Multi-Resolution Analysis of the Convective Structure of Tropical Cyclones for Short-Term Intensity Guidance

Elizabeth Cucuzzella[1], Tria McNeely[1], Kimberly Wood[2], Ann B. Lee[1,3]

[1] Department of Statistics and Data Science, Carnegie Mellon University, [2] Department of Hydrology and Atmospheric Sciences, University of Arizona, [3] Machine Learning Department, Carnegie Mellon University

Abstract

Accurate tropical cyclone (TC) short-term intensity forecasting with a 24-hour lead time is essential for disaster mitigation in the Atlantic TC basin. Since most TCs evolve far from land-based observing networks, satellite imagery is critical to monitoring these storms; however, these complex and high-resolution spatial structures can be challenging to qualitatively interpret in real time by forecasters. Here we propose a concise, interpretable, and descriptive approach to quantify fine TC structures with a multi-resolution analysis (MRA) by the discrete wavelet transform, enabling data analysts to identify physically meaningful structural features that strongly correlate with rapid intensity change. Furthermore, deep-learning techniques can build on this MRA for short-term intensity guidance.

Motivation

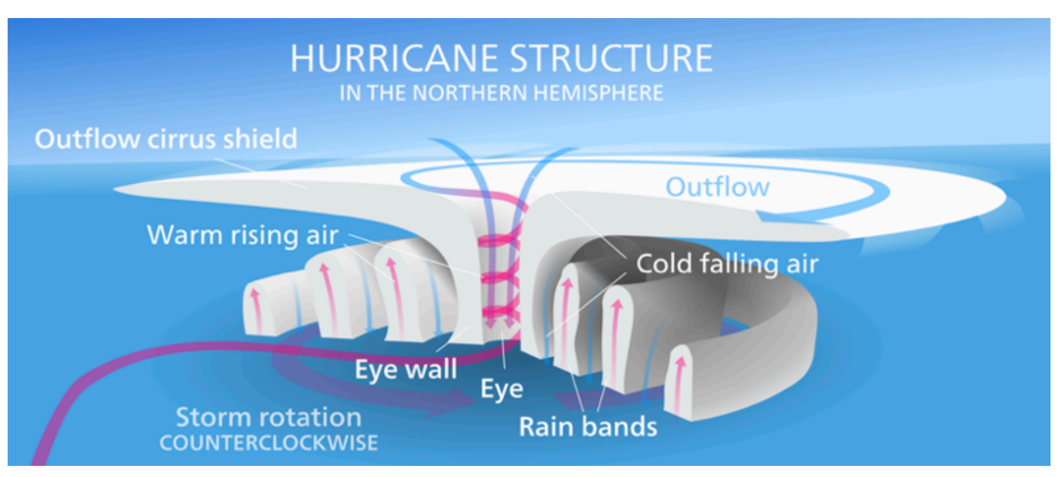

Figure 1: Diagram of Tropical Cyclone, courtesy of the Interdisciplinary Teaching about Earth for a Sustainable Future Center.

Since 1980, TCs have cost **over $1.5 trillion in damages** in the United States.

Rapid intensification (RI) events post a threat to life and property, and are difficult to predict. RI = $\geq$30 knot intensity increase in 24 hours.

Accurate prediction of TC intensities is a critical component of disaster preparation and response. However, short-term intensity guidance (24h window) is highly unreliable. RI events are both hard to predict and destructive.

TC intensity is tied to its convective structure. Intense TCs are characterized by deep convection in the eye wall and a warm-core structure. **Infrared (IR) imagery serves as a proxy for the convective structure of TCs.**

Goal:
Use TC convective structure to predict RI events.

Challenge #1:
Finding a concise, interpretable, and descriptive approach to capture TC structures at different scales.

Discrete Wavelet Transform

Solution:
Forecasting RI events using multi-resolution analysis (MRA) of satellite imagery and compression via wavelets.

IR images from the Geostationary Operation Environmental Satellites (GOES) are high-dimensional and noisy.

Wavelets allow us to decompose images into structures at different scales and directions. We can express each GOES IR image $f(x)$ as

$$f(x) = \sum_{j,n,k} c_{j,n}^k \psi_{j,n}^k(x)$$

where

$$\psi_{j,n}^k(x) = 2^{-j}\psi^k(2^{-j}x - n) \quad \forall j \in \mathbb{Z}^+, n \in \mathbb{Z}^2, 1 \leq k \leq 3$$

where $\psi_{j,n}^k$ are orthogonal, Daubechies wavelet functions at scale j in the horizontal, vertical, and diagonal direction, indexed by k.

Through the discrete wavelet transform coefficients, we **encode directional changes of the convective structure at both fine and coarse resolutions** corresponding to scales $j = 1,2,3$.

Wavelet coefficients have a small amplitude if the signal is regular over the support of $\psi_{j,n}^k$. Since we are interested in regions with the largest gradients in convective structure, we can **threshold** the wavelet coefficients to retain the top 10% highest magnitude coefficients.

We achieve a **total compression of the original image by a factor of 1/20**.

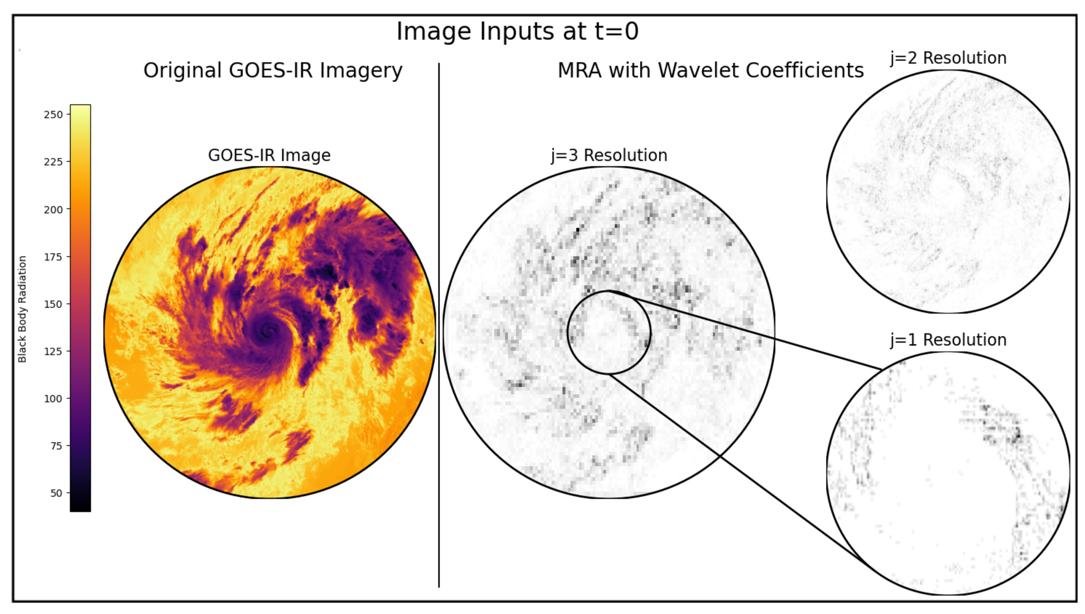

Figure 2: Example images at time $t = 0$ (i.e. the last frame in a sequence $S_{\leq 0}$ that is inputted to the respective CNNs to nowcast TC intensities for Hurricane Eta (2020) which underwent RI at $t = 0$. Left: The high-resolution GOES-IR imagery. Right: The thresholded wavelet coefficients used as model inputs. In this case, $j = 3$ represents the coarsest scale and $j = 1$ represents the finest scale used.

Nowcasting Rapid Intensification

	Years	Non-RI	RI	Total
Training	2000 - 2015	1361	49	1440
Testing	2016 - 2022	741	26	767

Table 1: The number of unique 24-hour sequences of GOES-IR images in both the training and testing data sets. In order to extrapolate to future storms, we trained on storms from 2000-2015, and tested on storms in the following years. These numbers show that roughly 3.4% of GOES-IR sequences are structurally primed for rapid intensification.

We train a convolutional neural network (CNN) to classify 24-hour sequences $S_{\leq t}$ of wavelet images as structurally primed for an RI event ($Y = 1$) or a non-RI event ($Y = 0$). For comparison, we train a similar classifier with the full GOES-IR image. We assign each sequence a score

$$p_t = \mathbb{P}(Y_t = 1 \mid S_{\leq t}) - \mathbb{P}(Y_t = 1)$$

If $p_t > 0$, we label the sequence $S_{\leq t}$ as **structurally primed for RI.**

Results:
MRA approach has a TPR of 80.77%, a 3.85% improvement over using the GOES-IR images.

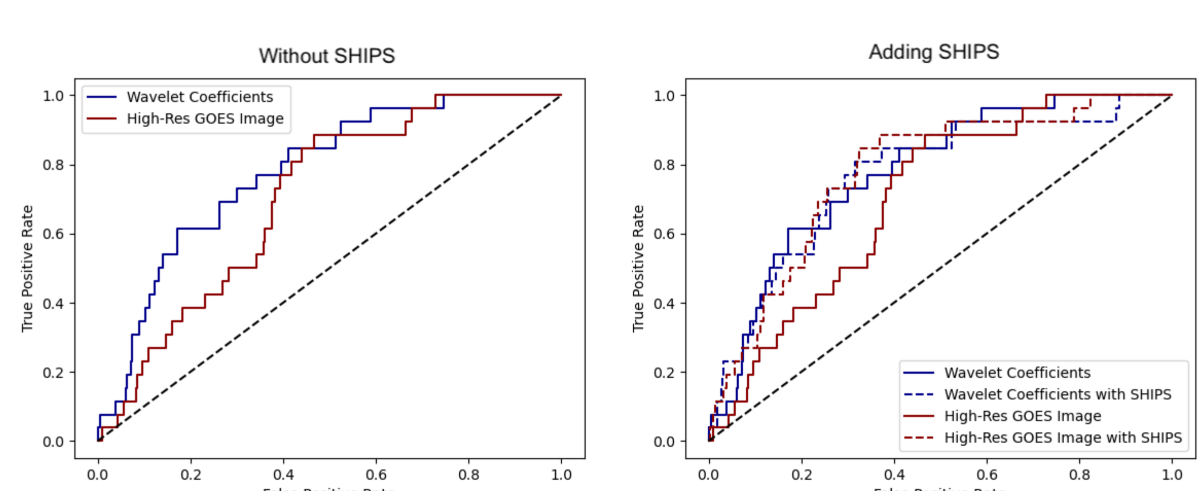

Figure 3: Left: CNNs trained with our wavelet coefficients (solid blue) lead to much better TC intensity predictions, as indicated by a larger area under the ROC curve, than when working directly with the original GOES imagery (solid red). Right: Adding SHIPS variables marginally improves the wavelet results (dashed blue), but is necessary for GOES (dashed red after adding SHIPS) to be competitive with wavelet results without SHIPS (solid blue).

A benefit of using wavelet coefficients over the high-resolution GOES images is **enhanced interpretability, data compression, and robustness to spurious noise**. It is easier in the wavelet space to identify key structures associated with a label of RI or non-RI through a class-activation map.

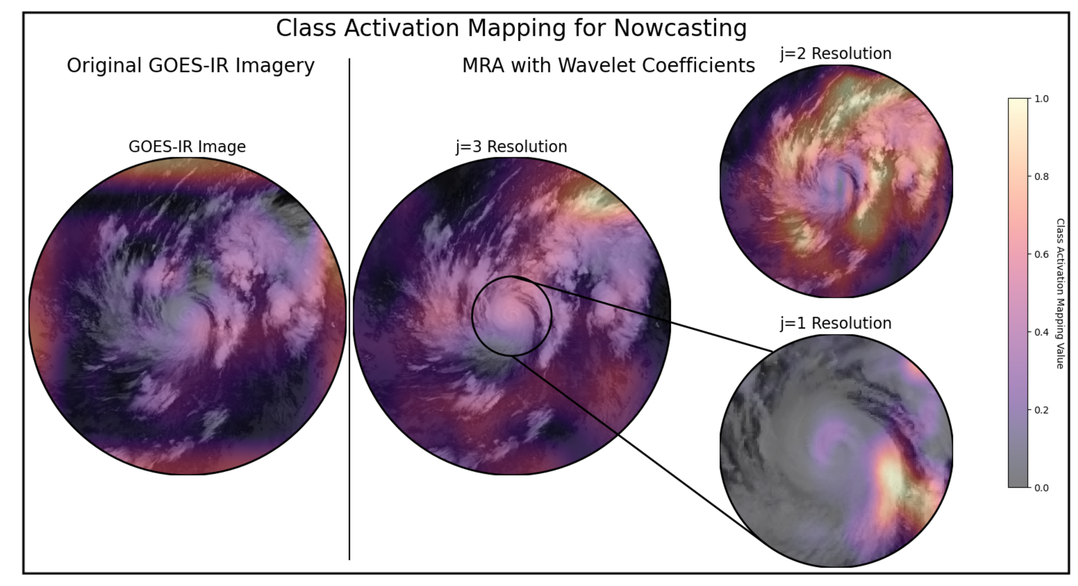

Figure 4 Example of class activation maps (CAMs) for the inputs at $t = 0$ seen in Figure 2. Left: The CNN trained on the original GOES-IR imagery had a hard time discerning structural aspects of the storm, instead applying weight at the input's edges. Right: For the wavelet approach, the CNN was able to identify unique and specific structural aspects of the storm correlated with intensification, such as the storm's curvature and cloud coverage. Specific convective features were identified at all resolutions.

Challenge #2:
Transitioning from nowcasting to forecasting at a 24-hour lead time with scientific interpretability.

Structural Forecasting

Solution:
Propagate wavelet coefficients for structural forecasting via transformers then predict intensities at 24-h lead time with CNNs.

Accurate structural forecasts are imperative to improve 24-hour intensity forecasts, and to allow human forecasters to relate intensity predictions to physical processes. The sparse nature of wavelet coefficients allows for more efficient NN architectures with generative models.

We propose building an encoder-decoder architecture based on transformer blocks with multi-head attention for **autoregressive forecasting of wavelet coefficients at future time steps.** By discretizing wavelet coefficients into a discrete vocabulary based on distribution, we can apply positional embeddings to tokenized inputs to **effectively learn complex temporal dependencies**.

Our proposed framework combines **the power of deep learning networks** to propagate sequences of images and nowcast TC intensities with **the invaluable expertise of human forecasters**.

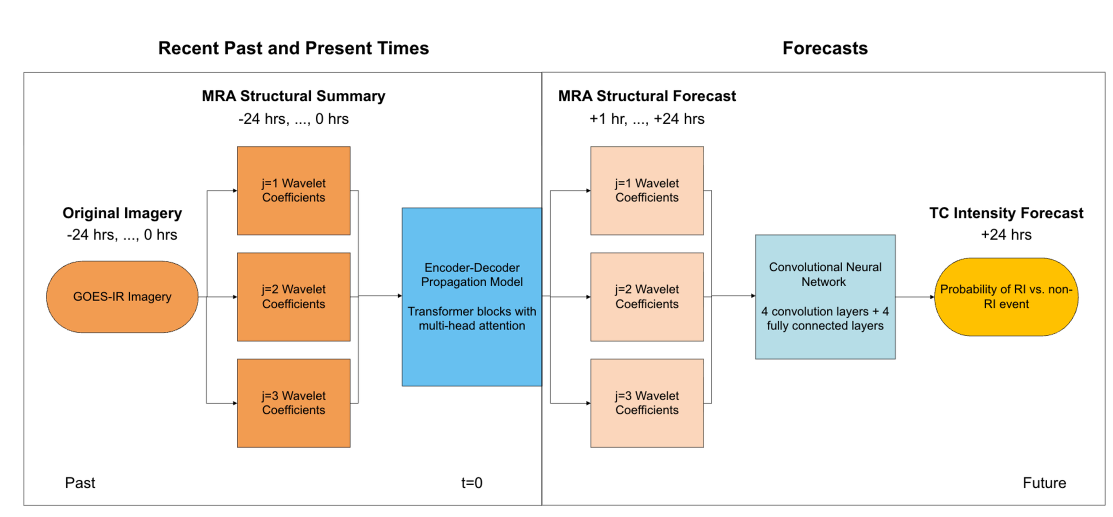

Figure 5: Our proposed framework for propagation of wavelet coefficients to forecast RI events. Representing GOES-IR images in the wavelet space allows for efficient generation of future time stamps using an encoder-decoder propagation model. The generated structural forecasts in the wavelet space then serve as the input to our pre-trained CNN nowcasting model. This method yields the probability of an RI vs. non-RI event at $t + 24$ hours.

Selected References

Luca Masserano et al. "Enhancing Foundation Models for Time Series Forecasting via Wavelet based Tokenization". In: *International Conference on Machine Learning* (2025).

Stephane Mallat. *A Wavelet Tour of Signal Processing*. Academic Press, 1998.

Tria McNeely et al. "Unlocking GOES: A Statisical Framework for Quantifying Evolution of Convective Structure in Tropical Cyclones". In: *Journal of Applied Meteorology and Climatology* (2020).

To read more, see our proposal "Multi-Resolution Analysis of the Convective Structure of Tropical Cyclones for Short-Term Intensity Guidance" on arXiv (https://doi.org/10.48550/arXiv.2510.19854)