Sea Surface Temperatures: Seasonal Persistence and Trends

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ABSTRACT

This paper addresses analysis of the global monthly sea surface temperatures using a reconstructed dataset that goes back to 1884. We use fractional integration methods to examine features such as persistence, seasonality, and time trends in the data. The results show that seasonality is a relevant issue, finding evidence of seasonal unit roots. With the seasonal component removed, persistence is also very significant, and, when looking at the data month by month, evidence of significant linear trends is detected in all cases. According to these results, monthly sea surface temperatures increase by between 0.07° and 0.11°C every 100 years.

1. Introduction

The interest in global warming and climate change has increased rapidly in recent years. There is agreement that Earth's surface temperature has increased over the last 100 years by between $\sim 0.3^\circ$ and $\sim 0.6^\circ\text{C}$. (IPCC 1995; Cane et al. 1997; Hansen and Lebedeff 1988; Nicholls et al. 1996; Jones and Wigley 2010; Folland et al. 2018; etc.). The causes of this temperature increase may be a response to anthropogenic forcing (industrialization and the effect of burning and emissions of fossil fuel, increases in the greenhouse gas concentration that affect the atmosphere, etc.), a part of the climate system's innate natural variability (e.g., solar irradiance), or a combination of the two. However, most of the scientific community maintains an almost unanimous agreement on this topic supporting the anthropogenic origin of climate change (Anderegg et al. 2010; Beckage et al. 2018).

The surface air temperature is considered as the usual variable to determine climate change, and many articles have investigated the presence of time trends in air temperatures either at a global level (Santer et al. 1995; Hegerl et al. 1996, 1997; Jones and Hegerl 1998; Hansen et al. 2010; Rajaratnam et al. 2015; Poppick et al.

2017; etc.) or at a local and regional temperatures (Ghil and Vautard 1991; Hasselmann 1993; Schlesinger and Ramankutty 1994; North and Kim 1995; North et al. 1995; Papalexiou et al. 2018; King et al. 2018; etc.). However, sea surface temperature (SST) is a fundamental physical parameter for the understanding of climate dynamics and climate change because of the oceans' large thermal inertia as compared with that of the atmosphere and land (Deser et al. 2010).

In this research we focus on understanding sea surface temperatures and their behavior with a monthly time frequency. This paper is a contribution to the literature on the analysis of sea surface temperature from a time series viewpoint focusing on features such as seasonality, time trends, and persistence. To this purpose, we examine the time series properties of the global monthly sea surface temperatures from January 1884 to January 2019. Another contribution of this work is that by the first time we jointly examined the three features (time trends, persistence and seasonality) in a unified treatment based on long memory and fractional integration, which has not been jointly studied so far in SST data. The dataset was obtained from the KNMI Climate Explorer, which is a web application to analysis climate data statistically. This tool is made available by the World Meteorological Organization along with the European Climate Assessment and Data.

The rest of the paper is organized as follows: In section 2 we briefly review the literature on sea surface

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FIG. 1. Times series plot of the original sea surface temperature data obtained from KNMI. The monthly time period analyzed is from January 1884 to January 2019.

temperatures. In [section 3](#) we present the techniques used in the paper. [Section 4](#) describes the dataset. [Section 5](#) contains the empirical results. [Section 6](#) concludes the paper.

2. Sea surface temperatures

Temperatures of the sea surface are used as a key factor connecting the oceans to the global climate system. An example of this affirmation is collected in the research done by [Yaya and Akintande \(2018\)](#) that relates global and regional sea surface and land air surface temperatures finding evidence of a high correlation between them. Also, SST anomalies in the tropical Pacific are commonly used indicators for diagnosing the El Niño–Southern Oscillation (ENSO) state, and the impact of global warming on SST-based ENSO monitoring indices have been analyzed recently ([Turkington et al. 2019](#)).

SST might present certain irregularities and its potential nonlinear pattern creates difficulties to measure it. Nevertheless, reliable data can be found at the Hadley Centre ([Rayner et al. 2003, 2006, 2009](#); [Minobe and Maeda 2005](#); etc.), and also at the National Oceanic and Atmospheric Administration ([Smith et al. 2008](#)) and in [Kaplan et al. \(1998\)](#), among other sources.

One of the main assumptions regarding the classical definition of temperature anomalies is that the annual cycle is constant and does not change over time. To analyze the SST anomalies, several statistical methods have been used, such as optimal smoothing, the Kalman filter, and optimal interpolation ([Kaplan et al. 1998](#)). However, more accurate data, achieved by including

bias-adjusted satellite data, and accurate analysis are required to minimize errors ([Smith et al. 2008](#); [Banzon et al. 2016](#)).

On the other hand, several authors have claimed that the climate system presents memory or persistence across different regimes. In 2003, Gil-Alana introduced fractional integration techniques to analyze the central England temperature from 1659 to 2001, which is the longest available instrumental record of temperature in the world. The results show that central England temperatures have increased by approximately $0.23^{\circ}\text{C} (100\text{ yr})^{-1}$ in recent history ([Gil-Alana 2003](#)). Also, he evaluated the warming in both the Northern and Southern Hemispheres ([Gil-Alana 2005](#)). Other authors that have also found persistence and evidence of long memory in temperatures and sea temperatures are [Eichner et al. \(2003\)](#), [Lennartz and Bunde \(2009\)](#), [Franzke \(2012a, 2013\)](#), [Bunde et al. \(2014\)](#), [Ludescher et al. \(2016\)](#), [Massah and Kantz \(2016\)](#), [Yaya and Akintande \(2018\)](#), and [Deng et al. \(2018\)](#), among many others. On the other hand, [Álvarez-Ramírez et al. \(2008\)](#) showed that ocean temperatures are more persistent than land temperatures and several authors have studied recently the SST locally, in different areas, for instance, in the Mediterranean Sea ([Shaltout and Omstedt 2014](#)), Baltic Sea ([Stramska and Białogrodzka 2015](#)), and southwest coast of Portugal ([Goela et al. 2016](#)), pointing at a general increasing of the local temperature, hence contributing to global warming ([Mudelsee 2019](#)). Interestingly, [Breaker \(2019\)](#) has recently estimated long-range persistence in the ocean surface temperature of the coast of central California, a region where similar observations had not been made. Other papers that analyze time structure

FIG. 2. Time series plots of sea surface temperatures for different time periods.

dependencies and dynamics in temperatures are [Stern and Kaufmann \(2000\)](#), [Kaufmann and Stern \(2002\)](#), [Jones and Moberg \(2003\)](#), [Gil-Alana \(2003, 2005\)](#), [Moberg et al. \(2005\)](#), [Mills \(2004, 2006, 2007\)](#), [Gil-Alana \(2008b, 2015\)](#), [Deng et al. \(2018\)](#) and [Yaya and Akintande \(2018\)](#).

3. Method

Because the main goal in the paper is to show whether there is a linear trend in the sea surface temperatures across the years, our initial model is based on the following regression:

$$y_t = \alpha + \beta t + x_t; \quad t = 1, 2, \dots, \quad (1)$$

where y_t refers to the observed data, that is, the anomalies over sea surface temperatures; α and β are unknown coefficients that refer, respectively, to a constant and a potential linear trend in time; and x_t is the error term (or the detrended series) that is supposed to be well behaved. Thus, for example, if this error term in Eq. (1) is a random variable independently and normally distributed with mean zero and a constant variance, the ordinary least squares (OLS) estimate of β can be obtained, and statistical inference based on the classical F and t statistics can be applied here

([Hamilton 1994](#)). Thus, if we are able to reject the null hypothesis of

$$H_0 = \beta = 0 \quad (2)$$

versus the alternative,

$$H_a = \beta > 0, \quad (3)$$

we can then claim that temperatures are increasing over time. Nevertheless, a pattern that is observed in monthly sea surface temperatures is that they display several features that are not consistent with standard models, for example, seasonality, along with strong dependence between the observations across time.

Following [Hylleberg \(1986, 1992\)](#) seasonality can be defined as a systematic, although not necessarily regular, variation around trend in time series. This author classifies seasonality in three categories when modeling seasonal data: 1) purely deterministic models (by means of seasonal dummy variables), 2) seasonal stochastic stationary models [using seasonal autoregressive moving-average (ARMA) processes], and 3) seasonal nonstationarity (by means of seasonal differences). The first group based on seasonal dummies simply allows for the mean of the series to vary by season, and therefore it raises no statistically

TABLE 1. Estimated coefficients in the model given by Eq. (8), with no autocorrelation. The values in parentheses in the intercept column are t values. Thus, values above 1.645 in absolute value indicate statistical significance at the 5% level.

Series	d (95% band)	Intercept	Time trend	Seasonal coef
1884–2018	0.74 (0.69, 0.78)	18.366 (107.19)	—	0.917
1904–2018	0.75 (0.70, 0.80)	18.368 (110.40)	—	0.916
1922–2018	0.81 (0.76, 0.86)	18.275 (109.89)	—	0.922
1947–2018	0.86 (0.81, 0.92)	18.765 (116.07)	—	0.923

interesting issues. In the empirical application carried out below we use stochastic approaches using first a simple autoregressive of order 1 [AR(1)] process of the form

$$u_t = \varphi u_{t-1} + \varepsilon_t, \quad t = 1, 2, \dots, \quad (4)$$

assuming so far that $x_t = u_t$, and where ε_t is a white noise process. Thus, φ indicates the degree of seasonal serial dependence.¹ If nonseasonal dependence is also permitted, we can add the following model:

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, \dots, \quad (5)$$

with $x_t = u_t = 0$ for $t \leq 0$, where L indicates the lag operator, that is, $L^k x_t = x_{t-k}$, and d can be any real value. Clearly, if $d = 0$, $x_t = u_t$, there is no dependence at all, and the classical estimation of β in Eq. (1) and based on OLS or generalized least squares still remains valid. However, allowing for $d > 0$, dependence is permitted, and the higher the value of d is, the higher the level of dependence between the observations is, noting that the polynomial on the left-hand side of Eq. (5) can be expressed, for all real d , as

$$\begin{aligned} (1 - L)^d &= \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j \\ &= 1 - dL + \frac{d(d-1)}{2} L^2 - \dots, \end{aligned}$$

and thus Eq. (5) can be expressed as

$$(1 - L)^d x_t = x_t - dx_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \dots + u_t.$$

Then it is said that x_t is integrated of order d and denoted as $I(d)$. This type of process displays the property of long memory because of the strong degree of association between observations that are far distant in time. They were introduced in the earlier 1980s by Granger (1980,

¹ In the empirical application carried out in section 5, the seasonal AR parameter is found to be very close to 1, suggesting the need for seasonal differentiation. In fact, after performing seasonal unit root tests, the results support this hypothesis in all series.

TABLE 2. Estimated values of d on the first seasonal differences. The values in parentheses indicate the 95% confidence band for the values of d ; boldface font indicates the selected model for each series.

Series	No terms	With intercept	With time trend
With no autocorrelation			
1884–2018	0.73 (0.69, 0.77)	0.73 (0.69, 0.77)	0.73 (0.69, 0.77)
1904–2018	0.74 (0.70, 0.79)	0.75 (0.70, 0.79)	0.75 (0.70, 0.79)
1922–2018	0.79 (0.75, 0.83)	0.79 (0.75, 0.84)	0.80 (0.75, 0.84)
1947–2018	0.85 (0.80, 0.91)	0.86 (0.81, 0.91)	0.86 (0.81, 0.91)
With autocorrelation			
1884–2018	0.82 (0.69, 0.90)	0.81 (0.71, 0.89)	0.81 (0.71, 0.89)
1904–2018	0.79 (0.69, 0.91)	0.80 (0.70, 0.90)	0.80 (0.70, 0.90)
1922–2018	0.86 (0.75, 0.99)	0.85 (0.76, 1.00)	0.85 (0.76, 1.00)
1947–2018	0.99 (0.87, 1.15)	1.02 (0.86, 1.16)	1.02 (0.86, 1.16)

1981), Granger and Joyeux (1980) and Hosking (1981) and since then have been widely employed in the analysis of aggregate data including climatological and meteorological data (Bloomfield 1992; Koscielny-Bunde et al. 1998; Percival et al. 2001; Monetti et al. 2003; Gil-Alana 2005, 2008a, 2015, 2018; Rybski et al. 2006, 2008; Fatichi et al. 2009; Franzke 2010, 2012b; Bunde et al. 2014; Yuan et al. 2015; Ludescher et al. 2016; Bunde 2017; Gil-Alana et al. 2019; Gil-Alana and Sauci 2019; among many others). In this context of fractional integration, the estimation of β in Eq. (1) must take into account the additional dependence structure on the error term.

We estimate the model by using the Whittle function in the frequency domain (Dahlhaus 1989). The Whittle function is an approximation to the likelihood function, and we use this function in the context of a testing procedure developed in Robinson (1994) that is very convenient with our dataset. This method allows us to test the null hypothesis

$$H_0 = d = d_0, \quad (6)$$

for any real value d_0 , in a model given by Eqs. (1) and (5) independent of the specification of u_t in Eq. (5), which may be a seasonal AR(1) process as in Eq. (4). The test statistic has a standard null $N(0, 1)$ limit distribution and is the most efficient method in the Pitman sense against local departures from the null. Moreover, this standard behavior holds for any value of d_0 , including thus stationary ($d_0 < 0.5$) and nonstationary ($d_0 \geq 0.5$) hypotheses.

4. Data

The data examined in this work are the anomalies over the global monthly sea surface temperatures and have been obtained from the KNMI Climate Explorer (https://climexp.knmi.nl/select.cgi?id=someone@somewhere&field=coads_sst), which is part of the World

TABLE 3. Seasonal persistence and trends with sample size: 1884–2018. The values in parentheses in the second and fourth columns indicate the 95% confidence band for the values of d ; those reported in the third and fifth columns are t values.

Month	No autocorrelation		With autocorrelation	
Jan	0.55 (0.45, 0.67)	0.0078 (5.20)	0.54 (0.37, 0.74)	0.0078 (5.14)
Feb	0.63 (0.52, 0.77)	0.0071 (3.38)	0.54 (0.36, 0.78)	0.0071 (4.57)
Mar	0.58 (0.46, 0.73)	0.0085 (5.25)	0.43 (0.25, 0.66)	0.0086 (8.01)
Apr	0.55 (0.46, 0.68)	0.0084 (6.36)	0.53 (0.36, 0.76)	0.0084 (6.34)
May	0.63 (0.54, 0.76)	0.0073 (4.41)	0.62 (0.48, 0.79)	0.0073 (4.46)
Jun	0.60 (0.50, 0.76)	0.0076 (5.30)	0.52 (0.36, 0.69)	0.0077 (6.78)
Jul	0.58 (0.48, 0.71)	0.0077 (5.47)	0.54 (0.38, 0.70)	0.0078 (6.01)
Aug	0.61 (0.52, 0.75)	0.0075 (4.91)	0.54 (0.38, 0.71)	0.0076 (6.16)
Sep	0.62 (0.52, 0.75)	0.0076 (5.07)	0.65 (0.45, 0.85)	0.0075 (4.34)
Oct	0.66 (0.55, 0.80)	0.0075 (3.73)	0.58 (0.36, 0.80)	0.0077 (5.00)
Nov	0.56 (0.46, 0.67)	0.0077 (4.92)	0.63 (0.44, 0.87)	0.0077 (3.65)
Dec	0.44 (0.36, 0.55)	0.0082 (7.70)	0.63 (0.44, 0.80)	0.0077 (3.57)

Meteorological Organization, and from the European Climate Assessment and Data. The monthly time period examined stretches from January 1884 to January 2019.

Figure 1 plots the original data of the sea surface temperature time series obtained from KNMI. As can be observed, there are periods of time during which the information is incomplete. For this reason, first we have analyzed the time periods where we have complete data (see Fig. 2a), with data starting in 1947. Then we have also linearized the time series with the purpose of being able to analyze periods of longer duration in the data, starting in 1922 (Fig. 2b), 1904 (Fig. 2c), and 1884 (Fig. 2d).²

5. Results

On the basis of the monthly nature of the data, we start by using the model given by Eqs. (1), (4), and (5), that is,

$$y_t = \alpha + \beta t + x_t, \quad (1 - L)^d x_t = u_t, \quad (1 - \phi L^{12}) x_t = \varepsilon_t, \quad (7)$$

testing the H_0 in Eq. (6) for d_0 values equal to 0, 0.01, 0.02, ..., 1.99, and 2. As earlier mentioned, this parameter is very relevant in the sense that it is informing us about the degree of dependence in the data and thus can be taken as an indicator of the level of persistence. The higher the differencing parameter is, the higher the level of persistence is.

We conduct the estimation of d_0 under three different setups: 1) with no deterministic terms, that is, assuming that $\alpha = \beta = 0$ in Eq. (7), 2) with an intercept, that is, imposing $\beta = 0$, and 3) with an intercept and a linear time trend, that is, estimating α and β along with the other parameters in the model. We selected the appropriate

models by using their corresponding t values, and the results showed that the time trend is not required in any of the four series, the intercept being sufficient to describe the deterministic components. The results of the estimated coefficients are reported in Table 1. The estimated values of d are 0.73 for the sample starting in 1884, 0.74 for the one starting in 1904, and slightly higher (0.81 and 0.86) for those starting in 1922 and 1947. If we look at the confidence intervals, we see that all values belong to the interval $[0.5, 1)$, implying nonstationary mean reverting behavior. However, if we focus on the seasonal AR coefficients, we see that they are all very close to 1, suggesting that the series may contain seasonal unit roots.

On the basis of these high seasonal AR coefficients, we next conducted seasonal unit root tests that are based on the methods of Dickey et al. (1984), Beaulieu and Miron (1993), and Hylleberg et al. (1990), and the results, although not reported, suggested evidence of unit roots in the four series.³ Thus, we perform seasonal first differences, and work next with the differenced series. Here, noting that seasonality has been removed, we consider the model given only by Eqs. (1) and (4), that is,

$$y_t = \alpha + \beta t + x_t, \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, \dots, \quad (8)$$

under the assumptions that u_t is both white noise, that is, $u_t = \varepsilon_t$, and autocorrelated. However, in the latter case, instead of imposing a particular parametric (ARMA) structure on u_t , we use a nonparametric approach that is due to Bloomfield (1973) and that approximates ARMA models with very few parameters.⁴

³ The same evidence in favor of seasonal unit roots was obtained when using seasonal fractionally integrated methods (see Gil-Alana and Robinson 2001).

⁴ Nonlinear deterministic terms of the form advocated by Cuestas and Gil-Alana (2016) were also employed, but the coefficients were found to be statistically insignificant in all cases.

² All reconstructions are based on linear extrapolation using the last observation prior to the break and the first one after the break.

TABLE 4. Seasonal persistence and trends with sample size: 1904–2018. The values in parentheses in the second and fourth columns indicate the 95% confidence band for the values of d ; those reported in the third and fifth columns are t values.

Month	No autocorrelation		With autocorrelation	
Jan	0.46 (0.35, 0.1)	0.0100 (7.44)	0.43 (0.25, 0.68)	0.0101 (7.17)
Feb	0.49 (0.34, 0.73)	0.0084 (5.28)	0.31 (0.12, 0.72)	0.0092 (8.91)
Mar	0.52 (0.40, 0.70)	0.0100 (6.29)	0.37 (0.19, 0.62)	0.0101 (8.63)
Apr	0.42 (0.31, 0.57)	0.0104 (9.99)	0.35 (0.18, 0.61)	0.0104 (9.55)
May	0.50 (0.37, 0.68)	0.0103 (8.49)	0.33 (0.14, 0.57)	0.0105 (11.28)
Jun	0.43 (0.30, 0.63)	0.0103 (10.66)	0.24 (0.07, 0.44)	0.0105 (13.67)
Jul	0.43 (0.31, 0.62)	0.0100 (9.65)	0.32 (0.15, 0.63)	0.0102 (10.82)
Aug	0.47 (0.35, 0.66)	0.0103 (9.23)	0.30 (0.15, 0.51)	0.0105 (12.05)
Sep	0.50 (0.38, 0.68)	0.0105 (8.97)	0.41 (0.24, 0.71)	0.0105 (9.68)
Oct	0.56 (0.42, 0.74)	0.0106 (6.25)	0.39 (0.21, 0.64)	0.0106 (9.16)
Nov	0.47 (0.36, 0.62)	0.0106 (7.61)	0.47 (0.28, 0.79)	0.0106 (6.77)
Dec	0.30 (0.21, 0.43)	0.0107 (12.66)	0.40 (0.22, 0.66)	0.0106 (7.55)

The top half of Table 2 displays the estimates under the assumption of white noise errors, whereas the bottom half focuses on the case of autocorrelation. The values are very similar in the two cases, and the first thing we observe is that the time trend is not required in any single case. The estimates of d are large, though smaller than 1 in all cases, with the exception of the dataset starting in 1947 with autocorrelated errors. These results indicate that the data are highly persistent but no evidence of time trends is detected on the data.

As a final step in the analysis, we focus on the data separated by months, testing once more the degree of persistence and the significance of the time trend coefficients in the model given by Eq. (8) for the two types of residuals (uncorrelated and following the model of Bloomfield). The results for the reconstructed dataset starting in 1884 are presented in Table 3. The first thing we observe is that all estimated values of d are positive and smaller than 1 implying, once more, fractional integration. The values range between 0.43 (March with autocorrelation) and 0.66 (October with no

autocorrelation). However, the most interesting feature is that the time trend coefficients are now statistically significant in all cases, implying an increase in the temperatures during the sample period. Under no autocorrelation, the highest increases take place in March (0.085) and April (0.083), implying an increase of about 0.8°C in the temperatures every 100 years, and a very similar result is obtained under autocorrelated errors.

Tables 4, 5 and 6 display the results for the subsamples starting at 1904, 1922 and 1947, respectively. For the first two of these subsamples, the estimated values of d are very similar to those in Table 3 (with values of d ranging from 0.24 to 0.57); however, the time trend coefficients are much higher than those in Table 3, with values above 0.010 in practically all cases, implying increases above 0.10°C $(100\text{ yr})^{-1}$ for each month of the year. In Table 6, the results refer to the observed data between 1947 and 2018. Here, the values of d are much smaller than in the previous cases, ranging from 0.12 to 0.46 with no autocorrelation and being much smaller with the model of Bloomfield. In fact, the $I(0)$ hypothesis of short memory (i.e., $d = 0$) cannot be

TABLE 5. Seasonal persistence and trends with sample size: 1922–2018. The values in parentheses in the second and fourth columns indicate the 95% confidence band for the values of d ; those reported in the third and fifth columns are t values.

Month	No autocorrelation		With autocorrelation	
Jan	0.46 (0.35, 0.60)	0.0108 (6.61)	0.44 (0.23, 0.70)	0.0107 (6.25)
Feb	0.47 (0.34, 0.62)	0.0104 (5.94)	0.34 (0.12, 0.58)	0.0101 (7.33)
Mar	0.57 (0.43, 0.76)	0.0107 (4.85)	0.37 (0.15, 0.65)	0.0104 (17.66)
Apr	0.49 (0.36, 0.68)	0.0110 (7.44)	0.31 (0.08, 0.60)	0.0115 (9.28)
May	0.54 (0.39, 0.75)	0.0117 (6.93)	0.29 (0.08, 0.59)	0.0109 (9.86)
Jun	0.46 (0.32, 0.69)	0.0112 (8.69)	0.17 (−0.02, 0.42)	0.0105 (12.44)
Jul	0.47 (0.35, 0.65)	0.0109 (8.14)	0.36 (0.14, 0.58)	0.0107 (8.97)
Aug	0.53 (0.40, 0.72)	0.0115 (7.31)	0.31 (0.09, 0.58)	0.0109 (10.26)
Sep	0.51 (0.38, 0.69)	0.0115 (7.67)	0.42 (0.18, 0.73)	0.0112 (8.06)
Oct	0.60 (0.46, 0.80)	0.0118 (5.10)	0.44 (0.17, 0.76)	0.0113 (7.12)
Nov	0.48 (0.36, 0.64)	0.0113 (6.56)	0.57 (0.30, 0.92)	0.0116 (4.82)
Dec	0.29 (0.20, 0.42)	0.0109 (10.64)	0.43 (0.23, 0.69)	0.0113 (6.25)

TABLE 6. Seasonal persistence and trends with sample size: 1947–2018. The values in parentheses in the second and fourth columns indicate the 95% confidence band for the values of d ; those reported in the third and fifth columns and are t values.

Month	No autocorrelation		With autocorrelation	
Jan	0.14 (0.00, 0.35)	0.0070 (7.75)	0.01 (−0.25, 0.32)	0.0060 (8.21)
Feb	0.18 (0.04, 0.38)	0.0072 (7.20)	0.07 (−0.17, 0.38)	0.0071 (7.30)
Mar	0.30 (0.16, 0.51)	0.0076 (6.16)	0.12 (−0.11, 0.45)	0.0075 (7.43)
Apr	0.37 (0.23, 0.60)	0.0082 (5.89)	0.12 (−0.13, 0.42)	0.0083 (8.64)
May	0.40 (0.25, 0.64)	0.0088 (5.76)	0.20 (−0.01, 0.46)	0.0086 (7.47)
Jun	0.40 (0.25, 0.68)	0.0089 (5.70)	0.13 (−0.04, 0.36)	0.0094 (9.27)
Jul	0.40 (0.27, 0.62)	0.0090 (5.70)	0.27 (0.10, 0.49)	0.0090 (6.90)
Aug	0.46 (0.33, 0.68)	0.0090 (4.94)	0.30 (0.13, 0.53)	0.0090 (6.47)
Sep	0.46 (0.31, 0.70)	0.0096 (5.41)	0.28 (0.08, 0.59)	0.0093 (6.80)
Oct	0.20 (0.25, 0.64)	0.0093 (5.77)	0.22 (−0.02, 0.54)	0.0089 (6.91)
Nov	0.24 (0.11, 0.42)	0.0083 (7.38)	0.27 (0.02, 0.60)	0.0083 (5.62)
Dec	0.12 (−0.02, 0.31)	0.0080 (8.42)	0.13 (−0.16, 0.54)	0.0080 (6.31)

rejected in eight of the months, and long memory patterns are only detected for July, August, September, and November. Nevertheless, the time trend coefficients are once more statistically significant in all cases, with values close to those given for the whole sample period (1884–2018).

These results are in line with other work conducted on sea surface temperature in the Mediterranean zone (see Pastor et al. 2019). They conclude that there is a consistent warming trend for the Mediterranean Sea in the period 1982–2016, finding different linear trends for seasons and months. Alexander et al. (2018) conclude that the warming trend projected in their research is positive (from 0.05° to $0.5^{\circ}\text{C decade}^{-1}$) and is generally higher in summer than in winter. Our findings are also consistent with many other studies, including Friedland and Hare (2007), Chollett et al. (2012), López García and Belmonte (2011), Shaltout and Omstedt (2014), Thomas et al. (2017) and others.

6. Conclusions

In this article we have examined the global monthly sea surface temperatures using a reconstructed dataset that goes back to 1884. We use fractional integration techniques to investigate issues such as the degree of persistence in the data, the seasonality, and the presence of time trends. This specification is more general than other standard methods and includes the classical stationarity $I(0)$ and nonstationarity $I(1)$ as particular cases of interest. Our results indicate first that seasonality is a very relevant issue in the data, and, after testing for seasonal unit roots, the results provide strong evidence in favor of this hypothesis. Removing the seasonal component, throughout seasonal differentiation, the data are still very persistent and significant trends are observed across different sample periods. We provide evidence that the temperatures

have increased between 0.07° and 0.11°C during the last 100 years.

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