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It has long been known that studying connection between solar flares and properties of magnetic field in active regions is very important for understanding the flare physics and developing space weather forecasts. The Helioseismic and Magnetic Imager onboard the Solar Dynamics Observatory (SDO/HMI) obtains tremendous amounts of the magnetic field data products. However, the operational NOAA Space Weather Prediction Center (SWPC) forecasts of solar flares still represent prediction probabilities issued by the experts. In this research we investigate the possibilities to enhance the daily operational flare forecasts performed at the SWPC/NOAA by developing a synergy of the expert predictions and physics-based criteria, and by employing machine-learning methods. Among the physics-based criteria, we consider the descriptors of the Polarity Inversion Line (PIL), previously tested by Sadykov and Kosovichev 2017) and Space weather HMI Active Region Patches (SHARP, Bobra et al. 2014) and derive from them daily characteristics of the entire Sun. We also consider the daily descriptors of the GOES Soft X-ray (SXR) 1-8Å flux such as the flare history of the previous days and averaged X-ray flux. We estimate the effectiveness in separation of flaring and non-flaring cases for each characteristic, as well as for the expert prediction probabilities, and find that some PIL, SHARP, and SXR descriptors are as effective as the expert prediction probabilities and should be considered to issue the flare forecast. Finally, we train and test several Machine-Learning classification algorithms (Support Vector Classifiers with various kernel functions, k-Nearest Neighbor Classifier, Random Forest Classifier, and Neural Networks) using the most effective descriptors and expert prediction probabilities, and compare the obtained predictions with the current SWPC/NOAA forecasts.

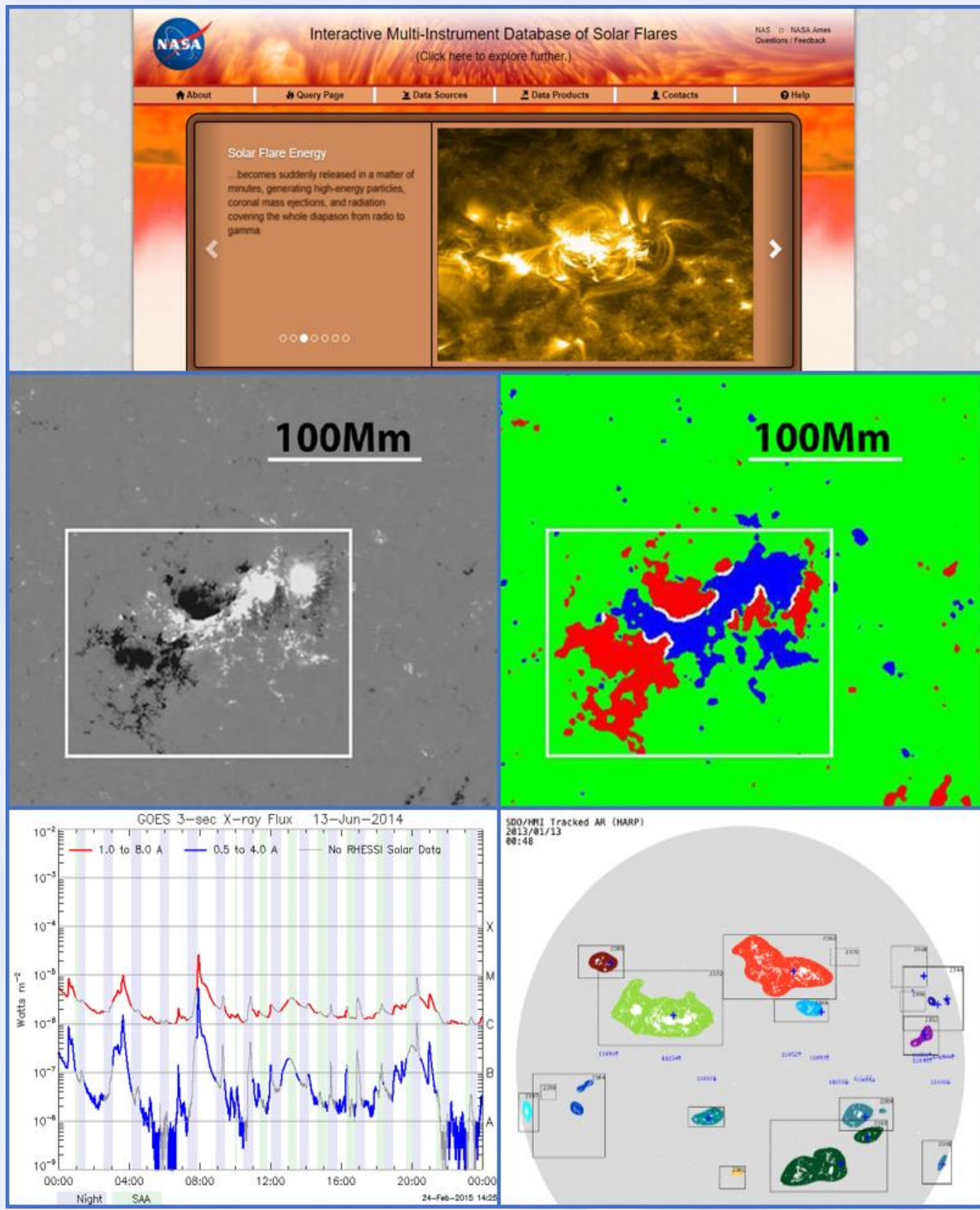
Primary goal: investigate the possibility of enhancement of the SWPC NOAA operational forecasts by employing machine-learning algorithms to combine expert predictions with magnetic field and soft X-ray flux characteristics

Data Sources and Descriptors

- SWPC NOAA operational forecasts (probabilities) of M/X-class flares for the next day (<ftp://ftp.swpc.noaa.gov/pub/warehouse/>)
- Statistics of M/X-class flares from <https://heliportal.nas.nasa.gov/>
- SXR 1-8Å flux obtained by GOES/XRS
- Polarity Inversion Line (PIL) characteristics obtained from SDO/HMI line-of-sight magnetic field data (Sadykov and Kosovichev, 2017)
- Space Weather HMI Active Regions Patches for NOAA ARs (SHARPs, Bobra et al. 2014)

The data are obtained for May 01, 2010 – Dec 31, 2017 time period. For each day for the midnight time, we obtain the following features of the solar activity:

- Averaged and peak SXR fluxes during the 1-3 preceding days
- Total number of M-class and X-class flares during the 1-3 preceding days
- Daily mean and maximum values of the PIL characteristics (maxima over ARs are selected)
- Daily mean and maximum values of the SHARP characteristics (maxima over ARs are selected)



Credits: <https://heliportal.nas.nasa.gov/>, Sadykov and Kosovichev 2017, Bobra et al. 2014, RHESSEI Browser (<http://sprg.ssl.berkeley.edu/~tohan/brower/>)

Feature Selection Algorithm

- The labels for the data set are assigned: 1 if there is an M/X-class flare which happened on the next day, 0 otherwise. The days when the flares were only located close to the limb are ignored.
- The features are ranked according to their Fisher ranking score $F(i) = \frac{(\bar{x}_i^+ - \bar{x}_i)^2 + (\bar{x}_i^- - \bar{x}_i)^2}{\frac{1}{n^+ - 1} \sum_{k=1}^{n^+} (\bar{x}_{i,k}^+ - \bar{x}_i^+)^2 + \frac{1}{n^- - 1} \sum_{k=1}^{n^-} (\bar{x}_{i,k}^- - \bar{x}_i^-)^2}$
- The dataset is randomly shuffled and divided 10 times into the train-test subsets with the ratio 2/1.
- For each classification algorithm, metrics to maximize, and feature type (PIL, SHARP, SXR), the following algorithm is performed:
 - Select two features with the highest F-score (or the feature of the highest F-score and SWPC prediction probabilities)
 - Find the classifier parameters which maximize the mean of the metrics (score) across the train-test data sets
 - Introduce the feature with the next highest F-score and temporarily add it to the previously-considered features
 - Find the classifier parameters which maximize the mean of the metrics across the train-test data sets
 - If the score is higher than previously-obtained plus certain threshold, add the feature permanently. Discard it otherwise. Return to the step c.

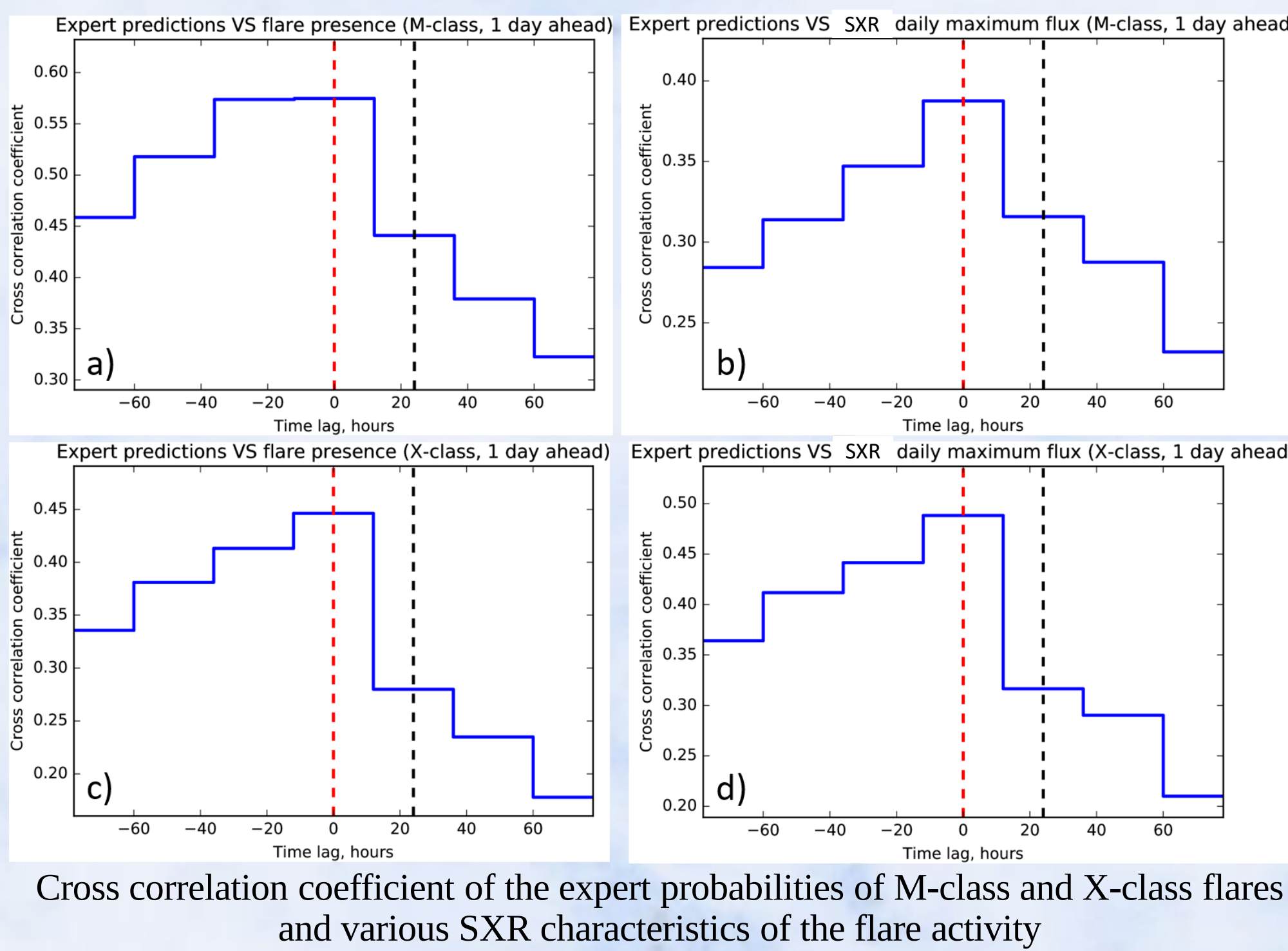
Considered classification algorithms: Support Vector Machines with linear (SVM linear), Radial-Basis Function (SVM RBF), and sigmoid (SVM Sigmoid) kernels; k-Nearest Neighbors (kNN), Random Forest (RF), Neural Networks with two hidden layers with 200 neurons each (NNA1), five hidden layers with 200-100-50-25-10 neurons (NNA2), and five hidden layers with 200 neurons each (NNA3)

Considered metrics: True Skill Statistics (TSS) and Heidke Skill Score (HSS) for the binary (yes/no) forecast, Brier Skill Score (BS) for probabilistic forecast. If TP is the number of correctly-predicted days with flares, TN – correctly-predicted non-flaring days, FP – incorrectly-predicted non-flaring days, and FN – incorrectly-predicted days with flares, P_i is the predicted flare probability for the day i , and Q_i is its label, then:

$$TSS = \frac{TP}{TP + FN} - \frac{FP}{FP + TN}, \quad HSS = \frac{2 \times [(TP \times TN) - (FN \times FP)]}{(TP + FN) \times (FN + TN) + (TP + FP) \times (TN + FP)}, \quad BS = \frac{1}{n} \sum_{i=1}^n (P_i - Q_i)^2$$

Properties of the SWPC NOAA Operational Forecasts

- The current daily operational forecasts at the SWPC are made by forecasters for each of the three upcoming days using a modified three-component Zurich class (McIntosh 1990) and magnetic class (Smith & Howard 1968) for each active region and historical look-up tables of flare probability as a function of active region class, flaring history, growth/decay of sunspots. The calculated probability is corrected by forecasters based on their experience.
- The flare prediction probabilities are correlated stronger with the current flare activity than with the next-day activity
- Nevertheless, the expert-based probabilities represent valuable information for the flare forecast.

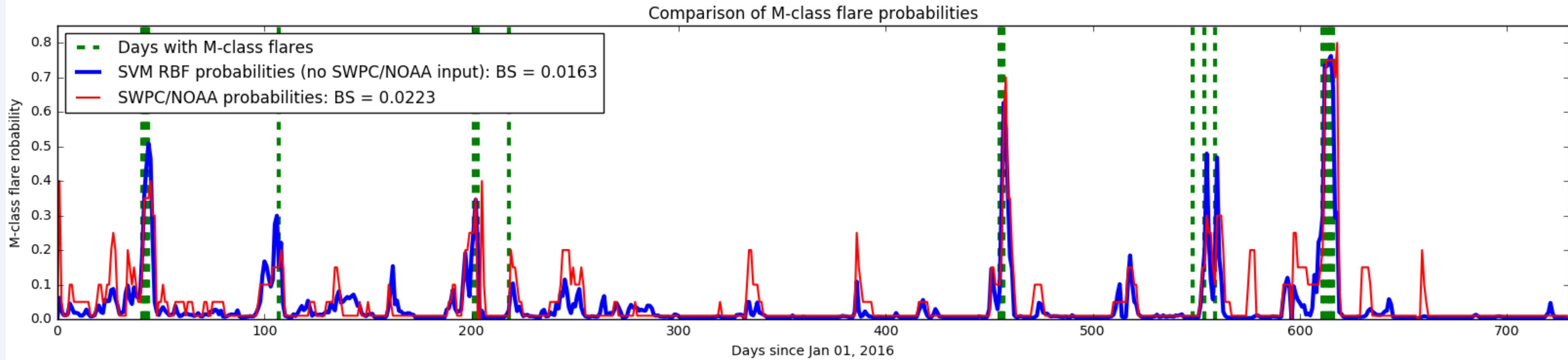


Cross correlation coefficient of the expert probabilities of M-class and X-class flares and various SXR characteristics of the flare activity

Enhancement of the Probabilistic Forecast

- Performance of the probabilistic forecast can be measured by Brier Skill Score $BS = \frac{1}{n} \sum_{i=1}^n (P_i - Q_i)^2$. Lower BS indicates better probabilistic forecast.
- Probabilities estimated by Support Vector Classifiers (Platt 1999) trained on all features except the SWPC NOAA expert predictions have lower BS (give better prediction) than expert-based probabilities.
- Operational probabilistic prediction for 2016-2017 also has lower BS than the SWPC NOAA predictions

BS, M flares	Expert scores (ES)	SVM RBF	SVM Sigmoid	BS, X flares	Expert Scores (ES)	SVM RBF	SVM Sigmoid
Expert scores (ES)	0.0918±0.0041	-	-	Expert scores (ES)	0.0111±0.0012	-	-
ALL + ES	-	0.0728±0.0043	0.0728±0.0043	ALL + ES	-	0.0067±0.0013	0.0066±0.0013
ALL – ES	-	0.0719±0.0042	0.0720±0.0042	ALL – ES	-	0.0067±0.0013	0.0062±0.0013



Acknowledgements and References

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Enhancement of the Binary (Yes/No) Forecast

We investigate the possibility to enhance the binary (yes/no) forecast of M-class and X-class flares by combining the SWPC NOAA expert predictions (probabilities) with various features (SXR, PIL, SHARP). The results are the following:

- Support Vector Machine Classifiers (SVMC, SVC) perform better than other considered machine-learning algorithms/classifiers (k-Nearest Neighbor, Random Forest, Neural Networks of different architecture)
- The classifier trained on just one of the feature group (SXR, PIL, SHARP) performs at the same level as expert predictions/probabilities
- The classifier trained on all available features except SWPC NOAA expert predictions significantly outperforms the SWPC NOAA expert predictions in terms of TSS and HSS

TSS, M flares	ES threshold	SVM Linear	SVM RBF	SVM Sigmoid	kNN	RF	NNA1	NNA2	NNA3
Expert scores (ES)	0.560±0.017	-	-	-	-	-	-	-	-
PIL + ES	-	0.601±0.041	0.598±0.035	0.601±0.040	0.541±0.033	0.295±0.045	0.572±0.042	0.574±0.041	0.577±0.042
SHARP + ES	-	0.560±0.024	0.586±0.030	0.579±0.029	0.515±0.045	0.285±0.033	0.551±0.041	0.537±0.035	0.506±0.059
SXR + ES	-	0.568±0.040	0.567±0.038	0.568±0.043	0.470±0.029	0.233±0.027	0.546±0.028	0.549±0.039	0.545±0.039
ALL + ES	-	0.612±0.039	0.632±0.031	0.617±0.041	0.550±0.032	0.294±0.049	0.563±0.063	0.522±0.042	0.539±0.039
PIL – ES	-	0.587±0.031	0.588±0.037	0.588±0.023	0.521±0.028	0.286±0.039	0.546±0.039	0.576±0.031	0.575±0.033
SHARP – ES	-	0.573±0.037	0.583±0.034	0.587±0.032	0.510±0.040	0.244±0.033	0.557±0.033	0.535±0.045	0.527±0.039
SXR – ES	-	0.564±0.043	0.570±0.039	0.569±0.036	0.463±0.035	0.216±0.027	0.541±0.039	0.543±0.028	0.535±0.042
ALL – ES	-	0.619±0.030	0.627±0.033	0.635±0.041	0.553±0.038	0.289±0.046	0.564±0.049	0.499±0.052	0.529±0.057
HSS, M flares	ES threshold	SVM Linear	SVM RBF	SVM Sigmoid	kNN	RF	NNA1	NNA2	NNA3
Expert scores (ES)	0.412±0.014	-	-	-	-	-	-	-	-
PIL + ES	-	0.444±0.031	0.445±0.035	0.444±0.029	0.396±0.023	0.352±0.044	0.428±0.039	0.424±0.028	0.431±0.023
SHARP + ES	-	0.403±0.030	0.426±0.034	0.411±0.042	0.372±0.040	0.335±0.028	0.400±0.041	0.401±0.051	0.405±0.043
SXR + ES	-	0.417±0.021	0.417±0.019	0.412±0.020	0.361±0.035	0.286±0.049	0.403±0.024	0.394±0.011	0.386±0.024
ALL + ES	-	0.467±0.040	0.477±0.034	0.467±0.036	0.408±0.011	0.350±0.038	0.435±0.031	0.441±0.040	0.420±0.053
PIL – ES	-	0.426±0.042	0.430±0.041	0.432±0.041	0.377±0.024	0.341±0.047	0.401±0.050	0.413±0.033	0.407±0.042
SHARP – ES	-	0.420±0.037	0.439±0.042	0.428±0.042	0.362±0.038	0.315±0.030	0.386±0.050	0.370±0.040	0.388±0.050
SXR – ES	-	0.406±0.025	0.415±0.027	0.412±0.019	0.332±0.028	0.268±0.030	0.398±0.019	0.379±0.046	0.396±0.010
ALL – ES	-	0.485±0.038	0.488±0.036	0.482±0.036	0.400±0.029	0.364±0.035	0.435±0.044	0.431±0.042	0.443±0.042
TSS, X flares	ES threshold	SVM Linear	SVM RBF	SVM Sigmoid	kNN	RF	NNA1	NNA2	NNA3
Expert scores (ES)	0.575±0.079	-	-	-	-	-	-	-	-
PIL + ES	-	0.610±0.126	0.605±0.150	0.679±0.129	0.583±0.095	0.071±0.075	0.352±0.218	0.135±0.141	0.254±0.146
SHARP + ES	-	0.505±0.226	0.556±0.166	0.608±0.179	0.367±0.168	0.031±0.067	0.164±0.093	0.154±0.137	0.199±0.187
SXR + ES	-	0.722±0.074	0.735±0.070	0.737±0.081	0.707±0.211	0.044±0.103	0.444±0.211	0.282±0.172	0.221±0.272
ALL + ES	-	0.743±0.073	0.735±0.070	0.768±0.070	0.707±0.211	0.044±0.103	0.132±0.134	0.111±0.106	0.040±0.072
PIL – ES	-	0.664±0.086	0.659±0.080	0.667±0.039	0.411±0.129	0.084±0.091	0.368±0.288	0.117±0.188	0.207±0.270
SHARP – ES	-	0.416±0.238	0.413±0.216	0.464±0.165	0.410±0.193	0.036±0.073	0.129±0.097	0.096±0.132	0.107±0.068
SXR – ES	-	0.774±0.066	0.755±0.078	0.761±0.069	0.581±0.146	0.047±0.077	0.494±0.205	0.321±0.214	0.406±0.219
ALL – ES	-	0.774±0.066	0.782±0.080	0.761±0.069	0.720±0.146	0.051±0.082	0.152±0.130	0.039±0.082	0.057±0.087

Summary

- SWPC NOAA operational forecasts (flare probabilities) are strongly correlated with the current flare activity rather than with the future activity.
- Support vector classifiers outperform other classifiers for the flare prediction problem
- Binary (yes/no) forecasts of M/X-class flares based on each feature group (PIL, SHARP, SXR) separately have the same or better performance than the SWPC NOAA operational forecasts.
- It is possible to significantly enhance binary forecast of M/X-class flares by considering joint magnetic (PIL, SHARP) and Soft X-ray characteristics.
- Probabilistic forecast of M-class and X-class flares based on the Support Vector Machine is better than the SWPC NOAA operational forecasts in terms of Brier Skill Score.