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Key Points:

- Global mean multiyear trends for Marine Heatwaves (MHW) days and frequency can be skillfully predicted for the following two to eight years
- In the Subpolar North Atlantic, yearly characteristics MHW days and frequency are predictable up to leadyear eight
- Any increase in SST in the Subpolar North Atlantic is accompanied by an increase in MHW and vice versa

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Decadal Prediction of Marine Heatwaves in MPI-ESM

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Abstract Marine Heatwaves (MHW) are SST extremes that can have devastating impacts on marine ecosystems and can influence circulation patterns in the ocean and the atmosphere. Here, we present a first attempt to study the decadal predictability of MHW in an ensemble of decadal hindcasts based on the Max Planck Institute Earth System Model. For the global mean we find significant skill for the multiyear MHW trends but we cannot predict the interannual to decadal variability of MHW. In the Subpolar North Atlantic, we can predict the interannual to decadal variability of MHW days and frequency up to lead year 8. We demonstrate that in the Subpolar North Atlantic, any increase in SST is accompanied by more MHW and vice versa. Thereby we gain additional information about the decadal evolution of SST that go beyond predicting the yearly mean SST.

Plain Language Summary Marine Heatwaves (MHW) are periods with extremely warm ocean temperatures that can be disruptive for many marine ecosystems. Here, we provide an attempt to predict the evolution of MHW in the global ocean for the following two to ten years. With this analysis we improve our understanding of the predictability of surface temperatures in the global ocean. We find that there are strong regional differences in the predictability of MHW. One region where MHW can be predicted successfully is the Subpolar North Atlantic. We show that an increase in mean ocean temperature also results in an increase in MHW.

1. Introduction

Marine Heatwaves (MHW) are defined as discrete anomalously warm water events in a particular location that can persist for days up to months and can cover up to thousands of kilometers (Hobday et al., 2016). MHW have been observed everywhere in the global ocean but hotspots of MHW are boundary current regions and the eastern equatorial Pacific (Oliver et al., 2018). In a warming climate, MHW can significantly impact marine ecosystems and can ultimately lead to socioeconomic consequences (Oliver et al., 2018). Consequently, Holbrook et al. (2020) argue that long term prediction of MHW would be beneficial to mitigate the impacts of MHW. Although several studies focus on the variability of MHW (Holbrook et al., 2019; Oliver et al., 2018, 2019), few studies analyze the monthly predictability of MHW at seasonal timescales and they all focus on specific regions or single events (Jacox et al., 2019). So far, no study focusing on the interannual to decadal predictability of MHW has been published. Here, we therefore aim to analyze the multi-year predictability of MHW in the global ocean.

While the mean increase in ocean temperatures is widely covered in the published literature (Gleckler et al., 2012; Stocker et al., 2013), global trends in ocean temperature extremes were mostly unexplored for many years. However, during the last couple of years, global assessments of MHW and their historical trends have emerged. A comprehensive assessment, analyzing SST data between 1925 and 2016 uses a multi-data approach to provide a historical overview of MHW during the past century (Oliver et al., 2018). Investigating the time period 1987–2016, Oliver et al. (2018) found a 34% increase in MHW frequency and a 54% increase in annual MHW days compared to the time period 1925–1954. Overall, the warming trend accelerates over the 1925–2016 period and most of the changes in MHW happened during the last few decades. Given the likelihood of continued ocean warming, it is expected that this increase in MHW is likely to continue over the following decades with ongoing global warming (Oliver et al., 2018). This is also confirmed by studies analyzing MHW in long term climate projections (Frölicher et al., 2018; Oliver et al., 2019).

During the last few years, there was an increasing research effort to produce reliable information on climate trends and climate variability for the interannual timescales between years and decades, as these cover the timescales that are important for decision makers in politics and economics (Kushnir et al., 2019; Stocker et al., 2013).

Nevertheless, decadal predictions of SST are still attached to high uncertainties (Kushnir et al., 2019). Due to this limited predictability of mean SST, we here analyze the decadal predictability of SST extremes: MHW.

One region, where the interannual variability of SST is rather predictable is the North Atlantic (Borchert et al., 2021; Brune & Baehr, 2020; Yeager & Robson, 2017). Holbrook et al. (2019) investigated MHW characteristics in the North Atlantic and found that the North Atlantic Oscillation (NAO) is the dominant climate mode influencing MHW. Thereby a negative phase of the NAO is associated with an increase in MHW frequency of up to 40%. In this study we particularly focus on the Subpolar North Atlantic to investigate the relationship between SST and MHW and which individual MHW characteristics are predictable.

We analyze the predictability of two MHW characteristics (MHW days and frequency) in the global ocean and in particular in the Subpolar North Atlantic. For this we use an ensemble of decadal hindcasts based on a coupled Earth System Model on a regional level as well as for the global mean. In addition we investigate the multiyear trends for MHW days and frequency.

2. Data and Methods

2.1. Hindcast Ensemble and Observational Reference

To detect and analyze the predictability of MHW, we use daily SST from an 16-member ensemble of decadal hindcasts based on the Max Planck Institute Earth System Model (MPI-ESM) in its low resolution configuration (Brune & Baehr, 2020; Polkova et al., 2019). In MPI-ESM-LR, the atmosphere is spectrally resolved with a truncation of T63/1.9° at 47 vertical levels, the ocean is nominally resolved at 1.5° at 40 levels (Giorgetta et al., 2013). The hindcasts are initialized from an assimilation experiments similar to the one described in Brune and Baehr (2020), but with the external forcing updated to CMIP6 (Eyring et al., 2016, historical forcing until 2014, SSP245 forcing after 2014). These simulations are complementing the ones for MPI-ESM-LR, which have been used by Borchert et al. (2021) a recent overview paper of CMIP5 and CMIP6 decadal predictions of SST in the North Atlantic subpolar gyre.

In the atmosphere, the model is nudged to ERA40/ERA Interim/ERA5 atmospheric reanalyzes data (Dee et al., 2011; Hersbach et al., 2020; Uppala et al., 2005) using spectral full value nudging. For the ocean, the assimilation comprises a 16-member Ensemble Kalman Filter (ENKF) based on the Parallel Data Assimilation Framework (Nerger and Hiller (2013)) and using EN4 temperature and salinity profiles (Good et al., 2013) once a month. The 16-member ensemble is generated by the ENKF and the hindcasts are initialized from the assimilation at November 1st every year between 1961 and 2019 where each hindcast runs for 10 years and two months.

As an observational reference we use NOAA OISST Version 2 and therefore analyze the predictability of MHW between 1982 and 2019 (Banzon et al., 2016). Additionally we also use daily sea ice concentrations from the hindcasts and the NOAA reanalysis for the SST quantification.

To compare the hindcast ensemble against historical model simulations we use 16 randomly chosen members of the Max Planck Institute Grand Ensemble (MPI-GE) (Maher et al., 2019).

2.2. Marine Heatwave Quantification

We analyze MHW in both data sets with the standard definition provided by Hobday et al. (2016), established to ensure comparability between different studies. Following Hobday et al. (2016), we regrid both data sets of daily SST to a horizontal resolution of 1°. For a 30-year baseline climatology (1983–2012), we calculate the 90th percentiles for every calendar day between January 1st and December 31st with an 11-day moving window for every grid point of the data set. Afterward, we smooth the daily 90th percentile thresholds with a 31-day running average to ensure a smooth climatology. For any threshold exceedance of at least five consecutive days, we classify these days as MHW days. If there are two MHW at one grid point that are separated by a gap of one or 2 days, we count them as one consecutive event and also the days in the gap are classified as MHW days. To exclude grid points from the analysis that have continuous sea ice cover, the corresponding daily sea ice concentration data from the re-gridded 1°-resolution NOAA data set or from the MPI-ESM hindcasts are used. The same algorithm that determines MHW is applied to every grid point to test whether there is a sea ice concentration larger than zero for at least five consecutive days (Hobday et al., 2016). Accordingly, these grid points are excluded.

For the calculation of MHW frequency, we count the number of start dates of MHW events for every year in every grid cell (Oliver et al., 2018). MHW that exist in two calendar years are assigned to the year they started. We further sum up the days of continuous threshold exceedance for every grid cell and every year between 1982 and 2019 to get the total number of MHW days per year (Oliver et al., 2018).

2.3. Predictability Analysis

To analyze prediction skill in the hindcast ensemble we rearranged the hindcasts into time series that show each lead year for each ensemble member. Here, we will refer to them as lead year time series. To quantify predictive skill of MHW in the ensemble hindcasts, we detrend each lead year time series by removing the linear trend from the daily SST data for each ensemble member. The reanalysis SST time series is also detrended. For each ensemble member and each lead year time series we apply the MHW quantification described above and calculate the two yearly MHW characteristics frequency and MHW days. Furthermore we calculate the MHW characteristics for the NOAA reanalysis and the 16 member of the MPI-GE.

To evaluate prediction skill, we then calculate the correlation coefficients between each lead year time series of the MPI-ESM hindcast ensemble mean and the NOAA reanalysis (1982–2019) for the two yearly MHW characteristics frequency and MHW days as well as for the yearly mean SST. The ensemble mean is computed after the MHW characteristics where calculated individually for each ensemble member and consequently describes the combined impact of MHWs in 1 year for each grid cell.

We further analyze multiyear trends in MHW and SST and therefore in addition to the lead year based analysis, we calculate the SST characteristics for each individual 10-year hindcast without detrending the SST. However for this specific analysis, a lead year dependent drift correction of the daily SST time series is required. This drift can be described as the systematic difference between the hindcasts and the data assimilation, which was used for the hindcast initialization. We perform the drift correction similar to the bias correction in Goddard et al. (2013), but use our 16 member data assimilation based on MPI-ESM instead of an observational reanalysis.

To investigate the multiyear MHW trends we compute the twoto ten year trends for each hindcast chunk following the method of Wiegand et al. (2019). This means we calculate linear trends over the years 1–2, 1–3, etc up to 1–10, resulting in nine linear trend values for each 10-year hindcast.

From the linear trends in MHW and SST of the individual hindcast, we construct trend time series representing the twoto ten year trends for each start year between 1982 and 2019. For the skill analysis, we determine the correlation between the reanalysis and the hindcast ensemble mean trend time series for both MHW characteristics and the yearly mean SST.

3. Results

For our analysis, we focus on the two MHW characteristics: MHW days and MHW frequency, which both (Figures 1a and 1b) show a clear trend in the global mean between 1982 and 2019 in both the NOAA OISST and in the lead year time series from MPI-ESM. Our analysis also reveals a bias between the model and the observational reanalyzes resulting in more MHW days but lower MHW frequencies in MPI-ESM than in NOAA OISST. The trend in both MHW characteristics agrees with the result of other studies analyzing the evolution of MHW over the past century (Holbrook et al., 2019; Oliver et al., 2018). Furthermore, previous studies and our comparison with the 16 members of the MPI-GE (Figure 4) confirm the biases of MHW in low resolution models as they often underestimate SST anomalies (Hobday et al., 2016).

The interannual variability of the global mean MHW days and frequency is predictable up to two years in advance with a high range of uncertainty within the ensemble (Figure 1c). However, if we analyze the multiyear trends of the MPI-ESM hindcasts and the NOAA reanalysis, we find significant correlations for MHW frequency up to trend year eight, as well with high uncertainties (Figure 1d). Consequently, although we can not predict the variability of the global mean MHW characteristics, we can describe the potential decadal evolution of MHW in the global ocean by predicting the two to 8 year trends. Furthermore, comparing the predictability of multiyear trends in MHW days and frequency against the predictability of the mean SST reveals that there is a higher prediction skill for the mean SST than for the extreme events (Figure 1d).

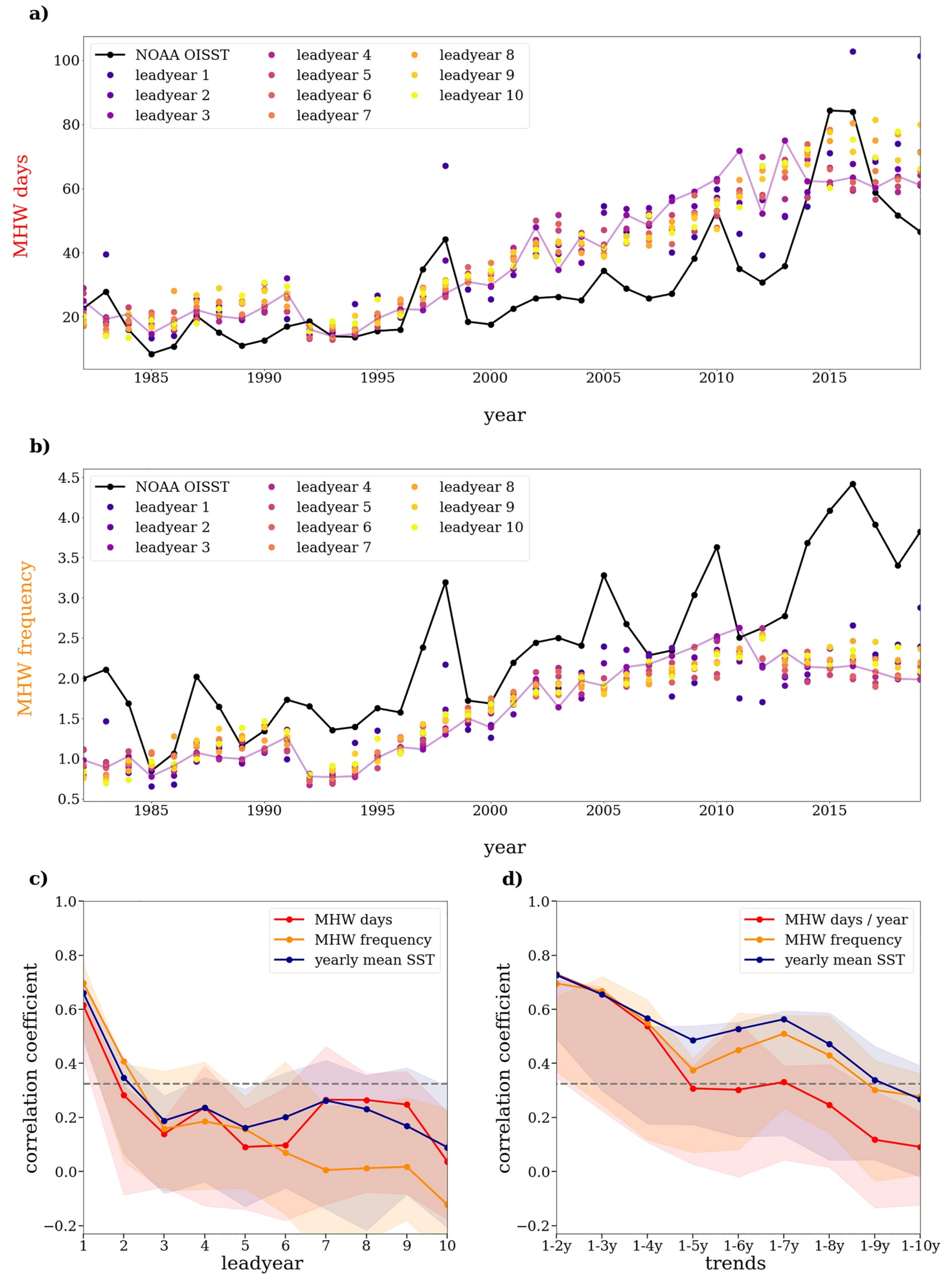

Figure 1. Timeseries of (a) global mean Marine Heatwaves (MHW) days per year and (b) global mean MHW frequency from 1982 to 2019 for the NOAA reanalysis and each lead year of the Max Planck Institute Earth System Model (MPI-ESM) ensemble mean. Lead year three is illustrated with an additional line. (c) Correlations between NOAA OISST and MPI-ESM for every leadyear calculated from detrended SST. (d) Correlations of 2- to 10-year trends between NOAA OISST and MPI-ESM. Shading shows the correlations of the individual ensemble members. The dashed line indicates significance with respect to the 0.95 confidence level.

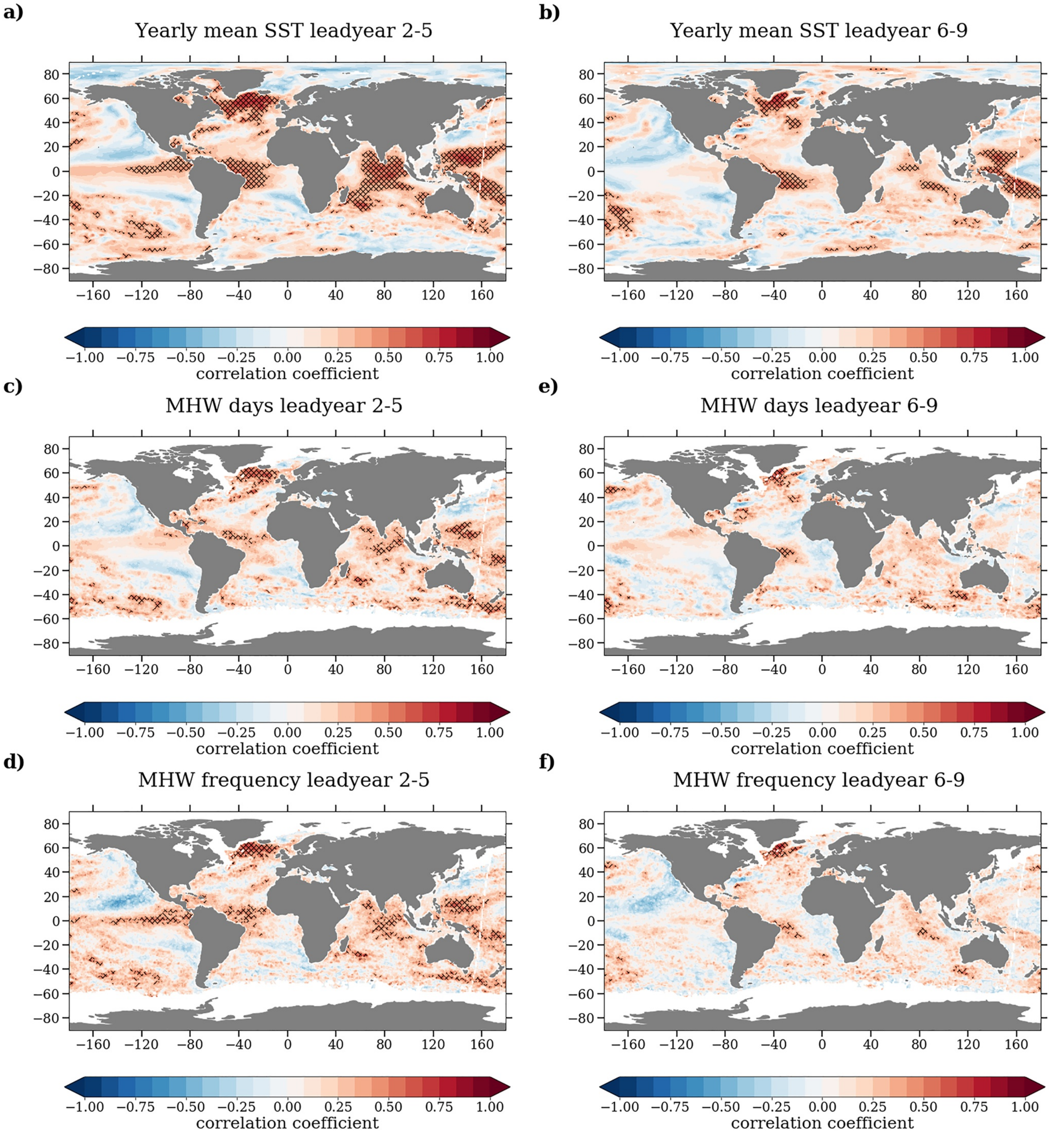

Figure 2. Correlation between detrended NOAA OISST and Max Planck Institute Earth System Model ensemble mean 1982–2019 for (a) leadyear 2–5 yearly mean SST (b) leadyear 6–9 yearly mean SST (c) leadyear 2–5 MHW days (d) leadyear 2–5 Marine Heatwaves frequency, (e) leadyear 6–9 MHW days, (f) leadyear 6–9 MHW frequency. Hatching indicates significance with respect to the 0.95 confidence level.

Despite the limited predictability of global mean MHW characteristics, there are strong regional differences in the prediction skill for the interannual variability of yearly mean SST, MHW days and MHW frequency (Figure 2). As previous research (Brune & Baehr, 2020; Kushnir et al., 2019; Stocker et al., 2013) and our analysis (Figures 2a and 2b) show, there are regions in the global ocean where the yearly mean SST can be predicted several years ahead. Although we are not able to predict MHW in all areas where skill for yearly mean SST

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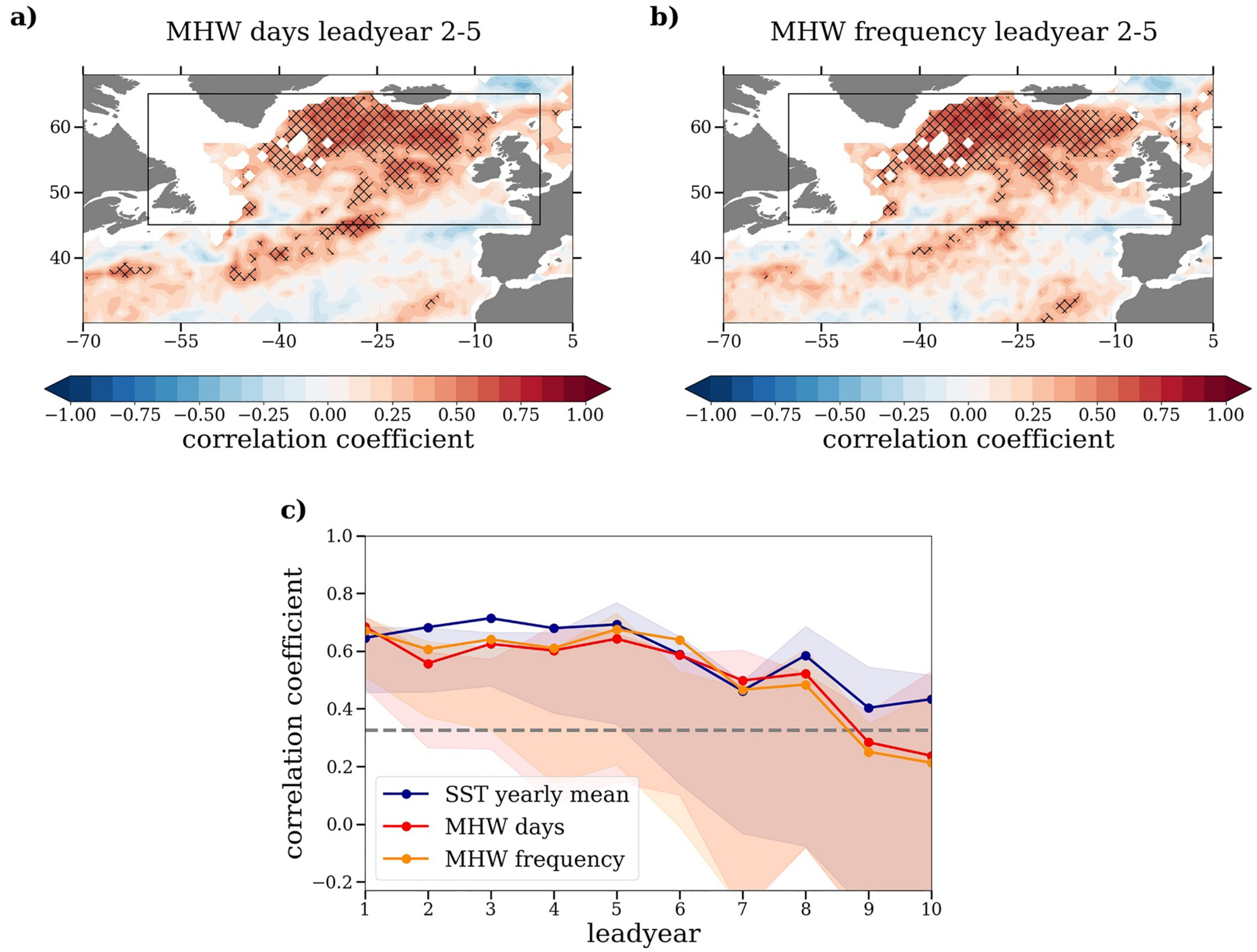

Figure 3. Correlation between detrended NOAA OISST and MPI-ESM-LR ensemble mean 1982–2019 for (a) leadyear 2–5 Marine Heatwaves (MHW) days and (b) leadyear 2–5 MHW frequency (zoomed in version of Figure 2c). and (d) Shading shows the correlations of the individual ensemble members. (c) Correlation between detrended NOAA OISST and MPI-ESM-LR for yearly mean SST, MHW days and MHW frequency averaged over the Subpolar North Atlantic (47–65°N, 0–60°W). The dashed line represents the significance threshold with respect to the 0.95 confidence level.

is significant, there are regions in the global ocean, for example, in the North Atlantic or the North and South Pacific, where we provide information about the potential evolution of SST by the successful prediction of MHW days or frequency in addition to yearly mean SST (Figures 2c–2f).

One of those regions is the Subpolar North Atlantic (47–65°N, 0–60°W) where correlations between the hindcast ensemble mean and the NOAA reanalysis are up to 0.73 for SST and up to 0.7 for MHW days and frequency. We analyze this region in more detail to investigate the relationship of MHW to the evolution of SST, and reasons for their respective predictability. The MPI-ESM hindcast ensemble mean successfully predicts the interannual variability of MHW days and frequency together with the yearly mean SST up to leadyear eight in the Subpolar North Atlantic with increasing uncertainties toward the later trend years (Figure 3). In contrast, the multiyear trends for MHW days and frequency are not predictable (not shown).

To understand predictability of MHW in the Subpolar North Atlantic, we further investigate the underlying time series of MHW days per year, yearly mean SST and the fraction of grid cells without any MHW per year (Figure 4). Comparing the evolution of MHW days in the hindcast against the reanalysis reveals that for a large part of the time series the evolution of NOAA OISST is reproduced by the hindcasts. Nevertheless, between 1999 and 2005 the earlier lead year time series (lead year 1–5) for MHW days follow the evolution of yearly mean SST and therefore diverge from the MHW days based on NOAA OISST, which first decreases and then increases

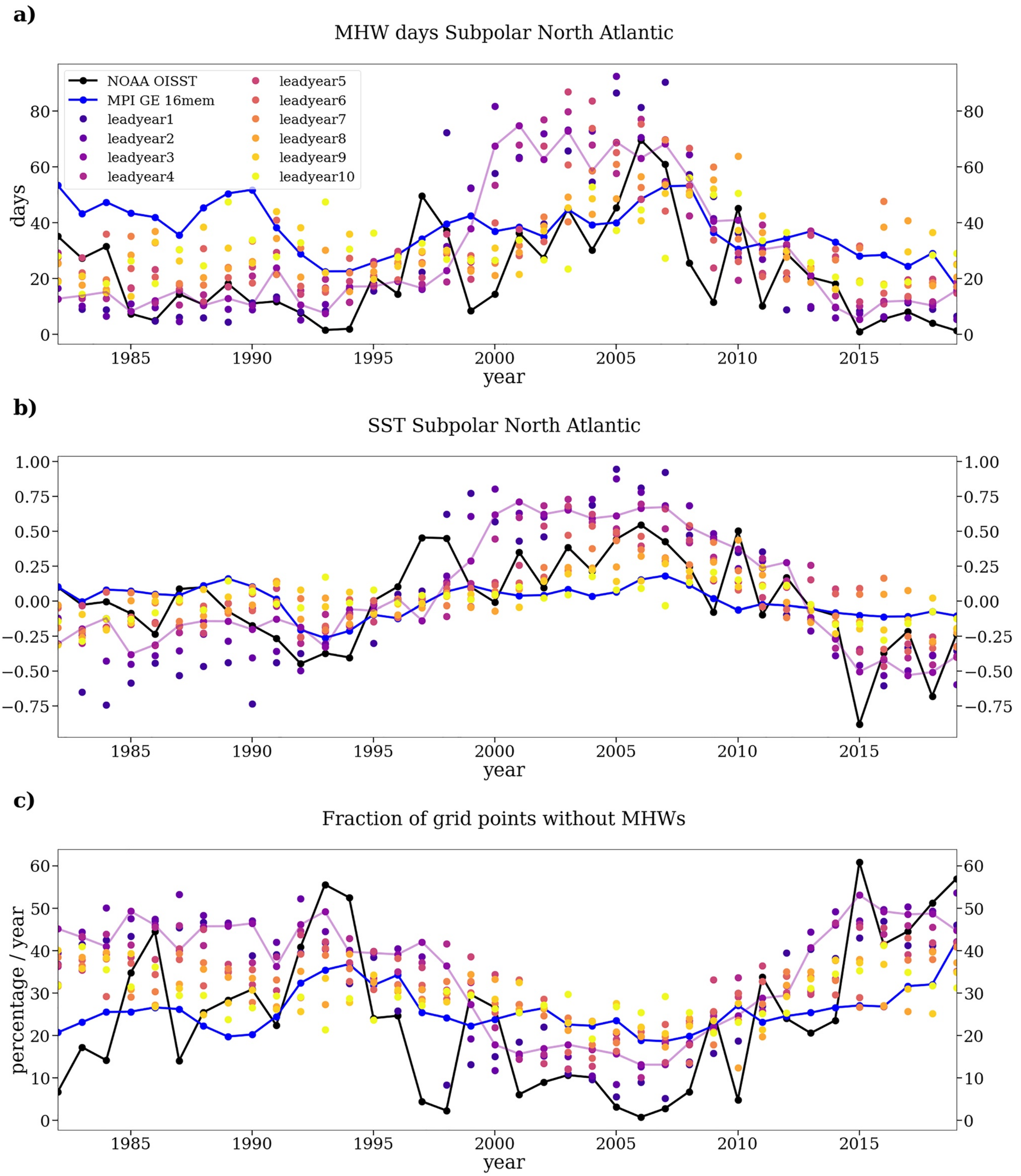

Figure 4. Timeseries of (a) Marine Heatwaves (MHW) days, (b) yearly mean SST and (c) fraction of grid cells without MHW in the Subpolar North Atlantic for NOAA OISST, all leadyears of MPI-ESM-LR ensemble mean and the 16 member ensemble mean of the Max Planck Institute Grand Ensemble. Lead year three is illustrated with an additional line.

again between 1999 and 2005. Consequently the lead years 6–10 are closer to the reanalysis for this time period than the lead years 1–5 (Figures 4a and 4b).

Comparing the evolution of MHW days and yearly SST in the hindcasts and the NOAA OISST to the 16 member ensemble mean of the MPI-GE reveals that the later lead years of the hindcasts follow the evolution of the historical model simulations (Figure 4). The later lead years are consequently drifting away from their initialization toward the background model. The background model, here represented by the 16 members of the MPI-GE shows the typical biases of low resolution models for MHWs because it underestimates the SST variability and has consequently longer MHWs with more MHW days for most parts of the time series (Hobday et al., 2016).

To investigate why there are significant correlation coefficients over the Subpolar North Atlantic for both MHW characteristics (Figure 3), we analyze the fraction of grid cells without MHWs for each year between 1982 and 2019 (Figure 4c). This reveals that in the background model and in the later lead years of the hindcasts there are on average less MHW-free gridcells than in the reanalysis toward the beginning and the end of the time series. However, during 1997–2010 there are less grid cells without MHWs in the NOAA reanalysis than in the background model and in most lead years of the hindcasts.

The significant correlation between the hindcast ensemble mean and the reanalysis for MHW days and frequency in the Subpolar North Atlantic can therefore partly be explained by correctly predicting the MHW occurences and MHW-free grid cells. Between 1997 and 2010, there is an increase in MHW days in the reanalysis (Figure 4a). In lead year one to four this increase is even stronger in the hindcasts although the fraction of grid points that are not experiencing a MHW in those calendar years is mostly larger in the hindcasts than in the reanalysis. Overall, comparing the timeseries of MHW days, yearly mean SST and fraction of grid cells without MHW we can conclude in the Subpolar North Atlantic the decadal evolution of SST is immediately mirrored in decadal variations in MHW (Figures 4a–4c).

4. Discussion and Conclusions

By analyzing a 16 member ensemble of decadal hindcasts based on MPI-ESM, our findings provide a first overview of the decadal predictability of MHW in the global ocean and in the Subpolar North Atlantic. One limitation of our analysis is that there are strong biases between MHW in the hindcast ensemble and in the NOAA reanalysis with more MHW days in the hindcasts but fewer MHW events per year than in the reanalysis (Figures 1a and 1b). These biases arise from the underlying low resolution earth system model and increasing the model resolutions might help resolving MHW and reduce such biases of low resolution Earth System models (Hobday et al., 2016).

Furthermore, to ensure that also decadal variability patterns like the Atlantic Multidecadal Variability or Pacific Decadal Oscillation are captured in our analysis, analyzing decadal MHW predictability for only 38 years (1982–2019) could be too short (Sienz et al., 2016). We therefore also test our analysis against the nearly 60-year long assimilation run (1961–2019) that was used to initialize the hindcasts (Brune & Baehr, 2020). For our analyses, using the assimilation run to evaluate the hindcasts does not alter our conclusions.

Several studies using initialized climate predictions suggest that there is enhanced predictability of yearly mean SST in the North Atlantic arising from variations in the Atlantic Meridional Overturning Circulation (Keenlyside et al., 2008) or from the correct initialization of the temperature and salinity field (Karspeck et al., 2015; Smith et al., 2007). Holbrook et al. (2020) argue that due to the high persistence and long propagation time scales of oceanic processes, MHW prediction is possible for longer lead times in regions where oceanic processes dominate. This potentially contributes to the predictability of MHW frequency and the number of MHW days in the Subpolar North Atlantic. This is further supported by a positive correlation of 0.6 between the 5-year running mean timeseries of MHW days per year in the Subpolar North Atlantic with the 5-year running mean of the Atlantic Multidecadal Oscillation (not shown here).

With this study we aim to gain additional information about the evolution of SST in the global ocean in the next two to ten years that go beyond predicting the yearly mean SST. For this we analyze the predictability of the two characteristics MHW days and MHW frequency and conclude:

- The year-to-year variations of global mean MHW days and MHW frequency are not predictable but the global mean MHW trends are predictable for two to 8 years ahead, as the mean SST trend is.

- In the Subpolar North Atlantic, MHW frequency and MHW days are predictable with significance up to lead year 8.
- The decadal evolution of SST in the Subpolar North Atlantic is immediately mirrored in decadal variations in MHW.

To fully understand why MHW characteristics are predictable in certain regions we have to continue our analysis of the decadal hindcasts based on MPI-ESM and also analyze the underlying physical mechanisms. Our regional analysis of MHW predictability focuses on the Subpolar North Atlantic. However, as Figure 2 shows there are other regions with prediction skill for MHW days and frequency like the Western Pacific. In these regions the predictability of MHW and their relationship to the evolution of SST should be investigated further. Additionally our analysis could be refined by analyzing the seasonal variability of MHW or considering different metrics of hindcast verification.

Overall, our analysis shows that it is possible to further our understanding of the decadal evolution of SST by analyzing the predictability of MHW in an ensemble of decadal hindcasts based on MPI-ESM. Thereby, we provide a first attempt of predicting ocean extreme events on a multiyear time scale.

Data Availability Statement

NOAA High Resolution SST data (Banzon et al., 2016) provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, can be obtained from their website at https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.highres.html. The SST from the decadal hindcasts can be accessed via http://hdl.handle.net/hdl:21.14106/f2fdc61b13828ed5284f4e4ab41e63f8a84c6e52.

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