MEMPSEP: A Multivariate Ensemble of Models for Probabilistic forecast of SEP Occurrence and Properties

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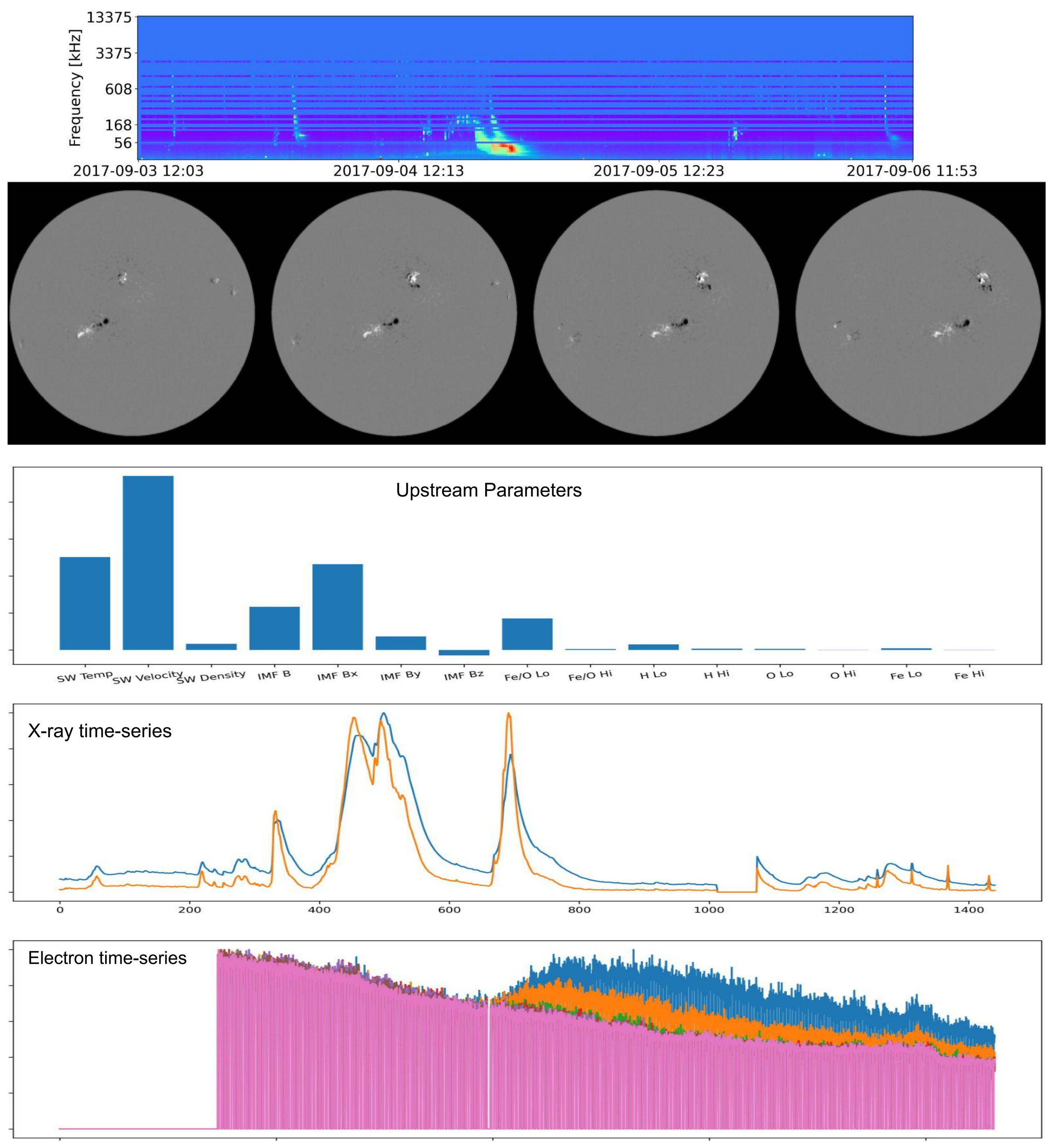
This work is fully supported by the O2R program (Grant no. 80NSSC20K0290)

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]
- Reliability Calibration is important to convert NN outcome to true probability [3,4]
- SEPs events being rare in nature, model-ensembles are desirable to estimate prediction uncertainty.

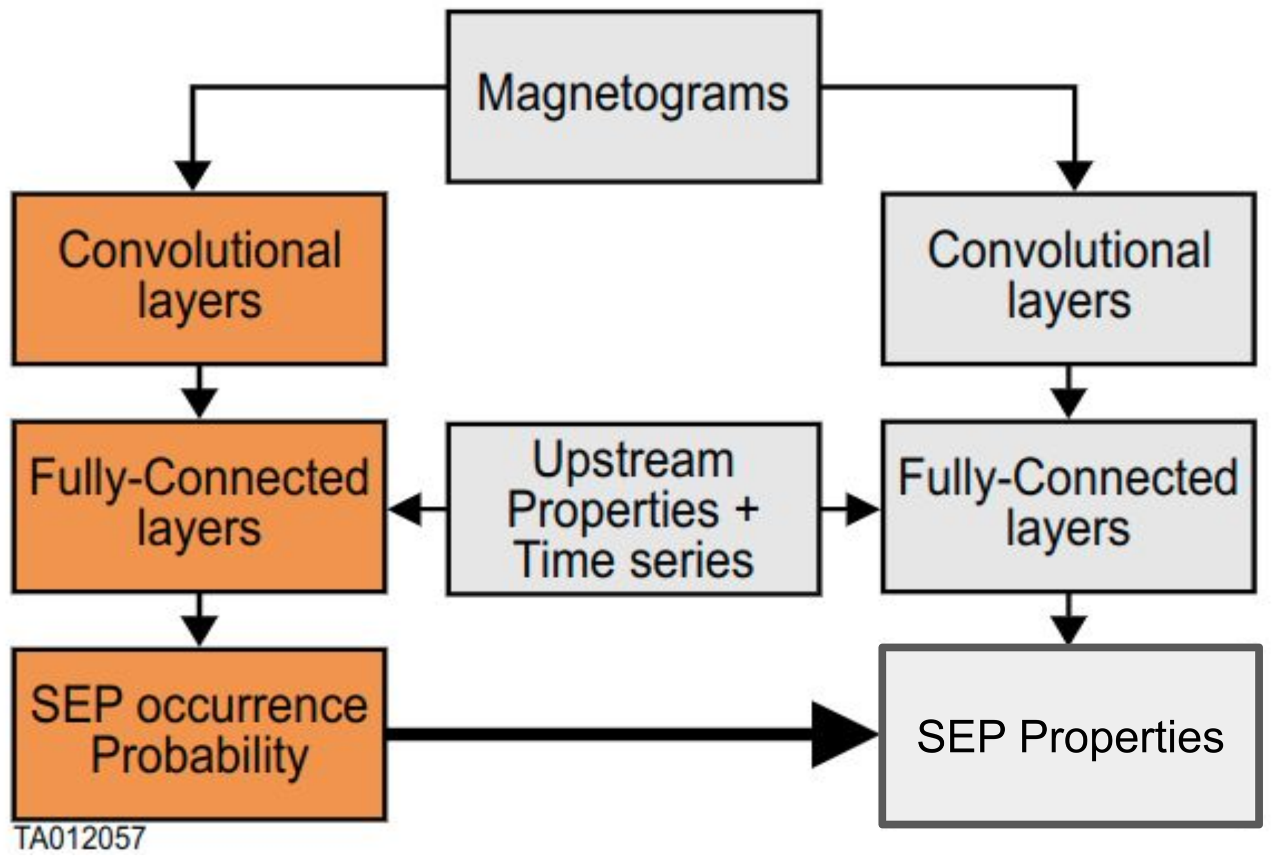
DATASET

- We use both remote sensing and in-situ data as predictors to forecast occurrence probability of SEP event.
- Inputs are collected over 3 days (at maximum) prior to flare onset
- A ground-truth of 'Event' is placed if integrated particle flux (>10 MeV) crosses 5 p.f.u. threshold within 6 hours from flare onset.
- Predictors in the form of images, time series and scalar entities.



MODEL ENSEMBLE

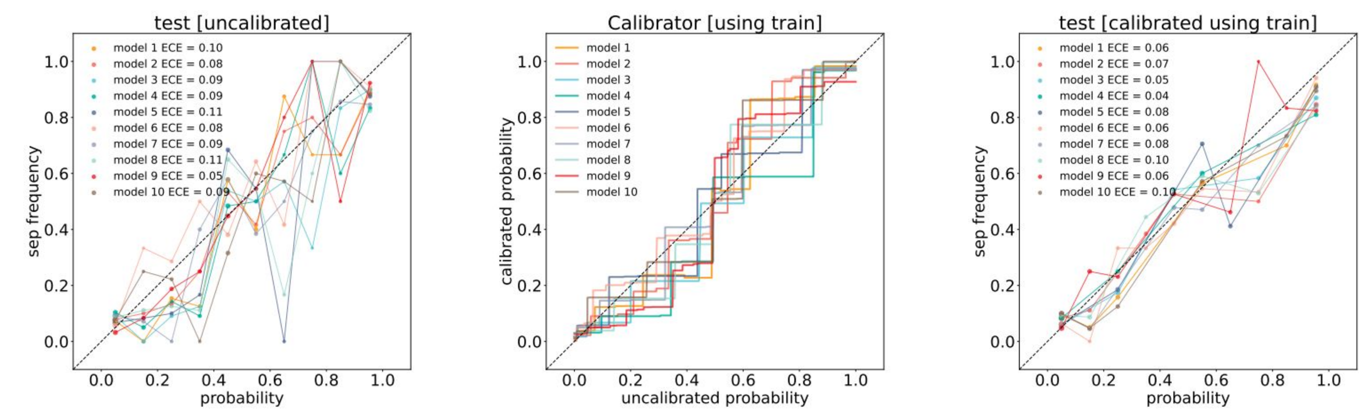
- We use the following multi-channel Convolutional Neural Network (CNN) architecture that ingests both Magnetogram video and in-situ parameters, time series to predict SEP occurrence probability and SEP properties.



- Raw outcome of model represents uncalibrated probability and needs to be calibrated to match frequency of events i.e. to make the outcome reliable.
- Large class imbalance between positives and negatives to train an ensemble of models
- 10 models: different training + validation sets with common positives and largely different negatives
- We first train the probability prediction branch, freeze all the weights/biases and use the outcome as weightage to the loss function of the branch for prediction of SEP properties

PREDICTING TRUE PROBABILITY OF SEP-event OCCURRENCE

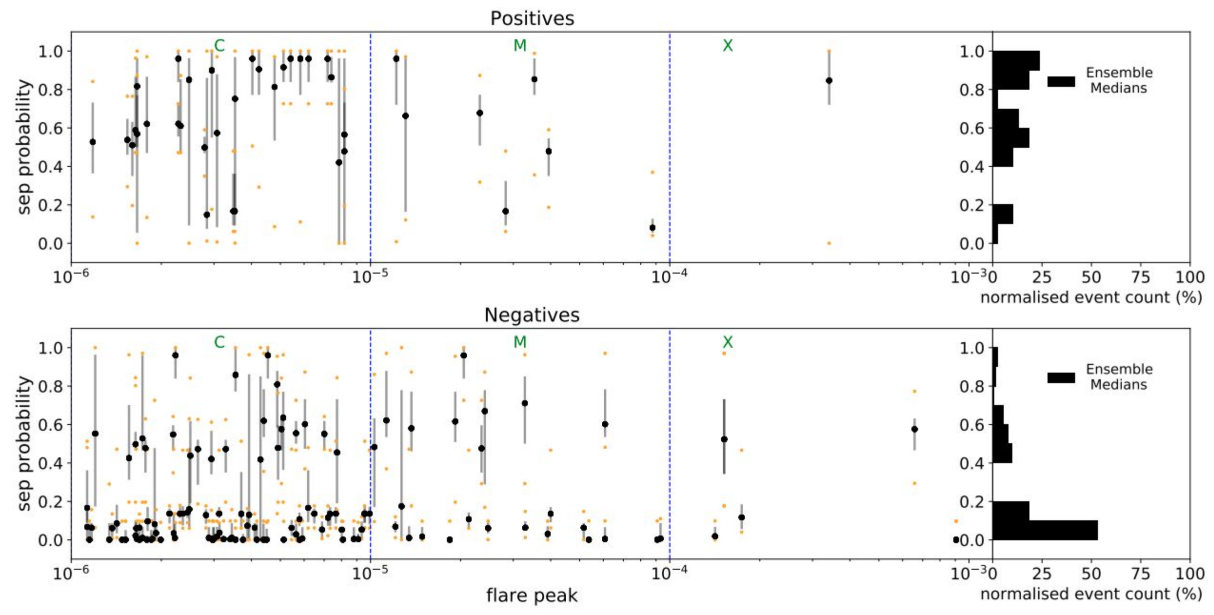
- We emphasize that our objective here is not to do just a binary classification. Instead, we focus on estimating true probabilities of SEP occurrence.
- We calibrate each CNN outcome using Bayesian Binning Quantile (BBQ) [4] method.



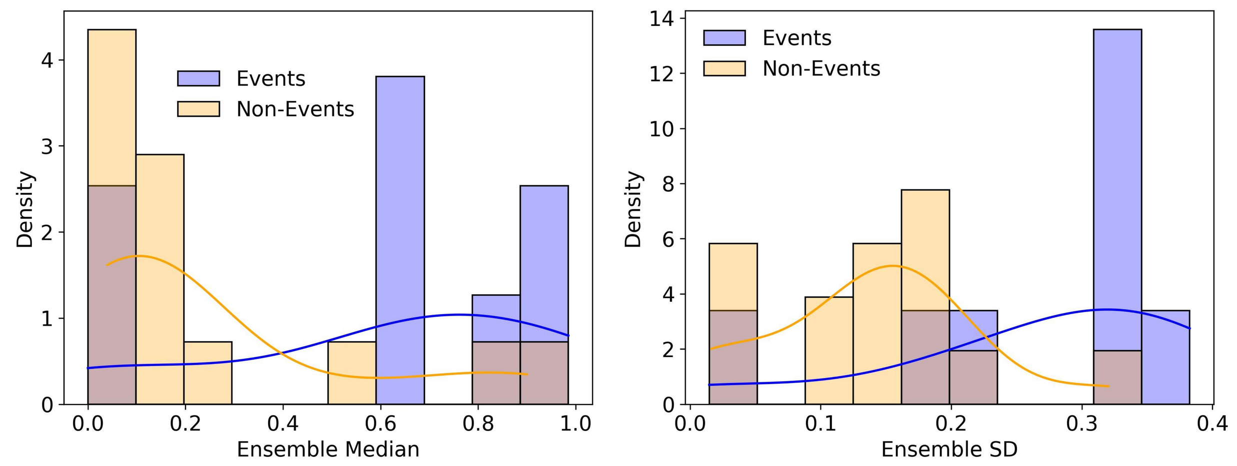
- Evaluating the model-ensemble with calibrated outcome on test data provides a clear picture of uncertainty in SEP occurrence probability.

Performance on test set

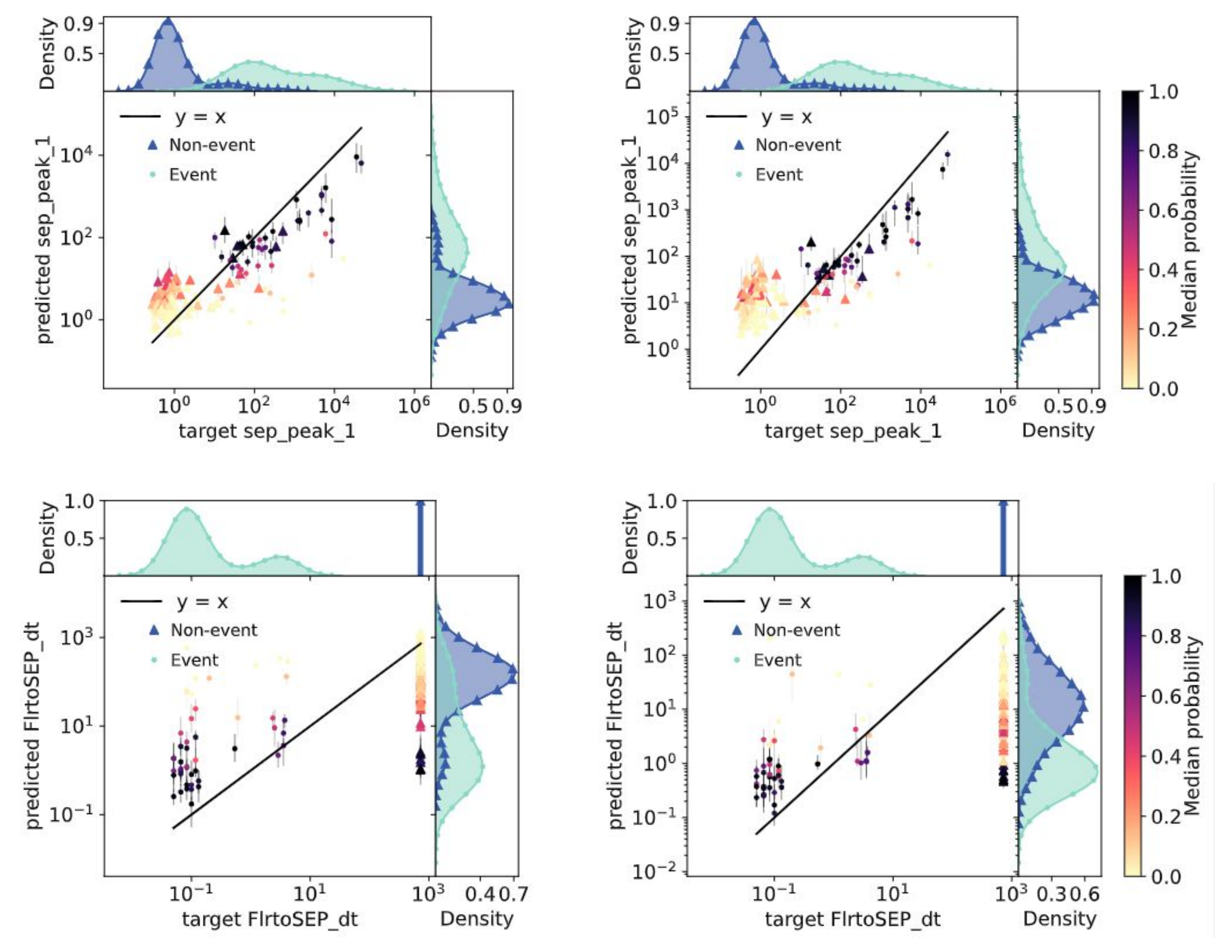
- We design a test set that is tailored to be non-modulated by the solar cycle phase and includes all flare classes (C, M, X)



- Event predictions are less confident in general compared to Non-event prediction: this could be a natural consequence of smaller variety of events seen by the model-ensemble as compared to the non-events.



- The ensemble makes tighter predictions for the test set data points with SEP occurrence probability ≥ 0.5 as compared to those with probability < 0.5.
- The difference of those two group become higher for probability weighted regression.



CONCLUSION

- We calibrate a model-ensemble to predict true probability of SEP occurrence
- True probability along with uncertainty provides enough flexibility to tune the model outcome to user-specific need.
- Our model-ensemble seems to predict the non-events more confidently as compared to the events: *events are not as well represented by training set as for non-events*
- We find that adding SEP occurrence probability as weightage in loss function causes improved forecast of SEP event properties as compared to simple mean squared error based regression set-up.

Papers (1) data, (2) SEP occurrence & (3) property forecast to be submitted soon

References

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