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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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Abstract

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

Keywords Indicator · Seaport · Climate vulnerability · Analytical hierarchy method · Composite Index · Expert elicitation

1 Introduction

1.1 Seaport vulnerability to climate and extreme weather

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

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

Port decision-makers have a responsibility to manage a multitude of risks and enhance port resilience to achieve the minimum downtime safely possible in any given circumstance. When regional systems of ports are considered, responsible decision-makers may wish to prioritize limited

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resources, or to identify outliers among a set of ports in terms of vulnerability to certain hazards. At the single-port scale, port decision-makers (e.g., a local port authority) may question which specific adaptation actions to take, or how to start with climate adaptation. At the multi-port scale, port decision-makers (e.g., the U.S. Army Corps of Engineers) may question which ports in a certain regional jurisdiction are the most vulnerable and hence the most in need of urgent attention. As climate adaptation decisions often involve conflicting priorities (e.g., politics, national priorities, local priorities), providing a data-driven, standard metric can help bring objectivity into the process.

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

1.2 Indicator-based composite indices

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

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

Indicator-based assessments and indices have provoked debate in the literature, and some researchers (Barnett et al. 2008; Eriksen and Kelly 2007; Hinkel 2011; Klein 2009; Gudmundsson 2003) have criticized attempts to assess theoretical concepts with them as lacking scientific rigor or lacking consistency. Nonetheless, policymakers are increasingly calling for the development of methods to measure relative risk, vulnerability, and resilience (Cutter et al. 2010; Hinkel 2011; Rosati 2015), and developing better indicators and expert-driven weighting schemes through participatory processes like AHP may lead to improvements in this field. Despite these criticisms of indicator-based vulnerability assessments (IBVA) and indicator-based composite indices in particular, such decision-support tools can play an important role in bringing objective data into the complex decision-making process. The use of such indicator-based decision-support products can provide guidance in identifying areas of concern, but they should always be supplemented with additional expertise as they lack the high-resolution found in more detailed case-study assessment approaches.

Whereas low-level, high-resolution analyses are better served by more comprehensive case-study approaches, e.g., (Hallegatte et al. 2011; McLaughlin et al. 2011; USDOT 2014), indicator-based composite indices are well suited to

[1] 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.

provide high-level overviews of relative outliers among a sample. Indicator-based assessments and indices, then, are simply one tool among a suite of tools that decision-makers should have at their disposal.

1.3 Selection of indicators

Researchers worked with port-experts to develop from open-sources and evaluate a set of high-level indicators of seaport vulnerability[2] to climate and extreme weather impacts for the 22 medium and high use ports[3] of the United States Army Corps of Engineers' (USACE) North Atlantic Division[4] (CENAD) (Fig. 1). The steps involved in compiling and evaluating this set of candidate indicators are illustrated in Fig. 2.

Researchers began by identifying indicators of vulnerability that were suitable for use in the AHP study (McIntosh and Becker 2019; McIntosh et al. 2019). A review of climate change vulnerability assessment (CCVA) and seaport-studies literature identified 108 candidate indicators of vulnerability. Of the 108 candidate indicators identified, 48 were found to have sufficient data for the sample of CENAD ports (Fig. 1). These 48 indicators were then further distilled to 34 viable candidate indicators via a mind mapping exercise with members of the Resilience Integrated Action Team[5] (RIAT) of the United States Committee on the Marine Transportation System[6] (US CMTS). The 34 candidate indicators chosen via this mind map exercise were then evaluated via a visual analog scale[7] (VAS) survey instrument by 64 port-experts. For each candidate indicator in the VAS survey, respondents were given the indicator's description, units, data source, and example values, and respondents were asked to determine whether the candidate indicator could be correlated with the exposure,[8] sensitivity,[9] and/or the adaptive capacity[10] of ports in the study area. Respondents indicated the magnitude and direction of correlation by dragging a slider along a VAS line segment (Fig. 3). In addition to evaluating 34 indicators of seaport vulnerability, respondents of the VAS survey also subjectively ranked the CENAD ports by magnitude of perceived vulnerability to climate and extreme weather impacts.

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

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

1.4 Analytic hierarchy process

Multi criteria decision analysis (MCDA) refers to a suite of decision support methods in the field of decision science that allows a structural approach to enable analysis of different alternatives, information, and judgements (Linkov and Moberg 2011; Kurth et al. 2017; Cegan et al. 2017). Benefits of MCDA include the ability to provide a formal platform for stakeholder engagement (Linkov and Moberg 2011; Kurth et al. 2017; Cegan et al. 2017).The Analytic Hierarchy Process (AHP) is a method of MCDA first described

[2] 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).

[3] Medium use here refers to ports with annual throughput > 1 M tons and high use refers to ports with annual throughput > 10 M tons.

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

[5] 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.

[6] 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).

[7] In visual analog scale (VAS), respondents measure their level of agreement by indicating a position along a continuous line segment.

[8] 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).

[9] The degree to which a system is affected, either adversely or beneficially, by climate-related stimuli (IPCC 2001).

[10] 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).

[11] 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.

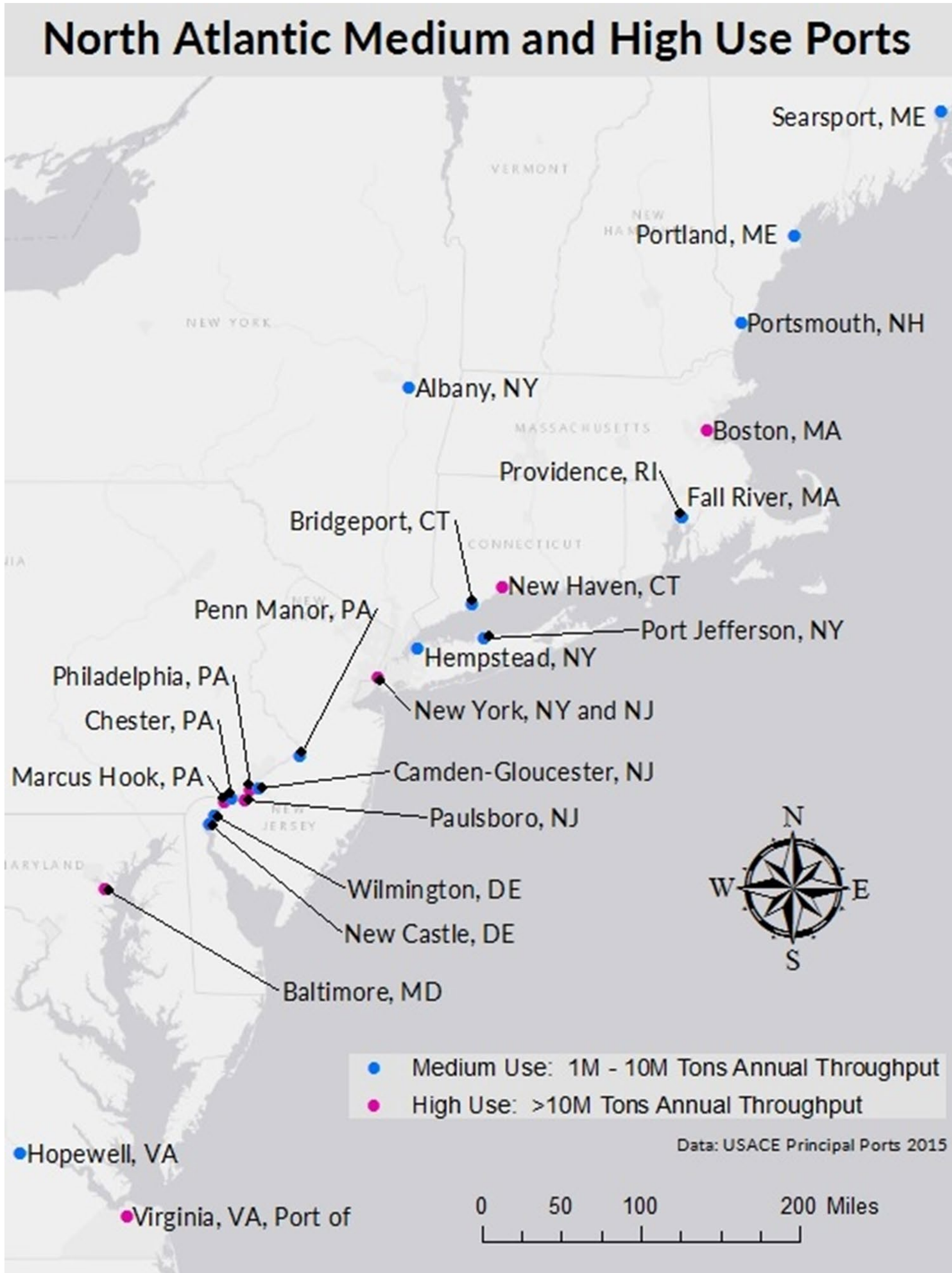

Fig. 1 Study area ports

by Thomas Saaty (Saaty 1977) that is based on the solution of an eigenvalue problem. Participants make pairwise comparisons, the results of which are arranged in a matrix where the dominant normalized right eigenvector gives the ratio scale (weighting) and the eigenvalue determines the consistency ratio (Goepel 2013; Saaty 1977, 1990b, 2006). AHP has become well established for group decisions based on the aggregation of individual judgements (Ramanathan and Ganesh 1994; Dedeke 2013; Goepel 2013). Psychologists have noted that respondents have an easier time making judgements on a pair of alternatives at a time than simultaneously on all the alternatives (Ishizaka and Labib 2011). AHP also allows consistency cross checking between the pairwise comparisons. Additionally, AHP uses a ratio scale, which, unlike methods using interval scales, does not require units in the comparison (Kainulainen et al. 2009; Hovanov et al. 2008). Compared to other MCDA methods, such as multi-attribute utility theory (MAUT) or multi-attribute value theory (MAVT), the assumption of a rational decision maker is much less stringent in AHP due to AHP's ability to

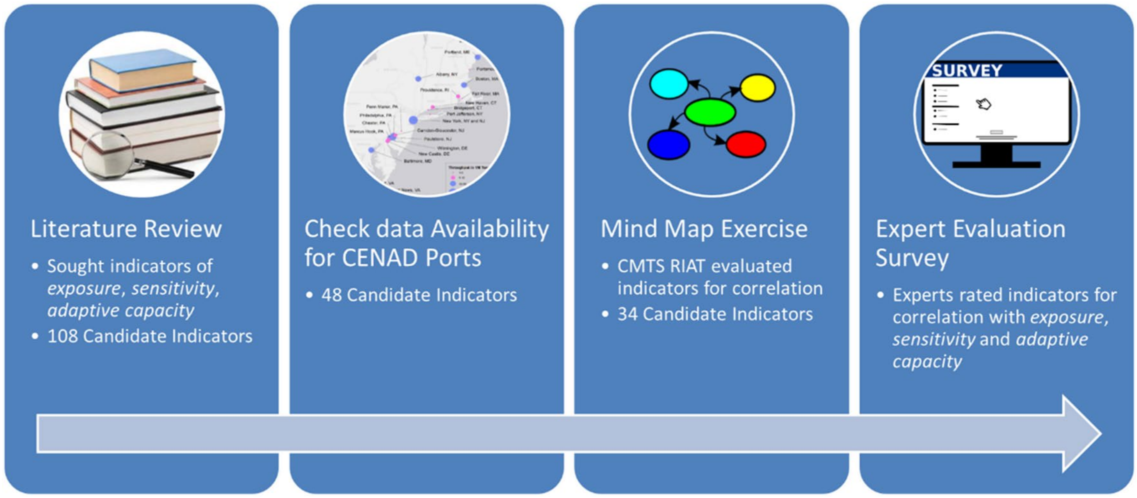

Fig. 2 Steps involved in compiling and evaluating candidate indicators. The AHP described in this paper uses the highest scoring indicators from the last step (survey) portrayed in this figure

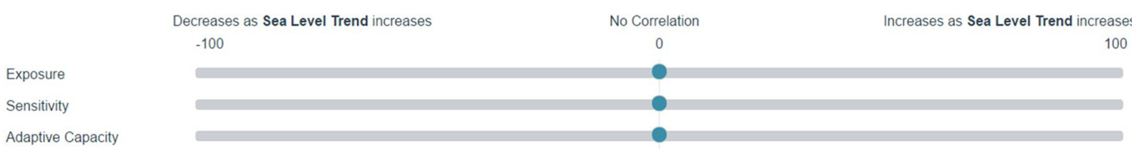

Fig. 3 VAS slider for indicating expert-perceived correlation between a candidate indicator and each of the components of vulnerability

incorporate consistency ratios (Linkov and Ramadan 2004; Linkov and Moberg 2011).

AHP has also proven useful as a standardized method for generating the weights of indicators in composite indices in a variety of different fields, e.g., environmental performance index (EPI) (Dedeke 2013), disaster-resilience index (Orencio and Fujii 2013), composite indicator of agricultural sustainability (Gómez-Limón and Riesgo 2009), and the urban public transport system quality (Pticina and Yatskiv 2015). While these studies assessed different theoretical concepts from performance, to disaster-resilience, to agricultural sustainability, they all employed AHP as a means of quantifying expert-preferences for weighting the relative importance of the indicators used. AHP simplifies the process of quantifying subjective weight preferences based on multiple criteria by using pairwise comparisons. Participants are given two items at a time and asked which is more important with respect to the given category. Using pairwise comparisons not only helps discover and correct logical inconsistencies (Goepel 2013), it also allows for translating subjective opinions into numeric relations, helping make group decisions more rational, transparent, and understandable (Goepel 2013; Saaty 2008).

2 Methodology

2.1 Expert selection

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

These experts were sought for their specialized knowledge and experience in seaport operations, planning, policy, data, and the vulnerability of the U.S. marine transportation system (MTS) to climate and extreme weather impacts. This group of expert-respondents was compiled via a knowledge resource nomination worksheet and peer snowball sampling. Out of this expert pool, 37 experts participated in this AHP exercise, representing the expert-affiliation categories of: federal (e.g., US Coast Guard, NOAA, USACE, MARAD), practitioners (e.g., port authorities), academics (e.g., professors, research analysts), and consultants (Fig. 4).

2.2 AHP

In the spring and summer of 2017, researchers held 21 separate webinars with a total of 37 participating port-experts. During each webinar, researchers guided participants

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

Category	Description	Indicator	Units	Data source
Exposure	Number of storm events in port county w/ property damage > $1 M	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 12 km 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 Mio	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

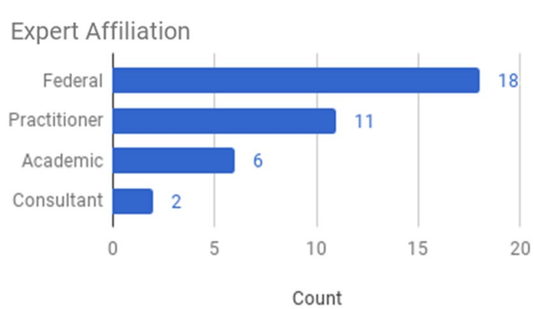

Fig. 4 Count of participating experts’ affiliations

through a web-based AHP system (Goepel 2017). Experts were given a data dictionary with descriptions, units, data sources, and example values for each of the 12 indicators to be weighted. For the AHP exercise, as with the VAS survey, respondents were instructed to consider port vulnerability holistically, inclusive of the port’s surrounding socioeconomic and environmental systems, and to focus on 22 the ports of the CENAD (Fig. 1).

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

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

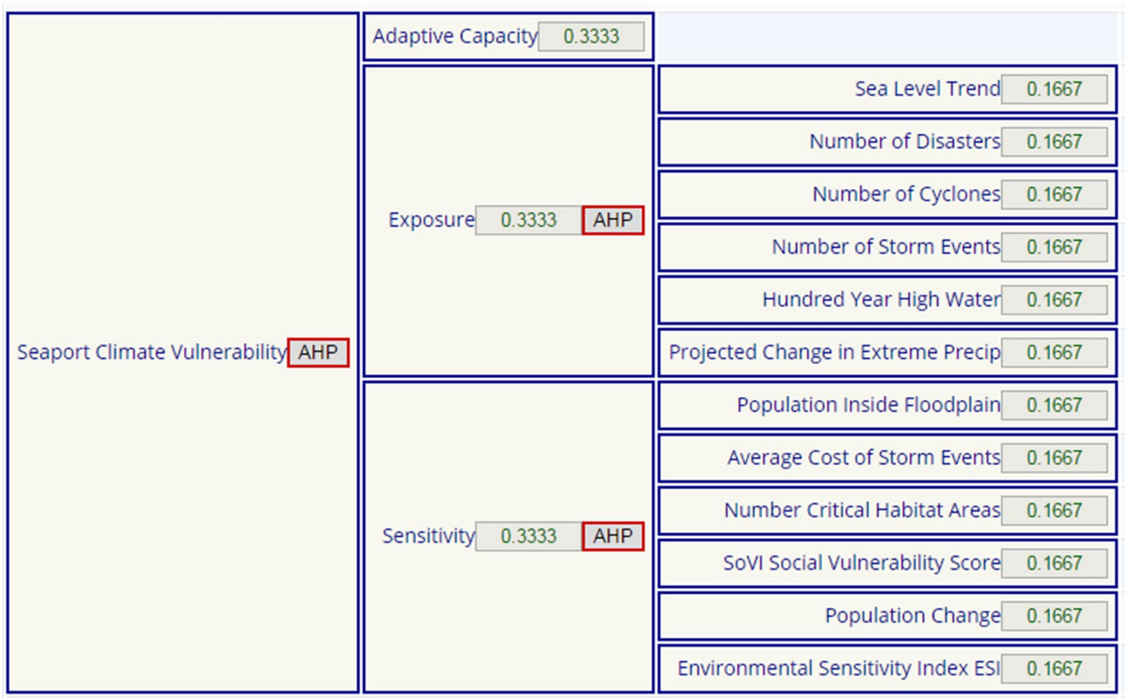

Fig. 5 AHP hierarchy showing equal weighting prior to pairwise comparisons. Each column represents a level of the AHP, and each red rectangle indicates a node (for which a priority vector will be calculated)

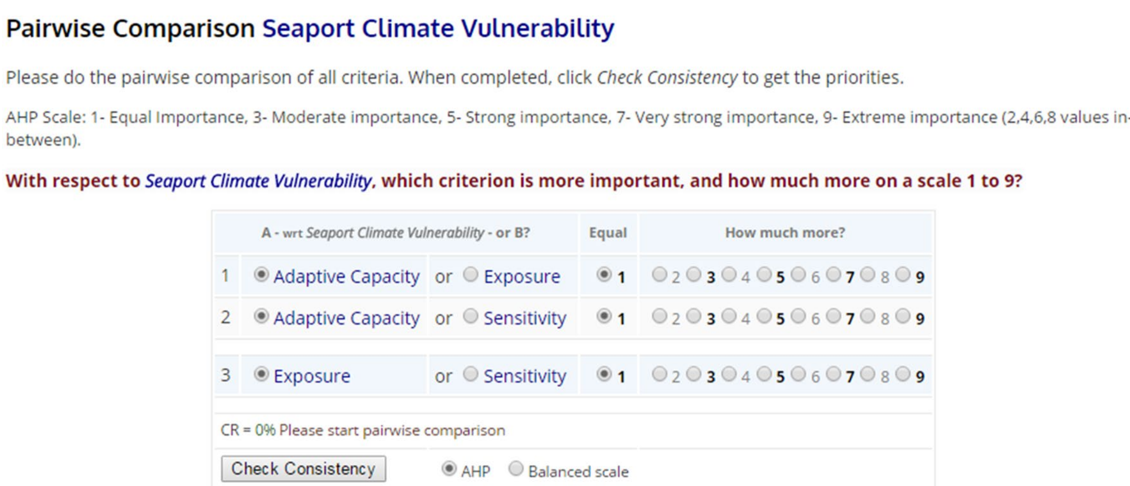

Fig. 6 Pairwise comparisons of the three components of seaport vulnerability

comparisons. Respondents were given two components at a time and asked, "With respect to seaport climate vulnerability, which criterion is more important, and how much more on a scale 1 to 9," where '1′ represents equal importance (Fig. 6).

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

Number of pairwise comparisons required for n indicators

$$\frac{(n)(n-1)}{2} \tag{1}$$

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

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

Preference matrix for AHP

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

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

After compiling a preference matrix for each expert for each node of the AHP, the dominant eigenvector of each matrix was then calculated using the power method(Larson 2016; Goepel 2013) with the number of iterations limited to 20, for an approximation error of 1×10^{-7} (Goepel 2013). This normalized principal eigenvector, also called a priority vector,[12] gives the relative weights of the indicators and components of vulnerability that were compared.

The consistency of a respondent's answers was checked using the linear fit method (Eq. 3) proposed by (Alonso and Lamata 2006) to calculate the consistency ratio, CR, for each respondent's preference matrix for each node of the AHP, where λ_{max} represents the principal eigenvalue obtained from the summation of products between each element of the priority vector and the sum of columns of the preference matrix, and n represents the number of dimensions of the matrix.

[12] Because the vector is normalized, the sum of all elements in a priority vector is equal to one.

Linear fit method of calculating consistency ratio

$$CR = \frac{\lambda_{max} - n}{2.7699 \cdot n - 4.3513 - n} \tag{3}$$

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.

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 pwc_k to derive a consolidated preference matrix, a_{ij}^{cons}. The WGM-AIJ process consisted of summing individual judgements, pwc, over K participants, squaring the sum, calculating the geometric mean of each pwc, and using the means to create a consolidated preference matrix (Eq. 4).

Consolidated preference matrix based on the geometric mean of individual judgements

$$a_{ij}^{cons} = (\Pi_{k=1}^{K} a_{ij})^{\frac{1}{K}} \tag{4}$$

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 pwc are completely distinct and $S = 1$, when the priorities of all pwc are identical (Goepel 2013).

2.3 Aggregating weighted indicators

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

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

Component	Weight	Rank
Exposure	0.394	1
Adaptive capacity	0.390	2
Sensitivity	0.216	3

Weighted sum model

$$A_i^{WSM-score} = \sum_{j=1}^{n} w_j p_{ij}, for i = 1, 2, 3 \ldots, m. \tag{5}$$

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

Z-score standardization

$$z = \frac{X - \mu}{\sigma} \tag{6}$$

A composite indicator for exposure was then created by summing the products of each exposure indicator and its weight. Next, a composite indicator for sensitivity was created by summing the products of each sensitivity indicator and its weight. The two composite indicators of exposure and sensitivity were then each multiplied by their respective component weights and summed together. The resultant composite indicator represents the combined exposure and sensitivity of the sample ports and was used to compile a composite index of seaport vulnerability (minus adaptive capacity) for the CENAD sample of ports based on publicly available data. The port-rankings generated by the composite index were then compared to the experts' subjective raking of port vulnerability obtained from the VAS survey.

3 Results

3.1 AHP-generated weights

The aggregation of judgements from the first level of the AHP, which weighted the three components of seaport vulnerability to climate and extreme weather, resulted in exposure ranked most important, with a ratio scale (weight) of 0.394 (Table 2). Adaptive capacity was ranked a close second, with a weight of 0.390, which is noteworthy since the component of adaptive capacity lacks expert-supported indicators. Sensitivity was ranked least important of the three components, with a weight of 0.216. For this node, the maximum consistency ratio, *CR,* was 0.1% (highly consistent) and the group consensus, *S*, was 50.1% (low).[13]

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

Indicator of exposure	Weight	Rank
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

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

Indicator of sensitivity	Weight	Rank
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

The second level of the AHP consisted of two nodes, the first evaluated six indicators for relative importance in terms of seaport exposure to climate and weather extremes, and the second node evaluated six indicators in terms of seaport sensitivity. The first node resulted in the indicator "number of disasters," ranked most important for the component of exposure with a weight of 0.200, and resulted in weights for the remaining indicators of exposure as shown in Table 3. For this node, the maximum consistency ratio, *CR,* was 0.3% (highly consistent) and the group consensus, *S*, was 53.6% (low).

The second node of the second AHP level resulted in the indicator "population inside floodplain," ranked most important for the component of sensitivity with a weight of 0.229, and resulted in the remaining indicators of sensitivity weighted as shown in Table 4. For this node, the maximum consistency ratio, *CR,* was 0.5% (highly consistent) and the group consensus, *S*, was 61.1% (low).

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

Table 5 Model-generated ranking of CENAD ports by vulnerability to climate and weather extremes

Port	Vulnerability score
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
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

Note that here, vulnerability includes exposure and sensitivity, but not adaptive capacity

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

3.2 Composite index of CENAD ports

To test the degree to which a ranking of ports by level of vulnerability to climate and extreme weather, created by a WSM using AHP-generated weights, would or would not resemble an a priori ranking generated[14] subjectively by the same participating experts, researchers compiled a composite index for the CENAD sample of ports. Applying the AHP-generated indicator weights to the z-score-standardized input variables for 22 CENAD ports, and aggregating them in a WSM yielded the following ranking (Table 5) where

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

Port	Experts' rank
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

a larger number corresponds to a higher degree of vulnerability. In Table 5, a score of zero represents the mean, a negative number represents a vulnerability score below the mean, and a positive number represents a vulnerability score above the mean.

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

One benefit of indicator-based composite indices is their ability to synthesize multiple variables into a single, measurable concept while still retaining the ability to explore the disaggregated substructure behind the composite construct. As such, their users are able to ask, "*Why* does a particular entity score high or low according to this index?" Fig. 7 shows the disaggregated substructure behind the composite 'vulnerability scores' of the three highest scoring ports from the composite index, in which the relative performance of a port can be explored in terms of the individual indicators. Similarly, Fig. 8 shows the disaggregated substructure for the three lowest scoring ports of the composite index.

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

[14] 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.

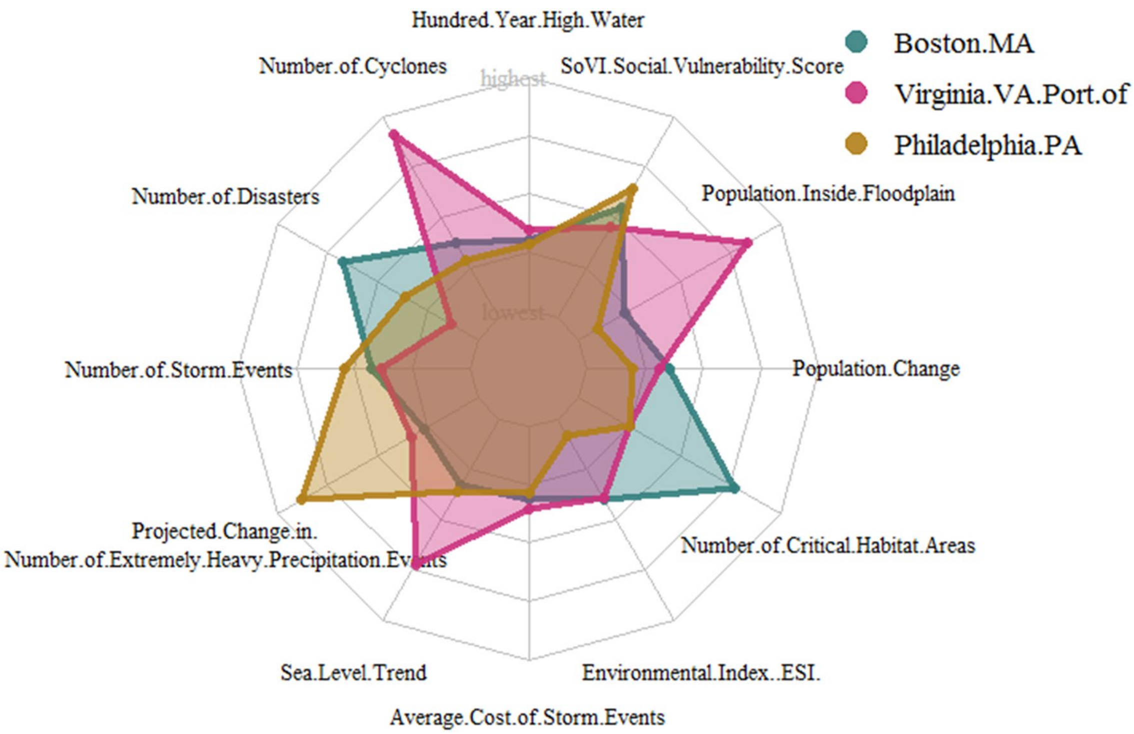

Fig. 7 Disaggregated substructure of the composite-index vulnerability scores of the three highest scoring ports. Indicators of exposure are shown on the left half of the plot, and indicators of sensitivity are shown on the right half

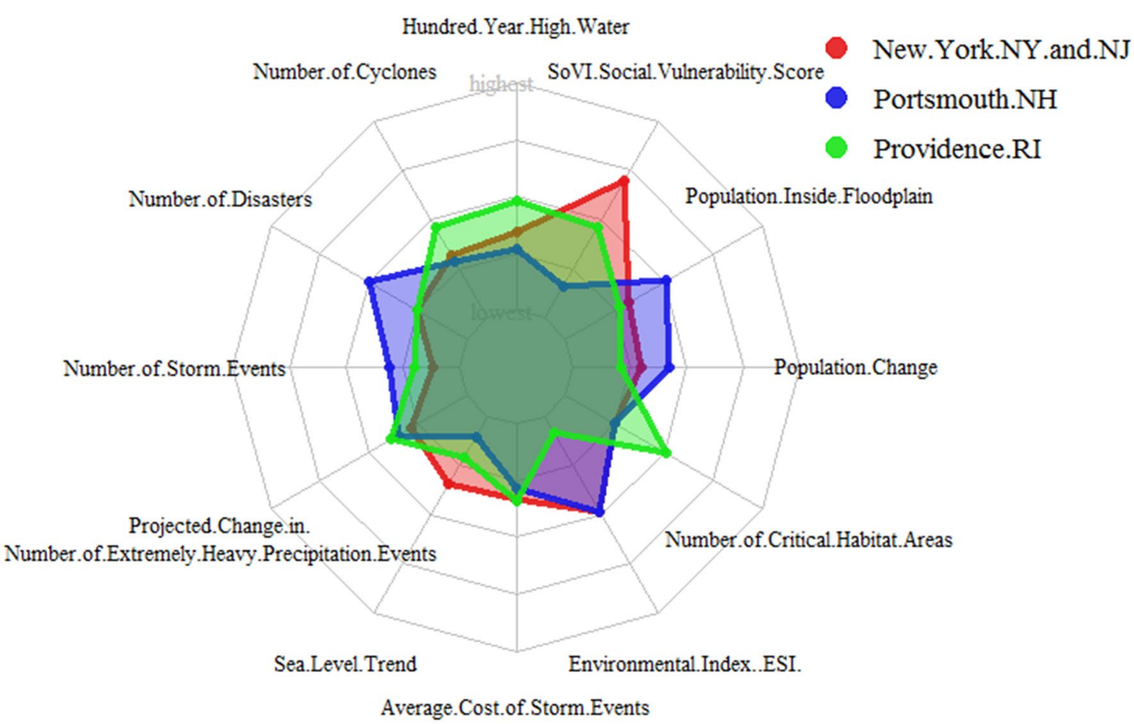

Fig. 8 Disaggregated substructure of the composite-index vulnerability scores of the three lowest scoring ports. Indicators of exposure are shown on the left half of the plot, and indicators of sensitivity are shown on the right half

Figure 8, showing the substructure of the three least vulnerable ports per the composite index, yields insight into the discrepancy between the index rankings and the subjective, expert-rankings. While the port of New York and New Jersey was considered second most vulnerable according to expert-perception, the weighted-index scored it second *least* vulnerable. Looking at Fig. 8, we can see that while the port of New York and New Jersey scored high (i.e., relatively more vulnerable) in the "SoVI social vulnerability score" indicator, it scored near the bottom of the sample in nearly every other indicator. This may be an artifact of the method of compiling the indicator data for the sample of ports. Most indicators were measured at the county-level, and while the port of New York and New Jersey spans multiple counties, for this experiment, the port of New York and New Jersey was represented solely by New York County. Similarly, the port of Providence was subjectively ranked sixth most vulnerable by port-experts yet scored least vulnerable of all in the composite index. Figure 8 reveals that while Providence scored near the middle of the sample for "number of critical habitat areas," "hundred year high water," and "number of cyclones," it scored near the bottom of the sample for "number of disasters," "number of storm events," and "environmental sensitivity index ESI," and did not score higher than average for any indicator.

4 Discussion

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

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

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

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

4.1 Adaptive capacity considered highly important

Adaptive capacity is defined in the glossary of the IPCC Fifth Assessment Report (IPCC 2014) as ' 'The ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences." As noted by Siders (Siders 2016), this definition bears some resemblance to generally accepted definitions of resilience, i.e., the ability to bounce back from an impact (McIntosh and Becker 2017; Linkov et al. 2014).

As such, Siders recommends that adaptive capacity can be distinguished from resilience by ascribing the latter to maintaining stability by "bouncing back" to pre-shock conditions, and by taking adaptive capacity, to refer to the broader ability of a system to self-organize, learn, and embrace change to limit future harms (Klein et al. 2003; Siders 2016).

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

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

4.2 Limitations

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

Though the aggregation of weighted indicators into a composite index was performed mainly as a means to validate the AHP-generated weights by comparing the port-rankings they produced via a WSM to a subjective port-ranking, the process also yielded insight into the benefits and limitations of such methods. As a means to identify relative outliers among a sample, this method showed promise by successfully matching the most vulnerable port and three of the four most vulnerable ports as ranked subjectively by port-experts. While partially successful at identifying the relative outliers among our sample of ports, the composite index also ranked several ports (e.g., Providence, New York and New Jersey) near the bottom of the sample that experts had subjectively ranked near the top. Some of this discrepancy may be due to the sensitivity of indicator-based composite indices to differences in the interpretation of data used for the indicators. For example, an indicator for an entity that spans multiple counties, like the port of New York and New Jersey, could be represented by a measure of central tendency of the data for the collection of counties, by the data from the county with most extreme value, or by a single representative county. In this experiment, the single county of New York was taken to represent the port of New York and New Jersey for the purposes of compiling the indicator data, which may have resulted in lower than expected values for that port in some of the indicators. Additionally, indicator-based assessments are always limited by the quality of data available to incorporate into them.

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

[15] 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.

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

5 Conclusion

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

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