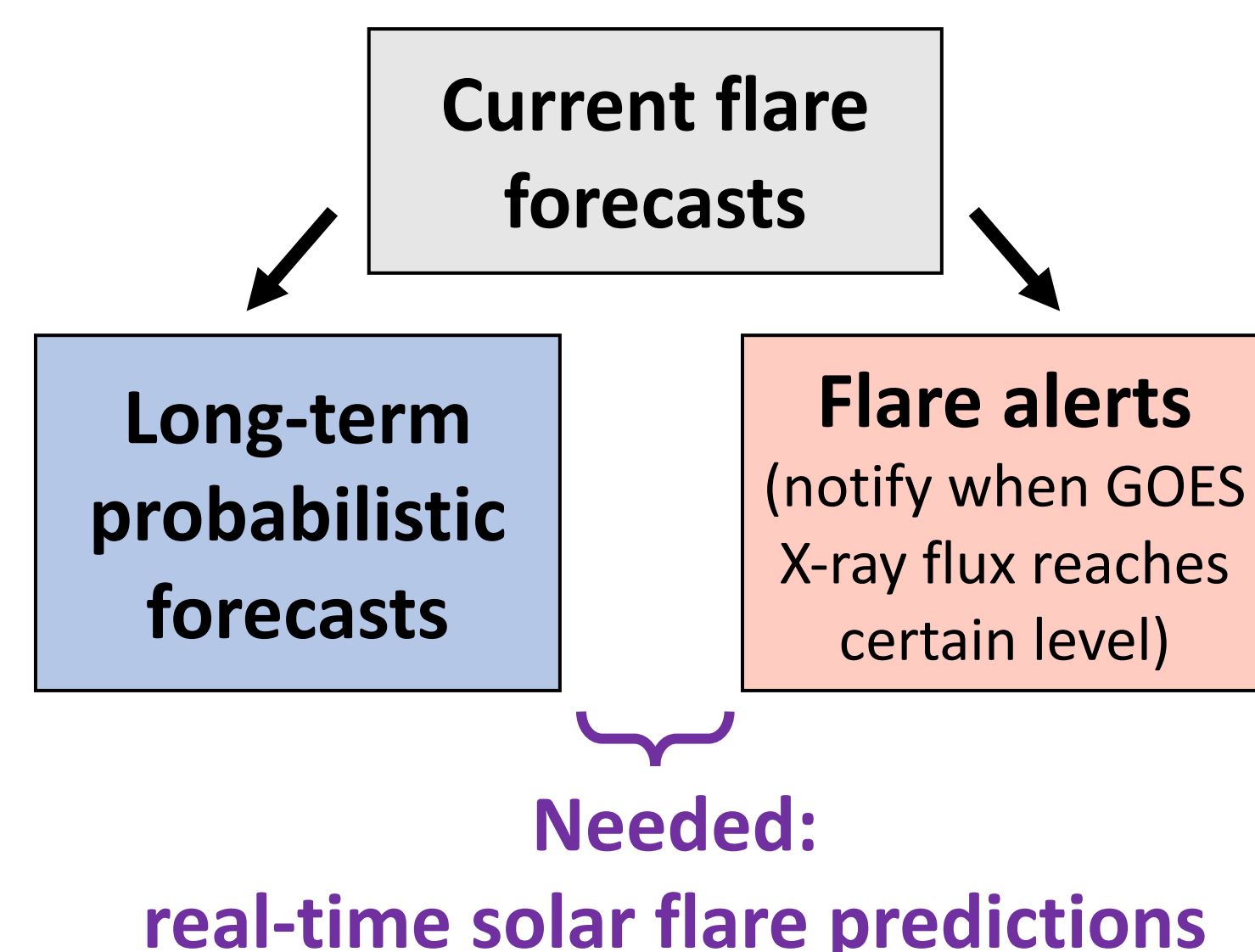


Real-Time Solar Flare Predictions Using Machine Learning

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Introduction

- Understanding when and where solar flares and eruptive events will occur continues to be an important goal for the heliophysics community, from both fundamental science and space weather perspectives.
- For a wide variety of operations and research purposes, we need to invest in the development of flare predictions that are more actionable than long-term (e.g., 24-hour) forecasts and provide earlier notice than current flare alerts.
- To address this need, we seek to develop a tool using machine learning that rapidly aggregates near-real-time signatures of flare onset, including X-ray and EUV irradiance measurements, to provide early prediction of the magnitude and duration of ensuing solar eruptive events.



Real-Time Solar Flare Predictions

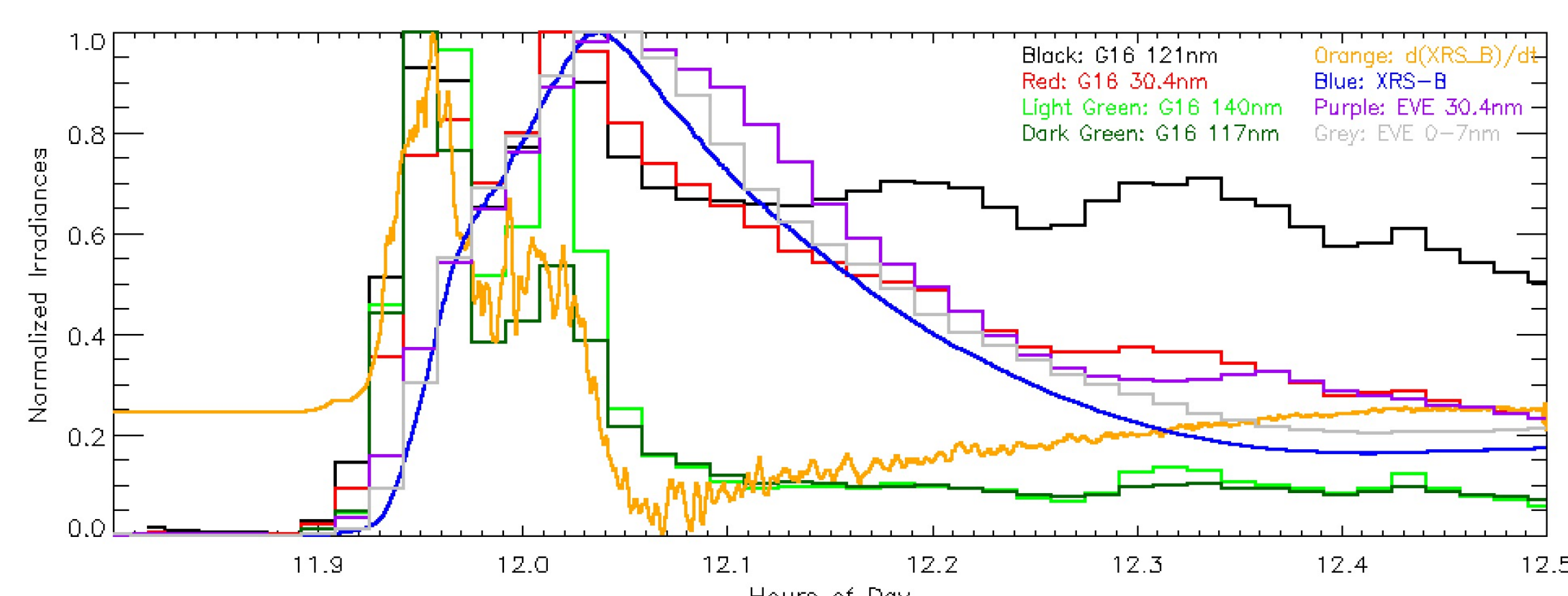
We propose developing a tool that rapidly aggregates near-real-time signatures of flare onset to provide early prediction of the magnitude and duration of ensuing solar eruptive events.

Multiple near-real-time data sets available:

- Solar irradiance (e.g., GOES/XRS, GOES/EUVS, SDO/EVE/ESP)
- Imaging (e.g., GOES/SUVI, SDO/AIA)

X-ray and EUV Irradiance

Example time series for the 6 Sep 2017 X-class flare from GOES/XRS, GOES/EUVS, and the SDO/EVE L0CS space weather product.



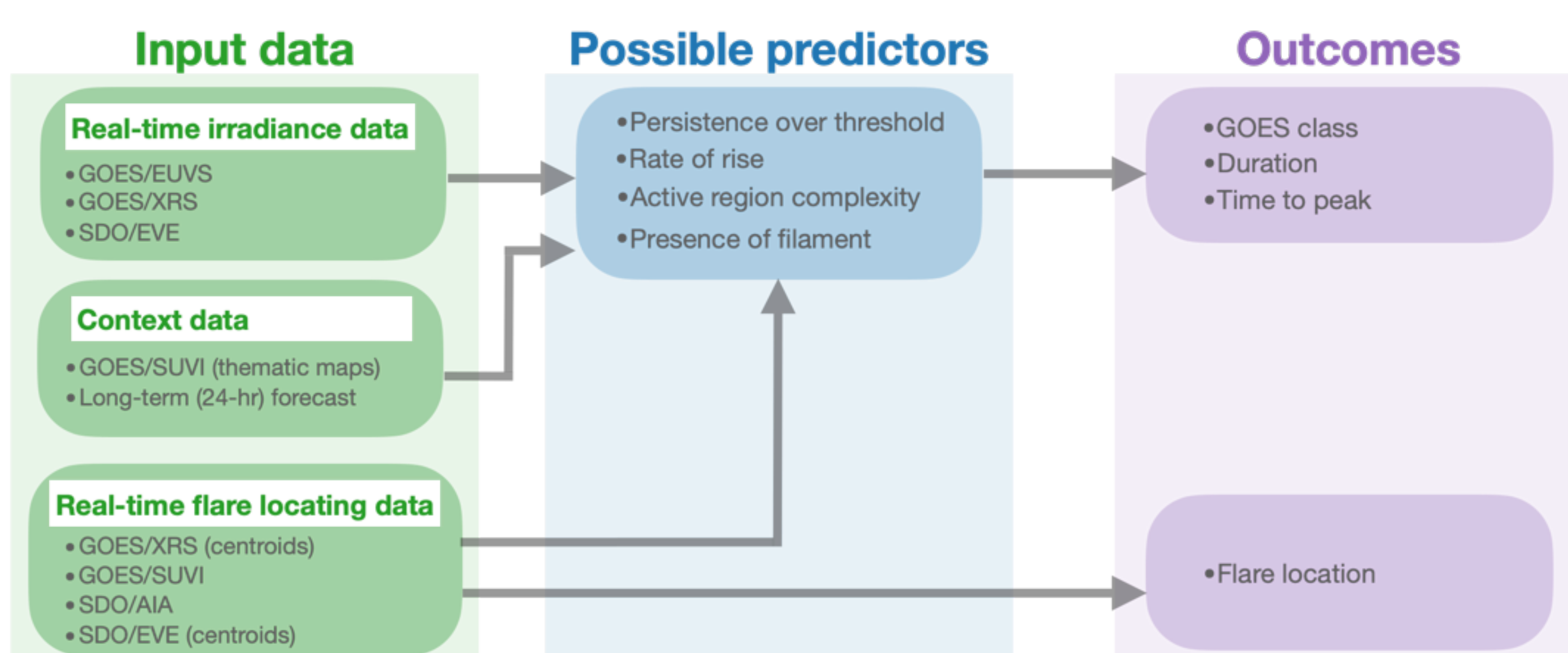
Real-time chromospheric and transition region UV measurements from EVE and EUVS provide a direct measure of impulsive phase heating and energy deposition in the low solar atmosphere, which provides early indication of flare onset.

Machine Learning

In recent years, machine learning techniques have been utilized for a wide variety of flare prediction studies (e.g., Nishizuka et al. 2018, Panos et al. 2020, Georgoulis et al. 2021, Reep et al. 2021). We intend to implement machine learning for real-time flare predictions.

Concept for Real-Time Solar Flare Predictions Tool

Using real-time data sets and machine learning techniques, we aim to identify the strongest predictors of flaring activity and how these predictors relate to the resulting flare magnitude and duration.



Exploring Machine Learning for Real-Time Predictions

The early stages of this project will focus on X-ray and EUV irradiance data that is available in real-time (GOES/XRS, GOES/EUVS, SDO/EVE/ESP).

In our preliminary work, we consider:

- What is the optimal machine learning algorithm for this application?
- What parameters can be computed in real time to be used as predictors?

Machine learning algorithm

One of the key requirements for a future real-time flare predictions tool is the capability for rapid data aggregation. A study by Reep et al. (2021) applies a random forest regression model for a similar application (predicting the remaining duration of a solar flare with GOES/XRS data), specifically citing the speed of this method as a critical factor. We use this study as a model in the initial exploration of machine learning for our work.

What other machine learning algorithms are suitable for this application?

Defining parameters of interest

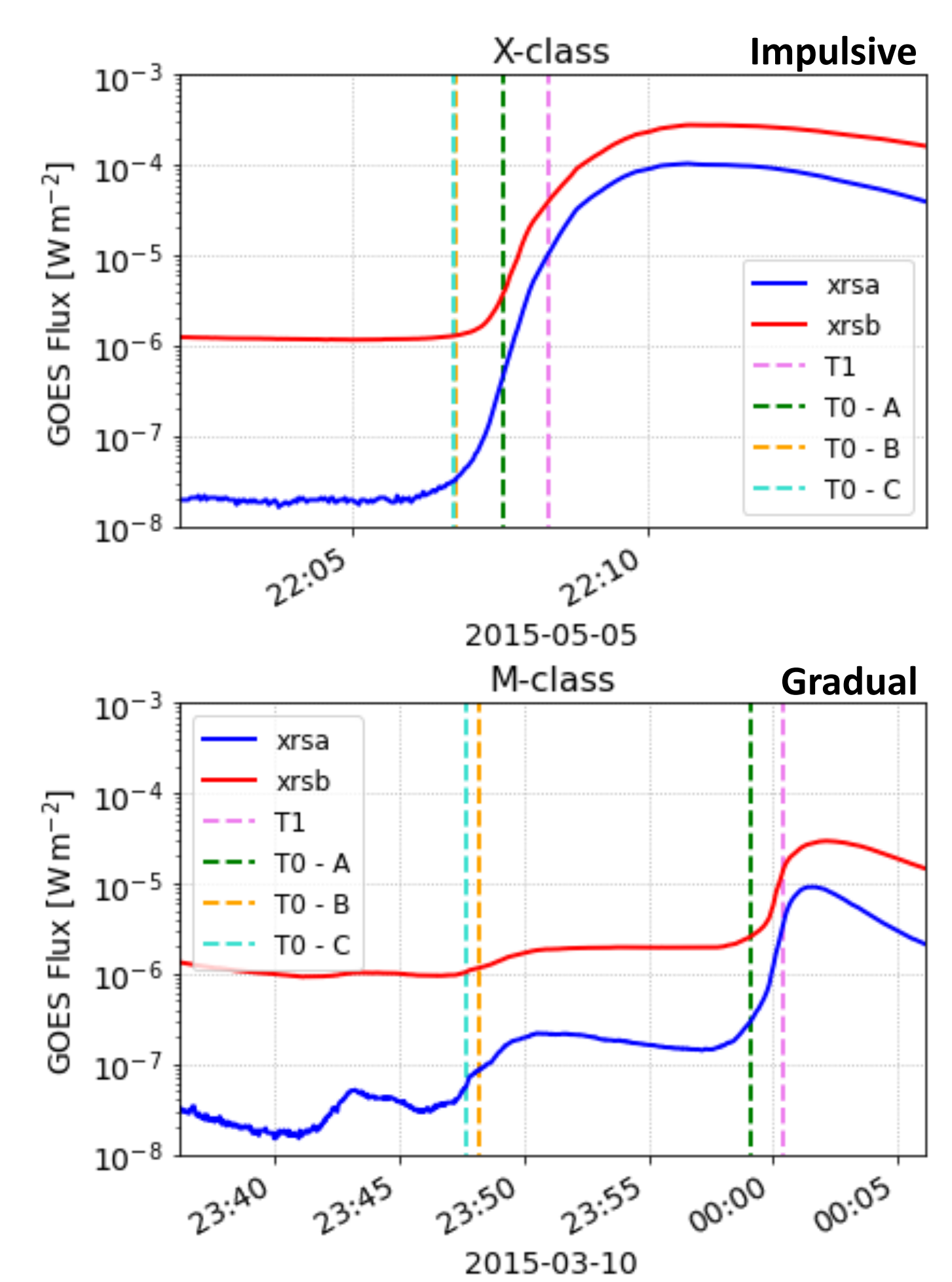
In order to provide timely/actionable flare predictions (~minutes before the flare peak), we need to define parameters of interest early in the flare that can be computed in real time.

We first explore accuracy/reliability of different start time criteria using GOES/XRS data for a variety of:

- Flare magnitudes (e.g., C, M, X)
- Flare characteristics (gradual/impulsive)

Example Start Time (T0) Criteria for XRS-B (1-8 Å)

- T0 - A:** flux exceeds threshold over background (average of 10 preceding data points) + peak in second derivative
- T0 - B:** flux exceeds threshold over minimum average background + peak in second derivative
- T0 - C:** first derivative > 1e-8 W/m²/s



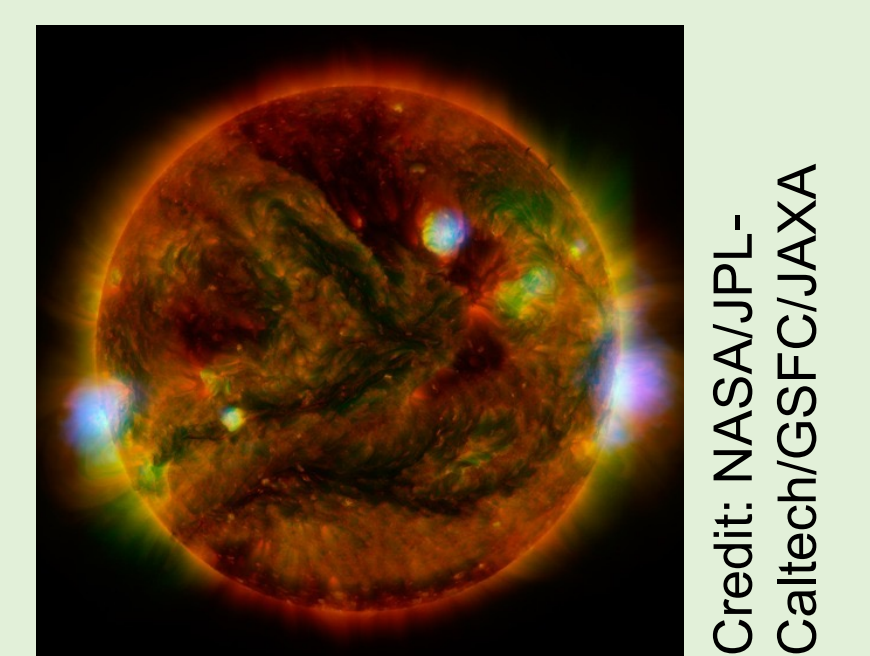
Plots created using modified versions of publicly available routines developed by Reep et al. (2021).

Continued work will explore additional times/parameters of interest for GOES/XRS and will also incorporate critical indicators of impulsive phase activity using the real-time chromospheric and transition region UV measurements from EVE and EUVS.

Measurements/Missions That Will Benefit

Missions

Improvements in near-term flare predictions are particularly important for observatories targeting flare physics that are restricted in field of view (e.g., IRIS, Hinode/SOT, Hinode/EIS, SOHO/CDS, SOHO/SUMER) and/or observing time (e.g., astrophysical observatories, CubeSats).



Technology Development

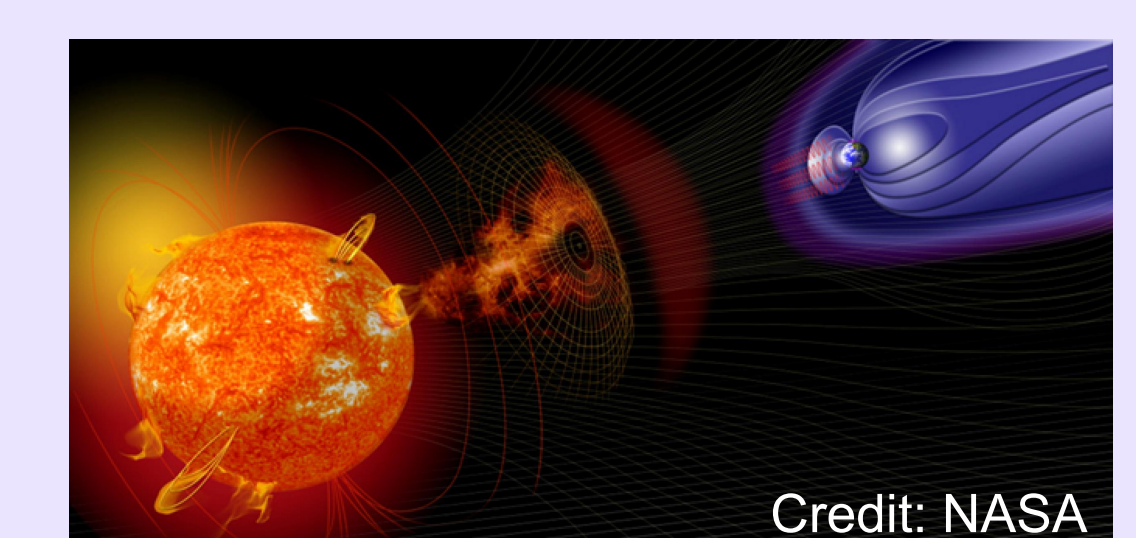
Sounding rocket flare campaigns

- Seek to perform a triggered launch to observe a large solar flare
- Important for developing novel instruments optimized for solar flare observations
- First solar flare campaign (2024) will feature FOXSI-4 (PI Glesener), Hi-C (PI Savage), and SNIFS (PI Chamberlin)



Space Weather

- The increase in SXR and UV irradiance from solar flares has an immediate impact on planetary atmospheres.
- Space weather impacts include satellite drag and radio blackouts (Frissell et al., 2019).



Contact

Have additional ideas for a real-time flare prediction tool and/or applications? Interested in this concept? Please reach out!

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Acknowledgements

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