Identifying Oceanic Cold Pools

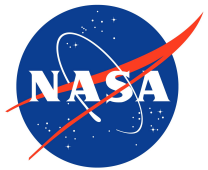
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Oceanic Cold Pools

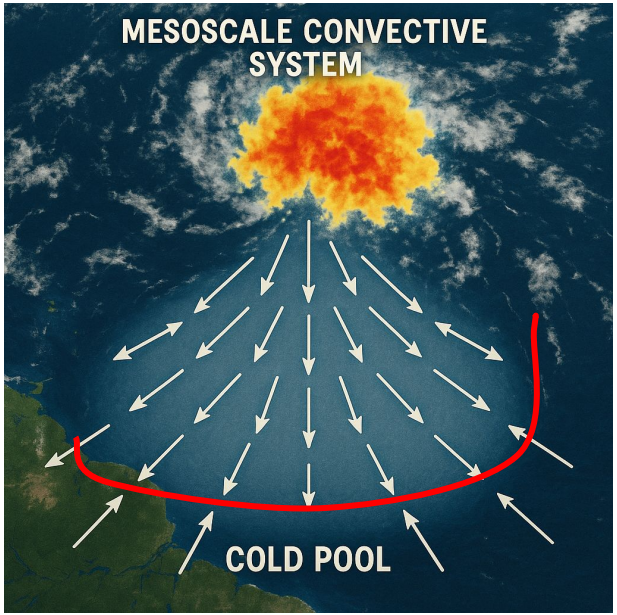


Fig.: Schematic representation of a cold-pool

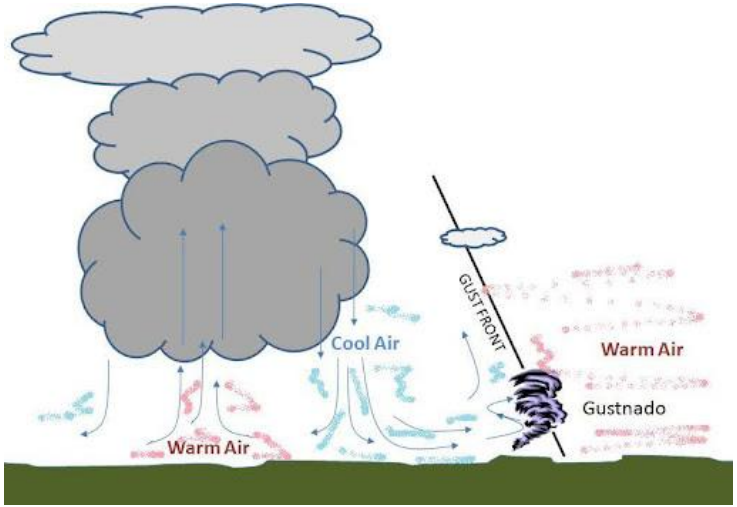


Fig.: Cold-pool dynamics/microphysical processes

- Changes in the wind speed associated with the density current
- Wind convergence at the leading edge of a cold pool

Satellite Wind Retrievals

Advanced Scatterometer (C-band):

- Polar orbiting
- Metop-a, -b and -c
- 2-daily samples

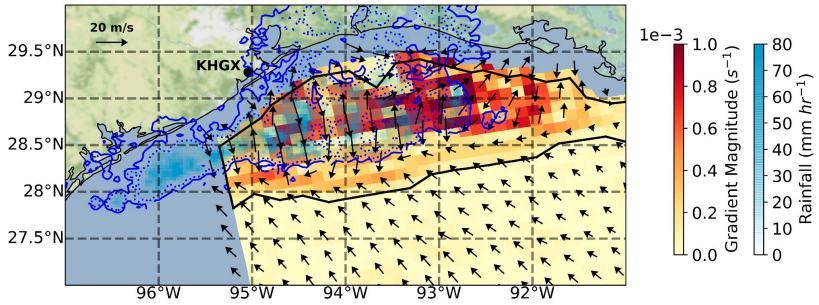


Fig.: ASCAT wind vectors and NEXRAD precipitation

CYGNSS (L-band):

- Non-sun-synchronous orbit
  - 38° S to 38°N
- 8 small satellites
- 3-6 hours sampling

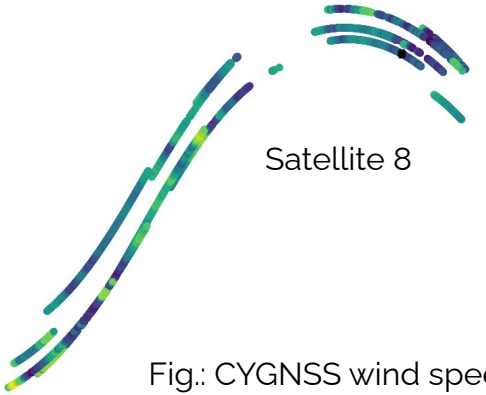


Fig.: CYGNSS wind speed retrieval

- Equivalent neutral **vector winds** are retrieved by **scatterometers** (sub-daily)
- **CYGNSS** retrieves **only wind speed** (3-6 hours sampling)

Research Objectives

- Combine CYGNSS with observations of winds, precipitation, and convective cloud characteristics together with reanalyses to better understand the genesis, structure, and evolution of tropical maritime cold pools

- In particular, use machine learning to identify cold pools from spaceborne measurements and create merged products leveraging CYGNSS combined with other scatterometer observations

Training

- Split swath in 40 x 40 windows
- u, v wind components
- Normalize data
  - Different scaling for u and v
- Cold-pools database:
  - Scatterometer based detection from wind gradient thresholding (Garg et al. 2020)
- Training, Validation data split: 80-20
  - > 2 million pixels
- Target
  - 1 = cold-pool
  - 0 = not cold-pool

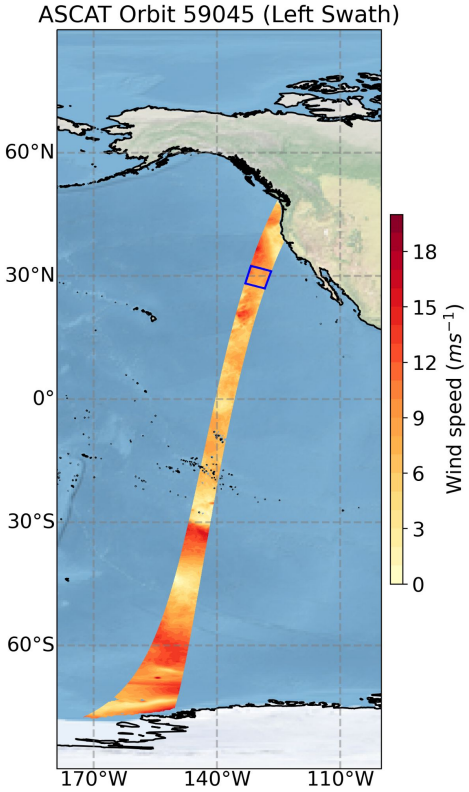


Fig.: Split swath in 40x40 windows (blue)

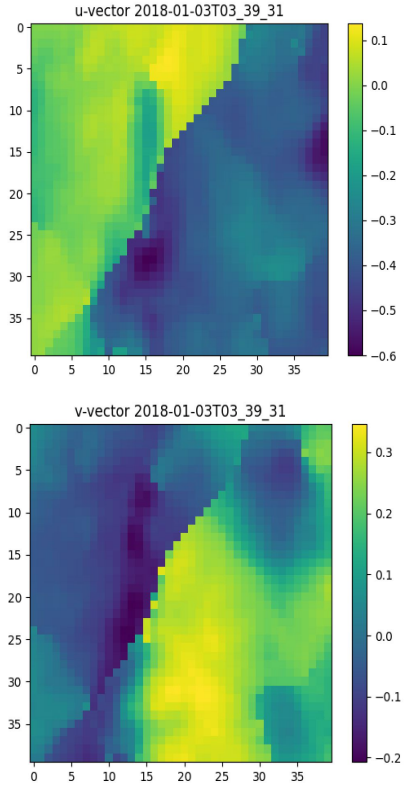


Fig.: Normalized vectors

U-Net Architecture

- Model: U-Net
  - Convolutional Neural Network (CNN)
  - Fixed set of learned features
- Loss function
  - Weighted binary-cross entropy
  - Accounts for class imbalance

CNN -> grid-like structure (images)

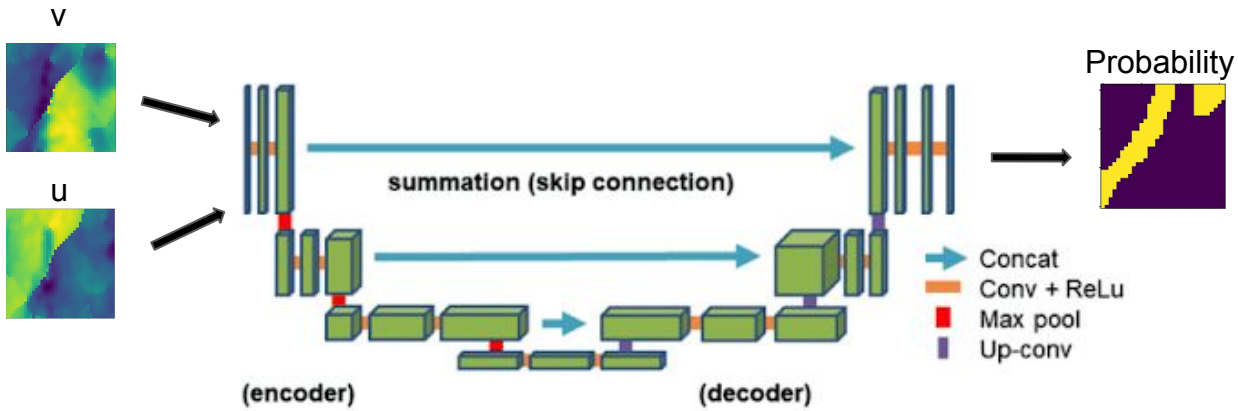


Fig.: U-Net Architecture



Fig.: Edge detection filters

Inferences & Validation

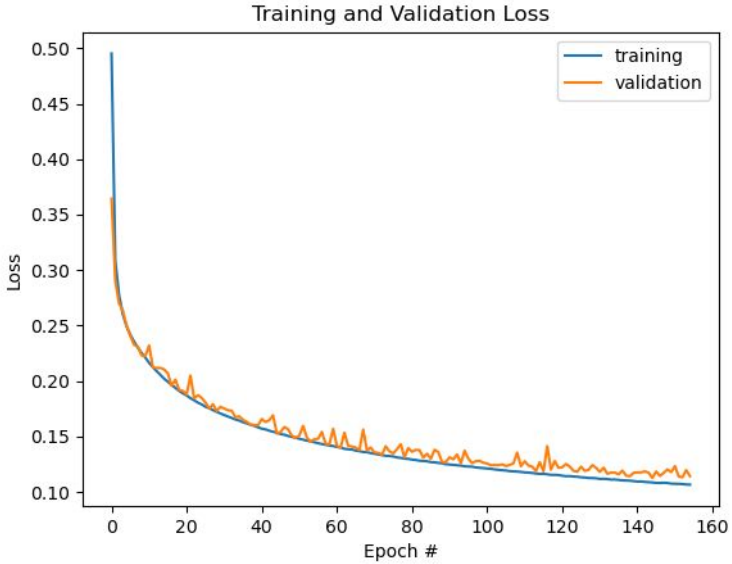


Fig.: U-Net training and validation plot

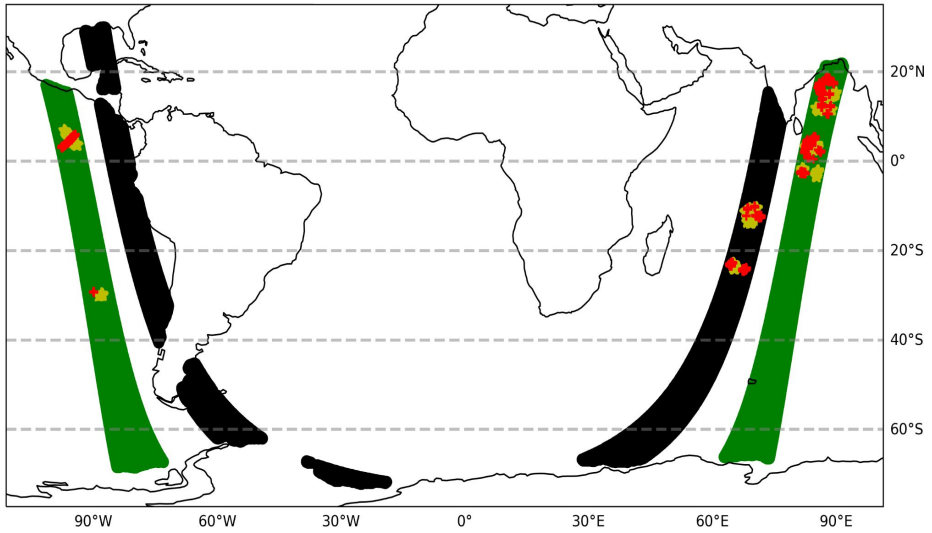
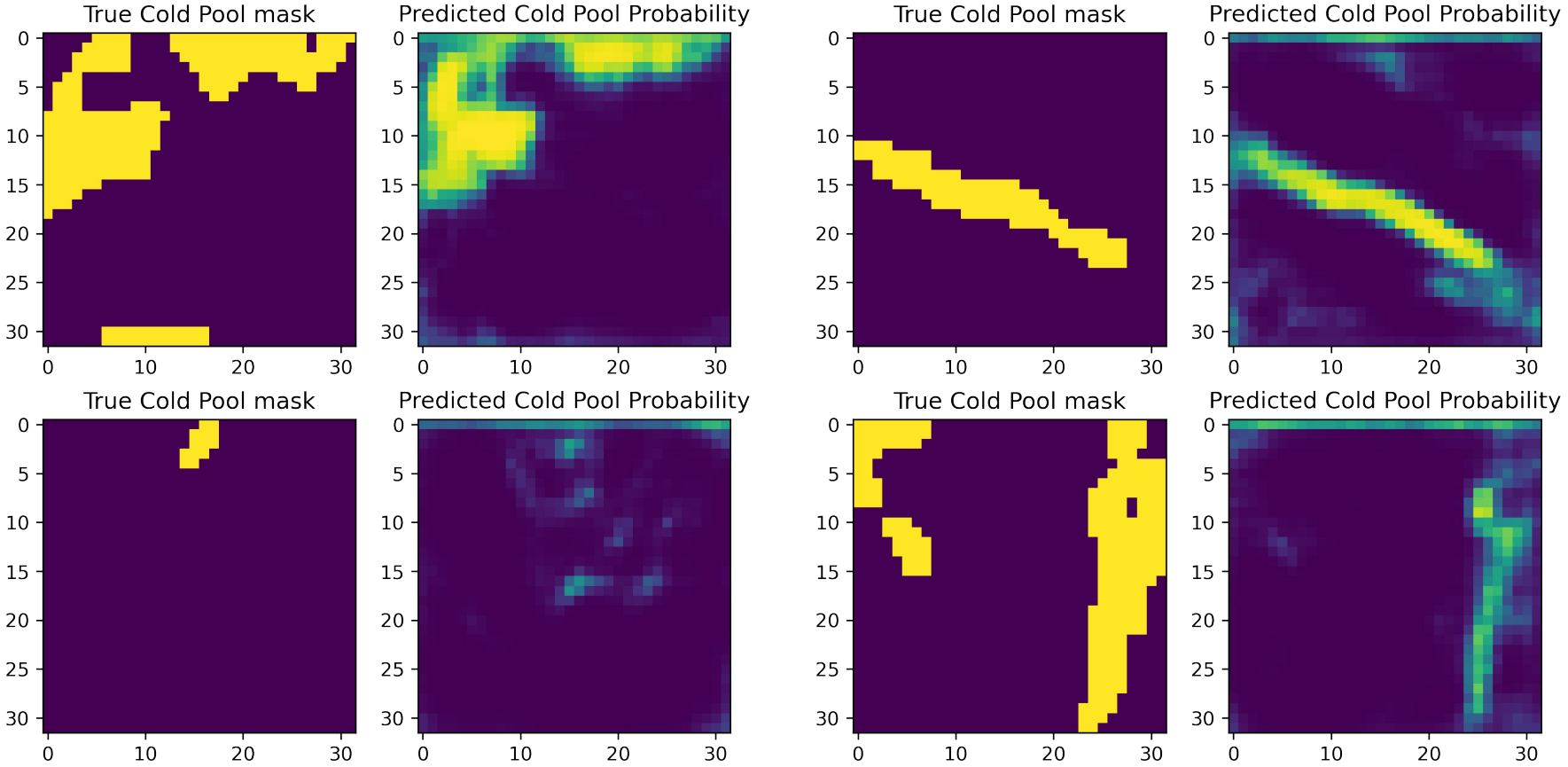


Fig.: GF coldpools (yellow) and U-Net predictions (red)

Inferences & Validation



Inferences & Validation

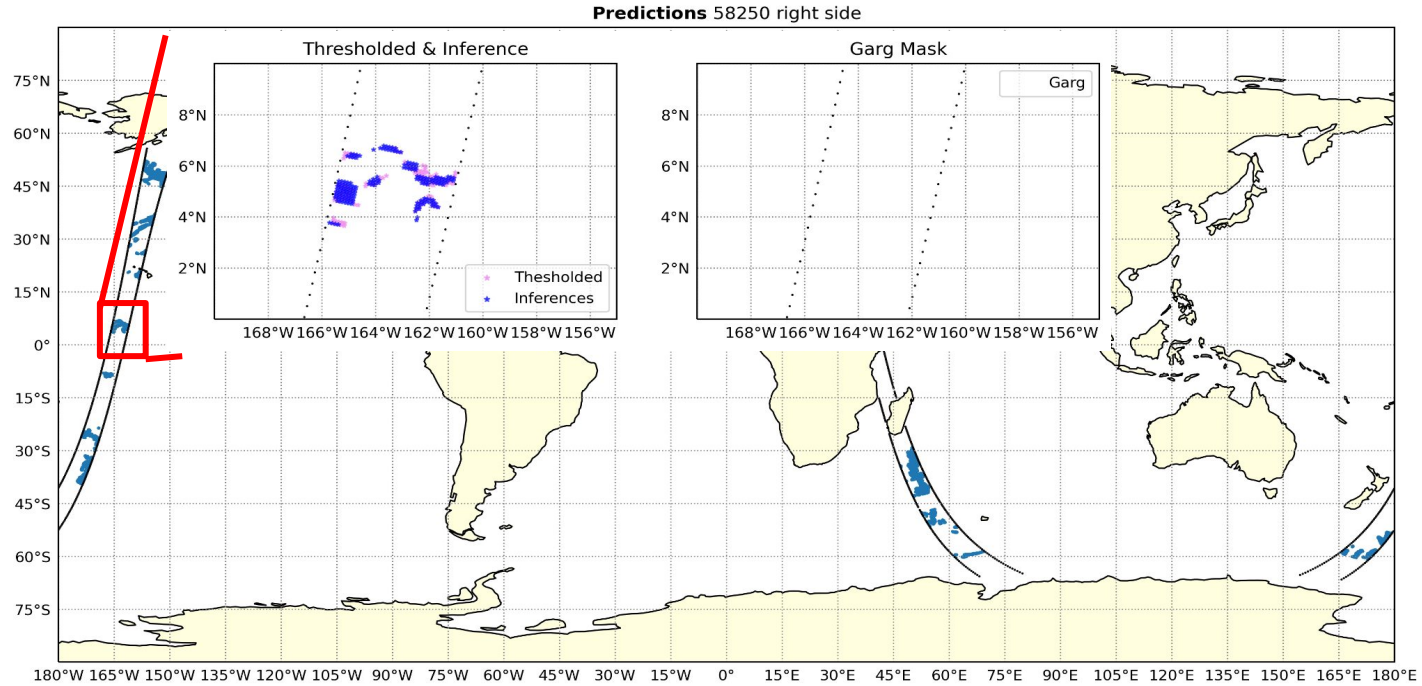


Fig.1: Swath predictions from U-Net (blue) and coldpools based on wind gradient threshold (pink).

Inferences & Validation



Fig.: U-Net performance in 2018

IoU score: 47% | POD: 78% | FAR: 8%

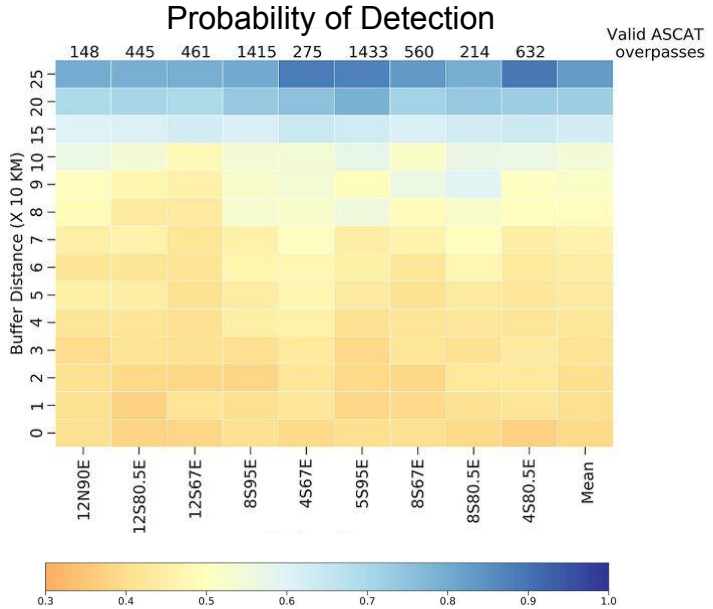


Fig.: GF method performance in Atlantic ocean (Garg et al. 2020)

<u>Buoy Evaluation</u>

- Atlantic Ocean (6)
- 2015-2019
- Coldpools: $T_{\text{hourly diff}}$ < -1.5°C

CYGNSS Cold Pool Statistics

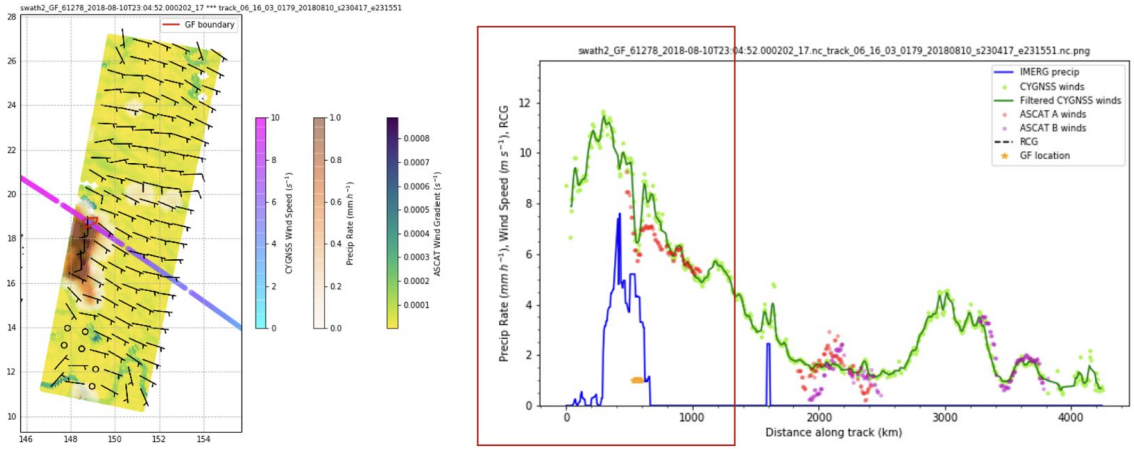
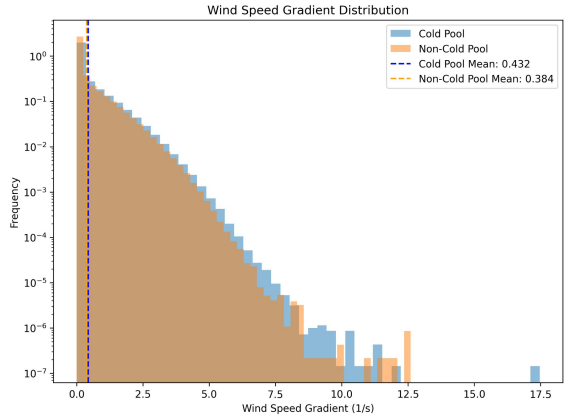


Fig.: CYGNSS and ASCAT wind overlap

- CYGNSS wind speed gradient in and near GF
- Larger wind speed gradient in GF



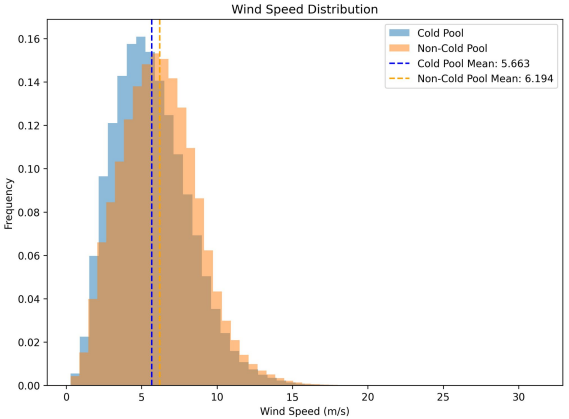


Fig.: CYGNSS wind speed and gradient for coldpool vs. non-coldpool

Seeded segmentation

- Compute histogram of wind speed within cold pools
- Select initial seed based on average peaks and valleys

Performance:

- IoU score: 11%
- POD: 48%
- FAR: 87%

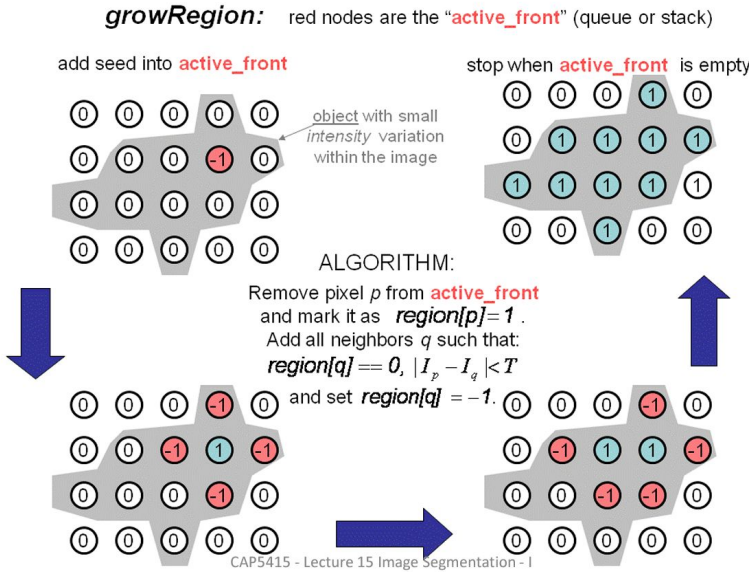


Fig.: Sedeed segmentation algorithm

1-D Transformer Architecture

- Transformer Encoder
  - **Multiple heads** allow the model to learn **different types of relationships** (e.g., spatial vs. temporal patterns)
  -
- Loss function
  - Dice loss ( )
    - Simila $\frac{2|X \cap Y|}{|X| + |Y|}$ ed measure
  - Accounts for class imbalance

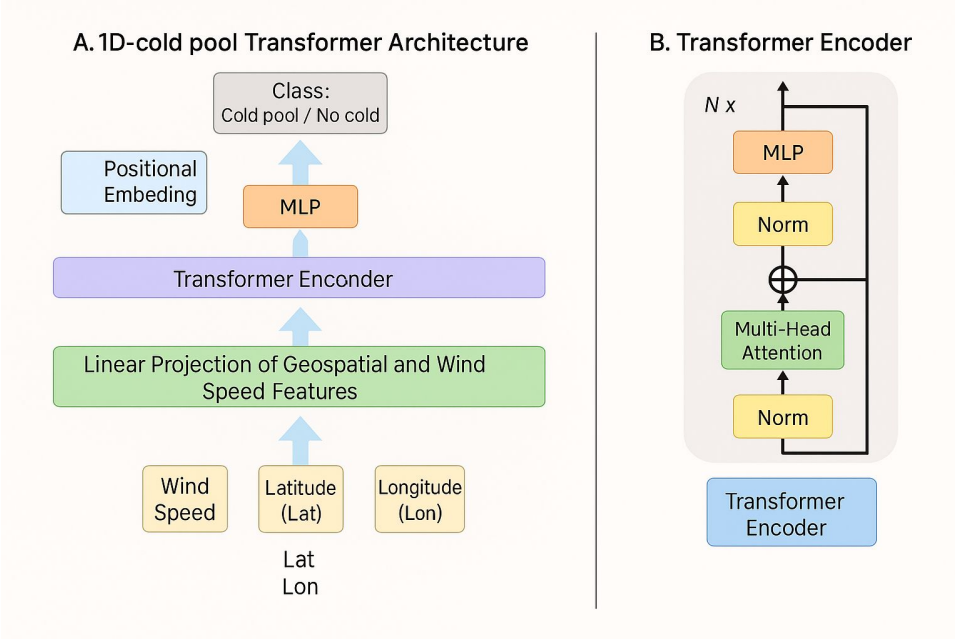


Fig.: 1-D Transformer Architecture

1-d Transformer -> sequential data

Training with CYGNSS

- CYGNSS Climate Data Record (2018-2019)
  - Wind speed, lat, lon, time, satellite id
- Pre-processing
  1. Wind speed: Fully Developed Seas
  2. Range corrected gain > 30
  3. Split data in hourly bins
  4. Build CYGNSS cold-pool mask
     - 4.1. ASCAT cold-pool database (U-Net)
     - 4.2. Spatial overlap: 300 km
     - 4.3. Temporal overlap: 3 hr
  5. Normalize data: Wind speed, lat, lon

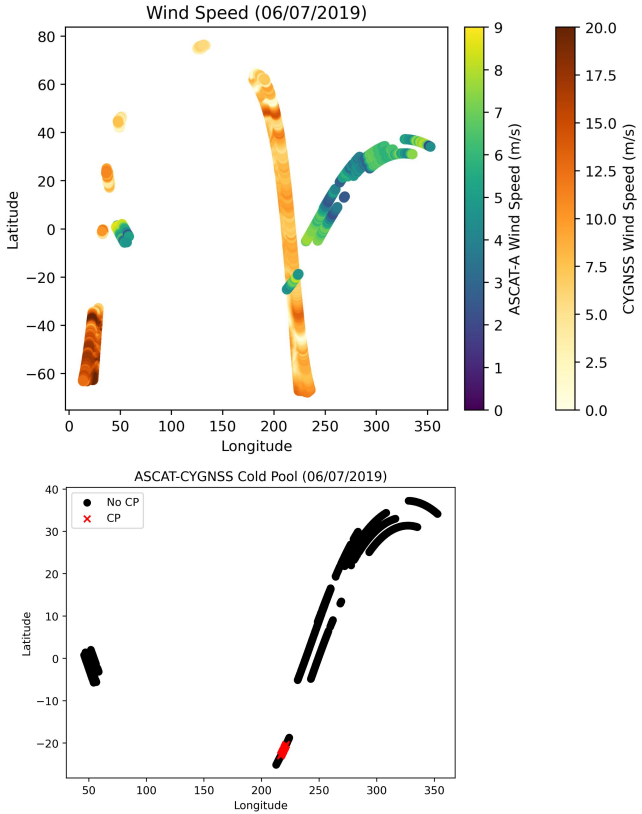


Fig.: ASCAT-A and CYGNSS wind speed, with cold pool location.

Training and Performance

- Input
  - Cold-pool mask
  - lat/lon, ws (normalized)
  - time, satellite-id
- Target
  - 1 = cold-pool
  - 0 = not cold-pool
- Training, Validation data split: 80-20
  - Total number of

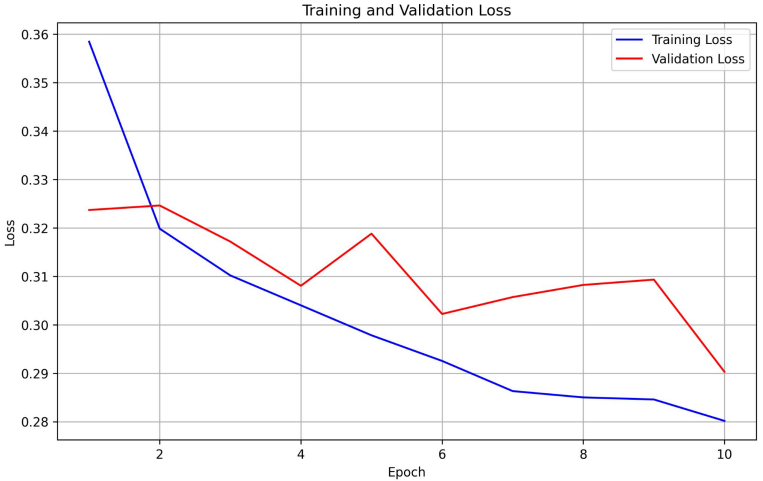


Fig.: 1-D Transformer training and validation plot

IoU score: 31% | POD: 62% | FAR: 18%

Key Takeaways

- Scatterometers (polar orbit) provide wind vectors:
  - Wind gradient increases at the leading edge of the cold-pool
  - AI advances facilitate climatology of oceanic cold-pools based on image processing
- How do we sample the diurnal cycle of cold pools?
  - CYGNSS samples approximately every 3-6 hours
  - Wind speed retrievals only
  - Deep learning shows promising results

Next Steps

- Expand ASCAT cold-pool database for ASCAT-b and -c
- Apply rolling pass filter to smooth CYGNSS data
- Transformer model tuning
- Fallback plan
  - Use image processing techniques on CYGNSS L3 gridded wind product
    - Degraded spatial and temporal resolution