Forecasting the Occurrence Probability and Properties of Solar Energetic Particle Events using a Multivariate Ensemble of Convolutional Neural Networks

Subhamoy Chatterjee[1], Maher Dayeh[1,3] Andrés Muñoz-Jaramillo[1], Kim Moreland[3,1], Hazel M. Bain[2]

(1) Southwest Research Institute, USA, (2) CIRES CU Boulder / NOAA SWPC, USA, (3) University of Texas, San Antonio, Texas, USA

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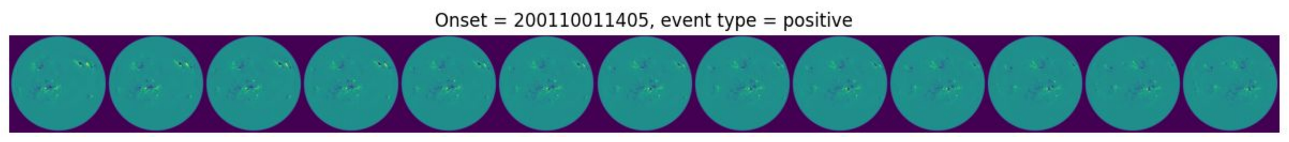
INTRODUCTION & MOTIVATION

- Solar Energetic Particle (SEPs) events can disrupt communication satellites and pose radiation hazards on astronauts [1]
- Reliable early prediction of SEPs is important [1]
- Neural Network (NNs) based prediction models are promising as they can ingest complex inputs [2]
- NN based binary classification models often suffer from low reliability [3,4]
- Perfect Reliability:
  - NN outcome = Positive event frequency [1,3,4]
- Reliability Calibration is important to convert NN outcome to true probability [3,4]

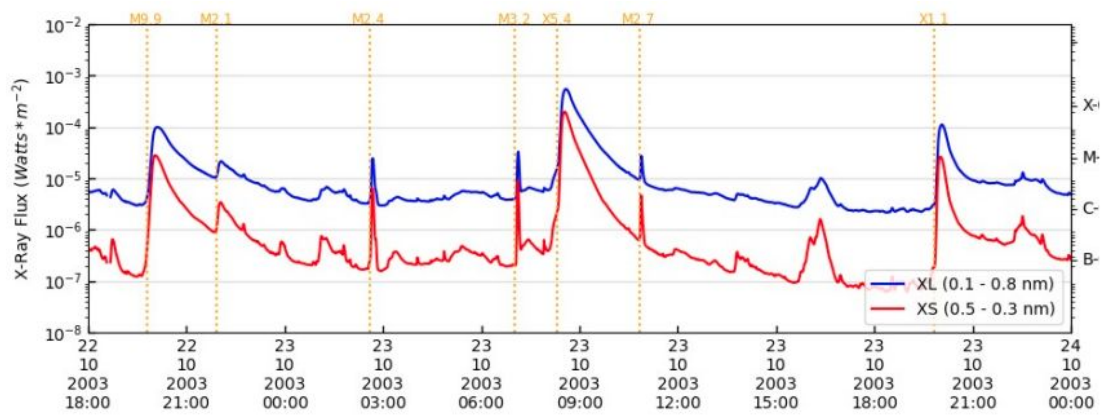
DATASET

- We currently consider the following inputs to predict *SEP occurrence probability* and *SEP peak*-

1. Full-disc (SoHO/MDI + SDO/HMI) magnetogram sequences spanning over 3 days prior to flare-onset with a temporal resolution of 6 hours.



2. Pre-flare upstream properties such as solar wind plasma (speed, density), interplanetary magnetic field components and elemental abundances etc.
3. GOES X-ray pre-flare time series for 24 hours with a temporal resolution of 1 minute.

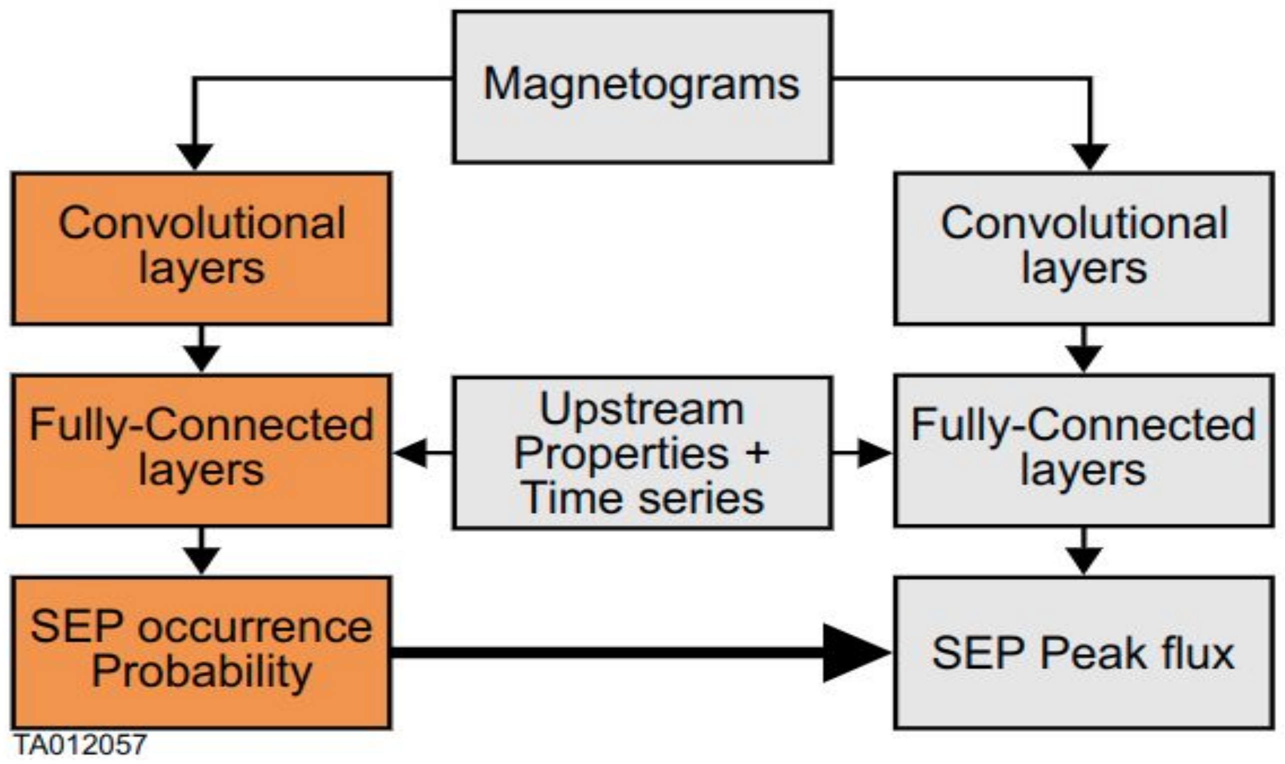


4. GOES Electron pre-flare time series for 24 hours with a temporal resolution of 5 minutes.

For more details on the background and data preparation look at Moreland et al. poster, ML-HELIO 2022

MODEL ARCHITECTURE

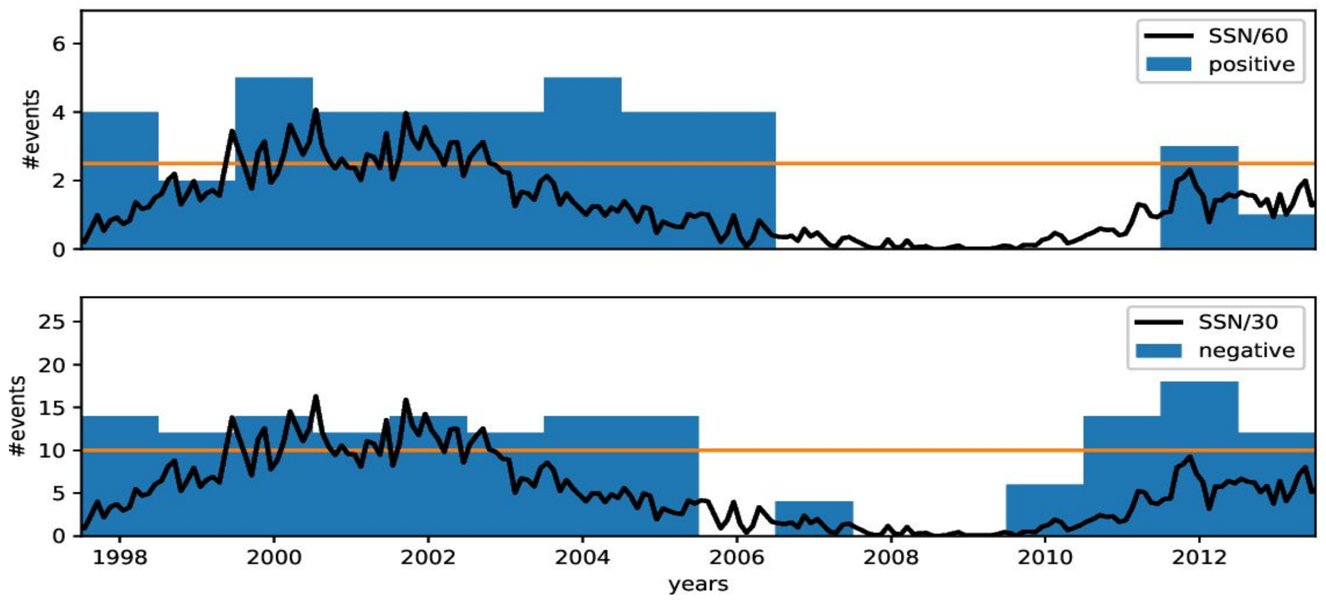
- We use the following Convolutional Neural Network (CNN) architecture that ingests both Magnetogram video and in-situ parameters, time series to predict both SEP occurrence and Peak.



- We first train the probability prediction branch, freeze all the weights, biases and use the outcome to put weightage to the loss function of the peak prediction branch (trained afterwards)

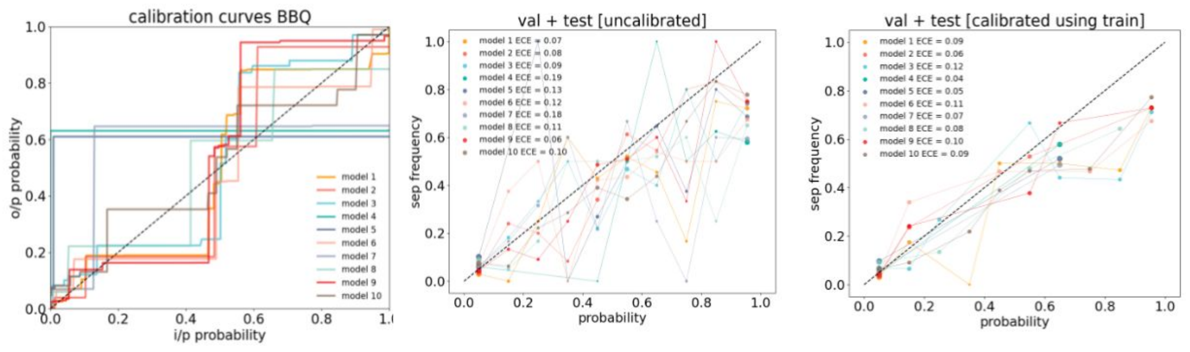
MODEL ENSEMBLE

- Large class imbalance between positives and negatives to train an ensemble of models
- 10 models: different training + validation sets with common positives and different negatives chosen from equal frequency flare strength histograms with minimal intersection
- We design a test set that is tailored to be non-modulated by the solar cycle phase and includes all flare classes (C, M, X)

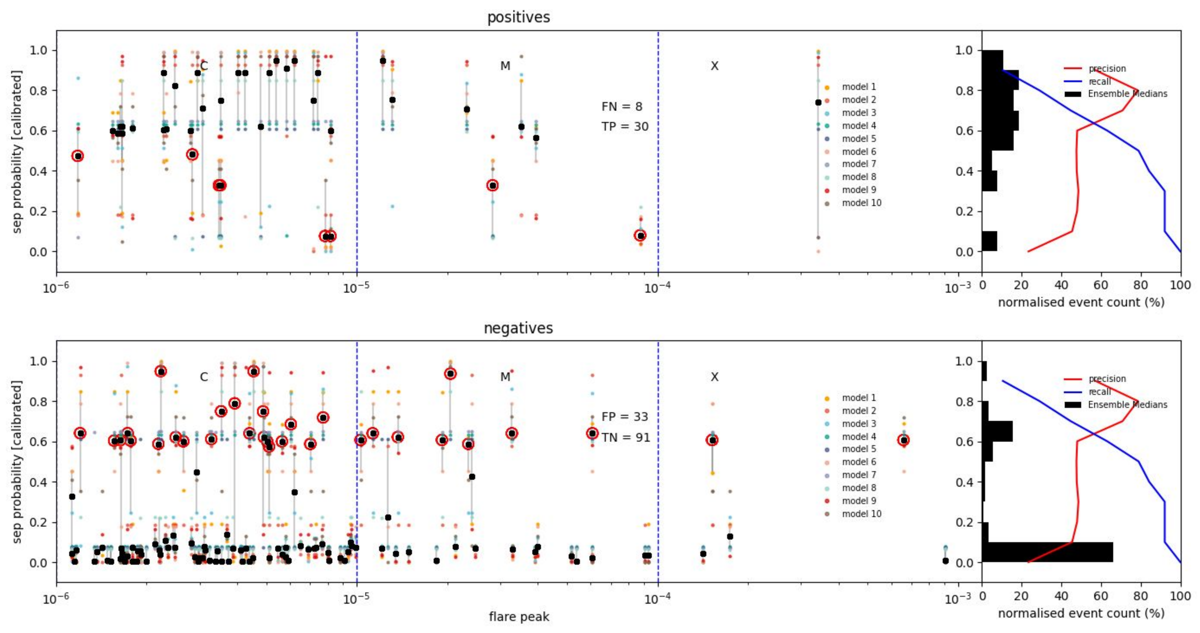


PREDICTING TRUE PROBABILITY OF SEP OCCURRENCE WITH UNCERTAINTY

- We emphasize that our objective here is not to do just a binary classification. Instead, we focus on estimating true probabilities of SEP occurrence.
- We calibrate each CNN outcome using Bayesian Binning Quantile (BBQ) [4] method.



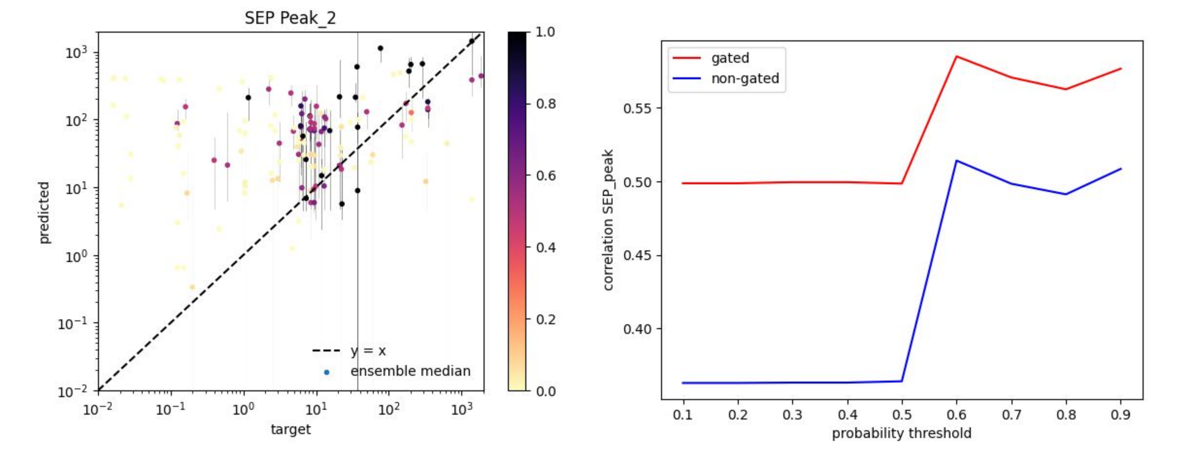
- Evaluating the model-ensemble with calibrated outcome on test-set events provides a clear picture of uncertainty in SEP occurrence probability.



- For model validation we evaluate classification metrics such Probability of Detection (TP/TP + FN), False Positive Rate (FP/FP + TN) True Skill Statistic, Heidke Skill Score and find their values to be 0.79, 0.27, 0.52 and 0.43 respectively.
- We also evaluate the metrics that do not depend on a single classification threshold such as AUC, Brier Score (BS) and find their values to be 0.85 and 0.14 respectively.

PREDICTING SEP PEAK FLUX WITH UNCERTAINTY

- We currently predict SEP peak flux (9-15 MeV) for each event on test set using the model-ensemble.
- We find improvement (correlation of model median vs. target > 0.55 at probability threshold of 0.6) in prediction by weighting the loss function with SEP occurrence probability (gating) during training.



CONCLUSION AND FUTURE SCOPE

- We train an ensemble of CNNs that ingests remote sensing and in-situ parameters to predict SEP occurrence probability and peak flux
- We calibrate CNN outcome to go beyond binary classification and predict true SEP probability that is correlated with SEP event frequency
- We put weightage to peak flux prediction task according to the predicted probability and find definite improvements in prediction
- We would like to convey that our model has capability to seamlessly ingest additional inputs such as EUV images, Coronagraph images, radio burst data and can predict properties such as peak flux (>5, 10, 30, 60, 100 MeV), onset time, peak time, end time and fluence. We are currently working on that aspect to evaluate the improvements.

References

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