



**POLITECNICO**  
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# An Evaluation of Data-Driven Interpretable Methods to Detect Tropical Cyclones

Marco Adriano Ferrero 977577

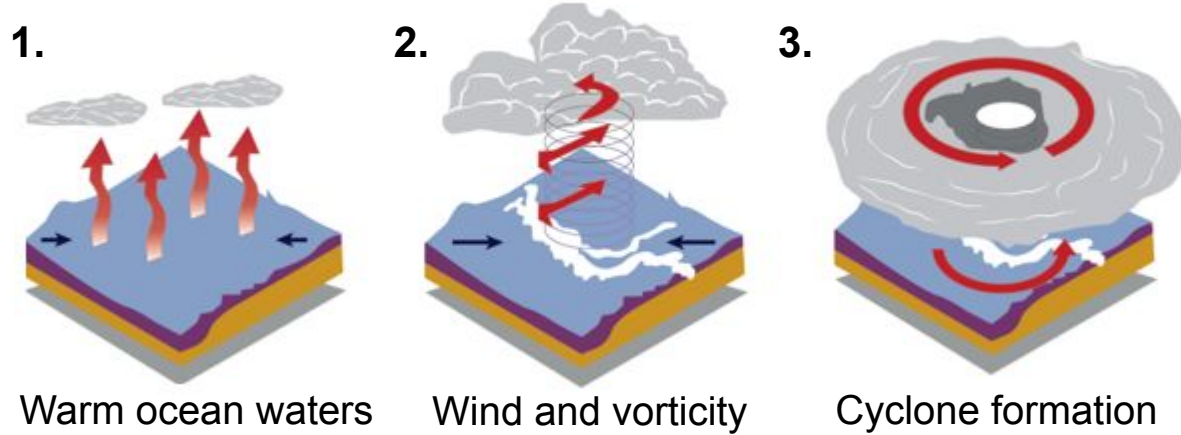
Academic Year: 2023-2024

Advisor: Francesco Amigoni

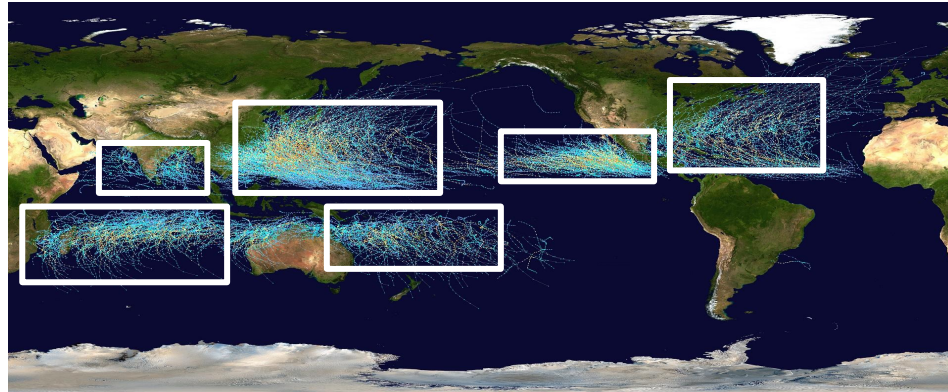
Co-Advisors: Federico Cerutti, Letizia Tanca, Davide Azzalini

# What is a Tropical Cyclone?

## Tropical Cyclones Formation



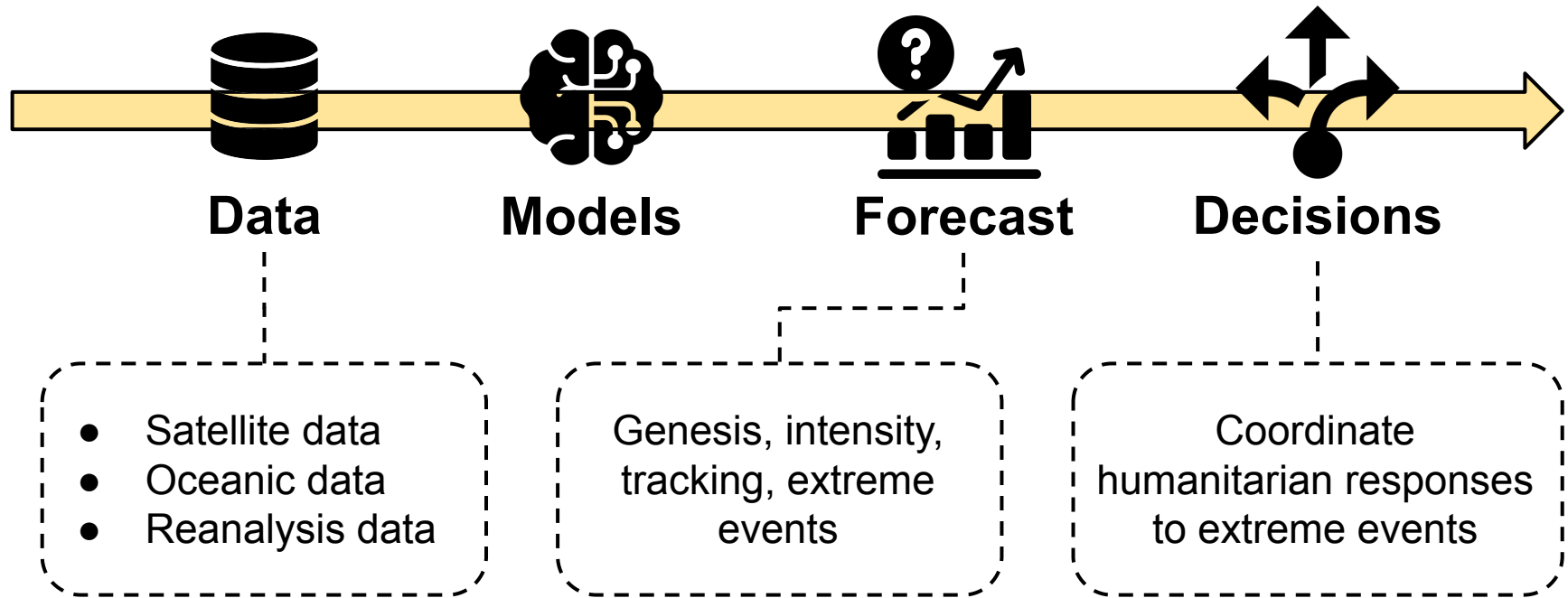
## Tropical Cyclones Basins



[Palmen, 1948]

Credits: NASA and IBTrACS

# Tropical Cyclones Forecasting Problem



[Pradhan et al., 2017]  
[Chen et al., 2020]

# Purpose of the Thesis



- Apply Machine Learning based methods to detect the presence of tropical cyclones in the South-West Indian Ocean basin
- Provide explanations to support decision processes

## Global Drivers



### El Nino Southern Oscillations

- Sea surface temperatures

### Madden-Julian Oscillation

- Real-Time Multivariate Index (RMM)

## Local Drivers



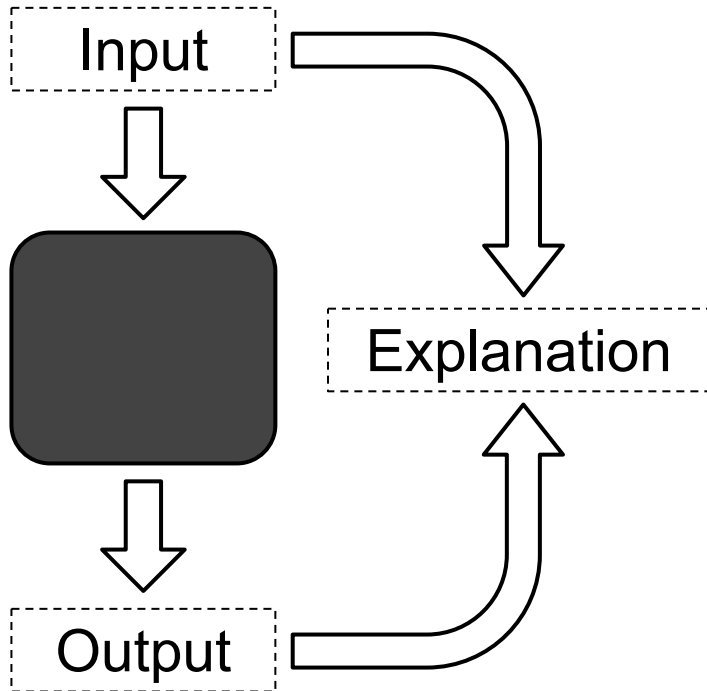
- Wind speeds
- Temperature
- Pressure
- Precipitation
- Relative vorticity
- Air density

ECMWF's 5th  
reanalysis system (ERA5)

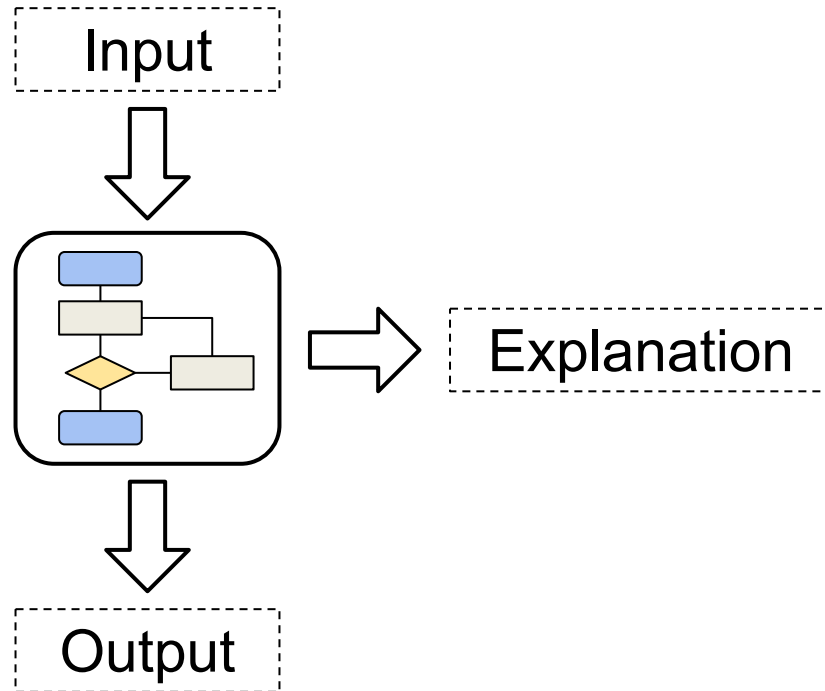


# Black-Box vs. White-Box

## Black-Box Model



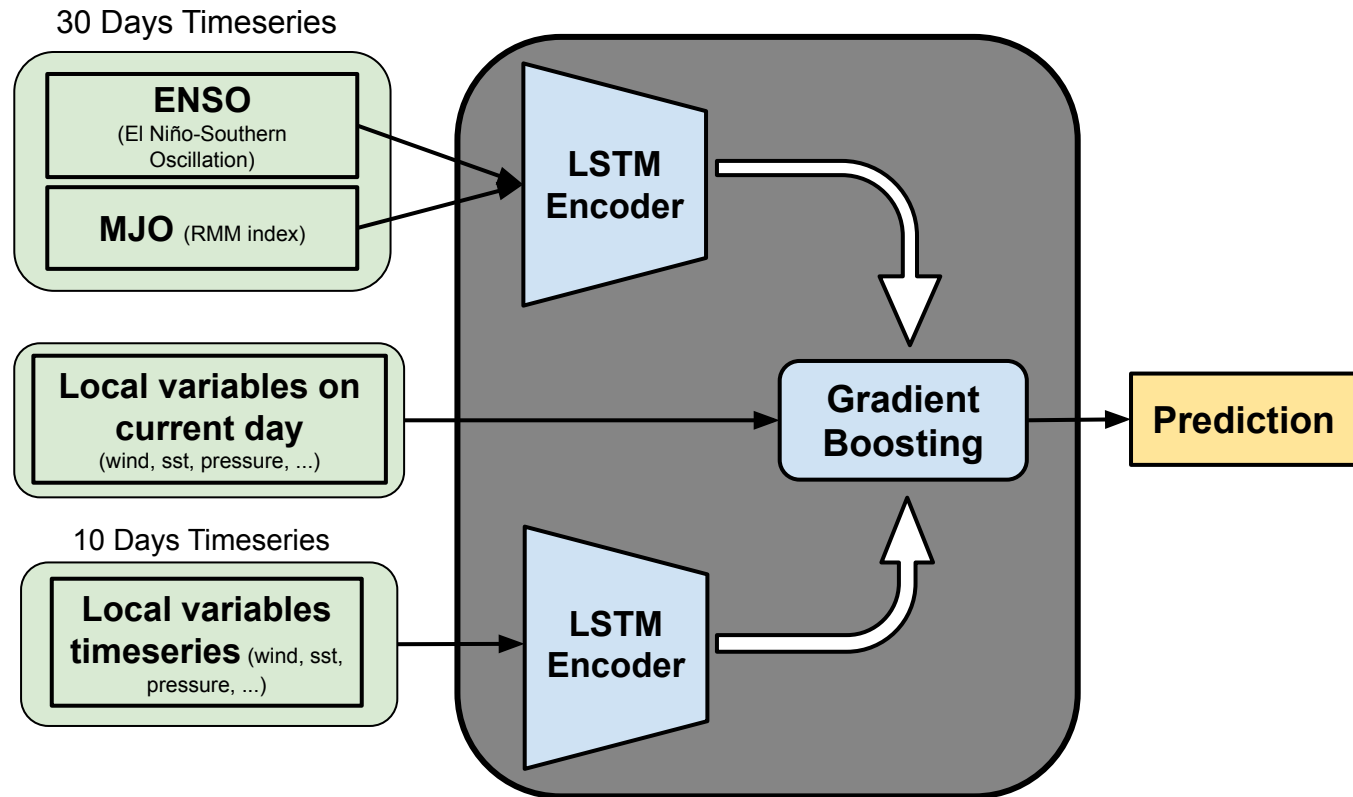
## White-Box Model



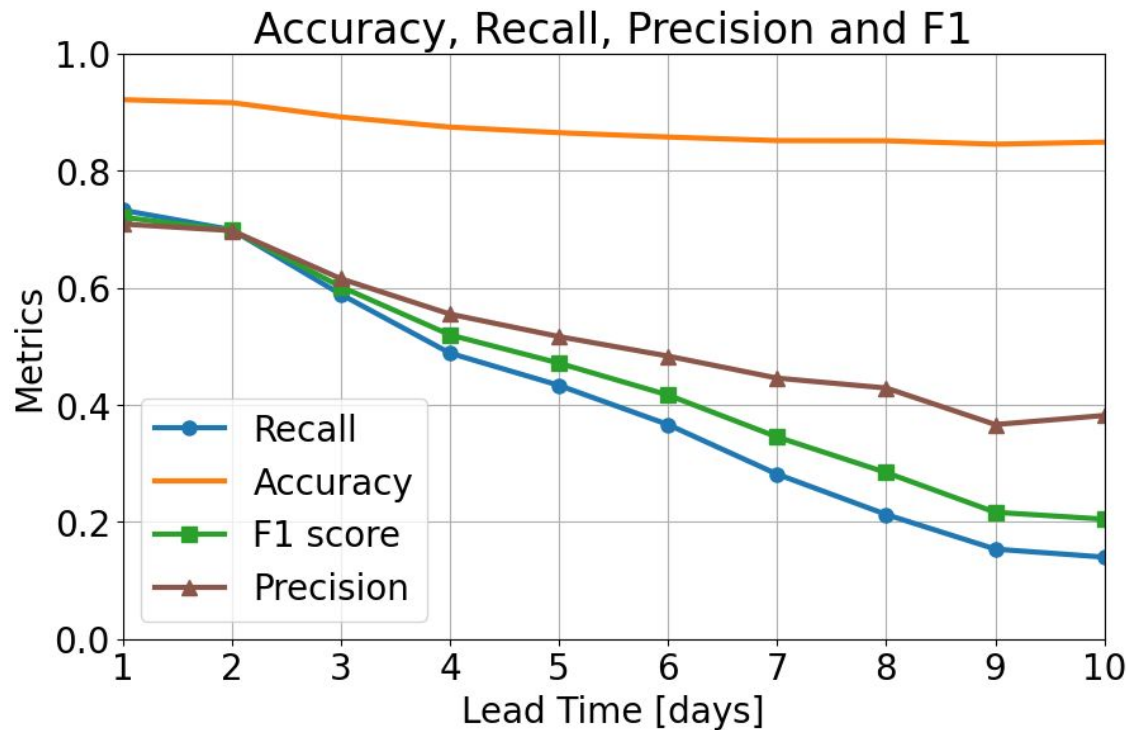
# Black-Box - LSTM Encoders + Gradient Boosting

## Black-boxes:

1. Gradient boosting decision trees (GBDTs)
2. LSTM networks
3. **LSTM Encoders + GBDTs**



# Black-Box - Results

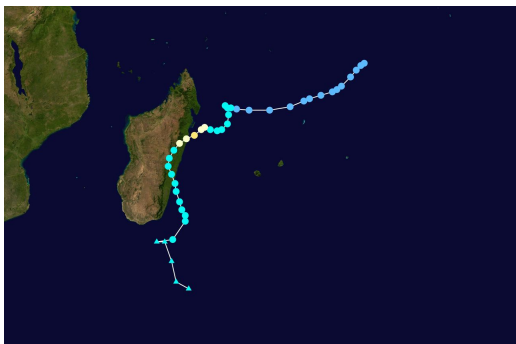


$$Precision = \frac{TP}{TP + FP}$$

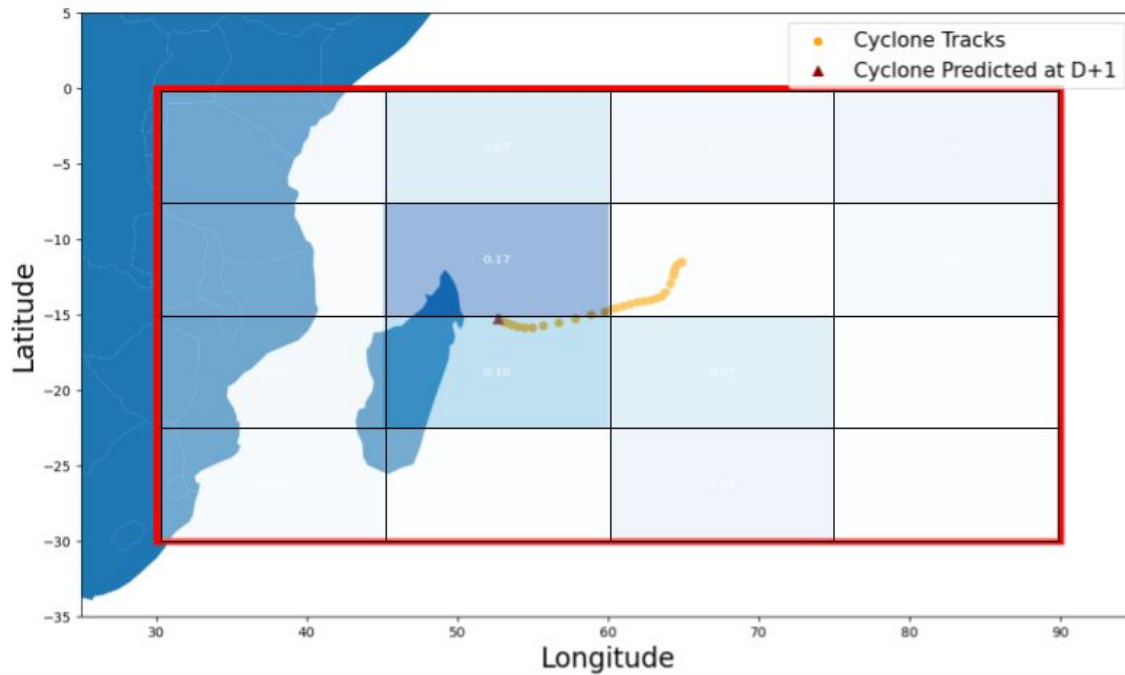
$$Recall = \frac{TP}{TP + FN}$$



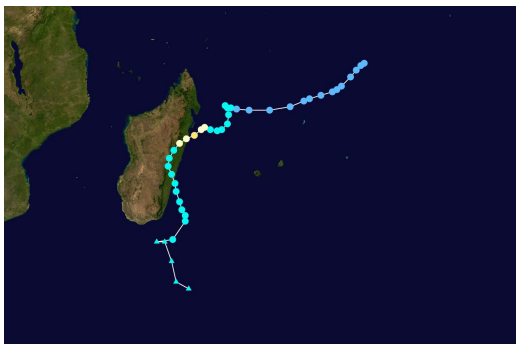
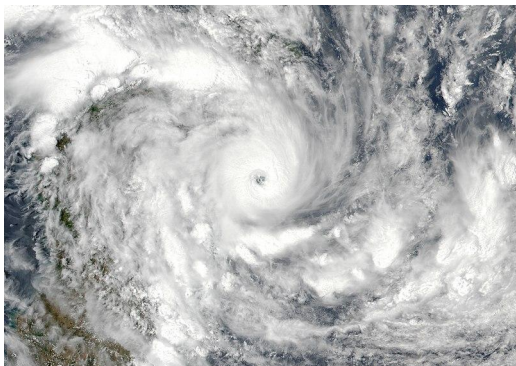
## Cyclone Ava - 3 January 2018



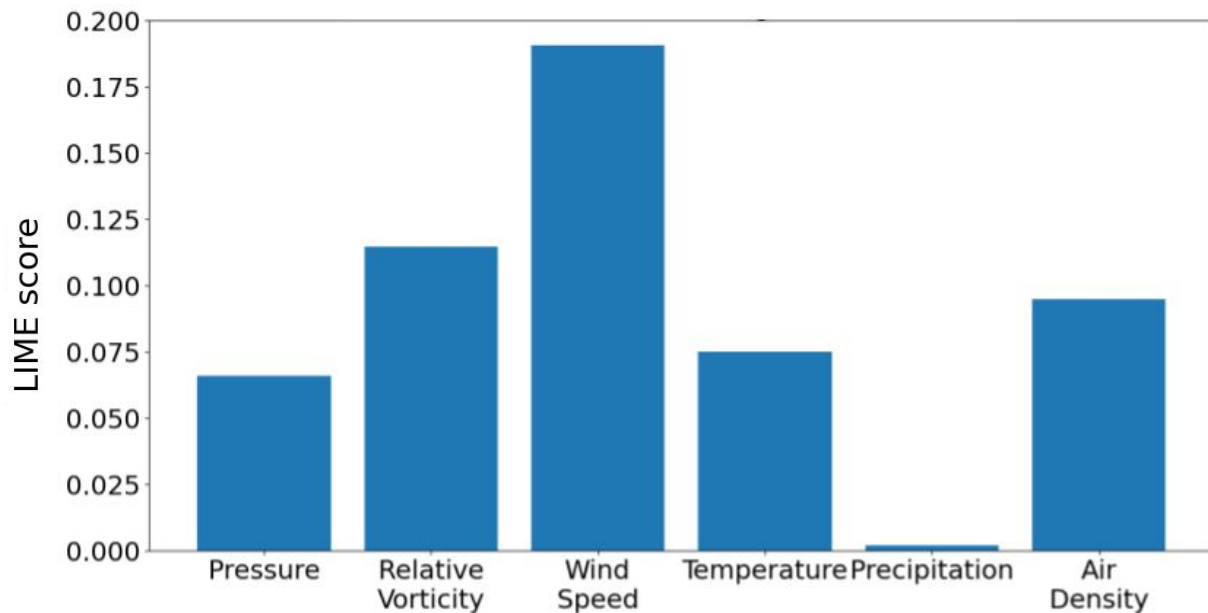
Credits: [earthobservatory.nasa.gov](https://earthobservatory.nasa.gov)



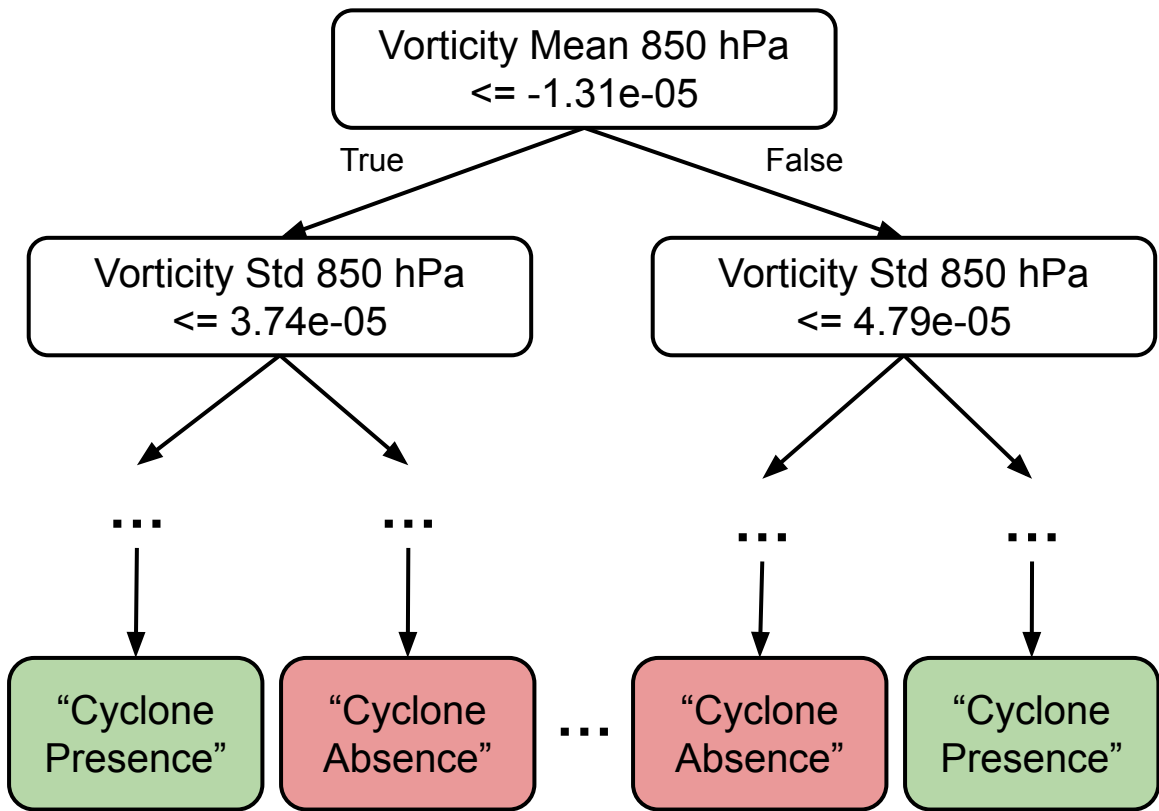
## Cyclone Ava - 3 January 2018



*Credits: earthobservatory.nasa.gov*



# White-Box - Decision Tree



## Predictive Results - 24 h Horizon

Recall	82%
Precision	88%
False Alarm Rate	12%

## Tree Structure

Max Depth	6
Number of Leaves	28

# White-Box - Bayesian Rule Lists

## Trained RuleListClassifier

```
=====
IF      P_Mean > 101230   and Wind_Gust_Std <= 2.11      THEN probability of class 1: 0.3% (0.2%-0.5%)
ELSE IF P_Mean > 101230   and Vor_850hPa_Std <= 3.26e-05 THEN probability of class 1: 0.6% (0.2%-1.1%)
ELSE IF P_Std <= 175      and Vor_850hPa_Mean >= -3.11e-06 THEN probability of class 1: 2.2% (1.5%-3.0%)
ELSE IF Vor_850hPa_Std <= 3.26e-05                        THEN probability of class 1: 10.7% (8.6%-13.1%)
ELSE IF P_Mean > 101230   and T_1000hPa_Std > 0.92      THEN probability of class 1: 6.0% (2.5%-11.0%)
ELSE IF Vor_850hPa_Mean >= -3.11e-06                    THEN probability of class 1: 26.4% (15.6%-38.9%)
ELSE IF P_Std <= 175                                      THEN probability of class 1: 29.4% (22.2%-37.1%)
ELSE IF -1.32e-05 < Vor_850hPa_Mean <= -3.11e-06      THEN probability of class 1: 55.8% (48.5%-62.9%)
ELSE IF Wind_850hPa_Mean <= 11.5                      THEN probability of class 1: 82.8% (75.6%-88.9%)
ELSE IF P_Std > 196                                      THEN probability of class 1: 97.8% (94.8%-99.5%)
ELSE                                                    probability of class 1: 33.3% (1.3%-84.2%)
=====
```

## Predictive Results - 24 h Horizon

<b>Recall</b>	70%
<b>Precision</b>	78%
<b>False Alarm Rate</b>	22%

## What has been done?

- Implementation of White-Box and Black-Box models to detect cyclones on multiple time horizons
- Global drivers have a weak influence on the overall forecasts, while local drivers better fit the problem
- Forecasting limitations due to poor quality and high dimensionality of meteorological data

## Future Work:

- Evaluate interpretable data-driven methods to address track, intensity, or seasonality forecasting
- Apply interpretable techniques to additional state-of-the-art models (CNNs, transformers, ...)

Thank you