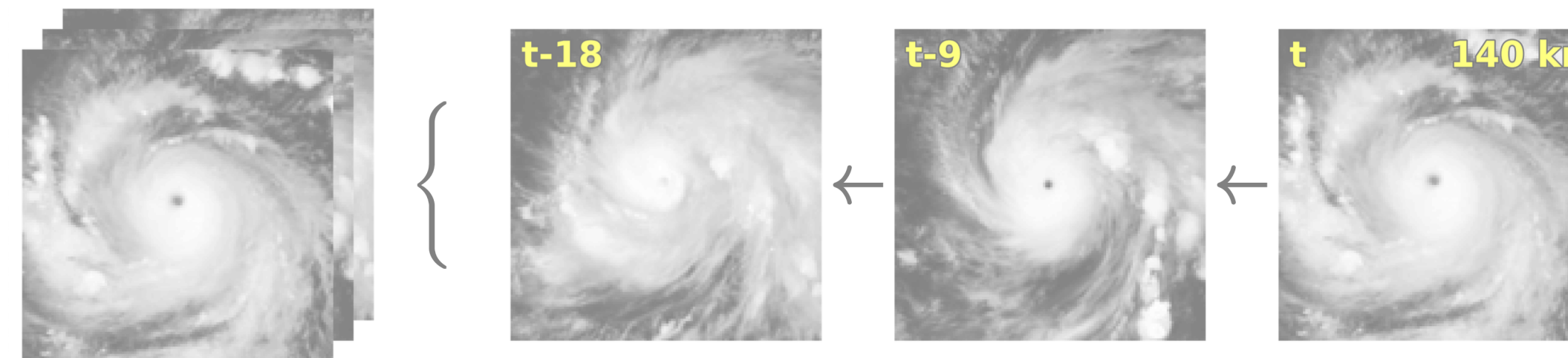


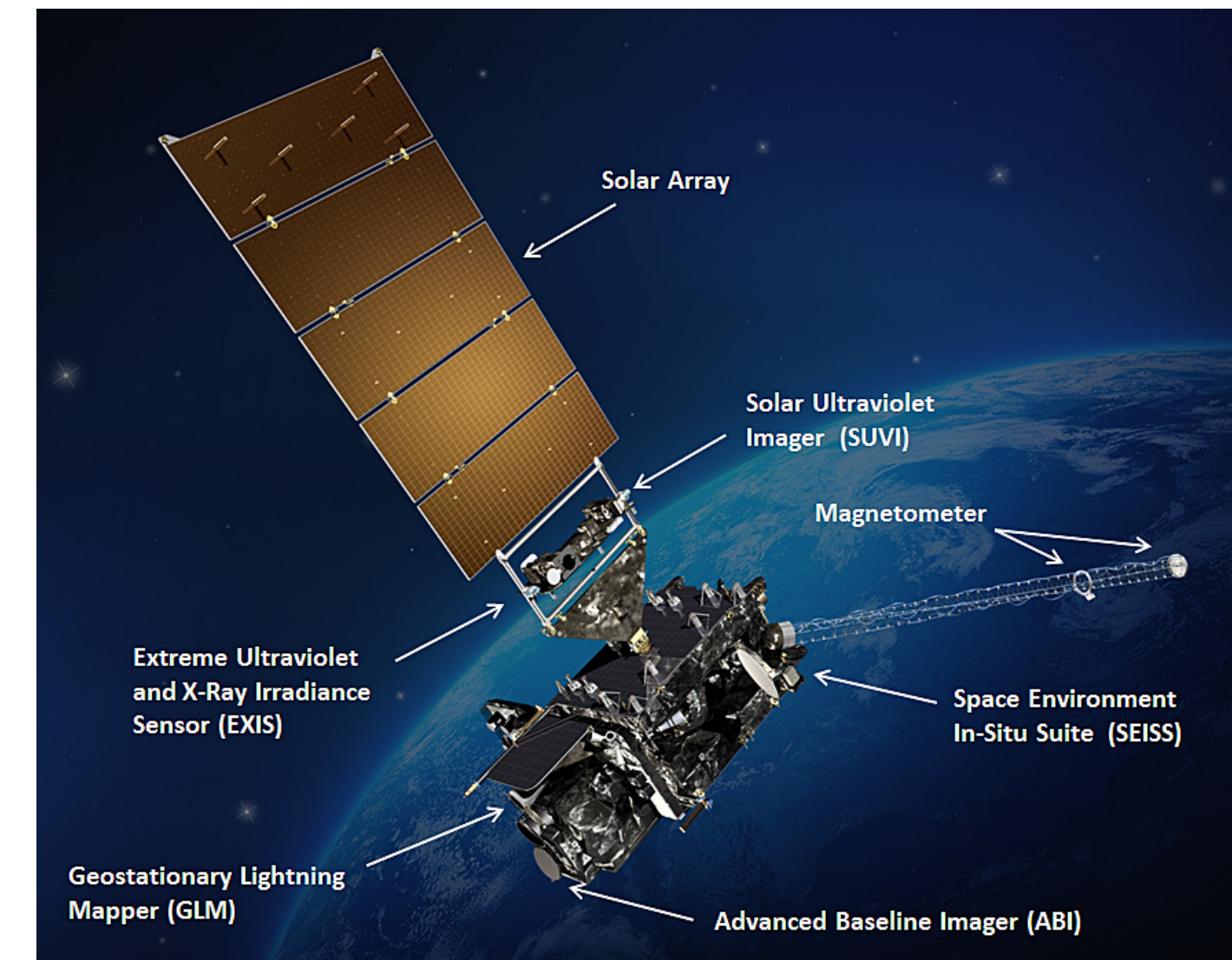
Attention-Based Scattering Network for Satellite Imagery

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Introduction

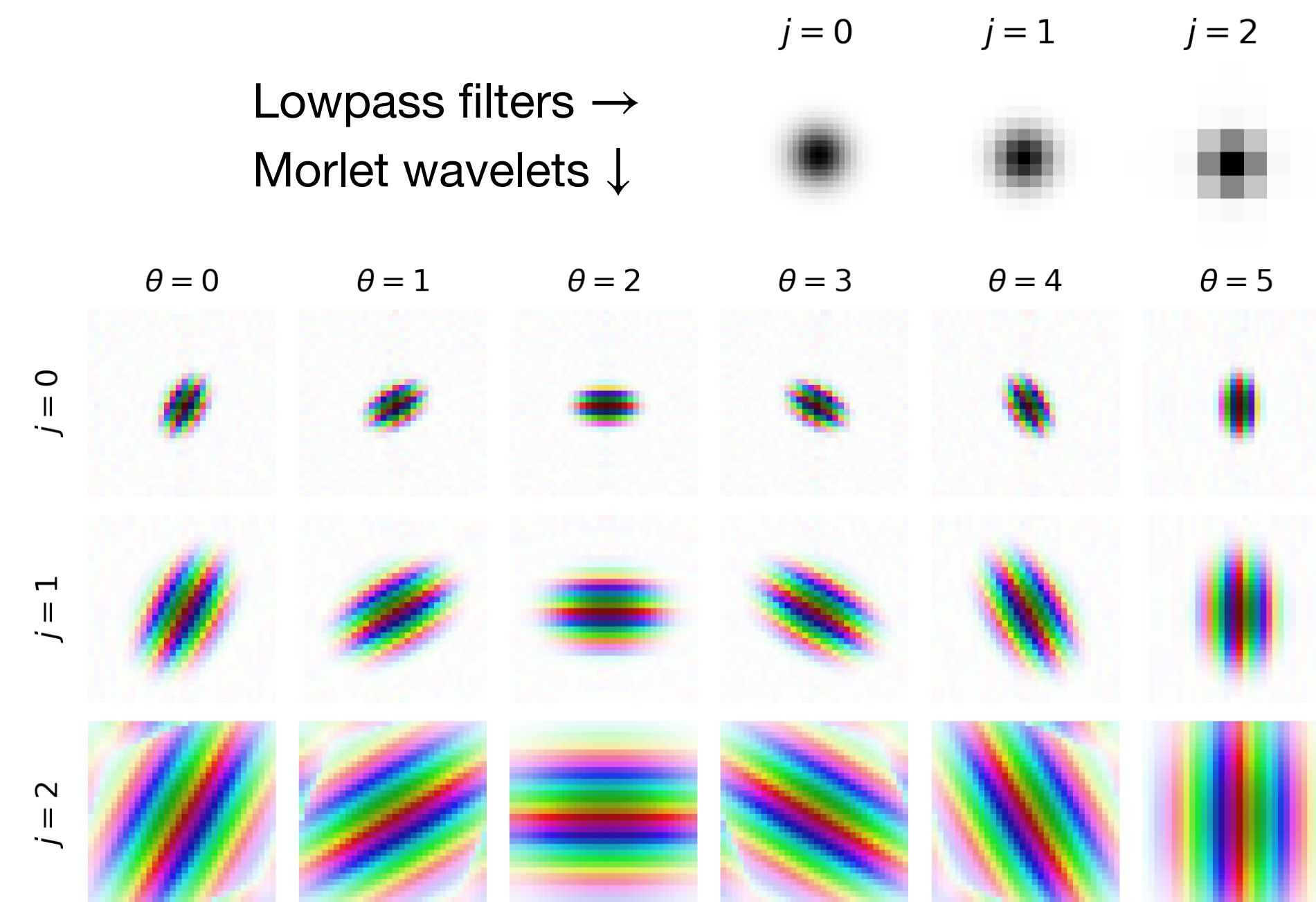
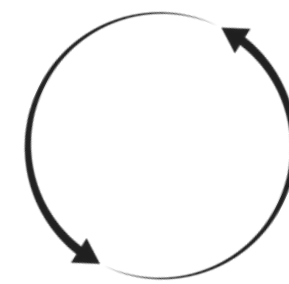
- **Multi-channel satellite imagery**, from stacked spectral bands or spatiotemporal data, have meaningful representations for various atmospheric properties
- Effectively combining these channels to create a **performant** and **trustworthy** model is important to forecasters and modeling experts
- Satellite-based applications + machine learning problems:
 - ▶ Deep neural networks **lack inherent interpretability**
 - ▶ Often limited by the **quantity of available labeled data**



NOAA/NASA GOES-R Satellite

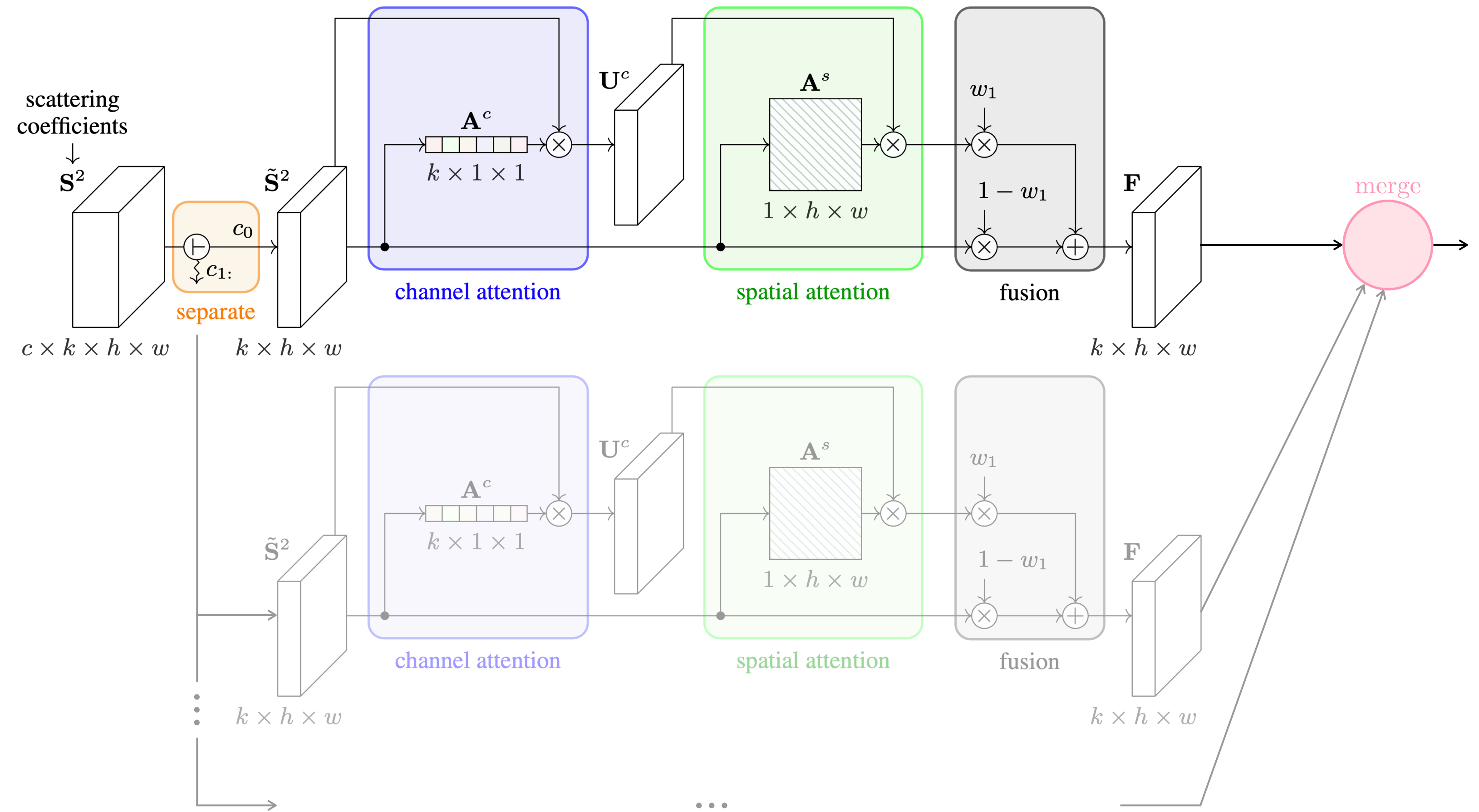
Scattering Transform

- Introduced by Stéphane Mallat (2012)
 - Strong geometric invariants (translation, rotation, scaling)
 - Robust to noise and stable to deformations
 - Defined as a convolutional neural network
 - Wavelet transform (convolution)
 - Lowpass filter (average pooling)
 - Complex modulus (non-linearity)
- ▶ Largely **underexplored in weather and climate** applications
- ▶ **Main contribution:** first approach applying local attention to individual scattering coefficients



Network Architecture

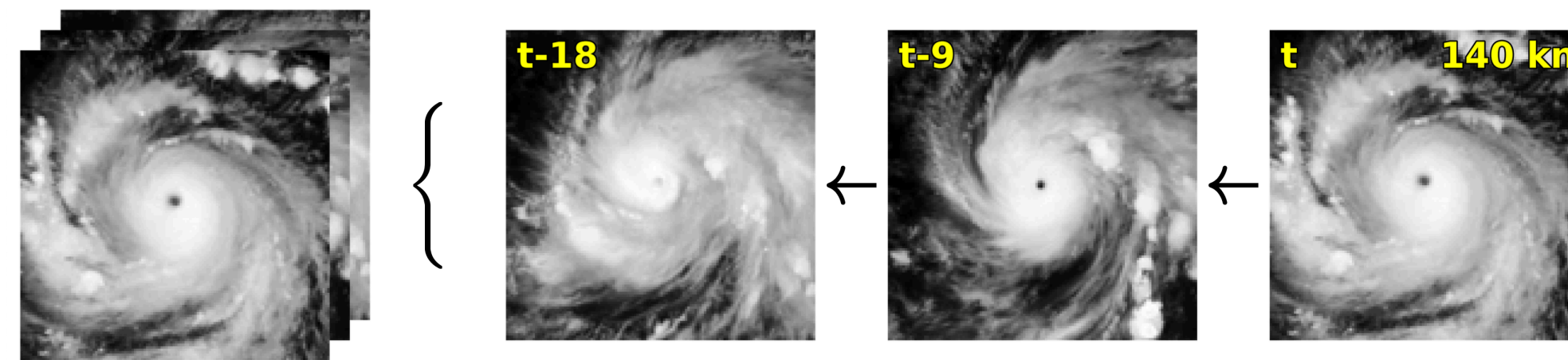
1. Scattering Transform
2. Channel Separation
3. Channel Independent Attention Modules
4. Feature Merging



Experimental Datasets

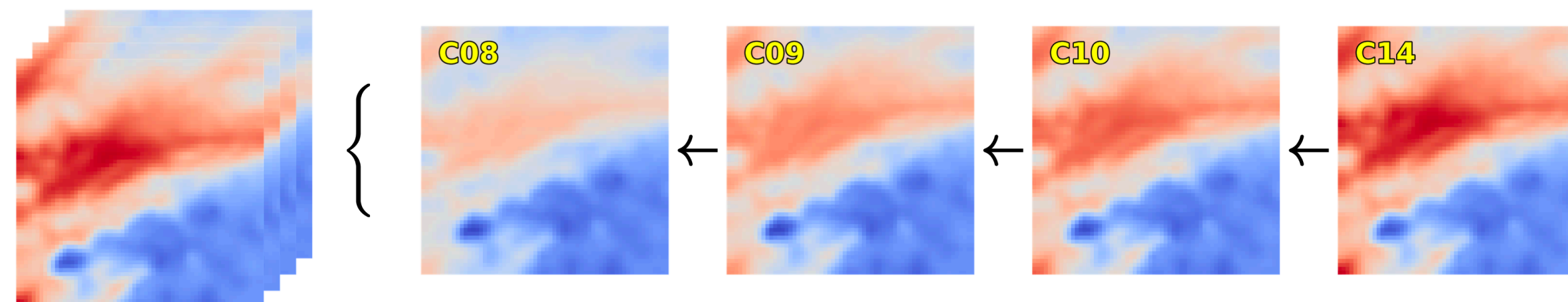
- **Estimating Tropical Cyclone Intensity**

- Single-band infrared imagery (10.3 μm) from **GOES-16 ABI** - 600 storms from 2000-2019
- Leverage temporal relationships of previous timesteps up to the point of prediction (regression)



- **Short Range Lightning Prediction**

- Water vapor bands (6.2, 6.9, 7.3, & 11.2 μm) from **GOES-16 ABI** and lightning counts from **GLM**
- Target flash counts, lagged by one hour, are converted to binary labels (classification)



Results

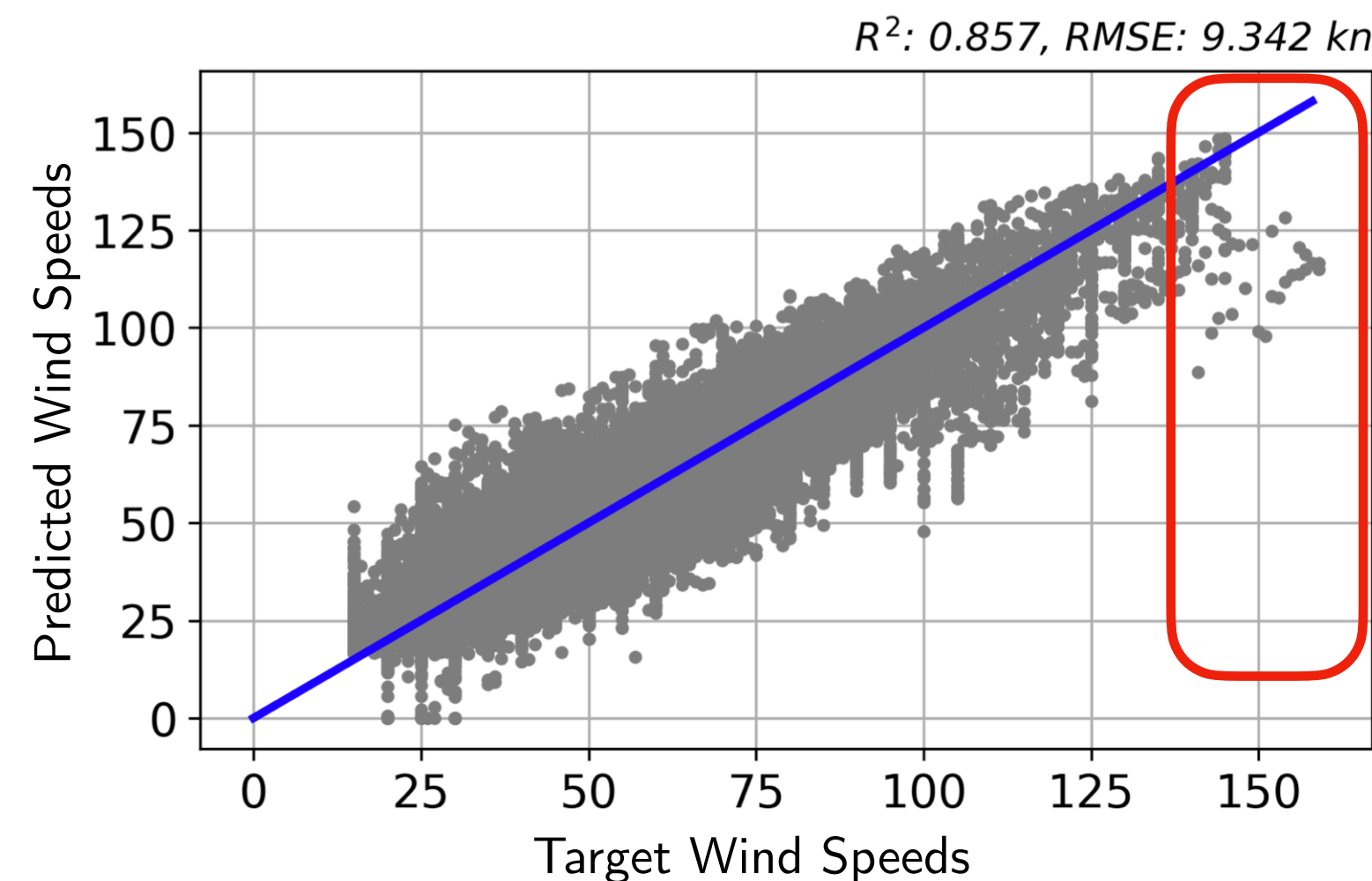
- Multiple trials with a reduced number of training samples
 - Great advantages primarily for **small sample sizes**,
 - While there are diminishing returns for very large sample sizes
- **Better generalization** than common state-of-the-art methods
 - Fewer trainable parameters than a linear model

Table 1: Experimental results using n training samples and p parameters.

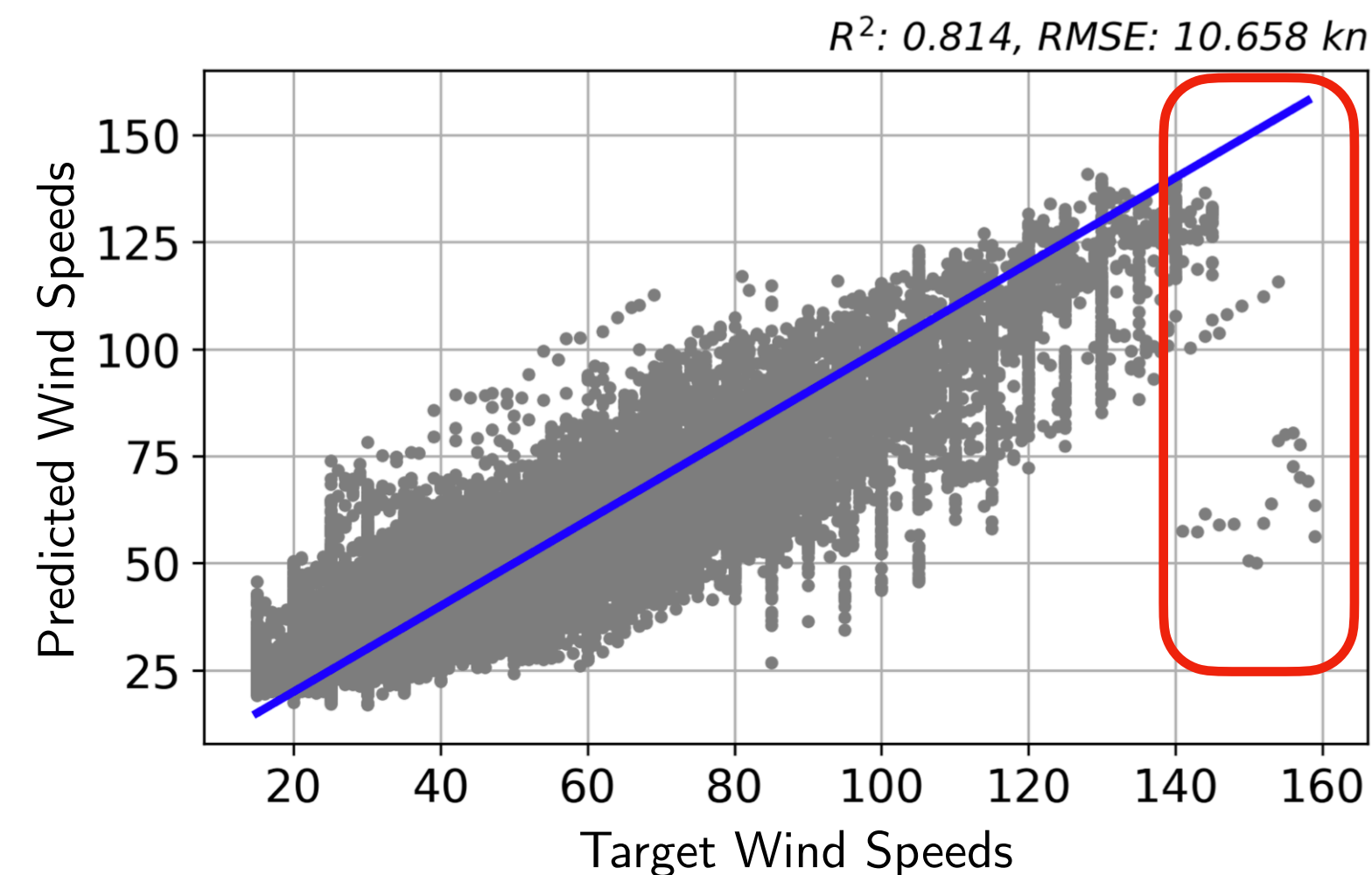
$n \downarrow p \rightarrow$	Scattering (51.8K)	ResNet18 (11.2M)	MobileNetV3 (1.5M)	Conv. (268.2K)
TC Intensity, rmse (R^2)				
1000	15.83 (0.59)	16.47 (0.56)	56.85 (-4.28)	17.51 (0.50)
5000	12.01 (0.76)	14.30 (0.67)	55.18 (-3.97)	13.34 (0.71)
10000	10.98 (0.80)	11.85 (0.77)	21.13 (0.27)	13.81 (0.69)
30000	10.35 (0.83)	10.74 (0.81)	13.07 (0.72)	11.68 (0.78)
47904	9.34 (0.86)	10.66 (0.81)	11.90 (0.77)	11.67 (0.78)
Lightning Occurrence, acc. (F1)				
1000	86.04 (0.85)	73.68 (0.74)	62.46 (0.39)	78.27 (0.74)
5000	88.01 (0.87)	87.59 (0.87)	68.82 (0.55)	82.35 (0.82)
10000	88.87 (0.88)	86.33 (0.85)	81.46 (0.83)	84.37 (0.84)
50000	89.58 (0.89)	89.20 (0.88)	87.49 (0.87)	87.99 (0.87)
212604	90.46 (0.90)	90.51 (0.90)	86.87 (0.88)	89.57 (0.89)

Estimating Tropical Cyclone Intensity

- Lowest errors observed with the **highest intensity samples** (where ResNet18 performs worst)
- Target wind speeds >140 kn
 - Scattering Net RMSE = **27.231 kn**
 - ResNet18 RMSE = **51.630 kn**



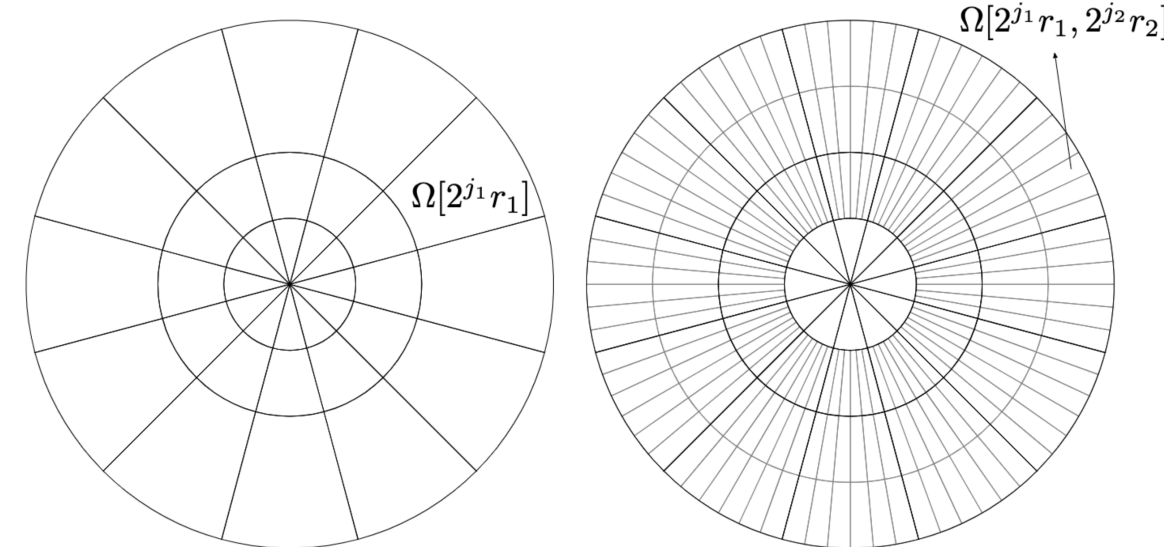
(a) Scattering Network



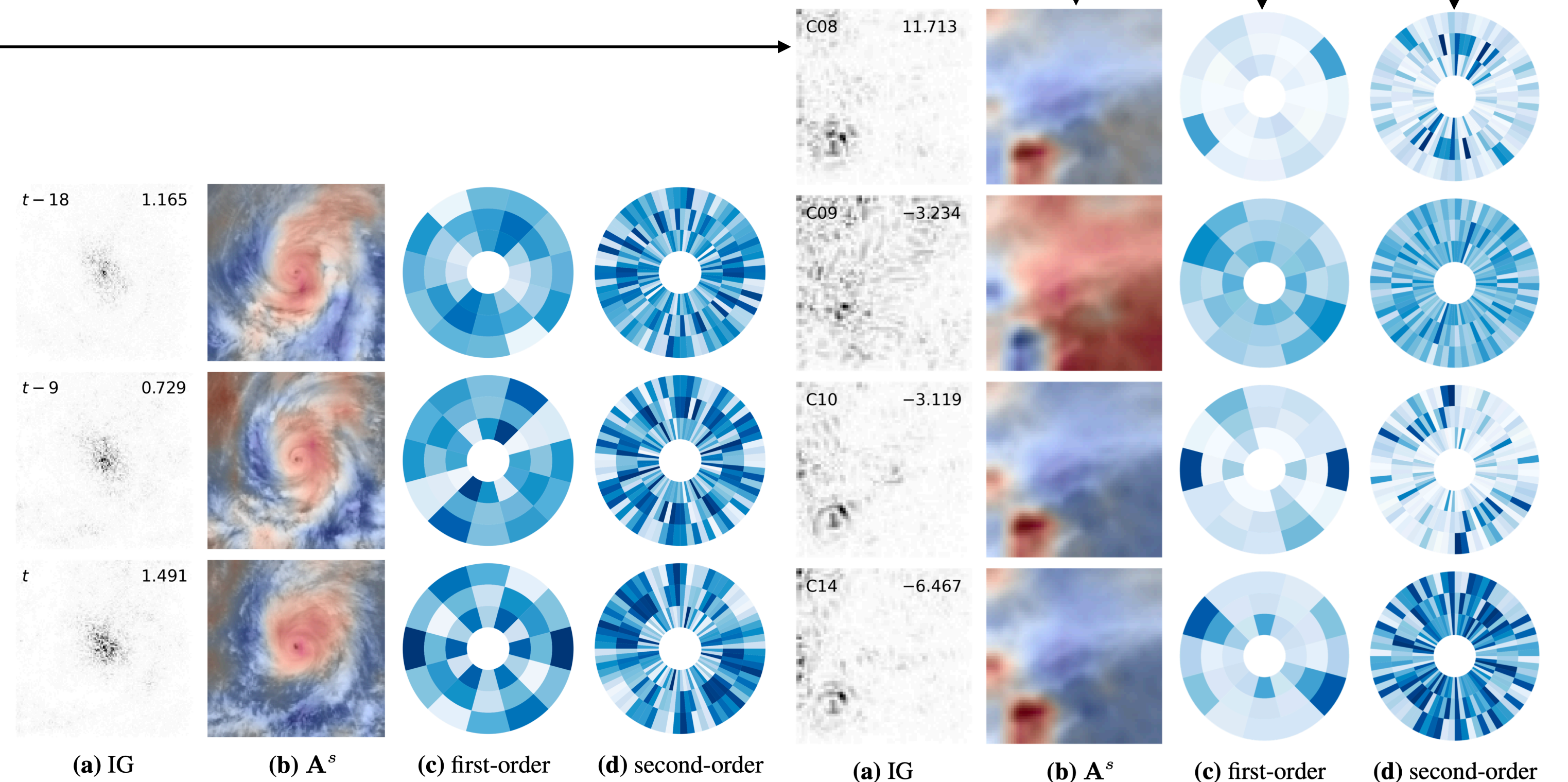
(b) ResNet18

Network Interpretations

- **Spatial attention features**
 - Feature maps superimposed for individual input channels
- **Scattering coefficient attention features**
 - Scalar weights of first- and second-order coefficients
- **Gradient based methods**
 - Demonstration of differentiable post hoc explainability methods



Bruna, J., & Mallat, S. (2013).
Invariant scattering convolution networks.



Tropical Cyclones

Lightning Prediction

Thank you!

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