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Scaling characteristics of ocean wave height time series

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ABSTRACT

Fluctuations in the significant wave height can be quantified by using scaling statistics. In this paper, the scaling properties of the significant wave height were explored by using a large data set of hourly series from 25 monitoring stations located off the west coast of the US. Detrended fluctuation analysis (DFA) was used to investigate the scaling properties of the series. DFA is a robust technique that can be used to detect long-range correlations in nonstationary time series. The significant wave height data was analyzed by using scales from hourly to monthly. It was found that a common scaling behavior can be observed for all stations. A breakpoint in the scaling region around 4–5 days was apparent. Spectral analysis confirms this result. This breakpoint divided the scaling region into two distinct parts. The first part was for finer scales (up to 4 days) which exhibited Brown noise characteristics, while the second one showed $1/f$ noise behavior at coarser scales (5 days to 1 month). The first order and the second order DFA (DFA1 and DFA2) were used to check the effect of seasonality. It was found that there were no differences between DFA1 and DFA2 results, indicating that there is no effect of trends in the wave height time series. The resulting scaling coefficients range from 0.696 to 0.890 indicating that the wave height exhibits long-term persistence. There were no coherent spatial variations in the scaling coefficients.

1. Introduction

Fluctuations in the significant wave height time series are important for the ocean engineering applications. Understanding the dynamics of these variations may be beneficial for breakwater design, shore protection studies, offshore platform design, and ocean wave energy conversion utilities, and in assessing extreme wave conditions [1]. The scale-related properties are of interest to researchers so as to identify characteristics of particular oceanic time series, make comparison between series, and detect features which are distinctive to individual data sets.

The generation of ocean waves is a complex system. There are several factors that affect the wave height such as wind speed, wind duration, fetch length, and wave dissipation. The relationship between these factors and waves is nonlinear. The significant wave height (SWH), which is generally used to represent the wave height is a combination of sea and swell waves. The sea surface height spectrum is used to calculate significant wave height which is approximately equal to the average of the highest one-third of the waves. Specifically, the SWH is calculated as SWH $= 4 * \sqrt{m_0}$, where m_0 is the variance of the wave displacement time series. The variance is calculated by using the nondirectional wave spectrum: $m_0 = \sum_{fl}^{fu} (S(f) * d(f))$, where $S(f)$ is the spectral density function, $d(f)$ is the bandwidth of each band, f_l and f_u are the lowest and highest frequency values [2,3]. In this study, the SWH signals were analyzed over a range of temporal scales, using Detrended Fluctuation Analysis (DFA) [4]. The DFA technique is attractive in that it can detect long-range correlations in nonstationary time series. Prior studies have established that nonstationarities in the data may affect the findings. For

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Table 1
Stations used in this study and their available periods along with the percent of missing data.

Station ID	Longitude	Latitude	Depth (m)	Period	% missing data
46002	−130.460	42.57	3525	1994–1996	0.8
46005	−131.020	46.05	2779.8	2001–2004	0.8
46015	−124.823	42.747	422.6	2005–2006	1.6
46022	−124.542	40.781	509.1	2005–2007	0.4
46027	−124.381	41.85	47.9	1999–2002	5.0
46029	−124.510	46.144	135.3	2002–2004	0.4
46030	−124.525	40.423	–	2000–2001	1.0
46041	−124.731	47.353	132	2003–2004	0.5
46050	−124.500	44.641	123	1999–2001	3.0
46006	−137.451	40.886	4023	1993–1996	1.6
46059	−129.997	37.983	4599	2006–2008	1.5
46014	−123.969	39.196	274.3	2003–2005	0.1
46013	−123.325	38.228	126.5	2004–2008	1.5
46026	−122.833	37.759	52.1	2003–2008	0.1
46012	−122.881	37.361	213.1	2004–2006	0.2
46042	−122.404	36.789	1574	2000–2006	1.7
46028	−121.884	35.741	1158.2	2003–2007	0.9
46011	−120.857	34.868	204	2007–2008	0.5
46023	−120.967	34.714	384.1	2003–2005	0.2
46063	−120.699	34.273	632	2002–2005	0.4
46054	−120.448	34.269	447.1	1999–2001	3.5
46053	−119.841	34.248	449.9	1999–2007	1.2
46069	−120.200	33.65	1004.6	2006–2008	0.3
46047	−119.533	32.433	1393.5	2003–2008	0.7
46086	−117.999	32.498	1856.2	2004–2006	0.3

instance, uncorrelated data may show spurious correlations if there are long-term trends. Similarly, data that is correlated over long horizons may be incorrectly characterized as uncorrelated when a trend exists [5].

In prior studies, researchers have applied DFA to various types of series such as DNA sequences [4], heartbeat time series [6], temperature [7], crude oil markets [8], tree-ring width time series [9], forest fires [10], seismic data [11–14], streamflow records [15], and rainfall time series [16]. Koscielny-Bunde et al. [17] studied the temporal correlations in the atmospheric variability using 14 meteorological stations. They found a universal persistence law, i.e., all the stations have nearly the same exponent. This was confirmed by Eichner et al. [5] using a larger sample. A more general analysis of the relationship between DFA and long-run correlations in time series is presented in [18].

To date, there have been a number of studies modeling wave height time series [19–29]. However, so far the scale behavior of SWH series has not been investigated. The scaling properties of SWH series may be helpful in the model applications at different temporal resolutions. Models which are established for smaller scales may be employed at larger scales by simply rescaling the model parameters. The scale invariance feature allows the investigator to exchange information among scales. For instance, once the parameters of a model are determined at coarser scales, it may be possible to obtain parameters at finer scales.

In this paper, the focus is on the scaling characteristics of SWH time series, and in particular detecting possible long-range correlations. The data is summarized in Section 2. A brief spectral analysis is presented in Section 3, but the main emphasis is on DFA, in Section 4. Section 5 contains a discussion of the findings and Section 6 concludes.

2. Data

The wave data used in this study were downloaded from NOAA's National Data Buoy Center (http://www.ndbc.noaa.gov/climate.phtml). Data from 25 buoys, located off the west coast of the US were used (see Fig. 1). The resolution is hourly. Table 1 gives the station ID, the longitude, latitude, depth, years covered, and that the share of the data was missing. In this respect, the main problem in the data sets was missing observations, which in some cases was limited to a few days, but in other cases could span weeks or months. This is an issue because the tests for scaling exponents require long time series. The preferred procedure was to use whole year data without large gaps. More specifically, the data sets were selected using two criteria: (1) that at least 90% of the data was available, and (2) that the gaps were smaller than 5 days. The gaps in the data were interpolated using an ARMA (3, 3) model. Several other interpolation methods were tried, but the ARMA (3, 3) was found to exhibit the lowest mean square error.

3. Spectral analysis

If the time series is stationary, it is possible to apply standard spectral analysis techniques, i.e., calculate the power spectrum $E(f)$ of the time series as a function of frequency f. Power law decay in the spectrum can be expressed as

$$E(f) = 1/f^{\beta}. \tag{1}$$