Applicability of machine learning for ESA mission Vigil

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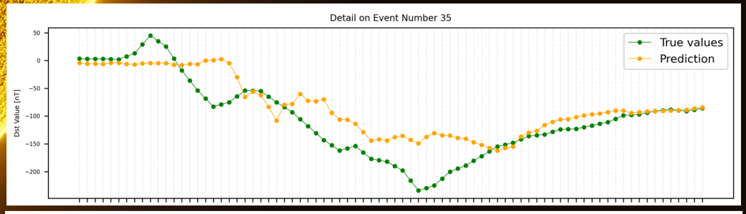
Motivation

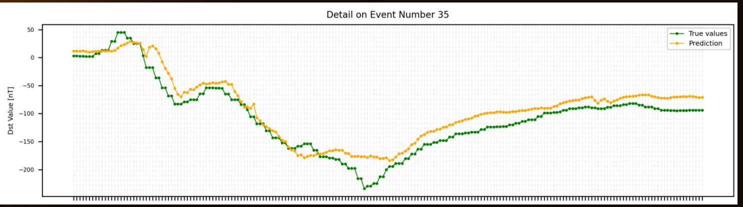
Space weather poses risks to Earth and modern infrastructure, disrupting communication systems and global transportation. Coronal Mass Ejections (CMEs) can trigger geomagnetic storms with severe consequences. The upcoming **ESA Vigil mission** will provide early alerts of dangerous solar activity. In this work, we primarily investigate whether **multimodal data** can improve deep learning models for predicting the Disturbance Storm Index (DST), a measure of geomagnetic activity, during most extreme solar activity periods.

Results

- Developed **Python tooling** for space weather scientists to easily access data comparable to Vigil.
- Released an open multimodal dataset: Most Extreme Space Weather Events (MESWE) for community experiments on Dst prediction.
- Findings were published in the peer-reviewed journal [1].
- Our model using extracted running difference features yields superior predictive performance.
- A second publication is currently under review (Submitted to The Astrophysical Journal).



Benchmark for DST prediction



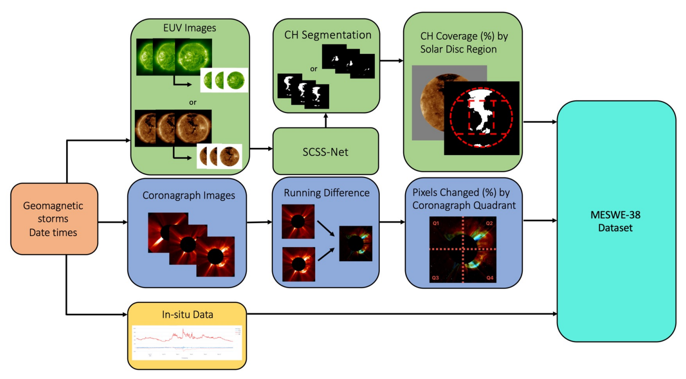
Ours DST prediction

Methodology

Outcomes were part of deliverables for the RPA SKR1-23 project **"Study toward enhancing reliability and timeliness of Vigil mission predictions through Machine Learning"**, funded by the European Space Agency.

The methodology combines multiple steps:

- **Data Collection:** We identify comparable instruments from 8 historical solar missions aligned with the planned ESA Vigil instrument payload.
- **Multimodal Dataset:** Data from similar historic missions were integrated into a joint dataset with over 30 most extreme periods of solar activity over the past 30 years. Dataset consist of 2 modalities:
  - **Remote sensing data** (Images of solar activity).
  - **Time series data** (solar wind speed, density, magnetic field, DST).
- **Event Partitioning:** We ensure robust evaluation by comparing extreme space weather events using the Wasserstein distance, so train, validation and test set have comparable event distributions. To the best of our knowledge, we are the first to explicitly address this step within the community.



Process of MESWE dataset creation

- **Development:** We implement multimodal deep learning architectures that integrate **time series** with **remote-sensing imagery**, combining **Time-Distributed Convolutional Neural Networks** for spatial feature extraction from images in time and **Gated Recurrent Units** for temporal dynamics of time series data.
  - To improve model efficiency and reduce input dimensionality, we investigate whether essential information can be distilled from imagery prior to ingestion. Specifically, we compute **running-difference transformations** of solar images to capture transient solar activity, which serve as derived features alongside in-situ measurements.
- **Evaluation:** We compare our models to benchmark model, trained with methods published in prior space weather forecasting studies using Dynamic Time Warping method.

[1] Majirský et al.: 2025a, Earth and Space Science, 12, e2024EA003937, https://doi.org/10.1029/2024EA003937