

USGS NCASC Science to Action Fellowship

Science to Action Fellowship Completion Report
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**Mapping Estuarine Vulnerability to Water Quality Change Under Future Climate
and Land-Use Conditions**

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1. BACKGROUND

Estuaries, also called “nurseries of the sea” (USEPA, 1993), are unique ecosystems that provide ecological (e.g., species habitat), cultural (e.g., recreation), and economic (e.g., fisheries, tourism) benefits (Elliott and Whitfield, 2011). Freshwater inputs from upstream lands control estuarine health and functioning, resulting in estuaries reflecting the conditions of their contributing basins. Anthropogenically-driven local and global change (e.g., land-use and land cover change, climate change) threatens to alter the quantity and quality of riverine discharges to estuaries, thereby threatening these systems' ecological integrity. The National Research Council identified nutrient over-enrichment as one of the leading drivers of ecological degradation in nearshore environments (National Research Council, 2000). Surface water runoff is a critical mechanism by which nutrients are delivered to estuarine systems. By draining the different land-use types of the upstream estuarine watershed, runoff collects and transports nutrients to the downstream coastal ecosystems. Excess nutrients lead to hypoxic waters and algal blooms that can drive fish kills and seagrass die-off, resulting in the loss of essential habitat for numerous species. In the future, the combined effects of land-use and climate change will influence the runoff and nutrients characteristics of the coastal watersheds (IPPC, 2007).

Yet, despite the importance of freshwater quality as a key determinant of estuarine health, prior research on estuarine and coastal vulnerability (Allison et al., 2009; Blasiak et al., 2017; Jepson and Colburn, 2013; Pollnac et al., 2015; Colburn et al., 2016; Gornitz et al., 2016) has neglected the effects of land-based drivers in mediating the quantity and quality of estuarine freshwater inputs. Research is needed to address this knowledge gap, such as through the development of a new vulnerability assessment framework that accounts for freshwater quality conditions.

The IPCC defines vulnerability as: “the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change” (IPPC, 2007). Vulnerability is driven by three key dimensions: exposure (i.e., magnitude and extent of exposure to climate change and land-use impacts), sensitivity (i.e., responses of the system when exposed to climate and land-use induced stress), and adaptive capacity (i.e., potential ability and opportunities to decrease the effect of the exposure and sensitivity of the system). These three components can be either qualitatively or quantitatively assessed through the use of indicators defined as a single measure of a characteristic (e.g., projected changes in annual average precipitation under a climate change scenario could serve as an exposure metric).

The present project aimed to assess estuarine vulnerability to water quality change under future climate and land-use conditions and develop a national-scale, interactive, web-based application to facilitate data access and visualization of estuarine systems across the conterminous US.

2. METHODS

2.1. Area of study

The study encompassed 112 estuarine watersheds across five large regions of the United States (Figure 1): The North Atlantic (n = 38), South Atlantic (n = 19), Gulf of Mexico (n = 24), North Pacific (n = 20), and South Pacific (n = 11).

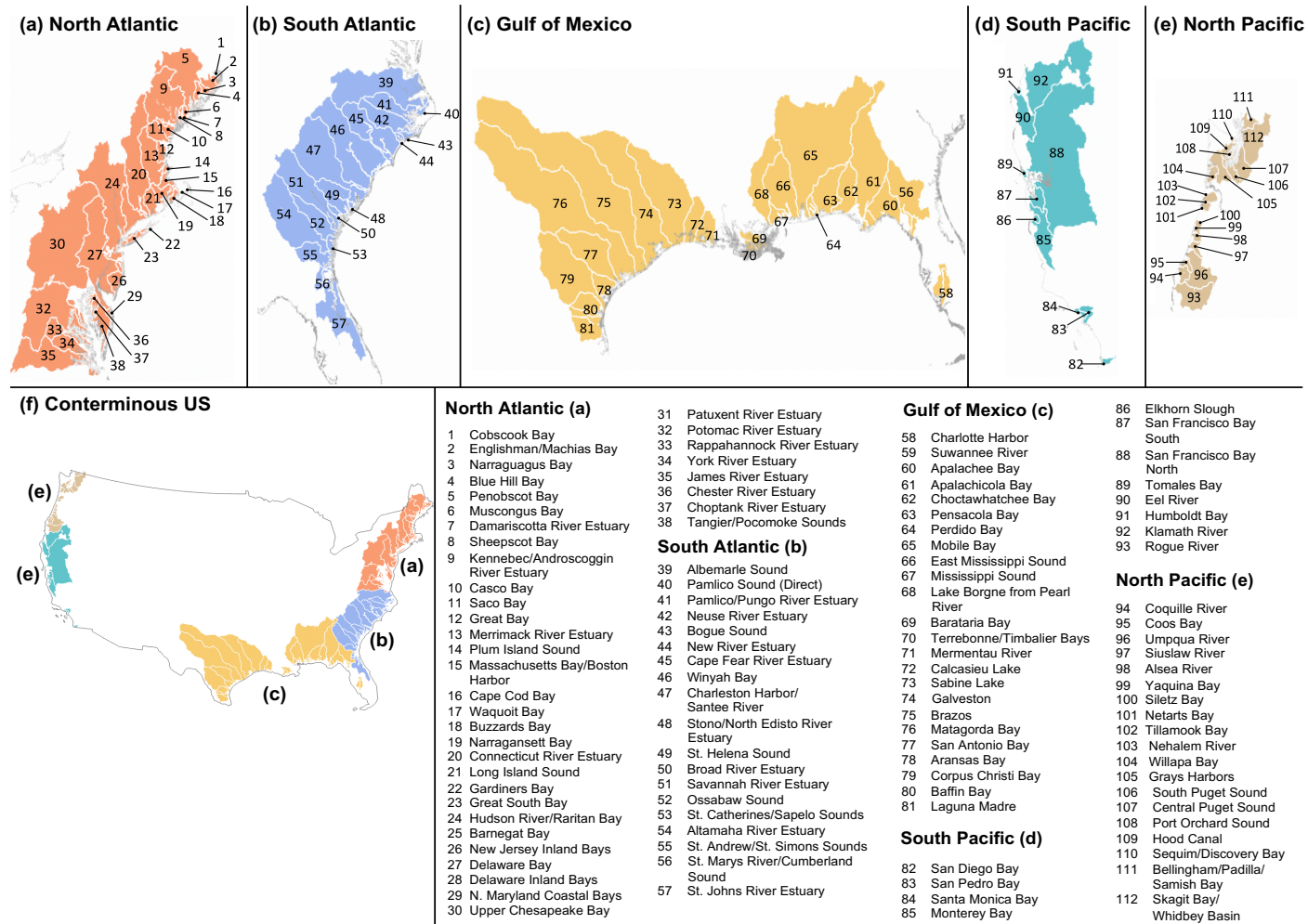


Figure 1. Watersheds studied in the vulnerability analysis (n = 112) from the (a) North Atlantic, (b) South Atlantic, (b) Gulf of Mexico, (d) South Pacific, and (e) North Pacific regions of the (f) conterminous US. The names associated with watershed ID numbers are shown in the bottom right panel. From Montefiore and Nelson (2022).

2.2. Construction of the vulnerability framework

The vulnerability assessment was developed using a well-established framework (Allison et al., 2009; Blasiak et al., 2017; Jepson and Colburn, 2013). Exposure, sensitivity, and adaptive capacity are the three main components of the vulnerability assessment (Figure 2). The vulnerability approach allows the use of indicators representing heterogeneous dimensions of the system's vulnerability (Table 1). Each indicator was re-rescaled from 0 to 1, with a score of 0 given to watersheds with the lowest value and a score of 1 given to those with the highest value.

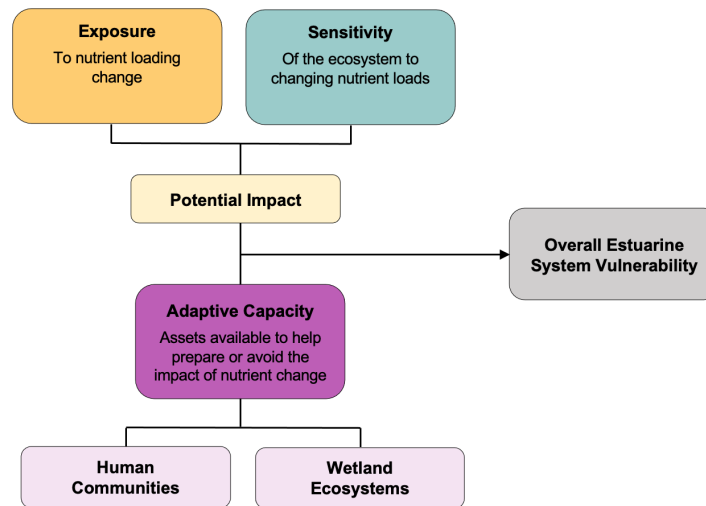


Figure 2. Vulnerability framework used in the analysis.

Table 1. Indices used in the vulnerability assessment.

Exposure	
<ul style="list-style-type: none"> • TN and TP loading change between the future (2035-2065) and historical (1990-2020) periods • Presence of upwelling currents 	
Sensitivity	
<ul style="list-style-type: none"> • Degree of eutrophication • Physical susceptibility to nutrient loading 	
Adaptive Capacity	
Human	Natural
<ul style="list-style-type: none"> • Local access to scientific knowledge <ul style="list-style-type: none"> - Number of peer-reviewed research articles - Number of academic staff in R1 and R2 universities - Long-term water quality monitoring stations • Legislative/governmental actions <ul style="list-style-type: none"> - Environmental state budget - Numeric water criteria - Climate adaptation planning 	<ul style="list-style-type: none"> • Wetlands proportions

2.2.1. Exposure assessment

For this assessment, exposure is defined as the magnitude and the spatiotemporal extent of change in water quality as a function of land-use and climate change. Many changes in water quality are expected, and notably, surface runoff that is strongly influenced by changes in precipitation. Several water quality models exist to simulate a wide range of water quality processes. For this project, we selected a lumped parameter model, the U.S. EPA Spreadsheet Tool for Estimating Pollutant Loads. This simple model can predict nutrient loading (e.g., TP and TN) based on runoff volume and runoff pollutant concentrations, where pollutant concentrations are determined as a function of precipitation and land-use patterns (Tetra Tech Inc, 2011). STEPL was previously tested and adapted to gridded data (STEPLgrid) (Montefiore and Nelson, 2022).

Model inputs included projected change in precipitation as predicted by twenty climate models (downscaled with the Multivariate Adaptive Constructed Analogs methods) (Abatzoglou and Brown, 2012) for the period of 2035-2065, as well as projected change in land-use as estimated by the FORE-SCE land-use model for the year 2050 (Sohl et al., 2007). Additionally, STEPLgrid was run for different combinations of climate scenarios (i.e., RCPs 4.5 and 8.5) and land-use scenarios (i.e., A1B, A2, B1, B2) to encompass different possible futures and account for uncertainty (i.e., eight land-use and climate scenarios combinations).

Average changes in TN and TP loads between the historical and future periods obtained from STEPLgrid were calculated annually ($\Delta_{TN,A}$ and $\Delta_{TP,A}$) (Equation 1). Δ_{TN} and Δ_{TP} were re-scaled from 0 to 1 for each nutrient using a linear relationship, where 0 represented estuarine watersheds with negative change (i.e., decreased nutrient loading under future climate and land-use scenarios) and 1 equated to watersheds with a positive change in nutrient loads equal to or greater than 200%.

$$\Delta_X = \frac{(\bar{X}_{Future} - \bar{X}_{Historical})}{\bar{X}_{Historical}} \times 100 \quad \text{Equation 1}$$

In Equation 1, X is either TN or TP, $\bar{X}_{Future,T}$ is the average TN or TP load or yield computed under projected climate and land-use scenarios from 2035-2065, and $\bar{X}_{Historical}$ is the average TN or TP load or yield computed under historical (1990-2020) climate and land-use conditions.

Besides the nutrient change, upwelling currents were also used in the vulnerability assessment. In some systems, upwelling can enrich coastal waters with nutrients (Small and Menzies, 1981). Upwelling zones and their degree of importance were mapped along the estuarine systems; scores were not calculated for this indicator.

2.2.2. *Sensitivity assessment*

Not all estuaries are sensitive to changes in nutrient loads. For some systems, small changes in nutrient loads can hugely disrupt ecological dynamics, whereas other systems can experience large fluctuations in nutrient loads with minimal impact. For example, estuarine systems that receive high nutrient loads and have high flushing rates (i.e., the amount of time it takes for an estuarine volume to be replaced) will be minimally susceptible to the effects of eutrophication despite having a large nutrient load. Two indicators were used to account for variation in sensitivity: the degree to which a system is (1) already eutrophic (Bricker et al., 2008) and (2) readily flushed or physically susceptible to increased nutrient loading (NOAA, 1989).

2.2.3. *Adaptive capacity assessment*

To represent a system's adaptive capacity, several indicators were considered in the analysis (Table 1) and grouped into two main categories: (1) human adaptive capacity and (2) natural adaptive capacity. The human and natural adaptive capacity categories were represented by scores ranging from 0 to 1, with 0 given to estuarine watersheds with low adaptive capacity (i.e., low ability to mitigate nutrient loading impact) and 1 to those with high adaptive capacity (i.e., high ability to mitigate nutrient loading impact).

2.2.3.1. Human adaptive capacity

A system's adaptive capacity is characterized by the system's ability to cope or adapt to change; a system with high adaptive capacity either has the ability to adapt or accommodate the combined effects of exposure and sensitivity. Adaptive capacity varies from system to system and region to region. Two main indicators were used: local access to scientific knowledge and legislative/governmental actions. Access to scientific knowledge allows decision-makers and environmental managers to implement science-based management strategies, while legislative and governmental actions already in place can support climate adaptation and eutrophication mitigation. Three sub-indicators were used to quantify a system's access to scientific knowledge: (1) the number of published peer-reviewed research articles related to climate change, nutrients, and eutrophication of the estuary, (2) the number of academic staff in research-intensive universities in the states where the watershed was located, and (3) the number of long-term monitoring stations present within the estuary and its watershed. Three other-sub indicators were used to quantify the legislative/governmental actions: (1) the existence of a climate adaptation plan, (2) the amount of the annual state budget dedicated to environmental and natural resources departments normalized by the area of the respective state, and (3) state adoption of numeric water quality parameter criteria.

2.2.3.2. Natural adaptive capacity

The natural adaptive capacity indicator was calculated as the density of wetlands per estuarine watershed and normalized by the surface area of each watershed. Values were linearly re-scaled from 0 to 1. The natural adaptive capacity score was not aggregated with the human adaptive capacity score.

2.3. Creation of the interactive web application

The web application was created using the statistical software R. The R packages Shiny and Shinydashboard packages (R Core Team, 2020) were used to build the web-based applications. The application was constructed in order to display the exposure, sensitivity, and adaptive capacity of the estuarine systems across the conterminous US. Exposure, sensitivity, and adaptive capacity were not aggregated together. For the adaptive capacity, the user can have the option to weigh the different indicators of the adaptive capacity.

3. RESULTS

The exposure, sensitivity, and adaptive capacity results are presented as a set of maps representing the overall estuarine vulnerability to water quality change under projected climate and land-use conditions.

3.1. Exposure

Under RCPs 4.5 and 8.5 and the four land-use scenarios, the median of Δ TN and Δ TP yields ranged from 0.14 to 0.30 and 0.30 and 0.60 for the conterminous US, respectively. Further, regional variability was observed. Watersheds in the North and South Atlantic and the eastern part of the Gulf of Mexico had the highest scores for Δ TN and Δ TP yields, while those in the North Pacific and western part of the Gulf of Mexico had the lowest scores under all climate and land-use scenarios. However, the North and South Pacific regions were associated with significant upwelling currents that could potentially contribute to an increase in nutrient inputs. In contrast, the other regions were less exposed to the upwelling effect.

3.2. Sensitivity

Half of the estuarine systems studied (i.e., 54%) were considered susceptible to nitrogen loading. The regions associated with the greatest number of watersheds with a high physical susceptibility to nitrogen loading were the South Pacific (73%) and the North Atlantic (69%). 53%, 50%, and 40% of watersheds in the South Atlantic, Gulf of Mexico, and North Pacific had a high degree of physical susceptibility to nitrogen loading, respectively.

Further, 75% of the estuarine systems were considered susceptible to phosphorus loading. The region associated with the highest number of watersheds with a high physical susceptibility to phosphorus loading was the North Atlantic (83%), followed by the South Atlantic (76%), Gulf of Mexico (72%), South Pacific (73%), and North Pacific (60%).

3.3. Adaptive capacity

3.3.1. Human adaptive capacity

The South Pacific comprises estuarine watersheds with the highest human adaptive capacity scores, followed by the North Atlantic, for which legislative/governmental actions and access to knowledge contributed to higher adaptive capacity. In contrast,

the North Pacific and Gulf of Mexico regions had the lowest human adaptive capacity scores. Notably, the North Pacific sub-indicators indicated relatively low access to knowledge and few legislative/governmental actions that have been undertaken, though state climate adaptation plans were developed. The South Atlantic had intermediate scores but a strong spatial pattern where estuarine watersheds in the northern part of the region had higher human adaptive capacity than those in the southern part. For example, Florida had a high human adaptive capacity due to intensive research and strong legislative/governmental action, while estuarine watersheds in Texas had lower legislative/governmental action scores.

3.3.2. *Natural adaptive capacity*

High contrast in the natural adaptive capacity score is observed across the conterminous US. The North and South Pacific regions had the lowest wetland density per watershed. On the contrary, the South Atlantic region had the highest natural adaptive capacity. The Gulf of Mexico and the North Atlantic regions had heterogeneous results. Estuaries located in the western part of the Gulf of Mexico had a lower natural adaptive capacity than the region's eastern part.

4. WEB-BASED APPLICATION FRAMEWORK

The web-based application is composed of four menu items named:

- “Background”: This section provides an overview of the vulnerability framework and the different indicators used. Further, the watersheds and the different regions are displayed (Figure S1).
- “Exposure”: This section displays the exposure results of the vulnerability assessment for TN and TP. The user can select the land-use and climate combination score of its choice. (Figure S2)
- “Sensitivity”: This section presents the sensitivity results for TN and TP. (Figure S3)
- “Adaptive Capacity”: This section displays two maps: one for the human adaptive capacity, and a second one for the natural adaptive capacity (Figures S4-5). Furthermore, the web-based application offers some flexibility and allows the user to weigh the sub-indicators and indicators of the human adaptive capacity.

Further, for each component of the vulnerability framework, the user can download the data in the tabular or shapefile format.

5. EXPERIENCE AS A SCIENCE TO ACTION FELLOW

Due to COVID-19, I could not visit the NECASC in Amherst, MA during the summer 2019. However, my mentor, Michelle Staudinger, involved me in several meetings to retrieve an experience from the Science to Action Fellowship. I attended several meetings and workshops that guided me through the process of developing the vulnerability assessment and the web-based application framework. The meetings and workshops were the following:

- Coastal Salinity Index Webinar (USGS)
- Coastal Threshold workshop (USGS)
- Vulnerability assessment meeting with NOAA scientists

- Monthly CASC Fish Meeting (USGS)
- Fall Northeast Climate Adaptation Science Center Fellow program
- Structured Decision Making: Decision Analysis for Natural Resource Management (USGS/Florida International University)
- Interactive Web-Based Visualizations and Decision Support Tools in Shiny/R for Quantitative Scientists workshop (SESYNC/University of Florida).

I was able to learn from the experience of other scientists who developed different vulnerability frameworks and web-based applications at different stages. I received valuable feedback from my committee and the people I engaged with to create the web-based application. The Science to Actions Fellowship helped broaden my research and potential applications, which would not have been possible otherwise.

My advice for future fellows is to identify pitfalls that might happen in your project and evaluate how you could remedy them before starting your project. Also, prospective fellows should be realistic about what they can accomplish during the fellowship year. In my case, I encountered several computation issues that delayed the project for several months.

To conclude, the Science to Action Fellowship was a rich and valuable experience where I could foster stakeholder engagement and help translate my research data into a tangible and actionable tool.

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Supplementary Figures

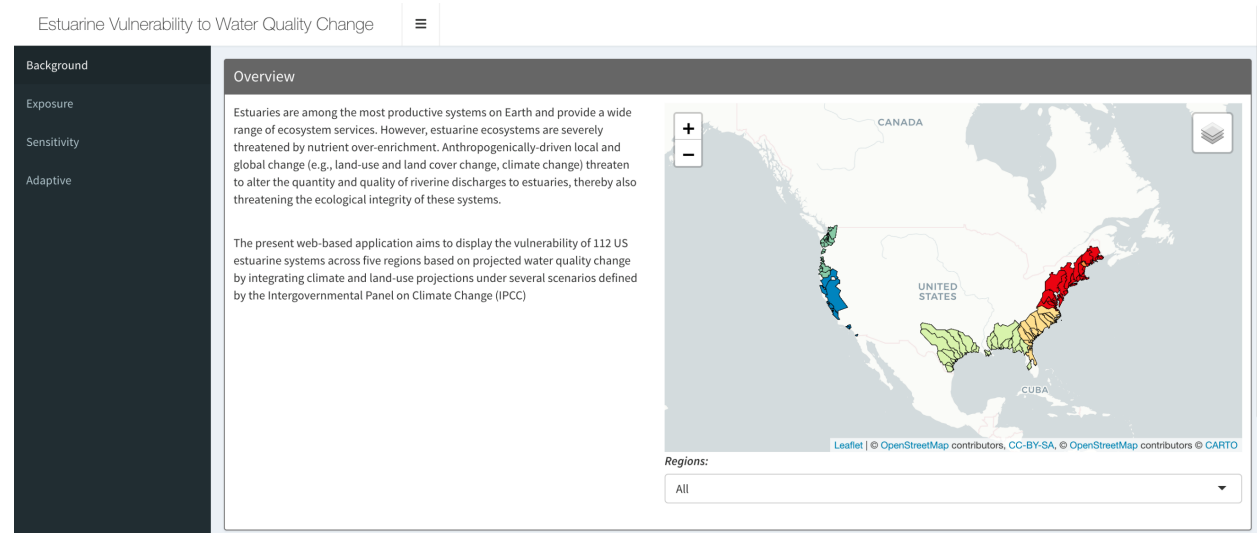


Figure S1: Background page of the web-based application. This page aims to give an overview of the vulnerability framework and the motivation behind it. The content introduces about the exposure, sensitivity, and adaptive capacity.

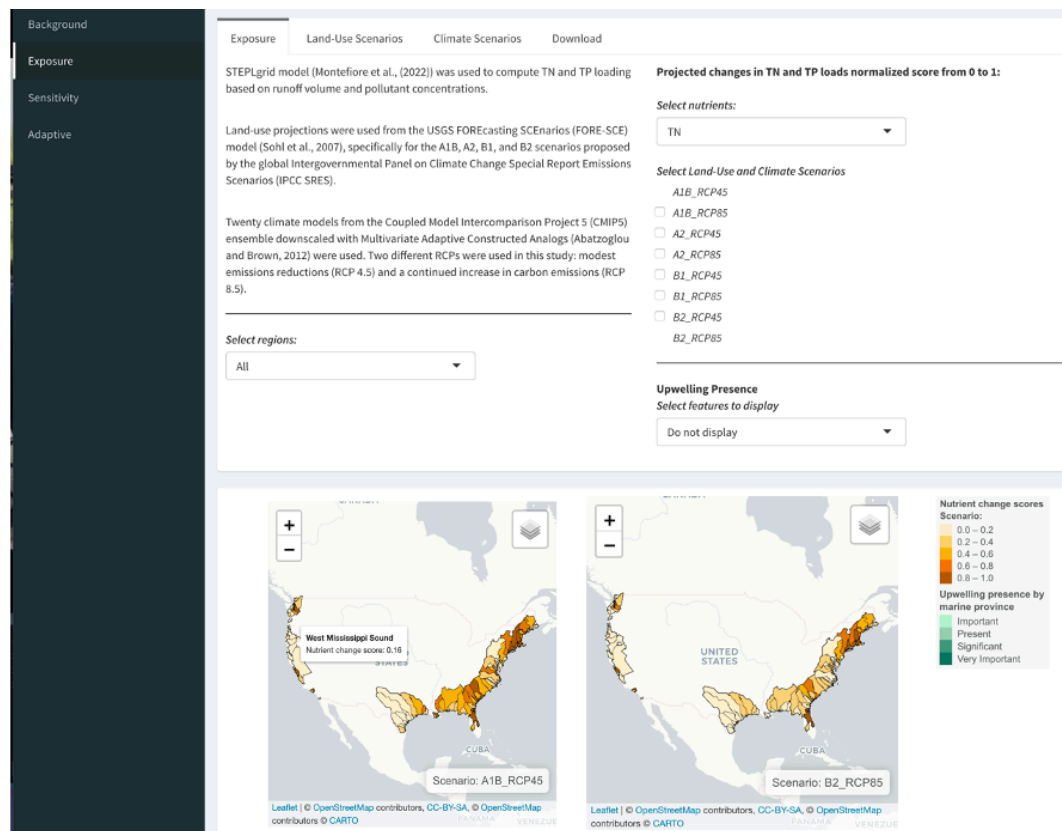


Figure S2: Exposure menu item. This page allows the user to display the nutrient load change score of its choice (i.e., TN or TP). Further the user can choose to display from one to eight maps based on the land-use and climate scenarios.

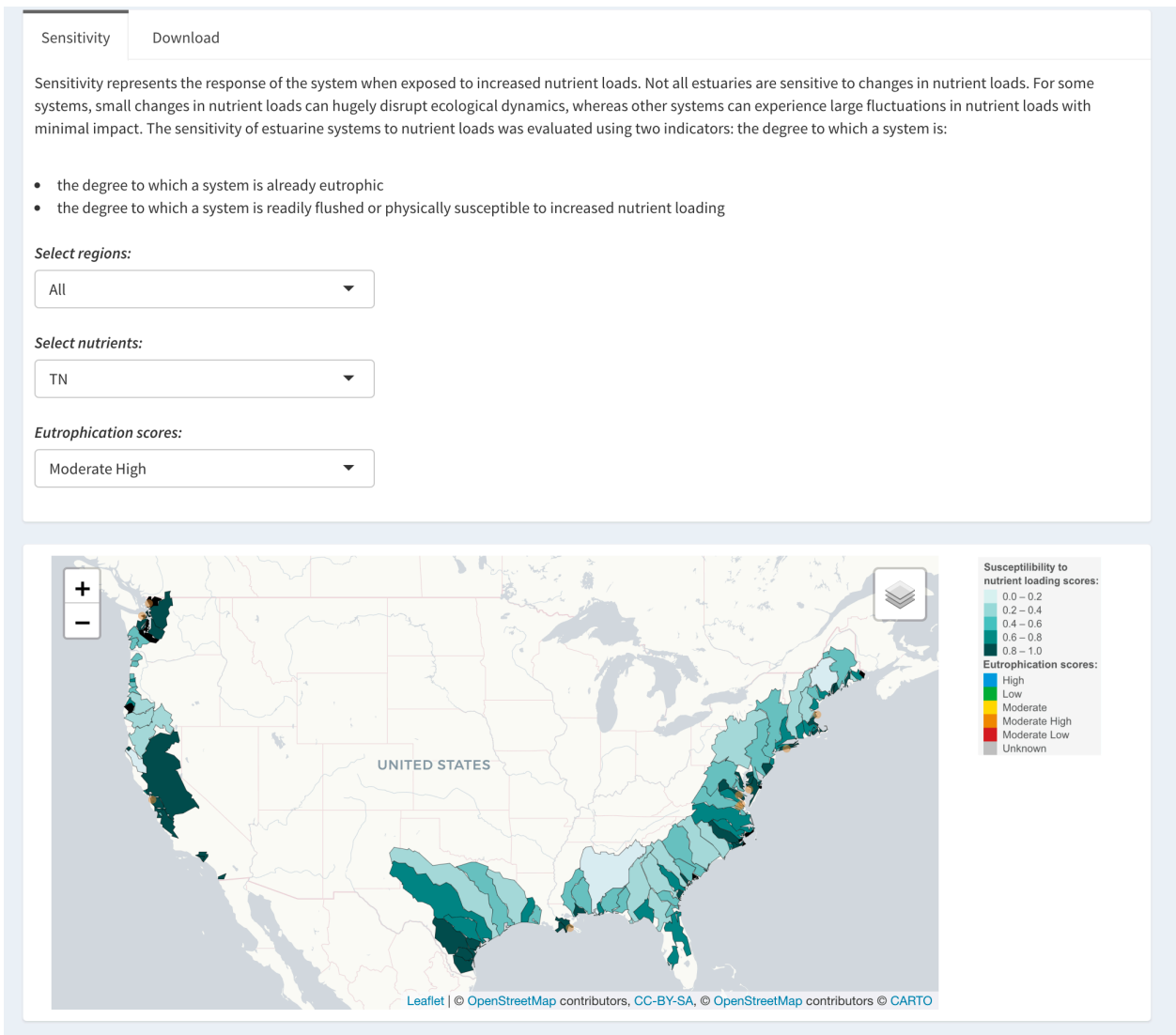


Figure S3: Sensitivity menu item. The user can select the nutrient of its choice, the eutrophic status, and the region.

Adaptive Capacity
Download

Adaptive Capacity is composed of the human adaptive capacity and the natural adaptive capacity. The natural adaptive capacity score was not aggregated with the human adaptive capacity score.

Estuarine systems with a high adaptive capacity score have a better ability and resources available to either reduce their exposure or alleviate their sensitivity.

Regions of interest

Select regions:

All

Human Adaptive Capacity

The Human Adaptive Capacity is composed of two indicators:

- Access to Scientific Knowledge
- Legislative/Governmental Actions.

Each of these indicators are composed of several sub-indicators. The user has the choice to weight each sub-indicator and indicator, and to choose the normalization procedure for some sub-indicators.

```

graph LR
    AC1a[Number of academic staff in R1 and R2 universities (AC1a)] -- weight --> AC1[Access to Scientific Knowledge (AC1)]
    AC1b[Number of peer-reviewed articles (AC1b)] -- weight --> AC1
    AC1c[Long-term monitoring information articles (AC1c)] -- weight --> AC1
    AC1 -- average --> AC1
    AC2a[Environmental state budget (AC2a)] -- weight --> AC2[Legislative/Governmental Actions (AC2)]
    AC2b[Numeric water quality criteria adoption (AC2b)] -- weight --> AC2
    AC2c[Climate adaptation planning (AC2c)] -- weight --> AC2
    AC2 -- average --> AC2
    AC1 -- weight --> HAC[Human Adaptive Capacity]
    AC2 -- weight --> HAC
    HAC -- average --> HAC
  
```

Step 1: Access to Scientific Knowledge (AC1):

AC1 is composed of 3 sub-indicators:

- Number of academic staff in R1 and R2 universities* (AC1a)
- Number of peer-reviewed articles (AC1b)

Human Adaptive Capacity

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Natural Adaptive Capacity

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Figure S4: Adaptive Capacity menu item. This page allows the user to display the human and natural adaptive capacity scores computed for each estuarine systems.

Step 1: Access to Scientific Knowledge (AC1):

AC1 is composed of 3 sub-indicators:

- Number of academic staff in R1 and R2 universities* (AC1a)
- Number of peer-reviewed articles (AC1b)
- Long-term monitoring information (AC1c)

*scores were re-scaled using an area-weighted average for watersheds that spanned several states

How to you want to normalize AC1a?

State population density

Do you want to weight the sub-indicators?

Yes No

(AC1a)	(AC1b)	(AC1c)
<input type="text" value="0.25"/>	<input type="text" value="0.25"/>	<input type="text" value="0.5"/>

Step 2: Legislative/Governmental Actions (AC2):

AC2 is composed of 3 sub-indicators:

- Environmental state budget* (AC2a)
- Numeric water quality criteria adoption* (AC2b)
- Climate adaptation planning* (AC2c)

*scores were re-scaled using an area-weighted average for watersheds that spanned several states

How to you want to normalize AC2a?

State population density

Do you want to weight the sub-indicators?

Yes No

(AC2a)	(AC2b)	(AC2c)
<input type="text" value="0.25"/>	<input type="text" value="0.25"/>	<input type="text" value="0.5"/>

Step 3: Overall Human Adaptive Capacity:

Human Adaptive Capacity is composed of the two indicators AC1 and AC2

Do you want to weight the two indicators?

Yes No

AC1	(AC2)
<input type="text" value="0.25"/>	<input type="text" value="0.75"/>

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Figure S5: Weighting option of the human adaptive capacity. The user has the option to weigh (from 0 to 1) the different indicators.