Regional Ionospheric Parameter Estimation by Assimilating the LSTM Trained Results Into the SAMI2 Model

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Abstract This paper presents a study on the possibility of predicting the regional ionosphere at midlatitude by assimilating the predicted ionospheric parameters from a neural network (NN) model into the SAMI2 is Another Model of the Ionosphere (SAMI2). The NN model was constructed from the data set of Jeju ionosonde (33.43°N, 126.30°E) for the period of 1 January 2011 to 31 December 2015 by using the long-term memory (LSTM) algorithm. The NN model provides 24-hr prediction of the peak density (NmF2) and peak height (hmF2) of the F2 layer over Jeju. The predicted NmF2 and hmF2 were used to compute two ionospheric drivers (total ion density and effective neutral meridional wind), which were assimilated into the SAMI2 model. The SAMI2-LSTM model estimates the ionospheric conditions over the midlatitude region around Jeju on the same geomagnetic meridional plane. We evaluate the performance of the SAMI2-LSTM by comparing predicted NmF2 and hmF2 values with measured values during the geomagnetic quiet and storm periods. The root-mean-square error values of NmF2 (hmF2) from Jeju ionosonde measurements are lower by 45% and 45% (30% and 11%) than those of the SAMI2 and IRI-2016 models during the geomagnetic quiet periods. However, during the geomagnetic storm periods, the performance of the SAMI2-LSTM model does not predict positive geomagnetic storms well. Comparing the quiet and storm periods for the SAMI2-LSTM model, the root-mean-square error (RMSE) of the storm period was calculated to be 2.76 (3.2) times higher at Jeju (Icheon) than in the quiet period. From these results, we demonstrated that in this study, the combination of the NN-LSTM model and physics-based model could improve the ionosphere prediction of existing theoretical and empirical models for midlatitude regions, at least in geomagnetically quiet conditions. We strongly suggest that this attempt, which has not been reported before, could be used as one of the keys to advance the physics-based model further.

1. Introduction

Ionospheric changes have a strong influence on GPS signal propagation, telecommunications, satellite communication, shortwave communication, geodetic, and traffic information, all of which are of high importance in our modern society. As such, the importance of monitoring and predicting the ionospheric environment is increasing. To accurately capture changes in the ionosphere, it is necessary to continuously observe and monitor its characteristics. Since the F2 layer has a major contribution to electron content in the ionosphere, and its maximum density (NmF2) and height (hmF2) can represent the ionospheric characteristics. If we observe and monitor the variation in these parameters, we may estimate the ionospheric impact on the transionospheric radio applications. For this reason, ionospheric conditions, including the F2 layer, have been monitored with various observation equipment, such as worldwide ionosonde networks (e.g., Galkin et al., 2006), incoherent scatter radars (e.g., Gordon, 1958), topside sounding (e.g., Chapman & Warren, 1968), and radio occultation from satellites (e.g., Hajj et al., 1994; Hardy et al., 1994). However, these observations not only have limitations in terms of time and spatial resolutions but also cannot predict future conditions. To overcome these shortcomings, many ionospheric models have been developed and studied.
Data assimilation techniques, such as Kalman filter algorithms (e.g., Chartier et al., 2016; Lee et al., 2012; Lin et al., 2015; Scherliess et al., 2004; Yue et al., 2011, 2012), 3D-Var (e.g., Aa et al., 2016; Bust et al., 2001, 2004, 2007), and 4D-Var techniques (e.g., Pi et al., 2003; Sessanga et al., 2019; Wang et al., 2004), have a considerable advantage in improving the performance of ionospheric models. In particular, since the data assimilation is based on observations, it can be a useful tool for nowcasting, which can simulate the current state of the ionosphere. However, it is still difficult to predict the future state of the ionosphere with a data assimilation model. In our previous study (Kim et al., 2019), to simulate and predict the ionospheric state better, we devised a simple data assimilation method, which was based on studies by Richards (1991) and Dandenault (2018). In this method, we estimated two ionospheric drivers (the neutral meridional wind and the total ion density) from hmF2 and NmF2 parameters from ionosonde measurements, and then, we utilized them in a first principle physic model, the Sami2 is Another Model of the Ionosphere (SAMI2), to calculate the state of ionosphere about 15 min later. The SAMI2 code is a two-dimensional ionospheric model originally developed by Huba et al. (2000) and now is available as an open source. Kim et al. (2019) showed that their method improved significantly the short-term (~15 min) forecasts of NmF2 and hmF2 at midlatitude locations in the same meridional plane. Unfortunately, their data assimilation method is only useful for predicting short-term future conditions. It is because long-term predictions are needed for the point of view in space weather prediction and surveillance. Thus, other approaches and methods are required.

Recently, many studies have been conducted to predict the GPS total electron contents (TEC) map using artificial neural networks (ANNs) algorithm (e.g., Habarulema et al., 2007; Hernández-Pajares et al., 1997; Leandro & Santos, 2007; Maruyama, 2002; Tulunay et al., 2006; Zhukov et al., 2018). More advanced algorithms, collectively called as deep neural network (DNN), have been developed in many application fields, including a recurrent neural network (RNN) and long-short term memory (LSTM). The RNN technique can solve the problem of long-term prediction (Elman, 1990) but has a vanishing gradient problem because of the limited range of input values (Bengio et al., 1994; Habarulema et al., 2009). On the other hand, the LSTM technique has an advantage over RNN in scenarios where a long-term input value is required. The LSTM algorithm has recently been utilized in studies of predicting ionospheric TEC (e.g., Srivani et al., 2019; Sun et al., 2017). For the ionospheric F2 parameter prediction, numerous studies have been utilizing the ANN algorithm (e.g., Athieno et al., 2017; Fan et al., 2019; McKinnell & Poole, 2000; Nakamura et al., 2009; Poole & Poole, 2002; Williscroft & Poole, 1996; Wintroft & Cander, 2000), but only recent studies are beginning to adopt the LSTM algorithm. For example, Hu and Zhang (2018) attempted the hmF2 prediction using the LSTM and bi-LSTM algorithms. Most recently, Moon et al. (2020) conducted a study using the LSTM model to perform long-term prediction. They trained long-term data of Jeju ionosonde, performed predictions for the next 24 hr, and produced better prediction values than existing models.

In this study, to overcome the limitations of the short-term (15 min) prediction, we adopt the LSTM algorithm for the F2 parameter prediction. As a first step, we utilize the predictive values of NmF2 and hmF2 for a longer-term period (24 hr) using the LSTM algorithm in the previous study (Moon et al., 2020). We then estimate the ionospheric drivers (equivalent winds and electron density scale factors) from the predictive NmF2 and hmF2 for the next 24 hr. The ionospheric drivers then input to a first principle model, the SAMI2 to calculate the ionospheric states on the meridional plane for the 24 hr. In this way, the longer-term (24 hr) predictions of NmF2 and hmF2 can be made with a good level of accuracy, not only at a reference location where observation data are used but also at other locations that are nearly on the same meridional plane. The comparison of the predicted NmF2 and hmF2 with measured values are then made in the geomagnetic storm and quiet periods. We believe that this can be used as one of the keys to advance the physics-based model further because no such attempt (combining between deep-learning and physics-based model) has been reported before.

The paper consists of the following sections. In section 2, the design of the LSTM algorithm is explained and the detailed depiction of the data is provided for two cases of the geomagnetic activity. Section 3 introduces the assimilation version of the SAMI2 model. In section 4, the results of the assimilated SAMI2 model linked with the LSTM method are compared to those of the SAMI2 original and IRI-2016 models, with discussion on further improvement strategy. In section 5, conclusion and summary are given.
2. Design of LSTM

Since the RNN, which is in a larger category than LSTM, is known to work for the short-term prediction problem but not for the long-term dependency problem (Bengio et al., 1994; Habarulema et al., 2009), we decided to use the LSTM, which is more suitable for solving the long-term prediction problem. Basically, RNN consists of a repeating chain of neural networks (NNs), as does the LSTM. However, the LSTM has four unique interoperable structures rather than a single network layer. Figure 1 shows the repetitive structure of the conventional RNN and the unique structure of the LSTM. In Figure 1, the $X_{t-1}$, $X_t$, and $X_{t+1}$ indicate the input values and the $h_{t-1}$, $h_t$, and $h_{t+1}$ mean the values of the hidden layer. As shown in Figure 1, the RNN and LSTM algorithms differ in the $A$ structures. The LSTM model adds a unique layer called the sigmoid layer ($\sigma$), which determines how much each component will affect. In other words, the sigmoid layer outputs a value of 0 or 1. It is responsible for deciding whether each component will be affected. The $\sigma$ value of 0 means that a component does not affect future results. The $\sigma$ value of 1 causes the data to flow, so that the component certainly affects future predictions. The RNN and LSTM models must use the hyperbolic tangent function (tanh), which is a nonlinear function, for the benefit of layering. More detailed description and discussion on the LSTM algorithm can be found in literature (e.g., Hochreiter & Schmidhuber, 1997; Moon et al., 2020).

2.1. Training and Validation Data Sets

In this study, we adopt the structure of LSTM made by Moon et al. (2020). Moon et al. (2020) designed the LSTM model using the Jeju (33.43°N, 126.30°E) ionosonde data ($f_{oF2}$, $h_{mF2}$) (https://spaceweather.rra.go.kr/observation/service/iono). In addition, they included the observed solar and geomagnetic indices such as the $F_{10.7}$, sunspot number (SSN), and Kp index (https://omniweb.gsfc.nasa.gov/ow.html) because ionospheric parameters are strongly related to these indices. They trained the LSTM model with the data set for the period of 1 January 2011 to 31 December 2015 and validated it with the data set for the whole period in 2016.

To organize the training and validation data into 1-hr units, Moon et al. (2020) reconstructed the missing ionospheric data by filling in with the data observed in the same local time on the previous day. Since the time resolutions of the solar and geomagnetic indices are different, they used the running mean method of 81 days (2 days) for the sunspot number (ap index), and individual values for Kp and $F_{10.7}$ itself in units of 1 hr. For the efficient performance of the algorithm, they set the ratio of the training and the validation data set to ~8.3:1.7. Detailed specifications and numbers of data points for the data sets are summarized in Table 1.

Moon et al. (2020) used the Deep learning Toolbox in Matlab-R2019b for training the LSTM model of Jeju ionospheric parameters. In the process, they conducted training verification using the collected training data to find the appropriate batch size, lookback, lookahead, and hidden layer count as the hyperparameters. Here, the batch size means the number of training examples utilized in one iteration, and the lookback size defines the number of recent data points to be used when predicting each future value in the time series. Conversely, the lookahead size means the number of data points to be predicted. For the $f_{oF2}$ LSTM model, they used 3 batch sizes, 24 lookback and lookahead sizes, and 21 hidden layers. For the $h_{mF2}$ model, 24 batch sizes, 24 lookback and lookahead sizes, and 41 hidden layers were used. Therefore, in testing in this study, the lookback is 24, so past data from 24 hr ago to the present is used to predict values until the next 24 hr (lookahead = 24).

2.2. Test Sets

As shown in Table 1, we select the 3-day period of 6–8 September 2017 for geomagnetic storm periods and the 2-week period of 18–31 October 2018 for quiet periods to test the LSTM model. We chose these particular periods for the test because ionosonde data from all three comparing stations (Jeju, Icheon, and Okinawa) were available. Icheon (37.14°N, 127.54°E) and Okinawa (26.68°N, 128.15°E) are located near the same geomagnetic longitude as Jeju (33.43°N, 126.30°E), so that results from the assimilated SAMI2 model with the LSTM model can be compared directly. The Korean ionosonde data (Jeju and Icheon) are available from the Korean Space Weather Center homepage (https://spaceweather.rra.go.kr/observation/service/iono), and we used it at intervals of 7.5 min for tests. The Okinawa (26.68°N, 128.15°E) ionosonde data (30 min interval)
can be obtained from the website of the National Institute of Information and Communications (NICT) in Japan (http://wdc.nict.go.jp/IONO/HP2009/ISDJ/index-E.html).

Figure 2 shows the geophysical condition data (IMF Bz component, SYM-H, Kp, F10.7, GOES X-ray data, and the observed NmF2 and hmF2 by Jeju ionosonde) during the storm test set. The geophysical condition data were obtained from the OMNI webpage mentioned in section 2.1, and the GOES data can be downloaded from NOAA NGDC (https://satdat.ngdc.noaa.gov/sem/goes/data/full/). As shown in Figure 2, 3 geomagnetic storms and 14 solar flares (>M class) occurred in succession during the storm test period. In particular, when the second storm occurred, the observed hmF2 and NmF2 values over Jeju station were abnormally increased. This is seen as a significant positive ionospheric effect due to the storm. On the other hand, although many solar flares occurred, there was no significant increase in electron density in the ionosphere over Jeju. Thus, we focus on the response to geomagnetic storms rather than the effects of solar flares.

Figure 3 shows the geophysical conditions, GOES X-ray data, and the ionospheric parameters during the

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Table 1

|                | Training                                      | Validation                                   | Test                          |
|----------------|-----------------------------------------------|----------------------------------------------|-------------------------------|
| **Input**      | 1-hr ahead prediction for foF2 and hmF2       | SSN, F10.7, Ap, Kp, foF2, and hmF2           | 1- to 24-hr ahead prediction for foF2 and hmF2 |
| **Output**     | 1 January 2011 to 31 Dec 2015 (5 years)       | 1 January to 31 December 2016 (1 year)       | 6–8 September 2017 (3 days)   |
| **Period**     | Storm                                        | Quiet                                       | Storm                        |
|                | 18–31 October 2018 (2 weeks)                  | 576                                          | Quiet                         |
| **Data points**| 43,824 (83%)                                  | 8,784 (17%)                                 | 2,688                         |
Geomagnetic quiet test set. During the quiet period, all values associated with geomagnetic activities were quiet, and solar activity also persisted without any change. The ionospheric parameters show typical diurnal variations. The empty values of ionosonde are due to the lack of observation, so that analysis of our model results excluded the data gap period.

3. Assimilated SAMI2 Model

The trained LSTM model with the Jeju data calculates the 24-hr predicted values of $hmF2$ and $NmF2$, from which the ionospheric drivers (effective meridional winds and electron density scale factor) are computed. The ionospheric drivers are then assimilated into the revised SAMI2 model to calculate the ionospheric states on the meridional plane for the 24-hr period. The assimilation method for the revised SAMI2 model is described in Kim et al. (2019) and the references therein. The assimilation method is based on two assumptions: (1) the variation of $hmF2$ is linearly proportional to the variation of neutral meridional winds at the middle latitudes or electric fields (collectively called as equivalent meridional winds) and (2) all the ion density fields of the ionosphere on the meridional plane follow the same scaling factor between the model and measured $NmF2$ at the reference location.

Using the first assumption, Richards (1991) proposed the following simple Equation 1.

$$\Delta hmF2 = \alpha_{wind} \times \Delta U$$

(1)

$$\alpha_{wind}(t) = \frac{hmF2_n(t) - hmF2_{n-1}(t)}{U_n(t) - U_{n-1}(t)}$$

(2)
where $\alpha_{\text{wind}}(t)$ is the proportionality constant at the time, $t$, and $U$ is the equivalent meridional wind. Kim et al. (2019) computed $\alpha_{\text{wind}}(t)$ for the SAMI2 model. Utilizing the computed $\alpha_{\text{wind}}(t)$ in Equation 3, we can predict $U$ at the next time step (~15 min) from the difference between the model and observed $hmF2$ values. The short term predicted $U$ leads to short term prediction of $hmF2$ fairly well, as demonstrated in Kim et al. (2019). In this study, we replace the term of $hmF2_{\text{sonde}}$ with predicted values ($hmF2_{\text{LSTM}}$) up to 24 hr by the trained LSTM model to achieve the longer-term prediction.

The second assumption is to adjust all uncertainty in the input parameters, such as neutral background density, solar extreme ultraviolet (EUV) flux, and transports of ions and other. The scale factor ($\alpha_{\text{ion}}(t)$) is derived from measured $NmF2$ at the reference location and then is applied to all the ion density fields, which are used as the initial ion densities in the SAMI2 model that runs to the next 15-min time step. The computed $NmF2$s at the next time step are reasonably close to the measured values at other locations, as demonstrated in Kim et al., 2019. In this study, the 24-hr predicted $NmF2$s, instead of measured $NmF2$ at the reference station, are used to compute the scale factor for the 24-hr period.

Figure 4 shows the predicted values of ionospheric parameters over 24 hr from the LSTM model developed by Moon et al. (2020). We updated the ionospheric drivers using these long-term predicted values. We tested whether the long-term prediction was possible not only in the Jeju station but also in other regions by inputting these into the physics-based model. Also, we use the Flare Irradiance Spectral Model (FISM).
(Chamberlin et al., 2008) as the input energy source to the SAMI2 model. In addition, the Horizontal Wind Model (HWM14) (Drob et al., 2015) and U.S. Naval Research Laboratory Mass-Spectrometer-Incoherent-Scatter model (NRLMSISE-00) (Picone et al., 2002) are used as the thermosphere background model, and the $E \times B$ drift model (Scherliess & Fejer, 1999) is used as the basic electric field model.

4. Results and Discussions

To evaluate the performance of the assimilated SAMI2 model with the trained LSTM model (hereafter, SAMI2-LSTM), we compare the model $N m F_2$'s and $h m F_2$'s with measured values at the three ionosonde stations. The model performance is quantitatively evaluated with four measures: the correlation coefficient, root-mean-square error (RMSE), mean absolute percentage error (MAPE), and relative difference (RD). The correlation coefficient values are obtained using the REGRESS function of the IDL program, and the RMSE, MAPE, and RD are calculated using the following Equations 5–7, respectively. Smaller values for both RMSE and MAPE mean better performance.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\text{model} - \text{ionosonde})^2}{n}}$$

$$\text{MAPE} (%) = \frac{100\%}{n} \times \frac{\sum_{i=1}^{n}|\text{model} - \text{ionosonde}|}{\text{ionosonde}}$$

$$\text{RD} (%) = 100\% \times \frac{\text{model} - \text{ionosonde}}{\text{ionosonde}}$$

The performance of the SAMI2-LSTM is then compared with those of the original SAMI2 model and the widely used empirical model IRI-2016 (Bilitza et al., 2017). All the models calculate the prediction

Figure 4. The ionospheric parameters predicted from LSTM algorithm designed by Moon et al. (2020) during two test periods. The dotted black (red) symbols mean the observed (predicted) one of Jeju ionosonde (LSTM). The bottom figures in (a) and (b) represent geomagnetic and solar activity indices.
values at 15-min intervals during each test period. The SAMI2-LSTM model proposed by us uses an updated ionospheric driver. In contrast, the IRI-2016 model used the FORTRAN version provided on the web (irimodel.org/IRI-2016/), which does not update any ionospheric drivers. Thus, it may be an unfair comparison evaluation. However, the IRI-2016 model is an empirical model using global observation data, so we think it has a data assimilation effect. Also, since ionosonde data in the middle-low latitudes were used a lot, we believe it is similar to the purpose of using Jeju ionosonde in this study. Above all, since it is an international reference ionosphere model designated by COSPAR, which is widely used in ionosphere forecasting and surveillance in the globe, so it was utilized as a reference for comparison in this study.

4.1. Geomagnetically Quiet Case

First, we evaluate the performance of each model for 2 weeks from 18 October 2018 (doy = 291) to 31 October (doy = 304) when the geomagnetic activity was quiet. As described in section 2.2, since the SAMI2-LSTM model can calculate the ionospheric parameters at different locations on the longitudinal plane, we compare the results not only for Jeju station but also for other locations (Icheon and Okinawa).

Figure 5 shows the observed and model values of $N_mF_2$ and $h_mF_2$ over each location. The black lines present the ionosonde observations, and the red (orange) lines indicate the SAMI2-LSTM (SAMI2 original) model results. In addition, the green lines mean the IRI-2016 model ones.
lines are the observed values from each ionosonde, and the solid red lines are those computed from the SAMI2-LSTM model that we developed in this study. In addition, we indicate the original SAMI2 model with solid orange lines and the IRI-2016 model with green. There are some measured data gaps, which are not included in the analysis because the reliability of the observations is low or not observed.

Looking closely at the values of $N_mF^2$ in Figures 5a, 5c, and 5e, the SAMI2-LSTM model (red line) calculates the closest to the measured values (black line). However, the original SAMI2 and IRI-2016 models overestimate the $F_2$ peak electron density during the daytime. The comparisons of $h_mF^2$ also show that the SAMI2-LSTM model results are close to the measured values, whereas the SAMI2-ORI and IRI model tends to overestimate.

To quantify the comparisons, we summarize the performance skill scores in Table 2. These results are the average values of all data for 2 weeks at each location. When interpreting this table, we should not make the mistake of evaluating only one score. For example, the correlation coefficient value represents only the correlating tendency of the model results toward the measured values, so the real difference between the model and measurement cannot be well evaluated by it. In the case of MAPE, the absolute values of each data are taken and averaged, so it is difficult to confirm in which direction the values are biased. Therefore, when interpreting this table, all performance scores should be considered together.

In Table 2, the SAMI2-LSTM model shows the best results among the models in all scores for $N_mF^2$ and $h_mF^2$ at the Jeju station. In addition, for comparison with previous studies related to $foF_2$, the $foF_2$ RMSE value of Jeju location was obtained as 0.57 MHz through the conversion relationship between $N_mF^2$ and $foF_2$. McKinnell and Poole (2000) developed a NN model by training it with the observed $foF_2$ data over 24 years in Grahamstown (26.5°E, 33.3°S), South Africa. Their model had the $foF_2$ RMSE of 0.733 MHz when performing a 25-hr prediction. In addition, Athieno et al. (2017) developed an NN model by training it using the $foF_2$ data observed in Resolute (74.7°N, 265.1°E), located at high latitudes in the Northern Hemisphere, for about 20 years from 1975 to 1995. In their study, the RMSE values of the NN model from 2009 to 2013 were distributed from about 0.3 to 1.0 MHz. Fan et al. (2019) conducted a comparison study between Elman neural network (ENN), improved particle swarm optimization (IPSO)-ENN, and backpropagation neural network (BPNN) by training with the $foF_2$ data observed from the Wuhan ionosonde during 2008 to 2016. The RMSE values for $foF_2$ of each model (IPSO-ENN, ENN, and BPNN) were 0.75, 0.81, and 0.85 MHz, respectively. Although it is difficult to make a direct comparison because the training and test data sets have different locations and periods, our model results show better performance than the RMSE values of $foF_2$ obtained using previously performed ANN (Athieno et al., 2017; Fan et al., 2019; McKinnell & Poole, 2000). To reliably compare the performance of various NN models, it is necessary to pursue further study using the same location and period data.

Next, we compare the results of Icheon and Okinawa based on the use of the ionospheric drivers estimated from Jeju data. At these two locations, the IRI model yields better results for the correlation coefficient, while the SAMI2-LSTM model received the best ratings for the rest of the scores. The performance shown in
Figure 5 and Table 2 indicates that the long-term predictions of $NmF_2$ and $hmF_2$ at other locations on nearly the same meridional plane as the reference location can be simulated by the SAMI2-LSTM model with relatively high accuracy. The scores of Icheon, which is located slightly further north, are better than those of Jeju, while the scores of Okinawa, which is located at a lower latitude, are the lowest. We speculate that this result is due to the following causes. First, since the background electron density increases as the altitude gradually decreases, the RMSE value may increase as the latitude decreases. Second, Okinawa’s geomagnetic latitude is $16.54^\circ$, close to the 10–15° region where the equatorial ionospheric anomaly peak exists. Therefore, the ionospheric parameters at the Okinawa station include the ionospheric variation associated with the equatorial anomaly, which cannot be seen in the midlatitude ionosphere during the quiet periods. Also, because there are more effects by the electric field as well as the neutral wind and density components at low latitudes, the RMSE values can be calculated higher. Consequently, the results of modeling the low-latitude ionosphere are less reliable.

We further calculate RD to examine the bias in model vs measurement differences that are difficult to identify in MAPE. As can be seen shown with the red bar plot in Figure 6, the SAMI2-LSTM model follows nearly the normal distributions of both $NmF_2$ and $hmF_2$ well centered on 0, implying little or no bias. However, the RD distributions of the IRI-2016 and SAMI2 original models are neither normal nor centered on 0 for both $NmF_2$ and $hmF_2$. Especially, all these model overestimate significantly $hmF_2$ for all three locations. The SAMI2-LSTM model corrected the $hmF_2$ bias fairly well by updating the effective meridional wind derived from the observations in the assimilation process. Because we obtained better $hmF_2$ prediction not only at one location but also at another, we think our method for the assimilation is sufficiently applicable to compensate for the ignorance of neutral wind and electric field that are need in the physics model.

In the case of $NmF_2$, the SAMI2 original model tends to overestimate slightly at all three locations, whereas the IRI1 model shows different patterns depending on the location. The problem of electron density overestimation in the SAMI2 model has been reported in some other research (Kim et al., 2016; Klenzing et al., 2013). This may be due to the overestimation in the neutral atmospheric density of the MSIS model (Emmert et al., 2010; Liu et al., 2017). To quantify the bias between the model and measurement, we calculated the proportion of positive vs negative RDs, as listed in Table 3. The SAMI2-LSTM model shows the least bias proportions for both $NmF_2$ and $hmF_2$ among all the models. Therefore, we verified that the LSTM model could improve the results of the physical model through longer-term predictions, not only for one location where the model had been trained with data but also at other locations. Obviously, it can also be a good criterion if someone develops assimilation devices and applies them to the IRI model. However, these tasks were beyond the scope of this study and could not be done.

4.2. Geomagnetic Storm Case

We evaluated the performance of each model for 3 days from 6 September 2017 (doy = 249) through 8 September 2017 (doy = 251), a geomagnetically disturbed period. Figure 7 shows the results for the geomagnetic storm days in the same format as in Figure 5. The blue arrows, numbers, and the vertical dashed lines indicate the time when solar flare events occurred, respectively.

First, it seems that there was a weak increase in electron density in the observations of Jeju and Icheon, which may be the effect of solar flares. Indeed, because the sixth, seventh, tenth, eleventh, and twelfth solar flares occurred during the daytime, it can be expected that they would have affected the ionosphere changes. However, none of the SAMI2-LSTM, SAMI2 original, and IRI-2016 models simulated the ionospheric responses due to solar flares. Indeed, the SAMI2-LSTM model uses the flared version of the FISM solar radiation model (Chamberlin et al., 2008). Although the effect of solar flares was expected, the SAMI2-LSTM model did not produce visible increase in the $F_2$ layer. We speculate that the moderate $M$ class flares affected very little the $F_2$ layer in the model. Studies of the ionosphere response to solar flares have shown that the ionosphere impact is considerably imperceptible when a flare of class $M$ or lower occurs (Barta et al., 2019). In addition, because its response depends not only on the solar flare class but also on the location of its occurrence (Donnelly, 1971; Donnelly & Puga, 1990). Since the SAMI2 original and the IRI-2016 models do not input flare increases of EUV and X-ray at all, any ionospheric responses to the solar flare are not expected. It may be possible to train an NN model for ionospheric increases due to solar flares once the ionosonde data set and solar flare data set are prepared appropriately. This idea will be probed in the future.
Figure 6. (a–f) The number of relative difference (RD) for the ionospheric F2 layer parameters at each location during the quiet geomagnetic period over three locations. (The red, orange, and green bar plots mean the SAMI2-LSTM, SAMI2 original, and IRI-2016 model results.)
In regard to geomagnetic storms, NmF2 and hmF2 observed in Jeju and Icheon show a significant increase during the main phase of the second storm, which may be called a positive ionospheric storm. The SAMI2-Original model seems to simulate NmF2 increases on all 3 days, whereas the observed values increased only during the first and second storm periods. In addition, the timing of peak increases does not match with the observation. Before the first storm, the SAMI2-LSTM model predicted closely the observed NmF2s, which is similar to the quiet case. However, during the first and second geomagnetic storm periods, the performance of the SAMI2-LSTM model does not predict positive geomagnetic storms well.

Table 4 summarizes the performance skill scores for the geomagnetically disturbed period. The performance analysis for Okinawa was

Table 3
The Proportion of Positive and Negative Relative Differences (RD) (SAMI2-LSTM Model Values Are Shown in Bold)

|            | SAMI2-LSTM | SAMI2-ORI | IRI-2016 |
|------------|------------|-----------|----------|
|            | NmF2 | hmF2 | NmF2 | hmF2 | NmF2 | hmF2 |
| Jeju       |      |      |      |      |      |      |
| RD > 0     | 40.6 | 55.8 | 74.2 | 69.8 | 49.4 | 69.9 |
| RD < 0     | 59.4 | 44.2 | 25.8 | 30.2 | 50.6 | 30.1 |
| Icheon     |      |      |      |      |      |      |
| RD > 0     | 35.9 | 82.1 | 70.9 | 84.9 | 53.0 | 91.7 |
| RD < 0     | 64.1 | 17.9 | 29.1 | 15.1 | 47.0 | 8.3  |
| Okinawa    |      |      |      |      |      |      |
| RD > 0     | 61.7 | 66.6 | 69.4 | 81.8 | 71.2 | 83.9 |
| RD < 0     | 38.3 | 33.4 | 30.6 | 18.2 | 28.8 | 16.1 |

Figure 7. The model and observed F2 parameters during a geomagnetically disturbed period. Each line color means the same in Figure 5. In addition, the red arrows, numbers, and the vertical dashed lines indicate the solar flare events.
excluded due to insufficient data. For \( NmF2 \) prediction averaged scores, the IRI-2016 model and SAMI2-LSTM show the best and second-best performance at both locations, whereas for \( hmF2 \) the SAMI2-LSTM performs better than the IRI-2016. Although the SAMI2 original model calculated \( NmF2 \) to a similar level for a positive ionospheric storm, the mismatched timing led to the low-performance scores. Also, the IRI-2016 model could not predict this storm at all. For the SAMI2-LSTM model for the geomagnetic storm periods, compared to the quiet periods, the averaged RMSE of \( NmF2 \) values was calculated to be 2.76 times higher in Jeju and 3.2 times higher in Icheon. Moreover, it has not caught any drastic changes in \( NmF2 \)

Table 4

|                | SAMI2-LSTM | SAMI2-ORI | IRI-2016 | SAMI2-LSTM | SAMI2-ORI | IRI-2016 |
|----------------|------------|-----------|----------|------------|-----------|----------|
| \( NmF2 (foF2) \) |            |           |          |            |           |          |
| Jeju           |            |           |          |            |           |          |
| Correlation coefficient | 0.72 | 0.67 | 0.74 | 0.67 | 0.38 | 0.69 |
| RMSE           | 1.88 (1.07) | 2.48 (1.32) | 1.97 (1.10) | 28.77 | 41.16 | 27.69 |
| MAPE (%)       | 26.47 | 36.05 | 23.44 | 7.58 | 12.53 | 7.18 |
| Icheon         |            |           |          |            |           |          |
| Correlation coefficient | 0.64 | 0.58 | 0.69 | 0.76 | 0.65 | 0.76 |
| RMSE           | 1.76 (1.06) | 2.22 (1.24) | 1.81 (1.07) | 27.86 | 37.19 | 27.02 |
| MAPE (%)       | 26.04 | 33.77 | 23.10 | 8.71 | 12.02 | 7.95 |

Note. \( NmF2 (foF2) \) unit = \#/cm\(^3\)×10\(^5\) (MHz); \( hmF2 \) unit = km.

Figure 8. Same as Figure 6, but during the storm period except for Okinawa location.
and $hmF_2$ on Day 251. Therefore, despite better performance scores of the IRI-2016 and SAMI2-LSTM models, in consideration of no storm-related ionospheric increase in these models, we conclude that they, too, failed ionospheric prediction during the geomagnetically disturbed periods.

Our analysis identified two reasons for the poor performance to predict geomagnetic storm-related ionospheric changes using the LSTM model. First, we trained the model using only a 5-year-long data set from the ionosonde in Jeju, which includes only 57 cases of geomagnetic storms. In other words, the model was trained mostly under the geomagnetically quiet condition, resulting in reasonable performance for quiet days but not for stormy days. For better performance during geomagnetic storms, it is necessary to collect and include much more ionospheric data for the storm case in the training of the LSTM model. The second reason is from the fact that we trained the LSTM model with a simple geomagnetic index input of $Kp$. Wintoft and Cander (2000) suggested that in the prediction study of $foF_2$ using NN models during the storm events, the model should be designed to extend the $AL$ or $AU$ index rather than the simple $AE$ index. In addition, Nakamura et al. (2009) discussed that the $Dst$ and the local $K$ index should be included in order to predict the storm case well. Thus, there is a need to create a new LSTM model with inputs of appropriate geomagnetic indices. We plan to develop and apply a new deep-learning model for storms in the near future to overcome these problems.

In Figure 8, we plot the histogram that shows the $NmF_2$ and $hmF_2$ differences between predicted and observed values at Jeju and Icheon stations, similar to Figure 6. The analysis for Okinawa station was difficult to interpret due to a lack of data. The SAMI2-LSTM and IRI-2016 models tend to underestimate the $NmF_2$, but the SAMI2 original model shows overestimation. In the case of $hmF_2$, the SAMI2-LSTM and IRI-2016 models follow a fairly normal distribution, while the other two models have a broad error range.

### 5. Summary and Conclusion

In this study, we utilized a deep-learning algorithm, LSTM, in an attempt to address the limitation in the short-term prediction of the assimilated SAMI2 model proposed by Kim et al. (2019). The LSTM algorithm is useful for time series data analysis to make forecast values reflecting the past data. We trained the LSTM model with a 5-year-long data set of the ionospheric $F_2$ layer parameters observed from the Jeju ionosonde and the observed space environment indices. Utilizing the predicted values of the $F_2$ parameters ($NmF_2$ and $hmF_2$) from the trained LSTM model, we estimated the ionospheric drivers (effective meridional winds and electron density scale factor), which were then input to the SAMI2 model as the assimilation procedure. The assimilated SAMI2-LSTM model calculates the prediction values of the ionosphere on the meridional plane crossing Jeju station for the 24-hr period. We evaluate the performance of the SAMI2-LSTM model for both geomagnetically quiet (2 weeks) and disturbed (3 days) periods by comparing the predicted $NmF_2$ and $hmF_2$ with observed values at Jeju, Icheon, and Okinawa stations that are nearly the same longitude.

The principal findings of this study are as follows:

1. On quiet geomagnetic days, the SAMI2-LSTM model showed a level of accuracy that was approximately 45% and 45% higher than the SAMI2 original model and IRI-2016 model, respectively, based on the RMSE values of $NmF_2$ at the Jeju station. The model also improves the accuracy by 49% and 34% (37% and 38%) from those of the SAMI2 original model and IRI-2016 model, respectively, at the Icheon (Okinawa) station.
2. On quiet geomagnetic days, the SAMI2-LSTM model shows the RMSE improvements of $hmF_2$ over Jeju, Icheon, and Okinawa by about 30%, 37%, and 30%, respectively, from the SAMI2 original model, and by about 11%, 28%, and 5%, respectively, from the IRI-2016 model.
3. The RDs in $NmF_2$ and $hmF_2$ between the SAMI2-LSTM model and observation are significantly closer to the normal distribution centered at 0, compared to other models, indicating little bias in the predicted values.
4. Although the SAMI2-LSTM model shows better RMSE performance in $NmF_2$ and $hmF_2$ prediction than other comparing models for the geomagnetically disturbed period, the model fails to predict positive ionospheric effects from either geomagnetic storms or solar flares.

The above-mentioned improvement stems from the fact that the SAMI2-LSTM model utilizes ionospheric drivers computed from the LSTM model that were trained by an observed data set at one location. In
conclusion, we have demonstrated that the combination of an NN model with a physics-based model can improve ionospheric predictions of existing theoretical and empirical models for the midlatitude region, at least under the geomagnetically quiet condition. Thus, this method of combining a deep-learning model with a physics-based model opens the opportunity to addressing the respective weaknesses of an empirical model and a theoretical model in the ionosphere forecasting.

Data Availability Statement

The Jeju and Icheon ionosonde data were obtained from the Korean Space Weather Center homepage (https://spaceweather.rra.go.kr/observation/service/iono). The Okinawa data were provided from the webpage of the National Institute of Information and Communications (NICT) in Japan (http://wdc.nict.go.jp/IONO/HP2009/ISDJ/index-E.html). The solar and geomagnetic indices data can be downloaded from the OMNI online system (https://omniweb.gsfc.nasa.gov/ow.html). The GOES X-ray data can be accessed through NOAA NGDC (https://satdat.ngdc.noaa.gov/sem/goes/data/full/). The FISM data sets were obtained from the LASP Interactive Solar Irradiance Datacenter website (http://lasp.colorado.edu/lisird/data/fism_flare_hr/). The LSTM simulation results were provided by the SSLab team (Su-In Moon, Se-Heon Jeong, and YongHa Kim) at Chungnam National University. The open source SAMI2 model was provided by NRL (https://www.nrl.navy.mil/pdp/branches/6790/sami2). Also, the IRI-2016 FORTRAN code can be downloaded from the webpage (irimodel.org/IRI-2016/). Our analyzed data in this paper are available from github site (https://github.com/Jeongheon-Kim/2020SW_assimilation_SAMI2).

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References

Aa, E., Liu, S., Huang, W., Shi, L., Gong, J., Chen, Y., et al. (2016). Regional 3-D ionospheric electron density specification on the basis of data assimilation of ground-based GNSS and radio occultation data. Space Weather, 14, 433–448. https://doi.org/10.1002/2015SW001363
Athieno, R., Jayachandran, P. T., & Themens, D. R. (2017). A neural network-based foF2 model for a single station in the polar cap. Radio Science, 52, 784–796. https://doi.org/10.1002/2016RS006192
Barta, V., Sátori, G., Alexandra Berényi, K., Kis, Á., & Williams, E. (2019). Effects of solar flares on the ionosphere as shown by the dynamics of ionograms recorded in Europe and South Africa. Annales Geophysicae, 37(4), 747–761. https://doi.org/10.5194/angeo-37-747-2019
Bengio, Y., Simard, P., & Frasconi, P. (1994). Learning long-term dependencies with gradient descent is difficult. IEEE Transactions on Neural Networks, 5(2), 157–166. https://doi.org/10.1109/72.279181
Bluitz, D., Altaidll, D., Trublik, V., Shubin, V., Galkin, I., Reinsich, B., & Huang, X. (2017). International reference ionosphere 2016: From ionospheric climate to real-time weather predictions. Space Weather, 15, 418–429. https://doi.org/10.1002/2016SW001593
Bust, G. S., Coker, C., Coco, D. S., Gaussian, T. L., & Lauderdale, T. (2001). IRI data ingestion and ionospheric tomography. Advances in Space Research, 27(1), 157–165. https://doi.org/10.1016/S0273-1177(00)00163-0
Bust, G. S., Crowley, G., Garner, T. W., Gaussian, T. L., Meggs, R. W., Mitchell, C. N., et al. (2007). Four-dimensional GPS imaging of space weather storms. Space Weather, 5, S02003. https://doi.org/10.1029/2006SW000237
Bust, G. S., Garner, T. W., & Gaussian, T. L. (2004). Ionospheric Data Assimilation Three-Dimensional (IDA3D): A global, multisensor, electron density specification algorithm. Journal of Geophysical Research, 109, L1105. https://doi.org/10.1029/2003JA010234
Chamberlin, P. C., Woods, T. N., & Epavril, F. G. (2008). Flare Irradiance Spectral Model (fism): Flare component algorithms and results. Space Weather, 6, S05001. https://doi.org/10.1029/2007SW000372
Chapman, J. H., & Warren, E. S. (1968). Topside sounding of the Earth’s ionosphere. Space Science Reviews, 8(5–6), 846–865. https://doi.org/10.1007/BF01751119
Charteris, A. T., Matsuo, T., Anderson, J. L., Collins, N., Hoar, T. J., Lu, G., et al. (2016). Ionospheric data assimilation and forecasting during storms. Journal of Geophysical Research: Space Physics, 121, 764–778. https://doi.org/10.1002/2014JA020799
Dandenaat, P. B. (2018). MENTAT: A new wind model for Earth’s thermosphere. Journal of Geophysical Research: Space Physics, 123, 7124–7147. https://doi.org/10.1002/2018JA025551
Donnelly, R. F. (1971). Extreme ultraviolet flashes of solar flares observed via sudden frequency deviations: Experimental results. Solar Physics, 20(1), 188–203. https://doi.org/10.1007/BF00146110
Donnelly, R. F., & Fuga, L. C. (1990). Thirteen-day periodicity and the center-to-limb dependence of UV, EUV, and X-ray emission of solar activity. Solar Physics, 130(1–2), 369–390. https://doi.org/10.1007/BF00156000
Drob, D. P., Emmert, J. T., Meriwether, J. W., Makela, J. J., Doornbos, E., Conde, M., et al. (2015). An update to the Horizontal Wind Model (HWM): The quiet time thermosphere. Earth and Space Science, 2, 301–319. https://doi.org/10.1002/2014EA000089
Elman, J. L. (1990). Finding structure in time. Cognitive Science, 14(2), 179–211. https://doi.org/10.1016/0364-0213(90)90002-E
Emmert, J. T., Lean, J. L., & Picone, J. M. (2010). Record-low thermospheric density during the 2008 solar minimum. Geophysical Research Letters, 37, L12102. https://doi.org/10.1029/2010GL043671
Fan, J., Liu, C., Lv, Y., Han, J., & Wang, J. (2019). A short-term forecast model of foF2 based on Elman neural network. Applied Sciences (Switzerland), 9(14). https://doi.org/10.3390/app9142782
Galkin, I. A., Khmyrov, G. M., Kozlov, A., Reinsich, B. W., Huang, X., & Kitrosser, D. F. (2006). Ionosonde networking, databasing, and Web serving. Radio Science, 41, RS5S33. https://doi.org/10.1029/2005RS003384
Gordon, W. E. (1958). Incoherent scattering of radio waves by free electrons with applications to space exploration by radar. Proceedings of the IRE, 46(11), 1824–1829. https://doi.org/10.1109/JRPROC.1958.566852
Habululuma, J. B., McKinnell, L. A., & Cilliers, P. J. (2007). Prediction of global positioning system total electron content using neural networks over South Africa. Journal of Atmospheric and Solar-Terrestrial Physics, 69(15), 1842–1850. https://doi.org/10.1016/j.jastp.2007.09.002
Habarulema, J. B., McKinnell, L. A., & Opperman, L. (2009). A recurrent neural network approach to quantitatively studying solar wind effects on TEC derived from GPS: Preliminary results. Annales Geophysicae, 27(5), 211–2125. https://doi.org/10.5194/angeo-27-2111-2009

Haji, G. A., Ibanez-Meier, R., Kurinski, E. R., & Romans, L. J. (1994). Imaging the ionosphere with the Global Positioning System. *International Journal of Imaging Systems and Technology, 5*(2), 174–187. https://doi.org/10.1002/ima.500050214

Hardy, K. R., Haji, G. A., & Kurinski, E. R. (1994). Accuracies of atmospheric profiles obtained from GPS occultations. *International Journal of Satellite Communications, 12*(5), 463–473. https://doi.org/10.1002/sat.4600120508

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Hu, A., & Zhang, K. (2018). Using bidirectional long short-term memory method for the height of F2 peak forecasting from ionosonde measurements in the Australian Region. *Remote Sensing, 10*(10). https://doi.org/10.3390/RSS10101658

Huba, J. D., Joyce, G., & Federer, J. A. (2000). Sami2 is Another Model of the Ionosphere (SAMI2): A new low-latitude ionosphere model. *Journal of Geophysical Research, 105*A10, 23,035–23,053. https://doi.org/10.1029/2000JA000035

Kim, J. H., Kim, Y. H., & Oh, S. J. (2016). Development of a data-verified ionospheric model with an ionosonde network. *Journal of the Korean Physical Society, 68*(11), 1359–1370. https://doi.org/10.3938/jkps.68.1359

Kim, J. H., Kim, Y. H., Sessanga, N., Jeong, S. H., Moon, S. I., Kwak, Y. S., & Yun, J. Y. (2019). Regional ionosphere speciﬁc storm forecasting using neural networks. *Journal of Geophysical Research, 117*, A10318. https://doi.org/10.1029/2019JA021770

Lin, C. Y., Matsuo, T., Liu, Y. J., Wang, W., Lin, C. H., & Araujo-Pradere, E. A. (2015). Ionospheric assimilation of radio occultation and ground-based GPS data using non-stationary background model error covariance. *Atmospheric Measurement Techniques, 8*(1), 171–182. https://doi.org/10.5194/amt-8-171-2015

Liu, H., Thayer, J., Zhang, Y., & Lee, W. K. (2017). The non-storm time corrupted upper thermosphere: What is beyond MSIS? *Space Weather, 15*, 746–760. https://doi.org/10.1002/2017SW001618

Maruyama, T. (2002). Retrieval of in situ electron density in the topside ionosphere from cosmic radio noise intensity by an artificial neural network. *Radio Science, 37*(5), 1077. https://doi.org/10.1029/2001RS002509

McKinnell, L. A., & Poole, A. W. V. (2000). The development of a neural network based short term foF2 forecast program. Physics and Chemistry of the Earth, Part C: Solar, Terrestrial, and Planetary Science, 25(4), 287–290. https://doi.org/10.1016/S1464-1917(00)00031-0

Moon, S. I., Kim, Y. H., Kim, J. H., Kwak, Y. S., & Yoon, J. Y. (2020). Forecasting ionospheric electron density profiles into a coupled thermosphere/ionosphere model using ensemble Kalman filtering. *Journal of Geophysical Research, 117*, A10318. https://doi.org/10.1029/2019JA021770

Nakamura, M., Maruyama, T., & Shidama, Y. (2009). Using a neural network to make operational forecasts of ionospheric variations and storms at Kokubunji, Japan. *Journal of the National Institute of Information and Communications Technology, 50*(1–4), 391–406. https://doi.org/10.1186/BF03352071

Pi, X., Wang, C., Haji, G. A., Rosen, G., Wilson, B. D., & Bailey, G. J. (2003). Estimation of E × B drift using a global assimilative ionospheric model: An observation system simulation experiment. *Journal of Geophysical Research, 108*A2, 1075. https://doi.org/10.1029/2002JA009235

Picone, J. M., Hedin, A. E., Drob, D. P., & Aikin, A. C. (2002). NRLMSISE-00 empirical model of the atmosphere: Statistical comparisons and scientific issues. *Journal of Geophysical Research, 107*(A12), 1468. https://doi.org/10.1029/2002JA009430

Poole, A. W. V., & Poole, M. (2002). Long-term trends in foF2 over Grahamstown using Neural Networks. *Annals of Geophysics, 45*(1), 155–162. https://doi.org/10.4401/ag-3485

Richards, P. G. (1991). An improved algorithm for determining neutral winds from the height of the F2 peak electron density. *Journal of Geophysical Research, 96*(A10), 17,839. https://doi.org/10.1029/91JA01467

Scherliess, L., & Fejer, B. G. (1999). Radar and satellite global equatorial F region vertical drift model. *Journal of Geophysical Research, 104*(A4), 6828–6842. https://doi.org/10.1029/1999JA000025

Scherliess, L., Schunk, R. W., Solja, J. J., & Thompson, D. C. (2004). Development of a physics-based reduced state Kalman filter for the ionosphere. *Radio Science, 39*, RS1S04. https://doi.org/10.1029/2002RS002797

Srivani, I., Siva Yara Prasad, G., & Venkata Ratnam, D. (2019). A deep learning-based approach to forecast ionospheric delays for GPS signals. *IEEE Geoscience and Remote Sensing Letters, 16*(8), 1180–1184. https://doi.org/10.1109/LGRS.2019.2895112

Sessanga, N., Kim, Y. H., Habarulema, J. B., & Kwak, Y. S. (2019). On Imaging South African Regional Ionosphere using 4D-Var Technique. *Space Weather, 17*, 1584–1604. https://doi.org/10.1029/2019SW003231

Sun, W., Xu, L., Huang, X., Zhang, W., Yuan, T., Chen, Z., & Yan, Y. (2017). Forecasting of ionospheric vertical total electron content (TEC) using LSTM networks. Proceedings of 2017 International Conference on Machine Learning and Cybernetics, ICMLC 2017, 2, 340–344. https://doi.org/10.1109/ICMLC.2017.8108945

Talaulay, J., Senalp, E. T., Radiélla, S. M., & Tulunay, Y. (2006). Forecasting total electron content maps by neural network technique. *Radio Science, 41*, RS4016. https://doi.org/10.1029/2005RS003285

Wang, C., Haji, G., Pi, X., Rosen, L. G., & Wilson, B. (2004). Development of the global assimilative ionospheric model. *Radio Science, 39*, RS1S06. https://doi.org/10.1029/2002RS002854

Williscroft, L. A., & Poole, A. W. V. (1996). Neural networks, foF2, unspot number and magnetic activity. *Geophysical Research Letters, 23*(24), 3659–3662. https://doi.org/10.1029/96GL03472

Winstone, P., & Cander, L. R. (2000). Ionospheric foF2 storm forecasting using neural networks. *Physics and Chemistry of the Earth, Part C: Solar, Terrestrial, and Planetary Science, 25*(4), 267–273. https://doi.org/10.1016/S1464-1917(00)00015-5

Yue, X., Schreiner, W. S., Kuo, Y. H., Hunt, D. C., Wang, W., Solomon, S. C., et al. (2012). Global 3-D ionospheric electron density reanalysis based on multisource data assimilation. *Journal of Geophysical Research, 117*, A09325. https://doi.org/10.1029/2012JA017968

Yue, X., Schreiner, W. S., Lin, Y. C., Rocken, C., Kuo, Y. H., & Zhao, B. (2011). Data assimilation retrieval of electron density profiles from radio occultation measurements. *Journal of Geophysical Research, 116*, A03317. https://doi.org/10.1029/2010JA015980

Zhukov, A., Sidorov, D. N., Mylnikova, A., & Vasyukovich, Y. (2013). Machine learning methodology for ionosphere total electron content nowcasting. *International Journal of Artificial Intelligence, 16*(1), 144–157. https://doi.org/10.13140/RG.2.1.9349.83685