Understanding Tropical Cyclone Transition using JPSS Data and Deep Learning

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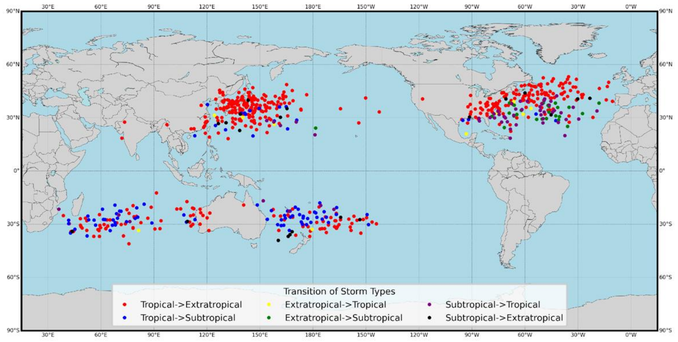
Introduction

- **Transitions between tropical cyclone (TC) types have associated changes in structure and hazards**
  - Tropical (T), Extratropical (ET), Subtropical (ST)
  - (T) to (ET) transition often involves increased rainfall and wind field expansion
- **Global weather forecast models do not always correctly diagnose storm transitions**
- **This study develops a machine learning TC classification model using LEO satellite temperature and moisture retrievals**
  - JPSS Extratropical Transition Classification (**JETClass**)

Damage caused by storm Fiona (2022), CBC news

Global TC Transition Locations



Statistics from 2000 - 2023

Methods for TC Type Classification

- **Cyclone Phase Space analysis**: Uses horizontal and vertical TC structure parameters from global models to estimate storm type *(Hart, 2003)*
  Most widely used
- **Statistical Hurricane Intensity Prediction Scheme (SHIPS):** Extratropical Transition Classification (**ETClass**) using LDA method based on GFS, GOES and ocean data *(DeMaria, et al., 2005)*
  Operational NHC/CPHC
- **Machine Learning**: Utilizes image recognition and deep learning for tropical/extratropical detection *(Kumler-Bonfanti, et al., 2020)*
  Recent research

Poster #250

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Input Data

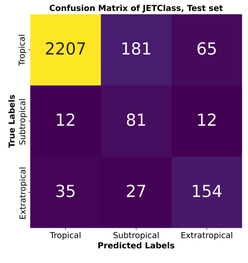
- **Dataset for Training, Validation and Testing**
  - Covers 2015–2023, including 830 TCS worldwide
- **ATCF Best tracks from NHC, CPHC, JTWC**
  Storm type classification "ground truth" for model training
- **JPSS and Met-Op ATMS and AMSU satellite products**
  - NOAA-15/19, MetOp-A/B/C, SNPP and NOAA20/21
  - Temperature and moisture from retrievals
  - Derived Geopotential height (Z) and Horizontal winds
  - Variables on 0.2 deg lat/lon at mandatory pressure levels
- **GFS model analysis**
  - Sea surface temperature
  - Boundary conditions for satellite Z and wind retrievals

TC Centric Predictors

- **ATCF Best track predictors**
  - TC latitude, max wind and translational speed
- **Satellite retrieval predictors**
  - Hart (2003) Cyclone phase space parameters
  - Temperature advection
- **GFS predictor:** *SST*

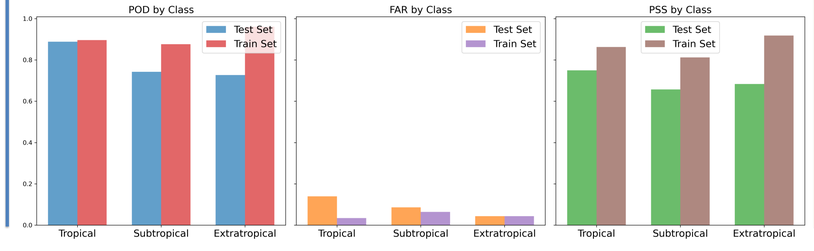
Model Architecture and Performance

- **JETClass is a fully connected neural network model designed for storm classification:**
  - Two hidden layers with 64 units each
  - Leaky ReLU activations for enhanced learning stability
  - Outputs probabilities for three storm types
- **Benchmark model: LDA/QDA utilized by ETClass**



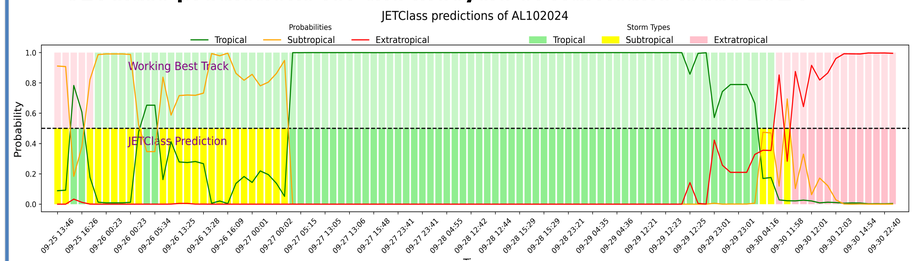
- Probability of Detection (POD)
  POD = TP / (TP+FN)
- False Alarm Rate (FAR)
  FAR = FP / (FP+TN)
- Peirce Skill Score (PSS)
  PSS = POD – FAR
- **Weighted Average PSS**

JETClass: 0.86 (Train set), 0.74 (Test set)
LDA/QDA: 0.45 (Train set), 0.31(Test set)

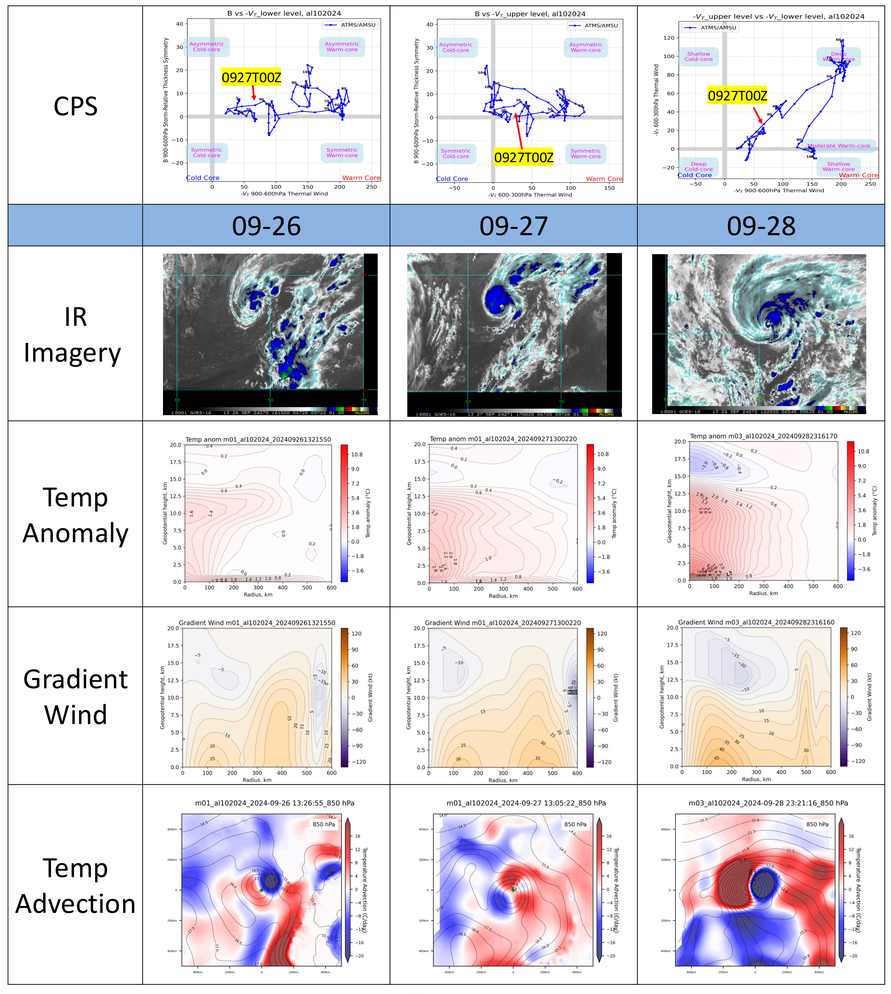


Model NRT Performance in Season 2024

- **JETClass predictions for the lifecycle of Hurricane Isaac 2024**



- Case Study: JETClass predictions of Subtropical-to-Tropical transitions around 09-27 00Z



Next Steps

- **Run and perform verifications in real-time**
- **Compare with operational SHIPS storm type classification**
- **Evaluate performance for individual storm types: Preliminary results indicate worst performance for ST cases**
- **Improve JETClass with new predictors, methods for balancing sample between T, S and ET cases**