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Predicting coastal erosion trends using non-stationary statistics and process-based models

Stefano Corbella [a,b], Derek D. Stretch [a,*]

[a] Centre for Research in Environmental, Coastal & Hydrological Engineering, School of Civil Engineering, Surveying & Construction, University of KwaZulu-Natal, Durban, 4041, South Africa
[b] eThekwini Municipality, Coastal Engineering & Drainage Unit, P.O. Box 680, Durban, 4001, South Africa

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ABSTRACT

Storms and water levels are subject to seasonal variations but may also have decadal or longer trends that need to be included when estimating risks in the coastal zone. We propose a non-stationary multivariate generalised extreme value model for wave height, wave period, storm duration and water levels that is constructed using Archimedean copulas. The statistical model was applied to a South African case study to test the impacts of decadal trends on beach erosion. Erosion was estimated using three process-based models — SBEACH, XBEACH, and the Time Convolution model. The XBEACH model provided the best calibration results and was used to simulate potential future long-term trends in beach erosion. Based on the simulated erosion results of 5 beach profiles for storms with 25, 50 and 100 year return periods, it is estimated that the erosion rate could increase by 0.20%/year/storm and should therefore be a significant factor in long-term planning.

1. Introduction

Increasing awareness of future climate change impacts has added a new dimension to traditional design practice. The predicted and/or the measured increases in storm intensity and frequency should be accounted for in failure risk assessment based on an average recurrence interval. Erosion of coastlines is dominated by three factors: sediment supply; wave forces and sea level rise. This paper attempts to consider all these factors and forecast the erosion potential of future storms using a non-stationary multivariate generalised extreme value statistical model based on Archimedean copulas together with process-based models of the beach response.

Numerous authors have proposed a combination of process-based models and statistical models to estimate the potential impacts of climate trends. Only the most relevant examples are mentioned here. Wang et al. (2004) analysed potential changes in significant wave heights using a global climate model and a non-stationary generalised extreme value distribution. They concluded that there was variability of about 20% between decadal extreme significant wave heights. Coles and Tawn (1990, 1991, 1994) provide methods relating to multivariate statistical modelling in a coastal context while Coles and Tawn (1994) used these methods with an empirical formula for overtopping of a seawall to estimate a probability zone of failure. Wang and Reeve (2010) presented a probabilistic model of long-term beach evolution near detached breakwaters using the numerical model developed by Hanson et al. (2006). Callaghan et al. (2008) used a joint distribution of wave parameters to estimate erosion in combination with the time convolution shoreline response model of Kriebel and Dean (1993). Zacharioudaki and Reeve (2011) performed a statistical analysis of beach response to wave conditions arising from climate change scenarios. Zacharioudaki and Reeve (2011) used a one-line beach response model which is appropriate for beaches dominated by long-shore sediment transport. Our study is concerned with storm waves and so uses cross-shore morphological models. Although much work has combined statistical models with numerical models this paper presents a unique use of a copula based non-stationary multivariate statistical model in combination with process-based models to quantify potential future storm induced erosion.

We initially provide a brief theoretical background to the statistical and process-based models and outline the methods used. The methodology is tested by applying it to a case study on the east coast of South Africa. The results are then presented and discussed before concluding.

2. Theoretical background and methods

2.1. Case study site

The east coast of South Africa has 18 years of reliable wave data from wave recording buoys near the city of Durban (Fig. 1). Corbella and Stretch (in press) provide details of the data set. A storm event was defined in terms of a significant wave height threshold similar to the triangular storm concept proposed by Boccotti (2000): a storm event begins when a significant wave height *Hs* exceeds a threshold of 3.5 m and ends when the significant wave height falls below 3.5 m for a period of at least 2 weeks based on the decay time of the autocorrelation. The

* Corresponding author. Tel./fax: +27 31 2601064.
E-mail address: stretchd@ukzn.ac.za (D.D. Stretch).

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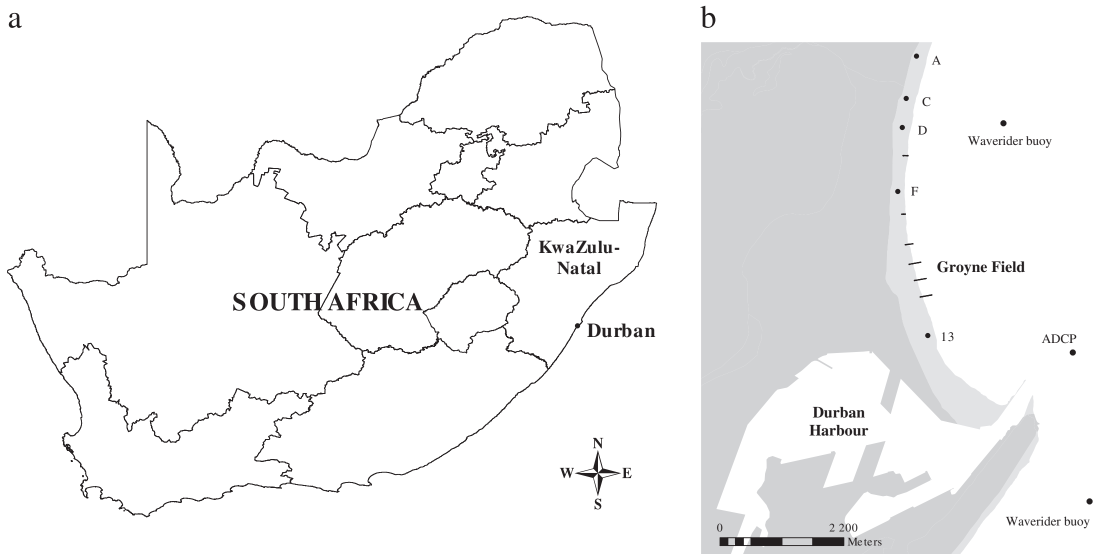

Fig. 1. A map of (a) South Africa showing Durban and a map of (b) the Durban Bight showing the locations of profile A, C, D, F and 13 and the Durban harbour.

reduced storm data set was then manually assessed to ensure that each storm event represented one meteorological event. Finally we selected the largest storms from the remaining group — the number chosen corresponded to an overall average of 3 storms per year. The period between the start and the end time is the storm duration *D* and the time between the events is the calm period *I*. The storm definition is illustrated in Fig. 2.

Corbella and Stretch (2011a) analysed Durban's wave data and identified increasing trends in significant wave heights exceeding the 3.5 m threshold. They also noted an increase in peak period *T* and in the frequency of storm events (or similarly a decrease in the average calm period). Only the increase in peak period was found to be statistically significant.

The case study site at Durban also has a 37 year record of beach profiles which exhibit a long term erosion trend (Corbella and Stretch, 2011a). The records of interest to this study are those that bound storm events. Only the 1998 and 2007 events met these requirements. The analysis is limited to profiles A, C, D, F and 13 (Fig. 1) as they have the most frequent bathymetry data and provide a good representation of the Durban Bight while avoiding most of the sheltering near the harbour entrance and the influence of perpendicular beach structures and sand bypass scheme.

In March 2007 Durban experienced its largest wave event on record. The 8.5 m significant wave height and 16.6 second peak period coincided with an extreme high tide of 2.2 m above chart datum[1] (CD) and devastated the coastline. This storm was a realisation that much of the current infrastructure is not capable of withstanding potentially more frequent and intense events in the future. Since the damage of the 2007 event can be easily quantified it will be used as a base line to demonstrate the potential impacts of storm and water level trends.

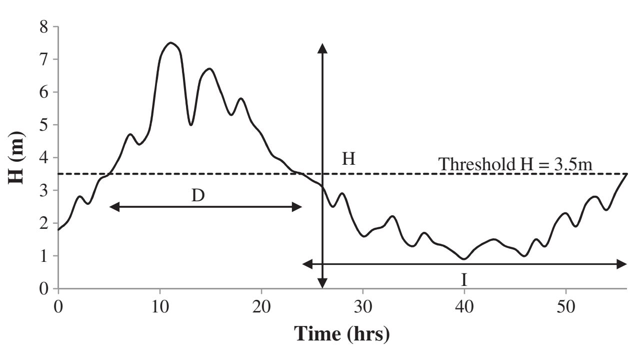

Fig. 2. Illustration of the storm definition showing the significant wave height *Hs*, storm duration *D* and calm period *I*.

2.2. The Generalised Extreme Value model

The Generalised Extreme Value (GEV) distribution has been used extensively for extreme value analysis of hydrological events and specifically for wave heights by Chini et al. (2010), Mendez et al. (2008), Minguez et al. (2010), Guedes Soares and Scotto (2004) and Ruggiero et al. (2010). The GEV encompasses three distributions often referred to as Types I, II and III. The probability density function is given by

$$y=\sigma^{-1}exp\left(-\left(1+k\frac{x-\mu}{\sigma}\right)^{-\frac{1}{k}}\right)\left(1+k\frac{x-\mu}{\sigma}\right)^{-1-\frac{1}{k}} \quad (1)$$

for $\left(1+k\frac{x-\mu}{\sigma}\right)<0$, where μ is the location parameter, σ is the scale parameter and k is the shape parameter. This traditionally stationary model can be adapted to model non-stationary events by making the GEV parameters time dependent (Katz et al., 2002; Mendez et al., 2008; Minguez et al., 2010). Non-stationarity is usually limited to time varying location and scale parameters $\mu(t)$ and $\sigma(t)$. For example Ruggiero et al. (2010) and Zhang et al. (2004) model the location parameter as a linear function of time and the shape parameter as an exponential function of time. Others who have been interested in cyclic behaviour (such as seasonality) have used trigonometric functions to model the location and shape parameters (Katz et al., 2002; Mendez et al., 2008; Minguez et al., 2010). For the present study we have assumed that the time dependency can be expressed simply as

$$\mu(t)=\mu_0+\mu_1 t,\ \sigma(t)=\sigma_0,\ k(t)=k_0, \quad (2)$$

where the location parameter is assumed to be linearly dependent on time and the shape and scale parameters are assumed to be constant based on the findings of Wang et al. (2004). Corbella and Stretch (2011a) identified increasing trends in *Hs*, *T* and the frequency of storm events. However, only the wave height *Hs* was modelled with a

[1] Mean sea level is approximately 1 m above chart datum at this location.