National Aeronautics and
Space Administration

Forecasting Space Weather Using Machine Learning

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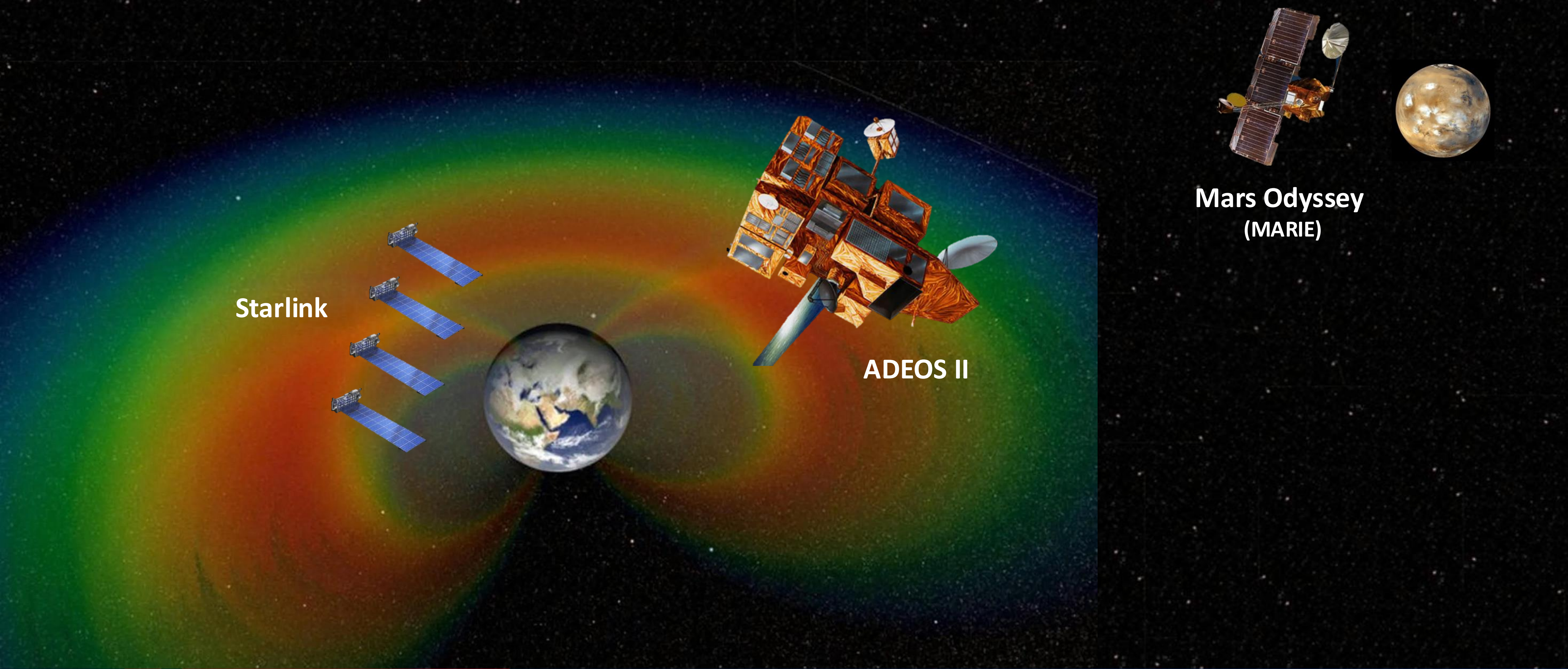
November 18, 2024

How does space weather affect us?

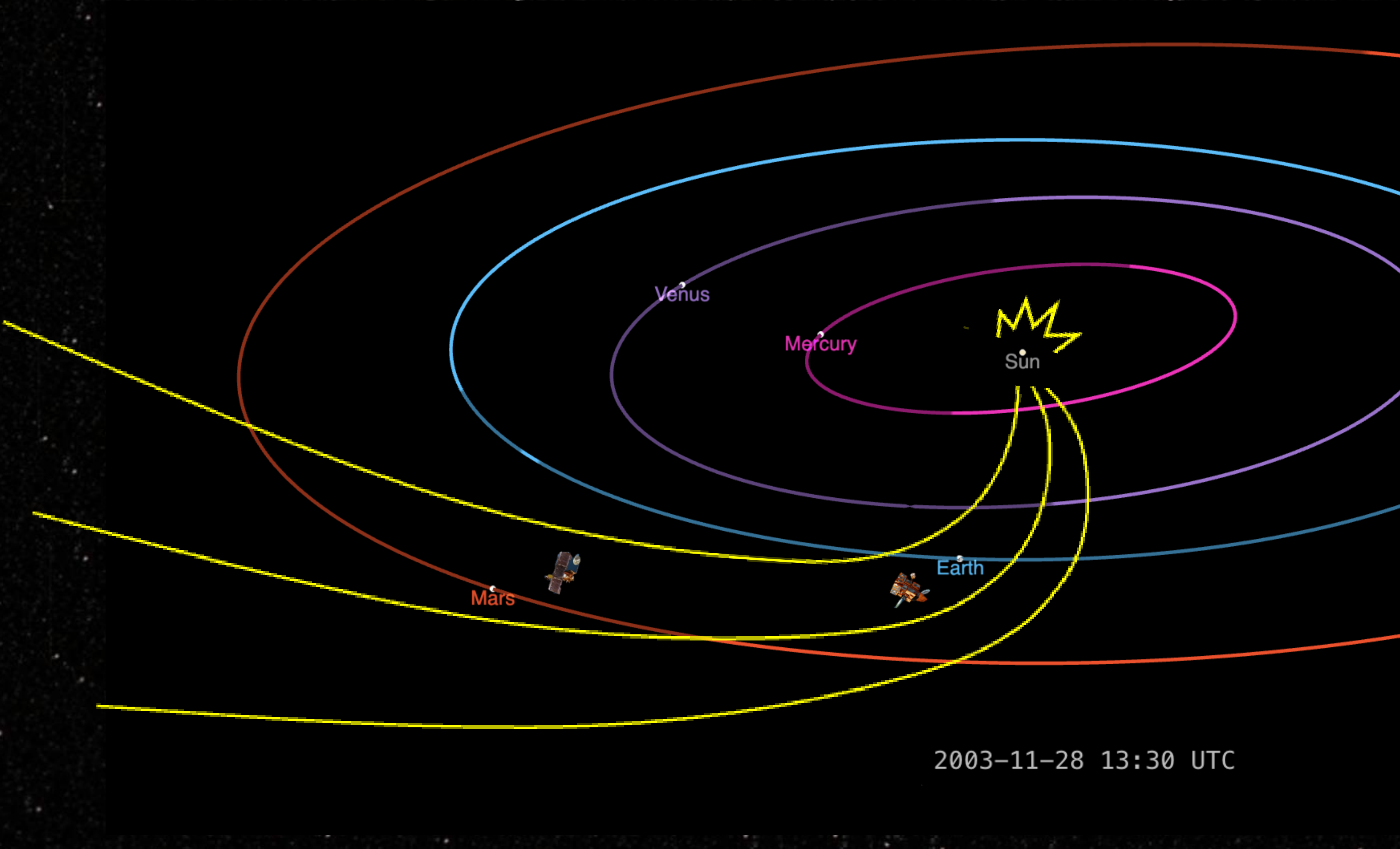
- **Satellite Damage**: High-energy particles from solar storms can damage satellite electronics and disrupt communication and GPS signals, affecting navigation and telecommunications.
- **Power Grid Disruptions**: Geomagnetic storms can induce electric currents in power lines, potentially causing power outages and damaging transformers and infrastructure in the power grid.
- **Radiation Exposure**: Solar energetic particles pose a radiation risk to astronauts and high-altitude flight crews, especially on polar routes, where Earth's magnetic shielding is weaker.
- **Navigation Errors**: GPS systems can experience signal degradation or complete outages during intense space weather events, leading to navigation issues for planes, ships, and other systems reliant on GPS.
- **Auroras**: While typically harmless, geomagnetic storms from space weather can produce beautiful auroras, which can be visible further south than usual, sometimes even in mid-latitude regions.

Space Weather Casualties

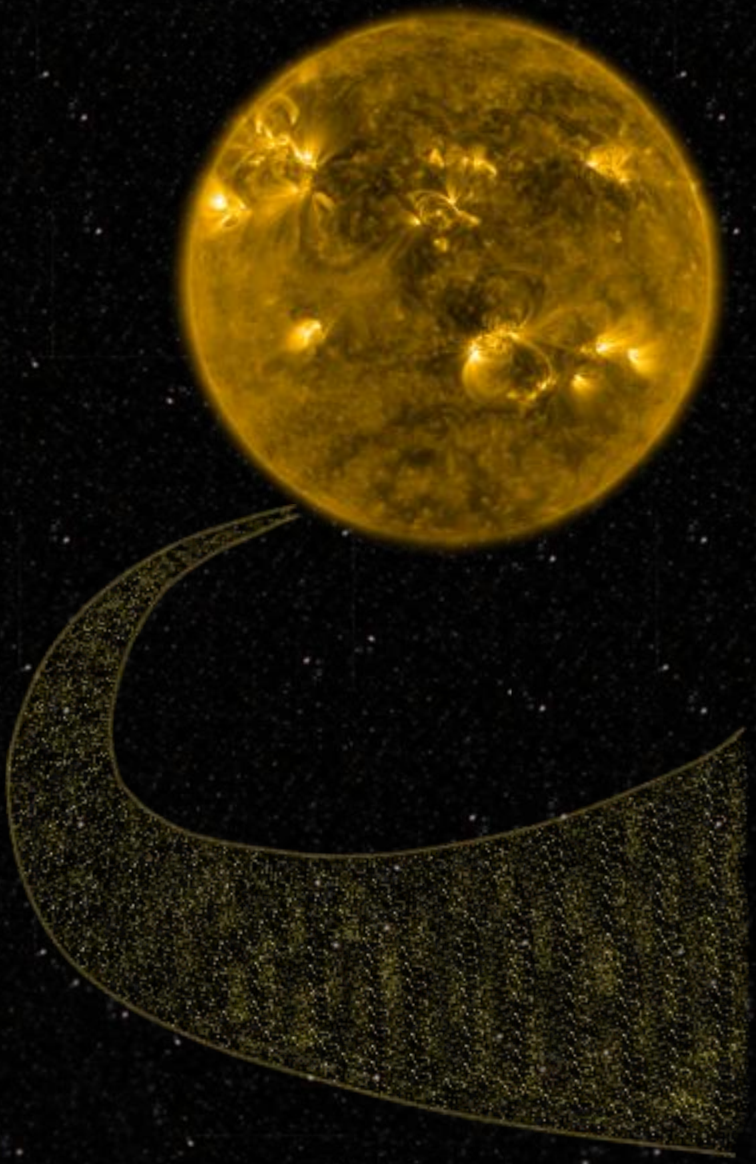


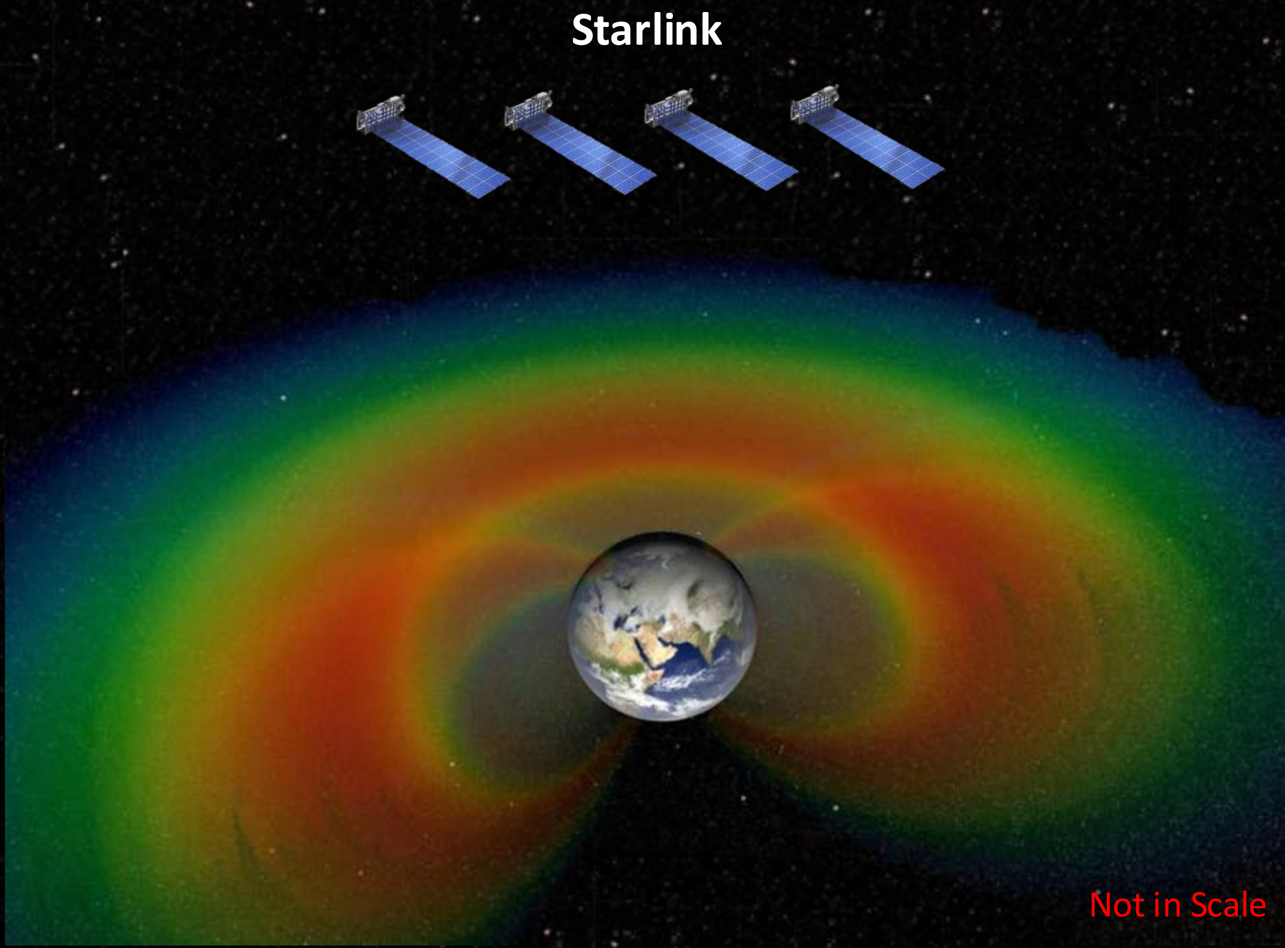
The Great Halloween Solar Storms

Current Sheet
(Parker Spiral)



February 2022 Starlink Event



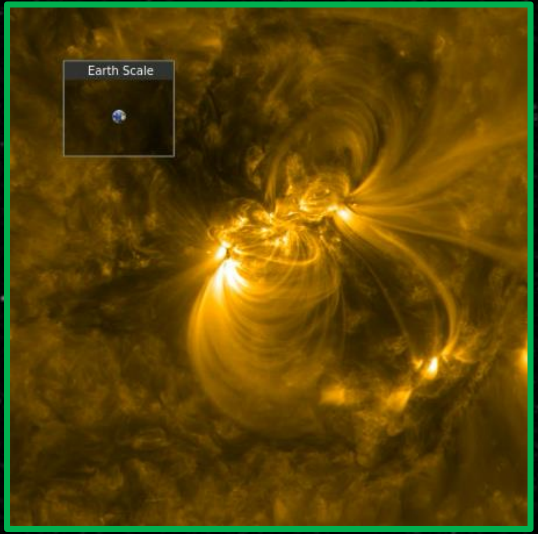


Sequence of Events

SDO / HMI Continuum Intensity

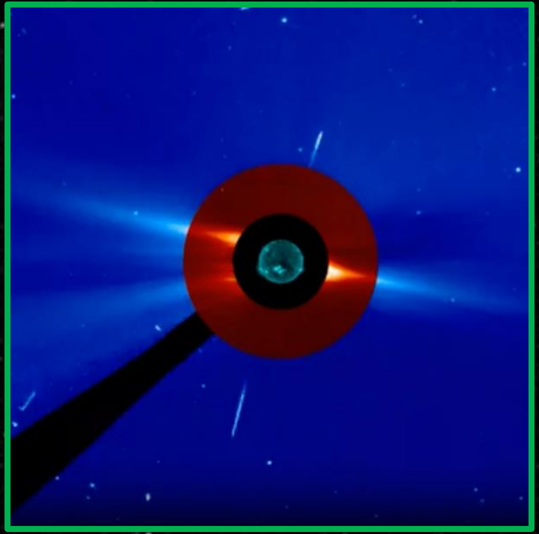
Active Region Emergence ... and Evolution

SDO / AIA 171 Å



Flare Eruption

SOHO / LASCO

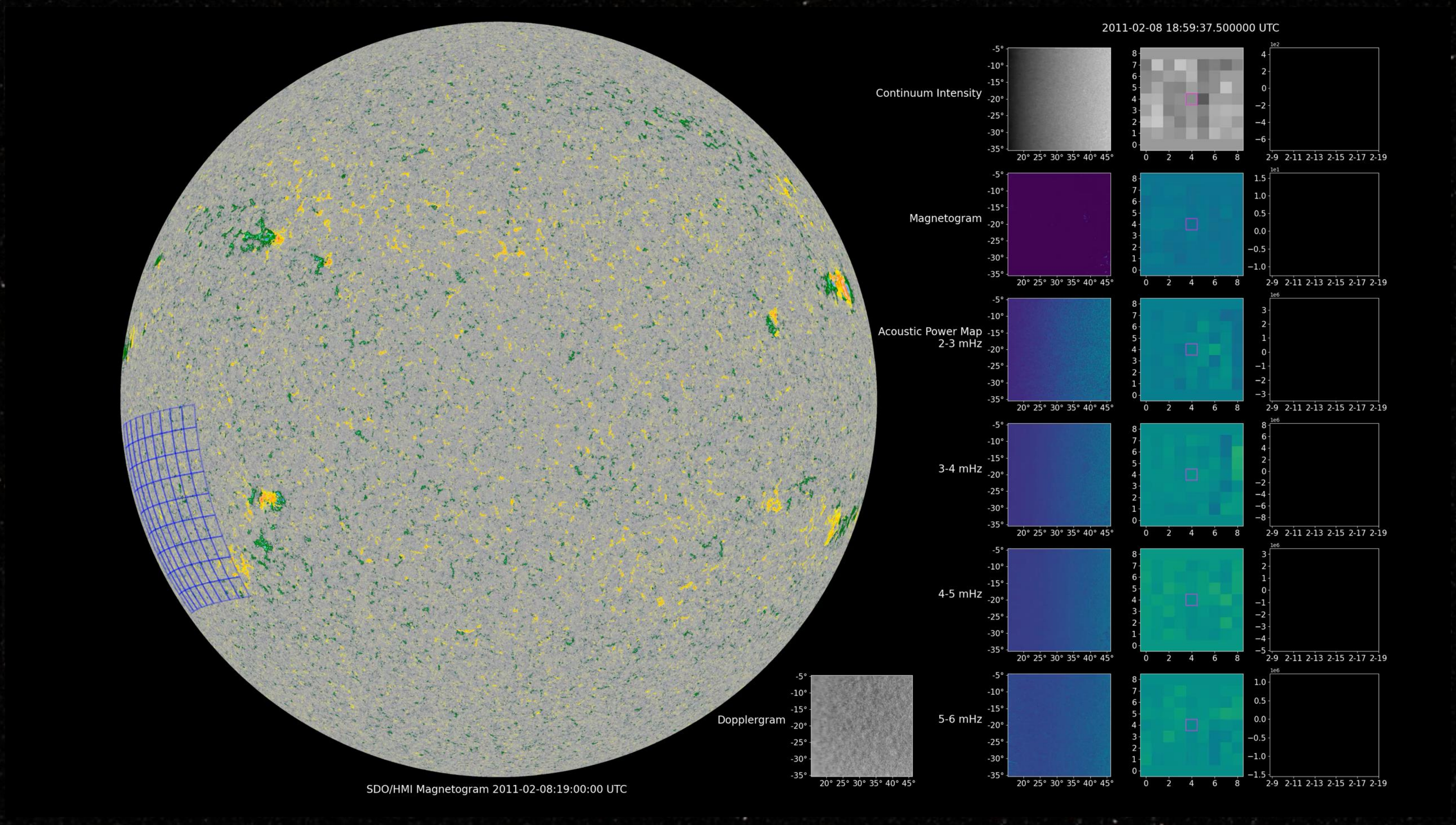


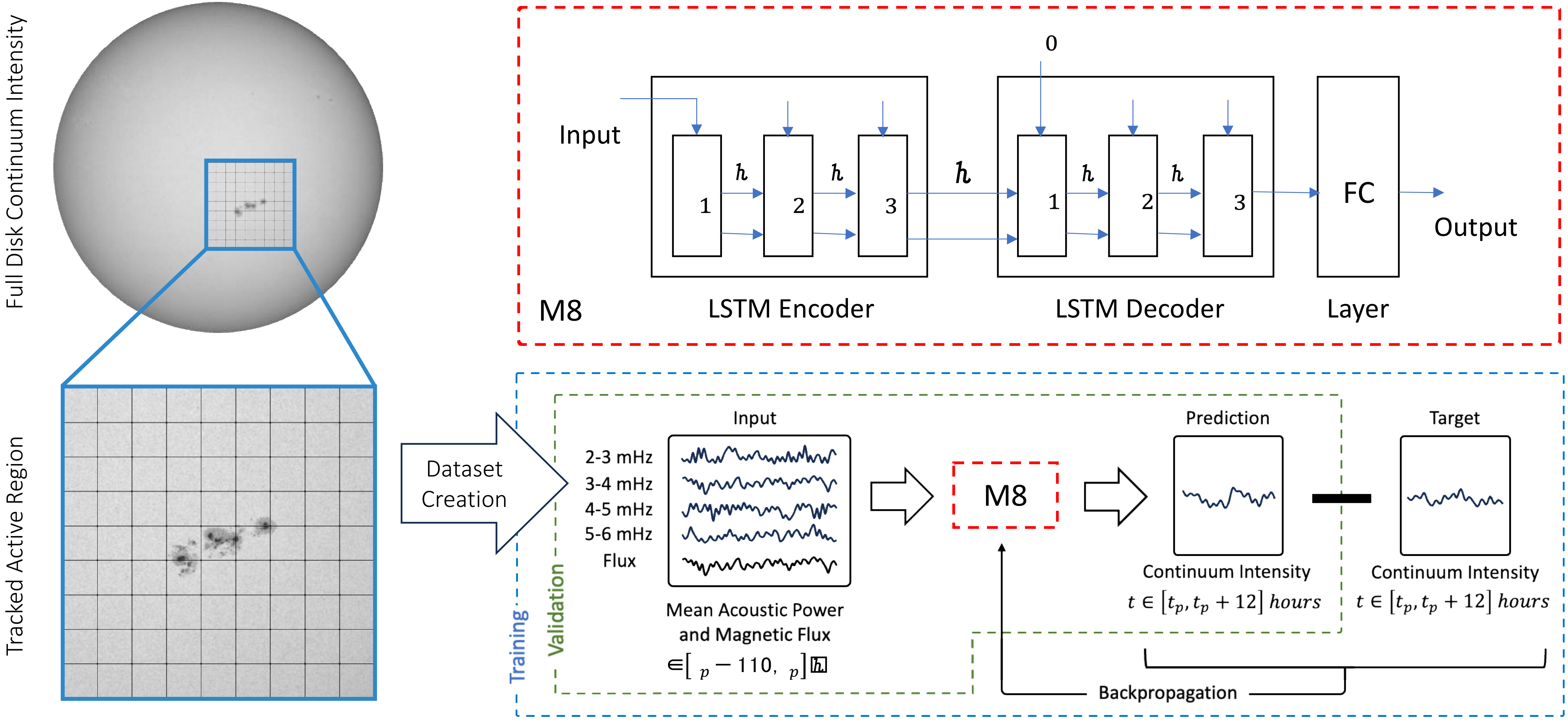
Solar Energetic Particle Event

Space Weather Prediction at NASA Ames

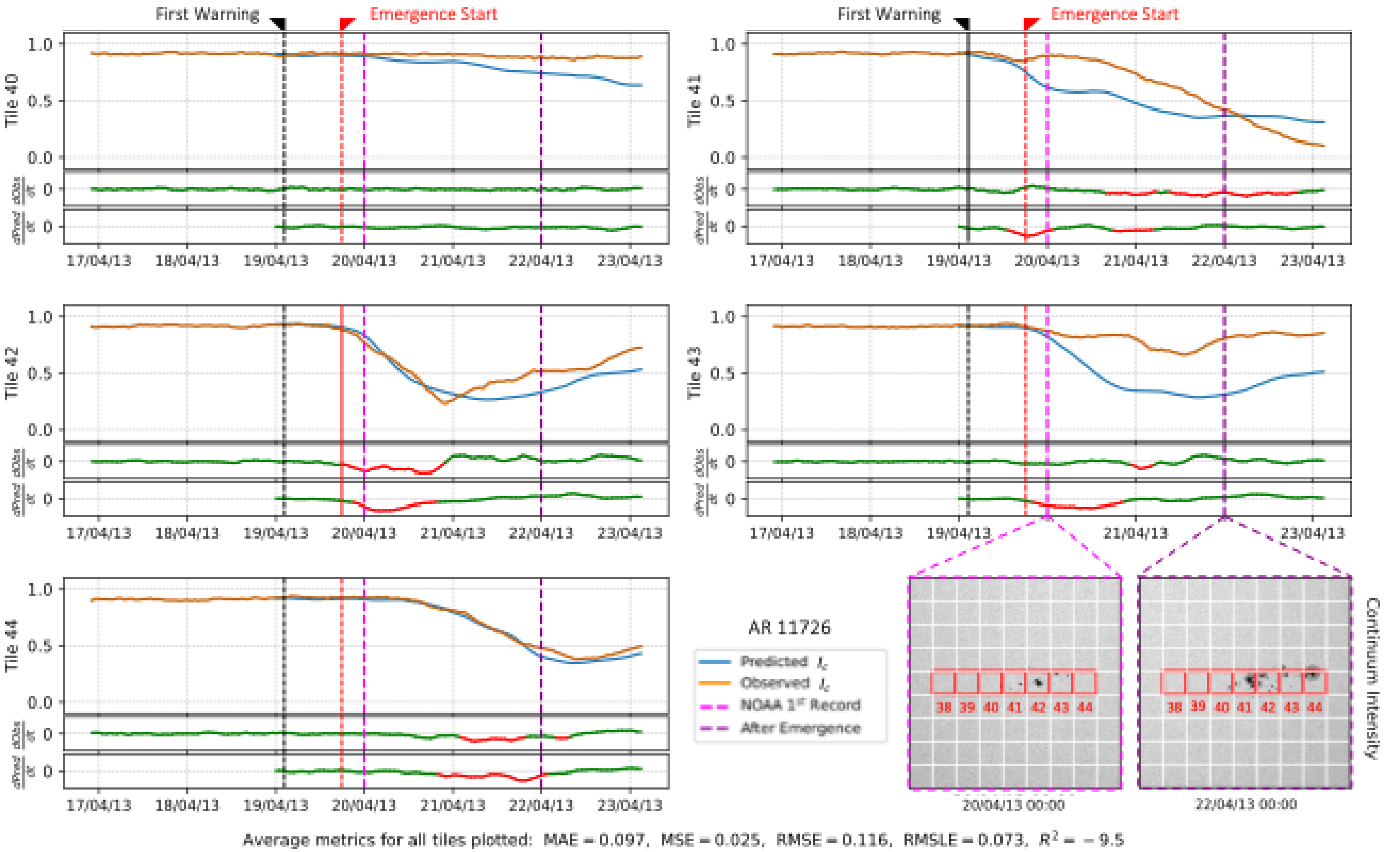
- Datasets:
  - Kosovich, P.A., Kosovichev, A.G., Sadykov, V.M., Kasapis, S., Kitiashvili, I.N., O'Keefe, P.M., Ali, A., Oria, V., Granovsky, S., Chong, C.J. and Nita, G.M., 2024. Time Series of Magnetic Field Parameters of Merged MDI and HMI Space-weather Active Region Patches as Potential Tool for Solar Flare Forecasting. The Astrophysical Journal, 972(2), p.169.
  - Kasapis, S., Kitiashvili, I.N., Kosovichev, A.G., Stefan, J.T. and Apte, B., 2024. Predicting the Emergence of Solar Active Regions Using Machine Learning. arXiv preprint arXiv:2402.08890.

- ML Models:
  - Kasapis, S., Zhao, L., Chen, Y., Wang, X., Bobra, M. and Gombosi, T., 2022. Interpretable machine learning to forecast SEP events for solar cycle 23. Space Weather, 20(2), p.e2021SW002842.
  - Kasapis, S., Kitiashvili, I.N., Kosovich, P., Kosovichev, A.G., Sadykov, V.M., O'Keefe, P., & Wang, V., 2024. Forecasting Solar Energetic Particle Events During Solar Cycles 23 and 24 Using Interpretable Machine Learning. The Astrophysical Journal, 974(1), p.131. DOI: 10.3847/1538-4357/ad6f0e
  - Kasapis, S., Kitiashvili, I.N., Kosovichev, A.G. and Stefan, J.T., 2024. Solar Active Regions Emergence Prediction Using Long Short-Term Memory Networks. arXiv preprint arXiv:2409.17421.


2011-02-08 18:59:37.500000 UTC
Continuum Intensity
Magnetogram
Acoustic Power Map
2-3 mHz
3-4 mHz
4-5 mHz
5-6 mHz
Dopplergram
20° 25° 30° 35° 40° 45°
-5° -10° -15° -20° -25° -30° -35°
2-9 2-11 2-13 2-15 2-17 2-19
SDO/HMI Magnetogram 2011-02-08:19:00:00 UTC



Full Disk Continuum Intensity
Tracked Active Region
Dataset Creation
Input
0
h
1
2
3
1
2
3
FC
Output
M8
LSTM Encoder
LSTM Decoder
Layer
Training
Validation
Input
2-3 mHz
3-4 mHz
4-5 mHz
5-6 mHz
Flux
Mean Acoustic Power
and Magnetic Flux
∈[p − 110, p] h
M8
Prediction
Continuum Intensity
$t \in [t_p, t_p + 12]$ hours
Target
Continuum Intensity
$t \in [t_p, t_p + 12]$ hours
Backpropagation



First Warning
Emergence Start
Tile 40
Tile 41
Tile 42
Tile 43
Tile 44
17/04/13
18/04/13
19/04/13
20/04/13
21/04/13
22/04/13
23/04/13
AR 11726
Predicted I_c
Observed I_c
NOAA 1st Record
After Emergence
38 39 40 41 42 43 44
20/04/13 00:00
22/04/13 00:00
Continuum Intensity
Average metrics for all tiles plotted: MAE = 0.097, MSE = 0.025, RMSE = 0.116, RMSLE = 0.073, R^2 = − 9.5

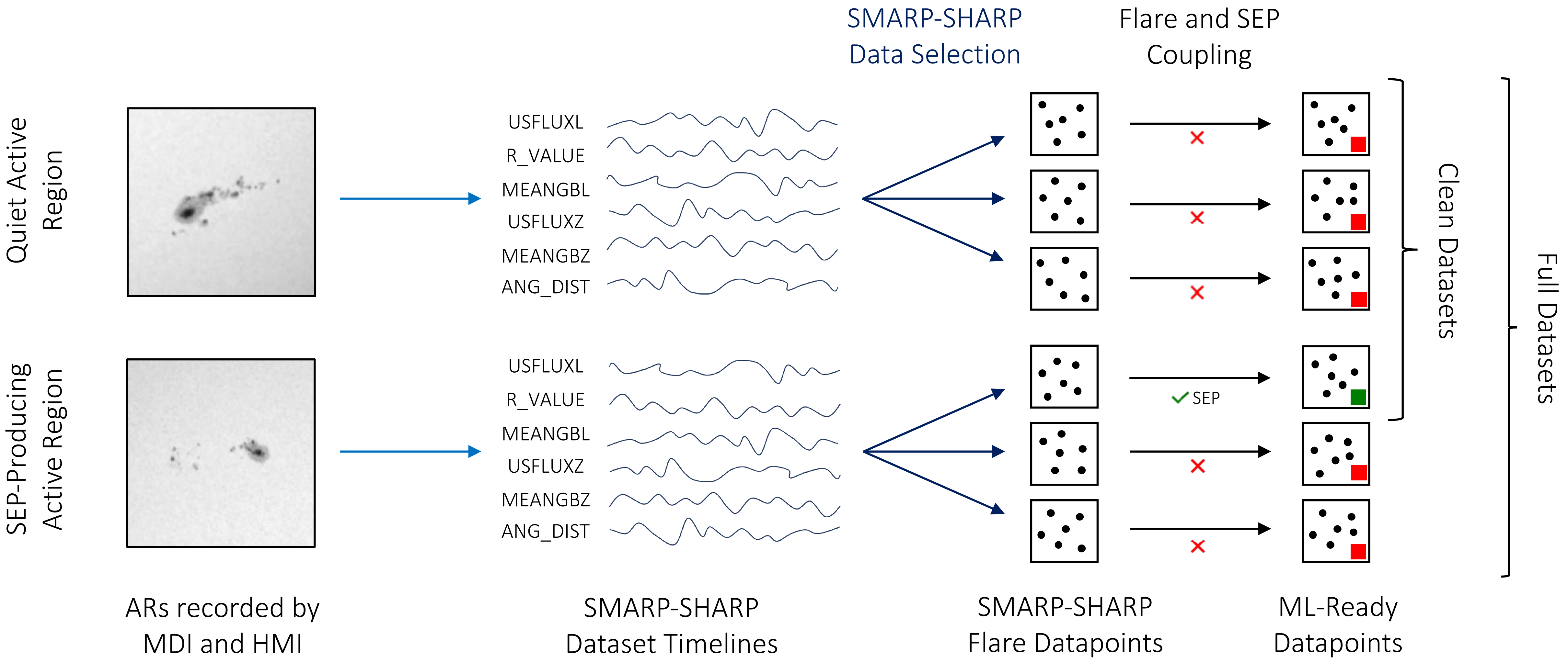
Conclusions and Future Work on AR Emergence

- Our LSTM model succeeded in predicting the emergence of all 5 testing ARs in an experimental setting and 3/5 in an operational setting (AR11726, AR13165 and AR13179).
- Although 45 emerging ARs are used in this research, 61 ARs have been tracked and the entire dataset will be published, along with the ML-ready data produced.
- Improvement suggestions in the dataset production process can be derived, such as the optimal frequency range, integration time range, tile arrangement and normalization methods.
- Improvements in the LSTM training methods and the use of more advanced ML methods such as transformers.
- Creation of a universal AR emergence definition which can be used in different works.

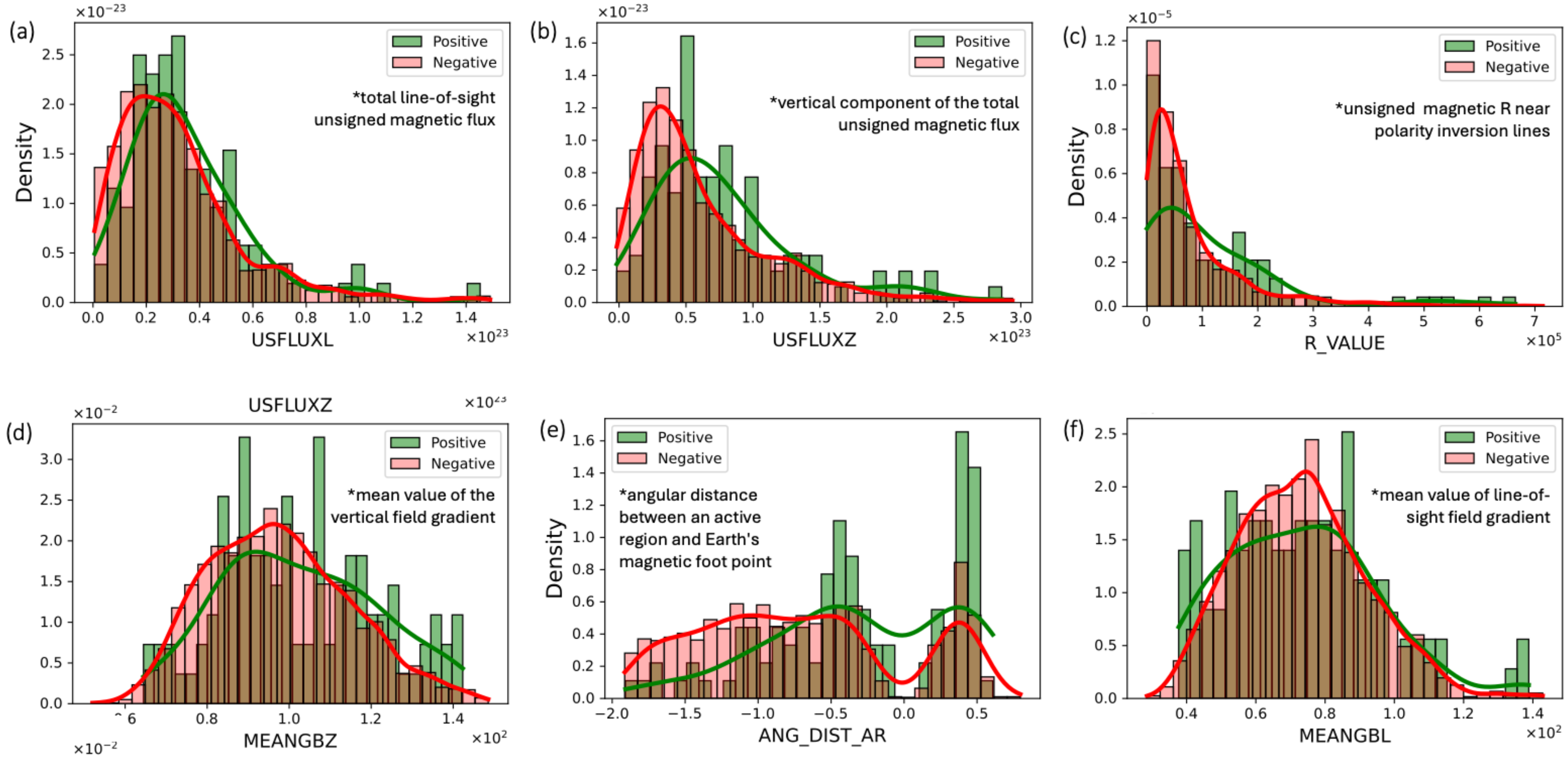
SHARP-SMARP Dataset for SEP Prediction

- Kosovich et al. (2024) combined SMARP (MDI) and SHARP (HMI) datasets into a single product for enhanced space weather forecasting.
- Filtering, rescaling, and merging of parameters, creating a uniform multivariate time series from April 4, 1996, to December 13, 2022.
- Identified time-lagged relationships between magnetic field properties of active regions and solar flare indices, suggesting predictive potential.
- The angular distance between an active region and Earth's magnetic foot point (assumed to be at W45°) is calculated using the SHARP-SMARP coordinates.

Keyword	Description
USFLUXL	Total line-of-sight unsigned flux (Maxwells)
R_VALUE	Unsigned flux R near polarity inversion lines (Maxwells)
MEANGBL	Mean value of line-of-sight field gradient (Gauss/Mm)
USFLUXZ	Vertical component of the total unsigned flux (Maxwells)
MEANGBZ	Mean value of the vertical field gradient (Gauss/Mm)
LAT_FWT	Stonyhurst latitude of flux-weighted center of active pixels (degrees)
CRLT_OBS	Carrington latitude of the observer (degrees)
LON_FWT	Stonyhurst longitude of flux-weighted center of active pixels (degrees)
CRLN_OBS	Carrington longitude of the observer (degrees)


Quiet Active Region
SEP-Producing Active Region
USFLUXL
R_VALUE
MEANGBL
USFLUXZ
MEANGBZ
ANG_DIST
SMARP-SHARP Data Selection
Flare and SEP Coupling
SEP
Clean Datasets
Full Datasets
ARs recorded by MDI and HMI
SMARP-SHARP Dataset Timelines
SMARP-SHARP Flare Datapoints
ML-Ready Datapoints

Assessing the Keywords Predictive Abilities



- The SMARP-SHARP dataset includes a continuous set of 21 keywords (only six of which are used here), representing homogeneous observations of active region patches from SoHO/MDI and SDO/HMI for the period between April 1996, and December 30, 2022
- Flare-based prediction: The final count for the flares that will be used for SEP prediction is **110 positive** (SEP productive) and **3246 negative** events (non-SEP productive).

SEP Prediction Results

- We compare the SHARP-SMARP trained models results with those of Kasapis et al. (2022) and Lavasa et al. (2021).
- We use five different metrics to evaluate our models performance: the accuracy (ACC), the True Skill Score (TSS), the Heidke Skill Score (HSS), the False Alarm Rate (FAR) and the F1.

Setting	Training	Dataset	Model	ACC	TSS	HSS	FAR	F1
Operational	Imbalance	Regular	SVM Linear	0.56 ± 0.04	0.32 ± 0.10	0.05 ± 0.02	0.24 ± 0.10	0.71 ± 0.04
Kasapis et al. (2022)	Imbalance	Regular	SVM Poly	0.52 ± 0.05	0.01 ± 0.01	0.01 ± 0.01	0.98 ± 0.05	0.58 ± 0.06
Semi-Operational	Balanced	Regular	SVM Linear	0.66 ± 0.10	0.33 ± 0.19	0.33 ± 0.19	0.26 ± 0.14	0.63 ± 0.12
Kasapis et al. (2022)	Balanced	Regular	SVM RBF	0.65 ± 0.13	0.33 ± 0.28	0.31 ± 0.26	0.31 ± 0.10	0.75 ± 0.04
Semi-Operational	Imbalance	Clean	SVM Linear	0.67 ± 0.04	0.35 ± 0.13	0.08 ± 0.03	0.32 ± 0.12	0.79 ± 0.03
Experimental	Balanced	Clean	SVM Linear	0.69 ± 0.09	0.38 ± 0.19	0.38 ± 0.19	0.26 ± 0.14	0.67 ± 0.11
Experimental	Balanced	Clean	Logistic Reg	0.70 ± 0.09	0.39 ± 0.19	0.37 ± 0.19	0.30 ± 0.14	0.69 ± 0.10

- The Lavasa et al. (2021) "Flare-Noisy" Linear SVM Model with an Imbalanced data setting indicates generally better performance, as it exhibits better TSS (+0.14) and HSS (+0.36) scores, as it is trained on significantly more positive data.
- The current model demonstrates a significantly lower FAR than that reported by Lavasa et al. (2021), suggesting that it is less prone to incorrectly predicting SEP events.

SEP Prediction Conclusions

- We utilize two Solar Cycles worth of data from the SOHO/MDI and the SDO/HMI instrument to train ML models in predicting SEP events.

- Statistical analysis shows that the vertical component of the total unsigned magnetic flux (USFLUXZ), the unsigned magnetic R near polarity inversion lines (R_VALUE) and the angular distance between an active region and Earth's magnetic foot point (ANG_DIST_AR) are the parameters related the most to the SEP prediction problem.

- When trained and tested in an operational setting, SVM and Regression models perform better in the presence of more data (two solar cycles instead of one).

- Although in an experimental setting the models ACC can reach 0.7, in an operational setting the accuracy decreases to 0.56, showing that the low dimensional SMARP-SHARP dataset can’t predict reliably an SEP.

- Future improvements in the problem of predicting SEP events using ML should be the use of high-dimensional data, deeper ML networks that can better capture the underlying dynamics of SEP production.

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