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ARIMA representation for daily solar irradiance and surface air temperature time series

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Abstract

Autoregressive integrated moving average (ARIMA) models are used to compare long-range temporal variability of the total solar irradiance (TSI) at the top of the atmosphere (TOA) and surface air temperature series. The comparison shows that one and the same type of the model is applicable to represent the TSI and air temperature series. In terms of the model type surface air temperature imitates closely that for the TSI. This may mean that currently no other forcing to the climate system is capable to change the random walk type variability established by the varying activity of the rotating Sun. The result should inspire more detailed examination of the dependence of various climate series on short-range fluctuations of TSI.

Introduction

Since November 1978 a set of total solar irradiance (TSI) measurements from space is available, yielding a time series of more than 25 years. Presently, there are three TSI composites at the top of the atmosphere (TOA) available online. The Active Cavity Radiometer Irradiance Monitor (ACRIM) composite was published by Willson (1997) and updated by Willson and Mordvinov (2003). The PMOD composite was presented by Fröhlich and Lean, 1998a, Fröhlich and Lean, 1998b and is updated periodically (Fröhlich, 2006). Recently a third composite, called IRMB, was presented by Dewitte et al. (2004). All three are constructed from the same original data, but use different methodology to construct the series. The problem is that no one sensor collected data over the entire period from 1978. Fröhlich and Lean, 1998a, Fröhlich and Lean, 1998b found that no increase in solar irradiance had occurred in the 1980s and 1990s. Willson and Mordvinov (2003) found a TSI trend of 0.04% per decade during solar cycles 21–23. Due to somewhat different construction of the composite series a mutual analysis of their temporal variability is useful.

The first goal here is to fit autoregressive and integrated moving average (ARIMA) models for describing long-range temporal variability in these series. The results are believed to show whether the different composing schemes produced the series still varying similarly in terms of the used models. Provided that one and the same model type appears to be applicable for all three versions the difference in fitted parameter values might serve as a measure of difference between the versions.

It is assumed that some influence of the temporal variability of TSI can be carried over to the climate system response series. Thus, the second goal here is to examine whether the same type of ARIMA models are applicable to represent temporal variability of the daily TSI and station based surface air temperature time series. The station based series are selected in order to get the longest available records for fitting.

The algorithm for fitting ARIMA models (Box and Jenkins, 1976) is used here. This is due to an earlier experience of applying random walk type models in order to represent the temporal variability of various atmospheric temperature series (e.g. Gordon, 1991; Kärner, 1996, Kärner, 2002). In the present paper our aim is to fit a model from the ARIMA family to daily series using a time step longer than one day. The longer time step leads to better fitting conditions because the TSI and temperature series are with varying intensity of non-stationarity in terms of the self-similarity parameter *H*. The latter is determined by means of the structure function (Monin and Yaglom, 1975).

Section snippets

Three versions for TSI

All three TSI versions are available online. An updated version of I_{PMOD} series (Fröhlich, 2006) contains also unpublished data from the VIRGO experiment on the cooperative ESA/NASA Mission SoHO. The version $d41\_61\_0710$ contains also an extended part by the proxy model calibrated during cycle 21. The file, created on October 19, 2007, and downloaded from PMOD/WRC ftp://ftp.pmodwrc.ch/pub/data/irradiance/composite/ ↗ is used in the current study. That is actually longer (from March 6, 1976, to…

Methodical background

The goal here is to fit a simple model to represent long-term variability in TSI and air temperature time series. Thus, one and the same modeling scheme is applied to both variables, TSI and temperature. Initially, it is useful to quantify variability in the series in order to determine possible changes in its intensity, and thus get information for choosing the time interval necessary to get rid of the short-range variability. The quantification is carried out by means of the structure…

Results

Estimation of the coefficient and diagnostic testing are well-known operations (see Box and Jenkins, 1976 for details). The coefficient $\Theta_{1,j}$ is calculated by means of the maximum likelihood method, separately for each sub-series. The values of $\Theta_{1,j}$ are then used with the same equation to compute the corresponding residuals, which are in turn used to test whether they can be treated as white noise. In the current study, the portmanteau test (e.g. Box and Jenkins, 1976) is used at the 99%…

Conclusions

To represent the temporal variability in various climate related time series it is important to take into consideration that the model type may depend on the time interval between the consecutive terms in the initial series. The daily series representing TSI at the TOA and local air temperature in the meteorological stations show strong short-range non-stationarity that weakens considerably together with increasing time scale (e.g. Kärner, 2005). Quantifying the variability by means of the…

Acknowledgments

The support was provided by the Estonian Science Foundation Grant 6814. Constructive critique by Jaan Pelt is gratefully acknowledged.…

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References (21)

G.E.P. Box *et al.*
Time Series Analysis, Forecasting and Control
(1976)

S. Dewitte *et al.*
Measurements and uncertainty of the long-term total solar irradiance trend
Solar Physics (2004)

P. Foukal *et al.*
Variations in solar luminosity and their effect on the Earth's climate
Nature (2006)

C. Fröhlich
Solar irradiance variability since 1978. Revision of the PMOD composite during solar cycle 21
Space Science Reviews (2006)

C. Fröhlich *et al.*
The Suns total irradiance: cycles, trends and related climate change uncertainties since 1978
Geophysical Research Letters (1998)

C. Fröhlich *et al.*
Total solar irradiance variations: the construction of a composite and its comparison with models

A.H. Gordon
Global warming as a random walk
Journal of Climate (1991)

D.I. Harwey *et al.*
Modeling trends in Central England temperatures
Journal of Forecasting (2003)

O. Kärner
Global temperature deviations as a random walk
Journal of Climate (1996)

O. Kärner
On nonstationarity and antipersistency in global temperature series
Journal Geophysical Research D (2002)

There are more references available in the full text version of this article.

Cited by (27)

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2023, Heliyon

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2022, Heliyon

> *Citation Excerpt :*

…A method to modify the ARIMA model to accommodate heteroscedasticity time series was proposed by calculating the mean of the differences between predicted and corresponding actual values and their 95% confidence intervals (Sun, 2021). Kärner used ARIMA to compare the long-term temporal variability of top-of-atmosphere total solar irradiance (TSI) and surface air temperature series, demonstrating the dependence of various climate series on short-term fluctuations in TSI (Kärner, 2009). Arora and Keshari used a combination of the adaptive neuro-fuzzy inference system (ANFIS) and the ARIMA model to obtain reaeration coefficients that measure the interaction between the air-water interface at each sampling location in the river.…

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…Therefore, local-scale statistical models and soft-computing methods are still used to predict air temperature changes with time on the basis of historical meteorological data. Various attempts to use statistical methods for air temperature predictions were used in previous studies, including ARIMA/SARIMA (De Gooijer and Hyndman, 2006; Kärner, 2009; Ye et al., 2013; Murat et al., 2018), exponential smoothing (Murat et al., 2016; Wanishsakpong and Notodiputro, 2017) and the Multivariate Adaptive Regression Spline – MARS (Ramesh and Anitha, 2014). An alternative approach was developed by Livera et al. (2011).…

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