Predicting 3D Atmospheric Structure from Geostationary Satellites with Deep Generative Models

Tropical Cyclone Observations and Research Forum (TCORF)
March 8, 2023

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Zeus AI

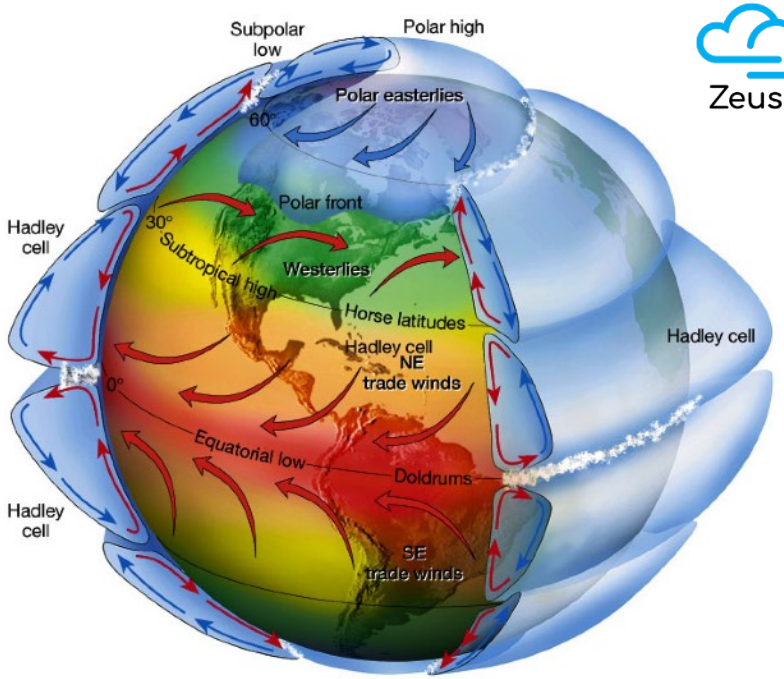
SILICON VALLEY
AMES RESEARCH CENTER

Bay Area Environmental Research Institute

NEX
NASA Earth Exchange

Goddard
SPACE FLIGHT CENTER

3D Atmospheric Structure

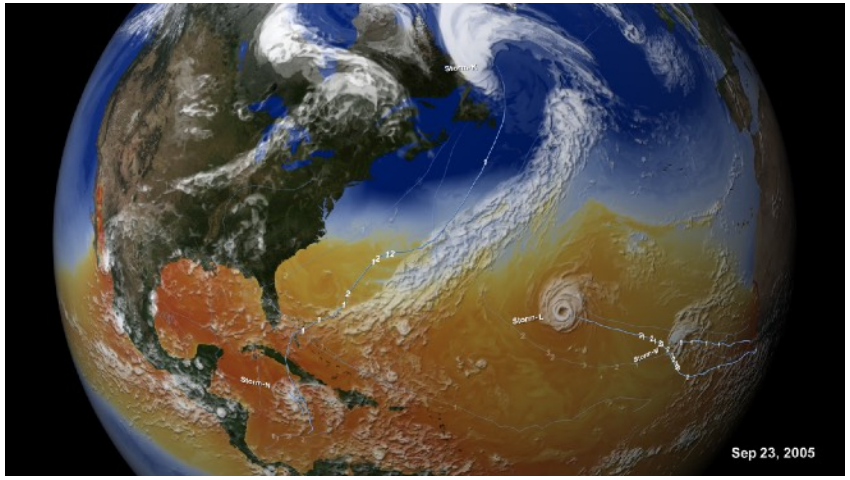


- Atmospheric structure is largely defined by the distribution of temperature, humidity, and winds.

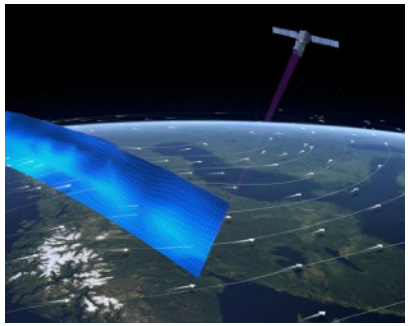
- Winds govern the transport of energy in the atmosphere and represent a fundamental component of the Earth system

- National academy of science named 3D atmospheric winds as key targeted observable in the decadal survey for quantifying movement of water vapor, pollutants/aerosols, cloud dynamics, and large scale circulation.

- Applications include: Numerical weather prediction, data assimilation, wildfire plumes, ocean currents/winds, mesoscale convection, and more.

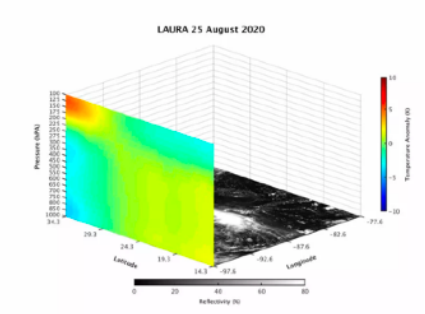


Observing the atmosphere

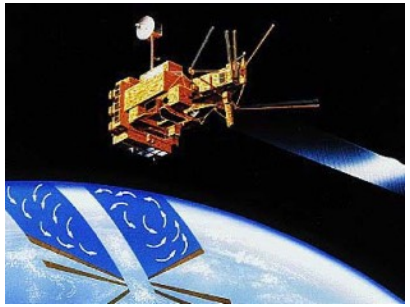


Lidar winds

Radiosonde



Sounders



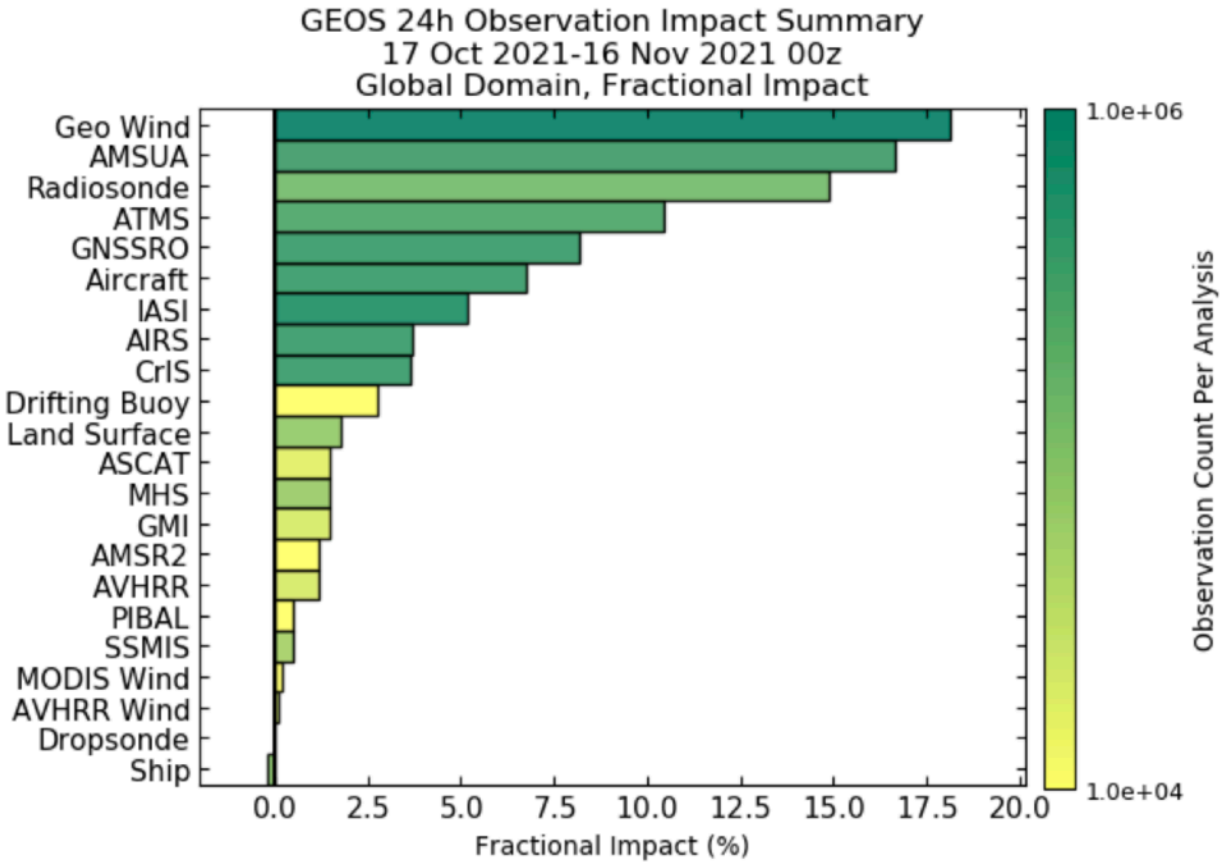
Scatterometer

Weather stations

Radar

- Rawinsondes and stations = ground truth observations.
- Activate sensors include Lidar, scatterometers, and radar
- Low earth orbit satellites have infrequent revisit times not well suite for global monitoring
- Observations are assimilated in numerical weather forecasts as initial conditions

Observations for data assimilation



- Atmospheric Motion Vectors (AMVs) from geostationary have the highest impact per observation.
- Radiosondes and Sounder observations also have high impact.
- Dense and higher resolution data could have a large impact in NWP.

NASA's Global Earth Observing System at the Global Modeling and Assimilation Office (GMAO)

Geostationary satellites

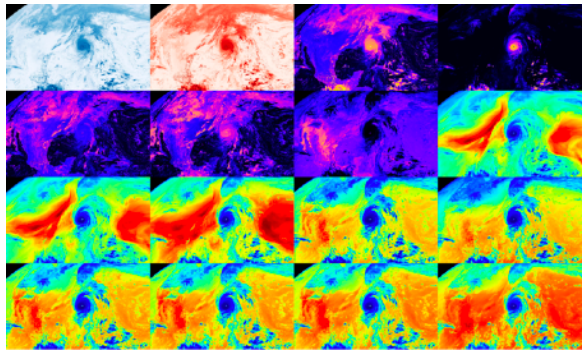
Specifications

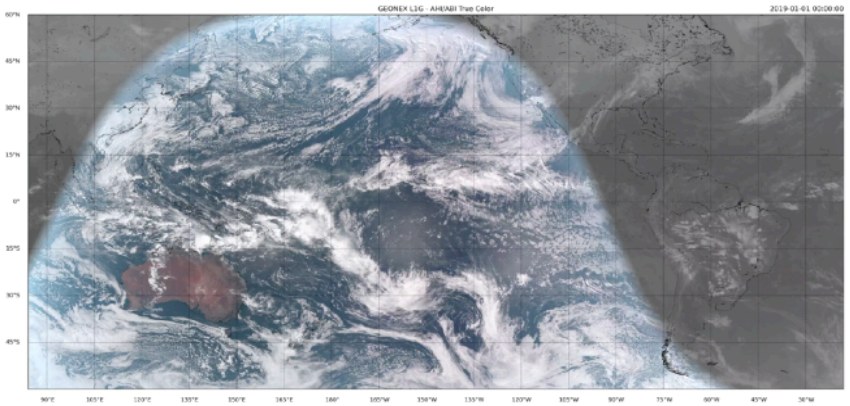
- GEO Imaging sensors produce high-frequency multi-spectral data
  - GOES-16/17/18, Himawari-8/9, GeoKompSat-2a, FY-4
- Spatial: 0.5-2 km resolution
- Temporal: 1-10 minutes
- 5-16 spectral bands
- Global coverage from multiple satellites

Some Applications

- Atmospheric motion vectors (Velden 1997; Apke 2022; Carr 2019)
- Quantitative precipitation estimation (Sadeghi 2019)
- Land surface temperature (Duffy 2022)
- Convective storm patterns, anvil plumes (Bedka 2021)
- Air quality (Kondragunta 2020)
- Vegetation (Hashimoto 2021)
- Wildfire detection (Xu 2017)
- ….

16 Visible and Infrared bands



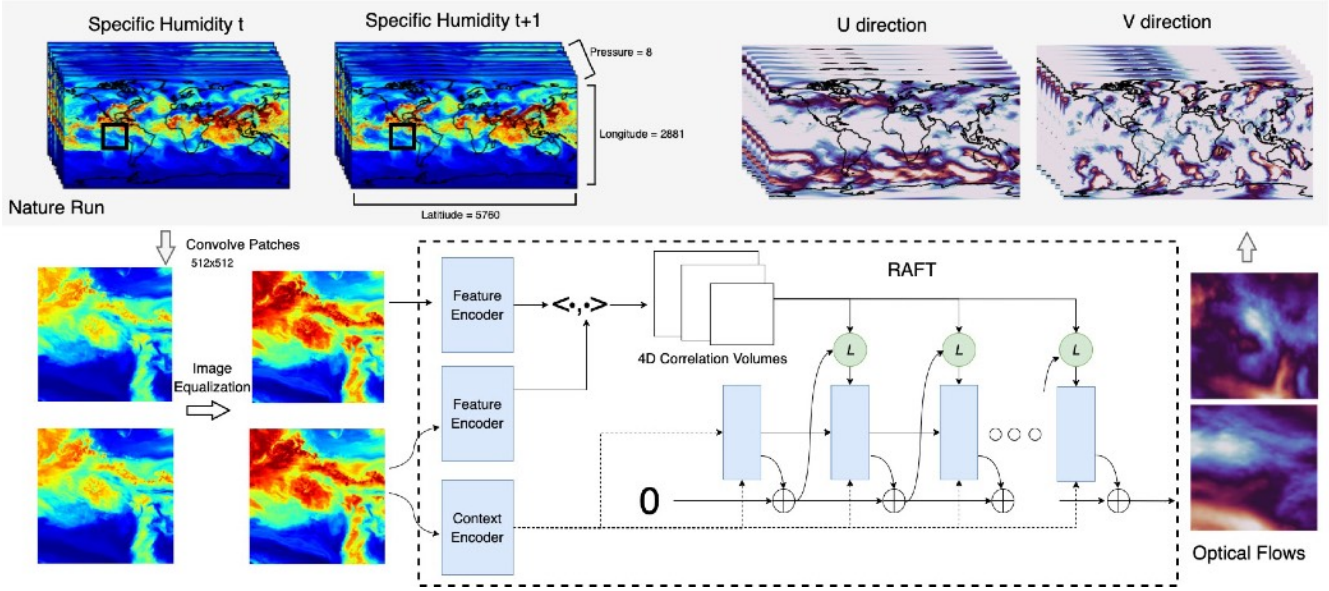


GeoNEX L1G dataset - Near global, 10 minute, 2km

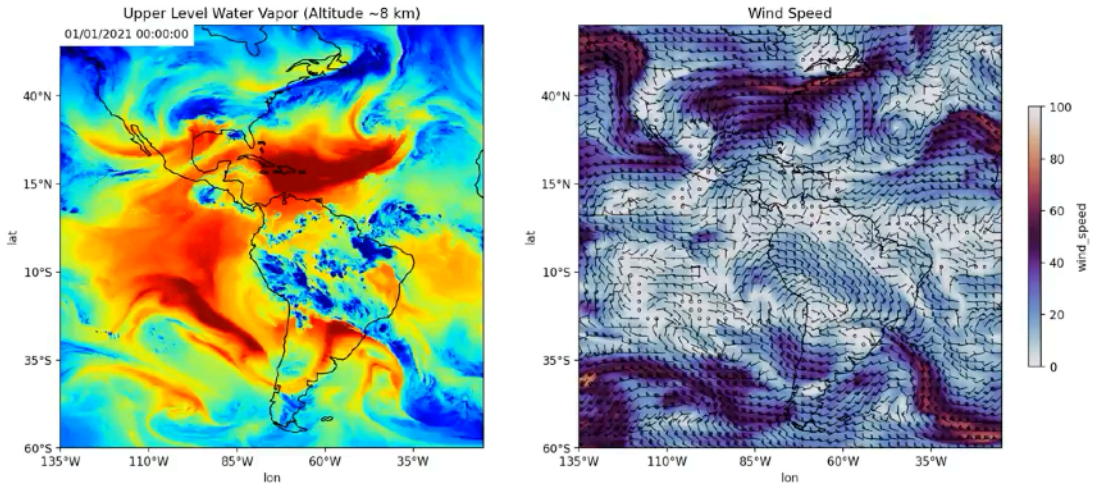
WindFlow

- ML for Atmospheric Motion Vectors (AMVs)
- Extract horizontal motion from sequences of humidity.
- Learn from Numerical weather simulations which are widely available as *synthetic* data. Apply to GEO.
- Flexible choice of optical flow architectures. Results compare four networks where we found RAFT to be the best performing.

Loss = $||Y-F(I_0,I_1)||_1$



Apply to Geostationary satellite data.



Vandal et al. (2022) "Dense Feature Tracking of Atmospheric Winds with Deep Optical Flow." SIGKDD Proceedings (Oral, 7% acceptance rate)

GEOS-5 Nature Run: Flows across dimensions and scales

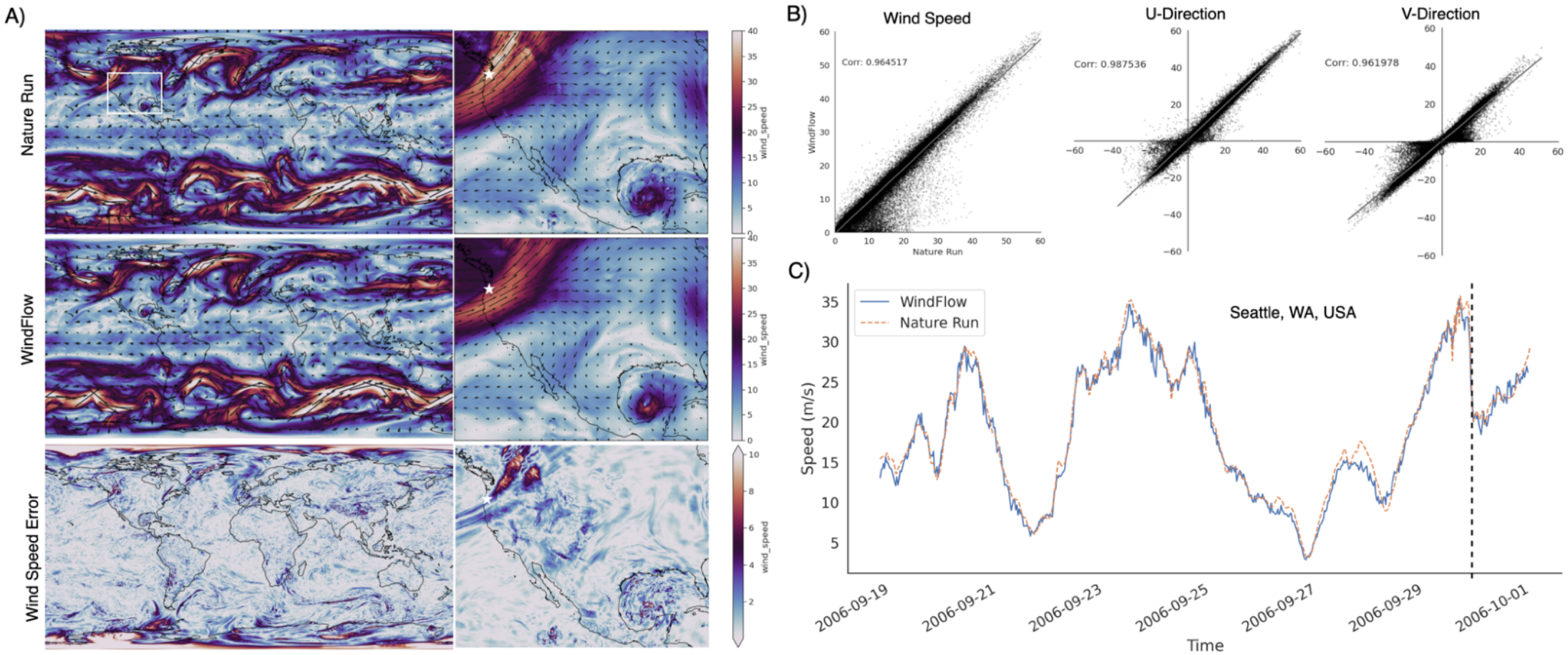
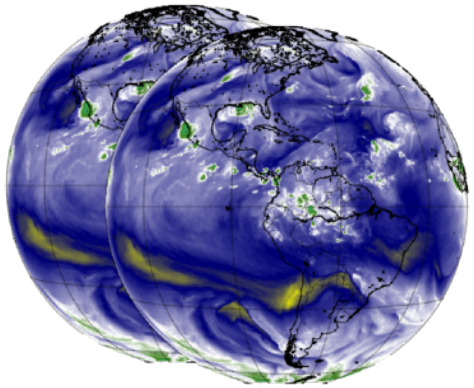
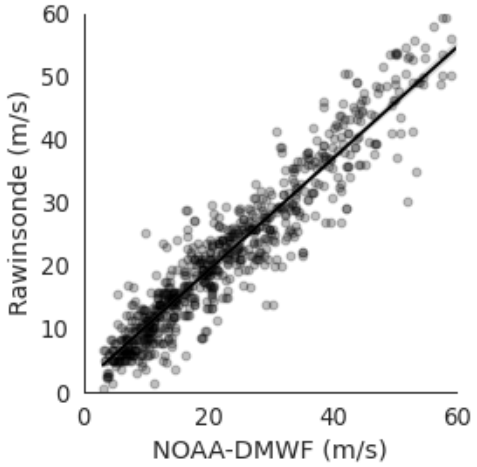


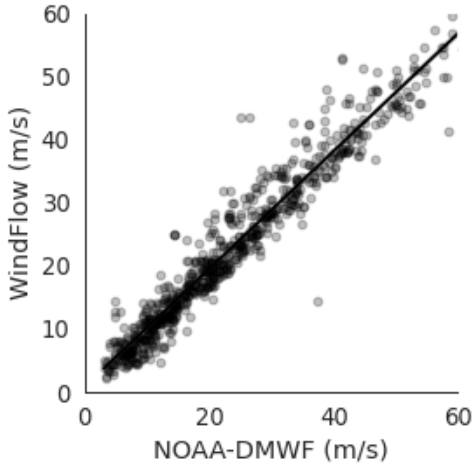
Figure: Results on nature run test set. A) Global and mesoscale comparison, B) U, V, and wind speed scatter plots, C) Time-series

Satellite based winds - Rawinsonde Comparison

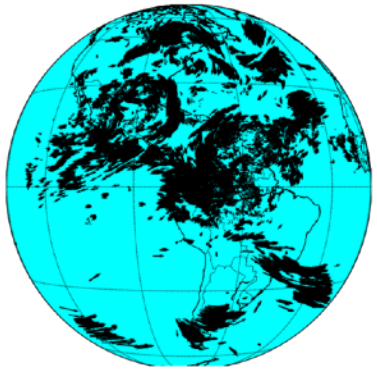
Input: Pair of GOES-16 Band 8 Infrared Water Vapor



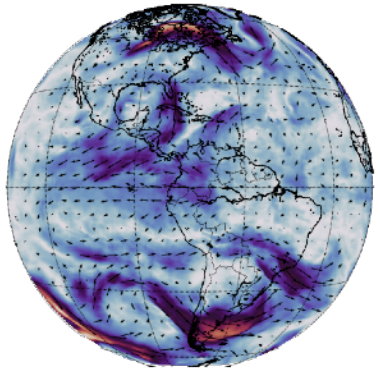


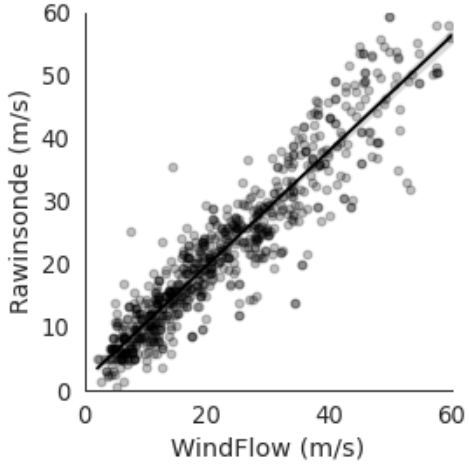


NOAA Derived Motion Winds



NEX-AI WindFlow





Combine models for 3D Structure

Can we reconstruct vertical profiles from GEO imagery?

Scientific observations

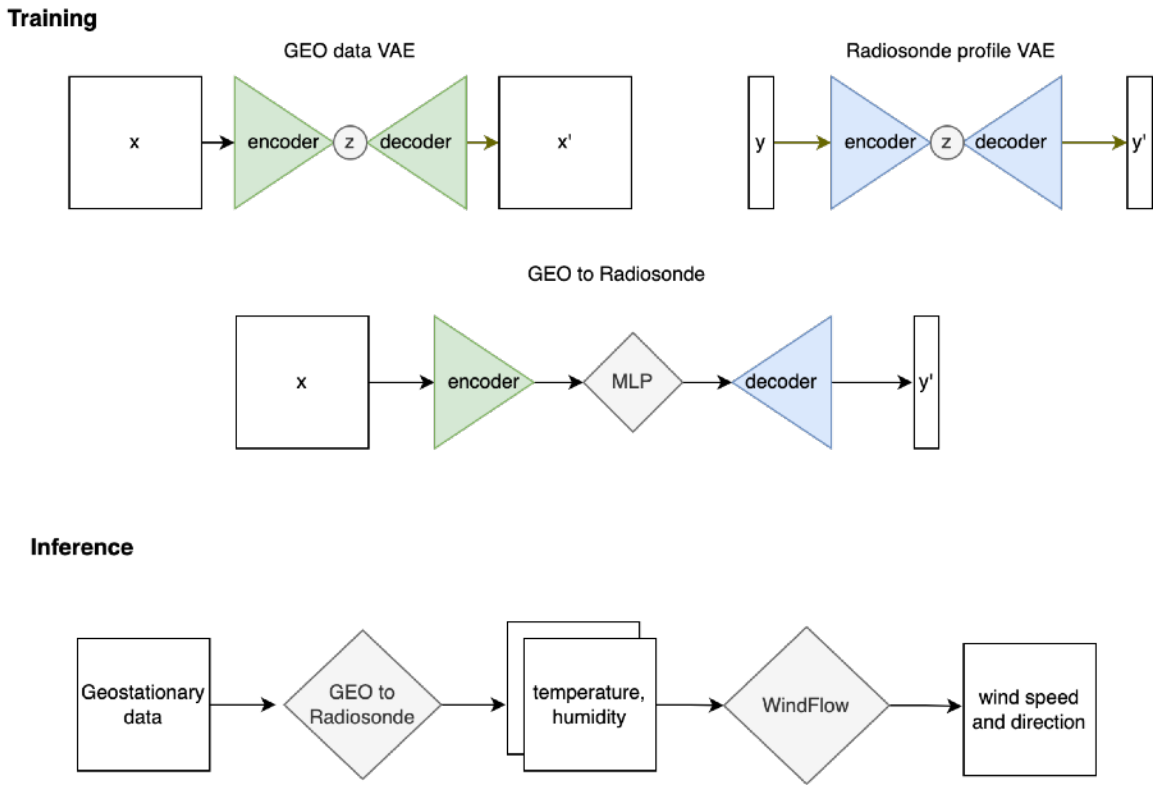
1. Atmospheric profiles can be categorized into “clusters” representing different, well defined weather conditions.

2. Meteorologists can visually identify features in GEO TIR imagery for most, if not all weather conditions.

Hypothesis - A generative model can be learned to translate GEO TIR to radiosonde profiles

Approach - Learn a translation between low dimensional representations of GEO TIR and radiosondes

Variational Autoencoders (VAEs) compress high-dimensional data to a probabilistic latent representation, preserving uncertainty and extracting useful features

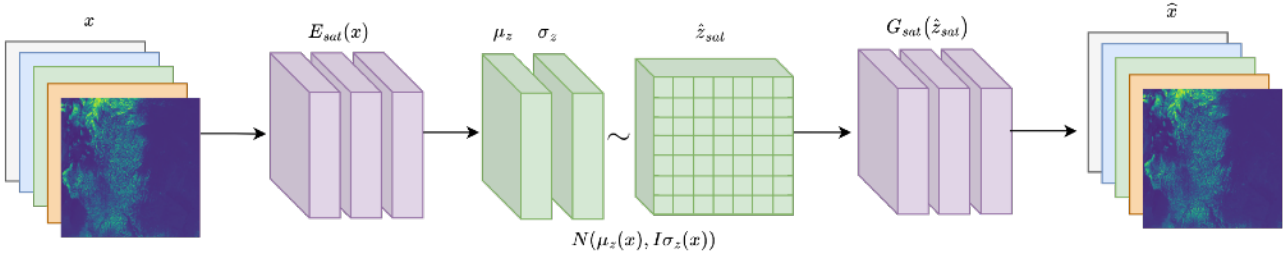


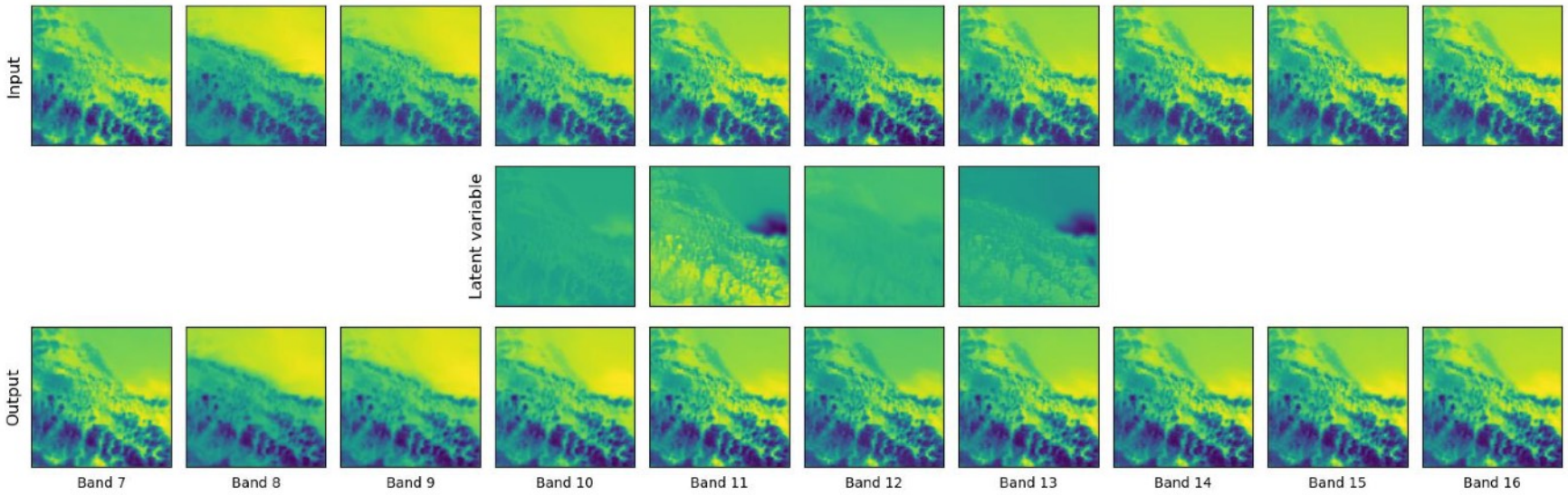
Geostationary VAE

High-fidelity VAE to learn a latent representation of GEO TIR

Compressed representation can reduce storage requirements

Trade-off between accuracy and compression ratio



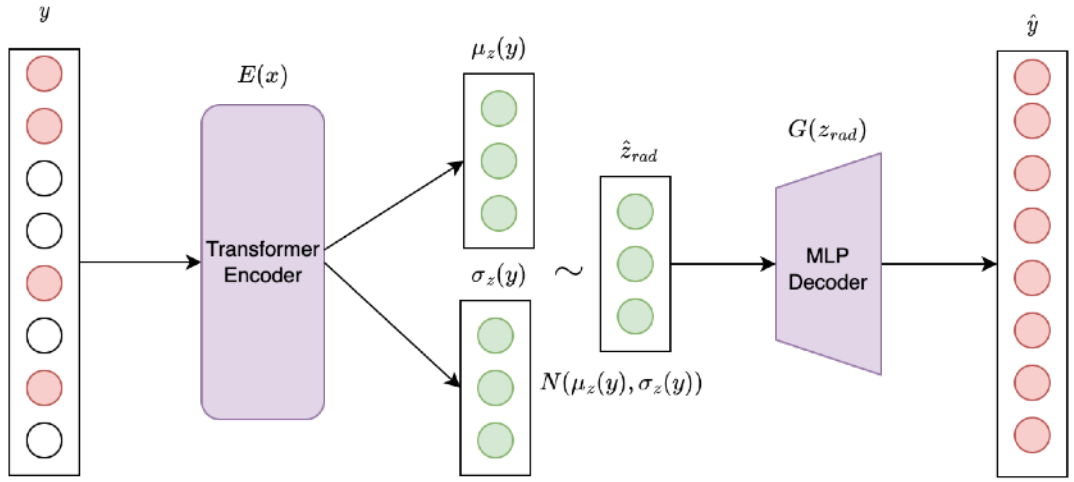


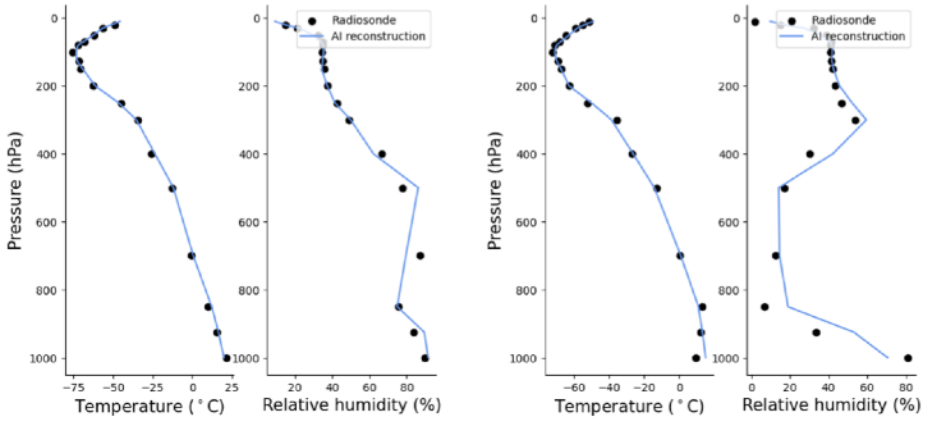
Vandal, TJ, et al. (2021) "Spectral Synthesis for Geostationary Satellite-to-Satellite Translation." *IEEE Transactions on Geoscience and Remote Sensing.*

Radiosonde data reconstruction - VAE

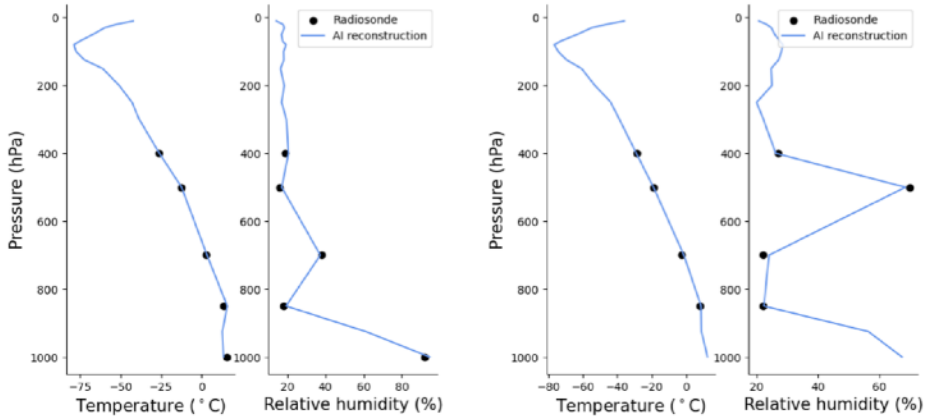
- VAE with transformer encoder layers and MLP decoder
- Automatically fills missing values
- Uncertainty aware sampling
- Errors (dropping 20% of obs)

  Temperature = 1.5° C, RH = 2.7%





Reconstructions



Gap Filled Profiles

Geostationary to 3D Profile

Predict radiosonde latent from GEO latent

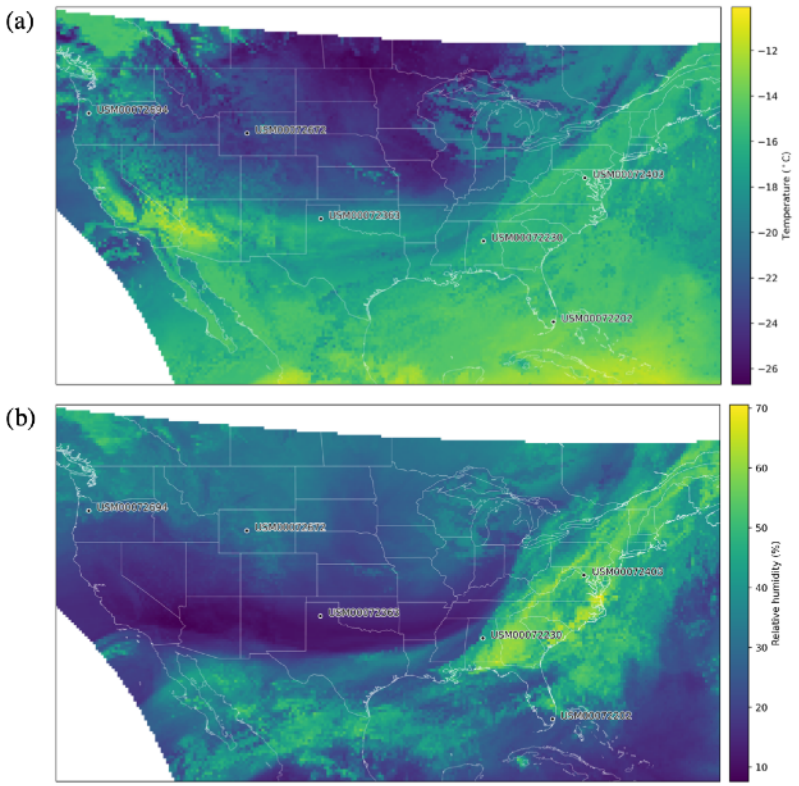
Train a model:

$$F(z_{geo}) = z_{rad}$$

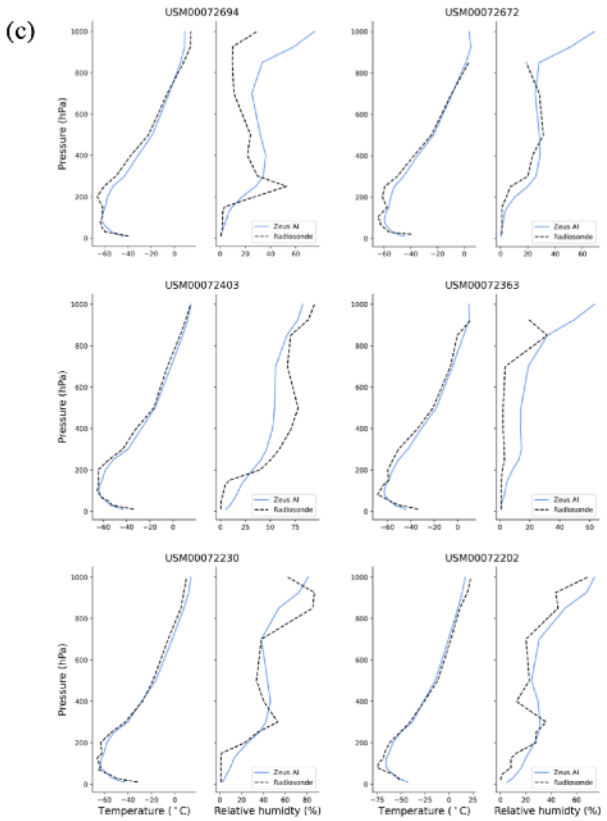
such that

$$z_{geo} = E_{geo}(GEO)$$

F is defined as an MLP with 4 input features and 9 output features



500 hpa a) Temperature and b) Relative Humidity Maps



c) Vertical profiles vs Radiosonde

Preliminary Analysis: Zeus AI vs ERA5

+ Improved spatial resolution and high-res atmospheric features
+ High-refresh rate every 10-minutes

- Underestimates warm core temperature

1:1 comparisons

Test set: January-April 2021

N = 1101

Relative humidity

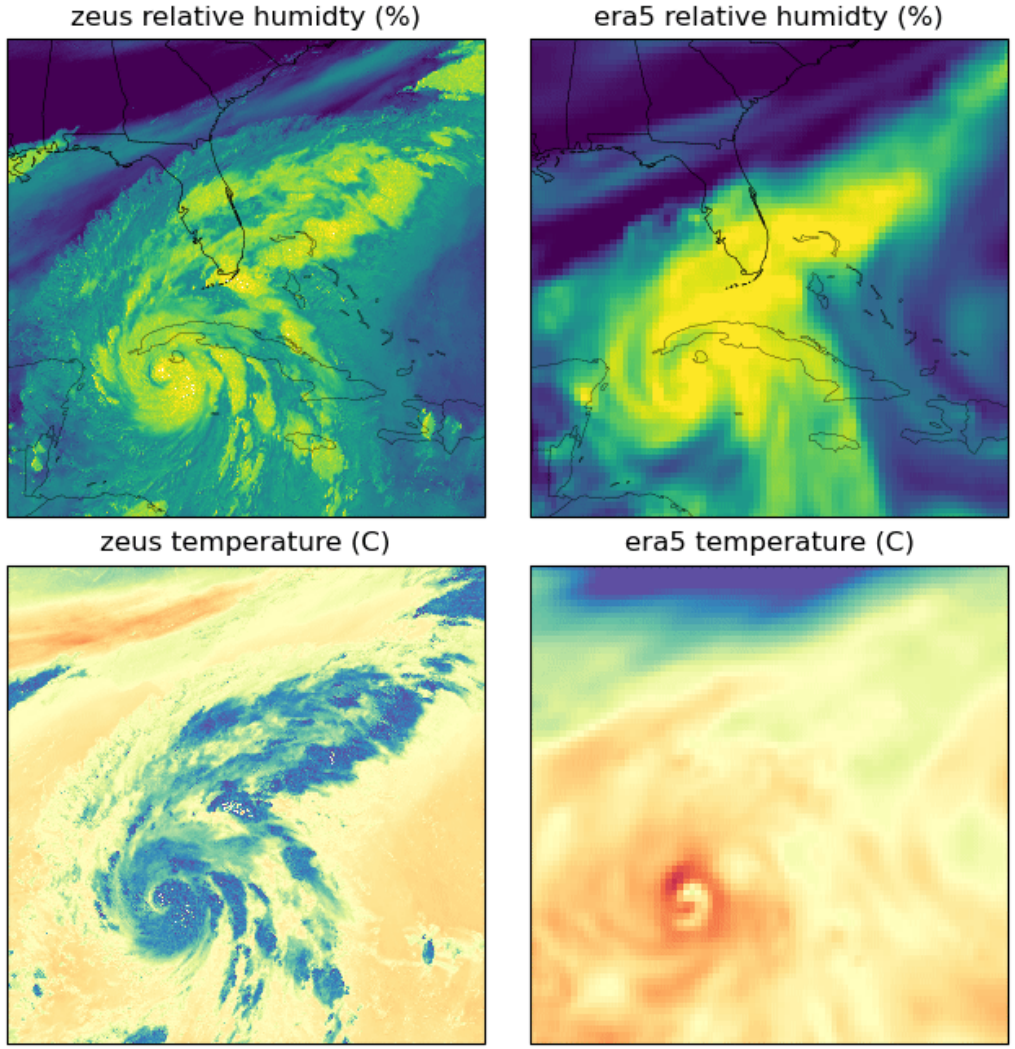
RMSE(zeus, igra) = 15.54%

RMSE(era5, igra) = 18.980%

Temperature

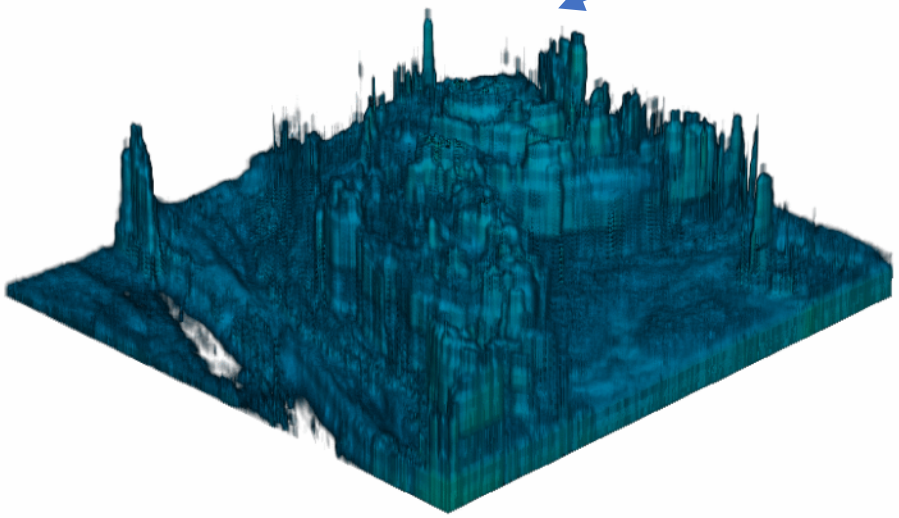
RMSE(zeus, igra) = 5.460 C

RMSE(era5, igra) = 3.364 C

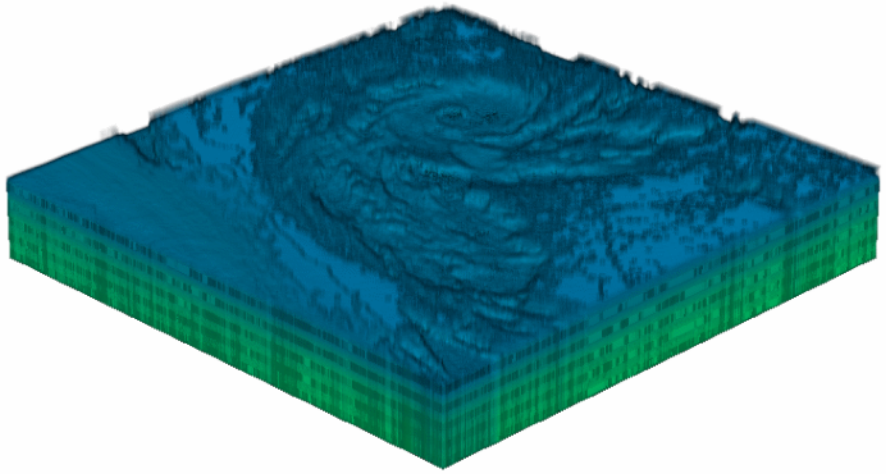


3D Hurricane Ian

Deep convection



Humidity



Temperature

Future Work

- Apply WindFlow to retrieved from multi-level relative humidity sequences to produce 3D winds.
- Evaluate data products using triple collocation analysis against models and observations.
- Evaluation performance for extreme events and case studies.
- Develop Neural Ordinary Difference Equations (NODEs) to effectively assimilate and smooth our 3D product.
- Apply NODE into future as a novel forecast.

Open source software

Windflow
https://github.com/tjvandal/windflow
Includes code for a suite of optical flow models, training, and dependencies

Windflow-light
https://github.com/tjvandal/windflow-light
Minimal dependencies
Efficient inference, runs on a laptop

CALIPSO cloud height prediction (In progress)
https://github.com/tjvandal/calipso-cloud-height-prediction

Temporal Interpolation
https://github.com/tjvandal/geostationary-superslomo

```
import torch
import datetime as dt

from windflow import inference_flows
from windflow.datasets import goesr

# load model runner
checkpoint_file = 'model_weights/windflow.raft.pth.tar'
inference = inference_flows.FlowRunner('RAFT',
                                       overlap=128,
                                       tile_size=512,
                                       device=torch.device('cpu'),
                                       batch_size=1)
inference.load_checkpoint(checkpoint_file)

# load data
file1 = 'data/OR_ABI-L1b-RadC-
M6C10_G16_s20222751101170_e20222751103554_c20222751103590.nc'
file2 = 'data/OR_ABI-L1b-RadC-
M6C10_G16_s20222751106170_e20222751108554_c20222751108596.nc'

g16_1 = goesr.L1bBand(file1).open_dataset()
g16_2 = goesr.L1bBand(file2).open_dataset()

# Perform inference
_, flows = inference.forward(g16_1[‘Rad’].values,
•     g16_2['Rad'].values)
```

Acknowledgements and contact

Funding:

NASA Small Business Innovation Research Phase I, GSFC (2022-2023)

NASA ROSES Operational Geostationary Satellite program (2020-2023)

NASA Earth eXchange (NEX), GeoNEX project (2018-2022)

Data provided by the NOAA GOES-R Team

Computing partially provided by NASA's Pleiades Supercomputer

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