Driving the SEPCaster Model with an Automated Solar Active Region Identification and Characterization Module

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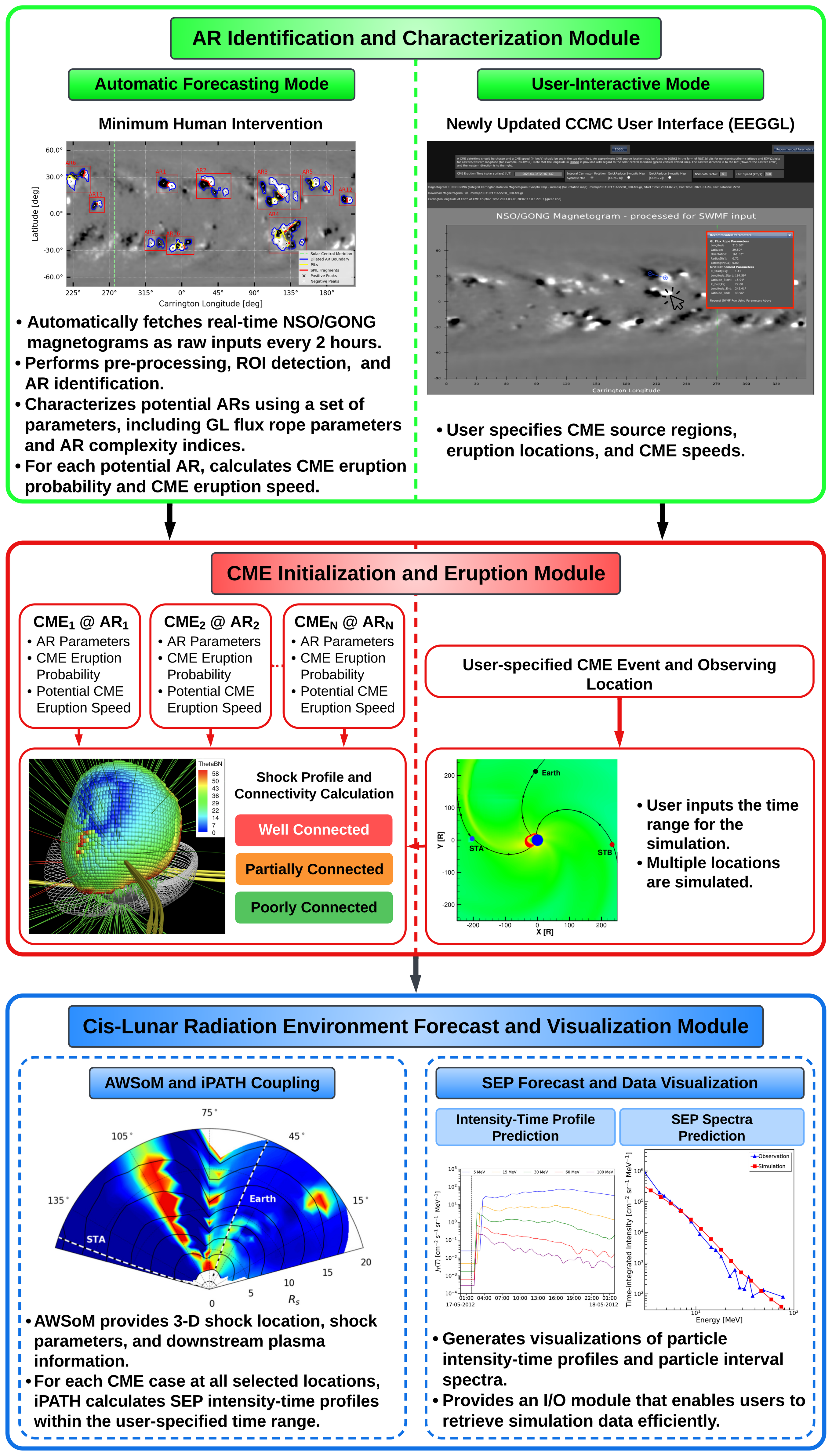
SCIENTIFIC BACKGROUND

Solar flares and coronal mass ejections (CMEs) can cause disruptive space weather conditions, including geomagnetic storms and solar energetic particle (SEP) events, which may severely damage ground- and space-based technological systems and affect our daily lives. Therefore, we require state-of-the-art forecasting models to accurately predict space weather phenomena. **This research aims to develop a physics-based operational SEP forecast model, SEPCaster, for the energetic particle radiation environment in the inner Solar System and Earth's magnetosphere.**

SEPCaster MODEL



This presentation focuses on our new automated Python-based module (shown in green) for identifying and characterizing solar active regions (ARs).

ROI DETECTION

- Pre-processes the acquired NSO/GONG magnetogram by applying a **Gaussian smoothing** filter with a 5 x 5 kernel. This step suppresses the complexity of the magnetic field configuration[1].
- Uses `photutils.segmentation`[2], an affiliated package of AstroPy[3], to detect positive and negative regions of interest (ROIs) with pixel values greater than pre-defined intensity thresholds (e.g., 1σ, 2σ, and 3σ). We apply a combination of **multi-thresholding**[2] and **watershed segmentation**[2] techniques to deblend relatively complex ROIs at an intensity threshold of 1σ.
- Computes **flux-weighted centroids** of the detected ROIs.
- Implements **structural thresholding** and removes ROIs smaller than a pre-defined area threshold (e.g., 10 pix^2).

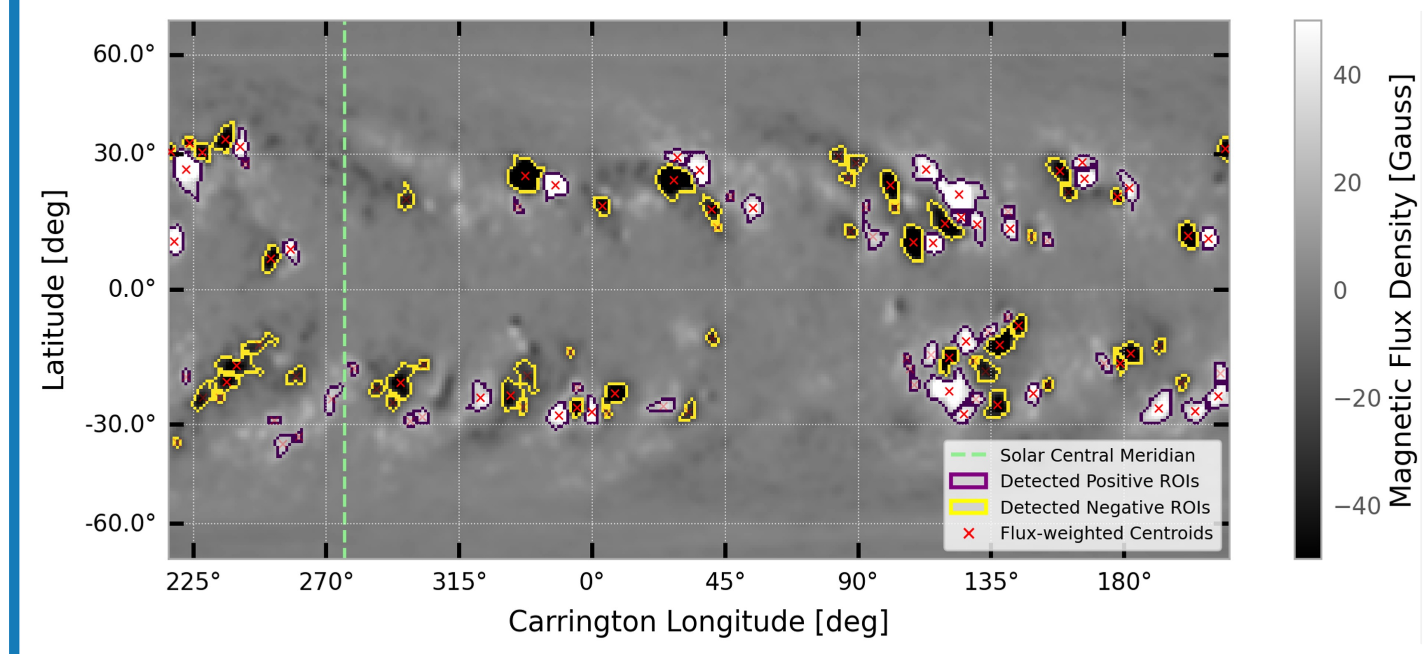


Figure 1: Pre-processed NSO/GONG MRBQS magnetogram for Carrington Rotation 2268 obtained on March 03, 2023 at 11:04 UTC. Positive and negative ROIs are detected at an intensity threshold of 1σ.

AR IDENTIFICATION

- Implements an **agglomerative hierarchical algorithm**[4] to identify potential ARs from the detected ROIs.
  - Validates the total number of clusters using the silhouette score[5], root-square[6] (RS) , and root-mean-square- standard deviation[6] (RMSSTD) indices.
  - Calculates the RMSSTD/RS ratio (i.e., the fraction of intra-cluster distances to inter-cluster distances) to determine the optimal number of clusters.
- Uses physics-informed constraints to refine results:
  - Adds/Removes ROIs to/from the acquired clusters using the **area-distance correlation criterion.**
  - Imposes the **flux-balance mechanism criterion**.
  - Verifies that each cluster contains at least **one ROI of opposite polarity**.

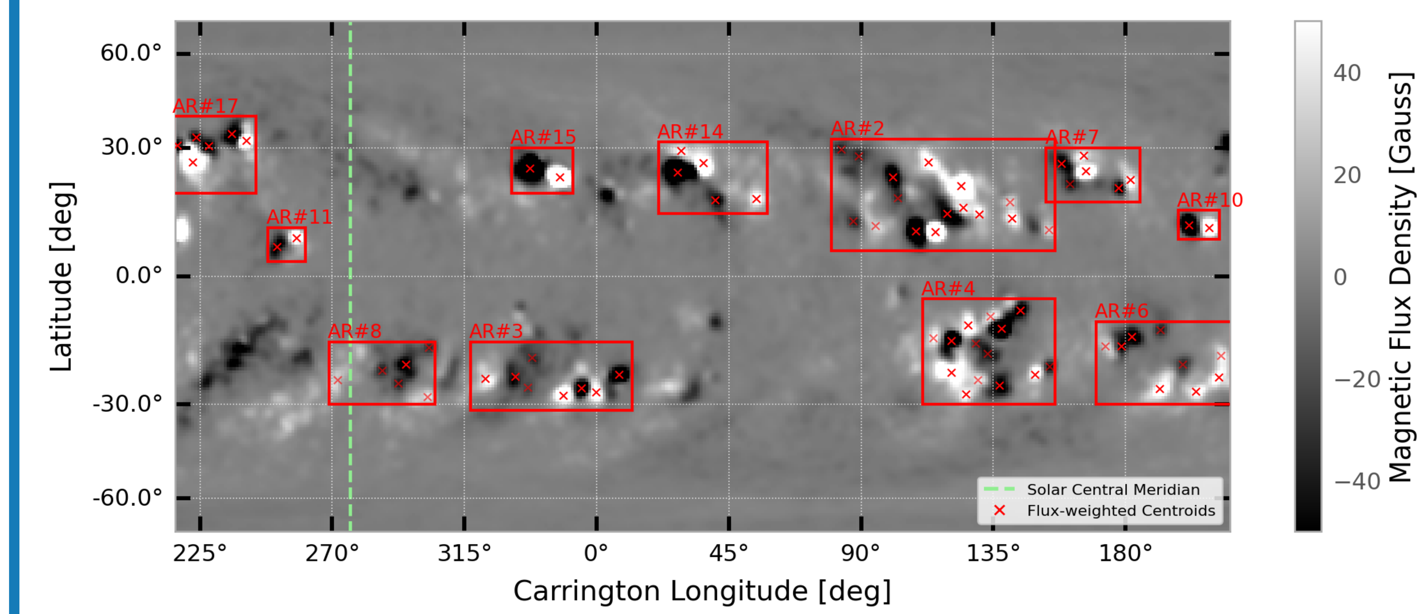


Figure 2: Potential ARs (red boxes) for the pre-processed NSO/GONG MRBQS magnetogram shown in Figure 1.

AR CHARACTERIZATION

- Characterizes the identified potential ARs using **parameters listed in Table 1 of Steward et. al. (2017)**. Some of the important parameters include number of flux peaks, total unsigned flux, total area, number of polarity inversion lines (PILs) and strong-gradient PILs (SPILs), length of PILs and SPILs, and longitudinal and latitudinal gradients.
- Calculates AR complexity indices using our modified version of **correlation dimension mapping[7] (CDM)**.

BOUNDARY- AND AREA-BASED AR COMPLEXITY INDICES

Mason & Uritsky (2022) originally introduced CDM to quantify the irregularities in coronal hole boundaries. We extend the application of CDM to ARs and define our own boundary- and area-based AR complexity indices. This provides an additional way to characterize the identified ARs and helps in determining their potential for eruptive activity.

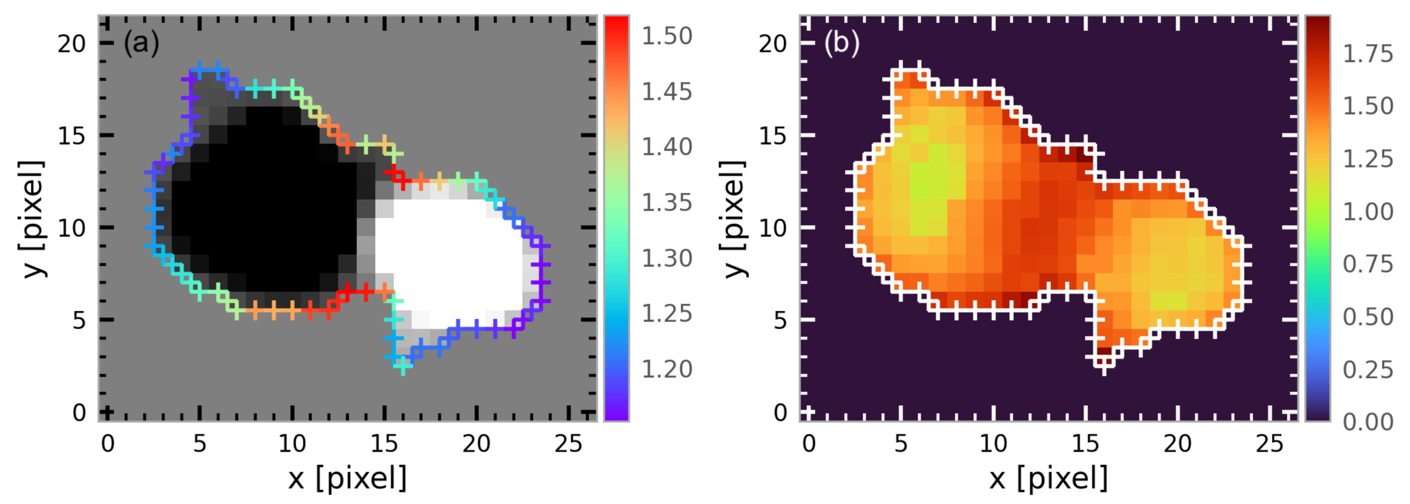


Figure 3: Examples of (a) boundary- and (b) area-based CDMs for AR1 identified in Figure 2. The boundary- and area-based CDM indices for AR1 are 1.301 and 1.435, respectively.

POTENTIAL CME ERUPTION SPEED

Based on the equation of the kinetic energy of a CME, we defined the potential CME eruption speed as follows:

$$V_{\mathrm{CME}}^2\ [\mathrm{km/s}] \approx c \left[\frac{\mathrm{km/s}}{\mathrm{G}}\right] \frac{\iint B^2/B_{\mathrm{avg}} dA_1 \Delta}{\iint dA_2 \Delta}$$

$$2 \ln V_{\mathrm{CME}} = \ln c + \ln \iint B^2/B_{\mathrm{avg}} dA_1 - \ln A_2$$

where *c* is a constant, *B* is the magnetic field in Gauss, *A* is an effective AR area, and Δ is an effective AR volume. We are currently testing our analysis using the NSO/GONG magnetograms acquired during Solar Cycle 23 and 24.

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