

Statistical and predictive study of the outer belt boundary and electron content using POES-15 and FY-3C observations

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Key Points:

- Distinct impacts of coronal mass ejections and corotating interaction regions are identified in the evolution of the outer radiation belt.
- The global radiation belt content and outer boundary dynamics are systematically investigated during different types of magnetic storms.
- Predictive models for radiation belt content and boundary location are developed using the support vector regression method.

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Abstract: The dynamics of Earth's radiation belts play a crucial role in space weather modeling. However, most existing studies have primarily focused on local electron fluxes, whereas systematic investigations of global parameters, such as the radiation belt content (RBC) and the outer belt boundary, remain limited. In this study, we conduct a superposed epoch analysis of different storm types to examine the distinct responses of electron fluxes, global parameters, solar wind conditions, and geomagnetic indices. Building on the statistical results, we further develop short-term predictive models for the RBC index and the outer boundary location by using support vector regression. By characterizing global variations through statistical analysis and incorporating physical understanding into machine learning models, this study not only advances the understanding of storm-driven radiation belt dynamics but also improves predictive capabilities for space weather applications.

Keywords: radiation belt content; outer radiation belt boundary; space weather prediction; superposed epoch analysis; support vector regression

1. Introduction

The Earth's outer radiation belt is a crucial region for space weather, especially because of its high-energy electron population. These electrons are closely linked to the radiation environment of spacecraft and the long-term operational safety of satellites in Earth's orbits. Variations in the intensity and distribution of high-energy electrons can substantially affect satellite electronic systems, leading to radiation damage, internal charging, and communication disruptions (Baker et al., 2018). These effects are especially pronounced during geomagnetic storms and substorms. Therefore, understanding and predicting the dynamic evolution of the radiation belts, particularly the variations in high-energy electrons, is crucial for space weather prediction and spacecraft protection.

Nevertheless, radiation belt dynamics are not confined to only geomagnetic storm intervals. Previous studies have shown that

the dynamics of electron radiation belts can also be observed during nonstorm or weakly disturbed periods (e.g., Su ZP et al., 2014; Anderson et al., 2015). These findings indicate that the outer radiation belt can exhibit substantial variability under a broad range of geomagnetic conditions. In this study, we focus on geomagnetic storms driven by coronal mass ejections (CMEs) and corotating interaction regions (CIRs) because they provide well-defined solar wind driving conditions for systematically investigating storm-time radiation belt responses and developing short-term prediction models.

The dynamic evolution of the outer radiation belt results from complex acceleration and loss processes (e.g., Reeves et al., 2003; Koskinen and Kilpua, 2022). Despite substantial progress in understanding these mechanisms (e.g., Baker et al., 1996; Thorne et al., 2013; Jaynes et al., 2015; Tang CL et al., 2017; Xiang Z et al., 2021), predicting high-energy electron flux responses to geomagnetic storms remains challenging. Reeves et al. (2003) showed that, based on 276 storms with $Dst < -50$ nT, 53% of storms led to flux enhancements, 19% led to depletions, and 28% showed little to no change, highlighting that the disturbance storm time (Dst) index alone is insufficient for reliable predictions. Xiong Y et al. (2015) further expanded this research, finding significant differ-

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ences in the responses of low- and high-energy electrons. Together, these studies established a foundation for identifying key drivers of electron dynamics, suggesting that additional solar wind and geomagnetic parameters, such as the solar wind speed (V_{sw}), interplanetary magnetic field (IMF) B_z , and auroral electrojet (AE) index, are necessary for more accurate prediction of the behavior of the outer radiation belt (e.g., [Chu XN et al., 2021](#); [Ma DL et al., 2022](#)).

Different types of geomagnetic storms, especially those driven by CMEs and CIRs, often result in distinct electron dynamics in the outer radiation belt ([Borovsky and Denton, 2006](#)). Prior studies have shown that CME-driven storms typically cause rapid dropouts leading to a deep depletion of relativistic electrons, whereas CIR-driven storms tend to result in more gradual variations and stronger poststorm recovery ([Miyoshi and Kataoka, 2005](#); [Shen XC et al., 2017](#)). The differences between CIR and CME storms suggest that comparing solar wind and geomagnetic parameters during these different types of storms may help explain the observed discrepancies in electron flux behavior.

Existing studies have mainly relied on local electron flux data, but because of limitations in orbital coverage, gaps often exist in both the spatial and temporal dimensions. To more comprehensively characterize the behavior of the radiation belt, in recent years, global parameters, such as the radiation belt content (RBC) index, inner and outer boundary positions, and flux peak locations, have increasingly been introduced to characterize radiation belt dynamics (e.g., [Baker et al., 2004](#); [Forsyth et al., 2016](#); [Wang X et al., 2024](#)). Compared with local electron flux measurements, global parameters help describe the overall state of high-energy electrons in the outer radiation belt and effectively capture the changes and evolution of the radiation belt under different space weather conditions ([Turner et al., 2014](#); [Forsyth et al., 2016](#)).

The RBC index is a global metric that quantifies the total number of high-energy electrons in the outer radiation belt, effectively capturing the net “inventory” of energetic electrons in the system ([Baker et al., 2004](#)). The evolution of the RBC index is highly sensitive to changes in solar wind speed, IMF B_z , and geomagnetic indices such as the Dst : high-speed streams and intense geomagnetic storms are often associated with sharp increases or decreases in the RBC ([Baker et al., 2004](#); [Forsyth et al., 2016](#)). Furthermore, [Forsyth et al. \(2016\)](#) demonstrated that the RBC index responds strongly to substorm activity, consistent with the sequence of substorm injection, electron acceleration, and buildup of the high-energy electron population in the outer radiation belt.

Radial boundaries of the outer radiation belt electron population also represent key global descriptors of belt morphology, including the inner boundary, outer boundary, and location of the flux peak. The inner boundaries often display strong energy dependence. For example, ultra-relativistic electrons are constrained by an apparent “impenetrable barrier” near $L \approx 2.8$, where L denotes the McIlwain L parameter ([Baker et al., 2014](#)), whereas hundreds of kilo electronvolt electrons can penetrate to much lower L -shells during geomagnetic storms ([Turner et al., 2014](#)).

The outer boundary position is highly variable and frequently modulated by interplanetary disturbances ([Turner et al., 2014](#)).

[Matsumura et al. \(2011\)](#) showed that the outer radiation belt boundary is closely related to the magnetopause location, highlighting the importance of magnetopause compression and shadowing. During intense storm phases, the compression of the magnetopause can trigger severe magnetopause shadowing. This process not only causes substantial inward motion of the outer boundary but also leads to a sharp reduction in phase space density at the outer edge. This depletion subsequently drives rapid outward radial diffusion, which is often amplified by steep gradients and enhanced ultra-low-frequency wave activity, ultimately resulting in massive dropouts of relativistic electrons across a wide range of L -shells ([Turner et al., 2012](#)). Recent observations of a sub-relativistic electron third-belt event further showed that shock-driven magnetospheric compression, magnetopause shadowing, and outward radial diffusion can substantially alter large-scale radiation belt structures ([Chen JL et al., 2024](#)). Therefore, the physical processes governing the outer boundary are inextricably linked to the overall depletion of the outer radiation belt.

The RBC index reflects the total amount of high-energy electrons in the outer radiation belt, and its variation is closely related to the movement of the outer boundary and flux distribution across L -shells. The inward movement of the outer boundary is usually accompanied by electron loss, leading to a decrease in RBC, whereas the outward expansion of the boundary incorporates additional electron populations, causing the RBC to increase. Correspondingly, changes in the radial flux distribution indicate regions of acceleration and injection within the radiation belt. Therefore, by jointly considering boundary dynamics and local flux variations, the RBC index provides a comprehensive measure for characterizing the overall state of the outer radiation belt and its space weather implications.

Although much progress has been achieved, some issues still require further investigation. Most previous studies have focused on local electron fluxes, whereas systematic analyses of global parameters, such as the RBC index and the outer boundary position, remain relatively scarce. Although CME- and CIR-driven storms are both known to produce distinct electron responses, their impacts on these global parameters have not been comprehensively compared. Moreover, many existing machine learning approaches rely on pure black-box training with arbitrary inputs and often lack a physical rationale for feature selection. Furthermore, modeling local fluxes in isolation (without considering the global structural context, such as boundary movements driven by magnetopause shadowing or convection) can hamper generalization of the model across different storm drivers. These gaps highlight the need for a physically informed, data-driven prediction framework. By integrating global radiation belt parameters and selecting input features based on physical mechanisms, such a framework can advance scientific understanding and improve predictive capability.

To address these issues, in this study we first perform a superposed epoch analysis (SEA) of electron flux, global radiation belt parameters, solar wind, and geomagnetic indices during different types of storms. On the basis of these results, we then identify appropriate input parameters and develop predictive models for the outer

boundary location and the RBC index by using support vector regression (SVR). By comparing CME- and CIR-driven geomagnetic storms, we further explore their distinct impacts on outer radiation belt dynamics. This dual approach allows us not only to elucidate the underlying physical mechanisms driving electron flux variations under different storm drivers, but also to enhance predictive capabilities for outer radiation belt dynamics. Section 2 describes the data and methodology. Sections 3 and 4 present the results of the SEA and the short-term prediction models, respectively. Section 5 offers a detailed discussion of the findings and outlines our main conclusions.

2. Data and Methods

2.1 Data

The electron flux data used in this study are obtained from observations by the National Oceanic and Atmospheric Administration's (NOAA's) Polar Operational Environmental Satellite-15 (POES-15) satellite and China's FengYun-3C (FY-3C) satellite.

The NOAA/POES series consists of Sun-synchronous polar-orbiting satellites at an altitude of ~ 800 km with an orbital period of ~ 100 minutes. The Medium-Energy Proton and Electron Detector (MEPED) instrument on board NOAA/POES-15 includes two pairs of directional electron telescopes. The 0° telescopes are oriented outward along the Earth-center-to-satellite direction, and the view direction of the 90° telescopes is normal to the 0° telescopes and antiparallel to the spacecraft velocity vector (Evans and Greer, 2000). Additionally, they both have four electron energy channels: >40 , >130 , >287 , and >612 keV (Green, 2013). In the L range 3–7, the 0° detector measures electrons within the loss cone, whereas the 90° detector mostly measures trapped electrons (Sandanger et al., 2009).

The FY-3C satellite is the first operational satellite of China's second-generation polar-orbiting meteorological satellites. It also operates in a Sun-synchronous orbit, with an altitude of ~ 830 km, an orbital inclination of $\sim 98^\circ$, and an orbital period of ~ 101.5 minutes. High Energy Electron Detector (HEED) is oriented normal to the orbital plane and provides data in five energy channels (0.15–0.35, 0.35–0.65, 0.65–1.2, 1.2–2.0, and 2.0–5.7 MeV) to monitor the trapped populations of energetically charged electrons with a 40° field of view (Wang CQ et al., 2013).

The solar wind and geomagnetic parameters used in this study are obtained from the OMNI database (ftp://cdaweb.gsfc.nasa.gov/pub/data/omni/omni_cdaweb/). In this work, we mainly use the southward magnetic field B_z , solar wind speed, dynamic pressure, Dst index, and AE index from the OMNI database.

2.2 Methods for Calculating the Boundaries and RBC

To calculate the RBC index in practice, we divide the procedure into two steps: (1) boundary identification and (2) integration of electron density between these boundaries.

2.2.1 Boundary Identification

Accurately identifying the inner and outer boundaries of the outer radiation belt is crucial for quantifying its dynamics and for

computing integrated parameters such as the RBC index. Previous studies, such as that by Yuan CJ and Zong QG (2012), have typically utilized an exponential fitting function with a constant index a_0 , defining the boundary locations as the L-shells where the flux decreases to e^{-a_0} of the peak flux. In their study, Yuan CJ and Zong QG (2012) adopted $a_0 = 4$ for the outer boundary and $a_0 = 2$ for the inner boundary. Although effective under moderate flux conditions, this approach tends to misidentify the boundary locations when the peak flux deviates substantially from typical levels. This can lead to systematic biases in boundary estimation, especially during geomagnetically disturbed periods and when the background flux at high L-shells is elevated.

To address these limitations and account for flux variability, we introduce a piecewise function $a(x)$, with x denoting the logarithm of the peak electron flux, to replace the constant a_0 . This formulation allows the fitting process to adapt to different outer belt intensity levels. On the basis of extensive testing, the selected piecewise function substantially improves the accuracy of boundary determination across a wide range of storm-time and quiet-time conditions, thereby enhancing the reliability of subsequent RBC calculations. For NOAA/POES-15 >612 keV electron flux data,

$$a(x) = \begin{cases} 0.5 & x \leq 6 \\ 0.5 + 1.3(x - 6) & 6 < x \leq 8 \\ 3.1 + 1.2(x - 8) & 8 < x \leq 9.5 \\ 4.9 + 0.9(x - 9.5) & x > 9.5 \end{cases}.$$

For FY-3C 0.65–5.7 MeV electron flux data,

$$a(x) = \begin{cases} 0.1 & x \leq 6 \\ 0.1 + 1.2(x - 6) & 6 < x \leq 8 \\ 2.5 + 0.9(x - 8) & 8 < x \leq 9 \\ 3.4 + 0.6(x - 9) & x > 9 \end{cases}.$$

As shown in Figure 1, the fitted boundaries obtained by using the dynamic $a(x)$ closely follow the observed flux drop-off regions from NOAA-15 and FY-3C across various storm- and quiet-time conditions. The curves accurately capture both sharp and gradual boundary transitions that occur under different outer belt intensities. This performance is achieved because the dynamic adjustment of $a(x)$ allows the fitting to adapt to changes in boundary steepness, reducing systematic biases at low and high flux conditions—advantages that cannot be achieved with a constant a_0 assumption.

Nonetheless, occasional discrepancies remain because of the complex nature of the outer belt, particularly under conditions of low overall flux levels or elevated background flux at high L-shells. To address these issues, the following preprocessing steps are implemented:

(1) Limiting the width between the peak location and the inner or outer boundary based on peak flux levels:

$$\text{Width}(x) = \begin{cases} 2, & x \leq 7 \\ 3, & 7 < x \leq 8 \\ 4, & 8 < x \leq 9 \\ 5, & x > 9 \end{cases};$$

(2) Applying a rolling median filter to the identified boundary

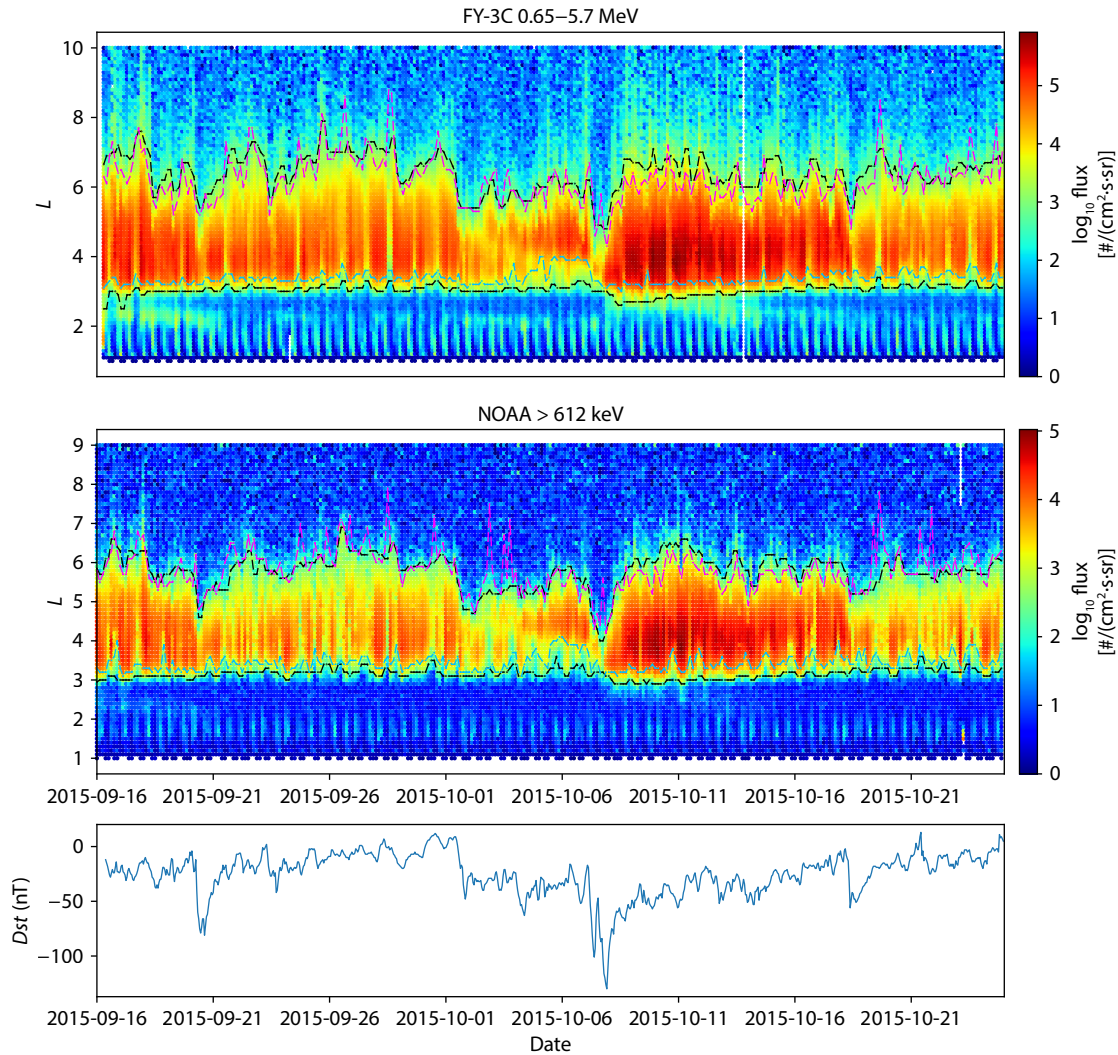


Figure 1. Original fitted boundaries of the outer radiation belt (September 15–October 24, 2015). The dashed black lines denote the inner and outer boundaries determined by using a variable fitting index $a(x)$. The dashed magenta and deep sky blue lines represent the outer and inner boundaries, respectively, derived by using constant fitting indices of $a_0 = 4$ and $a_0 = 2$.

locations over time;

(3) Removing data points where boundaries cannot be accurately determined, specifically including periods of extremely low electron flux and instances of missing data during several storms.

2.2.2 RBC Calculation

Once the inner and outer boundaries of the outer radiation belt are determined, the RBC index is calculated following the formulation by Baker et al. (2004):

$$\text{RBC} = \int_{L_{\text{in}}}^{L_{\text{out}}} n(L) dV(L),$$

where L_{in} and L_{out} are the inner and outer boundaries of the outer radiation belt, $n(L)$ is the electron number density, and $dV(L)$ is the volume element of a dipole magnetic field at a given L-shell.

Following the convention of Baker et al. (2001), we denote J as the energy-integrated directional flux ($\text{cm}^{-2} \cdot \text{s}^{-1} \cdot \text{sr}^{-1}$), obtained by integrating the differential directional flux $j(E)$ over the instrumen-

tal energy channel:

$$J = \int_{E_1}^{E_2} j(E) dE,$$

where E_1 and E_2 denote the lower and upper bounds of the instrumental energy channel, respectively.

Assuming an isotropic pitch-angle distribution (PAD) and relativistic velocity $v \approx c$ (where v is the electron speed and c is the speed of light), the electron number density proxy can then be approximated as

$$n = \frac{4\pi J}{c}.$$

This formulation has been widely adopted in radiation belt energetics studies (e.g., Baker et al., 2001; Reeves et al., 2003; Kanekal et al., 2005). The isotropic assumption provides a standardized approximation, although pitch-angle anisotropy may introduce systematic uncertainty. By using the commonly adopted parameterization $J(a) \propto \sin^m a$, where a is the electron pitch angle and m

is the pitch-angle anisotropy index, the sensitivity of the RBC to pitch-angle anisotropy can be quantitatively estimated. Statistical observations (e.g., Gu XD et al., 2011) indicate that typical PADs correspond to $m \approx 0\text{--}1.5$, implying uncertainties generally within $\sim 0\%\text{--}25\%$. For weak to strong pancake distributions ($m = 1\text{--}4$), the resulting RBC typically differs from the isotropic estimate by $\sim 20\%\text{--}50\%$.

Moreover, it is important to note that during the main phase of intense CME-driven storms, strong wave–particle interactions, such as pitch-angle scattering by electromagnetic ion cyclotron (EMIC) waves and chorus waves, together with magnetopause shadowing, can produce highly anisotropic PADs, including butterfly and flat-top distributions. Under such highly disturbed conditions, the isotropic assumption could introduce a larger systematic error to the quantitative RBC calculation, potentially exceeding the uncertainty ranges estimated above. Therefore, particularly during intense main phases, our calculated RBC should be interpreted as a standardized proxy based on equatorially mirroring electrons, rather than an absolute content measure. Accordingly, the RBC parameter provides a consistent and physically interpretable link between low Earth orbit (LEO) flux observations and the trapped relativistic electron population in the magnetosphere.

Under the dipole approximation, the volume between a given L-shell and the Earth's surface can be calculated by (Lyons and Williams, 1984)

$$V(L) = V_E \left[L^3 \left(1 - \frac{1}{L} \right)^{1/2} \times \left(\frac{0.43}{L^3} + \frac{0.171}{L^2} + \frac{0.229}{L} + 0.457 \right) - \left(1 - \frac{1}{L} \right)^{1/2} \right],$$

where V_E is the volume of the Earth, and $V(L)$ is the volume enclosed between the Earth's surface and the specified dipole L-shell.

Once the inner and outer boundaries are determined and flux data are available, the RBC index can be computed accordingly.

To rigorously verify the robustness of the method, we conduct dual sensitivity analyses on both the NOAA-15 and FY-3C datasets by independently perturbing the break points and slopes (detailed results are provided in Appendix C). When scaling the slopes by $\pm 20\%$, the mean absolute error (MAE) of the $\log_{10}$ RBC remains exceptionally low (0.002 to 0.008). Similarly, systematically shifting all flux break points by up to one order of magnitude yields a maximum MAE of less than 0.06 in $\log_{10}$ RBC. These tests confirm that the integrated RBC metric is overwhelmingly dominated by the high-flux core region, demonstrating that the integrated RBC metric is robust against reasonable variations in the empirical boundary parameters.

2.3 Methods for Modeling

After determining the locations of the outer radiation belt boundary and the RBC values, we proceed to develop predictive models for these parameters. The method selected is SVR incorporating kernel functions.

The choice of SVR is motivated by its proven capability in handling high-dimensional, nonlinearly separable problems and its robustness in scenarios with limited data—a common constraint in space physics studies. The objective of SVR is to search for the function with at most ε deviations from the observed target values for training data and one that must be as flat as possible, and kernel functions are used to map the data to a higher dimensional feature space, making SVR feasible for nonlinear problems (Awad and Khanna, 2015).

The radial basis function (RBF) kernel $K(\mathbf{x}, \mathbf{x}_i) = \exp(-\gamma \|\mathbf{x} - \mathbf{x}_i\|^2)$ is applied as the kernel function in this study, where $\mathbf{x}$ is a new input vector and $\mathbf{x}_i$ is a support vector from the training set. When $\mathbf{x}$ is close to $\mathbf{x}_i$, K approaches 1 and $\mathbf{x}_i$ strongly influences the prediction; as the distance increases, K decays toward 0 and the influence becomes negligible.

For SVR models with the RBF kernel, the main hyperparameters are the regularization parameter C , the epsilon-insensitive zone width ε , and the kernel width parameter γ . Specifically, C controls the trade-off between training error and model complexity; ε determines the tolerance for deviations between predicted and true values; and γ mainly influences the shape of the kernel function and the influence range of individual samples. Proper selection of these parameters is critical to balancing the fitting ability and generalization capability of the model.

3. Superposed Epoch Analysis

The dynamics of the outer radiation belt are strongly modulated by geomagnetic storms, yet different storm drivers—such as CMEs and CIRs—can produce distinct electron responses in terms of flux variations, boundary shifts, and recovery characteristics. Although previous studies have examined storm-time effects by using case studies or statistical analyses, there remains a lack of systematic comparisons between different storm types in terms of their impacts on both local and global parameters, such as the RBC index.

In this section, we apply the SEA technique to investigate the temporal evolution of the outer radiation belt during geomagnetic storms. This technique has been widely used in space weather research to identify consistent responses of the Earth's magnetosphere and outer radiation belt to various solar wind disturbances (e.g., Miyoshi and Kataoka, 2005; Ni BB et al., 2016; Shen XC et al., 2017). By aligning the events to a common time scale, we are able to compare the behavior of the radiation belt during CME- and CIR-driven storms, two of the most significant types of solar wind disturbances. This approach allows us to address key questions: Which storm drivers cause the most severe losses? Which conditions favor rapid recovery? And what roles do wave–particle interactions play in these processes?

In this study, 49 storms (listed in Appendix A) with minimum $Dst \leq -40$ nT, which exhibit clear features of a CME or CIR driver, are identified in the interval from 2013 to 2019. According to storm intensity and the characteristics of solar wind drivers, these storms are categorized into three groups: 12 moderate CME-driven storms, 31 CIR-driven storms, and 6 intense CME-driven storms.

The moderate CME and CIR groups share a comparable average minimum Dst of ~ -60 nT, whereas the intense CME group exhibits a much stronger average intensity of ~ -140 nT. It should be noted that because of the rarity of such extreme events during our study period, this group is relatively small. Therefore, it serves primarily as a collection of extreme case studies rather than a statistically robust sample. Phenomenologically, the CME-driven storms show key features of a strong magnetic field, rotating magnetic field, and declining velocity (Jian L et al., 2006a), whereas the CIR storms show typical signatures of gradual increases in solar wind speed (Jian L et al., 2006b). Moreover, the NOAA weekly reports, Preliminary Report and Forecast of Solar Geophysical Data, are used as references following the method of Bingham et al. (2018).

Figure 2 shows the SEA results of 3-hour averaged electron fluxes and RBC from NOAA/POES-15 across different energy levels, as well as associated geomagnetic indices and solar wind parameters. For each storm, the main phase has been time-normalized to 12 hours for CME- and CIR-driven storms, and to 14 hours for intense CME-driven storms, consistent with their respective average durations of ~ 12 and 14 hours. The time $t = 0$ corresponds to the minimum Dst , whereas the two vertical lines mark the onset and end of the main phase. The onset of the main phase is defined as the start of the Dst decrease.

3.1 Comparison of CME- and CIR-Driven Storms

Although CME- and CIR-driven storms exhibit comparable average Dst values, notable differences are observed in the solar wind conditions. As shown in Figures 2h and 2i, CIR-driven storms feature a gradual increase in solar wind with stronger transient compression, whereas CME-driven storms generally involve lower and steadier speeds.

In Figures 2d–2f, however, compared with CME-driven storms, CIR-driven storms produce smaller inward displacements of the outer boundary of the outer radiation belt and weaker reductions in RBC. Losses can occur through magnetopause shadowing and outward radial transport (e.g., Shprits et al., 2006; Ukhorskiy et al., 2006). Although CIR-driven storms often feature strong transient increases in dynamic pressure, which can induce rapid magnetopause shadowing at the outermost L-shells, this compression is typically short-lived. Conversely, CME-driven storms exhibit significantly stronger and more prolonged southward IMF B_z (Figure 2j). As demonstrated by Turner et al. (2012), this sustained mechanism effectively strips electrons from much deeper L-shells over a prolonged duration. Furthermore, statistical analyses of electron dropouts at $L \sim 4.2$ by Boynton et al. (2017) showed that the influence of solar wind dynamic pressure diminishes substantially at higher energies ($E > 1$ MeV), where the southward IMF B_z emerges as the dominant controlling factor for electron losses.

During the recovery phase, CIR-driven storms display more frequent and intermittent intervals of southward B_z , whereas CME-driven storms show a sustained northward B_z . Additionally, CIR storms are usually accompanied by a high AE index (Figure 2k), indicating intense substorm activity, which injects great quantities of low- to medium-energy electrons into the inner magneto-

sphere. This pattern is also evident in Figures 2a and 2b, where >40 keV and >130 keV electron fluxes demonstrate faster recovery in both magnitude and spatial coverage during CIR-driven storms.

Previous studies have shown that the flux ratio between 0° and 90° MEPED telescopes for 30–100 keV electrons, as observed by NOAA/POES satellites, can serve as a reliable proxy for chorus wave activity (e.g., Li W et al., 2013; Ni BB et al., 2014). In this study, we calculated $R = J_{0^\circ, 40-130 \text{ keV}}/J_{90^\circ, 40-130 \text{ keV}}$ using NOAA-15 measurements, as shown in Figure 2c. Results revealed stronger and more persistent chorus wave activity during the recovery phase of CIR storms, which likely contributes to more efficient acceleration of seed electron populations.

These statistical results indicate that CIR storms experience relatively weak electron losses during the main phase, thereby preserving a favorable energy spectrum for subsequent acceleration. During the recovery phase, CIR storms show substantially higher chorus wave proxy values compared with CME storms. These factors contribute to the rapid replenishment of high-energy electrons and the swift restoration of the outer radiation belt boundary—representing a characteristic response of limited losses and fast recovery.

3.2 Analysis of Intense CME-Driven Storms

The average minimum Dst of intense CME-driven storms reaches ~ -140 nT. Compared with moderate CME-driven storms, they exhibit the same overall loss characteristics but with usually much stronger and more prolonged southward IMF B_z , together with higher solar wind speed and dynamic pressure. These conditions typically drive substantial electron flux losses across all energy channels, particularly for >612 keV electrons in Figure 2e. As shown in Figures 2e and 2f, the average inward shift of the outer radiation belt boundary is the most severe among all categories, and the decrease in RBC is also the largest.

Compared with moderate CME storms, intense CME storms tend to maintain higher AE index values during both the main and recovery phases (Figure 2k). This can promote enhanced injection of low- and medium-energy electrons, allowing the recovery of >40 keV and >130 keV electron fluxes to begin unusually early, in some cases even before the end of the main phase, as can be seen in Figures 2a and 2b. Despite the sharp drop in RBC during the main phase, recovery is rapid and often exceeds average RBC levels observed in CIR storms, suggesting more efficient acceleration under extreme driving.

In Figure 2c, although the intensity and continuity of chorus waves during the recovery phase are weaker in intense CME storms compared with CIR storms, they exhibit stronger amplitudes and penetrate to lower L-shells on average during the main phase. These features provide a favorable environment for *in situ* energization and electron injections into the slot region. Consequently, these 6 intense CME storms represent the most extreme cases of strong loss followed by rapid and highly efficient recovery.

To verify that the superposed mean is not dominated by a single outlier, the individual temporal traces of these 6 events are

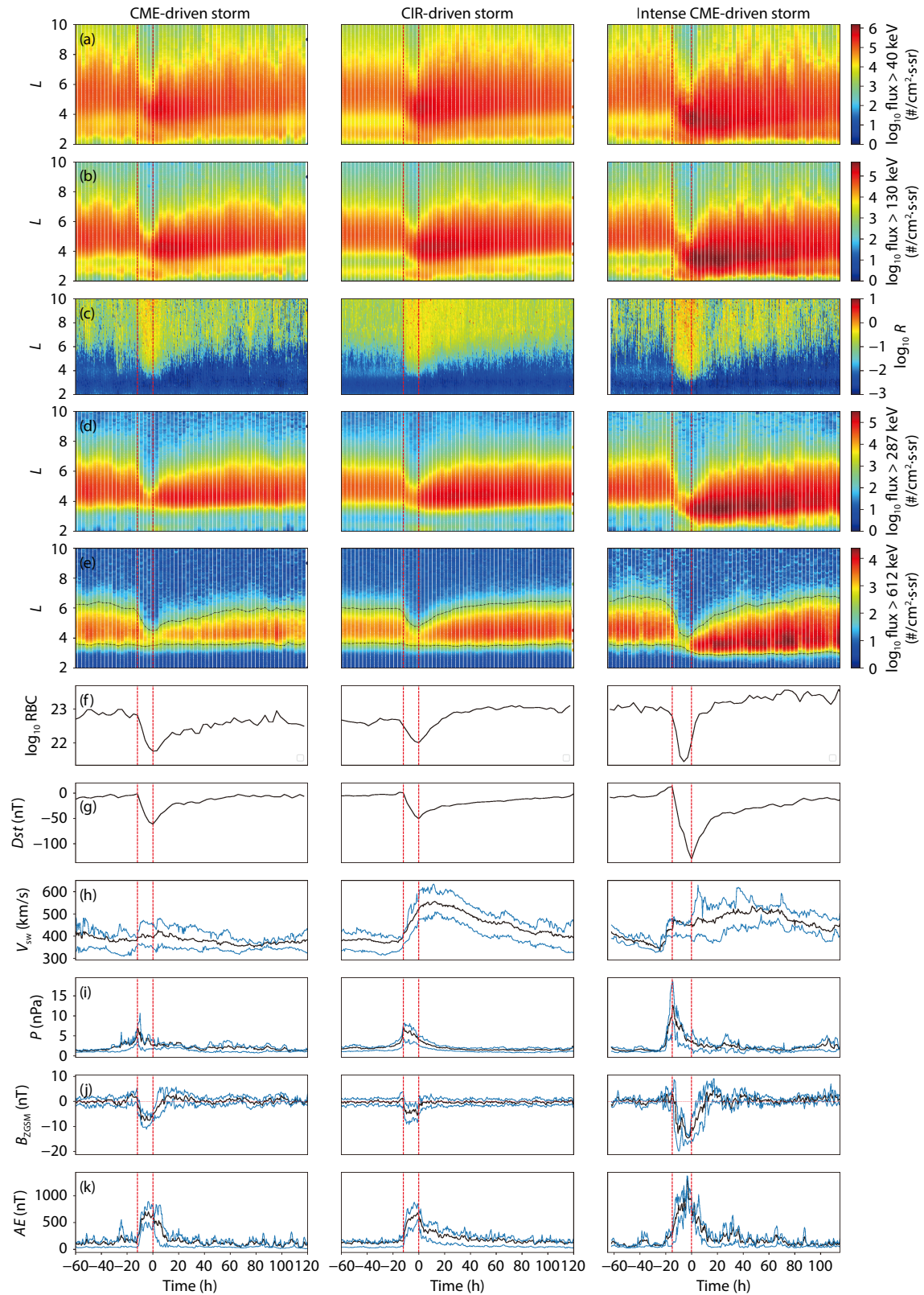


Figure 2. Superposed epoch analysis of electron flux, RBC, geomagnetic, and solar wind parameters during CME-driven, CIR-driven, and intense CME-driven storms. Panels (a), (b), (d) and (e) show the 3-hour average flux of >40, >130, >287, and >612 keV electrons obtained from the 90° detector; panel (c) shows $\log_{10} R$, where $R = J_{0^\circ, 40-130 \text{ keV}}/J_{90^\circ, 40-130 \text{ keV}}$ is used as a qualitative proxy for chorus wave activity; panel (f) shows the RBC of >612 keV electrons; panels (g)–(k) show the Dst index, solar wind speed, dynamic pressure, IMF southward component, and AE index. In panels (h)–(k), the black lines indicate the mean value, whereas the blue lines correspond to the 25th and 75th percentiles. The vertical dashed red lines mark the onset and end of the storm main phase, with $t = 0$ representing the minimum Dst .

provided in Appendix D. The individual traces confirm that the pronounced flux dropouts and subsequent robust enhancements are consistent features across the vast majority of the analyzed events.

These results highlight the impact of different types of geomagnetic storms on the outer radiation belt, providing key insights into the mechanisms driving changes in electron flux and boundary movement. In the next section, we explore predictive modeling methods aimed at the short-term prediction of these dynamic changes.

4. Prediction of the Outer Radiation Belt Boundary and RBC Index

We implement SVR with an RBF kernel to capture the nonlinear dependencies between selected physical drivers and the target variables (the RBC index and outer boundary location). The three key hyperparameters (C , ε , γ) are optimized jointly by using the Optuna-based approach. The tree-structured Parzen estimator sampler is adopted to search continuous hyperparameter spaces, and the objective function is defined as the MAE obtained from fivefold cross-validation on the training set. The selected hyperparameter set should be regarded as a high-performing configuration identified within the predefined search space and optimization budget, rather than as a mathematically unique global optimum. Detailed search ranges and procedures are provided in Appendix B.

A distinctive feature of our approach lies in the physically informed feature selection. Instead of using arbitrary predictors, we select input parameters based on their mechanistic relevance to the electron loss and recovery processes identified in Section 3. Specifically, the SEA reveals systematic differences in solar wind drivers and geomagnetic responses between CME- and CIR-driven storms. These results guide our feature selection: parameters are included if they show (1) a clear and systematic variation across storm types, and (2) a well-established physical role in controlling electron loss or recovery.

Accordingly, the model uses three categories of predictors:

- (1) Solar wind parameters (speed, dynamic pressure, and IMF B_z), which control convection, magnetopause compression, and reconnection;
- (2) Geomagnetic activity (Dst index), representing ring current strength;
- (3) System state variables (outer boundary position or RBC), incorporating memory of prior conditions.

Although the AE index is a crucial physical proxy for substorm activity and associated electron injection and acceleration, it is excluded from the final predictive model because of a combination of multicollinearity, inherent physical time lags, and operational constraints. First, the average AE index during magnetic storms strongly correlates with IMF B_z and V_{sw} (e.g., [Boroyev, 2019](#)). Second, although substorms supply necessary seed electrons, a typical lag of 1–3 days exists between substorm activity and peak radiation belt enhancements ([Forsyth et al., 2016](#)). Finally, from an operational space weather prediction perspective, definitive final

AE indices are not available in real time. Relying solely on solar wind parameters, the IMF B_z , and the Dst index yields a more robust and practically viable predictive framework.

In this study, the dataset is constructed with a uniform time resolution of 3 hours. The predictive models are designed to estimate the outer boundary position or the RBC value at the subsequent time step. For RBC models, a base-10 logarithmic transformation is applied to the RBC values before modeling. All input features are standardized to zero mean and unit variance by using the parameters estimated from the training set, and the same transformation is then applied to the independent test set.

Moreover, when modeling the RBC, the azimuthal asymmetry of the geomagnetic field causes satellites to periodically traverse regions of varying magnetic field strength as the Earth rotates, which introduces significant diurnal variations in the observed fluxes ([Green et al., 2021](#)). To decouple these periodic geographic effects within our model, we transform the local time (LT , expressed in hours) variable into two features, $\sin(2\pi LT/24)$ and $\cos(2\pi LT/24)$, and add them into the input parameters.

4.1 Prediction of the Outer Boundary

First, a predictive model for the outer boundary position is developed using >612 keV electron flux data from NOAA/POES-15. Data from 2013, 2014, 2016, and 2017 are used for training and validation, whereas 2015—characterized by multiple intense geomagnetic storms—is reserved as a test set. This configuration enables a robust evaluation of model performance under severe space weather conditions.

The selected hyperparameters identified by the Optuna-based optimization are $C = 10.547$, $\varepsilon = 0.001$, and $\gamma = 0.023$. [Figure 3a](#) shows a two-dimensional (2D) histogram of the model versus observed boundary position on the test set, yielding a coefficient of determination (R^2) of 0.91 and an MAE of 0.12 on the test dataset, indicating that the model effectively captures the overall trend of boundary variations. [Figure 4](#) further illustrates the model performance using NOAA/POES-15 data and the Dst index, and the time series comparison clearly demonstrates the model's capability of capturing the dynamic evolution of electron flux. As shown in [Figures 3a](#) and [4c](#), the predictions generally align closely with the $y = x$ line, and the residuals are mostly not beyond 0.5 and randomly distributed.

To evaluate the generalizability of this approach using data from other LEO satellites, we use the summed flux of channels 3, 4, and 5 (0.65–5.7 MeV) from FY-3C for predictive modeling. Because of limited valid in-orbit data, observations in 2014, 2016, and 2017 (up to May 12) are used for training and validation, whereas data from 2015 serve as an independent test set. A data gap exists from May 31 to September 15 in 2015, but it does not affect the training process. The exact temporal coverage of the FY-3C test set spans from January 1 to May 30, 2015, and from September 16 to December 31, 2015. Although this gap omits some storms, the active test periods still capture a highly diverse set of events, including several moderate CME and CIR storms, and several intense storms. Thus, the remaining data provide a sufficiently

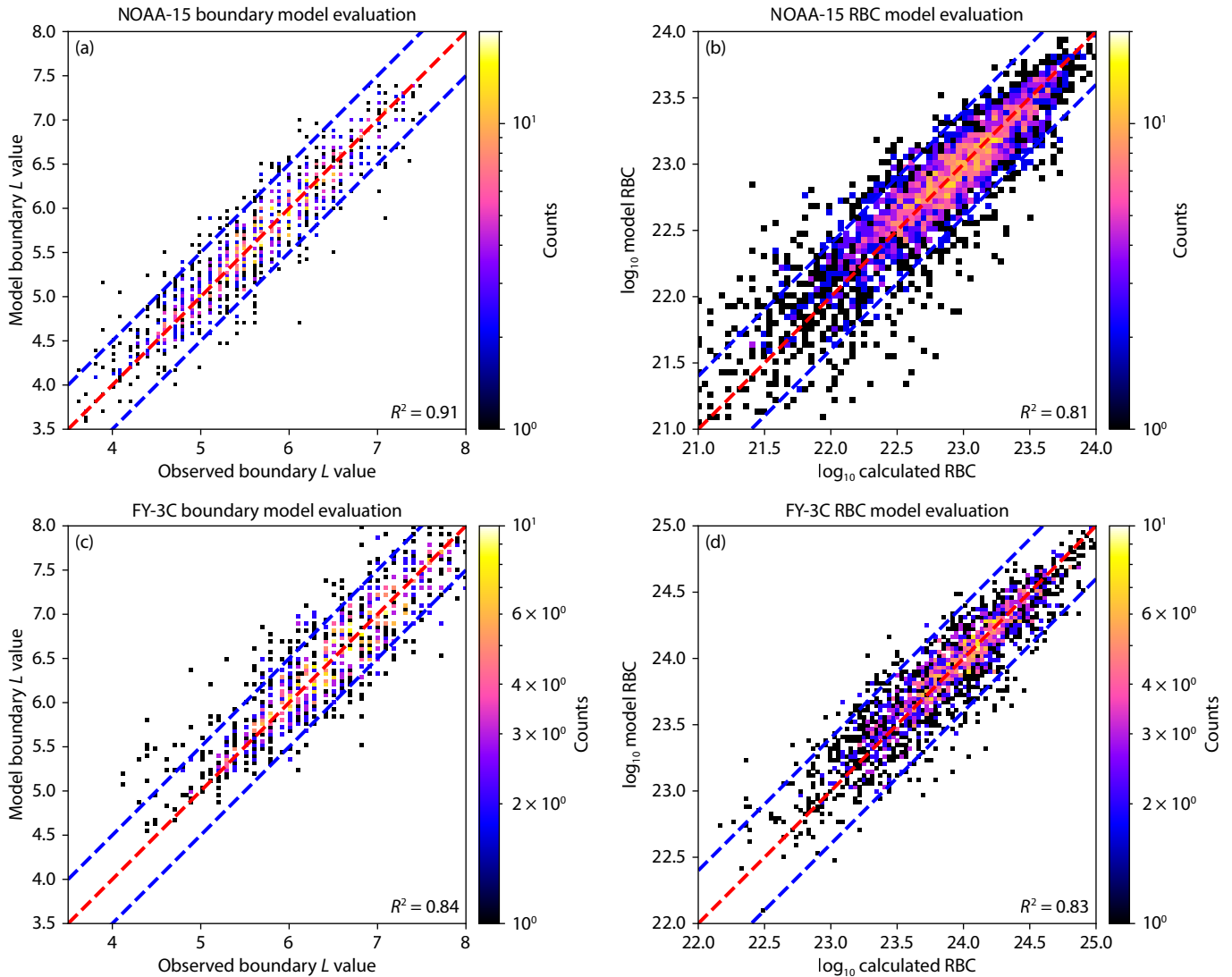


Figure 3. Evaluation of four models on the test set. The red lines indicate $y = x$, and the blue lines indicate $y = x \pm 0.5$ in panels (a) and (c), and $y = x \pm 0.4$ in panels (b) and (d).

robust sample to evaluate the performance of the model under various space weather conditions.

The selected model configuration used $C = 6.262$, $\varepsilon = 0.001$, and $\gamma = 0.019$. The model achieves an R^2 of 0.84 and an MAE of 0.16 on the test dataset. Figure 3c shows the 2D histogram of predicted versus observed boundary positions on the test set, indicating that most absolute boundary-position errors are within 0.5 in L . Figure 5c compares the model predictions with FY-3C observations and the Dst index. Prediction errors tend to increase during intense geomagnetic storms (e.g., the intense storms on March 17, 2015, and December 20, 2015), likely due to the limited number of extreme space weather events in the training data.

4.2 Prediction of the RBC Values

Subsequently, the RBC value is modeled using the same set of solar wind and geomagnetic parameters, along with its current value derived from NOAA-15 >612 keV electron flux observations.

The selected hyperparameters are determined to be $C = 14.391$,

$\varepsilon = 0.062$, and $\gamma = 0.024$. On the test dataset, the model achieves an R^2 of 0.81 and an MAE of 0.19. Figure 3b shows a 2D histogram of the model versus the observed RBC on the test set. Figure 4d further illustrates that most $\log_{10}$ RBC errors are within 0.4, corresponding to less than one order of magnitude in RBC. As shown in Figure 4d, in addition to underperforming during a few specific magnetic storms, the performance of the model also occasionally degrades during periods of low flux levels. A plausible explanation is that accurately determining the boundary position is inherently difficult (as discussed earlier), and even a small deviation in the boundary can lead to a large deviation in the RBC value when the overall flux level is low.

Finally, a model is developed for the RBC value by using FY-3C 0.65–5.7 MeV electron data, and it achieves an R^2 of 0.83 and an MAE of 0.15 on the test dataset. The model hyperparameters are found to be $C = 4.715$, $\varepsilon = 0.082$, and $\gamma = 0.024$. Figure 3d shows the 2D histogram of predicted versus observed RBC values on the test set, and Figure 5d compares the model predictions with FY-

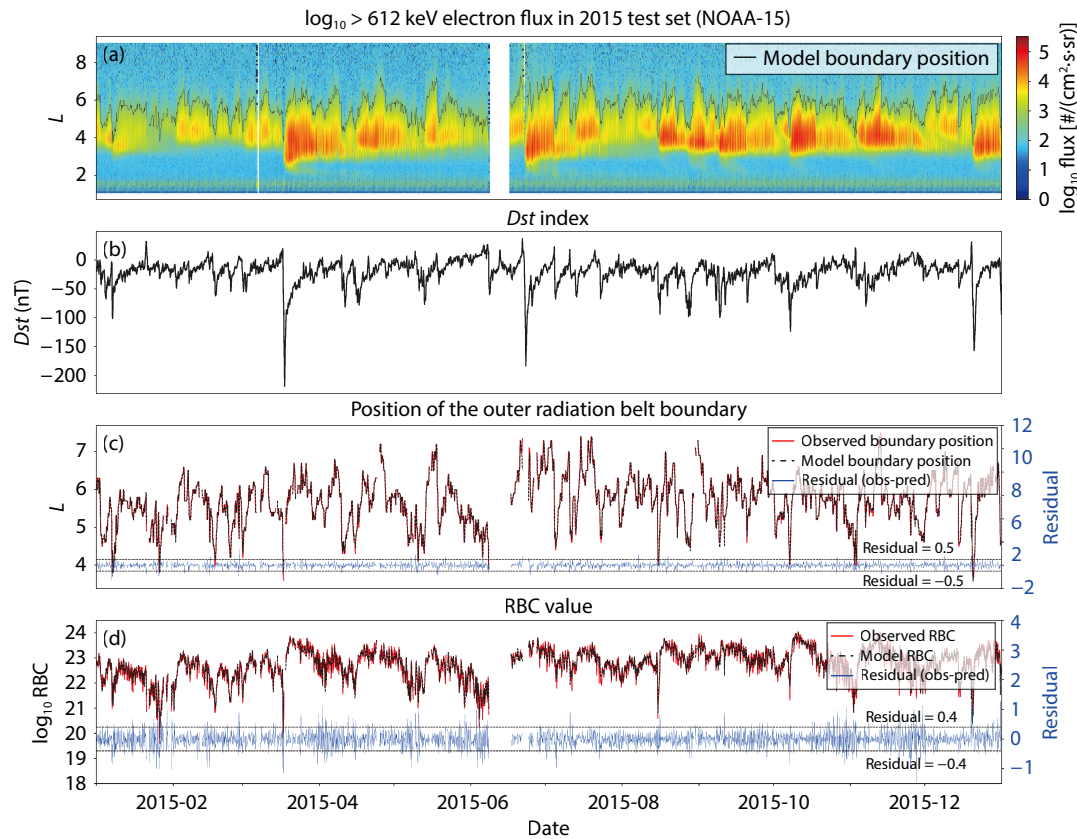


Figure 4. Comparison of model predictions with observations for boundary position and RBC value, together with $\log_{10}$ of >612 keV electron fluxes and the *Dst* index during the 2015 NOAA-15 test period. Panels (c) and (d) show observed (red), predicted (black), and residual (blue) values.

3C observations and the *Dst* index.

Because flux levels near the boundaries are relatively low and contribute little to the total content, the RBC index, as an integrated measure of flux, is less affected by boundary-fitting uncertainties or data gaps, which likely contributes to the strong performance observed on the test set.

5. Discussion and Conclusions

By performing an SEA of >40 , >130 , >287 , and >612 keV electron flux distributions in the outer radiation belt, this study characterizes the general L-shell evolution patterns for each storm category. The results are as follows:

- (1) CIR-driven storms: For >287 and >612 keV electrons, the storms exhibit weaker inward boundary motion during the main phase and stronger recovery afterward, characterized by higher average fluxes, broader spatial distributions, more outward outer boundary locations, and higher peak fluxes compared with CME storms.
- (2) CME-driven storms: During the recovery phase, they show distinct flux enhancement below 287 keV, but the enhancement at >612 keV is limited.
- (3) Intense CME-driven storms: They tend to exhibit rapid and strong RBC recovery during the recovery phase, suggesting overall higher acceleration efficiency.

This analysis highlights the strong dependence of electron flux evolution on the solar wind driving conditions. The CIR-driven storms, characterized by gradual disturbances, intermittent injections, and strong chorus wave activities, tend to provide more favorable conditions for high-energy electron enhancements. In contrast, the CME-driven storms are more likely to cause substantial electron losses and often lack a sustained and effective recovery mechanism. Intense CME-driven storms represent extreme cases, typically producing the deepest boundary inward shifts and RBC decreases, but also generally fast recovery facilitated by enhanced injections. However, we acknowledge the caveat that these findings are drawn from a limited sample size of 6 events. Although they successfully highlight the severity of storm-time outer belt dynamics, future studies incorporating a broader temporal baseline and more extreme events are needed to statistically solidify these patterns.

Building on these findings, we subsequently develop SVR models to predict RBC and the outer boundary position by using observational data from NOAA-15 and FY-3C. All four models achieve an $R^2 > 0.8$ on the independent test sets, with target-specific MAEs summarized in Table 1.

The RBC index provides a robust and physically meaningful target. As shown in Figure 3, the majority of short-term prediction errors in $\log_{10}$ RBC fall within an absolute value of 0.4. In contrast, outer boundary calculations rely heavily on empirical fitting formulas,

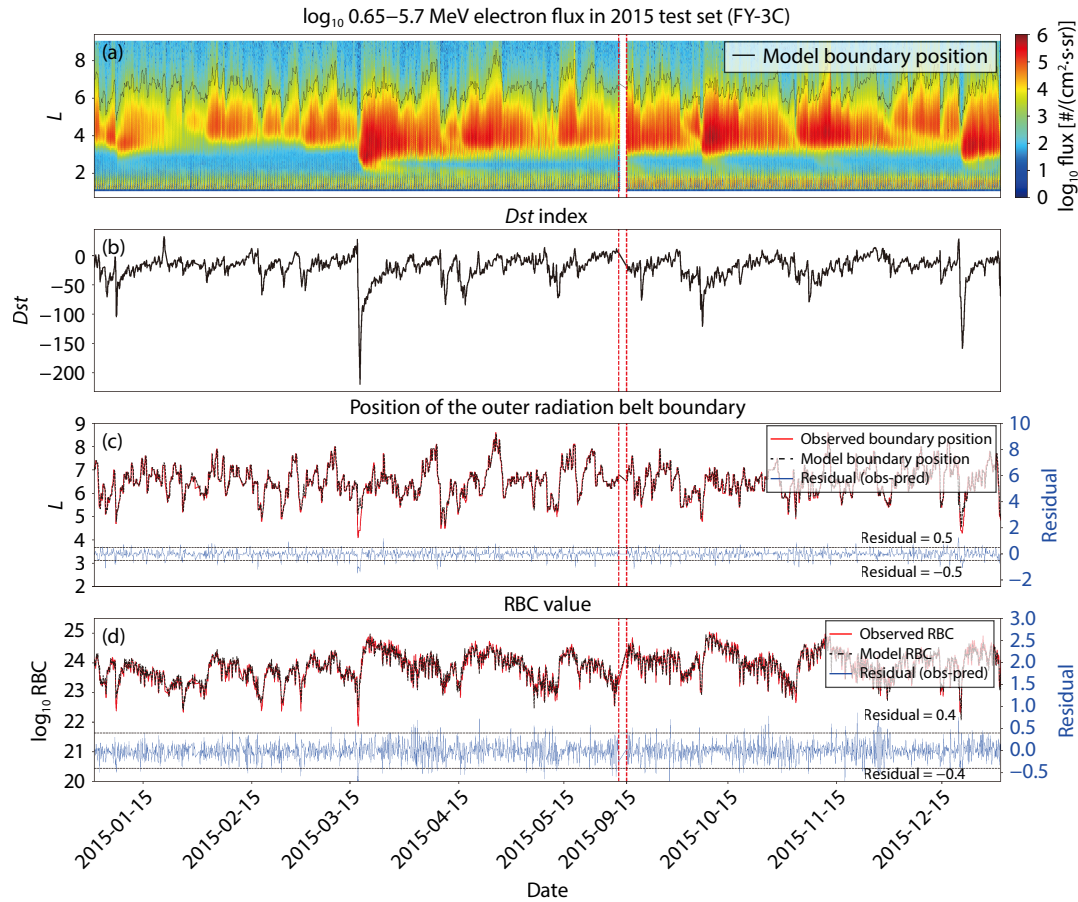


Figure 5. Comparison of model predictions with observations for boundary position and RBC value, together with $\log_{10}$ of 0.65–5.7 MeV electron fluxes and the Dst index during the 2015 FY-3C test period. Panels (c) and (d) show observed (red), predicted (black), and residual (blue) values. The interval between the two red vertical lines (May 31, 2015, to September 15, 2015) indicates the period when no FY-3C observations were available.

Table 1. Evaluation of SVR models for radiation belt dynamics.

Model	Target variable	R^2	MAE
Outer boundary model (POES)	L-shell location	0.91	0.12
Outer boundary model (FY-3C)	L-shell location	0.84	0.16
RBC model (POES)	$\log_{10}$ RBC (>612 keV)	0.81	0.19
RBC model (FY-3C)	$\log_{10}$ RBC (0.65–5.7 MeV)	0.83	0.15

whose precision may be limited by the dynamic and complex nature of the outer belt, whereas RBC calculations incorporate electron flux measurements. Because the low-flux regions near the fitted boundaries contribute little to the integrated content, the RBC calculation is relatively insensitive to moderate boundary-fitting uncertainties, thereby enhancing its robustness.

Additionally, the models show limitations in predicting extreme events, mainly because of the underrepresentation of extreme values in the training dataset and the regularization parameter C in the SVR model, which favors smoother predictions and may overlook extremes. To mitigate this issue and effectively address the long-tail distribution of severe space weather events, future prediction or forecast frameworks could utilize targeted data resampling strategies. Techniques such as the synthetic minority

oversampling technique for regression (SMOTER) or the implementation of adaptive sample weighting mechanisms during training would ensure that rare but critical extreme storm conditions are adequately penalized for errors and properly represented.

In summary, SVR models show strong and reliable performance in predicting RBC and outer boundary variations for energetic and relativistic electrons, particularly in capturing overall trends. To further improve model accuracy, future work should consider incorporating richer input features (e.g., wave activity, historical flux distributions, multi-satellite observations) or exploring more expressive methods, such as deep learning, which may better address the complex nonlinear dynamics of the outer radiation belt.

Beyond advancing scientific understanding, these models also offer potential practical applications. They could complement existing index- or flux-based forecasts at the Space Weather Prediction Center (SWPC) and domestic space weather centers, aid radiation risk assessments for geostationary Earth orbit satellites and navigation constellations (e.g., BeiDou/Global Navigation Satellite System), and provide more physically meaningful early-warning indicators for storm-time radiation belt disturbances.

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Availability of Data and Materials

The OMNI database is available from https://cdaweb.gsfc.nasa.gov/pub/data/omni/omni_cdaweb/. The NOAA-15 data can be accessed at https://cdaweb.gsfc.nasa.gov/pub/data/noaa/noaa15/sem2_fluxes-2sec/. The FY-3C data can be accessed at <https://satellite.nsmc.org.cn/DataPortal/en/home/index.html>. The storm list and SVR method are available in the Supplementary Materials.

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