Image2image Tropical Cyclone wind field diagnosis with Pix2Pix generative adversarial networks (GANs)

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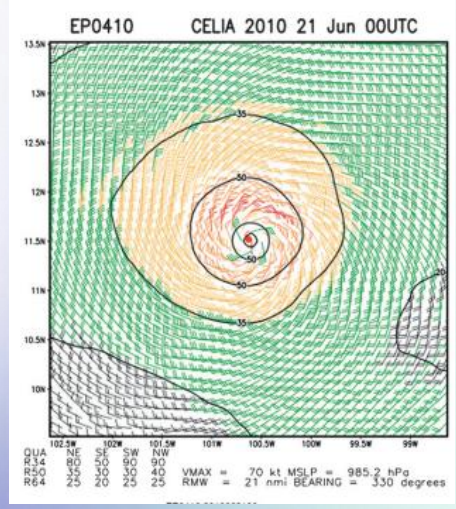
Problem | The unseen hurricane wind field

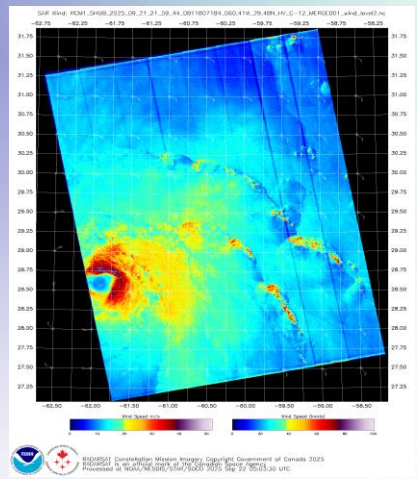
Operational Analyses

- Low temporal resolution (6 hourly)
- Low spatial resolution
- Inconsistent quality



Low-orbit satellites

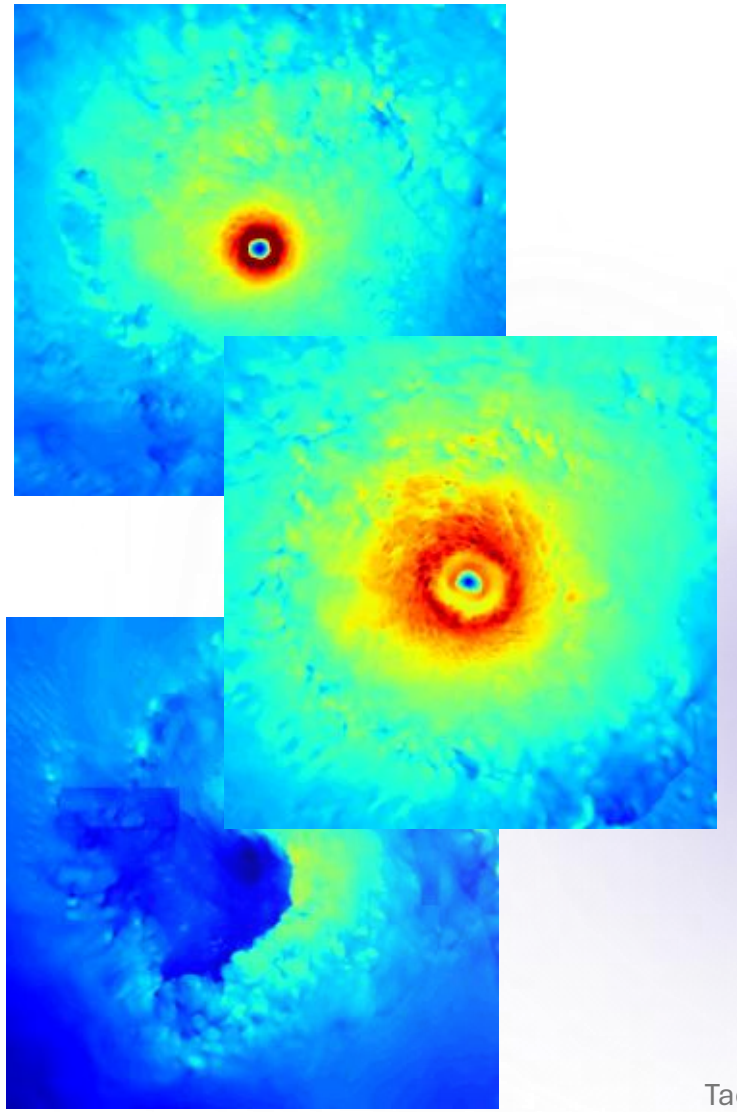
- Every 12-24 hours
- Often partial coverage
- Not yet well calibrated



Impact

Emergency managers and meteorologists could prepare better with faster, more detailed information.

Solution | high resolution wind fields



High spatial resolution: 6°×6° complete fields

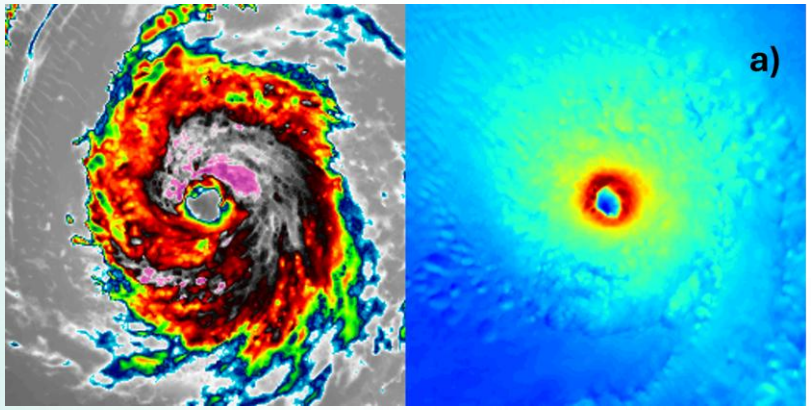
Increased temporal resolution: 10-15 minutes

Complete structure: inner core + outer rainbands

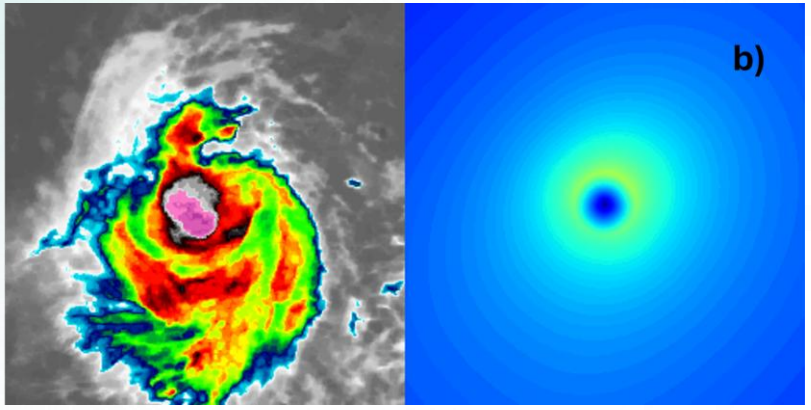
Efficient: Low computational cost

Data | Complimentary Synthetic and Real Data

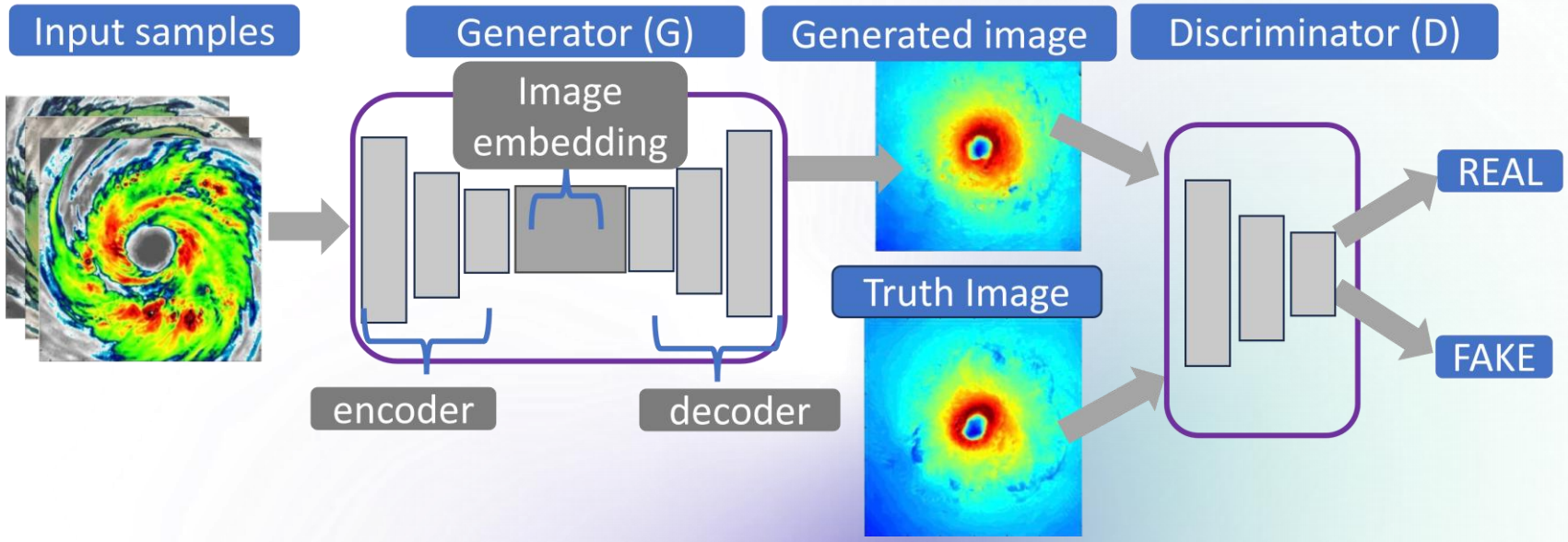
1. **wrf2wrf model**
   - 1,844 WRF simulation pairs



2. **mir2para model**
   - 1,984 real satellite + parametric wind pairs



Model Architecture | Pix2Pix GANs



Trained on NVIDIA L4 GPUs for efficiency

Generator
creates wind fields from IR images

Discriminator
distinguishes real from generated

Adversarial training
improves both components

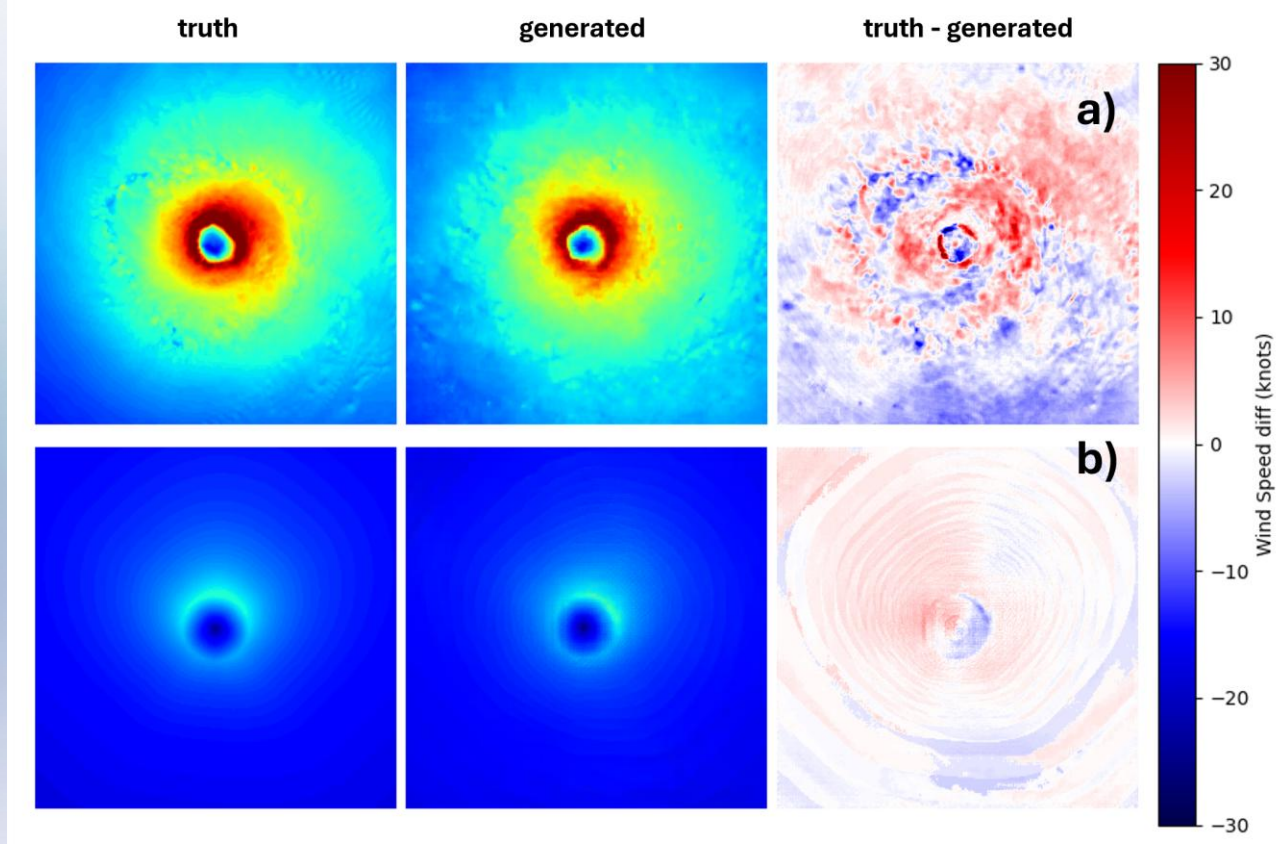
Results | Strong Performance Across Metrics

Pixel-wise RMSE:

- wrf2wrf: 7.3 kt (min 2.6 kt)
- mir2para: 6.7 kt (min 1.2 kt)

Cross-domain performance:

- wrf2wrf achieves 10.4 kt on real images without additional training



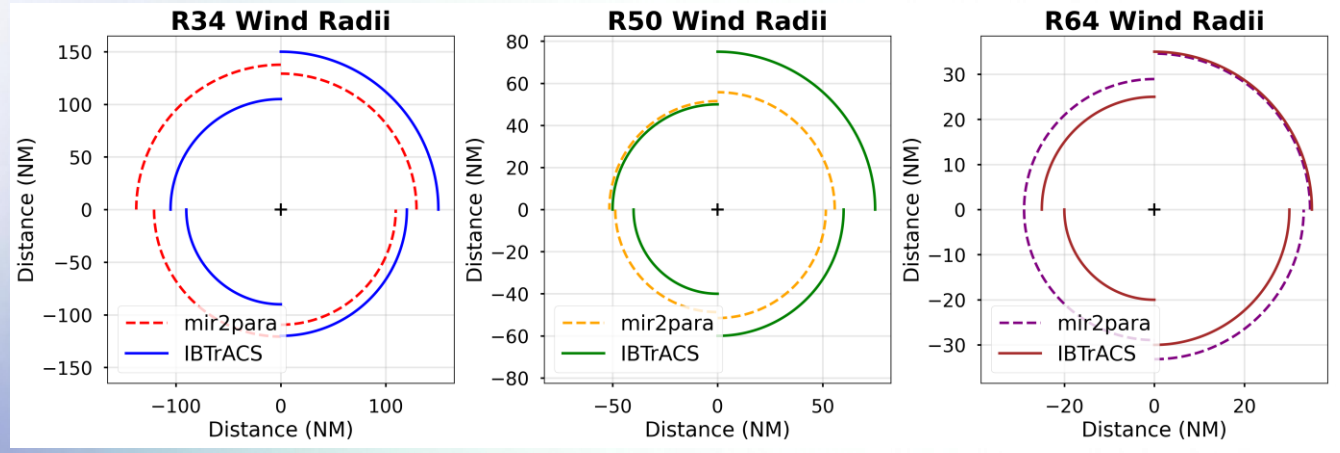
Results | Comparable to Best Track Data

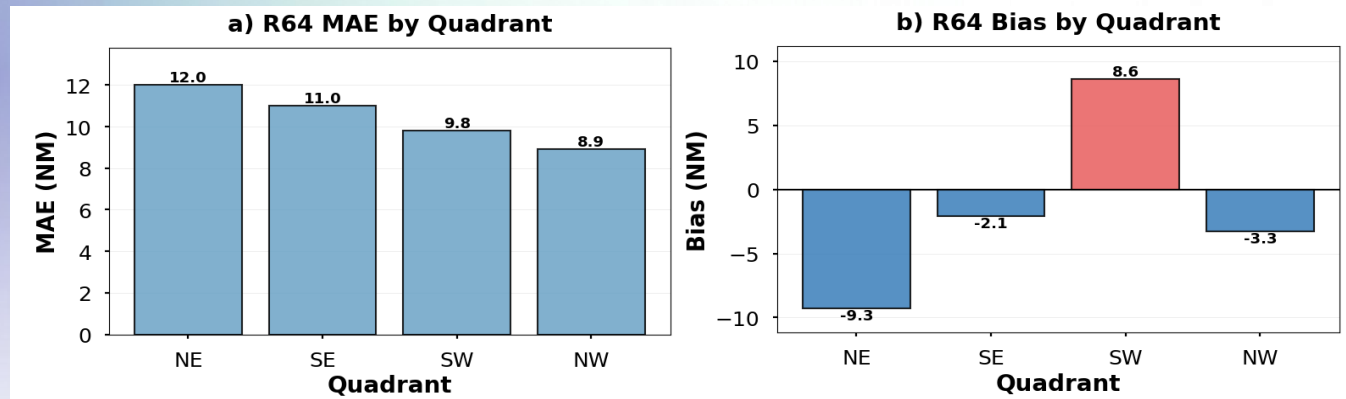
Wind radii comparison with IBTrACS (International Best Track Archive for Climate Stewardship):

- **MAE**: 8.9-12.0 NM across quadrants

Outperforms other AI methods:

- **RMW RMSE:** ~24 km vs. 53 km in prior work
- **Greater spatial coverage:** 6°×6° (~666 km) vs ~3.6°×3.6°.





Impact | Climate Mitigation

Earlier, faster high-resolution TC wind information for:

- Operational meteorologists
- Emergency managers
- Disaster preparedness teams
- Climate resilience planning

Real-time deployment potential

Next steps

- Category-specific tuning: Route to specialized models by intensity
- Physics-conditioned learning: Incorporate storm characteristics
- Operational deployment and validation
- Extension to other basins/regions

Key Takeaways

NEURAL INFORMATION PROCESSING SYSTEMS

- ✓ Successfully generate realistic TC wind fields from satellite imagery
- ✓ Low computational cost, high temporal/spatial resolution
- ✓ Performance comparable to operational data
- ✓ Ready for operational deployment

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Revolutionizing Climate Resilience with AI-Powered Weather Prediction