

22 **Abstract**

23 Physics-based simulations are important for elucidating the fundamental mechanisms behind the
24 time-varying complex ionospheric conditions, such as field-aligned currents (FACs) and plasma
25 convection patterns, against unprecedented solar wind variations incidents in the Earth's
26 magnetosphere. However, to perform a huge parameter survey for understanding the nonlinear
27 solar wind density dependence of the FAC and convection patterns, for example, a large-scale
28 cluster computer is not fast enough to run state-of-the-art global magnetohydrodynamic (MHD)
29 simulations. Here we report the impressive performance of a machine-learning based surrogate
30 model for the ionospheric outputs of a global MHD simulation, using the reservoir computing
31 technique called echo state network (ESN). The trained ESN-based emulator is exceptionally fast
32 to perform the parameter survey, suggesting a missing solar wind density dependence of the
33 ionospheric polar cap potential. We discuss future directions including the promising application
34 for the space weather forecast.

35 **Plain Language Summary**

36 We developed a machine-learning emulator to mimic a global magnetohydrodynamic (MHD)
37 simulation of a dynamically changing auroral oval. We conducted a state-of-the-art global MHD
38 simulation called REPPU for four magnetic storm events to experience large dynamic ranges of
39 input solar wind parameters changes. The long-term REPPU simulation results are then used to
40 train the machine-learning model called echo state network (ESN). Using the ESN-based
41 emulator, we confirmed one of the well-known solar wind parameter dependences of the auroral
42 activities on the solar wind magnetic field directions. From the parameter survey using the ESN-
43 based emulator, we further suggest a missing nonlinear solar wind density dependence.
44 Compared to the computationally expensive global MHD simulations, the ESN-based emulator
45 is surprisingly quick to run, leading to a breakthrough for operational space weather forecasting
46 and opening a pathway for future data assimilation studies of the solar wind-magnetosphere-
47 ionosphere coupling.

48

49 **1 Introduction**

50 Machine learning (ML) techniques have been recognized as a useful tool for predicting
51 geomagnetic activity indices, as represented by the AE, Kp, and Dst indices, using solar wind
52 parameters as inputs, such as the solar wind speed (V_{sw}), proton density (N_p), and interplanetary
53 magnetic field (IMF). Many such attempts have been thoroughly reviewed by Liemohn et al.
54 (2018). One of the latest studies used the ML technique called echo state network (ESN) to
55 successfully predict the AE index to diagnose the nonlinearity of a magnetosphere-ionosphere
56 coupled system using a synthetic solar wind time series (Nakano and Kataoka, 2022).

57 In principle, and in more detail, the high-latitude geomagnetic activity indices are
58 products of the two-dimensional (2D) distributions of ionospheric currents, as characterized by
59 the field-aligned currents (FACs) into and out of the ionosphere (Iijima and Potemra, 1978),
60 ionospheric horizontal plasma flow called ionospheric convection, and height-integrated
61 ionospheric conductivity. Detailed 2D patterns of ionospheric convection, FACs, and
62 ionospheric conductivity can be empirically modeled as a function of the solar wind parameters
63 and geomagnetic activity indices (Weimer, 1995; 2001; Weimer and Edwards, 2022). The

64 empirical models, however, have limitations in that they predict the averaged observed patterns
65 and cannot account for dynamic solar wind variations or unprecedented solar wind variations.

66 To overcome the limitations, a straightforward physics-based approach is to solve the
67 idealized magnetohydrodynamic (MHD) equations for the solar wind and magnetospheric
68 plasma flows, setting the appropriate height-integrated ionospheric conductivity layer as one of
69 the boundary conditions. In global MHD simulations, we can obtain 2D patterns of the
70 ionospheric convection and FACs, where auroral ovals are consistently represented by 2D
71 patterns of the ionospheric conductivity (e.g., Tanaka et al., 2022). State-of-the-art global MHD
72 simulations are also essential for understanding the mechanism behind the dynamically changing
73 auroral oval distribution (e.g., Ebihara and Tanaka, 2022). Further parameter surveys using such
74 simulations are still necessary to understand the nonlinear effects, for example, the density effect
75 on the ionospheric potential or energy deposition (Khachikjan et al., 2008; Ebihara et al., 2019;
76 Yang et al., 2020; Nakano and Kataoka, 2022). However, the practical use of the global MHD
77 simulation for such a parameter-survey purpose is still limited because it is computationally
78 expensive.

79 A reasonable next approach to addressing the time-consumption issue is emulate the
80 computationally expensive physics-based global MHD simulation by ML techniques, although
81 the physics behind the simulation becomes a black box. Once such an ML-based emulator is
82 developed, we can predict dynamically changing 2D maps of ionospheric conditions
83 instantaneously. It is therefore practically possible for a small computer to make a thorough
84 parameter survey by the ML-based emulator.

85 The purpose of this study is to develop such an ML-based emulator and to examine the
86 potential impacts. While an emulation that works with a global MHD simulation was attempted
87 for parameter tuning (Kleiber et al., 2013; Heaton et al., 2015), here we develop an ESN-based
88 emulator for predicting the dynamic ionospheric responses of the magnetosphere-ionosphere
89 system to variable solar-wind time-series input. The methods of emulating global MHD
90 simulation results by the ESN model are briefly introduced in Section 2. In Section 3, we
91 examine the obtained results from the newly developed ESN-based emulator. In Section 4, we
92 discuss the predictive capabilities of the ESN-based emulator and some future directions.

93 **2 Materials and Methods**

94 **2.1 Global MHD simulation**

95 REPPU (REProduce Plasma Universe) is an MHD simulation code developed for
96 studying the global magnetosphere-ionosphere coupling (Tanaka, 1995; Tanaka 2020). The
97 REPPU code is characterized by an excellent ionospheric reproduction of fundamental auroral
98 phenomena such as substorm onset (Ebihara and Tanaka, 2015a,b), sun-aligned arcs (Tanaka et
99 al., 2017), and the theta aurora (Tanaka et al., 2018). In this study, we used an improved REPPU
100 simulation, including the effects of a tilted dipole axis and seasonal changes of solar zenith
101 angles. The total number of grid cells in the magnetosphere is 30722 (horizontal) times 240
102 (vertical), where the unstructured grid system described by Moriguchi et al. (2008) is employed.
103 The number of grid cells in the ionosphere is 30722. The improved REPPU simulation is
104 essentially the same as that used for the real-time REPPU simulation of space weather forecast
105 executed by the National Institute of Information and Communications Technology (Nakamizo
106 and Kubota, 2021). We used high-resolution OMNI-2 one-min data (Bx, By, Bz, Np, Vx, Vy,

107 V_z , and proton temperature) for input. Note that we used B vectors in the GSM coordinate
 108 system and we provisionally used V vectors in the GSE coordinate system.

109 We ran a REPPU simulation to obtain several-days worth of activity outputs for training
 110 and testing the emulator. Four different long-term output datasets for moderate and intense
 111 magnetic storm events as driven by corotating interaction regions (CIR) or coronal mass
 112 ejections (CME) were connected and used for training (see Kataoka and Miyoshi (2006) for the
 113 difference between CIR and CME driven storms): Intense (Dst peak = -130 nT) CIR storm (~24
 114 hours from 2015/10/7 0000 UT), moderate (Dst peak = -56 nT) CIR strm (~21 hours from
 115 2015/10/18 0000 UT), moderate (Dst peak = -87 nT) CME storm (~34 hours from 2015/11/06
 116 1200 UT), and intense (Dst peak at -166 nT) CME storm (~36 hours from 2015/12/19 1200 UT).
 117 Further, we prepared the testing data from non-storm time 16.5-hour data from 2015/09/06 0000
 118 UT. Note also that we discarded the first one hour of data for each run, in which the global
 119 plasma distribution cannot yet be physically realistic.

120 We used 10-min averaged output data for the ionospheric potential Φ , FAC $J//$, and
 121 height-integrated conductivity maps. The ionospheric potential contours represent the
 122 ionospheric convection pattern. The FAC is positive for upward (out of the ionosphere) and
 123 negative for downward (into the atmosphere). The selected height integrated conductivity Σ_{xx} is
 124 a tensor component, where x is positive to the north and y is positive to the east. For coarse-
 125 graining purposes, as well as to clearly resolve the Region-1 and Region-2 FAC patterns, we
 126 binned the Φ , $J//$, and Σ_{xx} maps for the northern polar region (>50 deg latitude) into 15×32 in
 127 latitude and longitude, respectively, from the original resolution of 60×320 .

128 We then applied principal component analysis (PCA) to the 2D maps of the simulation
 129 results to reduce the dimensions. Note that Cousins et al. (2015) applied a similar method to
 130 evaluate variable FAC patterns. In this study we used the PCA module of Python 3 scikit-learn
 131 (<https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html>). To
 132 reproduce the > 90% variance of the original features, we decomposed the $J//$ pattern into 15
 133 PCA components, and the Φ and Σ_{xx} patterns into 10 PCA components (Supplemental
 134 Information Figures S1 and S2).

135 2.2 Machine learning technique

136 We require an ML technique that can be trained by a small training dataset because the
 137 REPPU simulation is still computationally expensive for long runs. Therefore, the standard deep
 138 learning technique is not appropriate. We also need a specific ML technique suitable for time-
 139 series prediction, because the ionosphere dynamically changes following the time history in the
 140 magnetosphere and ionosphere. Both needs can be satisfied by the reservoir computing method
 141 ESN (Jaeger, 2001; Jaeger and Haas, 2004), as reviewed by Tanaka et al. (2019). We used
 142 essentially the same ESN method as documented by Kataoka and Nakano (2021) and Kataoka et
 143 al. (2022). In this study we used the ESN module of Python 3 as developed by Tanaka et al.
 144 (2022) (See <https://github.com/GTANAKA-LAB/DTS-ESN/>).

145 The basic ESN model used in this study is described by the reservoir state vector \mathbf{x} and the
 146 model output vector \mathbf{y} (time series of PCA components of $J//$, Σ_{xx} , and Φ) at $t = n + 1$ steps as
 147 follows:

$$148 \mathbf{x}(n+1) = \tanh \left\{ W^in \mathbf{u}(n+1) + W\mathbf{x}(n) \right\}, \quad (1)$$

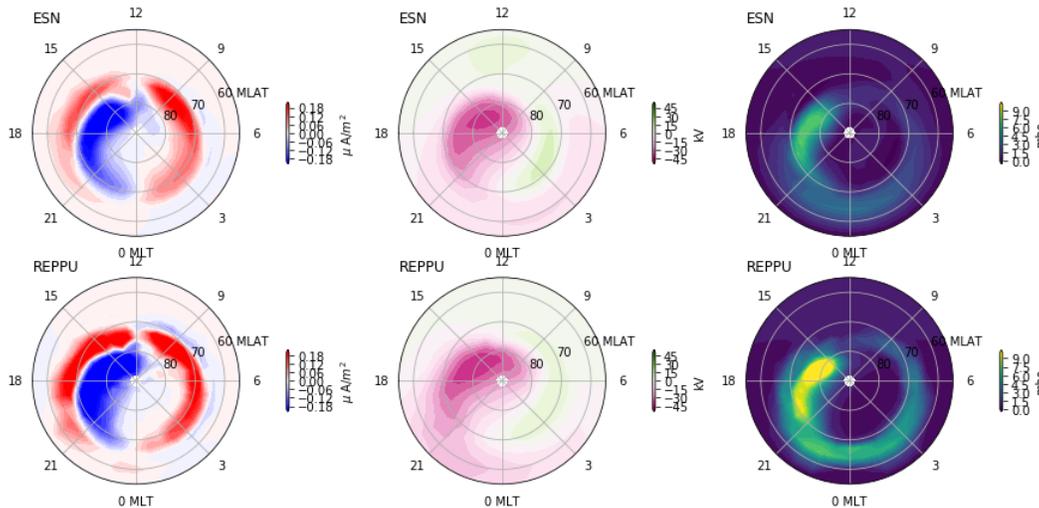
$$\mathbf{y}(n+1) = W^{out} \mathbf{x}(n+1). \quad (2)$$

Here, the weight matrices W^{in} and W are multiplied by the input vector \mathbf{u} (the solar wind time series) and the reservoir state vector \mathbf{x} , respectively. In this study, we set the number of the nodes (elements of \mathbf{x}) to be 300. These W^{in} and W are fixed, while only W^{out} is trained by the Ridge regularization with regularization parameter of 10^{-3} .

To create the random and sparse node connections of W , where only 10% of the matrix elements are random values between -1.0 and 1.0, and the remaining 90% are zero. We chose the optimal spectral radius (maximum eigenvalue of W) to be 0.55, 0.60, and 0.65 for $J//$, Σ_{xx} , and Φ , respectively, by evaluating the normalized root-mean square errors using both training and testing data (Supplemental Information Figure S3). As the input vectors \mathbf{u} , the solar wind speed and density are roughly normalized as $\log_{10} V_{sw} - 2.5$, and $\log_{10} N_p - 1.0$ before training the ESN model. It is noteworthy here that both the speed and density follow log-normal distributions (Burlaga and Lazarus, 2000).

We constructed the emulators for $J//$, Σ_{xx} , and Φ maps, independently. However, the current continuity $J// = \text{div}(\Sigma \text{ grad } \Phi)$ relates these three parameters and any inconsistencies among the three parameters therefore give hints of unphysical parts of the emulator to potentially fix, or avenues to evaluate errors in the emulation results for future applications.

3 Results and discussions

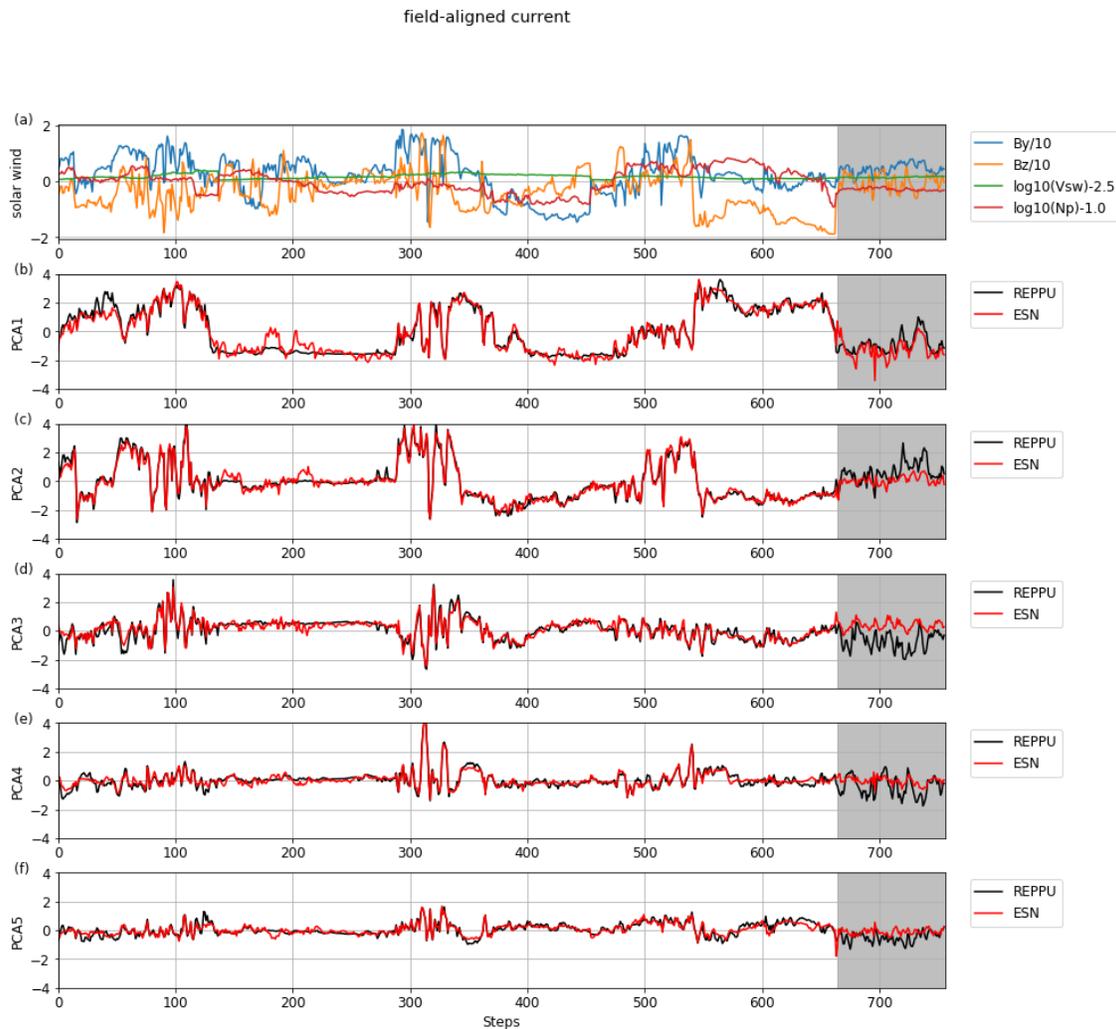


169

170 **Figure 1.** Snapshot example of field-aligned currents, ionospheric potential, and conductivity
 171 maps obtained from ESN emulator (top) and REPPU simulation (bottom) at a testing time of $t =$
 172 735 steps.

173

174 An example result from the ESN-based emulator compared with a REPPU simulation is
 175 shown in Figure 1. We can see a reasonable agreement between the results from ESN-based
 176 emulator and REPPU simulation; such as Region 1 and Region 2 FAC patterns and two-cell
 177 convection patterns, although the strong conductivity enhancement in the dusk sector was not
 178 reproduced. See Supplemental Information Movie S1-S3 for the other time intervals.



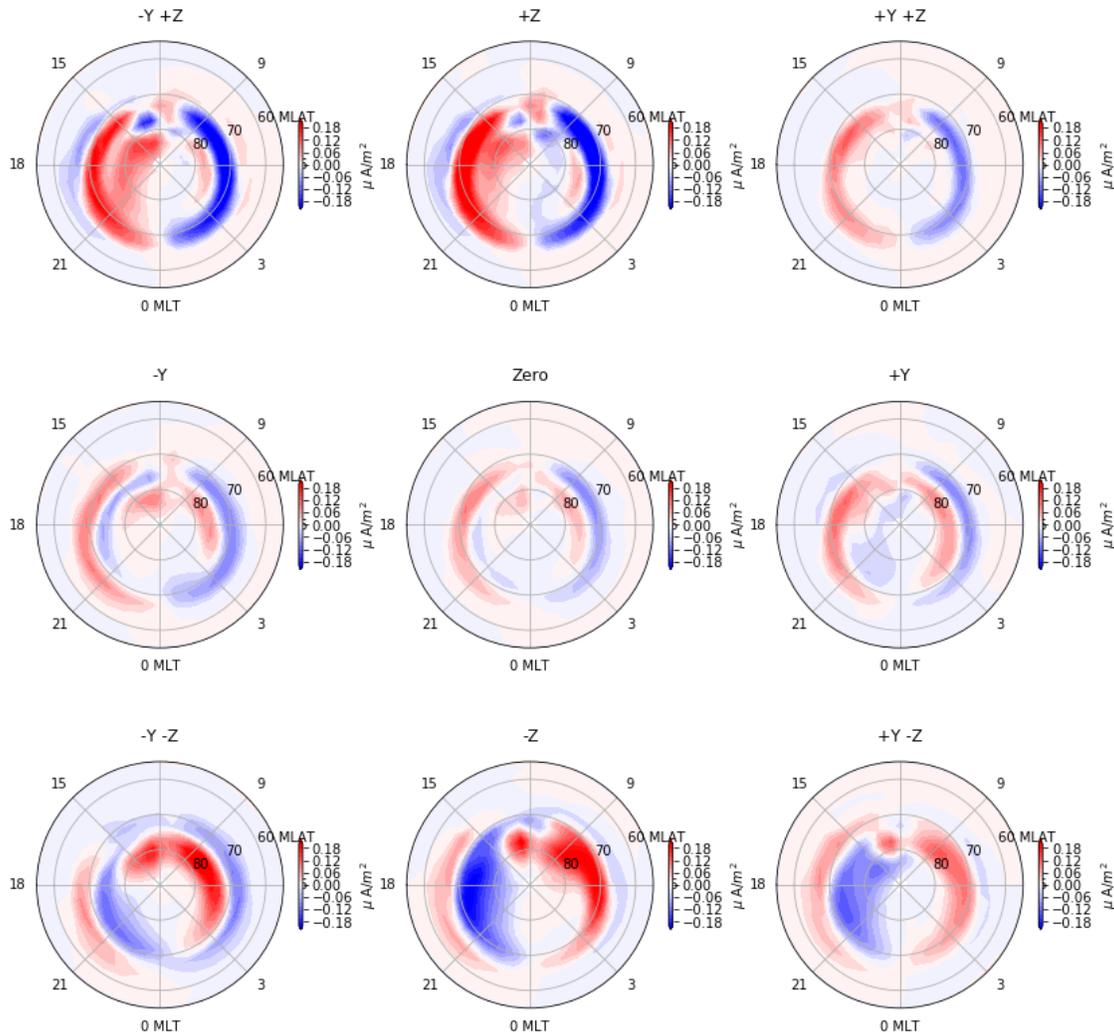
179

180 **Figure 2.** Solar wind parameters (a) and top five PCA components (b-f) for FAC. Black curves
 181 show the REPPU simulation results and the red curves are from the ESN model. The testing time
 182 interval, which are not used for training but used for score evaluation, is shown by the gray
 183 hatched time interval.

184

185 Figure 2 shows the performance of training and testing the ESN emulator of the FAC
 186 map. See Supplemental Information Figures S4-S5 for the same figures for potential and
 187 conductivity. The input solar wind parameters are shown in the top panel. The top five PCA
 188 components and the prediction from the ESN model are shown. The training interval is $t < 664$
 189 steps. The trained ESN model reproduces the time variation of PCA components for both the
 190 training and the testing intervals.

191

Field-aligned current, $V_{sw} = 400$ km/s, $N_p = 5.0$ /cc, $B = 5$ nT

192

193 **Figure 3.** Quasi-steady state FAC patterns as obtained from the ESN-based emulator for
 194 different IMF clock angles using synthetic solar wind data.

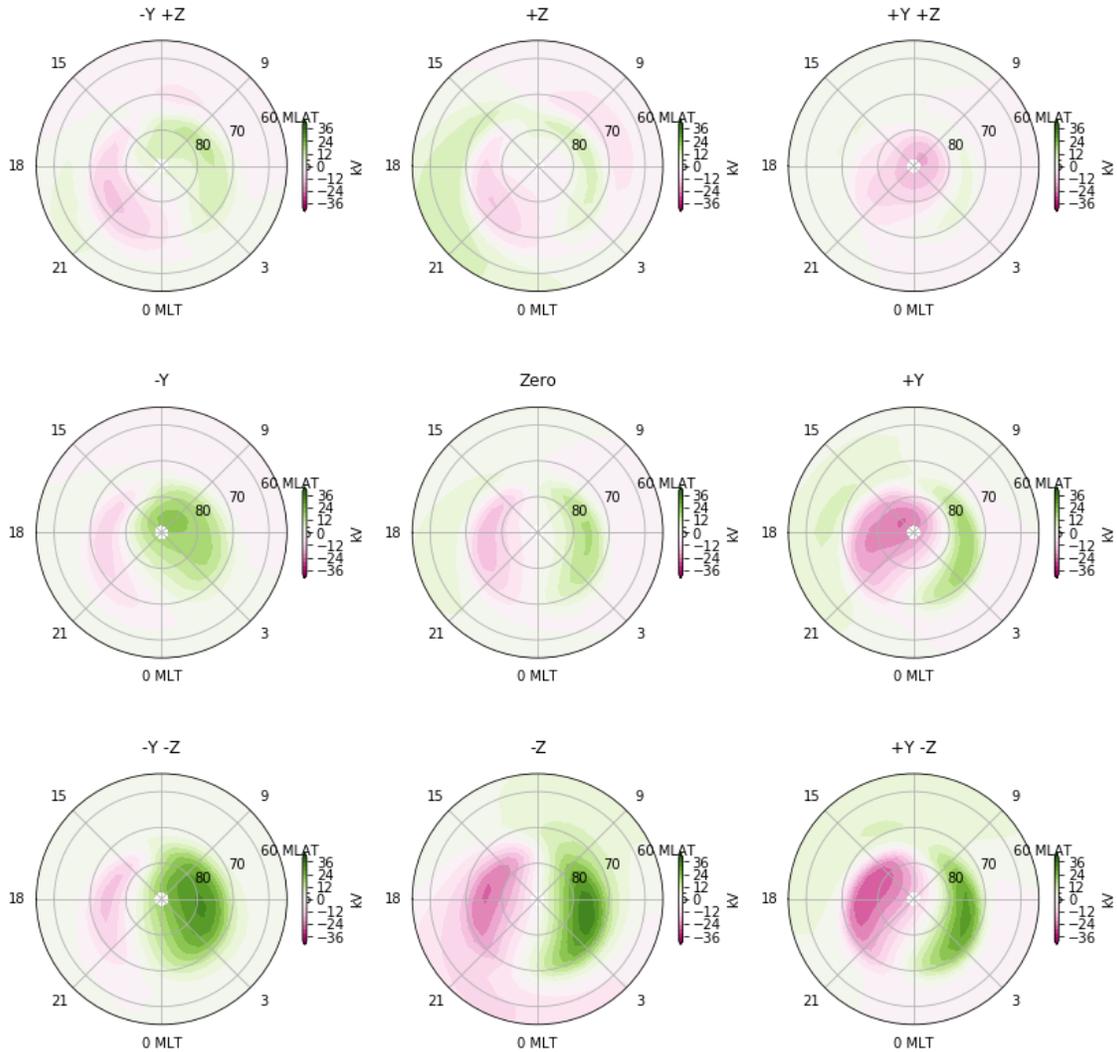
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196 Instead of directly comparing the emulation results with the observation data, which are
 197 available only for spatially limited areas, we benchmark the emulation results against the
 198 standard empirical models (Weimer, 1995; 2001). Figures 3 and 4 show an example of the IMF
 199 clock-angle dependence of FAC and convection patterns using synthetic solar wind data
 200 (Supplemental Information Figure S6), fixing the density at $N_p = 5$ /cc, the solar wind speed at
 201 $V_{sw} = 400$ km/s, and the IMF strength at $B_0 = 5$ nT. We selected the results from quasi-steady
 202 state time steps for each IMF directions (i.e., 15 steps = 150 min after the IMF changes). The
 203 IMF B_y and B_z dependence of the Region-1 and Region-2 FAC system as well as the overall
 204 convection pattern morphology show a reasonable agreement with those as they appears in the
 205 Weimer models (Weimer, 1995; 2001); such as pairs of Region 1 and Region 2 FAC patterns

206 (Figure 3) with round-cell and clecent-cell convection patterns (Figure 4) and their IMF By
 207 dependence during southward IMF Bz (SBZ) conditions.

208

Polar-cap potential, $V_{sw} = 400$ km/s, $N_p = 5.0$ /cc, $B = 5$ nT



209

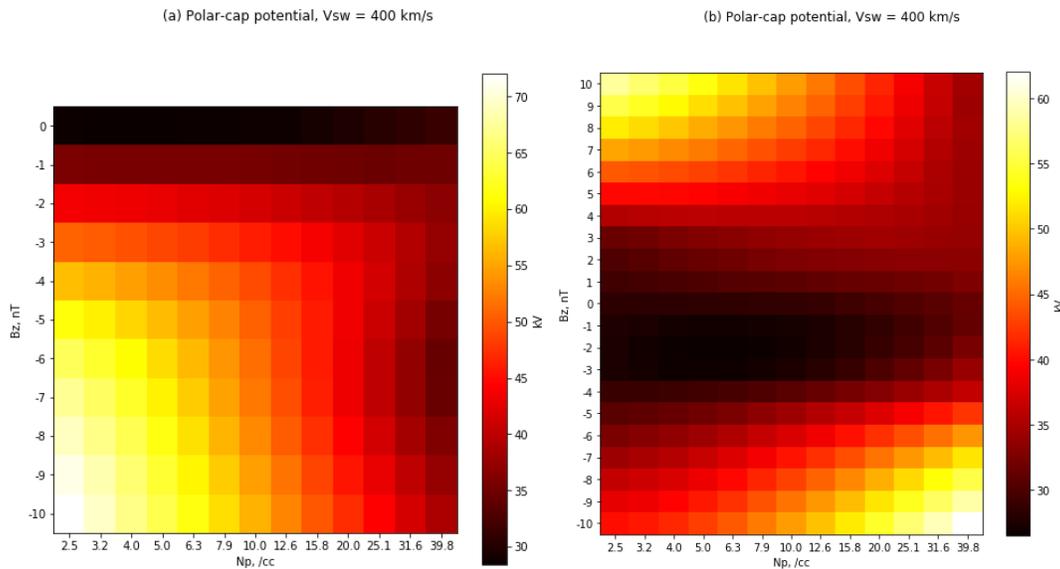
210 **Figure 4.** Quasi-steady state ionospheric potential map as obtained from the ESN-based
 211 emulator for different IMF clock angles using synthetic solar wind data.

212

213 For comparison with empirical models, there is a notable drawback of this study by
 214 selecting active-time magnetic storm events as the training data set. Note that the unrealistically
 215 large-amplitude of the Region-2 FAC appeared during the northward IMF (NBZ) due to a poor
 216 sample of the NBZ situation in the training data. Further dataset which includes plenty enough
 217 NBZ situation are therefore needed to correctly train the emulator model for NBZ conditions.

218 Note that the ESN-based emulator can even learn from the other global MHD simulation results
 219 if necessary, and the ring current coupled MHD simulation (e.g. Kataoka et al., 2005) would also
 220 be interesting to be included for further discussing the dynamic evolution of Region-2 FAC
 221 system in future.

222 The ESN-based emulator is exceptionally fast to run and it is useful for a thorough
 223 parameter survey of so-called heatmap analysis, which cannot be done by observations or
 224 simulations. As an example, we input the synthetic solar wind variations to the ESN-based
 225 emulator to examine the nonlinear density effect on the cross-polar cap potential (CPCP), as
 226 shown in Supplemental Information Figures S7-S8. Note that it is computationally expensive for
 227 the REPPU simulation to obtain the following heatmap results. Note also that we fixed the solar
 228 wind speed in the input, so that the density effect is essentially the same as the dynamic pressure
 229 effect.



230

231 **Figure 5.** Heatmap analysis of the parameter survey to examine the nonlinear density effect on
 232 the cross polar-cap potential, changing (a) SBZ and (b) By component using the ESN-based
 233 emulator.

234

235 As shown in Figure 5a, the CPCP has a negative dependence on the density during strong
 236 SBZ. In fact, the similar tendency has been identified by Khachikjan et al. (2008) using active-
 237 time SuperDARN observations. Khachikjan et al. (2008) discussed that the shrinking dayside
 238 magnetopause by high dynamic pressure may be relevant to reduce the possible effect of dayside
 239 reconnection that is powering the CPCP.

240 Recognizing that the overall IMF By dependence was fairly reproduced by the ESN-
 241 emulator as shown in Figures 3 and 4, we further diagnose the density dependence by changing
 242 the IMF By component, turning off the contribution of SBZ. From the heatmap analysis without
 243 SBZ component, Figure 5b shows that the density dependence is positive when $B_y < 4$ nT, while
 244 it is negative for larger B_y . The By-ymmetric density effect is a new problem “predicted” from
 245 the ESN-based emulator, which suggests that the nonlinear density effect on CPCP can be more
 246 complex than imagined from the SBZ reconnection hypothesis. Note that the IMF By

247 dependence does not clearly appear if we integrate the obtained By-Np heatmap in density, which
248 is consistent with SuperDARN observations (Mori and Kustov, 2013). Related future works
249 therefore include the observation-based identification of the By-asymmetric density effect as well
250 as the detailed analysis of the global MHD simulation results of both magnetosphere and
251 ionosphere to identify of the exact mechanism to cause the By-asymmetric density effect.

252 In this study we used simulation data for CIR- and CME-driven magnetic storm events
253 that occurred in the fall to winter seasons. The training data set is therefore limited to the
254 particular situation where the auroral activity is high and the northern hemisphere is darker than
255 the southern hemisphere. A detailed discussion of the sunlight effect associated with solar zenith
256 angles and the general north-south asymmetry are therefore interesting future subjects of study
257 when we have accumulated more long-term REPPU simulation results, including different
258 seasons.

259 More generally, the ESN-based emulator is capable of dynamic predictions following the
260 time history, and this study investigated the performance of reconstructing the 10-min scale
261 dynamics. In such a time scale, the ESN-based model developed in this study can be readily
262 applicable to the operational space weather forecast by replacing the input file by the real-time
263 solar wind data. Emulating more dynamic phenomena such as sudden commencements and
264 substorms is therefore the next technical challenge. The ESN method can be applied to diverse
265 temporal scales (Tanaka et al., 2022), and in future studies we plan to tune the ESN-based
266 emulator to a higher time resolution, choosing the right leaking rate matrix to reproduce both
267 min-scale to 10-min scale dynamics.

268 This paper presented the first kick-off results to demonstrate the potential impact of the
269 emulator. For a practical use, the accuracy must be improved by learning NBZ and other variable
270 conditions. Future studies using the ESN emulator of the REPPU simulation therefore include an
271 examination of the accuracy in reproducing observation data, such as SuperDARN convection
272 maps. Any partial data or point data can also be used with cutting-edge data assimilation
273 techniques (Nakano et al., 2020). For data assimilation, we need to increase the ensemble
274 number of simulation runs for integrating large probabilistic ensembles, and the ESN-based
275 emulator will play an essential role. In this manner, the ESN-based emulator can be expected to
276 become a basic technique for future space weather reanalysis studies.

277 **4 Conclusions**

278 Using the ESN model trained by long-term REPPU simulation runs for magnetic storm
279 events, we developed an emulator to instantaneously reproduce the REPPU simulation results for
280 the ionospheric conditions by inputting the solar wind parameter time series. The newly
281 developed ESN-based emulator reasonably reproduces the active-time 2D patterns of the
282 ionospheric potential, FAC, and conductivity. A missing By-asymmetric density effect is also
283 suggested from the parameter survey using the ESN-based emulator. The ESN-based emulator
284 can lead to breakthrough advances for real-time space weather forecasting operations as well as
285 for accelerating the data assimilation studies.

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296 **Open Research**

297 The python codes and the training dataset for the ESN-based emulator model used in this
298 study is open to public at <https://github.com/ryuhokataoka/REPPU-ESN> (v1.0.0 is released at
299 doi.org/10.5281/zenodo.7519025)

300

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