

Article

Seasonal Forecasting of North Atlantic Subtropical High Intensity Using a Multi-Algorithm Machine Learning Ensemble

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Abstract

Accurate seasonal prediction of the North Atlantic Subtropical High (NASH) intensity is crucial for regional climate disaster preparedness, yet it remains a major challenge for current dynamical models. This study proposes a multi-algorithm ensemble forecasting system for summer NASH intensity by integrating 24 machine learning algorithms with eight selected springtime predictors. Results from the independent test period (2011–2024) show that the multi-model ensemble (MME) delivered a robust forecast, with a mean absolute error (MAE) of 0.391 hPa and a correlation coefficient (CC) of 0.898. Compared to the dynamical forecast from SEAS5 over the 1981–2024 period, the MME reduced the MAE by 40.0% and increased the CC from 0.440 to 0.816. Time Series Cross-Validation (TSCV) further confirmed the robustness of the ensemble, which outperformed most of the individual models, with an average skill improvement of 12.97%. The SHapley Additive exPlanations (SHAP) analysis applied to the Ridge model reveals that $W1000_{ESP}$ and $VO500_{NEP}$ are the two most influential predictors, and their directional contributions represent atmospheric responses to sea surface temperature anomalies, effectively capturing the cross-seasonal impacts of air–sea interactions on NASH intensity. This study demonstrates that a multi-algorithm machine learning ensemble can substantially improve seasonal forecasts of NASH intensity, providing a valuable reference for operational climate prediction applications.

Keywords: North Atlantic Subtropical High (NASH); seasonal forecasting; machine learning; multi-algorithm ensemble; SHAP



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1. Introduction

The North Atlantic Subtropical High (NASH) is a major atmospheric circulation system that plays a key role in shaping the climate of the North Atlantic and its surrounding regions, with a substantial influence on the weather and climate of eastern North America, western Europe, and northwestern Africa [1]. Variations in NASH intensity modulate these regional climate patterns through their impacts on large-scale atmospheric circulation, moisture transport, and storm activity [2]. In particular, an anomalously strong summer NASH is often associated with persistent heatwaves and droughts over Europe and the Mediterranean region [3,4]. Under global warming, the increased variability of NASH has contributed to more frequent and severe extreme climate events, thereby increasing risks to regional socioeconomic systems, ecosystems, and public health [5]. Consequently, accurate

seasonal prediction of summer NASH intensity is essential for enhancing regional climate resilience and mitigating its socioeconomic impacts.

Previous studies have established that NASH intensity is modulated by climatic factors operating across multiple spatiotemporal scales. On climatological and longer timescales, the NASH is influenced by external forcings—including land–sea thermal contrasts, volcanic eruptions [5,6], the zonal distribution of tropical sea surface temperature (SST), and Tibetan Plateau orography [7]—as well as by large-scale ocean–atmosphere teleconnections, such as the Atlantic Multidecadal Oscillation (AMO) and the Pacific Decadal Oscillation (PDO) [8,9]. At the cross-seasonal scale, diverse precursor signals contribute to the predictability of summer NASH intensity through atmospheric teleconnections and ocean memory effects. For instance, utilizing NCEP–DOE reanalysis and HadISST data, Sun [10] revealed that a positive-phase spring Antarctic Oscillation (AAO) can excite warm sea surface temperature anomaly (SSTA) over the tropical Atlantic via a cross-hemispheric wave train; these anomalies persist into summer, hereby weakening the NASH. Furthermore, composite analyses by Zhang et al. [11] demonstrated that a positive-phase spring North Atlantic Oscillation (NAO) is associated with the development of NASH via the local wind–evaporation–SST feedback mechanism, consequently favoring a strengthened NASH. Similarly, warm spring SSTA associated with the Atlantic Warm Pool (AWP) has been linked to a low-level cyclonic anomaly on their northwestern flank through a Rossby wave response, ultimately weakening the NASH [12]. At the intraseasonal scale, local air–sea coupling processes over the North Atlantic further modulate NASH intensity on short timescales [13]. However, the synergistic influence of these multiple factors on NASH intensity is not simply additive; rather, their complex non-linear interactions constitute a primary challenge for accurate seasonal prediction. Currently, resolving such complex ocean–atmosphere interactions with traditional dynamical climate models is computationally expensive, and these models remain subject to pronounced biases in reproducing NASH interannual variability. Even the most advanced operational seasonal prediction systems—such as ECMWF’s fifth generation seasonal forecast system (SEAS5) [14] and the UK Met Office’s GloSea [15]—exhibit substantial biases in capturing this variability, with particularly large errors during the spring transition [16].

To mitigate the inherent limitations in traditional dynamical models, machine learning and statistical methods have been increasingly adopted in climate prediction, as comprehensively reviewed by Chen et al. [17]. Compared to conventional linear approaches, machine learning algorithms are capable of capturing the complex non-linear relationships between high-dimensional predictors and predictands, thereby potentially improving forecast accuracy [18,19]. In recent years, data-driven methods have demonstrated significant potential in the seasonal prediction of subtropical highs. For instance, Yang et al. [20] employed a ConvLSTM model to predict the summer Western Pacific Subtropical High (WPSH) intensity at a three-month lead time, achieving a correlation coefficient of 0.77 with observational data—a performance substantially superior to that of dynamical models. Furthermore, Li et al. [21] utilized a Gaussian Naive Bayes model to deliver robust categorical forecasts of summer WPSH area anomaly level. Similarly, Gan et al. [22] addressed the post-2000 decline in predictive skill by integrating spring tropical Atlantic SSTA into an LSTM model. These studies demonstrate that machine learning techniques can effectively capture the non-linear dynamics driving subtropical high variability, thereby providing a crucial methodological basis for the seasonal prediction of NASH intensity. Despite these advancements, studies directly targeting NASH prediction using machine learning remain limited. Moreover, existing studies on subtropical high prediction have predominantly relied on single-model approaches [20–23], leaving a notable gap in the systematic investigations of multi-model ensemble forecasting strategies.

The application of ensemble methods that combine multiple machine learning algorithms has demonstrated advantages over single-model approaches in predicting tropical cyclones, air temperature, and precipitation [24–27]. These ensemble frameworks operate by fusing predictions from various base models, leveraging the diversity in their parameters, architectures, and training data to reduce individual-model variance and enhance overall forecasting stability [28,29]. To this end, this study proposes a multi-algorithm ensemble forecasting framework built upon a unified set of precursor signals. By integrating the predictive strengths of multiple heterogeneous algorithms, this research systematically evaluates the applicability and potential performance gains of this approach in the seasonal prediction of NASH intensity.

Furthermore, machine learning models are frequently criticized for their “black-box” nature—a limitation that is particularly acute in climate prediction, a domain heavily reliant on physical mechanistic understanding. To enhance model interpretability, recent studies have increasingly integrated explainable artificial intelligence (XAI) methods to elucidate the physical basis of data-driven predictions. For example, Yao et al. [30] applied the SHAP method to quantify the contributions of six predictors to the Pacific Decadal Oscillation (PDO), revealing that the Niño3.4, NPI, and SSH_KOE indices emerged as the three most influential features. Similarly, Xiao et al. [27] first quantified the marginal effects of nine predictors and subsequently utilized SHAP dependence plots to unveil the complex non-linear responses and threshold effects among the five most important factors, thereby providing additional physical insights into the variability of summer extreme precipitation days over the middle and lower reaches of the Yangtze River. Accordingly, the present study also adopts the SHAP interpretable machine learning framework to conduct feature attribution analysis, thereby quantifying the relative contribution of each precursor signal.

The remainder of this paper is structured as follows. Section 2 describes the data and methods. Section 3 presents the selected core predictors and evaluates the forecast performance of the proposed ensemble system in comparison with individual models. Section 4 provides a SHAP-based analysis of predictor contributions. Section 5 offers the conclusions and discussion.

2. Materials and Methods

2.1. Data Description

A large body of research has examined the factors and mechanisms driving the variability of NASH intensity [11,12,31,32]. To capture these signals, a candidate predictor pool was assembled comprising both preceding oceanic and atmospheric variables: 5 surface variables (e.g., SST) and 6 upper-air variables (e.g., vorticity) (see Supplementary Table S1 for details). All predictor variables were extracted from the ERA5 monthly reanalysis provided by the European Centre for Medium-Range Weather Forecasts (ECMWF), which spans 1950–2024 at a horizontal resolution of $0.25^\circ \times 0.25^\circ$. These predictors are publicly available.

For comparison with our MME forecasts, we also used the ECMWF SEAS5 seasonal forecast system. SEAS5 mean sea level pressure forecasts initialized in May were used, and the June–August seasonal mean was computed by averaging the forecasts at lead times of 1–3 months. The dataset consists of a 25-member reforecast (1981–2016) and a 51-member real-time forecast (2017–2024), covering the period 1981–2024. All SEAS5 data were obtained from the Copernicus Climate Data Store.

All variables were interpolated to a common $2.5^\circ \times 2.5^\circ$ grid. Anomalies were computed by using a forward 15-year rolling baseline; consequently, the effective analysis period spans 1965–2024. The 1965–2010 interval was used for model training, and 2011–2024 was reserved for independent testing.

2.2. Method

2.2.1. Definition of the NASH Intensity Index

Following the methodology of Song et al. [33], the NASH intensity index is defined as the area-averaged summer (June–August) mean sea level pressure (SLP) anomaly over the North Atlantic domain (25–45° N, 70–20° W). The resulting time series of this index is provided in Supplementary Figure S1.

2.2.2. Predictor Selection and Model Construction

Following the NASH intensity index prediction and evaluation workflow (Figure 1), correlation coefficients between the target NASH index and a comprehensive suite of environmental physical quantities were calculated using the processed data from the preceding summer to the current spring. Spring (March–May) predictors exhibited the highest correlations and were therefore selected. To mitigate spurious signals, only contiguous regions of each environmental variable with an absolute correlation coefficient exceeding 0.3 (surpassing the 95% statistical significance threshold) and containing no fewer than 20 grid points were retained as candidate predictors.

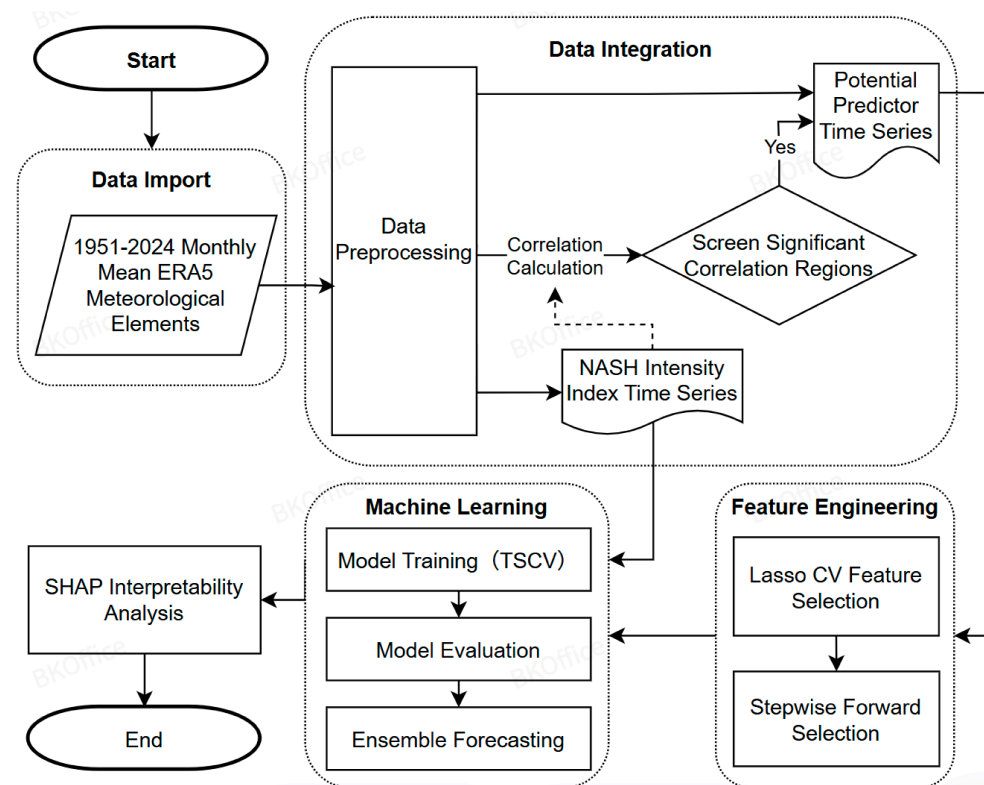


Figure 1. Flowchart for predicting and evaluating the NASH intensity index, covering data import, data integration, feature engineering, machine learning, and SHAP explainability analysis.

To alleviate the risks of overfitting and prediction instability caused by multicollinearity and a high feature-to-sample ratio [30], the Least Absolute Shrinkage and Selection Operator (LASSO) was applied on the training set for rigorous predictor screening. A stepwise forward regression, guided by 5-fold cross-validation confined to the training data, was subsequently applied to the screened variables. Only the feature subset that optimized cross-validation performance during training was retained, yielding a predictor combination with optimal generalization capability.

To construct an ensemble prediction model, 24 distinct machine learning algorithms were selected within a Python 3.12 environment (Table S2-1). Among these, Convolutional

Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and Gated Recurrent Unit networks (GRUs) were implemented using TensorFlow, whereas the remaining 21 models, including Partial Least Squares regression (PLS), Extra-Trees regression (ET), and Multi-Layer Perceptron regression (MLP), were sourced from the Scikit-Learn library.

To combine the individual forecasts, the multi-model ensemble (MME) prediction for a given year t , denoted as $\hat{y}_{t,MME}$, is computed as the simple arithmetic average across all M base models ($M = 24$):

$$\hat{y}_{t,MME} = \frac{1}{M} \sum_{m=1}^M \hat{y}_{t,m} \quad (1)$$

where $\hat{y}_{t,m}$ represents the forecasted NASH intensity index generated by the m -th model in year t .

Model performance was evaluated using a comprehensive suite of metrics, including three standard quantitative measures—Mean Absolute Error (MAE), Pearson Correlation Coefficient (CC), and Coefficient of Determination (R^2) [26,34]—along with the Index of Agreement (d), the relative forecast skill of the multi-model ensemble against individual models (S), and the Proportion of Correct Sign (PCS) [26]. Detailed definitions for d , S , and PCS are provided in Supplementary Text S1.

2.2.3. Interpretable Machine Learning Framework SHAP

To overcome the inherent opacity of “black box” machine learning models, whose internal decision-making processes lack interpretability [35], this study utilizes the SHapley Additive exPlanations (SHAP) framework. This framework quantifies the marginal contribution of each feature to the model’s prediction for an individual sample [36], thereby offering insights into the model’s predictive behavior.

Grounded in the Shapley value from cooperative game theory, SHAP, as proposed by Lundberg and Lee [37], calculates a feature’s SHAP value as the weighted average of its marginal contributions across all possible feature subsets. The formula is as follows:

$$\Phi_m = \sum_{L \subseteq N \setminus \{m\}} \frac{|L|! \cdot (M - |L| - 1)!}{M!} \cdot [v(L \cup \{m\}) - v(L)] \quad (2)$$

where Φ_m is the SHAP value of the m -th feature; N is the set of all input features; L represents any feature subset that does not contain the m -th feature; $v(L)$ is the model’s prediction when only the feature subset L is used; and $v(L \cup \{m\})$ is the model’s prediction after adding the m -th feature to subset L , with the difference between the two representing the marginal contribution of the m -th feature under that specific subset. The weighting term $\frac{|L|! \cdot (M - |L| - 1)!}{M!}$ computes the weighted average across all feature subsets, thereby eliminating any influence of feature input order on the contribution calculation.

The sign of a SHAP value indicates the direction of a feature’s influence on the prediction result. A positive value signifies that the feature pushes the predicted NASH intensity index upwards, contributing positively to its enhancement, while a negative value indicates the opposite effect. The absolute magnitude of the SHAP value represents the degree of the feature’s marginal contribution, with a larger absolute value reflecting a more substantial regulatory effect on the model’s prediction.

3. Results

3.1. Results of Feature Engineering and Predictor Selection

Following the workflow shown in Figure 1, ultimately identifying the following eight core predictors as input variables (Figure 2; Table 1; Figure S2): 1000 hPa vertical velocity anomaly over the eastern South Pacific (W1000_{ESP}); 850 hPa zonal wind anomaly over eastern North America and the adjacent North Atlantic (U850_{NA}); surface latent heat flux

anomaly over the subtropical South Pacific (AVG_{STSP}); 500 hPa vorticity anomaly over the northeastern Pacific ($VO500_{NEP}$); total precipitation anomaly over the Kara Sea (TP_{KS}); 500 hPa vertical velocity anomaly over the Indian Ocean sector of the Southern Ocean ($W500_{SOIS}$); 500 hPa vorticity anomaly over the tropical South Pacific ($VO500_{TSP}$); and 200 hPa meridional wind anomaly over the southwestern Indian Ocean ($V200_{SWIO}$). The output variable is the NASH intensity index.

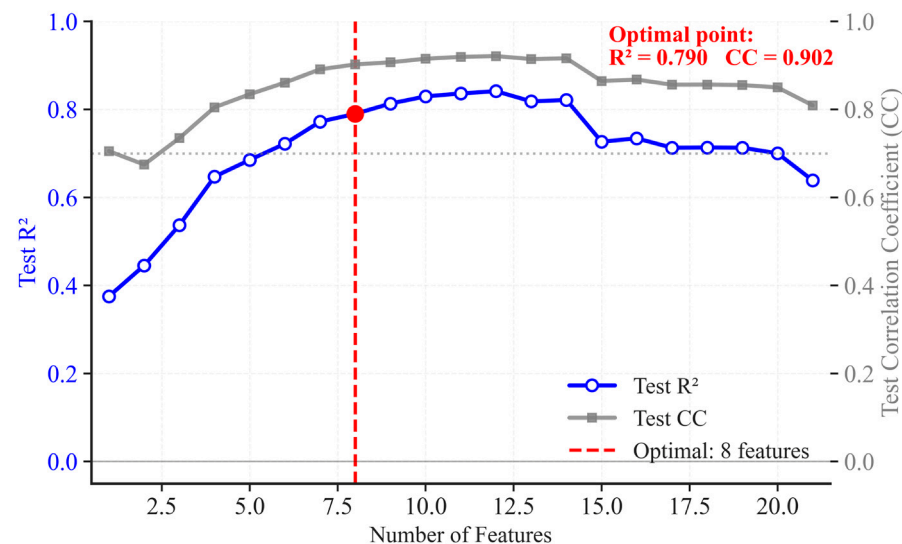


Figure 2. Stepwise forward selection process: feature number versus performance on the testing set.

Table 1. Summary of the input and output variables used in the multi-model ensemble.

Category	Variable	Description
Input	$W1000_{ESP}$	1000 hPa vertical velocity anomaly over 57.5–30.0° S, 165.0–140.0° W
	$U850_{NA}$	850 hPa zonal wind anomaly over 35.0–37.5° N, 95.0–70.0° W
	AVG_{STSP}	surface latent heat flux anomaly over 42.5–25.0° S, 167.5–135.0° W
	$VO500_{NEP}$	500 hPa vorticity anomaly over 47.5–57.5° N, 165.0–142.5° W
	TP_{KS}	total precipitation anomaly over 75.0–82.5° N, 55.0–90.0° E
	$W500_{SOIS}$	500 hPa vertical velocity anomaly over 70.0–45.0° S, 85.0–110.0° E
	$VO500_{TSP}$	500 hPa vorticity anomaly over 17.5–10.0° S, 162.5–130.0° W
	$V200_{SWIO}$	200 hPa meridional wind anomaly over 22.5–10.0° S, 40.0–62.5° E
Output	NASH Index	area-averaged summer (JJA) mean SLP anomaly over 25.0–45.0° N, 70.0–20.0° W

3.2. Examination of the Optimal Forecast Lead Time

To determine the optimal predictor initialization season for forecasting NASH intensity, we conducted hindcasts of the NASH intensity index during the independent test period (2011–2024) using predictors derived from four distinct seasonal windows: the preceding summer (JJA(0)), preceding autumn (SON(0)), preceding winter (D(0)JF(1)), and current spring (MAM(1)). Among these, the multi-model ensemble (MME) based on spring predictors achieved the lowest mean absolute error (MAE = 0.39 hPa), along with the highest correlation coefficient (CC = 0.90) and index of agreement ($d = 0.93$) (Figure S3). These results suggest that spring is the optimal initialization season for forecasting NASH intensity using the selected predictors.

3.3. Model Performance Evaluation

3.3.1. Model Generalization Performance During the Independent Test Period

Hyperparameter optimization for each model was performed via Grid Search coupled with Time Series Cross-Validation (TSCV) confined to the training period (Tables S2-2 and

S2-3). The optimized models were subsequently integrated into a multi-model ensemble (MME) using the simple arithmetic averaging strategy defined in Equation (1). Evaluated over the independent test period (2011–2024; Figure 3), the MME demonstrated highly robust predictive skill. Notably, intra-ensemble consensus regarding the predicted sign exceeded 50% in 11 of the 14 years, achieving complete unanimity (100% agreement among all models) in 8 of those years. The three years characterized by lower consensus corresponded exclusively to relatively weak NASH anomalies, meaning the MME successfully captured all anomalously strong or extreme NASH events without any misses.

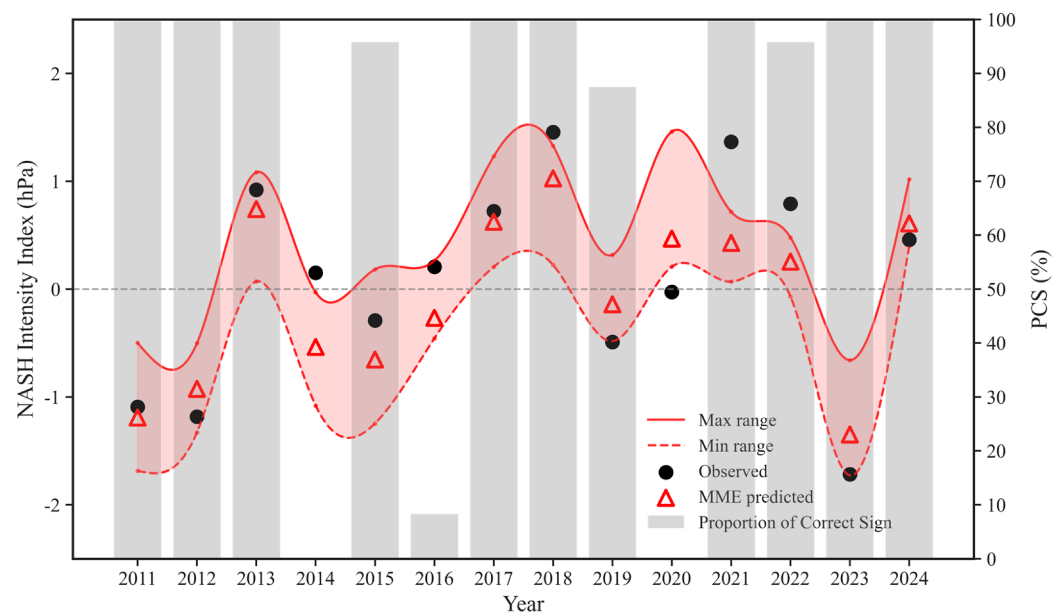


Figure 3. Ranges (red shading) of the NASH intensity index predicted by the 24 models during the independent test period; Proportion of Correct Sign (PCS, grey bars) between the predicted NASH intensity index and the observations for the 24 models. Red triangles and black solid circles represent the multi-model ensemble (MME) mean and the observed values, respectively.

Over the full study period (1965–2024), the baseline NASH intensity index exhibited a natural standard deviation (σ) of 0.81 hPa (range: -1.82 to 1.90 hPa). Against this baseline, the MME’s deterministic forecast achieved a mean absolute error (MAE) of 0.39 hPa during the independent test period. This MAE represents only 48% of the index’s characteristic σ , demonstrating that the forecast error is tightly constrained well within the system’s natural interannual variability. Ultimately, the finalized MME not only predicted the correct anomaly sign in 11 of the 14 years but also maintained an absolute error of less than 0.5 hPa in those same 11 years, successfully reproducing the interannual evolutionary dynamics of the NASH.

Table 2 summarizes the forecast performance of the 24 individual models and the MME during the independent test period. With optimized hyperparameters, all 24 models reproduced the temporal evolution of the NASH intensity index, with correlation coefficients (CC) ranging from 0.77 to 0.90. Notably, linear models—including PLS, Ridge, and LR—achieved the lowest mean absolute errors and the highest CCs, suggesting that the springtime predictors are largely linearly related to summer NASH intensity. In contrast, several tree-based and deep-learning models (e.g., ET, LSTM, CNN, and AdaB) exhibited substantially larger errors, with MAEs exceeding 0.50 hPa.

Table 2. Performance statistics of the forecasted NASH intensity index for each model and the ensemble model during the independent test period.

No.	Model	MAE (hPa)	CC	R ²	<i>d</i>
1	LR	0.351	0.902	0.79	0.943
2	Ridge	0.348	0.904	0.789	0.935
3	BRidge	0.347	0.903	0.792	0.939
4	EN	0.35	0.902	0.791	0.942
5	Lasso	0.351	0.902	0.791	0.941
6	Lars	0.351	0.902	0.79	0.943
7	PLS	0.346	0.902	0.791	0.943
8	OMP	0.361	0.891	0.772	0.933
9	Huber	0.36	0.901	0.771	0.94
10	RANSAC	0.432	0.889	0.731	0.92
11	TS	0.372	0.896	0.779	0.937
12	SVR	0.381	0.9	0.767	0.935
13	KRR	0.442	0.894	0.691	0.878
14	KNR	0.471	0.82	0.578	0.811
15	XGB	0.521	0.803	0.606	0.866
16	GBR	0.417	0.874	0.743	0.918
17	AdaB	0.528	0.784	0.513	0.785
18	LGBM	0.415	0.891	0.73	0.916
19	CB	0.497	0.849	0.643	0.866
20	ET	0.573	0.845	0.496	0.738
21	MLP	0.384	0.892	0.758	0.918
22	GRU	0.438	0.88	0.7	0.922
23	LSTM	0.576	0.77	0.548	0.868
24	CNN	0.529	0.81	0.537	0.856
25	MME	0.391	0.898	0.765	0.925

By comparison, the multi-model ensemble (MME) delivered a more robust and balanced forecast, achieving an MAE of 0.391 hPa, a CC of 0.898, and an R² of 0.765. Although certain linear models produced marginally lower MAEs, the MME's CC remained among the top performers. By leveraging algorithmic diversity to mitigate the high-variance risks inherent in individual tree-based or deep-learning models, this strategy ensures that the MME exhibits superior fault tolerance and structural stability when forecasting future years or extreme anomalies. This collective integration acts as a robust safeguard for the prediction system against the catastrophic failure of any single model, ultimately establishing the MME as a highly reliable and resilient forecasting framework.

3.3.2. Comparison with Dynamical Model Forecast Results

To further quantify the predictive skill of the constructed models, the MME hindcasts were compared with the seasonal forecasts from the SEAS5 dynamical model (Figure 4). Over the period 1981–2025, the MME achieved an MAE of 0.382 hPa—40.0% lower than that of SEAS5 (0.637 hPa)—and a CC of 0.816, compared with 0.440 for SEAS5, thereby demonstrating significantly superior accuracy. Notably, although SEAS5's forecast consistency improved markedly after 2011, the MME still exhibited considerably better performance during this subperiod, with a 30.3% reduction in MAE and a CC of 0.903, compared with 0.757 for SEAS5. These results indicate that, compared with SEAS5, the machine learning-based MME provides higher accuracy and enhanced robustness in seasonal prediction of NASH intensity, highlighting its strong potential for operational application.

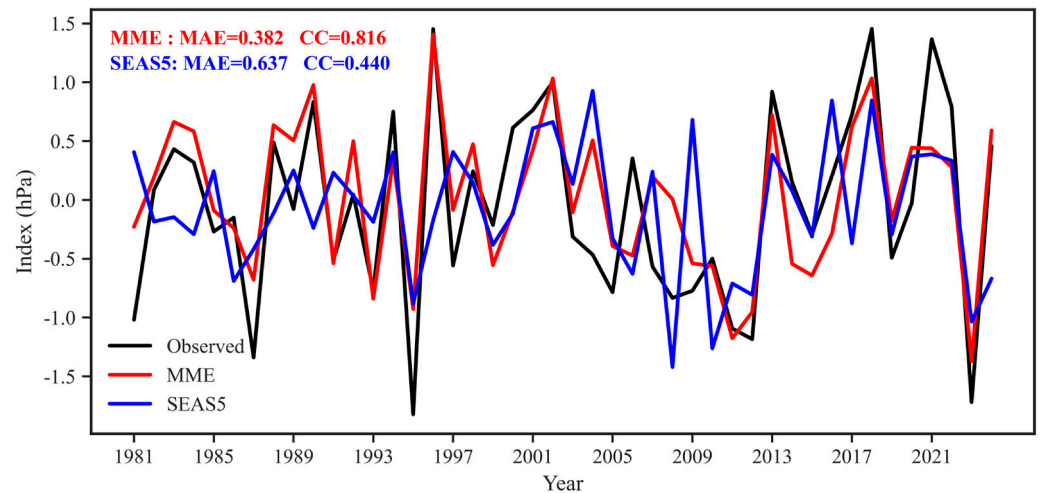


Figure 4. Time series of the observed (black line), MME-predicted (red line), and SEAS5-predicted (blue line) NASH intensity index during 1981–2024.

3.4. Model Robustness Verification Based on Cross-Validated Hindcast

To further verify the predictive robustness of each model over a longer time series, the cross-validated hindcast sequences obtained from TSCV were evaluated, as shown in Figure 5. Overall, the multi-model ensemble (MME) demonstrated stable and reliable predictive skill throughout the entire evaluable period: forecast errors were within 1.0 hPa for all years (Figure 5b), and 71% of the years exhibited an error below 0.5 hPa. Meanwhile, the MME successfully captured both the interannual variability and the decadal fluctuations of the NASH intensity (Figure 5a).

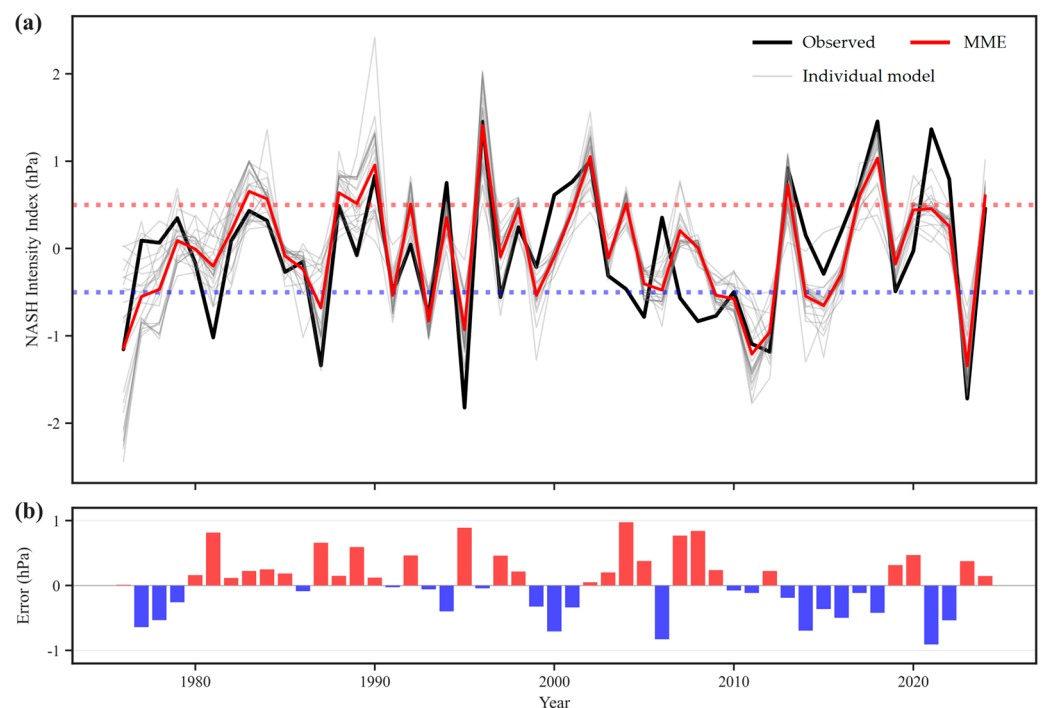


Figure 5. (a) Time series of the predicted NASH intensity index from the 24 models based on cross-validated hindcasts (TSCV) (grey lines) and the MME-predicted NASH intensity index time series (red line). The black curve represents the observed values. The dashed lines at ± 0.5 hPa in panel (a) mark the ± 0.5 hPa error threshold. (b) Year-by-year forecast errors of the MME. Red bars indicate that the predicted value is higher than the observed value, and blue bars indicate that the predicted value is lower than the observed value.

For the individual models, the correlation coefficients between predicted and observed NASH intensities ranged from 0.65 to 0.85, all reaching a level rated as good or higher (Table S3; Figure 6). Relative forecast skill (S) values show that, with the exception of Ridge, the MME outperforms the other 23 individual models, yielding an average skill improvement of 12.97%. While Ridge's outstanding overall performance qualifies it as an ideal candidate for the subsequent SHAP-based attribution analysis, a more comprehensive evaluation highlights the distinct advantages of the ensemble approach. Additionally, to evaluate model accuracy, we calculated the absolute errors of the cross-validated hindcasts and recorded the years in which each individual model secured the smallest absolute error. The results reveal that even compared to KNR—the individual model that most frequently captured the lowest annual absolute error—the MME still achieved a substantial skill gain of 15.15%. Concurrently, although the Ridge model exhibited exceptional predictive precision during long-term cross-validation and marginally surpassed the MME in overall skill, the ensemble framework provides vital structural stability and a superior capability to compress extreme error magnitudes that individual models cannot deliver. These results underscore that while individual algorithms may hit localized predictive optima in certain years, they lack the sustained, cross-regime stability required for reliable long-term forecasting.

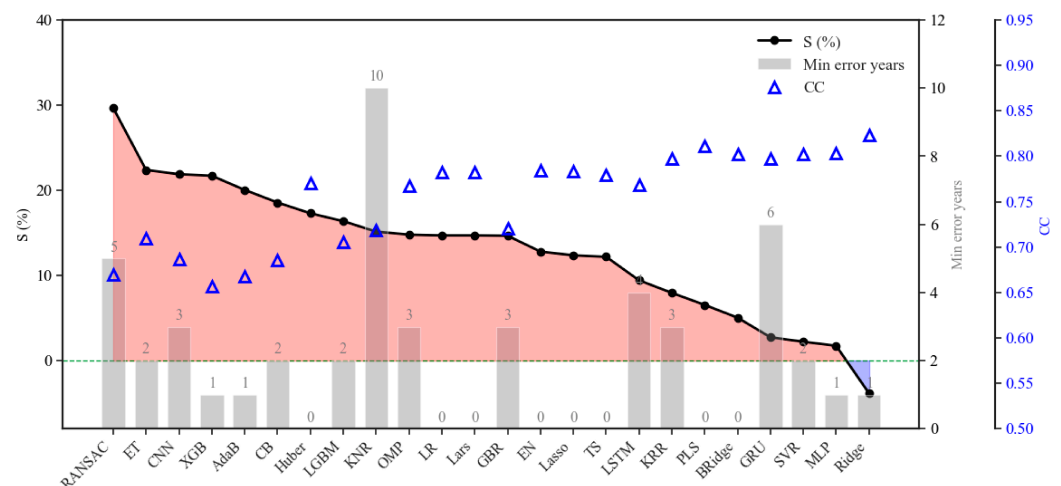


Figure 6. Number of years in which each model achieved the smallest absolute error (grey bars), correlation coefficient between the individual model-predicted NASH intensity index and the observations (blue triangles), and the forecast skill of the multi-model ensemble relative to each individual model (S %), black line). The green dashed line at $S = 0$ separates models that the MME outperforms (positive S) from those it does not (negative S). The red shading indicates positive S values (MME superior), and the blue shading indicates negative S values (single model superior).

Notably, several linear models (e.g., LR, Ridge, and PLS) that performed well and achieved comparable evaluation metrics during the independent test period diverged considerably in the cross-validated hindcast assessment, and the vast majority were outperformed by the MME, highlighting the inherent high-variance characteristics of individual models. This implies that for small-sample climate prediction problems characterized by a low signal-to-noise ratio—such as forecasting the NASH intensity—pursuing a single optimal model may not be the best strategy. By aggregating a diverse spectrum of algorithmic architectures, the MME capitalizes on the ensemble effect to effectively damp individual model instabilities, thereby enhancing overall forecasting robustness and delivering more stable, dependable predictions.

4. Attribution Analysis of Predictors Based on SHAP

To quantitatively assess the relative contribution of each predictor and to characterize the response patterns the model has learned from the given data distribution, we applied the SHAP framework to the Ridge model that performed best in the cross-validated hindcast assessment.

The feature importance plot (Figure 7) reveals that $W1000_{ESP}$ and $VO500_{NEP}$ achieve the highest marginal contributions in the model, accounting for 16.3% and 14.3%, respectively. In contrast to positive contributors, higher positive standardized values of both predictors tend to lower the predicted NASH intensity index, indicating a pronounced negative marginal effect (Figure 8a,b). This attribution pattern is directionally consistent with cross-basin teleconnection mechanisms documented in the literature. During boreal spring, positive low-level vertical velocity anomalies over the eastern South Pacific ($W1000_{ESP}$) typically signal a weakened South Pacific Subtropical High [38,39]. The resulting anomalous trade winds trigger the wind–evaporation–sea surface temperature (WES) feedback, which sustains oceanic thermal anomalies into summer and subsequently weakens the NASH via adjustments in the descending branch of the Walker and Hadley circulations [40–45].

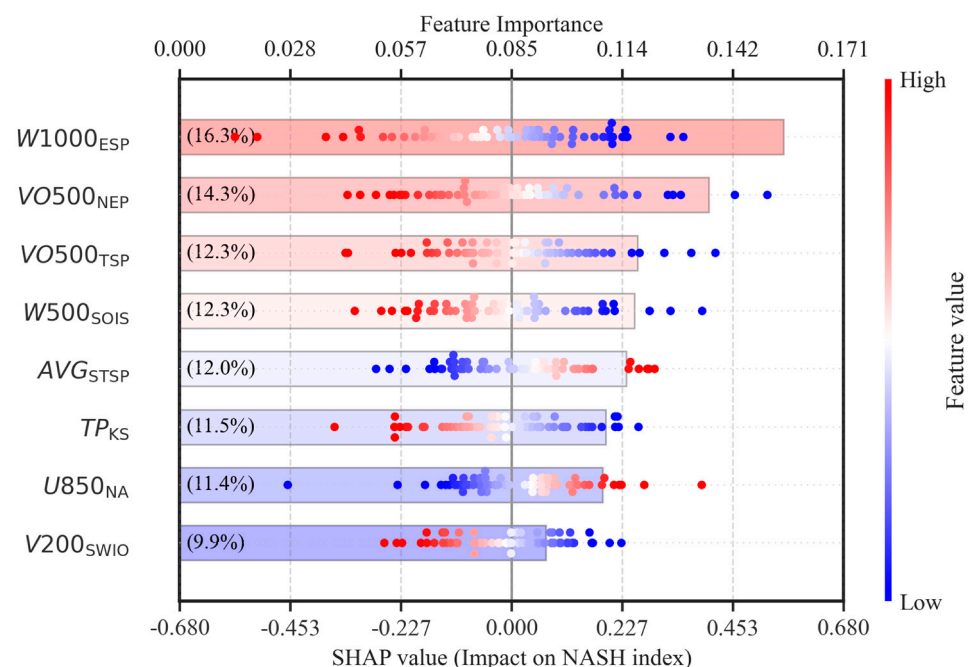


Figure 7. Feature importance plot and summary plot. The upper horizontal axis represents the mean absolute SHAP value of each feature, corresponding to the feature importance plot; the lower horizontal axis represents the SHAP value, corresponding to the summary plot. The vertical axis lists the feature variables in descending order of feature importance. Each dot represents a single sample for the corresponding feature, with the dot color gradient from blue to red indicating the variation of the standardized feature value from low to high.

Concurrently, positive mid-level relative vorticity anomalies over the Northeast Pacific ($VO500_{NEP}$)—often associated with a deepened Aleutian Low—can propagate via the “atmospheric bridge” effect across the Central American isthmus, reducing spring trade winds over the tropical North Atlantic [46–48]. The ensuing local spring SST anomalies persist into summer, serving as an anomalous heat source that ultimately weakens the summer NASH [6,49–51].

Additionally, $VO500_{TSP}$, $W500_{SOIS}$, AVG_{STSP} , and $U850_{NA}$ contributed 12.3%, 12.3%, 12.0%, and 11.4%, respectively, to the model predictions (Figure 7). Among these, AVG_{STSP} and $U850_{NA}$ exhibit predominantly positive marginal effects in the SHAP summary plot,

whereas $VO500_{TSP}$ and $W500_{SOIS}$ show pronounced negative effects. For instance, enhanced surface latent heat flux in the Subtropical South Pacific (AVG_{STSP}) reflects intensified oceanic evaporation and thermal forcing, which can provide cross-equatorial dynamical support to the Northern Hemisphere atmospheric circulation [52–54]. Furthermore, positive low-level zonal wind anomalies over North America ($U850_{NA}$) directly enhance the anticyclonic shear in the lower troposphere over the western North Atlantic. This acts as a localized dynamical precursor that strongly favors the intensification and westward extension of the summer NASH [5,55–57].

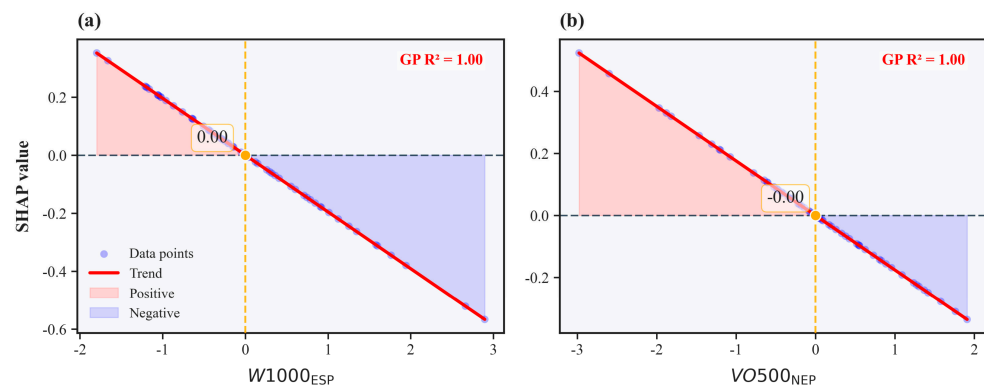


Figure 8. SHAP dependence plots for the top two predictors ranked by feature importance: (a) $W1000_{ESP}$; (b) $VO500_{NEP}$. The horizontal axis shows the standardized predictor values, and the vertical axis shows the SHAP value of each sample for that predictor. Blue dots represent individual samples. The red solid line is the nonlinear fitting curve based on GP regression, and the grey shaded area indicates the 95% confidence interval of the fitted curve. The R^2 of the GP regression is annotated in the figure to reflect the goodness of fit of the curve to the data points.

To further elucidate the specific response patterns of the core precursors, Gaussian Process (GP) regression was applied to fit the trajectories within the SHAP dependence plots (Figure 8). Focusing on the top two cross-basin predictors, $W1000_{ESP}$ and $VO500_{NEP}$, the Ridge model resolves an inherently linear and strictly monotonic negative dependence, quantified by a GP regression R^2 of 1.00. As shown in Figure 8, positive standardized anomalies for both predictors consistently yield negative SHAP values, thereby exerting a suppressive effect on the summer NASH. The underlying physical mechanisms driving these linear negative responses—specifically the WES feedback and the atmospheric bridge teleconnection—are detailed in the preceding feature importance analysis and faithfully mirror the established cross-basin frameworks.

Collectively, the above predictors account for the majority of the cumulative importance, and the directional contributions revealed by the SHAP analysis are largely consistent with established physical understanding. This general consistency lends a degree of physical plausibility to the model’s pronounced dependence on these predictors. It is important to recognize that SHAP attribution captures association patterns embedded in the training data distribution rather than providing a rigorous causal inference. The underlying physical mechanisms linking these predictors to NASH intensity therefore warrant further investigation through dynamical diagnostics or targeted numerical experiments. Nonetheless, this attribution analysis remains valuable, as it yields useful insights into model prediction behavior and informs the future optimization of predictor combinations.

5. Conclusions and Discussion

This study developed a multi-algorithm ensemble forecasting system for summer NASH intensity by integrating 24 machine learning algorithms with eight springtime predictors. The hindcast performance was evaluated against observations and a traditional

dynamical model, and the SHAP framework was employed to quantify predictor contributions. The key findings are as follows: (1) All 24 models effectively captured the interannual variability of NASH intensity (CC 0.77–0.90), with linear models generally outperforming tree-based and deep-learning counterparts. The multi-model ensemble (MME) delivered a robust forecast (MAE = 0.391 hPa, CC = 0.898, R^2 = 0.765), successfully capturing the interannual variability of NASH intensity during the independent test period. (2) Compared with the SEAS5 dynamical forecast over 1981–2025, the MME reduced the MAE by 40.0% and increased the CC from 0.440 to 0.816. (3) Time Series Cross-Validation (TSCV) further confirmed the robust predictive skill of the MME, which exceeded most of the individual models, with an average skill improvement of 12.97%. (4) The SHAP attribution analysis reveals that $W1000_{ESP}$ (16.3%) and $VO500_{NEP}$ (14.3%) are the two most important predictors. The directional contributions of these predictors are broadly consistent with cross-basin teleconnection mechanisms documented in the literature.

Notably, while previous studies highlight the sensitivity of NASH intensity to SSTA [8,13], the eight predictors finally retained in our framework (Table 1) are predominantly atmospheric. This does not imply a disconnect from oceanic forcing. Rather, the two most critical features— $W1000_{ESP}$ and $VO500_{NEP}$ —are established atmospheric responses to underlying SSTA via localized air–sea coupling. Because SST anomalies possess intrinsic cross-seasonal persistence, these antecedent atmospheric predictors act as concurrent footprints of sustained oceanic memory. They effectively bridge long-lead oceanic signals and subsequent tropospheric circulation. Ultimately, the exclusion of raw SSTA indices suggests that large-scale atmospheric anomalies offer a more dynamically integrated, high-signal-to-noise-ratio representation of climate forcings. Future efforts will focus on refining feature-construction strategies to explicitly couple these boundary-layer and free-tropospheric atmospheric bridges.

Furthermore, the predictor screening in this study was based on correlation analysis conducted over the entire training period, which implicitly assumes stationary statistical relationships between the predictors and NASH intensity. However, the coupling between climate precursors and the target can exhibit pronounced interdecadal variability, a common challenge in long-term climate forecasting. To diagnose this, we performed a 21-year sliding correlation analysis and applied the Pettitt test [58] (Text S2, Figure S4). The results (Figure S4) reveal significant abrupt changes in the mean values of the sliding correlations for all eight predictors. For example, the correlations of AVG_{STSP} , $W500_{SOIS}$, and $VO500_{TSP}$ dropped by 30–50% around 1997, 1998, and 2001, respectively, whereas those of $VO500_{NEP}$ and $V200_{SWIO}$ increased sharply around 2000 and 1998, rising from below 0.3 to above 0.5. Such interdecadal non-stationarity in the predictor–NASH relationships suggests that operational forecasting should account for the shifting weights of dominant predictors under different climatic regimes. Future work should examine how these abrupt changes in correlation affect the prediction stability of machine learning models.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16157596/s1>, Figure S1: Time Series of the NASH intensity index; Figure S2: Spatial correlation coefficients between the NASH intensity index and the spring predictors ($W1000_{ESP}$, $U850_{NA}$, AVG_{STSP} , $VO500_{NEP}$, $VO500_{TSP}$, TP_{KS} , $W500_{SOIS}$, $V200_{SWIO}$); Figure S3: Comparison of prediction skill among forecast predictors from different antecedent seasons; Figure S4: 21-year running correlation series and Pettitt test results for abrupt change detection; Table S1: List of environmental physical variables; Table S2-1: Performance statistics of the 24 models during the training period; Table S2-2: Hyperparameter grid search spaces and parameter settings; Table S2-3: Performance parameter statistics during training; Table S3: Performance parameter statistics of individual models and the ensemble based on TSCV; Text S1: Definitions of model performance evaluation metrics (d , S , and PCS); Text S2: Pettitt test for abrupt change detection.

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Abbreviations

The following abbreviations are used in this manuscript:

NASH	North Atlantic Subtropical High
SST	sea surface temperature
AMO	Atlantic Multidecadal Oscillation
PDO	Pacific Decadal Oscillation
AAO	Antarctic Oscillation
NAO	North Atlantic Oscillation
AWP	Atlantic Warm Pool
WPSH	Western Pacific Subtropical High
ConvLSTM	Convolutional Long and Short-Term Memory
ECMWF	The European Centre for Medium-Range Weather Forecasts
SEAS5	ECMWF's fifth generation seasonal forecast system
GloSea	Global Seasonal forecast system
XAI	explainable artificial intelligence
NCC	The National Climate Centre
SLP	sea level pressure
Lasso	Least Absolute Shrinkage and Selection Operator
MAE	Mean Absolute Error
CC	Pearson Correlation Coefficient
R^2	Coefficient of Determination
d	Index of Agreement
S	Relative Prediction Skill Improvement
PCS	Proportion of Correct Sign
SHAP	SHapley Additive exPlanations
$W1000_{ESP}$	1000 hPa vertical velocity anomaly over the eastern South Pacific
$U850_{NA}$	850 hPa zonal wind anomaly over eastern North America and the adjacent North Atlantic
AVG_{STSP}	surface latent heat flux anomaly over the subtropical South Pacific
$VO500_{NEP}$	500 hPa vorticity anomaly over the northeastern Pacific
TP_{KS}	total precipitation anomaly over the Kara Sea

W500 _{SOIS}	500 hPa vertical velocity anomaly over the Indian Ocean sector of the Southern Ocean
VO500 _{TSP}	500 hPa vorticity anomaly over the tropical South Pacific
V200 _{SWIO}	200 hPa meridional wind anomaly over the southwestern Indian Ocean
JJA(0)	preceding summer
SON(0)	preceding autumn
D(0)JF(1)	preceding winter
MAM(1)	current spring
MME	multi-model ensemble
TSCV	Time Series Cross-Validation
GP	Gaussian Process
SSTA	sea surface temperature anomaly

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