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A Prediction Model for the Summer Western Pacific Subtropical High

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Abstract

The Western Pacific Subtropical High (WPSH) is a key atmospheric circulation system regulating extreme weather events in East Asia, yet its prediction remains challenging. In this study, we developed a prediction framework to individually forecast the WPSH for June, July, and August using the global monthly 500hPa eddy geopotential height (He500) during 1951–2024. The framework integrates predictors extraction with a Multi-head Attention (MHA) based Temporal Convolutional Network (MHA-TCN). Specifically, the principal components (PCs) from the Empirical Orthogonal Function (EOF) were employed in an Automatic Clustering Algorithm to derive 584 potential factors including multiple monthly indices. From these candidates, the 100 optimal predictors were selected based on the composition of Embedding layer weights and Attention query weights, and subsequently incorporated into the prediction model based on Attention mechanism. The results show that the proposed model exhibits substantial predictive skill for the monthly evolution of the WPSH from June to August. The correlation coefficients (R) between the predicted and observed monthly WPSH area and intensity index reach 0.64 and 0.72, respectively, significantly outperforming the ECMWF seasonal forecast system (EC). Model comparison experiments further demonstrate that both the predictor extraction and the MHA mechanism are indispensable for ensuring prediction stability. The prediction model also effectively captured WPSH distribution of extreme years in 2020 and 2023, whereas the EC system underestimated the intensity and displaced the center. Interpretability analysis further identifies the dominant predictors for each month and reveals the related physical mechanisms underlying WPSH predictability. These results show the potential of combining physically informed predictor extraction with attention-based deep learning for seasonal climate predicting of the WPSH.

Keywords: Western Pacific Subtropical High, deep learning, prediction, eddy geopotential height, interpretability analysis

1 Introduction

The Western Pacific Subtropical High (WPSH) is a pivotal circulation system that regulates the East Asian climate, the area, intensity and location of WPSH affects the East Asian climate significantly (Zhou et al 2009), including monsoon progression (He et al 2007; Chen and Huang 2012), distribution of drought and flood in China (Zhao et al 2020; Chen and Zheng 2025), the activities of tropical cyclones (Ho et al 2004; Zhou and Yu 2005; Wang et al 2013; Fan et al 2022),

and the occurrence of extreme weather (Yang and Sun 2003; Liu et al 2019; Cao et al 2022; Chen and Zheng 2025; Wu et al 2025). Therefore, effective prediction of the WPSH is of great importance for climate prediction in East Asian (Gan et al 2026).

Previous studies have indicated that the WPSH has significant seasonal predictability, integrating and bridging climate signals from various global oceans effectively (Pan and Lu 2022), while El Niño Southern Oscillation (ENSO) is considered to be the dominant source of predictability for interannual fluctuations of the WPSH (Zhou et al 2019). According to Ye et al (2025), the predictable signals for the WPSH over the past century have predominantly been rooted in the tropical central-eastern Pacific, the tropical North Atlantic, and the Indo-Pacific. In recent years, the WPSH prediction signal has been further mined. By employing the causality of information flow method, Liu et al (2025) identified key predictors beyond ENSO signals, revealing that the springtime Pacific Meridional Mode (PMM) affects the dominant WPSH modes significantly. Gan et al (2026) suggested that the springtime Atlantic sea surface temperature anomalies become the crucial predictor for summertime WPSH intensity and that these anomalies continue to strengthen in the 21st century (Hong et al 2015; Wang and Yu 2018). Tseng and Ho (2024) revealed that a dipole vorticity pattern over the Philippine, South China Sea (SCS) and Japan serves as key precursor. In addition, the Pacific–Japan (PJ) pattern and the Madden–Julian oscillation (MJO) are important teleconnections modulating the WPSH and East Asian summer climate (Nitta 1987; Huang and Sun 1992; Wang et al 2022; Hu et al 2023; Zhao et al 2025). Therefore, under the background of global warming, extracting significant predictors from numerous signals remains a challenge for improving the prediction efficiency of the WPSH.

At present, WPSH prediction mainly depends on numerical models and statistical models. Existing mainstream model data reasonably predict the location and intensity of the WPSH in early summer, but perform poorly for the persistent and enhanced midsummer period (Ma et al 2023). The Beijing Climate Center Atmospheric General Circulation Model (BCC_AGCM2.2) not only exhibits a bias in simulating the position of the WPSH but also underestimates its area and intensity (Liu et al 2021). The Asia-Pacific Economic Cooperation Climate Center (APCC) has employed a multi-model ensemble (MME) seasonal forecast system (Min et al 2017), while the APCC MME has limitations in reproducing air-sea interactions, leading to a misrepresentation of the well-organized meridional wave train propagating from the Philippine Sea, which in turn causes significant deviations in WPSH prediction (Kim and Lim 2023). This limitations can be more

significant in extreme events. The decadal climate prediction system IAP-DecPreS, developed by the State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, simulated the extreme northward shift of the WPSH in 2021, and the unpredictable component of atmospheric internal variability reached 72% (Hu et al 2023). Meanwhile, the predictive capacity of statistical models have been diminishing under the influence of global warming. Gan et al (2026) pointed out that the linear statistical model established by Wang et al (2013) has exhibited potential limitation and significant skill degradation after 2000. Therefore, there is an urgent need to develop models capable of mining spatiotemporal correlation and exhibiting strong nonlinear predictability, so as to break through the limitations of current models.

To overcome the limitations of existing models, this study developed a predictive framework that combines predictors extraction with a Multi-head Attention mechanism (MHA) based Temporal Convolutional Network (TCN), achieving spatial prediction of the WPSH with a six-month lead time, thus providing a robust technical approach for seasonal climate predicting. This study is organized as follows. Section 2 presents the data and method. Section 3 examines the prediction results and possible physical mechanism. Section 4 summarizes the research.

2 Data and Methods

2.1 Data

This study utilizes the monthly reanalysis data product from European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis fifth-generation (ERA5) for potential factors mining and physical mechanism analysis of the WPSH, including 100hPa, 200hPa, 500hPa, 850hPa geopotential height (H100, H200, H500, H850), sea level pressure (SLP), sea surface height (SSH), sea surface temperature (SST), downward long-wave radiation flux (dLW), net long-wave radiation flux (nLW), downward short-wave radiation flux (dSW), net short-wave radiation flux (nSW), surface latent heat flux (LHF), surface sensible heat flux (SHF). The indices used in this study include monthly climate/oceanic indices provided by the Physical Sciences Laboratory (PSL) of the National Oceanic and Atmospheric Administration (NOAA), the monsoon index defined by Li and Zeng (2002), and 130 monitoring indices provided by the National Climate Center of the China Meteorological Administration (NCC). In addition, this study also uses the H500 prediction data provided by the ECMWF Seasonal Forecasts System (EC) for comparison. It should be noted that the initial month is March, and the lead time cover June, July and August.

2.2 Methods

2.2.1 Calculating indices

To avoid the artificial positive bias in traditional geopotential height (H) under global warming, which affects the information provided by WPSH prediction, Huang and Li (2015) suggested employing eddy geopotential height (He) as a replacement for H. Accordingly, this study calculates 500hPa He (He500) to characterize the spatial structure of the WPSH. Specially, the He500 is calculated by removing the background zonal mean, which is the zonal belt mean of H between 0° and 40° at 500hPa. Furthermore, Huang and Li (2015) followed the method of the NCC, the WPSH area index is defined as the total number of grid points where the He500 exceeds 10gpm within the domain of 0°–40°N and 110°E–180°, while the WPSH intensity index is defined as the accumulated values of He500 exceeds 10gpm within the same domain.

2.2.2 Prediction model

This study illustrates the detailed prediction workflow in Figure 1. Firstly, this study conducts Empirical Orthogonal Function (EOF) analysis on the monthly He500 from June to August (JJA) during 1951–2024, identifying the first three modes (EOFs) and principal components (PCs) as the necessary spatiotemporal patterns (Figure 1a). Specifically, conducting EOF analysis on He500 (longitude × latitude, month × year), the EOFs and PCs dividing into 1951–1996 and 2010–2024, which are served as the training set and independent testing set (the rest part is validation set), the predictor mining and mechanism analysis are based on the training set, then the predicted He500 can be reconstructed by EOFs in the independent testing periods.

For potential factors mining (Figure 1b), in addition to the established climate/oceanic indices, potential factors are identified based on correlation analyses between the monthly PCs and preceding monthly global variables during the training period, including He100, He200, He500, He850, SLP, SSH, SST, dLW, nLW, dSW, nSW, LHF, and SHF. Specially, the significant regions are defined using an Automatic Clustering Algorithm, a binary masks generated by selecting the statistical significance exceeding 99% confidence level, then grouping adjacent cells into distinct significant regions, where exceed 15 grid points are retained for regional averaging under the resolution of 5° × 5°.

After factors integrating, the dataset contains 584 potential factors, thereby a prediction model combining predictors extraction and prediction is developed for the WPSH prediction. The

composition of Embedding layer weights and Attention query weights is used to represent the importance of input predictors in the attention layer (Song et al 2025). Then, the weights for each predictor are accumulated over 100 iterations and normalized, and the 100 optimal predictors with the highest average importance are selected (Figure 1c).

The extracted 100 predictors are input into the MHA and two TCN blocks (MHA-TCN) (Figure 1d), which can capture long-term correlation between variables (Wan et al 2022). For model structure, the Convolutional Layer and Fully Connected Layer follow Kaiming initialization, while the Attention Layer utilizes Xavier initialization. For parameter settings, the model is optimized using Stochastic Gradient Descent (SGD) with a momentum of 0.9, a weight decay of 0.001, and an initial learning rate of 0.0002. For data preprocessing, the dataset is divided chronologically in an 8:2 ratio. Specifically, the period from 1952 to 2009 is used as the training set, within 1998–2009 serve as the validation set (accounting for 20% of the training period). The independent test set covers 2010–2024. Finally, the predicted PCs are reconstructed with the EOFs of the He500 decomposed by the EOF analysis in Figure 1a to obtain the predicted He500 field.

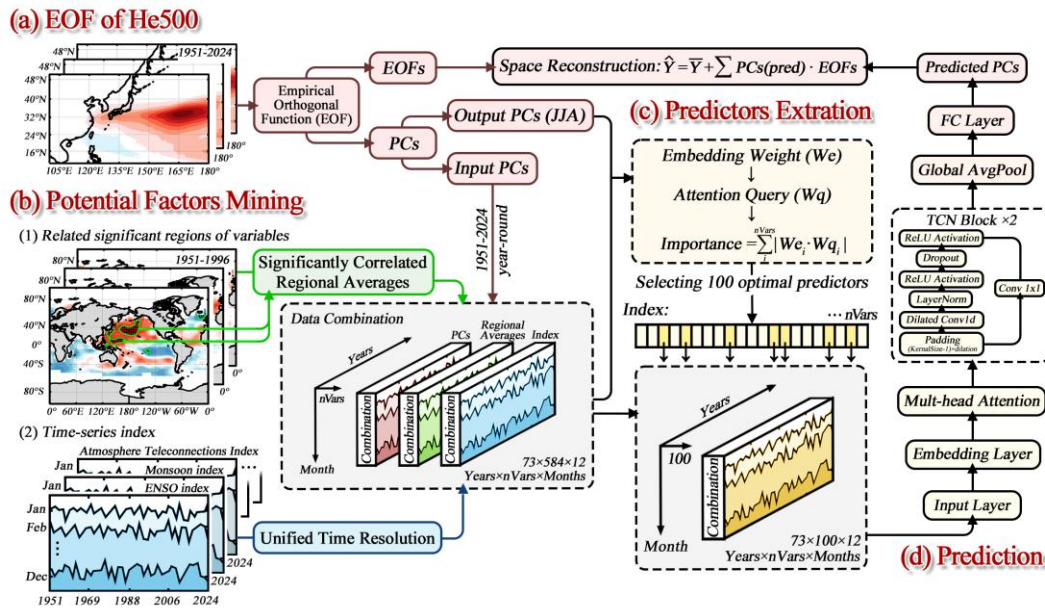


Figure 1. Schematic framework of the WPSH prediction workflow. (a) EOF analysis on the monthly He500 to obtain EOFs and PCs from June to August during 1951–2024. (b) Mining potential factors through the identification of significantly correlated regional averages of variables in training period (1951–1996) and established climate/oceanic indices, combining into a unified multi-dimensional dataset. (c) The predictors extraction process, 100 optimal predictors are selected based on the importance calculated from the Embedding

weights and Attention queries. (d) The prediction model structure, which can output the predicted PCs and uses them to reconstruct the spatial field of the WPSH.

2.2.3 Metrics

Notably, this study uses the root mean square error (RMSE) and two different correlation coefficient (R) are calculated as follows to analyze the evaluation of the model prediction accuracy. R^* is used for mining potential factors, and R is applied to assess the prediction skill due to the 15-year period for the independent test set (2010–2024), which measures the prediction skill of the variability (Qian et al 2025).

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (p_i - o_i)^2}{N}}, \quad (1)$$

$$R^* = \frac{\sum_{i=1}^N (p_i - \bar{p}) \times (o_i - \bar{o})}{\sqrt{\sum_{i=1}^N (p_i - \bar{p})^2} \times \sqrt{\sum_{i=1}^N (o_i - \bar{o})^2}}, \quad (2)$$

$$R = R^* \times \left(1 + \frac{1 - R^{*2}}{2(N - 4)} \right), \quad (3)$$

where N is the length of the targeted time series, p_i and o_i are the values of the prediction and observation, respectively, an overbar represents the average over all values.

3 Results

3.1 Dominant EOF modes of the WPSH interannual variability

Following the monitoring standard for the WPSH provided by the NCC, the EOF method is applied to decompose the monthly He500 field over the study region (90°E–180°, 10°N–50°N) for JJA from 1951 to 2024, in order to identify the dominant modes of interannual variability of the WPSH (Figure 2). In June (Figures 2a1–a3), the first three modes account for 32.27%, 19.61%, and 13.88% of the total variance, respectively. The EOF1 in June (Figure 2a1) exhibits a zonally distributed positive He500 anomaly with its center located eastward near 150°E–180°, while a negative anomaly appears to the north. EOF2 in June (Figure 2a2) exhibits a dipole structure in the zonal direction, and EOF3 in June (Figure 2a3) is dominated by a zonally extended positive

187 anomaly center. The corresponding PCs (Figures 2A1–A3) are predominantly characterized by
188 high-frequency interannual oscillations, with PC1 also exhibiting noticeable interdecadal
189 variability.

190 In July (Figures 2b1–b3), the variance explained by the first three modes is 29.40%, 18.37%,
191 and 14.68%. For EOF1 in July (Figure 2b1), the extent of the positive He500 anomaly gradually
192 contracts westward, with its center positioned further west and north than in June, while the
193 northern negative anomaly moves northeastward. For EOF2 in July (Figure 2b2), the positive
194 anomaly center shifts westward, and the negative anomalies to the southwest weaken, while EOF3
195 in July (Figure 2b3) features a negative-positive contrast between the Japan region and its eastern
196 sea region. The associated PCs (Figures 2B1–B3) emphasize pronounced interannual variability.

197 In August (Figures 2c1–c3), EOF1, EOF2, and EOF3 account for 24.48%, 18.39%, and 12.99%
198 of the variance, respectively. The EOF1 in August (Figure 2c1) positive anomaly continues to
199 contract, with its center and the northern negative anomaly both shifting further northeastward.
200 EOF2 in August (Figure 2c2) transforms into a distinct meridional dipole, while EOF3 in August
201 (Figure 2c3) exhibits a triple distribution across the study region. Similarly, the PCs (Figures 2C1–
202 C3) in August are dominated by interannual fluctuations across the entire study period.

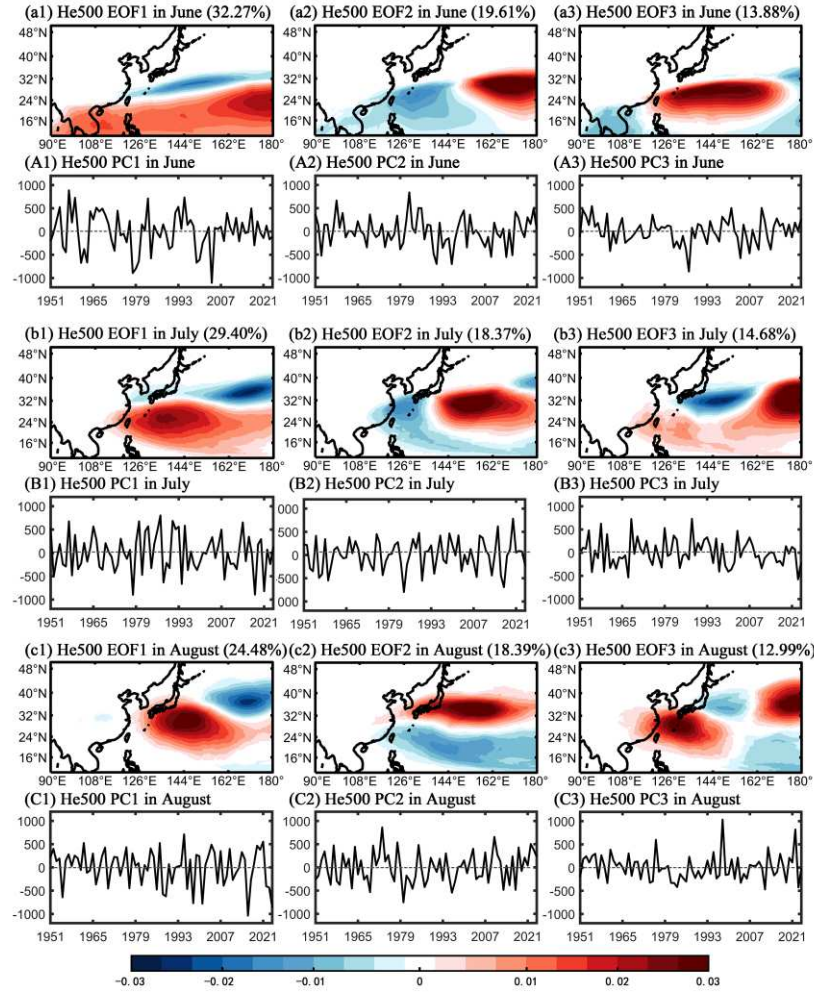


Figure 2. Monthly He500 of first three modes for JJA from 1951 to 2024. (a1)–(c1) EOF1 for (a) June, (b) July, and (c) August. (A1)–(C1) Corresponding normalized time series of PC1 for (A) June, (B) July, and (C) August. (a2)–(c2) and (a3)–(c3) are the same as (a1)–(c1), but for EOF2 and EOF3. (A2)–(C2) and (A3)–(C3) are the same as (A1)–(C1), but for PC2 and PC3.

3.2 Prediction skills

To validate the model accuracy, this study evaluates the prediction during the independent test period (2011–2024), and compares the model prediction with the EC prediction (Figure 3). Specially, the R values between the model prediction of monthly PC1 from June to August and observation (Figures 3a1–c1) reach 0.71, 0.66, and 0.84, while the EC prediction exhibit predominantly weak correlation, with R values of 0.10, 0.41, and 0.01 for the same months. The similar performance is predicted for PC2 (Figures 3a2–c2) and PC3 (Figures 3a3–c3), where the model maintains R values consistently above 0.60, whereas EC prediction show the weak and

statistically insignificant correlations. Furthermore, regarding the WPSH indices, the model prediction for the area index (Figures 3a4–c4) yields R values of 0.35, 0.68, and 0.89 for June, July, and August, whereas EC produces notably weaker results with R values of 0.24, 0.59, and -0.19, respectively. For the intensity index (Figures 3a5–c5), the model demonstrates stable predictive skill, with R values of 0.59, 0.84, and 0.72 for June, July, and August, respectively. The model significantly outperforms EC prediction, which yields R values of -0.32, -0.17, and -0.28, respectively. These results demonstrate that the model maintains stable predictive capabilities for the WPSH indices throughout the summer period.

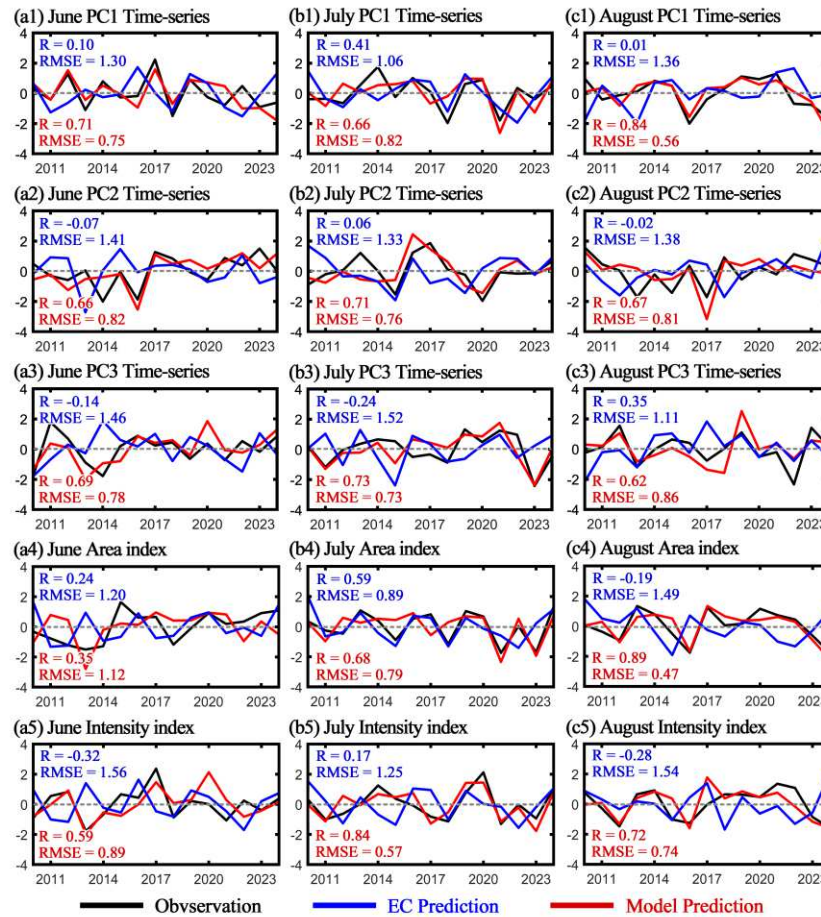
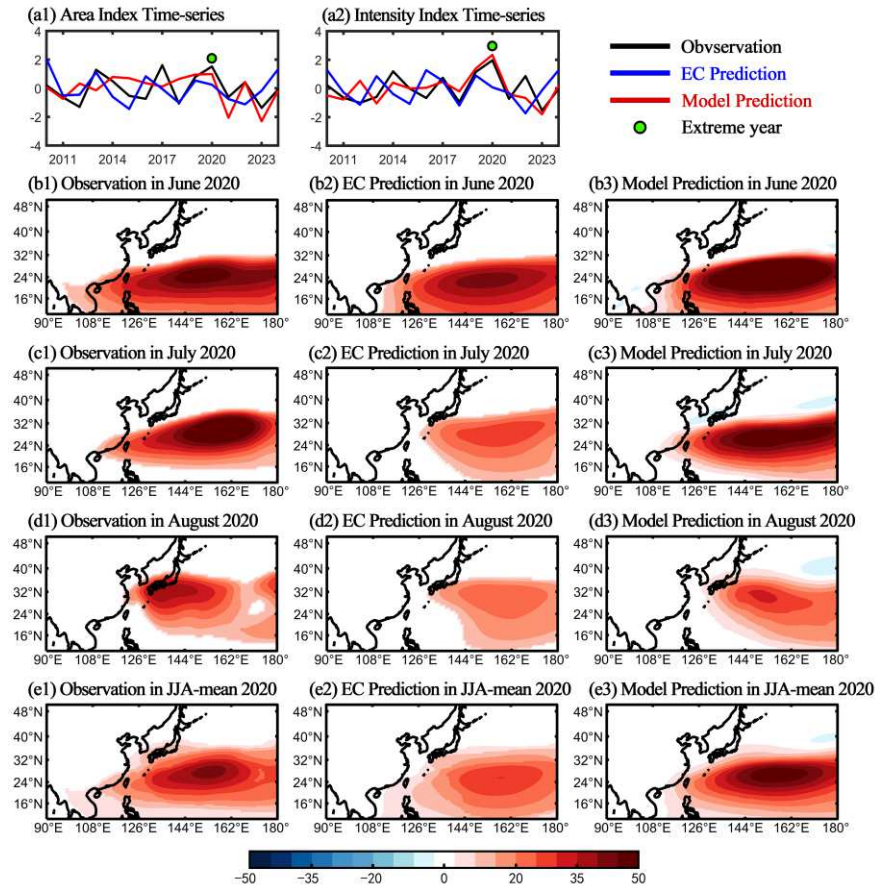


Figure 3. Evaluation of model prediction of the WPSH indices. (a1)–(a5) time series of PC1, PC2, PC3, area index, and intensity index for June during the testing period (2011–2024). (b1)–(b5) and (c1)–(c5) are the same as (a1)–(a5), but for July and August, respectively. Black, blue, and red lines represent the observation, EC prediction, and model prediction, respectively.

To evaluate the model's capability in predicting the spatial distribution of the WPSH during extreme years (Figure 4), this study first calculates the JJA-averaged area index (Figure 4a1) and

231 intensity index (Figure 4a2) in the test period (2011–2024) to identify extreme years. The time
 232 series of both indices indicate that the model accurately captures the extreme strong WPSH state
 233 in 2020 (highlighted by green dots). The comparison between the predicted and observed spatial
 234 distributions of the WPSH for this year further demonstrates that the prediction model not only
 235 reproduces the June–August monthly (Figures 4b3–d3) and JJA-averaged WPSH intensity (Figure
 236 4e3) but also accurately identify the location of the WPSH center. While the EC predictions not
 237 only significantly underestimate the WPSH intensity (Figures 4b2–d2) during the 2020 extreme
 238 event but also fail to accurately pinpoint its center location (Figure 4e2).



239

240 **Figure 4.** Evaluation of model prediction in 2020 (strong year). (a1) Comparison of the JJA-averaged WPSH
 241 area index from model prediction with observation and EC prediction, where green dots indicate WPSH
 242 extreme strong year. (a2) is the same as (a1), but for intensity index. Black, blue, and red lines represent the
 243 observation, EC prediction, and model prediction, respectively. (b1)–(b3) are the spatial distribution of WPSH
 244 in June 2020 from observation, EC prediction, and model prediction, respectively. (c1)–(c3), (d1)–(d3), and
 245 (e1)–(e3) are the same as (b1)–(b3), but for July, August, and JJA-averaged.

In addition to the strong state in 2020, this study calculates the JJA-averaged area index (Figure 5a1) and intensity index (Figure 5a2) in the test period (2011–2024) to identify the extreme weak year of 2023. The time series of both indices indicate that the model accurately captures the extreme weak WPSH state in 2023 (highlighted by green dots). The spatial comparison of the extreme year reveal that the prediction model can reproduce the weakened and eastward state of the WPSH, specially for the JJA-averaged spatial distribution (Figure 5e3). While the EC predictions fail to accurately pinpoint its center location (Figures 5b2–e2). In summary, these results confirm that the prediction model possesses stable predictive capabilities for both extreme strong and extreme weak states of the summer WPSH, providing technical support for the prediction of extreme summer climate events in East Asia.

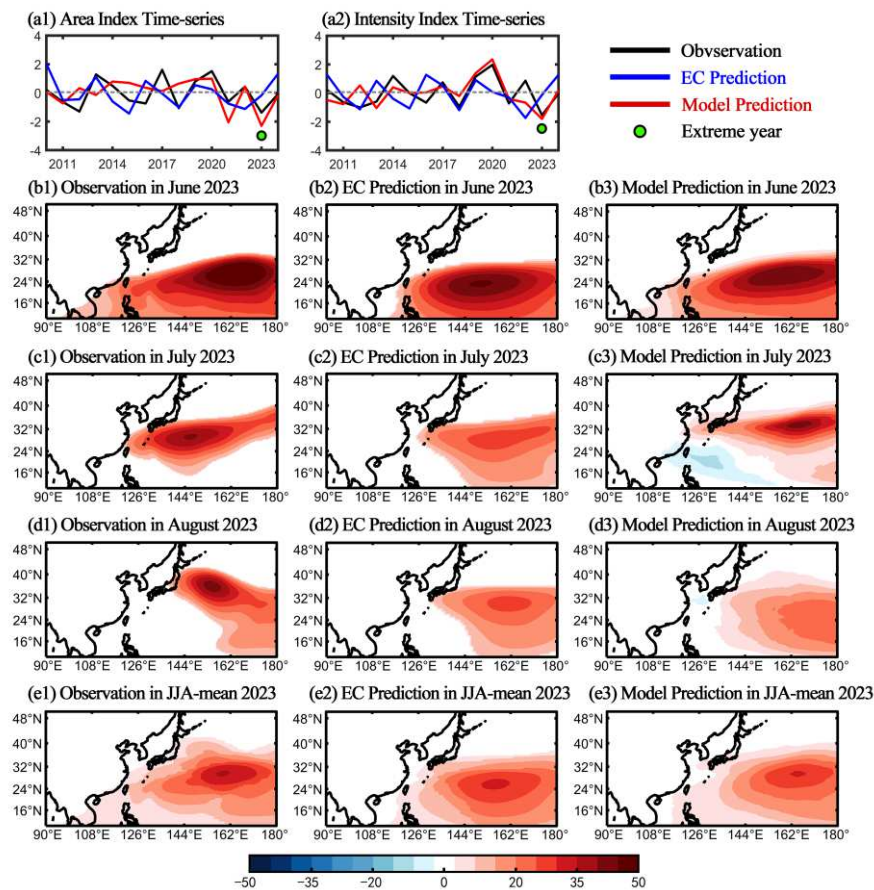


Figure 5. Evaluation of model prediction in 2023 (weak year). (a1) Comparison of the JJA-averaged WPSH area index from model prediction with observation and EC prediction, where green dots indicate extreme weak year. (a2) is the same as (a1), but for intensity Index. Black, blue, and red lines represent the observation, EC prediction, and model prediction, respectively. (b1)–(b3) are the spatial distribution of WPSH in June 2023

from observation, EC prediction, and model prediction, respectively. (c1)–(c3), (d1)–(d3), and (e1)–(e3) are the same as (b1)–(b3), but for July, August, and JJA-averaged.

3.3 The necessity of model architecture

To further assess the necessity and efficacy of the attention-based predictors extraction, as illustrated in Figure 6, this study compares the model that employs the full dataset of 584 potential factors without predictors extraction against the model that incorporates this extraction. For the monthly PC1 predictions from June to August (Figures 6a1–c1), the R values between model outputs and observations are 0.71, 0.66, and 0.84, respectively, whereas the model without predictors extraction yielded corresponding R values of 0.58, 0.61, and 0.71. Similar characteristics are observed for PC2 (Figures 6a2–c2) and PC3 (Figures 6a3–c3). The predictors extraction model consistently maintains R values above 0.60, while the model without predictors extraction exhibits weaker correlations. Regarding the WPSH indices, the model prediction for the area index (Figures 6a4–c4) yields R values of 0.35, 0.68, and 0.89 for June, July, and August, whereas the model without predictors extraction exhibits the R values of -0.19, 0.38, and 0.79, respectively. For the intensity index (Figures 6a5–c5), the prediction model demonstrates stable performance with R values of 0.59, 0.84, and 0.72 in June, July, and August, respectively, while the model without predictors extraction yields R values of 0.18, 0.69, and 0.44. These results indicate that, although the model without predictors extraction can capture the WPSH related indices, there remains considerable errors compared with the observations. While the inclusion of the predictors extraction leads to an improvement in predictive skill across all indices and months. In conclusion, the proposed predictors extraction process is essential for enhancing the reliability of the MHA-TCN model prediction.

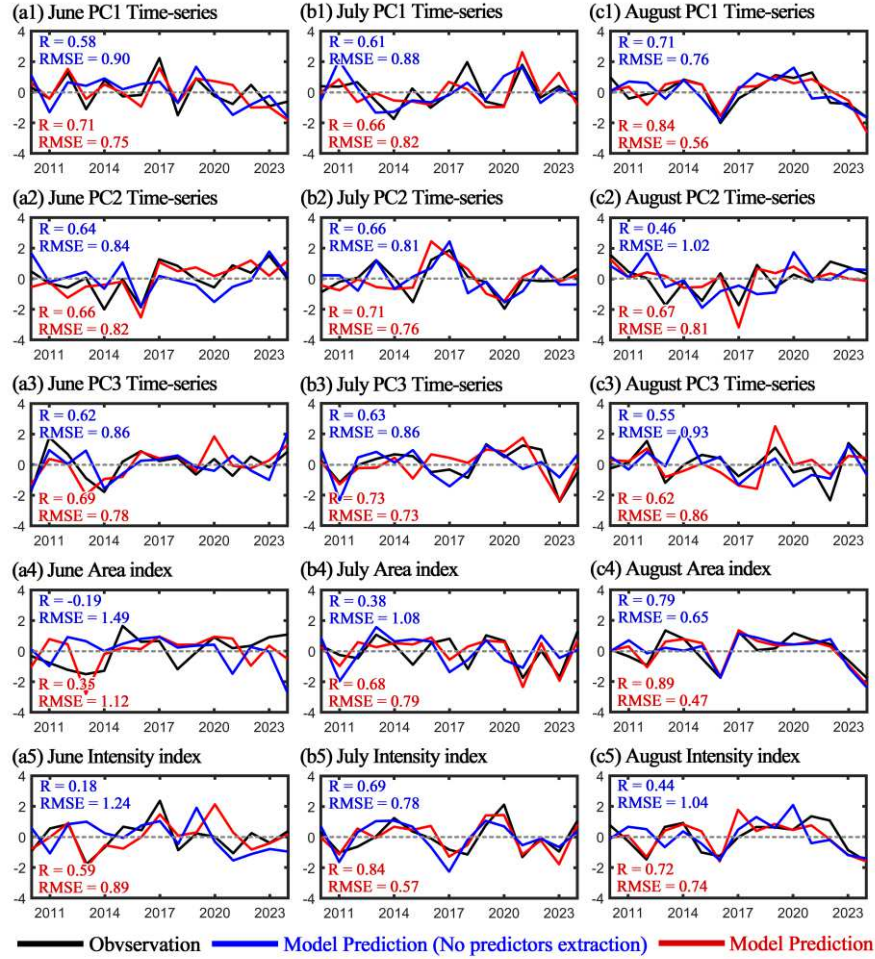


Figure 6. The evaluation of predictors extraction on WPSH prediction. (a1)–(a5) time series of PC1, PC2, PC3, area index, and intensity index for June during the testing period (2011–2024). (b1)–(b5) and (c1)–(c5) are the same as (a1)–(a5), but for July and August, respectively. Black, blue, and red lines represent the observation, model prediction without predictors extraction, and model prediction utilizes predictors extraction, respectively.

In addition to the predictors extraction, a sensitivity analysis was conducted to determine the optimal number of selected predictors. By evaluating the model performance with varying dimensions, the prediction skills measured by R and $RMSE$ across JJA-averaged WPSH indices were analyzed in Figure 7. Specially, retaining only 50 predictors leads to underfitting due to insufficient information, while increasing to 150 or 200 predictors, the performance exhibiting decreases which is attributed to the introduction of noise and overfitting caused by redundant predictors. Consequently, this study selects 100 optimal predictors for retaining physical signals and avoiding redundant noise, thereby validating the architectural robustness of the proposed framework.

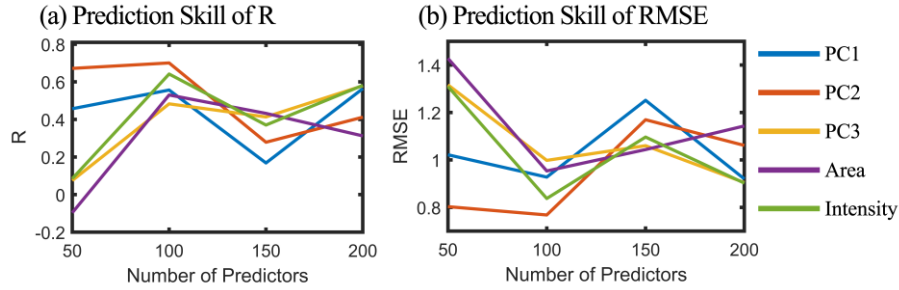


Figure 7. Sensitivity of prediction skill to the number of selected predictors. (a) R and (b) RMSE across different numbers of selected predictors for PC1, PC2, PC3, area index, and intensity index for JJA-averaged.

Furthermore, the contribution of the MHA mechanism to the model architecture was systematically evaluated in Figure 8. When the MHA layer is removed, the prediction skill experiences significant decline across these indices. For monthly PC1 (Figures 8a1–c1), the R values of the model without MHA drop significantly to 0.45, 0.46, and 0.51 from June to August. Similar degradation is observed for PC2 (Figures 8a2–c2) and PC3 (Figures 8a3–c3), where the model without MHA yields substantially lower correlation. Crucially, the R value for the area index in June drops to a negligible 0.04 (Figure 8a4), and the R value for the intensity index reduce to 0.28, 0.24, and 0.36 from June to August (Figures 8a5–c5). These results highlight the indispensable role of the MHA mechanism in capturing the interactions and dynamically in each predictor.

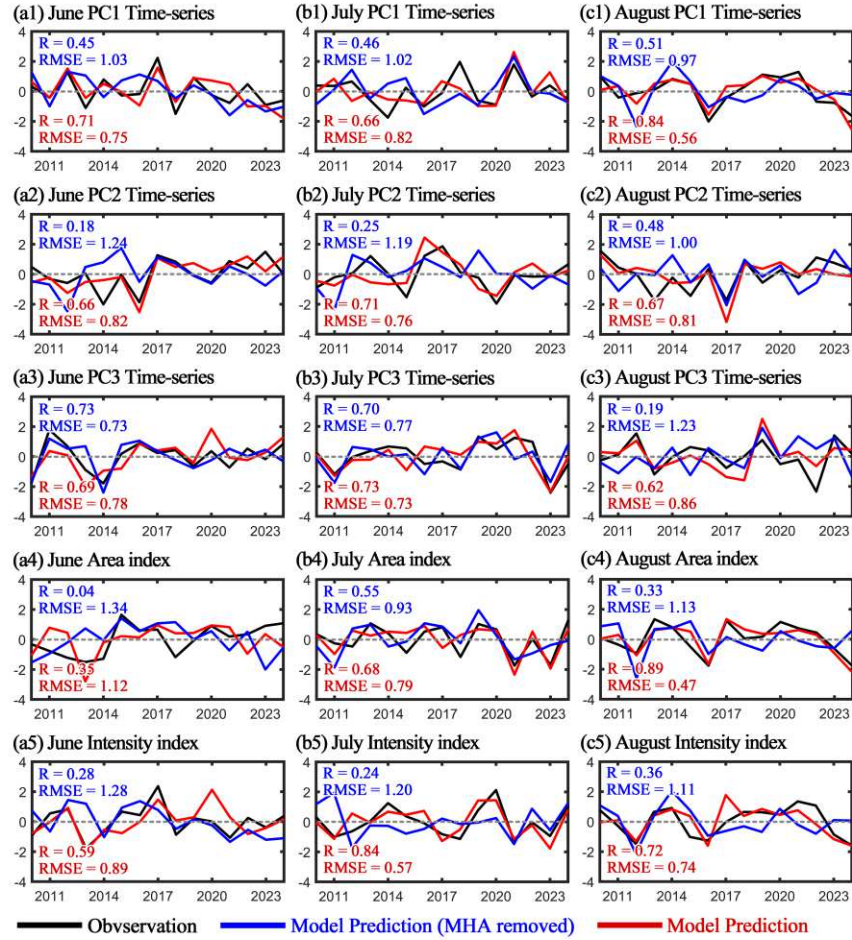


Figure 8. The evaluation of MHA mechanism on WPSH prediction. (a1)–(a5) Time series of PC1, PC2, PC3, area index, and intensity index for June during the independent testing period (2011–2024). (b1)–(b5) and (c1)–(c5) are the same as (a1)–(a5), but for July and August, respectively. Black, blue, and red lines represent the observation, the model prediction without MHA, and the complete MHA-TCN model prediction, respectively.

3.4 Sources of predictability

To further analysis and evaluate the sources of predictability, this study rank the potential predictors by importance, a sensitivity experiment was conducted by retraining the MHA-TCN model with these specific predictors excluded firstly, then focus on the physical mechanisms of the first 5-predictor. To further the significance of the identified first 5-predictor.

As illustrated in Figure 9, the removal of the 5-predictor leads to a significant decreasing in the predictive performance across each month of June, July, and August for PCs and indices. The results demonstrate that the R values between the observations and predictions decrease

significantly compared to the complete model, particularly for the WPSH both indices (Figures 9a4–c4, a5–c5). Specially, the R values between the complete model prediction of monthly area index from June to August and observation (Figures 9a4–c4) reach 0.35, 0.68, and 0.89, while the model removed 5-predictor prediction exhibit predominantly weak correlation, with R values of 0.05, 0.57, and 0.07 for the same months. For the intensity index (Figures 9a5–c5), the complete model demonstrates stable predictive skill, with R values of 0.59, 0.84, and 0.72 for June, July, and August, respectively, while the model removed 5-predictor prediction yields R values of 0.20, 0.71, and -0.23, respectively. The results demonstrate that that the identified first 5-predictor provide indispensable information for the predicting skill.

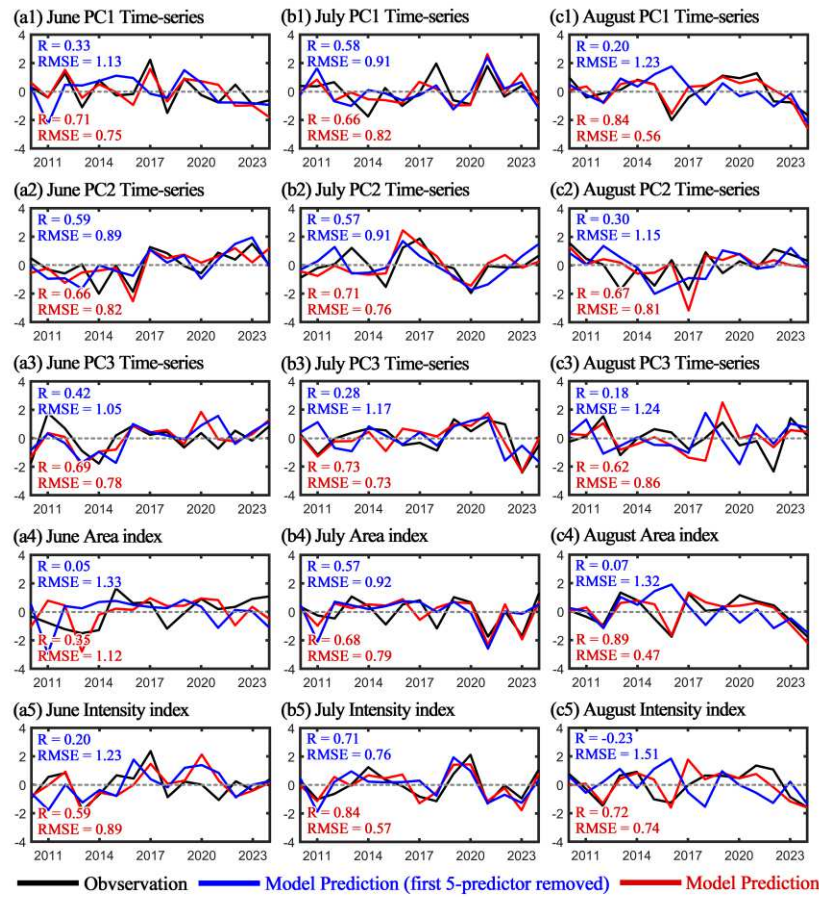


Figure 9. The evaluation of first 5-predictor on WPSH prediction. (a1)–(a5) time series of PC1, PC2, PC3, area index, and intensity index for June during the testing period (2011–2024). (b1)–(b5) and (c1)–(c5) are the same as (a1)–(a5), but for July and August, respectively. Black, blue, and red lines represent the observation, model prediction remove first 5-predictor, and complete model prediction, respectively.

Because of the distinct distribution characteristics of He500 EOFs from June to August (Figure 2), indicating that the physical mechanisms influencing the variation of the WPSH in June,

July, and August may different. Based on the North Test (North et al 1982), EOF1 is statistically significant and well-separated from subsequent modes. Wang et al (2013) pointed out that the EOF1 of He500 mainly reflects the interannual variability of WPSH intensity, providing an important reference for WPSH prediction (Hu et al 2023; Ma et al 2023).

The primary mechanism of the WPSH PC1 in June is influenced by the variations of South Atlantic Subtropical High (SASH) (Figures 10a1, a2, a4), which drive the South Atlantic Subtropical Dipole (SASD) mode (Venegas et al 1997), this SST pattern exhibits robust seasonal phase-locking (Wang et al 2025), significantly intensifying the WPSH (Ham et al 2013a, 2013b; Gan et al 2026). Additionally, in the preceding autumn, under the influence of the monsoon, SSH anomalies and heat content accumulation in the Western Pacific Warm Pool (WPWP) (Figure 10a3), this anomalies will reaching peak after seven months, subsequently affecting the WPSH intensity (Meinen and McPhaden 2000; Huang et al 2016). By winter, atmospheric circulation anomalies triggered by the Arctic Oscillation (AO) lead to anomalous snow cover over high-latitude regions (Figure 10a5), affecting the subsidence movement of the WPSH (Yao et al 2022; Jiang et al 2024; Sang et al 2025).

For July, begins in the preceding summer, disturbance in the South Asian monsoon region (Figure 10b1) will trigger the Indian Ocean Capacitor (IOC) effect to strengthen the WPSH intensity (Xie et al 2009; Ke et al 2023). Entering the preceding autumn, influenced by the Atlantic-European Circulation anomalous (Figure 10b2), a North Atlantic SST three-pole pattern emerges, strengthening the WPSH intensity (Shi et al 2015; Zhang et al 2024). Meanwhile, SST anomalies in the tropical Pacific (Figure 10b3) induce anomalous circulations through a Gill-type response to influence the WPSH (He et al 2015). By winter, the Aleutian Low (AL) (Figure 10b4) modulates the monsoon and SST affecting the WPSH (Gong et al 2011; Liu et al 2019). Simultaneously, driven by the Mascarene High (Figure 10b5), transport of warm and moist air providing thermodynamic support for the WPSH (Xue et al 2003; Ke et al 2023).

For August, begins in the preceding spring, influenced by anomalies in the Bolivian High (BH) (Figure 10c1), the intensity of the Inter-Tropical Convergence Zone (ITCZ) is modulated, which in turn affects the WPSH (Melo et al 2025; Gao et al 2025). Subsequently, in the preceding summer, affected by the AO, resulting in a meridional anomalous circulation prevailing over high-latitude regions (Figure 10c2), thereby affecting the WPSH (Li et al 2017). Meanwhile, variations of the North African Subtropical High (NASH) (Figure 10c3), modulating the snow and soil

moisture over the Tibetan Plateau (TP) (Jia et al 2002), which in turn affects the WPSH (Yao et al 2022; Jiang et al 2024; Sang et al 2025). By the preceding autumn, H anomalies in the tropical Pacific (Figures 10c4, c5) induce anomalous circulations over the Northwest Pacific affecting the WPSH (He et al 2015).

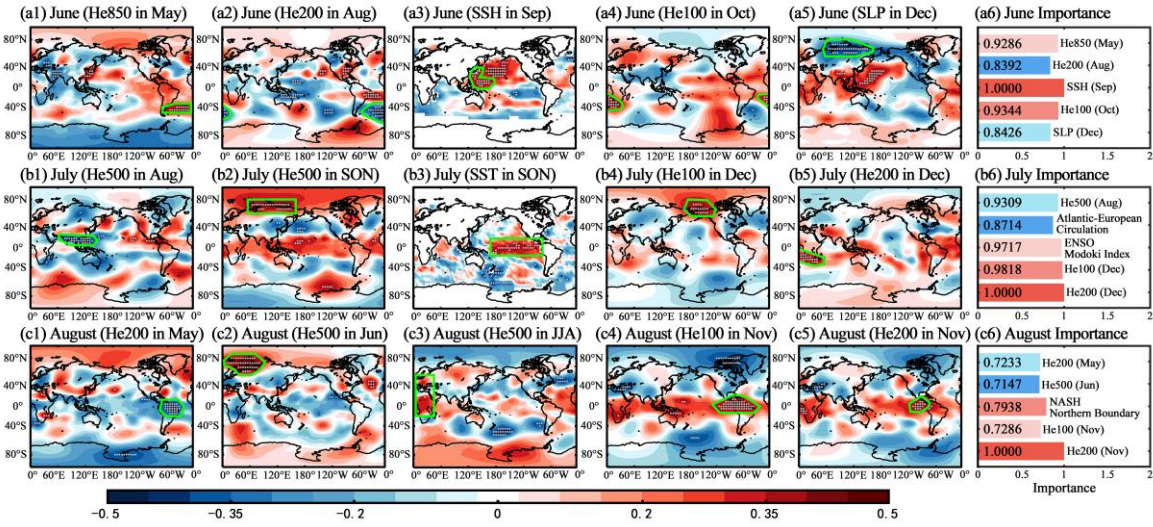


Figure 10. Potential predictors and importance of monthly He500 PC1 from June to August. (a1)–(a5), (b1)–(b5), (c1)–(c5) Global correlation between PC1 and preceding variables in (a) June, (b) July, and (c) August, with gray dots indicate 99% significance, and green polygons highlight the significant regions. (a6), (b6), (c6) are the importance of the five most influential factors for (a6) June, (b6) July and (c6) August.

4 Discussion and Conclusion

The WPSH is a key atmospheric circulation system regulating extreme weather events in East Asia, while its prediction is still a challenge issue. Traditional numerical models often exhibit systematic biases in capturing position and tend to underestimate its intensity (Ma et al 2023), while the predictive skill of linear statistical models (Wang et al 2013) has been constrained under the background of global warming, making prediction accuracy more challenging. (Gan et al 2026). This study is based on global monthly potential predictors from 1951 to 2024 developing a hybrid WPSH prediction model that integrates the predictors extraction with MHA-TCN for predicting the summer WPSH. This study conducts EOF analysis on the monthly He500 identifying the EOFs and PCs on the monthly He500 from June to August as the necessary spatiotemporal patterns, and an automatic clustering algorithm is then employed to identify statistically significant connected components and derive 584 potential predictors, including

oceanic, atmospheric, and regional-mean variables. From these candidates, the 100 optimal predictors were subsequently selected and incorporated into the prediction model based on attention mechanism. The prediction model achieves a six-month lead time prediction with the resolution of $0.5^{\circ} \times 0.5^{\circ}$, surpassing the ECMWF Seasonal Forecasts System. The results demonstrate that the prediction model can capture the interannual variability of the WPSH effectively, with the R values between predicted PCs and observation exceed 0.60, and the average R values for the monthly area and intensity index of the WPSH between prediction and the observation reach 0.64 and 0.72, respectively. Furthermore, the prediction model accurately reproduces the spatial pattern of WPSH in extreme years of 2020 and 2023, confirming that the prediction model possesses stable predictive capabilities for extreme states of the summer WPSH. Then examines physical mechanisms through interpretability analysis of the WPSH predictability for each month of JJA. Specifically, the June WPSH is driven by the SASD mode, heat content accumulation in the WPWP during the preceding autumn, and AO inducing high-latitude snow cover anomalies in the preceding winter. In July, the intensity variations are modulated by the preceding summer IOC effect, preceding autumn North Atlantic SST tripole pattern, tropical Pacific Gill-type response, as well as the preceding winter AL and Mascarene High. For August, the dominant drivers originate from the preceding spring BH modulating the ITCZ, preceding summer AO related high-latitude circulations, NASH influencing TP land surface processes, and preceding autumn tropical Pacific H anomalies. These findings highlight the dynamic monthly transition of primary WPSH drivers, providing a technical reference for climate predicting of the WPSH.

Although the prediction model demonstrates high performance overall, several inherent limitations warrant further consideration. First, while the intensity index as a cumulative measure that integrates signals across the entire domain, the area index is highly sensitive to small-scale spatial fluctuations and boundary gradients (Liu et al 2024). Minor biases in the prediction can lead to significant jumps in the grid-point count near the threshold, especially in the presence of complex wave train disturbances. Additionally, we must note that the relationships between these predictors and the WPSH PCs may change overtime. Although the currently optimal prediction model ensures stable and reliable predicting capacity throughout test period, this non-stationarity relationships is the challenge of WPSH prediction within a changing climate background (Gan et

al 2026). The future prediction framework can be predicted by integrating accurate prediction data to maintain reliability over longer timescales.

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Author Contributions

Xiao Su, Qiong Wu, and Danwei Qian: conceptualization, writing original draft, resources, formal analysis, validation; Bo Li: investigation, methodology. All authors have read and agreed to the published version of the manuscript.

Data availability

The atmospheric / oceanic reanalysis data are provided by Hersbach et al (2023a, 2023b) and available at <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels-monthly-means?tab=download> and <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-pressure-levels-monthly-means?tab=download>. The EC predicted data are provided by Copernicus Climate Change Service and Climate Data Store (2018a, 2018b) and available at <https://cds.climate.copernicus.eu/datasets/seasonal-monthly-single-levels?tab=download> and <https://cds.climate.copernicus.eu/datasets/seasonal-monthly-pressure-levels?tab=download>. The monthly climate / ocean indices are from the Physical Sciences Laboratory of NOAA available at <https://www.psl.noaa.gov/data/timeseries/month/>. The monsoon indices are provided by Li and Zeng (2002) and available at <http://lijianping.cn/dct/page/1>. The 130 monitoring indexes are provided by NCC and available at https://cmdp.ncc-cma.net/Monitoring/cn_index_130.php.

Declarations

All authors declare that they have no competing interests.

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