

Deep Learning Kp Computational Prediction Combined Multimodal Data of Solar Wind and EUV Images*

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Abstract This study presents a deep learning framework for multi-scale prediction of the geomagnetic Kp index by integrating multi-modal solar data. Unlike models that rely solely on upstream solar wind measurements from the Advanced Composition Explorer (ACE), which offer a short-term forecast horizon of 0.5–2 h, our approach synergistically incorporates Extreme Ultraviolet (EUV) images of coronal holes from the Solar Dynamics Observatory (SDO). These images provide precursor signals of solar activity, enabling medium-term forecasts. This study constructed a multi-year dataset (2011–2019) with carefully designed features to ensure physical meaning and sample balance. And several models were developed and evaluated: a direct solar wind model, an indirect multi-scale model using EUV images, and a model incorporating coronal hole location information. While all models showed similar and superior performance in 3-hour-ahead predictions, the model incorporating coronal hole location information demonstrated a significant advantage at extended forecast horizons, maintaining a Correlation Coefficient (CC) of approximately 0.23 even at a 72 h lead time. This work underscores the critical value of fusing solar source images with *in-situ* measurements to achieve reliable, long-lead space weather forecasts.

Key words Geomagnetic index, Deep learning, Computational prediction, Coronal hole, Multi-modal data, Space weather forecasting

Classified index P353

0 Introduction

Geomagnetic storms are global, intense disturbances of Earth's magnetosphere, originating from solar activity. The arrival of high-speed solar wind plasma from sources such as coronal holes can induce significant space weather events that disrupt various technological systems. These disturbances pose risks to power transmission grids, satellite communications, GPS navigation services, and other critical infrastructure on Earth, alongside potential effects on human health^[1]. The intensity of

a geomagnetic storm, which reflects the influence of the solar wind on Earth's magnetosphere, is quantified by indices such as the Kp and Dst . The Dst index is optimal for characterizing the ring current during intense storms, while the Kp index provides a comprehensive, global measure of mid-latitude geomagnetic disturbance at a high 3-hourly cadence that is more commonly applied in early warning systems. Consequently, for the purpose of developing an operational forecasting tool that aligns with global monitoring practices, the Kp index is the more suitable and impactful target variable.

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The *Kp* index serves as a globally recognized indicator of geomagnetic activity, based on data from a network of ground-based magnetometers. It is a dimensionless value on a scale from 0 to 9, representing the intensity of geomagnetic disturbances in 3 h intervals. The index is derived from the processing of local *K*-index values reported by observatories across the globe, thereby synthesizing a worldwide perspective. Updated every 3 h, the *Kp* index facilitates the timely monitoring of geomagnetic conditions.

Forecasting the *Kp* index requires connecting solar sources to terrestrial impacts. Our approach leverages two complementary data modalities to capture this chain of events: firstly, solar wind measurements from the ACE spacecraft, which provide direct, *in-situ* observation of this plasma that directly drives geomagnetic activity about 0.5~2 h before impact^[2]; and secondly, Extreme Ultraviolet (EUV) images from SDO/AIA, which allow for the identification of coronal holes—the primary sources of recurrent, high-speed solar wind streams. This creates a causal chain from source to impact: the coronal holes observed in EUV imagery serve as the medium-term precursor, enabling forecasts several days in advance by identifying the solar source. The subsequent *in-situ* solar wind measurements then capture the immediate cause of the activity. Current research is advancing towards models that can integrate this entire process^[3,4]. A key development is the shift to deep learning, which is uniquely suited to fuse these disparate data types, thereby improving accuracy and enabling reliable, physically-grounded medium-term forecasts.

The proliferation of Artificial Intelligence (AI), particularly deep learning, offers an ideal methodology for

leveraging such multi-modal data^[5,6]. The demonstrated capability of artificial intelligence in classifying visual data (such as EUV images) and modeling complex sequential data (like solar wind time series) makes it uniquely suited to integrate these diverse data sources^[7]. Therefore, the combination of solar source images and upstream solar wind data is not merely beneficial but necessary for achieving the stated goal of reliable medium or long-term forecasts, moving beyond the limitations of models based on a single data source.

On the different time lags originated from the distinct physical origins of the data, the 0.52~2.08 h lag for solar wind parameters is the direct propagation time from the ACE satellite at L1 (about 1.5 million km from Earth) to our magnetosphere, calculated from the standard solar wind speed range of 200~800 km·s⁻¹ as follows:

$$T = \frac{D_L}{v_{sw}} = \frac{1.5 \times 10^6 \text{ km}}{200 \sim 800 \text{ km} \cdot \text{s}^{-1}} = 0.52 \sim 2.08 \text{ h}, \quad (1)$$

where D_L is the distance from the L1 point to the Earth, and v_{sw} is the solar wind speed.

Conversely, the 3~4 days lag or more for EUV images accounts for the full journey from the Sun. It includes the time for a coronal hole to rotate to an Earth-facing position and for the resulting high-speed solar wind stream to travel the full Sun-Earth distance (about 1.5×10^8 km). This integrated process consistently produces the cited multi-day delay, as supported by observational studies of coronal hole recurrence.

To directly illustrate the framework enabling these forecasting advantages, Figure 1 presents our multi-source, multi-modal data environment. It depicts the spatial relationships of the Sun-Earth observatories, paired with representative data: EUV images of coronal holes

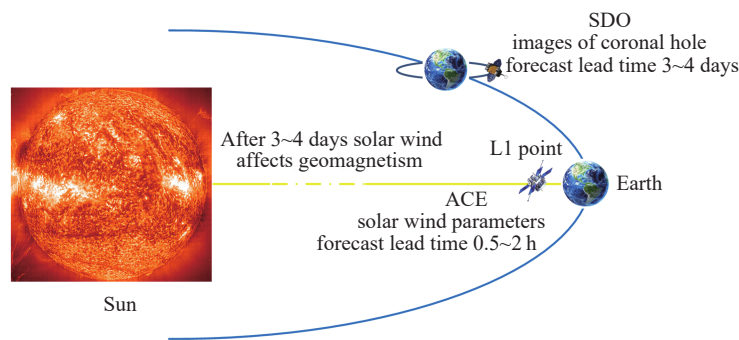


Fig. 1 Locations, orbits and data types of solar observatory for *Kp* prediction

and solar wind parameters. The synergy of these modalities is the key to enhanced prediction. While solar wind measurements offer short-term drivers, EUV images contain earlier magnetic storm signals from the solar source. By integrating them, our model leverages this informational head start to achieve longer lead times and improved accuracy for explicit geomagnetic indices^[8,9]. Therefore, this multi-modal dataset serves not merely as isolated measurements but as a coherent digital fingerprint of the underlying physical reality. The data constitutes a comprehensive representation of the solar activity—a structured record that encodes its fundamental nature, current state, and dynamic evolution, thus providing a solid empirical foundation for our model.

This study develops a deep learning model to forecast the Kp index by integrating multi-source data, including solar wind parameters from the ACE satellite and coronal hole images from SDO/AIA EUV observations. The research is designed to address the following principal questions.

(1) How can heterogeneous data modalities (*in-situ* measurements and remote sensing images) be effectively fused within a deep learning framework to enhance the accuracy and lead time of space weather forecasts?

(2) What is the model's performance across different forecasting timescales, particularly in short-term (hours ahead) and medium-term (days ahead) predictions?

In summary, the integration of comprehensive solar observational data with advanced artificial intelligence presents a transformative opportunity for space weather science. By directly learning from empirical data, these AI-driven models can generate predictive descriptions of solar activity and its geoeffective impacts. In many cases, the forecasting performance of such data-centric approaches can rival or even surpass that of traditional methods reliant on incomplete physical models^[10–12].

1 Preparation and Analysis of Multi-scale and Multimodal Solar Data for Kp Prediction

Unlike general and common datasets in the field of artificial intelligence, there is explicit and clear physical

meaning in the solar wind data and EUV images, there are correlations and causal relationships between these parameters and information on which space weather forecasting is based. This study tries to construct the characteristics of solar wind data reasonably according to the physical meaning, establish the yearly dataset in terms of the solar activity cycle for the sake of equilibrium of samples, and apply these multimodal data, including the solar wind parameters and EUV images, fully to carry out multi-scale geomagnetic index forecasting based on deep learning^[13].

1.1 DM (Difference Mean) Feature Construction of Solar Wind Parameter Data

On geomagnetic index prediction of solar wind, traditional statistical models are generally suitable for a small number of samples or the typical condition of geomagnetic storm, but are not efficient to match big data intelligently. When the observed data from SDO, ACE and STEREO A/B increase rapidly and massively, since solar eruption mechanisms have not been established completely, there are two problems to address: unknown correlations between the geomagnetic index and solar wind parameters, and the problem of data missing, data abnormal, and data duplicate in the dataset.

The original observation parameters of solar wind generally include proton density n , solar wind velocity v , magnetic field B , the components B_x , B_y and B_z on the axes of x , y and z , respectively, and so on. Feature selection and feature construction aim to screen out the best subset of performance features from the original feature set, so as to reduce the dimensionality of input features, enhance the correlation between features and features, features and targets, eventually to contribute to the interpretability of a practical problem. The following principles are complied with the feature selection and construction of solar wind data.

(1) Since the solar wind detected at the L1 point affects Earth within 0.5~2 h, a 3 h sliding window was applied to compute the maximum, minimum, and average values of parameters n , v , and B . This window duration aligns with the cadence of the Kp index, maintaining temporal consistency between solar wind inputs and geomagnetic response predictions.

(2) Referred every 3 h record of Kp , the difference of the magnetic field, *i.e.*, delta, the difference between

the maximum and the minimum on the x , y , and z axes, respectively, is calculated, and the maximum difference data on the three directions of the magnetic field is constructed, expressed as delta_max .

(3) Due to the positive and negative signs for the three components of the magnetic field only representing the direction, in order to avoid introducing errors during normalization, here the average value of the absolute value of the three components respectively are constructed, expressed as abs .

So the above feature construction method could be named as the Difference of Absolute (DA) value. Pearson correlation coefficient between the feature values and various prediction ranges Kp could be calculated, its heat map is shown in Figure 2.

In Figure 2, delay 3 h, delay 6 h, delay 9 h, delay 12 h, and delay 15 h represent the Kp values of the corresponding delay times of 3 h, 6 h, 9 h, 12 h, and 15 h, respectively. The darker the blue of the lattice in Figure 2, the stronger the positive correlation between the two variables. The darker the red, the stronger the negative correlation between the two variables. The closer the color is to white, the correlation between the variables is

near to 0.

It can be seen that the correlation between feature n_{delta} and Kp is 0.29, the correlation between v_{delta} , B_{delta} , $B_{x,\text{delta}}$ and Kp is 0.35, and the correlation between $B_{y,\text{delta}}$, $B_{z,\text{delta}}$ and Kp is 0.44. The correlations between the absolute mean value $B_{x,\text{avg,abs}}$, $B_{y,\text{avg,abs}}$, $B_{z,\text{avg,abs}}$ and Kp for the three components of the magnetic field were 0.37, 0.39 and 0.43, respectively, and the one between the maximum value of the difference, *i.e.*, $B_{\text{delta,max}}$, and Kp was 0.49. These results show that the DM feature construction greatly improves the correlation between the input features and Kp .

This feature construction strategy is designed to transform the raw, signed IMF components into parameters that encapsulate their geoeffectiveness. The delta features are engineered to capture the dynamic variability of the solar wind driver. Specifically, $B_{z,\text{delta}}$ serves as a robust proxy for the occurrence and intensity of southward IMF conditions, which are the primary driver of magnetic reconnection and energy injection into the magnetosphere. Consequently, a high $B_{z,\text{delta}}$ value is physically indicative of a high potential for geomagnetic activity. The abs features, meanwhile, provide a stable

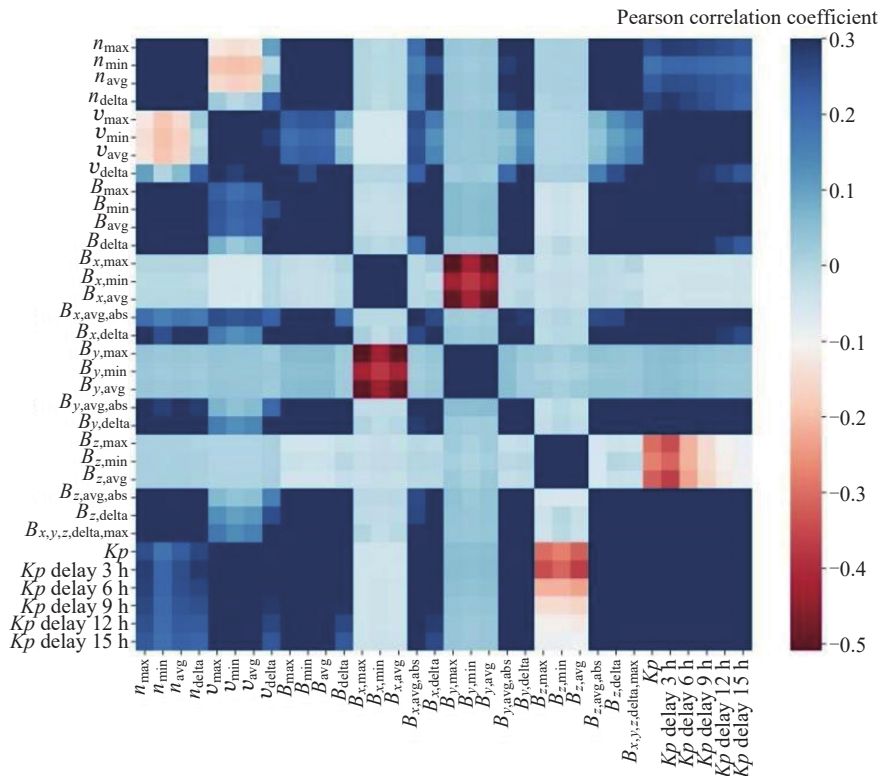


Fig. 2 Thermodynamic diagram for MMA feature construction

baseline measure of the field's strength in each direction, mitigating potential normalization issues. The correlation analysis in Figure 2 confirms that these constructed features, particularly $B_{z,\text{delta}}$, exhibit a strong linear relationship with the Kp index, validating their physical relevance for prediction.

Moreover, here the features with correlation value 0 of the geomagnetic index Kp : $B_{x,\text{max}}$, $B_{x,\text{avg}}$, $B_{x,\text{min}}$, $B_{y,\text{max}}$, $B_{y,\text{avg}}$, $B_{y,\text{min}}$ are removed. Consequently, through the means of DM feature construction and feature selection, the 23-dimensional solar wind input feature parameters are built and shown in Table 1.

This feature engineering strategy is designed to extract the physically significant information embedded in the IMF vector while ensuring numerical stability for model training. The absolute values (*e.g.*, $B_{x,\text{avg,abs}}$) provide a stable measure of the field's magnitude in each direction, circumventing potential normalization issues inherent to signed parameters. Crucially, the range parameters (*e.g.*, $B_{z,\text{delta}}$) are engineered to capture the dynamic variability of the IMF, which is a key proxy for its geoeffectiveness. Large fluctuations in these components, particularly in the B_z direction, are directly linked to enhanced energy transfer into the magnetosphere through magnetic reconnection.

1.2 Dynamic and Location Information of

Coronal Hole in EUV Images

The geomagnetic impact of coronal holes exhibits strong positional dependence. During solar rotation and Earth's orbital motion, coronal holes located near the central meridian of the solar disk demonstrate the most significant influence on geomagnetic activity, while polar coronal holes show minimal effects^[14,15]. Extended coronal

holes spanning from polar regions to approximately 20° in the opposite hemisphere progressively enhance their geomagnetic influence as they approach the disk center^[16].

Figure 3 illustrates this spatial dependence through a sequence of SDO/EUV images (panels a~d). The series clearly reveals that coronal holes generate the strongest Kp index response when positioned near the central meridian. Furthermore, coronal holes in the left hemisphere produce more pronounced effects than those in the right hemisphere or near the solar limb. These observations confirm that accurate geomagnetic prediction requires analyzing both the dynamic evolution and positional characteristics of coronal holes across the solar disk.

The forecasting framework maintains precise temporal synchronization through a structured 3 h sliding window approach. The processing pipeline ensures exact alignment between input features and prediction targets by operating on synchronized 3 h intervals corresponding to the native Kp index cadence. For each prediction window, the system exclusively utilizes solar observations completed prior to the target interval, thereby preserving causal relationships. This architectural design inherently eliminates temporal discrepancies without requiring post-processing corrections, while effectively capturing the evolutionary dynamics visualized in Figure 3.

To accurately determine coronal hole locations, a quantitative image processing pipeline was developed to extract position information from SDO/EUV images. It should be noted that the latitude and longitude coordinates used in this analysis refer to the projected coordinate system of the solar disk as observed from Earth, which differs from standard heliographic coordinates. This projected coordinate system enables a specific focus on the central regions of EUV images that demonstrate the strongest influence on Kp index variations. The data processing workflow, illustrated in Figure 4, consists of three main stages.

(1) Solar disk alignment *via* Hough transform: the Hough transform is first applied to automatically detect the solar limb and precisely determine the disk center. This step establishes an accurate reference frame for all subsequent coordinate calculations.

Table 1 23 features of solar wind parameter with DM construction

Feature construction	Parameters of solar wind
max	n, v, B, B_z
min	n, v, B, B_z
avg	n, v, B, B_z
delta	n, v, B, B_x, B_y, B_z
avg_abs	B_x, B_y, B_z
max (difference of absolute value)	$\max(B_{x,\text{delta}}, B_{y,\text{delta}}, B_{z,\text{delta}})$
true	Kp

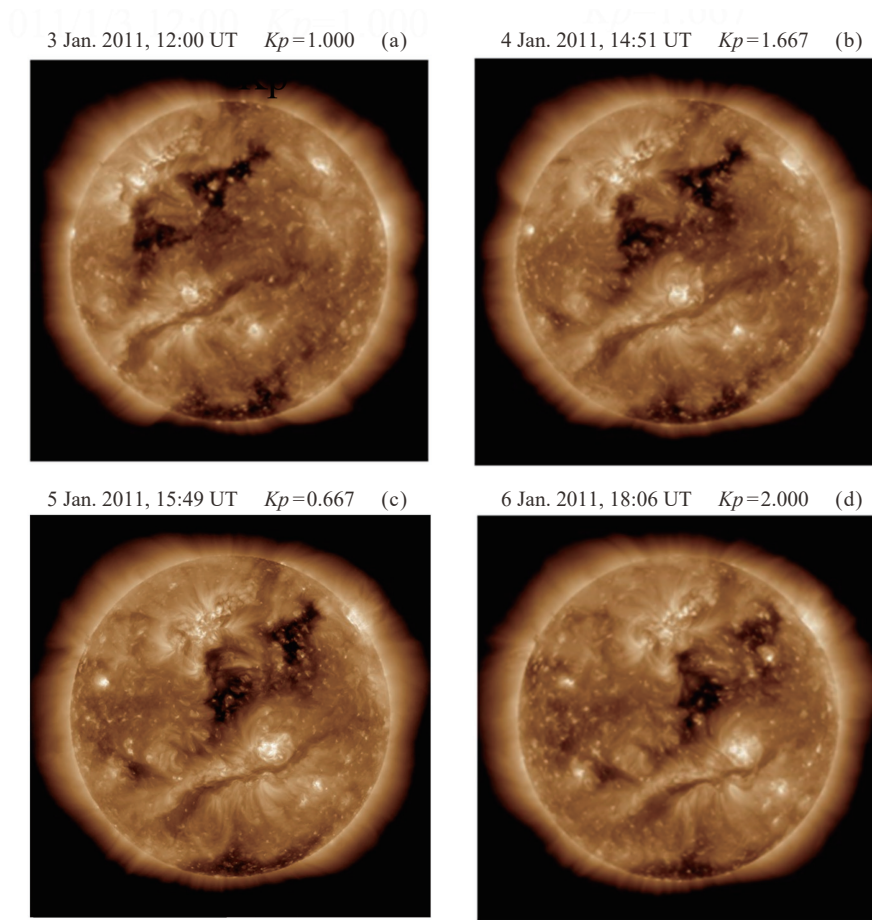


Fig. 3 Images of the dynamic coronal hole with time from SDO

(2) Coordinate transformation and noise masking: the image coordinates are transformed from the original Cartesian (x, y) system into a latitude-longitude grid. During this process, noise masking is applied to suppress artifacts outside the region of interest.

(3) Projection to a 2D map: the three-dimensional spherical coordinates of the solar surface are mapped onto a two-dimensional rectangular grid. This projection facilitates the straightforward identification and tracking of coronal holes.

Figure 4(a) shows a schematic of the coordinate transformation geometry. Point O denotes the Sun's center, with r representing the solar radius. The horizontal plane defines the equatorial plane, while the vertical plane through O constitutes the central meridian (0° longitude plane). For point P on the solar surface, its latitude α is defined as the angle between the radius vector OP and the equatorial plane. The longitude β corresponds to the dihedral angle between the meridian plane

containing P and the central meridian plane. The projected lengths are derived as follows: $MP = r \sin \alpha$ represents the latitudinal component, while $QN = r \sin \beta$ gives the longitudinal component, accounting for the reduced radius of the parallel circle at latitude α . This coordinate transformation enables accurate mapping of coronal hole positions from spherical to planar coordinates. Figure 4(d) shows the result of the Hough transform. The original solar disk image in Figure 4(c) has a resolution of 512×512 pixel with its center at coordinates (256, 256). The Hough transform calculated a circle center at (254, 254) and a solar disk radius of 200 pixel. Figure 4(b) shows the longitude-latitude mapping network derived for the 2D image. This graticule consists of longitude and latitude lines at 15° intervals, covering the ranges of 90°E to 90°W and 90°N to 90°S , respectively.

1.3 Evaluation Indicators and Parameters for Kp Prediction of Multimodal Solar Data

In the field of deep learning, the confusion matrix is

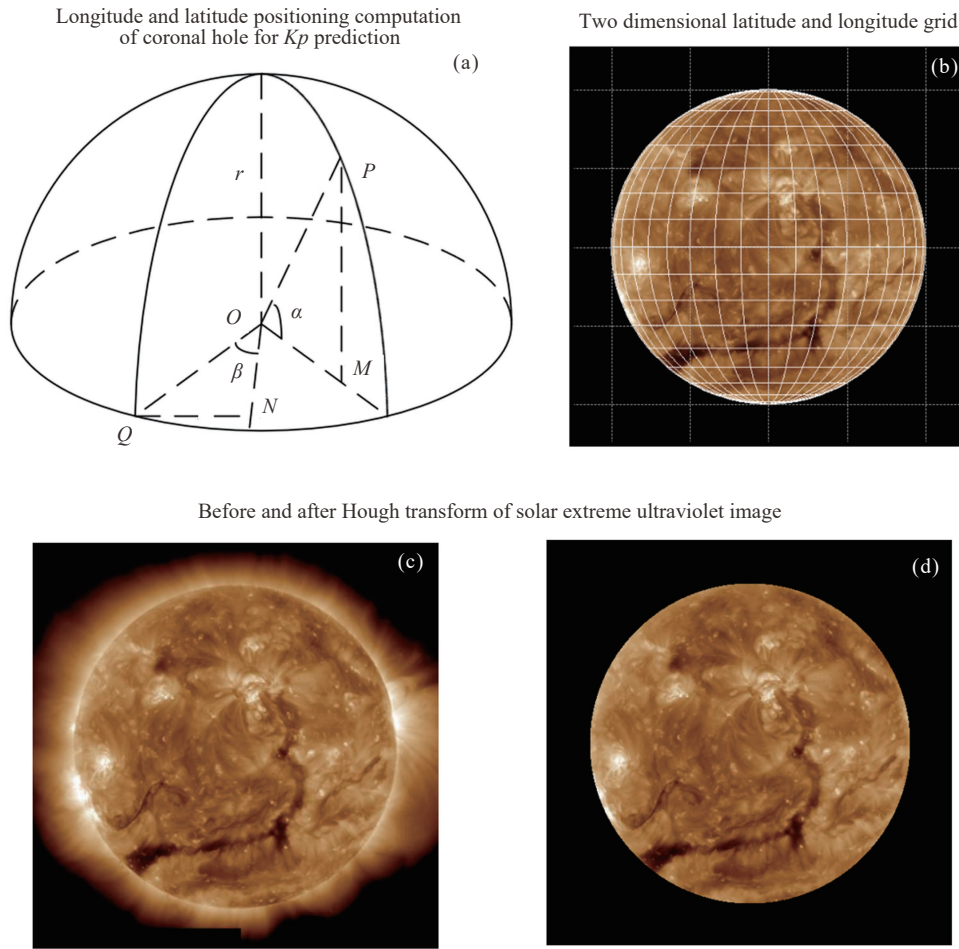


Fig. 4 Quantification process of the position information of the solar extreme ultraviolet image

commonly used to evaluate performance, especially for pattern classification. Due to the differences in the equilibrium and statistical characteristics of the sample data, this study follows the evaluation indicators in the field of space weather, *i.e.*, RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), Pearson Correlation Coefficient (CC) and SD (Standard Deviation).

MAE represents the mean of the absolute error between the predicted value and the true value of all samples, the smaller the MAE, the smaller the absolute error between the predicted value and the true value, that is, the closer to the true value, the better the model effect. RMSE indicates how much the model's predicted value deviates from the true value, and the smaller the RMSE, the smaller the deviation between the predicted value and the true value, that is, the better the model.

The Pearson correlation coefficient shows the linear correlation between the predicted value and the true va-

lue, which is calculated by using the following formula

$$R = \frac{\sum_{n=1}^N (f_n - \bar{f})(r_n - \bar{r})}{\sqrt{\sum_{n=1}^N (f_n - \bar{f})^2} \sqrt{\sum_{n=1}^N (r_n - \bar{r})^2}}, \quad (2)$$

where $f_n, \bar{f}$ represent predicted value and the mean of the samples, respectively, $r_n, \bar{r}$ represent the truth and the mean of the samples, and N is the total number of samples. The larger the correlation coefficient, the higher the correlation between the predicted value and the true value, and the better the predictive model will be.

SD is the arithmetic square root of the variance, defined as the square root of the arithmetic mean of the squared values for the difference between each sample value and the mean of the overall sample value. SD is used to reflect how discrete a set of data is, and the smaller the SD, the less discrete the data. For simplicity, detailed formulas are no longer listed here.

2 Deep Learning Prediction Models of Kp Index for Solar Big Data

2.1 Direct Kp Prediction of Solar Wind Parameters-based (DKPW)

Geomagnetic storms are a typical catastrophic event of space weather, and one of the main origins is the coronal hole. With the violent eruption of the sun, the high-speed stream of charged particles ejected outward from the coronal hole quickly forms a high-speed solar wind, which is coupled with the interplanetary magnetic field to produce a huge amount of energy brought into the geomagnetic field and finally cause geomagnetic storms^[13,16–18].

During the eruption of solar storm, the EUV of images information observed by SDO will affect the geomagnetic field in 3~4 days, the solar wind monitored by ACE will affect the geomagnetic field in 0.5~2 h respectively, obviously the solar wind parameters do not contain enough information to predict in more advanced time, that is to say, the EUV images contain information about magnetic storms earlier than the solar wind data.

Based on feature construction and selection, this study designs a Direct Kp Prediction of solar Wind parameters-based (DKPW), shown as the red solid arc in Figure 5. Because the correspondence between the characteristics of EUV images and the geomagnetic index, which could be regarded as a label here, is unique and not fixed when the EUV images are applied to predict Kp index, thus poor performance may result, so a multimodal prediction model combining solar wind data with EUV images is proposed. The multimodal and Multi-scale Kp Prediction EUV Image-based (MKPI) will firstly forecast the solar wind speed based on EUV images, as shown by the bright blue dashed line in Figure 5, then apply the obtained parameter of solar wind speed to forecast the geomagnetic index indirectly, as shown by the bright blue solid arc in Figure 5. Consequently MKPI method not only improves the forecast accuracy, but al-

so achieves more advanced time for space weather warning and forecasting.

The Long Short-Term Memory (LSTM) network was employed for this study due to its proficiency in modeling temporal dependencies. This capability is essential for capturing the dynamic nature of the coronal hole evolution process and has proven effective in related domains^[19], such as forecasting the solar radio flux index $F_{10.7}$ ^[20]. In the DKPW prediction networks, the pre-processed solar wind time series dataset is the network input, and the geomagnetic index Kp is the network output^[21,22].

Because of the fact of the periodicity of solar activities, the time series properties of the geomagnetic index, and the samples of magnetic storms are much less than the samples without magnetic storms, especially, the larger the Kp is than 7, the less of the samples, thus the yearly dataset is preferred rather the random segmentation, since the latter tends to have the training and sample sets unevenly distributed. However, the way of yearly division does not ensure homogeneity between the training and test datasets. Therefore, in this experiment, the proportion between samples with and without magnetic storms is guaranteed same as between the training set and the test set. The experimental results of 2012 and the random division datasets could be achieved and illustrated in Table 2.

It can be seen that the best performance at 3 h prediction range has been achieved through direct prediction by solar wind while the dataset is divided by year, and RMSE is 0.656, MAE is 0.505, and CC is 0.866. Furthermore, compared with random data, the indicators of RMSE and MAE decrease 2.8%, 4.3% respectively, and CC increases 1.6%.

2.2 Multimodal and Multi-scale Kp Prediction EUV Image-based (MKPI)

EUV images contain earlier information on the solar wind, which means they could predict Kp index in advance. However, due to solar eruption leading to the vio-

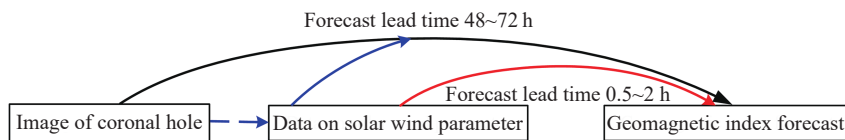


Fig. 5 Different forecasting procedures for Kp prediction in terms of ACE parameters and SDO images

lent changes in the shape and position of coronal holes, it is impossible to extract the relatively fixed relationship between the feature of EUV images and Kp index, for example, EUV images features maybe very different under the same Kp label value, or similar EUV images maybe assigned different Kp labels, so an indirect geomagnetic index prediction method is designed for multi-scale Kp prediction based on multimodal data including solar wind and EUV images, simplified MKPI. Firstly, the solar wind speed is predicted *via* EUV images, and then it is combined with other solar wind parameters to compute and predict Kp index, as shown in the deep learning schematic of multimodal solar data for Kp prediction in Figure 6.

The deep learning multimodal Kp prediction model based on EUV images is composed of two processes: the first is to predict the solar wind speed by EUV images, as shown by the module of bright blue dashed line in Figure 6, and the second is to adopt the obtained solar wind speed with other solar wind parameter data as the input data of Kp prediction networks, as shown in the module of orange dotted dash line in Figure 6.

Table 2 Comparison of prediction between random and yearly dataset of DKPW

Dataset form	RMSE	MAE	CC
Random	0.675	0.528	0.852
Yearly	0.656	0.505	0.866

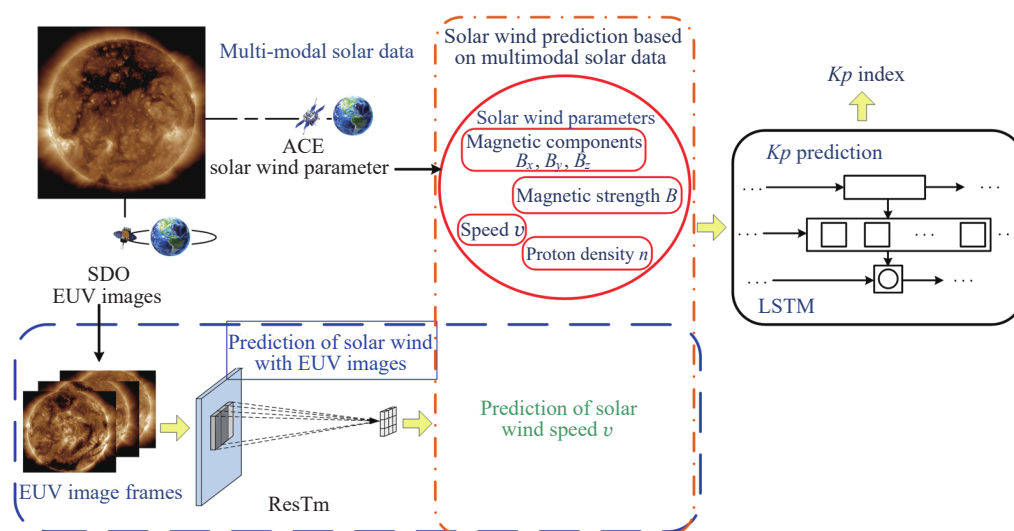


Fig. 6 Deep learning schematic of multimodal solar data for Kp prediction

Firstly, the convolution neural network is applied to extract the features of EUV images in time series, and then the features in different time scales are input to the recurrent neural network, the LSTM network module calculates and outputs the multi-scale Kp index values, as shown in the module of the black solid line in Figure 6. In processing the timescale features of EUV images, here a deep learning type of ResTm networks is designed in terms of ResNet and LSTM models.

Next ResTm deep learning diagram for Kp prediction of EUV images is shown in Figure 7, including the top ResNet and the bottom LSTM. On the left of ResNet the feature map and the number of channel $\times$ height $\times$ width are listed, *i.e.*, if the input is $64\times128\times256$, that indicates the image has a channel of 64, a height of 128, and a width of 256. After experimental verification, ResNet18 model has shown good performance, but the efficient improvement of ResNet50 model, with high time-consuming, is not obvious in performance, so here ResNet18 is chosen and applied as the basic structure.

Simultaneously, in order to maximize the performance of the whole model, here ResTm is no longer defined by the term of the full connection layer of ResNet18, instead of that the width of the final feature map is adjusted as a hyperparameter by using the automatic mean pooling technique. On the solar wind speed prediction task, ResNet18 achieved comparable performance to ResNet50 (correlation > 0.8 in Figure 8) with significantly reduced computational cost, making it the

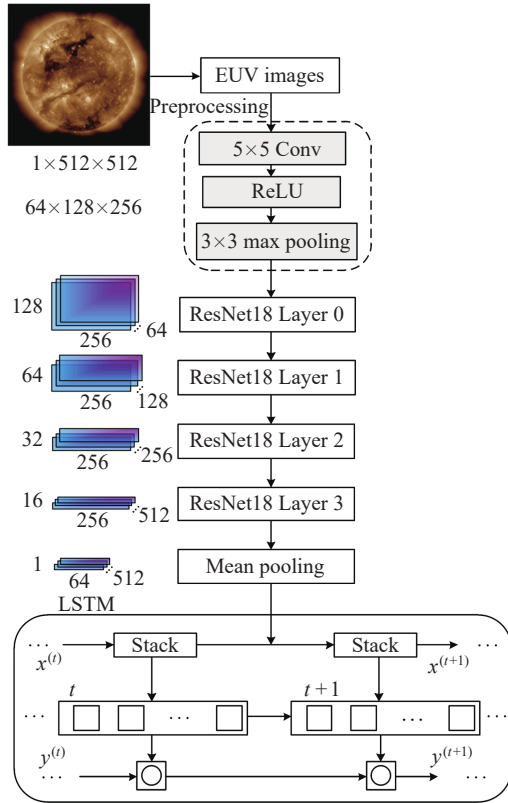


Fig. 7 ResTm deep learning diagram for Kp prediction by EUV images

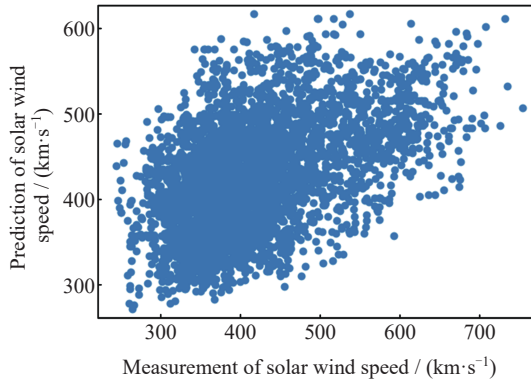


Fig. 8 Scatter plot of correlation between measurement and prediction value of solar wind speed

optimal choice for our application. When the ResNet18 model computes the input EUV images, the height of the output feature map is transferred to 1, which is suitable for the input requirement for LSTM, then the time series data are loaded into the bottom LSTM in Figure 7.

Finally, the LSTM time step is designated as the width from feature map extraction, and the input dimen-

sion of the LSTM step is designated as the number of channels. For more detailed super parameters, after try and trial experiments, LSTM time step 64, the number of hidden layers 2, and with 512 neurons in each layer are chosen and designated, simultaneously the learning rate 10^{-4} , the optimizer Adam function, and the loss function SmoothL1 loss.

3 Deep Learning Experiments and Results of Multimodal and Multi-scale Solar Big Data for Kp Prediction

3.1 Feasible Prediction of Solar Wind Speed via EUV Images

Compared to solar wind parameter data, EUV images have more abundant physical significance, but more noise. For example, one sheet of EUV images may contain several types of solar activities due to the coronal holes, and the corona is generally on the same violet wavelength images. Though deep neural networks are designed to extract image features, but mostly focus on the local connection between pixels, so different features of solar activity on EUV images may confuse each other, which will cause less accuracy in image processing.

The means of indirect prediction for solar wind speed via EUV images is feasible that the scatter plots verify the matched data in Figure 8. The horizontal axis represents the true value of solar wind speed, and the vertical axis represents the predicted value of solar wind speed. It can be seen that the predicted value and the true value of solar wind speed are strongly relevant. Consequently, earlier information on solar wind speed will provide adequate and instructive data to assure the prediction of the geomagnetic index from EUV images.

3.2 Multimodal and Multi-scale Kp Prediction EUV Image-based (MKPI)

Since EUV images of 193 on coronal hole from SDO contain earlier information of solar eruption than the information of solar wind data influencing the geomagnetic near the Earth, in order to predict Kp and warn of geomagnetic storms in advance time, a multimodal Kp index prediction scheme based on solar wind speed was proposed and designed in Section 2.2.

To fully compare and analyze the prediction performance, on the basis of inspecting RMSE, MAE and CC above, the evaluation index SD (Standard Deviation) is computed too, *i.e.*, the arithmetic square root of variance, which could reflect the degree of dispersion of a set of data. SD is calculated as

$$\sigma_f = \sqrt{\frac{1}{N} \sum_{n=1}^N (f_n - \bar{f})^2}, \quad (3)$$

where $f_n, \bar{f}$ represent the predicted value and the mean of the samples, respectively, N is the total number of samples. The smaller the SD, the less discrete the data. The experiments in this section are based on the solar data from 2011 to 2019^[22].

Performance of Kp index prediction based on solar wind prediction at different advanced time scales is shown in Table 3. The advance time represents the prediction range where the unit is hour. When the prediction range is 3 h, the performance is the best. With the extension of the prediction range, RMSE and MAE increased, SD and CC gradually decreased, which means the performance became worse continuously. Whereas, while the prediction range was from 3 h to 9 h, the performance was significantly different, only from 3 h to 6 h, RMSE increases by 42.86%, MAE increases by 107.69%, and SD and CC decrease by 26.17% and 16.28%, respectively. Till the prediction range exceeds 9 h, the difference between adjacent prediction ranges becomes smaller and smaller, revealing that the sensitivity of the performance indicators decreases with the extension of the prediction range. Even at a prediction range of 45 h, the SD and CC mutations are 0, indicating that the model loses its predictive capability.

3.3 Kp Prediction EUV Image-based with Coronal Hole Location Information (KPCL)

It is well-known that there are significant advantages for deep learning in mining massive data to explore the connection between data and phenomena, discover the rules between phenomena and facts by virtue of mapping, reasoning and judgment of complex neural networks. On space weather forecast and warning, coronal holes in the central region of EUV images contribute mostly to geomagnetism, but the relation between the coronal hole images and Kp in the previous two methods, DKPW and MKPI, in previous sections. To pursue greater performance and bring forward the forecast time earlier, this

Table 3 Advance time and performance of Kp prediction with MKPI

Advance time/h	RMSE	SD	MAE	CC
3	0.63	1.07	0.39	0.86
6	0.90	0.79	0.81	0.70
9	1.00	0.67	1.00	0.63
12	1.05	0.58	1.1	0.57
15	1.05	0.48	1.11	0.52
18	1.07	0.45	1.15	0.47
21	1.10	0.37	1.22	0.42
24	1.13	0.31	1.27	0.38
27	1.15	0.25	1.32	0.33
30	1.16	0.20	1.35	0.30
33	1.18	0.15	1.39	0.24
36	1.19	0.11	1.41	0.18
39	1.19	0.09	1.43	0.15
42	1.20	0.07	1.43	0.16
45	1.21	0.00	1.45	0.00

section will investigate and verify the relationship between coronal hole factors and geomagnetic indices through the experiment.

In order to expand the advanced time of prediction, the EUV image deep learning geomagnetic index prediction of multimodal data will take the information of location and area of coronal hole factors into account, for simplicity, noted as KPCL. The first step of KPCL is to quantify the solar EUV images by the method of Section 1.2, compute the coronal hole factors related to the information on position and area of coronal holes, the second is to join the solar wind parameters obtained by feature structure and feature selection in Section 1.1 to together input into the prediction network, also, the LSTM model in Section 2.2 is adopted for the geomagnetic index prediction module. Therefore, as the output of the network, the final prediction result is obtained, as shown in Table 4.

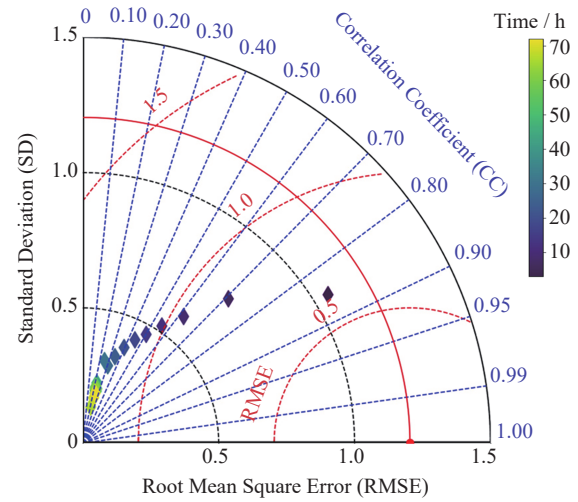
It could be seen that when the prediction range exceeds more than 33 h, CC value still oscillates around 0.23, and as the prediction range extends about 72 h, KPCL still illustrates predictive ability, these results show that KPCL utilizes the information of EUV images of the solar surface and consequently achieves the goal to predict Kp from the source of geomagnetic storms. The stable correlation (about 0.23) beyond 33 h arises from KPCL capturing recurrent space weather pat-

Table 4 Earlier advance time and better performance of K_p prediction of KPCL

Advance time/h	RMSE	SD	MAE	CC
3	0.63	1.06	0.4	0.85
6	0.93	0.76	0.87	0.71
9	1.05	0.60	1.10	0.62
12	1.08	0.52	1.17	0.56
15	1.10	0.46	1.21	0.50
18	1.13	0.43	1.28	0.45
21	1.14	0.38	1.31	0.39
24	1.16	0.34	1.34	0.35
27	1.18	0.30	1.39	0.30
30	1.18	0.32	1.40	0.25
33	1.18	0.21	1.38	0.24
36	1.18	0.20	1.38	0.23
39	1.18	0.19	1.39	0.23
42	1.19	0.21	1.39	0.22
45	1.18	0.23	1.38	0.23
48	1.18	0.21	1.39	0.23
51	1.18	0.20	1.39	0.25
54	1.17	0.21	1.38	0.25
57	1.18	0.22	1.39	0.22
60	1.18	0.21	1.39	0.22
63	1.18	0.20	1.38	0.24
66	1.18	0.21	1.40	0.23
69	1.18	0.20	1.39	0.23
72	1.18	0.19	1.38	0.24

terns. Persistent coronal holes create repeating solar wind streams with about 27-day periods. While predicting exact K_p intensity becomes harder (increasing RMSE/MAE), the model maintains timing prediction capability for geomagnetic activity onset, yielding stable correlation coefficients. Thus, KPCL method successfully extends the effective prediction of K_p index to 3-day.

To clearly discuss the prediction results, a Taylor diagram is drawn to illustrate the performance that could represent RMSE, CC and SD in the same figure as shown in Figure 9. In the Taylor diagram, each point simultaneously represents the root mean square error RMSE, the standard deviation SD and the correlation coefficient CC between the predicted value and the true value of K_p . The red solid dot on the horizontal axis represents the true value of the K_p index, and the solid red line is SD of the true value, and the black lines are the tick marks related SD, the closer to the true value, the better the performance. The red dashed lines are tick

**Fig. 9** Taylor chart of K_p performance including coronal hole factor

marks related to RMSE, similarly, the smaller the radial distance, the better the performance. And the blue line is CC, the smaller the angle to the horizontal axis, the stronger the relationship with the true value.

In Figure 9, with the increasing of forecast lead time, the larger of RMSE, the declining of correlation and prediction performance. On the other hand, since the solar images are directly applied for KPCL, the forecast lead 3-day have been realized, and the correlation between the predicted value and the true value could still remain at about 0.23 or so.

3.4 Comparison and Analysis of Multi-scale K_p Prediction Using Multimodal Solar Data Deep Learning

This section provides a comprehensive comparative analysis of the three proposed models (DKPW, MKPI, and KPCL) using Taylor diagram visualization. The analysis focuses on quantitative performance metrics across forecast horizons ranging from 3 h to 72 h.

The Taylor diagram in Figure 10 enables simultaneous comparison of three key statistical metrics through its visual representation: correlation coefficient (angular coordinate), standardized standard deviation (radial distance), and root-mean-square error (concentric circular lines). This integrated visualization reveals distinct performance patterns among the models across different forecast horizons.

In short-term forecasting (3~6 h), all three models demonstrate comparable performance, with correlation coefficients exceeding 0.85 and minimal differences in

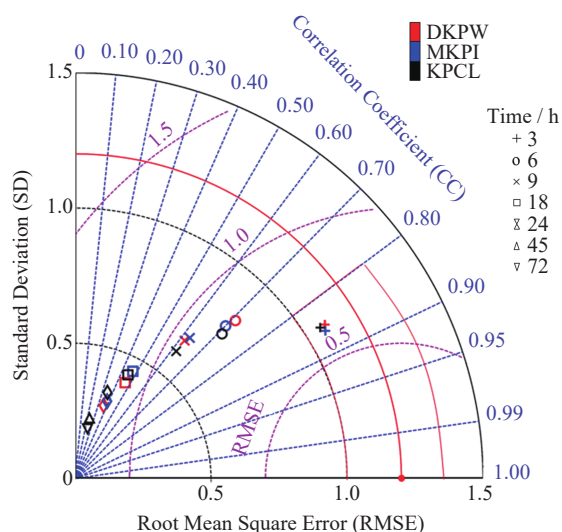


Fig. 10 Taylor chart of K_p prediction and performance comparison of three methods

RMSE (0.63~0.66). This indicates that for immediate predictions, the additional complexity of multimodal approaches provides a limited advantage over the baseline DKPW model.

As we extend to medium-term forecasting (9~18 h), the MKPI model shows distinct advantages by maintaining correlation above 0.63 at 9 h and 0.47 at 18 h, while DKPW performance deteriorates more rapidly. This demonstrates the value of incorporating EUV images for medium-range predictions, as the model can leverage earlier solar information beyond what's available from L1 point solar wind measurements alone.

For long-term forecasting (24~72 h), KPCL exhibits superior performance preservation, maintaining approximately 0.35 correlation at 24 h and stabilizing around 0.23 from 33 h to 72 h. This sustained performance stems from the model's ability to capture recurrent geomagnetic activity patterns driven by persistent coronal holes, which typically exhibit 27-day recurrence periods.

The progressive performance advantage of increasingly sophisticated models with extended forecast horizons underscores the critical importance of incorporating solar source information for long-range space weather prediction. While DKPW relies solely on immediate solar wind conditions, MKPI integrates earlier EUV observations, and KPCL further incorporates coronal hole location data. Each additional information source extends the useful prediction horizon, demonstrating that

the degradation of prediction accuracy with extended lead times can be effectively mitigated through strategic incorporation of multi-modal solar data. KPCL achieves the most substantial extension of useful forecast capability to 72 h, representing a significant advancement in space weather forecasting.

4 Discussion and Conclusion

This study has developed and validated a series of advanced deep learning frameworks for multi-scale K_p geomagnetic index prediction, systematically demonstrating the value of integrating multi-modal solar data. Our work establishes that the strategic incorporation of solar source imagery—from EUV observations to quantified coronal hole parameters—significantly extends prediction horizons beyond traditional methods relying solely on solar wind measurements.

The three proposed models each demonstrate distinct advantages across different forecast horizons. For short-term predictions (0~6 h), the LSTM-based DKPW model provides optimal performance with correlation coefficients exceeding 0.85 using only solar wind parameters. In the medium range (6~24 h), the MKPI model delivers superior results by incorporating EUV images to predict solar wind speed in advance, effectively bridging solar observations and L1-point measurements. For extended predictions (24~72 h), the KPCL model maintains stable correlations (about 0.23) by leveraging coronal hole recurrence patterns, enabling unprecedented capability for identifying geomagnetic activity timing days in advance.

Compared to existing K_p forecasting studies that typically achieve about 12 h prediction horizons, our approaches extend this boundary to 72 h while maintaining quantifiable skill. This represents a substantial advancement for operational space weather forecasting, where extended warning times significantly enhance mitigation strategies for geomagnetic disturbances.

While acknowledging limitations in current architectures and dataset coverage, particularly in long-term prediction accuracy, we propose concrete improvement strategies including: multi-wavelength solar imagery integration, transformer-based architectures for capturing spatiotemporal dependencies, physics-informed data augmentation, transfer learning methodologies, and en-

semble methods. These approaches address the current constraints while building upon our demonstrated achievements.

In summary, this research establishes a scalable deep learning framework for heterogeneous space data. By addressing the current limitations, this work paves the way for operational medium to long-term space weather forecasting^[20], ultimately advancing toward more reliable prediction systems to better protect modern technological infrastructure.

Conflict of Interests The authors declare that there is no conflict of interests

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