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RESEARCH ARTICLE

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The nature of the trend in global and hemispheric temperatures

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Abstract

The aim of this note is to provide evidence about the existence or non-existence of a stochastic trend in the global temperatures time series by using standard unit root tests. Three sets of data are considered in this paper: global, Northern Hemisphere and Southern Hemisphere monthly temperature anomalies. Our main finding is that there is not a stochastic trend in the temperatures time series and they are stationary around a deterministic trend.

KEYWORDS

deterministic trend, global warming, stochastic trend, temperature anomalies, time series

1 | INTRODUCTION

In climate studies, detection is defined as "the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%" (IPCC, 2013).

Detection studies clearly show that the recent trend of global temperature led temperature itself over the limit of natural variability of the previous century. Attribution studies show that this change has to be attributed mainly to external anthropogenic forcings (Bindoff *et al*., 2013). This attribution result derives specifically from modelling studies with Global Climate Models (GCMs; see, for instance, Hegerl and Zwiers, 2011) but it seems very robust as it is confirmed by at least two other kinds of independent data-driven models (Triacca *et al*., 2013; Mazzocchi and Pasini, 2017; Pasini *et al*., 2017).

In this well-established framework, it is interesting to perform a different deep time-series analysis in order to investigate the nature of the global and hemispheric temperature trends starting just from univariate analyses of temperature data. Several authors made investigations of this kind in the past (Woodward and Gray, 1993; 1995; Kärner, 1996; Stern and Kaufmann, 2000; Gay-Garcia *et al*., 2009; Estrada *et al*., 2010; Estrada and Perron, 2017; Gil-Alana, 2008).

Here, we briefly review these studies, discuss their results and limits, and perform a new analysis which contributes to the scientific debate on this topic. Compared to standard detection studies, all these investigations permit to extract further information from a univariate analysis. In particular, from the test applied here, we are able to establish if the observed temperature trends are stochastic or deterministic.

Although researchers generally agree that global and hemispheric temperatures exhibit trend characteristics, there are still existing differences and disputes on the inherent mechanism of this trend. One approach is to model the long-run behaviour as a deterministic function of time, typically through a polynomial in time, and to model the fluctuations around the trend as a stationary and invertible autoregressive moving-average (ARMA) process. Such processes are called trend-stationary (TS) processes. An alternative to the trend stationary assumption for a trending time series is the difference-stationary assumption. A time series is a realization of a difference-stationary (DS) process if its first difference follows a stationary and invertible ARMA model. This implies that the level of the time series has a unit root in its autoregressive part (the series contains a stochastic trend). The debates focus on whether the time temperatures are TS or DS.

A number of statistical tests (unit root tests) have been proposed for discriminating between TS and DS time series. Dickey and Fuller (1979), Phillips and Perron (1988) and Elliott *et al*. (1996) are a small sample. In this paper, we test the hypothesis that the time series for global and hemispheric temperatures contain a stochastic trend by means of augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979), the augmented Dickey–Fuller generalized least squares (ADF-GLS) test (Elliott *et al*., 1996) and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test (Kwiatkowski *et al*., 1992).

It is important to note that the standard unit root tests are often biased toward non-rejection of the null hypothesis. Schwert (1987), Lo and MacKinlay (1989) and others have shown such tests have low power in finite samples against the local alternative of a root close to but below unity. Many papers tackled the problem to increase the power of the unit root tests.

A way to increase the power is to increase the frequency of observations. Choi and Chung (1995) find that using high-frequency data improves the power of the ADF test. Ng (1995) finds that as far as the ADF and Phillips–Perron tests are concerned, increasing the frequency of observations with the data span fixed also increases power. In the context of the cointegration, Hooker (1993) finds that temporal disaggregation increases the power of the ADF cointegration test.

Temperature data are available both annually and monthly. Thus, using monthly rather than yearly data should help in increasing the power. It is singular that all the studies mentioned above use annual data. The approach taken in this paper is different. Just because the use of high-frequency data could increase the power of the unit root tests, we use monthly rather than yearly time series.

Power gains can be obtained also by an appropriate specification of the deterministic component in the auxiliary regression (Maddala and Kim, 1998; Enders, 2003). In climatological literature a linear trend has often been used. Consider, for example, Kaufmann and Stern (2002) and Vitale and Bilancia (2013) among others. All these studies conclude that the global temperature is difference-stationary. However, this specification of the deterministic trend could be non-appropriate. Thus, in this paper, we also consider a quadratic trend.

The remainder of the paper is structured as follows. Section 2 summarizes previous work. Section 3 provides a brief theoretical background on the concepts of DS and TS process. Section 4 describes the used dataset. Section 5 provides a short description of the utilized unit root tests. Section 6 presents the empirical results. Section 7 concludes.

2 | RELATED WORK

The global and hemispheric temperatures are dominated by an increasing trend. The issue of the nature of this trend (TS vs. DS) has been addressed by a number of authors.

The first studies on this topic (Bloomfield, 1992; Galbraith and Green, 1992; Zheng and Basher, 1999) claimed that the temperature time series can be considered TS and this deterministic trend is produced by the trend of greenhouse gases, so that it is a clear sign of anthropic causes.

Later on, other studies (Woodward and Gray, 1993; 1995; Kärner, 1996) argued that the temperature time series are DS and interpreted their results as an evidence of the non-anthropic nature of the recent global warming. In particular, if the trend is stochastic, we could hope that this warming is temporary and we could expect it will not continue in the long term.

At a later time, Kaufmann and Stern (1997), Stern and Kaufmann (1999), and Kaufmann *et al.* (2006a, 2006b)) substantially agree with the stochastic nature of the temperature trend, but showed that even the CO_2 trend is stochastic and the two series are cointegrated, so that this implies a causal nexus between these two variables, more specifically from CO_2 to temperature. Finally, Gay-Garcia *et al.* (2009), Estrada *et al.* (2010) and Estrada and Perron (2017)) showed that temperature trend is TS around a deterministic trend with break.

3 | DETERMINISTIC VERSUS STOCHASTIC TREND

Since the publication of an influential paper by Nelson and Plosser (1982), the econometric literature has emphasized the need of modelling the nature of the underlying trend of a time series. In particular, it has become commonplace to distinguish between two kinds of nonstationary behaviour: (a) a time series with a deterministic trend and (b) a time series with a stochastic trend or a unit root. Statistical implications on the long run behaviour of a series having a deterministic underlying trend are very different compared with those from a series with an underlying stochastic trend.

3.1 | Trend-stationary processes

Following Nelson and Plosser (1982), we define a trend stationary process as a stochastic process that consists of a deterministic trend (any function of time) plus a stationary stochastic process which is assumed to have a representation as a stationary and invertible ARMA process.

A stochastic process $\{y_t; t \in \mathbb{Z}\}$ is said to be trend stationary (TS) if

$$y_t = f(t) + x_t,$$

where f is any function mapping from the reals to the reals, and $\{x_t; t \in \mathbb{Z}\}$ is a stationary process that admits the Wold representation,

$$x_t = \sum_{j=0}^{\infty} c_j u_{t-j} = C(L) u_t, \quad t \in \mathbb{Z},$$

where $u_t \sim WN\left(0, \sigma_u^2\right)$, while

1. $\sum_{j=0}^{\infty} |c_j| < \infty$.
2. $C(L)$ has no zeros of modulus less than unity.
3. $C(0) = c_0 = 1$.

In particular, a linear TS process has the form

$$y_t = \alpha + \beta t + x_t,$$

where α and β are real numbers.

3.2 | Difference-stationary processes

The second class of non-stationary processes considered here is referred to as difference-stationary.

Let $\{y_t; t \in \mathbb{Z}\}$ be a non-stationary process such that the process $\{\Delta y_t; t \in \mathbb{Z}\}$ is stationary and admits the Wold representation,

$$\Delta y_t = b + \sum_{j=0}^{\infty} c_j u_{t-j} = b + C(L) u_t, \quad t \in \mathbb{Z},$$

where $u_t \sim WN\left(0, \sigma_u^2\right)$ and L is the lag operator defined by $L x_t = x_{t-1}$ for any time series x_t, while

1. $\sum_{j=0}^{\infty} |c_j| < \infty$.
2. $C(L)$ has no zeros of modulus less than unity.
3. $C(0) = c_0 = 1$.

The process $\{y_t; t \in \mathbb{Z}\}$ is said to be difference-stationary (DS) if

$$C(1) = \sum_{j=0}^{\infty} c_j \neq 0.$$

Accumulating changes in y_t from any initial value, say y_0, we obtain

$$\sum_{j=1}^{t} \Delta y_j = bt + C(1) \sum_{j=1}^{t} u_j + C^*(L) u_t,$$

where $C^*(L)$ is an infinite order polynomial with coefficients given by

$$c_j^* = -\sum_{h=j+1}^{\infty} c_h.$$

On the other hand, we have

$$\sum_{j=1}^{t} \Delta y_j = y_t - y_0.$$

Thus

$$y_t = y_0 + bt + C(1) \sum_{j=1}^{t} u_j + C^*(L) u_t.$$

The term

$$C(1) \sum_{j=1}^{t} u_j$$

is called stochastic trend. It is a scaled random walk. The relative strength of the stochastic trend is measured by the magnitude of the coefficient $C(1)$.

Conceptually, a trend-stationary process is very different from a difference-stationary process. In fact,

- The shocks of a trend-stationary process have transitory effects.
- The shocks of a difference-stationary process have permanent effects.
- The mean of a trend-stationary process is time varying, but the variance is constant in time.
- The mean of a difference-stationary process is time varying. The variance of the process increases with time and diverges as $t \to \infty$.

4 | THE MONTHLY GLOBAL TEMPERATURE ANOMALIES

The dataset considered in this paper consists of 2025 monthly observations from 1850:1 to 2018:9 on global, Northern Hemisphere and Southern Hemisphere temperature expressed as differences (or anomalies) between the actual monthly temperature and the average temperature for 1961–1990. Data have been obtained from Met Office Hadley Centre website: http://www.metoffice.gov.uk/hadobs/hadcrut4/data/current/download.html (for more details, refer to this website).

We will indicate with G, NH and SH the global, Northern Hemisphere and Southern Hemisphere monthly temperature anomalies, respectively. The time plots of these series are presented in Figure 1. We see from the time plots that there is an upward trend indicating an increase in the temperature over the years.

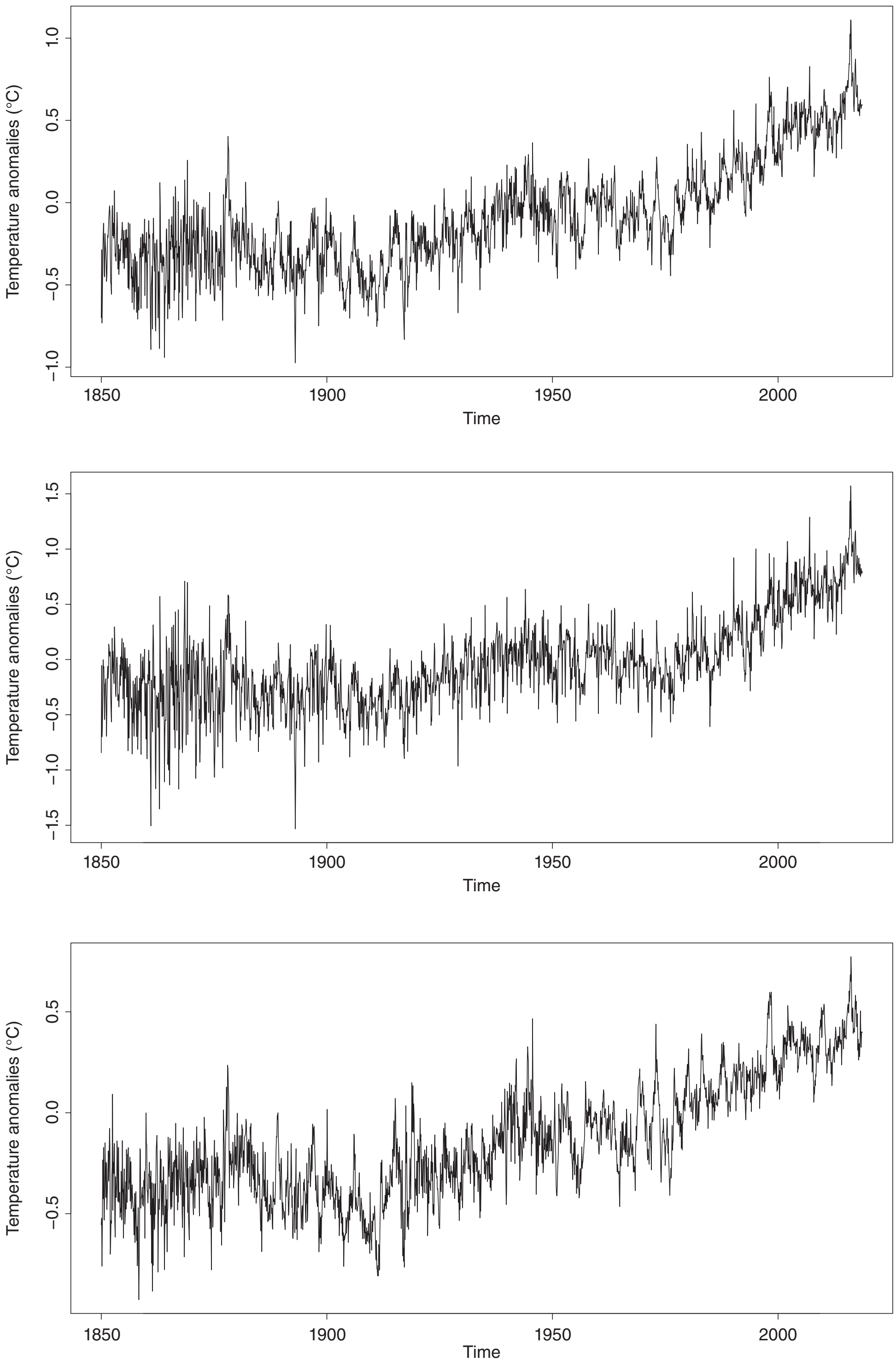

FIGURE 1 Global (top), Northern Hemisphere (middle) and Southern Hemisphere (bottom) monthly temperature anomalies over the period 1850–2018

5 | UNIT ROOT TESTING

Many different tests have been developed in the literature for discriminating between difference-stationary and trend-stationary time series. This section outlines the econometric tests employed in this paper. We use the ADF test, the ADF-GLS test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test.

The ADF test permits several alternative assumptions regarding deterministic components in the data-generating process for a given series and time period: (a) the data generating processes includes neither constant nor trend; (b) it includes a constant but no trend; (c) it includes both constant and trend; and (d) it includes linear and quadratic trend. In particular, we consider the presence of a linear trend and of a quadratic trend. Thus, to carry out the ADF tests, we estimate the following auxiliary regressions for each variable of interest y:

$$\Delta y_t = a + bt + cy_{t-1} + c_1 \Delta y_{t-1} + \dots + c_k \Delta y_{t-k} + u_t, \quad (1)$$

$$\Delta y_t = a + bt + dt^2 + cy_{t-1} + c_1 \Delta y_{t-1} + \dots + c_k \Delta y_{t-k} + u_t, \quad (2)$$

where Δ is the first difference operator, $u_t \sim WN\left(0, \sigma_u^2\right)$.

The inclusion of a trend in the regressions ensures that the unit root hypothesis is not falsely accepted when the series is really trend stationary. In this parametric framework, we test $H_0: c=0$ (the process is difference stationary) against $H_1: c<0$ (the process is trend stationary) using the test statistic,

$$\text{ADF}_t = \frac{\hat{c}}{\text{SE}(\hat{c})},$$

where $\hat{c}$ is the ordinary least square estimate of c in a regression like Equation (1) or (2) and $\text{SE}(\hat{c})$ is its standard error. Under $H_0: c=0$, this statistic follows asymptotically a Dickey–Fuller distribution. We reject H_0 if $t-$statistic is less of the critical value. An important practical issue for the implementation of the ADF test is the specification of the lag length k. The lag length should be chosen so that the residuals are not serially correlated. If k is too small then the remaining serial correlation in the errors will bias the size of the test. If k is too large then the power of the test will suffer. There have been several articles written on this subject. Ng and Perron (1995) suggest the following data dependent lag length selection sequential procedure: First, set an upper bound $k_{\max}$ for k . Next, estimate the ADF test regression with $k = k_{\max}$. If the absolute value of the t-statistic for testing the significance of the last lagged difference is greater than 1.6, then set $k = k_{\max}$ and perform the unit root test. Otherwise, reduce the lag length by one and repeat the process. We will adopt this procedure. In order to determine $k_{\max}$ we will use the rule of thumb suggested by Schwert (1987), posing

$$k_{\max} = \left[12 \left(\frac{T}{100} \right)^{\frac{1}{4}} \right],$$

where $[x]$ denotes the integer part of x and T is the sample size. See Hayashi (2000, p. 594) for a discussion of the selection of this upper bound.

The ADF-GLS test is a variant of the Dickey–Fuller test for a unit root, for the case where the variable to be tested is assumed to have a non-zero mean or to exhibit a trend. The difference is that the de-meaning or de-trending of the variable is done using the generalized least squares (GLS) procedure suggested by Elliott *et al.* (1996). The ADF-GLS test is performed by testing the hypothesis $c_0 = 0$ in the regression,

$$\Delta y_t^d = c y_{t-1}^d + c_1 \Delta y_{t-1}^d + \dots + c_k \Delta y_{t-k}^d + u_t,$$

where y_t^d is the GLS de-trended series y_t. For a data generating process (DGP) with a linear trend, $\beta_0 + \beta_1 t$, we have that

$$y_t^d = y_t - \hat{\beta}_0 - \hat{\beta}_1 t,$$

where $\hat{\beta}_0$ and $\hat{\beta}_1$ are the GLS estimates of β_0 and β_1, respectively. Similarly, for a DGP with a quadratic trend, $\beta_0 + \beta_1 t + \beta_2 t^2$, it is removed using

$$y_t^d = y_t - \hat{\beta}_0 - \hat{\beta}_1 t - \hat{\beta}_2 t^2,$$

where $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$ are the GLS estimates of the parameters β_0, β_1 and β_2, respectively.

Essentially, the test is an augmented Dickey–Fuller test except that the time series is transformed via a generalized least squares regression before performing the test. Elliott et al. (1996) and later studies have shown that this test has significantly greater power than the previous versions of the augmented Dickey–Fuller test.

The KPSS test is based on the model

$$y_t = \alpha + \delta t + \mu_t + \varepsilon_t,$$

where α and δ are two constants, ε_t is a stationary process and μ_t is a random walk given by

$$\mu_t = \mu_{t-1} + u_t, \quad u_t \sim iid\left(0, \sigma_u^2\right).$$

The null hypothesis of stationarity is formulated as

$$H_0 : \sigma_u^2 = 0,$$

which implies that μ_t is a constant. The KPSS test statistic is the Lagrange multiplier or score statistic for testing $\sigma_u^2 = 0$ against the alternative that $\sigma_u^2 > 0$. It is important to note that the KPSS testing procedure differs from standard unit root tests since the null hypothesis is that the variable in question is stationary around a deterministic linear trend.

6 | RESULTS

The results of the ADF tests for the temperature time series are presented in Table 1. Our results provide evidence against the unit root hypothesis and suggest that global temperature series are stationary around a deterministic trend (see Table 1). The ADF tests indicate that all the variables are better characterized as trend stationary rather than difference stationary at the 5% level.

It is interesting to note that the evidence against the unit root hypothesis becomes stronger if we consider the presence of a quadratic trend in the auxiliary regression (see Table 2). We observe that allowing for a quadratic trend does not necessarily seek to obtain a realistic description of the data generating process, but it appears to be a useful device to approximate nonlinearity in the unknown deterministic components of the series (see Harvey *et al*., 2011). In particular, as noted in Ayat and Burridge (2000), a quadratic trend provides a simple means of proxying a linear trend which undergoes a break at some unknown point, or even repeated shifts in the deterministic level of the process. Under this point of view, our results seem to be consistent with the evidence that Gay-Garcia *et al*. (2009) have recently provided that global temperature time series could be modelled as stationary around a broken trend.

The results obtained using the ADF-GLS test (see Tables 3 and 4) reinforce our previous analysis. Also in this case it can be concluded that the temperatures series can be considered realizations of trend stationary processes. Figure 2 shows the ADF-GLS statistic and the corresponding critical values (at 5 and 1% significance level) for a recursive ADF-GLS test applied to the global temperature anomalies starting with 612 observations and increasing sample size adding 12 observations at a time. We note that since the middle of the last century, the ADF-GLS test leads to a rejection of the unit root hypothesis, with a tendency which is always stronger when reaching the most recent years. It is worthwhile to note also that just few years show a counter-tendency, as a matter of fact years characterized by strong El Niño episodes (see, for instance, the peak in 2016).

On the other hand, applying the KPSS test we reject the null hypothesis for all time series (see Table 5). Thus, the ADF and KPSS tests conflict.

The approach suggested in the literature to overcome this problem (Charemza and Syczewska, 1998; Carrion-i-Silvestre *et al*., 2001; Keblowski and Welfe, 2004) is to test the joint confirmation hypothesis (JCH) of a unit root

TABLE 1 Augmented Dickey–Fuller test

Estimated model: $\Delta y_t = a + bt + cy_{t-1} + c_1 \Delta y_{t-1} + \ldots + c_k \Delta y_{t-k} + u_t$

Series	Null hypothesis	Test statistic τ_{ct}	p-value
G	$c = 0$	−3.80374	0.01628
NH	$c = 0$	−3.59866	0.02987
SH	$c = 0$	−4.57294	0.001095

Note: MacKinnon (1996) one-sided p-values.

TABLE 2 Augmented Dickey–Fuller test

Estimated model: $\Delta y_t = a + bt + dt^2 + cy_{t-1} + c_1 \Delta y_{t-1} + \ldots + c_k \Delta y_{t-k} + u_t$

Series	Null hypothesis	Test statistic τ_{ctt}	p-value
G	$c = 0$	−5.55168	0.000000
NH	$c = 0$	−4.94677	0.001223
SH	$c = 0$	−6.49957	0.000000

Note: MacKinnon (1996) one-sided p-values.

TABLE 3 ADF-GLS test with linear trend

Series	Test statistic	p-value
G	−3.71902	0.000199
NH	−3.24366	0.001154
SH	−4.80174	0.000051

Note: MacKinnon (1996) one-sided p-values.

TABLE 4 ADF-GLS test with quadratic trend

Series	Test statistic	p-value
G	−3.79346	0.000148
NH	−3.41517	0.000626
SH	−5.43852	0.000000

Note: MacKinnon (1996) one-sided p-values.

using symmetric critical power values, instead of conventional individual critical values for each type of test (ADF and KPSS). So, to check if the JCH is rejected for a given variable, we worked with asymptotical approximations for the critical values of ADF and KPSS tests statistics estimated by Keblowski and Welfe (2004) using Monte Carlo simulations. They are interpreted as follows. If the value of ADF statistic is less (greater) than the critical value, and the value of the KPSS statistic is less (greater) than the critical value, then the series is considered stationary (non-stationary). Otherwise, the series cannot be confirmed to be a unit root and is therefore considered stationary. From Table 1, we have that the ADF statistics for the series G, NH, SH are −3.80374, −3.59866, −4.57294, respectively. From Table 5, we have that the KPSS statistics for the series G, NH, SH are 2.32817, 1.98755, 2.22697, respectively. The critical values of ADF and KPSS tests statistics estimated by Keblowski and Welfe are (−4.224, 0.102) at 1%, (−3.604, 0.1622) at 5% and (−3.224, 0.201) at 10%. Thus for the global monthly temperature anomalies (G), we reject the JCH of a unit root at the 5% level, for the Northern Hemisphere monthly temperature anomalies (NH) we reject the JCH of a unit root at the 10% level and for the Southern Hemisphere monthly temperature anomalies (NS) we reject the JCH of a unit root at the 1% level.

We observe that the obtained results do not depend on the used procedure to determine the numbers of lags in the auxiliary regressions. In particular, we have also used the rule $k_{\max} = \left[\sqrt[3]{T}\right]$ together AIC criterion in order to select the number of lags. The results (not reported, available upon request), confirm those obtained and often the empirical evidence against the presence of a unit root appears to be stronger.

Finally, it is important to note that when monthly time series, as in our case, are considered, attention have to be given to the possibility that the series are integrated at some seasonal frequencies. In order to do this, we use the monthly version of the Hylleberg Engel Granger Yoo (HEGY) test (Hylleberg *et al.*, 1990), which was developed by Beaulieu and Miron (1993). The results of the HEGY tests for seasonal frequencies reported in Table 6 allow us to reject the existence of seasonal unit roots for all the variables.

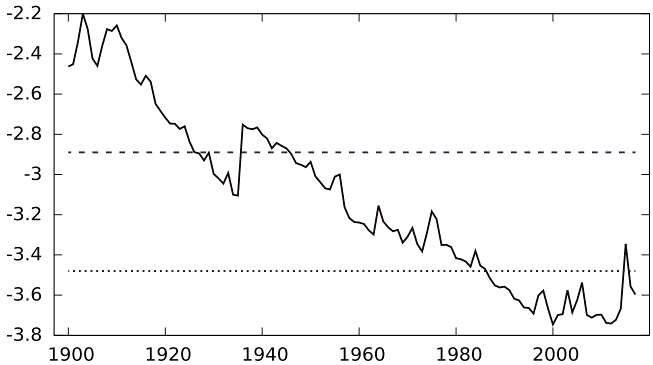

FIGURE 2 Recursive ADF-GLS test for an increasing sample size of the global temperature anomalies. ADF-GLS test statistic (—), critical value at 5% (- - -), critical value at 1% (···)

TABLE 5 The KPSS stationarity test

Series	Test statistic	*p*-value
G	2.32817 (8)	<0.01
NH	1.98755 (8)	<0.01
SH	2.22697 (8)	<0.01

Note: The numbers in parentheses are the lags truncation selected automatically by Newey–West bandwidth using Barlett's kernal spectral estimation method.

7 | CONCLUSIONS

Global and hemispheric surface temperatures continue to rise. There is a clear upward trend in these time series. Here, we have investigated the nature of this trend. In particular, by using a battery of unit root tests, we have found a strong evidence against the unit root hypothesis and suggest that global and hemispheric temperature series are stationary around a deterministic trend.

It is important to underline that this result appears more robust than previous ones, because it has been obtained using a monthly rather than yearly time series and this increases the power of the unit root tests.

TABLE 6 HEGY seasonal unit root test

Series	t_0	$F_{\pi/6}$	$F_{\pi/3}$	$F_{\pi/2}$	$F_{2\pi/3}$	$F_{5\pi/6}$	t_π
G	−3.86*	65.26**	65.67**	97.90**	101.66**	67.80**	−8.86**
NH	−3.57*	46.30**	61.67**	93.95**	97.23**	64.39**	−9.18**
SH	−4.82**	71.01**	69.60**	83.91**	84.35**	84.35**	−8.08**

Note: HEGY regression includes a constant, 11 seasonal dummies, and a time trend. The order of augmentation for the augmented HEGY regression is 12 (determined by AIC with max-order $= \left[\sqrt[3]{T}\right] = \left[\sqrt[3]{2025}\right] = 12$) *Indicates rejection of the null hypothesis at 5% level. **Indicates rejection of the null hypothesis at 5% level. The critical values are taken from Beaulieu and Miron (1993).

A consequence of our findings is that it seems inappropriate in empirical work to assume that global and hemispheric surface temperatures are difference stationary or to employ cointegration analysis.

Definitely, we believe that the present study and its results can provide an effective contribution to the recent debate led by Gay-Garcia, Estrada, Kaufmann and coworkers.

AUTHOR CONTRIBUTIONS

Umberto Triacca: Conceptualization; data curation; formal analysis; investigation; methodology; software; writing-original draft; writing-review & editing. **Antonello Pasini:** Conceptualization; investigation; methodology; supervision; validation; writing-original draft; writing-review & editing.

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REFERENCES

Ayat, L. and Burridge, R. (2000) Unit root tests in the presence of uncertainty about the non-stochastic trend. *Journal of Econometrics*, 95, 71–96.

Beaulieu, J.J. and Miron, J.A. (1993) Seasonal unit root in aggregate US data. *Journal of Econometrics*, 55, 305–328.

Bindoff, N.L., Stott, P.A., AchutaRao, K.M., Allen, M.R., Gillett, N., Gutzler, D., Hansingo, K., Hegerl, G., Hu, Y., Jain, S., Mokhov, I.I., Overland, J., Perlwitz, J., Sebbari, R. and Zhang, X. (2013) Detection and attribution of climate change: from global to regional. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V. and Midgley, P.M. (Eds.) *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge and New York, NY: Cambridge University Press.

Bloomfield, P. (1992) Trends in global temperature. *Climatic Change*, 21, 1–16.

Carrion-i-Silvestre, J.L., Sanso-i-Rossello, A. and Ortuño, M.A. (2001) Unit root and stationarity tests' wedding. *Economic Letters*, 70, 1–8.

Charemza, W. and Syczewska, E. (1998) Joint application of the Dickey–Fuller and KPSS tests. *Economic Letters*, 61, 17–21.

Choi, I. and Chung, B.S. (1995) Sampling frequency and the power of tests for a unit root: a simulation study. *Economics Letters*, 49, 131–136.

Dickey, D.A. and Fuller, W.A. (1979) Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74, 427–431.

Elliott, G., Rothenberg, T.J. and Stock, J.H. (1996) Efficient tests for an autoregressive unit root. *Econometrica*, 64, 813–836.

Enders, W. (2003) *Applied Econometric Time Series*, 2nd edition. New York, NY: John Wiley & Sons.

Estrada, F., Gay, C. and Sánchez, A. (2010) A reply to does temperature contain a stochastic trend? Evaluating conflicting statistical results? By R. K. Kaufmann et al. *Climatic Change*, 101, 407–414.

Estrada, F. and Perron, P. (2017) Extracting and analyzing the warming trend in global and hemispheric temperatures. *Journal of Time Series Analysis*, 38, 711–732.

Galbraith, J. and Green, C. (1992) Inference about trends in global temperature data. *Climate Change*, 22, 209–221.

Gay-Garcia, C., Estrada, F. and Sánchez, A. (2009) Global and hemispheric temperatures revisited. *Climatic Change*, 94, 333–349.

Gil-Alana, L. (2008) Time trend estimation with breaks in temperature time series. *Climatic Change*, 89, 325337.

Harvey, D.I., Leybourne, S.J. and Taylor, A.M.R. (2011) Testing for unit roots and the impact of quadratic trends, with an application to relative primary commodity prices. *Econometric Reviews*, 30, 514–547.

Hayashi, F. (2000) *Econometrics*. Princeton, NJ: Princeton University Press.

Hegerl, G.C. and Zwiers, F.W. (2011) Use of models in detection and attribution of climate change. *WIREs Climate Change*, 2, 570–591.

Hooker, M.A. (1993) Testing for cointegration: power versus frequency of observation. *Economics Letters*, 41, 359–362.

Hylleberg, S., Engle, R.F., Granger, L.W.J. and Yo, B.S. (1990) Seasonal integration and cointegration. *Journal of Econometrics*, 44, 215–238.

IPCC, 2013: Annex III: glossary Planton, S. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge and New York, NY.

Kärner, O. (1996) Global temperature deviations as a random walk. *Journal of Climate*, 9, 656–658.

Kaufmann, R.K., Kauppi, H. and Stock, J.H. (2006a) Emissions, concentrations, & temperature: a time analysis. *Climatic Change*, 77, 249–278. https://doi.org/10.1007/s10584-006-9062-1.

Kaufmann, R.K., Kauppi, H. and Stock, J.H. (2006b) The relationship between radiative forcing and temperature: what do statistical analyses of the instrumental temperature record measure? *Climatic Change*, 77, 279–289.

Kaufmann, R.K. and Stern, D.I. (1997) Evidence for human influence on climate from hemispheric temperature relations. *Nature*, 388, 39–44.

Kaufmann, R.K. and Stern, D.I. (2002) Cointegration analysis of hemispheric temperature relations. *Journal of Geophysical Research*, 107(D2), 4012. https://doi.org/10.1029/2000JD000174.

Keblowski, P. and Welfe, A. (2004) The ADF-KPSS test of the joint confirmation hypothesis of unit autoregressive root. *Economic Letters*, 85, 257–263.

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P. and Shin, Y. (1992) Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we demand and supply of aggregate exports of goods and services that economic time series have a unit root? *Journal of Econometrics*, 54, 159–178.

Lo, A. and MacKinlay, C. (1989) The size and power of the variance ratio test in finite samples: a Monte Carlo investigation. *Journal of Econometrics*, 40, 203–238.

MacKinnon, J.G. (1996) Numerical distribution functions for unit-root and cointegration tests. *Journal of Applied Econometrics*, 11, 601–618.

Maddala, G.S. and Kim, I.M. (1998) *Unit Roots, Cointegration and Structural Change*. Oxford: Oxford University Press.

Mazzocchi, F. and Pasini, A. (2017) Climate model pluralism beyond dynamical ensembles. *WIREs Climate Change*, 8, e477.

Nelson, C.R. and Plosser, C.I. (1982) Trends and random walks in macroeconomic time series: some evidence and implications. *Journal of Monetary Economics*, 10, 139–162.

Ng, S. (1995) Testing for unit roots in flow data sampled at different frequencies. *Economics Letters*, 47, 237–242.

Ng, S. and Perron, P. (1995) Unit root tests in ARMA models with data dependent methods for the selection of the truncation lag. *Journal of the American Statistical Association*, 90, 268–281.

Pasini, A., Racca, P., Amendola, S., Cartocci, G. and Cassardo, C. (2017) Attribution of recent temperature behaviour reassessed by a neural-network method. *Scientific Reports*, 7, 17681.

Phillips, P.C.B. and Perron, P. (1988) Testing for a unit root in time series regression. *Biometrika*, 75, 335–346.

Schwert, G.W. (1987) Effects of model specification on tests for unit roots in macroeconomic data. *Journal of Monetary Economics*, 20, 73–103.

Stern, D.I. and Kaufmann, R.K. (1999) Econometric analysis of global climate change. *Environmental Modelling and Software*, 14, 597–605.

Stern, D.I. and Kaufmann, R.K. (2000) Detecting a global warming signal in hemispheric temperature series: a structural time series analysis. *Climatic Change*, 47, 411–438.

Triacca, U., Attanasio, A. and Pasini, A. (2013) Anthropogenic global warming hypothesis: testing its robustness by Granger causality analysis. *Environmetrics*, 24, 260–268.

Vitale, D. and Bilancia, M. (2013) Role of the natural and anthropogenic radiative forcings on global warming: evidence from cointegration–VECM analysis. *Environmental and Ecological Statistics*, 20, 413–444.

Woodward, W.A. and Gray, H.L. (1993) Global warming and the problem of testing for trend in time series data. *Journal of Climate*, 6, 953–962.

Woodward, W.A. and Gray, H.L. (1995) Selecting a model for detecting the presence of a trend. *Journal of Climate*, 8, 1929–1937.

Zheng, X. and Basher, R.E. (1999) Structural time series models and trend detection in global and regional temperature series. *Journal of Climate*, 12, 2347–2358.

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