Ocean and Coastal Management 160 (2018) 46–51

Contents lists available at ScienceDirect

Ocean and Coastal Management

journal homepage: www.elsevier.com/locate/ocecoaman

# Evaluation of two common vulnerability index calculation methods

Andrew Cogswell*, Blair J.W. Greenan, Philip Greyson

*Bedford Institute of Oceanography, Fisheries and Oceans Canada, 1 Challenger Drive, Dartmouth, Nova Scotia, B2Y 4A2, Canada*

A R T I C L E I N F O

*Keywords:*
Vulnerability index
Geometric mean
Risk assessment
Coastal vulnerability
CVI

A B S T R A C T

The potential benefits of using a geometric mean method for computing a vulnerability index are presented using both simulated variables as well as data from a Canadian coastal geodatabase (CanCoast). The assessment of vulnerability of natural and built coastal infrastructure to sea level rise is used to demonstrate the advantages of this method for climate change adaptation planning and decision-making. As with most real world datasets the probability distribution of individual variables in CanCoast may be skewed; this can significantly impact the resulting vulnerability index depending on the calculation method employed. The primary advantage of using a geometric mean is that the index output will remain within the original range and maintain the distributional characteristics of the input variables. This can reduce the need for subjective expert opinion in the process of assessing the vulnerability index. A comparison of the resulting computation using both the Gornitz (1991) method and the geometric mean is provided for the Atlantic Canada coastline.

## 1. Introduction

In the field of risk assessment, the term vulnerability has been broadly applied and equated to concepts such as resilience, marginality, susceptibility, adaptability, fragility, and risk (Liverman, 1990; IPCC, 2014a). It is an elusive term that continues to provide challenges in the consistency of its application (Timmerman, 1981; Fussel and Klein, 2006). Nonetheless, the concept continues to be used and has recently been described by the Intergovernmental Panel on Climate Change (IPCC, 2014b) as:

> "The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt."

In coastal assessment research, numerous indices have been devised to evaluate the vulnerability of a shoreline to the effects of climate change (Preston et al., 2011; Ramieri et al., 2011; Abuodha and Woodroffe, 2006.). Each index is a composite of multiple quantitative and qualitative indicators that, via some formula and weighting, delivers a single numerical result that is indicative of coastal vulnerability to a hazard (e.g. climate change). Regardless of the ambiguity surrounding the term and the various methods of assessing it, the primary purpose of a vulnerability assessment is to provide information that assists in decision-making and coastal adaptation planning (McLaughlin and Cooper, 2010; Smit and Wandel, 2006; Kelly and Adger, 2000). One of the early methods in this area of research that has been broadly adopted is the Gornitz (1991) Coastal Vulnerability Index (GVI) (Boruff et al., 2005; Pendleton et al., 2004; Thieler and Hammer-Klose, 2000; Shaw et al., 1998). The GVI method yields a vulnerability index for the coastline segments within study extents but does not accurately represent the frequency distribution or range of the input variables. As a result, researchers are then left to ordinate the index distribution into vulnerability categories (e.g. low, medium and high vulnerability) for graphical display (e.g. GIS output showing coastlines of varying degrees of vulnerability) using either expert opinion or by splitting the data into percentiles (Shaw et al., 1998).

Gibb et al. (1992) noted early on some deficiencies in using this calculation, including its tendency to distort the output range and distribution of the final index. Despite these known deficiencies, the GVI method is still commonly used in calculating a vulnerability index. In a search of published literature over the period 2014–2017, approximately 30% of the papers on coastal vulnerability used the GVI calculation for aggregating vulnerability variables (for example: Ferreira Silva et al., 2017; López Royo et al., 2016; Martínez-Graña et al., 2016; Tano et al., 2016).

In addition to the impact on data distribution, it should also be noted that Gornitz (1991) incorrectly describes GVI (Equation (1)) as the square root of the geometric mean:

$$GVI = \sqrt{\frac{a_1 * a_2 * \ldots a_n}{n}} \tag{1}$$

The GVI is more accurately described as the square root of the

* Corresponding author.
*E-mail address:* Andrew.Cogswell@dfo-mpo.gc.ca (A. Cogswell).

https://doi.org/10.1016/j.ocecoaman.2018.03.041
Received 12 October 2017; Received in revised form 7 March 2018; Accepted 30 March 2018

product of the variables ($a_i$) divided by the number of variables (n) (or as it is sometimes described, the square root of the product mean). The true geometric mean (GM) is the nth root of the product of the variables ($a_1 - a_n$):

$$GM = \sqrt[n]{a_1 * a_2 * \ldots a_n} \quad (2)$$

Due to the prevalence of GVI in the current literature, this paper quantifies and compares the distributional impact of applying the GVI and the GM to both simulated input variables and an existing dataset of Canadian shoreline segments with environmental exposure variables (sea level rise, wind speed, wave height, coastal materials, and change in sea ice coverage). The importance of choosing an appropriate methodology when calculating vulnerability indices for climate change adaptation planning is discussed.

## 2. Methods and data

The following methodology will quantify and compare the distributional implications of the GVI and GM coastal vulnerability assessment methods using simulated variables. This will enable us to isolate the causes of observed differences in calculated vulnerability index distributions. Both indices will then be applied to actual coastal segment environmental variables to further demonstrate the “real-world” implications of assigning coastal vulnerability using different methods.

### 2.1. Simulated coastal segments

A model was written using R Statistical Software (R Core Team, 2016) to compare the resulting range and distribution characteristics for two vulnerability indices (GVI and GM). For a total of 1000 simulated coastal segments or data rows, scenarios using varying numbers of randomly generated coastal variables (3, 7, 10, 25, 50, 100 and 200) with means between 1 and 100 and a standard deviation of 1 were created. Using the R cut () function to divide the distribution into 5 equal parts, the distribution of each variable was recoded to a scale of 1–5, with 5 representing the most vulnerable and 1 representing the least vulnerable state. Each scenario was run a total of 30 times and the skewness, kurtosis, mean, median and range of the resulting coastal index distribution was captured for each run. The average for each distributional statistic for all runs was then calculated for each model scenario.

### 2.2. Application to a coastal dataset

The following is an applied example that compares the effects of using the GVI and the GM on CanCoast (Shaw et al., 1998), a Canadian coastal dataset. This dataset is a 1:50,000 scale dataset of the Canadian coast with updated values of five environmental/exposure variables. The variables used in this exercise are: predicted sea level change, wind speed, wave height, coastal materials, and change in sea ice coverage. The coastal materials dataset was already scored on an ordinal scale (1–5 based on increasing erodibility), but it was necessary to score the four other environmental datasets on an identical scale. The frequency distributions of each of these four coastline variables were tested for skewness and, if necessary, transformed prior to scoring so their distributions were approximately normal. Scoring of these four environmental variables was achieved by dividing each variable range into five equal intervals.

#### 2.2.1. Sea level change

The regional projections of relative sea level (RSL) rise from the IPCC Assessment Report 5 (AR5) include effects of steric and dynamic changes, atmospheric loading, plus land ice, glacial isostatic adjustment (GIA), and terrestrial water sources (IPCC, 2013). The steric and dynamic changes were derived from 21 Atmosphere– Ocean General Circulation Models (AOGCMs) from the Coupled Model Intercomparison Project, Phase 5 (CMIP5). A 1-degree resolution grid of relative sea level change was calculated for all years between 2006 and 2100 for RCP4.5 and RCP8.5.

#### 2.2.2. Wind speed and wave height

Modeled hindcasts of yearly maximum significant wave height (1990–2014) and maximum wind speed (1990–2012) were used. Both datasets were generated from IFREMER wave hindcasts using the WAVEWATCH III model with wind data from NCEP Climate Forecast System Reanalysis (CFSR) (Saha and Coauthors, 2010). Two high resolution (10 min) grids of Atlantic and Pacific maximum modeled wind speeds and maximum significant wave height were used for southern Canadian coastal areas while a coarser (30 min) worldwide grid was used for the Arctic areas. From these datasets maximum significant wave height over 25 years and maximum wind speed over 23 years were calculated.

#### 2.2.3. Coastal materials

The base layers from which the coastal materials layer were derived were the Fulton surficial geology and the Wheeler bedrock geology, both at scales of 1:25 million (Wheeler et al., 1996). Where the surficial geology was greater in thickness than veneer, a score of 3–5 was assigned, with 5 being most erodible (muds, marine clay, materials that will flow) and three being less erodible (sands, gravels). Where there were surficial materials with a thickness of veneer or less, the bedrock geology was used as the basis for the score. Scores based on bedrock geology were assigned 2 if the geology was sedimentary, and 1 if igneous or metamorphic (Dr. Gavin Manson, Natural Resources Canada, Bedford Institute of Oceanography, Dartmouth, Nova Scotia, personal communication, 2015).

#### 2.2.4. Change in sea ice coverage

Sea ice data from the Canadian Ice Service were acquired for each of the four regions (i.e. Atlantic, Eastern Arctic, Western Arctic and Hudson Bay), representing percent ice coverage for each week over four decades (1970s, 1980s, 1990, 2000s). For each region and decade, a single dataset was calculated to represent the sum of all weeks with ice coverage in excess of 50%, with a maximum possible score of 52 weeks for each decade. To measure change in ice coverage, the summary sheet from the 2000s was subtracted from the 1970s summary sheet. The final dataset represents the number of weeks of change in ice coverage greater than 50%. A positive number indicates a reduction in weeks of ice coverage, a negative number an increase in ice coverage.

#### 2.2.5. Assignment of vulnerability scores to coastal variables

Variable values were categorized on a scale of 1–5 (low risk to high risk) (Table 1) by breaking the range into 5 equal divisions, except for Coastal material which were already categorized on a 1 to 5 scale in increasing erodibility.

## 3. Results

This section will provide an overview of the results using both simulated and real world data sets. The section with simulated variables will allow us to address the differences that result from the GVI and GM methods. The section using the CanCoast geodatabase will demonstrate the application of these approaches in Atlantic Canada.

### 3.1. GVI and GM comparison with simulated input variables

Using the simulated input variables as described in Section 2.1, calculations comparing the influence of the number of variables on the distributional output for both the GVI and the GM methods are provided in Table 2 and Fig. 1. The four key statistical measures chosen to