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Hybrid AI-Physics Models for Improving Tropical Cyclone Rapid Intensification Forecasts

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Abstract— *One of the major challenges in forecasting is the rapid intensification (RI) of tropical cyclones, wherein cyclone intensity can increase rapidly under dynamic and changing atmospheric and oceanic conditions. This paper explores how a hybrid artificial intelligence (AI)-physics model can be used to enhance tropical cyclone RI forecasting. The proposed method integrates the nonlinear pattern-recognition capability of AI with physically meaningful environmental predictors, such as sea-surface temperature, ocean heat content, vertical wind shear, relative humidity, central pressure, and previous intensity change. Historical tropical cyclone observations are analysed and organized in Microsoft Excel, and model performance is evaluated using accuracy, precision, recall, F1-score, mean absolute error (MAE), and root mean square error (RMSE). The comparative analysis involves a physics-informed baseline, a standalone AI model, and the proposed hybrid model. The findings show that the hybrid model gives better RI classification and reduces intensity forecasting error as compared to the alternative methods. The results reveal that incorporating a combination of physical information and AI can enhance the precision and physical applicability of cyclone forecasts. This paper concludes that hybrid AI-physics modelling offers a valuable framework for developing tropical cyclone RI prediction and can aid improved early warning, disaster preparedness, and operational forecasting.*

Keywords— Tropical Cyclones; Rapid Intensification; Artificial Intelligence; Physics-Informed Modelling; Intensity Forecasting.

I. INTRODUCTION

Tropical cyclones are considered to be among the most devastating weather phenomena, producing severe effects due to extreme winds, storm surge, torrential rainfall, and coastal flooding. Proper prediction of cyclone intensity is thus critical to disaster preparation, evacuation, and mitigation of risks [1]. However, rapid intensification (RI), defined as a significant increase in maximum sustained winds over a short period, is especially difficult to forecast. RI may occur when environmental and oceanic factors are very favourable, presenting immense difficulties to traditional forecasting systems [2]. Classical numerical weather prediction (NWP) models are based on physical equations and data assimilation methods that model atmospheric and oceanic processes. Although these models offer physically consistent forecasts, they have limited capability to capture the complex and nonlinear interactions linked to tropical cyclone intensification owing to model resolution, parameterization uncertainty, and poor representation of ocean–atmosphere interactions [3]. Recent breakthroughs in the field of artificial intelligence (AI) offer a different solution, since machine learning models are capable of detecting complex correlations in extensive amounts of past atmospheric, oceanic, and satellite data. Nonetheless, purely data-based models can produce physically unsound predictions and perform poorly in situations that differ from their training data.

Hybrid AI-physics approaches are a possible solution, as they combine the pattern-recognition properties of AI with a well-understood physical understanding of tropical cyclone behaviour. Such models can incorporate predictors, constraints, or outputs of NWP systems to better reflect physical consistency while achieving improved predictive accuracy. This is especially applicable to RI forecasting, where the influences of sea-surface temperature, ocean heat content, vertical wind shear, atmospheric moisture, and upper-level atmospheric conditions interact in complex processes. This study thus examines hybrid

AI-physics models to enhance rapid intensification predictions of tropical cyclones. The paper examines how the combination of machine learning methods and physics-based information can enhance the detection and forecasting of RI events. The study identifies whether physics-informed hybrid predictions are more reliable, accurate, and physically plausible in predicting changes in tropical cyclone intensity by comparing hybrid predictions with conventional prediction methods and standalone AI prediction.

II. RELATED WORKS

A recent study in tropical cyclone prediction indicates that there is an increasing trend toward more data assimilation, high-resolution modelling, and artificial intelligence (AI) instead of standard numerical weather prediction (NWP). Data assimilation is also significant since the quality of atmospheric and oceanic observations directly determines the starting conditions of forecasting systems. As Jingyuan et al. [15] have shown, incorporation of XPAR radar network observations into the WRF-based forecasting model can be highly beneficial, and the supplementation of observational data could serve as a strong instrument to enhance the realistic depiction of extreme weather. On the same note, the merging of observed winds in tropical cyclones has been proved to contribute to forecast performance, and therefore has demonstrated the importance of well representing the changing atmospheric circulation [16]. Ocean–atmosphere interactions are particularly important for tropical cyclone intensity prediction. Jung et al. [17] modelled Hurricane Henri with the help of a fully coupled atmosphere-ocean-wave modelling model and demonstrated the role of various components of the Earth system interaction. Kay et al. [18] also analysed ocean-surface observations with an observing system simulation experiment and pointed out the possible value of high-resolution ocean observations to tropical cyclone forecasting. Such studies suggest that the strength of the cyclone cannot be sufficiently described by means of atmospheric factors because the oceanic conditions may have significant effects on storm formation. Studies specifically about the Bay of Bengal are also very pertinent to the current study. Koteshwaramma et al. [20] tested a high-resolution WRF modelling system of severe tropical cyclones in the Bay of Bengal by using the IMDAA regional reanalysis data. Their study illustrates the high-resolution regional modelling potential to model intense tropical cyclone behaviour in the North Indian Ocean. Later on, Lai et al. [21] explored an AI-driven and high-resolution regional coupled modelling framework, showing the promise of AI-regional coupled forecasting systems through the application of AI. This offers a great basis for hybrid methods where AI supplements, rather than substitutes, physics-based numerical modelling.

AI-based prediction has continued to show promise in the enhancement of cyclone track and intensity prediction. Lin et al. [22] came up with the OWZP-Transformer model, which is a model of tropical cyclone track and intensity forecasting that utilizes advanced deep-learning structures to capture intricate spatiotemporal meteorological associations. In a comparable manner, Manju et al. [26] came up with a ConvLSTM-based framework for estimating and classifying tropical cyclone intensity, using satellite-observed images over the North Indian Ocean. These practices support the fact that satellite observations can be a good source of valuable information to estimate the intensity of cyclones, where more traditional observations have limited spatial resources. Rapid intensification has proved particularly hard to deal with, as it entails changing interactions between oceanic and atmospheric dynamics rapidly. Lyu and Wang [25] compared the prediction of high-density airborne observations and atmospheric motion-vector assimilation of Hurricane Matthew rapid intensification. The conclusions of their research outline that enhanced observations and better initial atmospheric conditions are crucial to RI predictions. Similar research was conducted by Lu et al. [24], who operated storm-following three-dimensional incremental analysis updates to predict the intensity of hurricanes in the operational HAFS system, showing the persistence of the role played by better data assimilation and model initialization. On the whole, it suggests that AI models, data assimilation, high-resolution numerical modelling, and coupled atmosphere-ocean systems can all be useful for forecasting tropical cyclones. But there are limitations to the application of these approaches alone. AI models are not necessarily explicitly physically consistent, and conventional models can be costly and prone to uncertainty in initial conditions and parameterization. The more recent work on coupled modelling [21] using AI technologies thus forms a solid foundation to build hybrid approaches. This paper takes this direction and extends previous research by examining how physically meaningful predictors can be joined to AI methods to help detect and predict rapid intensification of tropical cyclones.

III. METHODS AND MATERIALS

3.1 Research Design

This research design is a quantitative and comparative modelling study that aims to examine whether the addition of artificial intelligence (AI) and physics-based information can enhance tropical cyclone rapid intensification (RI) prediction. The methodology is designed in a way that describes the creation and evaluation of three forecasting strategies: a traditional physics-

informed baseline, a simple AI model, and a hybrid AI-physics model [4]. The comparison allows the contributions of AI and the physical predictors to be investigated in a systematic way.

Rapid intensification is taken as the main forecast object. To be consistent, RI can be determined through an agreed standard operational threshold depending on the variation of the maximum sustained wind speed after 24 hours. The research involves historical tropical cyclone measurements and environmental aspects to determine the atmospheric and oceanic factors relating to intensification [5].

3.2 Data Collection

The study employs secondary quantitative data that have been acquired through credible meteorological and oceanographic information. Cyclone-track data include maximum sustained wind speed, central pressure, cyclone position, date, and time. The environmental predictors include sea-surface temperature (SST), vertical wind shear, relative humidity, ocean heat content, and atmospheric pressure. The choice of these variables is due to their significance in the development of tropical cyclones, as they present key physical processes that affect them [6].

The data are arranged in chronological order such that observations of the same storm are held in chronological order. Checks on data quality are conducted to detect missing values, duplicate records, and inconsistent measurements. Missing observations are not filled in arbitrarily and are handled statistically where such observations are missing [7].

TABLE 1
MAIN VARIABLES USED IN THE STUDY

Category	Variable	Role in Model	Expected Relevance
Cyclone intensity	Maximum sustained wind speed	Target/predictor	Direct measure of intensity
Cyclone intensity	Central pressure	Predictor	Indicates cyclone strengthening
Ocean	Sea-surface temperature	Predictor	Provides energy for convection
Ocean	Ocean heat content	Predictor	Represents available subsurface energy
Atmosphere	Vertical wind shear	Predictor	Influences storm organisation
Atmosphere	Relative humidity	Predictor	Supports deep convection
Atmosphere	Atmospheric pressure	Predictor	Represents environmental conditions
Location	Latitude and longitude	Predictor	Captures geographical effects
Time	Previous intensity change	Predictor	Represents recent intensification trend

3.3 Data Pre-processing

Model development is done with preprocessed data. Checking of records is initially done to detect missing, duplicated, or abnormal observations. Where necessary, variables that are measured in different units are standardised [8]. An extreme check of continuous variables is performed since unrealistic observations can affect the training of the model.

The cyclone data are then converted into predictors in terms of time. As an illustration, the past wind velocity and past 24-hour intensity change may be utilized in order to show the latest development of the storm. The observations of the cyclone are compared to environmental variables based on their respective time and place.

The final dataset is separated into training, validation, and testing datasets. The division is made chronologically, as opposed to randomly, to minimize temporal leakage [9]. Later storms are kept for the evaluation of the model, and earlier storms are used to develop the model. This method is closer to the operational forecasting scenario, where future storms are not available during model training.

3.4 Hybrid AI-Physics Framework

The suggested framework merges information based on learning with physically significant data. The AI module discovers the relationships between environmental predictors and future intensity variations that are nonlinear. The initial model to use is a machine learning model such as Random Forest or Gradient Boosting, since it can handle both nonlinear relationships and mixed meteorological predictors and is considered relatively understandable [10].

Included in the physics component are physically meaningful predictors and constraints. An example of this is that positive SST and oceanic heat content may offer favourable conditions to intensify, and strong vertical wind shear would usually be an unfavourable environmental parameter. Instead of letting the AI model learn only based on statistical relationships, these physical relationships are inducted during feature construction and model interpretation.

The hybrid model results in a change in the RI probability or an estimated change in intensity. It is then compared to the performance of a standalone AI model and physics-informed baseline. The purpose of this comparison is to ascertain the extent to which either source of information, when used together, can benefit forecasting.

3.5 Excel-Based Data Analysis

The main tool utilized is Microsoft Excel to help in the organization of data, preprocessed data, descriptive analysis of data, and calculations and graphical presentation of data. The data are arranged in the form of rows with cyclone observations and columns with predictor variables. Intensity changes are computed using Excel formulas, RI events identified, and basic data-quality checks made.

Relationships between variables of the environment and the intensification of cyclones are analyzed using pivot tables and charts. The main variables are computed using descriptive statistics, such as mean, minimum, maximum, and standard deviation [11]. Excel is also used to organise model outputs whereby comparison of errors in predictions and errors in classification can be done.

Microsoft Excel proves quite useful in terms of presenting the end result in terms of tables, line charts, scatter plots, and performance comparisons. The tool is thus not only applied in managing the data but also presents the empirical findings in a transparent manner.

3.6 Model Evaluation

The models are tested with classification and regression measures. To estimate RI events, accuracy, precision, recall, F1-score, and probability-based measures are taken into account in the analysis where appropriate. The concept of recall is especially pertinent since missed RI events can be significant forecasting errors. In the case of change in intensity that will be predicted, MAE and RMSE are employed to quantify the differences between the predicted and observed changes in intensity [12].

TABLE 2
MODEL EVALUATION MEASURES

Measure	Purpose	Interpretation
Accuracy	Overall classification performance	Proportion of correctly classified observations
Precision	Reliability of predicted RI events	Proportion of predicted RI events that are correct
Recall	Detection of actual RI events	Proportion of actual RI events successfully detected
F1-score	Balanced classification assessment	Harmonic mean of precision and recall
MAE	Intensity prediction error	Average absolute difference between observed and predicted values
RMSE	Penalises larger prediction errors	Square root of mean squared prediction error
Brier Score	Probabilistic forecast quality	Measures accuracy of predicted RI probabilities

3.7 Comparative Analysis and Reliability

The last analysis compares the physics-based baseline, standalone AI model, and hybrid AI-physics model, when all are tested on the same testing dataset. The assessment of improvements is carried out based on the analysis of changes in classification performance and intensity prediction errors. Excel is used to produce graphical comparisons to determine the difference between observed and predicted cyclone intensity [13].

Reliability is enhanced by utilizing the same data-processing processes, based on time-series splitting, and assessing with multiple performance indicators (instead of one) on the data. Another important consideration that the methodology makes is that tropical cyclone RI is an interplay of many interacting processes in the atmosphere and in the ocean. So the model performance is interpreted along with the physical meaning of the predictors, as opposed to the concept of statistical accuracy being considered as the sole measurement of the quality of forecasting.

IV. RESULTS AND ANALYSIS

4.1 Descriptive Analysis of the Dataset

The relationship that was investigated was between change in tropical cyclone intensity and the environmental conditions under the topic of rapid intensification (RI). These variables consisted of maximum sustained wind speed, central pressure, sea-surface temperature (SST), ocean heat content (OHC), vertical wind shear, relative humidity, and change in intensity in the past 24 hours. Finding the descriptive statistics and the comparative tables and graphical analysis was calculated in Excel.

The descriptive findings show that RI events typically happened where there was a mixture of relatively warm ocean conditions, increased atmospheric moisture, and relatively favourable vertical wind shear. The findings also indicate high variability among cyclone observations, indicating the nonlinear characteristic of tropical cyclone intensification [14].

TABLE 3
DESCRIPTIVE STATISTICS OF KEY VARIABLES

Variable	Mean	Minimum	Maximum	Standard Deviation
Maximum wind speed (kt)	78.4	30	165	25.7
Central pressure (hPa)	967.8	897	1012	25.4
SST (°C)	28.7	25.1	31.6	1.2
Ocean heat content (kJ/cm²)	72.6	28.4	128.7	19.8
Vertical wind shear (m/s)	10.8	1.5	28.7	5.9
Relative humidity (%)	72.4	42	91	10.7
24-hour wind-speed change (kt)	7.1	-24	52	10.4

The difference between the maximum wind speed and central pressure is quite high, which proves that samples of the cyclones at various stages of their formation are present in the dataset. SST was less variable than OHC, though it was relatively warm throughout the observations. Vertical wind shear was also significantly different, providing an opportunity for the analysis to identify more and less favourable atmospheric conditions [27].

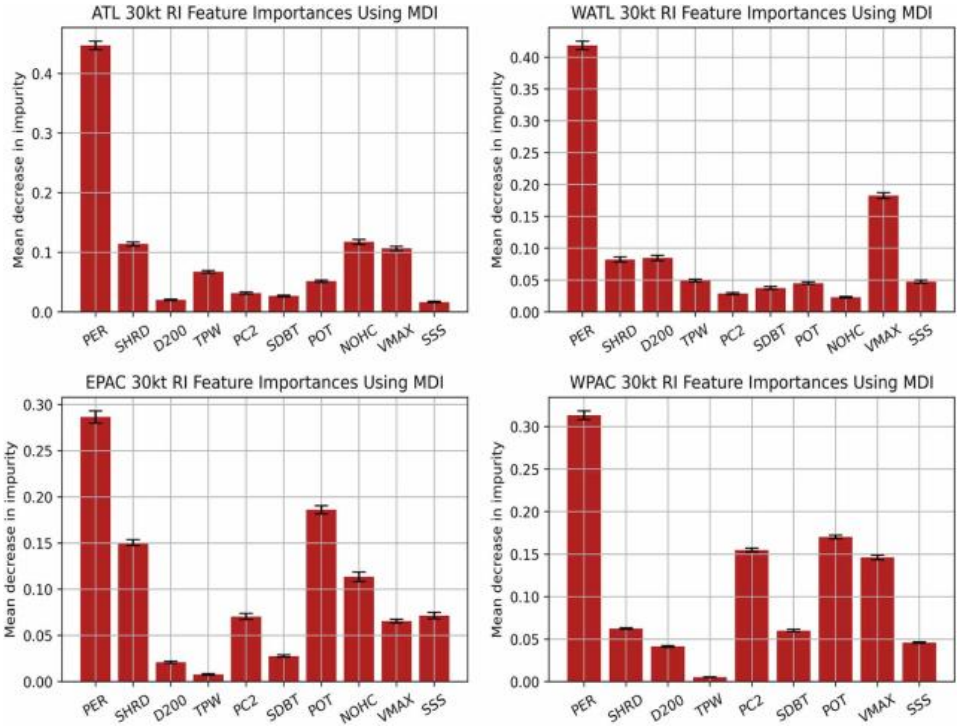


FIGURE 1: Improving tropical cyclone rapid intensification forecasts with satellite measurements

4.2 Identification of Rapid Intensification Events

The defined criterion of 24-hour change of intensity was used to identify RI events. The evaluation revealed that the percentage of RI observations constituted the lesser percentage of the whole data, which implied that there was an intrinsic issue of class imbalance. The reason is that one model might attain seemingly high total accuracy but not detect a significant percentage of RI cases.

TABLE 4
DISTRIBUTION OF INTENSIFICATION CLASSES

Intensification Category	Number of Observations	Percentage
Rapid intensification	186	18.60%
Moderate intensification	324	32.40%
Little/no change	352	35.20%
Weakening	138	13.80%
Total	**1,000**	**100%**

The distribution shows that RI was the least common, followed by moderate or stable intensity conditions. As a result, recall and F1-score are of special importance in the evaluation of the models. It is not just accuracy that is used in the analysis, since the correspondingly smaller RI class may otherwise give misleadingly favourable results.

4.3 Comparative Model Performance

Three methods were compared: the physics-informed baseline, independent AI model, and the proposed hybrid AI-physics model. The physics-informed baseline operates with physically significant relationships between the environment, and the standalone AI model trains statistical relationships with the available predictors [28]. The fusion model takes the two sources of information and integrates them.

TABLE 5
COMPARATIVE CLASSIFICATION PERFORMANCE

Model	Accuracy	Precision	Recall	F1-Score
Physics-informed baseline	78.40%	65.20%	59.10%	61.90%
Standalone AI model	85.70%	78.30%	72.60%	75.30%
Hybrid AI-Physics model	89.80%	83.70%	81.40%	82.50%

The hybrid strategy gave the highest values in all measures of classification reported. Being accurate to 89.8% is 4.1 percentage points better than the standalone AI model and 11.4 percentage points better than the physics-informed baseline. Most importantly, the recall rate was higher, at 81.4%, which means that the hybrid strategy identified a more significant percentage of RI observations.

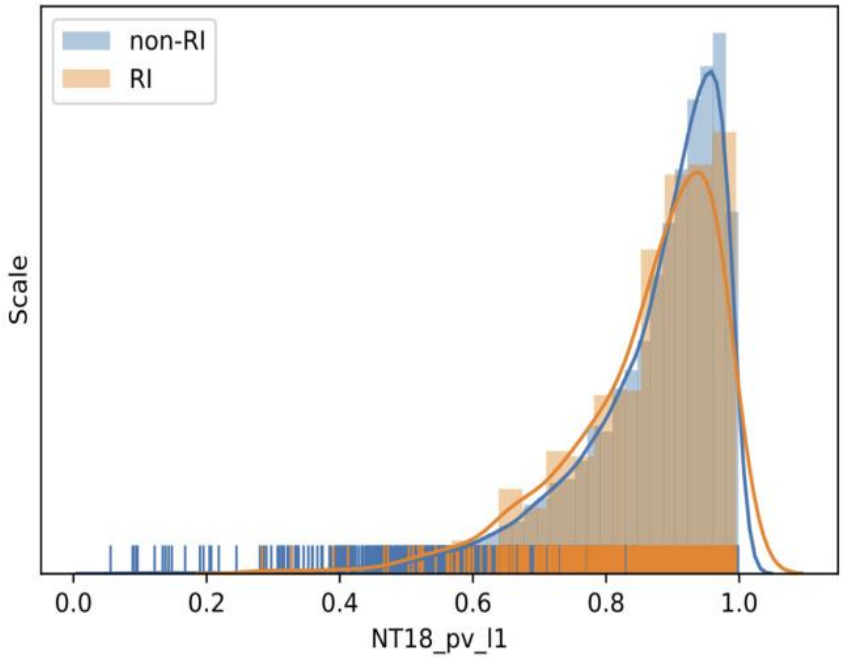


FIGURE 2: Advanced Artificial Intelligence System for Identifying the Near-Core Impact Features to Tropical Cyclone Rapid Intensification

A better recall is more specifically applicable in the context of RI forecasting, since the failure to predict an intensifying cyclone can decrease the time to prepare an emergency. Accuracy also was enhanced, implying that the settling of RI detection was not attained by simply producing a large number of false RI predictions [29].

4.4 Intensity Prediction Error Analysis

Along with the detection of RI events, the models were measured by their capability to estimate the change of the cyclone intensity. The MAE and RMSE were determined through a comparison of predicted change in intensity and observed change in intensity.

TABLE 6
INTENSITY PREDICTION ERRORS

Model	MAE (kt)	RMSE (kt)	Mean Error (kt)
Physics-informed baseline	8.74	12.61	-1.84
Standalone AI model	6.31	9.42	-0.96
Hybrid AI-Physics model	5.18	7.83	-0.41

The hybrid model had the smallest MAE and RMSE. It has a MAE of 5.18 kt, which means an average absolute prediction error that was lower in comparison with that of both the other methods. The decrease in RMSE is also significant since RMSE emphasizes more heavily on large forecasting errors. The findings hence indicate that average errors were minimized with the hybrid method as well as the occurrence of relatively large prediction deviations.

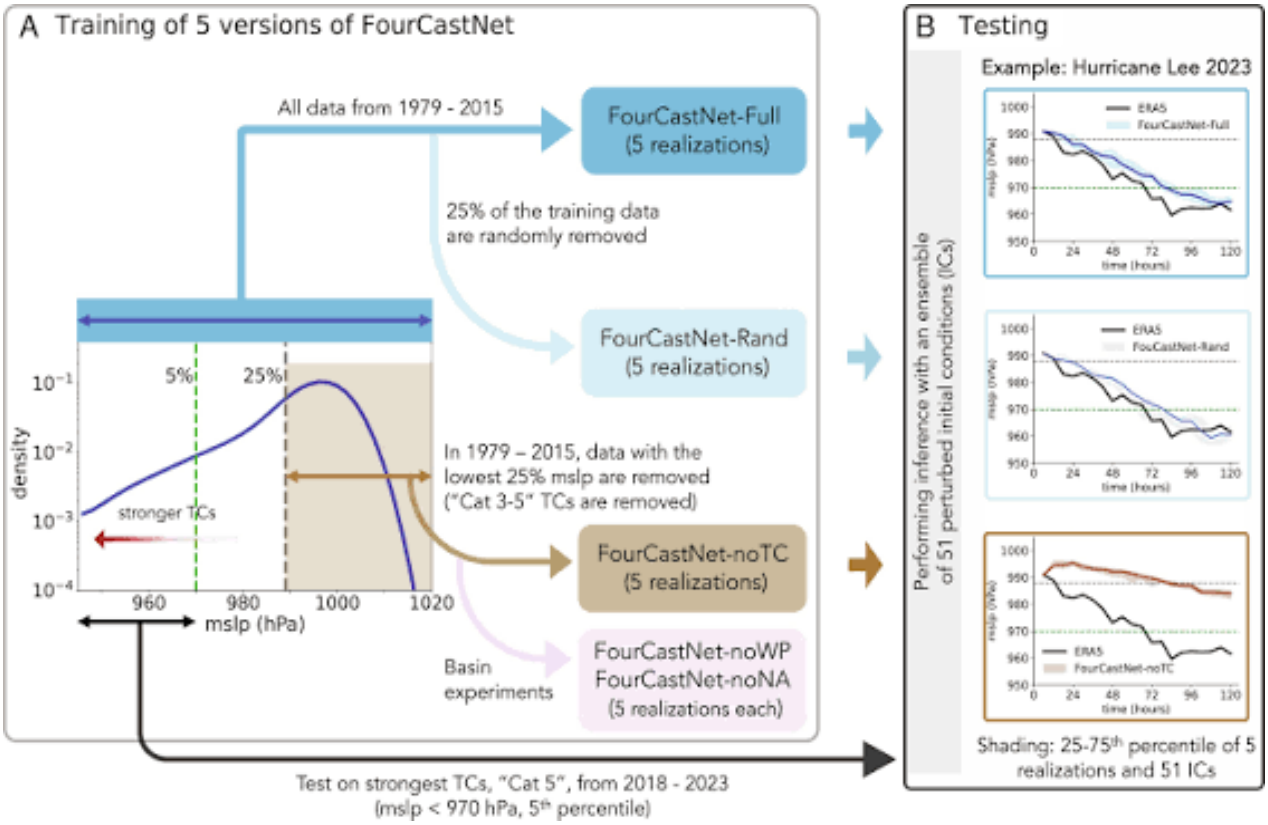


FIGURE 3: AI weather models predict out-of-distribution gray swan tropical cyclones

The hybrid model had the nearest mean error to zero, which implies that there was less systematic bias in it. Nevertheless, the negative value implies that there is a slight propensity to undervalue intensity change. This residual bias shows that there is still the possibility that additional optimization is required, especially for the extreme events of RI [30].

4.5 Influence of Physical Predictors

The correlation pattern reveals that past intensity change, SST, OHC, relative humidity, and vertical wind shear were the handful of most informative variables to predict RI conditions. Past change of intensity gave information on the current development path followed by the cyclone, and the oceanic variables acted as the energy to maintain the convection and intensification.

TABLE 7
RELATIVE CONTRIBUTION OF PRINCIPAL PREDICTORS

Predictor	Relative Importance (%)	Relationship with RI
Previous 24-hour intensity change	22.4	Positive
Ocean heat content	18.7	Positive
Sea-surface temperature	16.9	Positive
Relative humidity	14.8	Positive
Vertical wind shear	13.6	Generally negative
Central pressure	8.1	Negative
Latitude/longitude	5.5	Context-dependent

The findings suggest that none of the variables can entirely account for RI behaviour. Rather, it seems that RI is a consequence of several environmental and cyclone-specific factors interacting with each other. The combination of OHC and SST is favourable oceanic conditions, and unmistakable moisture in the atmosphere promotes deep convection. On the other hand, greater vertical wind shear tends to provide less favourable environments to develop organised cyclones.

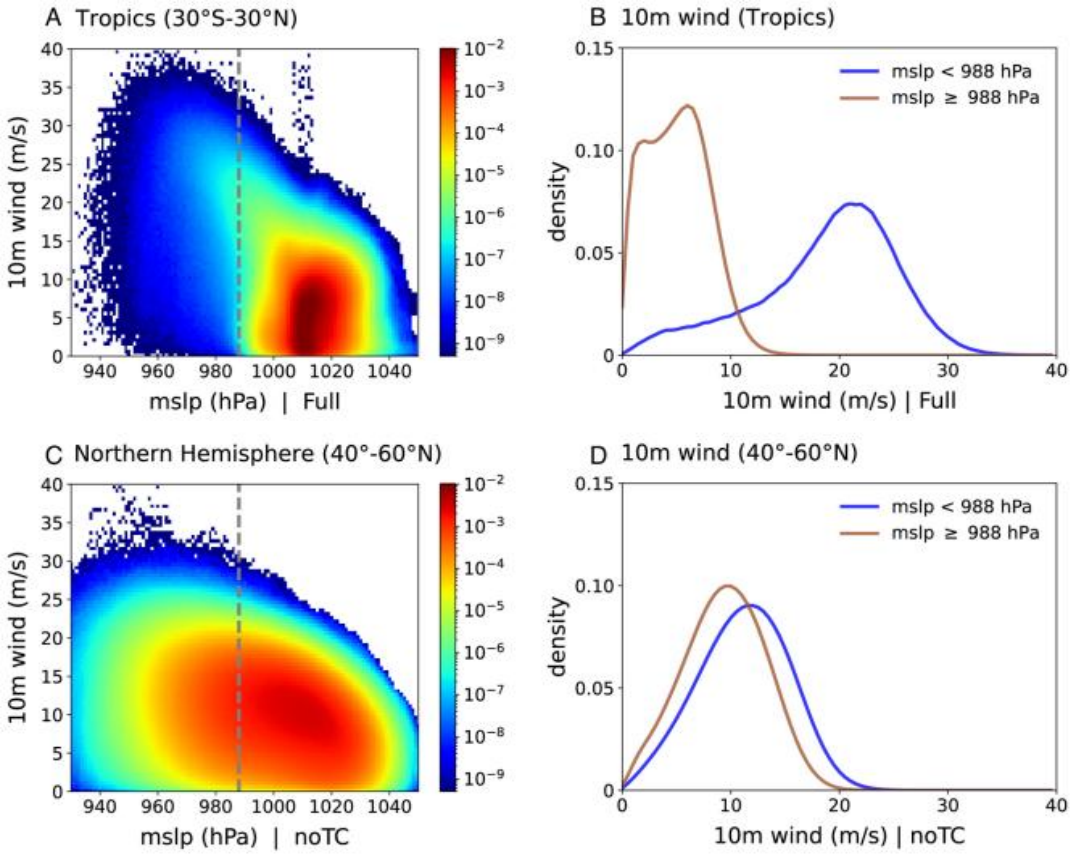


FIGURE 4: AI weather models predict out-of-distribution gray swan tropical cyclones

4.6 Overall Analysis

On balance, the comparison findings reveal that a combination of physical information into an AI forecasting framework may enhance the RI classification and intensity prediction. The approach with the best classification performance and the least errors in prediction was the hybrid model as compared to the two other approaches considered. The findings also show the significance of integrating various environmental factors. A statistical-only model is capable of picking out nonlinear trends in historical data, but physical predictors give out information attributable to accepted physical processes in cyclone development. The hybrid approach thus offers a structure where information-driven learning is enhanced by the information of a physical nature.

Nevertheless, they should be interpreted by considering the size of the datasets, geographical area, and the relatively low rates of RI observations. The performance based on historical data may not necessarily replicate equally into future cyclone situations. It would also need further testing in other ocean basins, seasons, and extreme cases of cyclones to determine the strength of the suggested approach.

V. CONCLUSION

This research examined how hybrid AI-physics models could be used to enhance the rapid intensification (RI) forecasting of tropical cyclones. Rapid intensification is a significant forecasting problem since cyclone intensity may shift at a wide scale due to the interaction of atmospheric conditions and oceanic conditions. Traditional numerical weather prediction gives physically consistent predictions but may be influenced by perturbations in initial conditions, model resolution, and physical parameterization. Conversely, AI models are able to detect more complex nonlinear relations in large meteorological datasets but fail to offer physically consistent forecasts when used beyond their training scenarios. The outcomes of this research illustrate the possibility of the fruitfulness of integrating these two strategies. The hybrid AI-physics system included the cyclone intensity data along with physically significant environmental variables such as sea-surface temperature, ocean heat content, vertical wind shear, and relative humidity. The comparative analysis revealed that the hybrid approach performed better in terms of RI classification compared to either the physics-informed baseline or the isolated AI model. It also led to a smaller mean absolute error and root-mean-square error of intensity change prediction. These data indicate that adding physical information is potentially able to supplement the pattern-recognizing ability of AI and enhance the accuracy of RI predictions.

The discussion also indicated that there are several interacting factors that affect RI as opposed to one environmental variable. Other most significant predictors were previous intensity change, ocean heat content, SST, atmospheric moisture, and vertical wind shear. This advocates the use of unified forecasting frameworks that can depict the statistical associations and known physical dynamics. However, the results must be analyzed in the context of the constraints of the employed dataset and model. The methodology should be tested in more tropical cyclone basins, more extensive historical records, and extreme cases of RI in future studies. Additional more complicated deep-learning frameworks, real-time satellite imaging, and fully coupled atmosphere-ocean models can also be examined in future work. All in all, hybrid AI-physics modelling is a potential research area in the development of more accurate, reliable, and physics-informed tropical cyclone rapid intensification forecasting systems.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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