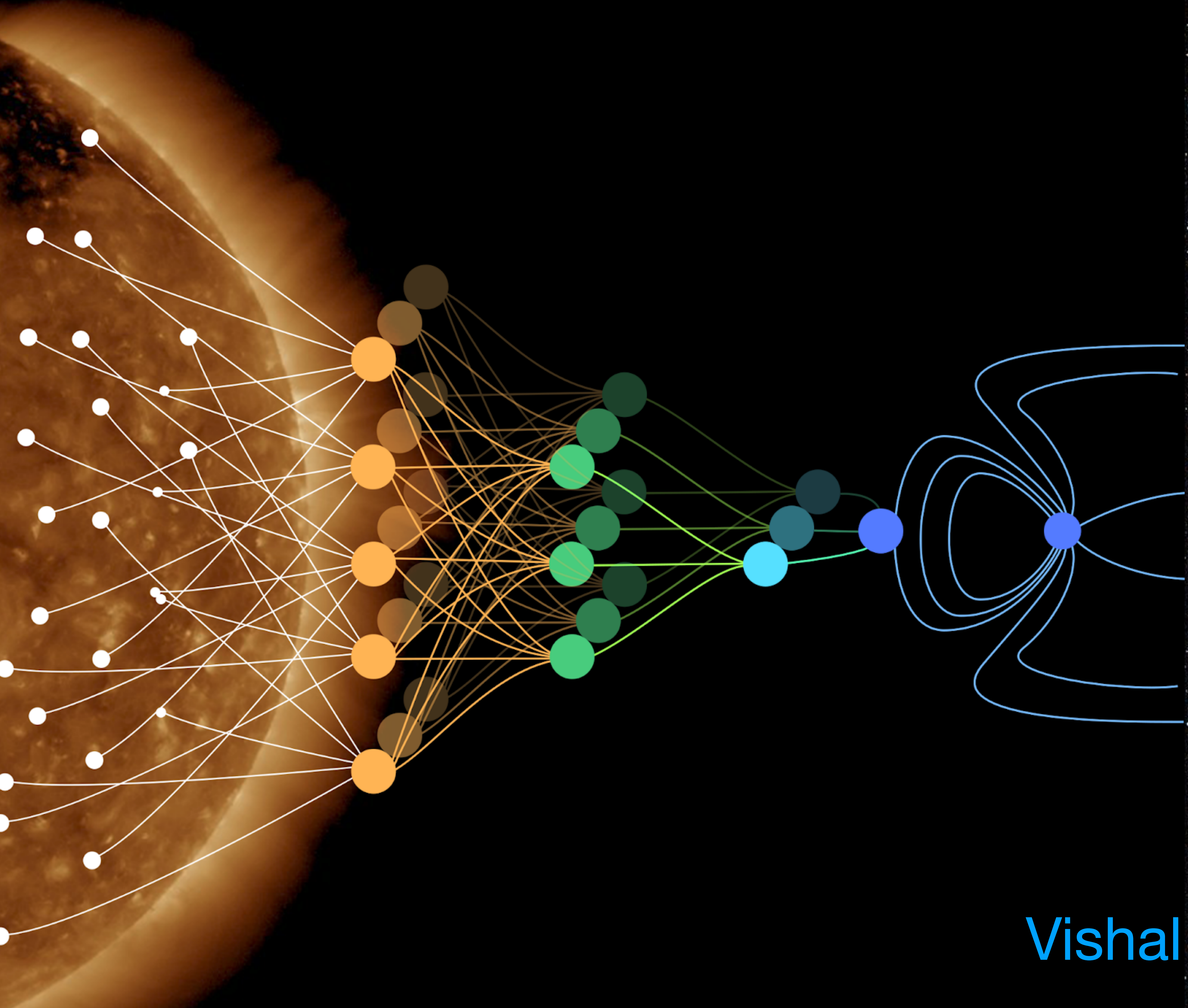


vishal@lmsal.com

From subtle to the vast: A multi-scale understanding of the Sun aided by artificial intelligence

Vishal Upendran

Lockheed Martin Solar and Astrophysics Laboratory | Bay Area Environmental Research Institute

Heliosphere as a system [Certainly NOT to scale!]

Credits:
Disc: SDO/HMI
Eclipse: **Chromosphere**: Credit: Luc Viatour; UCAR
Solar wind: NASA SVS; data from Craig DeForest, SwRI

AI applications to Heliosphere

Simulation-based inference

Explainable AI for model evaluation and scientific discovery

Physics-incorporated deep learning

Atmospheric dynamics

Free streaming wind

Magnetosphere interaction

Aurora from my phone at Sierra Vista in May 2024, San Jose, CA, USA

Length: ~ 10^6 m, Time: ~ seconds to mins

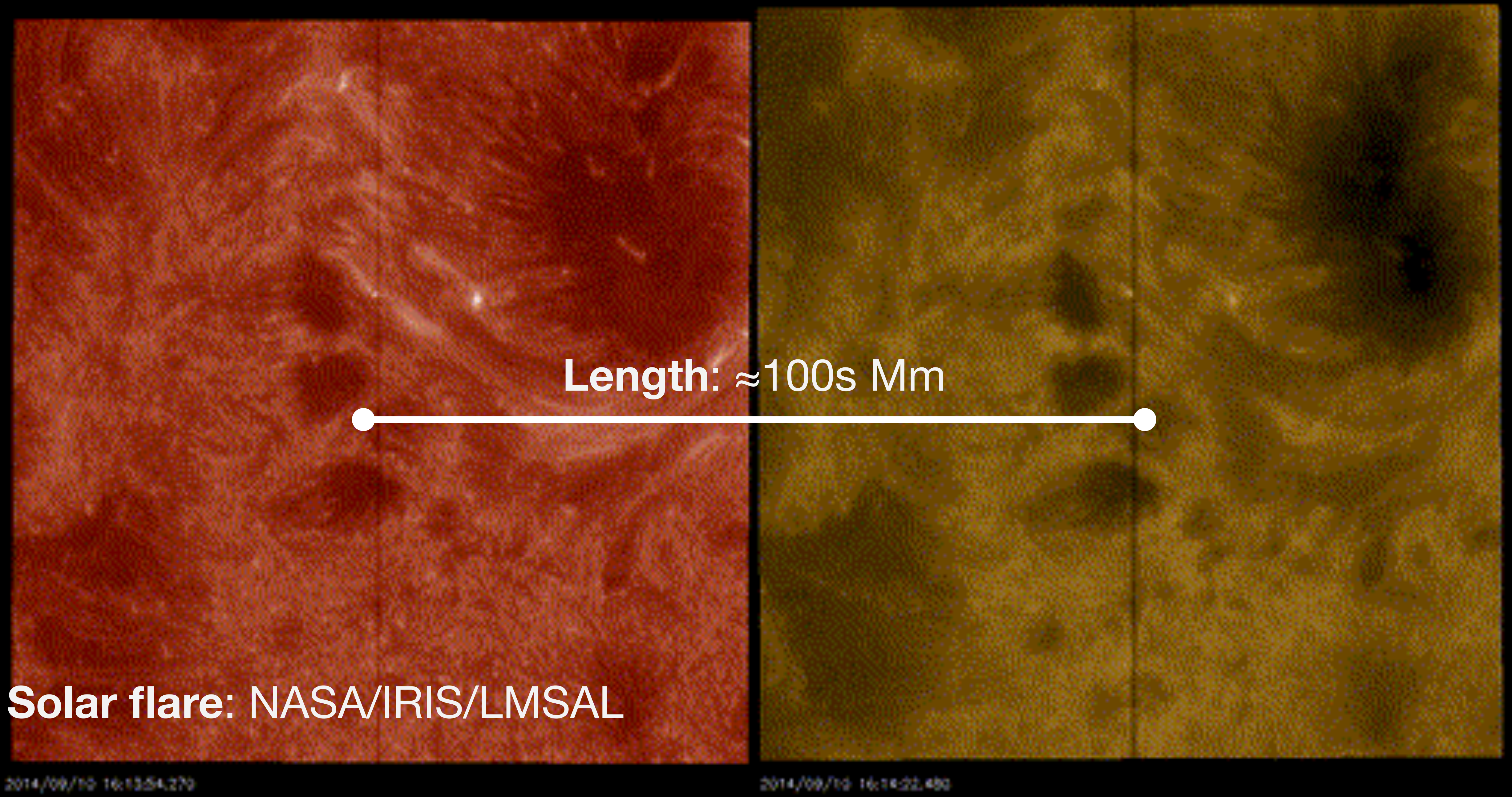
Simulation-based inference using machine learning

Application: Parameter estimation for >1,000,000 light curves

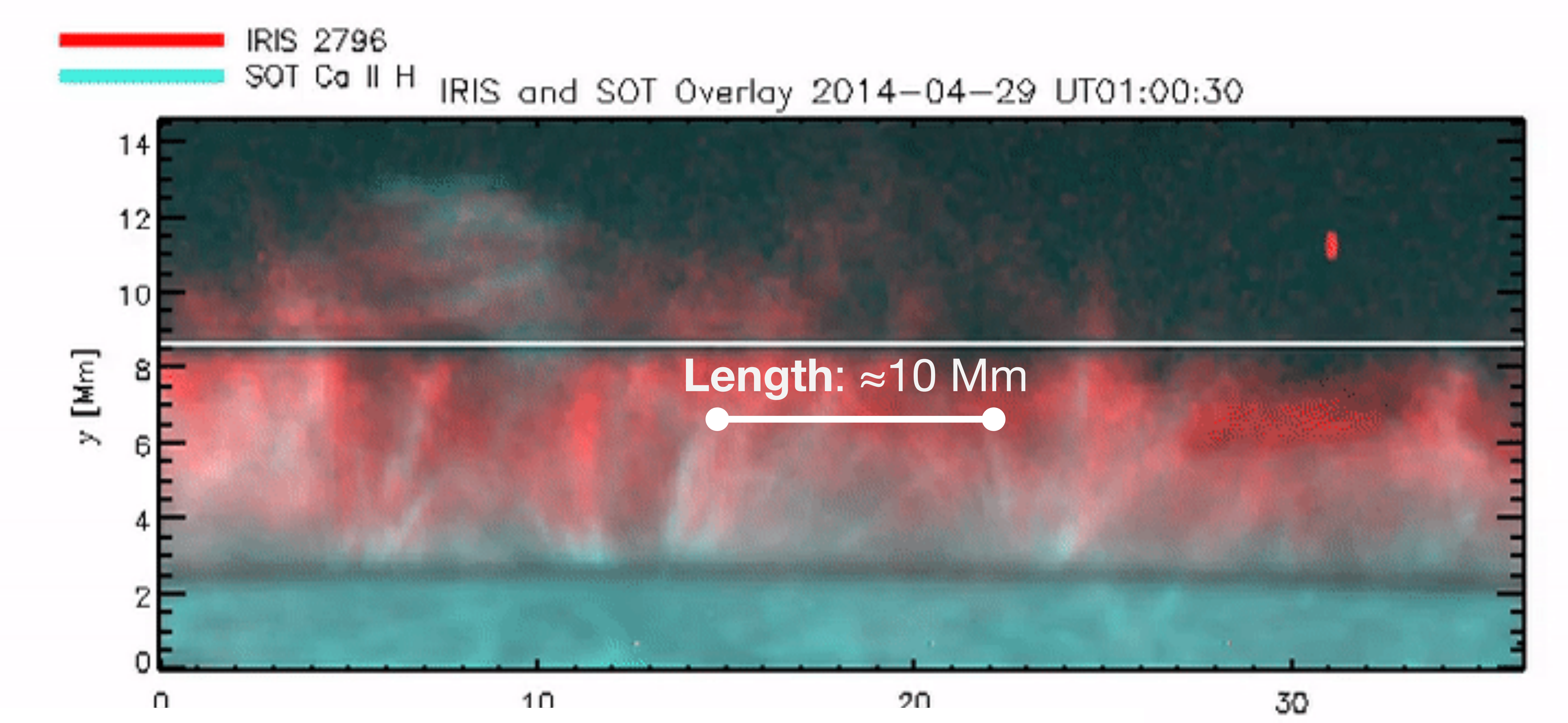
Upendran and Tripathi (2021) ApJ 916 59

Upendran et. al. (2022) ApJL 940 L38

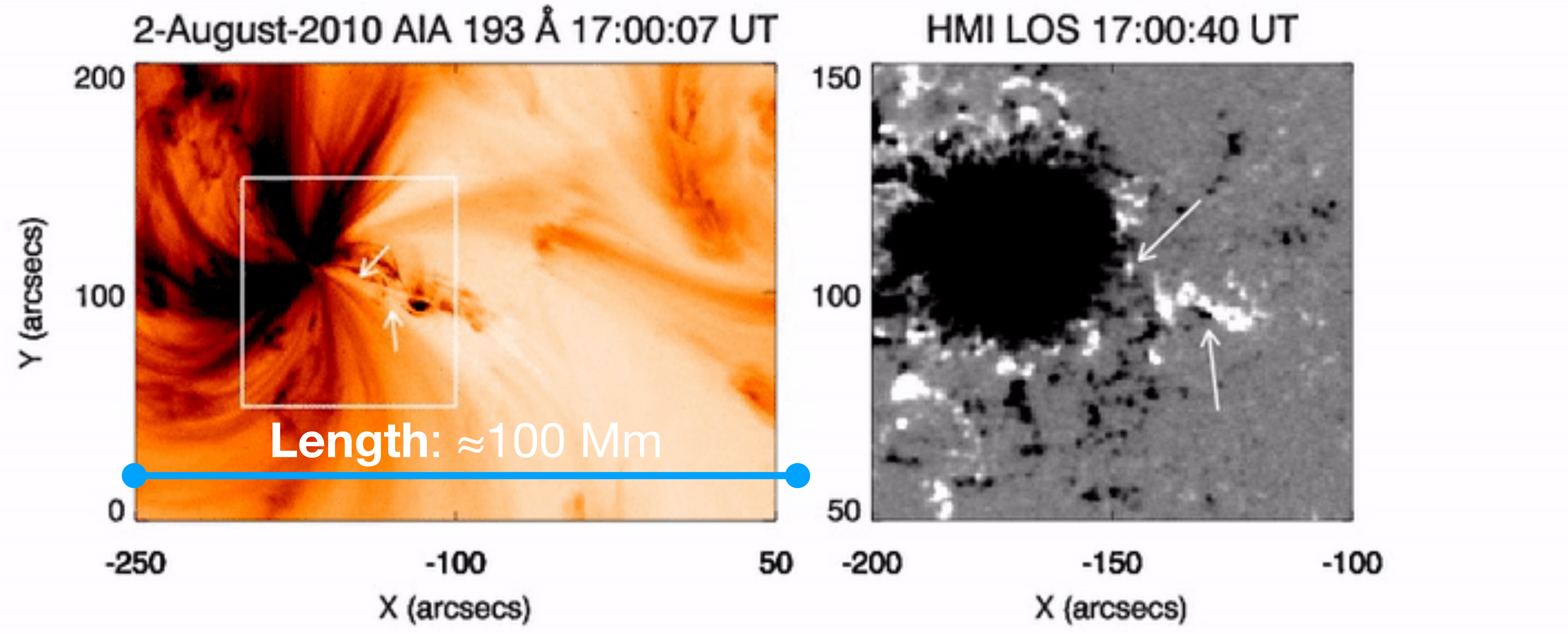
Energy release at multiple scales



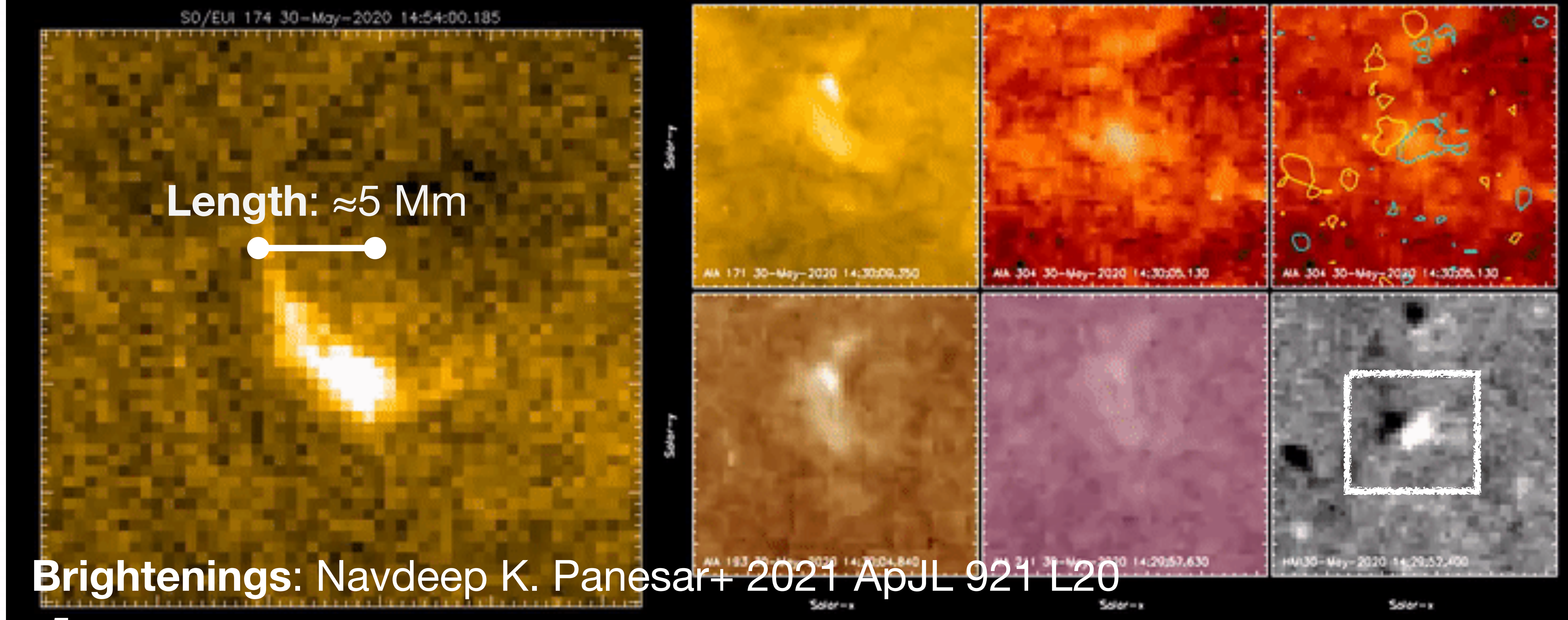
Solar flare: NASA/IRIS/LMSAL



Spicular motion: From P. Antolin et al 2018 ApJ 856 44

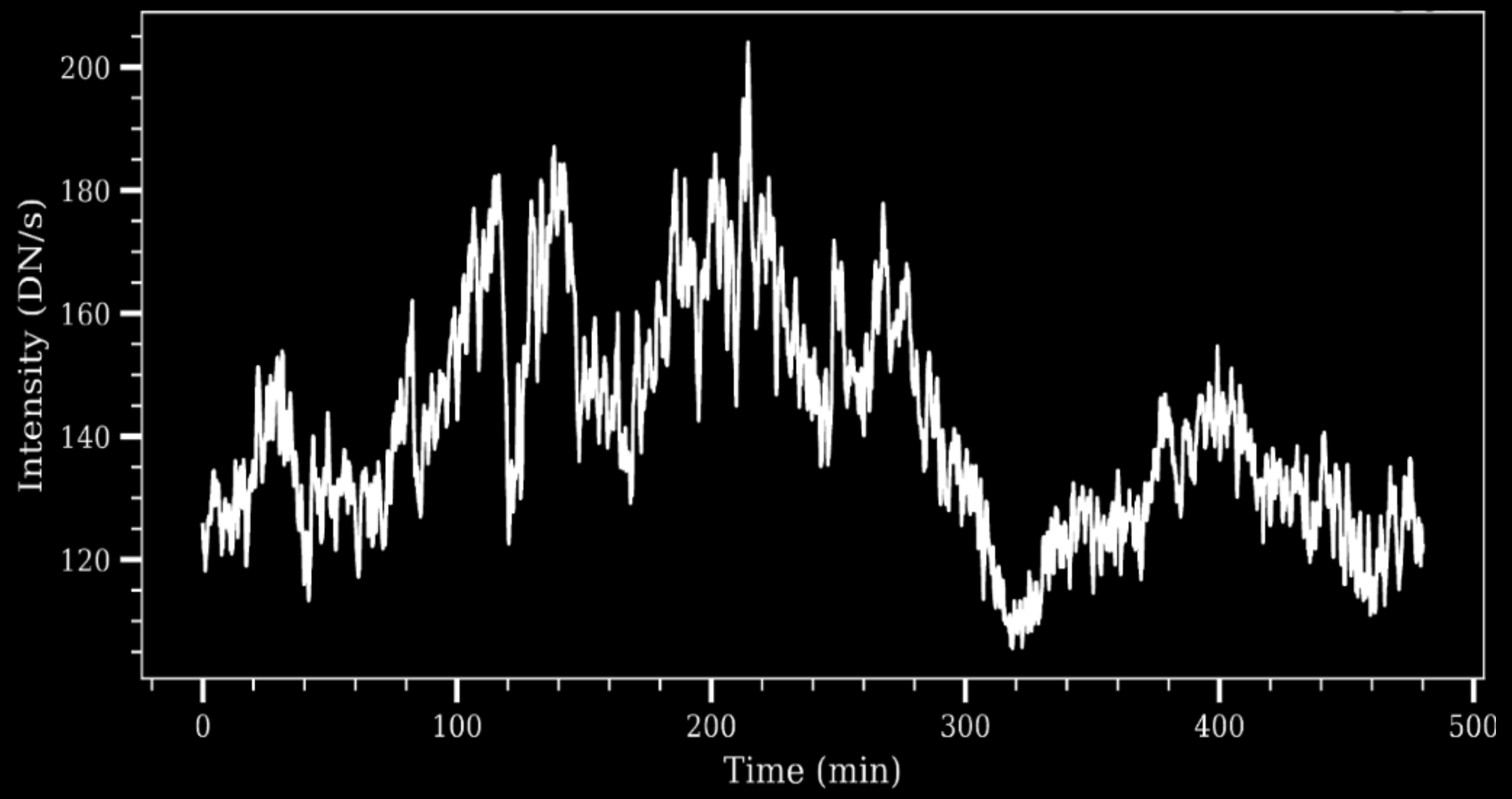


Coronal jet & flux cancellation: From Mulay+ 2016, A&A 589, A79

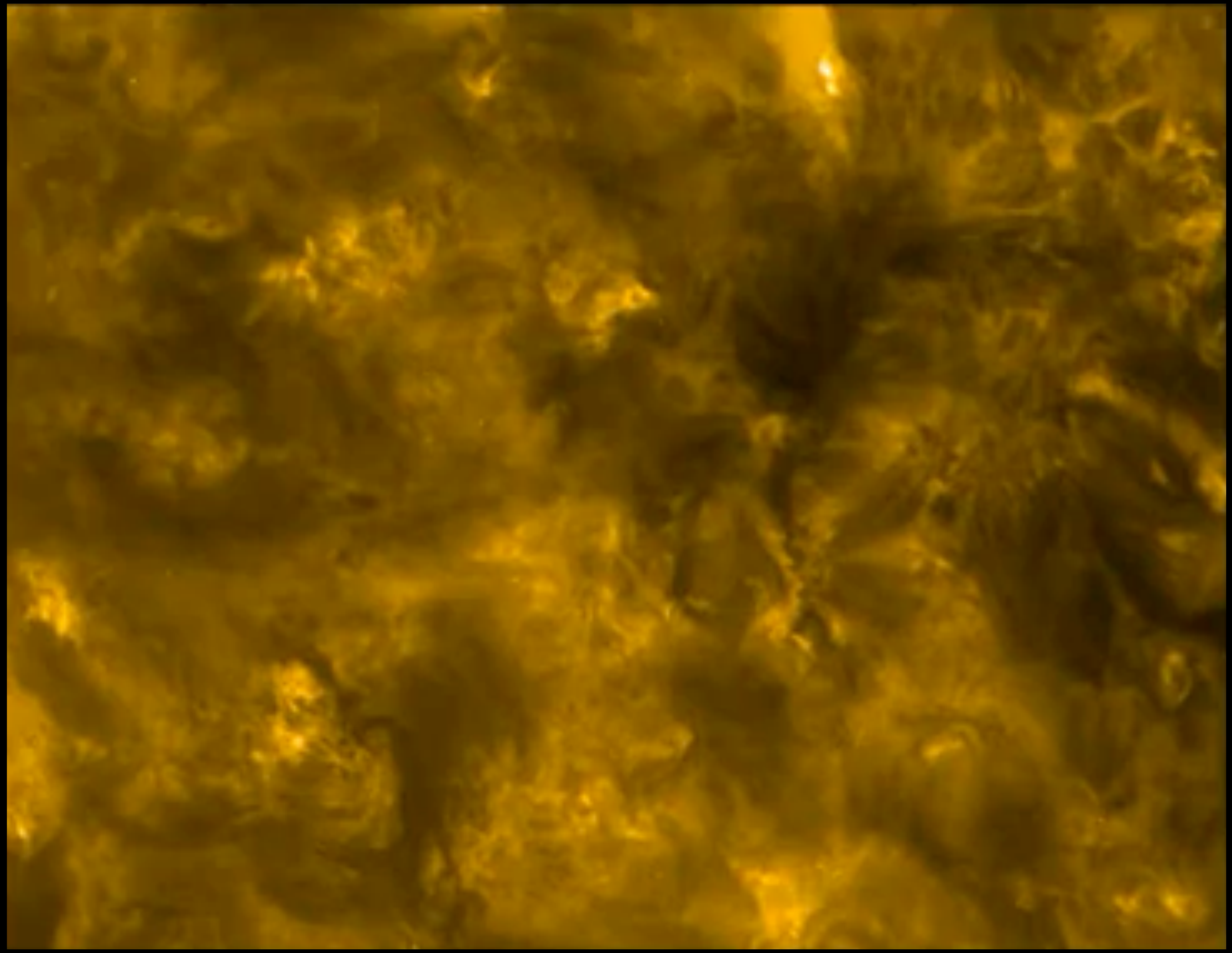


Brightenings: Navdeep K. Panesar+ 2021 ApJL 921 L20

Unresolved impulsive events powering the solar corona.



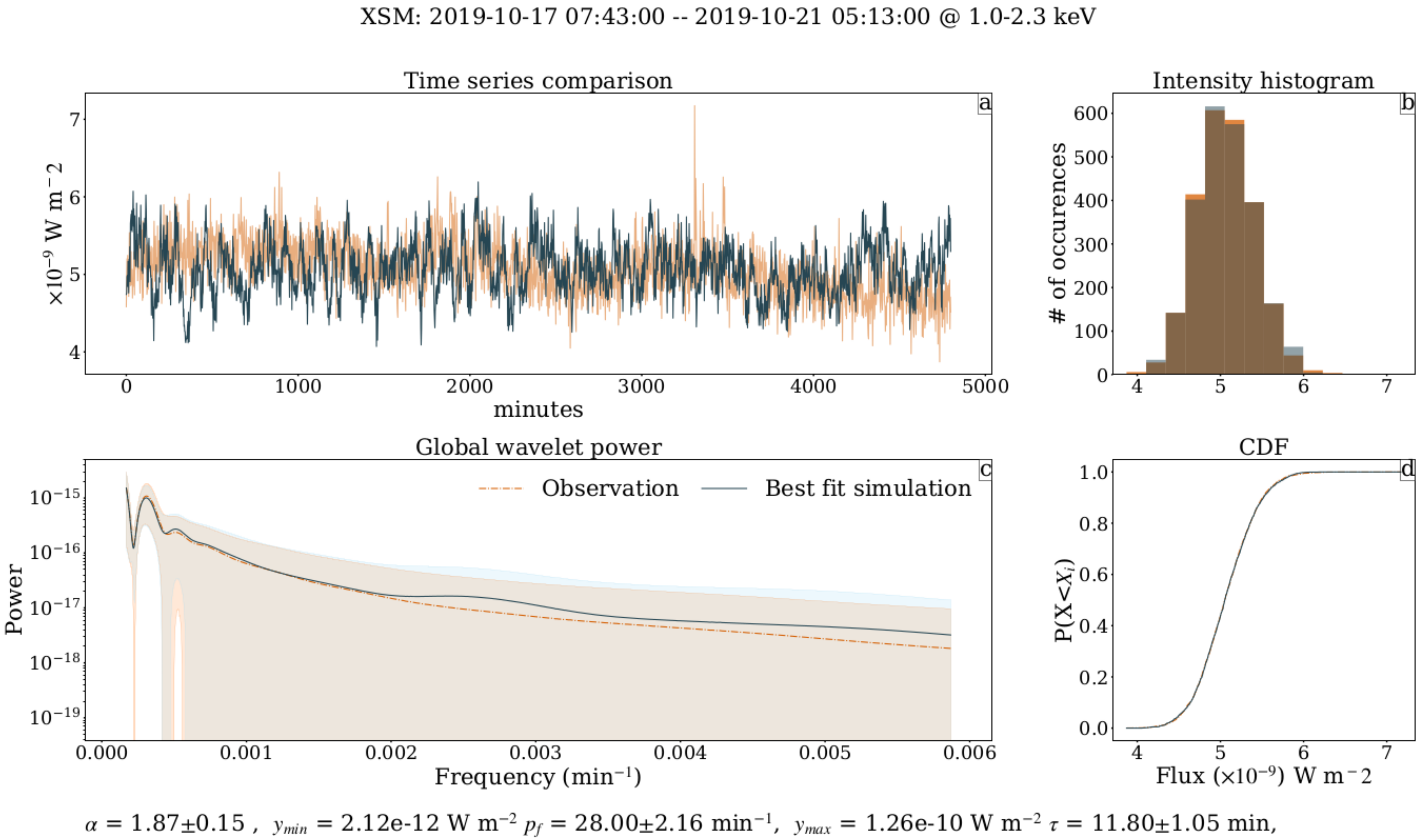
Quiet Sun

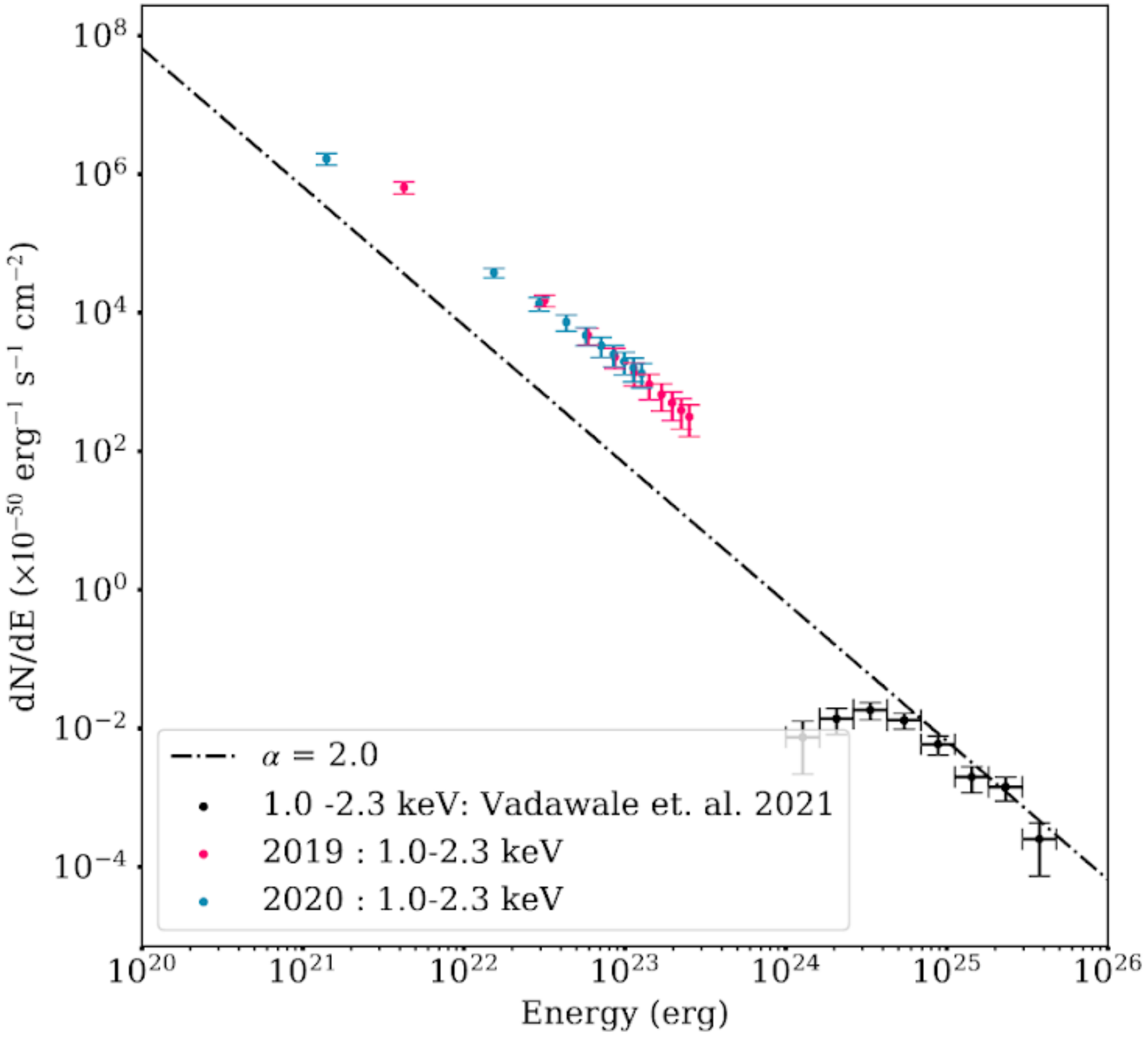


- Unresolved impulsive events make up this light curve.
- Statistical constraints on properties of these events => Use statistical simulations to constrain model parameters given data!

ML inversion scheme for simulation

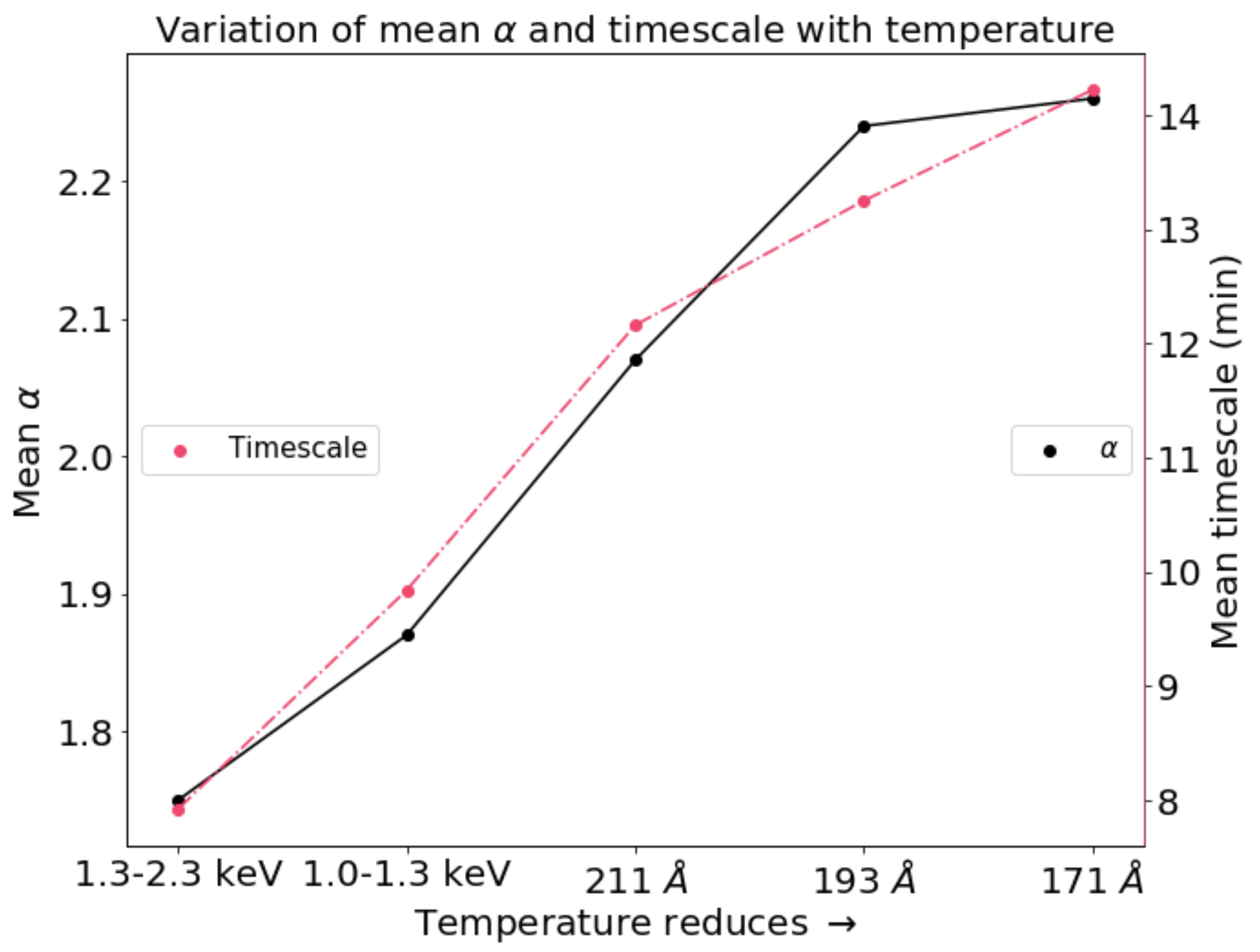
Powering the solar atmosphere

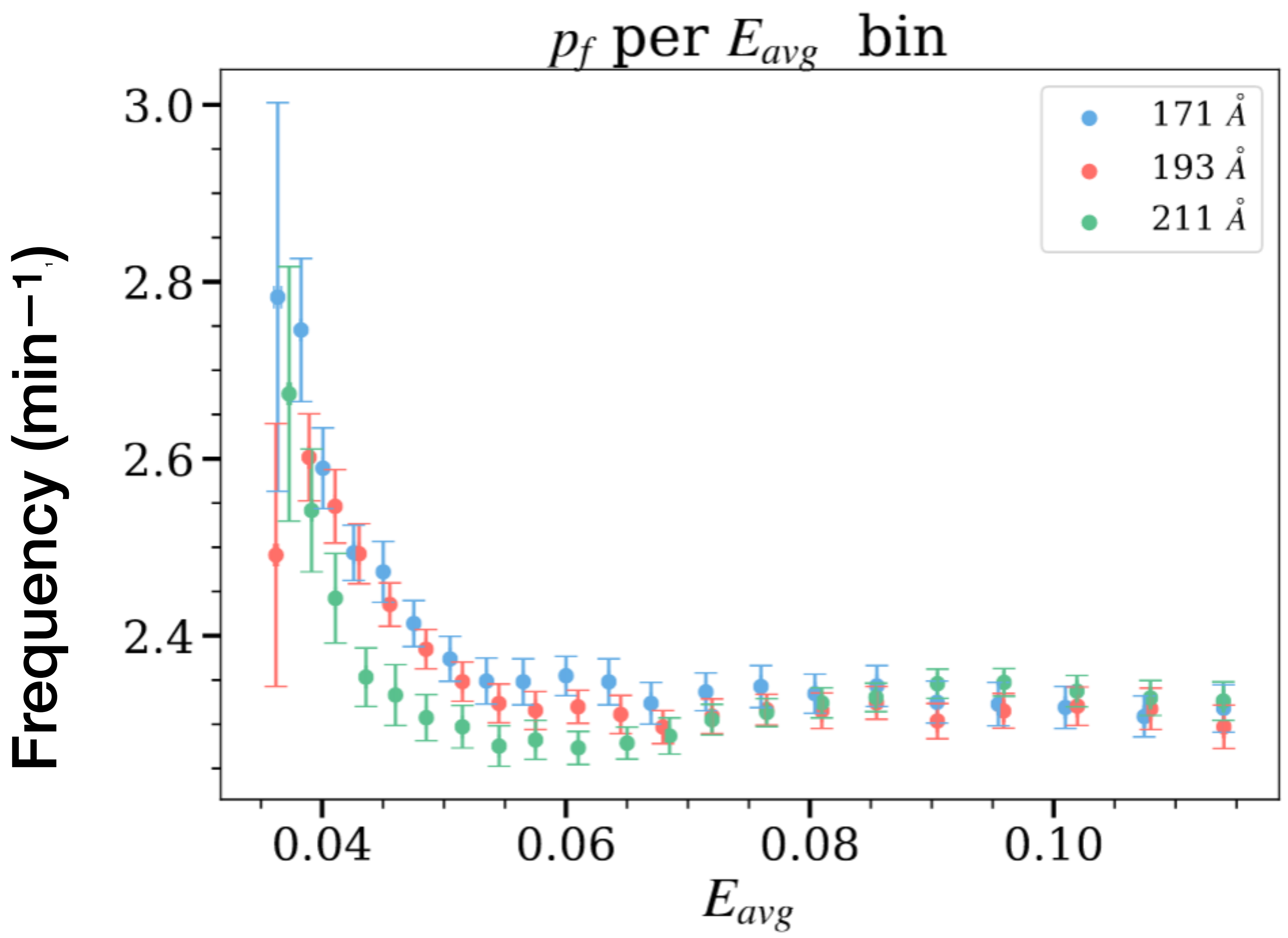


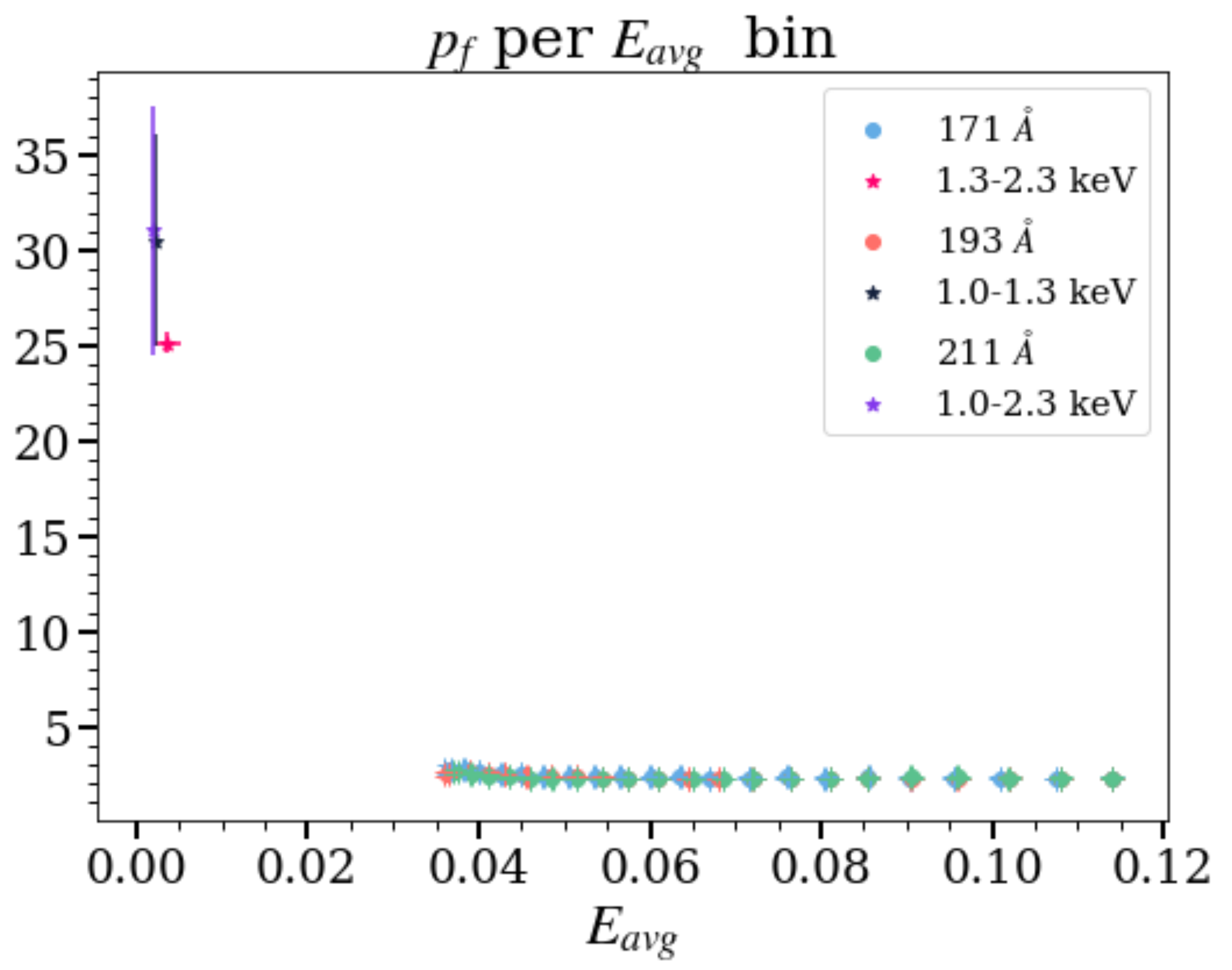


Estimate the parameters of impulsive events for light curves across Extreme Ultraviolet and X-ray energy bands. X-ray events have $\approx 10^{21}$ erg of energy per event — regime of “nano / pico” flares powering the solar corona.

.. we uncover more interesting properties of these events!







1. The more frequent events are, smaller is their amplitude -> presence of energy reservoir.
2. Events get more transient with increasing temperature of plasma.
3. Possible change in energizing mechanism between low and high temperatures?

These results are not possible without ML-based inversion scheme!

Length: ~ 10^{11} m, Time: ~ days

Explainable AI for model evaluation and scientific discovery

Application: Understanding source regions of the solar wind.

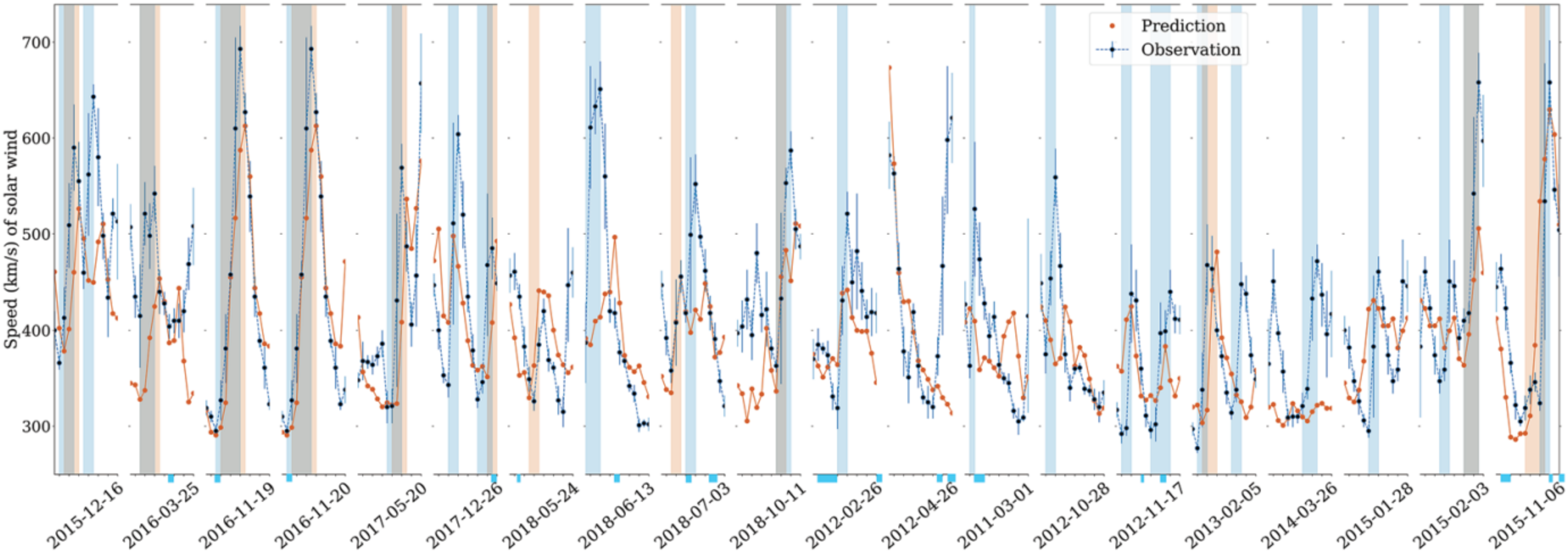
Vishal Upendran, Mark Cheung, Shravan Hanasoge, Ganapathy Krishnamurthi 2020. Space Weather, 18, e2020SW002478

Credit: JHUAPL/NASA Ben Smith

Morphological structures in the corona show association with solar wind structures.

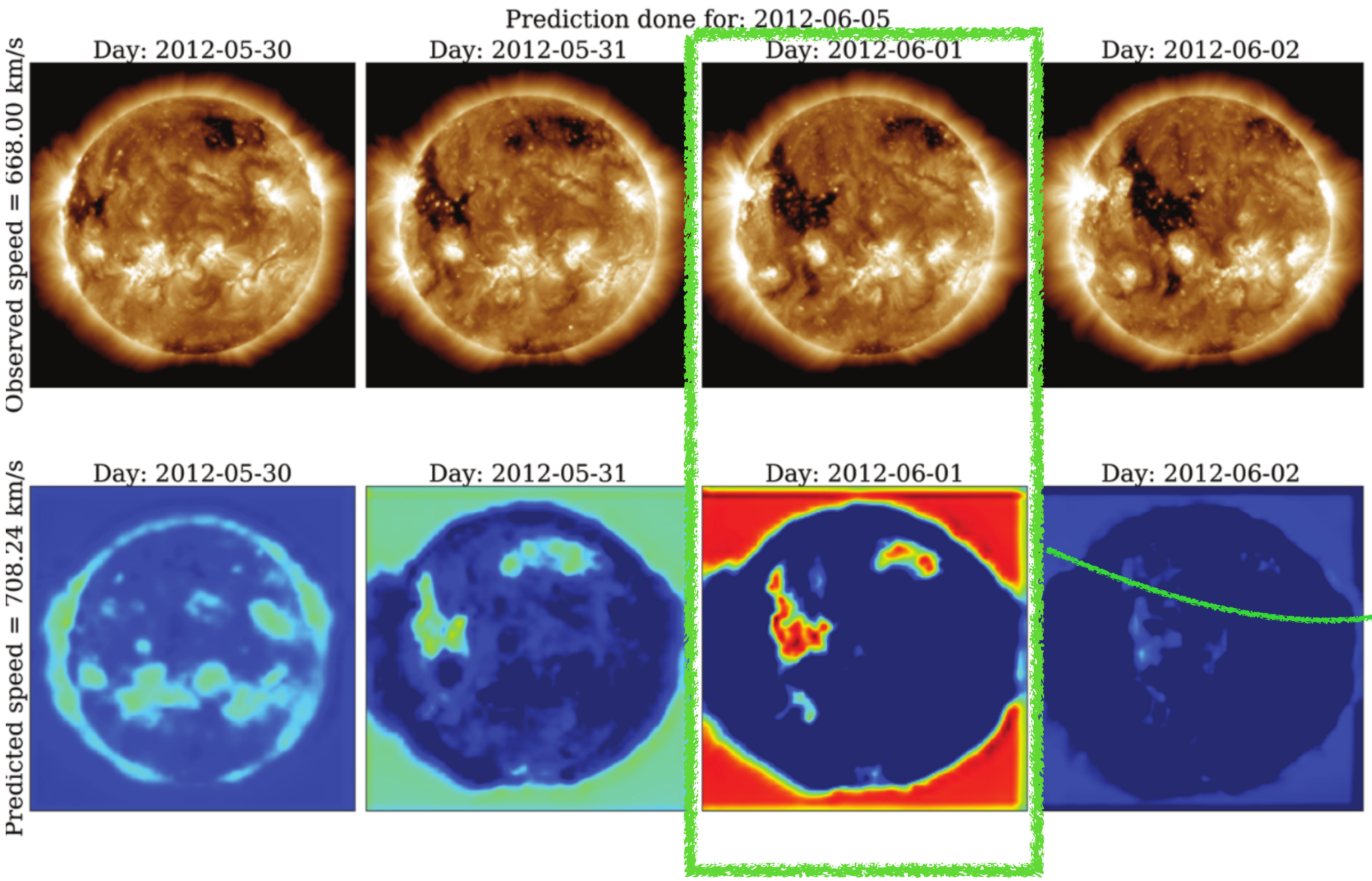
Translate a sequence of solar images into solar wind measurements

Forecasting solar wind 3-days before it reaches Earth!



Pearson r: **0.61**, RMSE: **76.4 km/s**; Uncertainty normalized squared error: **19.35**

Grad-CAM: Dissecting model to infer solar wind sources!



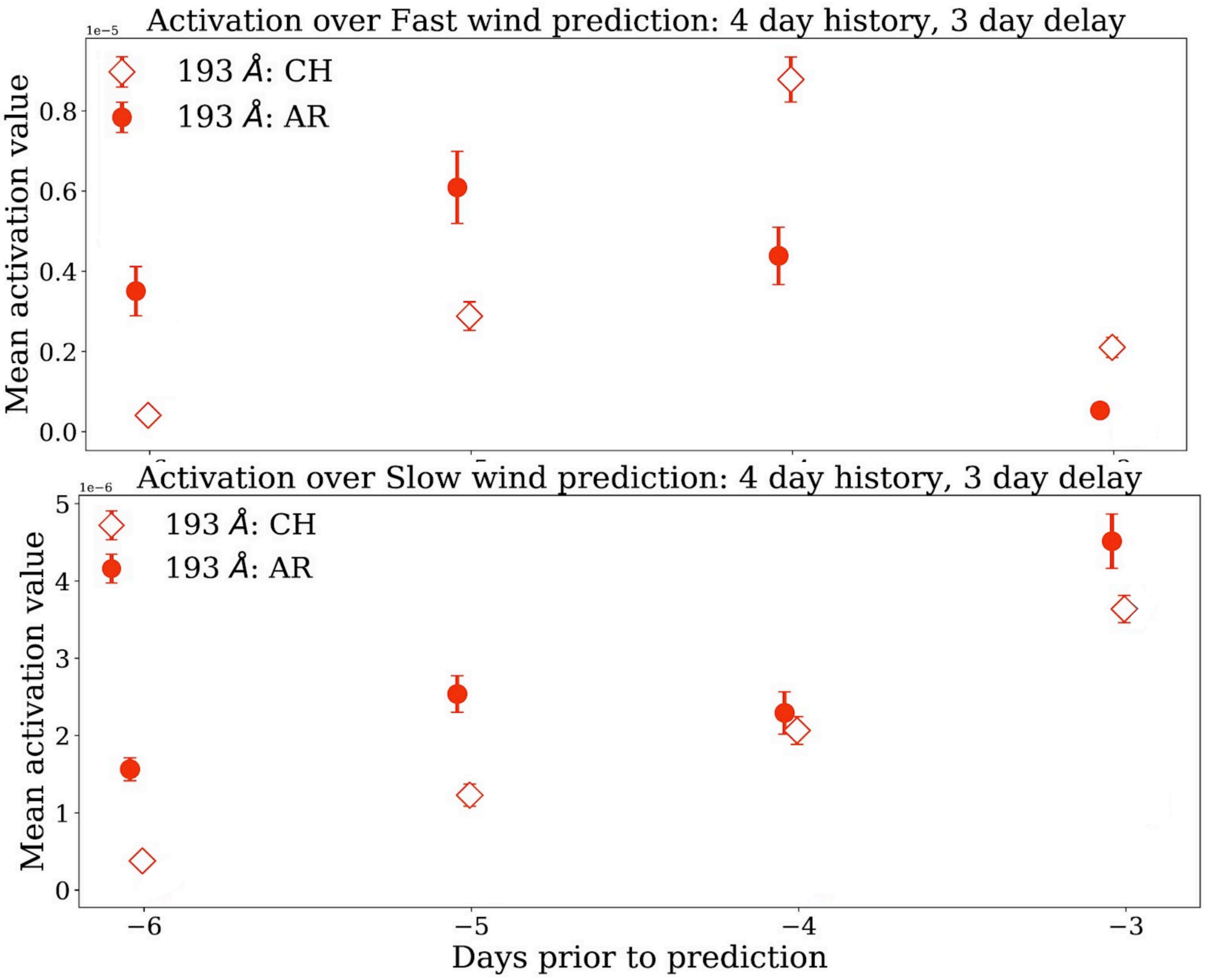
Spatio-temporal coincidence with physics

Fast wind - Coronal Hole association 4 days before forecast

Grad-CAM: Dissecting model to infer solar wind sources!

Statistical quantification: Activation per unit area

1. CH - fast wind consistent with physics.
2. AR - slow wind partially consistent with physics. Time coincidence not seen due to AR lifetime.
3. AR - fast wind needs study.



Length: ~ 10^8 m, Time: ~ mins to hours

Explainable AI for model evaluation and scientific discovery

Understanding pre-flare signatures in flaring Active Regions

With Linn Abraham, Durgesh Tripathi, ***The SUIT Team***

(In-prep)

PhD thesis of Mr. Linn Abraham as part of ISRO - RESPOND project on interpretable solar flare forecasting algorithm development

Credits: SUIT Team/ Soumya Roy

Our approach to investigation:

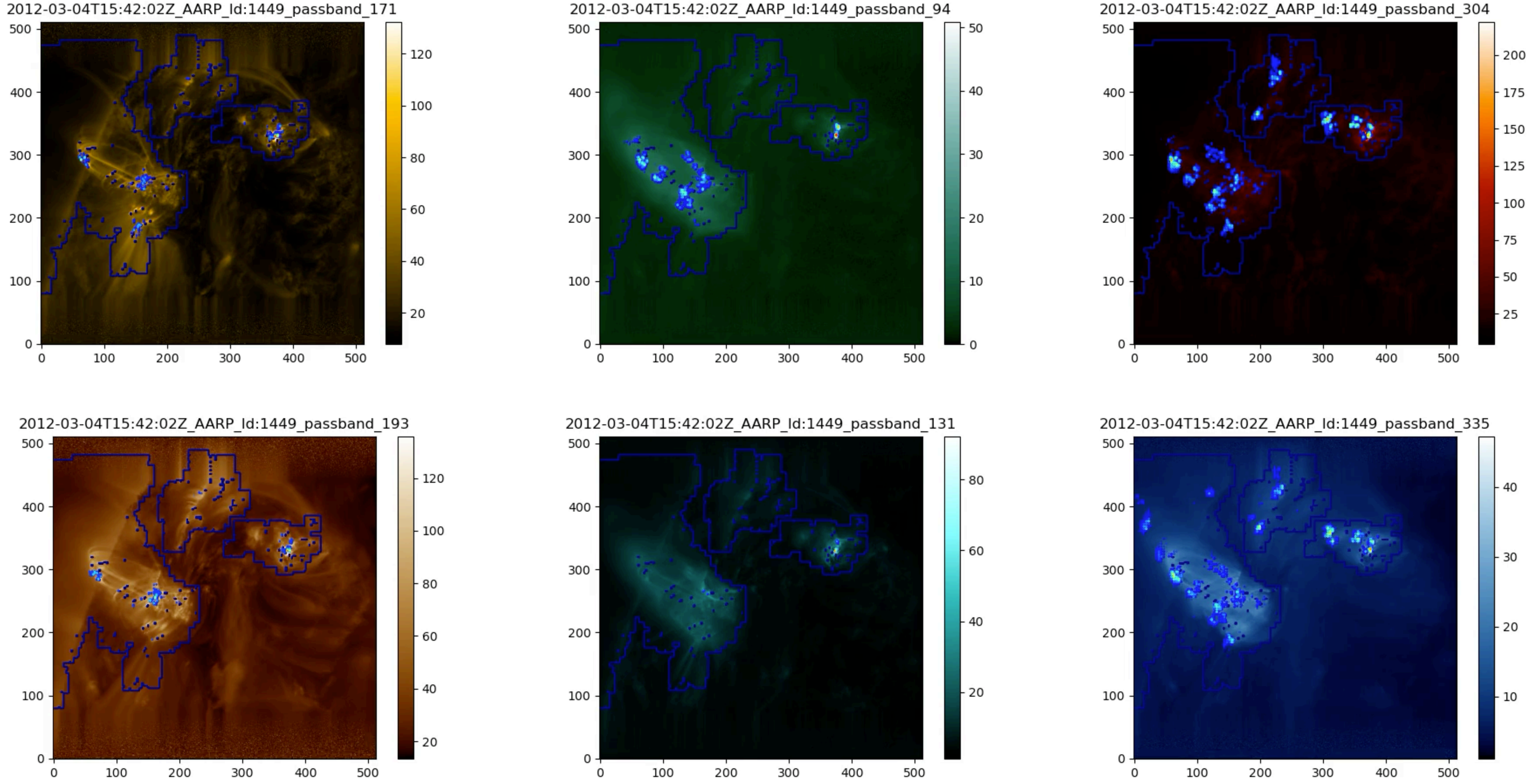
Can we classify multi-wavelength AIA images of Active Regions in Flaring / Non-flaring regions to understand pre-flare signatures?

Model

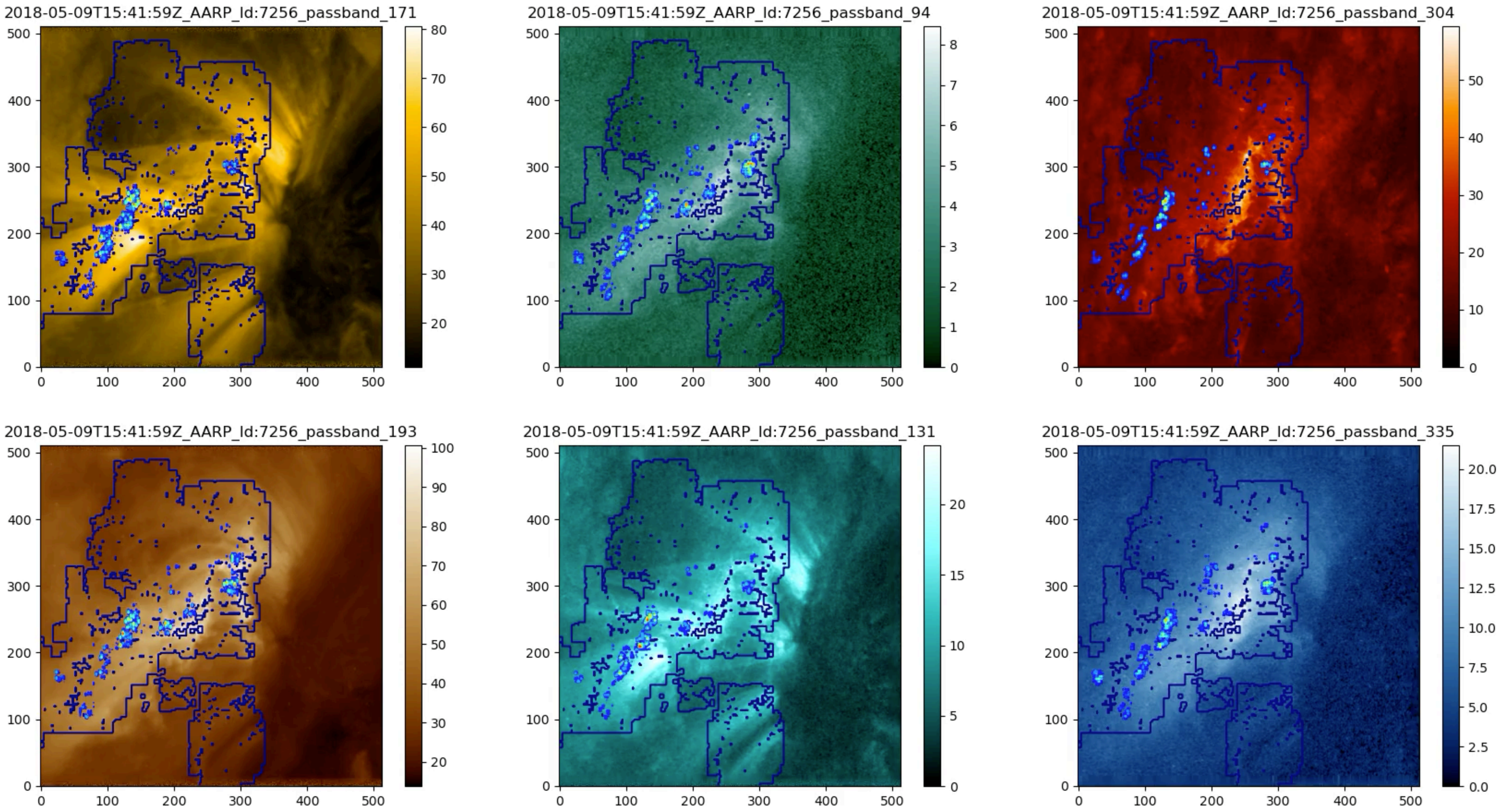
Flaring

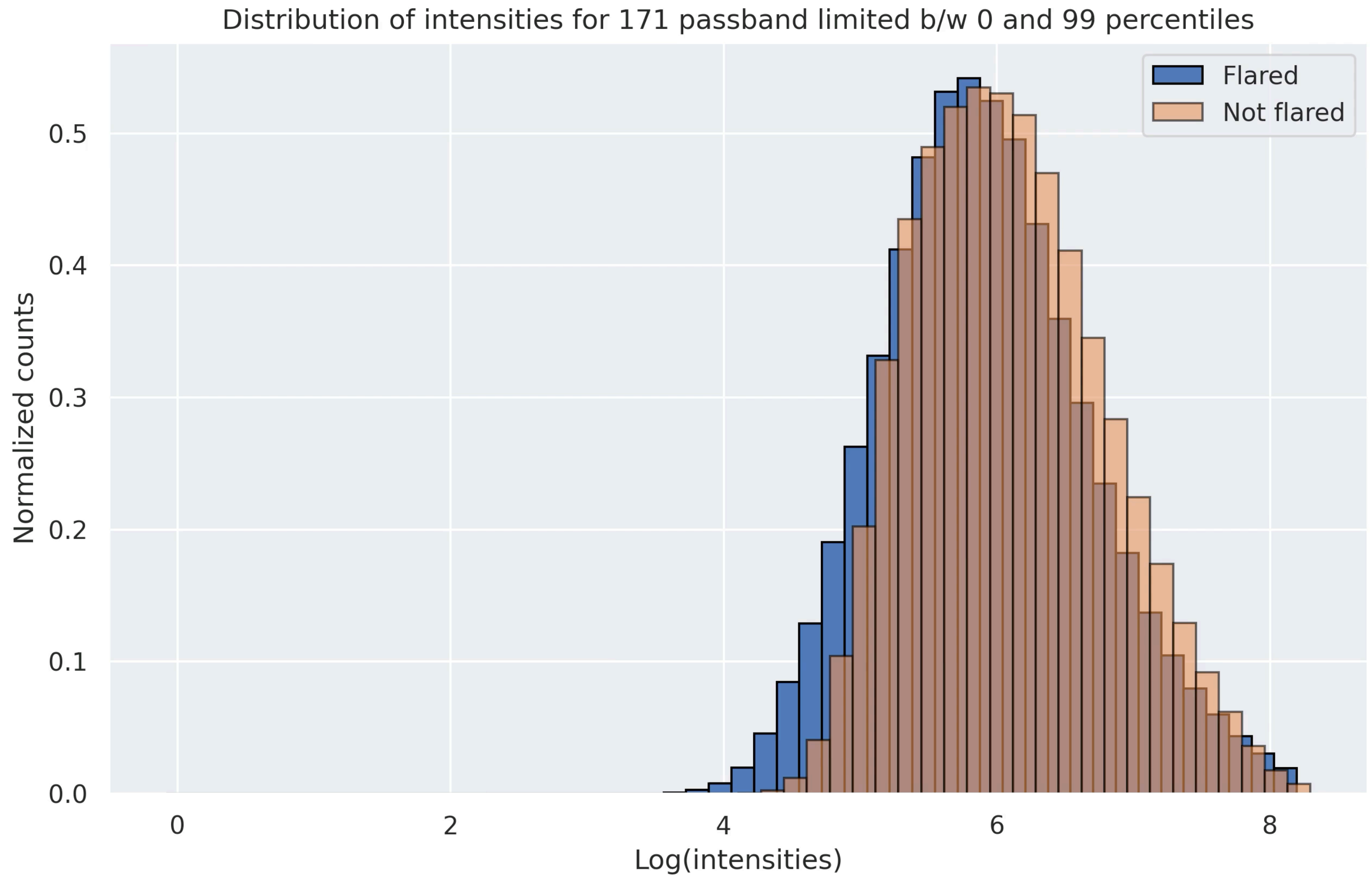
Non-Flaring

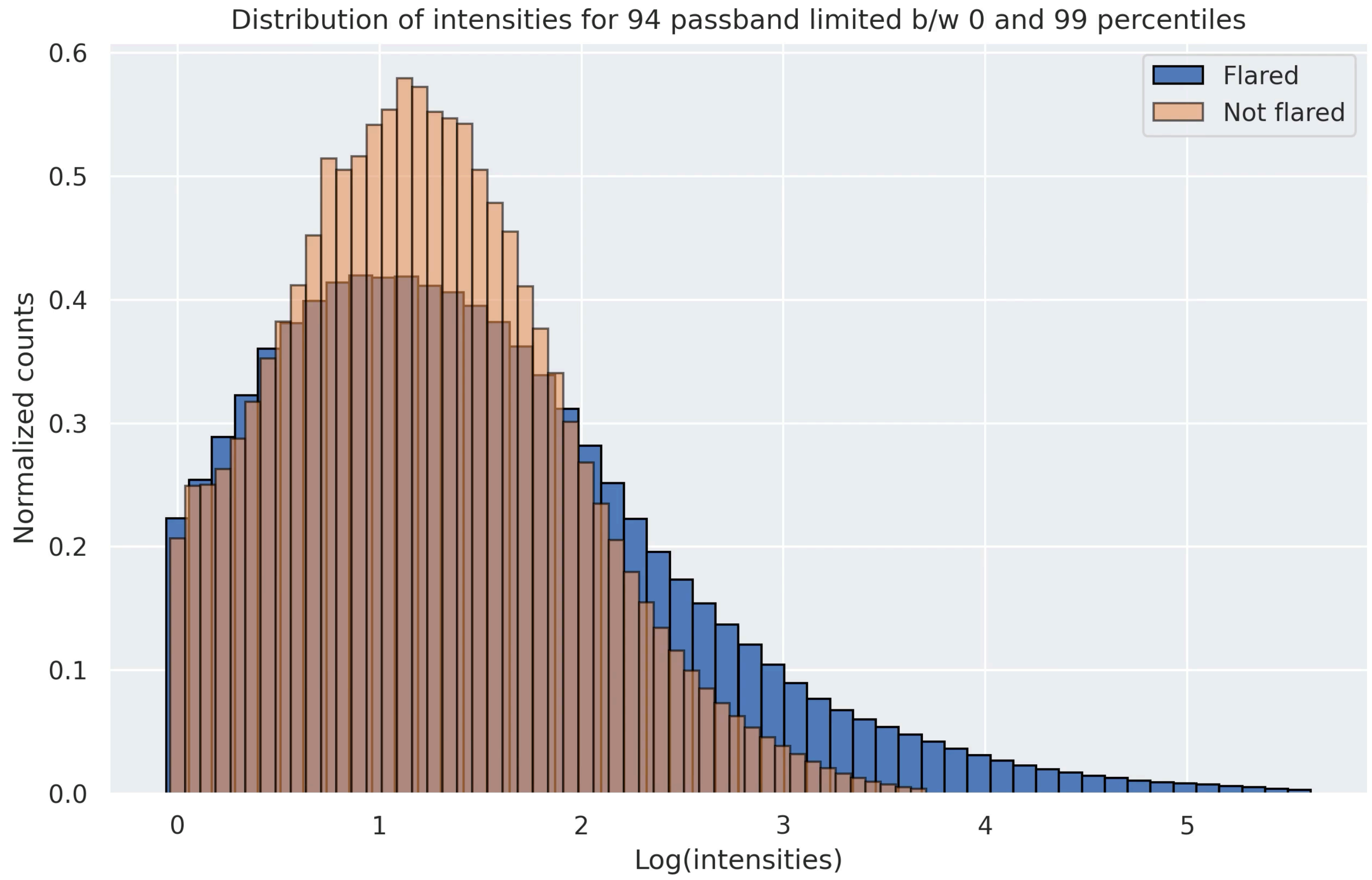
Our work: Classify AR patches to Flaring

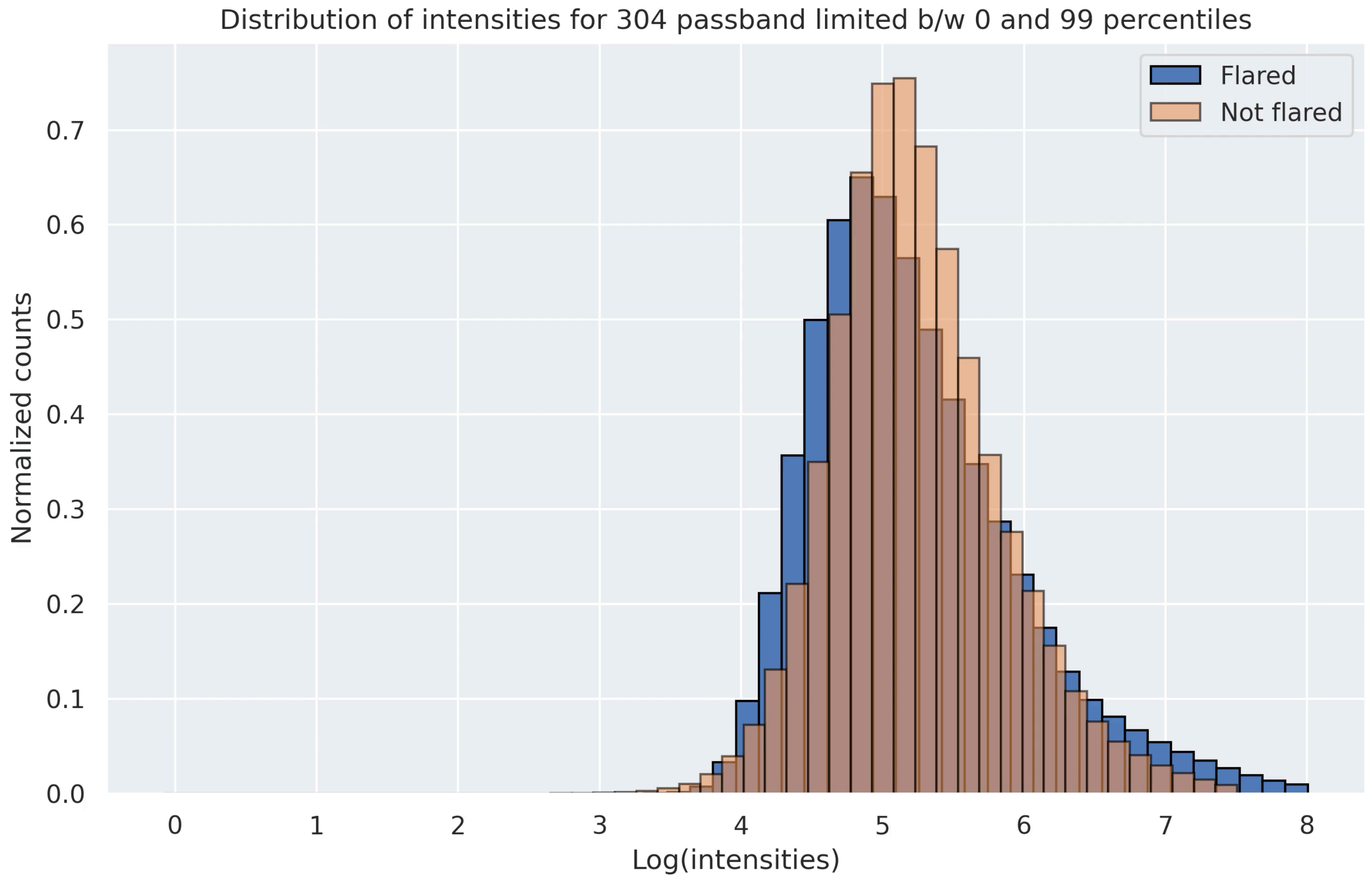


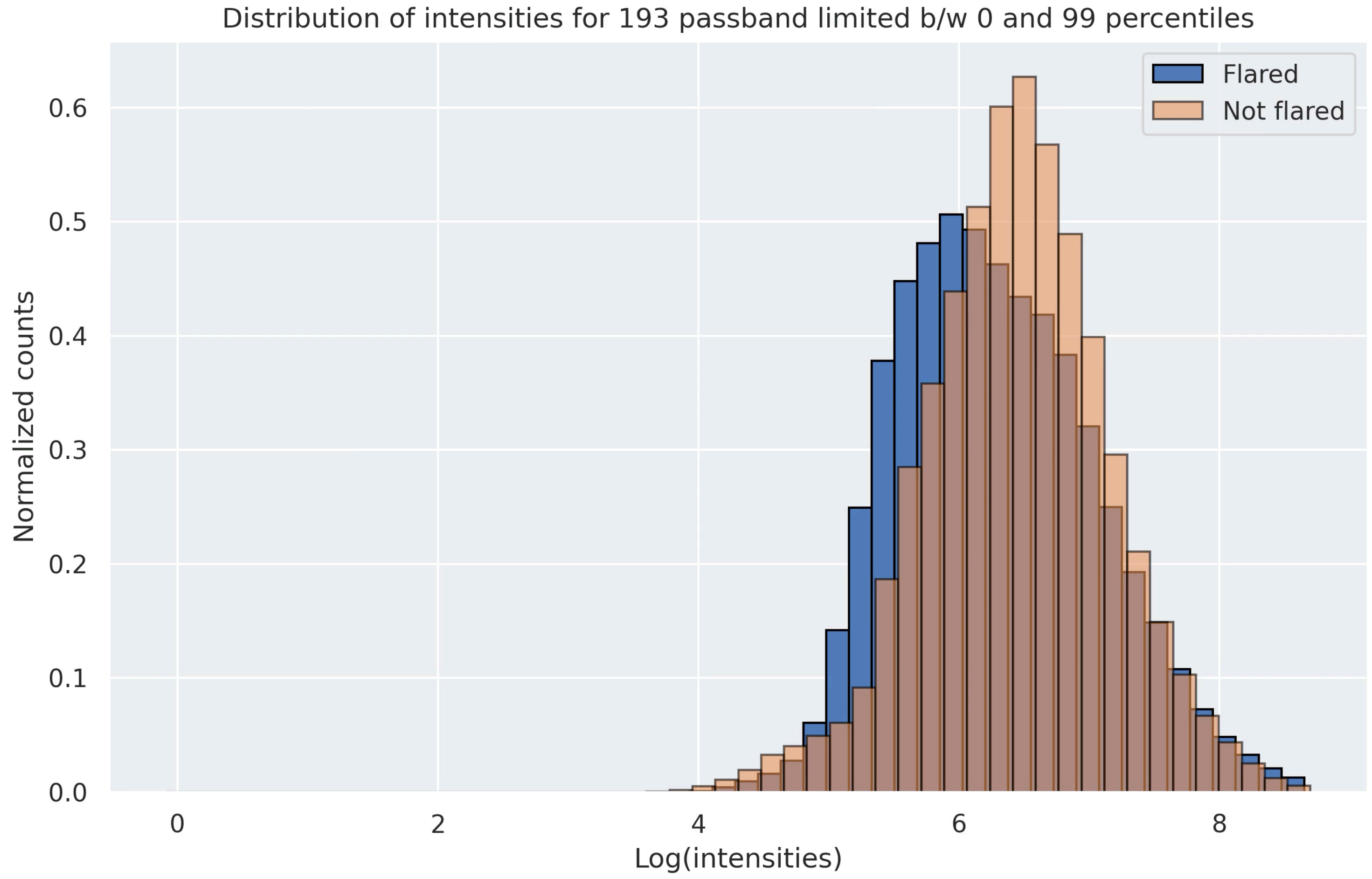
Classify AR patches to non-Flaring

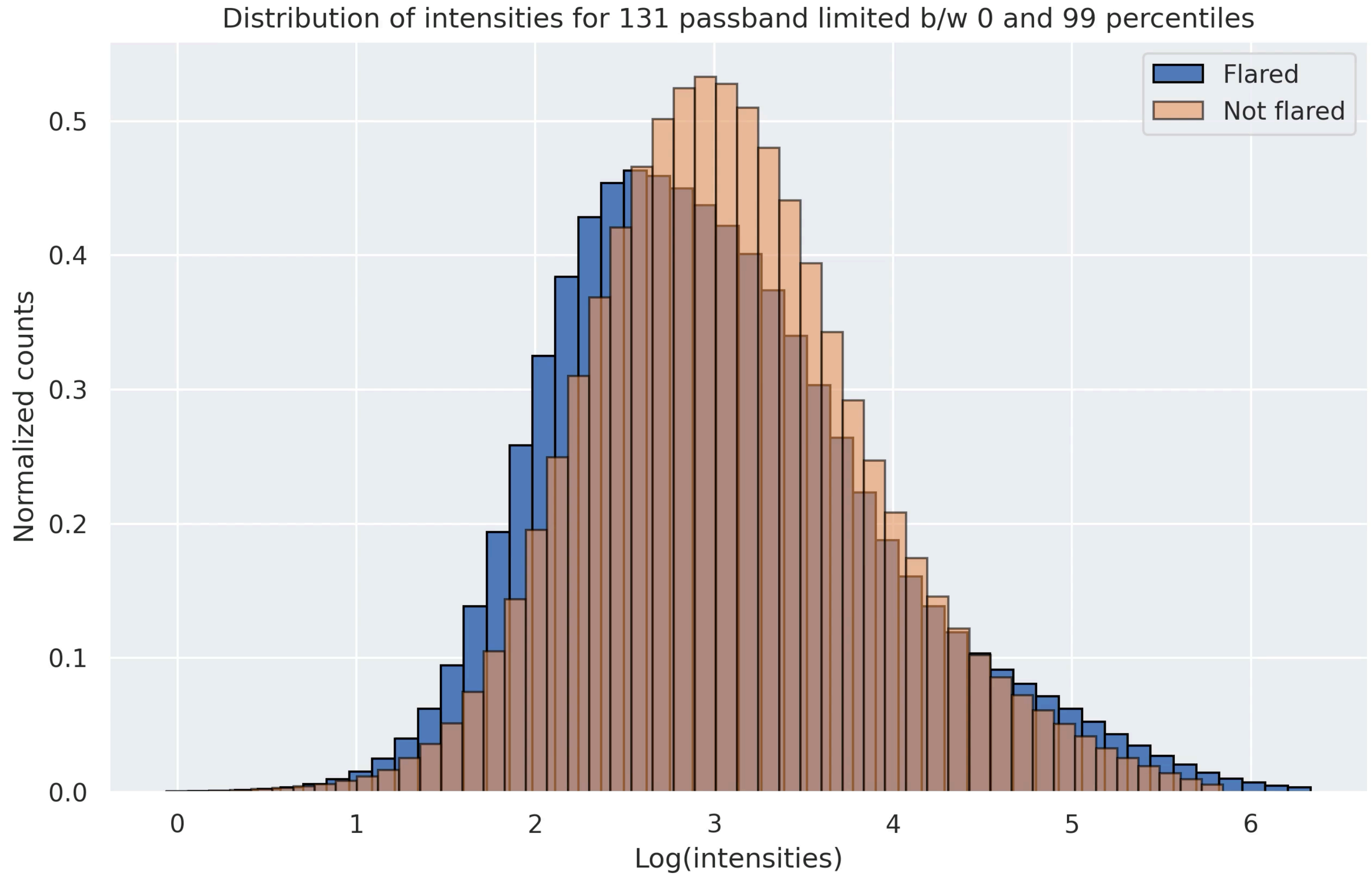


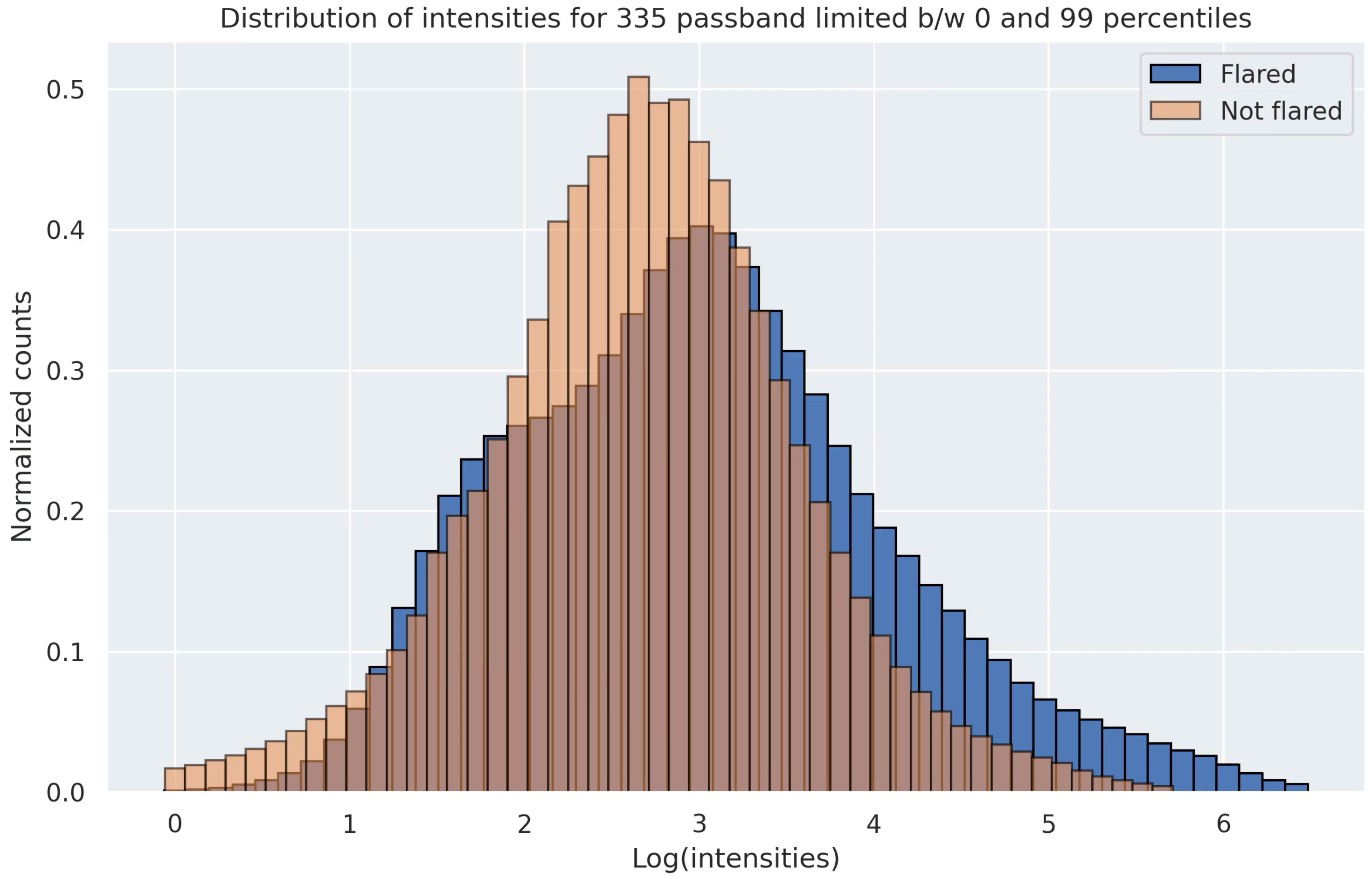

Distribution of intensities for 171 passband limited b/w 0 and 99 percentiles
Flared
Not flared
Normalized counts
Log(intensities)


Distribution of intensities for 94 passband limited b/w 0 and 99 percentiles
Flared
Not flared
Normalized counts
Log(intensities)


Distribution of intensities for 304 passband limited b/w 0 and 99 percentiles
Flared
Not flared
Normalized counts
Log(intensities)


Distribution of intensities for 193 passband limited b/w 0 and 99 percentiles
Flared
Not flared
Normalized counts
Log(intensities)


Distribution of intensities for 131 passband limited b/w 0 and 99 percentiles
Flared
Not flared
Normalized counts
Log(intensities)


Distribution of intensities for 335 passband limited b/w 0 and 99 percentiles
Flared
Not flared
Normalized counts
Log(intensities)

Length: ~ 10^6 m, Time: ~ mins to hours to years

HELIOPHYSICS

FDL 2020

The DAGGER Team

NVIDIA

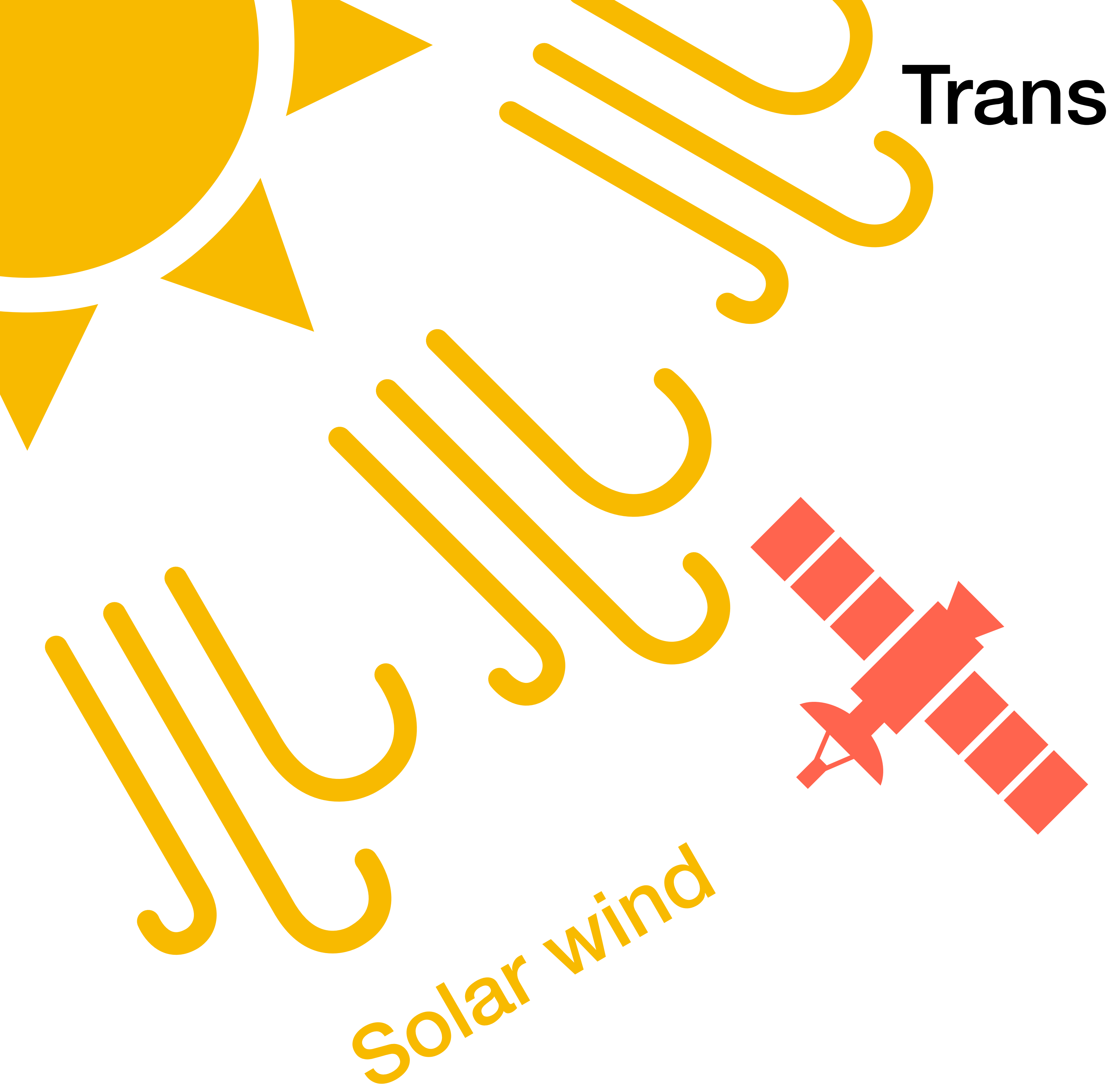
Google Cloud

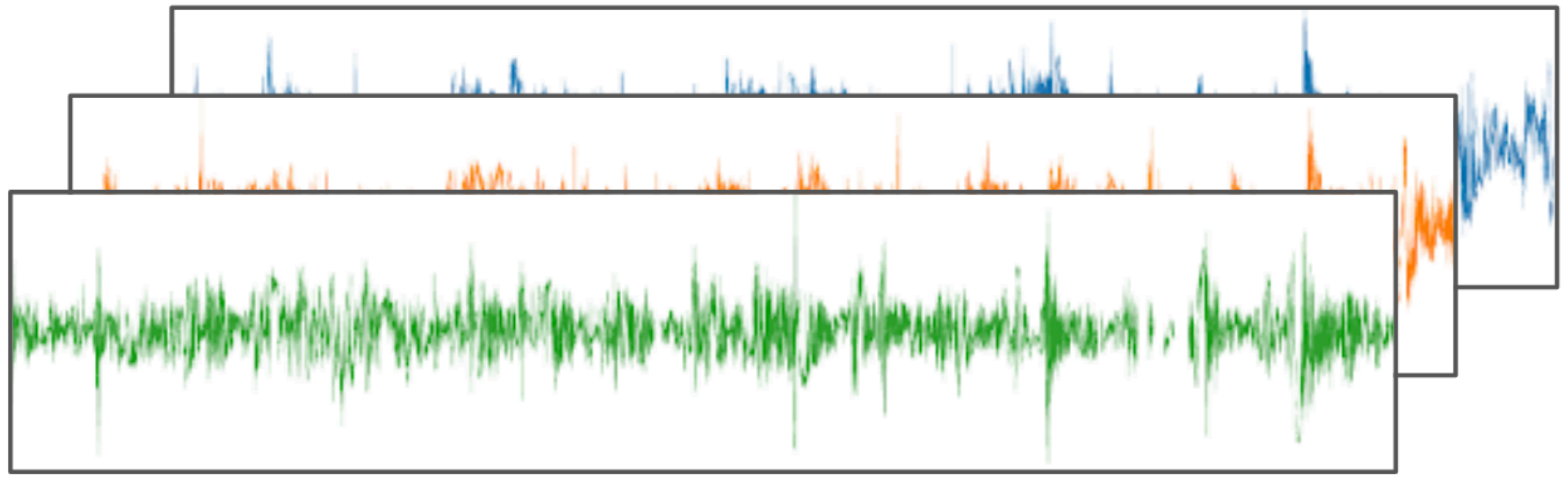
Physics-incorporated deep learning for sparse sampled regression

Application: Ground magnetic field perturbation forecasting

Upendran+ 2022. Space Weather, 20, e2022SW003045

Translating from time series of a single point in space to global effect on the Earth



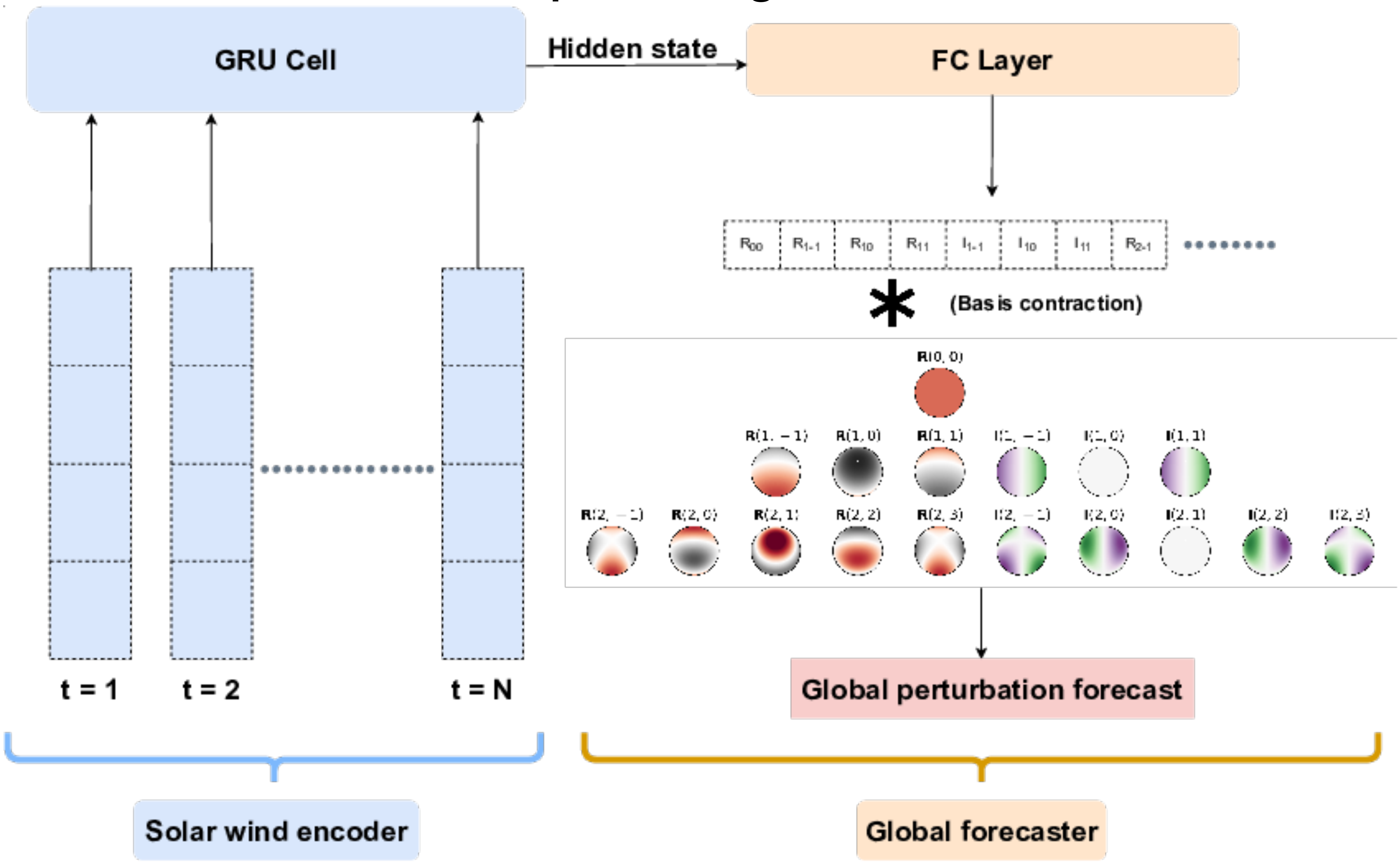


Solar wind measured in space, just outside of Earth’s magnetosphere

Fluctuations in Earth’s magnetic field (δb_i) sampled at various locations on the ground

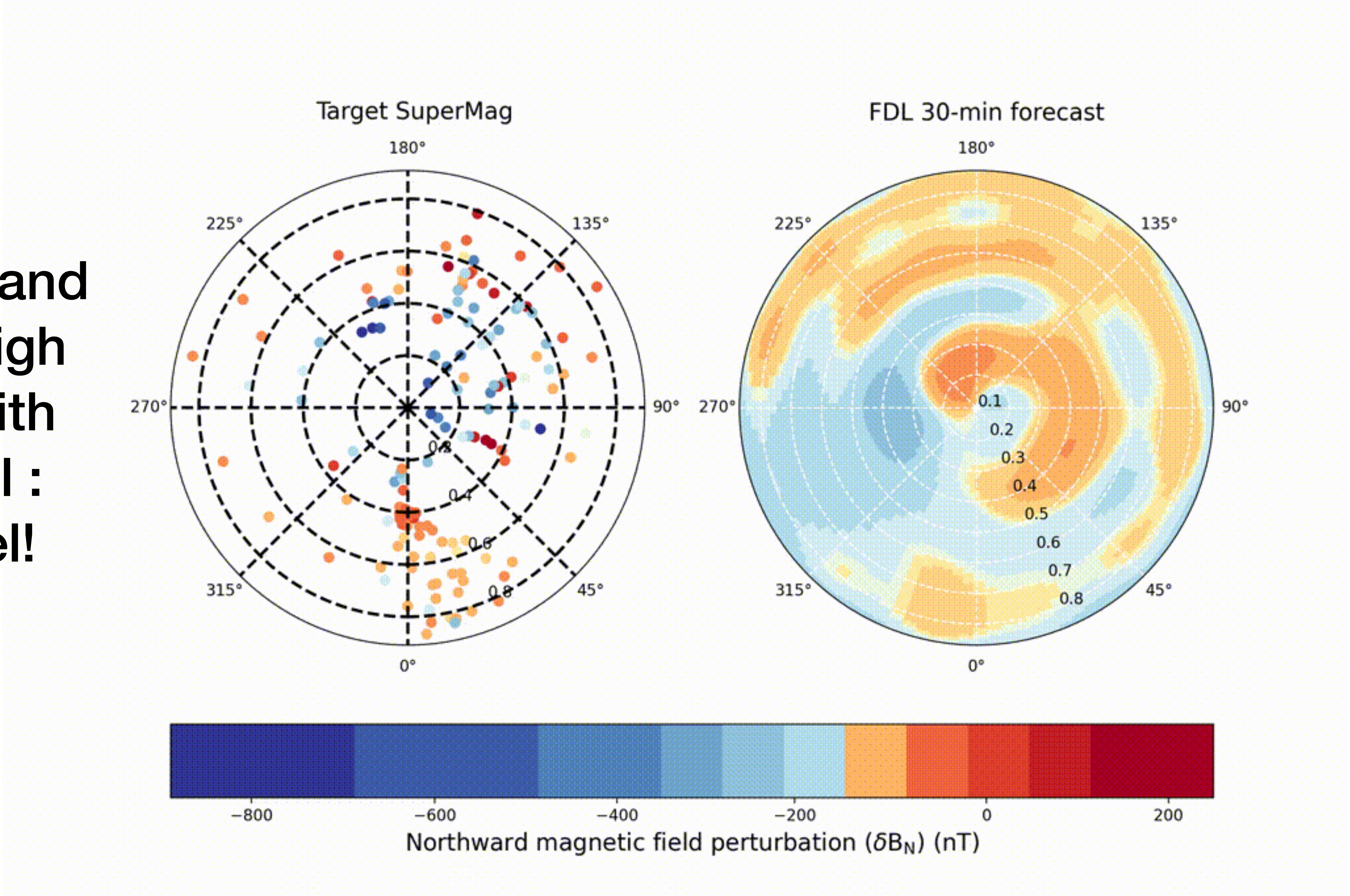
Stations on the Earth

A deep learning solution!



Forecasting across the globe at 1-minute cadence

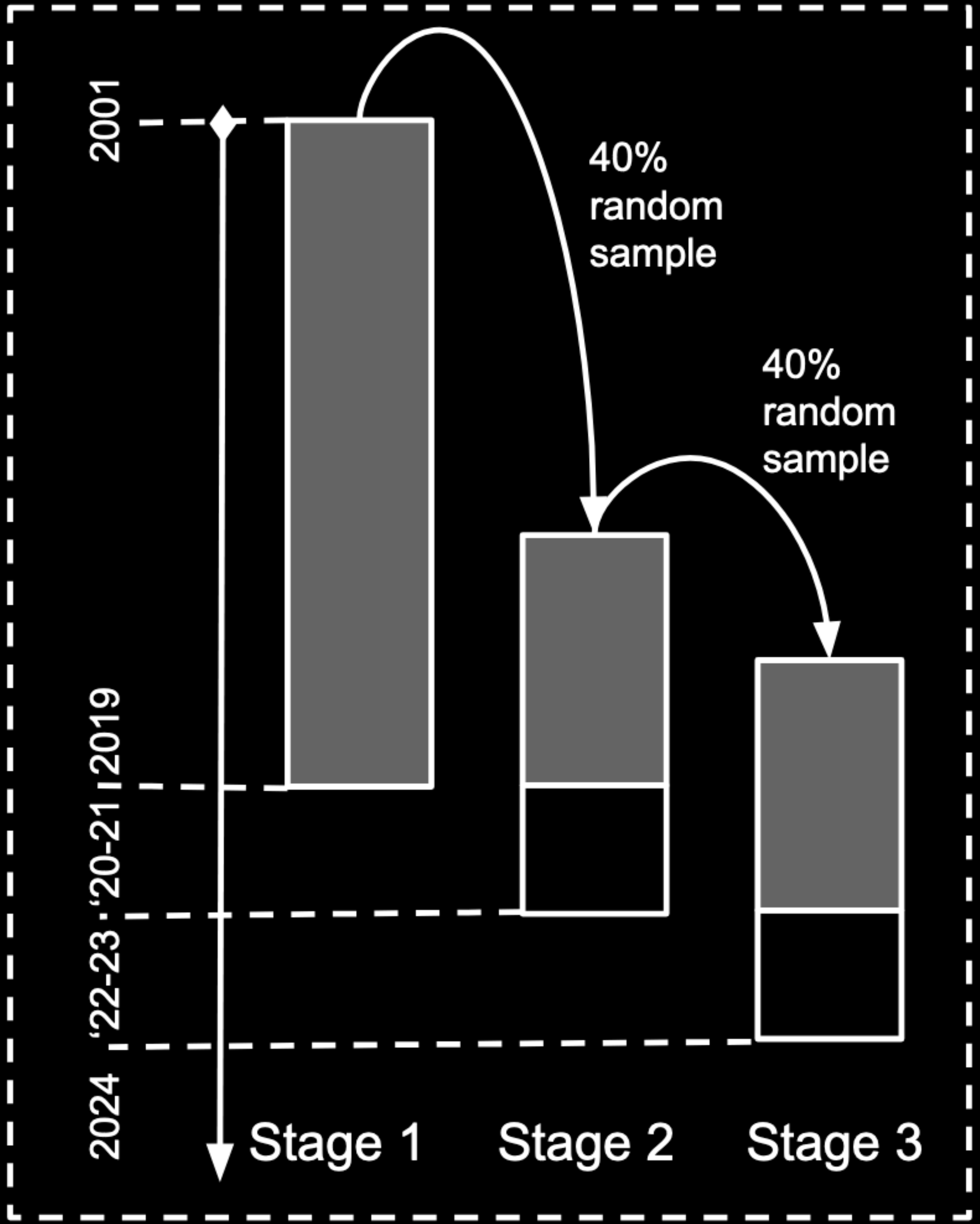
Capturing global and local scales at high time cadence with the same model : first such model!



DAGGER CL: Continual Learning

Domain Incremental Learning

- Data resampling strategy
  - Experiments conducted in 3 stages
  - Data from both ACE and DSCOVR
  - Repeated data for handling catastrophic forgetting
  - Random samples to reduce bias accumulation



In-prep work!

Global Predictions with Quantified Uncertainties

GEOCLOAK

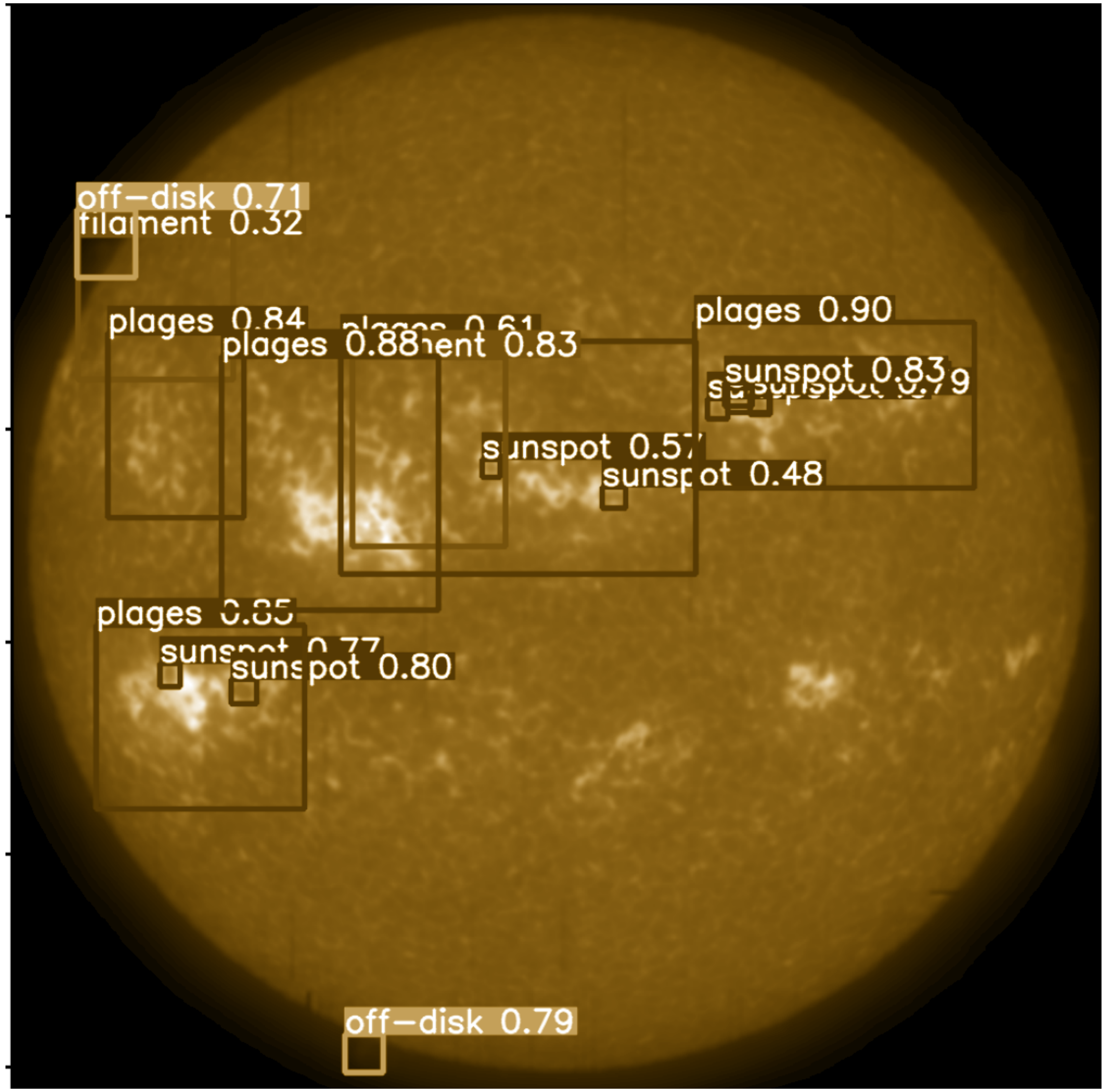
Web App: fdl.ai/geocloak

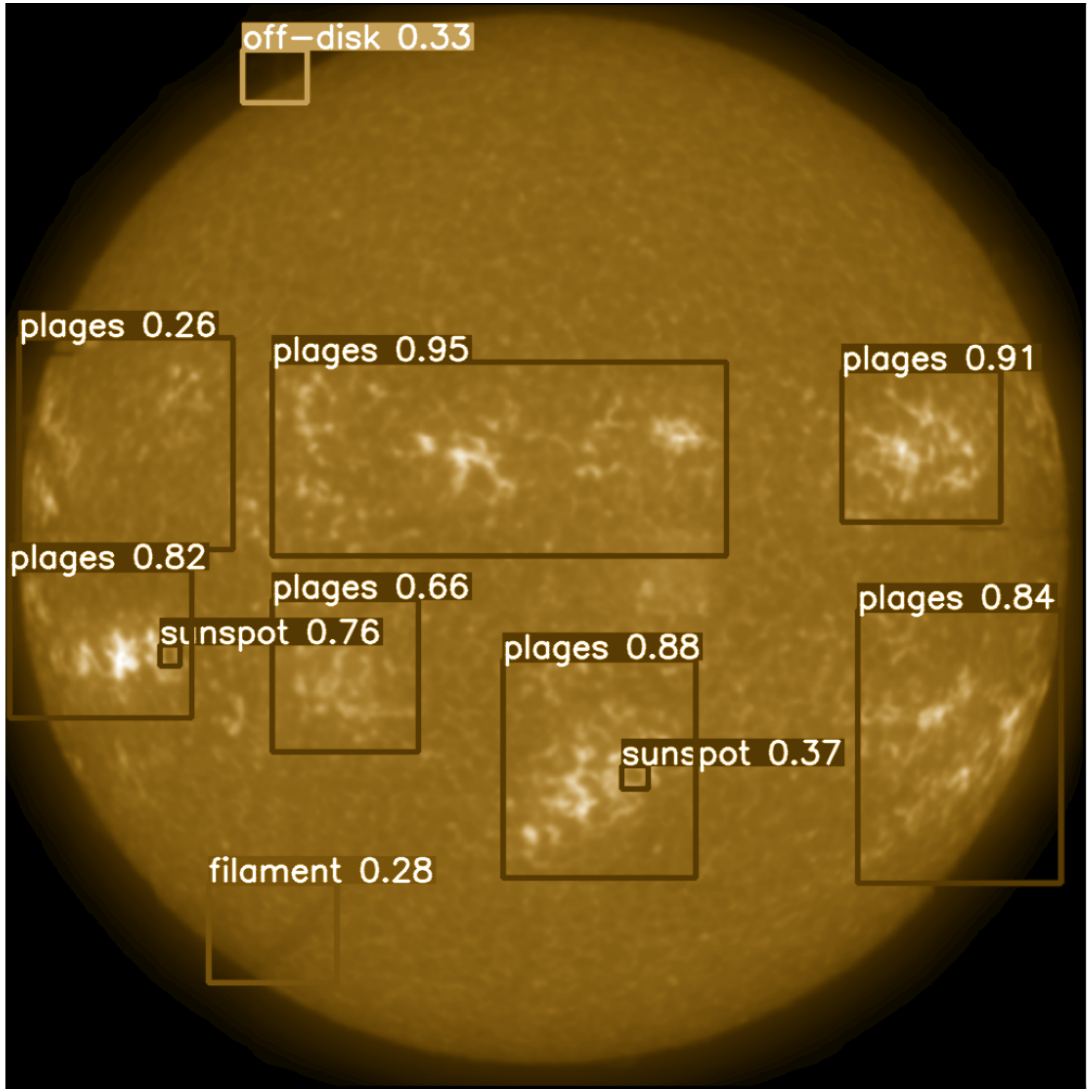
GeoCLoak provides:

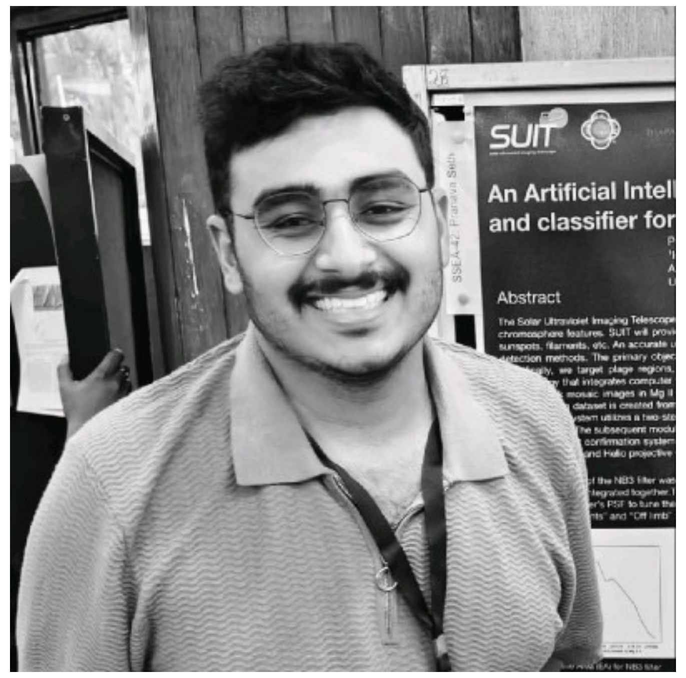
- **Actionable forecasts** of global ground geomagnetic perturbations
- **Near real time** online inference
- A fit for the future **continual learning (CL) framework**

Supported by SMD/NASA Heliophysics Grant #80NSSC24MO122

Feature extraction for the Solar Ultraviolet Imaging Telescope (SUIT) onboard Aditya-l1



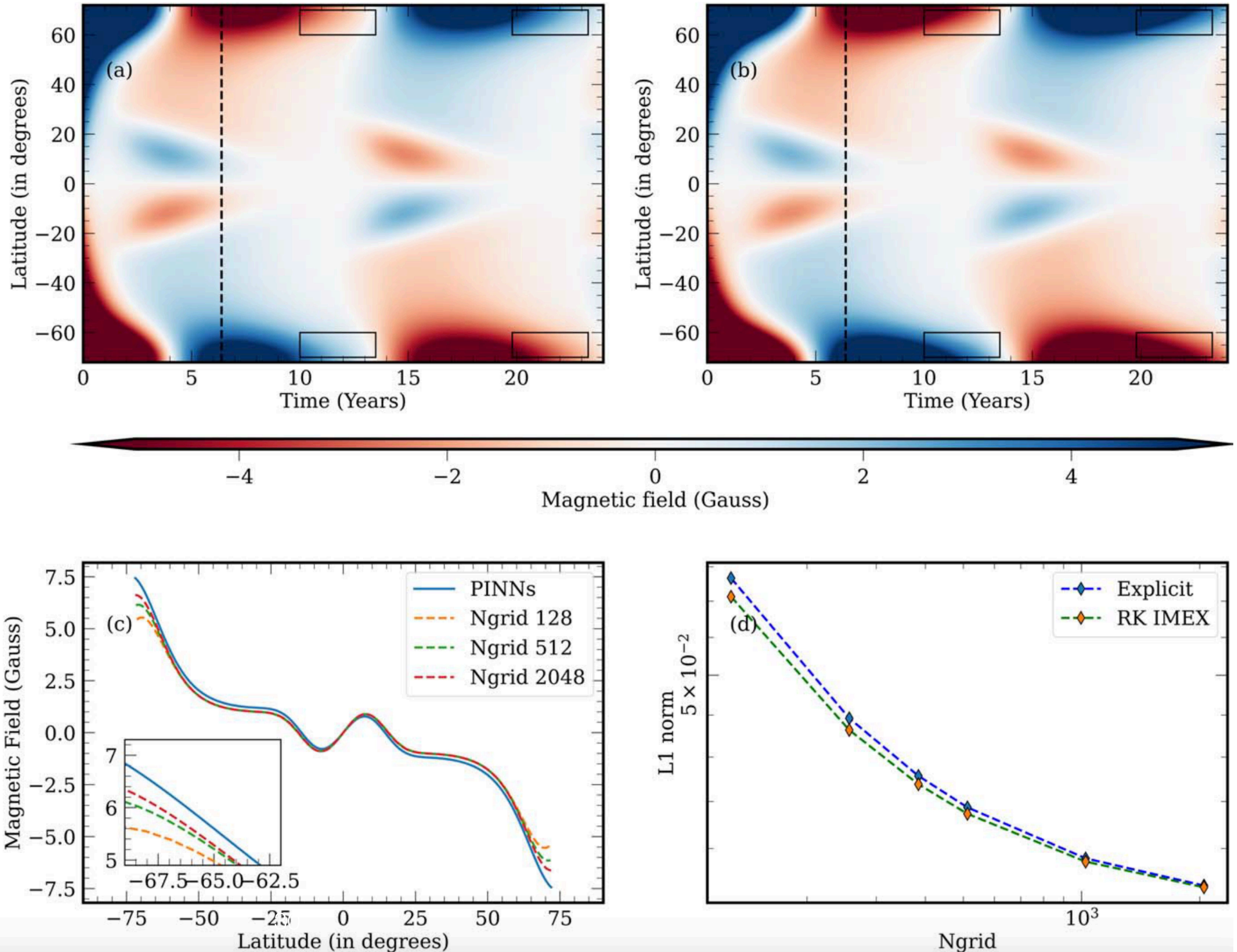




Pranava Seth, Vishal Upendran et. al SolPhys (under review): ***The SUIT Team***

Physics-Informed Neural Networks for advection-diffusion equation

- Classical solver tends to PINN solution with grid resolution.
- Diffusive nature of classical solvers - underestimation of polar flux —> underestimation of solar wind!
- Shows strong potential for data assimilation!



Jithu J Athalathil, … , Vishal Upendran, ..
ApJ 2024 (975:258)

Key takeaways

- Machine/Deep learning can be potentially used to accelerate inference, provide very fast predictions and at very high cadence - accelerated by large datasets and compute.
  - Can either be used for simulation based inference or for generating large labelled datasets.
- Deep models learn some aspects of the physics of the system: Needs careful quantification, evaluation and validation through physics.
  - Solar wind sources are clearly seen, while solar flare triggers are potentially estimated.
- Alternatively, formulate model scheme by baking in physical constraints to generate realistic constraints on parameter space.
- Cross disciplinary collaboration and open source data / open science methodology critical !

Paths to future

- Simulation based inference: Inference using physics based statistical models to constrain properties of small-scale impulsive events [Rajhans et al, ApJ, under review].

- Interpretable AI for solar wind sources: Constrain source regions using solar wind composition and multiple wavelength bands. [Soon!]

- Interpretable AI for flares: Temporal coincidence and analysis with magnetic field topology.

- Physics-incorporated forecasting: For operations: Bias reduction, change of basis functions, and full evaluation of the continuous learning framework [Kirkpatrick+ 2016, Raghavan+ 2024].