ELSEVIER

Contents lists available at SciVerse ScienceDirect

### Journal of Atmospheric and Solar-Terrestrial Physics



journal homepage: www.elsevier.com/locate/jastp

# On the relationship between global, hemispheric and latitudinal averaged air surface temperature (GISS time series) and solar activity

M.P. Souza Echer<sup>a,b,\*</sup>, E. Echer<sup>a</sup>, N.R. Rigozo<sup>c</sup>, C.G.M. Brum<sup>d</sup>, D.J.R. Nordemann<sup>a</sup>, W.D Gonzalez<sup>a</sup>

<sup>a</sup> Instituto Nacional de Pesquisas Espaciais, Caixa Postal 515, CEP 12245-970, São José dos Campos, SP, Brazil

<sup>b</sup> Faculdade de Tecnologia Thereza Porto Marques, CEP 12308-320, Jacareí, SP, Brazil

<sup>c</sup> Centro Regional Sul de Pesquisas Espaciais—CRS, Caixa Postal 5091, CEP 90105-970, Santa Maria, RS, Brazil

<sup>d</sup> National Astronomy and Ionosphere Center, Arecibo Observatory, HC 3 Box 53995, Arecibo 00612, Puerto Rico

#### ARTICLE INFO

Article history: Received 29 March 2010 Received in revised form 12 September 2011 Accepted 2 October 2011 Available online 22 October 2011

Keywords: Air surface temperature Spectral analysis Wavelet analysis Sun-climate relationships Sunspot Number Solar variability

#### ABSTRACT

The air surface temperature is a basic meteorological parameter and its variation is a primary measure of global, regional and local climate changes. In this work, the global, hemispheric and latitudinal averaged air surface temperature time series, obtained from the NASA/Goddard Institute for Space Studies (GISS), and the Sunspot Number ( $R_z$ ) for the interval 1880–2005, are decomposed in frequency bands through wavelet multi-resolution analysis. We have found a very low correlation between global, hemispheric and latitudinal averaged air surface temperature and  $R_z$  in the 11 yr solar cycle band (8–16 years) from ~1880 to ~1950. Afterwards the correlation is higher. A very significant correlation ( $R \sim 0.57$  to 0.80) is found in the ~22 yr solar Hale cycle band (16–32 years) with lags from zero to four years between latitudinal averages air surface temperature and  $R_z$ . Therefore it seems that the 22 yr magnetic field solar cycle might have a higher effect on Earth's climate than solar variations related to the 11 yr sunspot cycle.

© 2011 Elsevier Ltd. All rights reserved.

#### 1. Introduction

During the last  $\sim$ 150 years, an upward trend of about 0.6 °C in the global air surface temperature data has been observed, which has been considered to be the main signature of the so called global climatic warming (IPCC, 2007; Haigh, 2007; Souza Echer et al., 2009). The largest part of this climatic warming is usually attributed to the anthropogenic effects due to the enhanced greenhouse gases concentrations (Parker et al., 1994; Jones et al., 1999; Barnett et al., 2001; IPCC, 2007). Nevertheless, there seems to be evidence that natural phenomena can contribute significantly with the temperature variability (Eddy, 1976; Haigh, 2007; Scafetta and West, 2008). Scafetta (2010) found empirical evidences that the climate oscillations within the secular scale are likely driven by astronomical cycles. Scafetta (2010) also found in all major surface temperature records cycles with periods of 5, 9-to-11, 12, 15, 20-to-22, 30 and 60 years that are present in common with astronomical cycles. Therefore, climatic changes

Tel.: +55 12 3208 6797; fax: +55 12 3208 6810. *E-mail addresses*: mariza@dge.inpe.br (M.P. Souza Echer),

echer@dge.inpe.br (E. Echer), nivaor.rigozo@crs.inpe.br (N.R. Rigozo), cbrum@naic.edu (C.G.M. Brum), nordeman@dge.inpe.br (D.J.R. Nordemann), gonzalez@dge.inpe.br (W. Gonzalez). have been considered to be composed of natural and anthropogenic influences.

The sunspot number variability and the associated solar activity cycle are known to have important impacts in the geomagnetic activity and space weather variability (Echer et al., 2005). Both the solar irradiance variation and geomagnetic disturbances could have some impact on Earth's climate, although this is a topic of intense debate and research (Currie, 1974; Herman and Goldberg, 1978; Pittock, 1978; Friss-Christensen and Lassen, 1991; Lacis and Carlson, 1992; Lean and Rind, 1999; Krivova and Solanki, 2004; Vieira and Da Silva, 2006; Haigh, 2007; Hoyt and Schatten, 1997; Scafetta and West, 2007, 2008; Scafetta, 2009). Furthermore, the influence of these natural solar oscillations on the air surface temperature can be dependent on local conditions, such as ocean–land contrast, latitude and altitude effects (Souza Echer et al., 2007, 2009).

In this work we analyze the global, hemispheric and latitudinal averaged air surface temperature time series, obtained from the NASA/Goddard Institute for Space Studies (GISS) database and the Sunspot Number ( $R_z$ ), in order to search for information about the correlation between  $R_z$  and temperature. The time series were decomposed using the Meyer wavelet transform in five levels (or bands). We performed the cross correlation analysis between the band-pass filtered data around the 11 and 22 years for the global and hemisphere temperatures and  $R_z$ . The most significant frequencies for the temperatures and  $R_z$  are determined and inter-correlated.

<sup>\*</sup> Corresponding author at: Instituto Nacional de Pesquisas Espaciais, Caixa Postal 515, CEP 12245-970, São José dos Campos, SP, Brazil.

<sup>1364-6826/\$ -</sup> see front matter  $\circledcirc$  2011 Elsevier Ltd. All rights reserved. doi:10.1016/j.jastp.2011.10.002

#### 2. Data and methodology of analysis

#### 2.1. Data sets

The longest solar activity index is the Sunspot Number ( $R_z$ ), which was first compiled by Wolf in the XIX century and it is available as annual averages since 1700 (Eddy, 1976; Hoyt and Schatten, 1997; Echer et al., 2005; Hathaway, 2010).  $R_z$  is defined as  $R_z = k(10g+f)$ , taking into account the number of individual (f) and groups (g) of spots visible on the solar disk, and a scaling factor k (usually < 1) used to correct observational differences. The annual averages of  $R_z$  were obtained from the Sunspot Index Data Center—SIDC. The time interval for  $R_z$  used in this study is from 1880 to 2005.

We have also used the compiled air surface temperature series during the same period (1880-2005) from NASA/GISS. This period corresponds to the interval when the spatial coverage of stations permits a good estimation of the global-and-latitudinal averaged temperatures. These time series have as its source for analysis the Global Historical Climatology Network (GHCN), (Hansen and Lebedeff, 1988; Hansen et al., 1996, 1999). The basic GISS temperature analysis scheme was defined in the late 1970s by James Hansen. The analysis method was documented by Hansen and Lebedeff (1988), showing that the correlation of temperature changes was reasonably strong for stations separated by up to 1200 km, specially at middle-to-high latitudes. They obtained quantitative estimates of the error in the annual and 5 year averages temperature changes by sampling at station locations a spatially complete data set of a long run of a global climate model, which was shown to have realistic spatial and temporal variability.

Fig. 1 presents the behavior of the Air Surface Temperature Anomaly (AST  $^{\circ}$ C) for nine different geographical regions on Earth. Fig. 2 displays the Sunspot Number for the same period (panel a) and the AST for Global (panel b), Northern (panel c) and Southern (panel d) Hemispheres. The anomaly temperatures used are the monthly deviations in relation to the 1951–1980 (GISS data) interval average.

#### 2.2. Methodology of analysis

The techniques used in this work were the wavelet transform (Torrence and Compo, 1998) and the Iterative Regression Analysis—ARIST (Rigozo et al., 2005). The wavelet analysis was performed using the orthonormal discrete Meyer wavelet transform (Kumar and Foufoula-Georgiou, 1997; Percival and Walden, 2000). The Meyer transform is a continuous wavelet transform, which is composed by a mother wavelet and a scaling function. It is orthogonal, which means that, when applied to a time series, it decomposes the signal in orthogonal frequency levels, permitting the operation of band-pass filtering in different frequencies, each one limited by powers of 2 (i.e.,  $2^n$ , where *n* is related to the time series steps). In the wavelet decomposition analysis, the signal (S) is decomposed in approximations (A) and in details (D). The details contain the high-frequency part of the signal and they inserted in a period range limited by  $2^n$  and  $2^{(n+1)}$ , whereas the approximations contain most of the characteristic frequencies of the signal. In the first step of the decomposition, S = A1 + D1. In a next step, the approximation itself is split in a second level approximation, A1 = A2 + D2, and S = A2 + D2 + D1. The most suitable decomposition of a given signal is selected on an entropybased criterion and the process is repeated until this criterion is reached. In our analysis, the wavelet decomposition was performed until the  $D_5$  level with approach of the  $A_5$  (Kumar and Foufoula-Georgiou, 1997; Echer et al., 2004; Scafetta and West, 2005). The frequency bands used in this work are presented in



**Fig. 1.** Air surface temperature anomaly (AST) time series from Goddard Institute for Space Studies (GISS) for nine different geographical regions (each geographical region is pointed out in its respective panel). We are considering the Equatorial region as the region between 24° North and 24° South.

Table 1. The approximation  $A_5$  is the scaling level corresponding to the long term periods ( > 64 years).

After decomposing the original data set (as shown in Figs. 1 and 2), we applied the Iterative Regression Analysis method to the AST series. The method of the minimum squares iterative regression process is applied for every valid frequency region, to a single sine function at a time, with peak frequency, phase and amplitude used as starting values for the first iteration. The iteration process leading to the best fit values for these parameters is then repeated to reach the convergence or no convergence criteria. The iterative regression offers the possibility to weight data points according to their experimental uncertainties and to give for every searched parameter its own uncertainity interval. The general description of ARIST is given by Wolberg (1967), Rigozo and Nordemann (1998) and Rigozo et al. (2005). This method uses simple sine functions with three unknown parameters. The starting point of the method is the definition of the so-called conditional function (*F*) given by

$$=Y-a0_N\sin(a1_Nt+a2_N)$$

F

Download English Version:

## https://daneshyari.com/en/article/1777050

Download Persian Version:

https://daneshyari.com/article/1777050

Daneshyari.com