HelioIndex

A Python Library for Reproducible Construction of Machine-Learning Datasets from Solar Observations and Event Catalogs

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THE PROBLEM

Without HelioIndex	With HelioIndex
– Ad-hoc scripts per group	✓ One unified pipeline
– No shared standards	✓ Shared, reproducible
– Data leakage risk	✓ Leakage prevention
– Non-reproducible splits	✓ Comparable results
– Results incomparable	✓ Config-driven splits

Every group rebuilds the same pipeline independently — *incompatibly, without publishing code, producing incomparable results.*

WHAT IS HELIOINDEX?

An open-source Python library that standardizes ML-ready dataset construction for solar event forecasting — from raw observation tables and event catalogs.

Observation Table + **Event Catalog** ⟶ **PyTorch Dataset**

→ Flexible observation windows — single frame to multi-frame sequences
→ Configurable prediction horizons & event-labeling rules
→ Missing observation handling & explicit temporal gap tokens
→ Reproducible chronological and active-region-aware splits

DATA SOURCES

HelioIndex ingests user-provided tables — no hardcoded downloads. Works with any timestamped observation series.

SDO / HMI & AIA (NASA)
Magnetogram & EUV timestamps; FITS paths

GOES X-Ray Flare Catalog (NOAA)
Event start/peak/end; flare class A–X

NOAA Active Region Lists (HARP)
Region ID, centroid, HALE classification

Future: CME & SEP Catalogs
Extensible to DONKI, CDAW, SEP event lists

END-TO-END PIPELINE

`obs_table + event_catalog → HelioIndex.createIndex() → Indexed samples → PyTorch-ready splits`

Inputs
Observation Table
+ Event Catalog

→

Cadence Norm.
Normalize timestamps
fill / flag gaps

→

Windowing
Build observation windows
+ prediction horizon

→

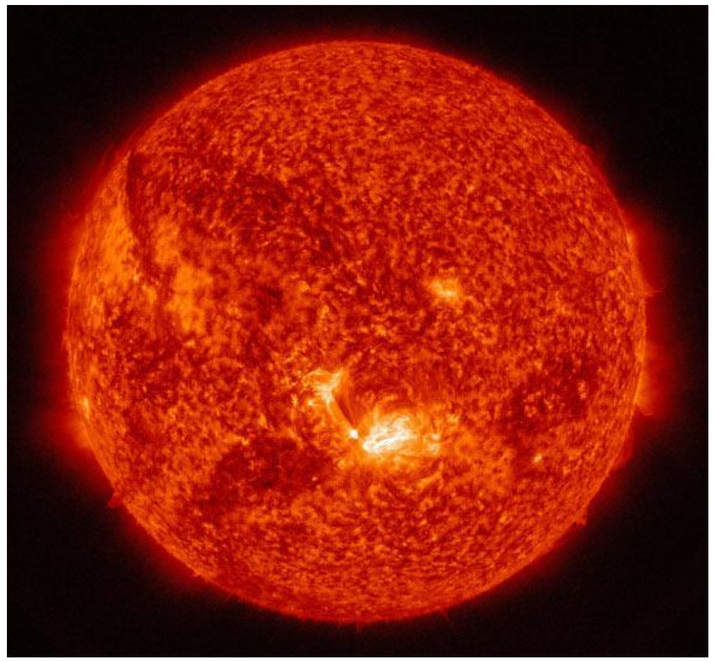
Event Labeling
Assign flare class
configurable rules

→

Dataset Splitting
Time-based / class-based
/ AR-aware

→

Dataset
train / evaluate / test
DataLoader ready



USE CASE EXAMPLES

Full-Disk Flare Forecasting
- 24-hour prediction horizon from observation cutoff
- Strict chronological train / evaluate / test split
- Active-region grouping prevents leakage by location

Active-Region Classification
- NOAA region-level sequences from HARP patches
- AR-aware split — same region never in train + test
- Multi-class target: B / C / M / X peak flare class
- Region grouping prevents temporal leakage by AR

Sequence Modeling with Gaps
- Explicit missing-image tokens preserve sequence length
- Temporal gap flags maintain causal order during outages
- Tri-monthly cross-validation for seasonal robustness
- Handles SDO/GOES data gaps & reduced-cadence periods

KEY BENEFITS

1 Eliminates Redundancy
No group rebuilds the same pipeline. One standardized library replaces dozens of incompatible ad-hoc scripts across the community.

2 Uniform & Shareable Splits
Reproduce any group's exact dataset partition from a config file. Identical splits enable fair, apples-to-apples comparisons.

3 Flexible Pipeline Filtering
Drop specific images, exclude low-quality frames, or swap event catalogs without rewriting any pipeline logic.

4 Prevents Data Leakage
Chronological and AR-aware splits are first-class features — rigorous experimental design by default, not by accident.

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