Summary of Changes

The authors would like to thank all the reviewers for their constructive comments. We provide below a detailed account on the changes that we have made in response to the comments that the editor and the reviewers have raised. For comments from different reviewers, we have marked the corresponding changes in the revised version in *red, green* and *purple* color respectively.

Response to Anonymous Referee #1:

The reviewed manuscript contains some interesting statistical findings based on advanced machine learning methods.

1. My main concern is that the mathematical correlations between the position and size of the auroral oval and some physical variable describing the near-Earth space environment are not interpreted in physical terms. It's been known for a long time that the aurorally oval represents the open/closed field boundary of the Earth's magnetosphere which is responsive to the solar wind driver and reflects the dynamics of the Dungey substorm cycle. A careful discussion of these physical processes in the context of the reported machine learning results is required before this manuscript can be considered for publication.

Author's reply:

The main purpose of this paper is to explore the possible relationship between physical parameters and auroral events in a new way. In our previous work, some useful machine learning methods, such as deep learning and generalized regression neural network (GRNN) are used to model the relationship between the IMF and solar wind indexes and the auroral oval boundaries[1]. But we have no certain fact that whether the physical variables except IMF and solar wind indexes can affect auroral oval boundary. Therefore, we want to obtain some unknown conclusions between more physical variables and auroral oval boundary by using our method in this paper. So, this paper is devoted to designing a new method rather than exploring the specific physical explanations between physical parameters and auroral oval boundary. The more exact physical connections for specific aurora events will be analyzed in future works.

[1] HanB, LianHF, HuZJ. Modeling of ultraviolet auroral oval boundaries based on neural network technology (inChinese). SciSinTech, 2019, 49:531–542, doi: 10.1360/N092018-00227.

2. What do the machine learning correlations show? Do they support or challenge the existing substorm models? Do the enable a more accurate prediction of substorm magnitude and timing?

Author's reply:

In the manuscript, we design a new nonlinear and trainable mapping model to construct the relationship between auroral oval boundary and complex space physical parameters (including 18 parameters) to discuss the influence of every single space physical parameter on auroral oval boundary sufficiently. The experiment results in our paper show that some space physical parameters play a crucial role to locate the auroral oval position, which is consistent with the conclusion available in most of references. In the other hand, some interesting results have been obtained during the experiment. These conclusions maybe discuss with space physics in the future.

In the task of predicting the substorm magnitude and timing, we cannot give an exact conclusion now. Our proposed method can model the relationship between different types of data, such as space physical data and auroral oval images. So, we think the proposed model in this manuscript can predict the substorm magnitude and timing after adjusting the model parameters according to the occurrence conditions and the data forms of substorm. We can give some researches on this problem in the future work. As a summary, our proposed model in this paper give the new way to analysis the relationship between many space physical parameters (such as: PC and SYM/H) which not mentioned in other literature sand auroral oval boundary.

3. To make this analysis more informative it would be important to differentiate between the southward and northward IMF directions associated with drastically different solar wind driving conditions.

Author's reply:

According to the reviewer comments, the additional two experiments are performed under southward and northward IMF directions conditions respectively according to your suggestion. The experiment results are shown in Table 5.

Revision:

Table 5: Pearson correlation coefficient of some space physical parameters from Dec. 1996 to Mar. 1997

Parameter name	MAE(poleward/equatorward)
IMF	1.6313/1.4759
Solar wind index	1.6495/1.4877
Geomagnetic index	1.6569/1.5124
AE, AU, AL, PC	1.6734/1.5272
Vp, Np, Pdyn, SYM/H	1.6611/1.4919

→

Table 5: The MAE influenced by different combinations of space physical parameters.

Parameter name	MAE(poleward/equatorward)
IMF	1.6313/1.4759
IMF(Bz>0)	1.6365/1.7595
IMF(Bz<0)	1.7163/1.6193
Solar wind index	1.6495/1.4877
Geomagnetic index	1.6569/1.5124
AE, AU, AL, PC	1.6734/1.5272
Vp, Np, Pdyn, SYM/H	1.6611/1.4919

Whether the northward or southward IMF direction are input to the proposed model, the MAE have marked change in both poleward and equatorward boundaries. Nevertheless, we can observe the more evident increasement of MAE in equatorward boundaries compared with the MAE of poleward boundaries by using northward IMF direction as the input of

our model. Meanwhile, there has an opposite result under southward IMF direction condition. The variation of MAE in poleward boundaries are bigger than equatorward boundaries when the input of our model is southward IMF direction. Therefore, we can know that the northward IMF direction has a great influence on the equatorward boundaries, and the southward IMF direction has a significant effect on poleward boundaries.

4. The presentation style is clear but there are multiply typing errors; I encourage the authors to proofread their manuscript before resubmitting.

Author's reply:

Thanks for your kind suggestion. We already carefully check our manuscript to correct the typing errors. Details are given below.

Revision:

(1) Line 3 in Introduction, 'which can implicit for the coupling process between solar wind, ionosphere and magnetosphere'. → 'which can implicit for the coupling process among solar wind, ionosphere and magnetosphere'.

(2) Line 5 in Introduction, 'So, the segmentation and prediction for auroral oval boundary is very significant for studying on certain physical events'. →'So, the segmentation and prediction for auroral oval boundary are very significant for studying on certain physical events'.

(3) Line 12 in Introduction, 'Variations of the size of polar cap, auroral oval and diffuse aurora are regarded as three independent function variables of AL index (Starkov, 1994(b)).' → 'Variations of the size of polar cap, auroral oval and diffuse aurora were regarded as three independent function variables of AL index respectively (Starkov, 1994(b))'.

(4) Line 15 in Introduction, 'Sigernes com-pared methods which proposed by Zhang and Starkov to calculate the size and position of auroral oval using a Kp-based function.' →'Sigernes used a Kp-based function to calculate the size and position of auroral oval, and compared the Kp-dependent model with methods which proposed by Zhang and Starkov to explain the superiority of his proposed model.'

(5) Line 41 in Introduction, 'Sect. 2 describes our proposed algorithm to predict auroral oval boundary in detail.' →'Sect. 2 describes our proposed algorithm in detail.'

(6) Line 3 in section 2, 'In the training phase, auroral oval images are usually affected by heavy noise and other interference.' →'In the training phase, auroral oval images are usually affected by heavy noise and other interferences.'

(7) Line 15 in section 2, 'The computational processing of RBM and RBF is illustrated by Eq. (1)-(4).' →'The computational processing of RBM and RBF are illustrated by Eq. (1)-(4).'

(8) Line 14 in section 3.1, 'According to the effect from other circumstance factors,' →'According to the effect derived from other circumstance factors,'

(9) Line 22 in section 3.1, 'Table 1 shows 18 space physical parameters we used in this paper.' →'Table 1 shows 18 space physical parameters which we used in this paper.'

(10) Line 7 in section 3.2, 'The corresponding MAE is shown in Fig. 3(a).' →'The corresponding MAE are shown in Fig. 3(a).'

(11) Line 12 in section 3.2, 'The corresponding MAE is shown in Fig. 3(b), and MAE reaches the minimum when the training error of RBF net-work is 4 magnetic latitudes.' →'The corresponding MAE are shown in Fig. 3(b), and MAE reaches the minimum when the training error of RBF network is 4 magnetic latitudes.'

(12) Line 16 in section 3.2, 'To demonstrate the availability of our proposed model, we compare the proposed model with Back Propagation (BP) network (Rumelhart, 1986) and Yang's model (Yang et al., 2016).' →'To demonstrate the availability of our proposed model, we compared the proposed model with Back Propagation (BP) network (Rumelhart, 1986) and Yang's model (Yang et al., 2016).'

(13) Line 17 in section 3.2, 'The subjective prediction results obtained by the three method are shown in Fig. 4, circles and squares stand for poleward boundary points and equatorward boundary points which are obtained from the segmented image, '＋' and '×' marks represent poleward boundary points and equatorward boundary points which are obtained from our prediction model.' →'The subjective prediction results obtained by the three method are shown in Fig. 4, circles and squares stand for poleward boundary points and equatorward boundary points respectively which are obtained from the segmented image, '＋' and '×' marks represent poleward boundary points and equatorward boundary points respectively which are obtained from our prediction model.'

(14) Line 21 in section 3.2, 'it is obviously that our method can obtain the more accurate boundaries than the other two compared methods, where marked by blue rectangle and red rectangle in Figure 4.' →'it is obviously that our method can obtain more accurate boundaries than the other two compared methods, where marked by blue rectangle and red rectangle in Fig. 4.'

(15) Line 6 in section 3.3, 'we sort boundary data with respect to the value of all space physical parameters, and divide evenly boundary data into 10 groups.' → 'we sort boundary data with respect to the value of all space physical parameters, and divide boundary data into 10 groups evenly.'

(16) Line 15 in section 3.3, 'And a correlation analysis experiment is con-structed to study the connection between combination of different space physical parameters and auroral oval boundary.' → 'And a correlation analysis experiment is constructed to study the connection between combination of different space physical parameters and auroral oval boundary.'

(17) Line 16 in section 3.3.1, 'Such as, Karlson's observations suggests that IMF By component is related to prenoon-postnoon asymmetry of poleward activity (Karlson et al., 1996).' → 'Such as, Karlson's observations suggested that IMF By component is related to prenoon-postnoon asymmetry of poleward activity (Karlson et al., 1996).'

(18) Line 11 in section 3.3.4, 'The MAE of boundary position is 1.6076 and 1.4545 respectively when we only use boundary positions at the previous moment to predict poleward and equatorward boundaries. We take this MAE as standard, called S-MAE.' → 'The MAE of boundary position are 1.6076 and 1.4545 respectively when we only use boundary positions at the previous moment to predict poleward and equatorward boundaries. We take this MAE as standard, called S-MAE.'

(19) Line 1 in section 3.3.5, 'For the sake of analyzing the influence of space physical parameters on auroral oval efficiently,' → 'In order to analyse the influence of space physical parameters on auroral oval efficiently,'

(20) Line 7 in section 3.3.5, 'The formula of Pearson correlation coefficient is can presented as Eq. (6),' → 'The formula of

Pearson correlation coefficient can be represented as Eq. (6),'

(21) Line 4 in Conclusion, 'Those method based is not very suitable for the complex and changeable space physical data.' → 'Those methods are not very suitable for the complex and changeable space physical data.'

(22) Line 9 in Conclusion, 'we analyze the effect of all 18 space physical parameters on the location of auroral oval boundary based on several statistical and prediction experiments.' → 'we analyse the effect of all 18 space physical parameters on the location of auroral oval boundary based on several statistical and prediction experiments.'

Response to Reviewer Zanyang Xing:

1. This manuscript designed a new model based on deep learning to construct the relationship between the physical variables and auroral oval boundaries. Did the authors consider some specific aurora forms (such as, substorms, transpolar arcs) when you did the experiments? Is it possible to construct the connection among other forms of data? Such as: the relationship between physical variables and auroral oval intensity in the process of a specific aurora event (for example: substorms, polar cap arc). Please give an expatiation.

Author's reply:

In this paper, the main purpose is only to explore the possible and unknown relationship between physical parameters and auroral oval boundary over a period of time. But it is possible to occur any auroral events during December 1996 to March 1997. We analyzed all phenomenon that we observed in our experiments(Section 3.3.1-3.3.5),more than the relationship between specific aurora event (for example: substorms) and the variations of some specific physical parameters (such as, AE).The advantage of our model is that it can construct the connection among different forms of data. So, we think the proposed model in this manuscript can predict the auroral oval intensity by adjusting the model parameters according to the occurrence conditions and the data forms of substorm or polar cap arc. We can give some researches on this problem the reviewer mentioned in the future work.

2. As we known that the aurora dynamics are influenced by many factors, not only the variation of physical variables. Why the authors chose these 18 space physical parameters? Could you give an explanation? Whether this model can establish a connection between a specific aurora event and multiple forms of data, not only one parameter of data?

Author's reply:

In this paper, we chose 18 space physical parameters from OMNI dataset to train our model. Firstly, the common physical variables include IMF, solar wind parameters and geomagnetic indexes, which were discussed in previous work (Niu et al., 2015; Milan, 2010; Hu et al., 2017; Yang et al., 2016). The remaining physical variables are related to those common physical variables. So, we select these 18 space physical parameters as the research targets in this manuscript.

There are two ways to use multiple forms of data as the input of our model. Firstly, we can unify the different forms of data into a same data space. The other way is that we can extend our model as a new model which can input multi-source data. These two methods both can address the problems of establishing a relationship between multiple forms of data and a specific aurora event.

3. In the Introduction section, the authors described many previous studies. It seems to lack intrinsic and progressive connections among these previous studies. Could you rewrite them and make them more logically?

Author's reply:

In the Introduction section, we revised the part of previous studies according your suggestion. Details are as follow.

Revision:

(1) Page 1, Line 25, In early research, Feldstein proposed that the position of auroral oval boundary is correlated with the Q-

index of magnetic activity on the nightside of earth (Feldstein and Starkov, 1967). Starkov and Holzworth expressed that inner and outer boundaries of auroral oval can change with geomagnetic indexes and IMF (Holzworth and Meng, 1975; Holzworth and Meng, 1984; Starkov, 1994(a)).

(2) Page 1, Line 28, Starkov designed some simple formulas on the location of auroral oval and diffuse aurora. Variations of the size of polar cap, → "The conclusions in this paper are based on mathematical statistics. Therefore, Starkov designed some simple formulas to describe the relationships between the specific physical parameter and different type of aurora. Variations of the size of polar cap,"

(3) Page 2, Line 2, Since then, many scholars had been explored the connections between different physical parameters and auroral oval boundary or other auroral events.

(4) Page 2, Line 11, After 2010, there are more and more new methods to construct connection between the position of auroral oval boundary and auroral oval boundary with the development of machine learning.

4. In section 3.3, please explain why the authors use the boundary data which calculated by 'Quadratic Equation' instead of the original boundary data to discuss the influence of space physical parameters on auroral oval boundary.

Author's reply:

The original boundary data are chaotic because of the uncertain aurora events and complex space environment. It is hard to explore clearly variations of auroral oval boundary associated with space physical parameters. To obtain the variable patterns of auroral oval boundary clearly, we use the boundary data which calculated by 'Quadratic Equation' instead of the original boundary data in this paper.

5. Some figures in this manuscript are not clear enough, and the readers may need high quality figures.

Author's reply:

We use high quality figures instead of original figures in this manuscript according your suggestion. Details are as follow.
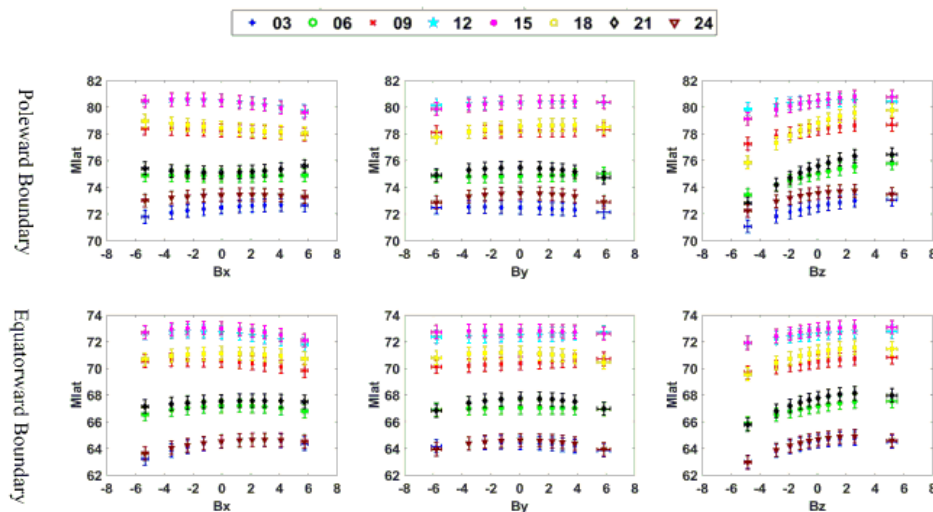
Revision:

Figure 5: Response of magnetic latitude of poleward (left column) and equatorward (right column) boundaries to Bx, By and Bz respectively at 0030,0060,0090,1200,1500,1800,2100 and 2400 MLT.
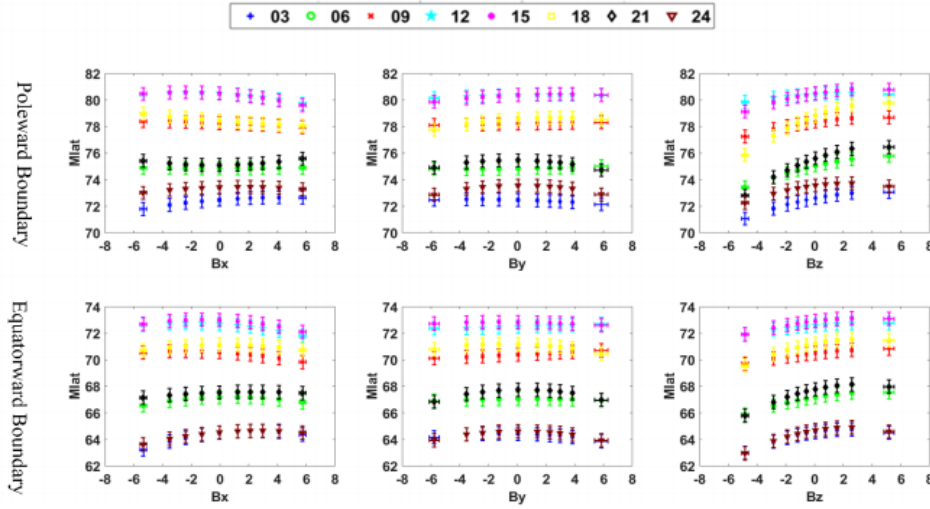
→

Figure 5: Response of magnetic latitude of poleward (top row) and equatorward (bottom row) boundaries to Bx, By and Bz respectively at 0030,0060,0090,1200,1500,1800,2100 and 2400 MLT.

6. When an abbreviation of term first appears in the manuscript, the term should have a full name first. Such as MRSM, MLT-MLAT et al. Please check them.

Author's reply:

We added the abbreviation of term first appears in the manuscript according your suggestion. Details are as follow.

Revision:

(1) In Abstract section, Line 5, "UVI image" → "Ultraviolet Imager (UVI) image";

(2) In Section 2, Line 4, "MRSM" → "Maximal Similarity Based Region Merging (MRSM)";

(3) In Section 2, Line 6, "magnetic local time-magnetic latitude coordinate" → "magnetic local time-magnetic latitude coordinate (MLT-MLAT)".

7. The paper is easy to follow, but there are some writing mistakes or misleading descriptions which make the readers confused. Such as, Page 1, Line 24 "ex-tensive"; Page 2, Line 14 "be-tween"; Line 22, 26. Figure caption of Figure 5-7, should not be "left column", "right column". Please check and revise them. Please proofread this manuscript carefully.

Author's reply:

We revised these writing mistakes and misleading descriptions according your suggestion. Details are as follow.

Revision:

(1) Page 1, Line 24, "In the past few decades, scholars have constructed ex-tensive researches on the relationship between location of auroral oval boundary and space physical parameters (Niu et al., 2015)"; → "In the past few decades, scholars

have constructed extensive researches on the relationship between location of auroral oval boundary and space physical parameters (Niu et al., 2015)";

(2) Page 2, Line 19, "those methods mentioned above just only used one or several space physical parameters to explore the relationship be-tween space physical parameters and auroral oval boundary." → "those methods mentioned above just only used one or several space physical parameters to explore the relationship between space physical parameters and auroral oval boundary."

(3) Page 2, Line 30, "The experiment results show that the model pro-posed in this paper can predict aurora oval boundary accurately by using space physical parameters and the location of auroral oval boundary at the previous moment." → "The experiment results show that the model proposed in this paper can predict aurora oval boundary accurately by using space physical parameters and the location of auroral oval boundary at the previous moment."

(4) Figure caption of Figure 5-7, "left column" → "top row", "right column" → "bottom row".

Response to Reviewer Unnikrishnan Kaleekkal:

In this manuscript, authors have proposed a new automatic auroral oval boundary prediction model, based on deep learning method, using space physical parameters, and the location of auroral oval boundary at the previous moment. The proposed model is well explained with flow chart, and the procedure of training/testing of sufficient data sets supported by interpretation of results.

1. A significant aspect of this model is, several probable parameters that can influence the variation of auroral oval have been fed as the inputs, which is a prerequisite to model complex system. More specifically, 18 space physical parameters and the 48 coordinates value of aurora oval boundary points at the previous moment were utilised for training/ testing, leading to the reasonable prediction of the position of poleward and equatorward boundaries at 24 MLTs. Identification of optimum choice of input parameters is a crucial aspect. In this work, it is shown that, different space physical parameters have different effects on auroral oval boundary, especially interplanetary magnetic field (IMF), geomagnetic indexes and solar wind parameters. Out of the input parameters used for training and testing the present model, authors can check how does the prediction capability of the model vary when inputs with least significance were removed. Or they can add some more probable parameters as inputs and observe the performance of the model. Finally, a combination of input parameters can be selected, based on which model performance is highest. This kind of a procedure will help to identify an optimum choice of input parameters, thereby establishing an input-output relation, and refine the existing model further. The authenticity of the proposed model can be improved further, by this way.

Author's reply:

Thanks for the kind suggestion. We have conducted the experiments to find how will the prediction capability of the proposed model change when the inputs are different combinations of physical variables. And we considered all the possible combinations of physical variables which we mentioned in Table 5 to find an optimum choice of input parameters. However, we cannot give all the experiment results in this manuscript because of the huge numbers of all supplement experiments. The number of experiments which can be calculated by the following equation:

$$C_{11}^2 + C_{11}^3 + C_{11}^4 + C_{11}^5 + C_{11}^6 + C_{11}^7 + C_{11}^8 + C_{11}^9 + C_{11}^{10} + C_{11}^{11} = 2036$$

Therefore, we give the best experiment results (MAE value) obtained from different combinations of physical variables in Table 6. And other results are given in the supplementary materials.

Revision:

1. According to the revision above described, we revised the manuscript further as followings

(1) In section 3.3.5:

Page 15, Line 9, 'Secondly, from Table 5, when Np, Vp, Pydn and SYM/H are sent to our model, the MAE of auroral oval boundary reaches the minimum. They are 1.6611 and 1.4919 respectively, which shows that the combinations of these four parameters have great influence on the location of aurora oval boundary'.

→

"Secondly, when Np, Vp, Pydn and SYM/H are as input to our model, the MAE of auroral oval boundaries are 1.6611 and 1.4919 in poleward and equatorward respectively in Table 5, which is bigger than the MAE of auroral oval boundaries when the inputs are Np, Vp and Pydn. So, we can conclude that the combinations of these four parameters strengthen mutual influence on the location of aurora oval boundary. According to the statistics from Table 6, the physical variables that appears most frequently are Bx, By, Vp and SYM/H. When the inputs of our model are the combination of these four variables or the combination of Bx and By, the MAE of auroral oval boundary reaches the minimum, which proves that these four parameters have great influence on the location of aurora oval boundary."

Page 15, Line 9, 'As a summary, it can be seen that these space physical parameters shown in Table 5 play a crucial role in determining the location of auroral oval boundary based on the above conclusions'.

→

"As a summary, it can be seen that these space physical parameters, which include Bx, By, Vp and SYM/H, play a crucial role in determining the location of auroral oval boundary based on the above conclusions."

(2) In Conclusion:

Page 16, Line 3, 'Some space physical parameters have a great influence on the position of auroral oval boundary, especially the space physical parameters which are shown in Table 5'.

→

"Some space physical parameters, Bx, By, Vp and SYM/H, have a great influence on the position of auroral oval boundary."

Table 6: The MAE influenced by different combinations of space physical parameters.

Parameters name	MAE (poleward/equatorward)
Bx, By	1.6145/1.5003
Bx, Vp, SYM/H	1.6359/1.5129
Bx, By, Vp, SYM/H	1.6118/1.5056
Bx, By, Vp, Pdyn, PC	1.6242/1.5084
Bx, By, Np, AU, SYM/H	1.6154/1.5181
Bx, By, Vp, Np, SYM/H, PC	1.6324/1.5017
Bz, Vp, Pydn, AE, AU, AL, SYM/H	1.6282/1.5125
Bx, By, Bz, Vp, Np, Pdyn, AE, AU	1.6149/1.5044
Bx, By, Bz, Vp, Np, Pdyn, AE, AU, PC	1.6994/1.5028
Bx, By, Bz, Vp, Np, Pdyn, AL, AU, SYM/H, PC	1.6771/1.5716
Bx, By, Bz, Vp, Np, Pdyn, AE, AL, AU, SYM/H, PC	1.6669/1.5743

Prediction and variation of auroral oval boundary based on deep learning model and space physical parameters

Yiyuan Han [1], Bing Han[1], Zejun Hu[2], Xinbo Gao[1], Lixia Zhang[1], Huigen Yang[2], Bin Li[2]

5   [1]School of Electronic Engineering, Xidian University, Xi'an 710071, China
[2]SOA Key Laboratory for Polar Science, Polar Research Institute of China, Shanghai 200136, China

Correspondence to: Bing Han (bhan@xidian.edu.cn)

Abstract. The auroral oval boundary represents important physical process with implications for the ionosphere and magnetosphere. An automatic auroral oval boundary prediction method based on deep learning in this paper is applied to study

10   the variation of auroral oval boundary, associated with different space physical parameters. We construct an auroral oval boundary dataset to train our proposed model, which consists of 184416 auroral oval boundary points extracted from 3842 Ultraviolet Imager (UVI) image captured by Ultraviolet Imager of the Polar satellite and its corresponding 18 space physical parameters selected from OMNI dataset during December 1996 to March 1997. Furthermore, several statistical experiments and correlation analysis experiment are performed based on our dataset to explore the relationship between space physical

15   parameters and the location of auroral oval boundary. The experiment results show that the prediction model based on deep learning method can estimate auroral oval boundary efficiently, and different space physical parameters have different effects on auroral oval boundary, especially interplanetary magnetic field (IMF), geomagnetic indexes and solar wind parameters.

1 Introduction

Auroral oval is a circular belt of auroral emission around magnetic poles (Loomis, 1890; Akasofu, 1964). The auroral oval
20   poleward and equatorward boundaries are related to geophysical parameters, which can implicit for the coupling process among the solar wind, ionosphere and magnetosphere. For example, the polar cap ionosphere, which is considered as an area of opening magnetic field inside auroral oval poleward boundary. This area is closed related with energetic particle entrance from heliosphere to earth's atmosphere. So, the segmentation and prediction for auroral oval boundary are very significant for studying on certain physical events.

25   In the past few decades, scholars have constructed extensive researches on the relationship between location of auroral oval boundary and space physical parameters (Niu et al., 2015). In early research, Feldstein proposed that the position of auroral oval boundary is correlated with the Q-index of magnetic activity on the nightside of earth (Feldstein and Starkov, 1967). Starkov and Holzworth expressed that inner and outer boundaries of auroral oval can change with geomagnetic indexes and IMF (Holzworth and Meng, 1975; Holzworth and Meng, 1984; Starkov, 1994(a)). The conclusions in this paper are based

on mathematical statistics. Therefore, Starkov designed some simple formulas to describe the relationships between the specific physical parameter and different type of aurora. Variations of the size of polar cap, auroral oval and diffuse aurora were regarded as three independent function variables of AL index (Starkov, 1994(b)). Since then, many scholars had been explored the connections between different physical parameters and auroral oval boundary or other auroral events. Carbary

5   constructed a-Kp-related model of auroral oval boundary by binning UVI images from different months (Carbary, 2005). For describing the particle precipitation characteristics, Zhang proposed a-Kp-dependent model of the mean energy and energy flux precipitating electrons in auroral oval (Zhang and Paxton, 2008). Sigernes used a Kp-based function to calculate the size and position of auroral oval, and compared the Kp-dependent model with methods which proposed by Zhang and Starkov to explain the superiority of his proposed model (Sigernes et al., 2011). Milan proposed a model based on average proton and

10   electron of auroral images from three years observed by the IMAGE spacecraft. The experiment demonstrated that Kp, solar wind parameters including solar wind velocity, density, and pressure, interplanetary magnetic field (IMF) magnitude and orientation have effect on the intensity and shape of auroral oval (Milan, 2010). After 2010, there are more and more new methods to construct connection between the position of auroral oval boundary and auroral oval boundary with the development of machine learning. Hu and Yang used the segmentation results of auroral oval obtained from UVI on Polar

15   satellite to build connection between the position of auroral oval boundary and AE index, IMF and solar wind parameters by using multiple regression method (Hu et al., 2017; Yang et al., 2016). Ding presented a C-means clustering algorithm based on fuzzy local information to extract auroral oval poleward and equatorward boundaries from merged images with filled gaps captured from both GUVI and SSUSI (Ding et al., 2017). However, the position of auroral oval boundary is not determined by one space physical parameter, those methods mentioned above just only used one or several space physical parameters to

20   explore the relationship between space physical parameters and auroral oval boundary. We can't determine whether other space physical parameters can influence the location or size of auroral oval. And we also don't know whether the mapping relationship between space physical parameters and auroral oval boundary is linear or nonlinear.

As we know, machine learning has been applied to many fields, including medical, traffic, space physics and other interdisciplinary fields. Recently, deep learning models have led to a series of breakthroughs on image classification, object

25   detection, image recognition and other fields. Conventional machine learning methods have some limitations for processing complex data, especially in space physics field. There are no suitable internal features, such as shape, colour and so on. Therefore, many effective machine learning methods can't obtain satisfied performance on processing space physics data. While, deep learning methods are representation-learning methods with multiple levels of representation. It has turned out to be very good at discovering intricate structures in high dimensional data and multimodal data (LeCun et al., 2015).

30   In this paper, a new automatic auroral oval boundary prediction model is proposed based on deep learning method. The experiment results show that the model proposed in this paper can predict aurora oval boundary accurately by using space physical parameters and the location of auroral oval boundary at the previous moment. In addition, we explore the effect of every space physical parameter on auroral oval boundary. The rest of this paper is organized as follows. Sect. 2 describes our proposed algorithm in detail. The experiment analysis and discussion are given in Sect. 3, including dataset construction,

subjective and objective evaluation, the selection of model parameters and the discussion about influence of every space physical parameter on auroral oval boundary. Finally, we draw several conclusions in Sect. 4.

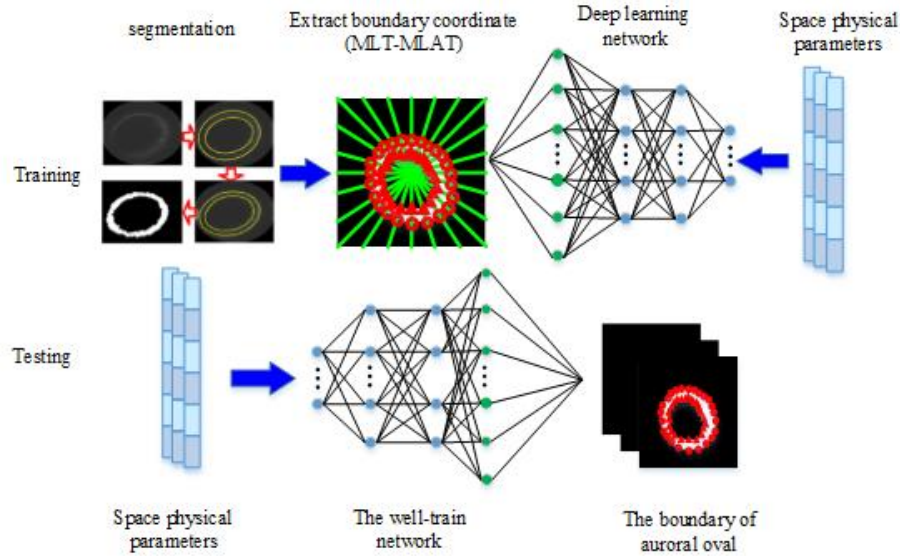## 2 Prediction of auroral oval boundary based on deep learning method

The flowchart of auroral oval boundary prediction model is shown in Fig. 1. There are two major steps in our proposed model, pre-training on our dataset and online prediction. In the training phase, auroral oval images are usually affected by heavy noise and other interferences. So, the auroral oval boundary is blurred and it is difficult to find from background. Compared with other image segmentation methods, Maximal Similarity Based Region Merging (MRSM) (Liu et al., 2013) can eliminate the
10 cumbersome process of adjusting parameters and has better segmentation accuracy. We use MRSM firstly to extract positions of auroral oval boundary. The center of auroral oval spatial distribution in magnetic local time-magnetic latitude coordinate (MLT-MLAT) is located in the geomagnetic pole. The magnetic latitude of auroral oval usually ranged from 57.5 degree to 73.5 degree according to the statistic studies on previous work (King and Papitashvili, 2014). In order to unify the distribution of aurora oval boundary, the coordinates of those extracted boundary points are transformed into MLT-MLAT coordinate
15 secondly. Finally, these transformed boundary points and its corresponding space physical parameters were input into deep learning network to train our prediction model. In the testing phase, we can obtain the corresponding boundary points of auroral oval by sending those space physical parameters and the position of auroral oval boundary points at the previous moment to our well-trained network.

The deep learning network is constructed by a two-layer Restrict Boltzmann Machine (RBM) network (Hinton et al.,
20 2006; Yu and Deng, 2011) and a Radial Basis Function (RBF) network (Łukaszyk, 2004). The computational processing of

14

RBM and RBF are illustrated by Eq. (1)-(4). In the training phase, the input of RBM network are 18 space physical parameters from OMNI dataset and coordinate values of auroral oval poleward and equatorward boundaries extracted from segmented UVI images with MRSM. It can be represented as $X = [x_1, x_2, \cdots, x_m]^T$, where m is the number of network nodes. The first layer of RBM network is denoted as $\theta_1 = \{w_{i_1 j_1}, a_{i_1}, b_{j_1}\}$, where $w_{i_1 j_1}$ is the weight between the visible unit i_1 and the hidden

5 unit j_1, a_{i_1} is the bias of visible unit i_1, b_{j_1} is the bias of hidden unit j_1. The hidden layer of the first layer in RBM network is the visible layer of the second layer in RBM network, which is denoted as $\theta_2 = \{w_{j_1 j_2}, a_{j_1}, b_{j_2}\}$, where $w_{j_1 j_2}$ is weight between the visible unit j_1 and the hidden unit j_2, a_{j_1} is the bias of visible unit j_1, b_{j_2} is the bias of hidden unit j_2. The output of the first layer of RBM network is denoted as $Y_1 = [y_{11}, y_{12}, \cdots, y_{1n}]^T$, where n denotes the nodes number of the first layer in RBM network.

10
$$y_{1j_1} = \sum_{i=1}^{m} x_{i_1} w_{i_1 j_1} + b_{j_1} \quad j_1 = 1,2,\cdots,n \tag{1}$$

The output of the second layer of RBM network is denoted as $Y_2 = [y_{21}, y_{22}, \cdots, y_{2c}]^T$, where c denotes the nodes number of the second layer in RBM network.

$$y_{2j_2} = \sum_{j=1}^{n} x_{j_1} w_{j_1 j_2} + b_{j_2} \quad j_2 = 1,2,\cdots,c \tag{2}$$

Finally, since Contrastive Divergence (CD) (Hinton, 2002) is an approximation of the log-likelihood gradient what has been

15 found to be a successful update rule for training RBM, we can obtain a well-trained RBM network by CD.

The function of RBF network can make the output of RBM network infinitely approximate to the coordinate values of auroral oval boundary by a radial basis function. The input of RBF network is the output of second layer in RBM network. The output of RBF network is represented as $Y = [y_1, y_2, \cdots, y_d]^T$, where d denotes the number of the output layer nodes. $w_{j_3 o}$ is weight between hidden unit j_3 and the output node o. l is the number of radial basis function. φ_{j_3} is the j_{th} radius basis function and

20 c_{j_3} is the center of j_{th} radial basis function. σ_{j_3} is the center width of radial basis function.

$$y_o = \sum_{j_3=1}^{l} w_{j_3 o} \varphi_{j_3}(||Y_2 - c_{j_3}||) \quad o = 1,2,\cdots,d \tag{3}$$

$$\varphi_{j_3}(||Y_2 - c_{j_3}||) = exp(-\frac{||Y_2 - c_{j_3}||^2}{\sigma_{j_3}^2}) \quad j_3 = 1,2,\cdots,l \tag{4}$$

3 Experiments and results analysis

3.1 Dataset construction and evaluation criterion

25 The auroral oval images used in this paper are captured by Ultraviolet Imager (UVI) which is a 2-D snapshot type camera on Polar satellite. The UVI on Polar satellite has acquired more than several millions of images during its entire mission. In April 2008, it no longer works. There was no effective observation after 2000, because Polar satellite changed its view after 2000. In order to balance the relationship between spatial resolution and global coverage, the spatial resolution of UVI is 30KM at apogee, the CCD array on board has 224*220 pixels and the single pixel spatial resolution is 0.0036 degree and 0.04 degree

30 in two directions respectively. The unilluminated edges of CCD are discarded, which results in the frame size of an auroral

15

oval image is 200 by 228 pixels, and the frame rate is 37s. There are 4 band sensors aboard satellite usually, UVI images in our dataset are derived from Lyman-Brige-Hopfield long band (160-180mm). In our experiments, each auroral oval image is divided into 24 magnetic regions centered on geomagnetic pole according to magnetic local time (MLT). As shown in Fig. 2, the intersection points between auroral oval boundary and division line are extracted. 48 boundary points are gathered from

5   one auroral oval image. The poleward and equatorward boundary points are marked as red triangle and red circle respectively.
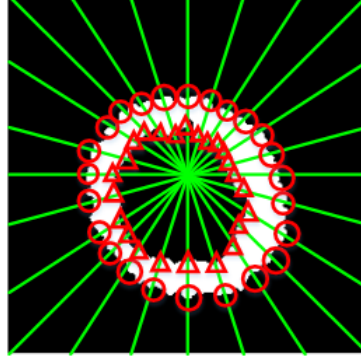

Figure 2: The schematic of extracting auroral boundary points.

The space physical parameters downloaded from NASA OMNI dataset with different time resolution. It is common knowledge that IMF, solar wind parameters, geomagnetic Indexes have a time resolution of 1 min, the other space physical parameters

10   maybe have a higher time resolution. According to the effect derived from other circumstance factors, such as, the time to traverse magnetosphere and Alfven wave, not all the response time of auroral events are equal to its propagation time. We align the time of all space physical parameters with the time of UVI images in our dataset to avoid the problem of different time resolution between space physical parameters and auroral oval images. In OMNI dataset, we selected 18 space physical parameters including the common parameters which has been verified to be related to the position of auroral oval boundary

15   (Holzworth and Meng, 1975; Starkov, 1994(a); Starkov, 1994(b); Milan et al., 2010; Hu et al., 2017) and some unfamiliar parameters which are never discussed in previous works. Therefore, our dataset includes 184416 auroral oval boundary points extracted from 3842 UVI images and its corresponding values of 18 space physical parameters. Table 1 shows 18 space physical parameters which we used in this paper.

In order to evaluate the precision of predicted auroral oval boundary points by our model, we use the common metric

20   MAE (Mean Absolute Error) to assess the error between predicted auroral oval boundary points and real auroral oval boundary points. The MAE (Mean Absolute Error) can be defined as Eq. (5).

$$MAE = \frac{1}{24}\sum_{i=1}^{24}\left(\frac{1}{k}\sum_{j=1}^{k}|F_{MLAT}^{ij} - S_{MLAT}^{ij}|\right) \tag{5}$$

S_{MLAT}^{ij} represents MLAT of the j_{th} test sample at j_{th} MLT region obtained from the segmented image, and F_{MLAT}^{ij} indicates MLAT of the j_{th} test sample at i_{th} MLT region acquired by our prediction model. k is the total number of test samples.

Table 1: Space physical parameters selected from OMNI dataset.

Parameter name	Units
Bx	nT
By	nT
Bz	nT
Flow Speed (Vp)	Km s^{-1}
Proton density (Np)	n cc^{-1}
Temperature	K
Flow pressure (pdyn)	nPa
Electric Field	Mv m^{-1}
Plasma beta	-
Alfven mach number	-
AE-1-min AE-index	-
AL-1-min AL-index	-
AU-1-min AU-index	-
SYM/D-1-minute SYM/D index	-
SYM/H-1-minute SYM/H index	-
ASY/D-1-minute ASY/D index	-
ASY/H-1-minute ASY/H index	-
PC-1-minute Polar Cap index	-

3.2 Parameters setup of deep learning network

Since the effectiveness of prediction model is influenced by the number of hidden layer nodes in RBM network (Hinton, 2012) and the training error of RBF network, we build two experiments to find the most suitable parameters for our network. For
5 both experiments, space physical parameters and position of poleward and equatorward boundary points in 24 MLT regions of 3000 UVI images are selected as training samples, the remaining are regarded as test samples. In experiment 1, the training error of RBF network is set to 4 magnetic latitude and the number of hidden layer nodes in RBM network are 32, 64, 96 and 128 respectively. We use the average MAE with 100 experiments to verify the stability of our model, because training samples and test samples were divided by random number. The corresponding MAE is shown in Fig. 3(a). From the Fig. 3(a), MAE
10 reaches the smallest value when the number of hidden layer nodes are set to 32. In experiment 2, the number of hidden layer nodes are set to 32 according to the results in experiment 1. There often has overfitting problem when we train a neural network (Krizhevsky et al., 2012). Overfitting can be interpreted as a phenome-non, which is the model performs well on training set and unsatisfactorily on test set. We set different training error to avoid overfitting problem. So, the training error of RBF

17

network is set to 2, 4, 6 and 8 magnetic latitudes empirically. The corresponding MAE is shown in Fig. 3(b), and MAE reaches the minimum when the training error of RBF network is 4 magnetic latitudes. From the two experiment results above, we set the number of hidden layer nodes in RBM network and the training error of RBF network to 32 and 4 respectively as the optimal parameters of deep learning network in the following experiments.
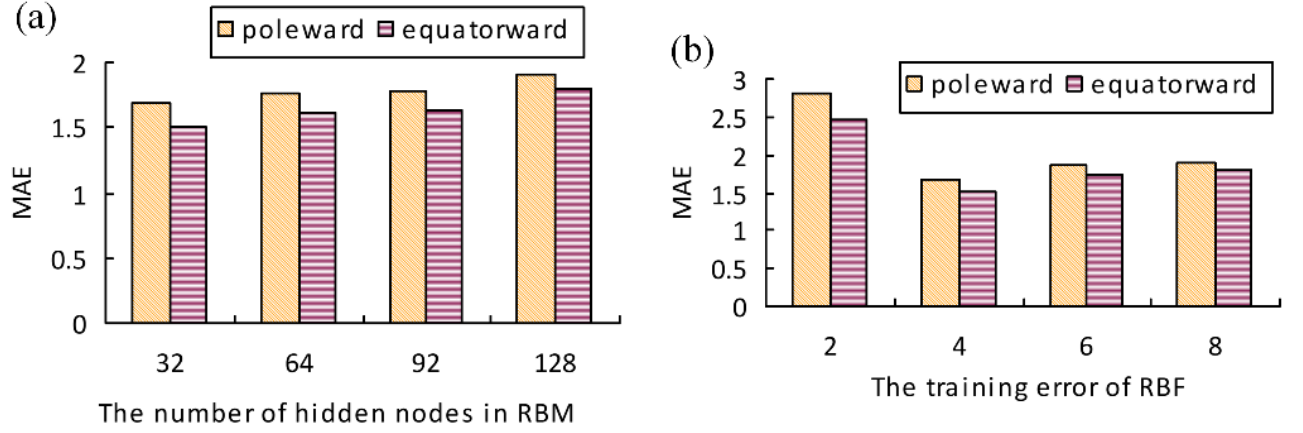
5

Figure 3: (a)The MAE value of different hidden layer node, (b) The MAE value of different training error.
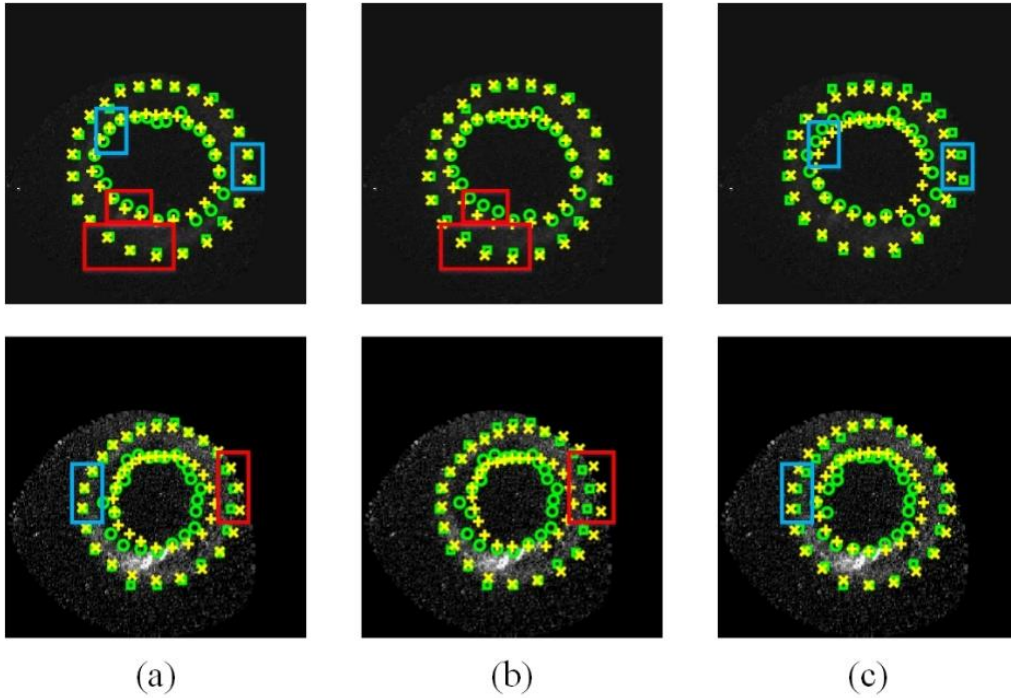

Figure 4: The different subjective results based on different methods. (a) The subjective results predicted by our method (b) The subjective results predicted by BP network (c) The subjective results predicted by Yang's method

To demonstrate the availability of our proposed model, we compared the proposed model with Back Propagation (BP) network (Rumelhart, 1986) and Yang's model (Yang et al., 2016). The subjective prediction results obtained by the three method are shown in Fig. 4, circles and squares stand for poleward boundary points and equatorward boundary points which are obtained from the segmented image, '＋' and '×' marks represent poleward boundary points and equatorward boundary points

5　respectively which are obtained from our prediction model. Although these three methods have similar prediction results in most areas on auroral oval boundary, it is obviously that our method can obtain more accurate boundaries than the other two compared methods, where marked by blue rectangle and red rectangle in Figure 4. In more detail, the results of BP model and our model are shown in Fig. 4(a) and Fig. 4(b) respectively, we can clearly see that the distances between auroral oval boundary points predicted by our method and real auroral oval boundary points are smaller than the distances between BP model's results

10　and real auroral oval boundary points in red rectangle areas. From Fig. 4(a) and Fig. 4(c), our prediction points are closer to real auroral oval boundary points compared with Yang's prediction points in blue rec-tangle area. Meanwhile, the MAE of different methods are shown in Table 2. From this table, our method has the smallest MAE not only in poleward boundary bur also in equatorward boundary, because our model can extract more useful information and feature from auroral oval images than the other two models. As a consequence, we can draw the conclusion that the proposed model in this paper is more suitable

15　for predicting auroral oval boundary.

Table 2: The MAE value of different methods.

methods	BP	Yang's	ours
Poleward boundary	2.20	2.01	1.69
Equatorward boundary	2.19	1.91	1.51

3.3 The influence of space physical parameters on auroral oval boundary

As we known, the location of auroral oval boundary is affected by a variety of space physical parameters. Variation of auroral
20　oval boundary in different MLT sectors are related to different space physical parameters. For sake of exploring the influence of space physical parameters on poleward and equatorward boundaries specifically, the boundary points are further processed as follows (Hu et al., 2017). Firstly, all poleward and equatorward boundary points are divided into 24 subsets of poleward and equatorward boundary points according to 24 MLT sectors. Secondly, in every MLT subset, we sort boundary data with respect to the value of all space physical parameters, and divide boundary data into 10 groups evenly. In order to observe the
25　variation tendency of each parameter in different MLT sectors clearly, in every MLT sectors, the relationship between each space physical parameter and the location of auroral oval boundary was represented as a Quadratic Equation based on the principles of the least square conic fitting (Fitzgibbon et al., 1999). Then, we calculate the location of poleward and equatorward boundary points for each space physical parameter using this function. Finally, we use the boundary data which calculated by Quadratic Equation to discuss the influence of space physical parameters on auroral oval boundary. In this section,

we build 3 statistical experiments to discuss how IMF, solar wind parameters and geomagnetic indexes influence on auroral oval boundary. An auroral oval boundary prediction experiment by inputting every single space physical parameter to explore the relationship between auroral oval boundary and 18 space physical parameters. And a correlation analysis experiment is constructed to study the connection between combination of different space physical parameters and auroral oval boundary.
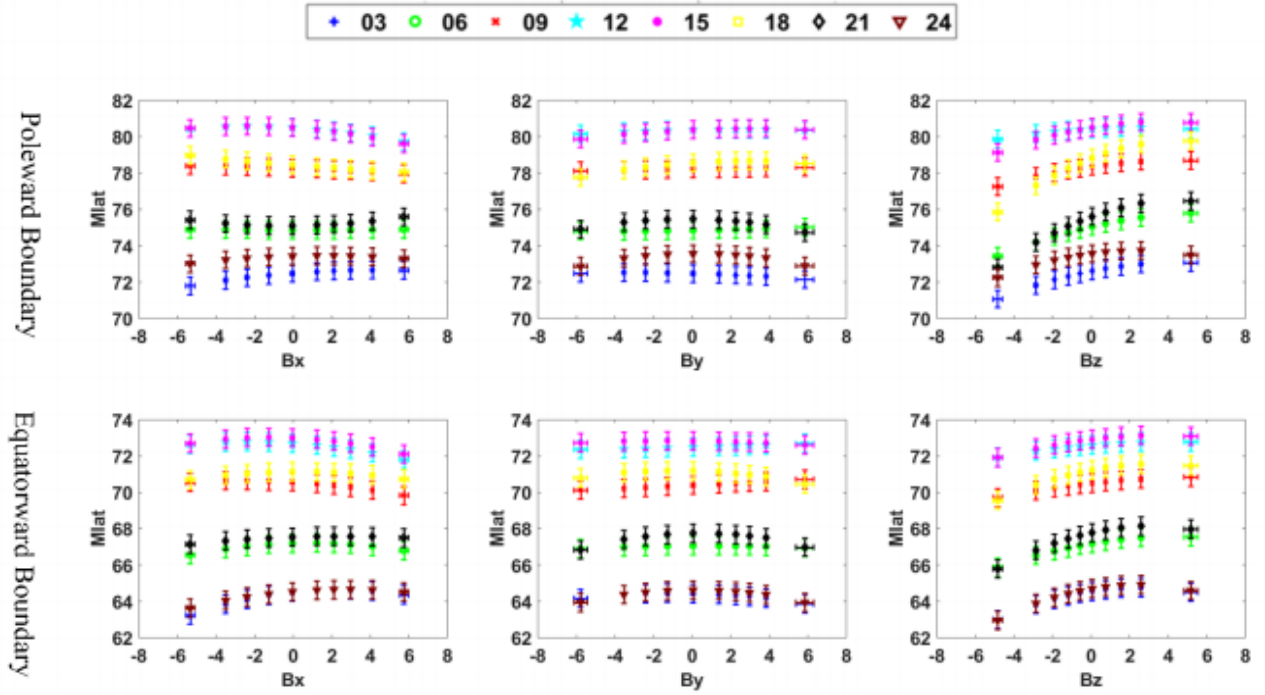

Figure 5: Response of magnetic latitude of poleward (top row) and equatorward (bottom row) boundaries to Bx, By and Bz respectively at 0030,0060,0090,1200,1500,1800,2100 and 2400 MLT.

3.3.1 Experiment 1: Influence of different IMF components on Aurora oval boundary

The IMF can affect auroral oval boundary through different space processes. In this experiment, response of different IMF components to auroral oval boundary are shown in Fig. 5. The different colour and shape markers represent different MLT sector. The vertical error bars represent one eighth of standard deviation from mean value of auroral oval boundary position, and the horizontal error bars represent standard deviation from mean value of different IMF components in each binned data. Therefore, the length of vertical error bar is fixed, the length of the horizontal error bars is changeable because of different standard deviation in each binned data.

From Fig.5, we can see that the poleward and equatorward boundaries in each MLT sector show a step-by-step poleward displacement with the increase of IMF Bz component. It has been widely accepted that IMF Bz controls the energy coupling between the solar wind and the magnetosphere (Cho et al., 2010; Makita et al., 1983). During a period of southward IMF (Bz < 0), poleward motion of auroral oval boundary is due to a higher reconnection rate in the process of dayside reconnection. However, most poleward motion of auroral oval boundary occurred during northward IMF (Bz > 0). Under northward IMF

20

(Bz > 0) condition, poleward activity of auroral oval boundary often related to IMF By component (Xing et al., 2013). The poleward and equatorward boundaries in 09:00-15:00 MLT show a gradually poleward displacement with the rise of IMF By component, and the poleward and equatorward boundaries in 18:00-06:00 MLT gradually approaches to pole with the decrease of absolute of IMF By component from Fig.5. This statistical discovery proves previous studies on IMF By component. Such as, Karlson's observations suggested that IMF By component is related to prenoon-postnoon asymmetry of poleward activity (Karlson et al., 1996). And it is well known that ionospheric convection is mainly controlled by IMF Bz and By components (Cowley and Lockwood, 1992; Huang et al., 2000), which implies the prenoon-postnoon asymmetry of pole-ward activity is similar to the procedure of ionospheric plasma convection. Both two space activities mentioned above are affected by the variety of IMF By component (Provan et al., 1999). The poleward and equatorward boundaries in 21:00-06:00 MLT show a gradually poleward motion with the ascent of IMF Bx component observed from Fig.5, which is consistent with IMF By and Bz.
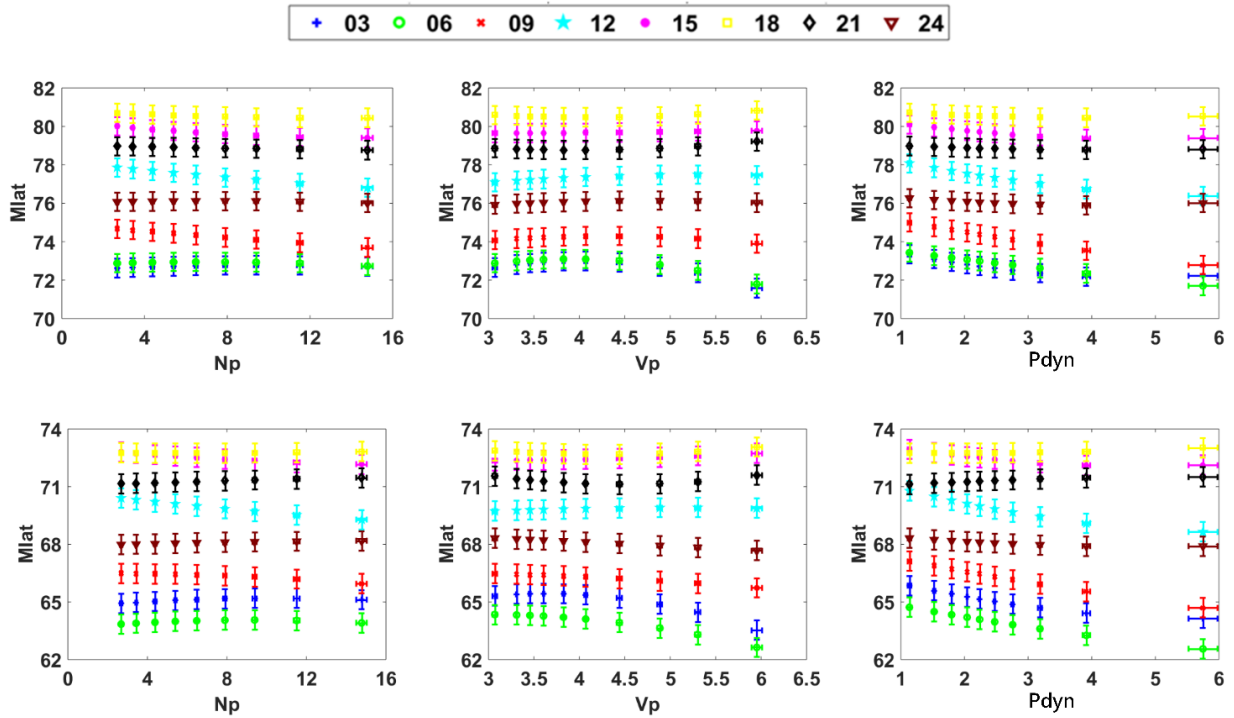

Figure 6: Response of magnetic latitude of poleward (top row) and equatorward (bottom row) boundaries to Np, Pdyn and Vp respectively at 0030,0060,0090,1200,1500,1800,2100 and 2400 MLT.

3.3.2 Experiment 2: Influence of different solar wind parameters on Aurora oval boundary

For sake of finding the variation trend of auroral oval boundary with the change of solar wind parameters, including solar wind density (Np), solar wind speed (Vp) and solar wind dynamic pressure (Pdyn) respectively, experiment 2 is performed. Fig.6 shows the response of different solar wind parameters on auroral oval boundary.

21

From Fig.6, both poleward boundary and equatorward boundaries shrink in 21:00-06:00 MLT when the value of Np rises. Meanwhile, poleward and equatorward boundaries in 09:00-18:00 MLT gradually approaches equator when the value of Np rises. Besides, we can obtain the following conclusions: The poleward and equatorward boundaries in 03:00-18:00 MLT expand to equator clearly with the increase of Pdyn. And equatorward boundary in 21:00-24:00 MLT has a poleward motion with the increase of Pdyn. There has an obvious poleward motion in nightside sector impacted by the increscent Pdyn and Np according the conclusions above. We can draw a coincident inference with previous studies. For examples, poleward displacement of auroral oval boundary along with the increscent Pdyn, which results from the shrunken polar cap (Cho et al., 2010). By extension, there must have some dependencies between the varying size of polar cap and nightside reconnection (Boudouridis et al., 2003). Compared with the change of auroral oval boundary in nightside sector, both poleward and equatorward boundaries are enlarged when the value of Pdyn and Np rise, which observed from Fig.6. Previous explorations and simulations shown that enlarged Pdyn can enhance ionospheric potential and the corresponding field-direction current intensity, which can lead to increasement of global auroral activity intensity. Meanwhile, the position of auroral oval boundary will ex-tend to low latitudes (Peng et al., 2011). From Fig.6, it appears a distinct equatorward movement with increase of Vp in 24:00-06:00 MLT for both poleward boundary and equatorward boundary. This changing pattern of Vp and auroral oval boundary which we illustrate above is consistent with Hu's study in 2017 (Hu et al., 2017).
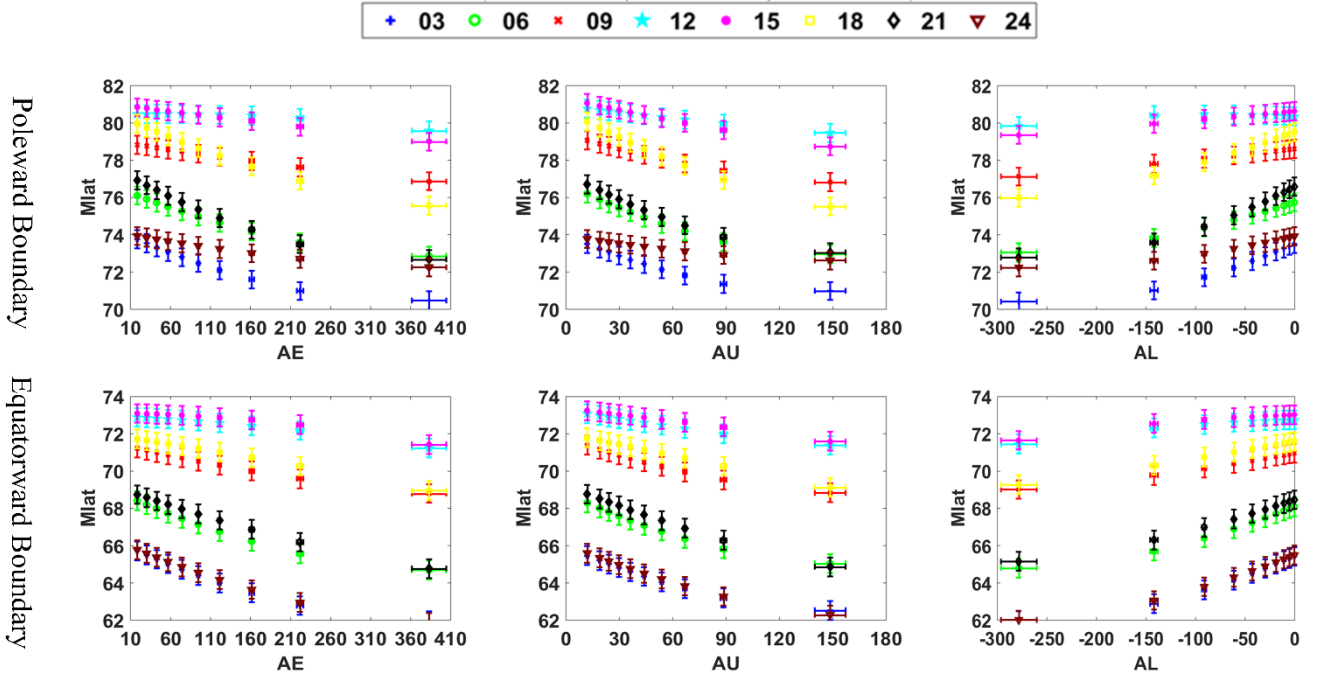

Figure 7: Response of magnetic latitude of poleward (top row) and equatorward (bottom row) boundaries to AE, AU and AL respectively at 0030,0060,0090,1200,1500,1800,2100 and 2400 MLT.

3.3.3 Experiment 3: Influence of geomagnetic indexes on Aurora oval boundary

In this experiment, the average tendency of poleward and equatorward boundaries influenced by geomagnetic indexes (AE, AL, AU) shows in Fig.7.

As we can see from Fig.7, in every MLT sector, pole-ward and equatorward boundary move to low magnetic latitude with the ascending AE and AU index. While, poleward and equatorward expand to high magnetic latitude with the ascending of AL index. AE index is often used to characterize the strength of substorm activity in magneto-sphere. Therefore, it can be considered that auroral oval expands to equator due to the enhancive substorm activity. Furthermore, the amount of energy enters magnetotail along with the strengthening of substorm activity. It means that AE index will increase when energy in magnetotail re-leased through substorm, which is coincident with our found about AE from Fig.7.

Table 3: The MAE influenced by different space physical parameters.

Parameter name	MAE(poleward/equatorward)
Bx	**1.6222/1.4448**
By	1.6134/1.4462
Bz	1.6139/1.4476
Flow Speed (Vp)	1.6117/1.4485
Proton density (Np)	**1.6285/1.4451**
Temperature	1.6129/1.4458
Flow pressure (pdyn)	**1.6242/1.4463**
Electric Field	1.6113/1.4430
Plasma beta	1.6118/1.4435
Alfven mach number	1.6193/1.4473
AE-1-min AE-index	1.6183/1.4562
AL-1-min AL-index	**1.6325/1.4668**
AU-1-min AU-index	1.6117/1.4517
SYM/D-1-minute SYM/D index	1.6187/1.4500
SYM/H-1-minute SYM/H index	1.6197/1.4581
ASY/D-1-minute ASY/D index	1.6137/1.4550
ASY/H-1-minute ASY/H index	1.6079/1.4500
PC-1-minute Polar Cap index	1.6120/1.4512

3.3.4 Experiment 4: Influence of all 18 space physical parameters on Aurora oval boundary

As we know, most of studies on how the space physical parameters affect auroral oval boundary are focus on solar wind parameters, geomagnetic indexes and IMF components. There are lots of corresponding conclusions about the influence of

23

those space physical parameters on auroral oval boundary up to now. Nonetheless, how the other space physical parameters not mentioned above affect the auroral oval location has not been addressed. In order to further explore the variation of auroral oval boundary influenced by different space physical parameters, the experiment 4 is performed. In experiment 4, we send one physical parameter selected from Table 1 at the present moment and the coordinates of auroral oval boundary points at the previous moment to our prediction model. And the output of our model are 48 coordinates values of auroral oval boundary points and the MAE between real boundaries and predicted boundaries. The MAE of poleward and equatorward boundaries influenced by different space physical parameters are given in Table 3. We can infer the response of auroral oval boundary to 18 space physical parameters through the different MAE of these space physical parameters.

The MAE of boundary position are 1.6076 and 1.4545 respectively when we only use boundary positions at the previous moment to predict poleward and equatorward boundaries. We take this MAE as standard, called S-MAE. Compared with the S-MAE, we can see that the MAE increase about 1.9% for poleward boundary by adding anyone space physical parameters into input of our model from Table 3. Meanwhile, the variety of MAE for equatorward boundary is between -0.7% and 0.7%. Although different space physical parameters have different influences on auroral oval boundary, compared to other space physical parameters in Table 3, the MAE of auroral oval boundary can display the greatest impact when AL, Bx, Np, Pdyn are used as the input of our model respectively, which suggests that these 4 space physical parameters mentioned above have a great influence on the position of auroral oval boundary.

Table 4: The Pearson correlation coefficient of all 18 space physical parameters from Dec. 1996 to Mar. 1997.

Parameter name	Correlation coefficient
Vp-Np	-0.5970
Vp-SYM/H	-0.5120
Np-Pdyn	0.7662
Np-SYM/H	0.5584
AE-AL	-0.9437
AE-AU	0.7139
AE-PC	0.8067
AL-PC	-0.7079
AU-PC	0.6924

3.3.5 Experiment 5: Correlation analysis of all 18 space physical parameters

In order to analyse the influence of space physical parameters on auroral oval efficiently, we not only consider the effect of each space physical parameter on auroral oval boundary, but also take the effect on auroral oval boundary with different combinations of space physical parameters into account in experiment 5. As a result, we first calculate the correlation of all 18 space physical parameters using Pearson correlation coefficient, which is a statistic value that reflects the degree of linear

correlation between two variables. The Pearson correlation coefficient of two variables (X, Y) equals the covariance of the two variables (X, Y) divided by the product of their standard deviations $(\sigma_X \sigma_Y)$. The formula of Pearson correlation coefficient can be represented as Eq. (6), and the Pearson correlation coefficient of all 18 space physical parameters are given in Table 4. The process of experiment 5 is similar to experiment 4 and the MAE of different space physical parameter combinations are given in Table 5.

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \qquad (5)$$

The MAE of poleward and equatorward boundaries by using three components of IMF and auroral oval boundary positions at the pervious moment as the input of proposed model are 1.6313 and 1.4759 severally in Table 5. The MAE of three components of IMF combination is bigger than S-MAE. When the input of our model includes Bx, By and Bz, it is obviously that the MAE of poleward and equatorward boundaries both have significant increasement compared with the MAE of poleward and equatorward boundaries by inputting anyone IMF components to our model, which suggests that the three components of IMF have similar influence on auroral oval boundary. Previous investigations illustrated that auroral oval boundary is connected with the variation of IMF Bx, By, Bz (Huang et al., 2000; Provan et al., 1999). Our experiment results also demonstrate that the auroral oval boundary should be related with the three components of IMF. Whether the northward or southward IMF direction are input to the proposed model, the MAE have marked change in both poleward and equatorward boundaries. Nevertheless, we can observe the more evident increasement of MAE in equatorward boundaries compared with the MAE of poleward boundaries by using northward IMF direction as the input of our model. Meanwhile, there has an opposite result under southward IMF direction condition. The variation of MAE in poleward boundaries are bigger than equatorward boundaries when the input of our model is southward IMF direction. Therefore, we can know that the northward IMF direction has a great influence on the equatorward boundaries, and the southward IMF direction has a significant effect on poleward boundaries.

We can see that AE has strong positively correlation to AU and PC, and AL has strong negative correlation to AE, AU and PC from Table 4. The linear correlation coefficient between AE and AL is -0.9437, which verified that AL index has the opposite effect on auroral boundary compared with AE index. In contrast, the impact of AU index on auroral boundary is similar to the impact of AE index on auroral boundary because of the strong positive correlation between AE and AU. Those conclusions mentioned above is consistent with the conclusions of the statistical experiment 3. In addition, the correlation coefficient between AE and PC is 0.8067, which implies PC should have homologous trend with AE in every MLT section. Fig.8 shows the response of poleward and equatorward boundaries to PC respectively. The PC index can serve as an indicator of auroral electrojet activity. Vennerstrøm found that PC is sensitive to electrojet activity and substorm intensifications of the westward electrojet in the midnight or post-midnight sector (Vennerstrøm et al., 1991). This conclusion matches to what we found about the impact of PC on auroral oval boundary in Fig.8. When the input of our model only included the three geomagnetic indices (AE, AL, AU) and auroral oval boundary positions at the previous moment, the MAE of equatorward and poleward boundaries are 1.6569 and 1.5124 severally from Table 5. we can clearly know that the MAE of poleward and

equatorward boundaries are both enlarged compared with S-MAE. As a result, we can draw the conclusion that the three geomagnetic indexes strengthen each other's effect when the combination of three geomagnetic indexes are inputted into our model. Beyond that, in Table 5, when AE, AU, AL, and PC are used as the input of our model, the MAE of poleward and equatorward boundaries are 1.6734 and 1.5275 respectively, which shows that the combinations of those parameters have the important influence on the location of aurora oval boundary.

Table 5: The MAE influenced by different combinations of space physical parameters.

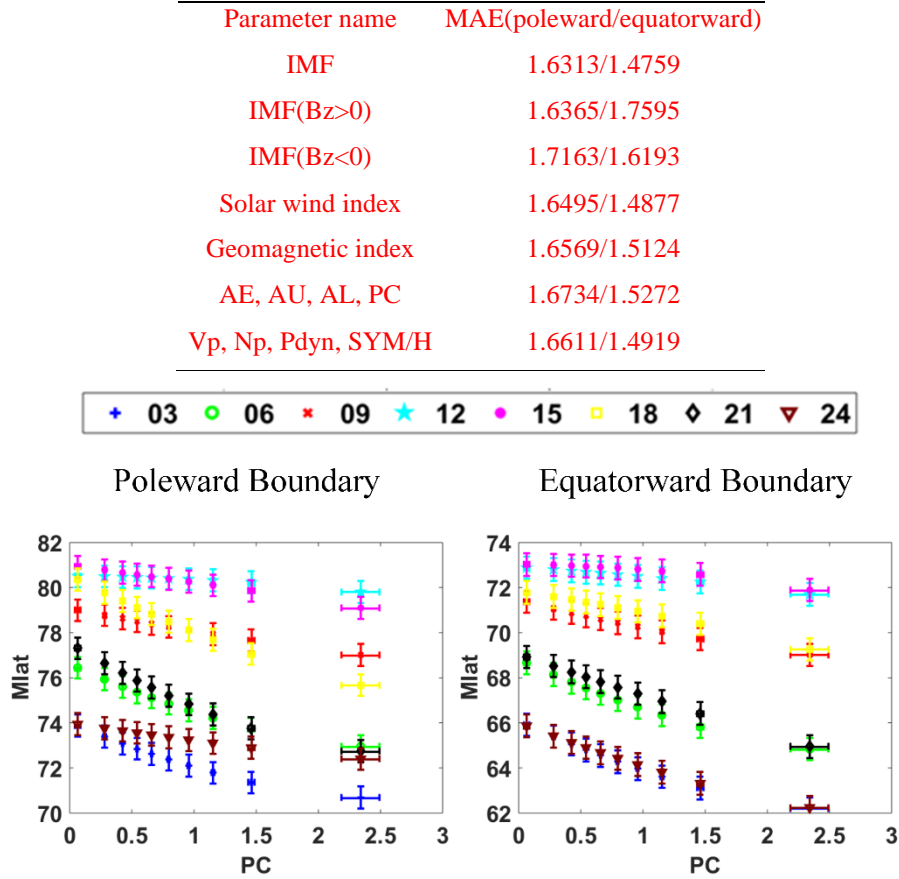| Parameter name	MAE(poleward/equatorward)
IMF	1.6313/1.4759
IMF(Bz>0)	1.6365/1.7595
IMF(Bz<0)	1.7163/1.6193
Solar wind index	1.6495/1.4877
Geomagnetic index	1.6569/1.5124
AE, AU, AL, PC	1.6734/1.5272
Vp, Np, Pdyn, SYM/H	1.6611/1.4919

Figure 8: Response of magnetic latitude of poleward (left column) and equatorward (right column) boundaries to PC at 0030, 0060, 0090, 1200, 1500,1800,2100 and 2400 MLT

According to Table 4, there has obvious correlation among the following space physical parameters. For the solar wind parameters, Vp and Np are positive correlations, while Np and Pdyn are negative correlation, and the three parameters all are related to SYM/H. Firstly, we can obtain the similar inference on the three geomagnetic indices to solar wind parameters (Vp, Np, Pdyn) according to the MAE of three solar wind parameter combinations from Table 5 and the strong correlation between them. In other words, the three solar wind parameters also strengthen each other's effect on auroral oval boundary when the combination of them are sent into our model. Secondly, when Np, Vp, Pydn and SYM/H are as input to our model, the MAE

of auroral oval boundaries are 1.6611 and 1.4919 in poleward and equatorward respectively in Table 5, which is bigger than the MAE of auroral oval boundaries when the inputs are Np, Vp and Pydn. So, we can conclude that the combinations of these four parameters strengthen mutual influence on the location of aurora oval boundary. According to the statistics from Table 6, the physical variables that appears most frequently are Bx, By, Vp and SYM/H. When the inputs of our model are the combination of these four variables or the combination of Bx and By, the MAE of auroral oval boundary reaches the minimum, which proves that these four parameters have great influence on the location of aurora oval boundary.

As a summary, it can be seen that these space physical parameters, which include Bx, By, Vp and SYM/H, play a crucial role in determining the location of auroral oval boundary based on the above conclusions.

Table 6: The MAE influenced by different combinations of space physical parameters

Parameters name	MAE (poleward/equatorward)
Bx, By	1.6145/1.5003
Bx, Vp, SYM/H	1.6359/1.5129
Bx, By, Vp, SYM/H	1.6118/1.5056
Bx, By, Vp, Pdyn, PC	1.6242/1.5084
Bx, By, Np, AU, SYM/H	1.6154/1.5181
Bx, By, Vp, Np, SYM/H, PC	1.6324/1.5017
Bz, Vp, Pydn, AE, AU, AL, SYM/H	1.6282/1.5125
Bx, By, Bz, Vp, Np, Pdyn, AE, AU	1.6149/1.5044
Bx, By, Bz, Vp, Np, Pdyn, AE, AU, PC	1.6994/1.5028
Bx, By, Bz, Vp, Np, Pdyn, AL, AU, SYM/H, PC	1.6771/1.5716
Bx, By, Bz, Vp, Np, Pdyn, AE, AL, AU, SYM/H, PC	1.6669/1.5743

4 Conclusion

In this paper, we establish a model to measure the relationship between space physical parameters from OMNI dataset on NASA website and poleward and equatorward auroral oval boundaries based on deep learning network. Our model overcomes some drawbacks in this field. Such as, some prediction method based on statistics and a few space physical parameters. Those methods are not very suitable for the complex and changeable space physical data. For our model, the inputs are 18 space physical parameters and the 48 coordinates value of aurora oval boundary points at the previous moment, and we can obtain position of poleward and equatorward boundaries at 24 MLTs from our well-trained model. At last, our experiment results show that the model proposed in this paper can better reflect the relationship between space physical parameters and auroral oval boundary. Therefore, it should be useful to predict the position of auroral oval boundary. In addition, we analyse the effect of all 18 space physical parameters on the location of auroral oval boundary based on several statistical and prediction

experiments. It can be show that different parameters have different effect on auroral oval boundary from our experiments. Some space physical parameters, Bx, By, Vp and SYM/H, have a great influence on the position of auroral oval boundary.

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Author contributions. The methodology has been developed by all of the authors. HYY have coded and run the experiments. All authors have discussed the theory, the interpretation of the results and edited the manuscript.

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Competing interests. The authors declare that they have no conflict of interest.

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