a majority vote of the results in Y;
return C';
```

the base classifier on the particular feature set is below a given threshold. One challenge with this approach is how to select a threshold to distinguish between effective and ineffective classifiers.

In this study, we propose a method for estimating a threshold that reflects a statistically significant improvement over an arbitrary feature selection. To determine this threshold for a given feature set, we randomly sample a large number of feature subsets (e.g., 1000) of the same size and build classifiers for each of these random feature sets. We then use Student's t-test to estimate a p-value for the difference in the training error between the classifier trained on the given feature set and the classifiers trained on the randomly selected feature sets. If this p-value meets a significance criterion (e.g., a significance level of 0.05), then the classifier trained on the given feature set is added to the ensemble.

3 Results

In this section, Forecaster will be tested on two spatio-temporal extreme events prediction problems: North Pacific tropical cyclone prediction, and North Atlantic tropical cyclone prediction.

3.1 Data

We use the North Atlantic tropical cyclone (TC) count series from 1950 to 2009 from the seasonal (July through November) Atlantic hurricane database (HURDAT) at the National Climatic Data Center to form the class labels. This dataset includes the hurricanes, tropical storms, and tropical depressions that occurred in the entire Atlantic basin. We also utilize the North Pacific seasonal (June through October) TC count series from 1970 to 2006 provided by the Central Weather Bureau [3]. These series cover tropical storms and typhoons in the area between 21–26°N and 119–125°E.

According to Chu *et al.* [3], the observed TC count series of North Pacific region were classified into three classes: "below," "normal," and "above," with a distribution of 40% as "normal" and 30% each as "below" and "above." (Years with fewer than three TCs are classified as "below," and years with at least five TCs are classified as "above.") In the case of the North Atlantic region, years with TC counts fewer than five are classified as "below," and TC counts larger than seven are classified as "above."

We use monthly mean sea level pressure (SLP), precipitable water (PW), sea surface temperature (SST), and tropospheric vertical wind shear (VWS) data in order to predict the North Atlantic and North Pacific TC class. SLP and PW are NCEP/NCAR reanalysis datasets. They are available at a $2.5° \times 2.5°$ latitude and longitude resolution. SST is from the NOAA Climate Diagnostic Center in Boulder, Colorado, at a resolution of $2° \times 2°$ latitude and longitude. VWS is calculated by computing the square root of the sum of the square of the difference in zonal wind component between 850 and 200 hPa levels and the square of the difference in meridional wind component between 850 and 200 hPa levels [4] from NCEP/NCAR reanalysis data.

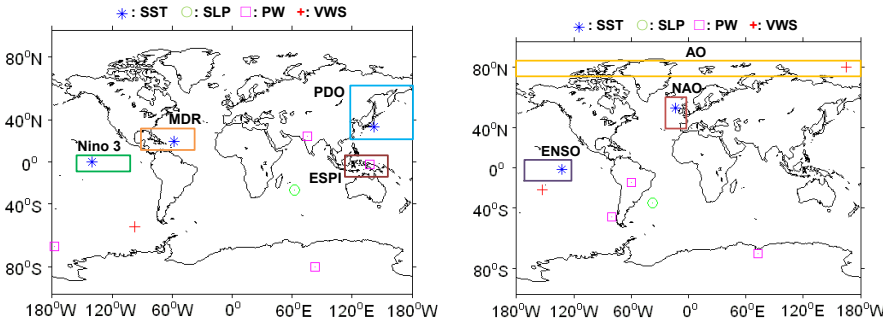
The global SLP, PW, VWS, and SST datasets in preceding June are used for the North Atlantic TC class prediction. The four variables combined contribute 47,556 features to F as columns in the matrix form as described in Section 2.1. For comparative purposes, only the data for the same type of four variables in preceding May over the western North Pacific (0–30°N and 100–180°E) region with 1,652 features is used for the North Pacific TC class prediction.

3.2 Performance Evaluation Method

Because of the small sample size of the spatio-temporal data, leave-one-out cross validation (LOOCV) is employed to evaluate Forecaster's robustness. We utilize several metrics to evaluate Forecaster's performances: accuracy, Heidke Skill Score (HSS) [11], Peirce Skill Score (PSS) [16, 11], and Gerrity Skill Score (GSS) [12]. Accuracy is defined as the ratio of the number of correctly classified data points to the total number of data points in the test set.

3.3 Forecaster Performance Comparison

Table 1 compares Forecaster's performance to seasonal tropical cyclone predictions by Chu *et al.* [3], Kim *et al.* [14], and Kim and Webster [13]. For the



(a) Model 1 (b) Model 2

Fig. 4. Features selected by two models for North Atlantic tropical cyclone prediction

North Pacific region, there is a roughly 8% increase over the 65.5% reported by Kim *et al.* [14]. For the North Atlantic Region, FORECASTER achieves an increase of nearly 13% in accuracy and GSS and nearly 20% in HSS and PSS.

Table 1. LOOCV performance for seasonal TC class prediction

Metric	North Pacific			North Atlantic	
	FORECASTER	Chu [3]	Kim [14]	FORECASTER	Webster [13]
Accuracy	0.73	0.623	0.655	0.75	0.621
HSS	0.584	0.424	0.483	0.60	0.437
PSS	0.596	0.424	0.521	0.62	0.446
GSS	0.603	0.541	0.592	0.63	0.567

3.4 Climatological Relevance

Fig. 4 shows two discriminating feature subsets included into the two selected classifier models. In the case of Model 1 (Fig. 4(a)), among all three SST features (star-shaped in Fig. 4(a)), one is located in the Niño 3 region. Niño 3 SST has a strong correlation with Atlantic hurricane activity [8, 13]. Another SST feature belongs to the hurricane main development region (MDR). SST values in MDR have been shown to contribute to the hurricanes generated in the MDR region [18, 26]. The last SST feature is from Pacific Decadal Oscillation (PDO) region. Shifts in the PDO phase can have significant implications for Atlantic hurricane activity, and significant differences are shown in hurricane intensity between El Niño and La Niño years when the PDO is in warm phase [23].

In the case of Model 2 (Fig. 4(b)), some other known climatic patterns related to the North Atlantic hurricane activity are found by our model. For example, NAO index, especially, June NAO index, has been found to be correlated with North Atlantic hurricane tracks of the incoming hurricane season [26, 5]. And ENSO has been found to modulate the tropical systems and strongly influence

North Atlantic tropical cyclones [20]. Our models also find some unknown patterns like PW in ESPI region and VWS in AO regions, which might affect the North Atlantic tropical cyclone activities as well.

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5 Conclusion

In this paper, the spatio-temporal extreme event prediction problem has been modeled as a supervised machine learning problem. We have presented FORECASTER, a feature elimination-based ensemble of classifiers for spatio-temporal extreme events prediction algorithm. FORECASTER can iteratively select small subsets of discriminating features in a multivariate and non-linear fashion. This property lets FORECASTER effectively and efficiently deal with the forecast-oriented classification of spatio-temporal extreme events problem as well as other highly undetermined classification problems. Our experimental results have shown that FORECASTER can improve prediction accuracy by up to 13% on two seasonal tropocial cyclone datasets.

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