

SUMMARY

- We implement a data-driven supervised binary classification framework on multivariate time-series data from solar cycles 22-24.
- We use ensemble modeling to combine results from three proton (I_p) channels ($E \geq 10$, ≥ 50 , and ≥ 100 MeV) and the long-band X-ray (1–8 Å) channel of the GOES missions.
- The model aims to distinguish strong SEP events from non-events.

- SEP event definition is based on the GOES ≥ 10 MeV integral channel & SWPC 'S1' threshold:
 - Strong: $I_p \geq 10$ pfu
 - Weak: $0.5 \geq I_p < 10$ pfu
- We include "non-SEP" periods following $\geq C6.0$ flares to introduce a natural class imbalance in the data set.
- The 'positive' class comprises 244 strong SEP events. The 'negative' class has 189 weak events and 2,460 SEP-quiet samples.

- We experimented with summary statistics, one nearest neighbor, and supervised time-series forest (STSF; Cabello et al. 2020) classifiers.
- We compare their performances for prediction windows from 5 to 60 minutes.
- STSF performs well under all circumstances.
- For a 60-minute prediction window, we get:
 - True skill statistic (TSS) = 0.850
 - Heidke skill score (HSS) = 0.878
- Results assure confidence in our approach.

DATA

- The strong and weak SEP samples are obtained from the Geostationary Solar Energetic Particle (GSEP) events data set (Rotti et al. 2022).
- For non-SEPs, large flares are identified that do not lead to significant variations in the GOES ≥ 10 MeV proton fluxes relative to the background.
- C6.0 is chosen as the bottom threshold for non-SEP flares (see Figure 1).

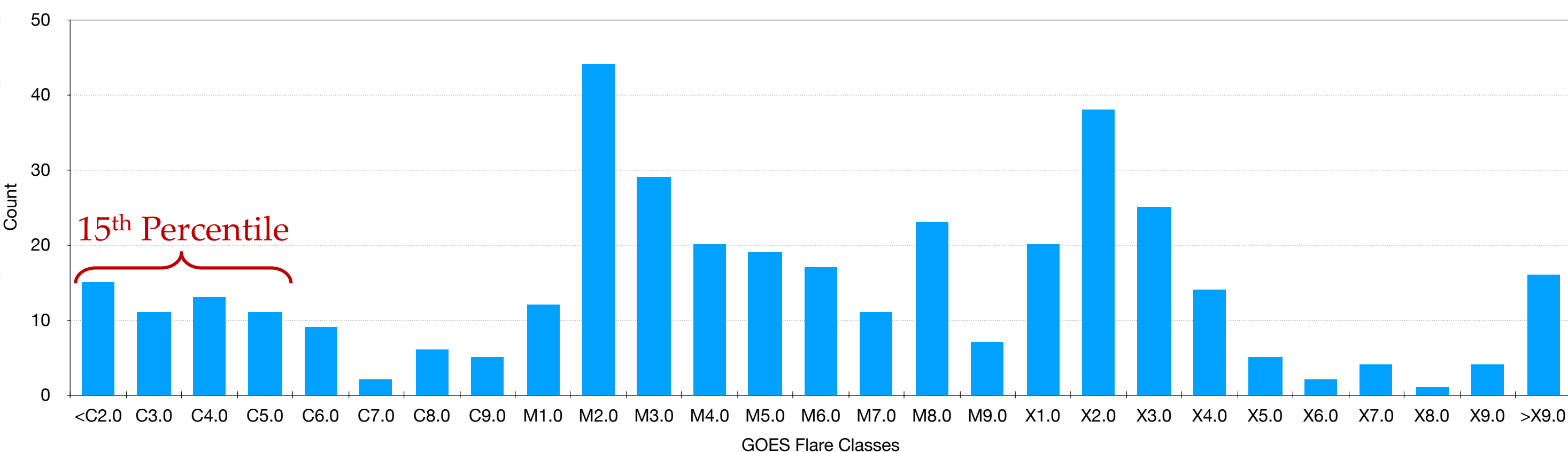


Figure 1: Distribution of 383 SEP-associated flares in the GSEP data set.

- Flares during an ongoing SEP event are not considered, and all consecutive flares within 11 hr of the onset of the flare at consideration are removed.
- 77(± 4)% of SEP event onsets occur within 11 hr after the associated flare.
- Total size of the dataset is 2,893 samples, with a class imbalance of $\sim 1:11$.

METHOD

- Data splitting on nonoverlapping years (# of samples shown in Table 1):

Table 1. Data Set Partitioning

	Train	Validation	Test
Positive	80	80	84
Negative	918	894	837

- **Training** – 1986 to 1992
- **Validation** – 1993 to 2002
- **Test** – 2003 to 2018
- Proton fluxes are interpolated to 1 minute to match with the X-ray flux.
- Each input series has a fixed length of 11 hr.
- The problem is framed as a time-series binary classification task, and we address it through multivariate time-series classification approaches.
- The model (late fusion) schema is obtained from Rotti et al. (2024) for short-term prediction windows of 5, 15, 30, 45, and 60 minutes.
- It is a parameter-wise ensemble of columns in which individual classifiers are applied to every parameter (column).
- The classifiers extract statistical features from input time-series intervals.
- Model Evaluation Metric:

$$1) \text{ TSS} = \frac{TP}{(TP+FN)} - \frac{FP}{(FP+TN)}$$

$$2) \text{ HSS} = \frac{2((TP \cdot TN) - (FN \cdot FP))}{(TP+FN)(FN+TN) + (TN+FP)(TP+FP)}$$

RESULT

- We find optimal classification thresholds for each model and assess their performance. Figure 2 compares TSS model performance.

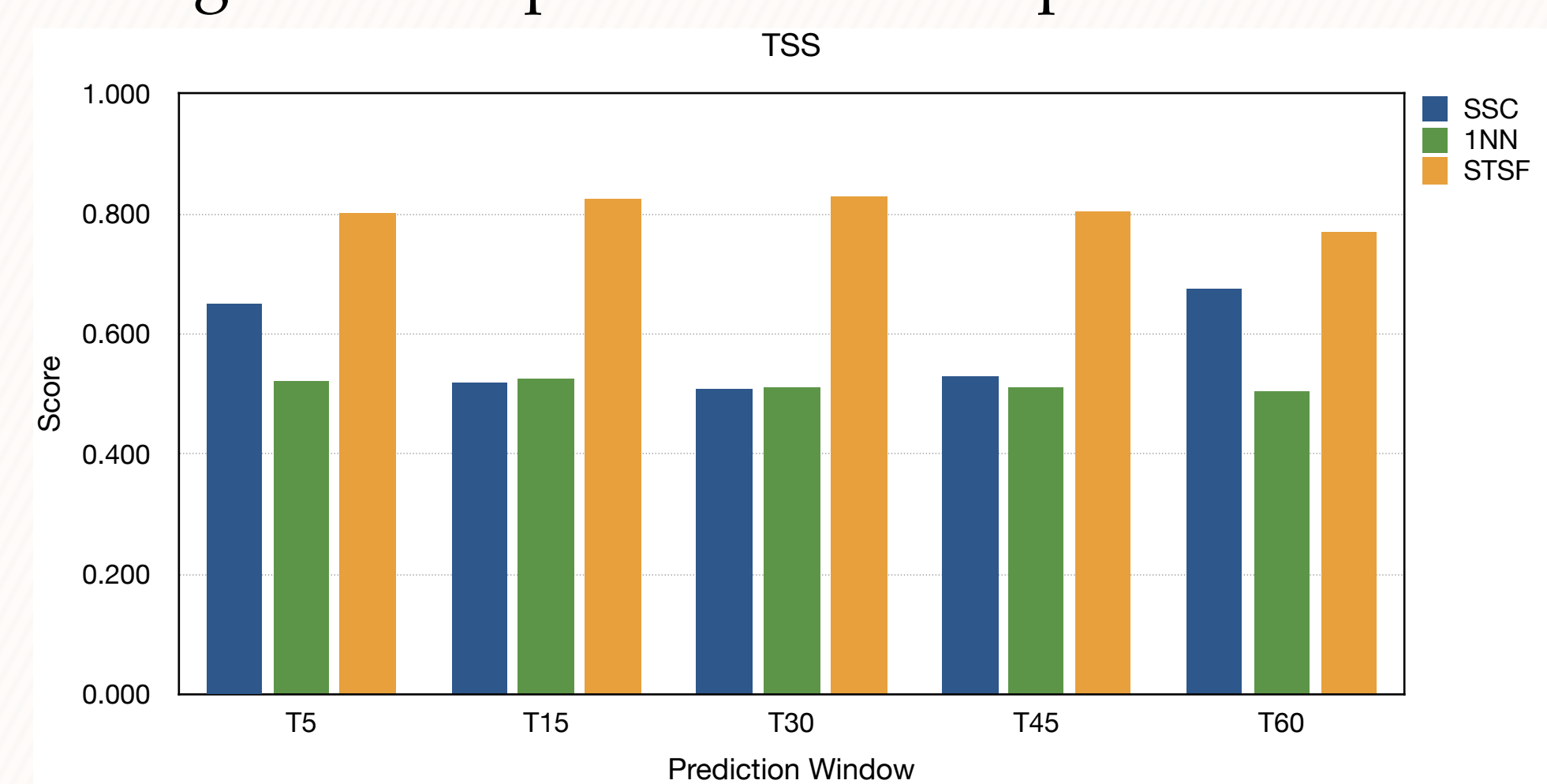


Figure 2: Model comparison for TSS variation on validation set.

- Thresholds are determined by analyzing ROC curves for each model. Figure 3 illustrates the ROC curve for the STSF classifier.

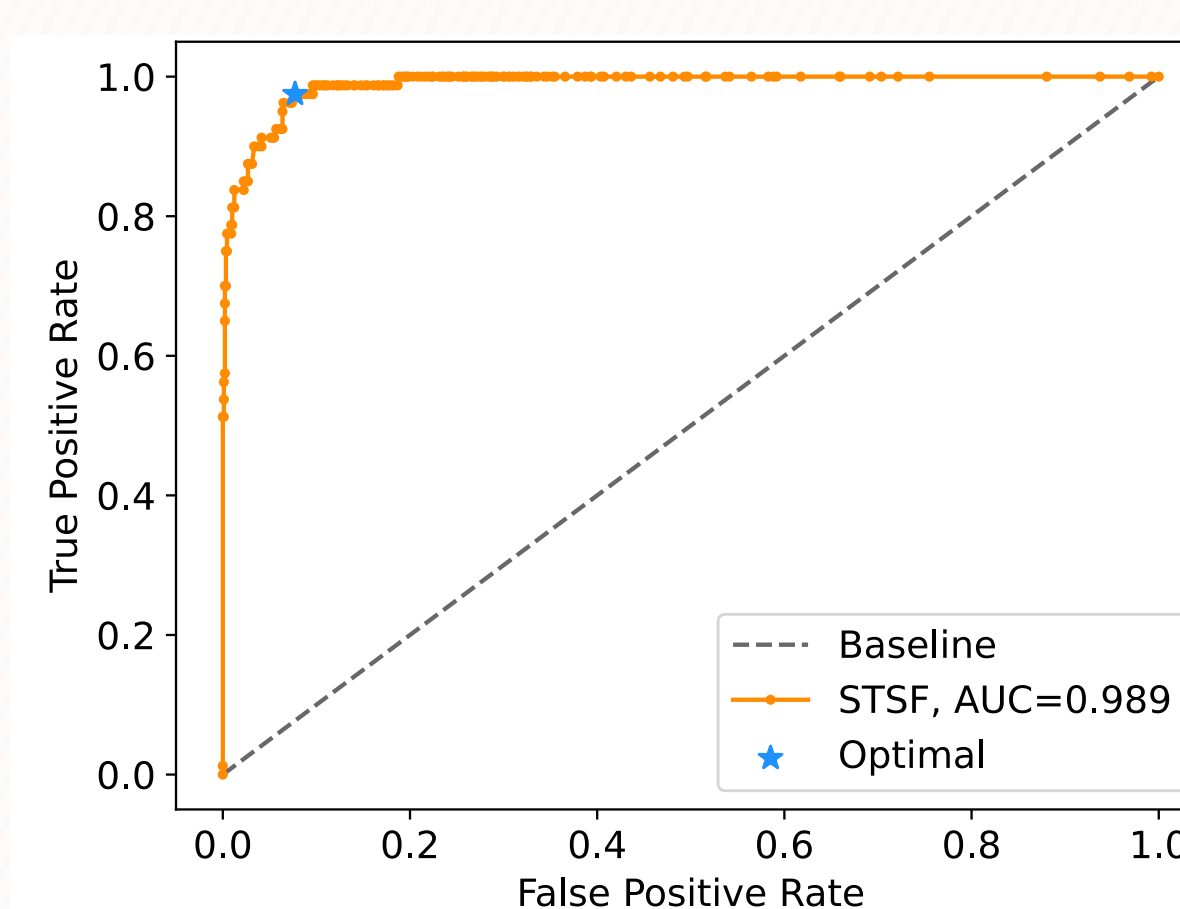


Figure 3: ROC curve for the best model.

Table 2. Contingency Table for STSF.

		Predicted	
		Strong	Weak
True	Strong	72	12
	Weak	6	831

- Table 2 summarizes the STSF model's contingency table on the test set.
- A comparison of the skill scores with different prediction windows on the unseen test set for STSF is presented in Figure 4.

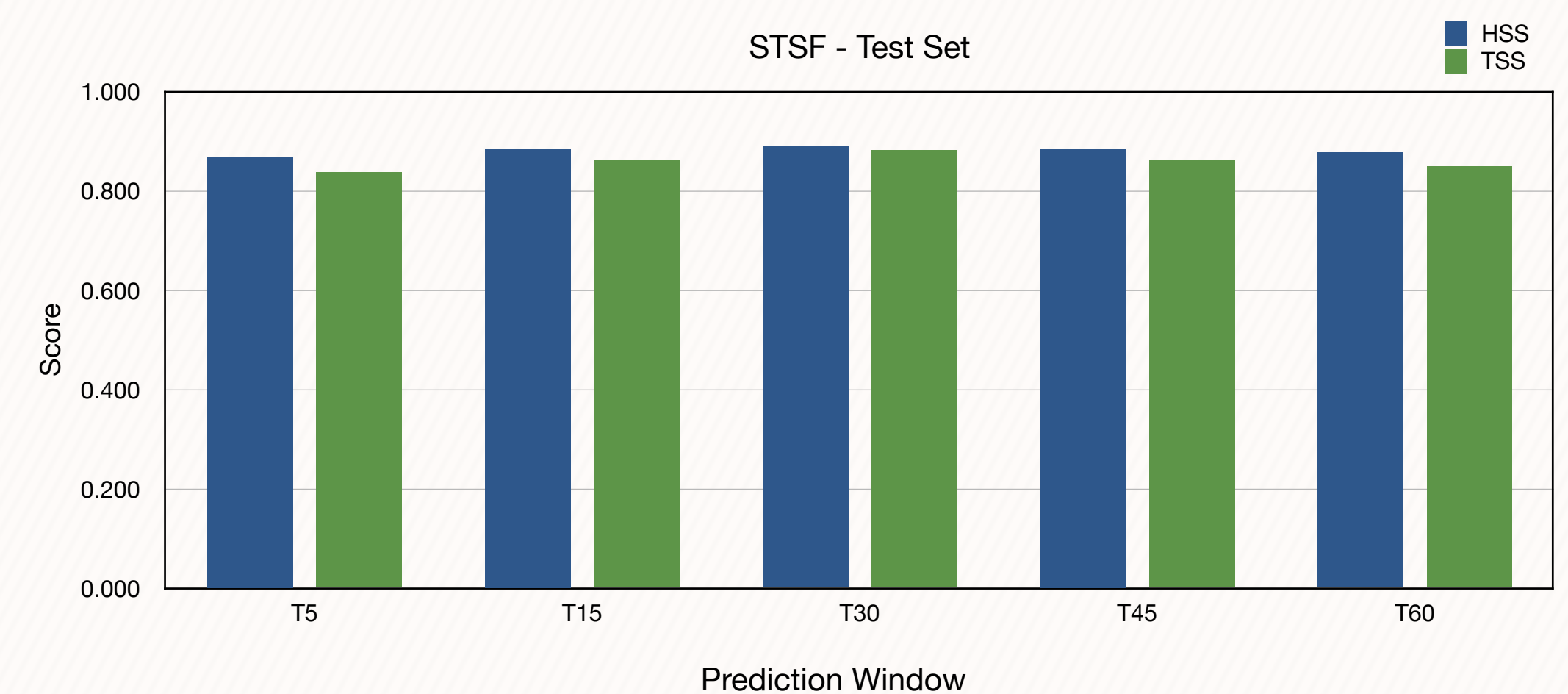



Figure 4: Comparison of TSS and HSS on the test set.

- Scores for T_{60} marginally reduced ($< 2\%$) compared to T_5 .
- A detailed discussion of the results has been published in ApJ and can be accessed via the QR code here. 

Acknowledgments

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References

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