A neural network model of relativistic electron flux in the outer radiation belt

Xiangning Chu[1], Donglai Ma[2], Jacob Bortnik[2], W. Kent Tobiska[3], Alfredo Cruz[3], S. Dave Bouwer[3], Hong Zhao[4], Qianli Ma[2,5], Kun Zhang[6], Dan Baker[1], Xinlin Li[1], Harlan Spence[7], Geoff Reeves[8]

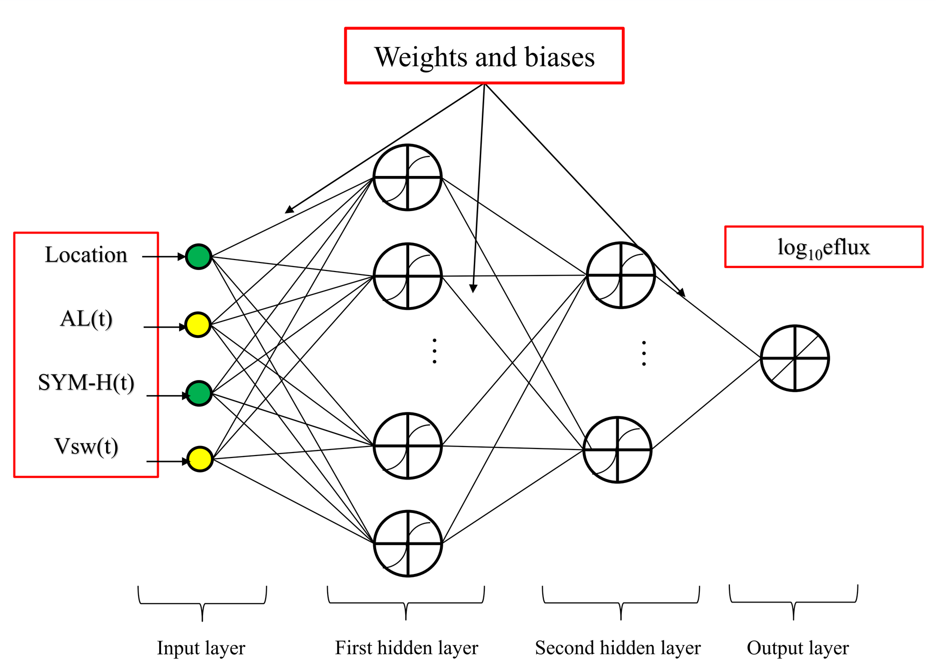
[1] Laboratory for Atmospheric and Space Physics, University of Colorado Boulder, Boulder, CO, USA [2] Department of Atmospheric and Oceanic Sciences, University of California, Los Angeles, California, USA [3] Space Environment Technologies, Pacific Palisades, CA, USA [4] Department of Physics, Auburn University, AL, USA [5] Center for Space Physics, Boston University, Boston, MA, USA [6] Space Science Institute, Boulder, CO, USA [7] Institute for the Study of Earth, Oceans and Space, University of New Hampshire, Durham, NH, USA [8] Space Science and Applications Group, Los Alamos National Lab, Los Alamos, NM, USA

Introduction

- The Earth's outer radiation belt consists of electrons in energy ranges from hundreds of keV to multiple MeV [Baker et al., 2017; Thorne, 2010]
- Existing models (not in chronological order):
  - First-principle physic-based modeling (Beutier et al., 1995; Glauert et al., 2014; Ma et al., 2015; Reeves et al., 2012; Subbotin et al., 2009; Tu et al., 2013;)
  - Static models covering L shells:AE8, AE9 (Ginet et al., 2013; Sawyer et al., 1976; Vampola, 1996)
  - GEO/MEO model with specific radial distance:
    - Linear prediction filter (Baker et al., 1990; McPherron et al., 2015; O'Brien et al., 2001a, 2001b)
    - Empirical statistical modeling (Li et al., 2001; O'Brien, 2003; Xiao et al., 2009)
    - Neural networks (Fukata et al., 2002; Koons et al., 1991; O'Brien and McPherron, 2003; Ling et al., 2010; Shin et al., 2016; Zhang et al., 2020a)
    - NARMAX (Balikhin et al., 2011; Boynton et al., 2013, 2015)
    - Light gradient boosting (Smirnov et al., 2020)
  - Dynamic models depending on precondition from LEO satellites
    - Neural network: SHIELD, PreMeV (Claudepierre et al., 2020; Chen et al., 2019; Lima et al., 2020)
    - Forecasting a few days ahead may be difficult
  - Dynamic model depending on solar wind and geomagnetic indices:
    - Bortnik [2016; 2018]; Chu [2017a, b]
    - It covers 2.6<L<6.5, and energy > 1 MeV
    - Forecasting a few days ahead is possible with existing prediction of solar wind parameters and geomagnetic indices.

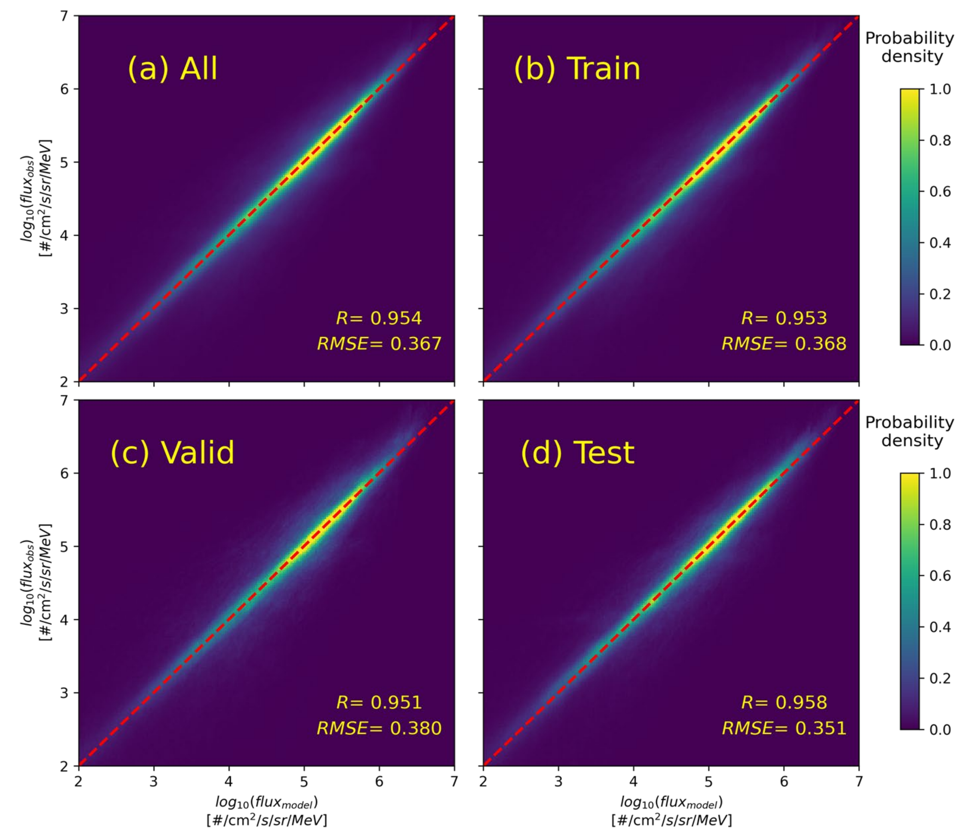
Data and Model description

- Relativistic electron fluxes obtained from REPT onboard Van Allen Probes in the energy range 1.5-20 MeV from September 2012 to October 2019
- There are 7.4 million data points in total.
- The input parameters, including solar wind parameters and geomagnetic indices, are obtained from the OMNI dataset
- A fully-connected neural network is employed with time series of input parameters and predicts the logarithm of the electron fluxes.
- The FNN is generalized using a few methods: normalization of input parameters, regularization, batch normalization, dropouts, early stopping.

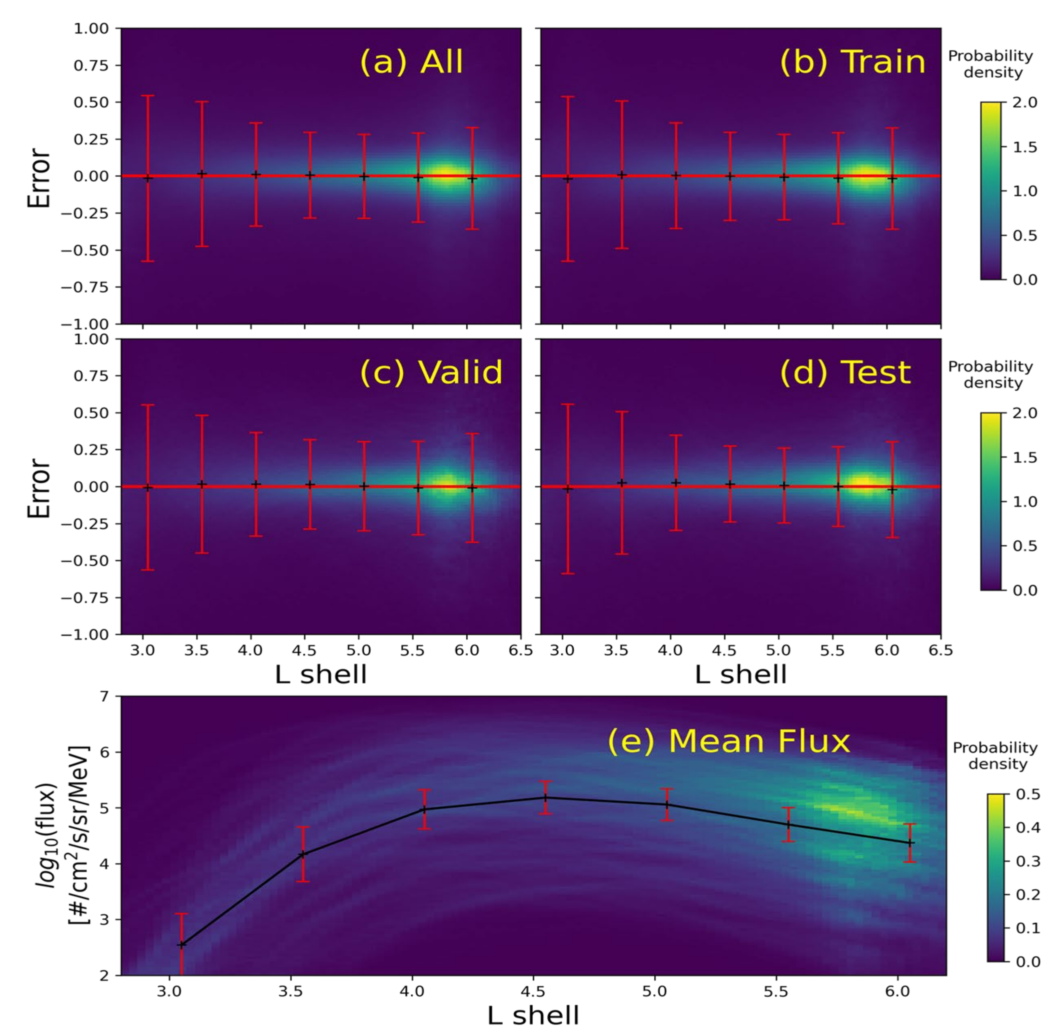


Model performance

- The comparison between the observed and reconstructed 1.8 MeV electron fluxes for the whole dataset, as well as the training, validation, and test datasets.
- The observation-model data pairs lie along the diagonal line (y=x), which suggests that the modeled density well represent the observations.
- The correlation coefficients are >0.95 for the test dataset, as well as other datasets.
- The RMSE of $\log_{10}$(eflux) is ~0.37, which translate to an uncertainty of a factor of 2 ($10^{0.37}$). This is close to the uncertainty of the measurements.
- The FNN model has an excellent ability to make out-of-sample predictions.

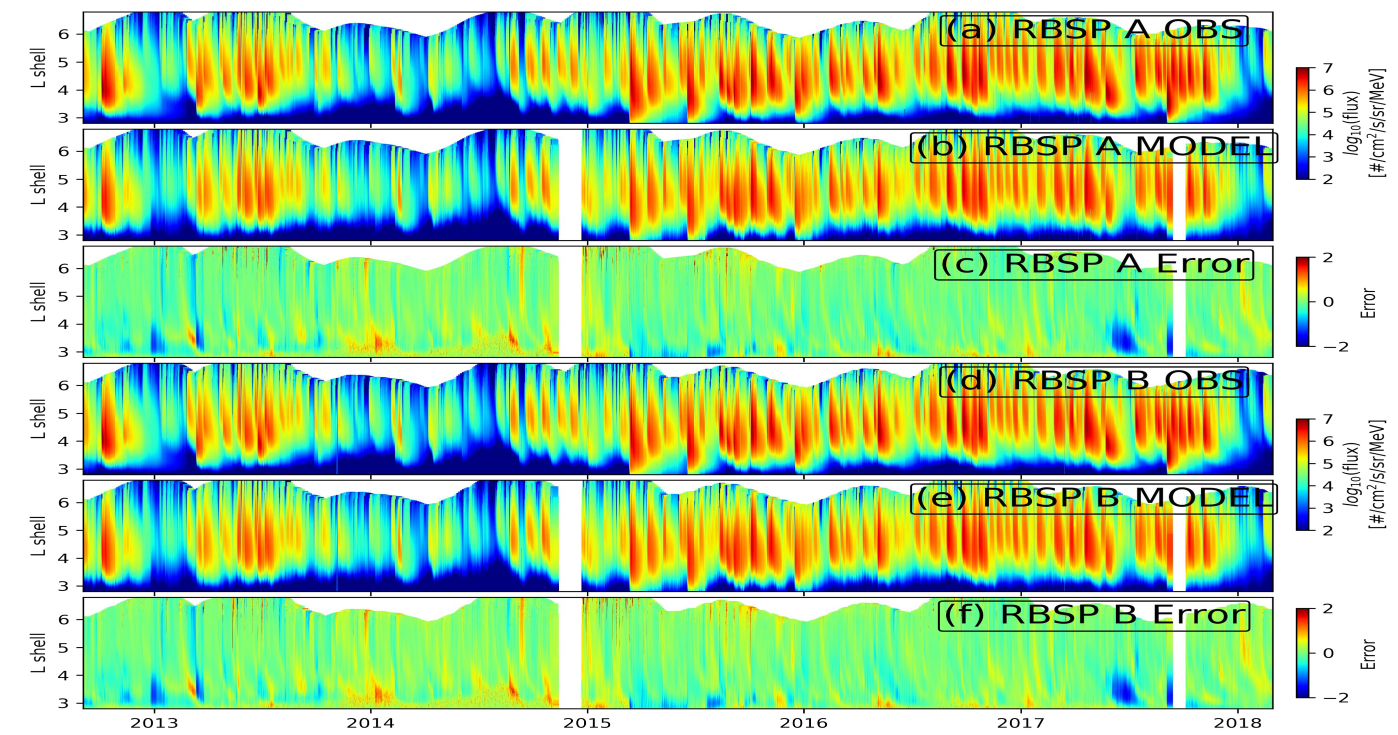


- The uncertainty as a function of L shell for four datasets.
- The uncertainty is generally smaller at the heart of the radiation belt (a factor of 2.0 = $10^{0.3}$)
- The uncertainty is larger near the slot region (a factor of 4.0=$10^{0.6}$), likely due to the low count of the REPT instrument near the slot region.



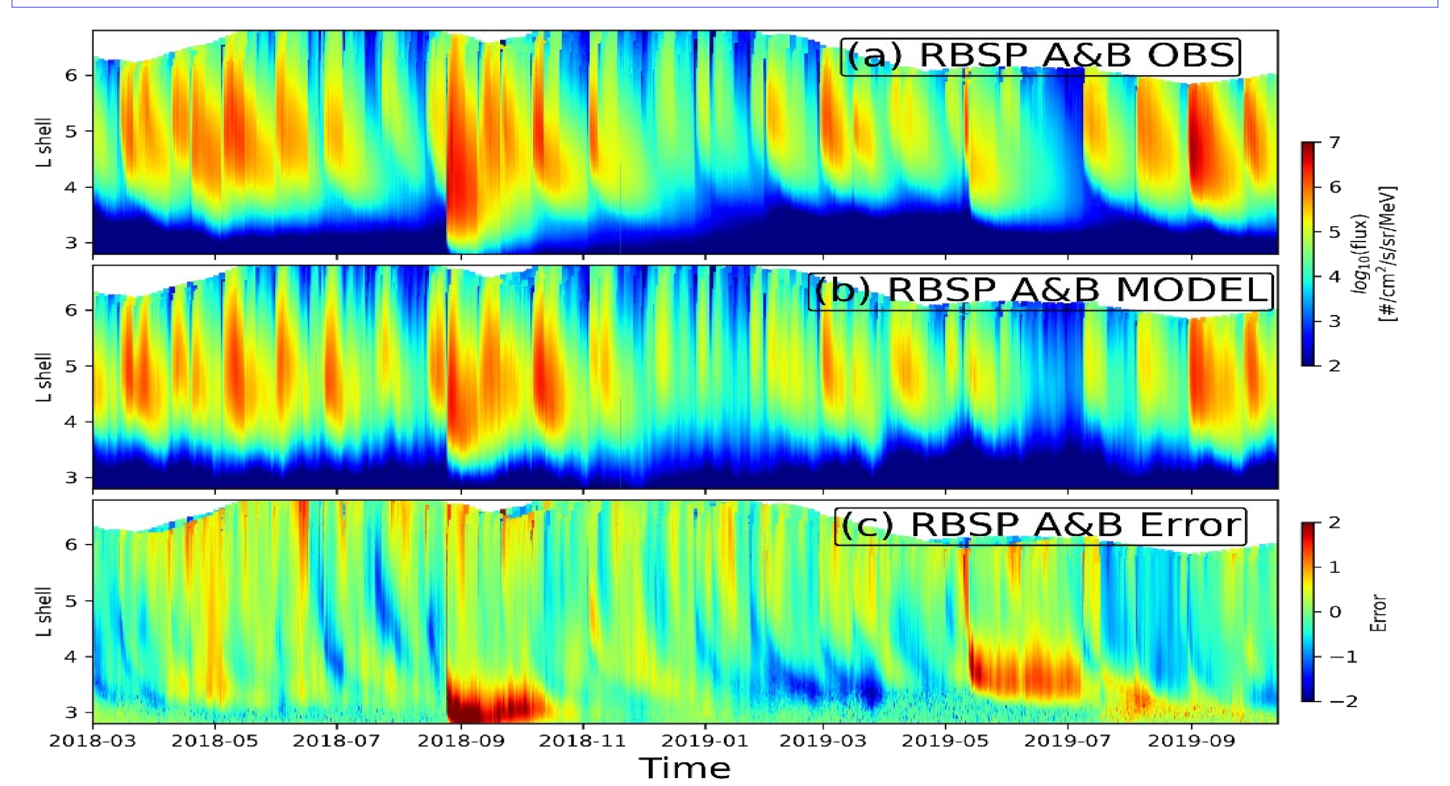
Model performance over RBSP era

- The comparison between the observed and modeled 1.8 MeV electron fluxes during Van Allen Probe era when the AL index was available before March 2018
- The variations of the electron fluxes are captured during all the storms in this 5-year period including:
  - minimum values of the electron fluxes during dropout events
  - the maximum of the electron fluxes during storms
  - the timing and L shell of the rapid local acceleration
  - the accurate magnitude of electron fluxes during each storm
  - solar cycle variations
  - electron flux enhancement at extremely low L shell during strong storms



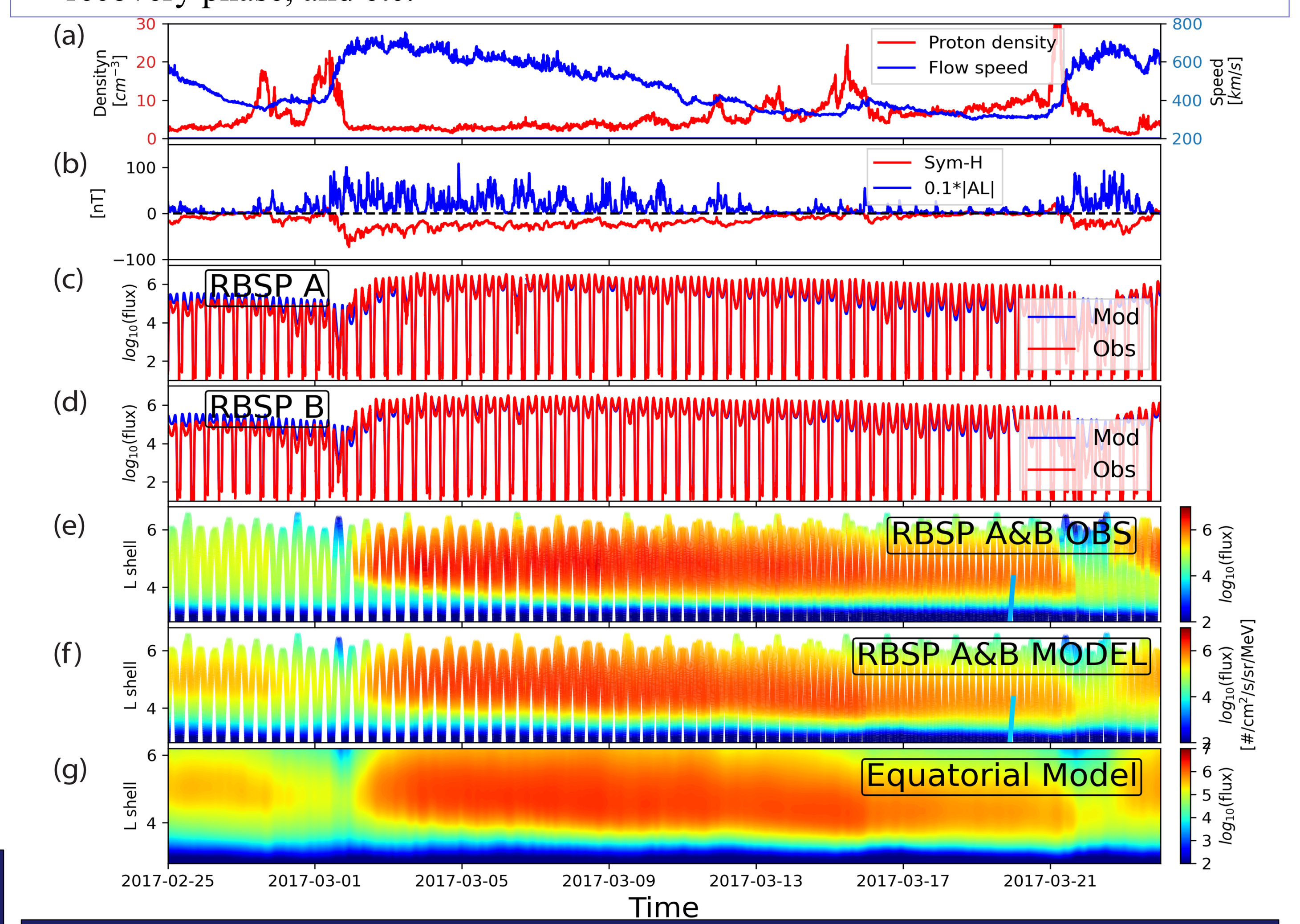
Out-of-sample performance

- The FNN model is validated using out-of-sample measurements along Van Allen Probes' trajectories after March 2018, when the AL index ended.
- We adopted the predicted AL index available at lasp.Colorado.edu/~lix, which has a linear correlation coefficient of 0.846 and a prediction efficiency of 0.715 (meaning that 71.5% of the variations in the AL index are captured) [Li et al., 2007; Luo et al., 2013].
- The FNN model has an out-of-sample correlation coefficient r=0.92, meaning that it can explain 85% of the observed variations in the electron fluxes, or an uncertainty of 3.0 ($10^{0.48}$).
- The uncertainty is higher during strong events due to imperfect input parameters.



Model performance: event analysis

- The comparison between the observed and modeled 1.8 MeV electron fluxes during a moderate geomagnetic storm in March 2017.
- The FNN model captured key features of the outer radiation belt dynamics including: the quiet-time profile of the outer radiation belt, the dropout likely due to dayside magnetopause shadowing, local acceleration, the effects of radial diffusion, the level and location of the peak flux, additional sporadic enhancements during the recovery phase, and etc.



Discussion and summary

- We present a neural network-based model of relativistic electron fluxes in the outer radiation belt, which utilizes a combination of the time history of geomagnetic indices and solar wind parameters as inputs (without any boundary conditions).
- The FNN model has an excellent capability to reconstruct the electron fluxes, as well as on out-of-sample data (even with imperfect input parameters).
  - The variations can be captured by >85%.
  - The uncertainty is within a factor of 3.0.
- **The FNN model captured key features in the outer radiation belt dynamics.**
- The phase space density distribution can be obtained using the electron fluxes from the FNN model, as well as another FNN model in the MAGEIS energy (Poster IMAG 2321, Donglai Ma).
- The FNN model is the first machine learning based model of the electron fluxes with only solar wind parameters and geomagnetic indices, which is important for forecasting.
  - ENLIL-WSA, Anemolilos, Rice DST for forecasted parameters as input.
- The FNN model has great value and wide application in the space physics community and space weather industry.
- This work is supported by NASA SWO2R award 80NSSC19K0239, NASA ECIP award 80NSSC19K0911 and NASA LWS award 80NSSC20K0196.
- https://doi.org/10.1029/2021SW002808