



# QUANTUM-INSPIRED CNNS FOR PREDICTING CYCLONE INTENSITY AND TRAJECTORY

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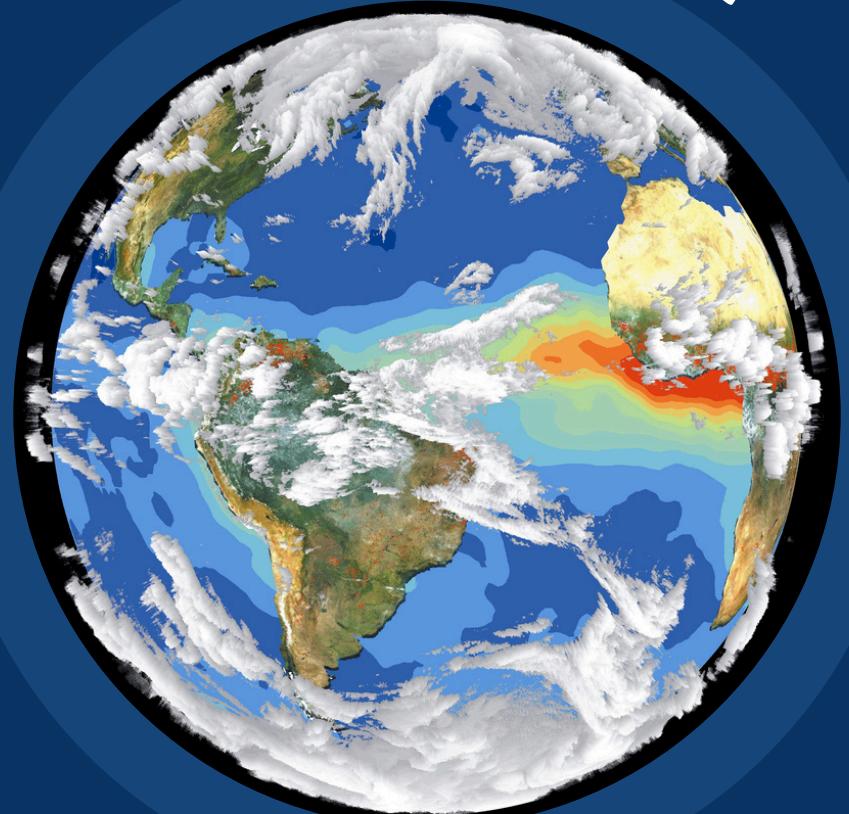


## ECONOMIC IMPACT



Hurricanes cost the global economy billions of dollars annually.

## CLIMATE CHANGE



As climate change intensifies, the frequency and severity of tropical cyclones are expected to increase, making accurate predictions even more critical.

## HUMANITARIAN IMPACT



Improved predictions can save lives by enabling timely evacuations and better resource allocation.

# PROBLEM STATEMENT

1

Tropical cyclones, commonly known as hurricanes, pose a significant threat to coastal regions, leading to loss of life and economic damage.

2

Accurate predictions allow for timely evacuations, infrastructure protection, and resource allocation.

3

Our team is focused on enhancing current prediction models to improve disaster response and mitigate the impacts of climate change-induced extreme weather events.

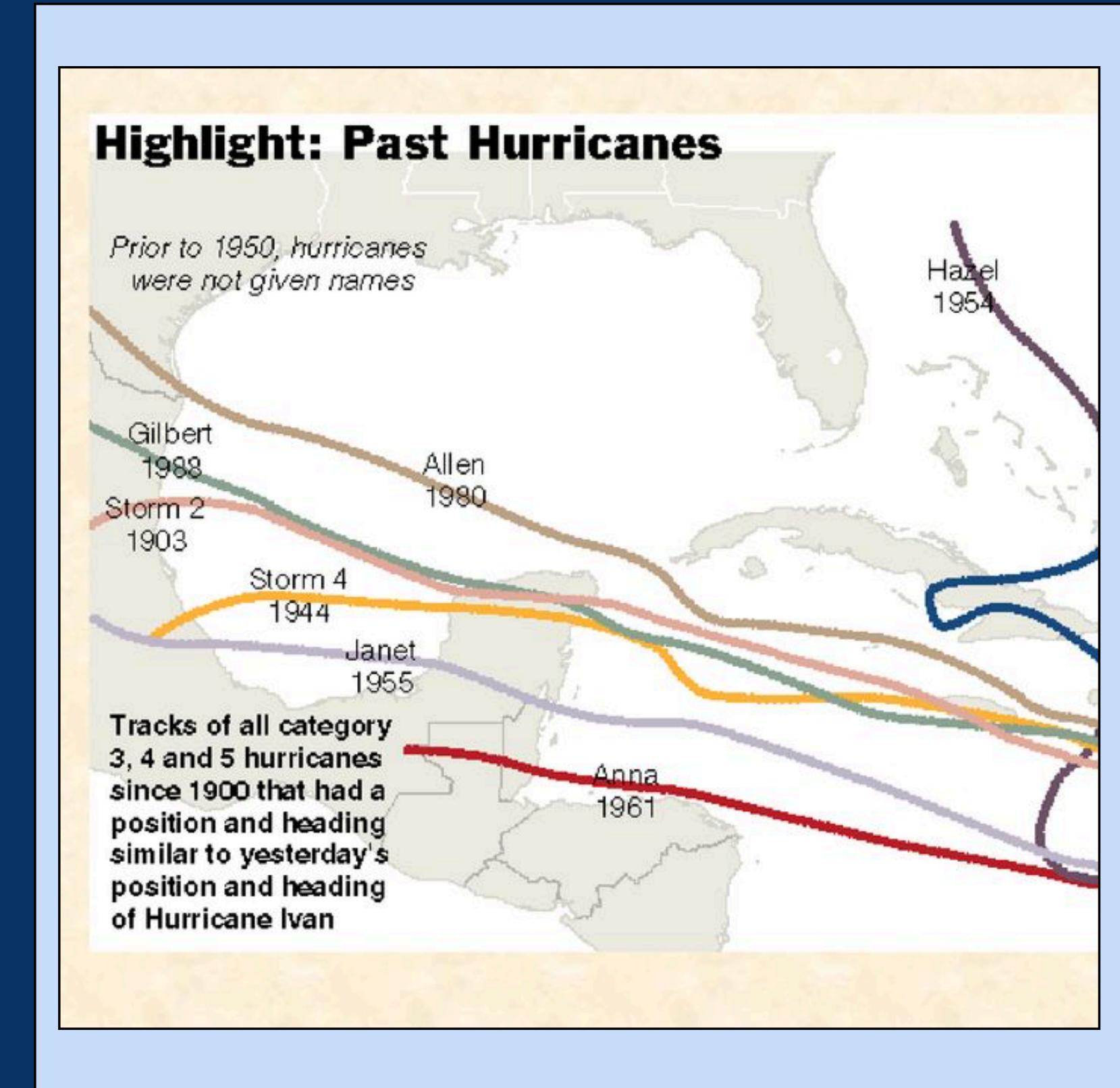
# LITERATURE REVIEW



# STATISTICAL-DYNAMIC MODELS

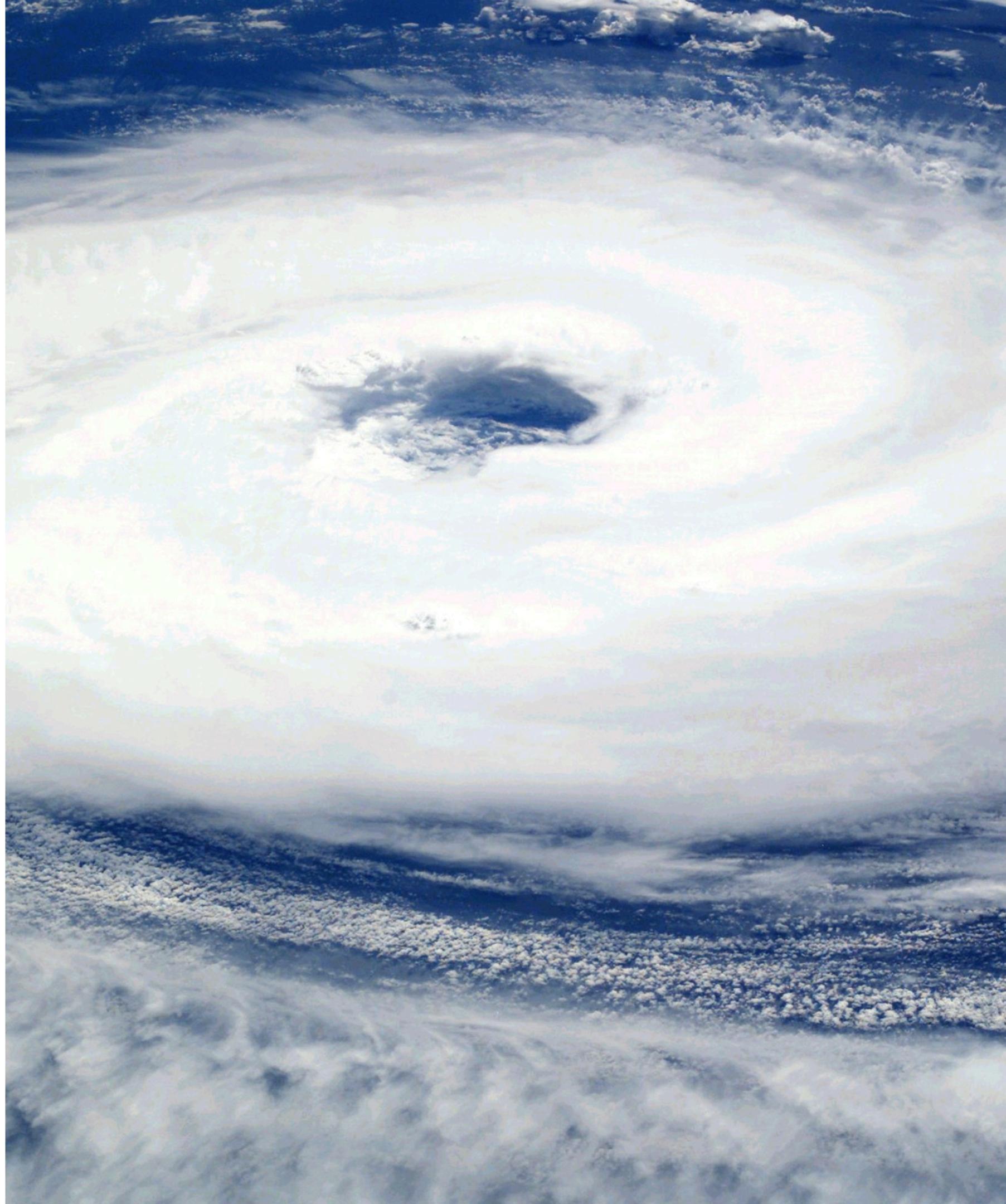
These models are often used for short-term forecasting but may struggle with long-term predictions.

These models are relatively fast and computationally efficient but may lack accuracy, particularly for rare and extreme events.



# NUMERICAL WEATHER PREDICTION MODELS:

Leading models like the Global Forecast System (GFS) and the European Centre for Medium-Range Weather Forecasts (ECMWF) simulate the physical processes that drive tropical cyclones. They are highly accurate but require immense computational resources.



# MACHINE LEARNING MODELS:

Recent studies have applied CNNs to satellite imagery to detect and predict cyclone paths and intensities.

They are effective for image-based detection but require large labeled datasets.

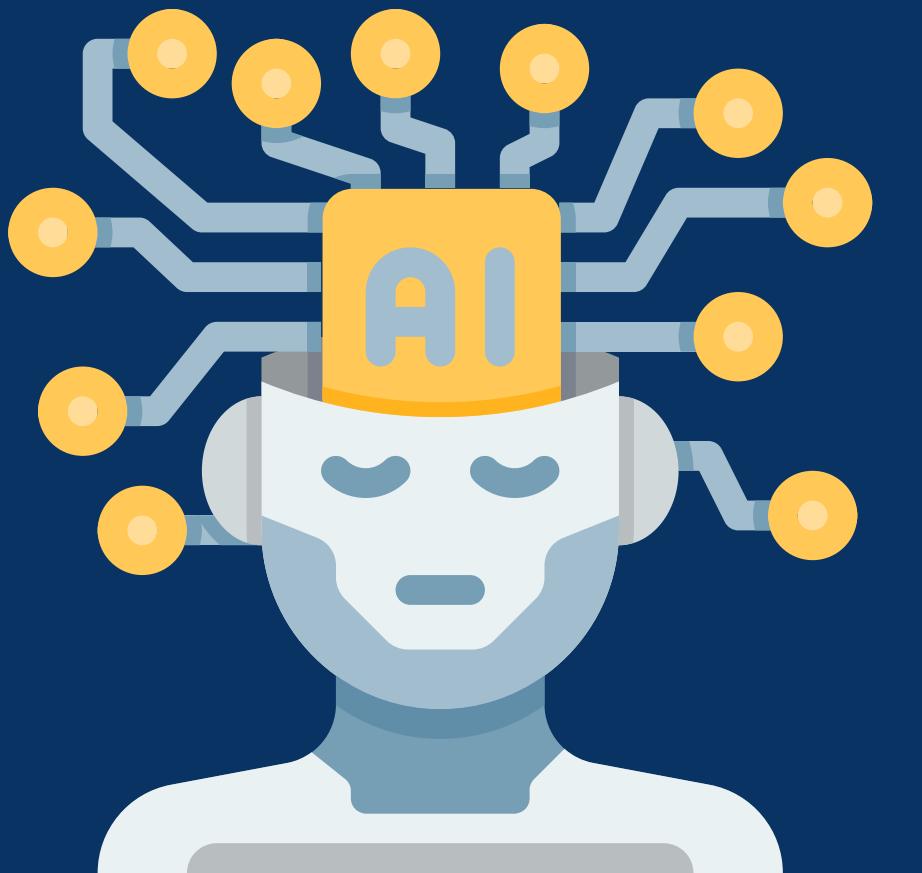


**PROPOSED  
SOLUTION?  
QUANTUM -  
INSPIRED CNN**



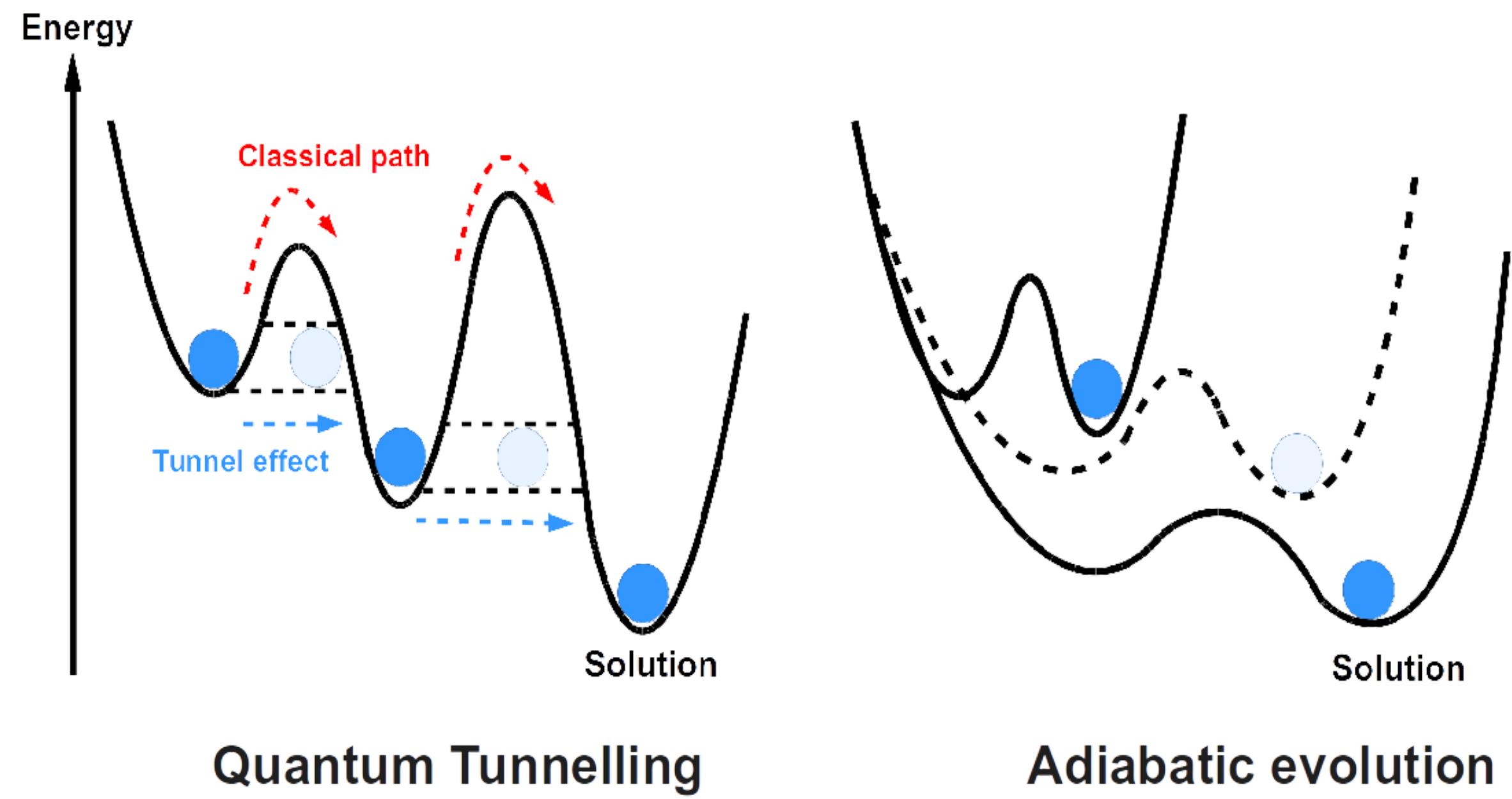
# CNN ARCHITECTURE

Using a deep CNN to analyze multi-channel satellite imagery (e.g., infrared, visible light, and water vapor channels) to predict the intensity and trajectory of tropical cyclones. The CNN will include several convolutional layers for feature extraction, followed by pooling layers to reduce dimensionality, and fully connected layers for final prediction.

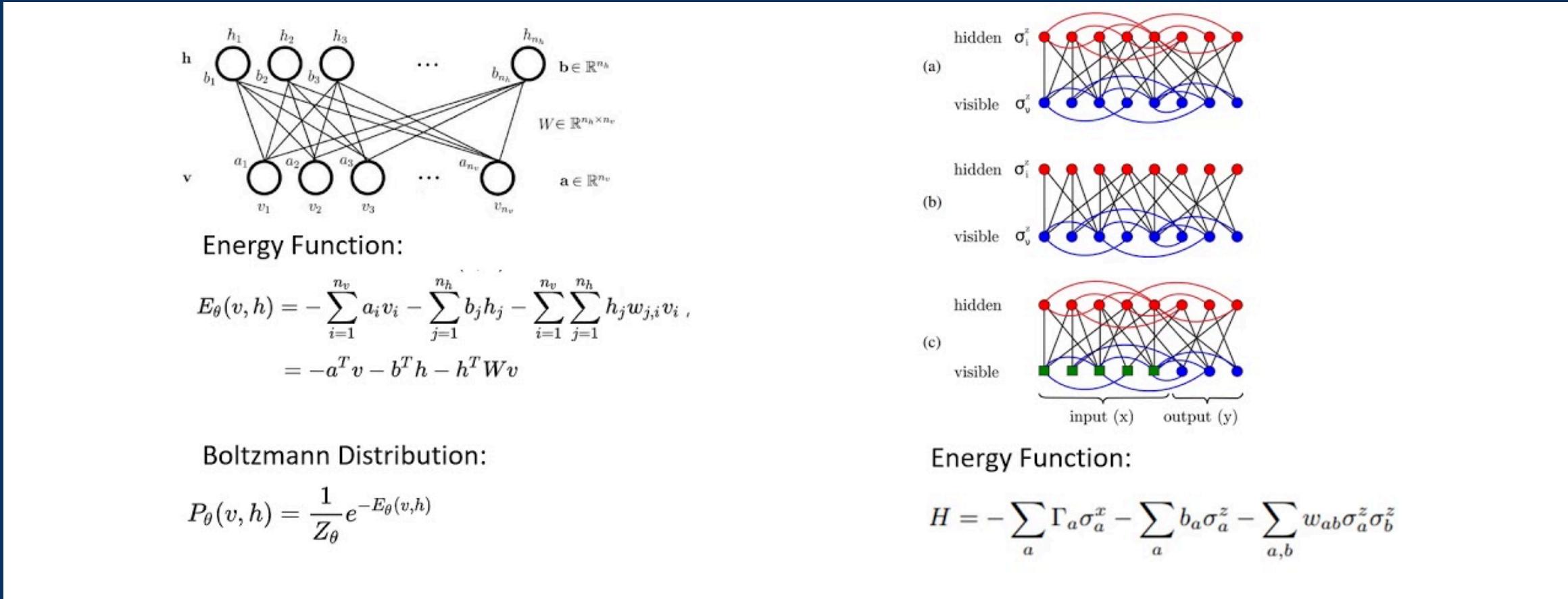


# QUANTUM ANNEALING

Optimize CNN weights by finding the global minimum of the loss function, avoiding local minima that can trap classical methods.



# QUANTUM BOLTZMANN



Train a probabilistic model to generate optimal weights for the CNN.

# BENEFITS

1

Increased  
Accuracy

2

Computational  
Efficiency

3

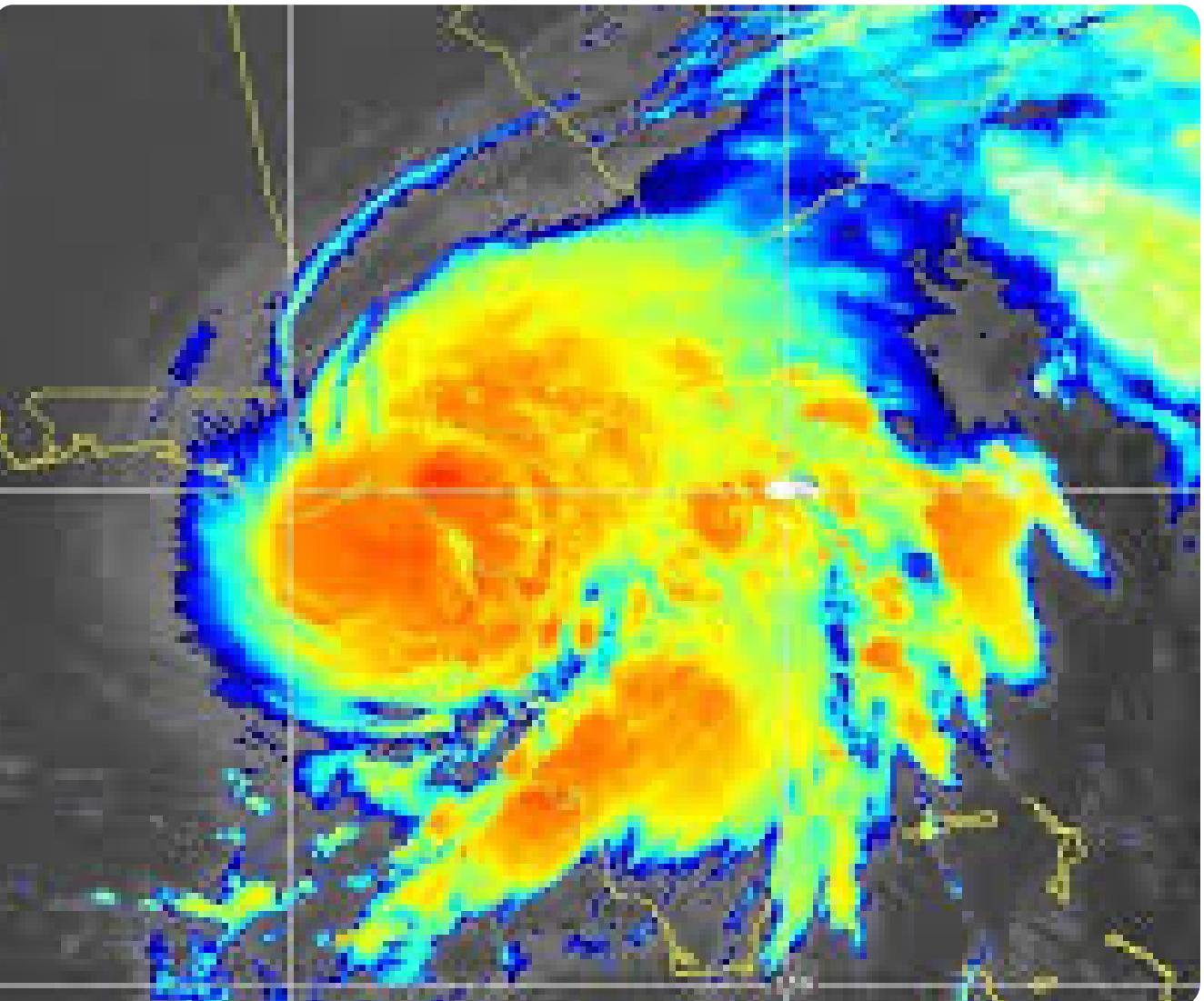
Safer  
neighborhoods

# CASE STUDY - HURRICAN DEBBY (2024)



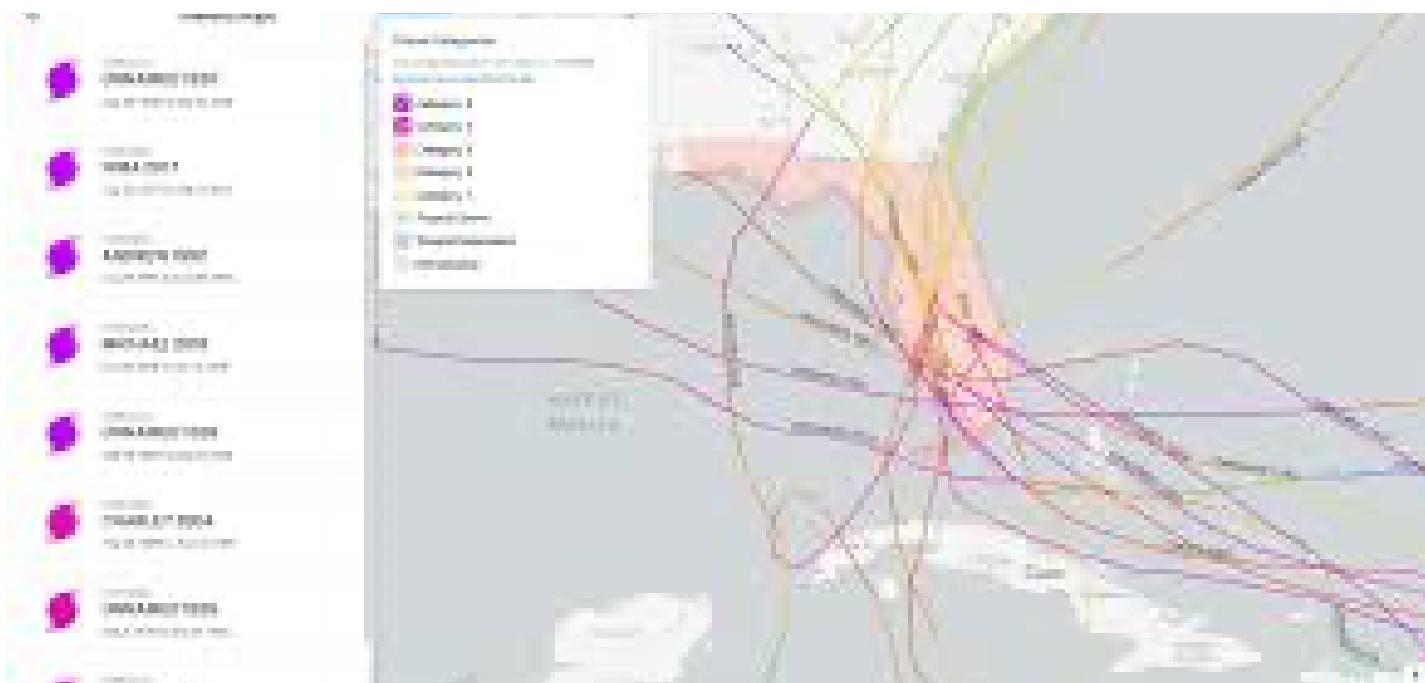
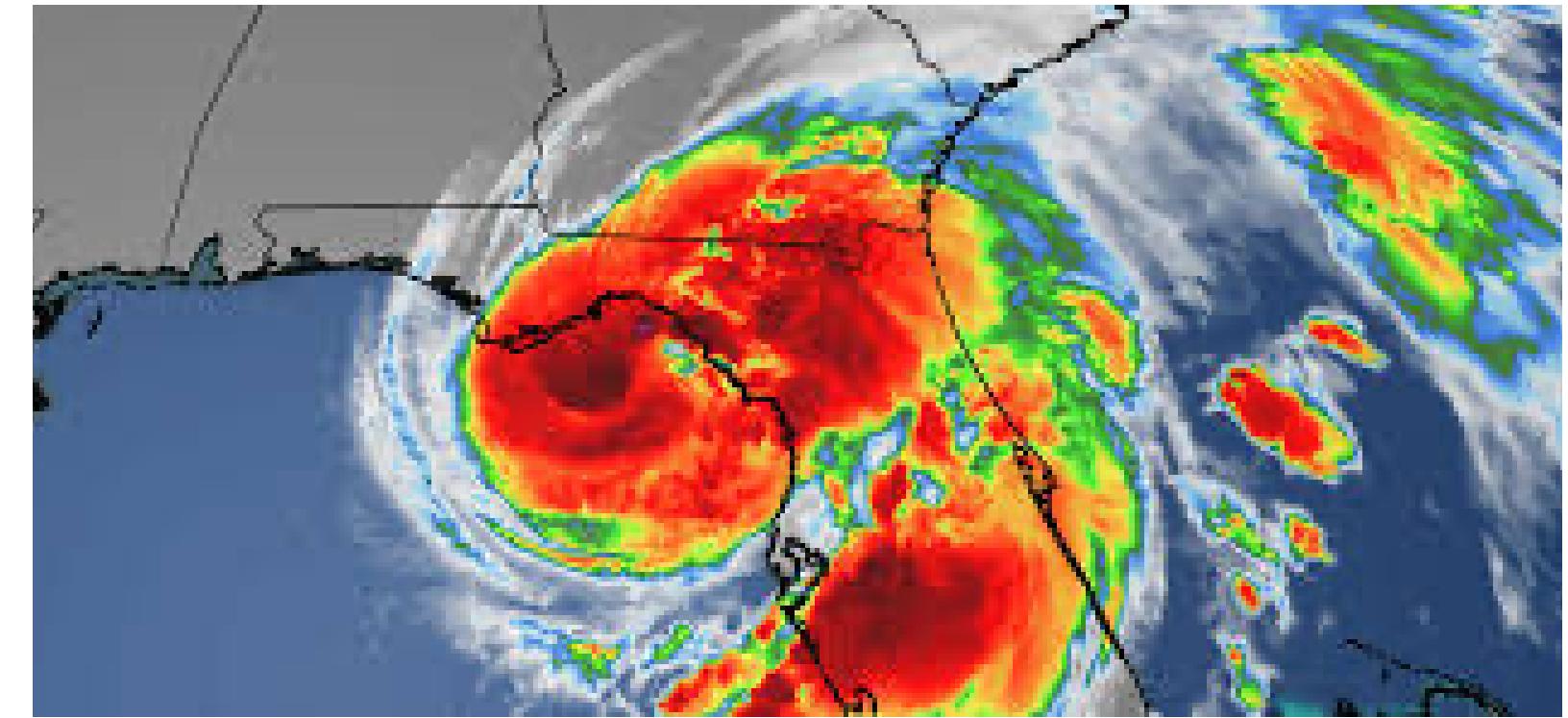
# HURRICANE DEBBY

Hurricane Debby recently passed through Florida, causing widespread damage and prompting evacuations. It serves as an ideal case study to evaluate the effectiveness of our quantum-inspired CNN model.



# DATA USED:

**Satellite Imagery:** multi-channel satellite data from NOAA, including infrared, visible light, and water vapor channels, captured during Hurricane Debby's progression.



**Historical Data:** The model was trained on historical hurricane data, including past storms in the Atlantic basin, to improve its predictive capabilities.

# PREDICTION OBJECTIVE

Predict Hurricane Debby's intensity and trajectory 72 hours in advance, giving authorities sufficient time for disaster response planning.



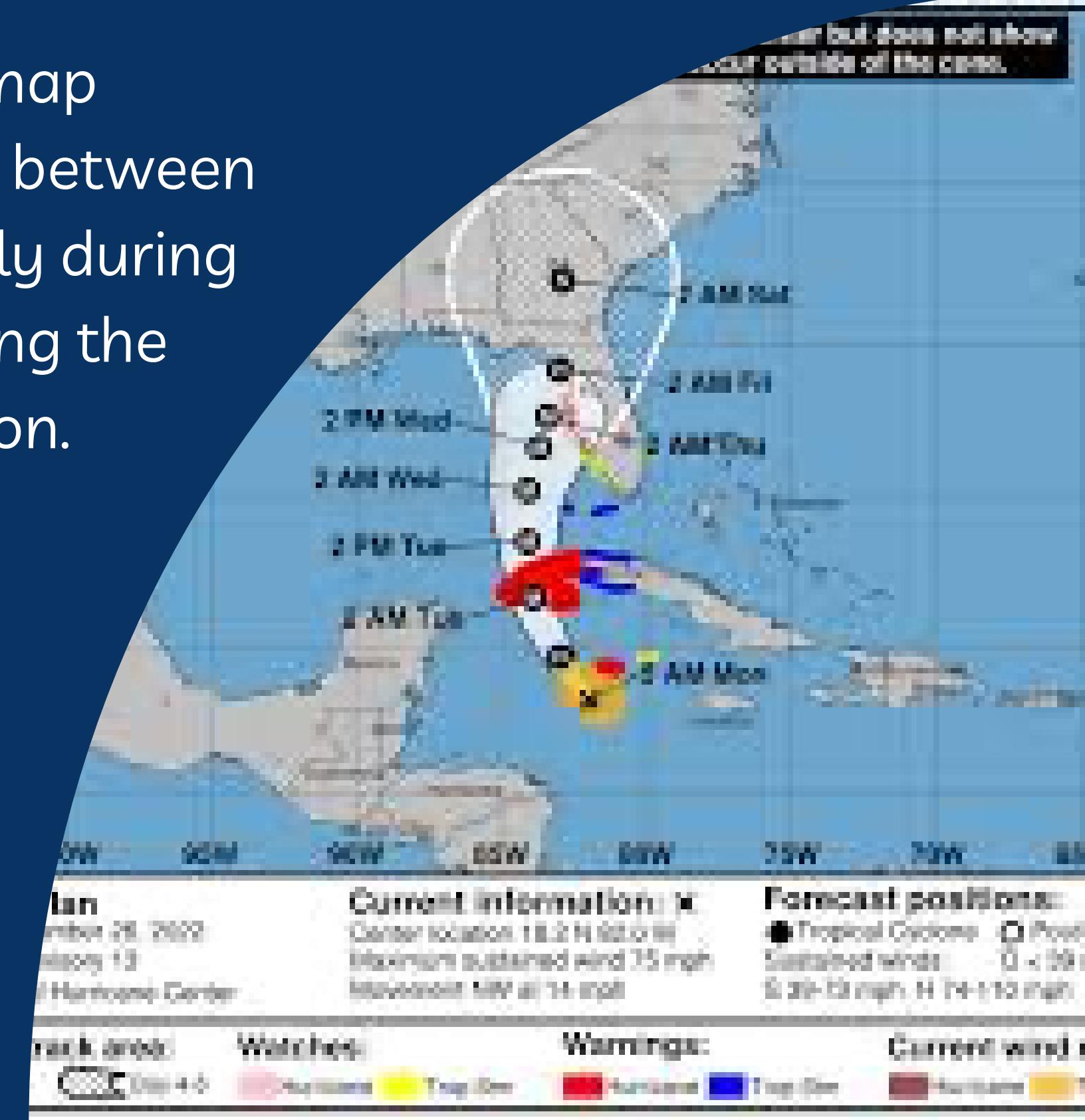
# CASE STUDY - HURRICANE DEBBY RESULTS



# TRAJECTORY

**Predicted vs. Actual Path:** A map comparison showed close alignment between predicted and actual paths, especially during key phases like landfall, highlighting the model's superior path prediction.

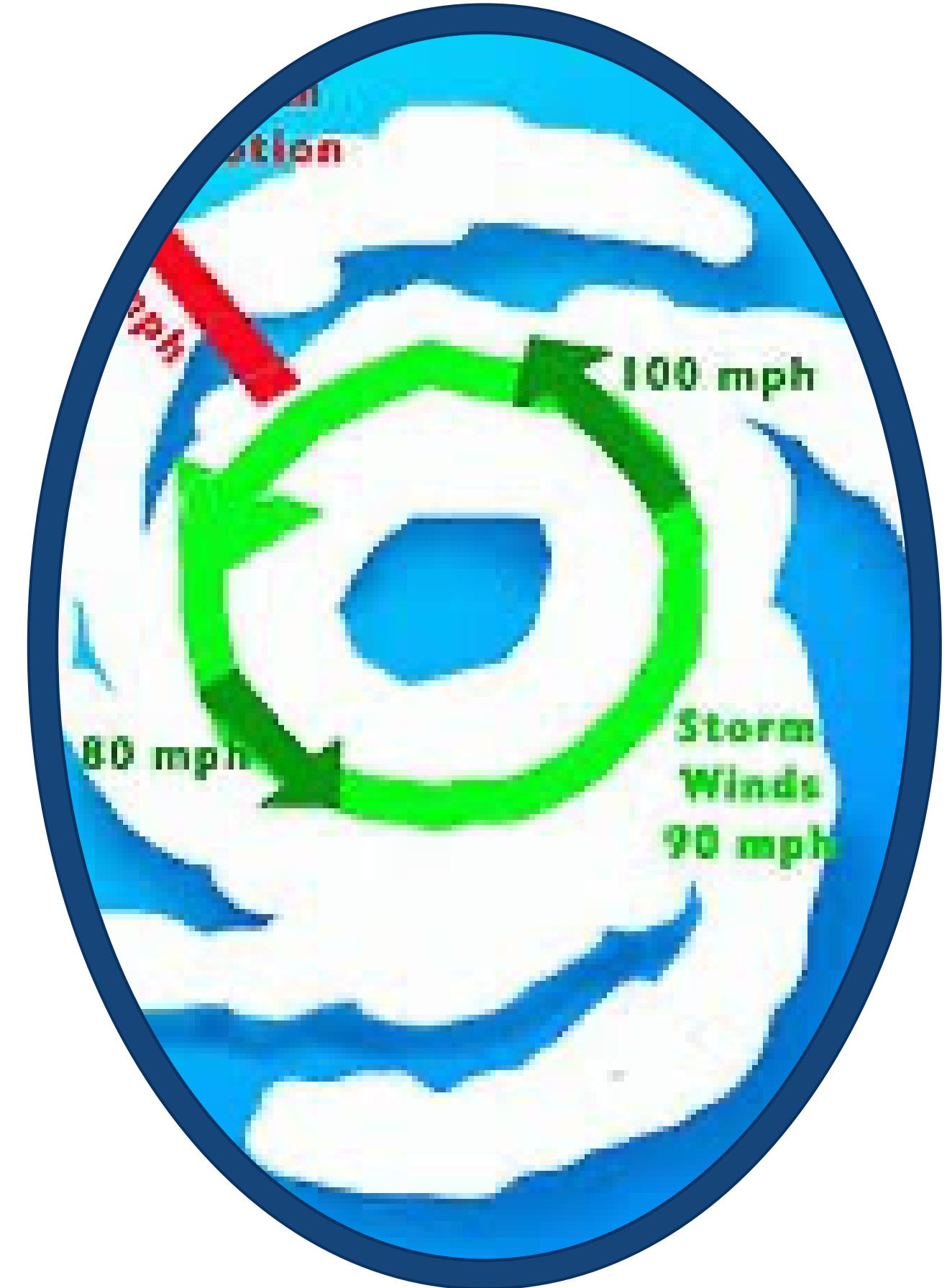
**Comparison with Other Models:** The quantum-inspired CNN outperformed traditional models (GFS, ECMWF) with a 15% lower MAE for path and 10% lower RMSE for intensity, showcasing the advantages of this approach.



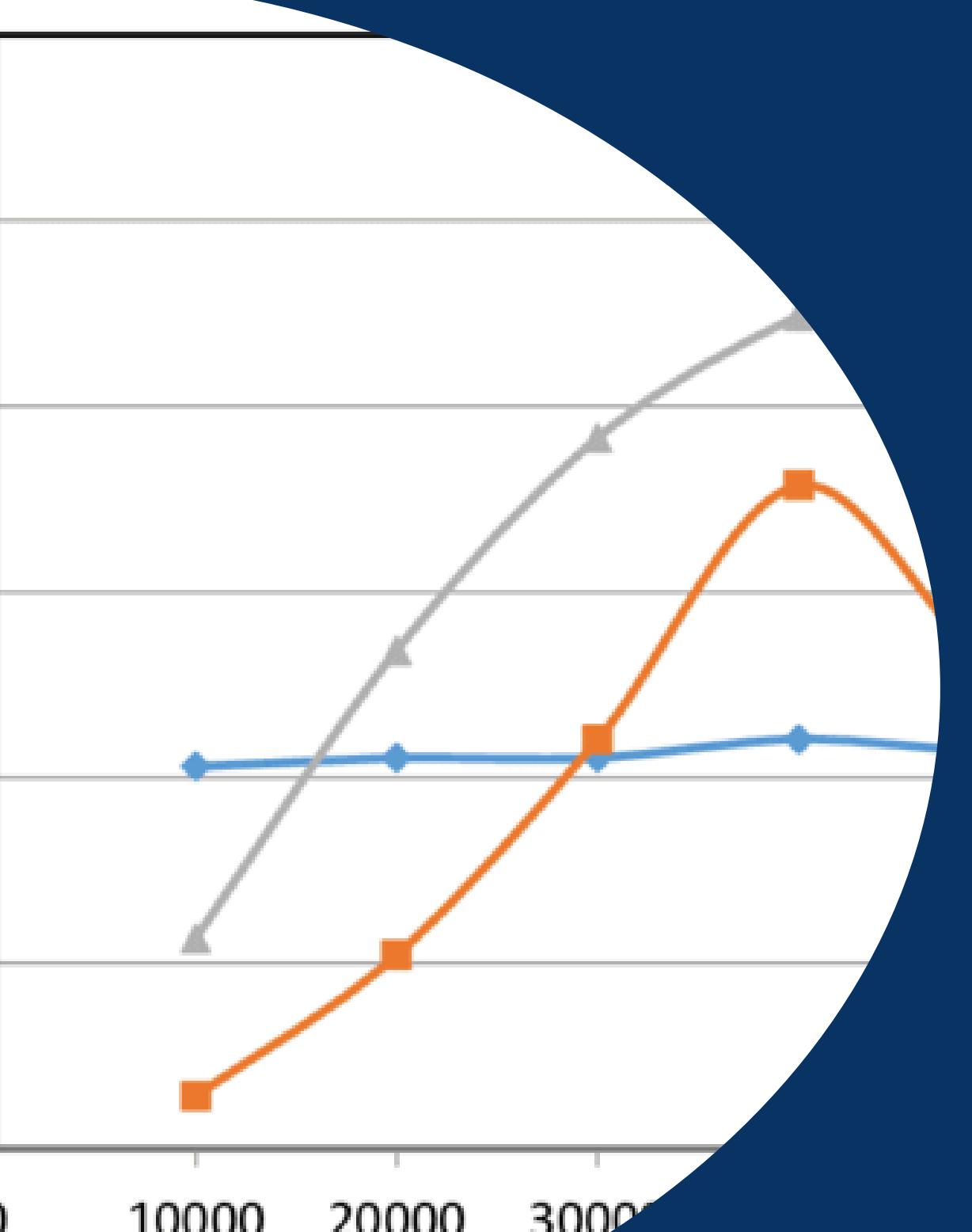
# INTENSITY

**Predicted vs. Actual Intensity:** Predictions closely matched actual intensity, with a Mean Absolute Error (MAE) of 10 mph for wind speeds and 3.2 hPa for pressure levels, accurately tracking the storm's behavior.

**Accuracy Metrics:** Achieved high accuracy with MAE of 25 miles for trajectory and 3.2 mph for wind speed. Metrics like RMSE demonstrated the model's reliability in forecasting both path and intensity.



# COMPUTATION EFFICIENCY



**Training Time:** Quantum-inspired optimization cut training time by 40%, enabling quicker updates and faster deployment during Hurricane Debby, ensuring predictions were based on the latest data.

**Real-Time Predictions:** The model provided near real-time updates every 2 hours, allowing for dynamic adjustments in response strategies during Hurricane Debby.

# IMPACTS AND IMPLICATIONS



# EVACUATION PLANNING:

The model's early and accurate predictions will allow for timely evacuations in Florida, potentially saving lives and reducing the impact of the storm.



# RESOURCE ALLOCATION

Emergency services will be able to allocate resources more effectively, such as positioning rescue teams and supplies in areas most likely to be affected.





**THANK  
YOU!**

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