“All-Clear” Prediction of Solar Energetic Particle Events with Machine Learning

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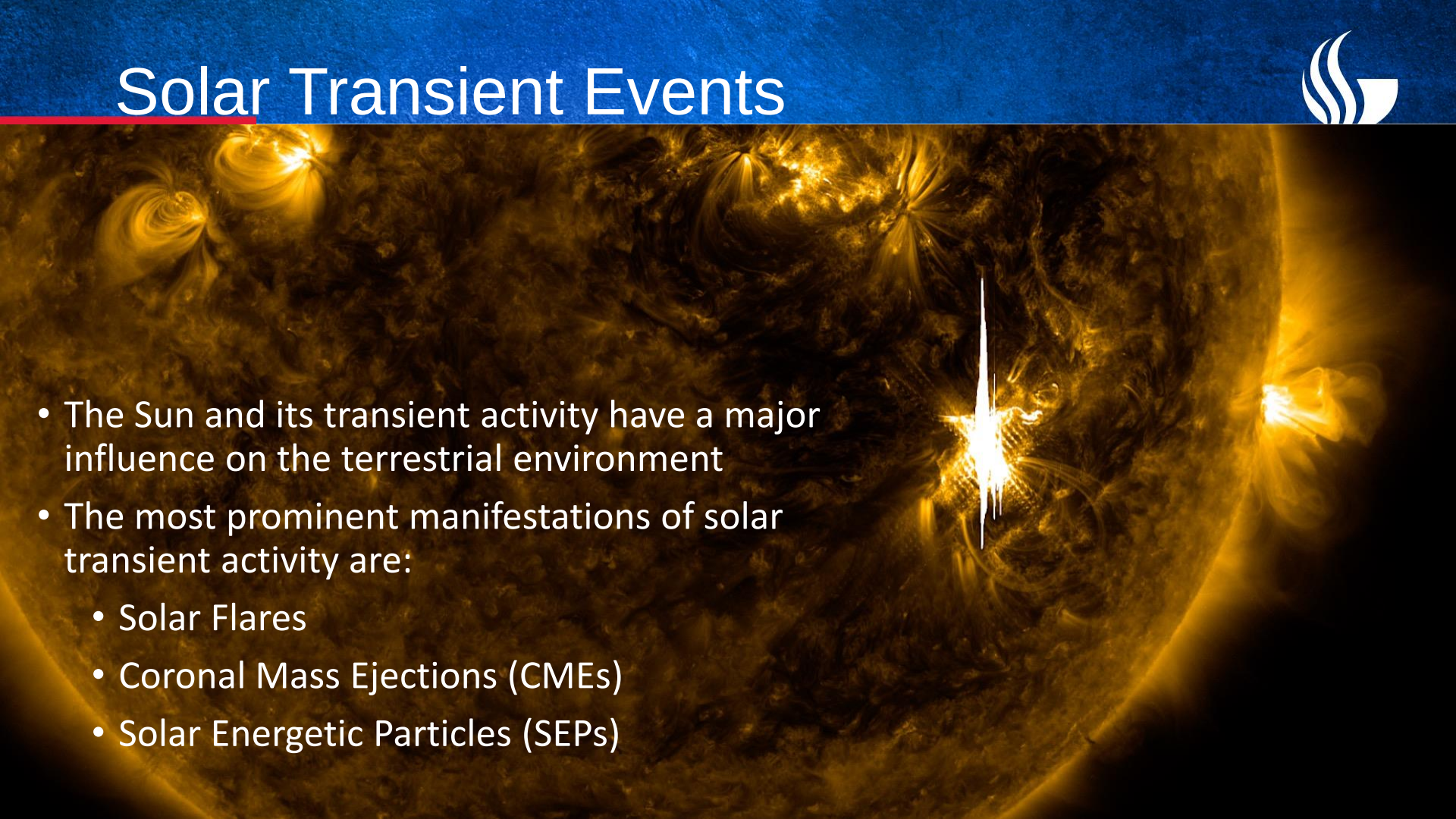
Advanced Modeling & Simulation (AMS) Seminar Series

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Outline

- Introduction. Solar Energetic Particles (SEPs) and Solar Proton Events (SPEs)
- NASA ESI project objectives
- Daily prediction of the Solar Cycle 24 proton events
  - Solar Energetic Particle Prediction Portal (SEP^3)
  - Description of the forecasting attempt
  - “All-clear” perspectives of the study
- Extending beyond daily Solar Cycle 24 attempt:
  - Prediction based on daily statistical properties of GOES measurements
  - Prediction based on historic McIntosh and magnetic classes of active regions
  - Flare-driven prediction of proton events
- Conclusions

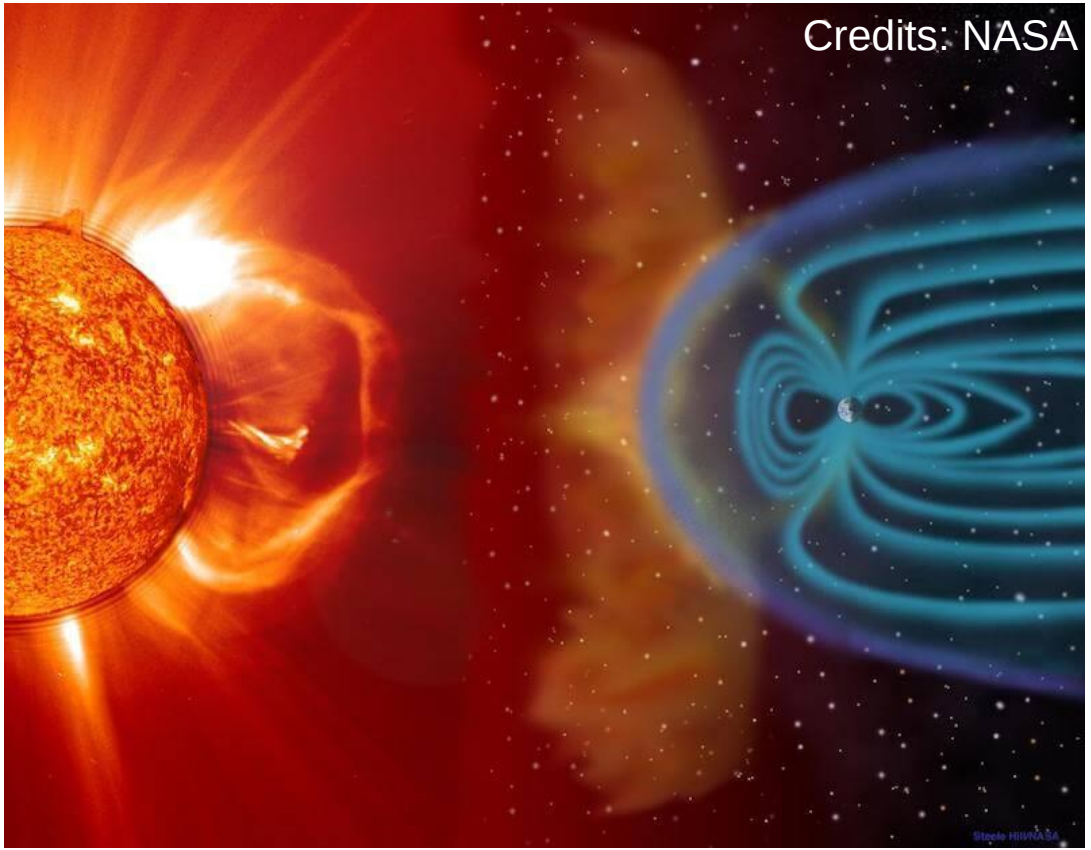
Solar Transient Events



- The Sun and its transient activity have a major influence on the terrestrial environment
- The most prominent manifestations of solar transient activity are:
  - Solar Flares
  - Coronal Mass Ejections (CMEs)
  - Solar Energetic Particles (SEPs)

Solar-Terrestrial Interactions

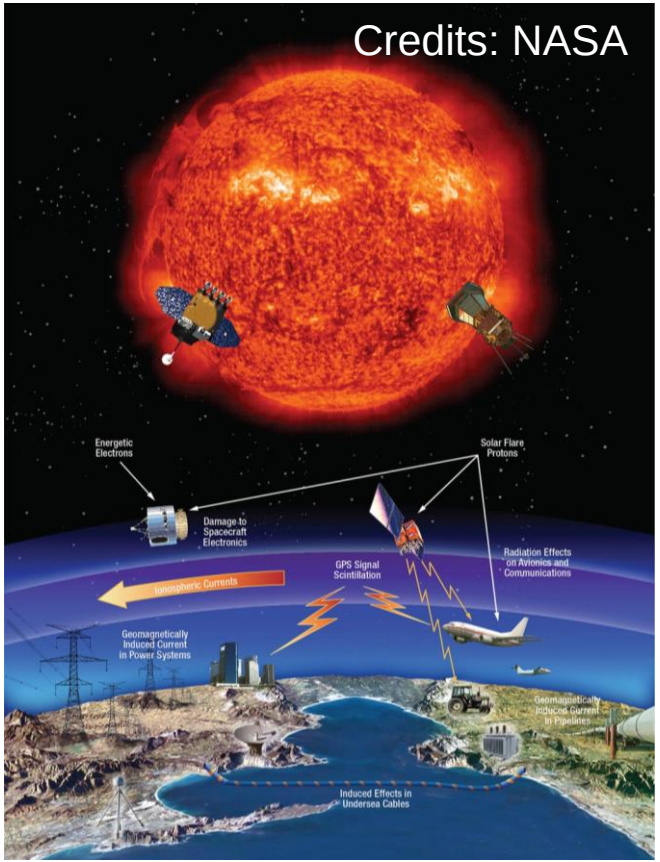
- The Sun and the Earth do not represent isolated systems
- They are interacting, both during the extreme events and at everyday scales
- These interactions are called solar-terrestrial interactions, or space weather



Space Weather Impact of SEPs

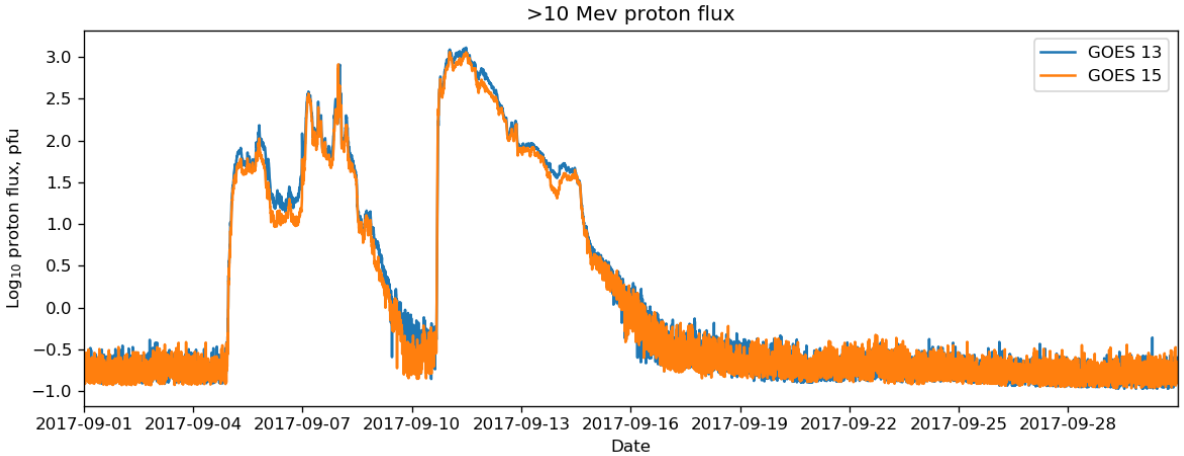
- Solar Energetic Particles (SEPs) can damage spacecraft electronics
- Radiation exposure at aviation altitudes increases during SEP events
- SEPs represent a potential danger for space exploration

Prediction of SEPs and, in particular, of Solar Proton Events (SPEs) is a critically important problem from both operational and research perspectives



SEPs and SPEs

- Solar Energetic Particle (SEP) events can be defined as significant enhancements of the particle flux coming from the Sun with respect to the stable background
- Solar Proton Events (SPEs) represent a major subclass of SEPs
- The terms “SEP event” and “SPE” are equivalent for this presentation and represent enhancements of energetic proton fluxes as measured by near-Earth satellites (like the Geostationary Operational Environmental Satellite, GOES)



An example of > 10 MeV proton flux measurements by the GOES-13 and GOES-15 satellites

ESI Project: Machine Learning Tools for Predicting Solar Energetic Particle Hazards

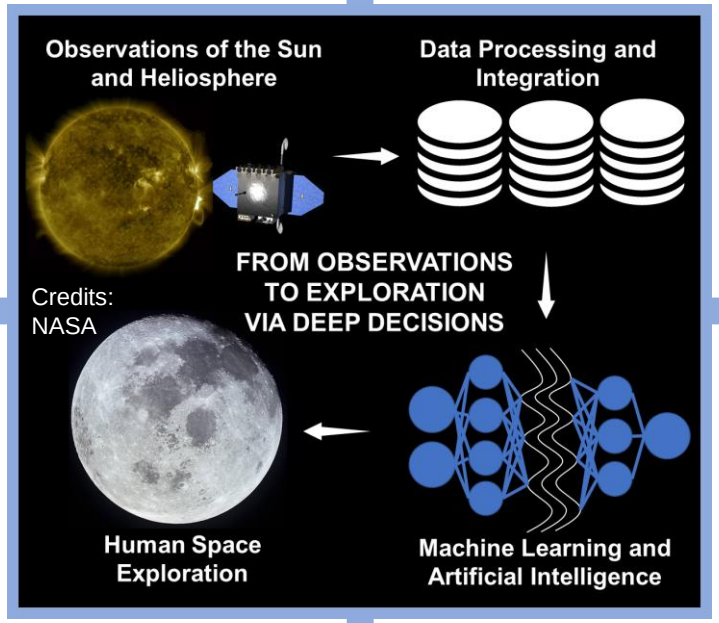
PI: Alexander Kosivichev (NJIT)

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Research Objectives

- Enhance predictions of solar energetic particles (SEP) by developing an online-accessible database of SEP-related data and implementing robust machine-learning-based "all-clear" forecasts;
- Innovation: unleashing machine learning technologies for SPE forecasts, enabling data discovery
- Enhancement of SOA: automatic forecasts without "forecaster-in-the-loop"



Approach

- Modern Machine Learning and database technologies with API-based online access to database entries and integrated data products
- Automated utilization and processing of multi-spacecraft observational data
- Customized Skill Score for "all-clear" forecasts
- Application of advanced Machine Learning algorithms for solving classification tasks and prediction of active region evolution

Potential Impact

- Robust "all-clear" forecasts, enhancing space exploration safety and advanced mission planning
- Availability of prepared and integrated data for the heliophysics community
- Data discovery possibilities for the broader community
- Replacement of current operational forecasting techniques by machine-learning-based approaches

Goals and Objective of the ESI project

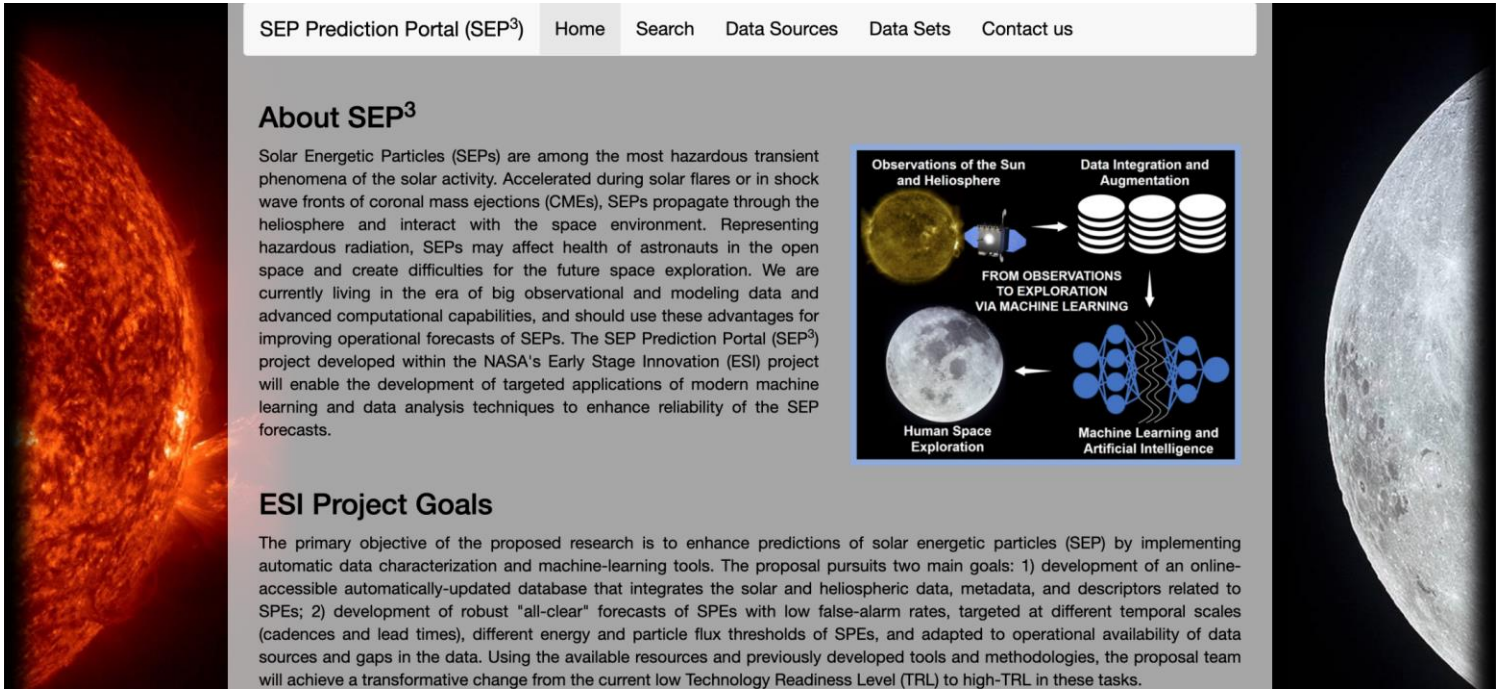
The primary objective of our longer-term research effort is to enhance predictions of solar energetic particles (SEPs) by implementing automatic data characterization and machine-learning tools

We pursuit two main goals:

- Develop an online-accessible database that integrates the solar and heliospheric data, metadata, and descriptors related to SPEs
- Develop robust “all-clear” forecasts of SPEs with low false-alarm rates, targeted at different temporal scales (cadences and lead times), different energy and particle flux thresholds of SPEs, and adapted to the operational availability of data sources and gaps in the data

Solar Energetic Particles Prediction Portal (SEP^3)

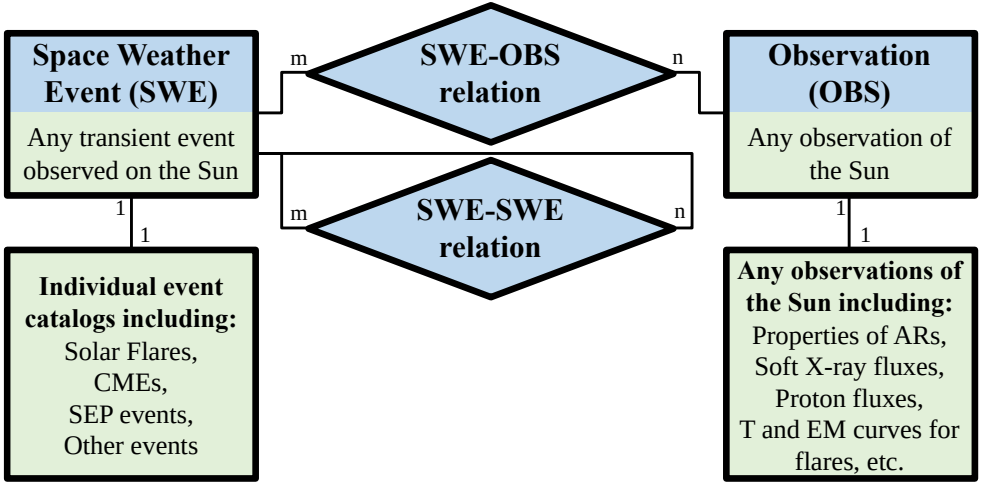
- The database and web portal will be available online for broader research community from the NJIT web server.
- Most of the database work is done by graduate students in the Physics and Computer Science departments at NJIT



Credits for background images: NASA

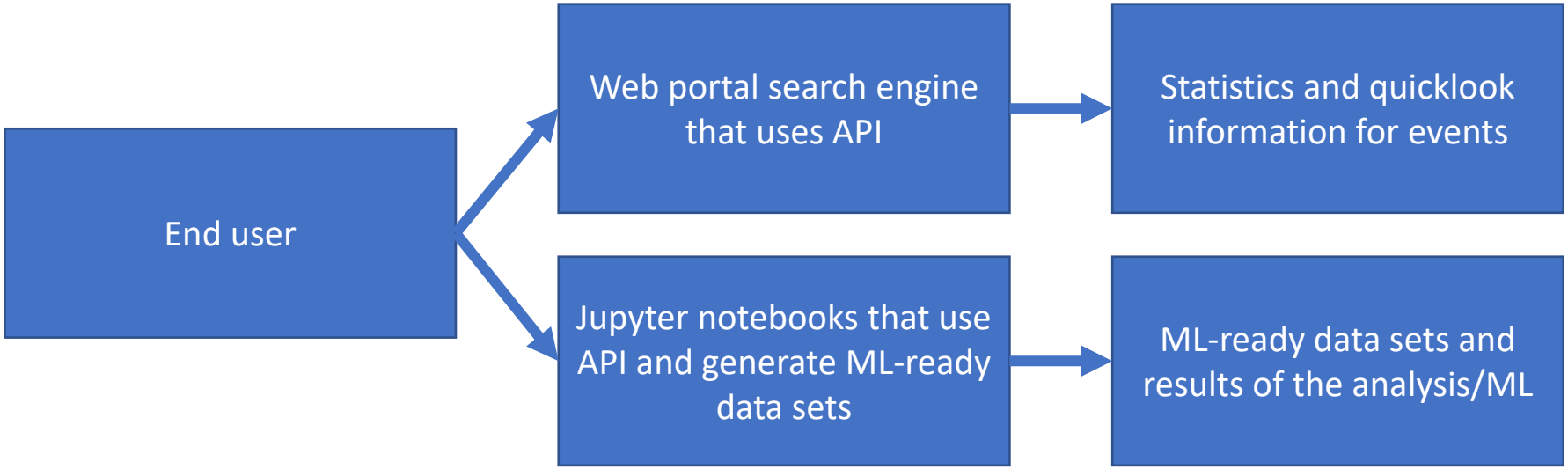
Data Sources and Structure

Solar Energetic Particle DB Data Sources	
Polarity Inversion Line (PIL) properties of Active Regions	GOES proton flux measurements and event catalogs
Space Weather HMI Active Region Patches (SHARPs)	GOES soft X-ray measurements
Flare lists from various flare catalogs (GOES, RHESSI, HEK)	GOES Temperatures and Emission measures
CME lists (LASCO/SOHO and CACTus catalogs)	Records of radio bursts (type II and IV)
Measurements of ground-based neutron monitors	Derived lists of SPE events and SPE-quiet periods
Historic classifications of sunspots & ARs (McIntosh and magnetic classes)	Other resources



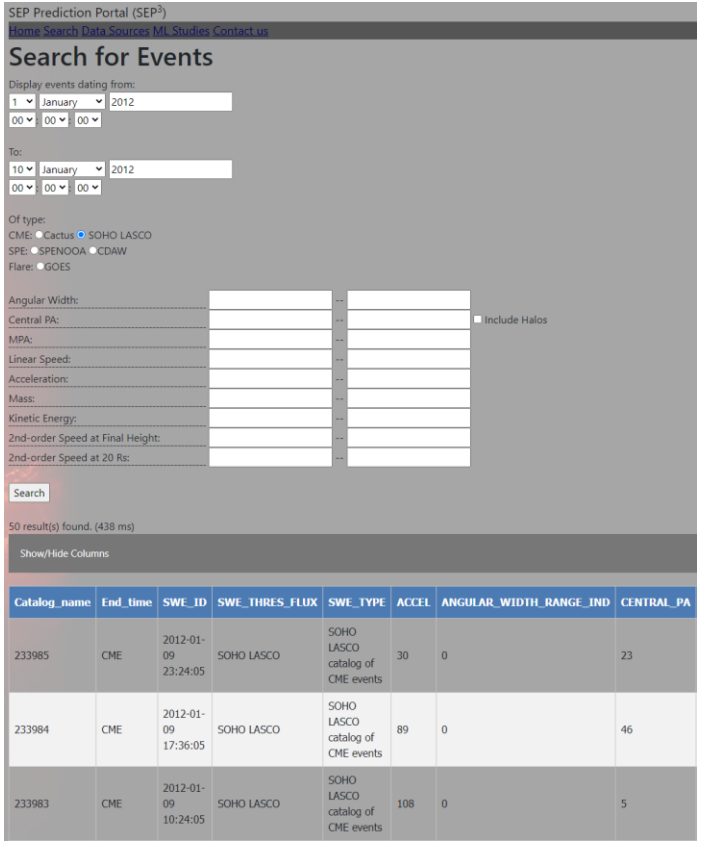
Schematic representation of the MySQL database structure

Approach For ML-Ready Data Sets

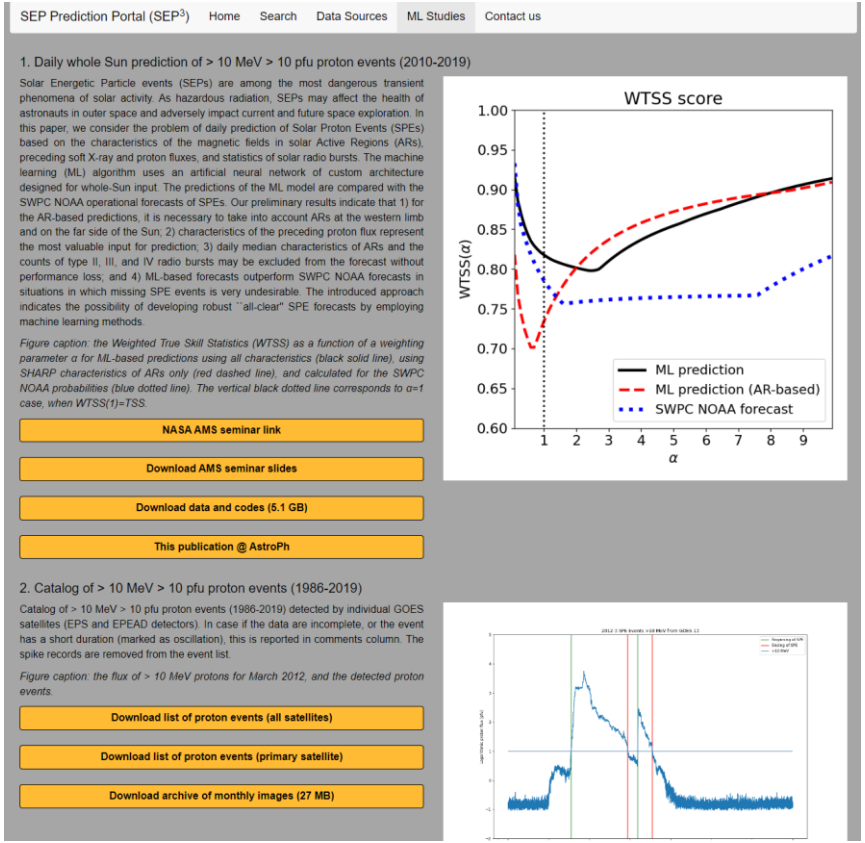


- Our approach is to include both the possibility to browse SEP and related transient activity events via the web search engine and visualizations, and to provide end-to-end Jupyter notebooks for ML-ready data set generation enhancing the project reproducibility and outcomes

Web Portal Overview



Current implementation of the web search page



Publicly-available data catalogs and ML pipelines

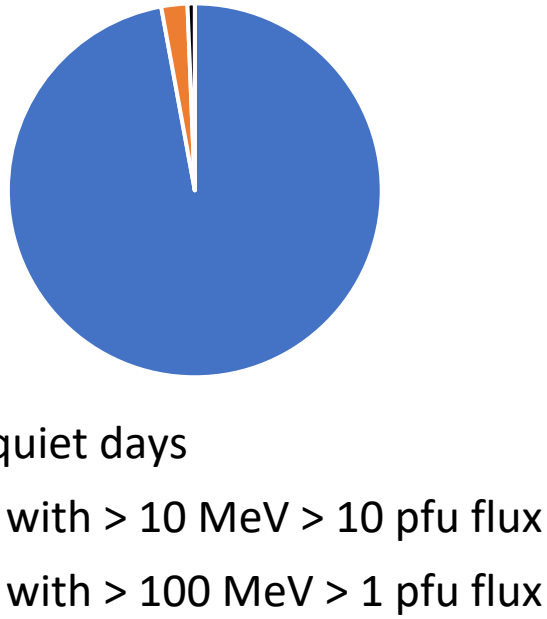
Challenge of SEP Prediction

- Severe class-imbalance ratio. The ratio of SPE-active to SPE-quiet days is:
  - 1/34 for > 10 MeV > 10 pfu events
  - 1/155 for > 100 MeV > 1 pfu events
  - Changes from cycle to cycle
- SPE onset may occur significantly later than the initiating flare.
- The locations of SPE initiations on the Sun are not known precisely. Some events are initiated on the far side of the solar disk.
- In the framework of this study, to predict an SPE event means:

- To predict at 12 AM UT whether the measured peak flux of > 10 MeV protons will exceed 10 particle flux units during the next day. Timeframe: June 2010 – December 2019.

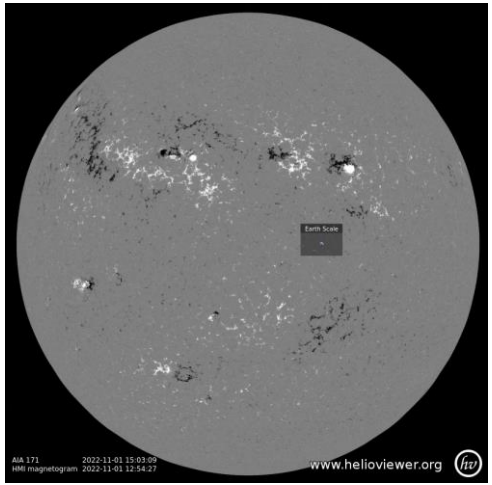
- The problem is formulated as a feature-based binary classification problem

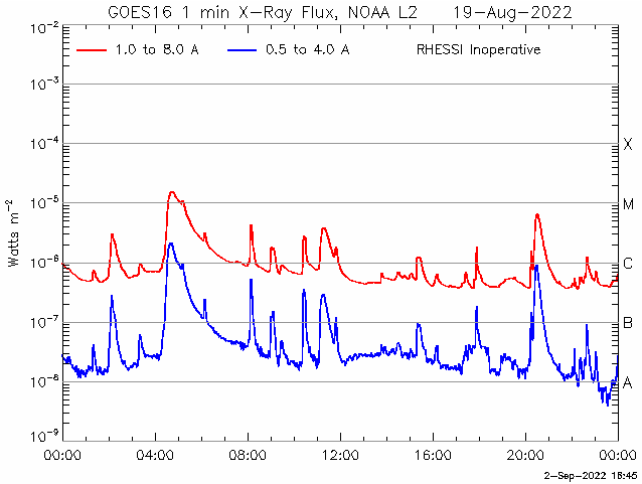
Statistics of SPE days (June 2010 - December 2019)

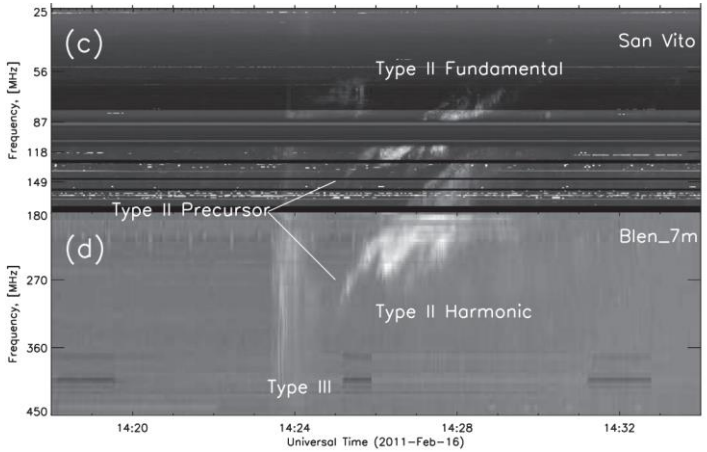


Data Utilized for Prediction

- Properties of the magnetic fields in solar active regions (Space Weather HMI Active Region Patches, SHARPs)
- GOES Soft X-ray radiation
- Detected radio bursts







Credits: https://helioviewer.org/, RHESSI Browser, Zimovets and Sadykov (2015)

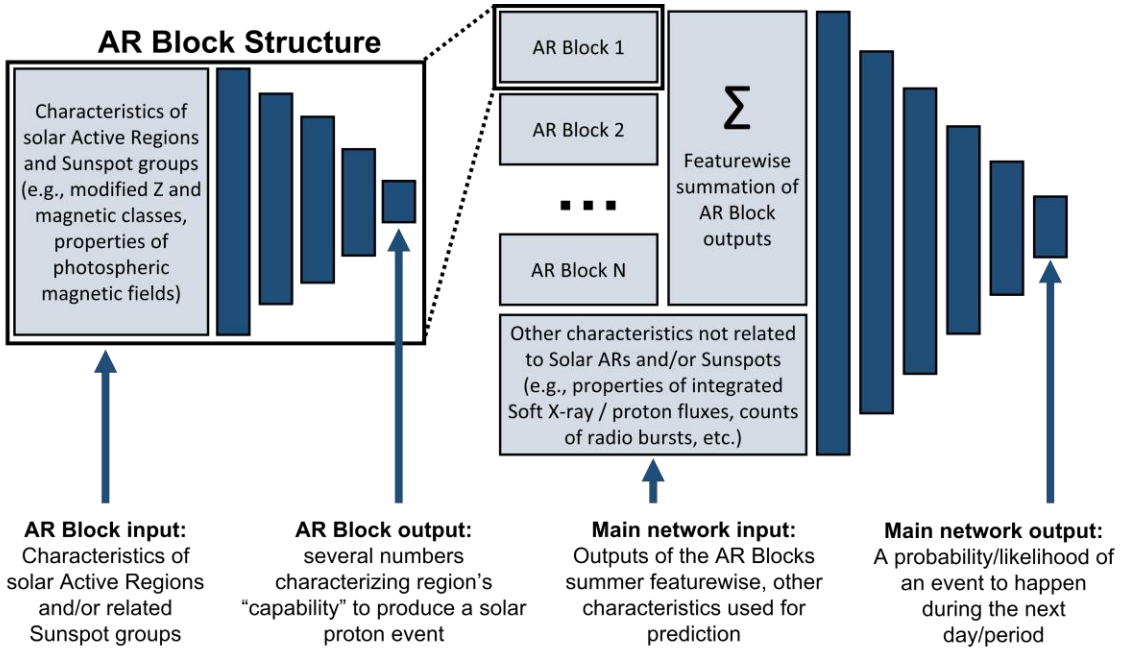
Extracted Characteristics

- Our data set has the following characteristics calculated on daily basis:
  - Median values of SHARP magnetic characteristics for 10 ARs with the largest unsigned magnetic fluxes present on the Sun (including ARs extended behind the Western limb)
  - Mean, median, min, max, and last value for the day for > 10 MeV proton flux
  - Mean, median, min, max values of the 0.5 – 4 Å and 1 – 8 Å SXR flux]
  - Statistics of Radio Bursts (number of type-II and type-IV bursts)
  - The predictions are compared with the SWPC NOAA daily operational forecasts. The details of the data set partition are presented in the table below.

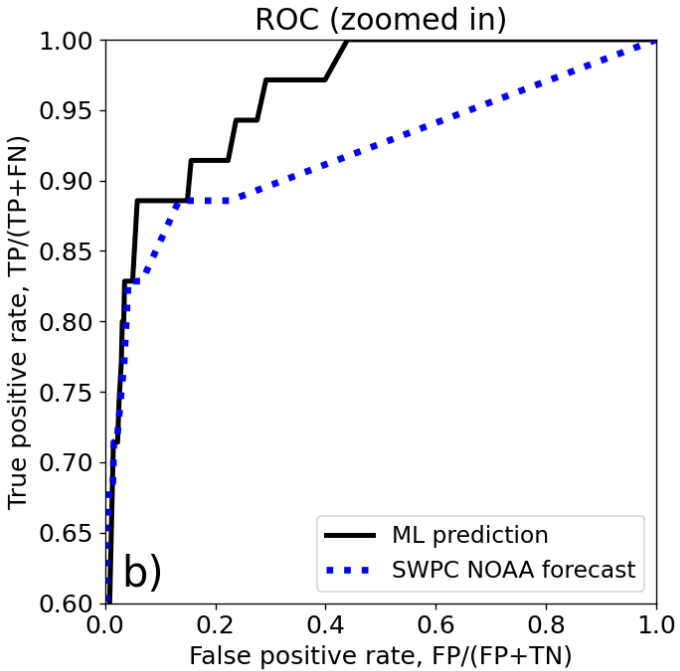
Data Set	Time coverage	SPE Days	Non-SPE Days	Class Ratio
Train	06/2010-12/2013, 01/2016-12/2016, 10/2018-12/2019	66	2222	about 1/34
Test	01/2014-12/2015, 01/2017-10/2018	35	1178	about 1/34

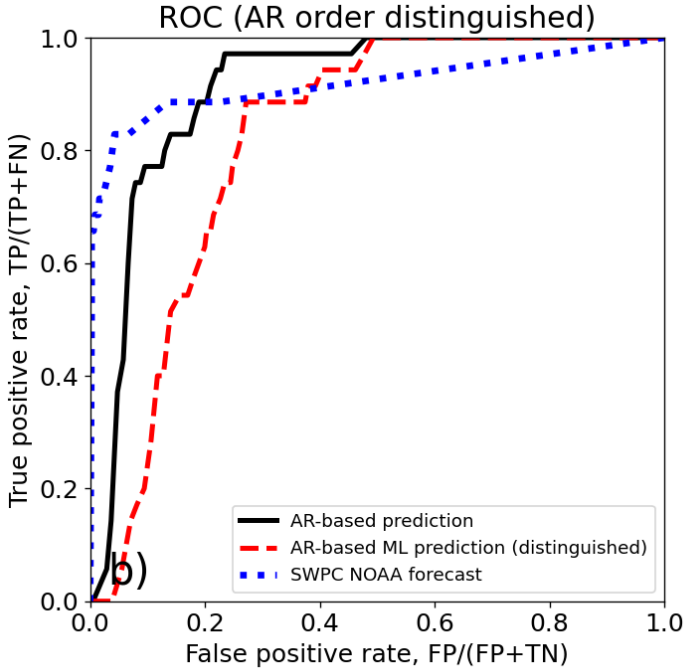
Neural Network for Whole-Sun SEP Prediction

- The network is capable to issue the whole-Sun prediction based on the characteristics of 10 ARs with the strongest unsigned magnetic fluxes, and the characteristics of the whole disk-integrated and in-situ observations
- The network allows to go around the annotation problem (one no longer needs an exact information about the host ARs for SPEs)
- The weight sharing inside the AR Blocks significantly reduces the total number of the network parameters (weights and biases) to be optimized



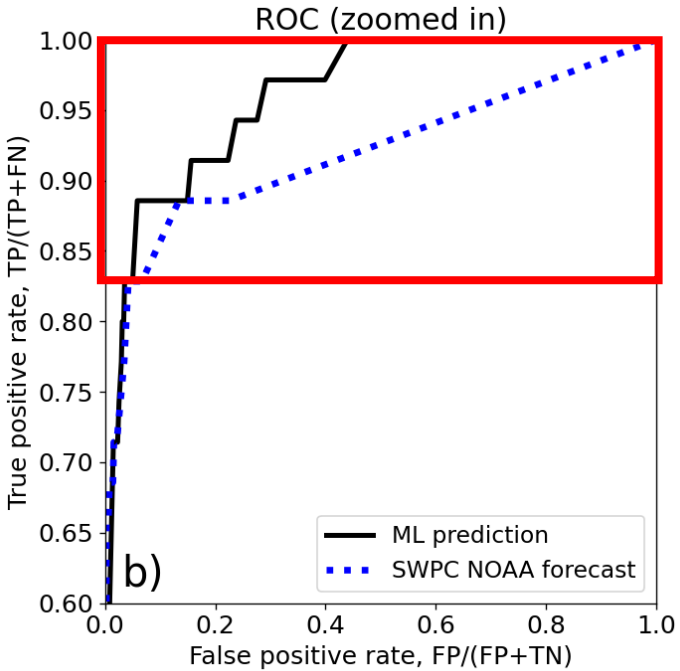
ROC Curves

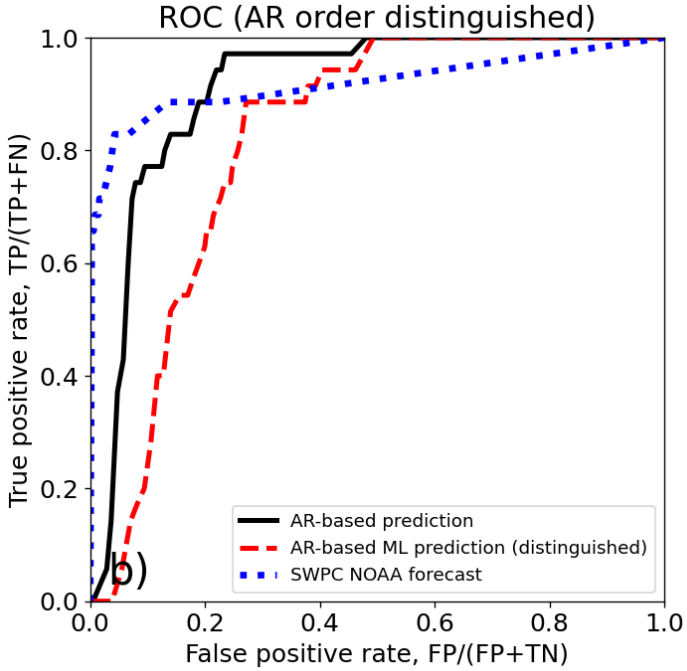




- We compare the predictions of the ML-based approach with SWPC NOAA forecasts based on the Received Operating Characteristic (ROC) curves.
- In addition, we investigated how the exclusion of various characteristics affects the performance.

ROC Curves: Results

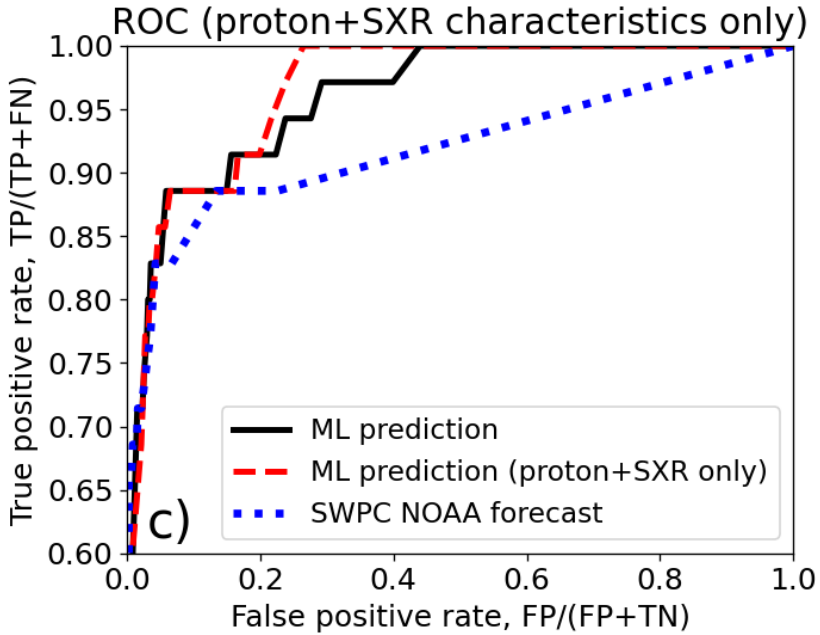


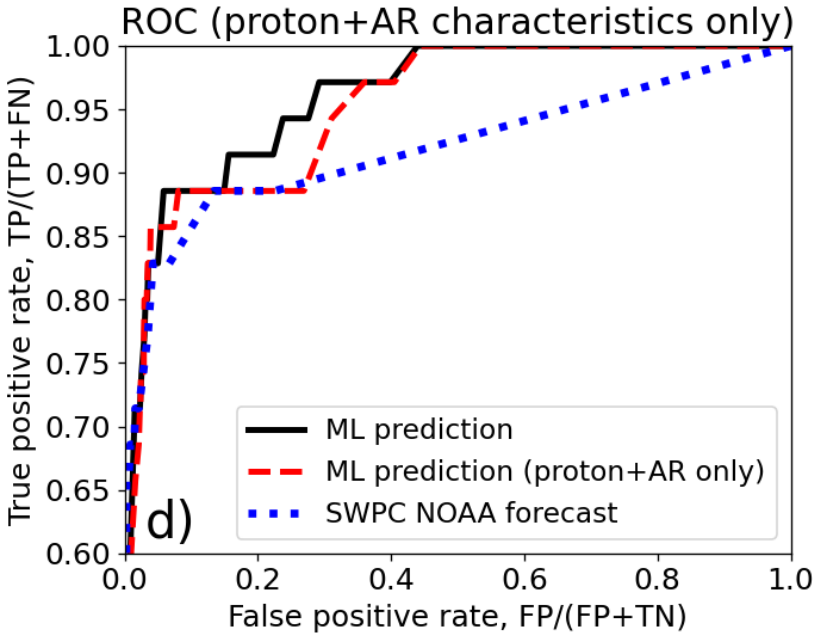


1. ML-based prediction demonstrates smaller looks very promising at the region of high True Positive Rates (top of the plot)

2. The AR-based prediction falls behind the one using all the characteristics. The prediction benefits from extension of ARs to the Western limb and the far side.

ROC Curves: Results





3. Predictions constructed only on > 10 MeV proton flux characteristics, and either AR characteristics or SXR characteristics in addition, have about the same performance as the predictions based on the entire set of characteristics.

Let's talk a little bit more about "all-clear" forecasts…

Evaluation of the Binary Forecast

- The primary outcome of the binary classification problem is a confusion matrix:
  - TP: number of correctly-predicted SEPs (hits)
  - TN: number of correctly-predicted non-SEPs
  - FP: number of incorrectly-predicted SEPs (false alarms)
  - FN: number of incorrectly-predicted non-SEPs (missed events)
- Traditional metrics used for the forecasting (like the TSS and HSS, presented below) are not sufficient to assess “all-clear” forecasts

$$TSS = \frac{TP}{TP + FN} - \frac{FP}{FP + TN}$$

$$HSS_2 = \frac{TP + TN - E}{P + N - E}$$

P = TP + FN

N = TN + FP

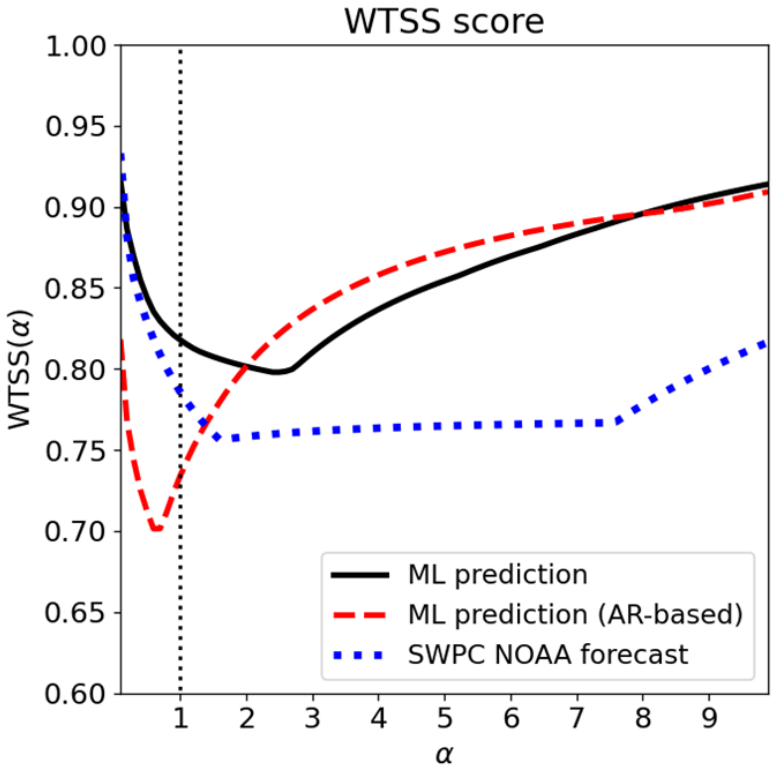
E – expected number of predictions due to chance

“All-clear” Forecast and WTSS metrics

- We define a new metric, a Weighted True Skill Statistics (WTSS), as:

$$WTSS(\alpha) = 1 - \frac{2}{\alpha + 1}\left(\alpha \frac{FN}{P} + \frac{FP}{N}\right)$$

- The SWPC NOAA operational forecast and ML-based prediction are almost the same for α < 1.
- The ML-based prediction are very promising in the α ≥ 1 situations (all-clear zone)



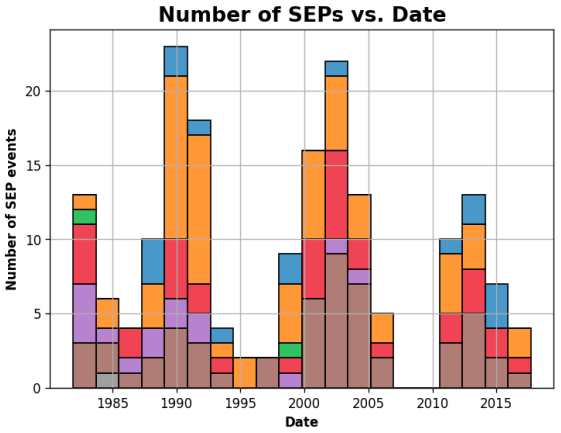
Takeaway Points (Solar Cycle 24)

We are developing an online-accessible database that integrates the solar and heliospheric data, metadata, and data products (SEP Prediction Portal). We also investigated the daily prediction of SPEs and the related "all-clear" approach for the SC24 data and concluded that:

- For AR-based predictions, it is necessary to consider ARs at the western limb and on the far side of the Sun;
- Characteristics of the preceding proton flux are the most important for prediction;
- Predictions constructed only on > 10 MeV proton flux characteristics, and either AR characteristics or SXR characteristics in addition, have the same performance as the predictions based on the entire set of characteristics.
- ML-based forecasts demonstrate promising results in “all-clear” forecast settings

Extending the SC24 Forecast

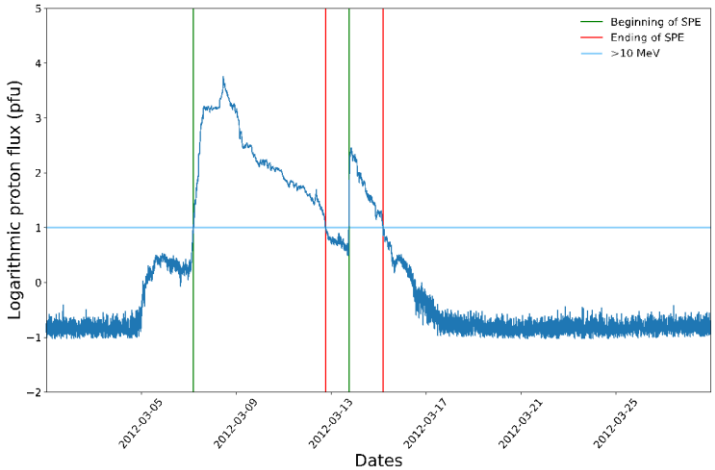
- One of the major problems of forecasting based on Solar Cycle 24 (2010-2020) is in the low number of SEP days (about 100) or SEP events (only about 45)
- To enlarge the statistics and investigate a cross-cycle transferability of the forecasting attempt, we extend our forecast to the Solar Cycle 23 (1997-2009) and Solar Cycle 22 (1986-1997)
- We are currently conducting two related studies:
  - Prediction of SEPs based on the statistical properties of GOES SXR and proton fluxes (1986-2020)
  - Statistical association of SEPs with the sunspot and active region classes (1981-2020)



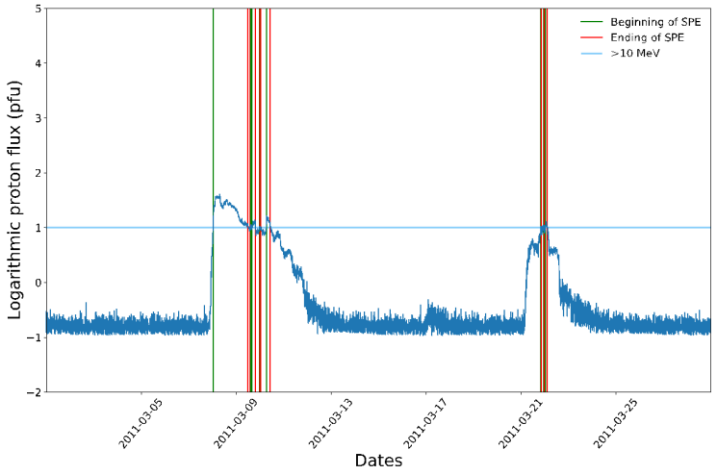
Credits: R. Marroquin

SXR Data Processing: Event Detection

- >10 MeV >10 pfu Solar Proton Events were identified using proton flux data and recorded for each GOES satellite. This catalog was successfully cross-checked with that produced by NOAA's Space Environment Services Center for validation



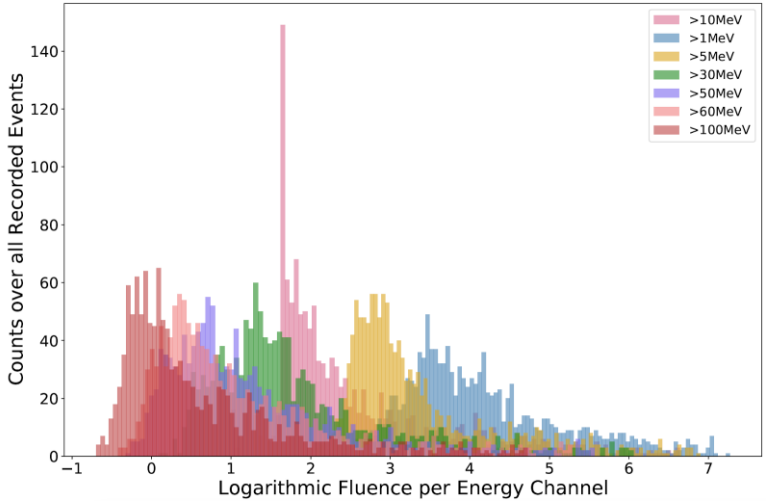
Example of the classification of an event with start & end times cataloged per month, for every year data is available.



Example of oscillations seen in the data along the threshold.

SXR Data Processing: Event Detection

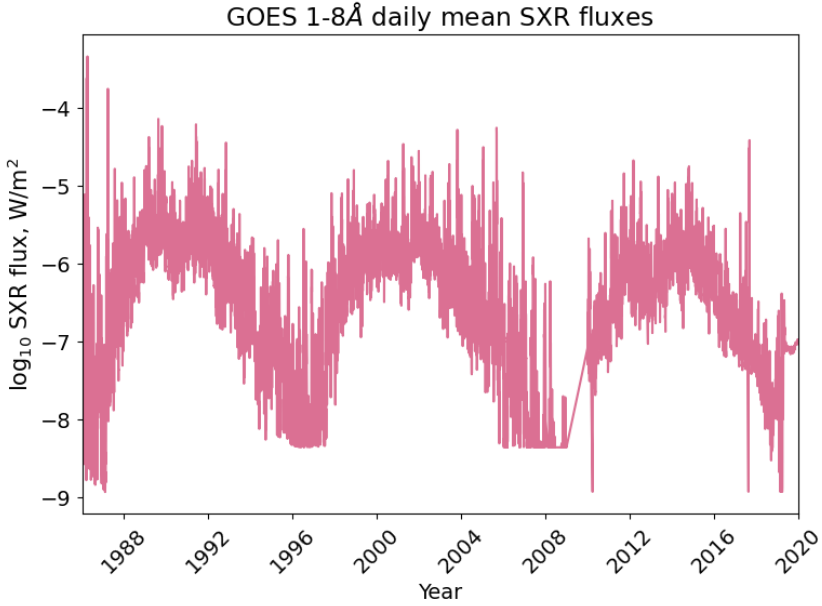
- The properties of the events in different energy channels (particle peak fluxes, fluences, etc) were recorded in the catalog
- In addition, a catalog containing the events from only the primary GOES satellite/detector was constructed
  - What does the “primary” GOES satellite mean? Because of gyration of protons in the Earth’s magnetic field, some orientations of the GOES detectors are more sensitive to protons arriving from the Sun than anothers



Fluence distribution across multiple energy channels during recorded SPEs

SXR Data Processing: Daily Statistics

- SXR data was revised according to NOAA scaling corrections and a catalog representing different parameters of daily SXR and Proton flux properties (mean, median, kurtosis, etc.) for 1986-2020 was built.
- Again, the version of the catalog corresponding to the primary GOES satellite was created.



Mean Soft X-ray flux over three solar cycles

Cross-Cycle Forecasting

- Given the timescale of the data set, one can train the ML algorithm on one Solar Cycles and investigate how transferable is the model to other Solar Cycles
- We have utilized Support Vector Machine (SVM) classifiers with the Radial Basis Function (RBF) kernels. The misclassification weights were proportional to the statistical appearances of the SEP events in the train data set

Cross-Cycle Forecasting

	SC22 (Training cycle)	SC23 (Training cycle)	SC24 (Training cycle)	Training on 2 Remaining Cycles
SC22 (Testing cycle)		0.75	0.63	0.73
SC23 (Testing cycle)	0.72		0.43	0.76
SC24 (Testing cycle)	0.68	0.66		0.69

Figure 10: True Skill Statistic (TSS) scores for RBF SVM (balanced weights).

	SC22 (Training cycle)	SC23 (Training cycle)	SC24 (Training cycle)	Training on 2 Remaining Cycles
SC22 (Testing cycle)		0.49	0.21	0.38
SC23 (Testing cycle)	0.69		0.08	0.51
SC24 (Testing cycle)	0.54	0.52		0.56

Figure 11: Heidke Skill Score (HSS_2) scores for RBF SVM (balanced weights).

$$TSS = \frac{TP}{TP + FN} - \frac{FP}{FP + TN}$$

$$HSS_2 = \frac{TP + TN - E}{P + N - E}$$

P = TP + FN

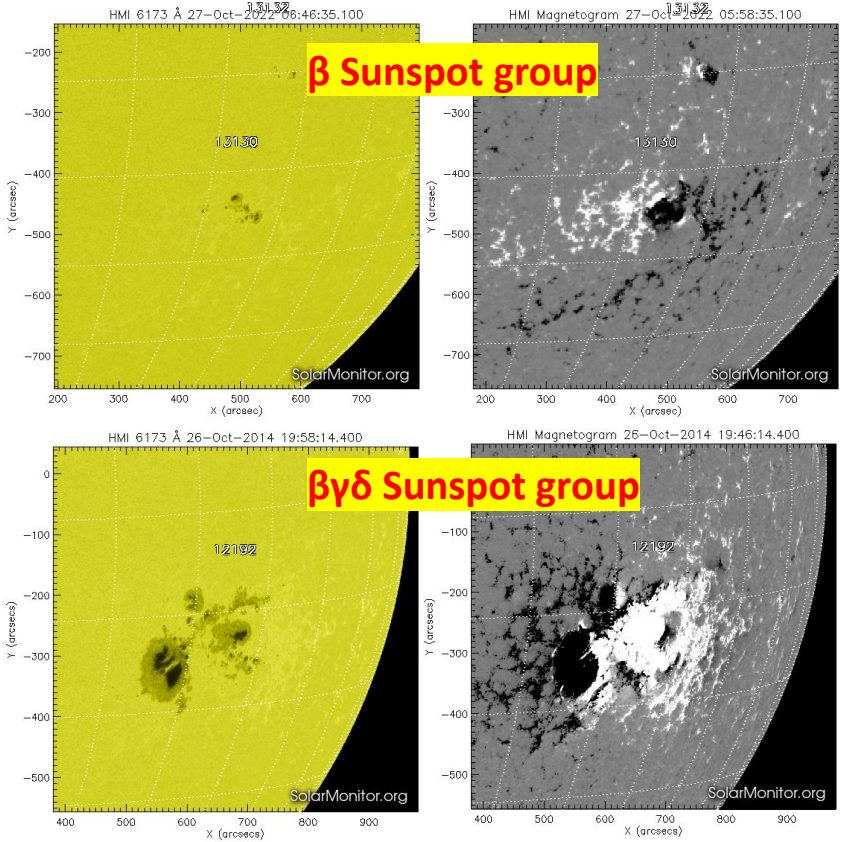
N = TN + FP

E – expected number of predictions due to chance

Credits: Aatiya Ali

Hale Classification of Sunspots/ARs

- α – a single spot connected to a plage
- β – a pair of spots of opposite polarity
- γ – a complex irregular spot
- δ – umbras of opposite polarity within the same penumbra
- The combinations (βγ, γδ, βγδ) are possible



McIntosh Classes

- McIntosh classification is a 3-letter classification describing:
  - Overall complexity (modified Zurich classes)
  - Properties of the penumbra
  - Distribution of sunspots
- Credits: McIntosh (1990)

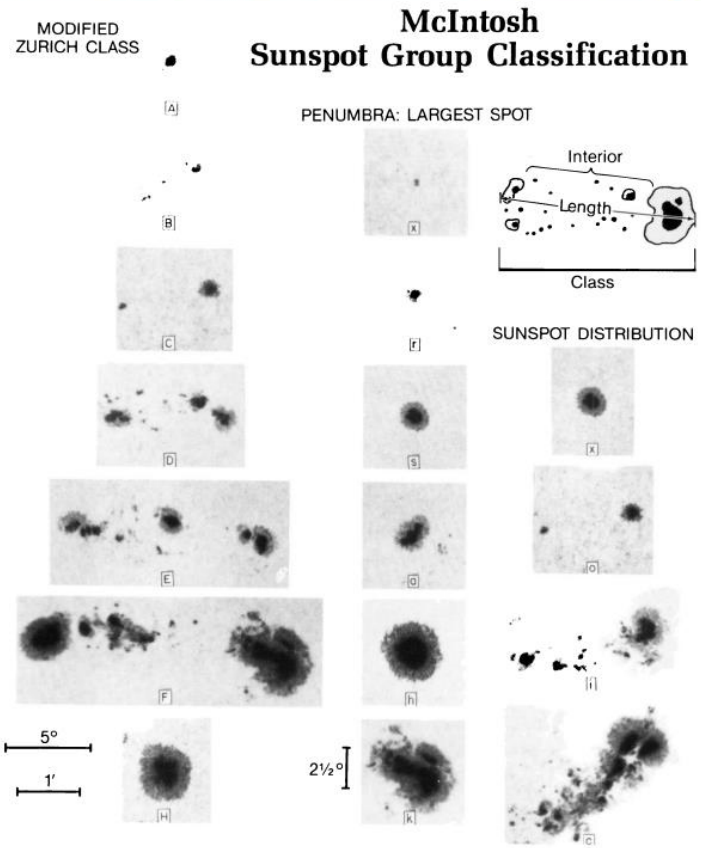


Fig. 1. The 3-component McIntosh classification, with examples of each category.

Merging SWPC NOAA and USAF Reports

- We created a dataset of McIntosh and magnetic AR classes spanning 1982-2020 by merging (1) SWPC NOAA SRS records and (2) USAF sunspot group reports (available via FTP at SWPC NOAA)
- Challenges while merging:
  - SWPC NOAA SRS records are available since 1996 and represent the daily AR records at midnight UT, one record per AR
  - USAF records are collected from different observing sites throughout the day, there might be several records per AR
- To homogenize the data set, USAF records were brought into the SWPC NOAA format. Original version of records is also available.

Merging SWPC NOAA and USAF Reports

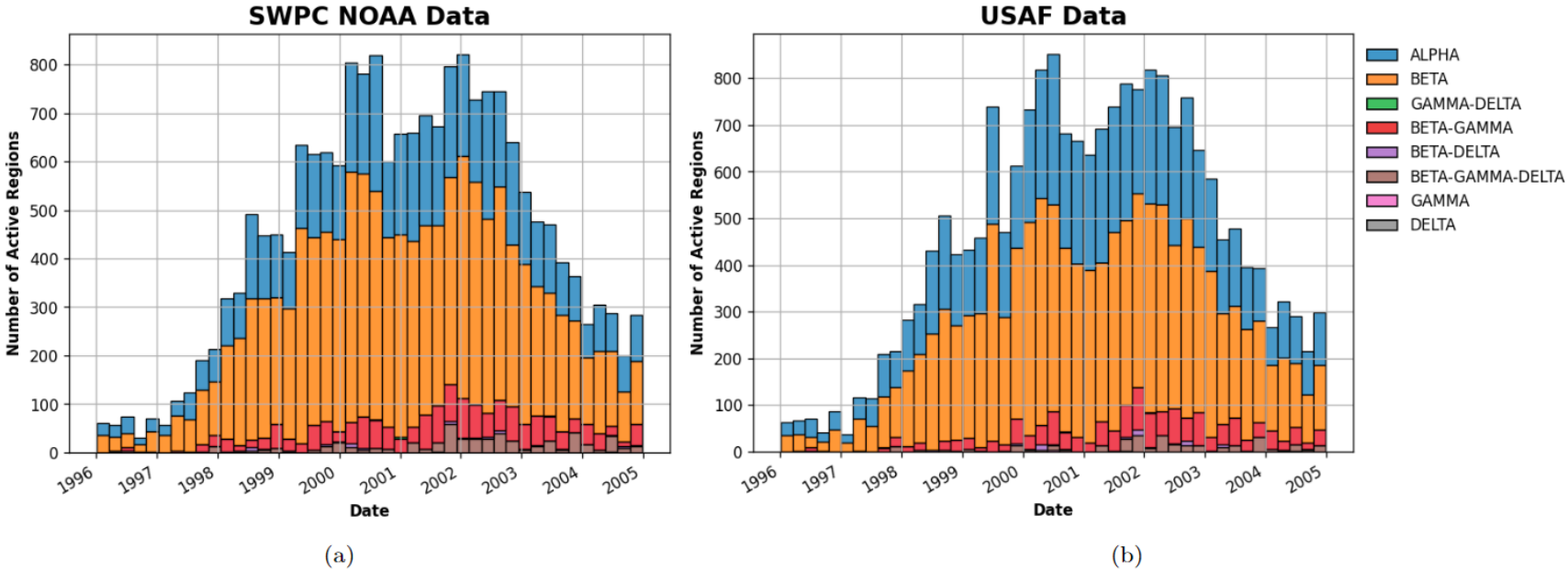
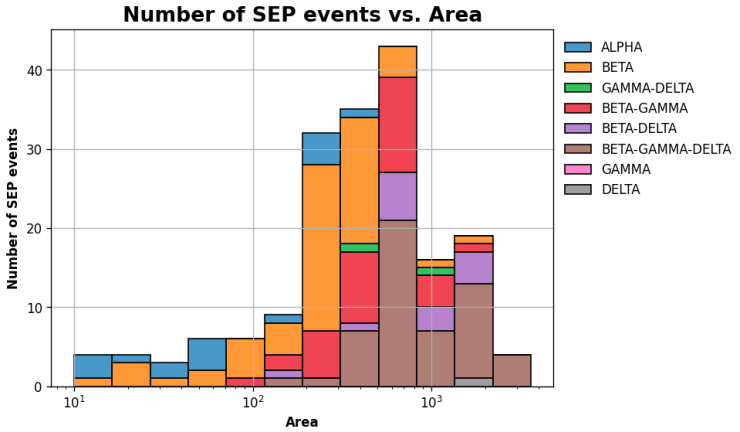


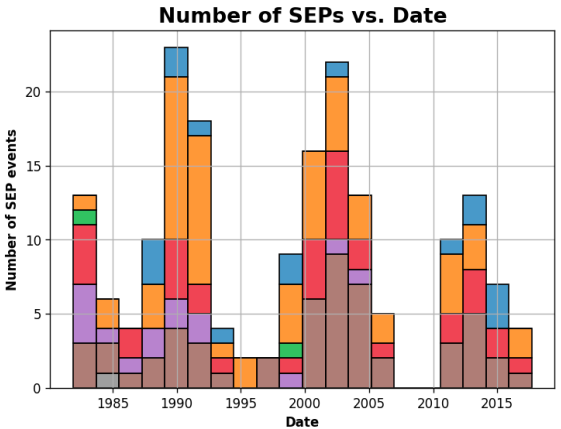
Figure 2. Histograms used to perform the homogeneity test. The left panel (a) shows data originating from the Space Weather Prediction Center of the North Oceanic and Atmospheric Administration (SWPC NOAA). Right panel (b) shows data from the US Air Force (USAF). The legend shows the Hale classifications and the contribution of Active Regions (ARs) in a respective Hale class to the total number number of ARs in each bin. Appearance of each class is consistent throughout the entire figure.

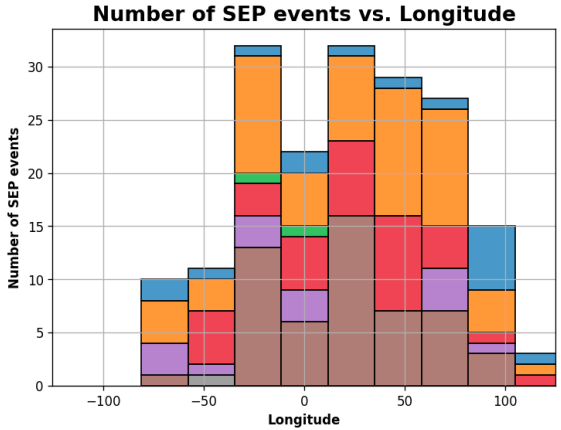
Credits: R. Marroquin

Linking SEPs to Active Regions

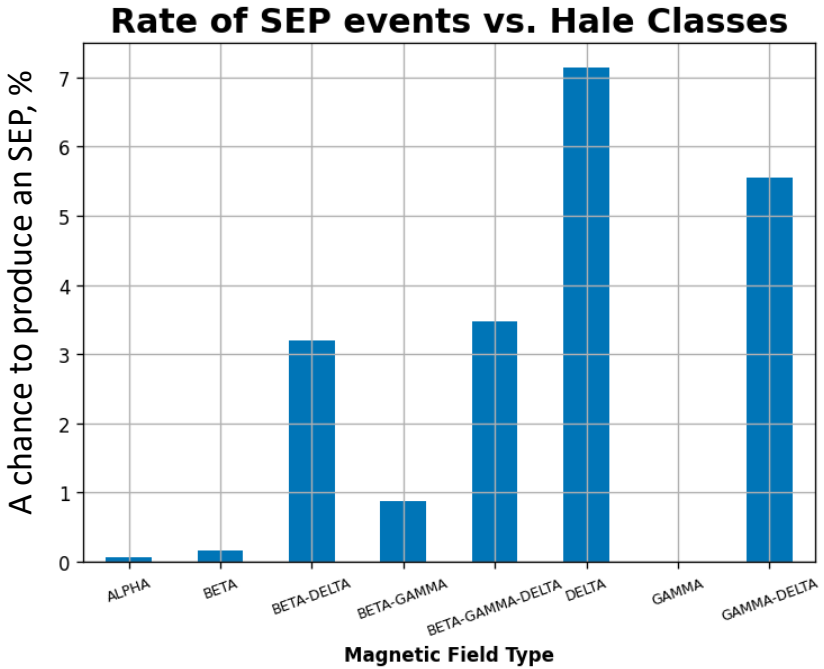
- SEP events from SWPC NOAA catalog contain associations with the host active regions => we can study the statistics of SEP-productive ARs

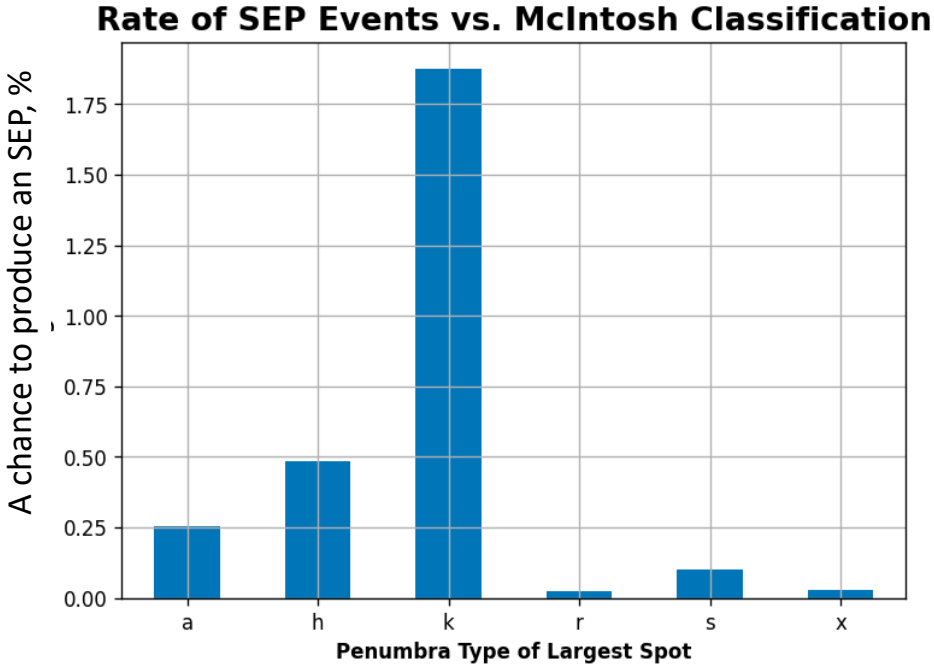






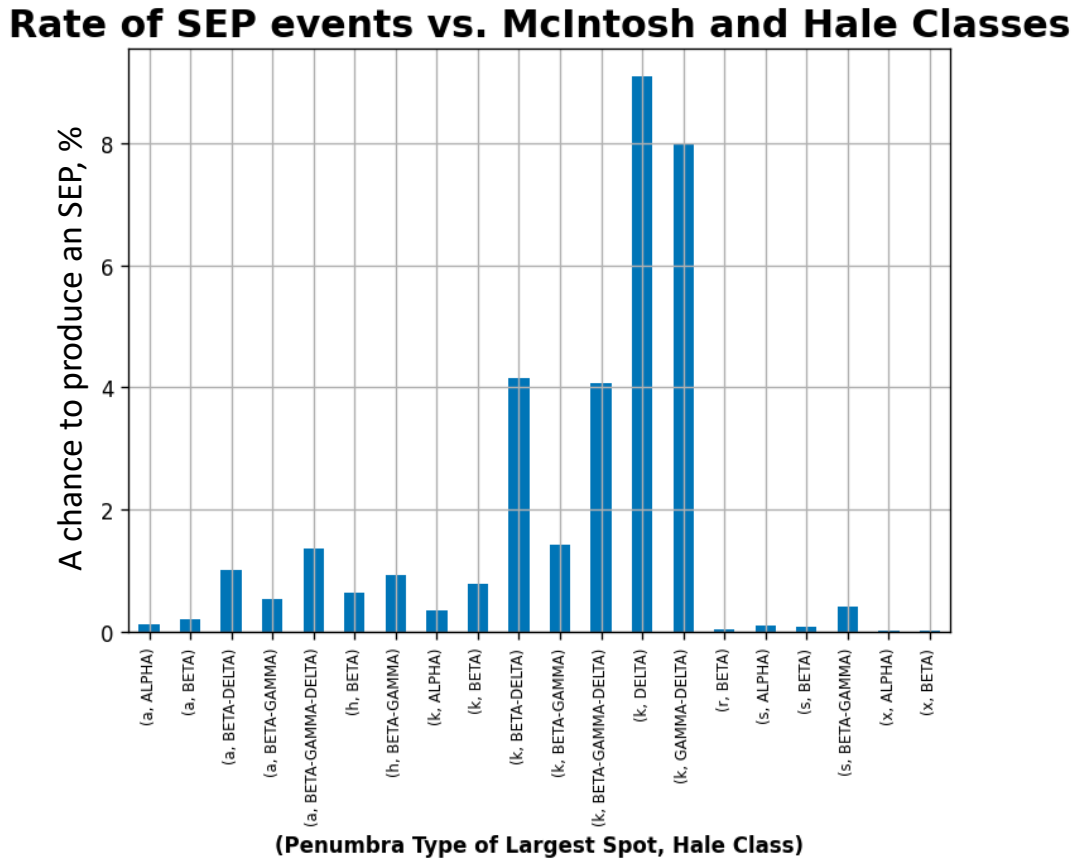
Combining McIntosh and Hale Classes





Combining McIntosh and Hale Classes

- Combining McIntosh and Hale classes is beneficial. It indicates active regions, appearance of which results in 10% chance of SPEs
- We are currently expanding this study and employing machine learning for prediction of SEPs based on the AR classes

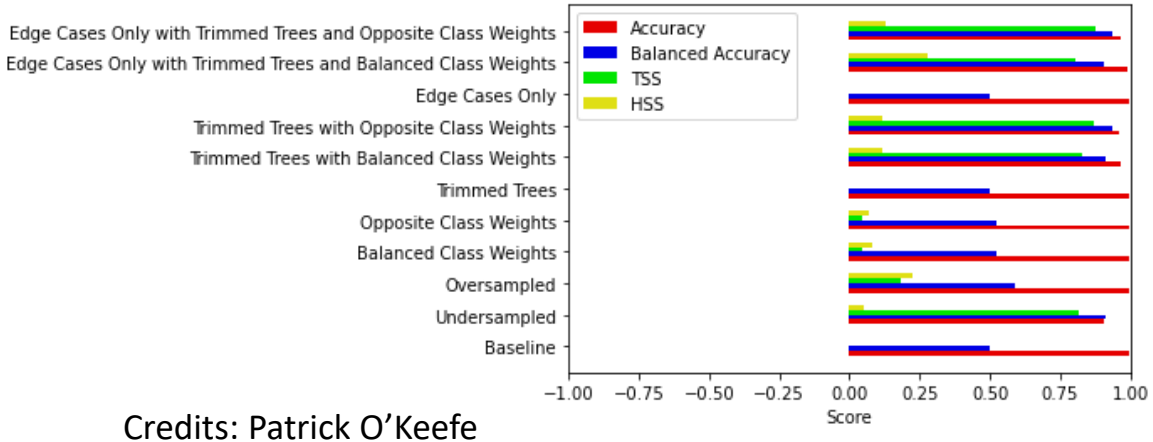


Takeaway Points (Historical Data)

- Attempts to predict the SEPs based on the statistical daily features of the GOES soft X-ray and proton fluxes reveal challenges with the cross-cycle transferability of the forecast
  - Seems to be related to the different frequencies of appearance of SEPs in different solar cycles
  - The effect is also mentioned by Stumpo et al. 2021
- Combination of the McIntosh and Hale classes of the solar active regions increases the SEP forecasting capabilities (based on the statistical study)
- We are currently combining both sets of descriptors to investigate the “all-clear” perspectives of the problem

Additions: Flare-driven SPE forecast

- In addition to the forecasts based on the statistical features, we are attempting to predict whether the solar flare is followed by the SPE.
- The prediction attempt is done based on the features of the GOES SXR flux (peak values of SXR at 0.5-4 Å and 1-8 Å channels, derived T and EM, as well as the timing properties).
- The Random Forest classification algorithm is currently under testing, as well as various strategies of working with the class-imbalance problem
- Novel approaches involving ensembles of neural networks (random hivemind) are under investigation



Credits: Patrick O'Keefe

Conclusion

- The prediction of the solar cycle 24 SPEs demonstrated promising results, especially in the direction of “all-clear” forecasts. “All-clear” settings remain to be a largely unexplored field.
- We are currently extending the study on historical data:
  - We see challenges with the cross-cycle transferability for prediction of SPEs based on daily statistical properties of GOES measurements (1986-2020)
  - We see promising statistical results of combining McIntosh and magnetic classes of active regions for SEP prediction
  - We are investigating prediction of SPEs based on the SXR properties of parental flares (2002-2020)

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