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Intra-annual variations of the thermospheric density at 400 km altitude from 1996 to 2006

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Abstract

We investigate the intra-annual variations of globally averaged thermospheric density at 400 km altitude from 1996 to 2006 by using Artificial Neural Network Method (ANNM). The results indicate that thermospheric density is governed by solar activity, and the absolute error of our model is 13.67%, less than NRLMSISE-00 model. Fourier representation can catch the intra-annual variations more accurately than NRLMSISE-00 model and JB2008 model especially during 2002. We find that the Autumn maximum is slightly greater than Spring maximum during solar minimum, while the reverse is correct during solar maximum. There is a strong linear relation between solar activity and the amplitude of annual/semiannual variations, and the correlation coefficients are 0.9534 and 0.9424, respectively. Moreover, the amplitude ratio of the annual to semiannual variation is about 1.3 averaged, and changes in different years, but it has little relation with solar activity. Besides that, the amplitude of annual variation is larger than semiannual variation during 1996 and 2006 except 1998 and 2000. The relative error of NRLMSISE-00 model is 14.95%, decreasing to 12.49% after revising, and the correlation coefficients between this empirical model and its improved results and the observation are 0.8185 and 0.9210, respectively. Finally, we suggest the revised version of MSIS series of model should use the Fourier representation to express the intra-annual variations.

Keywords: ANN method; Thermospheric density; Intra-annual variation; NRLMSISE-00 model

1. Introduction

Thermospheric density is an important operating environment for many satellites and the ISS (International Space Station), and it displays a strong seasonal variation, with maxim near the Spring and Autumn equinoxes, a primary minimum during northern hemisphere Summer, and a secondary minimum during southern hemisphere Summer.

Paetzold and Zschörner (1961) first observed the annual variation of thermospheric density by analyzing the satellite drag data, and they found that a 6-month periodicity maximum occured in April and October, minimum in January and July. Jacchia (1966, 1971a,b) first represented annual/semiannual variation in the density formula with temperature functions in J65 model, and updated this empirical model to J71 with amplitude as a function of height.

Bowman (2004) found that the annual/semiannual variation changes from year to year, and has a high correlation with solar EUV irradiance. Three years later, he updated the JB71 model to JB2006, including some new annual/semiannual formulas. In 2008, he found that the phase and amplitude of annual/semiannual density variation can be better parameterized by using combined solar indices S10 and M10 as opposed to using F10.7 index alone, and this new parameterization of annual/semiannual variation has been used in the JB2008 model (Bowman et al., 2007, 2008; Bowman, 2008). Guo et al. (2008) investigated the intra-annual variation (includes annual, semiannual, terannual and quatraannual harmonics) in the

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thermospheric density near 400 km by using CHAMP measurements, with the latitude dependencies and hemispheric asymmetries existing in both amplitude, and the phase has been observed at all latitudes with a decreasing trend from 2002 to 2005.

Using CHAMP data normalized to 400 km and a fixed solar activity level, Müller et al. (2009) found that the peak to peak amplitude of the annual/semiannual variation is 60% for solar minimum conditions. Qian and Solomon (2012) summarized the temporal and spatial variations and forcing mechanisms of the thermospheric density, using density data sets observed by the accelerometers onboard on CHAMP satellite and results simulated from the TIE-GCM and NRLMSISE-00 models, and discussed the seasonal variations of the density.

As we know, the thermospheric density is affected by solar and geomagnetic activities (Fang et al., 2012a; Niu et al., 2014; Weng et al., 2012a,b,c), so the intra-annual variations would be not exact enough if these two factors are not removed completely by using some simply empirical models. Besides that, the density inferred from single satellite measurement has temporal variation and spatial distribution, thus the conclusion used these data may vary with local time or geographic location, and this can not reveal the integral feature of the global thermosphere

In order to avoid the complicated effects of the solar and geomagnetic activities and the restricted measurements, we will derivate the intra-annual variations from the globally averaged thermospheric density at 400 km by using ANNM and mainly analyze the annual/semiannual components, evaluating the NRLMSISE-00 and JB2008 models. Finally, NRLMSISE-00 empirical model will be improved by replacing the annual harmonics.

2. Data source and method description

2.1. Data introduction

Since the thermospheric density is governed by solar force and influenced by geomagnetic activity, we will present these two indices in Fig. 1. We use solar 10.7 cm radio flux (F10.7) and Ap as solar and geomagnetic activities, respectively. The year-averaged F10.7 is about 70 at 1996, maximum at 2000, reaching another maximum value at 2002, and then decreasing to lower level shaky. Meanwhile, the geomagnetic activity is modulated by the sun, and it has remarkably seasonal variations in most years, with maximum near the equinoxes. For example, in year 2001, the value is about 20 in equinoxes but 10 in solstices. Besides that, owing to several geomagnetic storms, the value is larger in 2003 than other years. The solar and geomagnetic data is obtained from the SPIDR web (Space Physics Interactive Data Resource, http://spidr.ngdc.noaa.gov/spidr/).

In this paper, the globally averaged thermospheric density at 400 km altitude is created by Emmert (2009), which is derived from drag data of about 5000 orbiting objects at heights range from 200 to 600 km. The data have a temporal resolution of 3–6 days, with a typical short-term precision of 2%, and this is precise enough for our study.

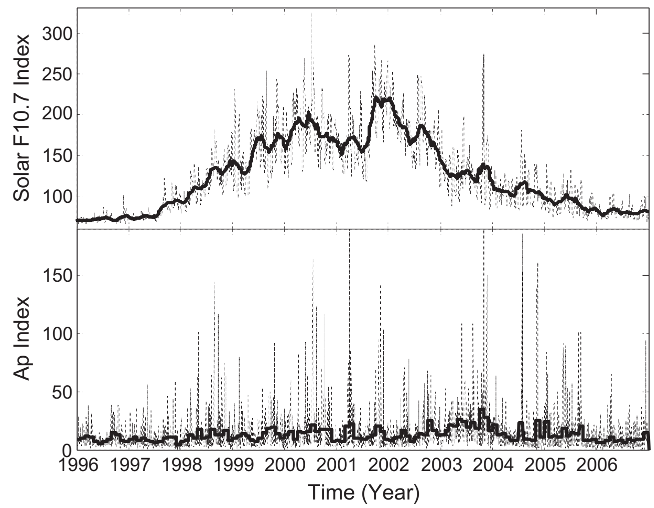

Fig. 1. (Top) The daily (dot line) and 81 day-averaged (solid line) solar F10.7 index. (Bottom)The daily (dot line) and monthly (solid line) geomagnetic Ap index during the interval of 1996–2006.

2.2. Method description

The Artificial Neural Network (ANN) is a system of interconnected computational elements, arranged in patterns similar to biological neural nets and modeled after the human brain. This method can acquire, store, and utilize experiential knowledge, or trained to identify the relationship between the input and output parameters. An ANN is typically defined by three types of parameters: the first layer is input neurons, which send input data via synapses to the second layer of neurons, and the third layer is output neurons.

We have used the ANN method to forecast ionospheric TEC successfully (Weng et al., 2012a,b,c), and Yue et al. (2006) derived long-term trends of the ionospheric foF2 at 19 ionosonde stations in the Asia/Pacific sector by using this same way. These papers indicate that the ANN method can play very well in space weather, and joint each region together effectively.

To find the best network, we have to choose a criterion to measure the modeling accuracy, and we choose the Root-Mean-Square Error (RMSE) as a suitable measure. The RMSE is defined in our investigation:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum(\rho_{obs} - \rho_{\mathrm{mod}})^2}$$

Where ρ_{obs} is the observation, ρ_{mod} is obtained by ANNM (Artificial Neural Network Method), n is the number of training samples. The optimal ANN method is defined as the network that gives the smallest RMSE on the validation set. The ANN method used here is a static