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# Seasonal predictions of summer compound humid heat extremes in the southeastern United States driven by sea surface temperatures



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Humid heat extreme (HHE) is a type of compound extreme weather event that poses severe risks to human health. Skillful forecasts of HHE months in advance are crucial for developing strategies to enhance community resilience to extreme events<sup>1,2</sup>. This study demonstrates that the frequency of summertime HHE in the southeastern United States (SEUS) can be skillfully predicted 0–1 months in advance using the SPEAR (Seamless system for Prediction and EArth system Research) seasonal forecast system. Sea surface temperatures (SSTs) in the tropical North Atlantic (TNA) basin are identified as the primary driver of this prediction skill. The responses of large-scale atmospheric circulation and winds to anomalous warm SSTs in the TNA favor the transport of heat and moisture from the Gulf of Mexico to the SEUS. This research underscores the role of slowly varying sea surface conditions in modifying large-scale environments, thereby contributing to the skillful prediction of HHE in the SEUS. The results of this study have potential applications in the development of early warning systems for HHE.

Summer heat extremes rank among the leading causes of fatalities from natural hazards<sup>3</sup>. Vulnerable populations, such as the elderly and children, are particularly susceptible to heat-related illnesses. In humid regions, the co-occurrence of high levels of humidity and heat increases the risk of human illness and mortality<sup>4–7</sup>. Humidity is important because it adversely affects the human body's cooling mechanism, making sweating and evaporation less efficient. Studies have shown that the danger of heat extremes is strongly amplified by humidity<sup>5,8–10</sup>. For instance, the July 1995 Chicago heat wave and the July–August 2003 Shanghai heat wave are notable examples where high relative humidity greatly exacerbated the consequences of the heat waves<sup>5</sup>.

Unlike the heat extremes that occur when high temperatures are accompanied by low levels of humidity in the air, humid heat extreme (HHE) events take into account the combined effects of high levels of humidity and heat on the body's ability to dissipate heat. HHE can be classified as a type of multivariate compound extreme event, characterized by a combination of multiple drivers and/or hazards that contribute to

societal or environmental risk<sup>11</sup>. These compound extremes are generally more impactful than univariate extremes and have received more attention in recent years. Observations indicate a rapid increase in HHE occurrences over the past four decades<sup>12</sup>. Additionally, climate model simulations have projected more frequent, intense, and widespread HHE with global warming<sup>5,13–16</sup>.

Despite the growing body of research on HHE, studies have primarily focused on future projections<sup>5,13–16</sup>. However, there is a notable gap concerning the predictability of HHE. To address the gap, this study investigates the prediction skill of summertime HHE in the southeastern United States (SEUS) using the geophysical fluid dynamics laboratory's (GFDL) Seamless system for Prediction and EArth system Research (SPEAR). Rather than studying individual HHE events, we examine the frequency of HHE occurrences during the summer season (June–August, i.e., JJA), defined as the number of HHE days in JJA divided by the total number of days (i.e., 92 days) in JJA. Furthermore, we explore the mechanisms that drive the year-to-year variability of the frequency of summertime HHE in the SEUS.

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## Results

### Climatology of relative humidity, temperature, and heat index in the June–July–August season

We first examine the climatology (during 1995–2022) of daily minimum relative humidity (RHmin), daily maximum temperature (Tmax), and heat index (HI) in the JJA season in the European Center for Medium-Range Weather Forecasts reanalysis version 5<sup>17</sup> (ERA5; also referred to as observations hereafter), as well as in the SPEAR hindcasts initialized on June 1st (Fig. 1, see “Methods” for the calculations of daily RHmin and Tmax and the definition of HI). The RHmin is the lowest in the western United States. In ERA5, most areas of the western United States show an average of RHmin below 30%. The RHmin is generally above 40% in Canada and the eastern United States. As can be shown from Eq. (2), relative humidity above 40% makes the apparent temperature (i.e., HI) higher than the actual air temperature. For example, an air temperature of 90 °F with a relative humidity of 60% produces an HI of 100 °F. On the contrary, the apparent temperature can be lower than the actual air temperature when the relative humidity is low.

The largest Tmax values occur over the southern states, particularly in southern California, Arizona, Texas, and northern Mexico. The spatial pattern of HI resembles that of Tmax but with high HI values primarily concentrated in the SEUS. This distribution is largely attributable to the relatively high levels of humidity in the SEUS region. Overall, the SPEAR hindcasts simulate the structure of the climatology of RHmin and Tmax reasonably well (Fig. 1d, e). Some warm biases are seen in the central United States (Fig. 1b vs. e). SPEAR overestimates the RHmin over most areas of North America but underestimates the RHmin in the central and western United States (Fig. 1a vs. d). As described in “Methods”, the daily RHmin and Tmax in the model are bias-corrected before computing the HI. Thus, the resulting climatology of the HI in SPEAR and ERA5 shows a significant agreement, both in spatial pattern and in magnitude (Fig. 1c vs. f). Bias correction of Tmax and RHmin reduces the overestimation of HI in the central United States, the underestimation of HI in the northwestern United States and northern Mexico, and consequently reduces the overcount of extreme days over the southern part of the central United States (Fig. S1).

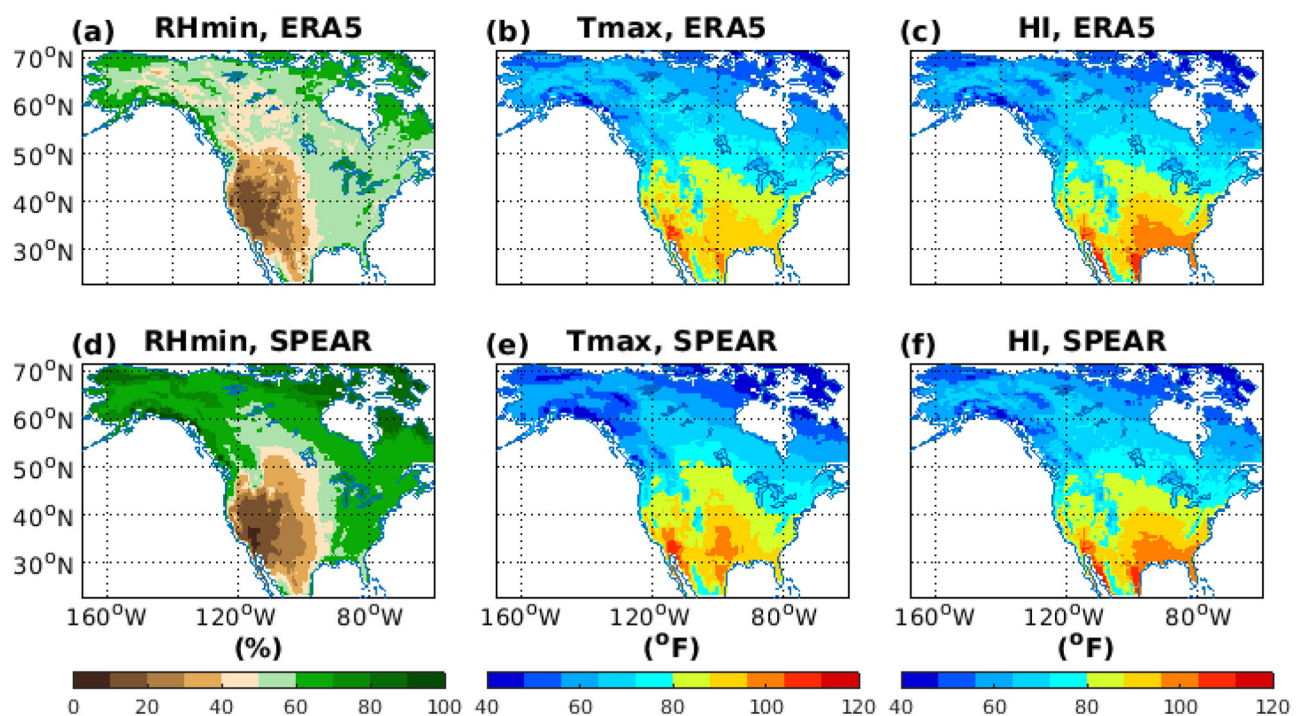
### The frequency of summertime HHE

The observed climatological frequency of summertime HHE (i.e., HI ≥ 105 °F, see “Methods” for the definition of HHE) shows the highest values in the SEUS, with a maximum occurring along its southern border. Additionally, high frequencies are also observed in a narrow area in southern Arizona and western Mexico (Fig. 2a). The elevated occurrence of HHE in this limited region is primarily due to the high air temperatures, as the humidity levels are low, as depicted in Fig. 1. The spatial structure of the frequency of HHE shown in ERA5 aligns with findings from earlier studies<sup>5,13,16</sup>, and is well represented in the SPEAR hindcasts initialized on June 1st, although small biases exist over regions with high frequency (Fig. 2c).

### Prediction skill of HHE over SEUS

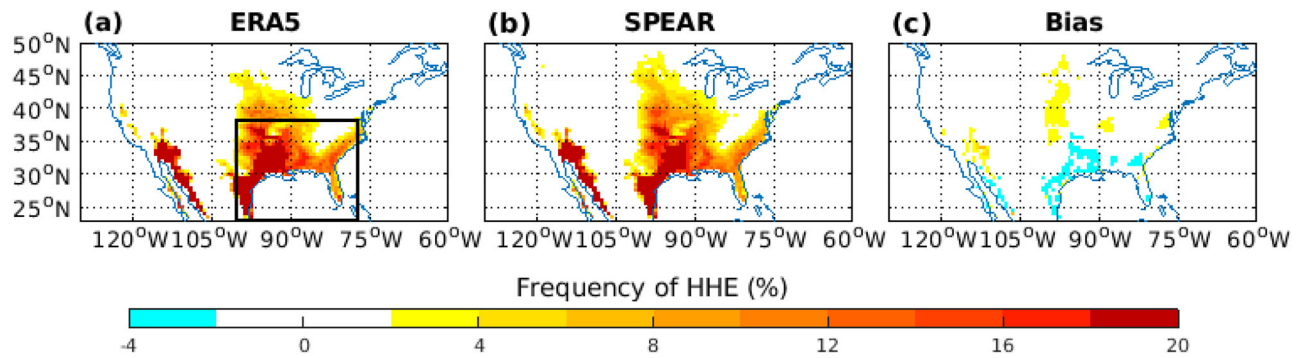
As shown in Fig. 2, the largest frequency of summertime HHE is located in the SEUS. We thus take the box average (23°–38°N, 77°–100°W; black box in Fig. 2a) of the frequency of HHE in the SEUS land areas to assess the averaged prediction skill. Figure 3a shows the time series of the frequency of summertime HHE in SEUS in the ERA5 reanalysis, and the SPEAR hindcasts initialized on June 1st (i.e., lead 0-month forecasts for the JJA season) and on May 1st (i.e., lead 1-month forecasts for the JJA season). Forecasts of HHE beyond a lead time of 1 month do not exhibit significant correlation skills and are therefore omitted from this study.

The observed frequency of HHE demonstrates large variability and exhibits a slightly increasing trend with a slope of 0.18 (i.e., the frequency of HHE increases by 0.18% per year) during the period 1995–2022. The SPEAR hindcasts also show an increase in the frequency of HHE, with a slope of 0.35 at lead 0-month and 0.48 at lead 1-month. Significant correlation skills are found at lead 0-month ( $R = 0.6$ ) and lead 1-month ( $R = 0.4$ ) hindcasts. The lead 0-month correlation skill is comparable to that in the AMIP experiment ( $R = 0.52$ ). Moreover, the detrended lead 0-month hindcasts and the AMIP experiment also show comparable correlation skill ( $R = 0.56$  vs.  $R = 0.63$ , Fig. 3b). As the AMIP experiment is forced by observed sea surface temperatures (SSTs), the comparable skill between the lead 0-month seasonal forecasts and the AMIP experiment indicates SST is



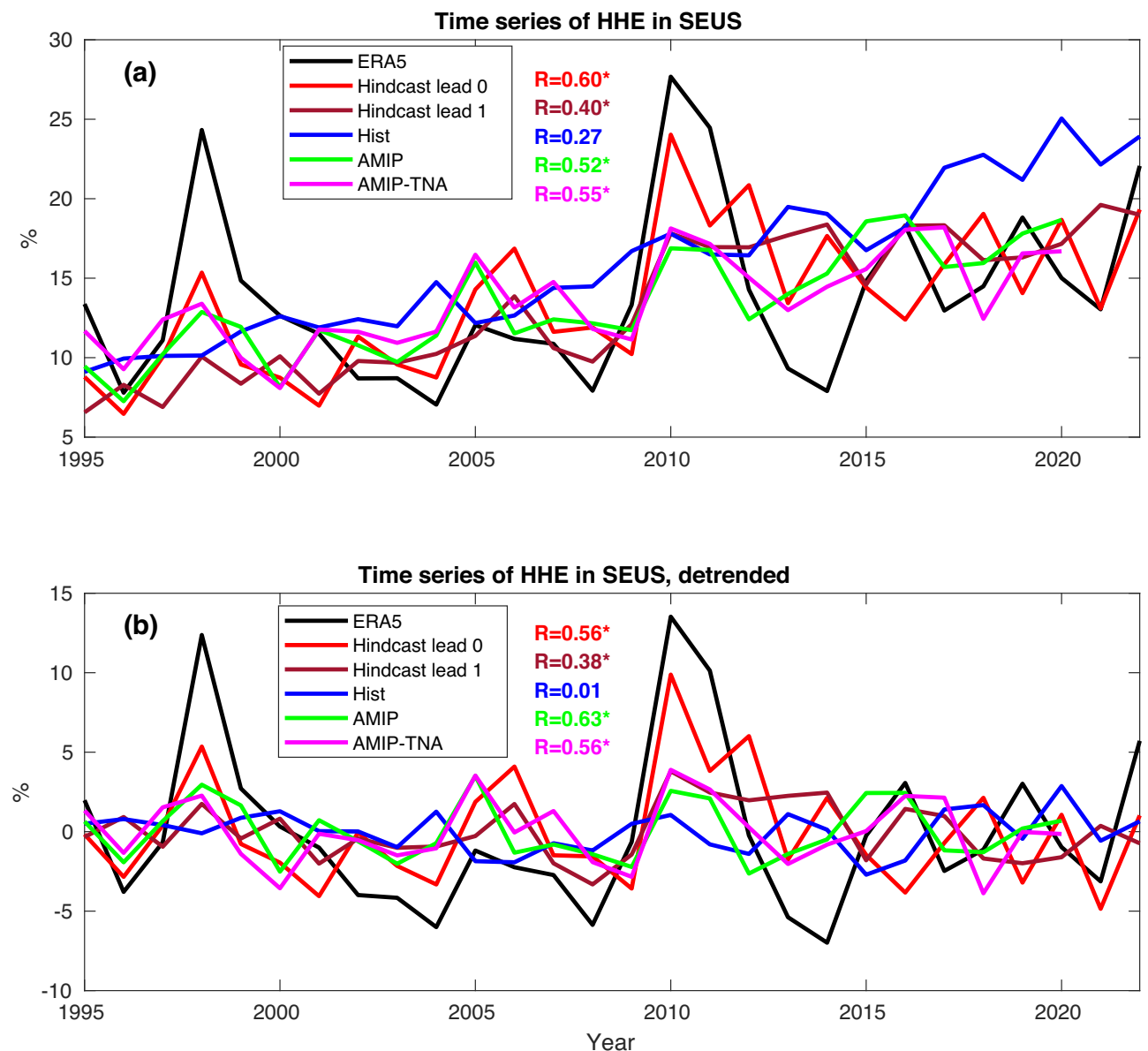
**Fig. 1 | Climatology of relative humidity, temperature, and heat index in JJA.** The climatology of **a** minimum relative humidity, **b** maximum temperature, and **c** heat index in the JJA season in ERA5 reanalysis. **d–f** same as (a–c), but in SPEAR hindcasts initialized on June 1st. The climatology for each variable is calculated as the

mean of its daily values over the JJA season during 1995–2022. The heat index in SPEAR hindcasts is computed from bias-corrected minimum relative humidity and maximum temperature. See “Methods” for the bias correction method.



**Fig. 2 | Climatology of the frequency of HHE in JJA.** The climatological frequency of summertime (i.e., JJA) HHE in **a** ERA5 reanalysis, **b** SPEAR hindcasts, and **c** the bias. The SPEAR hindcasts are initialized on June 1st, referred to as lead 0-month

seasonal hindcasts of the JJA season. The climatological base period is from 1995 to 2022. The black box in **a** indicates the high-frequency area that is averaged in the assessment of the prediction skill of HHE.

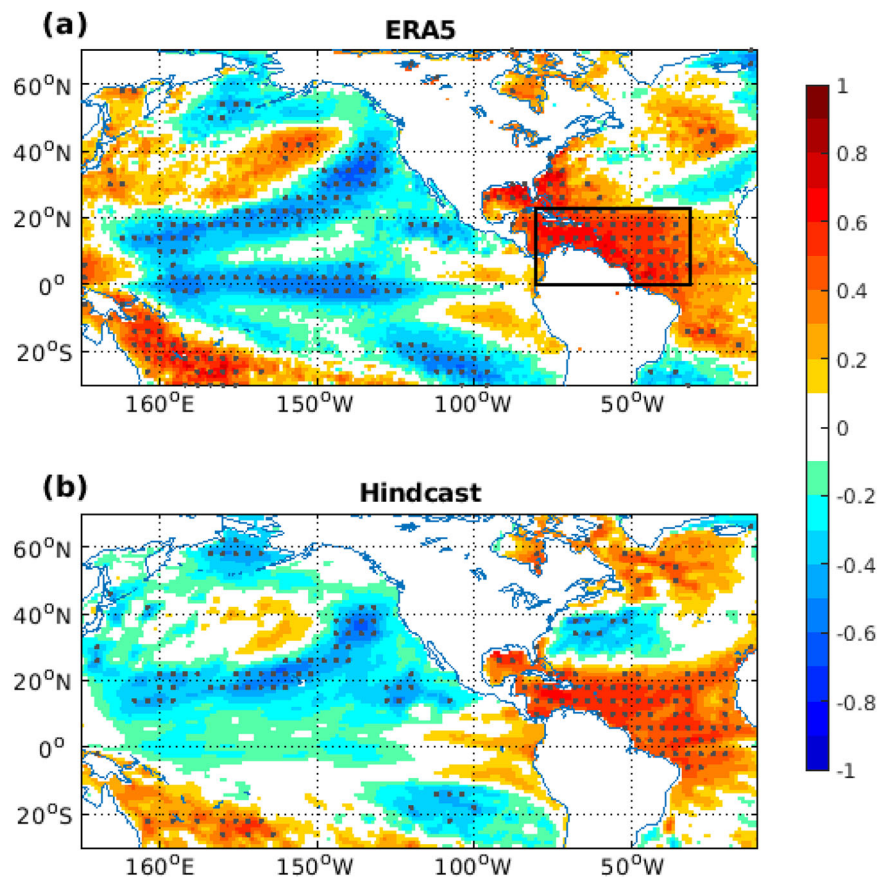


**Fig. 3 | Correlation skill of the frequency of HHE in SEUS.** **a** Time series of the frequency of HHE in the JJA season averaged over SEUS from ERA5 reanalysis (black), SPEAR hindcasts at lead 0-month (red) and lead 1-month (dark red), SPEAR historical simulations (blue), AMIP (green) and AMIP-TNA (magenta)

simulations. **b** Same as (a), but for the linearly-detrended time series. The correlation coefficients between the frequency of HHE in the ERA5 and model simulations are labelled in each panel. The asterisk indicates the correlation coefficient is significant at the 5% level.



**Fig. 4 | Relationship between SSTs and the frequency of HHE in SEUS.** The correlations of linearly-detrended JJA mean SST with the linearly-detrended frequency of JJA HHE averaged in the SEUS in **a** ERA5 and **b** SPEAR hindcasts. The dotted region denotes the correlation coefficients are locally significant at 5% level based on the *t*-test. The black box in **a** indicates the areas ( $0^{\circ}$ – $23^{\circ}$ N,  $80^{\circ}$ – $35^{\circ}$ W) in the tropical North Atlantic that show high correlations with the frequency of HHE in SEUS. The correlation pattern is field significant with a false discovery rate of 5% (15%) in ERA5 (SPEAR hindcasts)<sup>46,47</sup>.



the primary source of predictability in predicting the frequency of HHE over SEUS.

To assess the role of radiative forcing in the prediction of HHE, the time series of averaged frequency of HHE over SEUS in the SPEAR historical simulations (blue line) is also plotted (Fig. 3a). The historical simulations produce an increasing trend (slope = 0.5) in HHE that exceeds that of ERA5 by 0.32. However, its correlation with the observed time series ( $R = 0.27$ ,  $p = 0.16$ ) is positive but insignificant, and much smaller than that in the hindcasts. Additionally, the linearly-detrended time series in historical simulations shows no correlation skill ( $R = 0.01$ ), whereas the hindcasts still demonstrate significant skill after detrending (Fig. 3b). The above results suggest that external radiative forcing has little contribution to the skillful predictions of HHE in the SEUS.

#### The source of prediction skill of summertime HHE in the SEUS

To demonstrate that SST plays a primary role in predicting the frequency of summertime HHE in the SEUS, we present correlation maps showing the relationship between JJA mean SST and the frequency of HHE (Fig. 4). In ERA5 reanalysis, the largest positive SST correlations are observed over the tropical North Atlantic (TNA) as well as the coastal area of the SEUS, while negative correlations present over parts of the tropical and northern Pacific. The SST structures in the Pacific resemble the central Pacific La Niña pattern in the tropics and the negative phase of the Pacific Decadal Oscillation (PDO) pattern in the North Pacific. A high correlation ( $R = 0.62$ ,  $p = 0.0005$ ) is found between the frequency of HHE in the SEUS and the JJA mean SSTs in the TNA (the black box in Fig. 4,  $0^{\circ}$ – $23^{\circ}$ N,  $80^{\circ}$ – $35^{\circ}$ W). However, the frequency of HHE in the SEUS does not show a significant correlation ( $R = -0.2$ ,  $p = 0.31$ ) with the PDO index, although its correlation with the JJA mean Niño 4 index (averaged SST anomalies over the central equatorial Pacific:  $5^{\circ}$ S– $5^{\circ}$ N,  $160^{\circ}$ E– $150^{\circ}$ W) is significant ( $R = -0.45$ ,  $p = 0.02$ ). Similar structures are seen in the lead 0-month SPEAR hindcasts (Fig. 4b) in the TNA and North Pacific. However, SPEAR does not simulate the connection

between the HHE in the SEUS and the tropical Pacific Ocean, as found in ERA5.

Previous studies have demonstrated that the variability in the TNA leads to variability in the Pacific through oceanic processes and coupled ocean-atmosphere feedbacks such as the wind-evaporation-SST feedback<sup>18–20</sup>. Thus, the significant correlations observed in the tropical Pacific may result from remote forcing originating from the TNA (Fig. 4a). As revealed from the observed correlation between Niño 4 index and JJA mean SSTs in the TNA, significant negative correlations are found only when Niño 4 index is during August–December (i.e., lag of JJA mean SSTs in the TNA, Fig. S2). This suggests that the variability of the TNA leads to that of the tropical Pacific. Additionally, as shown in the correlations between SSTs in May and the frequency of HHE in JJA, the correlations during May are weaker compared to those during JJA in the Pacific region, yet they remain strong in the TNA (Fig. S3 vs. Fig. 4). This also implies that the variability in the TNA precedes that in the Pacific. Therefore, the source driver of the frequency of HHE in the SEUS is claimed to be the SSTs in the TNA. Moreover, the correlation skill of the detrended frequency of the HHE in the SEUS from the AMIP-TNA experiment ( $R = 0.56$ ), which by design is forced with prescribed SSTs in the TNA, is comparable to the correlation skills at lead 0-month forecast ( $R = 0.56$ ) as well as in the AMIP experiment ( $R = 0.63$ , Fig. 3b). This supports the argument that SSTs in the TNA is the primary driver of HHE in the SEUS. Skillful prediction of SSTs in the TNA would lead to skillful prediction of HHE in the SEUS. In fact, SSTs over TNA are highly predictable on seasonal time scales in SPEAR with correlation coefficients above 0.6 at 0 and 1-month leads (Fig. 5). And the correlation coefficients remain above 0.4 up to 4 months ahead. It is not surprising that SSTs in the TNA is more predictable than the frequency of HHE in the SEUS. In other words, the prediction skill of SSTs in the TNA does not necessarily directly translate to the prediction skill of HHE in the SEUS, as the association between SSTs in the TNA and HHE in the SEUS is not perfectly represented or forecasted in the model.

To further demonstrate the contribution of SSTs in the TNA to the prediction of HHE in the SEUS, Fig. 6 displays the regression coefficients of the detrended frequency of HHE with the detrended SST averaged over the TNA (black box in Fig. 4a). The highest frequency of HHE is shown in the southern border states of the SEUS in both the ERA5 reanalysis and SPEAR hindcasts, which bears great similarity with the spatial structure of the climatological frequency of HHE shown in Fig. 2.

### Mechanisms linking SSTs in the TNA to HHE in the SEUS

In order to understand the mechanisms connecting SSTs in the TNA and HHE in the SEUS, we assess the large-scale environments associated with the SST variability in the TNA. Figure 7 displays regression maps of JJA mean geopotential height at 200 hPa (Z200) and 850 hPa (Z850) with their associated wind vectors overlaid, 2 m temperature, and specific humidity at 850 hPa (Q850), with the areal-averaged SSTs in the TNA. In ERA5, significant positive anomalies of a crescent-shaped Z200 are observed from the mid-latitude North Pacific to the subtropical/tropical North Atlantic, including the SEUS. This circulation pattern suggests that warming in the TNA leads to a ridge at 200 hPa aloft of the SEUS area (Fig. 7a), resulting in higher than normal temperatures there (Fig. 7c). At the 850 hPa level, lower pressures are evident over the North American continent, Central American, and the North Atlantic. Over the TNA and the SEUS areas, the atmospheric response is consistent with the classic baroclinic structure, with cyclonic circulation in the lower troposphere and anticyclonic circulation in the upper troposphere. Positive Q850 anomalies are seen in the TNA, extending to the SEUS area, suggesting increased moisture in the air over the

SEUS when the TNA warms (Fig. 7d). Cyclonic winds at 850 hPa in the Gulf of Mexico facilitate the transport of hot and humid air from the southeast of the Gulf of Mexico to the SEUS (Fig. 7b).

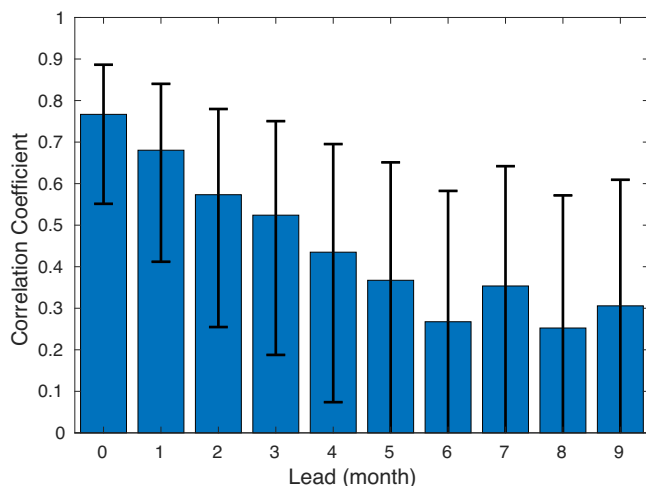
In summary, the above results suggest that the high temperature and moisture anomalies in the SEUS, as responses to the anomalous warm SSTs in the TNA, contribute to an increase in the frequency of HHE in the SEUS. Both dynamic and thermodynamic mechanisms play a role. Similar results are found in SPEAR hindcasts (Fig. 7e–h). The only notable difference is that the model underestimates the ridge of Z200 and its associated warm temperatures over the SEUS area. These results suggest that the model is capable of representing the mechanisms connecting SSTs in the TNA and the frequency of HHE in the SEUS.

### Summary and discussion

Summertime high temperatures occurring concurrently with high humidity pose adverse impacts on human health. Forecasting such humid heat extremes on seasonal time scales is crucial for developing strategies to help people cope with these extremes and minimize their impacts on climate-vulnerable sectors and society. In the North American continent, humid heat extremes occur most frequently in the SEUS. Here, we demonstrate that the frequency of summertime HHE in the SEUS is skillfully predicted at 0–1 month leads in the GFDL's SPEAR seasonal forecast system. The primary source of prediction skill for HHE in the SEUS is revealed to be the SSTs in the TNA basin. In contrast, historical radiative forcing demonstrates little contribution to forecasting summertime HHE in the SEUS.

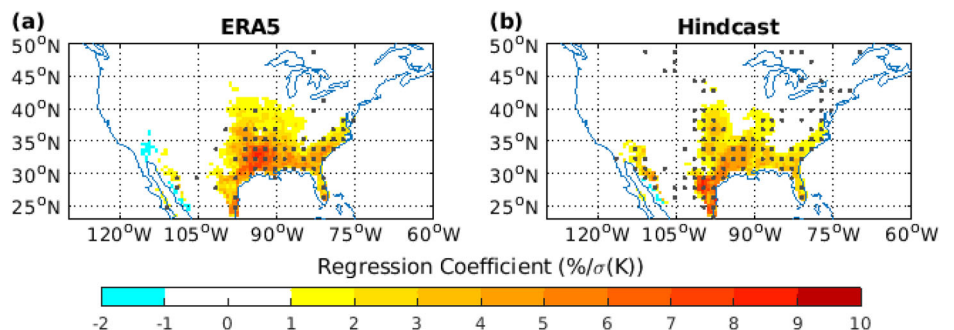
We also evaluate the large-scale environments to understand the mechanisms at play. Warm SSTs in the TNA lead to crescent-shaped high-pressure anomalies at 200 hPa, extending from the North Pacific to the North Atlantic with a ridge over the SEUS area, and relatively lower pressure over the North American continent and the North Atlantic at 850 hPa. The low-level winds over the Gulf of Mexico favor the transport of moisture and heat from the Gulf of Mexico to the SEUS. Consequently, the SEUS experiences increased humidity and higher temperatures than normal in response to the warm SSTs in the TNA, contributing to the high frequency of HHE in the SEUS.

Although several tools, including the Centers for Disease Control and Prevention (CDC) HeatRisk Forecast Tool and the National Weather Service HeatRisk tool, have been developed to forecast heat stress, they focus on short-term weather scales (e.g., up to 7 days). To our knowledge, this study is the first attempt at quantifying the prediction skill of HHE on seasonal time scales and identifying the source of this prediction skill. Potential tools for the seasonal forecast of HHE could be developed based on the findings of this study. The capability of the SPEAR model to skillfully forecast SSTs in the TNA on seasonal time scales, along with its reasonable representation of the physical processes linking SSTs in the TNA to the frequency of HHE in the SEUS, enables predictions of HHE in the SEUS 0–1 months in advance. A deeper understanding and better representation of the physical processes could further enhance forecast skills. Nevertheless, reliable predictions of HHE in the SEUS 0–1 months ahead are invaluable to society, particularly the heat health community. They can offer guidance for heat-related risk management and aid in better preparation for and response to extreme humid heat events. This study identifies SSTs in the TNA as the primary

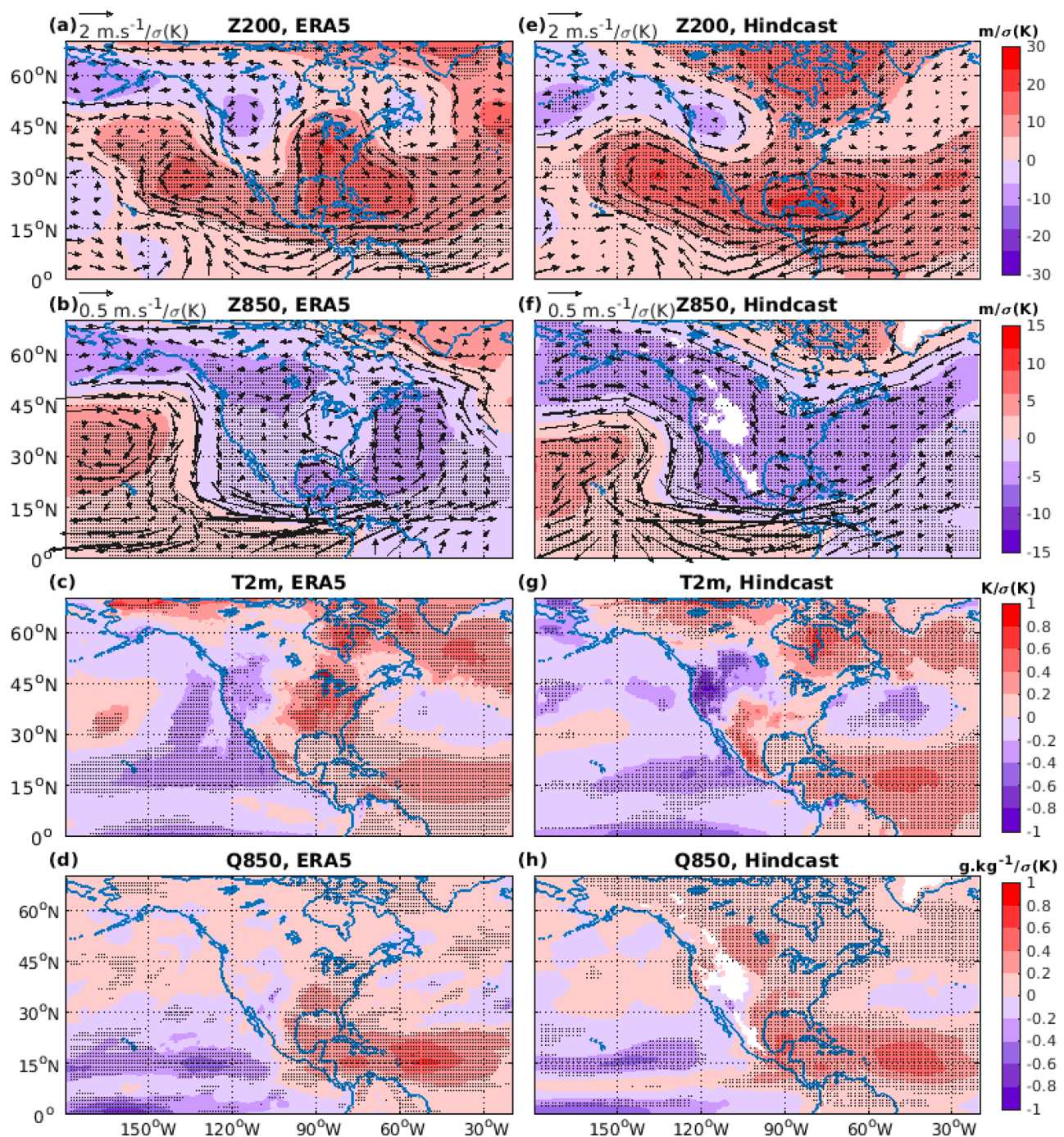


**Fig. 5 | Skill of JJA mean SSTs in the TNA.** The correlation coefficients of the SSTs in the TNA ( $0^{\circ}$ – $23^{\circ}$ N,  $80^{\circ}$ – $35^{\circ}$ W) between the ERA5 reanalysis and the SPEAR hindcasts, and their associated 95% confidence intervals for lead times from 0 to 9 months. As the confidence intervals do not contain zero for lead times of 0–4 months, their correlations are statistically significant at the 5% level. Lead 0-month means the hindcasts initialized on June 1st, lead 1-month indicates hindcasts initialized on May 1st, and so on.

**Fig. 6 | Regression patterns of HHE with SSTs in the TNA.** The regression coefficients of the frequency of HHE with the standardized box-averaged JJA mean SSTs in the TNA ( $0^{\circ}$ – $23^{\circ}$ N,  $80^{\circ}$ – $35^{\circ}$ W) in **a** ERA5 reanalysis and **b** SPEAR hindcasts initialized on June 1st. The dotted region denotes the regression coefficients are locally significant at a 5% level. The regression patterns are field significant with a false discovery rate of 5% in both ERA5 and SPEAR hindcasts<sup>46,47</sup>.







**Fig. 7 | Large-scale environments associated with the SSTs in the TNA.** The regression coefficients of geopotential height at 200 hPa and 850 hPa with wind vectors overlaid (arrows), 2 m air temperature, and specific humidity at 850 hPa onto the standardized box-averaged SSTs over TNA (0°–23°N, 80°–35°W) in ERA5 (a–d);

SPEAR hindcasts initialized on June 1st (e–h). The stippling shows regions are locally significant at the 10% level based on the *t*-test. The regression patterns are field significant with a false discovery rate of 10%<sup>46,47</sup> in all panels.

source of predictability. Other factors, such as land-atmosphere interactions, may also play a minor role, warranting further assessment beyond the scope of this study.

## Methods

### The SPEAR model and hindcasts

SPEAR is GFDL's latest prediction system optimized for studies in seasonal to multidecadal prediction and projection<sup>21</sup>. SPEAR is a coupled model including ocean, atmosphere, land and sea ice components. The atmosphere and land components are the GFDL AM4-LM4 models<sup>22</sup>; the ocean and sea

ice components use the MOM6 and SIS2 models<sup>23</sup>. The medium-resolution version of SPEAR used in this study has a horizontal resolution of approximately 50 km for the atmosphere and land. In the ocean, it has a horizontal resolution of 1 degree, refined to 1/3 degree near the equator.

This study utilized the SPEAR hindcast data from 1995 to 2022 to study the prediction skill of HHE in the SEUS. The hindcasts were conducted by initializing SPEAR on the first day of each month and integrating for 12 months. Each hindcast consists of 15 ensemble members. The initial conditions for the atmosphere, land, and sea ice were from a SPEAR ensemble of restoring simulations in which the atmospheric temperature,

moisture, and winds were strongly damped back towards values from the Climate Forecast System Reanalysis<sup>24</sup>; the SSTs were restored to the Optimum Interpolation Sea Surface Temperature version 2.1<sup>25</sup>. The oceanic initial conditions for the hindcasts were from an ensemble ocean reanalysis, which was produced by an ocean data assimilation (ODA) run in the coupled SPEAR model. An ocean tendency adjustment derived from the ODA increments is applied to seasonal predictions to reduce model drift. Details of the SPEAR seasonal forecast system, including the initialization and the bias correction method, can be found in ref. 26. In this study, for the target summer season (i.e., JJA), forecasts initialized on June 1st are referred to as lead 0-month forecasts, forecasts initialized on May 1st are referred to as lead 1-month forecasts, and so forth. The SPEAR seasonal forecast system has demonstrated significant prediction skill for a wide range of seasonal climate phenomena, including air temperature over land, the El Niño–Southern Oscillation (ENSO), mid-latitude baroclinic waves, Kuroshio Extension ocean variability, atmospheric rivers in western North America, North American temperature extremes, Arctic and Antarctic sea ice, wind energy resources, and more<sup>26–35</sup>.

### SPEAR historical simulations

The SPEAR historical simulations over the period of 1995–2022 are also utilized in this study to assess the role of external radiative forcing in predicting HHE. These historical simulations span from 1921 to 2100 and consist of 30 ensemble members. Initial conditions for the ocean, atmosphere, and sea ice were taken from widely separated points (20 years apart) of the SPEAR control simulation. The SPEAR control simulation was conducted with atmospheric forcing composition fixed at levels representative of the calendar year 1850. Estimates of the time-varying observed concentrations of atmospheric greenhouse gases, aerosols, and land use changes are applied from 1921 to 2014, after which future changes are projected following the Shared Socioeconomic Pathway 5–8.5 forcing scenario<sup>36,37</sup>. For consistency with the number of ensemble members in SPEAR hindcasts, only 15 members from the historical simulations are used in this study.

### SPEAR AMIP-style simulations

We conducted two sets of 15-member SPEAR AMIP-style simulations to investigate the role of SSTs in predicting HHE. The experimental design of the first set of AMIP-style simulations is identical to that of SPEAR historical simulations, except that the SST and sea ice concentration (SIC) were replaced with observations over the global ocean basins (referred to as AMIP experiment). The observed SST/SIC data were from the Hadley Center's SST/SIC version 1.1 merged with version 2 of the National Oceanic and Atmospheric Administration (NOAA) weekly optimum interpolation SST analysis<sup>38</sup>.

The second set of AMIP-style simulations (referred to as AMIP-TNA experiment) was performed identically to the above-mentioned classic AMIP-style experiment, which is forced with prescribed observed SST/SIC. However, for the basins outside of the TNA (0°–23°N, 80°–35°W), SST and SIC were forced with a repeating seasonal cycle of climatological SST and SIC. This experiment is designed to explore the contribution of SSTs in the TNA to the prediction of HHE. Due to data availability, we utilized data from 1995 to 2020 in both the AMIP and AMIP-TNA experiments.

### Verification data

The verification data used in this study are from the ERA5<sup>17</sup> (also referred to as observations in this study). The data used here are hourly 2 m dewpoint temperature and 2 m air temperature, from which we calculated the hourly relative humidity (RH) using the formula

$$RH = 100 \times \frac{e^{\frac{a \times T_d}{b+T_d}}}{e^{\frac{a \times T}{b+T}}}, \quad (1)$$

where  $a = 17.72$ ,  $b = 243.12$ ,  $T_d$  is the dewpoint temperature at 2 m in °C, and  $T$  is 2 m air temperature in °C. The daily maximum 2 m temperature is

calculated from the hourly 2 m air temperature. To maintain consistency with SPEAR's available data, we estimate the daily minimum RH in ERA5 as the minimum value of RH at 06, 12, 18, and 24 h of the day. Additionally, we utilize ERA5 monthly SST, 2 m temperature, 200 hPa and 850 hPa geopotential heights, horizontal and meridional winds at 200 hPa and 850 hPa, and 850 hPa specific humidity to investigate the mechanisms contributing to the prediction of HHE. The observed PDO index<sup>39</sup> was downloaded from [https://psl.noaa.gov/gcos\\_wgsp/Timeseries/Data/pdo.long.data](https://psl.noaa.gov/gcos_wgsp/Timeseries/Data/pdo.long.data). The observed Niño 4 index (averaged SST anomalies over the central equatorial Pacific: 5°S–5°N, 160°E–150°W) was downloaded from [https://psl.noaa.gov/gcos\\_wgsp/Timeseries/Data/nino4.long.anom.data](https://psl.noaa.gov/gcos_wgsp/Timeseries/Data/nino4.long.anom.data).

### Definition of the heat index and humid heat extreme

To consider the role of humidity in the “feels like” temperature, a heat index (HI), also known as apparent temperature, is adopted. It is one of a series of heat stress indicators developed to measure the thermal comfort of humans<sup>40</sup>. The US NOAA heat index is the most commonly known heat stress index and is used by NOAA for issuing heat warnings. The NOAA HI is defined as:

$$\begin{aligned} HI = & -42.379 + 2.04901523 \times T + 10.14333127 \times RH - .22475541 \times T \times RH \\ & - .00683783 \times T^2 - .05481717 \times RH^2 + .00122874 \times T^2 \times RH \\ & + .00085282 \times T \times RH^2 - .00000199 \times T^2 \times RH^2, \end{aligned} \quad (2)$$

where  $T$  is the air temperature in degrees Fahrenheit, and  $RH$  is the relative humidity in percent ([https://www.wpc.ncep.noaa.gov/html/heatindex\\_equation.shtml](https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml)). The above HI is obtained by multiple regression analysis<sup>41,42</sup> and has been widely used in previous studies<sup>5,43–45</sup>. This formula is not suitable for certain ranges of temperature and RH (i.e.,  $RH < 13\%$  and  $80^\circ\text{F} < T < 112^\circ\text{F}$ ;  $RH > 85\%$  and  $80^\circ\text{F} < T < 87^\circ\text{F}$ ;  $HI < 80^\circ\text{F}$ ), and adjustments were made to account for these relatively extreme combinations of temperature and humidity, as described on the referenced webpage. Note that the HI is higher than the actual temperature under elevated humidity levels and can be lower than the actual temperature when humidity is low.

Following refs. 45 and 5, we use an HI of 105 °F as the threshold to define HHE in this study. This is a general rule of thumb threshold at which the National Weather Service may issue an excessive heat warning (<https://www.weather.gov/safety/heat-ww>). The actual issuance of warnings also depends on additional factors such as the duration, nighttime minimum temperature, and geographic locations. Here, a day with an  $HI \geq 105^\circ\text{F}$  is called a humid and hot day or an HHE. Then, the frequency of HHE in the JJA season can be computed for each year. This study examines the prediction skill of the frequency of summertime HHE over the SEUS area. We estimate the daily maximum HI using the daily maximum temperature ( $T_{\max}$ ) and daily minimum RH ( $RH_{\min}$ ), assuming  $T$  and  $RH$  are inversely related. It has been demonstrated that HI estimated using  $T_{\max}$  and  $RH_{\min}$  best matches the recorded daily maximum HI<sup>45</sup>. Note that daily  $RH_{\min}$  is not available in SPEAR hindcasts; thus, we use 6-hourly RH to estimate the daily  $RH_{\min}$  as the minimum value of 6-hourly (at 06, 12, 18, and 24 h of the day) RH in a day. Due to the data availability in SPEAR, we use an alternative formula to that in (1) to calculate the 6-hourly RH:

$$RH = 0.263p \times q \times \left[ \exp\left(\frac{17.67(T - 273.16)}{T - 29.65}\right) \right]^{-1}, \quad (3)$$

where  $T$  is the 2 m air temperature in Kelvin,  $p$  is surface pressure in Pa, and  $q$  is the 2 m specific humidity in kg/kg.

As the absolute value of the HI is used to determine extremes, the model's bias matters. Therefore, before calculating the HI, we conducted bias correction of  $RH_{\min}$  and  $T_{\max}$  relative to their ERA5 climatologies (1995–2022) during the JJA season to make the calculation of HI more realistic. Specifically, at each grid point, the climatological biases of daily  $RH_{\min}$  and daily  $T_{\max}$  in the model were firstly calculated separately as the



model's seasonal (i.e., JJA) climatology minus the ERA5's seasonal climatology. The biases were then subtracted from the model. This was carried out separately for each lead time to remove the model's climatological bias. It is important to note that the biases of daily RHmin and Tmax were corrected relative to ERA5's seasonal climatologies (i.e., constant throughout the season) rather than being corrected on a daily basis. Consequently, the daily values of RHmin and Tmax in the model may not be identical to those of ERA5.

### Prediction skill metric

We utilize the correlation coefficient to measure the prediction skill of the frequency of HHE in the SEUS and the SSTs in the TNA. Let  $O$  be an observed time series of a quantify of interest,  $P$  be the prediction of  $O$ . The prediction skill is typically calculated as the Pearson correlation coefficient between  $O$  and  $P$ :

$$R = \frac{\sum_{i=1}^N (P_i - \bar{P})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^N (P_i - \bar{P})^2} \sqrt{\sum_{i=1}^N (O_i - \bar{O})^2}}, \quad (4)$$

where  $O_i$  is the observation at time  $i$ ,  $P_i$  is the prediction of  $O_i$ ,  $N$  is the number of time steps. The overbar denotes the temporal mean over the  $N$  time steps. The  $R$  ranges from  $-1$  to  $1$ . It indicates the linear relationship between the predicted values and the corresponding observed values.

### Data availability

The ERA5 datasets were downloaded from <https://cds.climate.copernicus.eu/#/search?text=ERA5&type=dataset>. The observed PDO index is available from [https://psl.noaa.gov/gcos\\_wgsp/Timeseries/PDO/](https://psl.noaa.gov/gcos_wgsp/Timeseries/PDO/). The observed Niño 4 index is available from [https://psl.noaa.gov/gcos\\_wgsp/Timeseries/Nino4/](https://psl.noaa.gov/gcos_wgsp/Timeseries/Nino4/). A subset of SPEAR data is available via the North American Multi-Model Ensemble Project (<https://www.cpc.ncep.noaa.gov/products/NMME/>). Other data from SPEAR hindcasts, historical simulations, and AMIP-style simulations are available from the corresponding author upon request.

### Code availability

Codes generated during this study are available from the corresponding author upon request.

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## Author contributions

L.J. initialized the study, conducted analysis, and wrote a first draft of the paper. W.C. conducted SPEAR historical simulations and helped with the AMIP-style simulations. L.J., T.L.D., X.Y., N.C.J., F.L., and C.M. contributed to the production of SPEAR seasonal hindcasts. All co-authors provided comments and contributed to the editing and revising of the paper.

## Competing interests

The authors declare no competing interests.

## Additional information

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