PreMevE: A New Predictive Model for Megaelectron-volt Electrons inside Earth’s Outer Radiation Belt

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1. Motivation and Background
2. Model Construction
3. Model Performance
4. Summary & Conclusions
1.1 Motivations: Morphology and Practical Needs

- MeV electron events: Outer-belt electrons often exhibit significant event-specific enhancements and decays during geomagnetic storms.
- Outer-belt MeV electrons are the main contributor to total ionization doses for high-altitude satellites [Daly et al., 1996]: AE9
- Sustaining high-level MeV electron fluxes can cause deep dielectric charge/discharge that are related to a list of satellite failures [Baker, 2001]: predictive model
1.2 Existing MeV Electron Predictive Models

- **SPACECAST** [Horne et al., 2013]: 3-hr forecast >800 keV electron fluxes at GEO with factors 2 - 10
- **UCLA NARMAX VERB model** [Pakhotin et al. 2014]: forecast energetic electron fluxes inside GEO
- **NOAA REFM >2MeV e- at GEO** [Baker et al, 1990]: 1-day (2-day) forecast >2M keV electron daily-averaged fluxes at GEO with PE=0.72 (0.49)
- **[Lyatsky and Khazanov, 2008]**: >2MeV e- at GEO
- **Latest Models**: NN model for GEO [Shin et al., 2016] and data assimilation (KF) model [Coleman et al., 2018]

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**Our Goal:** Using observations available from long-standing space infrastructures to develop a new model that can reproduce, nowcast and forecast event-specific behaviors of MeV electrons with high fidelity.
2.1 Satellites and Data Resources

- POES NOAA-15 in LEO (E2, E3 & P6)
- LANL-01A at GEO (SOPA)
- RBSP-A (across RB every ~5 hr)
- 2013/02/20 – 2016/08/31, 5hr time bin
- Steps: Informational event trigger(s); Triggering mechanism

RBSP+GEO: 1 MeV

E2 (>100 keV)

E3 (>300 keV)

P6 (> ~1 MeV)
Panel A: High CC for E2 at Lshells between 3.6 – 5 (cross-E and cross-PA)
Panel B: High CC for E3 extends to lower L-shells at ~3
Panel C: Cross-Lshell coherence are relatively high for L >= 5
Panel D: Cross-pitch-angle coherence are high for all Lshells but with negative lag times
Self-coherence at GEO
2.3 Constructing **Predictive MeV Electron (PreMevE) Model**

- **Static** linear predictive filters (LPF) are developed individually for each L-shell with no need of in-situ data for trapped e-

- Direct predictions are made for L between 2.8 and 6 as well as at GEO; then interpolate/extrapolate for rest L-shells

- **Submodel 1**: POES E2+E3 (>100 keV) used for predicting arrival timings of MeV electron events

- **SubModel 2**: POES E2+P6 data used for predicting flux values, particularly during decays; SOPA 1MeV data are used for predictions at GEO

- Different modes: **current, nowcast and forecast** (5-hr, 1-day/25-hr, 2-day/50-hr)
3.1 Overview of Prediction Results

- 1-day (25 hr) forecast results
- Data in first 63 days are used for determining LPF
- Nowcast (current) and other prediction (5-hr and 2-day) results look similar.

### 3. Model Performance

<table>
<thead>
<tr>
<th>Target</th>
<th>Submodel 1</th>
<th>Submodel 2</th>
<th>Dst</th>
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<tbody>
<tr>
<td><img src="image1" alt="A" /></td>
<td><img src="image2" alt="B" /></td>
<td><img src="image3" alt="C" /></td>
<td><img src="image4" alt="D" /></td>
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- 1-day (25 hr) forecast results
- Data in first 63 days are used for determining LPF
- Nowcast (current) and other prediction (5-hr and 2-day) results look similar.
3.2 Details of Prediction Results (260 Days)

- Ten major MeV e- events during the period
- Submodel 1 captures all starting times
- Submodel 2 predicts flux distributions well
3.3 Predictions for Individual L-shells (Submodel 1)

- Local WPI cannot reflect all changes in electron fluxes at large L-shells (e.g., ~GEO)

![Graph showing long-term 25 hr predictions of 1MeV e- at L-shells by SubModel 1 for different L-values (A1, B1, C1, D1, E1) with accuracy percentages (92%, 95%, 88%, 67%, 61%) indicated.]
3.4 Predictions for Individual L-shells (Submodel 2)

- Submodel 2 predicts fluxes with high-fidelity
3.5 Model Statistical Performance

- Prediction Efficiency (PE) for submodel 1 do not change much over prediction modes.
- Submodel 2 is better with predicting flux values.
- Four mode predictions can be all used for improving accuracy.

\[ PE = 1 - \frac{\sum_i[\log(j_{\text{p}}^i) - \log(j_{\text{m}}^i)]^2}{\sum_i[\log(j_{\text{p}}^i)]^2} \]
3.6 Individual Cases: Storm-time Enhancement Predictions

Observ. =>

Submod 1 =>

Submod 2 =>

Dst & Kp =>

3. Model Performance
3.7 Individual Cases: MeV e⁻ Event with NO (significant) Storm

3. Model Performance
3.8 Discussions

- Can predict higher-energy (e.g., 2MeV) electrons...
- Overall good predictions
- Lack of 2MeV precipitation fluxes
- Do better with dynamic LPFs
- Do better with in-situ data
4. Summary, Conclusions and Outlook

- Multiple kinds of coherence (including the newly discovered cross-energy cross-pitch-angle coherence) are identified, and used for developing PreMevE to nowcast and forecast MeV electron events in the outer belt, using inputs only from boundaries (POES and GEO observations (i.e., the canary)). High performance of PreMevE has been verified and validated by long-term in-situ data from RBSP, and can be an invaluable tool for satellite operators and decision makers.

- Here long-standing LEO data are used in innovative ways. Existing NOAA POES constellation can play an additional, brand-new role in space weather remote-sensing and prediction. New opportunity for next-generation LEO (low-cost) space weather mission: e.g., sensitive and reliable particle instruments with better energy resolution/coverage on board multiple nano- or cube-satellites...

- Future directions: Although not relying upon in-situ data, PreMevE can significantly improve its performance by incorporating in-situ data from such as the long-lasting US SNDD instruments.
4. Outlook (cont’d)

- Future directions: Including solar wind conditions to improve predictions at larger Lshells

- Future directions: Neural network will be the potential efficient solution dealing with multiple model input parameters…

Observations =>

Submodel 1 =>

Submodel 2 =>

Dst & Kp =>