



Observation-based Sea surface temperature trends in Atlantic large marine ecosystems

Augustin Kessler^{*}, Nadine Goris, Siv Kari Lauvset

NORCE Norwegian Research Centre, Bjerknes Centre for Climate Research, Bergen, Norway

ARTICLE INFO

Keywords:

Large Marine Ecosystems
SST trends
In-situ observations

ABSTRACT

Variations in Sea Surface Temperature (SST) are an important driver of marine species abundance in Large Marine Ecosystems (LMEs). Studies concerned with climate change induced SST trends within these LMEs have so far been relying on satellite data and reanalysis products, with the disadvantages of only having short time-periods available and having to rely on the ability of the models to correctly simulate SST-dynamics, respectively. Here, we provide for the first time a long-term trend analysis of SST for 17 LMEs of the Atlantic Ocean over two different time-periods (1957–2020 and 1980–2020) based on *in-situ* data gathered from three data collections. We sort our results according to warming categories that were established in an earlier study, i.e., “cooling” (below 0 °C/dec), “slow” (0–0.07 °C/dec), “moderate” (0.07–0.14 °C/dec), “fast” (0.14–0.21 °C/dec) and “superfast” (above 0.21 °C/dec). Our results show a persistent “slow” to “superfast” warming in all considered LMEs. However, the sparse data coverage induces large uncertainties, so that many LMEs cannot uniquely be assigned to one warming category only. We detect no systematic changes in the seasonal SST amplitude of the considered LMEs. We find that the LMEs of the North Atlantic warm faster than those of the South Atlantic and that this difference is increasing with time. Out of the North Atlantic LMEs, the Norwegian Sea, North Sea, Celtic-Biscay Shelf, Gulf of Mexico and the Northeast U.S. Continental Shelf belong exclusively to the superfast warming category for the period 1980–2020.

1. Introduction

Large Marine Ecosystems (LMEs) are categorized areas of ocean space along the Earth’s continental margins inhabited by complex ecosystems that are fueled by high primary productivity. About 80% of the global annual marine fishery biomass is obtained in these regions. They contain crucial natural living resources for 37% of the global human population who depend on them for food, income, and recreation (IOC-UNESCO and UNEP, 2016). Already strongly affected by human-related activities like overpopulation, agricultural run-off, pollution, overfishing and intense marine traffic, these regions additionally face an increase in sea surface temperature (SST) induced by the unabated release of greenhouse gases into the atmosphere (Cheng et al., 2020).

Variations in SST are a leading indicator for marine ecosystem variability by regulating the timing of seasonal migration, spawning events and peak of abundance of marine species (Macleod et al., 2007; Halpern et al., 2008; Baird et al., 2009). The Sixth Assessment Report of Working Group 1 (AR6 WG1) of the IPCC 2021 (Fox-Kemper et al., 2021) estimates that the global mean SST increased by 0.88°C from 1850

to 1900 to 2011–2020, with 0.60°C of this increase occurring between 1980 and 2020, pointing towards a recent acceleration of the warming. These climate induced changes in thermal conditions can have dramatic impacts on coastal marine ecosystems like coral bleaching (Sully et al., 2019), fish population changes (Vollset et al., 2022; Pershing et al., 2015) and poleward shift of marine species (Hastings et al., 2020). Therefore, monitoring changes in SST is crucial to anticipate and foresee potential marine ecosystem reconfiguration (Glibert et al., 2014; Baker-Austin et al., 2016; Collins et al., 2019).

Over the last decades, many studies have examined the temporal SST evolution of LMEs using reanalysis data (e.g., Belkin 2009; IOC-UNESCO and UNEP, 2016), model simulations (e.g., Bonino et al., 2019; Varela et al., 2022), gridded and gap-filled observation-based products from different platforms (e.g., Lima and Wetthey, 2012; Varela et al., 2018) and more recently satellite-derived data (e.g., Seabra et al., 2019; Sweijd and Smit, 2020). The outcome of these studies shows a wide range of different warming, and even cooling, rates in LMEs depending on the location and the time window considered. While satellite data are only available since the 80 s, making trend analysis more sensitive to decadal

^{*} Corresponding author.

E-mail address: auke@norceresearch.no (A. Kessler).

<https://doi.org/10.1016/j.pocean.2022.102902>

Received 7 June 2022; Received in revised form 9 September 2022; Accepted 14 September 2022

Available online 21 September 2022

0079-6611/© 2022 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

variability than longer time series, the other previously used methods highly depend on the availability and representativity of observations and the capability of models to correctly reproduce spatial distribution, inter-annual variability, and trends (Storto et al., 2019). To the authors' knowledge, a direct analysis of long-term warming trends based on *in-situ* data has so far not been performed for the LMEs. Yet, the consideration of *in-situ* data has the advantage of providing real snapshots of the ocean state and not relying on interpolation or a model's dynamics. Moreover, when considering *in-situ* measurements of oceanographic variables, SST is the most recorded variable with a long-standing record (Emery 2003) such that an estimation of long-term trends is possible beyond the satellite era. This study aims to provide the first long-term SST trend analysis for the LMEs of the Atlantic Ocean based exclusively on *in-situ* observations.

This paper is organized as follows: Sect. 2 introduces our data collection and the methods applied to calculate the SST trends in each LME. Sect. 3 presents the results for the long-term SST trends over two time periods (1957–2020 and 1980–2020) and classified each LME into warming categories. These results are further discussed with the literature in Sect. 4 and a summary and conclusion are given in Sect. 5.

2. Methods

2.1. Collection of SST data within the considered large marine ecosystems

We consider 17 LMEs along the coastline of the Atlantic Ocean. Their names and acronyms are given in Table 1, while their geographical positions and spatial boundaries, taken from Sherman (1991), are shown in Fig. 3. Observations of *in-situ* SST in these 17 LMEs are collected from three main ocean data sources. Here, the World Ocean Database (Boyer et al., 2018) provides observations mainly from the 20th century, while SOCAT version 2021 (Bakker et al., 2016) and GLODAPv2. 2021 (Lauvset et al., 2021) add additional observations over the last two decades. The SST data collected corresponds to the average ocean temperatures in the top 11 m and covers altogether the period from 1957 to 2020.

In total, our data collection represents more than 8.2 million observations with a 74.6% contribution from SOCAT, reflecting the recent growth of *in-situ* measurements across the ocean, 25.3% from the World Ocean Database and 0.1% (+7,243 observations) from GLODAP. The spatial and temporal distributions of these observations are non-uniform. Certain regions are well covered, like the Northern U.S. Continental Shelf (NUSC, > 45 observations per km²) and the North Sea (NS,

> 19 observations per km²), while most of the LMEs in the Southern Hemisphere are not well covered (<1 observation per km²). More details on the data density in each considered LME are given in Table 1.

2.2. Correction of the aliasing effect and long-term SST calculations

Analyzing observational data over large areas, like the here considered LMEs, may lead to the so-called aliasing effect. This effect is composed of a spatial and temporal dimension which originate from irregular or infrequent sampling through time and space, leading to trends that are biased towards more frequently sampled locations and timeframes. To overcome the spatial and temporal aliasing effects we use the methods of Stendardo and Gruber (2012) and Fay and McKinley (2013), respectively.

The method of Stendardo and Gruber (2012) overcomes the effect of spatial aliasing by adjusting all available observations to the average SST of their associated LME. To do so, we use the 0.25° gridded monthly World Ocean Atlas (WOA) SST-climatology for the period 1981–2010 (Locarnini et al., 2018) and calculate the difference between the climatological SST value of each grid box within the LME and the spatially-averaged climatological SST-value for the entire LME. These calculated differences inform us about the spatial SST gradient within an LME, and, when used as adjustments, they allow us to correct for potential biases caused by areas with higher density of observations. For example, in an LME with a strong north-to-south SST gradient and higher SST values in the south, a higher density of observations in the south would lead to a biased high SST value for the associated LME when simply averaging over all observational values. We correct this spatial aliasing effect by binning our monthly averaged observational data into a regular 0.25°x0.25° grid and subtracting the previously calculated spatial adjustments to remove the SST-gradient within the associated LME. Finally, we average the adjusted observations per LME for each month.

Subsequently, we use the average-adjusted SST values to identify and remove SST-outliers through usage of the “robustfit” function in Matlab, with “bisquare” weighting. The robustfit function assigns a weight to each data point using an iteratively reweighted least squares method (Holland and Welsch, 1977). The weight associated with each data point depends on the distance of this point to the fitted line and is calculated with a bisquare function which minimizes the weighted sum of least squares. Hence, the further away a data point is from the fitted line, the less weight it gets. This makes this method less sensitive to outliers than ordinary least squares linear regression. A data point is considered an

Table 1

SST data coverage of each considered LME when considering our data collection. Listed are the names and acronyms of the LMEs considered in this study, the availability of observations per LME in absolute and relative numbers, the percentage of months having at least one data point (100% = 768 months) and the number of SST-outliers that have been removed from the analysis (see Sect. 2.3).

LME Name	Acronym	Number of observations	Number of observations per km ²	% of months represented by observations over 1957–2020	outliers
Newfoundland and Labrador Shelf	NFL	279,111	0.31	99.3%	0
Scotian Shelf	SCO	212,232	7.45	98.8%	0
Northeast U.S. Continental Shelf	NUSC	1,464,322	45.43	99.7%	0
Southeast U.S. Continental Shelf	SUSC	481,519	15.91	99.3%	3
Gulf of Mexico	GMEX	806,182	5.24	97.7%	1
Caribbean Sea	CARI	1,088,680	3.32	100%	3
North Brazil Shelf	NBZ	34,472	0.32	77.3%	16
East Brazil Shelf	EBZ	91,999	0.85	23.9%	0
South Brazil Shelf	SBZ	27,620	0.49	71.6%	6
Patagonian Shelf	PAT	171,168	1.46	85.7%	0
Benguela Current	BEN	95,573	0.65	97.8%	3
Guinea Current	GUI	78,297	0.41	99.5%	12
Canary current	CAN	223,009	1.98	98.9%	3
Iberian Coastal	IB	197,351	6.48	98.0%	1
Celtic-Biscay Shelf	CELT	719,157	9.44	99.6%	0
North Sea	NS	1,381,201	19.91	100%	0
Norwegian Sea	NoS	865,081	8.18	36.3%	4

outlier when the calculated weight falls below 0.5. The remaining average-adjusted SST data are used to calculate (1) the long-term annual SST trends and (2) the long-term monthly SST trends. Both (1) and (2) are calculated for the periods 1957–2020 and 1980–2020, which allows us to compare the results over different time scales using the same dataset and to relate our results to the global SST warming of 0.15 ± 0.04 °C/dec for 1980–2020 (Fox-Kemper et al., 2021).

For the calculation of (1), we apply the method of Fay and Mckinley (2013) on our average-adjusted SST values per LME. This method removes the temporal dimension of the aliasing effect by fitting a sinusoidal cycle that mimics the seasonal cycle to the available data, thereby eliminating a seasonal bias towards more frequently measured months. More specifically, we fit a harmonic of the form $y = a + b*t + c*\cos(2\pi*t + d)$ to our data, where “t” is the decimal year starting on January 1st, 1957, and ending on December 31st, 2020. The coefficient “b” corresponds to the long-term annual SST trends reported in this study. Table 2 shows these calculated SST trends expressed both as a rate (in °C/dec) and as the total change (in °C) with a 95% confidence interval, for both time periods and per considered LME. The confidence intervals are calculated in MATLAB using an asymptotic normal distribution for parameter estimate (“nlparci”).

Fig. 1 shows an example of a harmonic fit for the monthly SST average of the PAT LME, which clearly shows the advantage of using this method compared to using annual averages whenever all month of the year have been observed (shown as green stars). While annual averages only cover 24 years (37%) of the period 1957–2020, monthly SST averages covers more than 85.7% (Table 1) of that period.

For the calculation of (2), we apply a linear regression with weighted least squares to our average-adjusted SSTs per month and per LME. The results of (2) inform us about changes in the seasonal SST cycle with time. We note that the method of Fay and Mckinley (2013) assumes a constant seasonal SST amplitude. Consequently, the impact of a heterogeneous change in the seasonal amplitude is not captured by our calculated long-term trend. Hence our results for (2) also inform us about the validity of our approach for calculating the long-term annual SST trends.

3. Results

3.1. From “slow” to “superfast”: LME warming rates

When presenting our results, we classify the considered LMEs into

Table 2

Total SST changes and corresponding warming rates for the periods 1957–2020 and 1980–2020 for each LME.

LME	1957–2020 total SST change [°C]	1957–2020 Warming rate [°C/dec]	1980–2020 total SST change [°C]	1980–2020 Warming rate [°C/dec]
NFL	0.61 ± 0.33	0.10 ± 0.05	0.93 ± 0.42	0.23 ± 0.10
SCO	1.12 ± 0.34	0.18 ± 0.05	1.10 ± 0.44	0.27 ± 0.11
NUSC	1.87 ± 0.27	0.29 ± 0.04	1.36 ± 0.33	0.33 ± 0.08
SUSC	1.11 ± 0.19	0.17 ± 0.03	0.86 ± 0.23	0.21 ± 0.06
GMEX	1.14 ± 0.17	0.18 ± 0.03	1.12 ± 0.21	0.27 ± 0.05
CARI	0.97 ± 0.10	0.15 ± 0.02	0.90 ± 0.12	0.22 ± 0.03
NBZ	0.94 ± 0.13	0.15 ± 0.02	0.70 ± 0.13	0.17 ± 0.03
EBZ	0.72 ± 0.38	0.11 ± 0.06	0.18 ± 0.38*	0.04 ± 0.09*
SBZ	1.00 ± 0.25	0.15 ± 0.04	0.55 ± 0.29	0.13 ± 0.07
PAT	0.43 ± 0.24	0.07 ± 0.04	−0.06 ± 0.26*	−0.01 ± 0.06*
BEN	0.64 ± 0.16	0.10 ± 0.03	0.24 ± 0.20	0.06 ± 0.05
GUI	0.91 ± 0.19	0.14 ± 0.03	0.77 ± 0.22	0.19 ± 0.05
CAN	1.17 ± 0.16	0.18 ± 0.03	0.84 ± 0.20	0.20 ± 0.05
IB	1.04 ± 0.19	0.16 ± 0.03	0.78 ± 0.23	0.19 ± 0.06
CELT	0.95 ± 0.16	0.15 ± 0.03	1.08 ± 0.20	0.26 ± 0.05
NS	1.17 ± 0.21	0.18 ± 0.03	1.58 ± 0.25	0.39 ± 0.06
NoS	1.03 ± 0.19	0.16 ± 0.03	1.22 ± 0.23	1.22 ± 0.23

* Not statistically significant at the 95% confidence level.

five different warming categories based on those defined in the Transboundary Water Assessment Programme (IOC-UNESCO and UNEP, 2016), hereafter abbreviated as the TWAP assessment. The TWAP assessment classified all 66 LMEs into categories based on the amount of warming that an LME experienced over the period 1957–2012. Here, we use the total warming ranges that were used for this categorization and express them as warming rates per decade, such that it is easily possible to use these warming categories for different periods. This leads to the following warming rates per category: “cooling”: < 0 °C/dec, “slow”: $0–0.07$ °C/dec, “moderate”: $0.07–0.14$ °C/dec, “fast”: $0.14–0.21$ °C/dec and “superfast”: > 0.21 °C/dec.

Our results reveal that all considered LMEs show significant long-term warming trends for the period 1957–2020 (Fig. 2 and Table 2), yet with different warming intensities. Most LMEs exhibit relatively large uncertainties associated with their warming trends, here represented by the 95% confidence level (Fig. 2, error bars). These uncertainties increase when considering the shorter timescale (1980–2020, Fig. 2, gray error bars), indicating strong decadal SST variability.

For the period 1957–2020, the NUSC LME of the North Atlantic is the only region belonging exclusively to the “superfast” category with an observed total SST change of 1.87 ± 0.27 °C (Fig. 3) corresponding to an average SST increase rate of 0.29 ± 0.04 °C/dec (Table 2). This is roughly two-times faster than the estimated global SST increase of 0.15 ± 0.04 °C/dec between 1980 and 2020 (IPCC 2019), highlighting the high sensitivity of this region to the ongoing global warming. In addition, our calculations show a similar trend for the NUSC LME when regarding the time period 1980–2020 (0.33 ± 0.08 °C/dec), indicating that this LME experiences a persistent strong warming.

In general, the LMEs of the North Atlantic warm faster than those of the South Atlantic (Fig. 2) with the exception of the NFL LME, which experienced a slower long-term (1957–2020) SST trend with a warming rate of about 0.10 ± 0.05 °C/dec (Table 2). Moreover, the warming rates of all the LMEs of the North Atlantic tend to increase from 1957 to 2020 to 1980–2020. For instance, the number of North Atlantic LMEs exclusively belonging to the “superfast” category increases from one to five LMEs between these time periods (from NUSC to NoS, NS, CELT, NUSC and GMEX). With a warming rate of 0.39 ± 0.06 °C/dec (Table 2), the NS LME is found to warm the fastest of all Atlantic LMEs for the period 1980–2020. On the contrary, our results suggest that the warming rates of the South Atlantic LMEs (EBZ, SBZ, PAT and BEN) decrease between 1957 and 2020 and 1980–2020, although the uncertainties remain relatively large.

The temporal data coverage is relatively dense for most of our considered LMEs and the percentage of months represented by observations is generally above 97% (Table 1) giving us high confidence in our results. A weaker data coverage is only found for the LMEs along the coast of South America. Here, we are still relatively confident in our results for the NBZ, SBZ, and PAT LMEs with 71.6% (SBZ) to 85.7% (PAT) of months represented by observations. We are less confident in our results for the EBZ LME where only a few observations could be collected, representing only 23.9% of considered covered months.

3.2. Seasonal warming trend deviations

We calculate the long-term SST trends for both periods (1957–2020 and 1980–2020) for each month separately (Figs. 4 and 5, respectively) and compare it to the previously described annual trends of the LMEs in the same period. The results of this comparison allow us to (1) test the assumption of our annual trend-estimation method which includes a harmonic fit that uses a constant amplitude for the seasonal cycle, and (2) identify whether the SST trends are uniform throughout the year or if there are seasonal trend variations within our considered LMEs.

The results show very sporadic seasonal trend deviations. For both periods, most of the monthly trends fall within the uncertainty range of the long-term annual SST, which indicates that the long-term surface ocean warming is relatively constant over a year with no clear sign of a

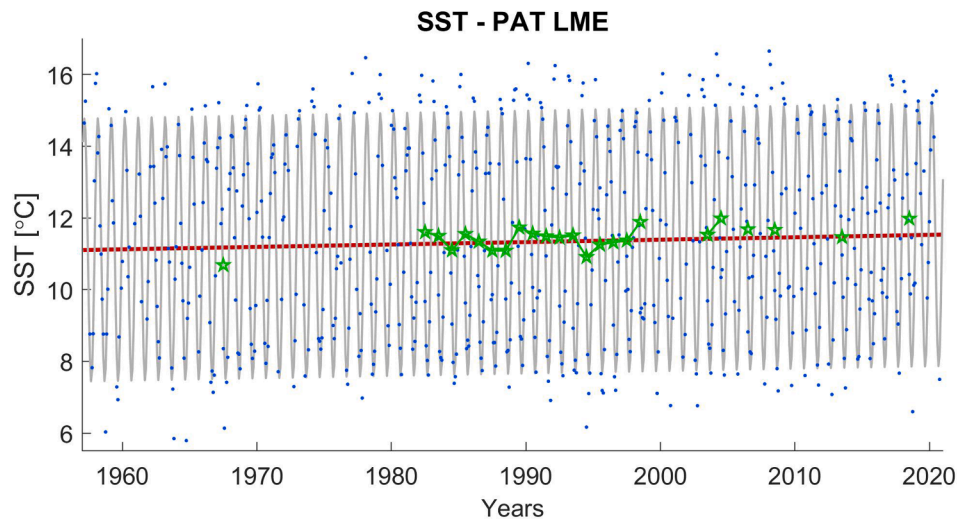


Fig. 1. Example of SST trends calculation using average-adjusted monthly SST averages (blue dots) and a non-linear regression with both a harmonic (gray sinusoid) and a linear (red thick line) term. The green stars mark annual averages calculated when all 12 months of the year are represented by observations.

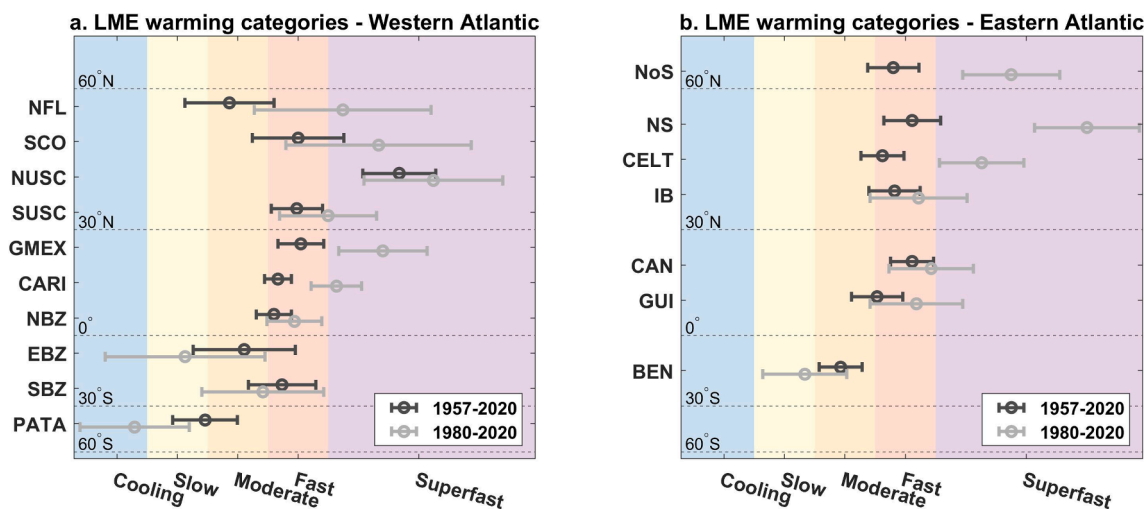


Fig. 2. Calculated warming rates in (a) the Western and (b) Eastern Atlantic LMEs. Results are categorized according to the scale of the TWAP assessment (IOC-UNESCO and UNEP, 2016): “cooling” (<0 °C/dec), “slow” ($0 - 0.07$ °C/dec), “moderate” ($0.07 - 0.14$ °C/dec), “fast” ($0.14 - 0.21$ °C/dec) and “superfast” (>0.21 °C/dec). The LMEs are sorted according to their approximate latitudinal position.

changing seasonal SST amplitude. Here, the use of a harmonic fit with a fixed seasonal amplitude is indeed suitable for the calculation of annual trends.

We count eleven and six significant deviations of the monthly trend from the long-term annual SST trends for the period 1957–2020 (Fig. 4) and 1980–2020 (Fig. 5), respectively. Only 3 of those deviations occur for both timeframes analyzed, indicating persistent change. These three persistent monthly deviations are a more pronounced warming in August in the NFL LME, a more pronounced warming in July in the PAT LME, and a weaker warming in March in the IB LME. The remaining observed monthly trend deviations change depending on the assessed period, suggesting that the current trends may have corrected the longer-term trend or that they arise from decadal variability.

4. Discussion

Our analysis of *in-situ* data shows a significant long-term warming in all considered Atlantic LMEs over the period 1957–2020. This is line with the results of previous studies (e.g., IOC-UNESCO and UNEP, 2016; Belkin 2009) showing a general warming in most Atlantic LMEs. Our

calculated warming rates for the NUSC LME (0.29 ± 0.04 °C/dec for 1957–2020 and 0.33 ± 0.08 °C/dec for 1980–2020) are very similar to the values provided by the TWAP assessment (0.25 °C/dec, IOC-UNESCO and UNEP, 2016) and Pershing et al. (2015) (0.30 °C/dec), with both studies using different methods and timeframes. The former study used reanalysis data for the time period 1957–2012 and the latter used satellite-derived SST data in the Gulf of Maine for the time-period 1982–2013. This indicates that the fast-warming rate of the NUSC LME has been relatively persistent and unabated since the 60 s, revealing the extreme sensitivity of this LME to global warming. This warming causes drastic changes in thermal habitat conditions, identified as a major driver for changes in the distribution and abundance of marine species in this region (Hare et al., 2010, 2016; Lynch et al., 2015). Currently, the cod population is greatly affected by the temperature increase (Pershing et al., 2015) and further damage to northern species populating this region is expected in the future (Kleisner et al., 2017). Changes in the production of cod have also been reported in the NS LME and linked to the recent increase in temperature (O’Brien et al., 2000). Our study shows that the increase in temperature in the NS LME is the fastest of all our considered Atlantic LMEs for the period 1980–2020 with a warming

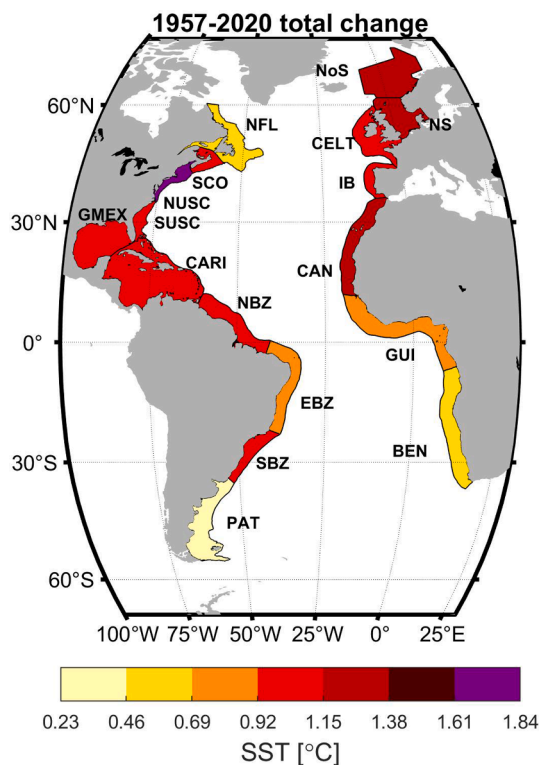


Fig. 3. Total mean SST change in the Atlantic LMEs from 1957 to 2020, associated uncertainties can be found in Table 2.

rate of 0.39 ± 0.06 °C/dec. This result is also consistent with the study of Belkin (2009), which found a similar warming trend for the NUSCL LME in the period 1982–2006 (1.31 °C, roughly equivalent to 0.52 °C/dec).

Although the uncertainties on our calculated trends cause most LMEs to belong to several warming categories, we find that 12 of our 17 considered LMEs have the mean value of their long-term warming trends (1957–2020) within the “fast” warming category, making this type of warming the most observed over that period. On the contrary, the TWAP assessment (IOC-UNESCO and UNEP, 2016) finds that only 4 of our 17 LMEs belong to this category. We find substantially higher warming

rates in the LMEs of the tropical and subtropical zones of the North Atlantic (especially for GMEX, CARI, SUSC and NBZ) where our values are up to 6 times stronger than those estimated in the TWAP assessment (IOC-UNESCO and UNEP, 2016). For the GMEX and CARI LMEs this difference might occur due to a recent acceleration of the warming trends (Fig. 2 and Table 2), which may not be fully represented by the TWAP assessment as it only incorporates data until the year 2012. We note that our estimates lie within the range of values found by other studies using satellite-derived data (Chollett et al., 2012; Good et al., 2007; Strong et al., 2008). Strong et al. (2008) estimated a range of warming rates between 0.2 and 0.6 °C/dec depending on the location in the Caribbean Sea, Good et al. (2007) provided an average estimate of 0.3 °C/dec for the entire Caribbean basin between 1985 and 2004 and Chollett et al. (2012) suggested a warming rate of 0.27 °C/dec within the Caribbean Sea between 1985 and 2009, which increases to 0.29 °C/dec when including the southeast Gulf of Mexico region. Hence, our results are backed-up and seem plausible, yet they also offer the benefit of a long-term picture beyond the satellite era. These results are concerning as these LMEs have a small seasonal SST amplitude, meaning that the ecosystems in place may have smaller tolerance to temperature changes (CMEP 2017).

Our results for the SUSC LME disagree with those of the TWAP assessment (IOC-UNESCO and UNEP, 2016) as we identify the SUSC LME to be a “fast” and “fast”-“superfast” warming system for the long-term (1957–2020) and the last decades (1980–2020), respectively, while it was categorized to be “cooling” in the TWAP assessment. We note that this region is strongly influenced by the Gulf Stream and is hence subject to significant decadal variability related to shifts in the position of the Gulf Stream (Lee et al., 1991). This leads to strong differences in warming rate values depending on the timeframe considered and a potential challenge for models (as used in the TWAP assessment) to correctly simulate these SST variations. Other studies using satellite-derived data (Robson et al., 2018) and *in-situ* observations (Shearman and Lentz, 2010) point toward a warming of the SUSC LME after 2005 and a nearshore warming since the mid-60 s, respectively. Through usage of NOAA interpolated SST data, Varela et al. (2018) also indicate a warming of the SUSC LME between 1982 and 2015 both nearshore and offshore. Our results strongly support an emerging warming trend in this region and suggest that it is speeding up. The effect of this warming on the ecosystem has already been detected and is affecting the coral reefs (Hughes et al., 2018) and the fish abundance (Rogers et al., 2014;

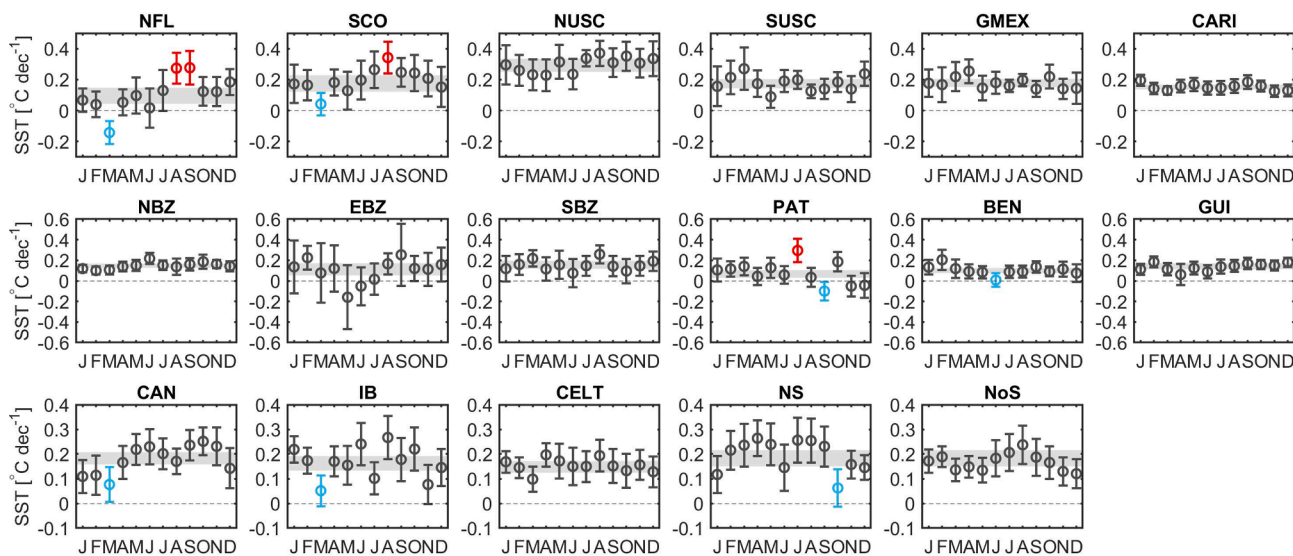


Fig. 4. SST warming rates per month for each LME over the 1957–2020 period. The gray shaded area represents long-term warming rates calculated with the non-linear regression, and their confidence interval, from 1957 to 2020. When the monthly SST trends and confidence interval are outside gray, they are displayed in red if higher and cyan if lower.

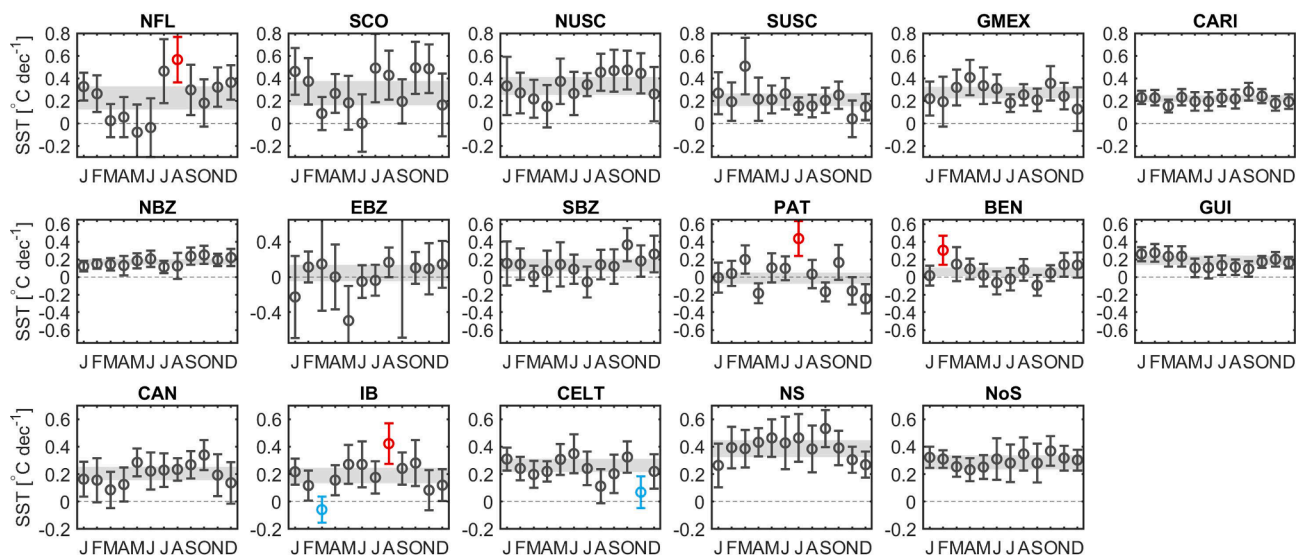


Fig. 5. SST warming rates per month for each LME over the 1980–2020 period. The gray shaded area represents long-term warming rates calculated with the non-linear regression, and their confidence interval, from 1980 to 2020. When the monthly SST trends and confidence interval are outside gray, they are displayed in red if higher and cyan if lower.

Pratchett et al., 2008).

We found diverging warming trend behaviors between the LMEs of the North and South Atlantic. Our calculated warming trends indicate an acceleration in the North Atlantic while there is an indication of a deceleration in the South Atlantic (Fig. 2), despite large uncertainties. In the South Atlantic, the LMEs on the Brazilian shelf (EBZ and SBZ) have the least data coverage in our study, which may challenge the accuracy of our results, but the PAT and BEN LMEs provide relatively good data coverage (85.7% and 97.8% of months are represented by data, respectively) making us confident in the results. These two regions experience the least warming and are located at the southernmost part of the western and eastern side of the Atlantic Ocean, respectively. The BEN LME is characterized by important nearshore upwelling activities which have been increasing over the past decades (Santos et al., 2012; Varela et al., 2015). This induces large cooling areas nearshore (Sweijd and Smit, 2020) that act against the global increase in temperatures. Although the impact of these upwelling systems on the entire LME SST status is not well established yet, these findings indicate that our estimated long-term (1957–2020) warming rate for the BEN LME (0.10 ± 0.03 °C/dec) and its apparent slow down between 1980 and 2020 (0.06 ± 0.05 °C/dec) are plausible. These warming rates are substantially higher than those provided in the TWAP assessment. However, using satellite-derived data between 1982 and 2019, Sweijd and Smit (2020) found also a stronger warming rate (0.167 °C/dec) and proposed to move this LME to a higher warming category than the “slow” warming identified in the TWAP assessment (IOC-UNESCO and UNEP, 2016), supporting our results.

Heterogeneity in temporal properties of SST warming is known and observed all across the globe (López García and Camarasa Belmonte, 2011; Trenberth et al., 2007). These heterogeneous changes can modify the value of our estimated long-term trends as our method for their estimation sets the amplitude of the seasonal cycle to be constant. Most of our calculated monthly trends are found to be within the uncertainty of the annual warming rate of each LME, indicating that there are no significant and heterogeneous changes in the seasonal cycle and that our method is hence suitable for long-term trend analysis. However, we denoted a few significant exceptions for the NFL, IB and PAT LMEs, which suggests that these LMEs might be affected by heterogeneous seasonal change, which is not taken into account in our estimation of long-term annual trends. While the reason for the stronger summer SST trend in IB and PAT LMEs are not understood by the authors, the cooling

trend occurring in March in the NFL LME is consistent with the future projection results from Alexander et al. (2018), a model study who simulated a large area over the Labrador Sea and the Northern North Atlantic with cooling SST trends for the month of March. Liu et al. (2020) linked the difference between winter and summer SST warming in the Northern Hemisphere to changes in mixed layer depth (MLD), with a thinner MLD in summer ultimately increasing the surface warming.

5. Summary and conclusion

We have assembled more than 8.2 million *in-situ* SST measurement from different data sources to calculate long-term (1957–2020) and more recent (1980–2020) SST trends over 17 LMEs of the Atlantic Ocean. The results for the long-term analysis show clear warming trends for all 17 LMEs with different intensities of warming classified from “slow” (0 – 0.07 °C/dec) to “superfast” (>0.21 °C/dec). This result emphasizes that the ongoing global warming has left a measurable impact on every considered LMEs.

Although the relatively large uncertainties cause most LME to belong to several warming categories, we find a more intense warming in the LMEs of the North Atlantic (Fig. 2) as well as a tendency of those North Atlantic warming trends to further accelerate over the recent decades, while the LMEs of the South Atlantic show an opposite behavior. For the North Atlantic, the number of LMEs belonging exclusively to the “superfast” warming category increases from 1 (NUSC) for the period 1957–2020 to 5 (NoS, NS, CELT, NUSC and GMEX) for the period 1980–2020, highlighting the extreme sensitivity of its coastal regions to the ongoing global warming. Here, changes in local ecosystems and fish populations are already observed and linked to the increase in thermal habitat conditions.

Our analysis of the monthly SST warming trends shows that only a few monthly trends deviate from the annual warming range. These deviations are in most cases not systematic and are potentially induced by the strong decadal variability and related uncertainties. Nevertheless, three LMEs (NFL, IB and PAT) show specific behaviors which are persistent regardless of the time period studied (1957–2020 and 1980–2020): the NFL LME warms faster in August, the PAT LME warms faster in July, and the warming in the IB LME slows down in March.

To conclude, our *in-situ* data analysis clearly shows that the ongoing global warming is leaving an imprint on all considered LMEs. More

observations are required to reduce the large uncertainties on our warming trends, especially along the coast of Brazil. Nevertheless, our results allow us to confidently declare that the LMEs of the North Atlantic are at risk. Specifically, the Norwegian Sea, North Sea, Celtic-Biscay Shelf, Northeast U.S. Continental Shelf, and the Gulf of Mexico LMEs have experienced profound changes since the 1980's, and a close monitoring and managing of their vulnerable ecosystems should be high priority.

CRedit authorship contribution statement

Augustin Kessler: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization. **Nadine Goris:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision. **Siv Kari Lauvset:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data are publicly available, the associated references are provided within the article.

Acknowledgements

This project was funded under the ASTRAL project (All Atlantic Ocean Sustainable, Profitable, and Resilient Aquaculture; EU H2020 grant agreement: 863034).

References

- Alexander, M.A., Scott, J.D., Friedland, K.D., Mills, K.E., Nye, J.A., Pershing, A.J., et al., 2018. Projected sea surface temperatures over the 21st century: changes in the mean, variability and extremes for large marine ecosystem regions of Northern Oceans. *Elem. Sci. Anth.* 6, 9. <https://doi.org/10.1525/elementa.191>.
- Baird, A.H., Guest, J.R., Willis, B.L., 2009. Systematic and biogeographical patterns in the reproductive biology of scleractinian corals. *Annu. Rev. Ecol. Syst.* 40, 551–571. <https://doi.org/10.1146/annurev.ecolsys.110308.120220>.
- Baker-Austin, C., et al., 2016. Heatwave-associated vibriosis, Sweden and Finland, 2014. *Emerg. Infect. Dis.* 22 (7), 1216–1220. <https://doi.org/10.32032/eid2207.151996>.
- Bakker, D.C.E., Pfeil, B., Landa, C.S., Metz, N., O'Brien, K.M., Olsen, A., Smith, K., Cosca, C., Harasawa, S., Jones, S.D., Nakaoka, S., Nojiri, Y., Schuster, U., Steinhoff, T., Sweeney, C., Takahashi, T., Tilbrook, B., Wada, C., Wanninkhof, R., Alin, S.R., Balestrini, C.F., Barbero, L., Bates, N.R., Bianchi, A.A., Bonou, F., Boutin, J., Bozec, Y., Burger, E.F., Cai, W.-J., Castle, R.D., Chen, L., Chierici, M., Currie, K., Evans, W., Featherstone, C., Feely, R.A., Fransson, A., Goyet, C., Greenwood, N., Gregor, L., Hankin, S., Hardman-Mountford, N.J., Harlay, J., Hauck, J., Hoppema, M., Humphreys, M.P., Hunt, C.W., Huss, B., Ibañez, J.S.P., Johannessen, T., Keeling, R., Kitidis, V., Körtzinger, A., Kozyr, A., Krasakopoulou, E., Kuwata, A., Landschützer, P., Lauvset, S.K., Lefèvre, N., Lo Monaco, C., Manke, A., Mathis, J.T., Merlivat, L., Millero, F.J., Monteiro, P.M.S., Munro, D.R., Murata, A., Newberger, T., Omar, A.M., Ono, T., Paterson, K., Pearce, D., Pierrot, D., Robbins, L. L., Saito, S., Salisbury, J., Schlitzer, R., Schneider, B., Schweitzer, R., Sieger, R., Skjelvan, I., Sullivan, K.F., Sutherland, S.C., Sutton, A.J., Tadokoro, K., Telszewski, M., Tuma, M., van Heuven, S.M.A.C., Vandemark, D., Ward, B., Watson, A.J., Xu, S., 2016. A multi-decade record of high-quality fCO₂ data in version 3 of the Surface Ocean CO₂ Atlas (SOCAT). *Earth Syst. Sci. Data* 8, 383–413. <https://doi.org/10.5194/essd-8-383-2016>.
- Belkin, I.M., 2009. Rapid warming of large marine ecosystems. *Prog. Oceanogr.* 81 (1–4), 207–213. <https://doi.org/10.1016/j.pocan.2009.04.011>.
- Bonino, G., Di Lorenzo, E., Masina, S., Iovino, D., 2019. Interannual to decadal variability within and across the major Eastern Boundary Upwelling Systems. *Sci. Rep.* 9 (1), 1–14. <https://doi.org/10.1038/s41598-019-56514-8>.
- Boyer, T.P., O.K. Baranova, C. Coleman, H.E. Garcia, A. Grodsky, R.A. Locarnini, A.V. Mishonov, C.R. Paver, J.R. Reagan, D. Seidov, I.V. Smolyar, K. Weathers, M.M. Zweng (2018): World Ocean Database 2018. A.V. Mishonov, Technical Ed., NOAA Atlas NESDIS 87.
- Cheng, L., Abraham, J., Zhu, J., Trenberth, K.E., Fasullo, J., Boyer, T., Locarnini, R., Zhang, B., Yu, F., Wan, L., Chen, X., Song, X., Liu, Y., Mann, M.E., 2020. Record-setting ocean warmth continued in 2019. *Adv. Atmos. Sci.* 37 (137–142), 2020. <https://doi.org/10.1007/s00376-020-9283-7>.
- Chollett, I., Müller-Karger, F.E., Heron, S.F., Skirving, W., Mumby, P.J., 2012. Seasonal and spatial heterogeneity of recent sea surface temperature trends in the Caribbean Sea and southeast Gulf of Mexico. *Mar. Pollut. Bull.* 64 (5), 956–965. <https://doi.org/10.1016/j.marpolbul.2012.02.016>.
- CMEP (2017) Caribbean Marine Climate Change Report Card 2017. (Eds. Paul Buckley, Bryony Townhill, Ulric Trotz, Keith Nichols, Peter A. Murray, Chantalle ClarkeSamuels, Ann Gordon, Michael Taylor). Commonwealth Marine Economies Programme, 12pp.
- Collins, M., Sutherland, M., Bouwer, L., Cheong, S.-M., Frölicher, T., Jacot Des Combes, H., ... Tibig, L. (2019). Extremes, Abrupt Changes and Managing Risk. In: H.-O. Pörtner, D.C. Roberts, V. Masson-Delmotte, P. Zhai, M. Tignor, E. Poloczanska, K. Mintenbeck, A. Alegria, M. Nicolai, A. Okem, J. Petzold, B. Rama, N.M. Weyer (eds.). IPCC Special Report on the Ocean and Cryosphere in a Changing Climate. Retrieved from: <https://www.ipcc.ch/srocc/cite-report>.
- Emery, W.J., 2003. Air-sea interaction: sea surface temperature. In: James, R.H. (Ed.), *Encyclopedia of Atmospheric Sciences*. Academic, Oxford, pp. 100–109.
- Fay, A.R., McKinley, G.A., 2013. Global trends in surface ocean pCO₂ from in situ data. *Global Biogeochem. Cycles* 27 (2), 541–557. <https://doi.org/10.1002/gbc.20051>.
- Fox-Kemper, B., H.T. Hewitt, C. Xiao, G. Aðalgeirsdóttir, S.S. Drijfhout, T.L. Edwards, N. R. Golledge, M. Hemer, R.E. Kopp, G. Krinner, A. Mix, D. Notz, S. Nowicki, I.S. Nurhati, L. Ruiz, J.-B. Sallée, A.B.A. Slangen, and Y. Yu, 2021: Ocean, Cryosphere and Sea Level Change. In *Climate Change 2021: The Physical Science Basis*. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1211–1362. <https://doi.org/10.1017/9781009157896.011>.
- García, M.L., Belmonte, A.C., 2011. Recent trends of SST in the Western Mediterranean basins from AVHRR Pathfinder data (1985–2007). *Global Planet. Change* 78 (3–4), 127–136. <https://doi.org/10.1016/j.gloplacha.2011.06.001>.
- Glibert, P.M., Icarus Allen, J., Artioli, Y., Beusen, A., Bouwman, L., Harle, J., Holmes, R., Holt, J., 2014. Vulnerability of coastal ecosystems to changes in harmful algal bloom distribution in response to climate change: projections based on model analysis. *Glob. Change Biol.* 20 (12), 3845–3858. <https://doi.org/10.1111/gcb.12662>.
- Good, S.A., Corlett, G.K., Remedios, J.J., Noyes, E.J., Llewellyn-Jones, D.T., 2007. The global trend in sea surface temperature from 20 years of advanced very high resolution radiometer data. *J. Clim.* 20 (7), 1255–1264. <https://doi.org/10.1175/JCLI4049.1>.
- Halpern, B.S., Walbridge, S., Selkoe, K.A., Kappel, C.V., Micheli, F., D'Agrosa, C., Bruno, J.F., Casey, K.S., Ebert, C., Fox, H.E., Fujita, R., Heinemann, D., Lenihan, H.S., Madin, E.M.P., Perry, M.T., Selig, E.R., Spalding, M., Steneck, R., Watson, R., 2008. A global map of human impact on marine ecosystems. *Science* 319, 948–952. <https://doi.org/10.1126/science.1149345>.
- Hare, J.A., Alexander, M.A., Fogarty, M.J., Williams, E.H., Scott, J.D., 2010. Forecasting the dynamics of a coastal fishery species using a coupled climate–population model. *Ecol. Appl.* 20 (2), 452–464. <https://doi.org/10.1890/08-1863.1>.
- Hare, J.A., Morrison, W.E., Nelson, M.W., Stachura, M.M., Teeters, E.J., Griffiths, R.B., et al., 2016. A Vulnerability Assessment of Fish and Invertebrates to Climate Change on the Northeast U.S. Continental Shelf. *PLoS ONE* 11 (2), e0146756.
- Hastings, R.A., Rutterford, L.A., Freer, J.J., Collins, R.A., Simpson, S.D., Genner, M.J., 2020. Climate change drives poleward increases and equatorward declines in marine species. *Curr. Biol.* 30 (8), 1572–1577. <https://doi.org/10.1016/j.cub.2020.02.043>.
- Holland, P.W., Welsh, R.E., 1977. Robust regression using iteratively reweighted least-squares. *Communications in Statistics-theory and Methods* 6 (9), 813–827. <https://doi.org/10.1080/03610927708827533>.
- Hughes, T.P., Anderson, K.D., Connolly, S.R., Heron, S.F., Kerry, J.T., Lough, J.M., Baird, A.H., Baum, J.K., Berumen, M.L., Bridge, T.C., Claar, D.C., Eakin, C.M., Gilmour, J.P., Graham, N.A.J., Harrison, H., Hobbs, J.-P.-A., Hoey, A.S., Hoogenboom, M., Lowe, R.J., McCulloch, M.T., Pandolfi, J.M., Pratchett, M., Schoepf, V., Torda, G., Wilson, S.K., 2018. Spatial and temporal patterns of mass bleaching of corals in the Anthropocene. *Science* 359, 80–83. <https://doi.org/10.1126/science.aan8048>.
- IOC-UNESCO, U. N. E. P. (2016). Large Marine Ecosystems: Status and Trends. United Nations Environment Programme (UNEP), Nairobi. TWAP Volume 4 Technical report.
- Kleisner, K.M., Fogarty, M.J., McGee, S., Hare, J.A., Moret, S., Perretti, C.T., Saba, V.S., 2017. Marine species distribution shifts on the US Northeast Continental Shelf under continued ocean warming. *Prog. Oceanogr.* 153, 24–36. <https://doi.org/10.1016/j.pocan.2017.04.001>.
- Lauvset, S. K., Lange, N., Tanhua, T., Bittig, H. C., Olsen, A. C., Kozyr, A., Álvarez, M., Becker, S., Brown, P. J., Carter, B. R., Cotrim da Cunha, L., Feely, R. A., van Heuven, S., Hoppema, M., Ishii, M., Jeansson, E., Jutterström, S., Jones, S. D., Karlsen, M. K., Lo Monaco, C., Michaelis, P., Murata, A., Pérez, F. F., Pfeil, B., Schirnick, C., Steinfeldt, R., Suzuki, T., Tilbrook, B., Velo, A., Wanninkhof, R., Woosley, R. J., and Key, R. M. (2021): An updated version of the global interior ocean biogeochemical data product, GLODAPv2. 2021. Earth System Science Data, 13(12), 5565–5589. <https://doi.org/10.5194/essd-13-5565-2021>.
- Lee, T.N., Yoder, J.A., Atkinson, L.P., 1991. Gulf Stream frontal eddy influence on productivity of the southeast US continental shelf. *J. Geophys. Res. Oceans* 96 (C12), 22191–22205. <https://doi.org/10.1029/91JC02450>.

- Lima, F.P., Wetthey, D.S., 2012. Three decades of high-resolution coastal sea surface temperatures reveal more than warming. *Nat. Commun.* 3 (1), 1–13. <https://doi.org/10.1038/ncomms1713>.
- Liu, F., Lu, J., Luo, Y., Huang, Y., Song, F., 2020. On the oceanic origin for the enhanced seasonal cycle of SST in the midlatitudes under global warming. *J. Clim.* 33 (19), 8401–8413. <https://doi.org/10.1175/JCLI-D-20-0114.1>.
- Lynch, P.D., Nye, J.A., Hare, J.A., Stock, C.A., Alexander, M.A., Scott, J.D., Curti, K.L., Drew, K., 2015. Projected ocean warming creates a conservation challenge for river herring populations. *ICES J. Mar. Sci.* 72 (2), 374–387. <https://doi.org/10.1093/icesjms/fsu134>.
- MacLeod, C.D., Weir, C.R., Pierpoint, C., Harland, E.J., 2007. The habitat preferences of marine mammals west of Scotland (UK). *Journal of the Marine Biological Association of the United Kingdom* 87 (1), 157–164. <https://doi.org/10.1017/S0025315407055270>.
- Locarnini Mm, Mishonov Av, Baranova Ok, Boyer Tp, Zweng Mm, Garcia He, Reagan Jr, Seidov D. *Weathers Kw, Paver Cr, Smolyar I* (2018): World Ocean Atlas 2018, Volume 1: Temperature. NOAA Atlas NESDIS 81, 52pp. <https://archimer.ifremer.fr/doc/00651/76338/>.
- O'Brien, C.M., Fox, C.J., Planque, B., Casey, J., 2000. Climate variability and North Sea cod. *Nature* 404 (6774), 142. <https://doi.org/10.1038/35004654>.
- Pershing, A.J., Alexander, M.A., Hernandez, C.M., Kerr, L.A., Leris, A., Mills, K.E., Nye, J.A., Record, N.R., Scannell, H.A., Scott, J.D., Sherwood, G.D., Thomas, A.C., 2015. Slow adaptation in the face of rapid warming leads to collapse of the Gulf of Maine cod fishery. *Science* 350 (2015), 809–812. <https://doi.org/10.1126/science.aac9819>.
- Pratchett, M. S., Munday, P. L., Wilson, S. K., Graham, N. A. J., Cinner, J. E., Bellwood, D. R., Jones, G. P., Polunin, N. V. C., McClanahan, T. R. (2008). Effects of climate-induced coral bleaching on coral-reef fishes—ecological and economic consequences *Oceanography and Marine Biology: An Annual Review*, 46 (2008), pp. 251–296.
- Robson, J., Sutton, R.T., Archibald, A., Cooper, F., Christensen, M., Gray, L.J., Holliday, N.P., Macintosh, C., McMillan, M., Moat, B., Russo, M., Tilling, R., Carslaw, K., Desbruyères, D., Embury, O., Feltham, D.L., Grosvenor, D.P., Josey, S., King, B., Lewis, A., McCarthy, G.D., Merchant, C., New, A.L., O'Reilly, C.H., Osprey, S.M., Read, K., Scaife, A., Shepherd, A., Sinha, B., Smeed, D., Smith, D., Ridout, A., Woollings, T., Yang, M.X., 2018. Recent multivariate changes in the North Atlantic climate system, with a focus on 2005–2016. *Int. J. Climatol.* 38 (14), 5050–5076. <https://doi.org/10.1002/joc.5815>.
- Rogers, A., Blanchard, J.L., Mumby, P.J., 2014. Vulnerability of coral reef fisheries to a loss of structural complexity. *Curr. Biol.* 24 (9), 1000–1005. <https://doi.org/10.1016/j.cub.2014.03.026>.
- Santos, F., DeCastro, M., Gómez-Gesteira, M., Álvarez, I., 2012. Differences in coastal and oceanic SST warming rates along the Canary upwelling ecosystem from 1982 to 2010. *Cont. Shelf Res.* 47, 1–6. <https://doi.org/10.1016/j.csr.2012.07.023>.
- Seabra, R., Varela, R., Santos, A.M., Gomez-Gesteira, M., Meneghesso, C., Wetthey, D.S., Lima, F.P., 2019. Reduced nearshore warming associated with eastern boundary upwelling systems. *Front. Mar. Sci.* 6, 104. <https://doi.org/10.3389/fmars.2019.00104>.
- Shearman, R.K., Lentz, S.J., 2010. Long-term sea surface temperature variability along the US East Coast. *J. Phys. Oceanogr.* 40 (5), 1004–1017. <https://doi.org/10.1175/2009JPO4300.1>.
- Sherman, K., 1991. The large marine ecosystem concept: research and management strategy for living marine resources. *Ecol. Appl.* 1 (4), 349–360. <https://doi.org/10.2307/1941896>.
- Stendardo, I., Gruber, N., 2012. Oxygen trends over five decades in the North Atlantic. *J. Geophys. Res. Oceans* 117 (C11). <https://doi.org/10.1029/2012JC007909>.
- Storto, A., Alvera-Azcarate, A., Balmesada, M.A., Barth, A., Chevallier, M., Counillon, F., Domingues, C.M., Drevillon, M., Drillet, Y., Forget, G., Garric, G., Haines, H., Hernandez, F., Iovino, D., Jackson, L.C., Lellouche, J.-M., Masina, S., Mayer, M., Oke, P.R., Penny, S.G., Peterson, K.A., Yang, C., Zuo, H., 2019. Ocean reanalyses: Recent advances and unsolved challenges. *Front. Mar. Sci.* 6, 418. <https://doi.org/10.3389/fmars.2019.00418>.
- Strong, A.E., Liu, G., Eakin, C.M., Christensen, J.D., Skirving, W., Gledhill, D.K., Heron, S.F., Morgan, J.A., 2008. Implications for our coral reefs in a changing climate over the next few decades – Hints from the past 22 years. In: *Proceedings of the 11th International Coral Reef Symposium*, Fort Lauderdale, Florida, pp. 1130–1134.
- Sully, S., Burkepille, D.E., Donovan, M.K., Hodgson, G., Van Woesik, R., 2019. A global analysis of coral bleaching over the past two decades. *Nat. Commun.* 10 (1), 1–5. <https://doi.org/10.1038/s41467-019-09238-2>.
- Sweijid, N.A., Smit, A.J., 2020. Trends in sea surface temperature and chlorophyll-a in the seven African Large Marine Ecosystems. *Environmental Development* 36, 100585. <https://doi.org/10.1016/j.envdev.2020.100585>.
- Trenberth, K.E., Jones, P.D., Ambenje, P., Bojariu, R., Easterling, D., Klein Tank, A., Parker, D., Rahimzadeh, F., Renwick, J.A., Rusticucci, M., Soden, B., Zhai, P., 2007. *Observations: surface and atmospheric climate change. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., Miller, H.L. (Eds.), Climate Change 2007: the Physical Science Basis. Contribution of Working Group 1 to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge University Press: Cambridge and New York, NY, pp. 235–336.
- Varela, R., Álvarez, I., Santos, F., DeCastro, M., Gómez-Gesteira, M., 2015. Has upwelling strengthened along worldwide coasts over 1982–2010? *Sci. Rep.* 5 (1), 1–15. <https://doi.org/10.1038/srep10016>.
- Varela, R., Costoya, X., Enriquez, C., Santos, F., Gómez-Gesteira, M., 2018. Differences in coastal and oceanic SST trends north of Yucatan Peninsula. *J. Mar. Syst.* 182, 46–55. <https://doi.org/10.1016/j.jmarsys.2018.03.006>.
- Varela, R., Rodríguez-Díaz, L., de Castro, M., Gómez-Gesteira, M., 2022. Influence of Canary upwelling system on coastal SST warming along the 21st century using CMIP6 GCMs. *Global Planet. Change* 208, 103692. <https://doi.org/10.1016/j.gloplacha.2021.103692>.
- Vollset, K.W., Urdal, K., Utne, K.R., Thorstad, E.B., Særgrov, H., Raunsgard, A., et al., 2022. Ecological regime shift in the Northeast Atlantic Ocean revealed from the unprecedented reduction in marine growth of Atlantic salmon. *Sci. Adv.* 8 <https://doi.org/10.1126/sciadv.abk2542>.