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Investigating the Relativistic Electron Precipitation Using Deep Learning Techniques

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1. INTRODUCTION

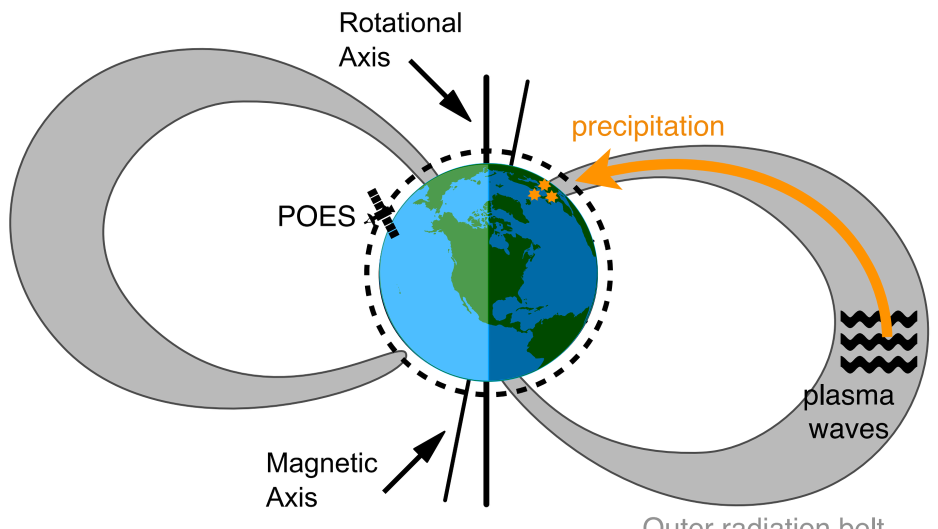


Figure 1

Energetic (>10s keV) electrons can precipitate from the outer radiation belt into the atmosphere due to interactions with **plasma waves** (Figure 1) or when magnetic field lines are significantly stretched away from Earth (**current sheet scattering**, CSS). These two drivers can be distinguished by the **profile of precipitation fluxes** (Figure 2) observed by low-Earth-orbiting (LEO) satellites as POES.

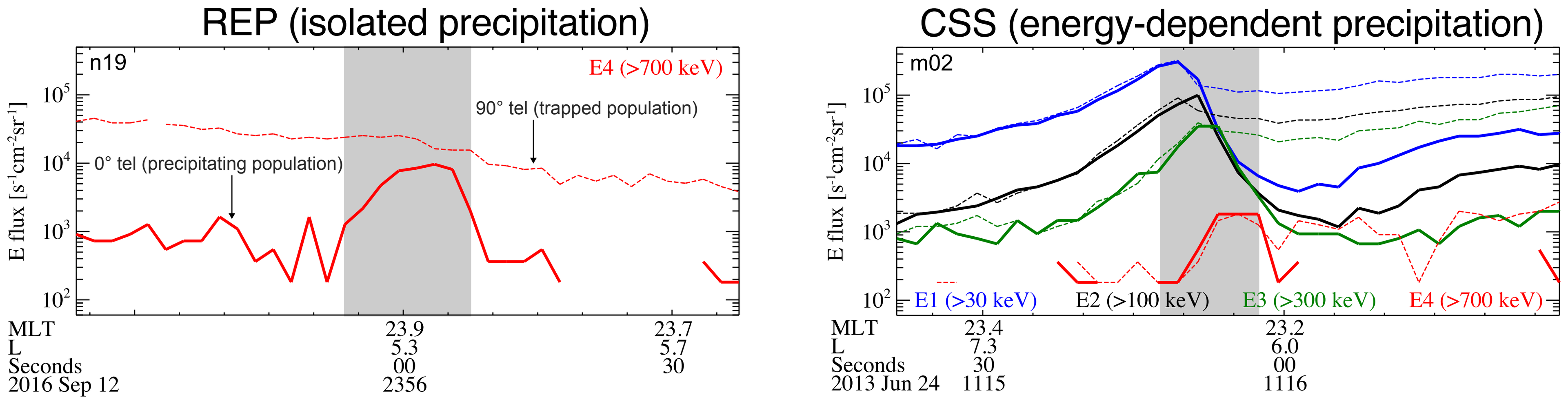


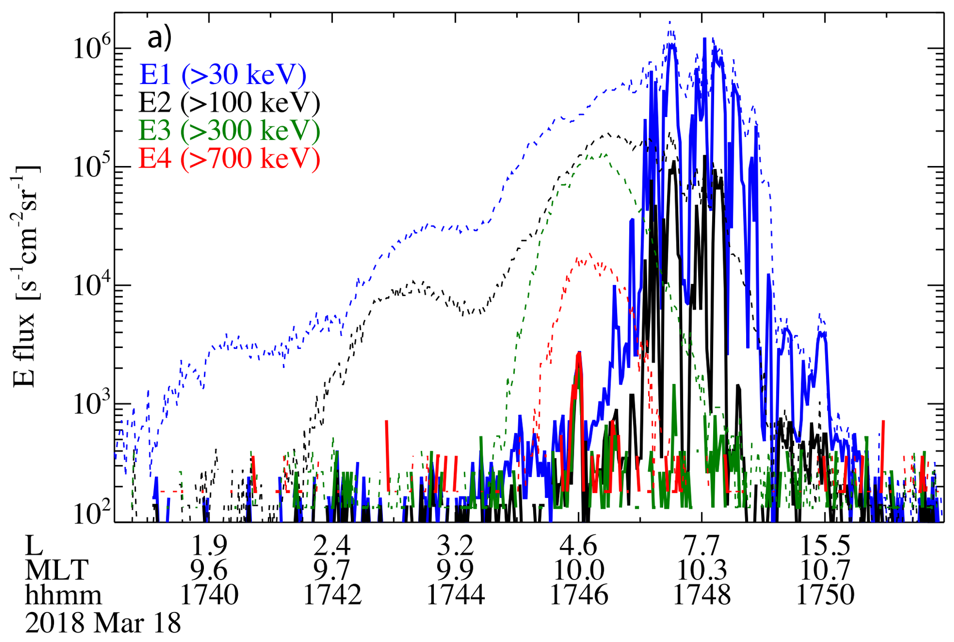
Figure 2: Examples of precipitation (gray) driven by waves (REP, left) and CSS (right).

2. MOTIVATION and GOALS

Precipitation is an important mechanism that leads to **depletion of the outer radiation belt flux** and **space weather effects** (e.g., ionization enhancements, chemistry changes, etc.). Finding precipitation events and identifying their associated driver is challenging and time-expensive.

We use **deep learning** to **identify the relativistic electron precipitation** within each radiation belt pass observed by POES and **categorize events** between those driven by waves and those driven by CSS. Ultimately, obtaining such dataset will allow us to study the **distribution of the precipitation** drivers at all MLTs and L shells, and understand the **respective contribution** to the total electron precipitation.

3. DATASET



Electron fluxes observed by POES is **highly variable** (Figure 3), thus we use a dataset of precipitation events stacked one after the other instead of using the POES data over a full orbit.

Figure 3: Examples of radiation belt electron flux observed by POES in a quarter orbit.

The dataset (Figure 5) used in the supervised deep learning classification is made of:

- Window of 50-point-long data points for each precipitation event
- **230 REPs** (label 1) & **174 CSSs** (label 2), randomly stacked, *visually classified*
- Label is 0 adjacent to the REP/CSS
- Each event is vertically mirrored (data augmentation)
- **8 Features**: electron flux from 4 POES electron channels (0° and 90° look-directions)
- **1 Target**: class (0:no-event, 1:REP, 2:CSS), one-hot encoded

4. MODEL ARCHITECTURE and PERFORMANCE

We use **LSTM** (Long Short-Term Memory), an artificial recurrent neural network architecture suited for time series classification as the one in this study. The model consists of one layer of **64 bidirectional LSTM units + 256 dense units**, with dropout at 0.5 rate after each layer.

We use the standard classification metrics: F1 score, AUC (area-under the ROC (receiver operating characteristics) curve, and AUPRC (area under the precision-recall curve). We obtain a model performance of **F1~0.95, AUC~0.99, and AUPRC~0.99** from the k-fold cross validation with k=10, with a confusion matrix in Figure 4.

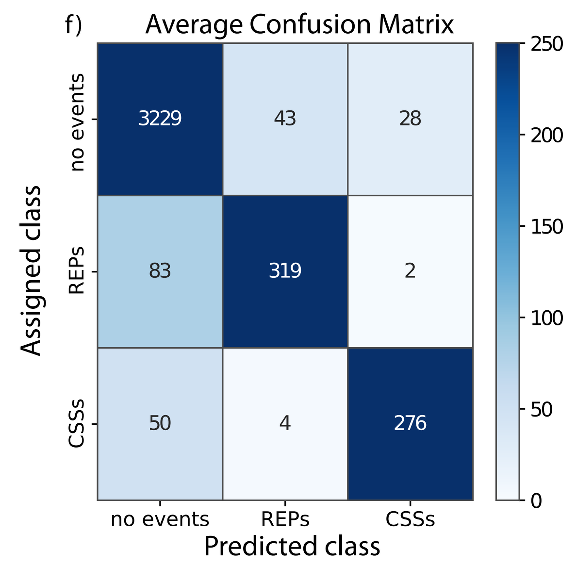
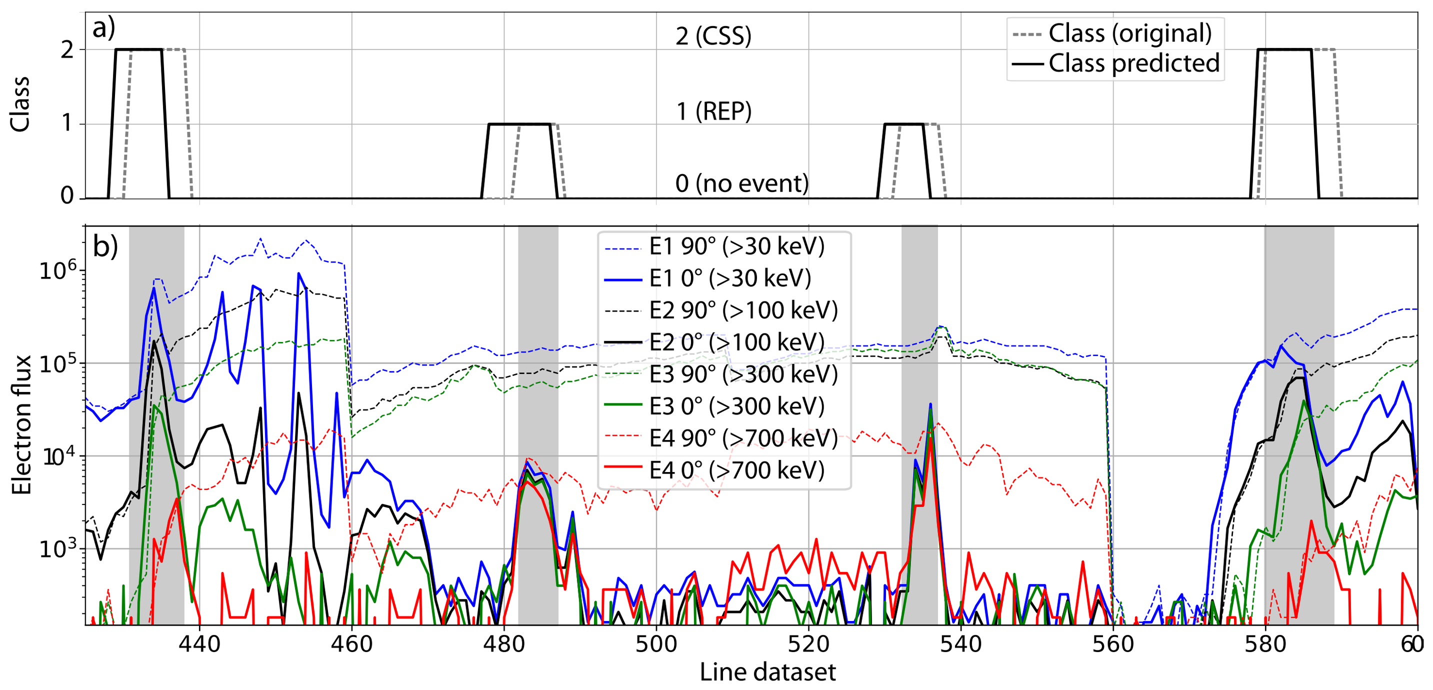


Figure 4: Confusion matrix.

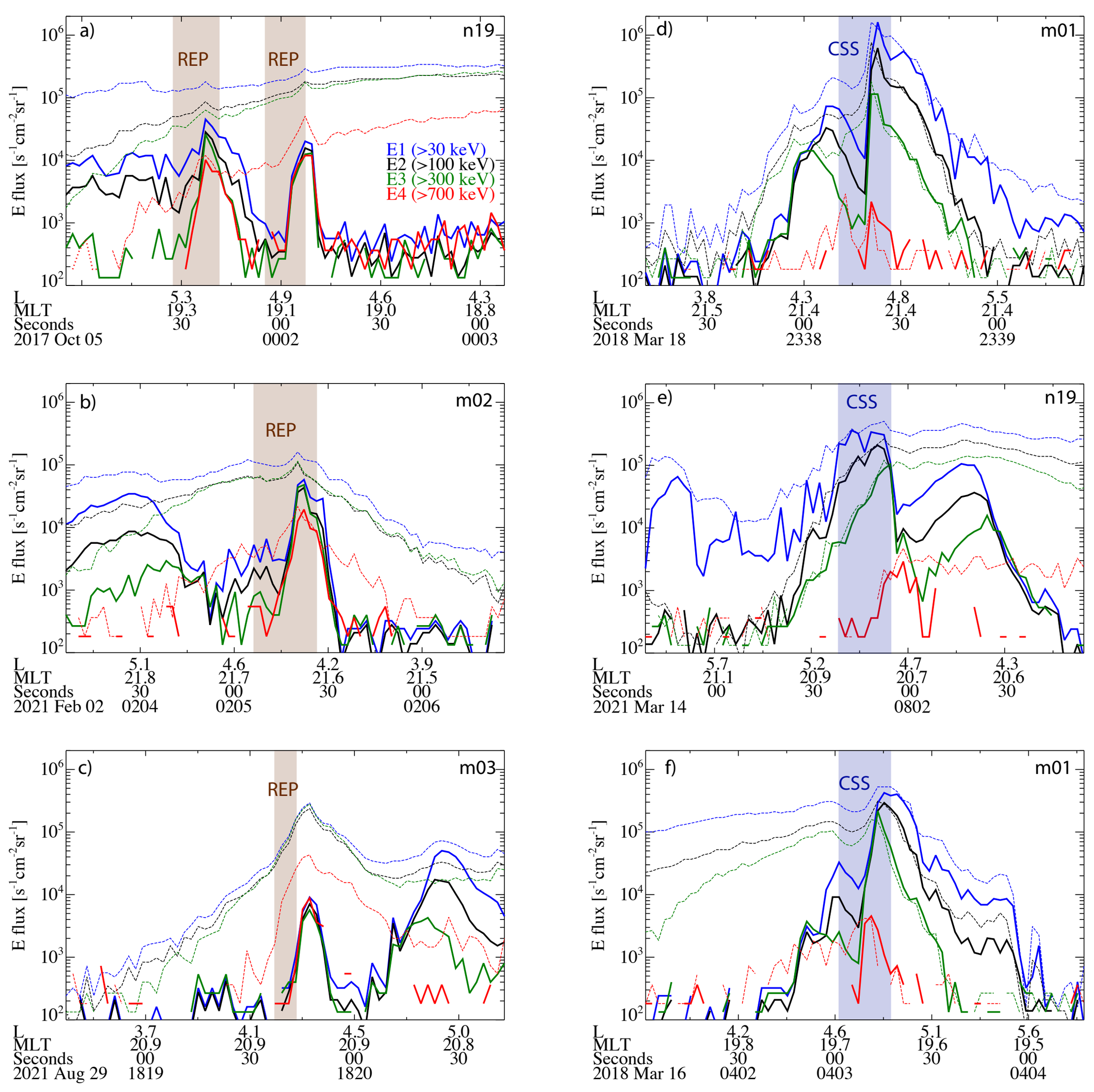


The model is able to **correctly identify precipitation** events and **classify their driver** (Figure 5).

Predicted class indices indicate a region where an event is found, not necessarily its exact boundaries.

Figure 5: Example of the test dataset: a) comparison between original and predicted class, b) electron flux with precipitation events (gray).

5. MODEL APPLICATION ON REALISTIC DATA



To test if the **model performs well on realistic data** (full POES orbits, as in Figure 3), we apply the model to several days of POES data.

The model is able to correctly identify and classify the precipitation events (Figure 6).

The shift in time is generally systematic and can be removed in (future) post-processing.

Figure 6: Examples of REP events (left) and CSS events(right) identified by the model

6. CONCLUSIONS

- Depending on the **shape of the electron precipitation** observed at LEO, we can **identify the associated driver** (waves or current sheet scattering)
- ML techniques are fast and effective in identifying relativistic electron precipitation and classifying events between wave-driven and CSS-driven
- Our **LSTM-based model is successful** at **identifying** the precipitation **events** and **categorizing** them by driver.

7. FUTURE PLANS

- Post-Processing of the model outputs (handle false positives and time shift)
- Obtain a dataset of REPs and CSSs for the entire POES dataset (from 2012 to present time) to study the REP vs. CSS L-MLT distribution and contribution to total electron precipitation
- Predict precipitation events from solar wind and/or geomagnetic indices (if you have any thoughts, please let's discuss!)

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