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**₁ The system science development of local time
₂ dependent 40 keV electron flux models for
₃ geostationary orbit**

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4 **Abstract.** At Geosynchronous Earth Orbit (GEO), the radiation belt/ring
5 current electron fluxes with energies up to several hundred keV, can vary widely
6 in Magnetic Local Time (MLT). This study aims to develop Nonlinear Au-
7 toRegressive eXogenous (NARX) models using system science techniques,
8 which account for the spatial variation in MLT. This is difficult for system
9 science techniques, since there is sparse data availability of the electron fluxes
10 at different MLT. To solve this problem the data are binned from GOES 13,
11 14, and 15 by MLT, and a separate NARX model is deduced for each bin
12 using solar wind variables as the inputs to the model. These models are then

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13 conjugated into one spatiotemporal forecast. The model performance statis-
14 tics for each model varies in MLT with a Prediction Efficiency (PE) between
15 47% and 75% and a correlation coefficient (CC) between 51.3% and 78.9%
16 for the period from 1 March 2013 to 31 December 2017.

1. Introduction

17 The radiation belt/ring current electrons with energies from tens of keV to several MeV
18 can pose a serious threat to the satellites that our society is becoming increasingly reliant
19 [*Horne et al.*, 2013a]. Therefore, models that are able to forecast the periods when the
20 radiation belts or ring current electrons will be hazardous to these spacecraft are highly
21 valuable to the satellite operators. Increases in the number of these electrons can lead
22 to various problems on the satellite. High energy electrons, typically above 1 MeV, can
23 cause deep dielectric charging, which can irrevocably damage the electronic components
24 onboard the satellite [*Baker et al.*, 1987; *Wrenn et al.*, 2002; *Gubby and Evans*, 2002;
25 *Lohmeyer and Cahoy*, 2013; *Lohmeyer et al.*, 2015]. 1 keV to 100 keV energy electrons
26 can also be problematic to satellite operators, as they can contribute to surface charging,
27 particularly at ~ 10 keV, which interferes with the satellite electronic systems [*Olsen*,
28 1983; *Mullen et al.*, 1986; *O'Brien and Lemon*, 2007; *Thomsen et al.*, 2013; *Ferguson*,
29 2018; *Sarno-Smith et al.*, 2016]. This can potentially turn off vital systems onboard the
30 spacecraft, which may be the cause of the anomaly on the Galaxy 15 spacecraft when it
31 stopped responding to any ground commands [*Loto'aniu et al.*, Aug. 2015].

32 The dynamics of the radiation belts are known to be due to a balance between transport,
33 acceleration and loss processes. The solar wind is known to drive the acceleration through
34 wave-particle interactions and radial diffusion [*Friedel et al.*, 2002], while magnetopause
35 shadowing [*Kim and Chan*, 1997; *Bortnik et al.*, 2006; *Turner et al.*, 2012] and precipita-
36 tion through wave particle interaction [*Bailey*, 1968; *Bortnik et al.*, 2006] lead to the loss
37 of these energetic electrons. However, the radiation belt models based on first principles

38 struggle to provide accurate forecasts of the radiation belt electron fluxes [*Horne et al.*,
39 2013b].

40 An alternative approach to first principles based forecast models is the system identi-
41 fication or machine learning approach, where the models are automatically derived from
42 input-output data by computer algorithms. These algorithms include linear prediction
43 filters [*Baker et al.*, 1990; *Rigler et al.*, 2004], dynamic linear models [*Osthus et al.*,
44 2014], neural networks [*Koons and Gorney*, 1991; *Freeman et al.*, 1998; *Ling et al.*, 2010],
45 and Nonlinear AutoRegressive Moving Average with eXogenous inputs (NARMAX) [*Wei*
46 *et al.*, 2011; *Boynton et al.*, 2013a, 2015]. Neural networks and NARMAX methodologies
47 are more suited to modelling the radiation belts, as the system is nonlinear with respect
48 to the solar wind input. Linear prediction filters and dynamic linear models are only
49 suitable for linear systems or local linearities within a nonlinear system. NARMAX and
50 neural networks have both been shown to provide accurate models for geospace systems
51 [*Freeman et al.*, 1998; *Boynton et al.*, 2011a, 2015], however, the advantages that NAR-
52 MAX methodologies have over neural networks are that it is physically interpretable and
53 less prone to overfitting. This study uses the NARMAX methodology to model the 40
54 keV electron fluxes observed by the Geostationary Operational Environmental Satellites
55 (GOES), situated in Geostationary Earth Orbit (GEO).

56 The > 2 MeV electrons at Geostationary Earth Orbit (GEO) have been modelled
57 using NARMAX, which results in a high forecast accuracy and a forecast horizon of
58 one day [*Boynton et al.*, 2015]. *Balikhin et al.* [2016] showed that the NARMAX model
59 provides forecasts superior to the one provided by the National Oceanic and Atmospheric
60 Administration (NOAA), which employs the model by *Baker et al.* [1990]. Higher energy

61 electrons take time to be accelerated after responding to the solar wind variations [*Li*
62 *et al.*, 2005; *Balikhin et al.*, 2012; *Boynton et al.*, 2013b]. This means that it is possible
63 to forecast the dynamics of the high energy electrons further into the future than the
64 lower energies. *Boynton et al.* [2016a] developed NARMAX models for the electron flux
65 energy ranges observed by the third generation GOES (40 keV, 75 keV, 150 keV, 275 keV,
66 475 keV, > 800 keV and > 2 MeV). The developed models predict the daily averaged
67 electron fluxes and were shown to provide an accurate forecast. Although the models
68 provide a good forecast of the average conditions over a day in time and an orbit in
69 space, they will be unable to forecast any spatial variations over the orbit. For the high
70 energies, the electron fluxes are uniform in Magnetic Local Time (MLT) along the same
71 drift shells. Due to the distorted dipole, the electron fluxes measured by GOES will
72 vary in MLT as GEO does not follow drift shells or stay fixed at constant geomagnetic
73 latitudes. The tens to hundreds of keV electrons that populate the ring current, provide
74 the seed population of the radiation belts, and also drive the whistler mode chorus waves,
75 which lead to both the acceleration of the energetic electrons and loss by precipitation.
76 The injections of the tens to hundreds of keV electrons cause a fast localized electron
77 flux variation on shorter time scales (less than 24 hours), which the *Boynton et al.* [2016a]
78 models would average out. The Inner Magnetosphere Particle Transport and Acceleration
79 Model (IMPTAM) [*Ganushkina et al.*, 2013, 2014, 2015] can provided a nowcast of the
80 short time scale variations using current values of geomagnetic indices [*Ganushkina et al.*,
81 2015]. An empirical model of the 1 eV to 40 keV has been developed by [*Denton et al.*,
82 2016] as a function of local time, energy, and the strength of the solar wind electric field.

83 The aim of this study is to develop a reliable model that is able to forecast the short
84 spatiotemporal variations of the 40 keV electron fluxes. The NARMAX methodology used
85 to deduce the models is described in detail in Section 2, while the instrumentation and
86 data are discussed in Section 3. In Section 4.1, the data are truncated every 1 hour MLT
87 and 24 models are developed at each MLT. The performance and details of the models
88 are discussed in Section 5 and the conclusions from this study are presented in Section 6.

2. NARMAX methodology

89 NARMAX is a system identification methodology [*Leontaritis and Billings, 1985a, b*]
90 and was initially developed in the field of system science. In control theory, an applica-
91 tion of system science, a mathematical model of the system is needed in order to build a
92 robust controller. However, with complex engineering systems, the derivation of such a
93 mathematical model from first principles often leads to assumption which are not valid
94 and, hence, a poor controller. System identification aims to automatically derive a math-
95 ematical model that governs the system's dynamics from input-output data. NARMAX
96 is able to deduce models for a wide range of nonlinear systems and was originally applied
97 to complex engineering systems [*Billings, 2013*]. The potential of the methodology to
98 develop nonlinear models from data has since been utilised by a diverse range of scien-
99 tific fields. It has been used in analyzing the adaptive changes in the photoreceptors of
100 *Drosophila* Flies [*Friederich et al., 2009*], modelling the tide at the Venice Lagoon [*Wei*
101 *and Billings, 2006*], the dynamics of Synthetic bioparts [*Krishnanathan et al., 2012*], and
102 the Belousov-Zhabotinsky chemical reaction [*Zhao et al., 2007*]. In geospace the method
103 was first used to model the Dst index and analyze the dynamics in the frequency domain
104 [*Boaghe et al., 2001; Balikhin et al., 2001*]. A number of other Dst forecast models have

105 also been developed, using single inputs [Zhu *et al.*, 2006], multiple inputs [Zhu *et al.*,
 106 2007], and wavelets [Wei *et al.*, 2004]. Boynton *et al.* [2011b] utilized the NARMAX
 107 model structure detection methodology to identify a solar wind coupling function for geo-
 108 magnetic storms, which was derived from first principles by Balikhin *et al.* [2010] and then
 109 employed as an input to model the Dst index [Boynton *et al.*, 2011a]. The method of using
 110 the physical interpretability of the NARMAX model structure detection has since been
 111 used in many other studies to identify relationships between the solar wind and various
 112 aspects of the magnetosphere. Examples include studies of SYM-H index Beharrell and
 113 Honary [2016], proton fluxes at GEO [Boynton *et al.*, 2013c], the electron fluxes [Balikhin
 114 *et al.*, 2011; Boynton *et al.*, 2013b], and electron flux dropouts at GEO [Boynton *et al.*,
 115 2016b] and at the GPS orbit [Boynton *et al.*, 2017].

116 A Multi-Input Single-Output (MISO) NARMAX model was used in this study to model
 117 the electron fluxes. This is represented by

$$\begin{aligned}
 \hat{y}(t) = & F[y(t-1), \dots, y(t-n_y), \\
 & u_1(t-1), \dots, u_1(t-n_{u_1}), \dots, \\
 & u_m(t-1), \dots, u_m(t-n_{u_m}), \dots, \\
 & e(t-1), \dots, e(t-n_e)] \tag{1}
 \end{aligned}$$

118 where an estimate of the output \hat{y} at time t is a nonlinear function F of past outputs
 119 y , inputs u , and residual, $e = y - \hat{y}$. m is the number of system inputs and $n_y, n_{u_1}, \dots,$
 120 n_{u_m}, n_e are the maximum time lags for the output, each of the m inputs, and the error,
 121 respectively.

122 For this study, the nonlinear function F was chosen to be a nonlinear polynomial.
123 When this polynomial is expanded there will be many monomials, most of which have no
124 influence on the system and keeping them would most likely lead to an overfit model. To
125 overcome this problem, *Billings et al.* [1988] developed the Forward Regression Orthogonal
126 Least Squares (FROLS) algorithm, which detects a small model structure from the larger
127 polynomial and estimates the coefficients for each of the detected monomials. The model
128 structure is detected using the Error Reduction Ratio (ERR), which indicates the influence
129 that a monomial has on the output variance. This study employs the Iterative Orthogonal
130 Forward Regression (IOFR) algorithm, which is a variant of the original FROLS. This is
131 more likely to detect the optimal model when the data is oversampled [*Guo et al.*, 2014].
132 A more detailed description of the NARMAX methodology is described by *Billings* [2013]
133 or *Boynton et al.* [2018].

3. Instruments and data

134 The data used in this study are from the third generation GOES MAGnetospheric Elec-
135 tron Detector (MAGED) [*Hanser*, 2011]. The data for these instruments can be accessed
136 from <http://www.ngdc.noaa.gov/stp/satellite/goes/dataaccess.html>. The MAGED has 9
137 telescopes covering a range of different directions and measures the differential electron
138 fluxes in 5 energy channels: 40 keV, 75 keV, 150 keV, 275 keV and 475 keV [*Hanser*,
139 2011]. The time period used to derive and test the models was from 1 January 2011 to
140 13 December 2017. Three GOES spacecraft have carried this instrument, GOES 13, 14
141 and 15. These spacecraft were situated at GEO at various longitudes over North America
142 and were in operation at different times during this period.

143 The following MAGED data have been removed from this study due to anomalies:
144 GOES 13 on telescope 6 throughout this period; GOES 14 between 30 March 2010 and
145 2 May 2010 on telescopes 2, 5, and 8; and GOES 15 between 25 November 2017 and 31
146 December 2017 on telescope 1.

147 Solar wind data were used as input data for training and testing the models. The 1-
148 minute solar wind velocity, density and Geocentric Solar Magnetospheric (GSM) IMF data
149 were obtained from the OMNI website (http://omniweb.gsfc.nasa.gov/ow_min.html).

4. Individually binned MLT models

150 The method of choice of applying system identification to spatially varying systems
151 with different physics occurring in different locations is often to bin the data into different
152 spatial bins and then develop an individual model for each of the spatial bins. This
153 raises two questions: What should be the size of the spatial bin? And what should be
154 the temporal resolution of the data? With most system science applications to geospace
155 the temporal resolution is usually the resolution of the output, e.g., the Dst index has a
156 resolution of 1 hour and is modelled with a 1 hour resolution [*Klimas et al.*, 1996]. The
157 temporal sampling frequency should be fast enough to extract the desired information
158 from the signal. Shannon's theorem states that if the desired information has a frequency
159 f_c then to recover the desired information a sampling frequency of at least $2f_c$ is required.
160 Oversampling is not beneficial for system science modelling as the model will require the
161 inclusion of more lags, which will overcomplicate the model and increases the computation
162 time. The same is true for sampling the spatial frequency. Therefore, we need to know the
163 spatial and temporal frequency of the high flux variations of keV electrons. The electron
164 losses are due to either precipitation to the atmosphere from pitch angle scattering or

165 magnetopause shadowing with radial diffusion. Both these mechanisms should occur at
166 a wide range of MLT but take place over a short time period. Increases in electron flux
167 from radial diffusion will transpire over longer periods of time and increases from enhanced
168 convection will occur over a wide range of MLT at the same time. The mechanism that
169 leads to the high spatiotemporal frequency variations is due to the substorm associated
170 injections from the plasma sheet. The spatial and temporal scales at which injections
171 can occur are known to vary from one substorm to another [*Sergeev and Tsyganenko,*
172 *1982; Ganushkina et al., 2013; Gabrielse et al., 2014*], and further studies are required to
173 determine the azimuthal extent of the injection fronts. However, this study still requires
174 a spatiotemporal sampling frequency to deduce the electron flux model.

175 Figure 1 shows the 40 keV electron flux from the MAGED onboard GOES 13 (blue),
176 14 (orange) and 15 (yellow) from 27 October 2012 to 29 October 2012 and when each
177 of the spacecraft is at midday (GOES 13 - blue dashed, 14 - orange dashed, and 15 -
178 yellow dashed) and midnight (GOES 13 - blue dot dashed, 14 - orange dot dashed, and
179 15 - yellow dot dashed). During this period, GOES 13 is 1 hour MLT ahead of GOES 14
180 and 4 hours MLT ahead of GOES 15. Up until 06 UTC on 28 October 2012, all three
181 measurements follow the same trend, with GOES 13 and 14 recording almost exactly
182 the same values and GOES 15 having a small offset. GOES 13 and 14 then observe an
183 increase of electron fluxes of approximately one order of magnitude at a post midnight
184 MLT that lasted 2 hours in time, which is not measured by GOES 15 at the pre midnight
185 MLT. This spatiotemporally localized bump in the electron flux time series is most likely
186 caused by an injection of energetic electrons from the plasma sheet. There are then a
187 series of peaks in the electron fluxes observed by all three spacecraft with GOES 13 and

188 14 again observing almost exactly the same values and GOES 15 having an offset. Then
189 another bump in the fluxes probably caused by an injection was observed by GOES 13
190 and 14 but not GOES 15. This increase lasted ~ 2 hours and was observed by GOES
191 13 from 2.2 to 4.3 MLT and by GOES 14 from 1.3 to 3.4 MLT, while at the same time
192 GOES 15 moved from 22.2 to 0.3 MLT. These two potential injection structures both had
193 a temporal length of ~ 2 hours and a spatial width larger than 1 hour MLT, but did not
194 extend 4 hours MLT back from GOES 13 to GOES 15. Inspecting longer periods of data
195 in which all three spacecraft are in operation does show structures with narrower temporal
196 widths but a structure observed by the middle spacecraft is almost always observed by
197 one of the other two spacecraft. Therefore, a sampling of 1 hour MLT and 1 hour time
198 was selected as a good compromise between sampling the majority of high spatiotemporal
199 frequency injections and model complexity since a higher resolution will lead to more
200 temporal lags. Electron flux enhancements through convection and radial diffusion will
201 both be oversampled in space, since convection will occur simultaneously over a broad
202 range of MLT and radial diffusion will take place at all MLT simultaneously.

4.1. Spatiotemporally sampled 40 keV electron flux model

203 The GOES 13, 14 and 15 40 keV electron flux data from the MAGED were sampled at
204 1 hour time resolution and at 1 hour MLT, smoothing over 12 minutes MLT around each
205 hour MLT, and averaging over the 9 telescopes from each spacecraft with pitch angles
206 between 20° and 160° (excluding the errors mentioned in Section 3). This resulted in
207 24 time series datasets for each MLT, which were then individually modelled using the
208 NARMAX methodology described in Section 2. Here, the time series of the electron flux at
209 one of the 24 MLTs is the output data, $J(MLT, t)$. Most of the points in each of the time

210 series datasets were empty since for the majority of the time there will be no spacecraft
 211 in the MLT bin. The input data employed were the solar wind velocity $v(t)$, density
 212 $n(t)$, square root of the pressure $\sqrt{p}(t)$, and the IMF factor $B_f(t) = B_T(t) \sin^6(\theta(t)/2)$
 213 (where $B_T(t) = \sqrt{B_y(t)^2 + B_z(t)^2}$ and $\theta = \tan^{-1}(B_y(t)/B_z(t))$) deduced by *Boynton et al.*
 214 [2011b] and *Balikhin et al.* [2010]. The output lags were selected as the value 24 hours
 215 previous. This is the most consistent data point that will be available, since any other
 216 output lag will most likely be empty in the constructed time series dataset. The input
 217 time lags were selected as 1, 3, 5, ..., 23 hours as it has been shown that 10 to 100 keV
 218 electrons have short response times with solar wind variations compared to MeV electrons
 219 [Li et al., 2005; Boynton et al., 2013b]. The noise terms were not included in the model
 220 because these data were sparse. This reduces the NARMAX model to the following NARX
 221 model:

$$\begin{aligned}
 \hat{J}(MLT, t) = & F[J(MLT, t - 24), \\
 & v(t - 1), v(t - 3), \dots, v(t - 23), \\
 & n(t - 1), n(t - 3), \dots, n(t - 23), \\
 & \sqrt{p}(t - 1), \sqrt{p}(t - 3), \dots, \sqrt{p}(t - 23), \\
 & B_f(t - 1), B_f(t - 3), \dots, B_f(t - 23)] \tag{2}
 \end{aligned}$$

222 The nonlinear function F was chosen to be a third degree polynomial, thus, the model
 223 can include linear monomials of the lagged inputs and outputs as well as cross coupled
 224 combinations of the lagged inputs and outputs.

225 The IOFR algorithm was run for each of the 24 datasets using the same NARX model
 226 on data from 00:00 UTC 1 January 2011 to 23:00 UTC 28 February 2013. These models

227 were then assessed statistically on data from 1 March 2013 to 31 December 2017 using the
 228 Prediction Efficiency (PE), Eq. (3), Correlation Coefficient (CC), Eq. (4), Mean Square
 229 Error (MSE), and the variance of the observed flux, which are commonly used to assess
 230 models [Temerin and Li, 2006; Li, 2004; Boynton et al., 2011a; Wei et al., 2004; Boynton
 231 et al., 2015; Rastatter et al., 2013]. The equations for PE and CC are:

$$E_{PE} = \left[1 - \frac{\sum_{t=1}^N [(y(t) - \hat{y}(t))^2]}{\sum_{t=1}^N [(y(t) - \bar{y})^2]} \right] 100\% \quad (3)$$

$$\rho_{y\hat{y}} = \frac{\sum_{t=1}^N [(y(t) - \bar{y})(\hat{y}(t) - \bar{\hat{y}})]}{\sqrt{\sum_{t=1}^N [(y(t) - \bar{y})^2] \sum_{t=1}^N [(\hat{y}(t) - \bar{\hat{y}})^2]}} 100\% \quad (4)$$

$$E_{MSE} = \sum_{t=1}^N [(y(t) - \hat{y}(t))^2] \quad (5)$$

232 Here, E_{PE} is the PE, ρ is the CC, E_{MSE} is the MSE, $y(t)$ is the measured output at
 233 time t , \hat{y} is the estimated output from the model, N is the length of the data and the
 234 bar signifies the average. The model performance statistics of each of these models are
 235 displayed in Table 1. The PE for each model varies by 47% and 75% while the CC varies
 236 between 51.3% and 78.9%. The highest PE and CC occur at 09 MLT and decreases to the
 237 lowest PE and CC at 22 MLT. The MSE and variance have a similar sinusoidal pattern
 238 with both having a minimum at 16 MLT of 0.045 and 0.090 respectively and the MSE
 239 having a maximum at 01 MLT of 0.208, while the maximum of the variance is 0.288 at
 240 05 MLT.

241 Figure 2 shows the model estimate of the 40 keV electron fluxes from 1 November 2017
 242 to 30 November 2017 for different MLT. During this period, the model forecasts a number
 243 of enhancements that are most intense at dawn MLTs and are lowest at evening MLTs.
 244 Even though all the estimates at each MLT are from a different model, the structure of the
 245 plots is consistent. A surface plot of the forecast is good for showing the evolution of the
 246 fluxes but will be not be able to illustrate the performance of the model compared to the
 247 observed fluxes, since, at each point in time, there will only be a few MLT measurements.
 248 Figure 3 (a) shows a comparison of the model with GOES 13 measurements for the same
 249 1 November 2017 to 30 November 2017 period displayed in Figure 2. The 1 minute GOES
 250 13 data is presented in blue, the spatiotemporal sampled GOES data in red and the
 251 model forecast at the GOES 13 location shown in green. Panel (b) displays the error
 252 between the sampled GOES 13 40 keV electron flux and the model forecast at the GOES
 253 13 location. The model forecast is shown to follow the enhancements and decreases of
 254 the measured electron flux data with a MSE of $0.083 \log_{10}$ for the displayed period. The
 255 model is able to forecast the large variations, for example, the decrease and the increase
 256 on 3 November 2017, but struggles to reproduce the higher frequency variations. A video
 257 of the variations in electron flux at different MLT for the period in Figures 2 and 3 are in
 258 the supplementary material.

5. Discussion

259 One advantage of NARMAX methodologies over neural network machine learning tech-
 260 niques, other than its resilience to overfitting, is that the models are physically inter-
 261 pretable. The resulting models from the NARMAX algorithm are polynomials consisting
 262 of approximately 5 to 20 monomials [Billings, 2013]. By inspecting the monomials that

263 were selected for the model, it is possible to gain some understanding into the underlying
 264 physical processes of the system [Balikhin *et al.*, 2010; Boynton *et al.*, 2011b; Balikhin
 265 *et al.*, 2012; Boynton *et al.*, 2013b; Billings, 2013]. The model for the 01 MLT 40 keV
 266 electron fluxes is

$$\begin{aligned}
 \hat{J}(01MLT, t) = & 3.21 \times 10^{-4} B_f(t-1)v(t-1) + 2.57 + 1.78 \times 10^{-3}v(t-5) \\
 & + 4.02 \times 10^{-2} B_f(t-5) - 4.51 \times 10^{-3} B_f^2(t-1) \\
 & + 1.07 \times 10^{-2} J^2(01MLT, t-24) - 1.46 \times 10^{-1} p(t-3) \\
 & + 5.91 \times 10^{-2} B_f(t-21) + 4.72 \times 10^{-1} \sqrt{p}(t-3) + 1.47 \times 10^{-3} v(t-17) \\
 & - 4.69 \times 10^{-3} B_f(t-20) B_f(t-21) - 3.74 \times 10^{-2} B_f(t-1) \sqrt{p}(t-1) \\
 & + 7.35 \times 10^{-2} B_f(t-13) - 3.41 \times 10^{-2} B_f(t-13) \sqrt{p}(t-14) \\
 & - 5.87 \times 10^{-3} B_f^2(t-7) + 5.16 \times 10^{-2} B_f(t-7) \\
 & - 1.34 \times 10^{-6} v(t-8)v(t-9) \tag{6}
 \end{aligned}$$

267 One interesting point about the models deduced by the algorithm using the initial NARX
 268 model structure in Eq. (2) is that only the 01 MLT, 04 MLT, and 18 MLT models
 269 out of the 24 models included the autoregressive $J(MLT, t-24)$ term out of the 24
 270 models. The autoregressive monomials in each of the three NARX models only have a
 271 small contribution to the variance of the output, indicated by the small ERR. The other
 272 models, with no past output terms and only consisting of exogenous terms, are known as
 273 Volterra Series models. The lack of autoregressive terms and the small ERR contribution
 274 when they are selected in the model means that the hourly MLT electron flux changes
 275 significantly from their value 24 hours ago.

276 The variable that is selected in all the models, and appears as a factor of the monomial
 277 that has the highest ERR in each of the models, is the IMF factor B_f . The monomial
 278 with the highest ERR controls most of the output variance. The solar wind velocity is
 279 the second most selected variable and it is in all the models in either the first or second
 280 highest ERR monomial, often coupled with B_f . The square root of the solar wind pressure
 281 is chosen by the algorithm in 23 of the models (not the 23 MLT model) and the solar
 282 wind density is only selected in 14 of the models but both are rarely selected in the top
 283 five terms in order of ERR (three times for both pressure and density) and, thus, only
 284 have a small contribution to the variance of the output.

285 The IMF factor B_f was automatically identified in a solar wind-magnetosphere coupling
 286 function by using the NARMAX FROLS methodology and then derived analytically from
 287 first principles by *Balikhin et al.* [2010]. This derivation is based on the geometry of
 288 the dayside magnetosphere reconnection with the solar wind. Therefore, the fact that the
 289 models attribute most of the variation of the electron fluxes to the IMF factor implies that
 290 the reconnection is the most important process. On the surface, this is in contrast to the
 291 higher energies where solar wind velocity [*Paulikas and Blake, 1979*] or density [*Balikhin*
 292 *et al., 2011*] was found to have the most influence. However, these studies investigated
 293 the daily averages of electron fluxes and solar wind, which will average out the turning
 294 of the IMF southward over the day, since these time scales are quite short (~ 1 hour).
 295 With the increased temporal resolution the turning of the IMF southward will not be
 296 averaged out and will have more influence. This averaging out over the timescales of
 297 the IMF variations is also true for the study by *Boynton et al.* [2013b] where they also
 298 found that southward IMF only had a small influence on the daily averaged 10 to 100 keV

299 electron fluxes. For example, if there is a high velocity solar wind event taking place over
300 several days and there are several periods of time when the IMF is southward for an hour,
301 the IMF may average out to be insignificant, while the velocity remains high. Therefore,
302 choosing a different time resolution may change the importance of the parameters.

303 The performance of the different electron flux models show a pattern with the MLT,
304 with the highest performance in terms of CC and PE in the late morning and the lowest
305 performance just before midnight. The lower performance just before midnight could
306 be due to the model not performing very well at forecasting the higher spatiotemporal
307 frequency injections that occur in this region. The MSE also exhibits a pattern with MLT
308 but it is shifted compared to PE and CC, with the highest MSE at 01 MLT and the lowest
309 at 15 and 16 MLT. The shift between PE and CC variation with MLT and the MSE MLT
310 variation is mainly due to the difference in the electron flux variance at each MLT, since
311 both PE and CC are normalized by the variance of the measured electron fluxes.

312 The highest performance in terms of PE and CC occur at dayside MLTs, where the
313 increases in the fluxes will mostly be due to convection or radial diffusion and are unlikely
314 to be caused by substorm particle injections. From Figure 3, the model estimates the
315 majority of the structures that last over half a day but a magnified figure would show more
316 detail. Figure 4 displays two magnified sections of Figure 3, panel (a) from 10 November
317 2017 to 12 November 2017, and panel (b) from 20 November 2017 to 22 November 2017.
318 The Figures show that the model follows the general trend of the measured GOES 13
319 data during this period. There is a sharp peak in the 1 minute GOES 13 measurements
320 (blue) on 10 November 2017 at 0400 UTC, which is averaged out in the sampled GOES
321 measurement (red), however, the model (green) does show an increase. Overall, the model

322 underperforms in forecasting the high spatial and temporal frequency variations, such as
323 the three peaks between 0600-1800 UTC on 11 November 2017, but follows the slower
324 variations. An increased temporal resolution of 30 minutes may help in identifying the
325 fast substorm associated injections. The inputs to the model are measured at L1 and using
326 a 1 hour time lag in the model, which may lead to changes in the solar wind occurring
327 inside the hour. For example, a fast flow of solar wind can transit from L1 to the bow
328 shock in under 30 minutes, which will cause a change in the magnetosphere that the 1
329 hour lags in the model will be unable to take into account. Therefore, in the training of
330 the model, these changes in solar wind cannot be identified as drivers of the changes in
331 the electron fluxes. However, a consequence of including shorter lags in the model will be
332 to reduce the forecast horizon of the model. Also, the averaging of the solar wind over the
333 hour, particularly the fast turning of the solar wind southward, may nullify the drivers
334 of the substorm, therefore, it will not be identified in the model. This problem could be
335 solved by including the maximum of the value of the solar wind parameters as inputs as
336 well as the average value, however, this would increase the computational complexity of
337 identifying the model due to an increased amount of monomials to search through.

338 Another option to spatially model the electron fluxes is to employ MLT as an input
339 into the model, rather than sampling the data in space and developing a separate model
340 for each spatial bin. However, this approach was not selected because at different MLTs
341 there should be different dynamics, and it would be better to isolate the individual physical
342 processes in the different models corresponding to each region.

343 A model of the 40 keV electron fluxes through all MLTs at geostationary orbit is not only
344 useful to satellite operators, who would be able to have a greater situational awareness of

345 the environment and be able to apply any mitigation procedures to help protect their space
346 based assets. The model could also be used as an outer boundary condition to physics
347 based radiation belt models such as the Versatile Electron Radiation Belt (VERB) model
348 [*Subbotin et al.*, 2011], Comprehensive Inner Magnetosphere-Ionosphere (CIMI) model
349 [*Fok et al.*, 2014] or IMPTAM [*Ganushkina et al.*, 2015].

350 The models developed in this study have been implemented to run in real time. A figure
351 of the real time output of this model is shown in Figure 5, which shows the model output
352 across all MLT in panel (a), the model output at the location of GOES 15 vs GOES 15
353 data, and (c) the error between the measured and model for March 2019. The model
354 performance for this period were a PE of 48.5% and a CC of 66.3%. The data gap at the
355 start of the month is due to a missing solar wind inputs, which were not available from
356 NOAA Space Weather Prediction Center (SWPC) at the time the forecast was made.

6. Conclusions

357 A data based spatiotemporal model has been developed for the 40 keV electron fluxes
358 at GEO. This model is comprised of 24 individual NARX models of the form shown
359 in Equation (2), where the output of each model is the electron fluxes for that region
360 of space in MLT at GEO. When the 24 models are conjugated together into the final
361 model, they give a forecast of the spatiotemporal evolution of the 40 keV electron fluxes
362 at GEO. At this energy, the electron fluxes can vary significantly over a narrow range of
363 MLTs due to substorm associated injections making it very challenging to model. The
364 development of a data based model using system science techniques is complicated by
365 the sparse availability of the electron fluxes at different MLT. This problem was solved
366 by binning the data from GOES 13, 14, and 15 by MLT and then deducing a separate

367 model for each bin then conjugating these to produce one spatiotemporal forecast. The
368 performance of this forecast was then assessed on a period from 1 March 2013 to 31
369 December 2017 where the PE varied between 47% and 75% and the CC varied between
370 51.3% and 78.9% at different MLTs.

371 The models developed in this study will be implemented online at the University of
372 Sheffield Space Weather Website (<http://www.ssg.group.shef.ac.uk/USSW2/UOSSW.html>)
373 to provide a real time forecast of the GEO 40 keV electron fluxes through all MLTs. This
374 will allow both satellite operators and scientists to have access to the outputs of the
375 models, which will also be archived.

376 **Acknowledgments.** The MAGED data can be accessed from
377 <http://www.ngdc.noaa.gov/stp/satellite/goes/dataaccess.html>. The solar wind data and
378 geomagnetic indices data were from the OMNI website (http://omniweb.gsfc.nasa.gov/ow_min.html).
379 The real time data were from the NOAA SWPC. The work was performed within the
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Model	MLT	PE (%)	CC (%)	MSE	Var(J)
00		50.2	53.4	0.177	0.228
01		50.3	54.9	0.208	0.269
02		53.6	58.0	0.197	0.272
03		58.4	63.2	0.178	0.276
04		60.2	65.9	0.170	0.276
05		65.0	70.2	0.157	0.288
06		69.6	74.0	0.127	0.268
07		72.9	76.6	0.106	0.251
08		74.7	78.6	0.089	0.226
09		75.0	78.9	0.077	0.198
10		73.3	77.3	0.074	0.178
11		73.3	77.3	0.064	0.153
12		71.6	75.3	0.062	0.140
13		71.1	74.7	0.056	0.124
14		70.6	74.3	0.048	0.106
15		69.9	73.0	0.045	0.096
16		67.9	70.8	0.045	0.090
17		64.3	66.6	0.050	0.091
18		64.0	64.4	0.053	0.095
19		62.1	64.1	0.059	0.100
20		54.0	55.7	0.084	0.117
21		51.4	53.7	0.106	0.141
22		47.0	51.3	0.144	0.175
23		51.6	56.3	0.161	0.213

Table 1. Table showing the PE, CC, MSE for each MLT model and the variance of the measured electron flux.

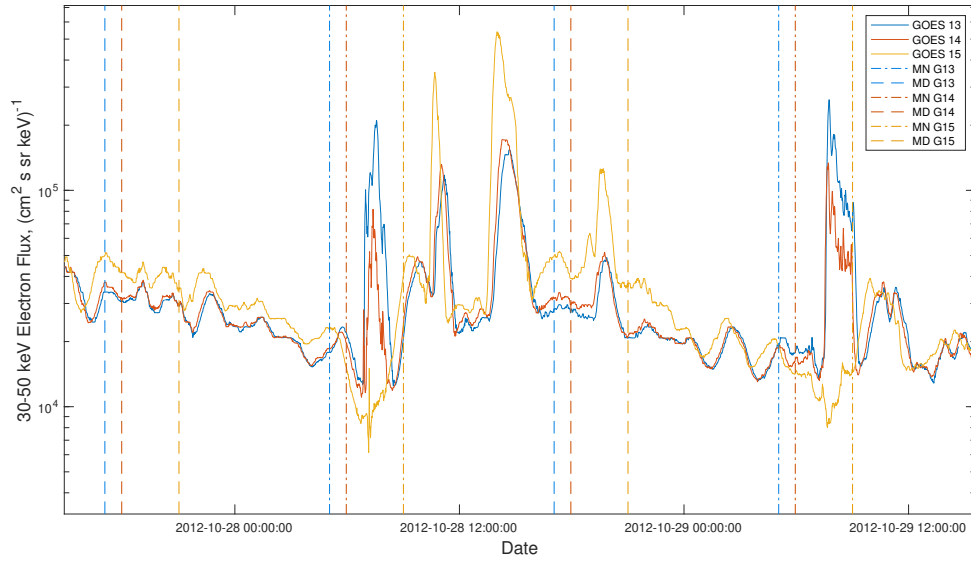


Figure 1. The 40 keV electron flux observed by the MAGED onboard GOES 13 (blue), 14 (orange) and 15 (yellow) between 27 October 2012 and 29 October 2012. The figure also shows when each of the spacecraft is at midday (GOES 13 - blue dashed, 14 - orange dashed, and 15 - yellow dashed) and midnight (GOES 13 - blue dot dashed, 14 - orange dot dashed, and 15 - yellow dot dashed).

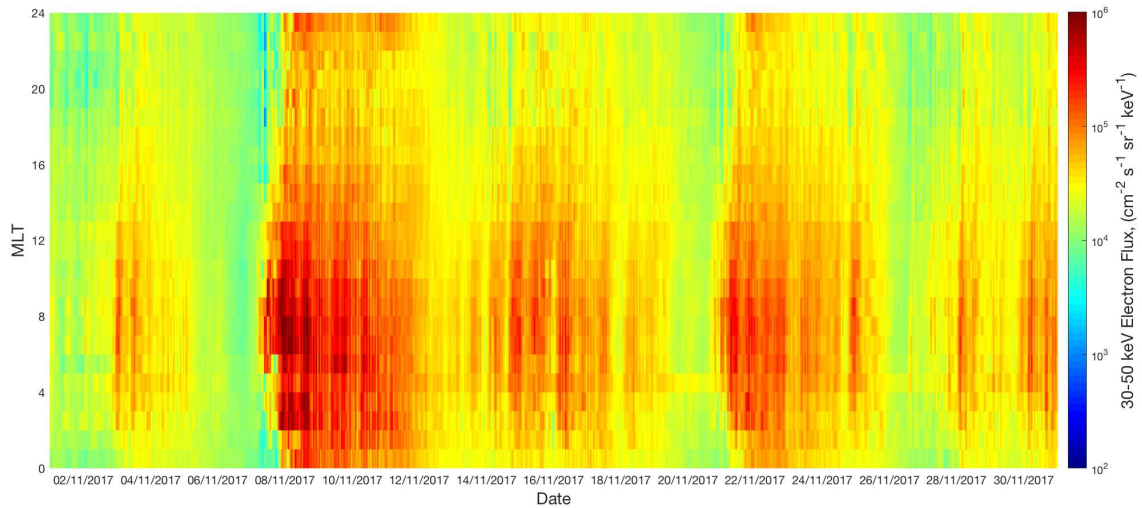


Figure 2. The model estimated 40 keV electron flux at all MLT from 1 November 2017 to 30 November 2017.

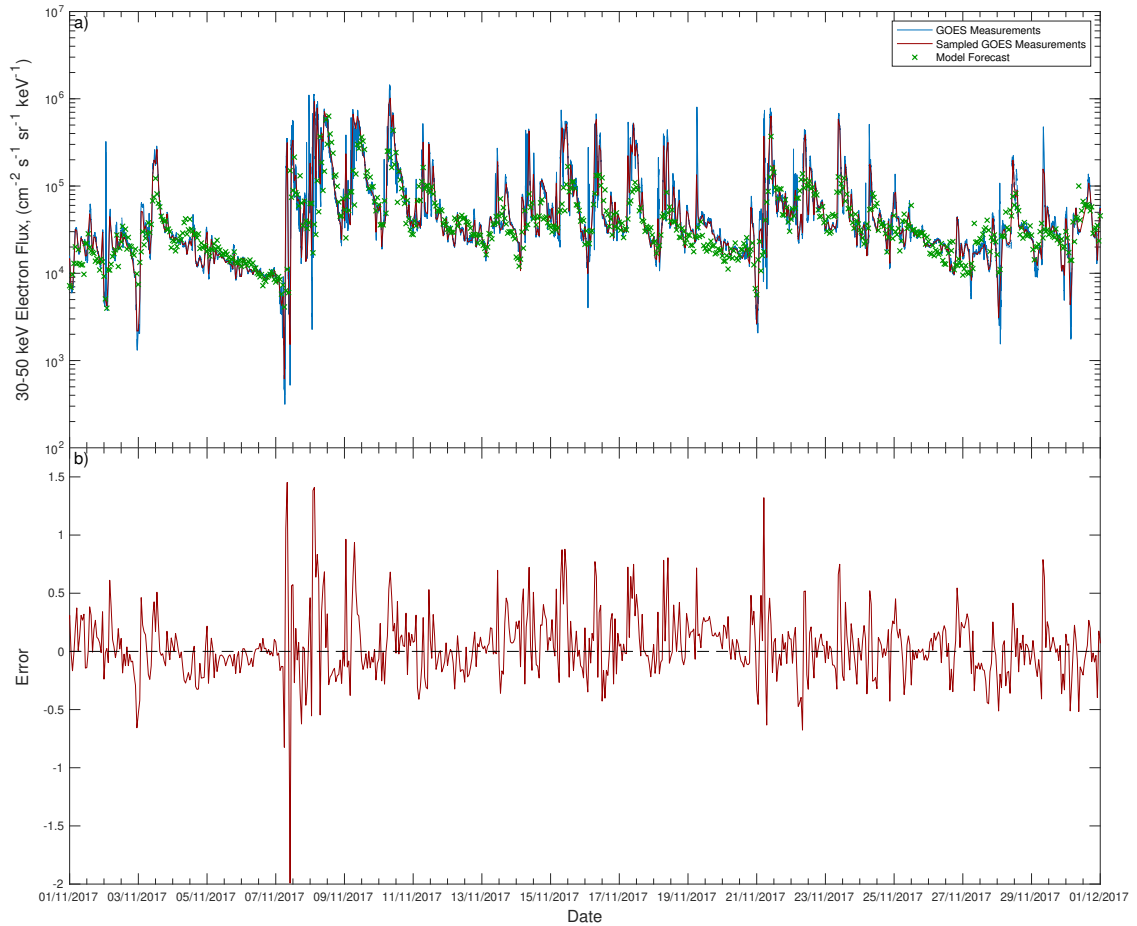


Figure 3. (a) The 40 keV electron flux observed by the MAGED onboard GOES 13 (blue), the sampled GOES 13 40 keV electron flux (red) and the model forecast at the GOES 13 location for November 2017. (b) The error between the sampled GOES 13 40 keV electron flux and the model forecast at the GOES 13 location for November 2017.

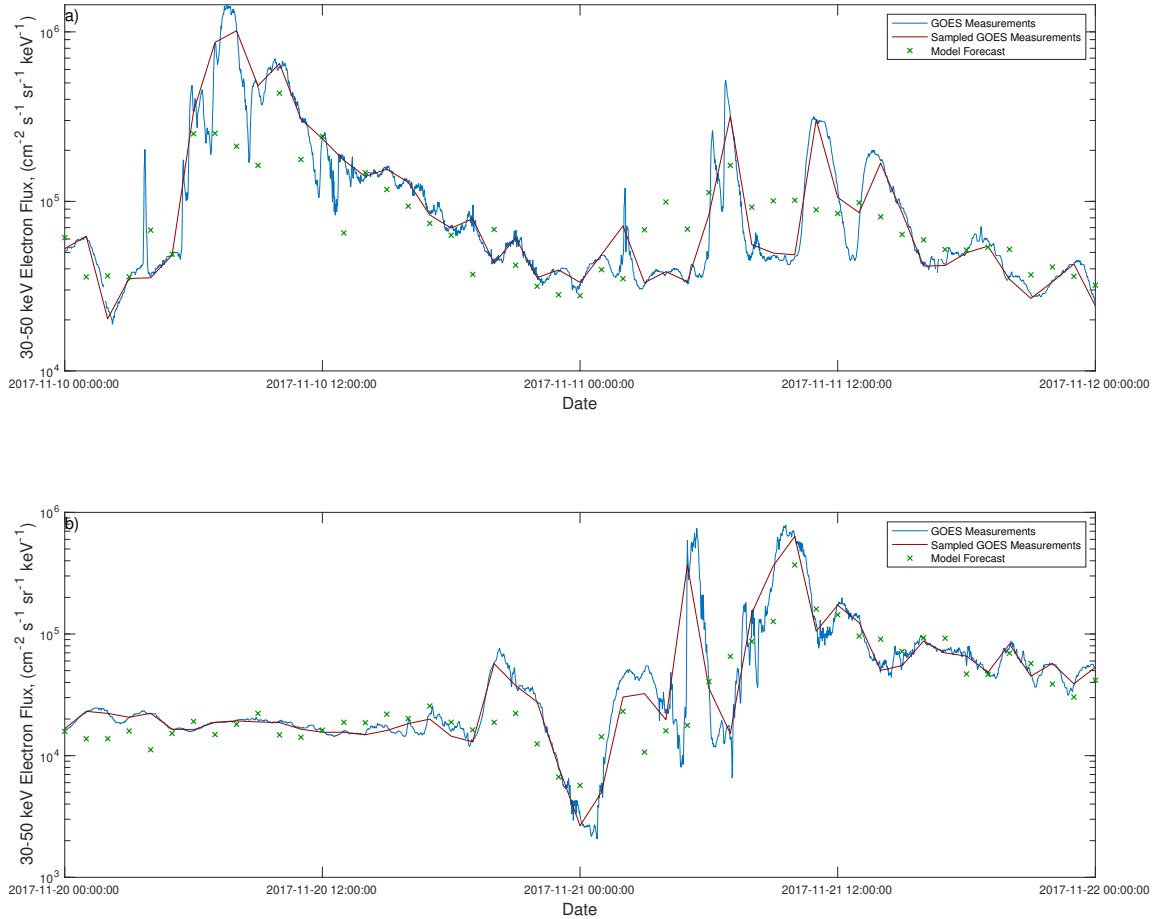


Figure 4. The 40 keV electron flux observed by the MAGED onboard GOES 13 (blue), the sampled GOES 13 40 keV electron flux (red) and the model forecast at the GOES 13 location for (a) 10-12 November 2017 and (b) 20-22 November 2017.

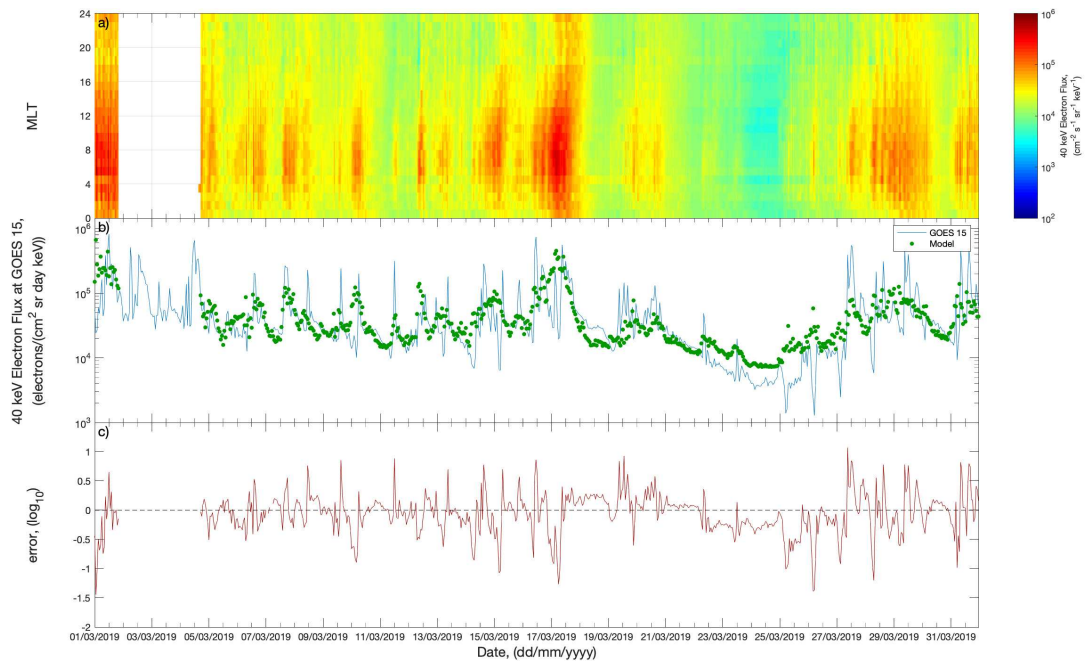


Figure 5. The real time output from the 40 keV electron flux model: (a) in MLT and time (b) at the GOES 15 location (green) vs GOES 15 data (blue), and (c) the error between the sampled GOES 15 40 keV electron flux and the model forecast at the GOES 15 location for March 2019