Water Science and Engineering 2016, 9(1): 21–32

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Water Science and Engineering

journal homepage: http://www.waterjournal.cn

Modeling nonstationary extreme wave heights in present and future climates of Greek Seas

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Received 23 June 2015; accepted 3 November 2015
Available online 11 March 2016

Abstract

In this study the generalized extreme value (GEV) distribution function was used to assess nonstationarity in annual maximum wave heights for selected locations in the Greek Seas, both in the present and future climates. The available significant wave height data were divided into groups corresponding to the present period (1951–2000), a first future period (2001–2050), and a second future period (2051–2100). For each time period, the parameters of the GEV distribution were specified as functions of time-varying covariates and estimated using the conditional density network (CDN). For each location and selected time period, a total number of 29 linear and nonlinear models were fitted to the wave data, for a given combination of covariates. The covariates used in the GEV-CDN models consisted of wind fields resulting from the Regional Climate Model version 3 (RegCM3) developed by the International Center for Theoretical Physics (ICTP) with a spatial resolution of 10 km × 10 km, after being processed using principal component analysis (PCA). The results obtained from the best fitted models in the present and future periods for each location were compared, revealing different patterns of relationships between wind components and extreme wave height quantiles in different parts of the Greek Seas and different periods. The analysis demonstrates an increase of extreme wave heights in the first future period as compared with the present period, causing a significant threat to Greek coastal areas in the North Aegean Sea and the Ionian Sea.

Keywords: Wave extremes; Climate change; Nonstationarity; GEV-CDN; Principal component analysis

1. Introduction

In the relevant literature, indicators of climate change are closely linked to changes in both the frequency and magnitude of extreme marine events. There have been many studies detecting non-negligible trends in these two variables in the Northeastern Atlantic (e.g., Grevemeyer et al., 2000; Wang and Swail, 2001; Debernard and Roed, 2008). Effects of climate change on the marine climate have also been observed in the Mediterranean area (e.g., Méndez et al., 2006; Gaertner et al., 2007; Lionello et al., 2008; Casas-Prat and Sierra, 2011). This contributes significantly to the nonstationary behavior of extreme marine events and necessitates the incorporation of certain techniques in the extreme value (EV) models, so that the process of extrapolation can be more reliable and unbiased. Nonstationarities can be incorporated into the extreme value models with their parameters expressed as functions of covariates.

Khaliq et al. (2006) and AghaKouchak et al. (2013) presented an overview of different mathematical frameworks

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This work was supported by the European Social Fund and Greek National Funds through the Operational Program "Education and Lifelong Learning" of the National Strategic Reference Framework (NSRF)-Research Funding Program: Thales. Investing in knowledge society through the European Social Fund.

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Peer review under responsibility of Hohai University.

http://dx.doi.org/10.1016/j.wse.2016.03.001

developed to incorporate nonstationarities in the extreme value models. Caires et al. (2006) introduced a nonstationary nonhomogeneous Poisson process whose parameters depend on covariates of sea level pressure in order to simulate wave height extremes. Méndez et al. (2006) developed nonstationary peaks over threshold (POT) models to simulate significant wave height extremes, taking account of climate covariates such as the North Atlantic Oscillation (NAO) index, and harmonic functions for periodic variations and long-term trends. Méndez et al. (2008) presented different models to characterize the long-term extreme value distribution of significant wave heights, considering the seasonality and storm duration. Menéndez et al. (2009) studied significant wave height extremes on a monthly scale, using a nonstationary generalized extreme value (GEV) model with parameters expressed by means of harmonic functions. Galiatsatou and Prinos (2014) used the aforementioned model to analyze extreme wave heights in the present and future climates of the Greek Seas.

Rigby and Stasinopoulos (2005) developed a general class of statistical models for nonstationary analysis of many theoretical distributions, the generalized additive models for location, scale, and shape parameters (GAMLSS). Yee and Stephenson (2007) introduced vector-generalized linear and additive models, which allow the parameters of the EV distribution to be modeled as linear or smooth functions of covariates. Villarini et al. (2009) developed a framework for flood frequency analysis of annual peak discharges in an urban basin based on the GAMLSS. Villarini et al. (2010) used the GAMLSS models to simulate extremes of seasonal precipitation and temperature in Rome, focusing on the influence of the selected covariates (teleconnection indices) on simulation and prediction of the extremes of seasonal precipitation and temperature. Cannon (2010) suggested a GEV-conditional density network (CDN) model for the nonlinear nonstationary analysis of hydrological extreme values.

In this study, the GEV-CDN model proposed by Cannon (2010) was used to assess nonstationarity in annual maximum significant wave heights for selected locations in the Greek Seas, both in the present and future climates. This paper is organized as follows: In section 2 the GEV-CDN model is briefly presented. In section 3, the basic ideas of principal component analysis (PCA), used to derive the covariates for analysis of extreme wave events, are described. Section 4 outlines the methodology of this study and presents the data sets utilized, the main results of PCA, and estimates of extreme wave heights for both present and future climatic conditions in the covariate space. Section 5 summarizes the main conclusions of this study.

2. GEV-CDN model

The univariate extreme value theory (EVT) includes the block maxima models and POT models. The former corresponds to the GEV distribution with a cumulative distribution function $G(z)$ for $\xi \neq 0$ given by the formula (Coles, 2001):

$$G(z) = \exp\left[-\left(1+\xi\frac{z-\mu}{\sigma}\right)^{-1/\xi}\right] \quad 1+\xi\frac{z-\mu}{\sigma}>0 \tag{1}$$

where μ, σ ($\sigma > 0$), and ξ are the location, scale, and shape parameters of the distribution, respectively. Within the EV modeling framework, nonstationarities can be considered by expressing the parameters of the GEV distribution as a function of covariates. The GEV-CDN model, developed by Cannon (2010), can be used to perform nonstationary GEV analysis, overcoming the pitfalls of both parametric and nonparametric models. In the GEV-CDN model, the parameters of the GEV distribution are specified as a function of covariates using a CDN (Bishop, 2006), which is a probabilistic extension of the standard multilayer perceptron (MLP) neural network. At time t, the input-layer nodes of the neural network are the covariates x_{it} ($i = 1, 2, \cdots, I$) with I being the number of covariates, while there are three output-layer nodes, corresponding to the three parameters μ_t, σ_t, and ξ_t of the nonstationary GEV distribution. Input- and output-layer nodes are connected via J hidden-layer nodes. Input- and hidden-layer nodes are linked using weights $w_{ji}^{(1)}$, while weights $w_{kj}^{(2)}$ are used to connect hidden- and output-layer nodes. Biases $b_j^{(1)}$ are added to the hidden-layer nodes, and biases $b_k^{(2)}$ are added to the output-layer nodes. The output from the jth hidden-layer node is as follows (Cannon, 2010):

$$h_{jt} = f\left(\sum_{i=1}^{I} x_{it}w_{ji}^{(1)} + b_j^{(1)}\right) \tag{2}$$

where $f(\bullet)$ is the activation function for the hidden layer. For linear nonstationary GEV-CDN models, the identity function is used for $f(\bullet)$, while for nonlinear nonstationary models, the activation function is the hyperbolic tangent function. The value of the kth output is (Cannon, 2010)

$$o_{kt} = \sum_{i=1}^{I} h_{jt}w_{kj}^{(2)} + b_k^{(2)} \tag{3}$$

The parameters of the nonstationary GEV distribution can be obtained from Eq. (3) using different activation functions $g_k(\bullet)$ for the output layer. The identity function is used for the location parameter, the exponential function is used for the scale parameter, and, for the shape parameter, the hyperbolic tangent function is judged to be appropriate. For the latter, the result is multiplied by 0.5 to limit the shape parameter to the interval (-0.5, 0.5). This limitation ensures that the asymptotic properties of the maximum likelihood estimators are not violated. According to Smith (1985), when the shape parameter, ξ, is in the interval (-1, -0.5), the maximum likelihood estimators do not have their standard asymptotic properties, while when $\xi < -1$ they are unlikely to be obtainable. The selection of the upper limit of the interval for the GEV shape parameter is based on the L-moment estimator of Hosking et al. (1985).

In the present study three different categories of GEV-CDN models were used. The first one includes the stationary GEV-