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## Applying MCDA to weight indicators of seaport vulnerability to climate and extreme weather impacts for U.S. North Atlantic ports

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# 1 Applying MCDA to Weight Indicators of Seaport Vulnerability to Climate and Extreme 2 Weather Impacts for U.S. North Atlantic Ports

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## 9 10 Abstract

11 This paper describes a case study applying multi criteria decision analysis  
12 (MCDA) to weight indicators for assessing the exposure and sensitivity of  
13 seaports to climate and extreme weather impacts. Researchers employed the  
14 Analytic Hierarchy Method (AHP) of MCDA to generate weights for a subset  
15 of expert-selected indicators of seaport exposure and sensitivity to climate and  
16 extreme weather. The indicators were selected from the results of a survey of  
17 port-experts who ranked candidate indicators by magnitude of perceived  
18 correlation with the three components of vulnerability; exposure, sensitivity,  
19 and adaptive capacity. As those port-expert respondents found significantly  
20 stronger correlation between candidate indicators and the exposure and  
21 sensitivity of a port than with a port’s adaptive capacity, this AHP exercise did  
22 not include indicators of adaptive capacity. The weighted indicators were  
23 aggregated to generate composite indices of seaport exposure and sensitivity  
24 to climate and extreme weather for 22 major ports in the North East United  
25 States. Rank order generated by AHP-weighted aggregation was compared to  
26 a subjective expert-ranking of ports by expert-perceived vulnerability to  
27 climate and extreme weather. For the sample of 22 ports, the AHP-generated  
28 ranking matched three of the top four most vulnerable ports as assessed  
29 subjectively by port-experts. These results suggest that a composite index  
30 based on open-data weighted via MCDA may eventually prove useful as a  
31 data-driven tool for identifying outliers in terms of relative seaport  
32 vulnerabilities, however, improvements in the standardized reporting and  
33 sharing of port data will be required before such an indicator-based assessment  
34 method can prove decision-relevant.

35  
36 **Key Words:** indicator, seaport, climate vulnerability, Analytical Hierarchy  
37 Method, composite index, expert elicitation

## 39 **Introduction**

### 40 **Seaport Vulnerability to Climate and Extreme Weather**

41           Seaports sit on the frontlines of our shores, consigned to battle the elements at the  
42 hazardous intersection of land and sea. Ports face projected increases in the frequency and  
43 severity of impacts driven by changes in water-related parameters like mean sea level, wave  
44 height, salinity and acidity, tidal regime, and sedimentation rates, and port functions are  
45 expected to be increasingly affected directly by changes in temperature, precipitation, wind,  
46 and storm frequency and intensity (Koppe et al. 2012; Becker et al. 2013). At the same time,  
47 ports are often located in environmentally sensitive ecosystems such as estuaries and river  
48 mouths, which provide important nursery habitat for juvenile marine organisms (Beck et al.  
49 2001).

50           As infrastructure assets, ports are critical to both the public and the private good,  
51 playing a key role in the network of both intranational and international supply-chains. Ports  
52 serve as catalysts of economic growth locally and regionally, as they create jobs and promote  
53 the expansion of nearby industries and cities (Asariotis et al. 2017).

54           Port decision-makers have a responsibility to manage a multitude of risks and enhance  
55 port resilience to achieve the minimum downtime safely possible in any given circumstance.  
56 When regional systems of ports are considered, responsible decision-makers may wish to  
57 prioritize limited resources, or to identify outliers among a set of ports in terms of  
58 vulnerability to certain hazards. At the single-port scale, port decision-makers (e.g., a local  
59 port authority) may question which specific adaptation actions to take, or how to start with  
60 climate-adaptation. At the multi-port scale, port decision-makers (e.g., the U.S. Army Corps  
61 of Engineers) may question which ports in a certain regional jurisdiction are the most  
62 vulnerable and hence the most in need of urgent attention. As climate adaptation decisions

63 often involve conflicting priorities (e.g., politics, national priorities, local priorities),  
64 providing a data-driven, standard metric can help bring objectivity into the process.

65 Port decision-makers faced with climate impact, adaptation and vulnerability (CIAV)  
66 <sup>1</sup> decisions involving multiple ports can benefit from information products that allow them to  
67 compare the mechanisms and drivers of vulnerability among ports. The indicator-based  
68 assessment described in this paper provides an example of such a product that can quantify  
69 complex issues and bring a standardized data-driven approach to measuring theoretical  
70 concepts, with the caveat that the decision-relevance of their results hinges on the quality of  
71 data available to serve as indicators.

72

### 73 **Indicator-Based Composite Indices**

74 Indicators are measurable, observable quantities that serve as proxies for an aspect of  
75 a system that cannot itself be directly or adequately measured (Gallopín 1997; Hinkel 2011).  
76 Indicator-based assessment methods are generally applied to assess or 'measure' features of a  
77 system that are described by theoretical concepts. Directly immeasurable, concepts such as  
78 resilience and vulnerability are instead made operational by mapping them to functions of  
79 observable metrics called indicators (McIntosh and Becker 2017). Indicator-based composite  
80 indices are multidimensional tools that synthesize multiple indicators into a single composite  
81 indicator that can represent a relative value of a theoretical concept (Dedeke 2013; McIntosh  
82 and Becker 2017). Examples of indicator-based composite indices include the Social  
83 Vulnerability Index (SoVI) (Cutter et al. 2003; Cutter et al. 2010), the Earthquake Disaster  
84 Risk Index (EDRI) (Davidson and Shah 1997), and the Disaster Risk Index (Peduzzi et al.  
85 2009). Indicator-based composite indices are meant to yield a high-level overview of the

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<sup>1</sup> CIAV decisions are choices, the results of which are expected to affect or be affected by the interactions of the changing climate with ecological, economic, and social systems.

86 relative values of a concept of interest, e.g., vulnerability, and as such, are more suited to  
87 high-level identification of relative outliers than to in-depth analyses of the concept of  
88 interest.

89         The SoVI, for example, compiles 29 input variables from the U.S. Census for over  
90 66,000 census tracts to construct an index (Cutter et al. 2003). The large number of variables  
91 is reduced using Principal Component Analysis (PCA), and the resulting 6-8 principal  
92 components are named according to the highest loading factors for each component. The  
93 SoVI produces a score by summing the indicators into components and the components into  
94 the total score. The SoVI weights each indicator and component equally as the researchers  
95 lacked a theoretical basis for determining weights. For the research described in this paper,  
96 the SoVI recipe was considered, but deemed to be unsuitable for ports as the small sample  
97 size and the sparseness of available data (compared to Census data) led to difficulty in  
98 identifying and naming the principal components. Instead of the purely theoretical approach  
99 described by the SoVI, this work takes a stakeholder-driven approach by including port-  
100 experts in the development and weighting of the indicators, as this has been shown to  
101 increase the creditability of the index as a tool (Barnett et al. 2008; Sagar and Najam 1998).  
102 With a small sample size and sparse data available to construct an index of seaport  
103 vulnerability, researchers sought to create a tool that would allow subject-matter experts to  
104 input their knowledge by determining the relative importance (weight) of the different  
105 indicators making up the index. Including stakeholders in the design-stage of decision-  
106 support tool development can increase the stakeholders' perceptions of the credibility,  
107 salience, and legitimacy of the tool (White et al. 2010).

108         Indicator-based assessments and indices have provoked debate in the literature, and  
109 some researchers (Barnett et al. 2008; Eriksen and Kelly 2007; Hinkel 2011; Klein 2009;  
110 Gudmundsson 2003) have criticized attempts to assess theoretical concepts with them as

111 lacking scientific rigor or lacking consistency. Nonetheless, policymakers are increasingly  
112 calling for the development of methods to measure relative risk, vulnerability, and resilience  
113 (Cutter et al. 2010; Hinkel 2011; Rosati 2015), and developing better indicators and expert-  
114 driven weighting schemes through participatory processes like AHP may lead to  
115 improvements in this field. Despite these criticisms of indicator-based vulnerability  
116 assessments (IBVA) and indicator-based composite indices in particular, such decision-  
117 support tools can play an important role in bringing objective data into the complex decision-  
118 making process. The use of such indicator-based decision-support products can provide  
119 guidance in identifying areas of concern, but they should always be supplemented with  
120 additional expertise as they lack the high-resolution found in more detailed case-study  
121 assessment approaches.

122         Whereas low-level, high-resolution analyses are better served by more comprehensive  
123 case-study approaches, e.g., (Hallegatte et al. 2011; McLaughlin et al. 2011; USDOT 2014),  
124 indicator-based composite indices are well suited to provide high-level overviews of relative  
125 outliers among a sample. Indicator-based assessments and indices, then, are simply one tool  
126 among a suite of tools that decision-makers should have at their disposal.

127

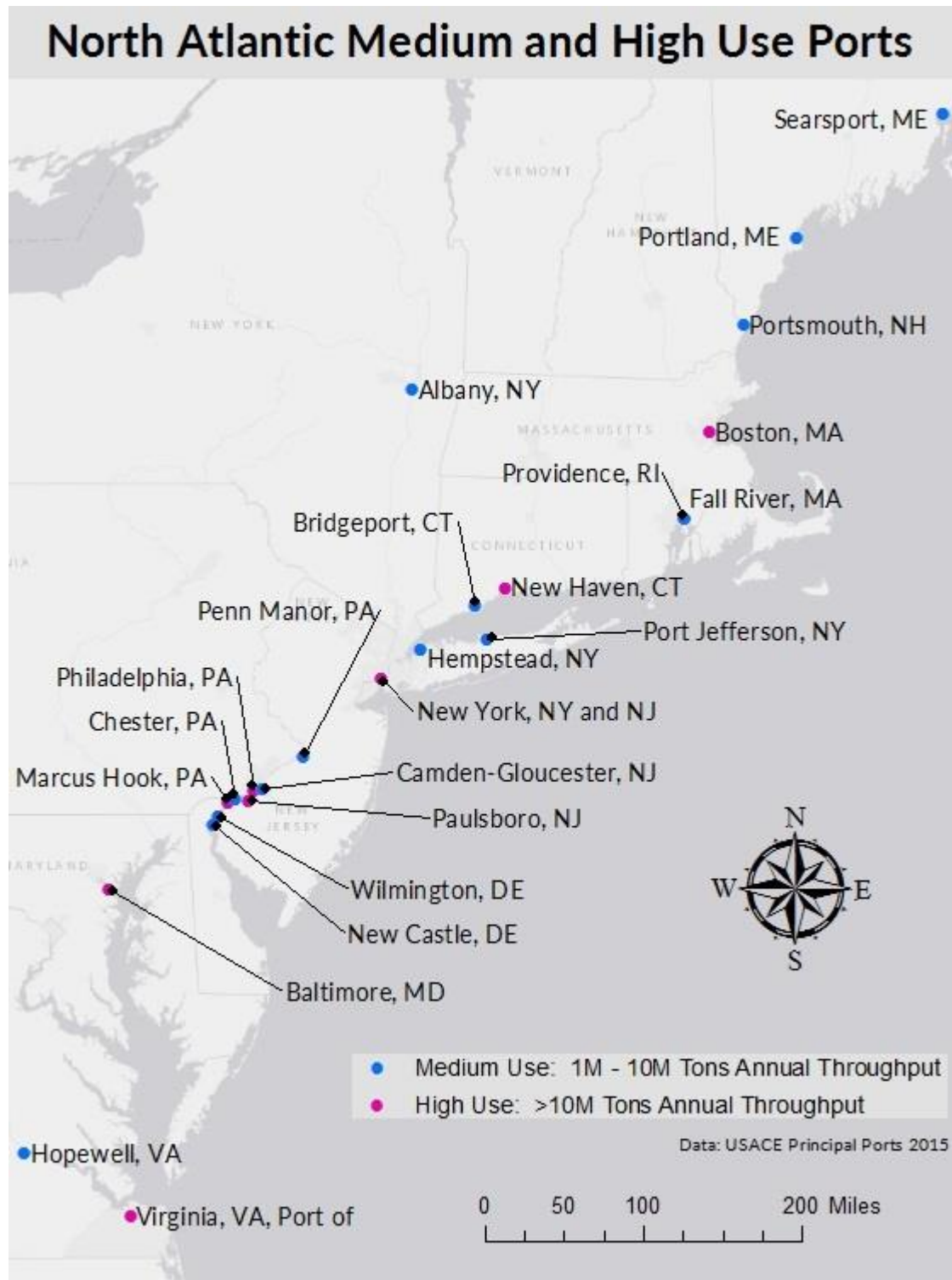
## 128 **Selection of Indicators**

129         Researchers worked with port-experts to develop from open-sources and evaluate a  
130 set of high-level indicators of seaport vulnerability<sup>2</sup> to climate and extreme weather impacts  
131 for the 22 medium and high use ports<sup>3</sup> of the United States Army Corps of Engineers'

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<sup>2</sup> The degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity. (IPCC 2001)

<sup>3</sup> Medium use here refers to ports with annual throughput > 1M tons and high use refers to ports with annual throughput > 10M tons



132

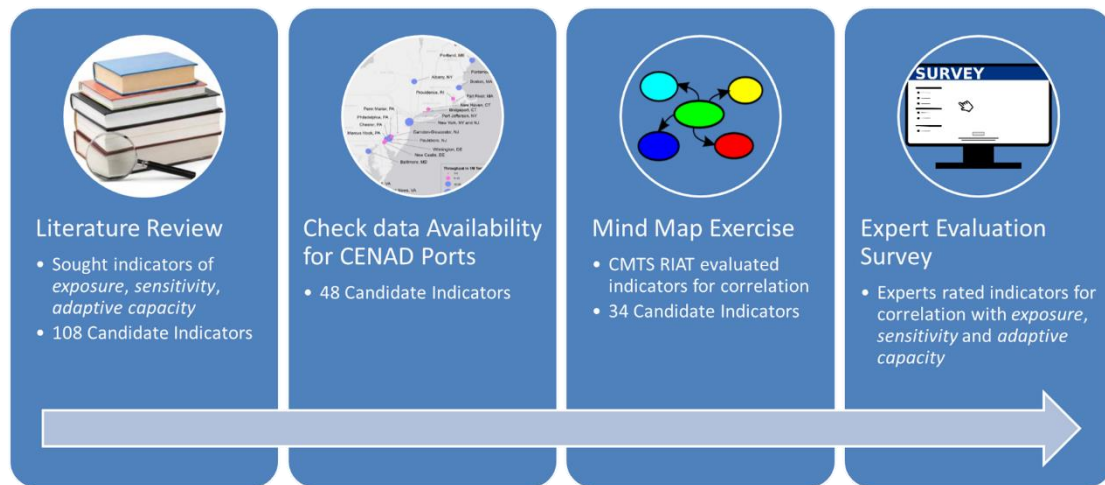
133 (USACE) North Atlantic Division<sup>4</sup> (CENAD) (Figure 1).

*Figure 1 Study area ports*

<sup>4</sup> The North Atlantic Division is one of nine USACE divisions and encompasses the U.S. Eastern Seaboard from Virginia to Maine (USACE 2014).



134 The steps involved in compiling and evaluating this set of candidate indicators are illustrated  
135 in Figure 2.



136

137 *Figure 2 Steps involved in compiling and evaluating candidate indicators. The AHP described in this paper uses the highest*  
138 *scoring indicators from the last step (survey) portrayed in this figure*

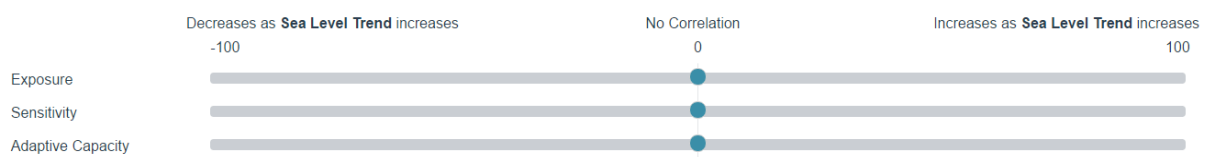
139 Researchers began by identifying indicators of vulnerability that were suitable for use  
140 in the AHP study (McIntosh and Becker 2019; McIntosh et al. 2019). A review of climate  
141 change vulnerability assessment (CCVA) and seaport-studies literature identified 108  
142 candidate indicators of vulnerability. Of the 108 candidate indicators identified, 48 were  
143 found to have sufficient data for the sample of CENAD ports (Figure 1). These 48 indicators  
144 were then further distilled to 34 viable candidate indicators via a mind mapping exercise with  
145 members of the Resilience Integrated Action Team<sup>5</sup> (RIAT) of the United States Committee  
146 on the Marine Transportation System<sup>6</sup> (US CMTS). The 34 candidate indicators chosen via  
147 this mind map exercise were then evaluated via a visual analogue scale<sup>7</sup> (VAS) survey  
148 instrument by 64 port experts. For each candidate indicator in the VAS survey, respondents

<sup>5</sup> The MTS Resilience IAT (R-IAT) was established to focus on cross-Federal agency knowledge co-production and governance to incorporate the concepts of resilience into the operation and management of the U.S. Marine Transportation System.

<sup>6</sup> The United States' CMTS is a Federal Cabinet-level, inter-departmental committee chaired by the Secretary of Transportation. The purpose of the CMTS is to create a partnership of Federal departments and agencies with responsibility for the Marine Transportation System (MTS).

<sup>7</sup> In visual analogue scale (VAS), respondents measure their level of agreement by indicating a position along a continuous line segment

149 were given the indicator’s description, units, data source, and example values, and  
150 respondents were asked to determine whether the candidate indicator could be correlated with  
151 the exposure<sup>8</sup>, sensitivity<sup>9</sup>, and/or the adaptive capacity<sup>10</sup> of ports in the study area.  
152 Respondents indicated the magnitude and direction of correlation by dragging a slider along a  
153 VAS line segment (Figure 3). In addition to evaluating 34 indicators of seaport vulnerability,  
154 respondents of the VAS survey also subjectively ranked the CENAD ports by magnitude of  
155 perceived vulnerability to climate and extreme weather impacts.



156

157 *Figure 3 VAS slider for indicating expert-perceived correlation between a candidate indicator and each of the components of*  
158 *vulnerability.*

159 For the 34 candidate indicators that were evaluated, none scored a median rating  
160 higher than 23 on the unitless VAS scale of correlation with adaptive capacity, compared to a  
161 high of 62 with exposure and 52 with sensitivity. This low level of perceived correlation with  
162 adaptive capacity suggests a dearth of open-data<sup>11</sup> sources suitable for representing the  
163 adaptive capacity of seaports to climate and extreme weather impacts. It also suggests that the  
164 concept of adaptive capacity is considered by port-experts to be more difficult to represent  
165 with quantitative data than the concepts of exposure or sensitivity. For these reasons, this  
166 AHP exercise did not include indicators of adaptive capacity but focused instead on  
167 generating weights for indicators of exposure and sensitivity.

---

<sup>8</sup> The presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected (IPCC 2014)

<sup>9</sup> The degree to which a system is affected, either adversely or beneficially, by climate-related stimuli (IPCC 2001)

<sup>10</sup> The ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences (IPCC 2014)

<sup>11</sup> Open-data refers to publicly available data structured in a way that enables the data to be fully discoverable and usable by end users without having to pay fees or be unfairly restricted in its use.

McIntosh, R.D., Becker, A. (2020), “Applying MCDA to Weight Indicators of Seaport Vulnerability to Climate and Extreme Weather Impacts for U.S. North Atlantic Ports.” Environment Systems and Decisions. Volume 40. Issue 1. 21 March 2020. doi:[10.1007/s10669-020-09767-y](https://doi.org/10.1007/s10669-020-09767-y)

168 As AHP best-practice recommends each category should have at least 4, but not more  
 169 than 7 to 10 sub-categories (Goepel 2013), researchers selected the 6 highest scoring  
 170 indicators for exposure and the 6 highest scoring indicators for sensitivity for inclusion in the  
 171 AHP exercise (Table 1) described in the following section.

172 *Table 1 The six indicators rated highest for correlation with seaport exposure and sensitivity to climate and extreme weather*  
 173 *impacts.*

Category	Description	Indicator	Units	Data Source
Exposure	Number of storm events in port county w/ property damage > \$1M	NumberStormEvents	events	NOAA Storm Events Database
	1% annual exceedance probability high water level which corresponds to the level that would be exceeded one time per century, for the nearest NOAA tide station to the port	HundredYearHighWater	m above MHHW	NOAA Tides and Currents: Extreme Water Levels
	Number of cyclones that have passed within 100 nm of the port since 1842	NumberCyclones	Number of cyclones	NOAA Historical Hurricane Tracks Tool
	Local Mean Sea Level Trend	SeaLevelTrend	mm / yr	NOAA Tides and Currents
	The percent change from observed baseline of the average number of “Extremely Heavy” Precipitation Events projected for the end-of-century, downscaled to 12km resolution for the port location	CMIP_NumberOfExtremelyHeavyPrecipEvents	%	US DOT CMIP Climate Data Processing Tool
	Number of Presidential Disaster Declarations for the port county since 1953	NumberDisastersCounty	Disaster Type	FEMA, Historical Declarations
Sensitivity	Number of Critical Habitat Areas within 50 miles of the port	NumberCriticalHabitat	Areas	U.S. Fish & Wildlife Service
	Environmental Sensitivity Index (ESI) shoreline sensitivity to an oil spill for the most sensitive shoreline within the port	ESI	ESI Rank	NOAA Office of Response and Restoration
	Average cost of property damage from storm events in the port county since 1950 with property damage > \$1 Million	AvgCostStormEvents	\$USD	NOAA Storm Events Database
	Rate of population change (from 2000-2010) in the port county, expressed as a percent change	PopulationChangeCounty	%	NOAA Office for Coastal Management
	Percent of the port county population living inside the FEMA Floodplain	PopulationInsideFloodplain	%	NOAA Office for Coastal Management
	Port County Social Vulnerability (SoVI) Score	SoVI	score number	SoVI® Social Vulnerability Index

174

## 175 Analytic Hierarchy Process

176 Multi criteria decision analysis (MCDA) refers to a suite of decision support methods  
 177 in the field of decision science that allows a structural approach to enable analysis of different

178 alternatives, information, and judgements (Linkov and Moberg 2011; Kurth et al. 2017;  
179 Cegan et al. 2017). Benefits of MCDA include the ability to provide a formal platform for  
180 stakeholder engagement (Linkov and Moberg 2011; Kurth et al. 2017; Cegan et al. 2017). The  
181 Analytic Hierarchy Process (AHP) is a method of MCDA first described by Thomas Saaty  
182 (Saaty 1977) that is based on the solution of an eigenvalue problem. Participants make  
183 pairwise comparisons, the results of which are arranged in a matrix where the dominant  
184 normalized right eigenvector gives the ratio scale (weighting) and the eigenvalue determines  
185 the consistency ratio (Goepel 2013; Saaty 1977, 1990b, 2006). AHP has become well  
186 established for group decisions based on the aggregation of individual judgements  
187 (Ramanathan and Ganesh 1994; Dedeker 2013; Goepel 2013). Psychologists have noted that  
188 respondents have an easier time making judgements on a pair of alternatives at a time than  
189 simultaneously on all the alternatives (Ishizaka and Labib 2011). AHP also allows  
190 consistency cross checking between the pairwise comparisons. Additionally, AHP uses a  
191 ratio scale, which, unlike methods using interval scales, does not require units in the  
192 comparison (Kainulainen et al. 2009; Hovanov et al. 2008). Compared to other MCDA  
193 methods, such as multi-attribute utility theory (MAUT) or multi-attribute value theory  
194 (MAVT), the assumption of a rational decision maker is much less stringent in AHP due to  
195 AHP's ability to incorporate consistency ratios (Linkov and Ramadan 2004; Linkov and  
196 Moberg 2011).

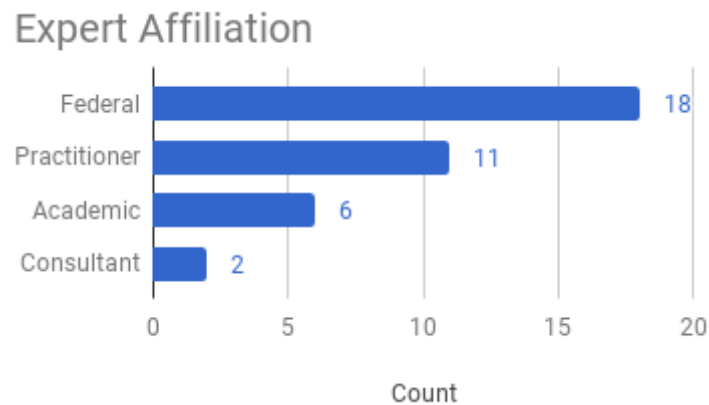
197 AHP has also proven useful as a standardized method for generating the weights of  
198 indicators in composite indices in a variety of different fields, e.g., environmental  
199 performance index (EPI) (Dedeker 2013), disaster-resilience index (Orencio and Fujii 2013),  
200 composite indicator of agricultural sustainability (Gómez-Limón and Riesgo 2009), and the  
201 urban public transport system quality (Pticina and Yatskiv 2015). While these studies  
202 assessed different theoretical concepts from performance, to disaster-resilience, to

203 agricultural sustainability, they all employed AHP as a means of quantifying expert-  
204 preferences for weighting the relative importance of the indicators used. AHP simplifies the  
205 process of quantifying subjective weight preferences based on multiple criteria by using  
206 pairwise comparisons. Participants are given two items at a time and asked which is more  
207 important with respect to the given category. Using pairwise comparisons not only helps  
208 discover and correct logical inconsistencies (Goepel 2013), it also allows for translating  
209 subjective opinions into numeric relations, helping make group decisions more rational,  
210 transparent, and understandable (Goepel 2013; Saaty 2008).

## 211 **Methodology**

### 212 **Expert Selection**

213 Researchers invited the same group of 64 experts who contributed to the evaluation of  
214 candidate indicators via the VAS survey to participate in this AHP weighting exercise.



215

216

*Figure 4 Count of participating experts' affiliations*

217 These experts were sought for their specialized knowledge and experience in seaport  
218 operations, planning, policy, data, and the vulnerability of the U.S. marine transportation  
219 system (MTS) to climate and extreme weather impacts. This group of expert-respondents was  
220 compiled via a knowledge resource nomination worksheet and peer snowball sampling. Out  
221 of this expert pool, 37 experts participated in this AHP exercise, representing the expert-

222 affiliation categories of: federal (e.g., US Coast Guard, NOAA, USACE, MARAD),  
223 practitioners (e.g., port authorities), academics (e.g., professors, research analysts), and  
224 consultants (Figure 4).

## 225 **AHP**

226         In the spring and summer of 2017, researchers held 21 separate webinars with a total  
227 of 37 participating port-experts. During each webinar, researchers guided participants through  
228 a web-based AHP system (Goepel 2017). Experts were given a data dictionary with  
229 descriptions, units, data sources, and example values for each of the 12 indicators to be  
230 weighted. For the AHP exercise, as with the VAS survey, respondents were instructed to  
231 consider port vulnerability holistically, inclusive of the port's surrounding socioeconomic and  
232 environmental systems, and to focus on 22 the ports of the CENAD (Figure 1).

233         The AHP involved two levels; the first comprised weighting the three components of  
234 vulnerability (i.e., exposure, sensitivity, and adaptive capacity), and the second comprised  
235 weighting the six indicators of exposure and the six indicators of sensitivity (Figure 5).  
236 Because the VAS survey failed to develop expert-supported indicators of adaptive capacity  
237 for seaport climate and extreme weather vulnerability, researchers were unable to include  
238 indicators of adaptive capacity for weighting in this AHP. The lack of indicators of adaptive  
239 capacity, however, did not prevent the derivation of weight for adaptive capacity as a  
240 component of seaport vulnerability to climate and weather extremes.

Seaport Climate Vulnerability <b>AHP</b>	Adaptive Capacity	0.3333	<b>AHP</b>
	Exposure	Sea Level Trend	0.1667
		Number of Disasters	0.1667
		Number of Cyclones	0.1667
		Number of Storm Events	0.1667
		Hundred Year High Water	0.1667
		Projected Change in Extreme Precip	0.1667
	Sensitivity	Population Inside Floodplain	0.1667
		Average Cost of Storm Events	0.1667
		Number Critical Habitat Areas	0.1667
		SoVI Social Vulnerability Score	0.1667
		Population Change	0.1667
	Environmental Sensitivity Index ESI	0.1667	

241

242

*Figure 5 AHP hierarchy showing equal weighting prior to pairwise comparisons. Each column represents a level of the AHP, and each red rectangle indicates a node (for which a priority vector will be calculated).*

243

244

For the first level of the AHP, respondents weighted the three components of seaport

245

vulnerability via pairwise comparisons. Respondents were given two components at a time

246

and asked, “With respect to seaport climate vulnerability, which criterion is more important,

247

and how much more on a scale 1 to 9,” where ‘1’ represents equal importance (**Error!**

248

**Reference source not found.**)

### Pairwise Comparison Seaport Climate Vulnerability

Please do the pairwise comparison of all criteria. When completed, click *Check Consistency* to get the priorities.

AHP Scale: 1- Equal Importance, 3- Moderate importance, 5- Strong importance, 7- Very strong importance, 9- Extreme importance (2,4,6,8 values in-between).

**With respect to Seaport Climate Vulnerability, which criterion is more important, and how much more on a scale 1 to 9?**

A - wrt Seaport Climate Vulnerability - or B?		Equal	How much more?							
1	<input checked="" type="radio"/> Adaptive Capacity or <input type="radio"/> Exposure	<input checked="" type="radio"/> 1	<input type="radio"/> 2	<input type="radio"/> 3	<input type="radio"/> 4	<input type="radio"/> 5	<input type="radio"/> 6	<input type="radio"/> 7	<input type="radio"/> 8	<input type="radio"/> 9
2	<input checked="" type="radio"/> Adaptive Capacity or <input type="radio"/> Sensitivity	<input checked="" type="radio"/> 1	<input type="radio"/> 2	<input type="radio"/> 3	<input type="radio"/> 4	<input type="radio"/> 5	<input type="radio"/> 6	<input type="radio"/> 7	<input type="radio"/> 8	<input type="radio"/> 9
3	<input checked="" type="radio"/> Exposure or <input type="radio"/> Sensitivity	<input checked="" type="radio"/> 1	<input type="radio"/> 2	<input type="radio"/> 3	<input type="radio"/> 4	<input type="radio"/> 5	<input type="radio"/> 6	<input type="radio"/> 7	<input type="radio"/> 8	<input type="radio"/> 9

CR = 0% Please start pairwise comparison

AHP  Balanced scale

249

250

*Figure 6 Pairwise comparisons of the three components of seaport vulnerability*

251

252 The second level of the AHP involved two nodes; weighting six indicators of exposure, and  
 253 weighting six indicators of sensitivity. For the former, respondents were given two indicators  
 254 at a time and asked, “With respect to seaport climate exposure, which criterion is more  
 255 important, and how much more on a scale 1 to 9.” For calculating the number of pairwise  
 256 comparisons required, Equation 1 is used where  $n$  is the number of components or indicators  
 257 (Saaty 1977, 1990a; Orenco and Fujii 2013).

258

*Equation 1 Number of pairwise comparisons required for n indicators*

259

$$(n)(n - 1)/2$$

260 For the six indicators of exposure (Figure 5), respondents completed 15 pairwise  
 261 comparisons, contrasting the relative importance of each indicator to every other indicator,  
 262 one pair at a time. Similarly, the second node of this level of the AHP repeated this process  
 263 with respect to sensitivity for the six indicators of seaport climate and extreme weather  
 264 sensitivity. For each respondent at each level of the AHP, the product of each paired  
 265 comparison was recorded in a  $n \times n$  square matrix, with  $n$  equaling the number of indicators  
 266 or components.



267 Let us denote the criteria that were ranked by experts as  $[I_1, I_2, \dots, I_n]$ , where  $n$  is the  
 268 number of components of vulnerability or the number of indicators compared. Based on  
 269 experts’ responses, a preference matrix was derived for each respondent, of the form:

270 *Equation 2 Preference matrix for AHP*

$$A = [a_{ij}] \begin{bmatrix} 1 & a_{ij} & \cdots & a_{1n} \\ 1/a_{ij} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix}$$

272 Where  $a_{ij}$  is the preference for indicator  $I_i$  over  $I_j$  when both were compared pairwise, for  $i, j$   
 273  $= 1, 2, \dots, n$ . If a respondent decided that indicator  $i$  was equally important to another  
 274 indicator  $j$ , a comparison of  $a_{ij} = a_{ji} = 1$  was recorded. If a respondent considered indicator  $i$   
 275 extremely more important than indicator  $j$ , the preference-matrix score was based on  $a_{ij} = 9$   
 276 and its reciprocal given as  $a_{ji} = 1/9$ , where  $a_{ij} > 0$ .

277 After compiling a preference matrix for each expert for each node of the AHP, the  
 278 dominant eigenvector of each matrix was then calculated using the power method (Larson  
 279 2016; Goepel 2013) with the number of iterations limited to 20, for an approximation error of  
 280  $1 \times 10^{-7}$  (Goepel 2013). This normalized principal eigenvector, also called a priority vector<sup>12</sup>,  
 281 gives the relative weights of the indicators and components of vulnerability that were  
 282 compared.

283 The consistency of a respondent’s answers was checked using the linear fit method  
 284 (Equation 3) proposed by (Alonso and Lamata 2006) to calculate the consistency ratio,  $CR$ ,  
 285 for each respondent’s preference matrix for each node of the AHP, where  $\lambda_{\max}$  represents the  
 286 principal eigenvalue obtained from the summation of products between each element of the  
 287 priority vector and the sum of columns of the preference matrix, and  $n$  represents the number  
 288 of dimensions of the matrix.

---

<sup>12</sup> Because the vector is normalized, the sum of all elements in a priority vector is equal to one.

289

*Equation 3 Linear fit method of calculating consistency ratio*

290

$$CR = \frac{\lambda_{max} - n}{2.7699 \cdot n - 4.3513 - n}$$

291

If a respondent completed a node of pairwise comparisons that yielded a CR greater than 10%, the software prompted the respondent to correct the inconsistencies by highlighting the three most inconsistent judgements and allowing adjustments.

294

Aggregation of individual judgements (AIJ) was based on the weighted geometric mean (WGM) of all participants' judgements (Aull-Hyde et al. 2006). The software calculated the geometric mean and standard deviation of all  $K$  participants' individual judgements  $p_{wck}$  to derive a consolidated preference matrix,  $a_{ij}^{cons}$ . The WGM-AIJ process consisted of summing individual judgements,  $p_{wc}$ , over  $K$  participants, squaring the sum, calculating the geometric mean of each  $p_{wc}$ , and using the means to create a consolidated preference matrix (Equation 4).

301

*Equation 4 Consolidated preference matrix based on the geometric mean of individual judgements*

302

$$a_{ij}^{cons} = (\prod_{k=1}^K a_{ij})^{\frac{1}{K}}$$

303

To measure the consensus for the aggregated group result, the AHP software used Shannon entropy and its partitioning in two independent components (alpha and beta diversity) to derive an AHP consensus indicator based on relative homogeneity  $S$  (Goepel 2013). The consensus of the complete hierarchy was calculated as the weighted arithmetic mean of the consensus of all hierarchy nodes. This similarity measure,  $S$ , is zero when the priorities of all  $p_{wc}$  are completely distinct and  $S=1$ , when the priorities of all  $p_{wc}$  are identical (Goepel 2013).

310

### **Aggregating Weighted Indicators**

311

After generating the indicator and component weights via AHP, the next step was to create a composite index of seaport vulnerability based on the weightings. Due to the lack of

312

313 expert-supported indicators of adaptive capacity, the AHP-based composite index was limited  
314 to the aggregation of two of the three components of vulnerability: exposure and sensitivity,  
315 yielding a composite score that may be considered similar to vulnerability minus the  
316 component of adaptive capacity. Researchers aggregated the indicators into a composite  
317 indicator of vulnerability (minus adaptive capacity) using a weighted sum model (WSM)  
318 (Equation 5). In Equation 5,  $n$  represents the number of decision criteria (i.e., indicators or  
319 components),  $m$  represents the number of ports,  $w_j$  represents the relative weight of indicator  
320  $I_j$ , and  $p_{ij}$  represents the performance of port  $A_i$  when evaluated in terms of indicator  $I_j$ .

321 *Equation 5 Weighted sum model*

$$322 \quad A_i^{WSM-score} = \sum_{j=1}^n w_j p_{ij}, \text{ for } i = 1, 2, 3 \dots, m.$$

323 To create the composite index for CENAD ports based on this WSM, researchers first  
324 compiled data on all 12 indicators for the 22 ports of the CENAD. Missing values were  
325 imputed with the indicator's mean value. The input variables were then standardized using z-  
326 score standardization (Equation 6), generating variables with a mean of 0 and a standard  
327 deviation of 1. This standardization allows for indicators with disparate units to be combined  
328 (Cutter et al. 2003).

329 *Equation 6 Z-score standardization*

$$330 \quad z = \frac{X - \mu}{\sigma}$$

331 A composite indicator for exposure was then created by summing the products of  
332 each exposure indicator and its weight. Next, a composite indicator for sensitivity was  
333 created by summing the products of each sensitivity indicator and its weight. The two  
334 composite indicators of exposure and sensitivity were then each multiplied by their respective  
335 component weights and summed together. The resultant composite indicator represents the

336 combined exposure and sensitivity of the sample ports and was used to compile a composite  
337 index of seaport vulnerability (minus adaptive capacity) for the CENAD sample of ports  
338 based on publicly available data. The port-rankings generated by the composite index were  
339 then compared to the experts' subjective ranking of port vulnerability obtained from the VAS  
340 survey.

## 341 **Results**

### 342 **AHP-Generated Weights**

343 The aggregation of judgements from the first level of the AHP, which weighted the  
344 three components of seaport vulnerability to climate and extreme weather, resulted in  
345 exposure ranked most important, with a ratio scale (weight) of .394 (Table 2). Adaptive  
346 capacity was ranked a close second, with a weight of .390, which is noteworthy since the  
347 component of adaptive capacity lacks expert-supported indicators. Sensitivity was ranked  
348 least important of the three components, with a weight of .216. For this node, the maximum  
349 consistency ratio, *CR*, was 0.1% (highly consistent) and the group consensus, *S*, was 50.1%  
350 (low)<sup>13</sup>.

351 *Table 2 Results of AHP consolidated group preferences for the relative importance of the components of seaport climate*  
352 *and extreme weather vulnerability*

353

<b>Component</b>	<b>Weight</b>	<b>Rank</b>
Exposure	0.394	1
Adaptive Capacity	0.390	2
Sensitivity	0.216	3

354

355 The second level of the AHP consisted of two nodes, the first evaluated six indicators  
356 for relative importance in terms of seaport exposure to climate and weather extremes, and the

---

<sup>13</sup> (Goepel 2013) considers the following interpretation of AHP consensus; <50% (very low), 50%-65% (low), 65%-75% (moderate), 75%-85% (high), >85% (very high)

McIntosh, R.D., Becker, A. (2020), “Applying MCDA to Weight Indicators of Seaport Vulnerability to Climate and Extreme Weather Impacts for U.S. North Atlantic Ports.” *Environment Systems and Decisions*. Volume 40. Issue 1. 21 March 2020. doi:[10.1007/s10669-020-09767-y](https://doi.org/10.1007/s10669-020-09767-y)

357 second node evaluated six indicators in terms of seaport sensitivity. The first node resulted in  
 358 the indicator “number of disasters,” ranked most important for the component of exposure  
 359 with a weight of .200, and resulted in weights for the remaining indicators of exposure as  
 360 shown in Table 3. For this node, the maximum consistency ratio, *CR*, was 0.3% (highly  
 361 consistent) and the group consensus, *S*, was 53.6% (low).

362 *Table 3 Consolidated group preferences for the relative importance of indicators of seaport exposure to climate and*  
 363 *weather extremes*

<b>Indicator of Exposure</b>	<b>Weight</b>	<b>Rank</b>
Number of Disasters	0.200	1
Number of Storm Events	0.196	2
Sea Level Trend	0.180	3
Hundred Year High Water	0.163	4
Number of Cyclones	0.143	5
Projected Change in Extreme Precip	0.118	6

364  
 365 The second node of the second AHP level resulted in the indicator “population inside  
 366 floodplain,” ranked most important for the component of sensitivity with a weight of .229,  
 367 and resulted in the remaining indicators of sensitivity weighted as shown in Table 4. For this  
 368 node, the maximum consistency ratio, *CR*, was 0.5% (highly consistent) and the group  
 369 consensus, *S*, was 61.1% (low).

370 *Table 4 Consolidated group preferences for the relative importance of indicators of seaport sensitivity to climate and*  
 371 *weather extremes*

<b>Indicator of Sensitivity</b>	<b>Weight</b>	<b>Rank</b>
Population Inside Floodplain	0.229	1
SoVI Social Vulnerability Score	0.213	2
Average Cost of Storm Events	0.210	3
Environmental Sensitivity Index ESI	0.125	4
Population Change	0.119	5
Number Critical Habitat Areas	0.104	6

372

373 These indicator weights were then used to generate a composite index of seaport vulnerability  
 374 (minus adaptive capacity) to climate and extreme weather impacts with a WSM (Equation 5).

375 **Composite Index of CENAD Ports**

376 To test the degree to which a ranking of ports by level of vulnerability to climate and  
 377 extreme weather, created by a WSM using AHP-generated weights, would or would not  
 378 resemble an a priori ranking generated<sup>14</sup> subjectively by the same participating experts,  
 379 researchers compiled a composite index for the CENAD sample of ports. Applying the AHP-  
 380 generated indicator weights to the z-score-standardized input variables for 22 CENAD ports,  
 381 and aggregating them in a WSM yielded the following ranking (Table 5) where a larger  
 382 number corresponds to a higher degree of vulnerability. In Table 5, a score of zero represents  
 383 the mean, a negative number represents a vulnerability score below the mean, and a positive  
 384 number represents a vulnerability score above the mean.

385 *Table 5 Model-generated ranking of CENAD ports by vulnerability to climate and weather extremes. Note that here,*  
 386 *vulnerability includes exposure and sensitivity, but not adaptive capacity*

387

<b>Port</b>	<b>Vulnerability Score</b>
Virginia.VA.Port.of	0.46
Boston.MA	0.24
Philadelphia.PA	0.11
New.Haven.CT	0.10
Port.Jefferson.NY	0.10
Portland.ME	0.10
Hopewell.VA	0.07
Searsport.ME	0.04
Fall.River.MA	0.02
Camden-Gloucester.NJ	0.02
Baltimore.MD	0.00
Bridgeport.CT	-0.03

<sup>14</sup> As part of the VAS survey, port-experts were asked to rank the top ten most vulnerable ports out of the sample of 22 CENAD ports. The rank distribution (Table 6) was generated from a sum of weighted values, which were weighted as the inverse of the number of ports the respondent chose to rank.

<b>Port</b>	<b>Vulnerability Score</b>
Hempstead.NY	-0.04
Paulsboro.NJ	-0.04
Albany.NY	-0.05
Wilmington.DE	-0.07
Marcus.Hook.PA	-0.09
Chester.PA	-0.10
Penn.Manor.PA	-0.11
Portsmouth.NH	-0.12
New.York.NY.and.NJ	-0.12
Providence.RI	-0.13

388

389 Interestingly, the most vulnerable port according to the model-generated port vulnerability  
 390 rankings matches the most vulnerable port as subjectively ranked by experts in the VAS  
 391 survey (Table 6). While the second most vulnerable port according to the subjective expert-  
 392 ranking, the Port of New York and New Jersey, was second to least vulnerable according to  
 393 the model rank, the model did capture three out of four of the most vulnerable ports  
 394 consistent with the experts’ rankings.

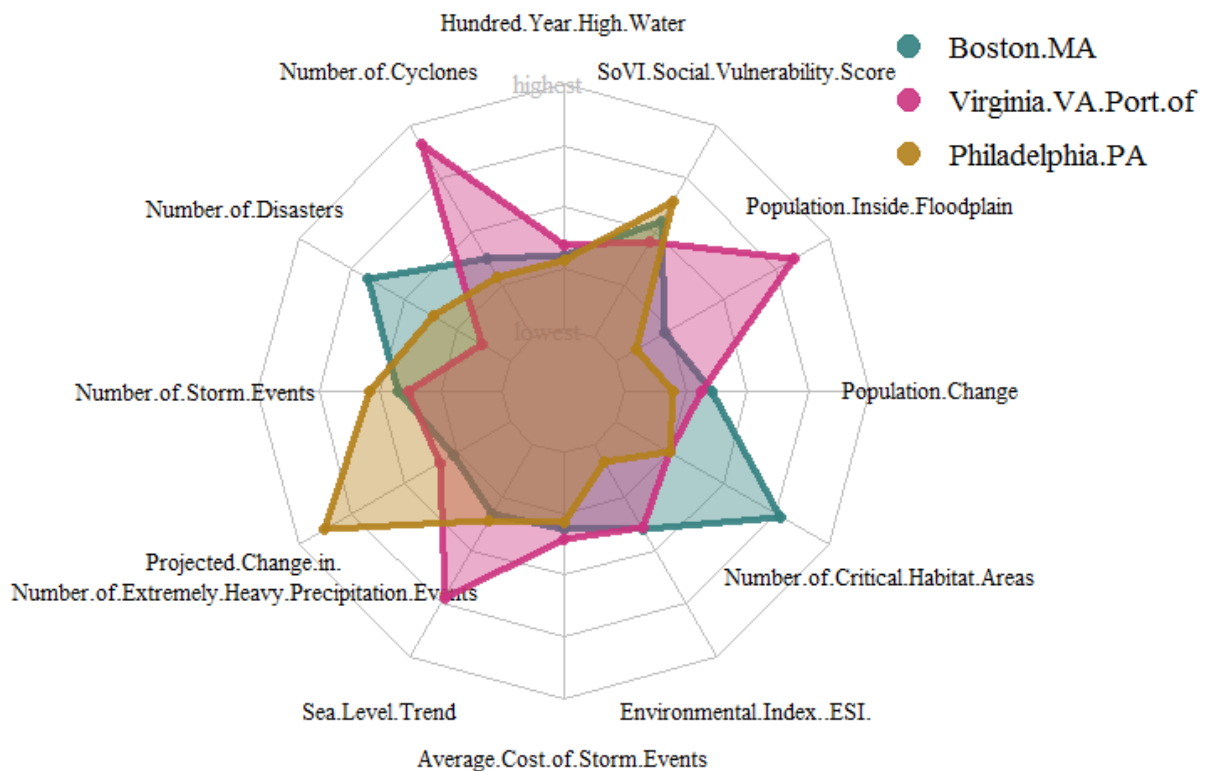
395 *Table 6 Port-experts' consolidated subjective ranking of the top ten CENAD ports most vulnerable to climate and extreme*  
 396 *weather.*

<b>Port</b>	<b>Experts' Rank</b>
Virginia.VA.Port.of	1
New.York.NY.and.NJ	2
Boston.MA	3
New.Haven.CT	4
Baltimore.MD	5
Providence.RI	6
Portland.ME	7
Portsmouth.NH	8
Philadelphia.PA	9
Hempstead.NY	10

397

398 One benefit of indicator-based composite indices is their ability to synthesize multiple  
 399 variables into a single, measurable concept while still retaining the ability to explore the  
 400 disaggregated substructure behind the composite construct. As such, their users are able to  
 401 ask, “*Why* does a particular entity score high or low according to this index?” Figure 7 shows

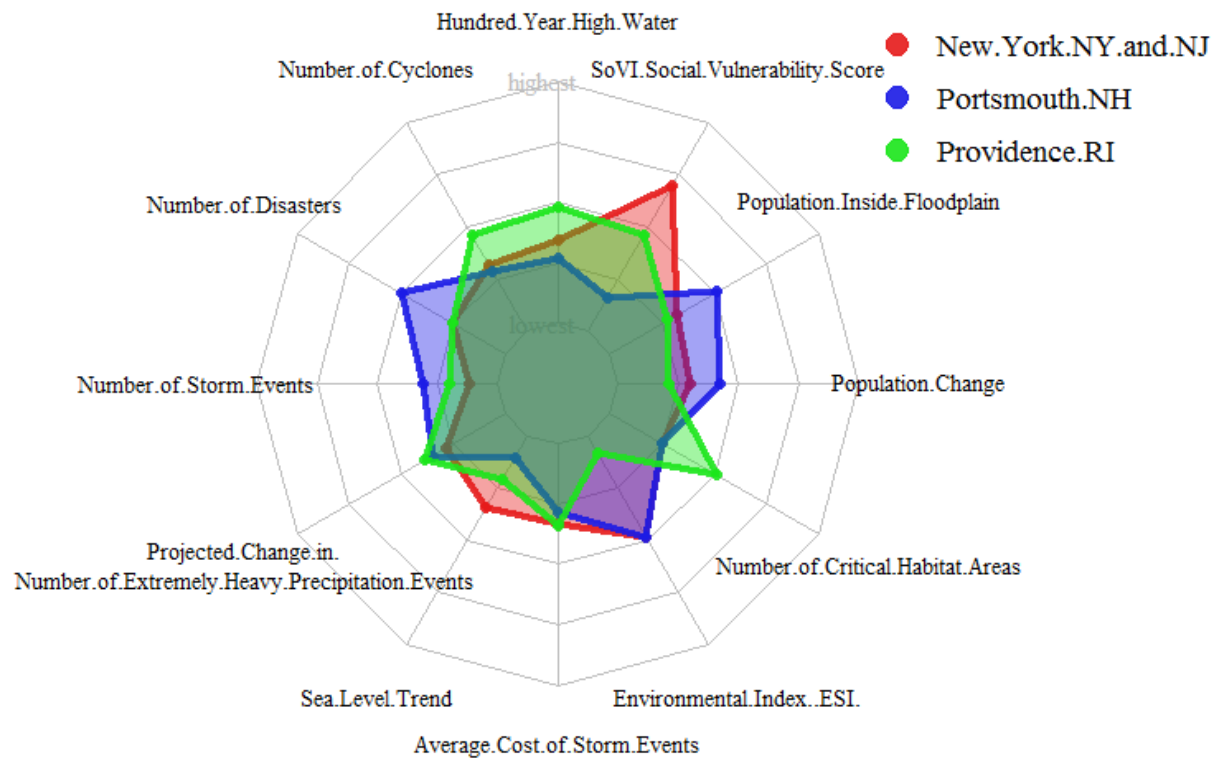
402 the disaggregated substructure behind the composite 'vulnerability scores' of the three  
403 highest scoring ports from the composite index, in which the relative performance of a port  
404 can be explored in terms of the individual indicators. Similarly, Figure 8 shows the  
405 disaggregated substructure for the three lowest scoring ports of the composite index.



406  
407 *Figure 7 Disaggregated substructure of the composite-index vulnerability scores of the three highest scoring ports.*  
408 *Indicators of exposure are shown on the left half of the plot, and indicators of sensitivity are shown on the right half.*

409 Comparing the three ports of Figure 7, reveals sharp differences in the underlying  
410 performance of each port in terms of the individual indicators. Whereas the port of Virginia  
411 scored high (i.e. relatively more vulnerable) in the 'number of cyclones' indicator and  
412 relatively low with respect to the 'number of disasters,' the opposite is seen for the port of  
413 Philadelphia. This type of differentiation can assist decision-makers in understanding the  
414 mechanisms and drivers behind a 'composite score,' and tools that allow exploration of the  
415 underlying substructure may add to the decision-relevance of indicator-based assessment  
416 efforts and especially indicator-based composite indices.





417

418 *Figure 8 Disaggregated substructure of the composite-index vulnerability scores of the three lowest scoring ports. Indicators*  
 419 *of exposure are shown on the left half of the plot, and indicators of sensitivity are shown on the right half.*

420 Figure 8, showing the substructure of the three least vulnerable ports per the  
 421 composite index, yields insight into the discrepancy between the index rankings and the  
 422 subjective, expert-rankings. While the port of New York and New Jersey was considered  
 423 second most vulnerable according to expert-perception, the weighted-index scored it second  
 424 *least* vulnerable. Looking at Figure 8, we can see that while the port of New York and New  
 425 Jersey scored high (i.e., relatively more vulnerable) in the “SoVI social vulnerability score”  
 426 indicator, it scored near the bottom of the sample in nearly every other indicator. This may be  
 427 an artifact of the method of compiling the indicator data for the sample of ports. Most  
 428 indicators were measured at the county-level, and while the port of New York and New  
 429 Jersey spans multiple counties, for this experiment, the port of New York and New Jersey  
 430 was represented solely by New York County. Similarly, the port of Providence was  
 431 subjectively ranked sixth most vulnerable by port-experts yet scored least vulnerable of all in  
 432 the composite index. Figure 8 reveals that while Providence scored near the middle of the

433 sample for "number of critical habitat areas," "hundred year high water," and "number of  
434 cyclones," it scored near the bottom of the sample for "number of disasters," "number of  
435 storm events," and "environmental sensitivity index ESI," and did not score higher than  
436 average for any indicator.

## 437 **Discussion**

438         The method of generating indicator weights based on aggregated expert-preferences  
439 using AHP described in this paper has shown both promise and limitations. Port rankings  
440 generated by a composite index based on a WSM using the AHP-derived weights, was  
441 compared to an a priori subjective ranking generated by port experts. Though the model  
442 lacked indicators of adaptive capacity, it matched (Table 5) the experts' ranking for the most  
443 vulnerable port, and also matched three of the four ports ranked most vulnerable by the  
444 experts (Table 6).

445         Whereas previous work on assessing the climate vulnerability of seaports has tended  
446 to focus on the single port scale, either as case studies (Koppe et al. 2012; Cox et al. 2013;  
447 USDOT 2014; Messner et al. 2013; Chhetri et al. 2014) or as self-assessment tools (NOAA  
448 OCM 2015; Semppier et al. 2010; Morris and Semppier 2016), this work contributes a first  
449 attempt at constructing an indicator-based composite-index for the purpose of developing  
450 seaport CCVA at the multi-port scale.

451         To the observed problem (i.e., the current difficulty of comparing relative  
452 vulnerability across ports), this work contributes a prototype composite-index (and a method  
453 to replicate such an index for other sectors) that allows rudimentary quantitative comparisons  
454 of exposure and sensitivity levels across ports. This prototype index was able to capture  
455 relative outliers in the sample of ports (i.e., the main objective of composite-indices) and  
456 shows the promise of an indicator-based approach to address this problem.

457 To validate the results of the AHP, the AHP-generated weighting scheme was applied  
458 using a WSM to create a composite index for 22 CENAD ports that was compared to a  
459 subjective ranking of the ports by the same experts. This comparison revealed that while the  
460 model showed promise in fulfilling the main objective of composite indices (i.e.,  
461 identification of relative outliers among a sample) by matching the top port and three out of  
462 the top four ports subjectively chosen as most vulnerable by the experts, there were  
463 considerable discrepancies between the model rank and the subjective, expert rank that point  
464 to some of the limitations of this method. Those limitations include the potential for low  
465 group consensus during the AHP, for which the remedy, Delphi-style iterations, contains its  
466 own limitation of increased time-cost. The validity of indicator-based methods is also limited  
467 by their sensitivity to small changes in the methods used to compile the individual indicators.  
468 Variations in spatial scale of available data can require subjective choices regarding the  
469 compilation of indicator data, e.g., how to compile indicator data for ports that span multiple  
470 counties. Additionally, the process of compiling indicators introduces other subjective  
471 decisions that affect model sensitivity, such as whether to use the max value or a measure of  
472 central tendency of a concept as an indicator. Because of both the sensitivity and subjectivity  
473 of these decisions, researchers recommend a stakeholder-based approach for the early stages  
474 of indicator development such as the expert-elicitation methods applied in (McLeod et al.  
475 2015; Teck et al. 2010). While this research has furthered the development of indicator-based  
476 assessment methods for the port sector by constructing and trialing a prototype composite-  
477 index of seaport climate vulnerability, it should be noted that further work exploring the  
478 sensitivity of results to data compilation methods and developing a measure of adaptive  
479 capacity will be needed before such methods are robust enough for use in critical decision-  
480 making. Finally, the main caveat of these methods is that they are always limited by the  
481 quality of the data that they incorporate.

## 482 **Adaptive Capacity Considered Highly Important**

483 Adaptive capacity is defined in the glossary of the IPCC Fifth Assessment Report  
484 (IPCC 2014) as "The ability of systems, institutions, humans and other organisms to adjust to  
485 potential damage, to take advantage of opportunities, or to respond to consequences." As  
486 noted by Siders (Siders 2016), this definition bears some resemblance to generally accepted  
487 definitions of resilience, i.e., the ability to bounce back from an impact (McIntosh and Becker  
488 2017; Linkov et al. 2014). As such, Siders recommends that adaptive capacity can be  
489 distinguished from resilience by ascribing the latter to maintaining stability by "bouncing  
490 back" to pre-shock conditions, and by taking adaptive capacity, to refer to the broader ability  
491 of a system to self-organize, learn, and embrace change to limit future harms (Klein et al.  
492 2003; Siders 2016).

493 It may be significant that the AHP resulted in adaptive capacity ranked a close second  
494 to exposure in terms of importance with respect to seaport climate and extreme weather  
495 vulnerability (Table 2). This suggests that port-experts consider adaptive capacity to be more  
496 important than sensitivity and practically equal in importance to exposure with respect to  
497 seaport vulnerability. Though experts place a high degree of importance on adaptive capacity  
498 as a component of vulnerability, VAS survey results suggest that adaptive capacity may be  
499 the most difficult of the three components of seaport vulnerability to represent with  
500 quantitative data. While this discrepancy may point to a need to improve the data collection  
501 and sharing of metrics that can capture the concept of adaptive capacity for ports, it also  
502 suggests that the concept of adaptive capacity may be better captured by other, less  
503 quantitative assessment methods. This finding also suggests a disconnect between what  
504 experts perceive as an important component to understanding seaport vulnerability to  
505 meteorological and climatological threats and the types of data that are currently being  
506 reported and available to represent that component.

507 As noted by Brooks et al. (Brooks et al. 2005), adaptive capacity is a component of  
508 vulnerability primarily associated with governance. Hence, next-step efforts to assess relative  
509 levels of seaport adaptive capacity should start by examining ports' governance structures to  
510 find measurable metrics to assess and compare the ports' ability to adjust, take advantage, or  
511 respond to climate and weather impacts.

## 512 **Limitations**

513 A limitation of this AHP method can be the difficulty of achieving high levels of  
514 group consensus. For each of the three nodes of this AHP, the consensus indicator,  $S$ , was  
515 low (50.1%, 53.6%, 61.1%), suggesting low relative homogeneity of expert preferences.  
516 Improvements in group consensus may be achieved by using iterative approaches such as the  
517 Delphi<sup>15</sup> method, in which participants are shown descriptive statistics of the group responses  
518 and given the opportunity to revise their answers during subsequent iterations of the AHP, as  
519 was employed in (Orencio and Fujii 2013). A drawback of this iterative approach, however,  
520 is the additional time required to complete the process. For this study, researchers held 20  
521 different webinars with a total of 34 experts to complete the AHP, lasting approximately 30  
522 minutes to one hour each webinar. Experts may be more reluctant to participate the longer the  
523 process proposes to take. As the number of pairwise comparisons increases quickly due to  
524 Equation 1, even a single-round AHP can become a considerable imposition on the time  
525 constraints of busy professional experts.

526 Though the aggregation of weighted indicators into a composite index was performed  
527 mainly as a means to validate the AHP-generated weights by comparing the port-rankings  
528 they produced via a WSM to a subjective port-ranking, the process also yielded insight into

---

<sup>15</sup> The Delphi method is a structured communication technique designed to obtain opinion consensus of a group of experts by subjecting them to a series of questionnaires interspersed with feedback in the form of a statistical representation of the group response. The goal of employing the Delphi method is to reduce the range of responses and arrive at something closer to expert consensus.

529 the benefits and limitations of such methods. As a means to identify relative outliers among a  
530 sample, this method showed promise by successfully matching the most vulnerable port and  
531 three of the four most vulnerable ports as ranked subjectively by port-experts. While partially  
532 successful at identifying the relative outliers among our sample of ports, the composite index  
533 also ranked several ports (e.g., Providence, New York and New Jersey) near the bottom of  
534 the sample that experts had subjectively ranked near the top. Some of this discrepancy may  
535 be due to the sensitivity of indicator-based composite indices to differences in the  
536 interpretation of data used for the indicators. For example, an indicator for an entity that  
537 spans multiple counties, like the port of New York and New Jersey, could be represented by a  
538 measure of central tendency of the data for the collection of counties, by the data from the  
539 county with most extreme value, or by a single representative county. In this experiment, the  
540 single county of New York was taken to represent the port of New York and New Jersey for  
541 the purposes of compiling the indicator data, which may have resulted in lower than expected  
542 values for that port in some of the indicators. Additionally, indicator-based assessments are  
543 always limited by the quality of data available to incorporate into them.

544         Although the AHP weighted all three components of vulnerability, including adaptive  
545 capacity, and the composite index incorporated the weights for the components of exposure  
546 and sensitivity into the WSM, it should be noted that this composite index of seaport  
547 vulnerability to climate and extreme-weather did not include indicators of adaptive capacity.  
548 As such, the composite index is more accurately described as a weighted measure of seaport  
549 exposure and sensitivity to climate and weather extremes. This may have also contributed to  
550 some of the discrepancy between model results and the subjective ranking of ports which was  
551 based on a definition of vulnerability that included all three components (e.g., exposure,  
552 sensitivity, adaptive capacity).

553            Additionally, indicator-based methods are inherently limited by the availability of  
554 data. For example, the lack of openly available data to serve as indicators of adaptive  
555 capacity resulted in the reduction of the composite index described here from an assessment  
556 of holistic vulnerability to one of exposure and sensitivity only.

## 557 **Conclusion**

558            To further the development of indicator-based assessment methods for the port sector,  
559 this study performed an AHP with 37 port-experts that developed weights for the three  
560 components of vulnerability (i.e., exposure, sensitivity, and adaptive capacity), and for a  
561 selection of 12 indicators of seaport exposure and sensitivity to climate and extreme weather  
562 impacts. The AHP resulted in adaptive capacity weighted higher than sensitivity and nearly  
563 equal to exposure in importance with respect to seaport climate and extreme weather  
564 vulnerability. This finding suggests a disconnect between what experts believe is an  
565 important component to understanding seaport vulnerability to meteorological and  
566 climatological threats and the types of data that are currently being reported and available to  
567 represent that component. While a composite index of seaport climate-vulnerability based on  
568 AHP generated weights showed promise in identifying relative outliers among a sample (i.e.,  
569 hotspots of vulnerability), there were considerable discrepancies between the model rank and  
570 the subjective, expert rank that point to some of the limitations of this method. An  
571 opportunity for future research exists to develop an answer to what types of data, if any,  
572 experts would accept as more representative of the concept of seaport adaptive capacity than  
573 what data is currently available.

574

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