Using Prior Knowledge to Inform Future Restoration Activities in the Gulf of Mexico

Introduction

Despite considerable investments over the last four decades in coastal and estuarine ecosystem restoration (Diefenderfer et al. 2016) these efforts continue to face many challenges that threaten to impede their success. In the Gulf of Mexico, chronic and discrete drivers contribute to the difficulty in restoring and managing coastal ecosystems. For example, the synergistic effects of widespread chronic coastal urbanization and climate change impacts may limit habitat management effectiveness in the future (Enwright et al. 2016). Competing management and policy directives for flood protection, national commerce and energy development complicate and prolong efforts to abate coastal hypoxia and other water quality issues (Rabotyagov et al. 2014; OTHERS). Disputes surrounding fair and equitable natural resource allocation often result in contentious implementation plans for the long-term sustainability of coastal resources (GMFMC 2017). And, discrete tropical storm (Greening et al. 2006; MORE RECENT?) and large-scale pollution events (Beyer et al. 2016) often reset, reverse or delay progress in restoring coastal ecosystems. These factors create a complex environment for successful implementation of ecosystem restoration activities along the Gulf Coast.

Notwithstanding these challenges, the difficulty in rigorously monitoring and understanding an ecosystem's condition and restoration trajectory at various spatial and temporal scales further constrain a recognition of restoration success (Hobbs and Harris 2001). The lack of long-term environmental monitoring is a primary impediment to understanding pre- versus post- restoration change (Schiff et al. 2016) – let alone identifying whether prolonged management, policy and restoration activities have led to actual improvements in coastal ecosystems. Where long-term coastal monitoring programs have been implemented, a broader sense of how management, policy and restoration activities affect coastal ecosystem quality can be attained (Borja et al.

2015). Utilizing lessons-learned from environmental monitoring programs new frameworks are starting to emerge to better understand and facilitate the implementation of coastal restoration ecology from a more informed perspective (Bayraktarov et al. 2016; Diefenderfer et al. 2016).

A very large, comprehensive and concerted effort to restore Gulf of Mexico coastal ecosystems is currently underway (GCERC 2013, 2016). Primary funding for this effort stems from the legal settlements resulting from the 2010 Deepwater Horizon oil spill. Funding sources include: early restoration investments that were made immediately following the spill, resource damage assessments resulting from the spill's impact (NRDA, 2016), a record legal settlement of civil and criminal penalties negotiated between the responsible parties and the US government with strict US congressional oversight (RESTORE Act), and matching funds from research, monitoring and restoration practitioners worldwide. These funds, equating to >$20B US, present the Gulf of Mexico community an unprecedented opportunity to revitalize regional restoration efforts that will span multiple generations (GCERC 2013, 2016). Consequently, the restoration investments being made with these funds will be highly scrutinized. Better understanding the environmental outcomes of past investments will facilitate where and when future resources are implemented to have the highest likelihood of achieving restoration success.

Because of the difficulties in demonstrating restoration success, new tools are needed to help guide and support the implementation of Gulf of Mexico restoration activities. Here, we present an empirical framework for evaluating the success of investments in water quality improvement activities to assign a probabilistic expectation of water quality benefits. The framework synthesizes monitoring data across spatiotemporal scales to demonstrate how the cumulative effects of coastal restoration activities could improve water quality in an estuary. Data on water quality and restoration projects in the Tampa Bay area (Florida, USA) were used to demonstrate application of the analysis framework. Tampa Bay is the second largest estuary in the Gulf of Mexico and has been intensively monitored since the mid-1970s. The ecological context of water quality changes in the Bay is well-described and a comprehensive history of restoration projects occurring in the watershed is available, making Tampa Bay an ideal test case for demonstrating the evaluation framework. The water quality and restoration data were evaluated to identify 1) types of restoration projects that produce the greatest improvements in water quality, and 2) which time frames and synergistic effects of projects are most relevant for having the largest perceived benefits. Changes in chlorophyll concentrations as a proxy of eutrophication were used to develop expectations of water quality changes from restoration activities. The final product is a decision support tool to evaluate alternative scenarios of restoration implementation strategies.

Methods

Study area

Tampa Bay is located on the western coast of Florida and its watershed is one of the most highly developed regions in Florida (fig. 1). More than 60 percent of land within 15 km of the Bay shoreline is a mix of urban and suburban uses (SWFWD 2011). The Bay has been a focal point of economic activity since the 1950s and currently supports a mix of industrial, domestic, and recreational activities. The watershed includes one of the largest phosphate production regions in the country, which is supported by port operations primarily in the northeast portion of the Bay (H. Greening and Janicki 2006). Water quality data have been collected since the 1970s when environmental conditions were highly degraded. Nitrogen loads into the Bay in the mid-1970s have been estimated as 8.2 x 106 kg year-1, most of which came from untreated wastewater effluent. In addition to reduced aesthetics, environmental conditions associated with hyper-eutrophy were common and included elevated chlorophyll concentrations, increased occurrence of harmful algal species, low concentrations of bottom water dissolved oxygen, low water clarity, reduced seagrass coverage, and declines in fishery yields for both sport and recreational species. Advanced wastewater treatment operations were implemented at municipal plants by the early 1980s. These efforts were successful in reducing nutrients loads to the Bay by 90%.

Current water quality in Tampa Bay is dramatically improved from historical conditions. Most notably, seagrass coverage in 2016 was reported as 16,785 hectares baywide, surpassing the restoration goal of coverage in the 1950s (E. T. Sherwood et al. 2017). These changes have occured in parallel with reductions in nutrient loading (Poe et al. 2005; H. Greening and Janicki 2006), chlorophyll concentrations (Wang, Martin, and

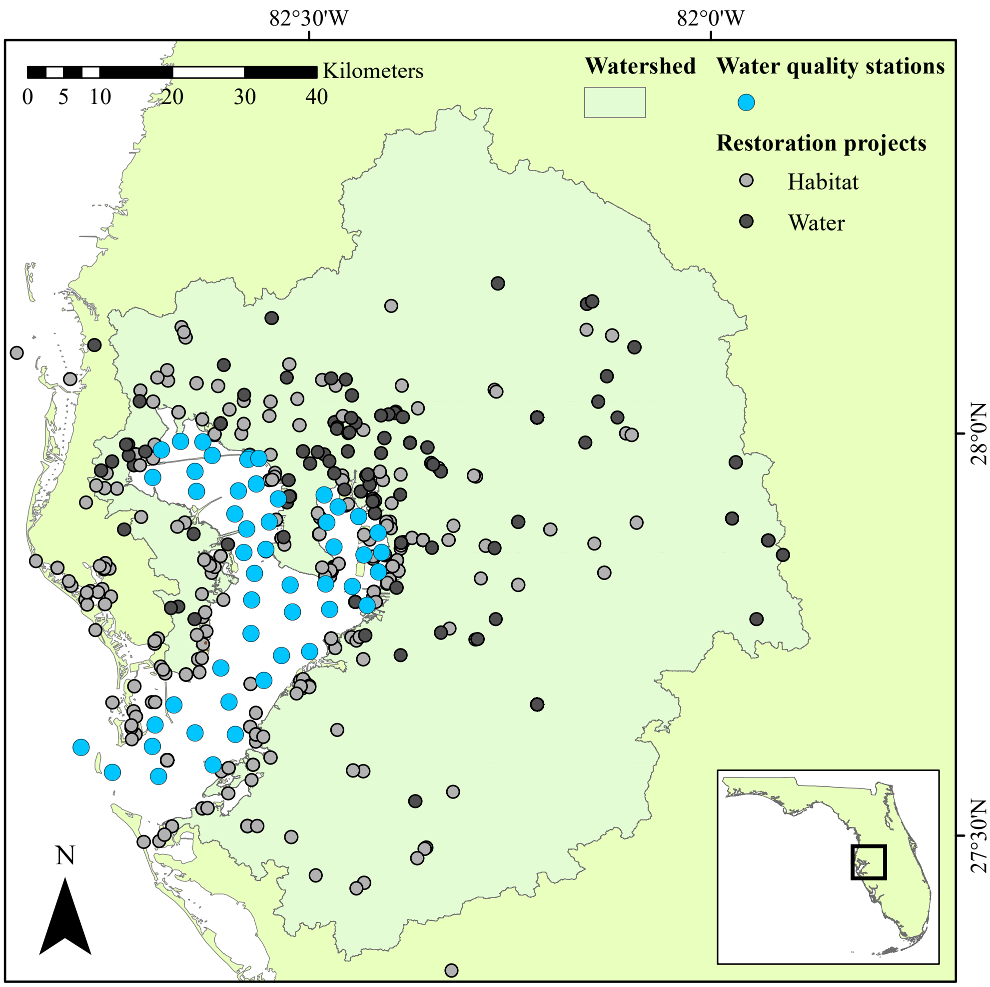

Figure 1: Water quality stations and restoration projects in the Tampa Bay area. Water qualtiy stations have been monitored monthly since 1974. Locations of restoration projects represent 571 records of habitat or water infrastructure projects from 1971 to present.

Morrison 1999; Beck and Hagy III 2015), and improvements in water clarity (Morrison et al. 2006; Beck, Hagy III, and Le 2017). Most of these positive changes have resulted from management efforts to reduct point source controls on nutrient pollution in the highly developed areas of Hillsborough Bay (Johansson 1991; Johansson and Lewis III 1992). However, the cumulative impacts of over 500 additional management activities have likely also contributed to improvements in water quality over time. Several hundred projects from both public and private entities have been completed since the 1980s. These projects represent numerous voluntary (e.g., habitat acquisition, restoration, watershed retention, etc.) and compliance-driven (e.g., site-level permitting, power plant scrubber upgrades, etc.) activities. Although it is generally recognized that these projects have contributed to overall Bay improvements, the cumulative effects relative to large-scale management efforts are not well understood. Understanding the impacts within relevant spatial boundaries and how these projects have jointly contributed to changes over time will provide an improved understanding of the link between Bay improvements and restoration activities.

Data sources

In addition to legacy improvements at wastewater treatment plants, over 500 restoration projects have been documented in the Tampa Bay area since 1971. Two databases were synthesized to provide a comprehensive history of projects that have occurred in Tampa Bay and its watershed. The first dataset was obtained from the Tampa Bay Water Atlas (version 2.3, http://maps.wateratlas.usf.edu/tampabay/, TBEP (Tampa Bay Estuary Program) (2017)) maintained as a joint resource by the University of South Florida and the Tampa Bay Estuary Program (TBEP). This database included 253 projects from 1971 to 2007 that were primarily focused on habitat establishment, restoration, or protection in the nearshore areas of the Bay or the larger watershed (e.g., planting of *Spartina alterniflora*, exotic vegetation control, etc.). The database was limited to basic information, such as year of completion, geographic coordinates, general activities, and areal coverage. The second database was obtained from the TBEP Action Plan Database Portal (https://apdb.tbeptech.org/index.php) to describe locations of infrastructure improvement projects. This database included 334 projects from 1992 to 2016 for county or municipal activities, such as implementation of best management practices at treatment plants, creation of stormwater retention or treatment controls, or site-specific controls of point sources.

Both project data sources were combined to provide a single dataset describing the location, year of completion, and project classification. The project classifications were described in two nested categories. The first described a high-level classification for each project as habitat or water infrastructure. The second was a lower-level classification for habitat projects as enhancement, establishment, and protection and water infrastructure projects as non-point source or point source controls. These categories were used to provide a broad characterization of restoration activites that were considered relevant for the perceived improvements in water quality over time. The nested categories were used to develop separate probabilistic models describing the likelihood of changes in water quality (described below). The final combined dataset included 571 projects from 1971 to 2016. Projects with incomplete information (i.e., missing date) were not included in the final dataset.

Water quality data in Tampa Bay have been consistently collected since 1974 by the Hillsborough County Environmental Protection Commission (TBEP (Tampa Bay Estuary Program) 2017). Data were collected monthly at forty-five stations using a water sample from mid-depth or a monitoring sonde depending on the parameter. Monitoring stations are fixed in a grid covering the entire bay from the northern oligohaline sections to the opening with the Gulf of Mexico. Water samples at each station are processed immediately after collection. Measurements at each site include temperature (C), secchi depth (m), dissolved oyxgen (mg/L), conductivity (μOhms/cm), pH, salinity (psu), turbidity (Nephalometric Turbidy Units), chlorophyll *a* (chl-*a*) (μg/L), total nitrogen (mg/L), and total phosphorus (mg/L). For the probabilistic models, all measurements of salinity, total nitrogen, and chl-*a* were combined for a total of 515 monthly observations of each parameter at each station.

Data synthesis and analysis framework

Combining the restoration and water quality datasets was a critical part of developing the analysis framework. Each dataset described events or sampling activities with unique dates and locations and simple pairing of restoration projects with water quality data was impractical. To address this challenge, observations in each

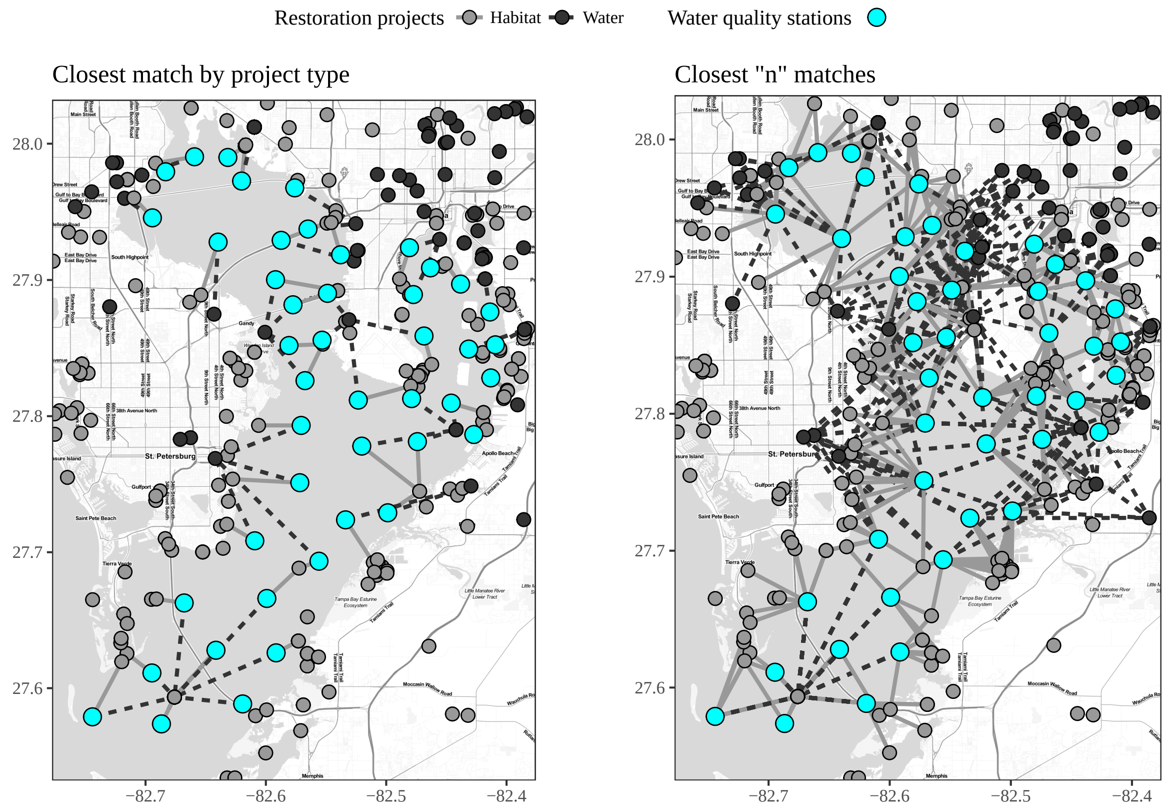

Figure 2: Spatial matching of water quality stations with restoration projects. Spatial matches of each water quality station with habitat (solid line) and water infrastucture (dashed line) projects are shown as the closest on the left and the "n" closest on the right. The matchings were repeated for the five restoration project types within the broader habitat and water categories.

dataset were spatially and temporally matched using an approach designed to maximize the potential of identifying a unique effect of the restoration projects on changes in water quality.

The matching between the two datasets began with a spatial join where the Euclidean distances between each water quality station and each restoration project were quantified. The spatial matches were used to create a ranking of project sites from each water quality station based on distance. The distances were also grouped by the five restoration project types (i.e., habitat protection, non-point source control, etc.) such that the closest n sites of a given project type could be identified for any water quality station (fig. 2). Temporal matching between water quality stations and restoration projects was obtained by subsetting the water quality data within a time window before and after the completion date of each spatially-matched restoration project (fig. 3). For the closest n restoration sites for each of five project types, two summarized water quality estimates were obtained to quantify a before and after effect of each project. Time windows that

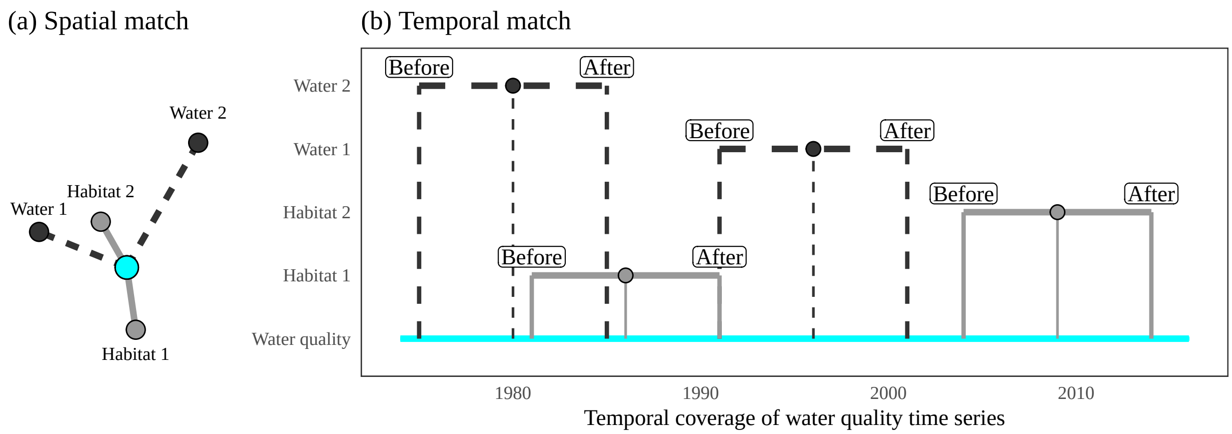

Figure 3: Temporal matching of restoration project types with time series data at a water quality station. The restoration project locations that are spatially matched with a water quality station (a) are used to create a temporal slice of the water quality data within a window of time before and after the completion date of each restoration project (b). Slices are based on the closest "n" restoration projects by type (n = 2 in this example) to a water quality station.

overlapped the start and end date of the water quality time series were discarded. The final two estimates of the before and after effects of the five types of restoration projects at each water quality station were based on an average of the n closest restoration sites, weighted inversely by distance from the monitoring station.

Change in water quality relative to each type of restoration project was estimated as:

$$\delta WQ = \frac{\sum_{i=1}^{n} \hat{wq} \in win + proj_{i,dt}}{n \cdot dist_{i \in n}} - \frac{\sum_{i=1}^{n} \hat{wq} \in proj_{i,dt} - win}{n \cdot dist_{i \in n}} \tag{1}$$

where δWQ was the difference between the after and before averages for each of n spatially matched restoration projects. For each i of n projects ($proj$), the average water quality ($\hat{wq}$) within the window (win) either before ($proj_{i,dt} - win$) or after ($win + proj_{i,dt}$) the completion date (dt) for project i was summed. The summation of water quality before and after each project was then divided by the total number of n matched projects, muliplied the distance of the projects from a water quality station ($dist_{i \in n}$). This created a weighted average of the before/after effects of each project that was inversely related to the distance from a water quality station. A weighted average by distance was used based on the assumption that restoration projects farther from a water quality station will have a weaker signal. The total change in water quaility for a project type was simply the difference in weighted averages.

The combined water quality and restoration data were used as input for developing the probabilistic models. Two parameters in eq. (1) affected the synthesis of the datasets which directly controlled the ability to identify an effect of each restoration project type, 1) n, the number of spatially-matched restoration projects used to average the cumulative effect of each project type, and 2) win, the time windows before and after a project completion date that were used to subset each water quality time series. Identifying the two values that maximized the difference between before and after water quality measurements was necessary to quantify how many projects induced a change in water quality, the time within which a change is expected, and the magnitude of a change differed between project types.

Bayesian network, simple models pre/post, large model whole record.

Results

Discussion

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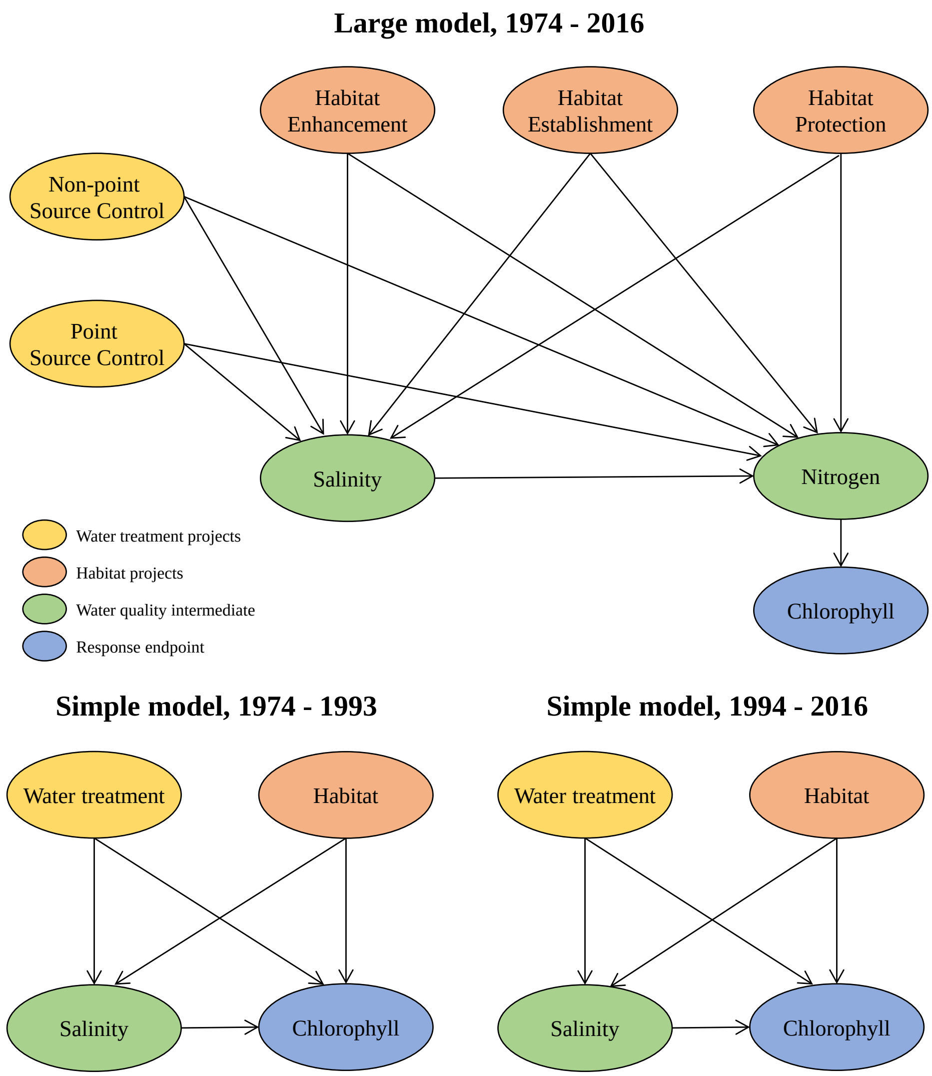

Figure 4: Networks developed with Bayesian models showing a large model (top) using the complete time series from 1994 - 2016 and two simple models (bottom) for 1974 - 1993 and 1994 - 2016. Inputs to each network are water treatment and habitat restoration projects. Intermediate nodes in the network are salinity and/or nitrogen depending on the model. Chlorophyll is the terminal response endpoint for water quality in each model.

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